Nature-based solution evaluation indicators: Environmental Indicators Review

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DOCUMENT PROPERTIES

Nature Document	Report comprising reviews of core and recommended evaluation indicators for evaluating the benefits, co-benefits, and trade-offs associated with nature-based solution indicators. Review comprises those indicators selected within the Connecting Nature WP1 indicators scoping co-production exercise carried out in collaboration with front-runner cities: Genk, Glasgow and Poznań.
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Contents

1. Background

Nature-based solutions (NBS) are living solutions inspired and supported by nature that simultaneously provide environmental, social and economic benefits and help to build resilience. These solutions bring more nature and natural features and processes into cities, landscapes and seascapes, through locally adapted, resource-efficient and systemic interventions. The idea of nature-based solutions has emerged as both a challenge and an opportunity to assist urban communities in the transition to greater sustainability and adaptation to climate change.

Nature-based solutions represent a complex problem for many city-makers, with barriers (capacity related, lack of understanding/policy, organisational, and pressures) still standing in the way of city-wide implementation. The EU H2020 project Connecting Nature recognises that cities globally hold much of the expertise and experience necessary to unlock these barriers. Individually, cities have been experimenting and testing countless site-specific solutions and strategies (from micro- to macro-scale) over the decades that continue to be living examples of effective urban transition strategies. The results and learning from these experiments represent a substantial pool of knowledge in relation to breaking down these barriers. However, much of this learning has been focused on long-established fields of evaluation. If Nature-based solutions are to become mainstreamed, unlocking up-scaling and out-scaling processes, then there is a need for a more holistic evaluation framework for understanding their benefits, co-benefits, and dis-benefits, so that informed cost-benefit decisions can be made. Connecting Nature's ambition is to provide a comprehensive suite of evaluation indicators from which stakeholders involved in nature-based solution planning, delivery and stewardship can select and implement. By doing so, it will create a mechanism to support all cities through this process of up-scaling and out-scaling nature-based solutions.

With this overarching aim in mind, Connecting Nature identified three cities with a track record in delivering nature-based solutions projects. These cities were selected as:

- being representative of the range of scales of cities found across Europe and beyond;
- holding leading expertise in specific aspects of nature-based solution delivery and, between them, covering a range of aspects of NBS delivery
- facing a range of economic, environmental and social challenges that were typical of current global patterns.

The three cities, termed Front Runner Cities (FRCs), selected were Genk (Belgium), Glasgow (Scotland) and Poznań (Poland). Throughout the CONNECTING Nature project, these FRCs are working with the CONNECTING Nature consortium to unlock the barriers necessary to transition from their current status as nature-based solution experimenters to a status whereby nature-based solution planning, delivery and legacy management is interwoven and embedded into their economic, environmental and social city-making processes. The CONNECTING Nature team will be working with the FRCs to support this transition by co-developing the processes and strategies necessary to achieve this level of embedding of NBS. The successes and barriers in relation to achieving these aims will be shared between CONNECTING Nature cities and beyond through peer-to-peer learning.

One step along this developmental pathway was for the Connecting Nature consortium to develop, for the first time, a holistic list of evaluation indicators for nature-based solutions. This list covered the diverse benefits that nature-based solutions can provide under the themes of environmental (Table 1), economic, social, and health & wellbeing benefits. Following this, the Connecting Nature review research leads worked collaboratively with each FRC's Connecting Nature team to better understand each city's priorities in relation to nature-based solution evaluation. This included consideration with city strategic objectives, alignment with United Nations Sustainable Development Goals, relevance to past nature-based solution initiatives in the city, and drivers for the nature-based solution exemplar being developed within the Connecting Nature project. Full details on the methodologies and results of the holistic lists and city scoping process can be found in Connecting Nature Deliverable 1 [*Dumitru, A, et al. (2019) Deliverable 1.1 - Report on the contributions of Tasks 1.1 to 1.4: Report on the outcomes of Task 1.1 (database), 1.2 (map), 1.3 (outcomes of the workshop), and 1.4 (organizational processes and criteria). Deliverable Report produced for the European Commission*]. The process provided a scoping mechanism that reduced the complete list of evaluation indicators for nature-based solutions to three categories of indicator:

i) *Core Indicators* – those indicators which are considered relevant to all nature-based solutions;

ii) *Feature Indicators* – those indicators which had strong relevance to the cities nature-based solution priorities but were not necessarily relevant in all cases

iii) *Other Indicators* – the remaining indicators that were not priorities of the cities but that might have relevance for some nature-based solution projects.

In order to support the Front-runner Cities in operationalising these indicators on their exemplar projects, a review was carried out to provide context in terms of the rationale and practicalities of implementing the indicators. For the Impact Category – Environmental Indicators, this review was carried out for all identified Core and Feature Indicators.

This report represents a compendium of all of the reviews for Environmental Indicators. Each review will also be uploaded to the Connecting Nature website to ensure Open Access to all Connecting Nature Front-runner Cities, Fast Follower Cities and Multiplier Cities, and, ultimately, for any stakeholder considering implementing and evaluating nature-based solutions in cities. The Connecting Nature Cities will then be provided with support by the authors of the reviews, and other Connecting Nature consortium partners, to implement these evaluation indicators on their nature-based solution exemplars.

In addition to these resources, Connecting Nature Reviews are also being included in an EU Guidebook to support all cities in planning, delivering, and managing Nature-based Solution evaluation. This is being developed through a Clustering Initiative in partnership with all nature-based solution projects funded under the European Commission Horizon 2020 Research & Innovation funding programme.

Table 1. Full list of Environmental Indicators for Nature-based solutions

1. Carbon storage OR Carbon sequestration in vegetation/soil
2. Carbon sequestration rate by tree species
3. Air temperature change
4. CO2 emissions reduced
5. Energy savings
6. Climate resilience strategy
7. Albedo
8. Rainfall storage/absorption capacity of NBS
9. Flood peak reduction/delay
10. Reduction of drought risk
11. Increase groundwater availability

12. Groundwater quality
13. Water exploitation index
14. Drinking water (surface/ground)
15. Water quality
16. Increase evapotranspiration
17. Air Temperature – Energy demand
18. Reduction of stormwater treated in public sewerage system (economic benefit)
19. Inundation risk for critical urban infrastructures (probability-economic)
20. Flood damage (economic)
21. Water consumption
22. Increase greywater and rainwater reuse
23. Public green space distribution
24. Recreational value of blue-green spaces
25. Cultural value of blue-green spaces
26. Community accessibility
27. Connectivity of urban green and blue spaces (structural and functional)
28. Ecological connectivity (general)
29. Supporting/increasing biodiversity conservation
30. Increase in pollinators (habitat)
31. Increase in pollinators (abundance of pollinators)
32. Urban forest pattern
33. Urban tree health
34. Number of native species
35. Species diversity
36. Species under nature conservation designation
37. Introductions
38. Mapping ecosystem services and spatial-temporal biodiversity legacies
39. Ecological connectivity (Ecological connectivity Index)
40. Fragmentation
41. Accessibility of greenspaces
42. Land-use change and greenspace configuration
43. Ratio of open spaces to built form
44. Reclamation of contaminated land
45. Citizen access to public transport
46. Quality of public transport
47. Access to vehicle sharing
48. Access to public amenities
49. Length of bike route network
50. Land devoted to roads
51. Road density
52. Leapfrog development index
53. Linearity development index
54. Area for pedestrians
55. Green space area
56. Blue space area
57. Population density
58. Local food production
59. Cultivated crops
60. Urban sprawl
61. Intensity of land use
62. Land-use intensity
63. Landuse mix
64. Brownfield use
65. Annual amount of pollutants captured by vegetation
66. Air quality change
67. Share of emissions (air pollutants) captured/sequestered by vegetation
68. Pollutant fluxes per m2 per year
69. Value of air pollution reduction
70. Total monetary value of urban forests
71. Atmospheric pollutant flux
72. NOx emissions
73. Fine particulate matter emissions
74. Air quality index
75. Noise mitigation by vegetation
76. Increase portion of sky visible from the ground
77. Index of habitat types
78. Targeted habitats
79. Proportion of landscape not in intensive management
80. Reduction in pesticide use
81. Soil sealing
82. O2 production by vegetation
83. Light levels at night
84. Noise pollution reduction
85. Change in ecosystem service provision
86. Temperature increase/wind shelter
87. Use of organic fertilizers
88. Tree shade for local heat change
89. community garden area per capita and in a defined distance
90. community garden area per child capita and in a defined distance
91. % of protected areas (ecologically and/or culturally sensitive)
92. % of buildings with NBS adaptation
93. Habitats restored

2. NBS Environmental Indicator Reviews

The following section presents all of the nature-based solution indicator reviews for the Environmental ‘Core’ and ‘Feature’ Indicators. Due to the priority hierarchy of the indicators, separate reviews were carried out for Applied/Participatory Approaches and Earth Observation/Remote Sensing Approaches to each of the Core Indicators. For the Feature Indicators, these approaches were combined into a single review. This was to ensure the reviews were still accessible to the target audience for the more comprehensive reviews carried out for the Core indicators.

2.1 NBS Environmental Indicator Reviews – Core Indicators

Indicators identified as Core during the co-produced scoping process were:

- Air temperature change (Env03)
- Rainfall storage (water absorption capacity of NBS) (Env08)
- Flood peak reduction/delay (Env09)
- Water quality (Env15)
- Inundation risk for critical urban infrastructures (probability) (Env19)
- Public green space distribution (Env23)
- Recreational value of blue-green spaces (Env24)
- Cultural value of blue-green spaces (Env25)
- Connectivity of urban green and blue spaces (structural and functional) (Env27)
- Supporting/increasing biodiversity conservation (Env29)
- Species diversity (Env35)
- Land use change and greenspace configuration (Env42)
- Access to public amenities (Env48)
- Blue space area (Env56)
- Soil sealing (Env81)
- Change in ecosystem service provision (Env85)
- Community garden area per capita and in a defined distance (Env89)

The Applied/Participatory and Earth Observation/Remote Sensing reviews for each of these Indicators are presented below:

2.1.1 Air temperature change (Env03)

2.1.1.1 *Air temperature change (Env03) Applied/Participatory Review*

Umbrella: Temperature reduction

Indicator: Air temperature change

Code: Env03

Description: Measurement of the cooling effect of NbS by evapotranspiration and/or shading using applied methods

Metric(s): Metrics are based on changes in air temperature and can be employed on a range of scales. Typically, this is in relation to the scale of the NbS being implemented. For example, small-scale interventions would not be expected to have a quantifiable impact in terms of city-wide temperatures but might provide local benefits in terms of providing an oasis from thermal stress for residents (impacting the urban canopy layer locally). As such, local scale monitoring metrics would be more appropriate. However, large-scale NbS projects, or city-wide replication of small-scale projects, might have a detectable impact at a city-wide scale (urban boundary layer).

It should be noted that, if NbS is poorly designed, leading to disruption of airflows, localised increases in air temperature could also be caused by NbS.

Basic measurements are typically carried out in relation to:

- Air temperature (how hot or cold the air is);
- Apparent temperature (is the temperature equivalent perceived by humans – based on air temperature, relative humidity and wind speed);
- Land surface temperature (the radiative skin temperature of the land derived from solar radiation);
- Thermal comfort - Physiological Equivalent Temperature (PET) (thermal perception of an individual including thermal physiology);

These temperature parameters are usually quantified in relation to specific thresholds:

- Decrease in mean/peak daytime local temperatures (in relation to mean radiant temperatures);
- Percentage change in annual/monthly temperatures (citywide);
- Heat stress (in Europe - exposure of people to temperatures >30°C);
- Heatwave risk (number of combined tropical nights (>20°C) and hot days (>35°C));
- Urban heat island (temperature difference between urban areas and surrounding rural landscapes).

For local measurements of air temperature, a variety of thermometers/thermocouples can be used, usually in combination with dataloggers. When using the most basic types of thermometers and thermocouples, it is important that they are kept shaded. If the equipment is exposed to direct solar radiation, it can heat them and the reading thus measures heating due to solar radiation rather than the true air temperature. To avoid this, thermometers/thermocouples need to be combined with some kind of insulation from solar radiation to ensure they are measuring air temperature (Yu and Hien 2006). An example of a very basic solution to this is the combination of datalogging thermocouples with polystyrene insulation to measure the air temperature above green roofs (Connop et al. 2013). By using networks of such insulated thermocouples, it is possible to measure temperature at increasing distances away from an NbS such as a living wall or park (Doick et al. 2014; Eisenberg et al 2015; Ottelé et al. 2017; Morakinyo et al. 2019).

For broader area measurements, standard practice for local temperature measurement involves the use of weather stations to monitor climatic parameters such as air temperature, windspeed, humidity. Such an approach is useful as it provides data on a wider range of temperature parameters in addition to air temperature, it also provides other climate parameters that can have synergies with other NbS indicators. Weather stations can range in size from off-the-shelf systems that have versatility in terms of installation location, to more accurate location-based monitoring, typically using a platinum resistance thermometer (*PRT*) inside a station fixed to the ground. The thermometer is exposed to air flow by natural ventilation through side louvers. This equipment includes a datalogger that takes readings at pre-programmed intervals to capture temperature changes for calculation of daily, monthly or annual temperature fluctuations (MET Office 2019).

Ambient air temperature quantification is commonly calculated using combined ventilated temperature and relative humidity sensors (Jänicke et al. 2014). Apparent air temperature, or the temperature equivalent perceived by people, is measured by Dry- and Wet-bulb temperatures. These are common parameters measured to assess the apparent temperature regulation associated with NbS implementation (Shashua-Bar et al. 2009; Fung and Jim 2017). Typically, values recorded are referenced to climatic data from a nearby meteorological station (Shashua-Bar et al. 2009).

Frequency or duration of exposure to heat stress is typically measured using Wet Bulb Globe Temperature (WBGT) heat stress meters. It is a measure of the heat stress in direct sunlight, combining temperature, humidity, wind speed, sun angle and cloud cover (solar radiation). These meters can be used to measure the effects of NbS on evapotranspiration/cooling in relation to how somebody would feel at different distances from an NbS.

Emerging approaches to thermal temperature analysis also include the use of thermal imaging cameras to measure air temperatures. Thermal cameras have previously been used to capture the impact of NbS interventions (Connop and Clough 2016; Ottelé et al. 2017), however this method generally captures a measure of surface temperature rather than air temperature. Surface temperature is assumed to correlate with air temperature as it is strongly affected by the mean radiant temperature (Matzarakis et al. 1999*), as such it should give a good indication of local human comfort. However, the magnitude of any cooling effect in relation to distance from the NbS will be correlated with the scale of the NbS in comparison to surrounding hard surfaces. This correlation makes assumptions on the impact of small-scale NbS on air temperatures unreliable for distances greater than a few centimetres from the NbS. However, methods for capturing air temperatures using thermal cameras are now being developed using white test sheets and foil (to estimate background radiation), and might have potential as a small-scale rapid method to measure local air temperatures (Chui et al. 2018).

Many studies investigating the performance of NbS combine the use of dataloggers with dynamic simulation tools for microclimate analysis (Toparlar et al. 2017). Such simulation enables potential cooling benefits of NbS interventions to be calculated at a planning stage (Zölch et al. 2019), and for NbS to be appraised compared to predicted values following installation (Chow et al. 2011). The software ENVI-met (Bruse and Fleer 1998) has emerged as the industry standard simulation technique with good results when compared to physical monitoring (Tsoka et al. 2018). However, there are limitations to the ENVI-met simulation results (Tsoka et al. 2018), with some evidence to suggest that its reliability decreases with decreasing NbS scale of NbS intervention (López-Cabeza et al. 2018).

For evaluation of larger-scale NbS interventions or city-wide impacts, surface temperature modelling approaches have generally been adopted (Rizwan et al. 2008; Hall et al. 2012; Li et al. 2018). Drones are also increasingly used to measure surface temperatures over large scales (Honjo et al 2017).

Networks of automatic weather stations have also been utilised to quantify urban heat islands over entire city scales (Yang et al. 2013).

Data on the reduction of air temperature by nature-based solutions collected in these ways can be used to:

- Quantify the benefits of NbS in terms of providing thermal comfort zones for residents;
- Quantify reduction in temperature extremes/heatwaves on a city-wide scale;
- Contribute towards health and well-being evaluation linked to temperature extremes.

Scientific solid evidence: Robustness of evidence depends upon the level of precision of the equipment, the spatial design of the monitoring and the duration of temperature recording. Generally direct measurement can provide greater confidence than microclimate simulations, particularly for small-scale interventions.

Level of expertise: Some expertise is required for the spatial design of the sampling and choice of instrumentation. Once installed though, basic measurements of air temperature associated data processing require little expertise. For more complex thermal parameters, analysis requires a greater level of expertise if equipment used does not process such data automatically. The ENVI-met microclimate analysis software requires some expertise to operate and collect the environmental data necessary. Once trained, however, data processing is relatively straightforward.

Cost: Can be low cost particularly if pre-existing weather stations can be used. If these are not available, cost is linked to the scale of monitoring and the complexity of equipment used. Basic digital thermometers and thermocouples are relatively cheap, cost increases when these are linked to dataloggers, but these additional costs are generally offset by decreased staff costs for data collection. Overall cost also tends to be linked to the level of precision of equipment and the number of sampling points. Costs can be reduced by participatory approaches that involve residents with mobile heat sensors (reducing staff costs), or temperature perception surveys of users (reducing equipment costs).

Effort: Automated in-site data gathering is very low effort, with installation, data analysis and equipment maintenance the only inputs required. The only onerous aspect can be the volume of data generated. If samples are taken manually, effort is related to frequency and number of measurements.

Participatory process: Opportunities are available for a participatory process, particularly in relation to carrying out measurements, and downloading and processing data. Weather stations located at local schools can be an effective method for engaging local communities in urban heat island education (Clough and Newport 2017). Participatory approaches can also include use of thermal comfort perception surveys (Canan et al. 2019). Other participatory methods include the use of wearable sensors to detect thermal stress (Sim et al. 2018) and the use of other types mobile dataloggers (e.g. attached to bicycles) (Yokoyama et al. 2018).

Data availability: Generates new data. Baseline data prior to intervention is not always necessary as it may be possible to measure temperature at increasing distances away from NbS to quantify effect. If comparison to a previous green or grey space is required though, establishing baseline data prior to installation can be of benefit.

Geographical scale: Typically, the type of metrics selected are based on the scale of the NbS being implemented. For example, small-scale interventions would not have a quantifiable impact on city-wide temperatures, thus city-wide networks of thermal sensors or remote sensing methods would not be appropriate. Small-scale NbS might, however, provide quantifiable local benefits in terms of creating an oasis from thermal stress for residents.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with days of extreme heat, or for long-term monitoring projects over months or years. Long-term in-situ monitoring is generally more effective in terms of capturing a more comprehensive overview of the performance of the NBS over a range of environmental conditions. Long-term monitoring is also recommended as NbS performance would be expected to change over time. Establishing a network of sensors across the city would provide a useful baseline as NbS is upscaled across the city.

Synergies: If weather stations are utilised, there are synergies in relation to capturing additional environmental parameters of relevance for other indicators (e.g. total rain fall for stormwater management indicators). Measurement of heat stress is also of relevance to health & well-being indicators associated with exposure to heat. Reducing temperatures in a specific location could also have links to social cohesion and accessibility in relation to people being more likely to use a space.

Earth observation/remote sensing/modelling: Numerous earth observation, remote sensing and modelling approaches have been developed to address this indicator. For further information on these, including those used on past and current EU projects, see indicator guidelines: Env03 – RS

Original reference(s) for indicator: Eklipse

Metric reference(s):

Bruse, M and Fleer, H (1998) Simulating surface–plant–air interactions inside urban environments with a three dimensional numerical model. Environmental Modelling & Software, 13(3), 373-384.

Canan, F, Golasi, I, Ciancio, V, Coppi, M and Salata, F (2019) Outdoor thermal comfort conditions during summer in a cold semi-arid climate. A transversal field survey in Central Anatolia (Turkey). Building and Environment 148, 212-224.

Chow, WTL, Pope, RL, Martin, CA and Brazel, AJ (2011) Observing and modeling the nocturnal park cool island of an arid city: horizontal and vertical impacts. Theoretical & Applied Climatology 103, 197-211.

Chui, AC, Gittelson, A, Sebastian, E, Stamler, N and Gaffin, SR (2018) Urban heat islands and cooler infrastructure – Measuring near-surface temperatures with hand-held infrared cameras. Urban Climate 24, 51-62.

Clough, J and Newport, D (2017) Renfrew Close Rain Gardens – Year two monitoring and project evaluation report. Report produced for the Environment Agency, UK.

Connop, S. and Clough, J. (2016) LIFE+ Climate Proofing Housing Landscapes: Interim Monitoring Report. London: University of East London

Connop, S., Nash, C., Gedge, D. Kadas, G, Owczarek, K and Newport, D. (2013) TURAS green roof design guidelines: Maximising ecosystem service provision through regional design for biodiversity. TURAS FP7 Milestone document for DG Research & Innovation.

Doick, KJ, Peace, A and Hutchings, TR (2014) The role of one large greenspace in mitigating London's nocturnal urban heat island. Science of The Total Environment 493, 662-671.

Eisenberg, B, Gölsdorf, K, Weidenbacher, S and Schwarz-von Raumer, H-G (2015) Report on Urban Climate Comfort Zones and the Green Living Room, Ludwigsburg, Stuttgart. Report produced FOR the EU FP7 project TURAS.

Fung, CKW and Jim, CY (2017) Assessing the Cooling Effects of Different Vegetation Settings in a Hong Kong Golf Course. Procedia Environmental Sciences 37, 626-636.

Hall, JM, Handley, JF and Ennos, AR (2012) The potential of tree planting to climate-proof high density residential areas in Manchester, UK. Landscape and Urban Planning 104(3–4), 410-417.

Honjo, T, Tsunematsu, N, Yokoyama, H, Yamasaki, Y and Umeki, K (2017) Analysis of urban surface temperature change using structure-from-motion thermal mosaicking. Urban Climate 20, 135-147.

Jänicke, B, Meier,F, Hoelscher, M-T and Scherer, D (2014) Evaluating the effects of facade greening on human bioclimate in a complex urban environment. Advanced Meteorology 2015, p. 15.

Li, H, Zhou, Y, Li, X, Meng, L, Wang, X, Wu, S and Sodoudi, S (2018) A new method to quantify surface urban heat island intensity. Science of The Total Environment 624, 262-272.

López-Cabeza, VP, Galán-Marín, C, Rivera-Gómez, C and Roa-Fernández, J (2018) Courtyard microclimate ENVI-met outputs deviation from the experimental data. Building and Environment 144, 129-141.

MET Office (2019) How we measure temperature. Available from: https://www.metoffice.gov.uk/weather/guides/observations-guide/how-we-measure-temperature

Matzarakis, A., Mayer, H., & Iziomon, M. G. (1999). Applications of a universal thermal index: physiological equivalent temperature. *International journal of biometeorology*, *43*(2), 76-84.

Morakinyo, TE, Lai, A, Lau, KK-L and Ng, E (2019) Thermal benefits of vertical greening in a high-density city: Case study of Hong Kong. Urban Forestry & Urban Greening 37, 42-55.

Ottelé, M and Perini, K (2017) Comparative experimental approach to investigate the thermal behaviour of vertical greened façades of buildings. Ecological Engineering 108(A), 152-161.

Rizwan, AM, Dennis, LYC, and Liu, C (2008) A review on the generation, determination and mitigation of Urban Heat Island. Journal of Environmental Sciences 20(1), 120-128.

Shashua-Bar, L, Pearlmutter, D and Erell, E (2009) The cooling efficiency of urban landscape strategies in a hot dry climate. Landscape and Urban Planning 92(3–4), 179-186.

Sim, KY, Yoon, S and Cho, Y-H (2018). Wearable Sweat Rate Sensors for Human Thermal Comfort Monitoring. Scientific Reports, 8. 10.1038/s41598-018-19239-8.

Toparlar, Y, Blocken, B, Maiheu, B and van Heijst, G (2017) A review on the CFD analysis of urban microclimate. Renewable and Sustainable Energy Reviews 80, 1613-1640.

Tsoka, S., Tsikaloudaki, A., & Theodosiou, T. (2018). Analyzing the ENVI-met microclimate model's performance and assessing cool materials and urban vegetation applications–A review. *Sustainable cities and society*, *43*, 55-76.

Yang, P, Ren, G and Liu, W (2013) Spatial and temporal characteristics of Beijing urban heat island intensity. Journal of Applied Meteorology and Climatology 52, 1803-1816.

Yokoyama, H, Ooka, R, and Kikumoto, H (2018) Study of mobile measurements for detailed temperature distribution in a high-density urban area in Tokyo. Urban Climate 24, 517-528.

Yu, C and Hien, WN (2006) Thermal benefits of city parks. Energy Build 38(2), 105-120.

Zölch, T, Rahman, MA, Pfleiderer, E, Wagner, G and Pauleit, S (2019) Designing public squares with green infrastructure to optimize human thermal comfort. Building and Environment 149, 640-654.

2.1.1.2 *Air temperature change (Env03) Earth Observation/Remote Sensing Review*

Umbrella: Temperature reduction

Indicator: Air temperature change

Code: Env03

Description: Measurement of the cooling effect of NbS by evapotranspiration and/or shading using earth observation/remote sensing indicators and tools for the effectiveness of NbS in cities based on the literature review and experience of the NbS projects presented in the CN database

Metrics: In order to assess exposure to heat stress, different methodological approaches can be applied. Along with the analysis of a single parameter, such as air temperature (Ta), surface temperature, or mean radiant temperature (Tmrt), either by taking regular measurements, the use of **remote-sensing or modelling-based approaches**, which are spatially explicit, are recognised in several research papers (e.g. Alavipanah et al., 2015; Chen et al., 2014; Lindberg & Grimmond, 2011).

The combined usage of high-resolution satellite images and thermal infrared (TIR) data helps understanding the thermal effect of urban fabric properties and the mechanism of urban heat island (UHI) formation. In particular, it is suggested to undertake typical urban functional zoning, e.g. of downtown, for quantifying the relationship between fine-scale urban fabric properties and their thermal effect. As a result, a particular number of land surfaces and a number of aggregated land parcels extracted from, for instance, a QuickBird image can be used to characterize urban fabric properties. The thermal effect can be deduced from land surface temperature (LST), intra-UHI intensity, blackbody flux density (BBFD) and blackbody flux (BBF). The net BBF can be retrieved from the Landsat 8. The products should be resampled to fine resolution using a geospatial sharpening approach and further validated. The final results can show for instance that:

> (i) On the level of urban functional zones, there is a significant thermal differential among land surfaces. Water, well-vegetated land, high-rises with light color and high-rises with glass curtain walls exhibited relatively low LST, UHI intensity and BBFD. In contrast, mobile homes with light steel roofs, low buildings with bituminous roofs, asphalt roads and composite material pavements showed inverse trends for LST, UHI intensity, and BBFD;
>
> (ii) It can be found that parcel-based per ha net BBF, which offsets the "size-effect" among parcels, is more reasonable and comparable when quantifying excess surface flux emitted by the parcels;
>
> (iii) When examining the relationship between parcel-level land surfaces and per ha BBF, a partial least squares (PLS) regression model can show that buildings and asphalt roads are major contributors to parcel-based per ha BBF, followed by other impervious surfaces. In contrast, vegetated land and water contribute with a much lower per ha net BBF to parcel warming.

Remote-sensing based indices used for this purpose:

- Temperature condition index (TCI) – Singh et al. 2003
- Satellite remote sensing with on-the-ground observations (combination of methods) - Lotze-Campen and Lucht, 2001

Methods for acquiring the surface air temperature include:

- temperature-vegetation index approaches (TVX)

- statistical approaches
- neural network approaches
- and energy balance approaches.

As underlined by a number of studies, remote sensing is one of the most used techniques to investigate the cooling effects of green infrastructures because large areas can be monitored and analysed simultaneously and continuously (Liwen et al., 2015). However, remote sensing does not allow for the prediction of the effects of possible NBS, or the prediction of how the NBS will develop in the future. For this purpose, modelling approaches are useful tools, that allow simulation of non-existing/future scenarios. The literature review has revealed that there are several studies which followed this methodology. Table 1 summarizes the reviewed studies that analysed NBS and urban temperature. However, in reality, heat stress is determined by multiple parameters, the most important being Ta, Tmrt, wind patterns and humidity (from the meteorological perspective), and metabolic rate, activity, age and clothing (from the physiological perspective) (Höppe, 1999). In this regard, use of ecosystem-based approaches can also have positive effects on a larger scale – for example a district of a city, or the whole city. Studies using remote sensing approaches (e.g. Alavipanah et al., 2015) or meso-scale climate modelling (e.g. Fallmann et al., 2014) show that the urban heat island effect can be significantly reduced by increasing the vegetative cover within a city, e.g. through green roofs or parks. Changes in albedo change the radiation balance of the urban environment, and lower surface temperatures (Zölch et al. 2016, 2017, 2018).

Table 1 Summary of the reviewed studies that analysed NBS and Urban temperature

Studies	Objective	Model
Boukhabla and Alkama, 2012	Study the impact of vegetation on air temperature	ENVI-MET
Feyisa et al., 2014	Examine the relationship between characteristics of the vegetation and observed temperature	LINEAR MIXED-EFFECT MODEL
Hu, et al., 2016	Quantify land surface temperature	MODIS LST
Kim et al. , 2016	Understand the cooling effect of changes in land cover on surface and air temperatures in urban micro-scale environments	ENVI-MET
Kong et al., 2014	Explore and quantify the combined effects of factors related to the urban cooling islands intensity	LINEAR REGRESSION MODELS
Kong et al., 2016	Examine the outdoor 3D thermal environmental patterns with and without green spaces	ENVI-Met
Koc et al., 2017	Methodological framework for a more accurate assessment of	Remote Sensing

	the thermal performance of green infrastructure	
Mackey et al., 2012	Attempt to analyse a real large-scale application by observing recent vegetated and reflective surfaces in LANDSAT images	LANDSAT
Lin & Lin, 2016	Characterize the influence of the spatial arrangement of urban parks on local temperature reduction	ENVI-MET
Sun et al., 2017	Assess the impacts of modifications in a park on the thermal comfort improving-effect of urban green spaces	ENVI-Met
Takebayashi, 2017	Examine air temperature rise in urban areas that are on the leeward side of green areas	Numerical Model
Wai et al., 2017	Determine the change in evapotranspiration from the new ecosystems	Variable infiltration capacity
Zölch, et al., 2016	Quantify the effectiveness of three types of UGI in increasing outdoor thermal comfort in a comparative analysis	ENVI-MET
Wu & Chen, 2017	Investigate how different spatial arrangements of trees in residential neighbourhoods affect the cooling effects of vegetation	ENVI-Met
Žuvela-Aloise, 2017	Evaluate the cooling potential of the blue and green infrastructure to reduce the UHI effect when applied to large areas of the city	MUKLIMO_3

As evidenced by the studies in Table 1, there is a plethora of models for studying the effects of NBS on urban air temperature. However, not all models are adequate for all objectives, and given a specific purpose, the models should be chosen accordingly.

In order to properly assess the urban heat component of a site, there is a need to analyse the heat fluxes (EEA, 2017a, 2017b). According to Rafael et al., (2016) the study of energy fluxes can be conducted in three main approaches:

i) studies that only consider the measurements of energy fluxes through the eddy covariance method, and usually compare different types of land;

ii) studies that combine flux measurements with model simulations;
iii) Studies that use models designed to simulate the key processes governing heat, moisture and momentum exchanges of the urban canopy for different applications.

All these approaches offer different benefits and present different challenges, and the chosen method should be dependent on the case study.

Scientific solid evidence: There are a great number of research projects which confirm the usefulness of approach to derive air temperature from satellites (see references provided above). Their work contributes to better understanding of climate monitoring and land-climate interactions.

Monitoring the status of air temperature at 2 metres above the land surface is essential for scientists to tackle climate change issues, because air temperature is a key element of all processes that guarantee life on Earth. While weather stations regularly detect and collect air temperature records, their number is limited and their distribution scattered over the Earth surface, with a stronger concentration in developed countries, mainly USA and EU. The resulting records are often patchy in both space and time. For this reason, scientists constantly test new methods to collect better and more complete global air temperature data. In this regard, an innovative method to enhance the quality of global air temperature information by analysing the land surface temperature records collected by weather stations and detected by satellites was recently developed. Based on this, a statistical model was developed that can improve monthly predictions of global air temperature. A novelty concerns the geographical coverage of the analysis: satellites can access remote areas of the planet with few weather stations or poor-quality information.

It is important to note, that there are errors in the factors used as input to these model simulations (these include factors due to anthropogenic gases and aerosols, volcanic aerosols, solar input, and changes in ozone), errors in the satellite observations (partially addressed by the use of the uncertainty ensemble), and sequences of internal climate variability in the simulations that are different from what occurred in the real world. We call these four explanations “model physics errors”, “model input errors”, “observational errors”, and “different variability sequences”. They are not mutually exclusive. In fact, there is hard scientific evidence that all four of these factors contribute to the discrepancy, and that most of it can be explained without resorting to model physics errors.

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing.

Costs: Satellite images are the easiest way to obtain geographic information. Generally, the average cost of a raw satellite image is approximately one dollar for each sq km. There are lots of considerations when purchasing imagery but in general satellite images are cheaper than aircraft, low resolution images are cheaper than high, and old images are cheaper then new. To get some idea, you can look at the cost per sq.km of newly acquired imagery to get an idea of comparison:

- Worldview 2, 50cm pan is about €30 / sqkm
- IKonos pan, 0.8-3m resolution is about €25 /sqkm
- Deimos -1, 22m res is 15c/sqkm
- Landsat, MODIS and MERIS sensors – free.
- A high quality airborne lidar survey would be in the order of €450/sq.km.

There are a lot of ways to analyze cost (e.g. per pixel worldview is much the cheapest of the three listed above). Also note as price per km may be quoted but you will often be obliged to have minimum order of a few hundred sq.km – which may compare project costs back toward airborne if you are only interested in a small area.

Effort: Although the satellite image is the easiest way to obtain geographic information and in general, average cost of a raw satellite image is approximately one dollar for each sq km, the important point here is whether the data which are obtained from satellite imagery will give the required accuracy in GIS or not. The strong improvement in space-borne data and consequently in the reference scale, can be evaluated by considering the following features:

- from 1 (Ikonos) to 0,61 m (Quick Bird) of panchromatic resolution at nadir

- from 4 (Ikonos) to 2,44 m (Quick Bird) of multi-spectral resolution at nadir

- simultaneous panchromatic and multi-spectral acquisitions

- radiometric range of 11 bits (2048 levels of grey) instead of the usual 8

- panchromatic band ranging from blue to near infrared

The two last characteristics in particular enable, through a proper spectral and radiometric enhancement (vs. analogical air photos e.g.), to reach a better contrast, visibility and information content and then a better target distinction

Participatory process: None

Data availability: It differs from the local context. In general, the easiest would be freely accessible RS data from:

- Glovis - Global Visualization Viewer, with easy-to-go navigation tolls, http://glovis.usgs.gov/
- NASA - http://reverb.echo.nasa.gov
- Hyperspectral Unmixing, Ground Truths: http://www.escience.cn/people/feiyunZHU/Dataset_GT.html
- http://openremotesensing.net – in this website, you not only can access to MATLAB codes of different remote sensing fields, but also you can reach some invaluable data freely.
- http://freegisdata.rtwilson.com - a categorised list of links to over 300 sites providing freely available geographic datasets - all ready for loading into a Geographic Information System.

For downloading users have to register. The images are provided as jpg for a quick preview, but also as the complete spectral-data set. There are the manuals to explain how to use the portal.

Geographical scale: Since meteorological stations are at a low spatial density that usually cannot satisfy the needs either in scientific research or in practical applications, and many spatial interpolation methods in order to extend the air temperature from a point scale to a regional scale usually cannot reflect the detailed spatial variability as well as produce large errors, the use of remote sensing data can be beneficial. Benefiting from the fast development of remote sensing techniques, spatially distributed information on the underlying surface can be obtained. Remote sensing techniques provide a straightforward and consistent way to estimate air temperature at a regional scale with more details than meteorological data. Many studies attempted to retrieve near surface air temperature by thermal infrared remote sensing data. In general, remotely sensed data are inherently suited to provide information on urban land cover characteristics, and their change over time, at various spatial and temporal scales. In most cases, however, methods of EO and RS have been used at meso-scales using satellite imagery to map and quantify the cooling effects of green infrastructures (Koc et al., 2017).

Temporal scale: Remotely sensed data are inherently suited to provide information on urban land cover characteristics, and their change over time, at various temporal scales.

Synergies: Unfortunately, conventional sources of information on urban areas are frequently inadequate: The necessary data are often generalized, outdated, unreliable, not in standard format, or in some cases simply unavailable. As one data source, remotely sensed data are inherently suited to provide information on urban land cover characteristics, and their change over time, at various spatial and temporal scales. Beyond this, Earth observation provides an independent data source.

Once purchased, spatial data can be used for many of the mapping indicators, including those for social and economic indicators.

Applied methods: For greater detail on applied and participatory methods for quantifying changes in air temperature related to NBS please see: Env03_Applied

Original reference(s) for indicator: Eklipse

Metrics references:

a) References from literature review:

Alavipanah, S., Wegmann, M., Qureshi, S., Weng, Q., Koellner, T. (2015). The Role of Vegetation in Mitigating Urban Land Surface Temperatures: A Case Study of Munich, Germany during the Warm Season. Sustainability, 7(4), 4689.

Boukhabla, M. and Alkama, D. (2012) Impact of vegetation on thermal conditions outside, thermal modeling of urban microclimate, case study: The street of the republic, Biskra. Energy Procedia, 18, pp. 73–84.

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Envi-MET – assessing thermal comfort values expressed by the physiologically equivalent temperature (PET) index. S. Huttner, Further development and application of the 3D microclimate simulation ENVI-met [Ph.D. thesis], Johannes Gutenberg-Universität Mainz, 2012.

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Hall, JM, Handley, JF and Ennos, AR (2012) The potential of tree planting to climate-proof high density residential areas in Manchester, UK. Landscape and Urban Planning, 104 (2012), pp. 410-417.

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Koc, C. B., Osmond, P., Peters, A., & Irger, M. (2017). A methodological framework to assess the thermal performance of green infrastructure through airborne remote sensing. *Procedia Eng*, *180*, 1306-1315.

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Kong, F., Yin, H., Wang, C., Cavan, G., & James, P. (2014). A satellite image-based analysis of factors contributing to the green-space cool island intensity on a city scale. *Urban forestry & urban greening*, *13*(4), 846-853.

Lin, B. S., & Lin, C. T. (2016). Preliminary study of the influence of the spatial arrangement of urban parks on local temperature reduction. *Urban Forestry & Urban Greening*, *20*, 348-357.

Lindberg, F., Grimmond, C. S. B. (2011b). Nature of vegetation and building morphology characteristics across a city: Influence on shadow patterns and mean radiant temperatures in London. Urban Ecosystems, 14(4), 617-634. doi: 10.1007/s11252-011-0184-

Liwen, H., Shen, H., Wu, P., Zhang, L., Zeng, C. (2015) Relationships analysis of land surface temperature with vegetation indicators and impervious surface fraction by fusing multi-temporal and multi-sensor remotely sensed data, Urban Remote Sensing Event (JURSE), 2015 Joint, pp. 1–

Lotze-Campen H. (2001) A Sustainability Geoscope – Observing, Understanding and Managing the Sustainability Transition Report on an international workshop sponsored by the German National Committee on Global Change Research and the Potsdam Institute for Climate Impact Research (PIK). [WWW Document].https://www.pik-potsdam.de/members/hlotze/geoscope_report_international_berlin_oct01.pdf Accessed date: 20 March 2019.

Mackey, C. W., Lee, X., & Smith, R. B. (2012). Remotely sensing the cooling effects of city scale efforts to reduce urban heat island. *Building and Environment*, *49*, 348-358.

Rafael, S., Martins, H., Sá, E., Carvalho, D., Borrego, C., Lopes, M. (2016) Influence of urban Direct and indirect impacts of nature-based solutions on urban heating Bruno Augusto 2017/2018 57 resilience measures in the magnitude and behavior of energy fluxes in the city of Porto (Portugal) under a climate change scenario. Science of the Total Environment, 566–567, pp. 1500–1510.

Singh, R.P., Roy, S., Kogan, F. (2003) Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing, 24:4393-4402

Skelhorn, C, Lindley, S and Levermore, G (2014) The impact of vegetation types on air and surface temperatures in a temperate city: a fine scale assessment in Manchester, UK. Landscape and Urban Planning, 121 (2014), pp. 129-14.

Sun, S., Xu, X., Lao, Z., Liu, W., Li, Z., García, E. H., ... & Zhu, J. (2017). Evaluating the impact of urban green space and landscape design parameters on thermal comfort in hot summer by numerical simulation. *Building and Environment*, *123*, 277-288.

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Zölch, T, Wamsler, C, Pauleit, S (2018). Integrating the ecosystem-based approach into municipal climate change adaptation strategies: The case of Germany. Journal of Cleaner Production, 170, 966-977.

Zölch, T, Maderspacher, J, Wamsler, C, Pauleit, S (2016). Using green infrastructure for urban climate-proofing: An evaluation of heat mitigation measures at the micro-scale. Urban Forestry & Urban Greening, 20, 305-316.

Zölch, T, Henze, L, Keilholz, P, Pauleit, S (2017). Regulating urban surface runoff through nature-based solutions - an assessment at the micro-scale. Environmental Research, 157, 135-144.

Žuvela-Aloise, M. (2017) Enhancement of urban heat load through social inequalities on an example of a fictional city King's Landing. International Journal of Biometeorology, 61(3), pp. 527–539

b) **References for Indicator based on the NbS projects from the CN database:** AMICA, OPERAs, OPPLA, Naturvation, URBAN Green-UP.

AMICA (Adaptation and Mitigation – an Integrated Climate Policy Approach)

http://www.amica-climate.net

One of the project tasks was Risk and Disaster management. In this regard it is based on:

- GIS data and tools for risk assessment and management as help for decision local and regional makers for planning and disaster preparedness,
- remote sensing data on impacts and damages and urgent needs in case of disasters (GMES),
- remote sensing of urban areas (Wilson et al. 2003) has revealed a patchwork of discrete heat islands related to the distribution and structure of buildings and streets, as well as areas with much lower temperatures associated with parks and green space (Yu & Hien 2006).

Charlesworth, S.M. 2010. A review of the adaptation and mitigation of global climate change using sustainable drainage in cities. *Journal of Water and Climate Change, volume 1* (3): 165-180. http://dx.doi.org/10.2166/wcc.2010.035

Wilson, J.S., Clay, M., Martin, E., Stuckey, D. & Vedder-Risch, K. 2003 Evaluating environmental influences of zoning in urban ecosystems with remote sensing. Remote Sensing of Environment. 85, 303–321.

OPERAs (Ecosystem Science for Policy & Practice)

http://www.operas-project.eu

- Remote sensing algorithms to estimate evapotranspiration are available but often not at sufficient resolution, and do not provide predictions on upcoming water use.
- More experience needs to be gained in combining technologies and scales: direct mapping of soil moisture as done with in-situ, air- or space borne radar, crop water stress mapping by thermal infrared sensors or derived from crop vigour and/or modelling of the crop/soil/atmosphere continuum.

Derkzen, M.L., van Teeffelen, A.J.A., Verburg, P.H. Quantifying urban ecosystem services based on high-resolution data of urban green space: an assessment for Rotterdam, the Netherlands. *Journal of Applied Ecology*, 52, 1020-1032, 2015.

OPPLA – open platform, an EU Repository of Nature-Based Solutions (https://oppla.eu)

Some projects (selected):

1) Amsterdam - NBS for greening the city and increasing resilience https://oppla.eu/amsterdam-nbs-greening-city-and-increasing-resilience

- Analysis of the cooling effect of evapotranspiration.
- Regulation of air quality by urban trees and forests
- Urban temperature regulation

Amsterdam is involved in several European research projects (Green Surge, Climate-ADAPT).

http://climate-adapt.eea.europa.eu

http://greensurge.eu

Azarakhsh R., Diasa E., Koomen E. (2016). Local impact of tree volume on nocturnal urban heat island: A case study in Amsterdam. Urban Forestry & Urban Greening 16 (2016) 50–61

City of Amsterdam (2014). Best-practices in Amsterdam Metropolitan Region. Amsterdam, 9 July 2014.
http://www.mbpr.pl/user_uploads/image/AKTUALNOSCI/akt%2011072014/Best_Practices_in_Amsterdam_Julian_Jansen.pdf

2) Barcelona: Nature-based Solutions (NBS) Enhancing Resilience to Climate Change

https://oppla.eu/casestudy/17283

• peri-urban forest of Collserola natural park and Montjuïc urban Park contributes to urban cooling, notably through evapotranspiration.

Laghai H. A., Bahmanpour H. (2012) GIS Application in Urban Green space Per Capita Evaluation. Annals of Biological Research, 2012, 3 (5):2439-2446.

3) Climate Proof Glasgow: Nature-based solutions as indicators towards a climate-just transition

One of the key indicators used – cooling effect of GI.

The hypothesis underlying the estimation of cooling potential is as follows:

- Cooling provided by different types of GIs is similar
- Cooling potential depends on the extent of the GI
- Cooling effect of GI is not confined to the exact area of GI but spreads outwards (more GI means greater the extent of cooling)

We used the methods proposed by Zardo et al. (2017), Keeley (2011), and Emmanuel and Loconsole (2015) to a) group the different types of GI available in Glasgow into 3 broad types of cooling classes of GI; b) assign weight factors for 'cooling' and c) amalgamate types of green from a) above according to their spatial extent.

Zardo L, Geneletti D, Pérez-Soba M, Van Eupen M. 2017. Estimating the cooling capacity of green infrastructures to support urban planning, *Ecosystem Services*, **26**, pp. 225-235

Dimitrov, S., Georgiev, G., Georgieva, M., Gluschkova, M., Chepisheva, V., Mirchev, P., Zhiyanski, M. 2018. Integrated assessment of urban green infrastructure condition in Karlovo urban area by *in-situ* observations and remote sensing. One Ecosystem 3:e21610. doi:10.3897/oneeco.3.e21610

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- modeling and detecting heat islands at different scales depending on a kernel smoothing and using remote sensing. Greenness and heat islands showed high correlation (input data: ASTER remote sensing images; output data: temperature in Kelvin).

- modeling the needs of green space for several ecosystem services, using GIS information, remote sensing and Pareto optimization (input data: GIS raster layers with information about green spaces; output data: air temperature.
- remote Sensing and LIDAR data used to estimate vegetation volume and NVDI. A 3D NVDI as constructed by multiplying the NVDI with the vegetation volume. Measured temperatures was modelled using Maximum Likelihood as a function of NVDI, 3D NVDI, distance to green / blue areas and built-area volume (input data: Remote images (1 m resolution), LIDAR data, temperature measurements; output data: temperature).
- a set of modelled GIS and remote sensing parameters used to model temperature as an effect of greenness, aerosols, buildings. Likely the method needs to be calibrated for each city/town separately (input data: GIS data of buildings, Landsat data; NVDI & AH CHRIS/PROBA satellite images, ASTER image data; output data: temperature).

URBAN Green-UP* (2017 – ongoing)

As based on Technical report by the Joint Research Centre (JRC), the European Commission's science and knowledge service and references below:

- mapping and assessing the contribution of urban vegetation to microclimate regulation (a) Deriving a map of Land Surface Temperature based on Landsat 8 Data, using a methodology based on (Du et al. 2015); b) Aggregating Land types to assess the changes in average temperature (see Figure 12), c) Estimate the Influence of green cover on surface temperature index (Under development)
- mapping urban temperature using remote sensing information (split window algorithm), using the model for assessing urban temperature and the indicator for microclimate regulation

Du C, Ren H, Qin Q, Meng J, Zhao S. 2015. A Practical Split-Window Algorithm for Estimating Land Surface Temperature from Landsat 8 Data. Remote Sens. 7:

Wegmann M, Leutner BF, Metz M, Neteler M, Dech S, Rocchini D. 2017. A grass GIS package for semi-automatic spatial pattern analysis of remotely sensed land cover data. Methods Ecol Evol. doi: 10.1111/2041-210X.12827

2.1.2 Rainfall storage (water absorption capacity of NBS) (Env08)

2.1.2.1 *Rainfall storage (water absorption capacity of NBS) (Env08) Applied/Participatory Review*

Umbrella: Stormwater storage

Indicator: Rainfall storage (water absorption capacity of NBS)

Code: Env08

Description: Calculating/predicting stormwater performance of NbS, for example run-off coefficients in relation to precipitation quantities measured in mm/% from NbS (e.g. green roofs, tree pits, grass etc).

Metric(s): Basic measures of stormwater storage volume can be calculated without detailed analysis of flowrates. Such metrics can provide a coarse measure of the performance of nature-based solutions, such as Sustainable Drainage System (SuDS) basins, under storm conditions.

Typically, a weather station or weather radar data are used to calculate total rainfall during a rain event. Data on the stormwater performance of the nature-based solution during the event is then generated using cameras (Connop et al. 2018; Connop and Clough 2016; Clough and Newport 2017), soil moisture sensors (Alves et al. 2014), and/or pressure sensors (Connop et al. 2018; Connop and Clough 2016; Clough and Newport 2017). This data is then analysed to monitor how long after the initiation of the rain event the nature-based solution began to fill, whether the capacity was ever exceeded resulting in the release of stormwater to storm drains, and how long it took to empty following the cessation of the rain event.

If duration of monitoring is a limitation (i.e. waiting for a 1 in 100 year storm can, by definition, take a long time), simulation of storm events can also be carried out (Alves et al. 2014; Connop et al. 2018; Connop and Clough 2016; Clough and Newport 2017). By doing so, it is possible to assess the performance of the nature-based solution during rain events of known magnitude without having to wait for such events to occur naturally. Such a method is not only a useful tool for testing the SuDS performance of nature-based solutions, it can also be an effective tool for engagement and understanding of SuDS for communities not familiar with the practice.

Data on the stormwater performance of nature-based solutions collected in these ways can be used to:

- provide approximated values for total rainfall diverted from storm drains;
- monitor performance of SuDS systems in relation to original designed-for capacity;
- assess the potential for any additional capacity in SuDS features and therefore potential for additional catchment areas to be diverted into existing SuDS systems;
- assess long-term performance and inform management requirements;
- provide proof-of-concept for testing new/novel systems;
- assess infiltration rates in soils beneath SuDS features;
- provide easily accessible data/demonstrations to communities and decision-makers to change perceptions of SuDS.

Scientific solid evidence: Strong evidence in terms of local performance but tends to be of a more binary nature (i.e. enough capacity to cope with storm event or not) compared to quantification of peak flows and delays (Env 09). These methods do however provide a good simple basis for production of infographics and figures to influence opinion. They are less valuable as methods for generating precise flowrate measurements to be embedded into flood management models.

Level of expertise: Some expertise required for installation. Data analysis/interpretation can be very basic once systems are in place.

Cost: Can be very low cost, depends on the level of sophistication and automation of the equipment.

Effort: It requires relatively low effort when using in-situ data gathering. The only onerous aspect can be the volume of data generated. If rain simulation is utilised, there can be a substantial time input in relation to planning and delivery. This is just for the duration of the testing though, so this can represent low time input compared to long-term in-situ monitoring.

Participatory process: Good approach for community/stakeholder participation. This can include participation in terms of data downloading, stewardship of equipment or nature-based solution, etc. The method can also include the appointment of SuDS champions to monitor and report on any evidence of basins being overloaded. Storm simulation on SuDS features can also be an excellent mechanism to demonstrate performance to local communities and decisionmakers. In so doing, it represents a mechanism for breakdown barriers to delivery and upscaling.

Data availability: Generates new data. Baseline data prior to intervention is not necessarily required unless adapting landscape from one green state to another.

Geographical scale: Implementation is typically on a component or site level. It can be scaled-up to much larger scales through replication. However, it is more typical to model the impacts of up-scaling once results have been obtained.

Temporal scale: Monitoring methods are generally required over a minimum 1 year time period. Because methods are dependent upon natural rain events and performance can vary seasonally, this represents a minimum recommended time. Long-term monitoring is more advisable as NbS performance would be expected to change over time.

Synergies: Very cheap and effective way to provide long-term monitoring to inform management requirements. Aspects of the method could also form the foundation of evaporative cooling monitoring.

Earth observation/remote sensing/modelling: For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env08 - RS

Original reference(s) for indicator: Eklipse

Metric reference(s):

Alves, L., Lundy, L., Ellis, J.B., Wilson, S. and Walters, D. The Design and Hydraulic Performance of a Raingarden for Control of Stormwater Runoff in a Highly Urbanised Area. In: ICUD (International Conference on Urban Drainage), 13th International Conference on Urban Drainage, Urban Drainage in the Context of Integrated Urban Water Management: A Bridge between Developed and Developing Countries, Sarawak, Malyasia, 7-12 September 2014. London, Middlesex University.

Clough, J and Newport, D. (2017) Renfrew Close Rain Gardens – Year two monitoring and project evaluation report, May 2017. London: University of East London.

Connop, S. and Clough, J. (2016) LIFE+ Climate Proofing Housing Landscapes: Interim Monitoring Report. London: University of East London.

Connop, S., Clough, J., Alam, R. and Nash, C. (2018) LBHF Climate Proofing Housing Landscapes: Monitoring Report 3 - October 2016 to September 2017. London: University of East London.

Connop, S., Nash, C., Gedge, D. Kadas, G, Owczarek, K and Newport, D. (2013) TURAS green roof design guidelines: Maximising ecosystem service provision through regional design for biodiversity. TURAS FP7 Milestone document for DG Research & Innovation

2.1.2.2 *Rainfall storage (water absorption capacity of NBS) (Env08) Earth Observation/Remote Sensing*

Umbrella: Stormwater storage

Indicator: Rainfall storage (water absorption capacity of NBS)

Code: Env08

Description: Earth observation and remote sensing methods for calculating/predicting stormwater performance of NbS, for eaxample run-off coefficients in relation to precipitation quantities measured in mm/% from NbS (e.g. green roofs, tree pits, grass etc).

Metric(s): The use of remote sensing and GIS in water monitoring and management has been long recognized. Potential application and management are identified in promoting the concept of sustainable water resource management. Remote sensing and GIS technologies coupled with computer modelling are useful tools in providing a solution for future water resources planning and management to government especially in formulating policy related to water quality.

Remote sensing of precipitation is pursued through a broad spectrum of continuously enriched and upgraded instrumentation, embracing sensors which can be ground-based (e.g., weather radars), satellite-borne (e.g., passive or active space-borne sensors), underwater (e.g., hydrophones), aerial, or ship-borne.

There are a variety of papers on all aspects of remote sensing of precipitation, including applications that embrace the use of remote-sensing techniques of precipitation in tackling issues, such as precipitation estimations and retrievals along with their methodologies and corresponding error assessment, precipitation modelling including validation, instrument comparison and calibration, understanding of cloud microphysical properties, precipitation downscaling, precipitation droplet size distribution, assimilation of remotely sensed precipitation into numerical weather prediction models, measurement of precipitable water vapor, etc. Recently, there have been several papers on new technological advances as well as campaigns and missions on precipitation remote sensing (e.g., TRMM (Tropical Rainfall Measuring Mission), GPM (Global Precipitation Measurement).

The latitude, longitude and elevation data for selected points within the urban area limits can be taken as input to the Surfer worksheet to generate a data file for Surfer Plotter. Kriging methods can be used for generating grid data. Using the map option, a 3D surface map with wire frame can be obtained. The flow direction can be obtained for the drainage system using the grid vector map option available in the Surfer 8.0. The vector map option provides direction and magnitude which can be derived from a grid.

In-fill of SuDS features such as detention basins can be measured using satellite imagery, but this is dependent upon the frequency of image capture over the area in question. Imagery is frequently used to measure flood extent (see Env09_RS).

There is potential to monitor water storage variation (e.g. ground water, soil water) surface waters (lakes, wetlands, rivers), water stored in vegetation and snow and ice using time variable gravity field satellite observation. The Gravity Recovery and Climate Experiment (GRACE), an Earth System Science Pathfinder mission, will provide highly accurate terrestrial water storage change estimates in large watersheds.

Scientific solid evidence: In general, it is relatively easy to delineate inundation areas using optical remote sensing data, as the water signal is much lower than the land signal, especially in the NIR spectrum due to significant water absorption. Unfortunately, the water storage of natural lakes or man-made reservoirs in some regions has rarely been studied, as it is difficult to characterize using traditional field surveys or remote sensing methods. Theoretically, the estimation of the water volume of a lake or reservoir requires both bottom topography and water level (or water surface elevation), where the water storage is the integration of the difference between the water level and the bottom. Water levels can be determined using gauged hydrological stations, but this is difficult at large scales and in less developed regions where hydrological stations are not available. Satellite radar altimetry provides a complementary means of obtaining water surface elevations. However, the sparsely distributed data constrain the large-scale application of this technique. With synoptic and frequent observations, optical remotely sensed images are able to delineate water/land the boundaries, where the water surface elevations can be determined based on their overlap with boundaries and the bottom typography. Conversely, determining the bathymetry of a lake or reservoir tends to be more challenging, requiring special equipment and considerable labour and money. Thus, the bottom topographical measurements of hundreds of large water bodies in the YRB appear to be practically impossible.

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing.

Costs: In hydrological and watershed modelling, remotely sensed data are found to be more valuable for providing cost-effective data input and for estimating model parameters

Effort: Urban run-off increases significantly due to increased impervious area and reduced drainage network. Evaluation of land use in urban areas plays a vital role as input to the estimation of runoff. The hydrological design standard for urban water resources planning and management is commonly based on the frequency of occurrence of heavy rainfall events. Earth observation/remote sensing/modelling approaches can play an important role in understanding how catchments function and change following NBS implementation. Effort for this tends to be related to accessibility of data and level of automation of analytical techniques.

Participatory process: A methodology for identifying the suitability for different rainwater harvesting interventions using a participatory GIS approach and field survey was proposed by Ziadat et al. (2012). Options for implementing different rainwater harvesting interventions can be identified with the participation of local communities. Field investigations indicated that the applied approach helped to select the most promising fields. The approach showed that participatory GIS approaches may be used to integrate socio-economic and biophysical criteria and facilitate the participation of farmers to introduce rainwater harvesting interventions in dry rangeland systems to mitigate land degradation.

Data availability: Remotely sensed data are nowadays commonly used for regional/global monitoring of hydrological variables including soil moisture, rainfall, water levels, flood extent, evapotranspiration or land water storage and the forcing, the calibration or the assimilation into hydrodynamics or hydrological or hydrometeorological models. In the years to come, recent and future satellite sensors, some of them specifically designed for hydrological purposes, will provide systematic observations of hydrological parameters (e.g., surface and sub-surface storages, and fluxes) at high spatial and temporal resolutions. This will offer new applications for the hydrological community.

Geographical scale: at various geographical scales, but tends to be better suited to larger scales than micro-scales.

Temporal scale: Can be used at various temporal scales. Access to high resolution historical data can be a limiting factor in assessing past change.

Synergies: Remote sensing systems will provide water managers with more and better data services than presently available and thus give the water managers better opportunities to apply remote sensing information for the solution of their problems. This could be helpful for product users to select the appropriate product(s) for their applications on hydrological modeling and are useful for the improvement of hydrological modeling based on remote sensing. The integration of satellite data into hydrological models, and improvements for hydrology can be expected from future satellite missions.

Data generated in this way has synergies with other mapping indicators, most specifically flood risk indicators.

Applied methods: Hydrologist have increasingly started using GIS-based distribution modeling approaches. However, more applied and participatory approaches are possible. For these approached please see: Env08_Applied

Metric references:

a) **From the literature review:**

Gabella, M.; Morin, E.; Notarpietro, R.; Michaelides S. (2013) Precipitation field in the Southeastern Mediterranean area as seen by the Ku-band spaceborne weather radar and two C-band ground-based radars. Atmos. Res., 119, 120–130.

Katsanos, D.; Retalis, A.; Tymvios, F.; Michaelides, S. (2016) Analysis of precipitation extremes based on satellite (CHIRPS) and in situ dataset over Cyprus. Natural Hazard., doi:10.1007/s11069-016-2335-8.

Lane, J.; Kasparis, T.; Michaelides, S.; Metzger, P. (2017) A phenomenological relationship between vertical air motion and disdrometer derived A-b coefficients. Atmos. Res., doi:10.1016/j.atmosres.2017.07.011.

Michaelides, S.; Levizzani, V.; Anagnostou, E.; Bauer, P.; Kasparis, T.; Lane, J.E. (2009) Precipitation: Measurement, remote sensing, climatology and modeling. Atmos. Res. , 94, 512–533.

Retalis, A.; Tymvios, T.; Katsanos D.; Michaelides S. (2017) Downscaling CHIRPS precipitation data: An artificial neural network modelling approach. J. Remote Sens., doi:10.1080/01431161.2017.1312031. ***

Schultz G A (1997) Use of remote sensing data in a GIS environment for water resources management. In: Remote sensing and geographic Information Systems for Design and Operation of Water Resources Systems (Proceedings of Rabat Symposium S3, April 1997). IAHS Publ. no. 242, 1997

b) based on the NbS projects from the CN database

OPERAs

http://www.operas-project.eu

- Remote sensing algorithms to estimate evapotranspiration are available but often not at sufficient resolution, and do not provide predictions on upcoming water use.

OPPLA – different projects.

2.1.3 Flood peak reduction/delay (Env09)

2.1.3.1 *Flood peak reduction/delay (Env09) Applied/Participatory Review*

Umbrella: Stormwater storage

Indicator: Flood peak reduction/delay

Code: Env09

Description: Assessment of co-benefits/dis-benefits of different SuDS options - in relation to peak flow reduction (e.g. % reduction in absolute height of peak floodwaters) and/or delay (e.g. increase in time to flood peak)

Metric(s): Monitoring of SuDS performance using in-situ gauges. Typically, a weather station or weather radar data is used in combination with flowrate or water depth monitoring devices (e.g. datalogging v-notch weirs, tipping bucket rain gauges, in-line turbine flowmeters, depth sensors, soil moisture sensors, and infiltrometers). The weather data is used to calculate total rainfall entering the study area (e.g. rainfall depth/unit time x catchment area). Monitoring devices are then used to calculate the rate that water enters and/or leaves a nature-based solution feature. If compared to a control feature (without nature-based solution) or a baseline calculated for the site before the nature-based solution was installed, it is possible to calculate the percentage reduction in absolute height of peak floodwaters and the delay to peak flow.

Several projects have reported the methods and results of such monitoring (Asleson et al. 2009; Royal Haskoning 2012; Alves et al. 2014; Perales-Momparler et al. 2014; 2017; Philadelphia Water Department 2014; Connop et al. 2013; 2018; Connop and Clough 2016; Clough and Newport 2017; De-Ville et al. 2018; Susdrain 2018).

A review of selected SuDS that were monitored to test hydrologic/hydraulic efficiency can be found in Lampe *et al.* (2005).

Key drivers for such monitoring include:

- ensuring that systems installed perform as designed following installation;
- to assess long-term performance and inform management requirements;
- proof of concept for testing new/novel systems;
- community engagement with new SuDS installations.

Scientific solid evidence: Strong evidence in terms of local performance. Can be scaled-up across many sites. Results need to be added into flood management models in order to understand the overall impact across a city/neighbourhood/site.

Level of expertise: Expertise needed for design and implementation and management of equipment. Relatively straightforward data analysis once systems are in place.

Cost: Can be relatively low cost. Depends on the level of sophistication and automation of equipment.

Effort: In-situ data gathering therefore relatively low effort. Data analysis can be more onerous depending on frequency and duration of data capture.

Participatory process: Can include participation in terms of data download, stewardship, etc.

Data availability: Generates new data. Baseline data prior to intervention is beneficial.

Geographical scale: Implementation is typically on a site or street level. It can be scaled-up to much larger scales. However, it is more typical to model the impacts of up-scaling once results have been obtained.

Temporal scale: Monitoring methods are generally required over a minimum 1 year time period. Because methods are dependent upon natural rain events and performance can vary seasonally, this represents a minimum recommended time. Long-term monitoring is more advisable as NbS performance would be expected to change over time.

Synergies: Data can be fed into large-scale hydraulic modelling to improve accuracy. Can also be combined with broader ecosystem service provision of SuDS (e.g. biodiversity, thermal cooling, air quality, water quality, place-making).

Earth observation/remote sensing/modelling: For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env09 - RS

Original reference(s) for indicator: Eklipse

Metric reference(s):

Alves, L., Lundy, L., Ellis, J.B., Wilson, S. and Walters, D. The Design and Hydraulic Performance of a Raingarden for Control of Stormwater Runoff in a Highly Urbanised Area. In: ICUD (International Conference on Urban Drainage), 13th International Conference on Urban Drainage, Urban Drainage in the Context of Integrated Urban Water Management: A Bridge between Developed and Developing Countries, Sarawak, Malyasia, 7-12 September 2014. London, Middlesex University.

Asleson, B. C., Nestingen, R. S., Gulliver, J. S., Hozalski, R. M. and Nieber, J. L. (2009), Performance Assessment of Rain Gardens. JAWRA Journal of the American Water Resources Association, 45: 1019–1031.

Clough, J and Newport, D. (2017) Renfrew Close Rain Gardens – Year two monitoring and project evaluation report, May 2017. London: University of East London.

Connop, S. and Clough, J. (2016) LIFE+ Climate Proofing Housing Landscapes: Interim Monitoring Report. London: University of East London.

Connop, S., Clough, J., Alam, R. and Nash, C. (2018) LBHF Climate Proofing Housing Landscapes: Monitoring Report 3 - October 2016 to September 2017. London: University of East London.

Connop, S., Nash, C., Gedge, D. Kadas, G, Owczarek, K and Newport, D. (2013) TURAS green roof design guidelines: Maximising ecosystem service provision through regional design for biodiversity. TURAS FP7 Milestone document for DG Research & Innovation

De-Ville, S., Menon, M. and Stovin, V. (2018) Temporal variations in the potential hydrological performance of extensive green roof systems. Journal of Hydrology 558, pp. 564-578.

Lampe L, Barrett M, Woods Ballard B, Kellagher R, Martin P, Jefferies C, Hollon M (2005). Post Project Monitoring of BMPs/SuDS to Determine Performance and Whole Life Costs: Phase 2. UKWIR/WERF, AwaaRF.

Perales-Momparler, S, Andrés-Doménech, I, Hernández-Crespo, C, Vallés-Morán, F, Martín, M, Escuder-Bueno, I and Andreu, J (2017) The role of monitoring sustainable drainage systems for promoting transition towards regenerative urban built environments: a case study in the Valencian region, Spain. Journal of Cleaner Production 163 (Supplement), S113-S124.

Perales-Momparler, S., Hernández-Crespo, C., Vallés-Morán, F., Martín, M., Andrés-Doménech, I. and Andreu Á, J. and Jefferies, C. (2014) SuDS efficiency during the start-up period under Mediterranean climatic conditions. Clean-Soil Air Water 42(2), pp. 178-186.

Philadelphia Water Department (2014) Green City, Clean Waters Comprehensive Monitoring Plan: City of Philadelphia Combined Sewer Overflow Long Term Control Plan Update. Available from: http://www.phillywatersheds.org/doc/Revised_CMP_1_10_2014_Finalv2.pdf

Royal Haskoning (2012) Lamb Drove SuDS monitoring project, final report. Report produced for Cambridge County Council. Available from: https://ccc-live.storage.googleapis.com/upload/www.cambridgeshire.gov.uk/business/planning-and-development/Final_Monitoring_Report.pdf?inline=true

Susdrain (2018) Counters Creek SuDS Retrofit Pilot Study, London. Susdrain case study: https://www.susdrain.org/case-studies/pdfs/suds_awards/005_18_03_28_susdrain_suds_awards_counters_creek_suds_retrofit_pilot_study_london.pdf

2.1.3.2 *Flood peak reduction/delay (Env09) Earth Observation/Remote Sensing*

Umbrella: Stormwater storage

Indicator: Flood peak reduction/delay

Code: Env09

Description: Assessment of co-benefits/dis-benefits of different SuDS options - in relation to peak flow reduction (e.g. % reduction in absolute height of peak floodwaters) and/or delay (e.g. increase in time to flood peak) using earth observation and remote sensing methods

Metric(s): The use of remote sensing and GIS in water monitoring and management has been long recognized.

Potential application and management is identified in promoting the concept of sustainable water resource management. In conclusion remote sensing and GIS technologies coupled with computer modelling are useful tools in providing a solution for future water resources planning and management to government, especially in formulating policy related to water quality.

Different studies have extracted flood extent from satellite images available for flood events that occurred in a particular period. That can then be compared with the flood extent derived from the flood extent obtained for the annual rainfall using HEC-HMS and HEC-RAS. Based on the flood extent, it is possible to develop, demonstrate and validate an information system for flood forecasting, planning and management using remote sensing data with the help of Flood Hazard Maps for different return periods (10, 20, 50 and 100 years). This supports assessment of the population vulnerability and physical vulnerability of the lowest administrative division subjected to floods.

Scientific solid evidence: Advances in remote sensing technology and new satellite platforms such as ALOS sensors widened the application of satellite data. One of the many fields that these technologies can be applied to is to validate flood inundation models. For a long-time flood extent from flood inundation models were validated using ground-truthed surveys with limited reliability. Where available, high resolution satellite data allows the simultaneous assessment of large areas for generating evidence of flooding extent.

Remotely sensed data are now commonly used for regional/global monitoring of hydrological variables including soil moisture, rainfall, water levels, flood extent, evapotranspiration or land water storage and the forcing, the calibration or the assimilation into hydrodynamics or hydrological or hydrometeorological models. In the years to come, recent and future satellite sensors, some of them specifically designed for hydrological purposes, will provide systematic observations of hydrological parameters (e.g., surface and sub-surface storages, and fluxes) at high spatial and temporal resolutions. This will offer new applications for the hydrological community.

Most of the time non-structural measures like flood forecasting, proper early warnings and conducting awareness programs among the flood affected community, etc., can be very effective. Modelling of watersheds with modern technology makes this easy. Application of GIS and remote sensing technology to map flood areas will make it easy to plan non-structural measures which reduce the flood damages and risks involved,

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing.

Costs: In hydrological and watershed modelling, remotely sensed data are found to be more valuable for providing cost-effective data input and for estimating model parameters.

Freely available remote sensing data include e.g. Rain Measurement Mission satellite precipitation data, Digital Elevation Model (DEM), Geographic Informational System (GIS), Hydrological model (Hydrologic Engineering Centre's Hydraulic Modelling System: HEC-HMS) and Hydraulic model (Hydrologic Engineering Centre's River Analysis System: HEC-RAS).

Effort: Effort is generally related to the automation of the data processing technique and the availability of data. In hydrological and watershed modelling, remotely sensed data are found to be more valuable for providing cost-effective data input and for estimating model parameters.

Participatory process: A participatory approach to monitoring flood extent can supplement remote sensing approaches. This can help to strengthen and increase awareness of non-structural measures like flood forecasting and early warning systems.

Data availability. Freely available remote sensing data include e.g. Rain Measurement Mission satellite precipitation data, Digital Elevation Model (DEM), Geographic Informational System (GIS), Hydrological model (Hydrologic Engineering Centre's Hydraulic Modelling System: HEC-HMS) and Hydraulic model (Hydrologic Engineering Centre's River Analysis System: HEC-RAS). However, there are some limitations in accuracy due to the course resolution of the precipitation and DEM data. The Rain Measurement Mission generated a global estimation of precipitation based on remote sensing observation. This algorithm, also known as Multi-Satellite Precipitation Analysis (TMPA), has high spatial (0.258) and temporal (3h) resolution, and is widely used in hydrological modelling, especially in data sparse regions. The result of flood modelling based on remote sensing rainfall data will be useful for developing regional flood early warning and flood mitigation systems in flood hazardous areas.

Geographical scale: Techniques are applicable at range of geographical scales. Automated methods are particularly valuable for large-scale analyses. High resolution data is needed for finer-scale analysis.

Temporal scale: Techniques can be applied at various temporal scales. Lack of access to high resolution data can be a limiting factor for historical studies.

Synergies: Much of the spatial data required can be used for many other of the mapping indicators, including those for social and economic indicators.

Applied methods: For greater detail on applied and participatory methods for quantifying flood peak/delay please see: Env09_Applied

Original reference(s) for indicator: Eklipse

Metric references:

a) **from literature review:**

Awadallah, A., and N. Awadallah, (2013) A novel approach for the joint use of rainfall monthly and daily ground station data with TRMM data to generate IDF estimates in a poorly gauged arid region. Open Journal of Modern Hydrology, 3, 1–7, doi:10.4236/ ojmh.2013.31001.

Li, X.-H., Zhang, Q. and Xu, C.Y (2012) Suitability of the TRMM satellite rainfalls in driving a distributed hydrological model for water balance computations in Xinjiang catchment, Poyang lake basin. Journal of Hydrology,(426–427) 28–38, doi:10.1016/ j.jhydrol.2012.01.013.

Khan, S. I. et al. (2011)Hydroclimatology of Lake Victoria region using hydrologic model and satellite remote sensing data. Hydrology & Earth System Sciiences, (15) 1, 107–117, doi:10.5194/ hess-15-107-2011.

Schultz G A (1997) Use of remote sensing data in a GIS environment for water resources management. In: Remote sensing and geographic Information Systems for Design and Operation of Water Resources Systems (Proceedings of Rabat Symposium S3, April 1997). IAHS Publ. no. 242, 1997

a) **From the CN database**

IMPRESSIONS (Impacts and risks from high-end scenarios: strategies for innovative solutions)

http://www.impressions-project.eu/

- Mapping land use, ecosystem functions, and ecosystem services using cutting-edge remote sensing and machine learning techniques
- A coordinated effort to integrate and analyse a higher quantity and quality of CO_2 and CH_4 data, from in situ and remote sensing observations encompassing atmosphere, land and oceans.
- Remote sensing of forestry

NAIAD (2016 – ongoing) (Nature Insurance Value: Assessment & Demonstration)

no data found on the use of remote sensing. However, there is an information in the task:

Demonstrating and assessing the insurance value of nature-based solutions to prevent flooding and drought risks

OPERANDUM (2018 – ongoing) (OPEn-air laboRAtories for Nature baseD solUtions to Manage environmental risks)

- design and development of the Natural based solutions planned for the Italian OAL: introduce a novel-vegetated sand dune in the complex land- marine environment of the north Emilia-Romagna coastline to reduce storm surge and related coastal erosion; install herbaceous perennial deep rooting plants as coverage of earth embankments for the mitigation of flood risk and salt wedge intrusion in the Po delta

https://www.operandum-project.eu/the-project/

OPPLA(https://oppla.eu)

The project in this regard selected from the OPPLA data base:

b) Wetlands to reduce flood risks in Aarhus (DK)
c) De Doorbrak (NL)

d) Urban hybrid dunes in Barcelona (ESP)
e) Natur in grauen Zonen (DE)
f) Ljubljana Region: Dealing with flood risk and mobility challenges (SLO)
g) SUDS (SUstainable Drainage Systems) (UK)
h) Embankments against flooding in Kristlandstad (SE)

2.1.4 Water quality (Env15)

2.1.4.1 *Water quality (Env15) Applied/Participatory Review*

Umbrella: Water Quality

Indicator: Water quality improvement

Code: Env15

Description: Calculating/predicting the change in water quality caused by diverting rainfall or surface water flow through an NbS (e.g. green roof, tree pit, bioretention pond, rain garden, wet woodland, naturalised waterway, etc). Implementing an NbS can result in a positive or negative impact on water quality. This is dependent upon: the quality of water entering the system, the type of NbS, the age of NbS, and the water quality parameters being investigated. Both positive and negative impacts of NbS on water quality are of relevance for this indicator.

Metric(s): Basic measurements of water quality associated with NbS have included:

- NO_3, NO_2 and NH_3 (Payne et al., 2014; Batalini de Macedo et al. 2019)
- Phosphorus (Bratieres et al. 2008a)
- Heavy metals (Blecken et al. 2011; Batalini de Macedo et al. 2019)
- Suspended/Sedimentary solids (Hatt et al 2008; Batalini de Macedo et al. 2019, Fowdar et al. 2017)
- Micropollutants (such as hydrocarbons and pesticides) (Zhang et al. 2014)
- Colour (Batalini de Macedo et al. 2019)
- Turbidity (Batalini de Macedo et al. 2019)
- Chemical Oxygen Demand (Batalini de Macedo et al. 2019; Leroy et al. 2016)
- Biological Oxygen Demand (Fowdar et al. 2017; Leroy et al. 2016)
- Pathogens (Bratieres et al. 2008b)
- Hydrocarbons (Hong et al. 2006)
- Total organic carbon (TOC) and dissolved organic carbon (DOC) (Fowdar et al. 2017)

Choice of parameter to measure should be related to issues of water pollution, the type of plant species and substrates used in the bioretention process, physio-chemical processes, and the desired quality of water at the end of processing (Dagenais et al. 2018; Payne et al. 2018, Batalini de Macedo et al. 2019).

Sampling can be done using in-situ stormwater sampling equipment (e.g. Teledyne ISCO 6712/7400 (Hong et al. 2006), ISCO GLS auto-sampler (Lucke and Ncihols 2015), ISCO Model 6712 Portable Sampler (Stagge et al. 2012)). This allows continuous and simultaneous sampling. Where this is not possible, or is prohibited by cost, v-notch weirs installed to monitor flow rate can be used to create a reservoir that can be sampled using a manual sampling technique (Hong et al. 2006). Alternatively, artificial drain/reservoir features can be incorporated into the NbS design from which water samples can be collected (Leroy et al. 2016). Laboratory analysis of each parameter is then carried out based on standardised analytical methods (e.g. Standard Methods for Examination of Water and Wastewater (APHA, 2015)).

An alternative, and more participatory method of monitoring water quality can be achieved through the use of biological indicators to monitor moving or still waterbodies. An example of this is the Biological Monitoring Working Party (BMWP) scoring system (Armitage et al. 1983) or adapted versions of this protocol (e.g. [Romero et al. 2017](#)). Samples are typically collected by kick sampling or surber sampling (Everall et al. 2017), providing opportunities for community engagement (including as part of school curricular activities). Wetland plants have also been used as biological indicators of water chemistry in wetland areas (US EPA 2002).

Simulated storm events with artificially created water pollution can be used as a mechanism to validate performance of NbS (Lucke and Nichols 2015). This is of particular value to ensure continuity of performance as the NbS ages/matures.

Data on the water quality performance of nature-based solutions collected in these ways can be used to:

- Quantify the benefits of NbS in terms of stormwater/waterway quality improvement;
- Assess any negative impact on water quality of diverting rainwater through NbS;
- Calculate total pollution loading being released from an NbS (when combined with flow rate calculations);
- Assess compliance with Water Framework Directives;
- Provide easily accessible data to communities and decision-makers to change perceptions of SuDS.

The water quality assessment for SuDS developments (SuDS manual) tool is a simple way of comparing the treatment effectiveness of various SuDS schemes. http://www.uksuds.com/drainage-calculation-tools/water-quality-assessment-for-suds-developments

Scientific solid evidence: Robustness of evidence depends upon the precision and accuracy of the method adopted. Frequency and design of sampling is also linked to the strength of evidence. For example, regular sampling may provide long-term and seasonal patterns but may miss significant short-term events such as 'first flush' of urban areas following long dry periods.

Level of expertise: Some expertise required for installation of equipment and/or sampling methodology. Expertise required for sample analysis depends on the level of automation of the sampling equipment (e.g. in stream dataloggers carry out sample analysis automatically). Samples taken may require specialist analytical methods, these are typically carried out through an accredited laboratory. Data analysis/interpretation against statutory guidelines can be very basic once systems are in place.

Cost: Can be low cost, but this is very dependent upon the level of sophistication, frequency of sampling, and automation of the equipment. The financial requirements associated with this indicator tend to be associated with a sliding scale of cost. Cost increases with: greater numbers of water quality parameters; greater numbers/frequency of sampling; and greater levels of precision and accuracy. Cheapest solutions are generally represented by the use of citizen science, particularly in relation to monitoring biological indicators.

Effort: Automated in-site data gathering is very low effort, with installation, data analysis and equipment maintenance the only inputs required. The only onerous aspect can be the volume of data generated. If samples are taken manually, effort can be substantially more with container preparation and site visits required. Effort under this scenario will be strongly linked with frequency of sampling. Effort can also be linked to the duration of the monitoring, with short term analysis of impact relatively low effort compared to long term monitoring schemes that evaluate change in NbS performance over time (linked to changing performance with maturation of the NbS).

Participatory process: Opportunities are available for a participatory process, particularly in relation to carrying out visual inspection of water (e.g. in relation to combined sewage overflow occurrences and water sampling (Farnham et al. 2017; Jollymore et al. 2017). Water quality analysis can be linked to local schools/universities, especially through schemes that use BMWP methodologies to monitor water quality in waterways. Automated dataloggers offer less opportunity for such participation with participation limited to observing and processing the data produced. There are also opportunities for stewardship of equipment or nature-based solution, etc.

Data availability: Generates new data. Baseline data prior to intervention is not always necessary as it may be possible to measure water quality entering and leaving the NbS to get a measure of water quality change. If comparison to a previous green or grey space is require though, establishing baseline data prior to installation can be of benefit.

Geographical scale: Implementation is typically on a component or site level. It can be scaled-up to much larger scales through replication. However, it is more typical to model the impacts of up-scaling once results have been obtained that can be fed into the model.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with specific pollution/flow/rain events, or for simulated pollution incidents. However, long-term in-situ monitoring is generally more effective in terms of capturing a more comprehensive overview of the performance of the NBS over a range of environmental conditions. Long-term monitoring is also recommended as NbS performance would be expected to change over time.

Synergies: There are synergies in relation to measuring flowrates as such data is necessary for calculating total pollutant loads over time. BMWP scoring can be linked to biodiversity indicators. Improved water quality can have correlations with nature, health and social value of a waterway.

Earth observation/remote sensing/modelling: For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env15 - RS

Original reference(s) for indicator: Eklipse; Davis et al., 2009

Metric reference(s):

Armitage, PD, Moss, D, Wright, JF and Furse MT (1983) The performance of a new biological score system based on macro-invertebrates over a wide range of unpolluted running-water sites. Water Research 17, 333-347.

Batalini de Macedo, M, Ambrogi Ferreira do Lago, C and Mario Mendiondo, E (2019) Stormwater volume reduction and water quality improvement by bioretention: Potentials and challenges for water security in a subtropical catchment. Science of The Total Environment 647, 923-931.

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Bratieres, K, Fletcher, TD, Deletic, A and Zinger, Y (2008a) Nutrient and sediment removal by stormwater biofilters: A large-scale design optimisation study. Water Research 42(14), 3930-3940.

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Davis, A, Hunt, W, Traver, R and Clar, M, (2009) Bioretention technology: Overview of current practice and future needs. Journal of Environmental Engineering 135, 109–117.

Dagenais, D, Brisson, J and Fletcher, TD (2018) The role of plants in bioretention systems; does the science underpin current guidance? Ecological Engineering 120, 532-545.

Everall, NC, Johnson, MF, Wood, P, Farmer, A, Wilby, RL, Measham, N (2017) Comparability of macroinvertebrate biomonitoring indices of river health derived from semi-quantitative and quantitative methodologies. Ecological Indicators 78, 437-448.

Farnham, DJ, Gibson, RA, Hsueh, DY, McGillis, WR, Culligan, PJ, Zain, N and Buchanan, R (2017) Citizen science-based water quality monitoring: Constructing a large database to characterize the impacts of combined sewer overflow in New York City. Science of The Total Environment 580, 168-177.

Fowdar, HS, Hatt, BE, Breen, P, Cook, PLM and Deletic, A (2017) Designing living walls for greywater treatment. Water Research 110, 218-232

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2.1.4.2 *Water quality (Env15) Earth Observation/Remote Sensing Review*

Umbrella: Water Quality

Indicator: Water quality improvement

Code: Env15

Description: Using earth observation and remote sensing to calculate the change in water quality caused by diverting rainfall or surface water flow through an NbS (e.g. green roof, tree pit, bioretention pond, rain garden, wet woodland, naturalised waterway, etc). Implementing an NbS can result in a positive or negative impact on water quality. This is dependent upon: the quality of water entering the system, the type of NbS, the age of NbS, and the water quality parameters being investigated. Both positive and negative impacts of NbS on water quality are of relevance for this indicator.

Metrics:

Remote sensing and earth observation approaches are only generally used to provide background/mapping data that can be fed into water quality modelling. However, some remote sensing techniques are emerging. Methods for delivering this include:

i) **In general:**

The remote sensing technology uses high resolution satellite or airborne optical imagery (visible and infrared), DSM (Digital Surface Model) height information and existing building out- lines maps (footprints) to estimate the percentage of vegetated areas on building roofs and to identify potential green roof sites.

The new remote sensing technology provides municipalities with the opportunity to use this data for urban planning decisions in the field of climate modelling, drainage system calculation and biodiversity networks.

According to Ritchie et al. (2003), remote sensing techniques can be used to monitor water quality parameters (i.e., suspended sediments (turbidity), chlorophyll, and temperature). Optical and thermal sensors on boats, aircraft, and satellites provide both spatial and temporal information needed to monitor changes in water quality parameters for developing management practices to improve water quality. Recent and planned launches of satellites with improved spectral and spatial resolution sensors should lead to greater use of remote sensing techniques to assess and monitor water quality parameters. Integration of remotely sensed data, GPS, and GIS technologies provides a valuable tool for monitoring and assessing waterways. Remotely sensed data can be used to create a permanent geographically located database to provide a baseline for future comparisons. The integrated use of remotely sensed data, GPS, and GIS will enable consultants and natural resource managers to develop management plans for a variety of natural resource management applications.

In addition, Massoudieh et al. (2017) developed a modelling framework to predict the water quality impacts of urban stormwater green infrastructure systems. Shi et al. 2017 demonstrated links between urban water quality and different landuse patterns that could be used to predict improvements in water quality.

Scientific solid evidence: Methods can provide robust data, but the range of water quality parameters that this can provide for is limited.

Level of expertise: Data processing expertise is needed.

Cost: Can be low cost but cost is dependent upon the availability of data and level of automation of the data processing.

Effort: Can be low effort compared to physical monitoring but depends upon the level of automation.

Participatory process: Low opportunity for participation.

Data Availability: Remote sensing techniques depend on the ability to measure these changes in the spectral signature backscattered from water and relate these measured changes by empirical or analytical models to a water quality parameter. The optimal wavelength used to measure a water quality parameter is dependent on the substance being measured, its concentration, and the sensor characteristics. Major factors affecting water quality in water bodies across the landscape are suspended sediments (turbidity), algae (i.e., chlorophylls, carotenoids), chemicals (i.e., nutrients, pesticides, metals), dissolved organic matter), thermal releases, aquatic vascular plants, pathogens, and oils. Suspended sediments, algae, oils, aquatic vascular plants, and thermal releases change the energy spectra of reflected solar and/or emitting thermal radiation from surface waters which can be measured using remote sensing techniques. Most chemicals and pathogens do not directly affect or change the spectral or thermal properties of surface waters, so they can only be inferred indirectly from measurements of other water quality parameters affected by these chemicals. Remote sensing tools provide spatial and temporal views of surface water quality parameters that are not readily available from in situ measurements, thus making it possible to monitor the landscape effectively and efficiently, identifying and quantifying water quality parameters and problems.

Geographical scale: Typically used on medium/large scale monitoring as resolution of satellite imagery can create a barrier to monitoring smaller scale areas.

Temporal scale: temporal scale is generally linked to frequency of data capture. If dependent upon aerial photography, this can be good for long-term studies, but not for capturing fluctuations between image capture dates. Satellite imagery can provide an opportunity for greater frequency, but often lower resolution.

Synergies: Synergies with water management and blue space area indicators.

Applied methods: For more information on applied and participatory methods see Env15_Applied

Metrics references:

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Kumar D (2015) Remote Sensing based Vegetation Indices Analysis to Improve Water Resources Management in Urban Environment. Pages 1374-1380 in G. S. Dwarakish, editor. International Conference on Water Resources, Coastal and Ocean Engineering.

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j) From the CN database

Projects related to the assessment Water Security supported by Earth observation remote sensing, Big Data, and citizens data.

OPERAs

http://www.operas-project.eu

- Remote sensing algorithms to estimate evapotranspiration are available but often not at sufficient resolution, and do not provide predictions on upcoming water use.

OPPLA

Aquaval (ESP)

White Cart Water Project – Glasgow, UK

Waterberging Rijssen-Holte (NL)

2.1.5 Inundation risk for critical urban infrastructures (probability) (Env19)

2.1.5.1 Inundation risk for critical urban infrastructures (probability) (Env19) Applied/Participatory Review

Umbrella: Reduction of Flood Risk

Indicator: Reduction of inundation risk for critical urban infrastructures (probability-economic)

Code: Env19

Description: Probability of a reduction of inundation risk for critical urban infrastructures based on more applied and participatory hydraulic modelling and GIS assessment.

Metric(s): Metrics are based on the quantification of infrastructure that has a reduced risk of flooding due to NBS implementation. Ultimately, this relates to a reduced economic cost of flooding, or increased health & wellbeing of communities due to reduced stress levels associated with flooding or risk of flooding. It should be noted that, if NBS is poorly designed or well-designed but poorly constructed, it has the potential to lead to increased local flooding risk for some areas.

Evaluation is typically based on simulation of storm events with hypothetical NBS components implemented to assess overall impact of flood risk to local infrastructure. Such models can be tested and supplemented by real-world data on stormwater management performance (Johannessen et al. 2019). Such monitoring is advisable after NBS installation to ensure that NBS design, construction and performance corresponds to that included in the simulation. For applied methods to evaluate stormwater management performance see metrics reviews Env08 and Env09.

Numerous simulation models exit, examples of commonly used models for such evaluation include:

- the EPA's Storm Water Management Model (SWMM) (Rossman 2015)
- OSTRICH-SWMM (Macro et al. 2019)
- SWMM-based TOPSIS multi-criteria decision analysis tool (Xu et al. 2017)
- the Landscape Green Infrastructure Design model, L-GriD (Zellner et al. 2016)
- Long-Term Hydrologic Impact Assessment (L-THIA) model (Lim et al. 2001)
- City Catchment Analysis Tool (CityCAT) (Pregnolato et al. 2016)

The models differ in relation to level of input necessary, and thus the level of expertise required for use. Typically, the models requiring more basic input also have less precision in relation to results. Comparative reviews of the performance of some of these models have been carried out in relation to the balance between data requirement and confidence in results and the need for validation (Bhaduri et al. 2001; Darabi et al. 2019).

These tools are typically used to compare the impact on infrastructure risk of centralized and distributed green infrastructure solutions (Damodaram et al., 2010; Loperfido et al., 2014), or to compare green with grey infrastructure solutions (Freni et al., 2010; Lucas and Sample, 2015), to support decision-making processes. However, they can also be used as a predictive evaluation tool following NbS implementation. Examples of their use can include assessment of specific NbS solutions such as green roofs (Johannessen et al. 2019) or rainwater harvesting systems (Palla et al. 2017), and also more general NbS implementation (Zellner et al. 2016).

Multiple criteria decision-making storm simulation tools can also facilitate participatory approaches, empowering stakeholders to make decisions about their local environment and promoting deeper understanding of the local environment (Voinov and Gaddis 2008; Voinov et al. 2016; Gray et al.

2018), or ground-truthing real world performance compared to simulation outputs (When et al. 2015). Fieldwork data can be collected through interviews with inhabitants and very detailed mapping can be carried out to clearly identify elements at risk. Information collected at the household level should concern: 1) socio-economic data, 2) information on the property, 3) flooded houses and 4) strategies of risk reduction. This local knowledge is an important tool to obtain accurate data useful for understanding flood hazard and vulnerability patterns. It provides quantitative data at the household level that can be used to complement conventional GIS and remote sensing data.

Although the participatory approach allows improving on the analysis of satellite images, it has some limitations. The local population can give inaccurate information, especially in terms of hazard mapping and spatial perception. However, if using neighbourhood scale paper maps, handheld GPS and mobile SIG, the accuracy of mapping can be increased. So, the integration of local knowledge together with remote sensing can improve data, for example when satellite images are covered by clouds, and also yield new or more accurate information in terms of hazard intensity, exposure and location of key infrastructures. This mixed approach is an alternative to the use of expensive high-resolution satellite images, when financial resources are scarce or when images are not available on the study area. Thus, this approach could be replicated for different risks in other contexts.

Reduction in flood-risk by nature-based solutions simulation can be used to:

- Support the development of strategic plans for NbS implementation to reduce flood risk and comply with Flood Risk Management;
- Predict the impact of individual NbS projects;
- Quantify the predicted impact of implemented NbS;
- Promote stakeholder engagement in NbS planning;
- Support the leveraging of finances necessary for delivering NbS projects.

Scientific solid evidence: Robustness of evidence depends upon the level of precision of the simulation software and the data analysed. Typically, simulations requiring the most basic data input are associated with the least precise results. This is not always the case, however, and model validation (either through real-world testing or validation against other models) is recommended.

Level of expertise: Expertise required is very much based on the complexity of the data requirements of the model. Very basic models exist that require very low levels of expertise and are ideal for use as community engagement tools. To maximise the value of participatory approaches, experience of managing such projects is beneficial.

Cost: If open source tools are used, cost can be very low. Cost increases if software purchase/registration is required, or consultancy service to process data. Participatory processes will have a cost too. The cost will depend on the level of engagement.

Effort: Similarly to the level of expertise required, effort is directly related to the data requirements of the simulation software. If the simulation software requires considerable data input and this is not freely available, effort for preparation can be considerable. However, if data is available, or data input is basic, the effort required can be low.

Participatory process: Opportunities are available for a participatory process, particularly in relation to stakeholder decision-making (Voinov and Gaddis 2008; Voinov et al. 2016; Gray et al. 2018) and or data-gathering through ICT-enabled citizen observatories (When et al. 2015). Involving stakeholders through active participation can increase the legitimacy of risk processes, public acceptance, commitment, and support with respect to decision-making processes (Inam et al. 2017).

Data availability: Baseline data to support simulation is generally a necessity, although basic simulation tools can derive data from open source mapping data (e.g. digital terrain models).

Geographical scale: Simulations are typically carried out on catchment scales identifying flood risk areas under different climate scenarios. Local impacts can also be modelled to assess impacts on storm sewer systems and local flood risk areas.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with single extreme events. They can also be adapted for long-term strategic simulations in relation to city-wide rollout programmes over long time periods and changes in flood risk with future climate change predictions.

Synergies: Simulation software often characterises multiple benefits of NBS implementation, often including impacts on water quality. Flood risk prediction also has synergies with the economic cost of such flooding, particularly in relation to insurance values. Flood risk reduction can also be related to health & wellbeing indicators associated with the stress caused by flood risk to properties, business and other infrastructure.

Earth observation/remote sensing/modelling: Metrics for this indicator are generally associated with simulation/modelling and are less orientated towards applied and participatory methods. A review of earth observation and remote sensing methodologies, including those adopted by past and current EU research and innovation projects can be found in: Env19_RS.

Original reference(s) for indicator: Eklipse; Pregnolato et al., 2016

Metric reference(s):

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2.1.5.2 Inundation risk for critical urban infrastructures (probability) (Env19) Earth Observation/Remote Sensing

Umbrella: Reduction of Flood Risk

Indicator: Reduction of inundation risk for critical urban infrastructures (probability-economic)

Code: Env19

Description: Probability of a reduction of inundation risk for critical urban infrastructures based on earth observation and remote sensing approaches.

Metric(s): Advances in remote sensing technology and new satellite platforms such as ALOS sensors widened the application of satellite data. One of the many fields that these technologies can be applied is to validate flood inundation models. For a long time, flood extent from flood inundation models were validated using ground-truth surveys which was not very reliable. Different studies have extracted flood extent from satellite images available for flood events occurring in particular periods. That can then be compared with the flood extent derived from the flood extent obtained for the annual rainfall using HEC-HMS and HEC-RAS. Based on the flood extent, it is possible to develop, demonstrate and validate an information system for flood forecasting, planning and management using remote sensing data with the help of Flood Hazard Maps for different return periods (10, 20, 50 and 100 years). This supports assessment of the population vulnerability and physical vulnerability of the lowest administrative division subjected to floods.

Most of the time non-structural measures like flood forecasting, proper early warnings and conducting awareness programs among the flood affected community can be very effective. Modelling of watersheds with modern technology makes this easy. Application of GIS and remote sensing technology to map flood areas will make it easy to plan non-structural measures which reduce the flood damages and risks involved. It will be a great benefit to communities to implement a flood management program.

Free available remote sensing data include e.g. Rain Measurement Mission satellite precipitation data, Digital Elevation Model (DEM), Geographic Informational System (GIS), Hydrological model (Hydrologic Engineering Centre's Hydraulic Modelling System: HEC-HMS) and Hydraulic model (Hydrologic Engineering Centre's River Analysis System: HEC-RAS). However, there are some limitations in accuracy due to the coarse resolution of the precipitation and DEM data. The Rain Measurement Mission generated a global estimation of precipitation based on remote sensing observation. This algorithm, also known as Multi-Satellite Precipitation Analysis (TMPA), has high spatial (0.258) and temporal (3h) resolution, and is widely used in hydrological modelling, especially in data sparse regions. The result of flood modelling based on remote sensing rainfall data will be useful for developing regional flood early-warning and flood mitigation systems in flood hazardous areas.

Flood mapping based on remote sensing is divided into three main steps:

1. The *detection of the flooded area*, which can be performed using a manual or a semi-automatic mapping approach:

    a) manual mapping which consists of the direct visual interpretation of the images (SAR amplitude or colour combinations of multispectral bands). In this case, the flooded areas were drawn manually directly on the georeferenced satellite images in QGIS software;

b) with the semi-automatic approach, which can help to produce an automatic flooded area map in raster format. The map can be extracted from SAR or multispectral satellite data using different methodologies such as band index, supervised classification or backscattering difference. In this step, an empirical threshold to detect flooded areas can be used; for this reason, it is not a fully automatic approach.

2. A possible *improvement and refinement of manual and automatic detection* which could be made using a cloud mask and permanent water body (from ancillary data or pre-flood images). Thus, additional information should be considered such as (a) water depth model derived from DEM, e.g., Shuttle Radar Topography Mission (SRTM) and ASTER, can be also used to estimate flood-prone areas (b) hillshade and aerial photos to detect the geomorphological features, and (c) ancillary data such as georeferenced photos or documents found on the web to have ground information about the flooded area extent. These data allow the creation of an improved final version of flooded area maps, manually drawn, both for the semi-automatic and manual approaches.
3. *The flood map validation.* This step is performed only when official flood maps or field survey maps are available. These maps should be used to evaluate the quality of the flooded area maps and in particular the performance of semi-automatic mapping (flood ratio and not flood ratio).

In addition, water storage data from the GRACE satellite or soil moisture data from ASCAT can be used to derive flood indicators. Each remote sensing technique for flood mapping presents advantages and drawbacks that must be evaluated on a case-by-case basis.

Scientific solid evidence. There are some limitations/barriers to the reliability of the evidence generated. This includes the expense associated with the most high-resolution satellite images when financial resources are scarce, or when images are not available on the study area. In addition, some areas can be covered with clouds causing a partial loss of information. The presence of dense urban areas and forests also affect both SAR and multispectral based flood mapping and requires a more-complex data processing which is not straightforward to accomplish with a user-friendly approach.

High spatial resolution is a key factor when mapping floods in dense urban areas, and it is one of the limitations of the free of charge satellite data approach. These services provide rapid mapping products that can be affected by uncertainty and are not always validated. Maps of flooded areas produced by official authorities and based on bespoke aerial photos and field surveys are more accurate, although they are time-consuming and require higher costs to be generated. Based on experience, however, on-demand high costs, high resolution data and field surveys are often necessary to ensure reliability of evidence.

Level of expertise: There a semi-automatic method for flood mapping, based only on free satellite images and open-source software. The proposed method is suitable to be applied by the community involved in flood hazard management, not necessarily experts in remote sensing processing. Multispectral satellite data acquired by MODIS, Proba-V, Landsat, and Sentinel-2 and synthetic aperture radar (SAR) data collected by Sentinel-1 can be used to detect flooded areas using different methodologies (e.g., Modified Normalized Difference Water Index, SAR backscattering variation, and supervised classification).

Much of this freely available data is available with the first level of atmospheric or radiometric calibration, allowing their use by different types of users and not only experts in remote sensing processing. An example of a user-friendly data portal is the Worldview service for the visualization of MODIS products or the G-Pod service of European Space Agency (ESA), which allows the on-line processing of ENVISAT and Sentinel-1 SAR data (Berger et al., 2012; EOSDIS 2019; Li et al., 2016; Moel et al., 2009; Notti et al., 2018; Wulder et al., 2012). In addition, free GIS plugins allow the downloading and processing of free multispectral satellite images. The availability of these resources is useful for the management of natural hazard effects. However, expertise will be needed in order to improve and manually refine the automatic mapping using free ancillary data such as the digital elevation model-based water depth model and available ground truth data.

Costs: Precise flood mapping and modelling are essential for flood hazard assessment, damage estimation and sustainable urban planning to properly manage flood risk. In such a context, satellite remote sensing is currently a low-cost tool that can be profitably exploited for flood mapping (Notti et al., 2018).

In recent years, the availability of free satellite data significantly increased in terms of type and frequency, allowing the study of many natural and human-made processes at low cost and has boosted research in many fields (Klein et al., 2017; Li et al., 2016; Notti et al., 2018). This includes the production of flood maps at low cost around the world. The frequent passes of satellites and the availability of rapid processing chains allowed the development of services providing automatic and quasi-real time flood mapping such as, for example, the Copernicus Emergency Management Service (EMS) performed by the European Union, the Global Flood Detection System and the NASA Global Flood Mapping System.

The Sentinel satellite constellation of the Copernicus program of the European Union provides synthetic aperture radar (SAR) and multispectral data with global coverage, high-frequency pass, and high spatial resolution. Other examples of free remote sensing programs are Landsat, which has provided data since 1972, and the MODIS daily satellites giving multispectral images.

Effort: Effort is generally associated with the level of automation of the data processing. Greater effort is required if automated data is refined or ground-truthed.

Participatory process: To assess flood risk at a neighbourhood level, accurate data on flood extent, exposure and vulnerability is required. One of the possible and useful ways to obtain these data is a combination of remote sensing data and local knowledge through participatory processes. Further detail can be found on participatory processes in Env19_Applied.

Data availability: In order to obtain land use map over the study area, high resolution satellite images available on Google Earth® can be used. The location of different land use categories (infrastructures, agricultural area, water bodies, etc.) and each house should be further photo-interpreted and digitized in Google Earth. Then Global mapper 15® can be used for the rapid conversion of the KML files into shapefiles with the reference system UTM. Finally, the preliminary database can be imported in ArcGIS 10® where a unique identification number can be attributed for each house affected (being in risk) by flooding. The flood extents for particular years can be obtained by comparing a reference high resolution satellite image before the flood and after it obtained in Google Earth using its historical satellite dataset. The Google Earth high-resolution imagery archive remains a largely unexploited resource for the analysis and description of the Earth's land surface. The high-resolution images (2.5 m resolution) used in this analysis come from Digital Globe's (e.g. Quick Bird—Ikonos) satellites. However, in some cases some areas can be covered with clouds causing a partial loss of information.

Geographical scale: Can be applied at various geographical scales, but is most commonly applied at a catchment scale.

Temporal scale: Can be applied over various temporal scales. Analysis of past extent can be a challenge thought if high resolution data is unavailable and reliable records are lacking.

Synergies: There some synergies between floodplain restoration, water policies and thematic policies which can be achieved. The knowledge currently available allows progress to continue on the implementation of sustainable flood risk management practices, including building synergies with other relevant environmental legislation such as the Water Framework Directive and the Birds and Habitats directives. According to reports of EEA (2018, 2018), the synergies exist between floods, climate change adaptation and disaster risk reduction. Synergies between managing flood risk, reaching or maintaining a good ecological status, promoting of ecosystem services and safeguarding the nature or ecosystem services in floodplains can be very complex.

Applied methods: For more applied and participatory approaches to assessment of reduction of flood risk see: Env29_Applied.

Original reference(s) for indicator: Eklipse; Pregnolato et al., 2016

Metric references:

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b) From the CN database

IMPRESSIONS (Impacts and risks from high-end scenarios: strategies for innovative solutions)

http://www.impressions-project.eu/

- Mapping land use, ecosystem functions, and ecosystem services using cutting-edge remote sensing and machine learning techniques
- A coordinated effort to integrate and analyse a higher quantity and quality of CO_2 and CH_4 data, from in situ and remote sensing observations encompassing atmosphere, land and oceans.
- Remote sensing of forestry

OPERANDUM (2018 – ongoing)

(OPEn-air laboRAtories for Nature baseD solUtions to Manage environmental risks)

- design and development of the Natural based solutions planned for the Italian OAL: introduce a novel-vegetated sand dune in the complex land- marine environment of the north Emilia-Romagna coastline to reduce storm surge and related coastal erosion; install herbaceous perennial deep rooting plants as coverage of earth embankments for the mitigation of flood risk and salt wedge intrusion in the Po delta

https://www.operandum-project.eu/the-project/

OPPLA

(https://oppla.eu)

The project in this regard selected from the OPPLA data base:

- Wetlands to reduce flood risks in Aarhus (DK)
- De Doorbrak (NL)

- Urban hybrid dunes in Barcelona (ESP)
- Natur in grauen Zonen (DE)
- Ljubljana Region: Dealing with flood risk and mobility challenges (SLO)
- SUDS (SUstainable Drainage Systems) (UK)
- Embankments against flooding in Kristlandstad (SE)

2.1.6 Public green space distribution (Env23)

2.1.6.1 Public green space distribution (Env23) Applied/Participatory Review

Umbrella: Greenspace accessibility

Indicator: Public greenspace distribution

Code: Env23

Description: Measure of the distribution of public greenspace (total surface or per capita) and categories (i.e. street trees, residential gardens, school green areas, parks) using more applied and participatory approaches as an index to increase quality/quantity of green/blue existing, restored and new NBS with a high degree of multifunctionality (informed by ES Valuation e.g. includes cultural ES value, needs of residents, socio-economics etc) and adapted to the type of urban area (e.g. size of urban area/landscape structure).

Metric(s): Public greenspace in cities contributes to quality of life in terms of environmental services and social and psychological services. Public greenspace distribution can therefore be an important factor for making a city sustainable. Decisions on where to create greenspace/NBS should be based on criteria related to maximising the equitability of distribution, focusing on areas lacking greenspace and in areas where ES valuation identifies greatest benefit/need.

Whilst it is possible to physically map greenspaces across cities, this tends to be a laborious and expensive process. As such, typically, public greenspace distribution would be measured through a mapping exercise that interrogates aerial photography and/or satellite imagery in a GIS environment (e.g. QuickBird satellite imageries analyses). This can be combined with census data to determine demographics in relation to population distribution (de la Barrera et al. 2016).

Such methods provide very basic insight into the distribution of greenspace in relation to population patterns. Supplementing these with methods to categorise urban greenspace (e.g. differentiating street trees, residential gardens, school green areas, parks, etc) and including variables that cover socio-economic, geographic and administrative aspects can provide greater evidence for supporting equality in urban greenspace distribution. Participatory approaches provide an opportunity for generating such data and/or ground-truthing the results from remote sensing data analyses. This includes the use of public participation GIS to map greenspaces overlooked by automated methods, and the use of public knowledge to categorise landuse types (Rall et al. 2019).

Mears and Brindley (2019) provide a comprehensive review of metrics for assessing the equity of greenspace in urban areas. Within this process, they highlight the importance of generating comparable data across cities and projects, and the importance of incorporating the neighbourhood as experienced by residents as accurately as possible.

Data on public greenspace distribution generated in these ways can be used to:

- Quantify the benefits of nature-based solution project in terms of improving the distribution of public greenspace;
- Support the planning of new nature-based solution greenspace initiatives;
- Underpin other indicators that require an understanding of greenspace distribution as a foundation.

Scientific solid evidence: Accuracy will be influenced by the resolution of satellite imagery and the complexity of metrics used to quantify distribution. Using more applied and participatory approaches as a sense check can strengthen the evidence generated.

Level of expertise: Expertise in relation to mapping and modelling will be necessary. Also expertise in leading participatory processes would be of value to maximise the quality of outputs.

Cost: Some map datasets and satellite imagery are freely available online, but higher resolution images and more comprehensive data needed for network-based measures potentially can involve a licence fees/higher costs. Costs for GIS specialists if not available in-house. Participatory GIS can also involve costs in relation to designing a portal, hosting the webpage, generating engagement, and analysing data.

Effort: The level of effort involved would be dependent on the scale and amount of data to be analysed, the level of automation of data processing, and the level of expertise already available.

Participatory process: It may be possible to validate greenspace type and distribution using a PPGIS type citizen science exercise and/or workshops with stakeholder groups holding tacit knowledge.

Data availability: Aerial photography and satellite imagery data is increasingly available but the quality and resolution can still be variable. Participatory data can be obtained in the form of already available data from local authorities, land managers, and non-government organisations, or generated through participatory engagement processes with organisations and individuals.

Geographical scale: Typically carried out over a city-scale but can be assessed at a local level also.

Temporal scale: Depending on the data available and the purpose of the exercise, could produce a current snapshot or a temporal view of change. Analysing past change can be a challenge if historical data of suitable resolution is not available.

Synergies: Synergies with other greenspace mapping indicators, and the data can be used as an index for other environmental and health/wellbeing indicators.

Earth observation/remote sensing/modelling: Spatial modelling/mapping is typically required but participatory and applied processes are possible to supplement this and enhance the level of confidence in the resulting maps. For more pure earth observation and remote sensing approaches, including those used on past and current EU projects, see: Env23 – RS

Original reference(s) for indicator: Eklipse

Reference (s):

de la Barrera, F., Reyes-Paecke, S. and Banzhaf, E. (2016) Indicators for green spaces in contrasting urban settings. Ecological Indicators 62, 212-219.

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2.1.6.2 Public green space distribution (Env23) Earth Observation/Remote Sensing Review

Umbrella: Greenspace accessibility

Indicator: Public greenspace distribution

Code: Env23

Description: Distribution of public greenspace (total surface or per capita) and categories (i.e. street trees, residential gardens, school green areas, parks) as an index to increase quality/quantity of green/blue existing, restored and new NbS with a high degree of multifunctionality (informed by ES Valuation e.g. includes cultural ES value, needs of residents, socio-economics etc) and adapted to the type of urban area (e.g. size of urban area/landscape structure)

Metric(s): Typically, public greenspace distribution would be measured through a mapping exercise, interrogating satellite imagery in a GIS environment (e.g. QuickBird satellite imageries analyses). This can be combined with census data to determine demographics in relation to distribution. De la Barrera et al. (2016) propose the following indicators for measuring greenspace distribution:

- Aggregation index of greenspaces (Municipal scale)
- Share of blocks served by greenspace > 0.5 ha (Local scale)
- Share of population served by greenspace > 0.5 ha (Local scale)

Table 1 shows indicators then used to measure quantity and quality of GS (according to de la Barrera et al., 2016).

Table 1
Description of the proposed indicators.

Indicators	Name	Scale
Quantity of GS	GS per inhabitant	Municipal
	GS per built-up area	Municipal
	GS per impervious cover	Municipal
	GS per bare soils	Municipal
	GS per vegetation cover	Municipal
Quality of GS	Mean size of GS (±SD)	Municipal
	Shape index of GS (±SD)*	Municipal
	Vegetation cover on GS (mean ± SD)	Municipal
	Vegetation cover on GS per inhabitant (mean ± SD)	Municipal
Spatial distribution and accessibility to GS	Aggregation index of GS*	Municipal
	Share of blocks served by GS > 0.5 ha	Local
	Share of population served by GS > 0.5 ha	Local

Remote sensing imagery has been widely adopted for population estimation in cities. Major techniques for population estimation by remote sensing include dasymetric mapping, regression models and geostatistical models (Joseph et al., 2012). There are various studies on greenspace accessibility which analyse the accessibility of urban parks using Euclidean distance or based on GIS network analysis. In order to calculate how many of the total population have access to green space, serving as the first index for evaluation. The analysis is composed of three steps:

- First, a Landsat image is classified to land cover using semi-automatic classification on the Quantum GIS platform, for further disaggregating population data. The population layer is a census tract map for particular year. Such aggregate data doesn't reflect the actual distribution, and its accuracy cannot meet the higher resolution analysis. To match the population data with physical elements, Landsat imagery is used. The Semi-Automatic Classification Plugin of QGIS provides an interactive way to search, display and download Landsat 8 images. Moreover, it allows semi-automatic supervised classification of remote sensing images, providing tools to expedite the creation of ROIs, the pre-processing phases (image clipping, Landsat conversion to reflectance), the classification process, and the post processing phases (accuracy assessment, land cover change). Using this plugin, the image is classified into four land cover classes (built-up, water, vegetation, and soil).

- Secondly, a population distribution map is created using dasymetric mapping technique. Dasymetric mapping means using ancillary data to disaggregate coarse resolution population data to a finer resolution (Eicher and Brewer 2001). The land cover map can be derived from Landsat imagery to disaggregate the population. In the meantime, by converting the census map to a 30m×30m cell raster, it achieves spatial down-scaling population simulation.

- The third step is to identify the ratio of service population based on ArcGIS network analysis. A network service area is a region of the case of NBS that encompasses all accessible streets. Service areas created by network analysis are converted to a raster and overlay with the disaggregated population distribution raster to identify how many people are within the service area, and figure out the areas short of accessibility.

The green space ratio is the most commonly used metric to refer to the availability of UGS (Atiqul Hag, 2011) within a neighbourhood. It consists of calculating the amount (number and/or acreage) of UGS within a city or its sub-parts to provide an aggregate (or per neighbourhood) picture of provision to a certain number of residents, i.e. potential users (Nicholls, 2001) as well as potential UGS congestion (Sister et al., 2010; Van Herzele and Wiedemann, 2003).

The proposed procedure is based on measures of urban green space location and characteristics derived from two classical types of data, Landsat imagery and official cadaster-based map, and the voluntary geographical information provided by OpenStreetMap (OSM). Landsat and OSM, being available in many places, should allow for generalisation and transfer while the cadaster-based map is supposed to reflect the kind of institutional information available at local scale with most accurate details about formal UGS.

Provision of and access to UGS are examined with respect to the spatial distribution of the four indicators discussed earlier in the literature section, namely (i) availability, (ii) fragmentation, (iii) privatisation and (iv) accessibility.

The indicators are computed as follows:

- (i) The availability index is measured by the share of land dedicated to urban green space per area, i.e. total UGS cover A divided by the reference surface.
- (ii) The fragmentation index is measured by the ratio of the total perimeter of UGS, P over their total area A. The fragmentation ratio P/A gives an indication of fragmentation with a higher value if the number of green parcels increases for a given total surface. It is also related to the shape of polygons, with lower values corresponding to a shape closer to a circle and larger values corresponding to elongated shapes.

- (iii) The privatisation index is measured by the ratio of private (denoted G for 'gardens') to total UGS cover (A), i.e. G/A.
- (iv) The accessibility index is measured by the average distance, per neighbourhood, from each cell to the nearest public UGS through the road network. The calculation is unweighted.

One of the common options is identifying UGS with Landsat. The Landsat 8 satellite image covering the European region can be downloaded from the Landsat Viewer website.

Santos et al. (2016) proposed a methodology based on 3D measure and analysis of green urban areas at the city scale. Two products are proposed: (1) measuring current vegetation cover at ground level through object-oriented classification of WorldView-2 imagery; and (2) estimating potential green cover at rooftop level using 3D data obtained by LiDAR sensor.

An Aggregation Index (AI) can be used to get a reference of how clustered public greenspaces are in a city. An AI of 100 indicates GS are adjacent to each other and 0 that GS is dispersed (FRAGSTATS - http://www.umass.edu/landeco/research/fragstats/fragstats.html).

The following data sources have been used to estimate the distribution of greenspace in Romania (Badiu et al., 2016):

Table 1
Data on the surface of UGS used in the analysis.

No.	Data source	Extraction approach/data type	Year	Urban green categories considered
1.	Aerial images	Extraction of UGS using ArcGIS 10.1	2008	Street trees, cemeteries, institutions' gardens, public residential gardens, school green area, parks, urban forests, squares, industrial green spaces, commercial green spaces, sports grounds
2.	TEMPO Database (National Institute of Statistics)	Statistical data	2008	The surface of green spaces in cities—parks, institutions' gardens, residential gardens, squares, sports grounds
3.	Environmental Protection Agencies	Statistical data	2008	All green categories as a whole
4.	Urban Atlas	Urban green surface	2010	Green urban areas, sports and leisure facilities

Using multiple correspondence analyses on four UGS categories: street trees, residential gardens, school green areas and parks; and variables that cover socio-economic, geographic and administrative aspects, factors influencing the surface of UGS per capita at the city level can be identified. Multiple linear regression models can be used to explore the influence of independent variables such as landscape, citizens education level, period when cities were founded etc. These can influence surface of UGS and explain patterns and variation of greenspace distribution.

Collating landcover characteristics using GIS and characterising above-ground vegetation by maximum height e.g. Herbaceous Vegetation and Shrub (mean height typically <2 m), Tall Shrub (mean height generally 2–5 m) and Tree (trees >5 m tall), it is possible to indicate biomass and calculate distribution of greenspace and estimate carbon storage (Davies et al., 2011). This type of metric can be used to inform ES valuation and estimate whether a type of NbS could be used/is needed in an area to increase, for instance, carbon storage.

Oh & Jeong (2007) argue that indices such as total park (or greenspace) area, park area per capita and number of parks does not reflect their distribution within a city, which could be aggregated at the outer limits, restricting access for some residents. The distribution of urban parks/greenspaces instead should be assessed in terms of the population density of residential areas, land use, and development density through GIS network analyses. Network analysis can be used to provide the boundaries of 'service areas' of parks/greenspaces, where citizens can access them within a given distance/time through actual routes. Urban park/greenspace service indices can be formulated with a population number and floor area within the service area of parks. Service indices consider the benefits to the surrounding population according to the spatial location of parks compared to conventional indices that rely on area ratio per capita. Therefore, the service area ratio and the service population ratio (which reflect the area and population serviced through footpaths based on the location of the parks) is deemed a more effective indicator of park/greenspace distribution. By synthesizing census data, land uses, and development density based upon actual locations, the assessment method can help understand the spatial distribution of urban parks/greenspaces more accurately.

Scientific solid evidence: Level of evidence generated is influenced by the resolution of satellite imagery and the complexity of metrics used to quantify greenspace distribution. There have been several notable recent studies in this field (Van De Voorde, 2016; Foster and Dunham, 2015; Taylor et al., 2011; Mitchell et al., 2011). One of them compares the quantity of green space derived from the European land cover dataset Coordination of Information on the Environment (CORINE) and from the British Ordnance Survey's master map (OSMM). They analyse their separate association with measures of mortality and morbidity at census ward level for the cities of York, Exeter, Edinburgh and Glasgow. They find that indicators based on the CORINE land cover tend to detect lower levels of green space exposure as the dataset mainly depicts the largest UGS. Interestingly, this does not affect the measured associations with the risk of mortality, suggesting a size effect in the mechanisms by which UGS influence health. Another survey compares land use percentage obtained with publicly available high-resolution aerial photography data (Google Earth in Brisbane; Microsoft Bing Maps in Sapporo), surveyed land use type in the field (visual estimation) and city supplied datasets. They find that informal UGS land use types are more sensitive to data selection than formal ones. There is also research which compares maps of urban forest cover derived from user-generated data (PhillyTreeMap) to the one obtained from the Pennsylvania Geospatial Data Clearinghouse (using remote sensing methods). Their results show effects of census block demographic profiles on the completeness of PhillyTreeMap coverage: population density, housing vacancy, median home value, and percentage of white residents have positive statistically significant effects.

These last three studies also show an emerging trend in UGS studies to embrace the digital turn in spatial data production and replace traditional data provision by governmental agencies and cartographic centres by data brought about by the Internet and social media such as Google Earth (Taylor et al., 2011), Google Street View (Seiferling et al., 2017).

The vegetation cover can be derived from satellite imagery (QuickBird). This sensor system comprises four spectral bands in the visual and near-infrared spectra (ground resolution of 2.4 m) and one panchromatic band (0.6 m ground resolution).

The structure-type classification system is exclusively based on structural parameters (length, width, height and coverage of the surface) in turn encourages the automatic categorization of parks (and other elements of UGI) structures by using remote-sensing techniques and data.

Some studies analyse availability of urban green space based on the mapping of land covers of cities using Landsat images and a random forest classifier running on Google Earth Engine. Then they calculated the availability and accessibility of urban green spaces using the land cover maps and gridded population data.

Level of expertise: Expertise in relation to mapping and modelling will be necessary. However, an increasing number of sensors, RS data products, processing algorithms, software and tools are available for the assessment of urban green space availability. Selecting an applicable data source and the method to process data is a complicated process which needs expert knowledge. Cost, time, expertise, and technical properties of remote sensing data are factors in this process. Thus, the assessment should be made by experts engaged in the NbS project who have expertise not only in RS, but also in urban planning, forestry, landscape ecology, regional planning. Each of them will then assess all built and land cover type combinations.

Costs: The land surveying of urban green space have enormous costs and also are very time consuming. Therefore, urban green space mapping using satellite images to have a time series and to be careful with high speed and cost is less. It should be noted, that the choice of a higher density point cloud increases data costs and data volume, which also demands for more sophisticated processing algorithms. Costs for GIS specialists if not available in-house.

Effort: The level of effort involved would be dependent on the scale and amount of data to be analysed, the level of automation of data processing, and the level expertise already available. Integrating remote sensing data and point-of-interest (POI) data (including location-rich semantic information) has been successfully applied in the identification of social functions of urban lands, but none were focused on a detailed and complete social functional map of UGS. Moreover, spatial patterns or distribution densities derived from the POI data have been extracted into feature vectors and then combined with physical properties derived from remote sensing data to improve the accuracy of land use identification.

Participatory process: The land cover classification either with low resolution or high-resolution images do not always completely represent the actual land cover in the city. However, it may be used in the future as a starting point for producing more accurate land cover maps by using two high resolution images. The validation of results on the ground as well as the participation of urban planner and policymakers is also essential.

Data availability: There is great debate regarding the reliability and use of data approaches to quantify and track the changes, trends, and patterns of UGS over long periods. Owning to the increasing availability of image data from multiple sources, the quantification of spatiotemporal patterns for green space frequently relies on remote sensing. However, data such as Lidar and high-resolution images are still not easily accessible for many regions or users due to the high costs of data acquisition. Moreover, it is usually impractical to provide full coverage of extensive metropolitan areas, with limited data available over long periods. With the advantages of global availability, repetitive data acquisition, and long-term consistency, Landsat series satellites have become the best compromise to overcome these limitations.

Geographical scale: at various geographical scales.

Temporal scale: at various temporal scales.

Synergies: remote sensing imagery provides powerful tools for master planning and policy analysis regarding green urban area expansion. However, measures of urban green space cannot be solely based on indicators obtained from 2D geographical information. In fact, 2D urban indicators should be complemented by 3D modelling of geographic data.

Applied methods: For more applied and/or participatory approaches please see: Env23_Applied.

Metric references:

c) From the literature review:

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a) based on the NbS projects from the CN database

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods

- remote sensing together with distributed lag nonlinear models used to assess the risk of death due to heat as an effect of distance to green and blue space (input data: Metrological, NVDI, distance to green and blue infrastructure)

- a framework using satellite images, remote sensing and statistical modelling to compute accessibility of parks and green space dependent on economic and population data (input data: percentage of green cover in a city, population density, GDP per capita, City land area, Per capita green space provision, Aggregation index; output data: Effects of and between the different types of in data)

PLUREL

(Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

References:

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2.1.7 Recreational value of blue-green spaces (Env24)

2.1.7.1 Recreational value of blue-green spaces (Env24) Applied/Participatory Review

Umbrella: Cultural value of greenspace

Indicator: Recreational value of blue-green spaces

Code: Env24

Description: This indicator represents a quantification of the number of visitors/recreational activities within a greenspace or blue-green space in order to evaluate, or measure an increase in, recreational benefits as a result of NbS. Examples of features and activities that can attract visitors to NbS include features such as large trees, benches, education days, and communication zones for picnicking.

Metric(s): The most basic measure for this indicator is increase/decrease in the number of visitors to a blue-green space before and after a change in how it is designed or managed. This data can be captured through a variety of methods including interviewing locals on likelihood of visiting the space (Coldwell and Evans 2018) and monitoring visitor numbers through physical counts or visitor profiling in relation to specific pursuits (Cope et al. 2000; Cessford and Muhar 2003).

Whilst these basic quantifications have a direct relevance to numbers of visitors, they do not necessarily provide information on the causal link between the features or activities available at a park and the presence of visitors (e.g. visitors might be there due to proximity). The most typical practice for assessing the recreational value of blue-green spaces is through generating direct feedback from users and/or local communities. This is generally done in the form of questionnaires applied to the visiting or neighbouring population to identify perceptions in relation to blue-greenspace characteristics (Kabisch and Haase 2014; Colley and Craig 2019). The majority of questionnaire techniques have focused on a single aspect of greenspace use, for example physical activity (Schipperijn et al. 2013; Akpinar 2016) or health (Akpinar et al. 2016).

Attempts have been made to quantify the 'offer' of the blue-green space by capturing a measure of the features and activities available. This has been done by classifying spaces according functional, physical characteristics considered to be associated with the attractiveness of a space (Sugiyama et al 2010; Brown et al. 2014; Kimpton 2017) Examples of characteristics used to measure blue-green space attractiveness in the Sugiyama et al. (2010) and Kimpton (2017) studies include:

- Presence of walking paths
- Shade, water features
- Irrigated lawn
- Lighting
- Birdlife
- Type of surrounding roads
- Being adjacent to a beach or river
- BBQs & Tables
- Buildings
- Dog Enclosure
- Place Managers (e.g. kiosk operators)
- Formal Sport Features
- Informal Sport Features
- Lighting
- Playground Features
- Public Transport Stop
- Seating

When applying an NbS approach to evaluation, evaluation criteria should cover characteristics associated with economic, social, health & wellbeing, environmental and ecological benefits (Faivre et al. 2017).

Surveys can be questionnaire based, directly interacting with blue-green space users or local residents (Akpinar 2016), or using online spatial mapping participatory processes (Brown et al. 2014). A combination of the number of visitor metrics and attractiveness of 'offer' metrics can generate the most useful data in relation to value of NbS interventions and promotion of learning for NbS delivery in other blue-green spaces.

Evaluation of recreational value of blue-green space can be used to:

- Ensure that changes related to NbS implementation has a positive impact on visitors;
- Ensure that green-blue spaces are providing a broad offer in terms of attractiveness for communities;
- Support the design of green-blue spaces to ensure they are providing a NbS offer in terms of social, economic and environmental benefits.

Scientific solid evidence: Robustness of evidence is very much based on the design of the questionnaire and the sample size of respondents. Visitor number count robustness can be a challenge due to the difficulty in capturing visitor numbers at some sites.

Level of expertise: Some expertise is needed for the design of the evaluation (e.g. survey method, question selection). Once decided though, a low level of expertise is required for carrying out the survey or carrying out counts. Similarly, data analysis can require low expertise if basic inventories or correlations are required.

Cost: Can be relatively low cost, particularly if citizen scientists/volunteers are used for data collection.

Effort: Effort is associated with the level of survey. Larger sample sizes/local community survey require a much greater effort than simple counts of visitors. Assessment of the characteristics of blue-green space is relatively low effort for all but the largest blue-green spaces.

Participatory process: Good opportunities for participation through which communication of the benefits of an NbS approach can be delivered. This can be achieved both through the questionnaire process and involving citizen science in data collection. Methods of amenity characterisation can also encourage stakeholders to consider what they would like in their local blue-green space and give a broader view of what is possible.

Data availability: Some sites might collect visitor data. Typically, amenity characteristics are not recorded formally, however, some data might be held on websites for more formal sites.

Geographical scale: Analysis is performed on a single site scale and can comprise sites ranging from very large parks and open spaces to micro-scale pocket parks. Typically, replication across sites is used for comparative purposes as city-wide assessment is possible, although generally spatial modelling methods would be applied for this to minimise effort required.

Temporal scale: Evaluation methods can be adopted for short-term snapshots associated with a change in management. They can also be adapted for long-term evaluation of sites as the 'offer' changes and matures, as the accessibility of a site changes, or as the demand on a site changes.

Synergies: Strong synergies with health and wellbeing indicators and social cohesion indicators in relation to public use of the sites for physical activity and social events. Also, synergies with environmental indicators (e.g. biodiversity measures, water regulation and air temperature) in relation to synergies and trade-offs in benefits driven by changes in use of blue-green spaces.

Earth observation/remote sensing/modelling: For greater detail on earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env15 - RS

Original reference(s) for indicator: Eklipse; Kabisch and Haase (2014)

Metric reference(s):

Akpinar, A (2016) How is quality of urban green spaces associated with physical activity and health? Urban Forestry & Urban Greening 16, 76-83.

Akpinar, A, Barbosa-Leiker, C and Brooks, KR (2016) Does green space matter? Exploring relationships between green space type and health indicators. Urban Forestry & Urban Greening 20), 407-418.

Brown, G, Schebella, MF and Weber, D (2014) Using participatory GIS to measure physical activity and urban park benefits. Landscape and Urban Planning 121, 34-44.

Cessford, G and Muhar, A (2003) Monitoring options for visitor numbers in national parks and natural areas. Journal for Nature Conservation 11(4), 240-250.

Coldwell, DF and Evans, KL (2018) Visits to urban green-space and the countryside associate with different components of mental well-being and are better predictors than perceived or actual local urbanisation intensity. Landscape and Urban Planning 175, 114-122.

Colley, K and Craig, T (2019) Natural places: Perceptions of wildness and attachment to local greenspace. Journal of Environmental Psychology 61, 71-78.

Cope A, Doxford, D and Probert, P (2000) Monitoring Visitors to UK Countryside Resources: the Approaches of Land and Recreation Resource Management Organisations to Visitor Monitoring. Land Use Policy 17(1), 59–66.

Faivre, N, Fritz, M, Freitas, T, de Boissezon, B and Vandewoestijne, S (2017) Nature-Based Solutions in the EU: Innovating with nature to address social, economic and environmental challenges. Environmental Research 159, 509-518.

Kimpton, A (2017) A spatial analytic approach for classifying greenspace and comparing greenspace social equity. Applied Geography 82, 129-142.

Schipperijn, J, Bentsen, P, Troelsen, J, Toftager, M and Stigsdotter, U (2013) Associations between physical activity and characteristics of urban green space. Urban Forestry and Urban Greening 12, 109-116.

Sugiyama, TP, Francis, JMPH, Middleton, NJB, Owen, NP and Giles-Corti, BP (2010) Associations between recreational walking and attractiveness, size, and proximity of neighborhood open spaces. American Journal of Public Health 100(9), 1752-1757.

2.1.7.2 Recreational value of blue-green spaces (Env24) Earth Observation/Remote Sensing Review

Umbrella: Cultural value of greenspace

Indicator: Recreational value of blue-green spaces

Code: Env24

Description: This indicator represents a quantification of the number of visitors/recreational activities within a greenspace or blue-green space in order to evaluate, or measure an increase in, recreational benefits as a result of NbS. Examples of features and activities that can attract visitors to NbS include features such as large trees, benches, education days, and communication zones for picnicking. This presents a description of the earth observation and remote sensing approaches to this indicator.

Metric(s): Direct contribution of earth observation / remote sensing tools for the assessment of the cultural value of blue and green spaces of NbS in cities was not identified through review. However, these tools could be used as an indirect way for mapping Land Use/Land Cover (LULC). Based on remotely sensed data, image classification is an important process for that since high-resolution remote sensing technology provides strong support for the monitoring methods and evaluation indicators of urban environment. A basic modelling approach currently emerging uses aerial photography to quantify NbS quality. For example Greencity Watch urban green classification index use park features as a way of classifying park quality: https://www.greencitywatch.org/researchanddevelopment

Image classification can also be important in the investigations for green spaces. Through visual interpretation based on remote-sensing imagery from Google Earth, different transects in cities can be established radiating from the city centre to edge. In each transect, different quadrats can be delineated as the study quadrat in order to illustrate the findings. The methodology proposed by De Ridder et al. (2004) help to analyse and visualise selected indicators for the possible enhancement of green infrastructure on different scale-levels (from street canyon to urban regions) in European cities by using GIS and remote sensing techniques.

The diversity and quality of urban green spaces (UGS) and human well-being are tightly linked, and UGS provide a wide range of ecosystem services (e.g., urban heat mitigation, storm water infiltration, food security, physical recreation). Analyses and inter-city comparison of UGS patterns and their functions requires not only detailed information on their relative quantity but also a closer examination of UGS in terms of quality and land use, which can be derived from the land cover composition and spatial structure. There is some research which presents an approach to UGS extraction from newly available Sentinel-2A satellite imagery, provided in the frame of the European Copernicus program (Kopecká et al., 2017). They investigate and map the spatial distribution of UGS in three cities in Slovakia: Bratislava, Žilina and Trnava. Supervised maximum likelihood classification was used to identify UGS polygons. Based on their function and physiognomy, each UGS polygon was assigned to one of the fifteen classes, and each class was further described by the proportion of tree canopy and its ecosystem services. The results document that the substantial part of UGS is covered by the class Urban greenery in family housing areas (mainly including privately-owned gardens) with the class abundance between 17.7% and 42.2% of the total UGS area. The presented case studies showed the possibilities of semi-automatic extraction of UGS classes from Sentinel-2A data that may improve the transfer of scientific knowledge to local urban environmental monitoring and management.

Greenery in different elements of UGI, e.g. sports facilities, such as football pitches or aqua parks, increases the recreational potential of a city. However, the recreational opportunities of urban ecosystems also vary with social criteria, including accessibility, penetrability, safety, privacy and comfort.

Scientific solid evidence: It can be difficult to link earth observation/remote sensing metrics to solid evidence due to the lack of a participatory aspect to the cultural value of specific features. Also, the finescale resolution of some greenspace features of cultural value makes identification from anything less than high resolution images unreliable. Combining participatory assessment of cultural value and mapping of greenspace features can increase the reliability of evidence generated.

Level of expertise: Knowledge and experience on the topic are needed. As such, the Sentinel Application Platform requires advanced expert sensing data, including derived knowledge.

Costs: The spatial structure of impervious-vegetated mix is heterogeneous at much finer scales in the urban landscape than elsewhere. As a result, for a long time, conventional methods of mapping urban vegetation have relied on a visual interpretation of aerial images and fieldwork. More recently, very high resolution (VHR) satellite remote sensing systems (IKONOS, QuickBird, GeoEye, RapidEye, WorldView, Pleiades) have been developed that are capable of providing imagery with similar detail to aerial photography, and they offer opportunities to overcome the lack of reliable and reproducible information on urban vegetation across large areas. However, the disadvantage of VHR satellites is their narrow swath and therefore limited coverage of the Earth’s surface. Also, VHR satellites are commercially oriented services, and the data cost is relatively high.

One of the most recent sources of information on land cover, including UGS, is Sentinel-2A (S2A), a high-resolution optical Earth observation mission. Although it has coarser spatial resolution than the VHR satellites, it offers higher spectral resolution and is provided free of charge. Sentinel missions are part of the Copernicus program (previously called GMES), a joint initiative of the European Commission and European Space Agency to establish a European capacity for the provisioning and use of information for environmental monitoring and security applications.

Effort: The presented case studies showed the possibilities of semi-automatic extraction of UGS classes from e.g. Sentinel-2A data that may improve the transfer of scientific knowledge to local urban environmental monitoring and management.

Participatory process: The variety of research indicates the emerging forms of collaboration, partnerships, and governance patterns that involve public and private sectors and increase participation by civil society actors. Cooperation amongst several interested groups and the collective reinvention of public urban spaces increase these spaces’ accessibility for multiple users and actors, as well as presenting possibilities for alternative and diversified uses and activities. This might underline the hypothesis that future cities will be governed in less formalised ways, and that urban forms will be created through spontaneous, temporary, mobile, and adaptive negotiation processes.

Data availability: There a variety a data freely available e.g. Sentinel Application Platform (SNAP) is a platform for processing remote data up to city scale. Not ultra-fine scale. vegetation indices. As a tool, can be used for quantifying metrics from RS / satellite data up to city scale. However, it requires advanced expert sensing data, including derived knowledge. Not ultra-fine scale.

Another example is Coordination of Information on the Environment (CORINE) which focus on Global land use classification can be applicable as a tool comprising of global NDVI estimates from remotely sensed data, can be incorporated into other metrics. However, it can be applicable only to regional scale not to neighbourhood scale which reduce usefulness for city scale due to resolution.

Geographical scale: Analysis at various geographical scales is possible.

Temporal scale: Analysis over various temporal scales is possible, although lack of availability of historical high resolution data can be limiting.

Synergies: Demographic, structural and remotely-sensed data can be combined to develop a set of indicators to assess green space, with consideration to three main dimensions: quantity (indicators include green space per inhabitant, green space per bare soils), quality (e.g., mean size of green space, shape index of green space) and spatial distribution (e.g., share of population served by green space, aggregation index of green space).

Applied methods: For more applied and participatory metrics for this indicator please see Env24_Applied

Original reference(s) for indicator: Eklipse; Kabisch and Haase (2014)

Metric references:

d) From the literature review:

Breuste J et al. (2015) Special Issue on Green Infrastructure for Urban Sustainability. In: Journal of Urban Planning and Development, 141(3), n.p. Online (15.2.17): https://www.researchgate.net/publication/278665439.

Brown, G., Schebella, M. F., & Weber, D. (2014). Using participatory GIS to measurephysical activity and urban park benefits. Landscape and Urban Planning, 121,34–44.

Dennis, M.; James, P. (2016) User participation in urban green commons: Exploring the links between access, voluntarism, biodiversity and well being. Urban For. Urban Green., 15, 22–31.

De Ridder et al. (2004): An integrated methodology to assess the benefits of urban green space. In: Science of the Total Environment 334-335, 489-497. Online (15.2.17): https://www.researchgate.net/profile/Christiane_Weber2/publication/8211761_Integrated_metho dology_to_ass ess_the_benefits_of_urban_green_space/links/00b49526772578934c000000/Integrated-methodology-to-assess- the-benefits-of-urban-green-space.pdf.

Herold, M., Liu, X., & Clarke, K. C. (2003). Spatial metrics and image texture for mapping urban land use. Photogrammetric Engineering & Remote Sensing, 69(9), 991–1001.

Kopecká M, Szatmári D, Rosina K (2017) Analysis of Urban Green Spaces Based on Sentinel-2A: Case Studies from Slovakia. Land 2017, 6, 25; doi:10.3390/land6020025

Nikolaidou, S., Klöti, T., Tappert, S., & Drilling, M. (2016). Urban Gardening and Green Space Governance: Towards New Collaborative Planning Practices. Urban Planning, 1(1), 5-19. https://doi.org/10.17645/up.v1i1.520

Vargas-Hernández J.G., Pallagst K., Zdunek-Wielgołaska J. (2018) Urban Green Spaces as a Component of an Ecosystem. In: Dhiman S., Marques J. (eds) Handbook of Engaged Sustainability. Springer, Cham. https://doi.org/10.1007/978-3-319-53121-2_49-1

b) based on the NbS projects from the CN database

No particular project was found to illustrate the use of RS and EO for the purpose of analysis of the Recreational value of blue-green spaces of NbS in cities.

2.1.8 Cultural value of blue-green spaces (Env25)

2.1.8.1 Cultural value of blue-green spaces (Env25) Applied/Participatory Review

Umbrella: Cultural value of greenspace

Indicator: Cultural value of blue-green spaces

Code: Env25

Description: A measure of the number of cultural events/number of people involved to evaluate the cultural benefits of blue-green spaces using applied methods.

Metric(s): The most basic measure for this indicator is counting an increase/decrease in the number of events promoting cultural benefits held in a blue-green space. This can be carried out before and after a change in how the blue-green space is designed or managed to assess the net benefit of a new NbS initiative. Cultural benefits are some of the non-material benefits of ecosystems, including providing opportunities for recreation, physical activity, socializing, and restoring capacities (Chen et al. 2019).

In addition to the basic information on number of events, additional detail can be captured in relation to how well attended events were. This can be captured by counting the numbers of attendees through ticket sales, ticket collection on the day of the event, sign-in processes or monitoring visitor numbers through physical counts or visitor profiling in relation to specific pursuits (Cope et al. 2000; Cessford and Muhar 2003).

Whilst these basic quantifications have a direct relevance to numbers of visitors or events, they do not always provide information on the causal link between the events at a park and the presence of visitors (e.g. visitors might be there due to proximity), or the demographics of visitors attracted to the events. The most typical practice for capturing such information is through generating direct feedback from users and/or local communities. This is generally done in the form of questionnaires (Schipperijn et al. 2013; Kabisch and Haase 2014; Akpinar 2016). Questionnaire sampling protocol should be delivered in such a way as to ensure that responders are representative of the attendees at an event (Kabisch and Haase 2014). Sampling procedures can be designed in a way to compare the demographics of attendees with the demographics of the surrounding neighbourhood or city to ensure that cultural events are being delivered that are attractive to all. Analysis of local/regional socio-demographic data to compare to event attendee data is generally done using interrogation of city social datasets such as the number of inhabitants, number of immigrants, and number of individuals aged ≥65 years (Kabisch and Haase 2014). This enables insight into how urban green-blue spaces are supporting socio-environmental justice in cities (Kabisch and Haase 2014; Snaith 2015; Cronin-de-Chavez et al. 2019).

A combination of the number of events/visitor metrics and the demographics of attendees can generate the most useful data in relation to the popularity and inclusivity of cultural events, and thus the 'value' of the NbS interventions.

Evaluation of cultural value of blue-green space can be used to:

- Monitor the value of cultural events in relation to visitor numbers;
- Assess that changes related to NbS implementation have a positive impact on visitors in relation to attending cultural events;
- Ensure that changes related to NbS implementation promote socio-environmental justice.

Scientific solid evidence: Robustness of evidence is very much based on the design of the questionnaire and the sample size of respondents. Event counts are straightforward and robust, but without the additional data on attendees and demographics, the value of the data is limited. Visitor number counts and demographic data robustness can be a challenge due to the difficulty in capturing representative visitor numbers at some sites.

Level of expertise: Some expertise is needed for the design of the evaluation (e.g. survey method, question selection). Once decided though, a low level of expertise is required for carrying out the survey or carrying out counts. Similarly, data analysis can require low expertise if basic inventories or correlations are required.

Cost: Can be relatively low cost, particularly if citizen scientists/volunteers are used for data collection.

Effort: Effort is associated with the level of survey. Larger sample sizes/local community demographic surveys require a much greater effort than simple counts of visitors. Counts of organised cultural events in blue-green space is relatively low effort but informal events might require greater effort to capture.

Participatory process: Good opportunities for participation through which communication of the benefits of an NbS approach can be delivered. This can be achieved both through the questionnaire process and involving citizen science in data collection. Capturing data on types of cultural events and demographics of attendees can also encourage community members to input information to blue-greenspace managers about the type of events that would be most attractive.

Data availability: Data on organised events is usually collected by most managed blue-green spaces. Data on attendees is also often available. Data on informal events is typically harder to obtain and demographic data on attendees is also often lacking. As such, establishing a baseline before any NbS intervention is important in relation to quantifying the impact of any changes to cultural events.

Geographical scale: Analysis is performed on a single site scale and can comprise sites ranging from very large parks and open spaces to micro-scale pocket parks. Typically, replication across sites is used for comparative purposes. City-wide replication would involve substantial effort as remote sensing data is not an option for quantifying attendees or events.

Temporal scale: Evaluation methods can be adopted for short-term snapshots associated with a change in management. They can also be adapted for long-term evaluation of sites as the events 'offer' changes, as the local demographics of a site changes, or as the demand on a site changes.

Synergies: Strong synergies with health and wellbeing indicators and social cohesion indicators in relation to public use of the sites for physical activity and social events. Also, synergies with environmental indicators (e.g. biodiversity measures, water regulation and air temperature) in relation to synergies and trade-offs in benefits driven by changes in use of blue-green spaces.

Earth observation/remote sensing/modelling: For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env25 - RS

Original reference(s) for indicator: Eklipse; Kabisch and Haase (2014)

Metric reference(s):

Akpinar, A (2016) How is quality of urban green spaces associated with physical activity and health? Urban Forestry & Urban Greening 16, 76-83.

Cessford, G and Muhar, A (2003) Monitoring options for visitor numbers in national parks and natural areas. Journal for Nature Conservation 11(4), 240-250.

Chen, X, de Vries, S, Assmuth, T, Dick, J, Hermans, T, Hertel, O, Jensen, A, Jones, L, Kabisch, S, Lanki, T, Lehmann, I, Maskell, L, Norton, L and Reis, S (2019) Research challenges for cultural ecosystem services and public health in (peri-)urban environments. Science of The Total Environment 651(2), 2118-2129.

Cope A, Doxford, D and Probert, P (2000) Monitoring Visitors to UK Countryside Resources: the Approaches of Land and Recreation Resource Management Organisations to Visitor Monitoring. Land Use Policy 17(1), 59–66.

Cronin-de-Chavez, A, Islam, S and McEachan, RRC (2019) Not a level playing field: A qualitative study exploring structural, community and individual determinants of greenspace use amongst low-income multi-ethnic families. Health & Place 56, 118-126.

Kabisch, N. and Haase, D., 2014. Green justice or just green? Provision of urban green spaces in Berlin, Germany. Landscape and Urban Planning, 122, pp.129-139.

Schipperijn, J, Bentsen, P, Troelsen, J, Toftager, M and Stigsdotter, U (2013) Associations between physical activity and characteristics of urban green space. Urban Forestry and Urban Greening 12, 109-116.

Snaith, B. (2015) The Queen Elizabeth Olympic Park: Whose Values, Whose Benefits? Unpublished Doctoral thesis, City, University of London.

2.1.8.2 Cultural value of blue-green spaces (Env25) Earth Observation/Remote Sensing Review

Umbrella: Cultural value of greenspace

Indicator: Cultural value of blue-green spaces

Code: Env25

Description: A measure of the number of cultural events/number of people involved to evaluate the cultural benefits of blue-green spaces using earth observation, remote sensing and modelling approaches.

Metrics: There is no real direct contribution of earth observation/remote sensing tools for the assessment of the cultural value of blue and green spaces of NbS in cities. However, these tools could be used in an indirect way for mapping Land Use/Land Cover (LULC) as a background layer for mapping and presenting indicator results. When using of remotely sensed data, image classification is an important process as high-resolution remote sensing technology can provide strong support for the monitoring methods and evaluation indicators applied in the urban environment.

It also can be important for the investigation of attributes of green spaces. By using visual interpretation based on remote-sensing imagery from Google Earth, different transects in cities can be established radiating from the city centre to edge. In each transect, different quadrats of e.g. 450 × 450 m can be delineated as the study quadrat as a framework for illustrating findings.

Scientific solid evidence: Not relevant.

Level of expertise: Not relevant.

Costs: Not relevant generally. However, cost implications may occur when using RS as an indirect way of mapping Land Use/Land Cover (LULC). When providing support for monitoring methods and evaluation indicators of urban environment and for the investigations of green spaces (visual interpretation based on remote-sensing imagery from Google Earth, different transects in cities can be established radiating from the city centre to edge), the use of analysed spatial data can increase costs. However, the use of open access satellite imagery can reduce the cost of this.

Participatory process: Not relevant.

Data availability: Visual interpretation based on remote-sensing imagery from Google Earth, for establishing different transects in cities radiating from the city centre to edge, are free for download from these websites:

- http://glovis.usgs.gov/
- http://www.escience.cn/people/feiyunZHU/Dataset_GT.html
- http://openremotesensing.net
- http://freegisdata.rtwilson.com

Geographical scale: City, city district

Temporal scale: not relevant

Synergies: not relevant

Applied methods: For greater detail on applied and participatory methods for quantifying cultural value of greenspace please see: Env25_Applied

Original reference(s) for indicator: Eklipse; Kabisch and Haase (2014)

Metrics references:

c) References from literature review:

Wu C.-D., McNeely E., Cedeno-Laurent J., Pan W.-C., Adamkiewicz G., Dominici F., Lung S.-C.C., Su H.-J., Spengler J.D. (2014) Linking student performance in Massachusetts elementary schools with the “greenness” of school surroundings using remote sensing. PLoS ONE. doi: 10.1371/journal.pone.0108548.

d) References for Indicator based on the NbS projects from the CN database:

No particular project was found to illustrate the use of RS and EO for the purpose of analysis of the cultural value of blue and green spaces of NbS in cities.

2.1.9 Connectivity of urban green and blue spaces (structural and functional) (Env27)

2.1.9.1 Connectivity of urban green and blue spaces (structural and functional) (Env27) Applied/Participatory Review

Umbrella: Connectivity of urban green and blue spaces (structural and functional)

Indicator: Connectivity of urban green and blue spaces (structural and functional)

Code: Env27

Description: A more applied and participatory focus to measuring the potential for green or blue areas to amplify the connectivity and multifunctionality of other urban green/blue areas.

Metric(s): Connectivity of landscapes can be evaluated in terms of:

- *Structural connectivity* – relating to the spatial configuration of patches, without considering the movement of individual organisms among these patches (Ioja et al. 2014)

and

- *Functional connectivity* – relating to the ability of organisms to move among patches (Tischendorf and Fahrig 2000).

Both types of connectivity can be quantified using metrics that span different ranges of scale and complexity.

Structural connectivity is measured by the proximity of blue-green spaces and the infrastructure matrix that these form across a city. These are typically measured through a blue-green space mapping exercise that orientates and measures distribution and proximity on a city or regional level (Zhang et al. 2019). Typically, such mapping is done using the interrogation of satellite imagery and or land use maps. Examples of methodologies for such mapping include STURLA (Hamstead et al 2016) and FRAGSTATS (Saura and Torné 2009). The outputs from such exercises are usually represented through green infrastructure network maps that provide a planning tool for protecting existing blue-green spaces and opportunity maps for identifying priority areas for enhancing structural connectivity (Carlsen et al. 2011; Zhang et al. 2019). Participatory processes are also possible using internet-based public participation GIS (PPGIS) surveys to map functional aspects of urban blue-green space (Kahila-Tani et al. 2016; Brown et al 2018a; Brown et al. 2018b) and map underused/unmapped microspaces (Crowe et al. 2016).

Functional connectivity is measured in relation to the ability of the landscape to support the movement of organisms through it (Peer et al. 2011). There has been a particular focus on functional connectivity in relation to urban biodiversity (Hess and Fischer 2001; Opdam 2006; Ahern 2007) because of the impact that fragmentation and the reduction in the number and area of natural habitats has on the ability of many species to persist (Fletcher et al. 2018). The predominance of grey infrastructure in urban areas can represent a physical barrier to the movement of many species. These barriers can occur to the extent that urban development can exclude many species (McKinney 2006). Similarly to biodiversity, lack of blue-green space connectivity can also present a barrier to the movement of humans through urban areas (Ioja et al. 2014), particularly in relation to the use of active transport (Giles-Corti et al. 2010) and physical activity (Davison and Lawson 2006).

Thresholds for connectivity differ between different species/groups. For some, connectivity must represent linear physical connections, for other species, 'stepping stones' of suitable habitat over appropriate spatial scale represent sufficient functional connectivity (Vergnes et al. 2012). Similar patterns are also reported for human activities associated with blue-green space (Wineman et al. 2014; Peschardt et al. 2012). This means that, for both biodiversity and human functional connectivity, it is vital to have an understanding of the spatial dynamics of connectivity of relevance to your target group and activity (e.g. for humans - active transport; for biodiversity – foraging, colonisation, etc) in order to set threshold values.

Methods for measuring connectivity are therefore based on the spatial thresholds for the group and activity of interest. The most basic method to achieve this is to use Geographical Information Systems (GIS) to apply buffer areas to mapped blue-green spaces that are known to be suitable for the target group and activity.

A more complex, but potentially more realistic approach is to combine distance data with data on the spatially heterogeneous impedance of the landscape matrix (i.e. a measure recognising that some non-target landuse types might be more permeable than others) (Hargrove et al. 2004). By adopting such an approach, it is possible to measure potential connectivity corridors using least-cost path tools using GIS software combined with gravity models and graph theory (Kong et al. 2010).

Conefor software in ArcMap can be used to calculate the integral index of connectivity (IIC). This represents a method for combining the distance between patches with the threshold dispersal distance of a certain species (Saura and Torné, 2009). Such a tool enables evaluation of functional connectivity and provides a suitable metric for landscape conservation planning (Pascual-Hortal and Saura, 2006). Another example of a method for capturing functional connectivity is the use of habitat suitability models (HSM) utilising remote sensed vegetation data to map landcover composition and species distributions across cities (Bellamy et al. 2017).

In general, the biggest barrier to the delivery of such mapping tends to be a lack of understanding of the spatial dynamics (in relation to what constitutes functional connectivity) for the target groups (LaPoint et al. 2015). Applied methods to study the spatial dynamics of target groups, and to assess the permeability of different habitat types by direct observation, can strengthen the validity of mapped data.

Evaluation of blue-green space structural and functional connectivity can be used to:

- Underpin green infrastructure and biodiversity spatial planning;
- Prioritise sites for interventions;
- Assess that impacts of NBS projects on pre-existing green networks;
- Promote active transport initiatives.

Scientific solid evidence: Robustness of evidence for structural connectivity tends to be based on the methodology used to identify and characterise urban greenspace, the scale of resolution of the data, and the age of the data in relation to current state. If up-to-date data from reliable sources is used, calculation of distances using GIS mapping provides solid evidence. For functional connectivity, the robustness of data tends to be correlated with the level of understanding in relation to the spatial dynamics of the target group or activity, and the suitability of habitat.

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing.

Cost: Cost is related to the data input requirements and the processing costs for specialist GIS analysis. Costs can be reduced if in-house expertise is available and if citizen scientists/volunteers are used for data collection.

Effort: Effort is generally associated with the scale of spatial analysis and the data input requirements. Once data is inputted, data analysis can be relatively low effort. Keeping databases updated can require additional effort.

Participatory process: Opportunities are available for participation. This can be in the form of mapping greenspaces using internet-based public participation GIS (PPGIS), assessing habitat suitability for target species and activities, or surveying for presence/absence/movement of species.

Data availability: Aerial photography data is widely available, although resolution of open access data can represent a barrier depending on the scale of investigation. Open access land use mapping can also be available for urban areas. Data on the habitat suitability and spatial scales associated with connectivity can be missing for many groups/species in urban areas.

Geographical scale: Analysis is generally performed on a city-wide or regional scale. Local connectivity analysis is also possible.

Temporal scale: Evaluation methods can be adopted for short-term snapshots associated with a change in land use, or strategic connectivity planning. Production of strategic maps can, however, represent a baseline for long-term evaluation of change in connectivity.

Synergies: Strong synergies exist with any indicators that require blue-green space mapping as the foundation for analysis.

Earth observation/remote sensing/modelling: Spatial modelling forms the foundation of this indicator. For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env27_RS.

Original reference(s) for indicator: Eklipse; Ioja et al., 2014

Metric reference(s):

Ahern, J. (2007) Green Infrastructure for Cities: the spatial dimension. In V. Novotny, L. Breckenridge, P. Brown (Eds.), Cities of the Future: Towards Integrated Sustainable Water and Landscape Management, IWA Publishers, London (2007), pp. 267-283.

Bellamy, CC, van der Jagt, APN, Barbour, S, Smith, M and Moseley, D (2017) A spatial framework for targeting urban planning for pollinators and people with local stakeholders: A route to healthy, blossoming communities? Environmental Research 158, 255-268.

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2.1.9.2 Connectivity of urban green and blue spaces (structural and functional) (Env27) Earth Observation/Remote Sensing Review

Umbrella: Connectivity of urban green and blue spaces (structural and functional)

Indicator: Connectivity of urban green and blue spaces (structural and functional)

Code: Env27

Description: Earth observation/remote sensing indicators and tools for measuring the potential for green or blue areas to amplify the structural and functional connectivity and multifunctionality of other urban green/blue areas.

Metric(s): One of the major impacts of urbanization is the *fragmentation of open spaces* into smaller and more isolated patches. Increased fragmentation of green in urbanized areas can reduce intra- and inter-species connectivity and lead to a loss of biodiversity (Kettunen *et al.*, 2007). Fragmentation of green areas and distance between habitat patches is thus an important factor in determining biodiversity. A *Green Infrastructure* approach, linking parks and other green spaces, is therefore considered essential for the preservation of biodiversity and to counter further habitat fragmentation (EEA, 2010). Fragmentation and isolation of urban green spaces can be described by means of spatial metrics, i.e. quantitative measures of spatial pattern that were originally developed by landscape ecologists to examine the link between the spatial patterning of ecosystem types in natural landscapes and ecological processes (Turner, 1989, 1990). Many metrics have been developed for characterizing patterns in landscapes and were later implemented in the *spatial analysis program FRAGSTATS* by McGarigal and Marks (1995), which today is a commonly used quantitative tool in the field of landscape ecology.

For instance, in the study of Van de Voorde et al. (2010) various spatial metrics available in FRAGSTATS were calculated to describe fragmentation and isolation of open and dense vegetation patches in the Brussels Capital Region, mapped from high resolution Quickbird data. Fragmentation can be described by the *total number of patches and by summary statistics* characterizing the frequency distribution of patch size (expressed in hectares), including mean patch size, median patch size, standard deviation of patch size and coefficient of variation. Isolation of open and dense patches can be described by two indicators: *the Euclidean nearest neighbor distance* of a patch to other patches of the same type, and the *proximity index*.

Satellite imagery is the fastest method for data collection for urban planning. Since the first development of satellite imagery, many studies have investigated extracting various types of vegetation information. Johansen & Phinn (2006) combined IKONOS and Landsat ETM+ data in order to map structural parameters and the species composition of vegetation. Dennison et al. (2010) used GeoEye-1 high spatial resolution satellite data to map canopy mortality caused by a pine beetle outbreak. Gašparović et al. (2018) used WorldView-2, RapidEye, and PlanetScope data to detect urban vegetation based on land cover classification. Kranjčić et al. (2018, 2019) used Sentinel-2 data to visualize bark-beetle-damaged forests in Croatia, and Wessel et al. (2018) tested object-based and pixel-based methods on Sentinel-2 imagery for two forest sites in Germany. They stated that Sentinel-2 data had high potential for applied forestry and vegetation analysis. Friedel et al. (2017) used unsupervised machine learning to map landscape soils and vegetation components from satellite imagery. Tsai et al. (2018) used machine learning classification in order to map vegetation and land use types. As seen from the abovementioned literature, a lot of work has been done with remote sensing and machine learning to extract vegetation information and measure the potential for green or blue areas to amplify the connectivity and multifunctionality of other urban green/blue areas.

Many studies highlighted landscape fragmentation which was caused by rapid urbanization and has resulted in an immense amount of damage to the ecological system. Taking city districts as study areas, Guo et al. (2018) distinguished the vital patches and corridors for landscape connectivity maintenance through morphological spatial pattern analysis (MSPA), the probability of connectivity (PC), and the least-cost path analysis. These methods are mostly adopted and combined from the existing research about landscape modeling and can be divided into two parameters: the resistance value and the distance threshold. In order to get a species-specific result, some focal species should be selected whose biological characteristics and habitat types are assumed to represent most of the habitats in the city being studied (umbrella species). The result of such studying can show the different habitats and corridors for such species. Then, the results of simulated scenarios can be used to obtain the final landscape pattern. Based on this study, one can propose a paradigm of ecological network identification of multiple species, which may contribute to landscape modeling and greenspace planning.

Landscape connectivity, the opposite of landscape fragmentation, describes the facilitating or impeding effect of the landscape on the dispersal of species among habitats. It is used to evaluate the ecological service function of a certain landscape by quantifying landscape patterns from a macro point of view. In recent decades, an interdisciplinary field called landscape ecology has proposed new methods to understand how landscape patterns influence ecological processes, for instance, biodiversity and the warmer microclimate-heat island effect.

The high-resolution remote sensing images (RS-images) can be used to extract land cover information. Image processing should be performed using ENVI (Harris Geospatial, Boulder, CO, USA) and eCognition (Trimble, Westminster, CA, USA), which can extract meaningful information from remote sensing image. Before classification, images have to be segmented. The scale parameter refers to the threshold of the heterogeneity variation allowed in the segmentation process (Dekavalla & Argialas, 2018). Scale parameter will affect the accuracy and efficiency of the extraction process. Multiscale segmentation was used to fix this problem. It is the foundation procedure of object-based image analysis (OBIA) to convert discrete pixels of RS-images into a homogeneous image object. Depending on the required land-cover categories (green space, agriculture land, built-up area, transportation area, and water), the segmentation scale parameter and the hierarchical relationship were identified according to their characteristics after several attempts to obtain a satisfactory result.

Difficulties in pixel-based classification caused by increasing satellite resolution led to the development of OBIA (Blaschke 2010). By identifying spectral and spatial information (the normalized difference vegetation index, geometry, brightness, texture, neighborhood attributes), adjacent pixels are grouped into multipixel objects (Aplin et al. 1999). For this reason, the K-nearest neighbor method can be adopted in order to obtain the land-cover categories by creating the following spectral characteristics: normalized difference vegetation index, standard deviation, maximum difference, brightness, length/width, roundness, and aspect ratio.

Landscape metrics, for example, the L-Z complexity method (Li et al. 2009) and mean patch shape fragmentation index can be developed to quantify landscape fragmentation. Landscape fragmentation processes can be classified into perforation, subdivision, shrinkage, and attribution, which can also be measured. However, these studies evaluate the overall landscape fragmentation without locating where fragmentation is taking place. According to the definition of landscape fragmentation, fragmentation will bring two results: one is the decrease in patch area, and the other is the increase in patch number. In other words, the mean patch area will decrease. Therefore, the mean patch area can be used to quantify the fragmentation. The RS-image can be clipped into grids (size = 1 km × 1 km) using the *Fishnet* tool in *ArcGIS*. The area and number of patches in each grid can be summarized, then the mean patch area can be calculated to indicate its landscape fragmentation.

Table 1. Remote-sensing based indices for the effectiveness and health of green (Wellmann et al., 2018)

Type of Index	Index Name	Abbreviation	Reference
Vegetation Indices	Vegetation fractions	Frac	(Haase et al., 2019)
	Normalized difference vegetation index	NDVI	(Tucker, 1979)
	Green NDVI	gNDVI	(Gitelson et al., 1996)
	Red edge normalized difference vegetation index	reNDVI	(Gitelson and Merzlyak, 1994)
	Vegetation health index	VHI	(Lausch et al., 2018) (Kogan, 1990, 1997)
	Vegetation condition index	VCI	(Kogan, 1995)
	Temperature condition index	TCI	(Singh et al. 2003)
Combination of methods	satellite remote sensing with on-the-ground observations	-	(Lotze-Campen and Lucht, 2001) (Haase et al., 2019)
Statistical Indices	Principal component analysis	1^{st} component 2^{nd} component 1^{st} and 2^{nd} component	(Jolliffe, 2002)

Note: No single approach is sufficient to monitor the complexity and multidimensionality of health of green and VH over the short to long term and on local to global scales (as stated by Haase et al., 2019; Lausch et al., 2018; Wellmann et al., 2017). Rather, every approach has its pros and cons, making it all the more necessary to link approaches. It is possible to realize within the frameworks proposed in the above mentioned publications and by reflecting crucial requirements for coupling approaches and integrating additional monitoring elements to form a multisource vegetation health monitoring network (MUSO-VH-MN) as suggested by Lausch et al. 2018. Thereby it is important to have in mind, that when it comes to linking the different approaches, data, information, models or platforms in a MUSO-VH-MN, big data with its complexity and syntactic and semantic heterogeneity and the lack of standardized approaches and VH protocols pose the greatest challenge. Therefore, Data Science with the elements of (a) digitalization, (b) semantification, (c) ontologization, (d) standardization, (e) Open Science, as well as (f) open and easy analyzing tools for assessing VH are important requirements for monitoring, linking, analyzing, and forecasting complex and multidimensional changes in health of green and VH.

Table 2. Statistical indicators that have been tested for the quantification of spectral plant trait variations (Wellmann et al., 2017).

Type	Name	Formula	Reference
GLCM *Stats group*	GLCM mean	$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$	(Haralick et al., 1973)
	GLCM variance	$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2$	(Haralick et al., 1973)
	GLCM correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{\left(i-\mu_i\right)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right]$	(Haralick et al., 1973)
GLCM *Contrast group*	GLCM homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+\left(i-j\right)^2}$	(Haralick et al., 1973)
	GLCM contrast	$\sum_{i,j=0}^{N-1} P_{i,j}\left(i-j\right)^2$	(Haralick et al., 1973)
	GLCM dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\left\|i-j\right\|$	(Haralick et al., 1973)
GLCM *Orderliness group*	GLCM entropy	$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right)$	(Haralick et al., 1973)
	GLCM angular second moment	$\sum_{i,j=0}^{N-1} P_{i,j}^2$	(Haralick et al., 1973)
Spatial	Geary's *C*	$C = \frac{n-1}{2*\left(\sum_i\sum_j w_{ij}\right)} * \frac{\sum_i\sum_j w_{ij}(x_i-x_j)^2}{\sum_i (x_i-\bar{x})^2}$	(Geary, 1954)

Autocorrelation	Moran's *I*	$I = \frac{n * \sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_i \sum_j w_{ij}\right) * \sum_i (x_i - x)^2}$	(Moran, 1950)
Descriptive Statistics	Standard Deviation	$\sigma = \sqrt{\frac{\sum(x - \overline{x})^2}{N}}$	
	Coefficient of Variation	$CV = \frac{\sigma}{\mu}$	(Datt, 1998)

Scientific solid evidence: The potential for satellite remote sensing to provide key data has been highlighted by many researchers, offering repeatable, standardized and verifiable information on long-term trends in biodiversity indicators and characteristics of connectivity and fragmentation. As concluded by a variety of research (listed in the references), remote sensing permits one to address questions on scales inaccessible to ground-based methods alone, facilitating the development of an integrated approach to natural resource management, where biodiversity, pressures to biodiversity and consequences of management decisions can all be monitored.

Remote sensing (RS)—taking images or other measurements of Earth from above—provides a unique perspective on what is happening within the urban landscape and thus plays a special role in green infrastructure analysis, environmental monitoring as well as biodiversity and conservation applications. The periodic repeat coverage of satellite-based RS is particularly useful for monitoring change and so is essential for understanding trends, and also provides key input into assessments of vegetation, connectivity and conservation management.

Level of expertise: The measure of the physical connectedness of the vegetation across a landscape, sometimes referred to as the 'structural vegetation connectivity' will typically be measured using remote sensing methods. It differs from 'ecological connectivity' which will usually be measured through on-ground observations and analysis. "Hyperspectral" sensors can have more than 200 bands and can provide a wealth of information to help, for example, identify specific species. Processing such datasets requires special expertise and satellite-based hyperspectral sensors are not yet common.

Costs: Historically, RS data have often been expensive and hard to use, but changes over the last decade have resulted in massive amounts of global data being available at no cost, as well as significant (if not yet complete) simplification of access and use.

Effort:RS data/techniques make the findings of ES studies more relevant, more appropriate to urban planning, and useful for guiding sustainable development in these areas (Tavares et al., 2019). There are many sources to access such data (see Figure below). However, there are several limitations that include inconsistent metadata, data access, intellectual property and privacy considerations. Satellite remote sensing measurements, on the other hand, are widely accessible, and offer a relatively inexpensive and verifiable means of deriving complete spatial coverage of environmental information for large areas at different spatial and temporal resolutions in a consistent manner, holding great potential for tracking changes in ecosystem functions.

Satellite remote sensing is, however, associated with intrinsic limitations, which include length, data processing, time capacity, etc. Integrated use of multiple remote sensing sources and increased remote sensing capacity can help overcome many of these known challenges, as long as data and product requirements are clearly identified: the prioritization of new satellite missions associated with freely accessible data for scientific use might indeed be facilitated by the formulation of clear, consensual demands from ecosystem researchers.

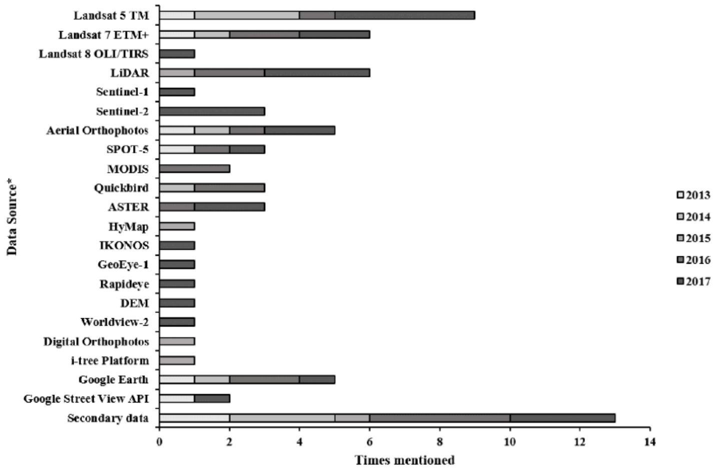

Figure 3. Identification of data source used by the authors, separated by year (2013–2017). * Abbreviations mentioned in the data source axis stands for TM, thematic mapper; ETM+, enhanced thematic mapper plus; OLI/TIRS, operational land imager/thermal infrared sensor; SPOT, satellite pour l'observation de la Terre; MODIS, moderate-resolution imaging spectroradiometer; ASTER, advanced spaceborne thermal emission and reflection radiometer; DEM, digital elevation model; API, application programming interface.

Source: Tavares et al., (2019)

Participatory process: Participatory processes can be used to support data analysis. For further information on this see: Env27_Applied.

Data availability: Availability of lidar data is quite limited, and although radar data are more widely available it may be expensive and its use is less intuitive than the interpretation of optical images. Free software exists to do supervised and unsupervised classification, for example, https://www.orfeo-toolbox.org/ and http://www.dpi.inpe.br/spring/. One additional very useful tool is the Rapid Land Cover Mapper (http://lca.usgs.gov/lca/rlcm/), which provides a very simple way of visually mapping Land Use/Land Cover and change; it is free though requires ArcGIS ArcMap software. And, increasingly, the open source R statistical software (http://www.r-project.org) is being used for image analysis, and many classification techniques and other geo- statistical models can be easily applied to images using existing user-supplied "packages".

Geographical scale: Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change at various geographical scales. However, the higher resolution required, the more expensive would be the RS data needed. In some cases, it would be better to use images provided by drones, but in this case permissions for survey mapping will be required and depends on the local and national/government regulations.

Temporal scale: Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change over time, at various temporal scales. Analysis of past change can be challenging if historical data of sufficient resolution is unavailable.

Synergies: Remote sensing is generally most useful when combined with in situ observations, and these are usually required for calibration and for assessing RS accuracy. RS can provide excellent spatial and temporal coverage, for example, though its usefulness may be limited by pixel size which may be too coarse for some applications. On the other hand, in situ measurements are made at very fine spatial scales but tend to be sparse and infrequent, as well as difficult and relatively expensive to collect. Combining RS and in situ observations takes advantage of their complementary features.

Synergies exist with other indicators that use greenspace mapping as a foundation for analysis.

Applied methods: For more applied and participatory approaches to assessing connectivity, please see: Env27_Applied.

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Green Surge (Green Infrastructure and Urban Bio- diversity for Sustainable Urban Development and the Green Economy)

www.greensurge.eu

One of the project tasks was “Identification, description and quantification of the full range of urban green spaces”. In this regard, the research was based on remote sensing results in combination with relevant case studies field observation.

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IMPRESSIONS (Impacts and risks from high-end scenarios: strategies for innovative solutions)

http://www.impressions-project.eu/

- Mapping land use, ecosystem functions, and ecosystem services using cutting-edge remote sensing and machine learning techniques

OpenNESS (Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

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OPPLA

(https://oppla.eu)

- *Growing with green ambitions. Case study of Leipzig*

An important lesson is that mapping should be combined with in situ green space monitoring of, for example, vegetation biomass. This would add value to remote sensing data and improve the capacity to assess ecosystem services provided by urban green space such as carbon dioxide removal. In addition, data were only available for 2012. An account based on a time series of land cover and land use would help city planners to better understand to what extent urban green infrastructure is under pressure.

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Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- remote Sensing and LIDAR data used to estimate vegetation volume and NVDI. A 3D NVDI as constructed by multiplying the NVDI with the vegetation volume. Measured temperatures was modelled using Maximum Likelihood as a function of NVDI, 3D NVDI, distance to green / blue areas and built-area volume (input data: Remote images (1 m resolution), LIDAR data, temperature measurements; output data: temperature).

- a set of modelled GIS and remote sensing parameters used to model temperature as an effect of greenness, aerosols, buildings. Likely the method needs to be calibrated for each city/town separately (input data: GIS data of buildings, Landsat data; NVDI & AH CHRIS/PROBA satellite images, ASTER image data; output data: temperature).

- remote sensing for ES matrix – the ES matrix approach is an easy-to-apply concept based on a matrix linking spatially explicit biophysical landscape units to ecological integrity, ecosystem service supply and demand. By linking land cover information from, e.g. remote sensing, land survey and GIS with data from monitoring, statistics, ecosystem service supply and demand can be assessed and transferred to different spatial and temporal scales. The ES matrix approach is a quick and simple way to get an overall spatially-explicit picture of the ES in case study areas (input data: land cover and land use data (GIS) (incl. Additional biotic and abiotic information (e.g. land use intensity, soil quality, climate data); output data: ES provision capacity per land use class (0-5 values & biophysical units).

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2.1.10 Supporting/increasing biodiversity conservation (Env29)

2.1.10.1 Supporting/increasing biodiversity conservation (Env29) Applied/Participatory Review

Umbrella: Biodiversity measure

Indicator: Supporting/increasing biodiversity conservation

Code: Env29

Description: Measure net change in individual (native) species numbers, functional richness, vegetation cover, conservation priority species in area affected by NBS using more applied and participatory methods.

Metric(s): Biodiversity generates a wide range of benefits to society (ecosystem services) therefore its conservation is essential to achieving Sustainable Development Goals (SDGs) and to meet the United Nations Convention on Biodiversity (CBD) Aichi Biodiversity Targets. Measuring net changes to biodiversity to monitor gains or losses as a consequence of NBS can be undertaken using various methodologies, involving either primary observations of species or assessments of habitat extent/quality as a proxy for biodiversity value. Counts of species (species richness) have commonly been used as a surrogate for measuring biodiversity for conservation at local and broader scales, and taxa are often categorized according to rarity/local conservation concern (see The Royal Society, 2003 for a framework for measuring biodiversity for conservation). Measurements of population sizes of individual species (abundance), particularly umbrella species (Roberge and Angelstam 2004) (species which if protected, indirectly protect many other species comprising the ecological community of their habitat), can be a more sensitive indicator of change. However, collecting the data on the population dynamics of single species can be resource intensive. Adopting participatory/citizen science approaches can provide a mechanism to reduce resource intensity but can, typically, only be applied to relatively easy to identify species.

Selecting appropriate metrics will depend on the objectives of the study, and whether direct measurement is required, or whether a proxy/surrogate measurement may be sufficient. Typically, extrapolations are made from collecting a stratified random sample. Repeat surveys must be undertaken to monitor change against a baseline survey. Analytical techniques will be related to sampling strategies (i.e. diversity or species quality indices, multivariate modelling, etc).

Pocock et al. (2015) have developed a checklist of priority attributes for developing a biodiversity monitoring programme that includes 25 attributes that range from elemental to aspirational. This can be used as a checklist to clarify objectives and justify investment in resources and provides an excellent resource for local authorities or city stakeholders wanting to establish monitoring programes. The National Biodiversity Network (James, 2007) has an online handbook which provides comprehensive guidance on running a biological recording scheme that could potentially be used for site assessment, land-use planning and environmental policy development. The Natural History Museum (NHM) has a guide for specifically developing citizen science recording schemes (Tweddle, 2012).

The Wildlife Trust Biodiversity Benchmark provides a framework to achieve continual biodiversity enhancement and protection on landholdings by developing an action plan, recording the baseline (PEA - habitats & species), and conducting periodic monitoring to assess performance against targets.

Examples of citizen science projects that could be applied to NBS projects:

Glasgow's buzzing - community bee recording project in partnership with Buglife, creating and enhancing wildflower meadows across the City, carrying out invertebrate surveys (sweep nets of parks before/after meadow creation/enhancement) and raising community awareness of biodiversity (Bairner, 2016)

Urban butterfly project - recording butterflies in urban greenspaces 3 times during spring/summer to measure species/abundance using iRecord Butterflies app

RSPB Big Garden Birdwatch/Big Schools Birdwatch – annual snapshot of bird diversity

NHM Bioblitz – community bioblitz, typically a 24 hour census, recording as many species as possible.

When selecting species to target for evaluation of benefits, there are generally to strategies: selecting species that are local, national or international conservation priority species, and selecting representative umbrella species that are indicators of high biodiversity. When selecting umbrella species, it is generally advisable to select a range of species that are representative of a range of taxa (Sattler et al. 2014) and ensure that there is a local focus to this selection in terms of species associated with site of high biodiversity (Caro 2010).

Key drivers include:

- Assisting local authorities to evaluate their progress in urban biodiversity conservation (for example against Aichi/national/local biodiversity targets);
- Ensuring NBS contributes positively to biodiversity conservation;
- Serving as a public platform upon which biodiversity awareness raising exercises can be launched.

Scientific solid evidence: ad-hoc, unstructured recording can restrict scientific value but can catalyse community engagement. Structured, systematic monitoring programmes, including citizen science, can be an important mechanism for ascertaining population trends over time.

Level of expertise: Professional ecological consultants and scientific/ecological expertise are needed to design and implement and/or support citizen scientists monitoring schemes and data analysis (depending on the scheme or whether an existing scheme is adopted). If identification of target species is not straightforward, expertise can be required for the monitoring also.

Cost: Variable. Consultancy costs would depend on the scale of the NBS project. If there are existing biodiversity monitoring schemes in place, implementation for a specific project could be relatively low, set-up costs for new schemes could be high.

Effort: Hiring professional consultants would involve the lowest effort. Co-ordinating citizen science projects can be more onerous but can also be lower effort for more substantial data than delivering the monitoring in-house.

Participatory process: Such monitoring schemes offer great opportunities for citizen participation. This can be a mechanism to increase the scale and extent of the monitoring, and to increase community engagement with, and awareness of, urban biodiversity.

Data availability: Using existing monitoring schemes can be a very effective mechanism for identifying long-term patterns. However, where such schemes don't exist, there may be a need to develop new programmes to capture the baseline data needed prior to the NBS intervention to capture change.

Geographical scale: Typically more local or project scale but can be used to capture data at city scale. Scale is typically related to recorded networks and their scale.

Temporal scale: can provide a snapshot or site inventory/baseline from which changes can be measured over time with repeated surveys. Long-term data can be generated if formal monitoring programmes are established.

Synergies: Direct measures of supporting/increasing biodiversity could have synergies with landuse change, greenspace area and accessibility to greenspace (wildlife areas).

Earth observation/remote sensing/modelling: For further information on modelling and remote sensing approaches, and examples of their use in past and current EU projects, see indicator guidelines: Env29_RS

Original reference(s) for indicator: UnaLab

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2.1.9.2 Supporting/increasing biodiversity conservation (Env29) Earth Observation/Remote Sensing Review

Umbrella: Biodiversity measure

Indicator: Supporting/increasing biodiversity conservation

Code: Env29

Description: Measure net change in (native) species numbers, functional richness, vegetation cover, conservation priority species in area affected by NBS using Earth Observation and Remote Sensing approaches

Metric(s): It is important to foster research and monitoring of biodiversity to determine the best assemblages of species to achieve the most efficient NBS, including the optimization of multiple economic, ecological and social benefits and exploration of trade-offs created by NBS. This can be achieved by collection of new data in the field and the use of remote sensing to gather comprehensive data on additional benefits, to complement existing data and observation.

Biodiversity includes multiscalar and multitemporal structures and processes, with different levels of functional organization, from genetic to ecosystemic levels. One of the most widely used methods to infer biodiversity is based on taxonomic approaches and community ecology theories. However, gathering extensive data in the field is difficult due to logistic problems, especially when aiming at modelling biodiversity changes in space and time, which assumes statistically sound sampling schemes. In this context, airborne or satellite remote sensing allows information to be gathered over wide areas in a reasonable time. Most of the biodiversity maps obtained from remote sensing have been based on the inference of species richness by regression analysis. Estimating compositional turnover (β-diversity) might add crucial information related to relative abundance of different species instead of just richness. Presently, few studies have addressed the measurement of species compositional turnover from space. There are novel techniques to measure β-diversity from airborne or satellite remote sensing proposed by Roccini et al. (2017), mainly based on:

- multivariate statistical analysis,
- the spectral species concept,
- self-organizing feature maps,
- multidimensional distance matrices,
- Rao's Q diversity.

Each of these measures addresses one or several issues related to turnover measurement.

High temporal resolution remote sensing images together with vegetation phenological features can achieve more accurate identification of vegetation types. Yan et al. (2018) integrated object-based classification data with vegetation phenological information derived from multi-temporal WorldView-2 images to identify grass and tree types. Senf et al. (2015) found that adding phenological patterns captured by multi-seasonal Landsat imagery can better discriminate shrublands and woodlands that would otherwise be a challenging task in single-date Landsat imagery. Moreover, utilizing the 3D structures provided by LiDAR imagery in combination with the hundreds of narrow spectral bands provided by hyperspectral (HS) imagery can enable the identification of more vegetation types. Xia et al. (2018) constructed an ensemble classifier to integrate HS and LiDAR data, and used it to identify several tree types and three grass types. Alonzo et al. (2014) used a crown-level integration of HS and LiDAR data to identify 29 common tree species in urban regions

Drone mapping is described as a tool for monitoring ecosystem restoration. Plant communities with different plant cover and species composition reflect spectral bands in different rates and this information reflects state and disturbances of mire ecosystems (peatlands). Usage of drones gives higher resolution data compared to other remote sensing options, and is suitable for plant community level monitoring, but at the same time there is a trade-off between spatial resolution and mapping area.

Various indicators are used to assess the status and trends of components of biodiversity, measure pressures, and quantify biodiversity loss at the level of genes, populations, species, and ecosystems, at various scales (Butchart et al. 2010; EEA 2012; Petrou et al. 2015). Several sets of such indicators have been proposed by organizations, scientists, and policy makers (EEA 2012; Feld et al. 2009; Petrou et al., 2015; Strand et al. 2007). They can be either directly measured or calculated using statistical models and may have a global, regional, or national applicability. Among the most widely adopted sets are the ones proposed by the United Nations (UN) Convention on Biological Diversity (CBD), aiming at monitoring the progress towards the achievement of the defined targets at global scale (AHTEG 2011). Further efforts include the definition of more directly measured variables, to enhance indicator extraction, such as the Essential Biodiversity Variables (EBV) proposed by the Group on Earth Observations Biodiversity Observation Network (GEO BON) (Pereira et al. 2013).

Although in-situ campaigns are the most accurate way of measuring certain aspects of biodiversity, such as the distribution and population of plant and animal species, in many cases, they have proven particularly costly, time demanding, or impossible (Buchanan et al. 2009; Gillespie et al. 2008). Alternatively, remote sensing (RS) data from airborne or satellite sensors are increasingly being employed in biodiversity monitoring studies (Nagendra et al. 2013; Bergen et al. 2009). Offering repetitive and cost-efficient monitoring of large areas, RS data can provide precious information nearly impossible to be acquired by field assessment alone (Nagendra et al. 2001, 2013).

Recently, essential biodiversity variables (EBVs) were identified (Pereira et al., 2013) (Table 1) and defined as variables, or a group of linked variables, that allows quantification of the rate and direction of change in one aspect of the state of biodiversity over time and across space (Pettorelli et al., 2018). EBVs are planned to harmonise assessment of biodiversity monitoring at any scales, and to support the aims of the Convention on Biological Diversity and IPBES. From the start, satellite remote sensing has been expected to be an important methodology for the derivation of EBVs, and indeed, satellite remote sensing EBVs (SRS-EBVs) have been conceptualised as the subset of EBVs whose monitoring relies largely or wholly on the use of satellite-based data (Luque S et al. 2018).

Table 2 gives a summary of the different types of remote sensing data that is useful in biodiversity monitoring.

Table 1. Essential biodiversity variables and use of RS (based on Walters et al., 2013)

ESSENTIAL BIODIVERSITY VARIABLES	SPATIAL RESOLUTION SATELLITE IMAGERY WITH TYPE OF MEASUREMENT SCALES (INCLUDING AVAILABLE REMOTE SENSING SENSORS)	RELEVANCE AND RELATED INFORMATION FOR BIODIVERSITY
TEMPORAL PHENOLOGY METRICS	Low/coarser spatial resolution (Global Scale) (MODIS, AVHRR etc.)	Phenology types, Forest / Non Forest, Deforestation and Biomass burning.

HABITAT STRUCTURE, ECOSYSTEM EXTENT AND FRAGMENTATION	Medium spatial resolution (Regional Scale) (Landsat, IRS, SPOT etc.)	Forest type distribution and agricultural expansion
HABITAT TYPES AND STRUCTURES, AND ECOSYSTEM COMPOSITION BY FUNCTIONAL TYPE	High spatial resolution (Local scale) (IKONOS, QuickBird, Rapid Eye historic GeoEye, WorldView-2 etc.)	Species-level distribution, canopy diameters, stand-level analysis, individual tree detection, to differentiate species at a finer scale.
HABITAT TYPES AND STRUCTURES	Active remote sensing data	Habitat degradation monitoring by generation of 3D structures

Table 2. Remote Sensing Data Useful for Biodiversity Monitoring

REMOTE SENSING DATA	**BIODIVERSITY MONITORING**
COARSE SPATIAL RESOLUTION (MODIS, AVHRR)	Forest / Non Forest, Biomass burning studies at global scale.
MEDIUM SPATIAL RESOLUTION (LANDSAT, IRS, SPOT)	Indicators of overall species richness and diversity at regional scales, forest type distribution and agricultural expansion
HIGH TEMPORAL RESOLUTION DATA (MULTI SEASON DATA OR IMAGES CORRESPONDING TO SPECIFIC SEASONS)	Information on invasion species and other species of interest (e.g. using images acquired corresponding to critical phonological stages of flowering or leaf senescence

Scientific solid evidence: Remote sensing has been increasingly contributing to timely, accurate, and cost-effective assessment of biodiversity-related characteristics and functions during the last years. Various studies have demonstrated how satellite remote sensing can be used to infer species richness. However, most relevant studies constitute individual research efforts, rarely related with the extraction of widely adopted Convention on Biological Diversity (CBD) biodiversity indicators (Petrou et al., 2015). Furthermore, systematic operational use of remote sensing data by managing authorities remains limited. The monitoring with CBD related indicators can be facilitated by remote sensing. Numerous studies using RS data to measure biodiversity-related properties are presented in the literature, covering a broad range of applications, study areas, data and methods. However, most studies are rarely explicitly connected to any widely adopted biodiversity indicator that could be extracted through them directly or indirectly. Instead, various indicators have been used by individual studies, resulting in numerous incompatible monitoring systems (Feld et al. 2009). Furthermore, despite the increasing availability of RS data, the connection between variables measured by RS and indicators required by the biodiversity and policy-making community is still poor (Secades et al. 2014). Thus, a link of RS approaches to a common set of indicators would be highly beneficial.

There are a number of recent remote sensing approaches able to extract related properties that exist for each headline indicator. Methods cover a wide range of fields, including: habitat extent and condition monitoring; species distribution; pressures from unsustainable management, pollution and climate change; ecosystem service monitoring; and conservation status assessment of protected areas. There are some advantages and limitations of different remote sensing data and algorithms. By virtue of the large spatial coverage, information-rich character, and high temporal resolution, remote sensing technology has been widely used in UGS research (Chen et al., 2018). At the end of the 20th century, low/medium spatial resolution remote sensing products began to be applied to the identification of vegetation types (Mucina, 2010). Recent developments in remote sensors offer an excellent opportunity to explore various aspects of different vegetation types. With the many advantages of new remote sensors, combining the advantages of different sensors optimized for vegetation features has attracted a significant amount of research interest and has enabled researchers to propose many promising new techniques for the identification of various vegetation types. For example, using high temporal resolution remote sensing images together with vegetation phenological features can achieve more accurate identification of vegetation types (Yan et al. 2018; Senf et al. 2015). Utilizing the 3D structures provided by LiDAR imagery in combination with the hundreds of narrow spectral bands provided by hyperspectral (HS) imagery can enable the identification of more vegetation types (Xia et al. 2018; Alonzo et al. 2014) However, although there has been much research that involved combining multi-source data sets or adopting better classification methods, these are still unable to identify different social function types of UGS.

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing. Typical "multi-spectral" sensors with 4 to 20 carefully selected and well-calibrated bands provide a great deal of information, and adding more bands can help with specific issues. "Hyperspectral" sensors can have more than 200 bands and can provide a wealth of information to help, for example, identify specific species. Processing such datasets requires special expertise and satellite-based hyperspectral sensors are not yet common. Other sensor types include radar and lidar which actively emit electromagnetic energy and measure the amount that is reflected—these sensors are useful for measuring surface height as well as tree canopy characteristics and surface roughness. Lidar is generally more precise than radar and ideal for measuring tree height. Radar is particularly useful where cloud cover is a problem (for instance, in the biodiversity-rich tropical rainforests) because it penetrates clouds.

Costs: free from Internet sites, or up to $600/image with very high resolution. Landsat data sets can be downloaded for free from the Global Land Cover Facility.

Among all the sensors used in remote sensing of biodiversity, the most commonly used and first civilian sensor is Hyperion (Hyperion Sensor EO-1 (Earth Observing-1) of NASA, which is controlled by the EROS (Earth Resources Observation and Science) at a fairly low cost to the general public. Other sensors include CHRIS (Compact High Resolution Imaging Spectrometer) of EEA, PROBA (Project for On-Board Autonomy) and FTHSI (Fourier Transform Hyperspectral Imager) of US Air Force Research Lab. Similar to the case with fine spatial resolution imagery, hyperspectral imagery is also an underutilized resource and due to its high cost problem, is putting it out of reach for research ecologists, predominantly those in e.g. developing countries.

As an overlay to create habitat patches, spatial patterns should be generated from high-resolution image data. Moderate-resolution sensors such as TM, SPOT, and IRS are used to delineate road systems and cover larger areas more quickly and cheaply. These high-resolution photos and digital sensors, typically 1–4 metres in resolution are air photos, IKONOS, and QuickBird. Images from these sensors allow direct spatial recognition of the spatial patterns and require less spectral contrast between the species and the surrounding landscape. Drawbacks to these sensors include the high image cost per unit area and the substantially larger volume of data required to cover a project area.

In most cases, regional or national projects with high-resolution data sets are not practical at this time because of cost and time required for analysis.

Effort: Satellite remote sensing offers smart solutions for biodiversity monitoring and to prepare conservation strategies with less effort. Due to the availability of multi-date, multi-resolution, multi-sensor datasets, it has become possible to acquire huge detail on the earth's surface without making time-consuming field visits. Since high spatial resolution datasets can acquire very fine details over small areas at a regular interval of time, this information will provide the basis for regional scale monitoring of biodiversity. Thus, remote sensing plays an important role in assisting environmentalists to characterize and map biologically rich zones, generating information on changes in biodiversity, alteration and distribution in species diversity.

Participatory process: It is today possible to integrate remote sensing data and *in situ* observations to monitor several essential biodiversity variables such as habitat structure and phenology. In this context, municipalities should explore the possibilities of launching citizen science projects and consider the possibility in general that within cities, local knowledge on biodiversity and ecosystem services may reside in many different groups within civic society. Here, we can face the challenges related to scaling, boundaries, locally adapted indicators and scoring which can be met by each municipality developing their interpretation of what scale and what boundary is the most appropriate, what definitions to use, and what set of sub-indicators may best reflect the local ecological and cultural context. However, there are some challenges that are not easily addressed at the municipal level and need input from the research community.

Data availability: availability of lidar data is quite limited, and although radar data are more widely available it may be expensive and its use is less intuitive than the interpretation of optical images.

The most cost-effective satellite sensors for distinguishing a smaller number of habitat classes are Landsat TM and ETM+), ASTER, and SPOT XS, with a 0–30-metre resolution. Landsat data time series (Landsat 5 TM and Landsat 7 ETM+) offer a cost-effective resource for large- scale reef surveys and for detecting large changes in coral or seagrass extent over time. If the habitat patches have already been mapped, IKONOS data can be used to measure small changes in patch location and boundary.

Geographical scale: at various geographical scales. Satellite remote sensing technology in the last decade has empowered interdisciplinary research at regional and local scale with high temporal resolution in order to provide information about changes in species distribution, habitat degradation and fine-scale disturbances of forests.

Temporal scale: at various temporal scales.

Synergies: The significance of urban land-system synergies and spatial governance are increasingly emerging towards sustainable targets (also regarding the biodiversity conservation) and liveable environments in cities. Satellite remote sensing, process-based models and big data are playing pivotal roles for obtaining spatially explicit knowledge for the purpose of biodiversity conservation and better planning for managing cities. Thus, synergy will be provided through the integration of governance with remote sensing, modelling and big data.

Applied methods: For more applied and participatory methods please see: Env29_Applied.

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b) based on the NbS projects from the CN database

Green Surge
(Green Infrastructure and Urban Bio- diversity for Sustainable Urban Development and the Green Economy) www.greensurge.eu

One of the project tasks was "Identification, description and quantification of the full range of urban green spaces". In this regard, the research was based on remote sensing results in combination with relevant case studies field observation.

Cvejić R., Eler K., Pintar M., Železnikar Š., Haase D., Kabisch N., Strohbach M. 2015. A typology of urban green spaces, ESS provisioning services and demands. GREEN SURGE project report.

Spronken-Smith, R. A., and Oke, T. R. (1998). The thermal regime of urban parks in two cities with different summer climates. International Journal for Remote Sensing, 19, 2085–2107.

Weeks J.R. (2010). Defining urban areas. In: Remote sensing of urban and suburban areas. Rashed T., Jürgens C. (eds.). Springer, Dordrecht, Heidelberg, London, New York: p. 33-45.

EKLIPSE

- digital mapping (e.g., remote sensing, GIS) of the potential for NBS and status of implementation (Giannico et al., 2016; Gómez-Baggethun and Barton, 2013).

Giannico, V., Lafortezza, R., John, R., Sanesi, G., Pesola, L., Chen, J., 2016. Estimating Stand Volume and Above-Ground Biomass of Urban Forests Using LiDAR. Remote Sens. 8, 339. doi:10.3390/rs8040339

Gómez-Baggethun, E., Barton, D.N., 2013. Classifying and valuing ecosystem services for urban planning. Ecol. Econ. 86, 235–245. doi:10.1016/j.ecolecon.2012.08.019

Raymond et al. 2016. An impact evaluation framework to guide the evaluation of nature-based solutions projects.

OpenNESS

Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Monitoring of results using GIS and/or remote sensing to help assess impacts on land cover.
- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

Smith A., Berry P., Harrison P. Sustainable Ecosystem Management. OpenNESS Synthesis Paper.

OPPLA

Great number of projects.

PLUREL

(Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Monitoring urban growth (area change, structures, land consumption, soil sealing
- Monitoring land cover/land-use changes (loss of agricultural area, wetland infringement, loss of areas important for biodiversity, spatial distribution of inner-urban green and open spaces and natural areas)

- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

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Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

URBES

(Urban Biodiversity and Ecosystem Services) https://www.biodiversa.org/121

- Remote Sensing of Urban Ecology (EO sensors, modelling algorithms)
- spatial and remote sensing data analyses, mostly engaged in WP2: Case study conditions and co-design workshops for identifying local policy solutions and WP5: Resilient supply of ecosystem services.

Larondelle N, Haase D, Kabisch N 2014. Diversity of ecosystem services provisioning in European cities. Global Environmental Change 26, 119-129.

Larondelle N, Hamstead Z A, Kremer P, Haase D, McPhearson T 2014. Comparing urban structure-function relationships across cities: Testing a new general urban structure classification in Berlin and New York. Applied Geography 53, 427-437.

Andersson E, McPherson T, Kremer P, Frantzeskaki N, Gomez-Baggethun E, Haase D, Tuvendal M, Wurster D 2015 Scale and Context Dependence of Ecosystem Service Providing Units. Ecosystem Services 12, 157-164.

Baró F, Frantzeskaki N, Gómez-Baggethun E, Haase D 2015. Assessing the match between local supply and demand of urban ecosystem services in five European cities. Ecological Indicators 55, 146-158.

Hamstead Z A, Kremer P, Larondelle N, McPhearson T, Haase D 2016. Classification of the heterogeneous structure of urban landscapes (STURLA) as an indicator of landscape function applied to surface temperature in New York City. Ecological Indicators 70, 574-585.

Baró F, Palomo I, Zulian G, Vizcaino P, Haase D, Gómez-Baggethun E 2016. Mapping ecosystem service capacity, flow and demand for landscape and urban planning: a case study in the Barcelona metropolitan region. Land Use Policy 57, 405-417 https://doi.org/j.landusepol.2016.06.006

2.1.11 Species diversity (Env35)

2.1.11.1 Species diversity (Env35) Applied/Participatory Review

Umbrella: Biodiversity measure

Indicator: Species diversity

Code: Env35

Description: Changes in overall number of species/species diversity/biodiversity indices within area affected by NBS using more applied/participatory methods.

Metric(s): Population counts for species or groups of species can provide an intuitive biodiversity metric which also has public resonance and the data can be used to populate indicators and measure progress towards conservation policy targets. Whilst survey of individual target conservation species and/or umbrella species can be of value in relation to specific conservation objectives, quantification of biodiversity indices can also have value in providing a more holistic insight into overall biodiversity and greater representation of a range of taxa (Buckland et al. 2005).

The City Biodiversity Index (CBI) (Chan et al 2014), was proposed to engage cities in the implementation of the Convention on Biodiversity's strategic plan for biodiversity. The CBI was intended to provide a benchmark of biodiversity conservation efforts of cities, it provides a self-assessment tool to monitor the progress of biodiversity conservation efforts against a city's baseline.

The first part of the framework involves a profile of the city, then 23 indicators are proposed that comprise 3 core components: 1) native biodiversity, 2) ES provided by biodiversity, and 3) governance and management of biodiversity. This framework could be used to undertake a full CBI self-assessment. Alternatively, those indicators that directly measure biodiversity could be used, for example Indicator 3: native biodiversity in built-up areas (bird species), or Indicators 4-8 which include three 'core indicator' groups that are most surveyed worldwide – plants, birds and butterflies. Cities can select two additional taxonomic groups (for instance those where data is already held or target groups of local importance/conservation interest). The data from the first year of implementing the Index provides the baseline for future monitoring. It is recommended that application of the Index take place every 3 years to allow sufficient time for the results of biodiversity conservation efforts (e.g. NBS implementation) to materialise. Example units of calculation are: number/abundance of **native** bird species per hectare. The net change in number of native species from the previous survey to the most recent survey is calculated as: total increase in number of species (as a result of re-introduction or restoration efforts, new species found, etc.) minus number of species that have gone extinct. Possible sources of data include agencies in charge of nature conservation/biodiversity (Wildlife Trusts, etc), city municipalities and urban planning agencies, biological records centres, nature groups, universities, etc.

The Urban Biodiversity Inventory Framework (UBIF 2017) offers an alternative 3 track methodology to collect species diversity information as follows: Track 1 - collating data from partners/stakeholders; Track 2 - presence/absence of surrogate species; Track 3 - relative abundance estimates of surrogate species. Track 1 requires the least additional resources but with limited scope for summary statistics, whereas Tracks 2 and 3 require increasing resources but generate increasingly detailed data e.g. comparing changes at a site over time.

The CBD agreed a set of 26 specific biodiversity indicators (2010 Biodiversity Indicators Partnership 2010), some of which reflect measures in the CBI (above) and others that could be extrapolated for use under this indicator:

- Trends in the abundance/distribution of selected species (e.g. birds/butterflies)
- Change in status of threatened and/or protected species (Red List species/species of European interest)
- Change in extent of habitats (e.g. vulnerable habitats/habitats of conservation importance)
- Coverage of protected areas (loss/gain of nationally/locally designated areas/sites)

Additional specific examples of general biodiversity measures typically undertaken by professional ecologists include:

The Defra Biodiversity Metric 0.2 (Natural England 2018) was developed to as a means of assessing changes in biodiversity value as a consequence of development or land-use change, primarily with the aim of quantifying biodiversity net-gain. It uses habitat as a proxy to measure biodiversity which is converted into measurable 'biodiversity units' according to the area of each habitat type. The metrics score different habitat types (e.g. woodland, grassland) according to their relative biodiversity value and adjusts this according to the condition and location of the habitat. Where new habitat is created or existing habitat is enhanced, then the associated risks of doing so are factored into the metric. It can be used to calculate losses and gains in biodiversity from actions. The metric sites within the 'mitigation hierarchy'. To apply the metric a site should be surveyed, mapped and divided into parcels of distinct habitat types present using a recognised habitat classification system. The biodiversity 'value' of a habitat parcel is evaluated on the basis of its area and the relative 'quality' of its habitat (distinctiveness, condition, strategic significance, habitat connectivity). The calculation uses the scores and the area of the habitat to give a number of biodiversity units that represent the biodiversity value of that habitat parcel. The relative value in biodiversity units 'post development' is then deducted from the 'baseline' to give a value for the extent of change e.g. 'Net Gain'. Net loss would require improvement to development proposal to improve the number of biodiversity units obtained or, if there is no scope for additional on-site compensation or enhancement, off-site measures will need to be considered.

BREEAM UK Strategic Ecology Framework (SEF) is a new framework for evaluating, protecting and enhancing ecology in the built environment (Yates, Abdul & Buchanan, 2016). BREEAM credits for ecology (BREEAM 2014) provides a scoring system for assessing the ecological value of a site before and after development (Land Use and Ecology LE01 – LE06). Both protocols start with a Preliminary Ecological Appraisal (PEA) and evaluate and monitor how proposed schemes will benefit biodiversity. The credit system awards high scores to schemes that deliver ecological enhancement.

Key drivers for such biodiversity monitoring include:

- Assisting local authorities to evaluate their progress in urban biodiversity conservation (for example against Aichi/national/local biodiversity targets);
- Ensuring NBS contribute positively to biodiversity conservation;
- Creating a foundation for development of Local Biodiversity Strategies/Action Plans (see example of Lisbon, Portugal in MAES reference below)
- Serving as a public platform upon which biodiversity awareness raising exercises can be launched.

Scientific solid evidence: Depends of the quality of the data used and the representativeness of the index selected to overall biodiversity patterns. Raw data can characterise species spatial and temporal distributions but are generally limited because of the time/costs involved in the detailed level of data collection needed to accurately detect change.

Level of expertise: Expertise needed for accurate monitoring of some species groups. Relatively straightforward data analysis based on the CBI calculation for example.

Cost: Can be relatively low cost if organisations are already collecting suitable data. Also, if data is not available from external organisations, use of citizen science participatory methods can reduce costs for data gathering.

Effort: Data needs to be captured every 3 years for CBI. Effort varies for 3 Tracks of UBIF.

Participatory process: Data capture could include public participation and citizen science data collection. Such practices are widespread including using volunteer recording groups.

Data availability: Can use existing data and capture new data.

Geographical scale: Devised to measure change at a city level but could be scaled-down to a borough/neighbourhood/site level.

Temporal scale: Devised to measure change over time. Measures should be repeated at least every 3 years. Impossible to get historical data if no past survey was carried out.

Earth observation/remote sensing/modelling: For further information on earth observation, modelling, and remote sensing approaches, and examples of their use in past and current EU projects, see indicator guidelines: Env35_RS

Synergies: Direct measures of supporting/increasing biodiversity could have synergies with landuse change, greenspace area and accessibility to greenspace (wildlife areas).

Original reference(s) for indicator: UnaLab

Reference (s):

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2.1.11.2 Species diversity (Env35) Earth Observation/Remote Sensing Review

Umbrella: Biodiversity measure

Indicator: Species diversity

Code: Env35

Description: Changes in species diversity/number of species within area affected by NbS using earth observation and remote sensing indicators

Metric(s): It is important to foster research and monitoring of biodiversity to determine the best assemblages of species to achieve the most efficient NBS, including the optimization of multiple economic, ecological and social benefits and exploration of trade-offs created by NBS. This can be achieved by collection of new data in the field and the use of remote sensing to gather comprehensive data on additional benefits, to complement existing data and observation.

Biodiversity includes multiscalar and multitemporal structures and processes, with different levels of functional organization, from genetic to ecosystemic levels. One of the most widely used methods to infer biodiversity is based on taxonomic approaches and community ecology theories. However, gathering extensive data in the field is difficult due to logistic problems, especially when aiming at modelling biodiversity changes in space and time, which assumes statistically sound sampling schemes. In this context, airborne or satellite remote sensing allows information to be gathered over wide areas in a reasonable time. Most of the biodiversity maps obtained from remote sensing have been based on the inference of species richness by regression analysis. Estimating compositional turnover (β-diversity) might add crucial information related to relative abundance of different species instead of just richness. Presently, few studies have addressed the measurement of species compositional turnover from space. There are novel techniques to measure β-diversity from airborne or satellite remote sensing proposed by Roccini et al. (2017), mainly based on:

- multivariate statistical analysis,
- the spectral species concept,
- self-organizing feature maps,
- multidimensional distance matrices,
- Rao's Q diversity.

Each of these measures addresses one or several issues related to turnover measurement.

High temporal resolution remote sensing images together with vegetation phenological features can achieve more accurate identification of vegetation types. Yan et al. (2018) integrated object-based classification data with vegetation phenological information derived from multi-temporal WorldView-2 images to identify grass and tree types. Senf et al. (2015) found that adding phenological patterns captured by multi-seasonal Landsat imagery can better discriminate shrublands and woodlands that would otherwise be a challenging task in single-date Landsat imagery. Moreover, utilizing the 3D structures provided by LiDAR imagery in combination with the hundreds of narrow spectral bands provided by hyperspectral (HS) imagery can enable the identification of more vegetation types. Xia et al. (2018) constructed an ensemble classifier to integrate HS and LiDAR data, and used it to identify several tree types and three grass types. Alonzo et al. (2014) used a crown-level integration of HS and LiDAR data to identify 29 common tree species in urban regions

Drone mapping is described as a tool for monitoring ecosystem restoration. Plant communities with different plant cover and species composition reflect spectral bands in different rates and this information reflects state and disturbances of mire ecosystems (peatlands). Usage of drones gives higher resolution data compared to other remote sensing options, and is suitable for plant community level monitoring, but at the same time there is a trade-off between spatial resolution and mapping area.

Various indicators are used to assess the status and trends of components of biodiversity, measure pressures, and quantify biodiversity loss at the level of genes, populations, species, and ecosystems, at various scales (Butchart et al. 2010; EEA 2012; Petrou et al. 2015). Several sets of such indicators have been proposed by organizations, scientists, and policy makers (EEA 2012; Feld et al. 2009; Petrou et al., 2015; Strand et al. 2007). They can be either directly measured or calculated using statistical models and may have a global, regional, or national applicability. Among the most widely adopted sets are the ones proposed by the United Nations (UN) Convention on Biological Diversity (CBD), aiming at monitoring the progress towards the achievement of the defined targets at global scale (AHTEG 2011). Further efforts include the definition of more directly measured variables, to enhance indicator extraction, such as the Essential Biodiversity Variables (EBV) proposed by the Group on Earth Observations Biodiversity Observation Network (GEO BON) (Pereira et al. 2013).

Although in-situ campaigns are the most accurate way of measuring certain aspects of biodiversity, such as the distribution and population of plant and animal species, in many cases, they have proven particularly costly, time demanding, or impossible (Buchanan et al. 2009; Gillespie et al. 2008). Alternatively, remote sensing (RS) data from airborne or satellite sensors are increasingly being employed in biodiversity monitoring studies (Nagendra et al. 2013; Bergen et al. 2009). Offering repetitive and cost-efficient monitoring of large areas, RS data can provide precious information nearly impossible to be acquired by field assessment alone (Nagendra et al. 2001, 2013).

Recently, essential biodiversity variables (EBVs) were identified (Pereira et al., 2013) (Table 1) and defined as variables, or a group of linked variables, that allows quantification of the rate and direction of change in one aspect of the state of biodiversity over time and across space (Pettorelli et al., 2018). EBVs are planned to harmonise assessment of biodiversity monitoring at any scales, and to support the aims of the Convention on Biological Diversity and IPBES. From the start, satellite remote sensing has been expected to be an important methodology for the derivation of EBVs, and indeed, satellite remote sensing EBVs (SRS-EBVs) have been conceptualised as the subset of EBVs whose monitoring relies largely or wholly on the use of satellite-based data (Luque S et al. 2018).

Table 2 gives a summary of the different types of remote sensing data that is useful in biodiversity monitoring.

Table 1. Essential biodiversity variables and use of RS (based on Walters et al., 2013)

Essential biodiversity variables	**Spatial Resolution satellite imagery with type of measurement scales (including available remote sensing sensors)**	**Relevance and related information for biodiversity**
Temporal phenology metrics	Low/coarser spatial resolution (Global Scale) (MODIS, AVHRR etc.)	Phenology types, Forest / Non Forest, Deforestation and Biomass burning.
Habitat Structure, Ecosystem extent and fragmentation	Medium spatial resolution (Regional Scale) (Landsat, IRS, SPOT etc.)	Forest type distribution and agricultural expansion
Habitat types and structures, and Ecosystem composition by functional type	High spatial resolution (Local scale) (IKONOS, QuickBird, Rapid Eye historic GeoEye, WorldView-2 etc.)	Species-level distribution, canopy diameters, stand-level analysis, individual tree

		detection, to differentiate species at a finer scale.
Habitat types and structures	Active remote sensing data	Habitat degradation monitoring by generation of 3D structures

Table 2. Remote Sensing Data Useful for Biodiversity Monitoring

Remote Sensing Data	**Biodiversity Monitoring**
Coarse Spatial Resolution (MODIS, AVHRR)	Forest / Non Forest, Biomass burning studies at global scale.
Medium spatial resolution (Landsat, IRS, SPOT)	Indicators of overall species richness and diversity at regional scales, forest type distribution and agricultural expansion
High temporal resolution data (Multi season data or images corresponding to specific seasons)	Information on invasion species and other species of interest (e.g. using images acquired corresponding to critical phonological stages of flowering or leaf senescence

Scientific solid evidence: Remote sensing has been increasingly contributing to timely, accurate, and cost-effective assessment of biodiversity-related characteristics and functions during the last years. Various studies have demonstrated how satellite remote sensing can be used to infer species richness. However, most relevant studies constitute individual research efforts, rarely related with the extraction of widely adopted Convention on Biological Diversity (CBD) biodiversity indicators (Petrou et al., 2015). Furthermore, systematic operational use of remote sensing data by managing authorities remains limited. The monitoring with CBD related indicators can be facilitated by remote sensing. Numerous studies using RS data to measure biodiversity-related properties are presented in the literature, covering a broad range of applications, study areas, data and methods. However, most studies are rarely explicitly connected to any widely adopted biodiversity indicator that could be extracted through them directly or indirectly. Instead, various indicators have been used by individual studies, resulting in numerous incompatible monitoring systems (Feld et al. 2009). Furthermore, despite the increasing availability of RS data, the connection between variables measured by RS and indicators required by the biodiversity and policy-making community is still poor (Secades et al. 2014). Thus, a link of RS approaches to a common set of indicators would be highly beneficial.

There are a number of recent remote sensing approaches able to extract related properties that exist for each headline indicator. Methods cover a wide range of fields, including: habitat extent and condition monitoring; species distribution; pressures from unsustainable management, pollution and climate change; ecosystem service monitoring; and conservation status assessment of protected areas. There are some advantages and limitations of different remote sensing data and algorithms. By virtue of the large spatial coverage, information-rich character, and high temporal resolution, remote sensing technology has been widely used in UGS research (Chen et al., 2018). At the end of the 20th century, low/medium spatial resolution remote sensing products began to be applied to the identification of vegetation types (Mucina, 2010). Recent developments in remote sensors offer an excellent opportunity to explore various aspects of different vegetation types. With the many advantages of new remote sensors, combining the advantages of different sensors optimized for vegetation features has attracted a significant amount of research interest and has enabled researchers to propose many promising new techniques for the identification of various vegetation types. For example, using high temporal resolution remote sensing images together with vegetation phenological features can achieve more accurate identification of vegetation types (Yan et al. 2018; Senf et al. 2015). Utilizing the 3D structures provided by LiDAR imagery in combination with the hundreds of narrow spectral bands provided by hyperspectral (HS) imagery can enable the identification of more vegetation types (Xia et al. 2018; Alonzo et al. 2014) However, although there has been much research that involved combining multi-source data sets or adopting better classification methods, these are still unable to identify different social function types of UGS.

Level of expertise: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing. Typical "multi-spectral" sensors with 4 to 20 carefully selected and well-calibrated bands provide a great deal of information, and adding more bands can help with specific issues. "Hyperspectral" sensors can have more than 200 bands and can provide a wealth of information to help, for example, identify specific species. Processing such datasets requires special expertise and satellite-based hyperspectral sensors are not yet common. Other sensor types include radar and lidar which actively emit electromagnetic energy and measure the amount that is reflected—these sensors are useful for measuring surface height as well as tree canopy characteristics and surface roughness. Lidar is generally more precise than radar and ideal for measuring tree height. Radar is particularly useful where cloud cover is a problem (for instance, in the biodiversity-rich tropical rainforests) because it penetrates clouds.

Costs: free from Internet sites, or up to $600/image with very high resolution. Landsat data sets can be downloaded for free from the Global Land Cover Facility.

Among all the sensors used in remote sensing of biodiversity, the most commonly used and first civilian sensor is Hyperion (Hyperion Sensor EO-1 (Earth Observing-1) of NASA, which is controlled by the EROS (Earth Resources Observation and Science) at a fairly low cost to the general public. Other sensors include CHRIS (Compact High Resolution Imaging Spectrometer) of EEA, PROBA (Project for On-Board Autonomy) and FTHSI (Fourier Transform Hyperspectral Imager) of US Air Force Research Lab. Similar to the case with fine spatial resolution imagery, hyperspectral imagery is also an underutilized resource and due to its high cost problem, is putting it out of reach for research ecologists, predominantly those in e.g. developing countries.

As an overlay to create habitat patches, spatial patterns should be generated from high-resolution image data. Moderate-resolution sensors such as TM, SPOT, and IRS are used to delineate road systems and cover larger areas more quickly and cheaply. These high-resolution photos and digital sensors, typically 1–4 metres in resolution are air photos, IKONOS, and QuickBird. Images from these sensors allow direct spatial recognition of the spatial patterns and require less spectral contrast between the species and the surrounding landscape. Drawbacks to these sensors include the high image cost per unit area and the substantially larger volume of data required to cover a project area. In most cases, regional or national projects with high-resolution data sets are not practical at this time because of cost and time required for analysis.

Effort: Satellite remote sensing offers smart solutions for biodiversity monitoring and to prepare conservation strategies with less effort. Due to the availability of multi-date, multi-resolution, multi-sensor datasets, it has become possible to acquire huge detail on the earth's surface without making time-consuming field visits. Since high spatial resolution datasets can acquire very fine details over small areas at a regular interval of time, this information will provide the basis for regional scale monitoring of biodiversity. Thus, remote sensing plays an important role in assisting environmentalists to characterize and map biologically rich zones, generating information on changes in biodiversity, alteration and distribution in species diversity.

Participatory process: It is today possible to integrate remote sensing data and *in situ* observations to monitor several essential biodiversity variables such as habitat structure and phenology. In this context, municipalities should explore the possibilities of launching citizen science projects and consider the possibility in general that within cities, local knowledge on biodiversity and ecosystem services may reside in many different groups within civic society. Here, we can face the challenges related to scaling, boundaries, locally adapted indicators and scoring which can be met by each municipality developing their interpretation of what scale and what boundary is the most appropriate, what definitions to use, and what set of sub-indicators may best reflect the local ecological and cultural context. However, there are some challenges that are not easily addressed at the municipal level and need input from the research community.

Data availability: availability of lidar data is quite limited, and although radar data are more widely available it may be expensive and its use is less intuitive than the interpretation of optical images.

The most cost-effective satellite sensors for distinguishing a smaller number of habitat classes are Landsat TM and ETM+), ASTER, and SPOT XS, with a 0–30-metre resolution. Landsat data time series (Landsat 5 TM and Landsat 7 ETM+) offer a cost-effective resource for large- scale reef surveys and for detecting large changes in coral or seagrass extent over time. If the habitat patches have already been mapped, IKONOS data can be used to measure small changes in patch location and boundary.

Geographical scale: at various geographical scales. Satellite remote sensing technology in the last decade has empowered interdisciplinary research at regional and local scale with high temporal resolution in order to provide information about changes in species distribution, habitat degradation and fine-scale disturbances of forests.

Temporal scale: at various temporal scales.

Synergies: The significance of urban land-system synergies and spatial governance are increasingly emerging towards sustainable targets (also regarding the biodiversity conservation) and liveable environments in cities. Satellite remote sensing, process-based models and big data are playing pivotal roles for obtaining spatially explicit knowledge for the purpose of biodiversity conservation and better planning for managing cities. Thus, synergy will be provided through the integration of governance with remote sensing, modelling and big data.

Applied methods: For more applied and participatory metrics please see Env35_Applied.

Metric references:

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Green Surge
(Green Infrastructure and Urban Bio- diversity for Sustainable Urban Development and the Green Economy) www.greensurge.eu

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EKLIPSE

- digital mapping (e.g., remote sensing, GIS) of the potential for NBS and status of implementation (Giannico et al., 2016; Gómez-Baggethun and Barton, 2013).

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OpenNESS

Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Monitoring of results using GIS and/or remote sensing to help assess impacts on land cover.
- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

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OPPLA

Great number of projects.

PLUREL

(Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Monitoring urban growth (area change, structures, land consumption, soil sealing
- Monitoring land cover/land-use changes (loss of agricultural area, wetland infringement, loss of areas important for biodiversity, spatial distribution of inner-urban green and open spaces and natural areas)
- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

References:

Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

URBES

(Urban Biodiversity and Ecosystem Services) https://www.biodiversa.org/121

- Remote Sensing of Urban Ecology (EO sensors, modelling algorithms)
- spatial and remote sensing data analyses, mostly engaged in WP2: Case study conditions and co-design workshops for identifying local policy solutions and WP5: Resilient supply of ecosystem services.

Larondelle N, Haase D, Kabisch N 2014. Diversity of ecosystem services provisioning in European cities. Global Environmental Change 26, 119-129.

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Andersson E, McPherson T, Kremer P, Frantzeskaki N, Gomez-Baggethun E, Haase D, Tuvendal M, Wurster D 2015 Scale and Context Dependence of Ecosystem Service Providing Units. Ecosystem Services 12, 157-164.

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Baró F, Palomo I, Zulian G, Vizcaino P, Haase D, Gómez-Baggethun E 2016. Mapping ecosystem service capacity, flow and demand for landscape and urban planning: a case study in the Barcelona metropolitan region. Land Use Policy 57, 405-417 https://doi.org/j.landusepol.2016.06.006

2.1.12 Land use change and greenspace configuration (Env42)

2.1.12.1 Land use change and greenspace configuration (Env42) Applied/Participatory Review

Umbrella: Greenspace distribution mapping

Indicator: Land use change and greenspace configuration

Code: Env42

Description: Records change in land use (e.g. from brownfield to green areas by adding vegetated brownfield to UGI resource) and accounting for configuration (e.g. individual gardens, groups of gardens and socio-economic factors impact on the utility of private gardens for native biodiversity conservation)

Metric(s): Identifying urban land-use patterns is important for decision-makers to ensure sustainable development. Typical metrics for this indicator comprise the use of land use and land cover maps. These are typically obtained by classifying and modelling Remotely Sensed (RS) data, for example Landsat in a GIS environment (for more detailed information on remote sensing and earth observation approaches see Env42 – RS).

Even with advances in RS, the ability to distinguish various urban land use types accurately using classification algorithms remains difficult due to the fine-scale heterogeneity of land cover types in urban areas (Pauleit & Duhme, 2000; Jia et al., 2018). Methods that combine RS and more applied approaches have been developed to establish a greater level of precision in relation to this micro-variation. For instance, Pauleit & Duhme (2000) used a combination of existing habitat inventory, mapping land cover, and units and types from aerial photographs to reproduce the fin-grained patterns of land covers in the city of Munich. This enabled delineation of distinct units (e.g. configurations of built-up and open spaces such as detached houses, hi-rise blocks, industrial areas, parks, agricultural lands etc) which were grouped into 24 urban land cover types (e.g. houses, factory block, roads, railways, lakes and ponds, woodlands, parks and green spaces, cemeteries, sports fields, etc). This enabled quantitative characterisation of physical features of units (% cover of sealed surfaces, vegetation, etc.) which was built into a GIS database. Environmental parameters (e.g. surface temperature, rainwater infiltration) were assigned to land covers to assess the likely environmental impacts of land cover changes, for instance rainwater infiltration.

When considering land use change and greenspace configuration, it is important to consider how green (vegetated) urban brownfields can supplement urban green infrastructure by providing habitat, microclimate and recreational services (Mathey et al., 2015). Changes in their land use and physical structure as a result of urban planning decisions will impact ecosystem service provision. Development of brownfield sites can often have a negative impact on ecosystem service provision compared to their undeveloped state. As such, their consideration as a part of land use change indicators is not straightforward. Brownfield registers and Environmental Impact Assessments can provide source data regarding pre-development brownfield habitat structure/quality. Parameters for habitat services provided by green urban brownfields can be based on successional stage typologies: brownfield with pioneer vegetation; with persistent ruderal vegetation; with ruderal tall herbaceous vegetation; with spontaneous wood; and three biodiversity parameters: structural diversity, specific plant and animal groups, regenerative functions. This information can be supplemented by modelling of microclimate regulation based on vegetation parameters can be done at site level (ENVI-met) and city level (HIRVAC-2D). Data relating to perception, acceptance and use of/forms of use of brownfields by residents can be collected by questionnaires. Scenario analysis can show how changes in land use can impact ecosystem services (e.g modelling future development proposals). These aspects should be integrated into analytical and evaluation algorithms when devising city strategies for brownfields to secure ecosystem services.

In terms of assessing the value of domestic gardens in relation to their ability to support biodiversity, several studies have developed methods for assessing/quantifying value. This includes methods for assessing value for urban birds (Daniels and Kirkpatrick 2006) and invertebrates (Smith et al. 2006). Goddard et al. (2010) present a comprehensive overview of a range of methods related to garden biodiversity.

Data on landuse change and greenspace configuration collected in these ways can be used to:

- Track landuse change on sites in relation to ecosystem service provision;
- Track trends in private garden use to monitor a substantial green infrastructure asset over which local authorities have little influence;
- Set targets for landuse change, for example recognising the highest quality brownfield sites for biodiversity and ecosystem service delivery and prioritising the beneficial reuse of brownfield sites with little environmental value.

Scientific solid evidence: Applied methods are used to support and supplement evidence generated through remote sensing metrics. As such, they should strengthen the evidence generated.

Level of expertise: As this indicator is generally associated with remote sensing, GIS expertise and a familiarity with modelling are required. Supplementing this with local ground-truthed data requires expertise in habitat assessment and, potentially, participatory processes.

Cost: Some map datasets and satellite imagery are freely available online, others involve a licence fee. Data on brownfield successional status could require ground-truthing by ecological survey. There would be costs associated with acquiring GIS software if not already available, and GIS specialists

Effort: If in-house GIS specialists already exist, this should be a moderate effort exercise. Effort related to the addition of supplementary ground-truthed data would be associated with the availability of such data (i.e. whether it has to be carried out or just collated from existing surveys) and the amount of such data.

Participatory process: Participatory processes are possible to supplement remote sensing data with ground-truthed data to avoid the pitfalls of the heterogeneity in land use of high-density urban areas. Citizen science and participatory GIS processes can be used for this.

Data availability: Some land cover data will be already available, more in-depth data such as brownfield successional stage is unlikely to be readily available.

Geographical scale: This indicator is generally applied at a city-scale, but neighbourhood and site level assessments can also be made.

Temporal scale: Intended to record change over time, but the ability to assess past change would depend on availability and resolution of historical data. Once current data has been obtained, a baseline can be established from which future changes can be assessed.

Synergies: Strong synergies with other mapping indicators and other environmental indicators such as UHI, drainage, air quality, biodiversity as well as health and wellbeing.

Earth observation/remote sensing/modelling: This indicator is primarily assessed using remote sensing, earth observation and modelling methods. Participatory and applied processes can be used to supplement this data. For more detail on remote sensing, earth observation and modelling approaches, including those used on past and current EU projects, see: Env42_RS.

Original reference(s) for indicator: Eklipse

Reference (s):

Daniels, G.D. and Kirkpatrick, J.B. (2006) Does variation in garden characteristics influence the conservation of birds in suburbia? Biological Conservation 133, 326–335.

Goddard, MA, Dougill, AJ and Benton, TG (2010) Scaling up from gardens: biodiversity conservation in urban environments. TREE 1175 1–9.

Jia, Y., Ge, Y., Ling, F., Guo, X., Wang, J., Wang, L., Chen, Y. and Li, X., 2018. Urban Land Use Mapping by Combining Remote Sensing Imagery and Mobile Phone Positioning Data. *Remote Sensing*, 10(3): 446.

Mathey, J., Rößler, S., Banse, J., Lehmann, I. and Bräuer, A. (2015) Brownfields as an element of green infrastructure for implementing ecosystem services into urban areas. *Journal of Urban Planning and Development*, *141*(3), A4015001.

Pauleit, S. and Duhme, F. (2000) Assessing the environmental performance of land cover types for urban planning. *Landscape and urban planning*, *52*(1), 1-20.

Smith, RM, Gaston, KJ, Warren, P and Thompson, K (2006) Urban domestic gardens (VIII): Environmental correlates of invertebrate abundance. *Biodiversity and Conservation*, 15, 2515–2545.

2.1.12.2 Land use change and greenspace configuration (Env42) Earth Observation/remote Sensing Review

Umbrella: Greenspace distribution mapping

Indicator: Land use change and greenspace configuration

Code: Env42

Description: Records change in land use (e.g. from brownfield to green areas by adding vegetated brownfield to UGI resource) and accounting for configuration (e.g. individual gardens, groups of gardens and socio-economic factors impact on the utility of private gardens for native biodiversity conservation) using earth observation and remote sensing approaches.

Metric(s). Use of remote sensing involves the application of multi-temporal datasets to quantitatively analyse the temporal effects of the land use changes as well as green space configuration. Due to the high degree of complexity of urban issues, GIS and remote sensing (RS) technologies have long been used to facilitate scientists to assess the overall state of urban environment, to manage the urban infrastructures and improve the efficiency and rationality of its spatial management. A necessary prerequisite for the improvement of urban environment is rationality of its spatial management – the optimal division of urban spaces by their functional predestination. One of approaches suited to this is functional zonation of the city – a spatial management of basic types of activities – labour, household, recreational.

Using RS data VHR QuickBird optical images the territory of the city can be classified depending on the type of the activities of the population, which predetermine industrial, inhabited, recreation zones with their morphotypes. The map of functional zonation of the city allows the identification of the optimal level of distribution of ecologically unfavourable, neutral and favourable plots on the territory of the city analysed regarding the implemented NbS.

On the next stage the RS technics can be used to study the ecological state of ecologically favourable plots. Some studies have investigated whether it is possible, using WorldView-2 data and in the context of an urban park, to map canopy stress assumed to be associated with pollution. For instance, small urban parks can be studied using biogeochemical analysis of the tree canopy, field spectral reflectance measurements of tree leaves, simulated WorldView-2 multispectral data generated from the leaf spectra, and summer images of real WorldView-2 data. There is some evidence confirmed through the high correlation between spectral reflectance values and leaves' heavy metal pollution levels, which also confirmed the importance of creating GIS and RS enabled pollution control and monitoring system.

Scientific solid evidence: During the last decades, geographic information systems (GIS), historical maps, aerial imagery, and remotely sensed images have proven very effective in studying land change dynamics. These tools have been widely used also on the city level to assess changes over time and to predict future scenarios based on long-term sets of observations. Agarwal et al. (2002) presented a framework to compare models of land use change with respect to scale (spatial and temporal), complexity, and their ability to incorporate space, time, and human decision making. Several different approaches have been developed to predict future land use transformations.

Level of expertise: It is a challenge and a critical need to understand the methods for extracting useful information from the data, as well as to interpret the time-series signals correctly. We need to be able to interpret both slow variations due to gradual ecosystem transformations, and faster variations due to disturbances or other rapid events. Methods based on remote sensing theory, process modelling, and statistical data analysis will help developing this understanding.

Costs: Remote sensing via satellite imagery is an excellent tool to study LULCC because images can cover large geographic extents and have a high temporal coverage. Remote sensing is also used to investigate historical LULCC and also provide data (e.g. ground truth) in areas that are inaccessible. The major disadvantages of remote sensing include: the inability of many sensors to obtain data and information through cloud cover, distinct phenomena can be confused if they look the same to the sensor, the resolution of the satellite imagery may be too coarse for detailed mapping and for distinguishing small contrasting areas and very high-resolution satellite imagery are very expensive. Despite these disadvantages, remotely sensed satellite data have been used to identify changes in a variety of aquatic and terrestrial environments including coastal, agriculture, forested, and urban areas. This is particularly true for remote regions, which are often inaccessible and therefore not easy to obtain the needed data using traditional methods (Fonji and Taff, 2014) LULCC researchers often use remotely sensed data to provide information on resource inventory and land use, and to identify, monitor and quantify changing patterns in the landscape.

There a lot of free and open source software for land monitoring, one of them is Collect Earth developed by the Food and Agriculture Organization of the United Nations (FAO). Built on Google desktop and cloud computing technologies, Collect Earth facilitates access to multiple freely available archives of satellite imagery, including archives with very high spatial resolution imagery (Google Earth, Bing Maps) and those with very high temporal resolution imagery (e.g., Google Earth Engine, Google Earth Engine Code Editor). Collectively, these archives offer free access to an unparalleled amount of information on current and past land dynamics for any location in the world. Collect Earth draws upon these archives and the synergies of imagery of multiple resolutions to enable an innovative method for land cover and land use change monitoring.

Effort: Remote sensing is the most resource-efficient method to monitor land cover and land uses changes, as well as impacts of climate change, which may be identified as glacier changes, changes in vegetation phenology or advance of new plant species to higher latitudes or elevations, for example. In addition to “traditional” satellite imagery to cover large areas we can also use advanced hyperspectral remote sensing data or laser scanning data for land change studies.

Participatory process: A combination of remote sensing, field observations and focus group discussions is often suggested to be used to analyse the dynamics and drivers of LULC change. Supervised image classification can be applied to map LULC classes. In addition, focus group discussions and ranking can support to explain the drivers and causes linked to the land cover changes.

There is some research which has proposed the analysis of very-high-resolution satellite imagery with participatory mapping based on workshops and field surveys.

Data availability: Fairly long time-series of Earth Observation data already exist for the whole area of the Earth. These time-series data make up an invaluable source of information for better understanding and management of our environment.

Remote sensing data is available from the USGS (http://glovis.usgs.gov) for free. ASTER GDEM is available from the Geospatial Data Cloud (http://www.gscloud.cn/) for free. Costs of RS data of higher resolution is as follows (cost per sq.km of newly acquired imagery):

- Worldview 2, 50cm pan is about €30 / sqkm
- IKonos pan, 0.8-3m resolution is about €25 /sqkm
- Deimos -1, 22m res is 15c/sqkm

- Landsat, MODIS and MERIS sensors – free.

A high quality airborne lidar survey would be in the order of €450/sq.km.

Geographical scale: method suitable for various geographical scales.

Temporal scale: method suitable for various temporal scales, although availability of historical data can sometimes be a barrier to studying past trends.

Synergies: The synergy between geographic information systems (GIS) and remote sensing comes into play here. To be interpreted accurately, remotely sensed data are often supplemented with other data. Often these ancillary geospatial data can be found or included in a GIS for analysis. But to be more valuable in decision-making contexts, GIS data layers should be up-to-date as is practical. Remotely sensed data are a key technology for updating many types of GIS data. Thus when environmental planners, resource managers, and public policy decision-makers want to measure, map, monitor, or model future scenarios in order to facilitate better management decision-making, remote sensing is being employed more and more within the context of a GIS as a decision support system.

Applied methods: For more applied and participatory approaches for quantifying greenspace distribution, please see: Env42_Applied.

Original reference(s) for indicator: Eklipse

Metric references:

g) **From the literature review**

Agarwal C., G. M. Green, J. M. Grove, T. P. Evans and C. M. Schweik (2002) A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice. Apollo the International Magazine of Art and Antiques, 1 (1).

Fonji, S. F., & Taff, G. N. (2014). Using satellite data to monitor land-use land-cover change in North-eastern Latvia. SpringerPlus, 3, 61. doi:10.1186/2193-1801-3-61

Hansen, M.C.; Loveland, T.R. A review of large area monitoring of land cover change using Landsat data. Remote Sens. Environ. 2012, 122, 66–74.

Yang, X.; Lo, C.P. Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. Int. J. Remote Sens. 2002, 23, 1775–1798.

Baumann, M.; Ozdogan, M.; Kuemmerle, T.; Wendland, K.J.; Esipova, E.; Radeloff, V.C. Using the Landsat record to detect forest-cover changes during and after the collapse of the Soviet Union in the temperate zone of European Russia. Remote Sens. Environ. 2012, 124, 174–184.

Taubenböck, H.; Esch, T.; Felbier, A. Monitoring urbanization in mega cities from space. Remote Sens. Environ. 2012, 117, 162–176

Vanonckelen, S.; Lhermitte, S.; van Rompaey, A. The effect of atmospheric and topographic correction methods on land cover classification accuracy. Int. J. Appl. Earth Obs. Geoinf. 2013, 24, 9–21.

h) **From the CN database**

OpenNESS

Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Monitoring of results using GIS and/or remote sensing to help assess impacts on land cover.
- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

Smith A., Berry P., Harrison P. Sustainable Ecosystem Management. OpenNESS Synthesis Paper.

OPPLA

(https://oppla.eu)

- *Growing with green ambitions. Case study of Leipzig*

An important lesson is that mapping should be combined with in situ green space monitoring of, for example, vegetation biomass. This would add value to remote sensing data and improve the capacity to assess ecosystem services provided by urban green space such as carbon dioxide removal. In addition, data were only available for 2012. An account based on time series of land cover and land use would help city planners to better understand to what extent urban green infrastructure is under pressure.

Limitations of the mapping approach: Mapping accuracy: The UFZ team used a remote sensing based approach utilizing digital ortho photos. All remote sensing techniques map from above, and overlaid featured cannot be detected. As a consequence, GI features at ground level such as lawn/meadow and blue structures may be underestimated if covered by large trees and / or dominant shrubland.

Banzhaf, E., Arndt, T., Ladiges, J. (2018a): Potentials of urban brownfields for improving the quality of urban space. In: Kabisch, S., Koch, F., Gawel, E., Haase, A., Knapp, S., Krellenberg, K., Nivala, J., Zehnsdorf, A. (eds.) Urban transformations - Sustainable urban development through resource efficiency, quality of life and resilience. Future City 10 Springer International Publishing, Cham, pp. 221 – 232. https://doi.org/10.1080/02513625.2018.1487643.

Banzhaf, E., Kollai, H., Kindler, A. (2018b). Mapping urban grey and green structures for liveable cities using a 3D enhanced OBIA approach and vital statistics. Geocarto International. DOI: 10.1080/10106049.2018.1524514.

Banzhaf, E., Kabisch, S., Knapp, S., Rink, D., Wolff, M., Kindler, A. (2017): Integrated research on land use changes in the face of urban transformations – An analytic framework for further studies. Land Use Policy, 60, 403-407.

PLUREL (Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

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The main application areas of these technologies in urban growth research within the project can be defined as follows:

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- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

References:

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URBES (Urban Biodiversity and Ecosystem Services) https://www.biodiversa.org/121

- Remote Sensing of Urban Ecology (EO sensors, modelling algorithms)
- spatial and remote sensing data analyses, mostly engaged in WP2: Case study conditions and co-design workshops for identifying local policy solutions and WP5: Resilient supply of ecosystem services.

Larondelle N, Haase D, Kabisch N 2014. Diversity of ecosystem services provisioning in European cities. Global Environmental Change 26, 119-129.

Larondelle N, Hamstead Z A, Kremer P, Haase D, McPhearson T 2014. Comparing urban structure-function relationships across cities: Testing a new general urban structure classification in Berlin and New York. Applied Geography 53, 427-437.

Andersson E, McPherson T, Kremer P, Frantzeskaki N, Gomez-Baggethun E, Haase D, Tuvendal M, Wurster D 2015 Scale and Context Dependence of Ecosystem Service Providing Units. Ecosystem Services 12, 157-164.

Baró F, Frantzeskaki N, Gómez-Baggethun E, Haase D 2015. Assessing the match between local supply and demand of urban ecosystem services in five European cities. Ecological Indicators 55, 146-158.

Hamstead Z A, Kremer P, Larondelle N, McPhearson T, Haase D 2016. Classification of the heterogeneous structure of urban landscapes (STURLA) as an indicator of landscape function applied to surface temperature in New York City. Ecological Indicators 70, 574-585.

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- a model based on remote sensing – MODIS NPP (Input data: allometric equations, net photosynthesis (PSNnet) data of 2010 provided by the MODIS, average growths in diameter of specific tree species, trees diameter at breast high), output data: Net primary productivity kg C per tree and year
- classification via remote sensing to determine tree species, LIDAR data to determine size of tree and allomeric equations to model above ground tree biomass (Input data: land cover (tree canopy %, spatial distribution of tree species), tree crown height, stem diameter (dbh), tree height, crown diameter & field surveys for tree data (# trees, tree location, stem

diameter) (for calibration and validation); output data: above-ground carbon storage (biomass) (tC/ha, MtC, kg)

- deterministic model based on allomeric equations, LIDAR data and remote sensing to estimate tree carbon sequestration over the city (input data: remote sensing data, urban structure type data (e.g. green space, streets, low buildings with yards etc.), tree characteristics (tree height, crown width, crown base height, diameter at breast height (DBH))(from models); output data: aboveground carbon storage (kg C/building type, tC/ha, total tC)
- remote sensing together with distributed lag nonlinear models used to assess the risk of death due to heat as an effect of distance to green and blue space (input data: Metrological, NVDI, distance to green and blue infrastructure)
- modeling and detecting heat islands at different scales depending on a kernel smoothing and using remote sensing. Greenness and heat islands showed high correlation (input data: ASTER remote sensing images; output data: temperature in Kelvin).
- modeling the needs of green space for several ecosystem services, using GIS information, remote sensing and Pareto optimization (input data: GIS raster layers with information about green spaces; output data: air temperature.
- remote Sensing and LIDAR data used to estimate vegetation volume and NVDI. A 3D NVDI as constructed by multiplying the NVDI with the vegetation volume. Measured temperatures was modelled using Maximum Likelihood as a function of NVDI, 3D NVDI, distance to green / blue areas and built-area volume (input data: Remote images (1 m resolution), LIDAR data, temperature measurements; output data: temperature).
- a set of modelled GIS and remote sensing parameters used to model temperature as an effect of greenness, aerosols, buildings. Likely the method needs to be calibrated for each city/town separately (input data: GIS data of buildings, Landsat data; NVDI & AH CHRIS/PROBA satellite images, ASTER image data; output data: temperature).
- a framework using satellite images, remote sensing and statistical modelling to compute accessibility of parks and green space dependent on economic and population data (input data: percentage of green cover in a city, population density, GDP per capita, City land area, Per capita green space provision, Aggregation index; output data: Effects of and between the different types of in data)
- deterministic model, using remote sensing of greenness as well as surface sealing to estimate recreation supply (input data: Remote sensing data, NVDI & surface sealing; output data: Spatially normalized minimum of green space provision per person suggested by the city administration (m² per Block; m²/m²)
- remote sensing & satellite imagery and digital orthophotos together with Geographic Information Systems (GIS) used to develop a digital elevation model and a digital surface model (input data: qualitative and GIS data; output data: quality of life, tree coverage; spending time in city parks, gardens, and open spaces)
- remote sensing for ES matrix – the ES matrix approach is an easy-to-apply concept based on a matrix linking spatially explicit biophysical landscape units to ecological integrity, ecosystem service supply and demand. By linking land cover information from, e.g. remote sensing, land survey and GIS with data from monitoring, statistics, ecosystem service supply and demand can be assessed and transferred to different spatial and temporal scales. The ES matrix approach is a quick and simple way to get an overall spatially-explicit picture of the ES in case study areas (input data: land cover and land use data (GIS) (incl. Additional biotic and abiotica information (e.g. land use intensity, soil quality, climate data); output data: ES provision capacity per landuse class (0-5 values & biophyscial units).

Banzhaf, E., Kollai, H. 2015. Monitoring the Urban Tree Cover for Urban Ecosystem Services-The Case of Leipzig, Germany. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 40(7), 301.

Burkhard B. F., Kroll, F. Müller, W. 2009. Wind horst Landscapes' capacities to provide ecosystem services – a concept for land-cover based assessments. Landscape Online, 15, 1-22.

Davis et al. 2016. Combined vegetation volume and "greenness" affect urban air temperature, Applied Geography, 71, 106–114

Karteris, M., Theodoridou, I., Mallini, G., Tsiros, E., and Karteris A. 2016. Towards a green sustainable strategy for Mediterranean cities: Assessing the benefits of large-scale green roofs implementation in Thessaloniki, Northern Greece, using environmental modelling, GIS and very high spatial resolution remote sensing data, Renewable and Sustainable Energy Reviews, 58, 510-525

Larondelle et al. 2016. Balancing demand and supply of multiple urban ecosystem services on different spatial scales, Ecosystem Services, 22, Part A, 18-31

Neema et al. 2013. Multitype Green-Space Modeling for Urban Planning Using GA and GIS, Environment and Planning B: Planning and Design, 40, 447-473

Other sources

- multi-sensor multi time-series approach to detect urban land cover changes.
- Landsat, Sentinel and RapidEye data (2005–2017) are combined in a robust procedure.
- variation and disturbances of different sensor characteristics are shown to offset.
- NDVI (Normalized Difference Vegetation Index is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land (Weier and Herring, 2000, Environmental Research, 2018) is calculated and transferred into a classified NDVI for more than one decade.
- results show success of approach to detect small scale vegetation development.

Kabisch, N.; Selsam, P.; Kirsten, T.; Lausch, A.; Bumberger, J. 2019. A multi-sensor and multi-temporal remote sensing approach to detect land cover change dynamics in heterogeneous urban landscapes. Ecological Indicators, 99, 273-282.
https://doi.org/10.1016/j.ecolind.2018.12.033

Lausch, A.; Bastian O.; Klotz, S.; Leitão, P. J.; Jung, A.; Rocchini, D.; Schaepman, M.E.; Skidmore, A.K.; Tischendorf, L.; Knapp, S. 2018. Understanding and assessing vegetation health by in-situ species and remote sensing approaches. Methods in Ecology and Evolution, Methods Ecol. Evol. 9 (8), 1799 - 1809. http://doi.org/10.1111/2041-210X.13025

2.1.13 Access to public amenities (Env48)

2.1.13.1 Access to public amenities (Env48) Applied/Participatory Review

Umbrella: Greenspace accessibility

Indicator: Access to public amenities

Code: Env48

Description: Share of population with access to at least one type of public amenity (social welfare points, social meeting centres, restrooms, information displays, public telephones, rain shelters, drinking fountains) within 500m (% of people) using more applied and participatory methods. By incorporating these features into NBS schemes it may be possible to increase accessibility and reduce transport distances and vehicle use.

Metric(s): Density of public amenities has been used as an indicator of compactness or urban sprawl (and less car use). Accessible local services and facilities can reduce travel, particularly by private cars and help ensure sustainable communities. It can also be viewed as an indicator of health/wellbeing and quality of life. Public amenities are services/facilities which are provided by the government or town/city councils for the general public to use, with or without charge, for instance libraries, social welfare points etc (CITYkeys). Access to public amenities partially measures the mix and distribution of different facilities and uses in a city and the proximity of public services to the residential location of city dwellers.

CITYkeys defines this indicator as the extent to which public amenities are available within 500 m (presumably of residential areas). The metric recommended is a Likert scale of 1 to 5, as follows:

1. No amenities: no public amenities whatsoever are available (e.g. no basic nor additional).
2. Relatively few amenities: only few basic public amenities are available (e.g. a small park).
3. A reasonable number of amenities: basic public amenities are available including a few important amenities such as a park and a community centre.
4. A sufficient number of amenities: basic public amenities are widely available (e.g. open green spaces, public recreation) as well as many important public amenities (theatres).
5. Relatively many amenities: the area surrounding the project's central living area includes a wide variety of public amenities including numerous basic amenities (e.g. green spaces, public recreation facilities) as well as numerous important public amenities (e.g. theatres, zoos).

The evaluation could also take into account the type of amenities in terms of a relative value, i.e. the availability of public recreation is more important than the availability of drinking fountains.

Burton (2002) use the following metrics to measure mix of uses in cities and these could be applied for measuring accessibility of public amenities:

1. Number of key facilities for every 1000 residents
2. Ratio of residential to non-residential urban land (or multiplying the number of households by an average house footprint area of 35 m^2 (this does not include garden area), and the total area of non-residential land)
3. Variation in the number of facilities per postcode sector: average standard deviation across all facilities.

4. Overall provision and spread of key facilities: variation in the number of facilities per postcode sector divided by the average number of facilities per sector

The indicator which gives the most accurate `picture' of how mixed a city is in terms of uses is probably (4), and indicators (1) and (2) were considered probably the one most closely related to quality of life. The ratio of non-residential to residential land uses (2) may reflect the incidence of industrial or commercial land rather than the provision of amenities. The authors also suggest indicators that use the metric: % of postcode sectors containing fewer than two key facilities, contain four or more, six or more, etc.

Spatial accessibility to amenities generally refers to the ease with which amenities can be reached and may also measure quality of the amenities. Neighbourhood Spatial Accessibility measures accessibility at the neighbourhood level and can give a general view of accessibility patterns in cities (Hewko, 2001; Smoyer-Tomic et al., 2004). Potential indices outlined in Talen (1998) include:

- The *container* approach-summation of number of amenities available within a neighbourhood (or specified radius around neighbourhood residents)
- *Minimum* distance – distance residents have to travel to closest amenity of interest (e.g. library)
- *Travel cost* - distance residents have to travel to reach all facilities in a study area
- *Gravity potential* – sum of, for all facilities, some function of facility attractiveness mitigated by distance

The choice of metric can produce markedly different accessibility spatial patterns and therefore choice should be based on the purpose of the study. Type of distance measurement can have implications (e.g. Euclidean, network-based etc – see 'accessibility of greenspaces indicator for further detail). These approaches can be combined with a 'needs analysis' to determine Spatial Equity of amenities and whether there is an association between neighbourhood need and accessibility. 'Need' indicators can be variables related to socio-economic factors (i.e. % low income, % attached house, % transient etc). Spearman Rank Correlations can be used to assess the association of relative need and relative accessibility. Modelling using Local Indicators of Spatial Associations (LISA) and local Moran statistics and scatterplots can provide an indication of equitably distributed amenities (see Smoyer-Tomic et al., 2004 for details).

MacDonald et al. (2013) extracted data from a Scottish study on 'Transport, Housing and Wellbeing' related to public amenities and perceptions of accessibility, rated as 'very well-placed', 'fairly well-placed', 'not very well-placed', or 'not at all well-placed'. Amenities were mapped in GIS and both Euclidean and network buffers used to measure presence/absence of a selection of amenities within 800 m, 1000 m and 1200 m from respondents postcode. Subjective (perceptions) and objective (GIS measures) were cross tabulated using Kappa statistics in SPSS.

Scientific solid evidence: the indicator is relevant to access to services, and can be linked to quality of the built environment. The CITYkeys scoring system allows for some subjectivity and does not explicitly account for quality of services or user acceptance. Density can be a perceived experience rather than an outcome of empirical calculations (Burton, 2000).

Data on access to public amenities collected in these ways can be used to:

- Quantify the benefits of NbS in terms of improving access to public amenities;
- Assess the distribution of key public amenities in relation to planning new greenspace;
- Prioritise public amenity delivery through NBS design.

Level of expertise: Generally some GIS expertise is needed for mapping aspects.

Cost: There would be costs associated with acquiring GIS software and GIS specialism, if it is not already available. There would be costs associated with the participatory processes for gathering data on public perceptions of accessibility if this needs to be gathered.

Effort: Compiling data on amenities and questionnaires regarding public perceptions of accessibility can be labour intensive depending on method adopted and level of engagement.

Participatory process: If used, public perception questionnaires would be the main participatory process.

Data availability: Data can be obtained from sources such as Google maps, Yellow Pages, census data, postcode directories, city planning offices.

Geographical scale: Typically city-scale, but can be used over smaller scales (e.g. smaller administrative units).

Temporal scale: Most likely to be used to provide a snapshot or baseline to be measured against a future snapshot. Historical analysis can be carried out if past data/knowledge is available.

Synergies: Mainly associated with health and wellbeing indicators. There might also be synergies with other greenspace mapping indicators.

Earth observation/remote sensing/modelling: Some spatial modelling/mapping is generally required but participatory and applied processes are possible to supplement this. For more pure earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: Env48_RS.

Original reference(s) for indicator: UnaLab

Reference (s):

Burton, E. (2002) Measuring urban compactness in UK towns and cities. *Environment and planning B: Planning and Design*, 29(2), 219-250.

Hewko, J. (2001) *Spatial equity in the urban environment: assessing neighbourhood accessibility to public amenities*. Masters Thesis: University of Alberta.

Macdonald, L., Kearns, A. and Ellaway, A., 2013. Do residents' perceptions of being well-placed and objective presence of local amenities match? A case study in West Central Scotland, UK. *BMC public health*, *13*(1): 454.

Smoyer-Tomic, K.E., Hewko, J.N. and Hodgson, M.J. (2004) Spatial accessibility and equity of playgrounds in Edmonton, Canada. *Canadian Geographer/Le Géographe canadien*, *48*(3): 287-302.

2.1.13.2 Access to public amenities (Env48) Earth Observation/Remote Sensing Review

Umbrella: Greenspace accessibility

Indicator: Access to public amenities

Code: Env48

Description: Share of population with access to at least one type of public amenity (social welfare points, social meeting centres, restrooms, information displays, public telephones, rain shelters, drinking fountains, etc) within 500m (% of people) using earth observation and remote sensing methods. By incorporating these features into NBS schemes it may be possible to increase accessibility and reduce transport distances and vehicle use.

Metric(s): Remote sensing imagery has been widely adopted for analysis of spatial inequalities in distribution and accessibility to public amenities in cities (Joseph et al., 2012). Major techniques for this include dasymetric mapping, regression models and geostatistical models (Jensen et al., 2004; Joseph et al., 2012), spatial visualization and overlay analysis with georeferencing and digitization (Borana and Yadav, 2017; Travland et. al., 2017). There are some studies on accessibility of public amenities where amenities services are shown with the help of the database management systems by using GIS and RS (Nilsson, 2014; Taylor et al., 2017). Research indicates that urban population today prefer more open, well designed, structured, and built amenities as opposed to wildland recreation areas (Johnson et al., 2004; Travland et. al., 2017). Thus, an urban park should offer a variety of facilities and amenities including playgrounds, ball fields, and walking trails to cater the needs of a multicultural society (Duncan et al., 2012; Travland et. al., 2017).

The spatial depiction of the public amenities and infrastructural facilities can be made quite user friendly with application of GIS. Some research analyses the accessibility of urban parks and public amenities using Euclidean distance or based on GIS network analysis. In order to calculate how many of the total population have access to the public amenities and estimate the provision of public amenities, Borana and Yadav (2017) suggest the analysis composed of three steps:

- the Location of Quietient technique and Gini coefficient can be used to determine the spatial concentration and deficiencies of the public amenities.
- Remote Sensing (RS) data and Geographical Information System (GIS) Technology can be used for mapping and visualisation of the public amenities.
- Lorenz Curve is used to examine the inequality in the distribution of public amenities in the study area.

In doing so, the Landsat data and Survey of toposheets should be used. For georeferencing and subset of the study area ENVI software can be used. ArcGIS software is used for preparation of base map and visualisation of the public amenities in different municipal districts. The spatial data can be collected from field survey using GPS. The non-spatial data of the facilities can be collected from municipal departments. The Location Quotient method and Gini Coefficient with Lorenz curve can be used for analysis of different public amenities of municipal districts of the city.

The Location Quotient is a method for comparing a municipal ward's (district's) percentage share of a particular amenity with its percentage share of its population. The Location Quotient of different wards in a city with respect to a particular facility provides knowledge about the level of concentration of that facility in those wards.

Finally, the analysis results can show where are the disparity in the distribution of amenities in the municipal districts within the city.

Scientific solid evidence: Theoretical frameworks used to explain the location of public services and amenities include central place theory, aspects of industrial location theory and spatial diffusion theory which are all described as normative theories being able to optimize with respect to defined criteria operating in prescribed environmental conditions (Rushton, 1979). However, recent advancement in geospatial technologies has led to several applications in geographically orientated challenges, hence, the adoption of an effective decision tool like Geographic Information System (GIS), high resolution products of satellite remote sensing as well as the Global Positioning System (GPS) in solving the rather challenging task of optimal location for public amenities and facilities with respect to necessary criteria. Today, cities worldwide are affected adversely by the problem of appropriate location of public facilities and amenities. They are either too far from their market zone or they are too congested in a particular location or hardly accessible by local citizens and in some cases, political consideration to the siting of these facilities dominate without given considerations to the necessary criteria for demands and public interest. A number of studies have aimed to investigate the optimal determination of the locations of some public facilities in cities using geospatial techniques. A fusion of remote sensing, geographic information system (GIS) and GPS techniques have been explored by recent studies in this field (Ahmed, 2007; Borana and Yadav, 2017; Duncan et al., 2012; Johnson et al., 2004; Michael, 2008; Travland et. al., 2017). Together they provide strong evidence on distribution and access. They underline the need for development of a Geodata base of existing public amenities and facilities, and the use of Euclidean-distance geometry to spatially analyse the appropriate locations with regards to the set of standard criteria.

According to existing studies, integrating remote sensing data and point-of-interest (POI) data (including location-rich semantic information) has been successfully applied in the identification of social functions of urban lands, but none were focused on a detailed and complete social functional map of UGS. Moreover, spatial patterns or distribution densities derived from the POI data have been extracted into feature vectors and then combined with physical properties derived from remote sensing data to improve the accuracy of land use identification.

Level of expertise: An increasing number of sensors, RS data products, processing algorithms, software and tools are available for the assessment of public amenities and urban green space availability. Selecting an applicable data source and the method to process data is a complicated process which needs expert knowledge. Cost, time, expertise, and technical properties of remote sensing data are factors in this process. Thus, the assessment should be made by experts engaged in the NBS project who have expertise not only in RS, but also in urban planning, forestry, landscape ecology, regional planning. Each of them will then assess all built and land cover type combinations.

Costs: The land surveying of urban green space can have enormous costs and is also generally very time consuming. Therefore, urban green space mapping using satellite images to have a time series is a faster and more cost-effective process. It should be noted that the choice of a higher density point cloud increases data costs and data volume. This also requires more sophisticated processing algorithms.

Effort: While GIS techniques provide an efficient tool for inventory management and classification of different public amenities and facilities within an urban park and urban environment, remote sensing techniques facilitate their accurate and objective mapping. They can also be used to record temporal changes. These changes may cause a feature to change its class/category, shift its position, expand, shrink, or change its shape and are important to record and monitor for effective management. Technologies like remote sensing and GIS can be used effectively to develop an information system for efficient management of an urban park and conservation area.

Effort for achieving this is generally related to the accessibility of data and level of automation required for analysis.

Participatory process: Uneven distribution of public amenities indicates that the existing planning might not produce acceptable results in terms of balanced development of different municipal wards. Since a number of the amenities are provided by the government, their availability and distribution must be planned carefully. A participatory approach can be an effective mechanism for assessing and ensuring the even distribution of urban amenities in a city. The results of the analysis of access to public amenities can help policy-makers and municipal authorities in proper planning in the distribution of public amenities. Validation of results on the ground as well as the participation of urban planner and policy makers is also essential.

Data availability: There is great debate regarding the reliability and use of data approaches to quantify and track the changes, trends, and patterns of UGS and public amenities over long periods. Owning to the increasing availability of image data from multiple sources, the quantification of spatiotemporal patterns for greenspace and public amenities frequently relies on remote sensing. However, data such as Lidar and high-resolution images are still not easily accessible for many regions or users due to the high costs of data acquisition. Moreover, it is usually impractical to provide full coverage of extensive metropolitan areas, with limited data available over long periods. With the advantages of global availability, repetitive data acquisition, and long-term consistency, Landsat series satellites have become the best compromise to overcome these limitations.

Geographical scale: Can be applied at various geographical scales.

Temporal scale: Can be applied over various temporal scales.

Synergies: Remote sensing imagery provides powerful tools for master planning and policy analysis regarding green urban area expansion. However, measures of public amenities cannot be solely based on indicators obtained from 2D geographical information. In fact, 2D urban indicators should be complemented by 3D modelling of geographic data.

The spatial locational analysis of public amenities plays an important role in the decision making of local planning and development of new utilities services. Mapping for this indicator can have synergies with other health and well-being indicators and greenspace mapping indicators.

Applied methods: For further information on more applied and participatory methods, please see: Env48_Applied.

Original reference(s) for indicator: UnaLab

Metric references:

i) **From the literature review**:

Ahmed, M.W. (2007) Combining GIS-Based Spatial Analysis and Optimization Techniques to Generate Optimum Facility Location. GIS/RS Consultant eMapDivision/ISSD/Aramco, Cairo.

Borana SL, Yadav SK (2017) International Journal of Research in Engineering, IT and Social Sciences, 7 (11), 57-63

Duncan DT, Aldstadt J, Whalen J, White K, Castro MC, Williams DR. (2012) Space, race, and poverty: Spatial inequalities in walkable neighborhood amenities? Demographic Research, 26(17):409–448. 10.4054/DemRes.2012.26.17

Jensen R, Gatrell J, Boulton J, Harper B. (2004) Using remote sensing and geographic information systems to study urban quality of life and urban amenities. Ecology and Society. 9(5):5–15. 10.5751/ES-01201-090505

Johnson, C. Y., Bowker, J. M., & Cordell, H. K. (2004). Ethnic variation in environmental belief and behavior: An examination of the new ecological paradigm in a social psychological context. Environment and Behavior 36(2), 157-186. doi:10.1177/0013916503251478

Joseph, M., Wang, L. & Wang, F.H. (2012) Using Landsat Imagery and Census Data for Urban Population Density Modeling in Port-au-Prince, Haiti. GI Science & Remote Sensing, 49:2, 228-250.

Macdonald, J., Franco, S. (2016) Tree canopies, urban green amenities and the residential real estate market: Remote sensing and spatial hedonic applications to Lisbon, Portugal, 56th Congress of the European Regional Science Association: "Cities & Regions: Smart, Sustainable, Inclusive?", 23-26 August 2016, Vienna, Austria, European Regional Science Association (ERSA), Louvain-la-Neuve

Manonmani R., Prabaharan S., R. Vidhya & M. Ramalingam (2012) Application of GIS in urban utility mapping using image processing techniques. Geo-spatial Information Science, 15 (4), 271–275.

Michael, D. (2008) Facility Location in Cities: The Optimal Location of Emergency Units within Cities. NOVA; The University of Newcastle Research Online, The University of Newcastle Australia, VDM Verlag Dr Muller Aktiengesellschaf, Uon, 5725

Nilsson P. (2014) Natural amenities in urban space—A geographically weighted regression approach. Landscape and Urban Planning.;121:45–54. 10.1016/j.landurbplan.2013.08.017

Rushton, G. (1979) Optimal Location of Facilities. Department of Geography, University of Iowa, Iowa

Taylor BT, Fernando P, Bauman AE, Williamson A, Craig JC, Redman S. (2011) Measuring the quality of public open space using Google Earth. American Journal of Preventive Medicine.;40(2):105–112. 10.1016/j.amepre.2010.10.024

Travland M, Raouf A, Shah T I (2017) An urban park information system using remote sensing and GIS techniques: A case study of Wakamow Valley, Moose Jaw, Saskatchewan. Prairie Perspectives: Geographical Essays, 19: 28–34

c) based on the NbS projects from the CN database

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods

- a framework using satellite images, remote sensing and statistical modelling to compute accessibility of parks, green space and public amenities dependent on economic and population data (input data: percentage of green cover in a city, population density, GDP per capita, City land area, Per capita green space provision, Aggregation index; output data: Effects of and between the different types of in data)

PLUREL

(Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment and provision of public amenities among different urban districts

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

References:

Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

2.1.14 Blue space area (Env56)

2.1.14.1 Blue space area (Env56) Applied/Participatory Review

Umbrella: Greenspace distribution mapping

Indicator: Blue space area

Code: Env56

Description: Measure change in blue space (ponds, rivers, lakes) in urban area (%, hectares or ha/100k) due to NbS based on more applied and participatory methods.

Metric(s): Measuring bluespace change in urban areas can provide an index representing:

- the degree of nature conservation, and
- improving public health and quality of life as they are directly related to the natural water circulation, environmental purification and the green/blue network.

More green and blue space also reduces vulnerability to extreme weather events like urban heat islands and flooding by heavy rainfall. Bluespace area can be used as an indicator of these environmental, social and economic benefits.

Metrics outlined for greenspace area (Env55) are also generally applicable for bluespace. Green and blue space area information has typically been collected from high-resolution satellite images and then mapped and measured (area) in a GIS environment (see Env56-RS for more information).

An example comprises the Integrated Landscape Map (ILM) methodology that uses open-source, high spatial and temporal resolution data with global coverage (e.g. the OS Mastermap Greenspace layer and Sentinel S2A data (see link below)) to generate a composite spatial dataset that can classify land cover in a way that produces a more refined green/blue infrastructure map for cities (Dennis et al., 2018). This method has the capacity to include public and private green and blue spaces and overcomes some of the shortcomings of the large minimum mapping units of other datasets. It can be used to measure and represent the landscape qualities of urban environments. ILM provides uses a classification system involving seven thematic land use types coupled with five land cover values which can be used to more accurately investigate social-ecological relationships.

Participatory mapping GIS portals or mapping workshops can help supplement remote sensing approaches with ground-truthing and local knowledge. An example of this is the BlueHealth SoftGIS (BSGIS) tool (Geertman et al. 2009) that was used in the BlueHealth study programme (Grellier et al. 2017).

Data on bluespace area collected in these ways can be used to:

- Quantify the distribution of bluespace across target areas;
- Support the equitable distribution of bluespace through urban planning for environmental, social and economic benefits;
- Provide underpinning data for other indicators such as ecosystem service mapping, stormwater management, biodiversity mapping, etc.

Scientific solid evidence: available greenspace datasets in the UK are pretty comprehensive and accurate, but there can be limitations for area i.e. >0.25ha depending on resources available. A weakness is it does not capture the quality/health of the green/bluespace which would influence ES benefits.

Level of expertise: Accessing the public datasets should be straightforward but likely some expertise in GIS needed, particularly for more comprehensive ILM methodology? (see RS section)

Cost: Some map datasets and satellite imagery are freely available online, others involve a licence fee. Would be costs associated with acquiring GIS software if not already available, and GIS specialists

Effort: Would depend on the level of in-house expertise available and scale

Participatory process: citizen participation could be through a PPGIS tool such as GLOBE app.

Data availability: There is existing greenspace map data available in the UK, and international satellite data available online, but may be variation in terms of spatial resolution

Geographical scale: City-scale typically, but may be possible to use the data to monitor local-level changes in greenspace

Temporal scale: Depending on the data available and the purpose of the exercise, could produce a current snapshot or a temporal view of change

Synergies: Synergies with other greenspace mapping indicators, and the data can be used as an index for other environmental and health/wellbeing indicators

Earth observation/remote sensing/modelling: This indicator is predominantly based on earth observation/remote sensing mapping techniques. For more detail on earth observation, remote sensing and modelling approaches, including those used on past and current EU projects, see: Env56_RS

Original reference(s) for indicator: Unalab

Reference (s):

Copernicus Sentinel S2A (available since 2015) available from the Copernicus Scientific Data Hub at https://scihub.copernicus.eu/dhus/#/home

Dennis, M., Barlow, D., Cavan, G., Cook, P.A., Gilchrist, A., Handley, J., James, P., Thompson, J., Tzoulas, K., Wheater, C.P. and Lindley, S., 2018. Mapping urban green infrastructure: A novel landscape-based approach to incorporating land use and land cover in the mapping of human-dominated systems. *Land*, *7*(1), 17-25.

Geertman, S, Stillwell, JCH, Kahila, M and Kyttä, M (2009) SoftGIS as a Bridge-Builder in Collaborative Urban Planning. In: Geertman S , Stillwell JCH , eds. Planning support systems best practice and new methods. Dordrecht: Springer Netherlands, 389–411.

Grellier J, White MP, Albin M, et al (2017) BlueHealth: a study programme protocol for mapping and quantifying the potential benefits to public health and well-being from Europe's blue spaces. BMJ Open 7:e016188. doi: 10.1136/bmjopen-2017-016188

2.1.14.2 Blue space area (Env56) Earth Observation/Remote Sensing Review

Umbrella: Greenspace distribution mapping

Indicator: Bluespace area

Code: Env56

Description: Measuring change in blue space (ponds, rivers, lakes) in urban area (%, hectares or ha/100k) due to NbS using earth observation/remote sensing and modelling approaches

Metric(s): In order to characterise urban blue infrastructure and assess changes of different bluespace types over varying time periods different remote sensing techniques and GIS are used. The most common use of RS data is for the purpose of greenness identification (the indices and statistical indicators could be found in the Tables 1 and 2). Many of these metrics are equally applicable to bluespaces.

Table 1. Remote-sensing based indices for the effectiveness and health of green and blue spaces (Wellmann et al., 2017)

Type of Index	Index Name	Abbreviation	Reference
Vegetation Indices	Vegetation fractions	Frac	(Haase et al., 2019)
	Normalized difference vegetation index	NDVI	(Tucker, 1979)
	Green NDVI	gNDVI	(Gitelson et al., 1996)
	Red edge normalized difference vegetation index	reNDVI	(Gitelson and Merzlyak, 1994)
	Vegetation health index	VHI	(Lausch et al., 2018)
			(Kogan, 1990, 1997)
	Vegetation condition index	VCI	(Kogan, 2001)
	Temperature condition index	TCI	(Singh et al., 2003)
Combination of methods	satellite remote sensing with on-the-ground observations	-	(Lotze-Campen et al., 2002)
			(Haase et al., 2019)
Statistical Indices	Principal component analysis	1st component	(Jolliffe, 2002)
		2nd component	

		1^{st} and 2^{nd} component	

Table 2. Statistical indicators that have been tested for the quantification of spectral plant trait variations (Wellmann et al., 2017).

Type	Name	Formula	Reference
GLCM *Stats group*	GLCM mean	$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$	(Haralick et al., 1973)
	GLCM variance	$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2$	(Haralick et al., 1973)
	GLCM correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{\left(i-\mu_i\right)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right]$	(Haralick et al., 1973)
GLCM *Contrast group*	GLCM homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+\left(i-j\right)^2}$	(Haralick et al., 1973)
	GLCM contrast	$\sum_{i,j=0}^{N-1} P_{i,j}\left(i-j\right)^2$	(Haralick et al., 1973)
	GLCM dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\left\lvert i-j\right\rvert$	(Haralick et al., 1973)
GLCM *Orderliness group*	GLCM entropy	$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right)$	(Haralick et al., 1973)
	GLCM angular second moment	$\sum_{i,j=0}^{N-1} P_{i,j}^{2}$	(Haralick et al., 1973)
Spatial Autocorrelation	Geary's *C*	$C = \frac{n-1}{2*\left(\sum_i\sum_j w_{ij}\right)} * \frac{\sum_i\sum_j w_{ij}(x_i-x_j)^2}{\sum_i (x_i-\bar{x})^2}$	(Geary, 1954)
	Moran's *I*	$I = \frac{n*\sum_i\sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\left(\sum_i\sum_j w_{ij}\right)*\sum_i (x_i-x)^2}$	(Moran, 1950)

Descriptive Statistics	Standard Deviation	$\sigma = \sqrt{\frac{\sum(x-\overline{x})^2}{N}}$	
	Coefficient of Variation	$CV = \frac{\sigma}{\mu}$	(Datt, 1998)

Remote sensing data has been the source of previously available ready-made European LC datasets such as CORINE Land Cover (CLC) and Urban Atlas (UA). The spatial detail of these datasets is, however, not sufficient for thorough evaluation of UGS. CLC has the minimum mapping unit of 25 ha, which can capture only the largest of greenspaces. However, many smaller patches 'hidden' in the urban fabric polygons are relevant too. The same principle applies to urban bluespaces with many spaces being overlooked by such datasets. UA data presents a significant improvement, mapping patches of at least 0.25 ha. Nevertheless, in spatially fragmented urban landscapes, smaller but frequently occurring patches of bluespace should be considered. The limitation of UA data is that they are updated only on six-year basis and released with delay after the reference year (UA 2012 was made public in 2015). A recent study presented the spatial distribution and (mostly) functional classification of UGS in Sofia and Bratislava, based on recently available Sentinel-2A (S2A) multispectral satellite imagery, provided free of charge in the frame of European Copernicus Earth observation program (Vatseva et al., 2016). The target minimum mapping unit represented a five-fold improvement compared to UA, i.e. 500 sq. m. Moreover, given the short revisit time of Sentinel 2 (5 days in mid- latitudes once the second satellite of the mission, Sentinel-2B, is launched in 2016), the proposed method can deliver more frequent and timely information on UGS compared to UA. Fifteen different classes of UGS were mapped and quantified with this method.

Dennis et al. (2018) presents a landscape approach, employing remote sensing, GIS and data reduction techniques to map urban green and blue infrastructure elements in a large U.K. city region. The method proposed by Dennis has three elements:

(1) the use of remote sensing and GIS techniques to combine measures of land use, land cover and associated landscape metrics in the characterisation of neighbourhoods according to census units;
(2) employing data reduction methods to identify common attributes of urban landscapes for the creation of meaningful typologies for social–ecological research;
(3) a demonstration of the merit of the approach through analysis of social–ecological relationships in a large urban conurbation.

The methodology presented by Dennis et al. (2018) demonstrates the possibility of integrating currently available land use data such as those published by the e.g. U.K. Ordnance Survey with a land cover classification derived from high-resolution satellite imagery. The resulting composite dataset exhibits the ability to capture landscape features (integrating land use and land cover), indices, and a related typology congruent with existing socio-geographic units (e.g. U.K. national census tracts). Use of the latter as spatial extents for processing and analysis is particularly advantageous given that they reflect statistical units at which population, socioeconomic and health-related data are regularly reported. The primary use of recently available high-resolution remotely sensed data with global coverage (Sentinel 2A satellites), combined with a universally applicable classification scheme based on simple ecological stratification, highlights the potential of the method for work in other urban and human-dominated landscapes in a range of climates. A novel composite spatial dataset covering the conurbation of Greater Manchester was achieved through a combination of remote sensing and GIS techniques that drew on the strengths of separately but freely available spatial data. The resulting dataset was then compared with other open-source and widely used datasets covering the same study area (Urban Atlas and Land Cover Map). The methodology may provide a useful template for developing refined green/blue infrastructure maps for other cities (Dennis et al. 2018).

Green and blue areas >0.25ha in a city can also be extracted from *European Settlement Map 2016* at 10 metre resolution, and the total population of the city and number of inhabitants can be extracted from the *EU 100m pop mosaic* Global Human Settlement Layer (GHSL) and the best available input census data for a city (Pafi et al., 2016). This data can be used to estimate green/blue area in relation to population. Calculating the bluespace area (according to UnaLab, CITYkeys report): the total blue area in hectares in the city divided by one 100,000th of the city's total population, or blue area per capita in m^2 (Pafi et al., 2016).

A variety of studies have demonstrated that the use of high-resolution data is effective in capturing total green and blue cover in greater detail than other available sources (LCM 2015, Urban Atlas 2012 and OS Mastermap Greenspace 2017 datasets used for comparison). Using available high-resolution, remote sensing images researchers can transform Earth observation data into useful information necessary for urban planning and decision making. The mapping method applied with the use of RS is well suited to provide reliable geoinformation based on satellite images and to produce high resolution maps of urban green and blue spaces in urban territories. Quantifying the urban green and blue spaces using remote sensing data proves to be key in the transfer of scientific knowledge to the urban environmental monitoring and management. However, the quantity of greenery and blue spaces is often measured using aerial photography or remote sensing techniques. Such data offer little information on the quality of the landscape view from the ground level, and other attributes, which may be important in terms of generating positive health outcomes. Participatory approaches or combining indicators can be necessary to generate such data.

Scientific solid evidence: Currently, there is a variety of research focused on mapping of UGS, based on remote sensing data including the mapping of bluespace. With the capacity to differentiate land cover (LC) types at a large scale, remote sensing has been widely used for vegetation mapping in various environments. Satellite imagery has been adopted for the monitoring of vegetation both in urban and rural areas. The techniques applied for this can generally be equally applicable for bluespace areas. As with greenspace mapping, strength of evidence is based on the scale of bluespace analysed compare to the resolution of the satellite data and confidence of identifying bluespace compared to surrounding infrastructure. However, with suitable data, strong evidence can be provided.

Level of expertise: Experience of working with large datasets related to remotely sensed, climatic and environmental parameters as well as their statistical analysis using tools is important. Knowledge of GIS techniques such as multi-criteria evaluation and sensitivity analysis are also desirable. Knowledge of ecosystem services is required and experience of their quantitative and/or spatial assessment is advantageous.

Costs: Generally, average cost of a raw satellite image is approximately one dollar for each sq km. There are lots of considerations when purchasing imagery but in general satellite images are cheaper than aircraft, low resolution images are cheaper than high and old images are cheaper than new. To get some idea, you can look at the cost per sq.km of newly acquired imagery to get an idea of comparison:

- Worldview 2, 50cm pan is about €30 / sqkm
- IKonos pan, 0.8-3m resolution is about €25 /sqkm
- Deimos -1, 22m res is 15c/sqkm
- Landsat, MODIS and MERIS sensors – free.
- A high quality airborne lidar survey would be in the order of €450/sq.km.

There are a lot of ways to analyze cost (e.g. per pixel worldview is much the cheapest of the three listed above). Also note as price per km may be quoted but you will often be obliged to have minimum order of a few hundred sq.km – which may compare project costs back toward airborne if you are only interested in a small area.

Effort: The creation of a spatial dataset incorporating freely available remote sensing data and cartographic layers is a useful step towards a bluespace dataset for a wide range of uses for research, policy and practice. The effort of achieving this is related to the scale of area being analysed, availability of suitable data, and level of automation of analysis.

During the past decades, remarkable efforts have been made in developing various methods for the task of remote sensing image scene classification and distribution of urban green and blue spaces because of its important role for a wide range of applications, such as natural hazards detection, LULC determination, geospatial object detection, geographic image retrieval, vegetation mapping, provision of green and blue spaces, environment monitoring, and urban planning.

Participatory process: The accuracy of the resulting classification derived from the RS can be improved by incorporating digitised landscape and environmental data available from local environmental NGOs (e.g. City of Trees etc.) or community groups, which served principally to correct misclassification.

Similarly, participatory approaches can also be vital to supplement quantity of bluespace data with quality assessments.

Data availability: differs from country to country. An example of good practice includes the UK national mapping agency (Ordnance Survey) that has produced a fine-scale vector dataset of urban green and blue space using spatial data at the highest available resolution for the United Kingdom. The data are available under licence (OS Mastermap Greenspace Layer) as well as in open-access format (OS Open Greenspace Layer).

Copernicus Sentinel S2A (available since 2015) data were obtained from the Copernicus Scientific Data Hub (scihub.copernicus.eu/dhus).

Geographical scale: Remote sensing and geographic information system (GIS) provide powerful tools for mapping and analysis of UGS at various spatial and temporal scales.

Temporal scale: Remote sensing and geographic information system (GIS) provide powerful tools for mapping and analysis of UGS at various spatial and temporal scales. Analysis of past trends can be a challenge if historical data is not available in a suitable resolution.

Synergies: With the availability of high-resolution remote sensing images and multi-source geospatial data, there is a great need to transform Earth observation data into useful information necessary for urban planning and decision-making. As such, synergies exist with greenspace mapping, health and access to bluespace/open space indicators.

Applied methods: For further detail on more applied and participatory methods, please see: Env56_Applied.

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a) **From the literature review:**

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b) based on the NbS projects from the CN database

AMICA (Adaptation and Mitigation – an Integrated Climate Policy Approach)

http://www.amica-climate.net

One of the project tasks was Risk and Disaster management. In this regard it is based on:

- GIS data and tools for risk assessment and management as help for decision local and regional makers for planning and disaster preparedness,
- remote sensing data on impacts and damages and urgent needs in case of disasters (GMES),
- remote sensing of urban areas (Wilson et al. 2003) has revealed a patchwork of discrete heat islands related to the distribution and structure of buildings and streets, as well as areas with much lower temperatures associated with parks and green space (Yu & Hien 2006).

Charlesworth, S.M. 2010. A review of the adaptation and mitigation of global climate change using sustainable drainage in cities. *Journal of Water and Climate Change, volume 1* (3): 165-180. http://dx.doi.org/10.2166/wcc.2010.035

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Green Surge (Green Infrastructure and Urban Bio- diversity for Sustainable Urban Development and the Green Economy) www.greensurge.eu

One of the project tasks was "Identification, description and quantification of the full range of urban green spaces". In this regard, the research was based on remote sensing results in combination with relevant case studies field observation.

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OpenNESS - Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Monitoring of results using GIS and/or remote sensing to help assess impacts on land cover.
- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

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OPERAs

http://www.operas-project.eu

- Remote sensing algorithms to estimate evapotranspiration are available but often not at sufficient resolution, and do not provide predictions on upcoming water use.
- More experience needs to be gained in combining technologies and scales: direct mapping of soil moisture as done with in-situ, air- or space borne radar, crop water stress mapping by thermal infrared sensors or derived from crop vigour and/or modelling of the crop/soil/atmosphere continuum.

OPPLA

(https://oppla.eu)

Different projects from the database

- *Growing with green ambitions. Case study of Leipzig*

An important lesson is that mapping should be combined with in situ green space monitoring of, for example, vegetation biomass. This would add value to remote sensing data and improve the capacity to assess ecosystem services provided by urban green space such as carbon dioxide removal. In addition, data were only available for 2012. An account based on time series of land cover and land use would help city planners to better understand to what extent urban green infrastructure is under pressure.

Limitations of the mapping approach: Mapping accuracy: The UFZ team used a remote sensing based approach utilizing digital ortho photos. All remote sensing techniques map from above, and overlaid featured cannot be detected. As a consequence, GI features at ground level such as lawn/meadow and blue structures may be underestimated if covered by large trees and / or dominant shrubland.

Banzhaf, E., Arndt, T., Ladiges, J. (2018a): Potentials of urban brownfields for improving the quality of urban space. In: Kabisch, S., Koch, F., Gawel, E., Haase, A., Knapp, S., Krellenberg, K., Nivala, J., Zehnsdorf, A. (eds.) Urban transformations - Sustainable urban development through resource efficiency, quality of life and resilience. Future City 10 Springer International Publishing, Cham, pp. 221 – 232. https://doi.org/10.1080/02513625.2018.1487643.

Banzhaf, E., Kollai, H., Kindler, A. (2018b). Mapping urban grey and green structures for liveable cities using a 3D enhanced OBIA approach and vital statistics. Geocarto International. DOI: 10.1080/10106049.2018.1524514.

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PLUREL (Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Monitoring urban growth (area change, structures, land consumption, soil sealing
- Monitoring land cover/land-use changes (loss of agricultural area, wetland infringement, loss of areas important for biodiversity, spatial distribution of inner-urban green and open spaces and natural areas)
- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

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Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

URBACT (European exchange and learning programme promoting sustainable urban development)

https://urbact.eu

- remote sensing (production of high spatial resolution, including the urban atlas, built-up areas, and air pollution) and so-called big data, a growing source of detailed data can now be used to compare and benchmark cities.

URBES (Urban Biodiversity and Ecosystem Services) https://www.biodiversa.org/121

- Remote Sensing of Urban Ecology (EO sensors, modelling algorithms)
- spatial and remote sensing data analyses, mostly engaged in WP2: Case study conditions and co-design workshops for identifying local policy solutions and WP5: Resilient supply of ecosystem services.

Larondelle N, Haase D, Kabisch N 2014. Diversity of ecosystem services provisioning in European cities. Global Environmental Change 26, 119-129.

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Baró F, Palomo I, Zulian G, Vizcaino P, Haase D, Gómez-Baggethun E 2016. Mapping ecosystem service capacity, flow and demand for landscape and urban planning: a case study in the Barcelona metropolitan region. Land Use Policy 57, 405-417 https://doi.org/j.landusepol.2016.06.006.

EKLIPSE

- digital mapping (e.g., remote sensing, GIS) of the potential for NBS and status of implementation (Badiu et al., 2016; Giannico et al., 2016; Gómez-Baggethun and Barton, 2013).

Badiu, D.L., Iojă, C.I., Pătroescu, M., Breuste, J., Artmann, M., Niță, M.R., Grădinaru, S.R., Hossu, C.A., Onose, D.A., 2016. Is urban green space per capita a valuable target to achieve cities' sustainability goals? Romania as a case study. Ecol. Indic. 70, 53–66. doi:10.1016/j.ecolind.2016.05.044

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Raymond et al. 2016. An impact evaluation framework to guide the evaluation of nature-based solutions projects.

ENABLE (Enabling Green and Blue Infrastructure Potential in Complex Social-Ecological Regions)

http://projectenable.eu/partners/

- spatial and remote sensing data analyses, mostly engaged in WP2: *Case study conditions and co-design workshops for identifying local policy solutions* and WP5: *Resilient supply of ecosystem services*.

Nature4Cities* (2017 – ongoing)

- identifying the needs for observation and modeling of coastal areas and examination of the current contributions of remote sensing (space and airborne).

International Space Science Institute (ISSI) (2017) Monitoring the evolution of coastal zones under various forcing factors using space-based observing systems. White Paper on Observing and Modeling Coastal Areas.

Gonçalves, J. A., et al. (2015). UAV photogrammetry for topographic monitoring of coastal areas. ISPRS Journal of Photogrammetry and Remote Sensing, 104, pp 101-111, DOI: 10.1016/j.isprsjprs.2015.02.009.

Long, N., et al. (2016). Monitoring the topography of a dynamic tidal inlet using UAV imagery. Remote Sensing, 8(5), pp. 387, DOI:10.3390/rs8050387.

Taramelli, A., et al. (2014). Modeling uncertainty in estuarine system by means of combined approach of optical and radar remote sensing. Coastal Engineering, 87, pp. 77-96, DOI: 10.1016/j.coastaleng.2013.11.001.

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Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- a model based on remote sensing – MODIS NPP (Input data: allometric equations, net photosynthesis (PSNnet) data of 2010 provided by the MODIS, average growths in diameter of specific tree species, trees diameter at breast high), output data: Net primary productivity kg C per tree and year
- classification via remote sensing to determine tree species, LIDAR data to determine size of tree and allomeric equations to model above ground tree biomass (Input data: land cover (tree canopy %, spatial distribution of tree species), tree crown height, stem diameter (dbh), tree height, crown diameter & field surveys for tree data (# trees, tree location, stem diameter) (for calibration and validation); output data: above-ground carbon storage (biomass) (tC/ha, MtC, kg)

- deterministic model based on allomeric equations, LIDAR data and remote sensing to estimate tree carbon sequestration over the city (input data: remote sensing data, urban structure type data (e.g. green space, streets, low buildings with yards etc.), tree characteristics (tree height, crown width, crown base height, diameter at breast height (DBH))(from models); output data: aboveground carbon storage (kg C/building type, tC/ha, total tC)
- remote sensing together with distributed lag nonlinear models used to assess the risk of death due to heat as an effect of distance to green and blue space (input data: Metrological, NVDI, distance to green and blue infrastructure)
- modeling and detecting heat islands at different scales depending on a kernel smoothing and using remote sensing. Greenness and heat islands showed high correlation (input data: ASTER remote sensing images; output data: temperature in Kelvin).
- modeling the needs of green space for several ecosystem services, using GIS information, remote sensing and Pareto optimization (input data: GIS raster layers with information about green spaces; output data: air temperature.
- remote Sensing and LIDAR data used to estimate vegetation volume and NVDI. A 3D NVDI as constructed by multiplying the NVDI with the vegetation volume. Measured temperatures was modelled using Maximum Likelihood as a function of NVDI, 3D NVDI, distance to green / blue areas and built-area volume (input data: Remote images (1 m resolution), LIDAR data, temperature measurements; output data: temperature).
- a set of modelled GIS and remote sensing parameters used to model temperature as an effect of greenness, aerosols, buildings. Likely the method needs to be calibrated for each city/town separately (input data: GIS data of buildings, Landsat data; NVDI & AH CHRIS/PROBA satellite images, ASTER image data; output data: temperature).
- a framework using satellite images, remote sensing and statistical modelling to compute accessibility of parks and green space dependent on economic and population data (input data: percentage of green cover in a city, population density, GDP per capita, City land area, Per capita green space provision, Aggregation index; output data: Effects of and between the different types of in data)
- deterministic model, using remote sensing of greenness as well as surface sealing to estimate recreation supply (input data: Remote sensing data, NVDI & surface sealing; output data: Spatially normalized minimum of green space provision per person suggested by the city administration (m² per Block; m²/m²)
- remote sensing & satellite imagery and digital orthophotos together with Geographic Information Systems (GIS) used to develop a digital elevation model and a digital surface model (input data: qualitative and GIS data; output data: quality of life, tree coverage; spending time in city parks, gardens, and open spaces)
- remote sensing for ES matrix – the ES matrix approach is an easy-to-apply concept based on a matrix linking spatially explicit biophysical landscape units to ecological integrity, ecosystem service supply and demand. By linking land cover information from, e.g. remote sensing, land survey and GIS with data from monitoring, statistics, ecosystem service supply and demand can be assessed and transferred to different spatial and temporal scales. The ES matrix approach is a quick and simple way to get an overall spatially-explicit picture of the ES in case study areas (input data: land cover and land use data (GIS) (incl. Additional biotic and abiotica information (e.g. land use intensity, soil quality, climate data); output data: ES provision capacity per landuse class (0-5 values & biophyscial units).

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Schreyer et al. 2014. Using Airborne LiDAR and QuickBird Data for Modelling Urban Tree Carbon Storage and Its Distribution-A Case Study of Berlin, Remote Sensing, 6(11), 10636-10655

Tigges et al. 2017. Modeling above-ground carbon storage: a remote sensing approach to derive individual tree species information in urban settings, Urban Ecosystems, 20(1), 91-111

Weng et al. 2011. Modeling Urban Heat Islands and Their Relationship With Impervious Surface and Vegetation Abundance by Using ASTER Images. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 49(10), 4080-4089

OPERANDUM (2018 – ongoing) (OPEn-air laboRAtories for Nature baseD solUtions to Manage environmental risks)

Mentioned in the Research provided by University of the Sunshine Coast, Institute of Remote Sensing and Digital Earth in order to:

- Contribute to a high resolution modeling of the estuarine and the coastal sea dynamics focusing on the Italian OAL.
- Contribute to build up present day and climate change scenarios for predicting and assessing storm surge, coastal erosion, salt wedge intrusion
- Contribute to the design and development of the Natural based solutions planned for the Italian OAL: introduce a novel-vegetated sand dune in the complex land- marine environment of the north Emilia-Romagna coastline to reduce storm surge and related coastal erosion; install herbaceous perennial deep rooting plants as coverage of earth embankments for the mitigation of flood risk and salt wedge intrusion in the Po delta

https://www.operandum-project.eu/the-project/

Think Nature platform https://platform.think-nature.eu/resources?page=13

- remote sensing from urban gardens in Barcelona, Spain, including municipal 'allotment gardens' and 'civic gardens' emerging from bottom-up initiatives (identifying different urban gardens types regarding the ES values they provide, and specific garden characteristics including biophysical garden properties etc.

Langemeyer J., Camps-Calvet M., Calvet-Mir L., Barthel S., Gómez-Baggethun E. 2018. Stewardship of urban ecosystem services: understanding the value(s) of urban gardens in Barcelona. Landscape and Urban Planning. https://doi.org/10.1016/j.landurbplan.2017.09.013

UnaLab

- technical handbook takes the Key performance indicators as basis for detailed evaluation of NBS. One of them is leaf area index which can be measured using remote sensing.

https://www.unalab.eu/

URBAN Green-UP* (2017 – ongoing)

As based on Technical report by the Joint Research Centre (JRC), the European Commission's science and knowledge service and references below:

- Mapping the removal of PM10 and ozone by urban trees (Rome, one of the EnRoute city labs) as well as at regional level. They combined high resolution remote sensing data with measured pollutant concentrations to estimate the physical removal of pollutants by trees. A damage cost approach was used to estimate the monetary value associated to pollutant removal. The overall pollution removal accounted for 5123 and 19,074 t of PM10 and O3, respectively, with a relative monetary benefit of 161 and 149 Million euro for PM10 and O3, respectively.
- mapping and assessing the contribution of urban vegetation to microclimate regulation (a) Deriving a map of Land Surface Temperature based on Landsat 8 Data, using a methodology based on (Du et al. 2015); b) Aggregating Land types to assess the changes in average temperature (see Figure 12), c) Estimate the Influence of green cover on surface temperature index (Under development)
- mapping urban temperature using remote sensing information (split window algorithm), using the model for assessing urban temperature and the indicator for microclimate regulation

Du C, Ren H, Qin Q, Meng J, Zhao S. 2015. A Practical Split-Window Algorithm for Estimating Land Surface Temperature from Landsat 8 Data. Remote Sens. 7:

Fusaro L, Marando F, Sebastiani A, Capotorti G, Blasi C, Copiz R, Congedo L, Munafò M, Ciancarella L, Manes F. 2017. Mapping and Assessment of PM10 and O3 Removal by Woody Vegetation at Urban and Regional Level. Remote Sens. 9:

Wegmann M, Leutner BF, Metz M, Neteler M, Dech S, Rocchini D. 2017. A grass GIS package for semi- automatic spatial pattern analysis of remotely sensed land cover data. Methods Ecol Evol. doi: 10.1111/2041-210X.12827

Zulian, G., Thijssen, M., Günther, S. Maes, J. 2018. Enhancing Resilience Of Urban Ecosystems through Green Infrastructure (EnRoute). Progress report, EUR 29048 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-79-77697-7, doi:10.2760/958542, JRC110402)

Other sources

- multi-sensor multi time-series approach to detect urban land cover changes.
- Landsat, Sentinel and RapidEye data (2005–2017) are combined in a robust procedure.
- variation and disturbances of different sensor characteristics are shown to offset.
- NDVI (Normalized Difference Vegetation Index is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land (Weier and Herring, 2000, Environmental Research, 2018) is calculated and transferred into a classified NDVI for more than one decade.
- results show success of approach to detect small scale vegetation development.

Kabisch, N.; Selsam, P.; Kirsten, T.; Lausch, A.; Bumberger, J. 2019. A multi-sensor and multi-temporal remote sensing approach to detect land cover change dynamics in heterogeneous urban landscapes. Ecological Indicators, 99, 273-282.
https://doi.org/10.1016/j.ecolind.2018.12.033

2.1.15 Soil sealing (Env81)

2.1.15.1 Soil sealing (Env81) Applied/Participatory Review

Umbrella: Soil sealing

Indicator: Soil sealing

Code: Env81

Description: De-sealing, reusing sealed sites to reduce land take/soil sealing (with impermeable surfaces), and use of permeable materials and surfaces e.g. green roofs.

Metric(s): Impermeable ground and modified ecosystems transform natural soil and alter important environmental processes (e.g. water cycle etc). Mapping impermeable surfaces provides an indicator of urban development e.g. densification/urban sprawl, and can aid assessments of drainage, urban heat island, biodiversity and health and wellbeing.

The majority of soil sealing metrics would be based on an earth observation and/or remote sensing approach. However, other more applied and participatory methods are available. At a site or project level, a Green Space Factor score (between 0 and 1) can be calculated based on score assigned (by a planning authority) to any particular surface-cover type (e.g. asphalt, lawn, green roof etc). The area for each surface cover type is calculated and multiplied by its factor, and the overall total score is divided by the total area of the project. The project score can then be compared to targets set by local authorities. GSF can provide certainty for developers regarding expectations for urban greening for new developments. It can identify planning proposals with insufficient quantity and functionality of greening, encourage improvements in greening, and compare and evaluate proposals for a site. Examples are Malmo's Green Space Factor and Green Points system (Kruuse, 2011) and the London Urban Greening Factor (Grant, 2017).

Citizen Science: LandSense https://lep.landsense.eu/Themes/Urban-Landscape-Dynamics/ is an EU project that aims to engage citizens in monitoring change in the urban landscape that can be integrated into local authorities databases to improve urban planning (Olteanu-Raimond et la., 2018). The LandSense Engagement Platform will become a marketplace where citizens can participate in Land Use and Land Cover (LULC) campaigns and can register new or reuse existing services. Citizens use a mobile app to validate current land use and add new information for land use changes (under the name PAYSAGES in France). Campaigns can be opportunistic or guided, and contributors would typically either: edit a feature, add new information about a feature, report of change or an error in existing data, take pictures of features depicted on the map (Olteanu-Raimond et la., 2018).

Data on soil sealing collected in these ways can be used to:

- Set targets for soil unsealing;
- Monitor changes in relation to loss of permeable surfaces;
- Linking to other indicators such as land use change and stormwater management;
- Support initiatives to improve soil health and promote groundwater recharge.

Scientific solid evidence: Not typically a method for generating solid evidence. Tends to be more of a focus on generating an index to help quantify change.

Level of expertise: Data is generally added to background digital maps, so some expertise in GIS is needed.

Cost: There are costs associated with satellite data, data processing and analysis but these depend on city access to resources. Greenspace factor assessment generally involves site visits. Participatory processing can help reduce mapping costs

Effort: Potentially time-intensive depending on resolution or scale.

Participatory process: Lots of opportunity for community participation. The LandSense app provides a mechanism to engage citizen participation and update data.

Data availability: There is existing satellite/map data available and pilot citizen science apps

Geographical scale: City-scale typically, but may be possible to use the data to monitor local-level changes in greenspace if high-resolution imagery available

Temporal scale: Can be used to provide a current snapshot or to look at trends but the RS section below suggests there may be a trade-off in the resolution of available historical data to map change in the past to now

Synergies: Synergies with other indicators mapping urban form, and the data can be used as an index for other environmental (i.e. UHI, flooding) and health/wellbeing indicators: for example impervious surface % and UHI (Yuan & Bauer, 2007) and flooding (Mejía & Moglen, 2009).

Earth observation/remote sensing/modelling: Some spatial modelling/mapping is required but participatory and applied processes are possible to supplement this. For more greater detail on earth observation, remote sensing and modelling approaches, including those used on past and current EU projects, see: Env81 - RS

Original reference(s) for indicator: Connecting Nature Review

Reference (s):

Grant, G (2017) Urban Greening Factor For London. Report produced by the Ecology Consultancy for the Greater London Authority. Available at: https://www.london.gov.uk/sites/default/files/urban_greening_factor_for_london_final_report.pdf)

Kruuse, A (2011) The green space factor and the green points system. GRaBS expert paper 6. Available from: https://www.tcpa.org.uk/Handlers/Download.ashx?IDMF=c6ecd8bc-a066-435f-80d6-d58e47ab39a7

Mejía, A.I. and Moglen, G.E. (2009) Spatial patterns of urban development from optimization of flood peaks and imperviousness-based measures. *Journal of Hydrologic Engineering*, *14*(4), 416-424.

Olteanu-Raimond, A.M., Jolivet, L., Van Damme, M.D., Royer, T., Fraval, L., See, L., Sturn, T., Karner, M., Moorthy, I. and Fritz, S. (2018) An Experimental Framework for Integrating Citizen and Community Science into Land Cover, Land Use, and Land Change Detection Processes in a National Mapping Agency. *Land*, *7*(3), 103.

Yuan, F. and Bauer, M.E. (2007) Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of environment*, *106*(3), 375-386.

2.1.15.2 Soil sealing (Env81) Earth Observation/Remote Sensing Review

Umbrella: Soil sealing

Indicator: Soil sealing

Code: Env81

Description: De-sealing - reusing sealed sites to reduce land take/soil sealing (with impermeable surfaces), and use of permeable materials and surfaces e.g. green roofs

Metric(s): The soil sealing level, or the percentage of impervious surfaces, is an important factor in environmental sciences. Surfaces of this type directly influence the natural water cycle and affect the energy balance of the area. The hydrological regime is influenced by the degree of soil sealing and the spatial pattern; the connectivity between impervious patches necessitates the implementation of remote sensing techniques. Impervious surfaces can also be treated as a reliable indicator of anthropopressure on the natural environment (Weng, 2011). Monitoring of the soil sealing level is an important issue where urban sprawl is concerned (Pabjanek et al., 2016).

Sensing and measuring soil sealing can be carried out on a municipal scale from digital cartography, multi-temporal aerial photography and satellite images from Landsat and Spot, provided by NASA or national remote sensing plans (Garcia and Perez, 2016). Mapping sealed surface cover for larger areas or for studying changes in sealed surface cover over a significant period of time are most effectively measured with medium resolution remote sensing data. The identification, analysis, measurement and evaluation of soil loss through sealing can then be obtained from various remote sensing techniques: spectral bands, Principal Component Analysis, tasselled cap, Normalised Difference Built-up Index (NDBI) (Zha et al., 2003), Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) etc. NDBI has been shown to be the most effective methodology for the densest sectors of cities, but greater precision and reliability of sealed surfaces can be obtained from classifications using SAVI images and principal components outside the densest areas (Garcia and Perez, 2016).

Alternatively, Wood et al. (2006) recommend the following process: collate data from the following two sources:

i) OS MasterMap® to identify a priori, areas of known sealing – principally roads and buildings; and
ii) Quickbird (or Orbview-3, or IKONOS) satellite imagery, which is classified and used in all remaining areas, i.e. not designated by OS MasterMap® as building or roads.

After geocorrection, the NDVI image is calculated and extracted, and a maximum likelihood pixel classification of the NDVI is used to classify the image into unsealed and sealed surfaces (vegetated and non-vegetated). The segmented layer of roads and buildings is classified as 100% sealed. All remaining OS MasterMap® polygons are used to automatically extract the average area of sealed pixels from the classified NDVI image, by counting the number of sealed pixels and dividing by the polygon area. The two data sets are then reconstituted to produce a single combined map of sealed and unsealed land.

In strongly fragmented landscapes such as in an urban and peri-urban environment, the larger pixel size of medium resolution imagery will result in the omnipresence of mixed pixels. The spectral response of such pixels is a combination of the spectral responses of each distinct land-cover type found within the pixel. To deal with these mixed pixels, subpixel classification techniques can be applied, enabling estimation of the fraction of sealed surface cover present within each pixel.

Different subpixel classification strategies have been proposed to map sealed surface cover fraction, using regression-based learning approaches, such as multi-layer perceptrons (MLP) (Hu and Weng, 2009; Van de Voorde et al., 2009), self-organizing maps (Hu and Weng, 2009), regression trees (Xian et al., 2007), support vector regression (Okujeni et al., 2014), or using physically-based unmixing methods, such as linear spectral mixture analysis (LSMA) (Weng et al., 2011) or multiple endmember spectral mixture analysis (MESMA) (Rashed et al., 2003; Demarchi et al., 2012). To avoid under- or overestimation of sealed surface cover fraction, due to spectral similarities between bare soil and substrate (Xian et al., 2007), several studies propose the delineation of an urban mask prior to applying the sub-pixel classifier (Weng et al., 2011; Van de Voorde et al., 2009). Outside the urban mask a complete absence of sealed surfaces is then assumed, whereas pixels belonging to the urban mask are considered to be composed of vegetation and/or sealed surfaces only.

Perhaps the most straightforward method to estimate the sealed surface cover fraction from a pixel's spectral properties is the use of linear or non-linear regression (Van de Voorde et al., 2009), where the fraction of sealed surface cover or its complement – the vegetation fraction – is directly inferred from the pixel’s reflectance in one or more spectral bands, and/or from spectral indices that can be related to the sealed surface or vegetation fraction. Yang and Liu (2005) propose the use of tasselled cap brightness and greenness to estimate the fraction of sealed surface cover from Landsat TM/ETM+ imagery for Pensacola, Florida (US) for two different moments in time to identify hot spots of urban growth. Bauer et al. (2004) apply non-linear regression to estimate sealed surface cover from Landsat tasselled cap greenness for the cities of St. Cloud and Rochester (Minnesota, US). Sawaya et al. (2003) report a strong linear relationship between NDVI, perhaps the most commonly used vegetation index, and the fraction of sealed surface cover for high-resolution Ikonos imagery covering the City of Eagan, Minnesota (US). Van de Voorde et al. (2009) use stepwise multiple regression to estimate the vegetation fraction from Landsat imagery for the Greater Dublin area and obtain the sealed surface fraction as the complement of the vegetation fraction within a predefined urban mask.

Scientific solid evidence: If appropriate pixel and/or sub-pixel classification is carried out, a high level of evidence can be generated. Error factors can also be calculated based on sample areas.

Level of expertise: There are many kinds of remote sensing data available, but to find out the best fitting ones needs expert knowledge. Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing. Given the large number of remote sensing data available, it is difficult to select the appropriate one because each satellite has different revisit times, ordering requirements, delivery schedules, pixel resolutions, sensors, and costs.

Costs: Despite the potential of high-resolution image data to map sealed surfaces at a high level of spatial detail, the limited footprint, high cost and time intensive processing of such images hampers their use at a regional or nationwide scale. In addition, the limited historical archive of high-resolution image data restricts their use for spatio-temporal monitoring. For mapping sealed surface cover for larger areas or for studying changes in sealed surface cover over a significant period of time, medium resolution remote sensing data seem therefore more suited.

If cost is no object the best procedure, and that which provides the most flexibility in end products, is to purchase a digital tape or CD and process the image on one's own system. The drawback is that it requires an image processing system, the knowledge to operate it and keep it updated, and the time to do the processing. For those with some latitude in the amount they can spend, there are a wide variety of products available from vendors with a wide range of costs. If the amount that can be spent is limited, the least expensive option is to purchase imagery off the shelf from a government agency or primary distributor.

Effort: Remote sensing imagery combined with techniques of image analysis can provide an up-to-date, detailed and spatially-differentiated analysis of soil sealing. Previous studies at the local and regional level have confirmed the potential of these techniques to determine the extent of soil sealing both in Germany (such as Agglomeration Cologne/Bonn, Stuttgart, North Rhine-Westphalia, Bavaria (Behnisch et al., 2016) and elsewhere (such as the Columbus Metropolitan Area, Ohio, large regions in the USA and Italy. Furthermore, efforts have been made to predict impervious surface extents based on urban growth models.

Participatory process: Since assessment of soil sealing is based on land use change data, modeling of future soil sealing and soil loss can also involve participatory impact assessment. The major data inputs for soil sealing are satellite image based land use maps and soil maps. The participatory impact assessment involved series of meetings with stakeholders and collecting their opinions in a semi-quantitative form.

Data availability: Recently available remote-sensing data provided by the European Environmental Agency (EEA) now enable the uniform detection of sealed surfaces for the whole of Europe. This also permits us to specify possible correlations with other economic, social, ecological and technical variables.

Data from the Landsat archive (for free) can be selected to obtain full coverage, and, together with high-resolution IKONOS data for selected areas, can be used in a multi-resolution linear regression modelling framework to obtain fraction estimates for each time step. Spatial trends of sealed surface growth should be analysed at the level of municipalities and for different land-use classes.

Geographical scale: Analysis possible at various geographical scales.

Temporal scale: Analysis can be carried out at various temporal scales. However, lack of availability of high resolution historical data can limit assessment of historical change over time.

Synergies: Strong synergies exist with any indicators that require blue-green space mapping as the foundation for analysis. Combining RS and in-situ observations takes advantage of their complementary features.

Applied methods: For more information on applied and participatory methods see Env81_Applied

Original reference(s) for indicator: Connecting Nature Review

Metric references:

j) From the literature review:

Atkinson P, Foody G, Curran P (2000) Assessing the ground data requirements for regional–scale remote sensing. International Journal of Remote Sensing, 2571–2587.

Behnisch M, Poglitsch H, Krüger T (2016) Soil Sealing and the Complex Bundle of Influential Factors: Germany as a Case Study. ISPRS Int. J. Geo-Inf. 2016, 5, 132; doi:10.3390/ijgi5080132

Bauer M, Heinert N, Doyle J, Fei Y (2004) Impervious surface mapping and change monitoring using Landsat remote sensing. ASPRS – 70 years if service to the profession, Denver, Colorado.

Demarchi, L., Canters, F., Chan, J., Van De Voorde, T., 2012. Multiple endmember unmixing of CHRIS/Proba imagery for mapping impervious surfaces in urban and suburban environments. IEEE Trans. Geosci. Remote Sens. 50 (9), 3409–3424.

García, P. and Pérez, E. (2016) Mapping of soil sealing by vegetation indexes and built-up index: A case study in Madrid (Spain). *Geoderma*, *268*, pp.100-107.

Hu, X. and Weng, Q. 2009. Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks. *Remote Sensing of Environment* 113 (2009) 2089–2102. doi:10.1016/j.rse.2009.05.014

Morris J., V. Tassone, R. de Groot, M. Camilleri, S. Moncada (2011) A framework for participatory impact assessment: involving stakeholders in European policy making, a case study of land use change in Malta. Ecology and Society 16(1): 12. [Online] URL: http://www.ecologyandsociety.org/vol16/iss1/art12/.

Okujeni A, van der Linden S, Jakimow B, Rabe A, Verrelst J, Hostert P (2014) A comparison of advanced regression algorithms for quantifying urban land cover. Remote Sens 6:6324–6346

Pabjanek P, Krówczyńska M, Wilk E, Miecznikowski M (2016) An accuracy assessment of european Soil Sealing Dataset (SSl2009): Stara miłosna area, poland - a case study. Miscellanea GeoGraphica – Regional Studies on development 20 (4), 59-63. DOI: 10.1515/mgrsd-2016-0019

Rashed, T., Weeks, J., Roberts, D. et al. 2003. Measuring the physical composition of urban morphology using multiple endmember spectral mixture models. Photogramm. Eng. Remote Sens 69, 1011-1020.

Sawaya KE, Olmanson LG, Heinert NJ, Brezonik PL, Bauer ME. 2003. Extending satellite remote sensing to local scales: land and water resource monitoring using high-resolution imagery. Remote Sensing of Environment. 88:144–156.

Vanderhaegen S, Canters F (2016) Use of Earth observation for monitoring soil sealing trends in Flanders and Brussels between 1976 and 2013. Belgeo (on-line), 2. DOI: 10.4000/belgeo.18025

Van de Voorde, T., De Roeck, T., Canters, F. 2009. A comparison of two spectral mixture modelling approaches for impervious surface mapping in urban areas. International Journal of Remote Sensing 30(18):4785-4806. DOI: 10.1080/01431160802665918

Xian, G., Crane, M., Su, J. 2007. An analysis of urban development and its environmental impact on the Tampa Bay Watershed. J Env. Man. 85:965-976.

Weng Q (2011) Remote sensing of impervious surfaces in the urban areas: Requirements, methods and trends. Remote Sensing of Environment, 117, 34-49.

Wood, G., Braganza, S., Brewer, T., Kampouraki, M., Harris, J., Hannam, J., Burton, R. & Deane, G. (2006) *Monitoring urban sealing from space. The application of remote sensing to identify and measure changes in the area of soil prevented from carrying out functions by sealing.* Technical report of GIFTSS project BNSC/ITT/54, Defra code SP0541. Cranfield University.

Yang, X., and Liu, Z. (2005) Use of Satellite-derived Landscape Imperviousness Index to Characterize Urban Spatial Growth. Computers, Environment, and Urban Systems, 29, 524-540

Yuan, F. and Bauer, M.E. (2007) Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of environment*, *106*(3), 375-386.

Zha, Y., Gao, J. and Ni, S., 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International journal of remote sensing*, *24*(3), 583-594.

k) From the CN database

PLUREL (Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages) www.plurel.net

- remote sensing and GIS for sustainable urban development science to provide geo-referenced information on the shape, size and distribution of different land-use classes of the urban environment

The main application areas of these technologies in urban growth research within the project can be defined as follows:

- Monitoring urban growth (area change, structures, land consumption, soil sealing
- Monitoring land cover/land-use changes (loss of agricultural area, wetland infringement, loss of areas important for biodiversity, spatial distribution of inner-urban green and open spaces and natural areas)
- Mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces).

References:

Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

OPPLA (https://oppla.eu)

There different projects in this regard presented in the OPPLA data base

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- deterministic model, using remote sensing of greenness as well as surface sealing to estimate recreation supply (input data: Remote sensing data, NVDI & surface sealing; output data: Spatially normalized minimum of green space provision per person suggested by the city administration (m^2 per Block; m^2/m^2)

- remote sensing & satellite imagery and digital orthophotos together with Geographic Information Systems (GIS) used to develop a digital elevation model and a digital surface model (input data: qualitative and GIS data; output data: quality of life, tree coverage; spending time in city parks, gardens, and open spaces)

2.1.16 Change in ecosystem service provision (Env85)

2.1.16.1 Change in ecosystem service provision (Env85) Applied/Participatory Review

Umbrella: Ecosystem service mapping

Indicator: Change in ecosystem service provision

Code: Env85

Description: Measure number/quantity of a suite of ecosystem services to evaluate change in ES provision in relation to NbS using more applied methods.

Metric(s): Studies such as the Millennium Ecosystem Assessment (2005) and the UK National Ecosystem Assessment (Watson et al., 2011) demonstrated the linkages between the natural environment, ecosystem services (ES) and human well-being. Urban greenspaces can deliver essential ES and a detailed map of urban GI can provide the baseline for measuring urban ES. Detailed spatial data is needed to identify service providing units, and GI is typically classified according to land cover and land use type. Most techniques therefore involve remote sensed data and modelling approaches, therefore the metrics have been grouped within the **remote sensing/earth obervations review indicator guidelines: ESmapping_Env85 - RS**

Mapping and measuring changes in land use and land cover that supply ES can support decision making for using NBS approaches to urban development, for instance by providing information regarding costs and benefits of NBS versus grey infrastructure. If undertaken with comparison to a non-NBS project or no change scenario, it can assist with environmental management decisions and support evidence-based decision-making to improve human well-being and ensure environmental sustainability (Value of Nature to Canadians Study Taskforce, 2017). Consideration needs to be given that synergies and trade-offs between ES can occur (de Groot et al., 2010).

Mapping ecosystem service provision in these ways can be used to:

- Set targets for ecosystem service provision;
- Monitor change in ecosystem service provision over time;
- Inform strategic planning decisions in relation to individual sites or networks of sites;
- Assess the effects of different scenarios of design/management change on sites.

Scientific solid evidence: see RS review

Level of expertise: see RS review

Cost: see RS review

Effort: see RS review

Participatory process: RS review includes two research papers that involve community participation

Data availability: see RS review

Geographical/Temporal Scale: see RS review

Synergies: see RS review

Earth observation/remote sensing/modelling: For earth observation, remote sensing and/or modelling approaches, including those used on past and current EU projects, see: ESmapping_Env85_RS

Original reference(s) for indicator: UnaLab

Reference (s):

De Groot, R.S., Alkemade, R., Braat, L., Hein, L. and Willemen, L. (2010) Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecological complexity*, 7(3): 260-272.

Millennium Ecosystem Assessment (2005*) Ecosystems and Human Well-being: Synthesis*. Island Press, Washington, DC.

Value of Nature to Canadians Study Taskforce (2017) *Completing and Using Ecosystem Service Assessment for Decision-Making: An Interdisciplinary Toolkit for Managers and Analysts*. Ottawa, ON: Federal, Provincial, and Territorial Governments of Canada.

Watson, R., Albon, S., Aspinall, R., Austen, M., Bardgett, B., Bateman, I., Berry, P., Bird, W., Bradbury, R., Brown, C. and Bullock, J. (2011) *UK National Ecosystem Assessment: understanding nature's value to society. Synthesis of key findings.* UNE

2.1.16.2 Change in ecosystem service provision (Env85) Earth Observation/Remote Sensing Review

Umbrella: Ecosystem service mapping

Indicator: Change in ecosystem service provision

Code: Env85

Description: Measure number/quantity of a suite of ecosystem services to evaluate change in ES provision in relation to NbS focusing on earth observation/remote sensing approaches.

Metric(s). The role of novel Earth observation techniques and data sets is becoming increasingly important in environmental monitoring, both for biodiversity (Vihervaara et al. 2017), and for ecosystem services (Cord et al. 2017). Satellite Earth observation, as well as airborne and drone observations, have huge potential to improve quantification, mapping, and assessment of ecosystems and their services. Optical, radar, and Light Detection And Ranging (LiDAR) data can be used for direct measurements, or to gather information that feeds into the models.

Data and software needs:

- Data – Satellite images, airborne images, LIDAR points.
- Software: Remote sensing softwares e.g. Erdas Imagine, ENVI, GIS softwares and tools e.g. QGIS, ArcGIS, TerraScan, LasTools, FUSION

The ES indicators are then applied to these high-resolution UGS datasets within a GIS environment using these bespoke tools. The area of each element is multiplied by the ES supply per m^2 of the respective UGS type (aggregated to neighbourhood and/or district level). Results can be interpreted at individual ES level or at ES bundle level (using cluster analysis) and in terms of an ES supply score in relation to their spatial distribution i.e. radius from the source of nuisance such as air/noise pollution. Synergies and trade-offs between the type and quantity of UGS and ES supply can also be identified e.g. cooling, carbon storage and air purification demonstrate synergies as these are primarily being supplied by the same UGS types. The method can reveal differences between neighbourhoods in terms of amount and type of ES supplied, and can highlight possible ES shortages in neighbourhoods. The following provides a summary from the literature of the state of available and feasible remote sensing variables used in the assessment and valuation of ecosystem services.

Examples of methods:

- Green oriented urban development
  Martinico et al. 2014 http://dx.doi.org/10.3832/ifor1171-007
  SIAM (Satellite Image Automatic Mapper) García-Feced et al. 2014
  http://dx.doi.org/10.1007/s13593-014-0238-1
- Data: Land cover data (GIS layers): terrain, vegetation, soil, bathymetry, habitat distribution etc.
  Software: Remote Sensing software e.g. ENVI, Erdas Imagine, GIS software e.g. ArcGIS
- Mapping examples: Emergy assessment Mellino et al. 2014
  https://doi.org/10.1016/j.ecolmodel.2012.12.023

The following figures are taken from a very recent systematic review on urban ES quantification using RS (Tavares et al. 2019). Figure 3 shows the most used data sources for the selected studies, Figure 4 the most cited methodologies used, and Figure 5 the four main ES groups (Provisioning, Regulating, Supporting, and Cultural) identified in the literature review and their ES sub-types.

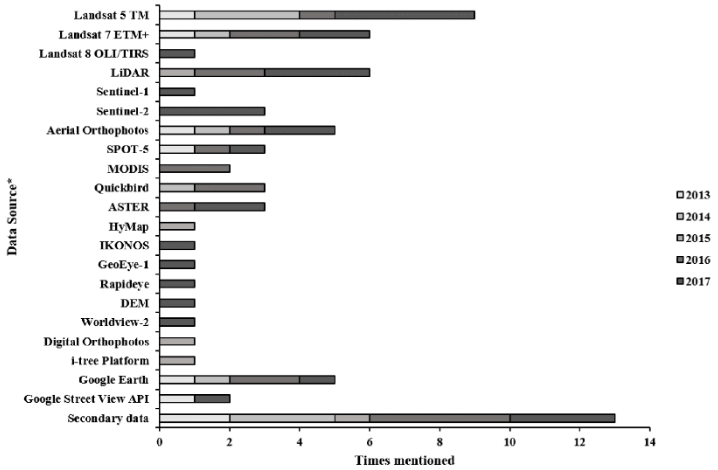

Figure 3. Identification of data source used by the authors, separated by year (2013–2017). * Abbreviations mentioned in the data source axis stands for TM, thematic mapper; ETM+, enhanced thematic mapper plus; OLI/TIRS, operational land imager/thermal infrared sensor; SPOT, satellite pour l'observation de la Terre; MODIS, moderate-resolution imaging spectroradiometer; ASTER, advanced spaceborne thermal emission and reflection radiometer; DEM, digital elevation model; API, application programming interface.

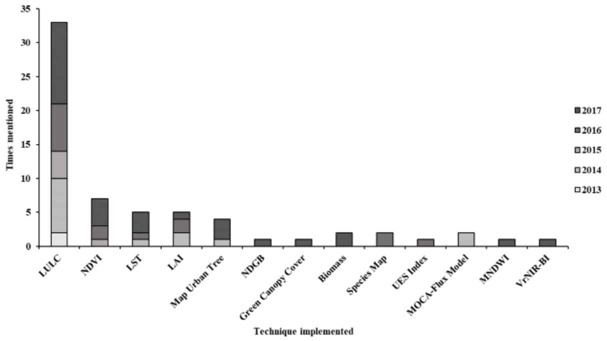

Figure 4. Methods implemented by the authors to infer UES results, separated by year (2013–2017).

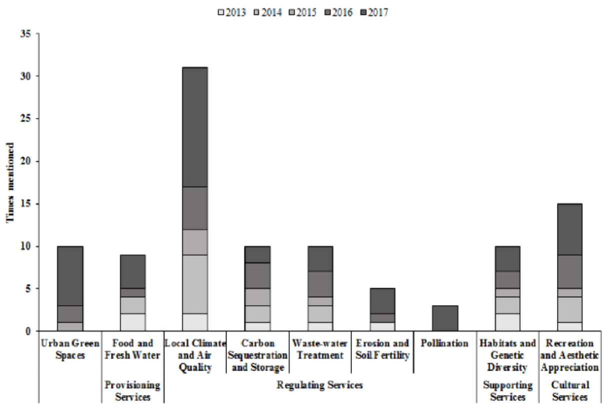

Figure 5. UES identified in the literature reviewed, separated by year (2013–2017).

All the four main classes of ES described by Costanza et al. [1] and TEEB [2] were found in the selected studies. The ES types mentioned in all five years considered were: local climate and air quality (70.45%), carbon sequestration and storage and wastewater treatment (22.73%) for regulating types of services habitats and genetic diversity (22.73%) for supporting services, and recreation and aesthetic contemplation (34.09%) representing cultural services.

ES maps can suffer from a lack of spatial and thematic detail to account for fine-scale NBS features that supply ES in cities close to people's demand, therefore Derkzen et al. (2015) propose a method to quantify a bundle of 6 urban ES supplied by different urban greenspace types. The six ES indicators derived from the literature are as follows:

- Air purification expressed as g PM_{10} captured per m^2 UGS per year;
- Carbon storage estimate expressed as g PM_{10} captured per m^2 UGS per year;
- Noise reduction expressed as attenuated dB(A) per 100 m^2;
- Run-off retention expressed as litres of retention per m^2;
- Cooling expressed as a weighted score between 0 and 1 based on UGS type;
- Recreation expressed as an index value m^2.

The ES indicators are then applied to high-resolution UGS data within a GIS environment, by multiplying the area of each element by the ES supply per m^2 of the respective UGS type (aggregated to neighbourhood and/or district level). Results can be interpreted at individual ES level or at ES bundle level (using cluster analysis) and in terms of an ES supply score in relation to their spatial distribution i.e. radius from the source of nuisance such as air/noise pollution. Synergies and trade-offs between the type and quantity of UGS and ES supply can also be identified e.g. cooling, carbon storage and air purification demonstrate synergies as these are primarily being supplied by the same UGS types. The method can reveal differences between neighbourhoods in terms of amount and type of ES supplied, and can highlight possible ES shortages in neighbourhoods. This can help prioritise locations for NbS interventions and match NbS type to the ES demand. For a more applied approach, direct measurement of ecosystem service provision for different UGS typologies within a city can provide more precision to the analysis, rather than relying on the generic values presented by Derkzen et al. (2015).

A weakness is that this method takes no account of biodiversity. Pedersen-Zari (2019) presents a method for assessing ecosystem service provision and needs that promotes a more urban biodiversity-based approach.

In the creation of models of ecosystem service supply and demand, EO can be used in a variety of ways. Currently, most ES supply models are based on thematic LULC maps, often derived from remotely sensed surface reflectance (Cord et al., 2017). Instead, models could use continuous variables from EO products that are more closely tied to ecosystem functions of interest; for example, Leaf Area Index (LAI) has been incorporated in mechanistic models to approximate air quality regulation (Braun et al., 2018). An emerging trend is the use of EO products for quantifying ecosystem structure and functional traits, such as vegetation height and leaf dry matter content, which are better indicators of biomass production than simple cover-based proxies (Díaz et al., 2007; Lavorel et al., 2011; Ramirez-Reyes et al., 2019). There is also tremendous potential to use EO for calibration and validation of existing or new ecosystem service models. On the demand side, ES models could be created using EO products representing populations and demographics, which represent where and how people benefit from ES (Watson et al., 2019). For instance, EO have recently been used to locate human settlements (Elvidge et al., 2017) and to estimate characteristics including social groups and poverty (Watmough et al., 2019; Wurm and Taubenböck, 2018). Poverty can then be used as a proxy for vulnerable populations that rely more heavily on ecosystem services such as access to fresh water and food production (Ramirez-Reyes et al., 2019).

EO products can also be used to drive ecosystem service models, providing forcing data and informing parameters. Inputs critical to modelling biophysical processes, such as precipitation and elevation, are globally available EO products, and these could be used to complement and extend local gauge data (Pasetto et al., 2018). Parameter coefficients in ES models are typically derived from field studies or literature review, but could be obtained through statistical regressions of in situ information with remotely sensed data (Ayanu et al., 2012). For example, estimates of cloud water interception could be related to and then predicted from canopy density instead of simple absence or presence of forest in cloudy sites (Ponette-González et al., 2015). The use of EO data to quantify how demand for ES varies over space and time is limited, representing a frontier for ES modelling (Ramirez-Reyes et al., 2019).

A Green Infrastructure Spatial Planning (GISP) model has been developed that provides an integrated, stakeholder-driven approach to maximize ecosystem services, revealing trade-offs, synergies and hotspots for future GI/NBS implementation (Meerow & Newell, 2017). This is a GIS-based multi-criteria approach that integrates six ES benefits: 1) stormwater management; 2) social vulnerability; 3) green space; 4) air quality; 5) urban heat island amelioration; and 6) landscape connectivity. Stakeholders then weight priorities to identify hotspots where green infrastructure benefits are needed most (23 expert stakeholders representing government agencies, local and national non-profits, and community development organizations). The results can be compared with locations of current GI to plan for future NbS so that it maximises social and ecological resilience, and provides a planning approach for evaluating competing and complementary ecosystem service priorities for a particular landscape. GISP model for Detroit available at: http://umich.maps.arcgis.com/apps/MapSeries/index.html?appid=4b257ce673ed4a178d11b4a267a9967e.

See also Kremer et al. (2016) who apply Spatial Multi-Criteria Analysis (SMCA) to evaluate the distribution of ecosystem services across New York City as a means to identify priority areas for green infrastructure. This uses spatially explicit calculations of physical properties of urban ES, which allows for fine resolution, quantitative evaluation of ecosystem services across the city's landscape.

Greater London Authority now has a 'GI Focus Map' for London that shows where there is more or less need for GI interventions based on different social and environmental (ES) issues that GI can address https://maps.london.gov.uk/green-infrastructure/ it shows which ES issues there is greatest need for in a particular area and so where best to target and focus GI investment, and highlights the issues GI should be designed to address.

The Natural Capital Planning Tool was developed to give local authorities, planners and developers a fit-for-purpose, easy-to-use tool that calculates an ES impact score indicating the direction of change and magnitude of impact http://ncptool.com/. The tool also states the maximum potential scores for each ecosystem service towards which designers can work to achieve the best outcomes in terms of ecosystem services delivery through smart design. Can be used to assess and monitor if a proposed plan or development provides a net-positive impact on ecosystem services and to compare different design options.

The TESSA toolkit is an easy-to-use workbook that leads the user through the steps needed to assess the ecosystem services provided at a particular site http://tessa.tools/. It is built around a comparison of the site in two alternative states, e.g. before and after restoration or conversion, and encourages a high level of stakeholder engagement.

EcoServ-GIS is a toolkit for mapping ecosystem services at a county or regional scale. It uses input GIS/map data to generate fine-scale maps that illustrate human need or demand for ecosystem services as well as the capacity of the natural environment to provide them. There isn't an official website but the latest version (3.3) can be downloaded here: https://drive.google.com/drive/folders/0B_v9QO2jyC4eNlVUbzY1UUstZU0

The National Ecosystem Approach Toolkit http://neat.ecosystemsknowledge.net/ecosystem-mapping-tool.html provides guidance on Ecosystem Mapping.

Natural England have an Ecosystem Services Transfer Toolkit in the form of an Excel spreadsheet with an accompanying User Guide and Quick Start Guide. http://publications.naturalengland.org.uk/publication/5890643062685696 The spreadsheet can be searched and queried to find evidence of the effects of specific land management actions on ecosystem services provided by urban areas. The toolkit indicates the magnitude of the effect on an ecosystem service and the strength of the supporting evidence. Where available, abstracts from the peer-reviewed papers are included in the toolkit.

ARIES (Artificial Intelligence for Ecosystem Services) is a software technology designed for rapid ES assessment and valuation. Prototypes of the software are available by experienced modellers for case studies and a web-based ARIES will come online for non-technical users http://aries.integratedmodelling.org/

The Ecosystem Knowledge Network's Tool Assessor has a list of the above tools and links to other websites and tool that may assist with ES avaluations https://ecosystemsknowledge.net/tool-assessor-list-of-tools

Mapping and measuring changes in land use and land cover that supply ES can support decision making for using NBS approaches to urban development, for instance by providing information regarding costs and benefits of NBS versus grey infrastructure. If undertaken with comparison to a non-NBS project or no change scenario, it can assist with environmental management decisions and support evidence-based decision-making to improve human well-being and ensure environmental sustainability (Value of Nature to Canadians Study Taskforce, 2017). Consideration needs to be given that synergies and trade-offs between ES can occur (de Groot et al., 2010).

Scientific solid evidence. The integration of RS technologies into ES concepts and practices leads to potential practical benefits for the protection of biodiversity and the promotion of sustainable use of Earth's natural assets. The last decade has seen the rapid development of research efforts on the topic of RS for ES (especially, in the context of spatially explicit RS and valuation of ES), which has led to a significant increase in the number of scientific publications. Remote sensing can be used for ecosystem service assessment in three different ways: direct monitoring, indirect monitoring, and combined use with ecosystem models. Some plant and water related ecosystem services can be directly monitored by remote sensing. Most commonly, remote sensing can provide surrogate information on plant and soil characteristics in an ecosystem. For ecosystem process related ecosystem services, remote sensing can help measure spatially explicit parameters. We conclude that acquiring good in-situ measurements and selecting appropriate remote sensor data in terms of resolution are critical for accurate assessment of ecosystem services.

The assessment of ES is often limited by data, however, a gap with tremendous potential can be filled through Earth observations (EO), which produce a variety of data across spatial and temporal extents and resolutions. Despite widespread recognition of this potential, in practice few ecosystem service studies use EO. There are some challenges and opportunities to using EO in ecosystem service modelling and assessment which we can identify:

- technical - related to data awareness, processing, and access (these challenges require systematic investment in model platforms and data management)

- other challenges – more conceptual but still systemic; they are by-products of the structure of existing ecosystem service models and addressing them requires scientific investment in solutions and tools applicable to a wide range of models and approaches.

As stated by variety of research, more widespread use of EO for ecosystem service assessment will only be achieved if all of these types of challenges are addressed. This will require non-traditional funding and partnering opportunities from private and public agencies to promote data exploration, sharing, and archiving. Investing in this integration will be reflected in better and more accurate ES assessment worldwide.

Remote sensing provides a useful data source that can monitor ecosystems over multiple spatial and temporal scales. Although the development and application of landscape indicators (vegetation indices, for example) derived from remote sensing data are comparatively advanced, it is acknowledged that a number of organisms and ecosystem processes are not detectable by remote sensing. The potential for applying remote sensing for analysis and mapping of ES efforts has not been fully realised due to concerns about ease-of-use and cost. Historically, RS data have not always been easy to find or use because of specialised search and order systems, unfamiliar file formats, large file size, and the need for expensive and complex analysis tools. That is gradually changing with increasing implementation of standards, web delivery services, and the proliferation of free and low-cost analysis tools. Although data cost used to be a common prohibitive factor, it is no longer a big stumbling block for most users except where high resolution commercial images are needed.

Level of expertise: It is important to clarify the resources that are needed to carry out ecosystem services assessments, such as technical and human resources, and the time needed for certain analyses. The methods vary greatly depending on the required expertise, availability of the data and its coverage, available software, time, and financial costs. The most suitable approach will depend on the research questions which need to be addressed, whether the study will be an assessment, or if maps are also required. For mapping methods, the level of scale should be considered. The limitations are often set by the availability of the data. For small research areas more detailed data sources, or even opportunities to conduct field measurements, may be available. However, for larger studies Earth Observation products may offer a solution for areas of poor data coverage. In addition to scale, it is also important to pay attention to the purpose of which the assessment is aimed at: Which biophysical units can and should be used to gain information on ecosystem services? Do we want to know if sufficient ecosystem service potential is available, or do we wish to quantify the rate at which the ecosystem service is delivered? Also, do we wish to deliver spatially explicit information for the chosen locations? The most suitable methods should be identified and selected according to the answers to these questions. Using a mixture of remote sensing and field methods appears to deliver the best results (e.g Mikolajczak et al., 2015; Vihervaara et al., 2017). Yet, this requires ecologists and remote sensing experts to collaborate closely with the newest methods and capabilities.

Cost: Many remotely sensed EO products, including those from MODIS (250 m+), Landsat (30 m), and Sentinel's Ocean Land Color Instrument (OLCI, 300 m), are freely available. However, EO data at finer resolutions (< 3 m) can be expensive to obtain.

Effort: According to Andrew et al. (2014), efforts to map the distribution of ESs often rely on simple spatial surrogates that provide incomplete and non-mechanistic representations of the biophysical variables they are intended to proxy. However, alternative datasets are available that allow for more direct, spatially nuanced inputs to ES mapping efforts.

Remote sensing data acquisition and processing requires financial, technological, and professional capacity. Even though there are some freely available data sets, the quantification of broad

categories of ecosystem services cannot be achieved with these datasets alone. Acquiring the commercially available satellite images (e.g., QuickBird) incurs higher costs which also applies to the current hyperspectral, RADAR, and LiDAR sensors. Data acquisition from these sensors is usually upon request by the users which creates inconvenience in obtaining data from a specific area. Besides the acquisition, processing and analysis of data like hyperspectral images demands a very high technical capacity and computers with storage capacities up to tens of Terrabytes or even Petabytes.

As stated by Ayanu et al. (2012), the quantification of ESs can be better and more correctly achieved by linking remotely sensed information to a limited number of in-situ observations using semi-empirical linear or nonlinear regression models. For example, vegetation indices derived from the near-infrared and red proportion of the electromagnetic spectrum can be linked to in-situ biomass measurements to derive a proxy for timber production. Irrespective of the regression type, the statistical relationship between the sensor signal and the data derived from field observations is affected by the sensor characteristics like spectral, spatial, and temporal resolution. Moreover, multiple boundary conditions like time of the day and year, actual state of ecosystem components, and the atmosphere also affect the statistical relationship and reduce its validity for monitoring and spatial transfers to other study areas.

The properties of remote sensing systems vary significantly among each other making selection of the sensor system and the optimal methodology prerequisites for an accurate delineation of the proxies for ecosystem services. For instance, many indicators can be delineated for extensive areas within a clearly defined range of uncertainty based on operationally available data and well-established methods. Other indicators useful for exact quantification of ecosystem services can be only derived experimentally at local scale. The success of remote sensing application therefore depends on careful selection of the data from which the relevant parameters are derived for the chosen indicators of ecosystem services.

The quantification of ecosystem services is limited by the respective resolution of the remote sensing system. While multispectral data (e.g., Landsat, MODIS) have been widely used, the retrieval of some variables is limited by the rather poor combination of spatial and spectral resolution. Thus, utilizing high resolution hyperspectral, radar and LiDAR sensors would be desirable. With respect to the current status of these sensors, the derivation of ecosystem parameters such assoil clay mineralogy, belowground biomass, or water quality indicators like chlorophyll-a content, nitrogen, and phosphorus loading is primarily restricted to experimental landscape scale studies. Therefore, in situ measurements are needed for validation when using remote sensing data.

Participatory process: Participatory activities can be combined with remote sensing analysis into an integrated methodology to describe and explain land-cover changes and changes in ES provision caused by them. In doing so, semi-structured interviews, focus group discussions, transect walks and participatory mapping can be used to identify and assess priority ES. Local community members and experts can together discuss which (positive) impact (benefits) the implemented NbS will have on various ES for local, regional, national and international users. This participatory process can help to identify priority ES (e.g. air purification, carbon sequestration, water regulation, soil protection, landscape beauty, biodiversity, etc.). The approach will reveal if there any strong variations in the valuation of different ES between local people and experts who apply RS techniques, between genders and between different status and income classes in the local communities. Scientific evidence has demonstrated that participatory tools, combined with free-access satellite images and repeat photography are suitable approaches to engage local communities in discussions regarding ES and to map and prioritise ES values (Brown & Donovan, 2014; Brown et al., 2012).

Data availability: Once ecosystem service analysts have identified a useful EO product and have the capacity to process it, they may still be unable to access it. Though many remotely sensed EO products, including those from MODIS (250 m+), Landsat (30 m), and Sentinel's Ocean Land Color Instrument (OLCI, 300 m), are freely available, EO data at finer resolutions (< 3 m) can be expensive to obtain (Schaeffer et al., 2013). While many assessments can be done at coarser resolutions, high resolution data are important for precise assessments, such as delineating urban canopies. Data producers could collaborate with public agencies to make EO data and products available at low or no cost for non-commercial research purposes. Since Landsat archives were released for free to the public, there has been a dramatic uptake and use of the data worldwide (Engel-Cox et al., 2004; Popkin, 2018; Wulder and Coops, 2014).

Data access may also be limited by restricted use permissions or lack of public availability, particularly derived data products that are not available in data archives. Many new EO products are generated through one-off analyses that are novel (and therefore seen as worthy of publication) but result in data products that quickly become outdated or that cannot be regenerated due to technical and resource limitations. Producing regularly updated EO products requires ongoing funding to operationalize such products and to allow for algorithm and product improvement to meet the continually evolving needs of end users. This does not align with traditional time-limited calls for research innovation, yet in the absence of such funding, the ecosystem services and broader geographic science community loses the value created by initial research outputs.

Geographical scale: Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change at various geographical scales. However, the higher the resolution required, the more expensive would be RS data needed. In some cases, it would be better to use images provided by drones, but in this case permissions for survey mapping will be required and depends on the local and national / government regulations. Methods can be applied from small to large geographical scales but are linked to the limitations of the data sources.

Temporal scale: Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change over time, at various temporal scales.

Synergies: In comparison to conventional sources of information on urban environment, remotely sensed data are inherently suited to provide information on urban land cover characteristics and ecosystem services provisioning, and their change over time, at various spatial and temporal scales. Synergies and trade-offs between the type and quantity of UGS and ES supply can also be identified e.g. cooling, carbon storage and air purification demonstrate synergies as these are primarily being supplied by the same UGS types. The method can reveal differences between neighbourhoods in terms of amount and type of ES supplied, and can highlight possible ES shortages in neighbourhoods.

Applied methods: For more applied and participatory approaches, please see: Env85_Applied.

Original reference(s) for indicator: UnaLab

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- remote sensing of urban areas (Wilson et al. 2003) has revealed a patchwork of discrete heat islands related to the distribution and structure of buildings and streets, as well as areas with much lower temperatures associated with parks and green space (Yu & Hien 2006).

Charlesworth S M (2010) A review of the adaptation and mitigation of global climate change using sustainable drainage in cities. *Journal of Water and Climate Change, volume 1* (3): 165-180. http://dx.doi.org/10.2166/wcc.2010.035

Wilson JS, Clay M, Martin E, Stuckey D, Vedder-Risch K. (2003) Evaluating environmental influences of zoning in urban ecosystems with remote sensing. Remote Sensing of Environment. 85, 303–321.

Yu, C., & Hien, W. N. (2006). Thermal benefits of city parks. *Energy and buildings*, *38*(2), 105-120.

Green Surge (Green Infrastructure and Urban Bio- diversity for Sustainable Urban Development and the Green Economy) www.greensurge.eu

One of the project tasks was "Identification, description and quantification of the full range of urban green spaces". In this regard, the research was based on remote sensing results in combination with relevant case studies field observation.

Cvejić R., Eler K., Pintar M., Železnikar Š., Haase D., Kabisch N., Strohbach M. (2015) A typology of urban green spaces, ESS provisioning services and demands. GREEN SURGE project report.

Spronken-Smith, R. A., and Oke, T. R. (1998) The thermal regime of urban parks in two cities with different summer climates. International Journal for Remote Sensing, 19, 2085–2107.

Weeks J.R. (2010). Defining urban areas. In: Remote sensing of urban and suburban areas. Rashed T., Jürgens C. (eds.). Springer, Dordrecht, Heidelberg, London, New York: p. 33-45.

iSCAPE (2016 – 08.2019) (Improving the Smart Control of Air Pollution in Europe) https://www.iscapeproject.eu

- 19 case studies on transport and air quality – remote sensing for measuring emissions from cars as they pass by
- Application of remote sensing instruments for the control of carbon emissions and air quality monitoring in European cities in the context of climate change

Pilla F., Broderick B., Gallagher J. et al. (2018) iSCAPE: Improving the Smart Control of Air Pollution in Europe. https://www.researchgate.net/project/iSCAPE-Improving-the-Smart-Control-of-Air-Pollution-in-Europe

IMPRESSIONS (Impacts and risks from high-end scenarios: strategies for innovative solutions)

http://www.impressions-project.eu/

- Mapping land use, ecosystem functions, and ecosystem services using cutting-edge remote sensing and machine learning techniques
- A coordinated effort to integrate and analyse a higher quantity and quality of CO_2 and CH_4 data, from in situ and remote sensing observations encompassing atmosphere, land and oceans.
- Remote sensing of forestry

OpenNESS Operationalisation of Natural Capital (NC) and Ecosystem Services (ES)

http://www.openness-project.eu

- Use of such indicators as vegetation health and functional diversity in applying of remote sensing techniques.

Smith A., Berry P., Harrison P. Sustainable Ecosystem Management. OpenNESS Synthesis Paper.

OPERAs

http://www.operas-project.eu

- Remote sensing algorithms to estimate evapotranspiration are available but often not at sufficient resolution, and do not provide predictions on upcoming water use.
- More experience needs to be gained in combining technologies and scales: direct mapping of soil moisture as done with in-situ, air- or space borne radar, crop water stress mapping by thermal infrared sensors or derived from crop vigour and/or modelling of the crop/soil/atmosphere continuum.

OPPLA (https://oppla.eu) – the platform presents many more studies on the analysis of the change in ES provision within the NbS. Here we selected only a few of them.

- *Mapping and assessment of pollutant removal by urban trees in Rome*

Mapping (Fusaro et al., 2017) the removal of PM10 and ozone by urban trees in Rome, one of the EnRoute city labs, as well as at regional level. They combined high resolution remote sensing data with measured pollutant concentrations to estimate the physical removal of pollutants by trees. A damage cost approach was used to estimate the monetary value associated to pollutant removal. The overall pollution removal accounted for 5123 and 19,074 tonne of PM10 and O3, respectively, with a relative monetary benefit of 161 and 149 Million euro for PM10 and O3, respectively.

Fusaro et al. (2017) Mapping and Assessment of PM10 and O3Removal by Woody Vegetation at Urban and Regional Level. Remote Sensing 2017, 9(8), 791; doi:10.3390/rs9080791

- *Growing with green ambitions. Case study of Leipzig*

An important lesson is that mapping should be combined with in situ green space monitoring of, for example, vegetation biomass. This would add value to remote sensing data and improve the capacity to assess ecosystem services provided by urban green space such as carbon dioxide removal. In addition, data were only available for 2012. An account based on time series of land cover and land use would help city planners to better understand to what extent urban green infrastructure is under pressure. Limitations of the mapping approach: Mapping accuracy: The UFZ team used a remote sensing-based approach utilizing digital ortho photos. All remote sensing techniques map from above, and overlaid featured cannot be detected. As a consequence, GI features at ground level such as lawn/meadow and blue structures may be underestimated if covered by large trees and/or dominant shrubland.

Banzhaf, E., Arndt, T., Ladiges, J. (2018a): Potentials of urban brownfields for improving the quality of urban space. In: Kabisch, S., Koch, F., Gawel, E., Haase, A., Knapp, S., Krellenberg, K., Nivala, J., Zehnsdorf, A. (eds.) Urban transformations - Sustainable urban development through resource efficiency, quality of life and resilience. Future City 10 Springer International Publishing, Cham, pp. 221 – 232. https://doi.org/10.1080/02513625.2018.1487643.

Banzhaf, E., Kollai, H., Kindler, A. (2018b). Mapping urban grey and green structures for liveable cities using a 3D enhanced OBIA approach and vital statistics. Geocarto International. DOI: 10.1080/10106049.2018.1524514.

Banzhaf, E., Kabisch, S., Knapp, S., Rink, D., Wolff, M., Kindler, A. (2017): Integrated research on land use changes in the face of urban transformations – An analytic framework for further studies. Land Use Policy, 60, 403-407.

PLUREL (Peri-urban Land Use Relationships - Strategies and Sustainability Assessment Tools for Urban-Rural Linkages)

www.plurel.net

- Based on the remote sensing and GIS, geo-referenced information was achived and mapping of environmental parameters (base data important for urban climate, access to and distribution of open space, calculation of sealed surfaces) was conducted.

Herold, M., Hemphill J., Dietzel, C. & Clarke, K.C. (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. Proceedings URS2005 conference, Phoenix, Arizona, March 2005.

URBACT (European exchange and learning programme promoting sustainable urban development) https://urbact.eu

- remote sensing (production of high spatial resolution, including the urban atlas, built-up areas, and air pollution) and so-called big data, a growing source of detailed data can now be used to compare and benchmark cities.

URBES (Urban Biodiversity and Ecosystem Services)

https://www.biodiversa.org/121

- Remote Sensing of Urban Ecology (EO sensors, modelling algorithms)
- spatial and remote sensing data analyses, mostly engaged in WP2: Case study conditions and co-design workshops for identifying local policy solutions and WP5: Resilient supply of ecosystem services.

Larondelle N, Haase D, Kabisch N (2014) Diversity of ecosystem services provisioning in European cities. Global Environmental Change 26, 119-129.

Larondelle N, Hamstead Z A, Kremer P, Haase D, McPhearson T (2014) Comparing urban structure-function relationships across cities: Testing a new general urban structure classification in Berlin and New York. Applied Geography 53, 427-437.

Andersson E, McPherson T, Kremer P, Frantzeskaki N, Gomez-Baggethun E, Haase D, Tuvendal M, Wurster D (2015) Scale and Context Dependence of Ecosystem Service Providing Units. Ecosystem Services 12, 157-164.

Baró F, Frantzeskaki N, Gómez-Baggethun E, Haase D (2015) Assessing the match between local supply and demand of urban ecosystem services in five European cities. Ecological Indicators 55, 146-158.

Hamstead Z A, Kremer P, Larondelle N, McPhearson T, Haase D (2016) Classification of the heterogeneous structure of urban landscapes (STURLA) as an indicator of landscape function applied to surface temperature in New York City. Ecological Indicators 70, 574-585.

Baró F, Palomo I, Zulian G, Vizcaino P, Haase D, Gómez-Baggethun E (2016) Mapping ecosystem service capacity, flow and demand for landscape and urban planning: a case study in the Barcelona metropolitan region. Land Use Policy 57, 405-417 https://doi.org/j.landusepol.2016.06.006.

EKLIPSE

- digital mapping (e.g., remote sensing, GIS) of the potential for NBS and status of implementation (Giannico et al., 2016; Gómez-Baggethun and Barton, 2013).

Giannico, V., Lafortezza, R., John, R., Sanesi, G., Pesola, L., Chen, J. (2016) Estimating Stand Volume and Above-Ground Biomass of Urban Forests Using LiDAR. Remote Sens. 8, 339. doi:10.3390/rs8040339

Gómez-Baggethun, E., Barton, D.N. (2013) Classifying and valuing ecosystem services for urban planning. Ecol. Econ. 86, 235–245. doi:10.1016/j.ecolecon.2012.08.019

Raymond et al. (2016) An impact evaluation framework to guide the evaluation of nature-based solutions projects.

ENABLE (Enabling Green and Blue Infrastructure Potential in Complex Social-Ecological Regions)

http://projectenable.eu/partners/

- spatial and remote sensing data analyses, mostly engaged in WP2: *Case study conditions and co-design workshops for identifying local policy solutions* and WP5: *Resilient supply of ecosystem services*.

Nature4Cities* (2017 – ongoing)

- identifying the needs for observation and modeling of coastal areas and examination of the current contributions of remote sensing (space and airborne).

International Space Science Institute (ISSI) (2017) Monitoring the evolution of coastal zones under various forcing factors using space-based observing systems. White Paper on Observing and Modeling Coastal Areas.

Gonçalves, J. A., et al. (2015). UAV photogrammetry for topographic monitoring of coastal areas. ISPRS Journal of Photogrammetry and Remote Sensing, 104, pp 101-111, DOI: 10.1016/j.isprsjprs.2015.02.009.

Long, N., et al. (2016). Monitoring the topography of a dynamic tidal inlet using UAV imagery. Remote Sensing, 8(5), pp. 387, DOI:10.3390/rs8050387.

Taramelli, A., et al. (2014). Modeling uncertainty in estuarine system by means of combined approach of optical and radar remote sensing. Coastal Engineering, 87, pp. 77-96, DOI: 10.1016/j.coastaleng.2013.11.001.

Taramelli, A., et al. (2015a). Remote Sensing Solutions to Monitor Biotic and Abiotic Dynamics in Coastal Ecosystems. Coastal Zones. Chap.8, pp. 125-135, DOI: 10.1016/B978-0-12-802748- 6.00009-7.

Naturvation (2017 – ongoing)

From the NATURVATION database on the value and benefit assessment methods for urban NBS:

- a model based on remote sensing – MODIS NPP (Input data: allometric equations, net photosynthesis (PSNnet) data of 2010 provided by the MODIS, average growths in diameter of specific tree species, trees diameter at breast high), output data: Net primary productivity kg C per tree and year
- classification via remote sensing to determine tree species, LIDAR data to determine size of tree and allomeric equations to model above ground tree biomass (Input data: land cover (tree canopy %, spatial distribution of tree species), tree crown height, stem diameter (dbh), tree height, crown diameter & field surveys for tree data (# trees, tree location, stem diameter) (for calibration and validation); output data: above-ground carbon storage (biomass) (tC/ha, MtC, kg)

- deterministic model based on allomeric equations, LIDAR data and remote sensing to estimate tree carbon sequestration over the city (input data: remote sensing data, urban structure type data (e.g. green space, streets, low buildings with yards etc.), tree characteristics (tree height, crown width, crown base height, diameter at breast height (DBH))(from models); output data: aboveground carbon storage (kg C/building type, tC/ha, total tC)
- remote sensing together with distributed lag nonlinear models used to assess the risk of death due to heat as an effect of distance to green and blue space (input data: Metrological, NVDI, distance to green and blue infrastructure)
- modeling and detecting heat islands at different scales depending on a kernel smoothing and using remote sensing. Greenness and heat islands showed high correlation (input data: ASTER remote sensing images; output data: temperature in Kelvin).
- modeling the needs of green space for several ecosystem services, using GIS information, remote sensing and Pareto optimization (input data: GIS raster layers with information about green spaces; output data: air temperature.
- remote Sensing and LIDAR data used to estimate vegetation volume and NVDI. A 3D NVDI as constructed by multiplying the NVDI with the vegetation volume. Measured temperatures was modelled using Maximum Likelihood as a function of NVDI, 3D NVDI, distance to green / blue areas and built-area volume (input data: Remote images (1 m resolution), LIDAR data, temperature measurements; output data: temperature).
- a set of modelled GIS and remote sensing parameters used to model temperature as an effect of greenness, aerosols, buildings. Likely the method needs to be calibrated for each city/town separately (input data: GIS data of buildings, Landsat data; NVDI & AH CHRIS/PROBA satellite images, ASTER image data; output data: temperature).
- a framework using satellite images, remote sensing and statistical modelling to compute accessibility of parks and green space dependent on economic and population data (input data: percentage of green cover in a city, population density, GDP per capita, City land area, Per capita green space provision, Aggregation index; output data: Effects of and between the different types of in data)
- deterministic model, using remote sensing of greenness as well as surface sealing to estimate recreation supply (input data: Remote sensing data, NVDI & surface sealing; output data: Spatially normalized minimum of green space provision per person suggested by the city administration (m^2 per Block; m^2/m^2)
- remote sensing & satellite imagery and digital orthophotos together with Geographic Information Systems (GIS) used to develop a digital elevation model and a digital surface model (input data: qualitative and GIS data; output data: quality of life, tree coverage; spending time in city parks, gardens, and open spaces)
- remote sensing for ES matrix – the ES matrix approach is an easy-to-apply concept based on a matrix linking spatially explicit biophysical landscape units to ecological integrity, ecosystem service supply and demand. By linking land cover information from, e.g. remote sensing, land survey and GIS with data from monitoring, statistics, ecosystem service supply and demand can be assessed and transferred to different spatial and temporal scales. The ES matrix approach is a quick and simple way to get an overall spatially-explicit picture of the ES in case study areas (input data: land cover and land use data (GIS) (incl. Additional biotic and abiotica information (e.g. land use intensity, soil quality, climate data); output data: ES provision capacity per landuse class (0-5 values & biophyscial units).

Banzhaf, E., Kollai, H. (2015) Monitoring the Urban Tree Cover for Urban Ecosystem Services-The Case of Leipzig, Germany. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 40(7), 301.

Burkhard B. F., Kroll, F. Müller, W. (2009) Wind horst Landscapes' capacities to provide ecosystem services – a concept for land-cover based assessments. Landscape Online, 15, 1-22.

Davis et al. (2016) Combined vegetation volume and "greenness" affect urban air temperature, Applied Geography, 71, 106–114

Karteris, M., Theodoridou, I., Mallini, G., Tsiros, E., and Karteris A. (2016) Towards a green sustainable strategy for Mediterranean cities: Assessing the benefits of large-scale green roofs implementation in Thessaloniki, Northern Greece, using environmental modelling, GIS and very high spatial resolution remote sensing data, Renewable and Sustainable Energy Reviews, 58, 510-525

Larondelle et al. (2016) Balancing demand and supply of multiple urban ecosystem services on different spatial scales, Ecosystem Services, 22, Part A, 18-31

Neema et al. (2013) Multitype Green-Space Modeling for Urban Planning Using GA and GIS, Environment and Planning B: Planning and Design, 40, 447-473

Schreyer et al. (2014) Using Airborne LiDAR and QuickBird Data for Modelling Urban Tree Carbon Storage and Its Distribution-A Case Study of Berlin, Remote Sensing, 6(11), 10636-10655

Tigges et al. (2017) Modeling above-ground carbon storage: a remote sensing approach to derive individual tree species information in urban settings, Urban Ecosystems, 20(1), 91-111

Weng et al. (2011) Modeling Urban Heat Islands and Their Relationship With Impervious Surface and Vegetation Abundance by Using ASTER Images. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 49(10), 4080-4089

Think Nature platform

www.platform.think-nature.eu

- remote sensing from urban gardens in Barcelona, Spain, including municipal 'allotment gardens' and 'civic gardens' emerging from bottom-up initiatives (identifying different urban gardens types regarding the ES values they provide, and specific garden characteristics including biophysical garden properties etc.

Langemeyer J., Camps-Calvet M., Calvet-Mir L., Barthel S., Gómez-Baggethun E. 2018. Stewardship of urban ecosystem services: understanding the value(s) of urban gardens in Barcelona. Landscape and Urban Planning. https://doi.org/10.1016/j.landurbplan.2017.09.013

UnaLab

- technical handbook takes the Key performance indicators as basis for detailed evaluation of NBS. One of them is leaf area index which can be measured using remote sensing.

https://www.unalab.eu/

URBAN Green-UP* (2017 – ongoing)

As based on Technical report by the Joint Research Centre (JRC), the European Commission's science and knowledge service and references below:

- Mapping the removal of PM10 and ozone by urban trees (Rome, one of the EnRoute city labs) as well as at regional level. They combined high resolution remote sensing data with measured pollutant concentrations to estimate the physical removal of pollutants by trees. A damage cost approach was used to estimate the monetary value associated to pollutant removal. The overall pollution removal accounted for 5123 and 19,074 t of PM10 and O3, respectively, with a relative monetary benefit of 161 and 149 Million euro for PM10 and O3, respectively.
- mapping and assessing the contribution of urban vegetation to microclimate regulation (a) Deriving a map of Land Surface Temperature based on Landsat 8 Data, using a methodology based on (Du et al. 2015); b) Aggregating Land types to assess the changes in average temperature (see Figure 12), c) Estimate the Influence of green cover on surface temperature index (Under development)
- mapping urban temperature using remote sensing information (split window algorithm), using the model for assessing urban temperature and the indicator for microclimate regulation

Du C, Ren H, Qin Q, Meng J, Zhao S. (2015) A Practical Split-Window Algorithm for Estimating Land Surface Temperature from Landsat 8 Data. Remote Sens. 7:

Fusaro L, Marando F, Sebastiani A, Capotorti G, Blasi C, Copiz R, Congedo L, Munafò M, Ciancarella L, Manes F. (2017) Mapping and Assessment of PM10 and O3 Removal by Woody Vegetation at Urban and Regional Level. Remote Sens. 9:

Wegmann M, Leutner BF, Metz M, Neteler M, Dech S, Rocchini D. (2017) A grass GIS package for semi- automatic spatial pattern analysis of remotely sensed land cover data. Methods Ecol Evol. doi: 10.1111/2041-210X.12827

Zulian, G., Thijssen, M., Günther, S. Maes, J. (2018) Enhancing Resilience Of Urban Ecosystems through Green Infrastructure (EnRoute). Progress report, EUR 29048 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-79-77697-7, doi:10.2760/958542, JRC110402)

ESMERALDA - Enhancing ecosystem services mapping for policy and decision making

www.esmeralda-project.eu

use of different data sources which rely on biophysical value in physical units, but this value needs further interpretation, certain assumptions, or data processing before it can be used. They can be based on remote sensing and Earth observation derivatives such as land cover, Normalised Difference Vegetation Index (NDVI), surface temperature, or soil moisture which are extracted from the original sources by specific procedures.

Different case studies. As a selected study – the Northern German case study area Bornhöved Lakes District, several provisioning ecosystem services were assessed with the direct measuring method based on a remote sensing approach. The aim of the study was to detect temporal changes in the supply area of the provisioning ecosystem services crops, fodder and biomass for energy.

Vihervaara P, Mononen L, Nedkov S, Viinikka A (2018) Biophysical Mapping and Assessment Methods for Ecosystem Services. Deliverable D3.3. Horizon 2020 ESMERALDA Project, Grant agreement No. 642007.

2.1.17 Community garden area per capita and in a defined distance (Env89)

2.1.17.1 Community garden area per capita and in a defined distance (Env89) Applied/Participatory Review

Umbrella: Greenspace accessibility

Indicator: Community garden area per capita and in a defined distance

Code: Env89

Description: A measure of per capita garden area per target distance - public community gardens provide active interaction with nature and opportunities for social cohesion.

Metric(s): Measuring community gardens as part of the greenspace network in cities gives an indicator of a range of factors such as: accessible greenspace provision and preservation, diversity of land use for humans and biodiversity, sustainable use of vacant land, climate regulation (cooling, stormwater, reduced GHG emissions associated with food transportation), food security, physical activity, access to healthy food/fruit and vegetable consumption, community cohesion and empowerment. Ultimately community gardens deliver a social function. Mapping exercises can also be used to identify areas where future community garden (CG) projects should be targeted (i.e. need for CGs).

Metrics will largely concern identification of CGs as part of the city's greenspace provision and then quantification in relation to population census data and an assessment of accessibility in relation to proximity measures.

Identification of CGs within a city will involve data gathering from land use plans on location, extent and characteristics, analysing official websites to identify additional CGs not included in planning documents, interrogating available satellite imagery provided on regional geoportals, and ground truthing by observation surveys (Senes et al., 2016). The collated data can then be entered into a GIS database for digitisation. From this, it would be possible to generate metrics regarding average CG area within the city (m^2), and distance from urban centres by overlaying a land use map and mapping buffer areas of 330 and 660 m (which correspond to a walking distance of 5 and 10 min respectively at a speed of 4km/h) (as outlined in Senes et al, 2016).

Alternative metrics that have been calculated in a GIS environment include: measuring the district area (ha) and the area of CGs (ha) and calculating a CG area proportion for the city as a % of the overall district area (Speak et al., 2015). Measuring the proportion of households within 0.25 miles of a CG, or a measure of the acreage used for CG per 1,000 residents as measures of accessibility and density (Jakubowski & Frumkin, 2010).

Metrics outlined in the 'accessibility of greenspaces' indicator review (Env41) can also be applied here to provide a 'defined distance' measure for this indicator, for instance La Rosa's 'simple distance indicators' which measures the Euclidean distance or Network distance to a greenspace, in this case CGs, at a fixed threshold distance of 300 m or 600 m. Within GIS, the total population present (taken from census data) within the considered distance thresholds can be calculated in relation to each CG.

Senes et al (2016) also provide a methodology for identifying possible sites suitable for CG projects. They identify areas potentially suitable for new CGs on the basis of the following criteria: i) proximity to residential road network, because the accessibility to the MCGs is a fundamental requirement for a public service (considers only the residential road network, usually not characterized by heavy traffic); ii) compatible land-use, in order to exclude areas with a land-use that doesn't allow a future transformation to CG; iii) identify areas with soils with land capability class 1 and 2 and exclude from the possible conversion into CG to allow the preservation of agriculture. The data is mapped in a GIS environment to generate a plan of potentially suitable and available areas for new CGs.

'Incredible Edible Lambeth' (IEL) have created an online map of community garden projects in the borough https://www.incredibleediblelambeth.org/map/ which can be updated by citizens who become a member (for free) online. As well as connecting citizens to CGs in the borough, this also provides a public participation mechanism for generating a comprehensive map of CGs in an area.

Mapping community garden accessibility in these ways can be used to:

- Identify deficits and inequalities in relation to community garden access;
- Assess changes in access in relation to new projects/sites;
- Inform strategic planning decisions in relation to community garden provision;
- Assess different types of accessibility;
- Set targets in relation to community garden provision and monitor progress towards targets.

Scientific solid evidence: Robustness of evidence will be biased by how detailed existing data is on CGs in a city and accuracy of census data. Similarly, the accuracy of distance to CG will vary based on the distance measure used. They can however represent a useful indicator basis for urban planning.

Level of expertise: some mapping/GIS expertise is likely to be needed.

Cost: Some map datasets and satellite imagery are freely available online, more comprehensive data needed for network-based measures potentially can involve a licence fee. Would be costs associated with acquiring GIS software if not already available, and GIS specialists.

Effort: The level of effort involved would be dependent on the amount of data already recorded by the city on community garden distribution, and the expertise available in terms of GIS

Participatory process: the project Incredible Edible Lambeth demonstrates it may be possible to validate CG distribution using a PPGIS-type citizen science exercise.

Data availability: some GS map data is freely available for mapping distance, aerial data is increasingly available but the quality and resolution can still be variable

Geographical scale: typically used at city-scale, but other scales are possible.

Temporal scale: can provide a snapshot or a temporal view of change over time if adequate historical data available

Synergies: Strong synergies with health and wellbeing indicators and social cohesion indicators in terms of physical activity, bringing together people from different backgrounds, education about nature and healthy food. Also, synergies with other environmental indicators (e.g. biodiversity measures, water regulation and air temperature) and possibly economic indicators if enterprises emerge selling produce.

Earth observation/remote sensing/modelling: no earth observation, remote sensing or modelling approaches were identified during the review.

Original reference(s) for indicator: SDG11; Kabisch et al., 2016; Eklipse

Metric reference(s):

Kabisch, N., Frantzeskaki, N., Pauleit, S., Naumann, S., Davis, M., Artmann, M., ... & Zaunberger, K. (2016). Nature-based solutions to climate change mitigation and adaptation in urban areas: perspectives on indicators, knowledge gaps, barriers, and opportunities for action. *Ecology and Society*, *21*(2).

La Rosa, D. (2014) Accessibility to greenspaces: GIS based indicators for sustainable planning in a dense urban context. *Ecological Indicators*, 42: 122-134.

Jakubowski, B. and Frumkin, H. (2010) Environmental Metrics for Community Health Improvement. *Preventing chronic disease*, 7(4): 1-10.

Senes, G., Fumagalli, N., Ferrario, P.S., Gariboldi, D. and Rovelli, R. (2016) Municipal community gardens in the metropolitan area of Milano: assessment and planning criteria. *Journal of Agricultural Engineering,* XLVII: 509 [82-87].

Speak, A.F., Mizgajski, A. and Borysiak, J. (2015) Allotment gardens and parks: Provision of ecosystem services with an emphasis on biodiversity. *Urban Forestry & Urban Greening*, 14(4): 772-781.

2.1.17.2 Community garden area per capita and in a defined distance (Env89) Earth Observation/Remote Sensing Review

See Applied methods as no Remote Sensing methods were found in the literature review

2.2 NBS Environmental Indicator Reviews – Feature Indicators

Indicators identified as Feature Indicators during the co-produced scoping process were:

- Carbon storage OR carbon sequestration in vegetation/soil (Env01)
- Albedo (Env07)
- Air Temperature – Energy demand (Env17)
- Flood damage (economic) (Env20)
- Community accessibility (Env26)
- Urban green space (Env38)
- Accessibility of greenspaces (Env41)
- Ratio of open spaces to built form (Env43)
- Green space area (Env55)
- Local food production (Env58)
- Cultivated crops (Env59)
- Intensity of landuse (Env61)
- Landuse mix (Env63)
- Air quality change (Env66)
- Tree shade for local heat change (Env88)
- Community garden area per child capita and in a defined distance (Env90)

The combined Applied/Participatory and Earth Observation/Remote Sensing reviews for each of these Indicators are presented below:

2.2.1 Carbon storage OR carbon sequestration in vegetation/soil (Env01)

Umbrella: Carbon storage OR carbon sequestration in vegetation/soil

Indicator: Carbon storage OR carbon sequestration in vegetation/soil

Code: Env01

Description: Carbon storage refers to the quantity of carbon locked away in vegetation or soil. Carbon sequestration is the process of capture and long-term storage of carbon. The metrics associated with these processes represent a measure of the carbon removed/stored by nature-based solutions in soil and vegetation per unit area/unit time or tonnes stored in vegetation/soil. This can be measured as a basic static volume stored, or a more fluid measure in relation to ongoing carbon balance and maintenance costs. Cities are typically net carbon sources (Velasco and Roth 2010), but evidence has been generated that this pattern could be reversed, at least during the growing season, if urban areas are designed sustainably and are heavily vegetated (Crawford et al. 2011).

Metric(s):

Typically, metrics associated with nature-based solutions are based on carbon storage in above ground vegetation, usually trees. This involves the estimation of annual carbon sequestration on individual trees, at a local scale, stand scale (Forestry Research 2019), or at the scale of the entire city. Calculations are made through the application of allometric equations, relationships between biomass (carbon stored) and physical dimensions (e.g., diameter and height) of trees, and predictive growth models applied to tree inventories (e.g., McPherson, Xiao, & Aguaron, 2013). Several tools exist for basic calculation of carbon dioxide storage estimates for vegetation in urban areas. These include i-Tree Eco (2019), i-Tree Canopy (2019), i-Tree Streets (2019), CUFR Tree Crown Carbon Calculator (CTCC) (2019), Urban General Equations (UGEs) (Schreuder et al. 2003). Based on their evolution from forestry calculation models, and the complexities of transferring these to urban woodlands and street trees, results from these tools can be varied. A comparative review of these in Sacramento found UGEs to produce the most conservative results (Agauron and McPherson 2012), however i-Tree tools appear to be becoming more commonly used for the many countries where they can be applied (iTree 2019).

The scale of analysis is one aspect that has been identified as bringing in variability in relation to the results of these various tools, with many broad-scale methods failing to capture the fine-scale variation associated with mosaic urban landcover (Davies et al. 2013). Capturing fine-scale data can present an opportunity for community participation in relation to ground-truthing vegetation. An example of such an approach was the London i-Tree project (Rogers et al. 2015). For this, i-Tree Eco was used to calculate a range of values in relation to the ecosystem service benefits of London's urban trees, including carbon storage. London-wide data was calculated based on a series of sample plots across the city. The majority of these plots were surveyed by volunteers trained as part of the programme.

Whilst the approach of focusing on above ground vegetation is relatively straightforward and can generate high-profile impactful data, one shortfall is that these methods do not take into account the complex carbon balance in urban ecosystems (Velasco et al. 2016). In order to get a more holistic measure of a nature-based solution's contribution to carbon sequestration, particularly a newly created nature-based solution that changes/impacts the underlying substrates, consideration should also be given to the below ground storage volumes, and emissions from soil respiration, and greenery management (Baldocchi 2008; Velasco et al. 2016).

Similarly to above ground carbon storage, tools exist for calculation of below ground carbon stores in relation to landuse type, for example InVEST (Sharp et al. 2018). Calculations have been made of typical carbon storage volumes per unit area for a variety of urban land use and land cover types (Pouyat et al. 2006), alternatively, soil sampling and analysis can be carried out to compare local patterns (Edmondson et al. 2014). However, as these models and methods tend to simplify the carbon cycle to enable ease of use, they can also lead to important limitations. Perhaps most significant being the tendency to represent landscapes as static over time, not gaining or losing carbon through soil respiration.

Soil respiration in relation to carbon is carbon efflux, typically driven by autotrophic respiration of plant roots and associated microorganisms, and heterotrophic respiration via microbial decomposition of soil organic matter (Hansen et al. 2000). The most commonly applied method for quantifying these carbon balances is the use of eddy covariance techniques (Velasco et al. 2016). These can be implemented to obtain ecosystem-scale measurements of CO_2 fluxes (Crawford et al. 2011) and methane fluxes (Le Mer and Roger 2001). A key finding from these studies with particular relevance to urban ecosystems and nature-based solution implementation is that recently disturbed ecosystems tend to lose carbon, unlike stable ecosystems such as old-growth forests and undisturbed peat bogs that usually act as carbon sinks (Baldocchi 2008; Luyssaert et al. 2008; Lindsay 2010; Yu et al. 2011; Stephenson et al. 2014). As disturbance of soil through the creation and management of nature-based solutions can have a substantial effect on soil respiration (Velasco et al. 2016), it should also be considered in calculations of carbon storage/sequestration. These are not typically considered as part of carbon/storage sequestration indicators though, as they capture a more holistic but complex evaluation of urban carbon balances.

One example of the risk of considering urban landuse types as being stable carbon stores over time is the potential underestimation of the value of brownfield (post-industrial) sites to urban carbon balance. Recent research has indicated that the high levels of calcium on such sites from demolition wastes (e.g. concrete dust and lime) could play a key role in urban carbon sequestration (Goddard 2016). This is due to rapid weathering of calcium silicate and hydroxide minerals derived from the demolition materials, which release calcium that combines with CO_2, precipitating as calcite - a long-term carbon store (Washbourne et al, 2015). Initial results have indicated potential sequestration rates of global significance. Such understanding opens the possibility of engineering carbon sequestration into urban nature-based solutions, and has implications in relation to how brownfield sites are managed (Goddard 2016).

Another example of how urban manure-based solutions can be engineered to offset any increased carbon loss caused by disturbance of soils is the potential to incorporate cradle-to cradle technology in nature-based solutions design to act as a source of carbon storage. The application of urban waste, for example through the recycling of waste materials into aggregates (Li et al. 2007; Molineux et al. 2016), offers a sustainable means to increase urban soil carbon reserves (Brown et al. 2012). If such techniques are incorporated into nature-based solution delivery, they can also be included in nature-based solution urban soil carbon calculations.

In addition to urban terrestrial habitats, urban wetland areas also need consideration. As with terrestrial habitats, basic calculations of total stored carbon can be carried out on above ground vegetation (Owers et al. 2018) and soils (Xiong et al. 2018). However, eddy covariance measuring stations are required to quantify the carbon balance of these systems in terms of being carbon sinks or sources (Mitsch and Mander 2018).

Since conventional methods for monitoring of carbon storage in soil and vegetation can be time consuming and costly (Angelopoulou et al., 2019; Omran, 2017), researchers have investigated implementation of alternative approaches that can be applied in different climate conditions, vegetation zones and soil types. Current trends are oriented towards the evaluation of Remote Sensing (RS) techniques as rapid, cost-effective and non-destructive, for the estimation of different soil properties, including carbon storage (Xu et al., 2017). Remote sensing techniques in the Visible-Near Infrared–Shortwave Infrared (VNIR–SWIR, 400–2500 nm) region could provide a more direct, cost-effective and rapid method to estimate important indicators for soil and vegetation monitoring purposes. Soil reflectance spectroscopy has been applied in various domains apart from laboratory conditions, e.g., sensors mounted on satellites, aircrafts and Unmanned Aerial Systems (Angelopoulou et al., 2019).

Remote sensing (Landsat Thematic Mapper (TM) image) can be used for land-cover classification and development of a total above-ground biomass estimation model. The relationships between above-ground biomass and remote sensing data (e.g., single TM band, various vegetation indices (VIs), and elevation) can be investigated using a multiple linear regression analysis. The results of the total carbon stock assessments from the ground data can reveal sites with the highest and lowest values.

Increasing resolution has enabled small-sized and fragmented vegetation analysis with high amounts of detail at multiple scales using satellite imagery like QuickBird (< 1 m pixel size), ultra-high resolution of airborne digital sensors (e.g., ADS40, < 10 cm pixel size) or recent developments and sensors attached to low-altitude unmanned aerial vehicles (Feng et al., 2015v). This has updated conventional moderate resolution remote sensing, which has been frequently applied using space-borne systems like Landsat (30 m pixel size). LiDAR (Light Detection and Ranging) data or stereo imagery has extended the spatial dimension and added very high-resolution height information, which has been successfully applied to improve delineating vegetation types or green volume estimates (Huang et al., 2013). New satellite imagery, for example RapidEye, offers high spatial resolution data (6.5 m), as well as consistent large area coverage (a swath width of 77 km with continuous observation coverage up to 1500 km).

For implementing greening actions, community participation is fundamental, and a general consensus can be crucial for successful operationalization. For instance, demand for carbon sequestration could be assessed using participatory methods at the local scale, then analyzed using proxy or expert-based methods at the global scale (Jacobs et al., 2014). Combining these methods would facilitate a wide range of ecosystem service assessments ranging in scope from education to accounting for human well-being to specific landscape planning and management problems. Research on integrating community-based participatory carbon measurement and monitoring with satellite remote sensing and GIS was conducted by Skutsch et al. (2009) and KTGAL (2009). They proposed field guides for field measurements and for assessing and monitoring vegetation degradation and carbon sequestration by local communities. In particular, they highlighted that to be most accurate, remote sensing tools and techniques for measuring and monitoring forest carbon should be integrated with ground-based forest and biomass inventories. Where available, National or Urban Forest Inventory data can be used. An alternative or a possible supplement to existing data is community-based carbon data collection. The inclusion of data collected by local communities provides a field-based sampling that can be used to validate and calibrate the remote sensing and GIS approaches to large areas carbon measurement and monitoring, thereby reducing uncertainty in the carbon estimates. In addition, the inclusion and involvement of local people and communities as stakeholders in project activities can empower them. Participatory Mapping Research has shown that the remote sensing data (including LiDAR-based tree height estimates) was integrated with field-based observations to map canopy cover and aboveground tree carbon storage at ~1 m spatial scale.

Data on the performance of nature-based solutions in relation to carbon storage and sequestration collected in these ways can be used to:

- Quantify the benefits of nature-based solutions in terms of carbon storage and sequestration;
- Assess the contribution of urban areas to national carbon balance targets;
- Calculate the impact of tree/vegetation/soil removal for development;
- Calculate the potential yield of urban biofuels.

Scientific solid evidence: Robustness of evidence depends upon the precision and accuracy of the method adopted. Precision of automated tools like i-Tree can be increased through greater sample sizes in terms of ground-truthing. Similarly, for soil carbon storage, greater numbers of soil core analyses can increase the accuracy compared to automated models. Type of soils on which calculations are being made can also affect the precision of results, for example CARBINE (Forest Research 2019) has a greater level of accuracy for calculations on mineral soils than organic soils. For greatest accuracy of change over time, eddy covariance monitoring techniques are necessary. In using remote sensing for assessment of carbon storage/sequestration in soil and vegetation, it was observed (Angelopoulou et al., 2019; Goetz et al., 2009; Jeyanny et al., 2014; Raciti et al.; 2014) that prediction accuracy reduces from Unmanned Aerial Systems (UASs) to satellite platforms, though advances in machine learning techniques could further assist in the generation of better calibration models. There are some challenges concerning atmospheric, radiometric and geometric corrections, vegetation cover, soil moisture and roughness that still need to be addressed.

Remote sensing is widely used to collect information regarding vegetation structure as well as to monitor and map vegetation biomass and productivity on large scales (Main-Knorn et al., 2011) by measuring the spectral reflectance of the vegetation (Lu, 2006). However, optical remote sensing does not directly assess above-ground urban forest biomass, and radiometry is sensitive to vegetation structure (i.e., crown size and tree density), texture, and shadow, which are correlated with above-ground biomass, particularly in the infrared bands. Remote sensing data are now considered to be the most reliable method of estimating spatial biomass in different regions over large areas. Nonetheless, remote sensing as a desk study cannot capture the entire picture and requires some level of ground-truthing for optimum accuracy (e.g. verification in the field, field survey, participatory mapping).

Level of expertise: For tools such as i-Tree a basic level of expertise is required for using the software. Dependent upon the i-Tree resource utilised, field skills in surveying and measuring vegetation may also be required. For more detailed direct measures, skills in soil and vegetation sampling and analysis are required. Similarly eddy covariance monitoring requires skills in equipment use and data analysis. For remote sensing, the selection of method used to interpret images is generally determined by the level of the analyst's expertise and familiarity with the particular urban landscape and the land cover area being analysed. For example, if the analyst has sufficient understanding of sophisticated remote sensing techniques and good knowledge of the sample area, a supervised classification technique and/or hierarchical decision tree classifier is recommended, using tools similar to Knowledge Engineer and Knowledge Classifier. For an area with no pre-existing land cover information the analyst may initiate the analysis using the unsupervised classification technique in order to see the spectrally similar and spatially contiguous spatial objects or phenomena. In general, unsupervised classification, supervised classification techniques and hierarchical decision trees and soil classification will be complementary to determine the classes of land cover in the study area and what issues regarding the carbon storage can be evaluated from them.

Cost: Use of basic automated tools such as i-Tree Canopy can be very low cost and just involve the time required to input and analyse the data. Costs for other i-Tree resources can become more expensive the greater the volume of sample sites and complexity of information required. Soil or vegetation sampling and analysis can be relatively cheap for small sites/sample numbers. Costs can also be reduced through the use of citizen science volunteers. Alternatively/additionally, the cost of such an approach can be reduced by partnering local universities to carry out laboratory analyses as student research projects. Equipment for eddy covariance gas analysers can be expensive. Again, cost can be reduced through academic collaborations. In comparison to conventional methods for monitoring of carbon storage in soil and vegetation, which can be time consuming and costly, remote sensing techniques are evaluated as rapid, cost-effective and non-destructive, for the estimation of different soil properties, including soil organic carbon and carbon stored in biomass (Angelopoulou et al., 2019; Goetz et al., 2009; Jeyanny et al., 2011; Raciti et al., 2014). Thus, high resolution remote sensing can provide a cost-efficient methodology to supply sufficient data on local differences and temporal changes.

Effort: Automated tools such as i-Tree Canopy are relatively low effort with reports generated automatically after minimal data input. More complex tools such as i-Tree Eco require more involved data generation and input. Direct vegetation and soil analysis require fieldwork for sample planning and collection. Analysis can be relatively low effort if commercial analytical laboratories are used. Eddy covariance data gathering can be relatively low effort if automated on-site equipment is used. For this installation, data analysis and equipment maintenance are the only inputs required. The only onerous aspect can be the volume of data generated. Remote sensing technology has been applied to biomass assessment in many studies because it can obtain forest information over large areas at a reasonable cost and with acceptable accuracy based on repetitive data collection with minimal effort (Lu, 2006).

Participatory process: Participatory processes are possible, particularly in relation to gathering samples (soil/vegetation) or gathering data ground-truthing vegetation for feeding into automated tools. Examples of the type of data the citizen science can generate include: number of trees and species of trees present; size of the trees (height, canopy spread and diameter of trunk); tree health. It is essential to increase awareness on the contribution of urban green space to carbon storage and to strengthen stakeholder participation and institutional capacities engaged in the management of urban green spaces. Opportunities for participatory processes include combining community-based participatory carbon measurement and monitoring in the field with satellite remote sensing and GIS approached. Complementing remote sensing analysis using participatory mapping can help provide information for an initial vegetation cover assessment, gain better understanding of how local land use might affect changes, and provide a way to engage local communities.

Data availability: Generates new data. If using automated methods, baseline data prior to intervention may be possible from historical aerial photos. Many tools use landuse data, a data form that is typically available for cities. Base maps can be developed from different sources of satellite images depending on the best resolution available and lowest cloud coverage (e.g. Landsat).

However, cloud-free coverage of the study area can be a limitation with such data and in some cases, cloud-free data during a particular time period may not be available for specific locations.

Geographical scale: Direct sampling tends to be focused on a component or site scale, but can be extended to a city scale if enough eddy covariance gas analysers are available. Analysis using automated tools can be carried out across all scales from individual street trees to entire urban, peri-urban and landscape scales. While remote sensing analysis provides a quick and precise assessment of the vegetation cover mostly on a large scale, it has more difficulty capturing locally driven changes and small-scale deforestation or changes in vegetation cover. In this regard, a combination of social science and remote sensing approaches can provide a more complete picture of the situation on the ground (e.g. participatory mapping described above).

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with current status and impacts immediately following nature-based solution implementation (or predicted impacts as part of planning). However, longer-term in-situ monitoring is generally more effective in terms of capturing a more comprehensive overview of how the carbon storage of the nature-based solution changes over time, both in terms of accumulation by maturing vegetation and the carbon balance of the soils. For remote sensing approaches, there is a limitation with time series regarding the availability of reliable satellite imagery for a given period. The multi-temporal data are also affected by seasonal factors. Participatory monitoring of land use changes, combined with remote sensing, could quickly verify the problems related to carbon storage and sequestration, assess the effectiveness of related interventions and provide local communities with incentivised alternative livelihoods (Beaudoin et al., 2016).

Synergies: Strong synergies with all aspects of greenspace mapping and landuse metrics as, for many of the evaluation metrics, similar baseline maps will be required. Regular remote sensing and participatory mapping of land use and its implications for land cover and carbon storage by soil and vegetation can be combined with livelihood and social data (e.g. tenure, source of income for local communities) to help monitor changes in local livelihood under activities promoting carbon sink and should be analysed when distributing benefits (Beaudoin et al., 2016).

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Eklipse; Davies et al., 2011; Pataki et al., 2006

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2.2.2 Albedo (Env07)

Umbrella: Climate resilience

Indicator: Albedo

Code: Env07

Description: Measuring albedo (reflecting power) of urban surfaces (e.g. average albedo or an area) as albedo impacts cooling (Urban Heat Island) and building energy use.

Metric(s): Metrics are typically based on measures of the proportion of incoming solar radiation reflected by the various surfaces in the urban environment (reflection coefficient), defined as the ratio of incoming to outgoing radiation. It is measured on a scale of 0 – environments that absorb all incoming radiation without reflection (e.g. a black body), and 1 – environments that reflect 100% of incoming radiation. Additonally albedo varies in accordance to (amongst other things) the incident solar radiation spectrum, the solar angle, surface texture and surface roughness.

Albedo can be measured at diverse scales either in a laboratory, in the field or using remote sensing methods. In the laboratory, solar spectrophotometer or commercial portable solar reflectometer tools are typically used, and in the field pyranometers, albedometers or field spectrometers (see Li, Harvey & Kendall, 2013; Qin & He, 2017 for some examples). There are various standard testing method guidelines available depending on the tools used (e.g. ASTM C1549 - 16 Standard Test Method for Determination of Solar Reflectance Near Ambient Temperature Using a Portable Solar Reflectometer). Larger surface areas (e.g. 1km^2) can be measured using remote sensing satellite-based tools such as Landsat 8 Operational Land Imager or advanced hyperspectral sensors like Airborne Visible/Infrared Imaging Spectrometer (AVIRIS).

Albedo values have been generated using coarse-scale remote sensing measurements and assuming generalised albedo values for different land cover categories in urban landscapes measurements, and by modelling the urban canyon and canopy albedos or combinations of these approaches (Qu et al. 2015; Trlica et al. 2017). Qu et al. (2015) provide a comprehensive review of algorithms and products for mapping surface broadband albedo with satellite observations. Remote sensing at higher resolutions is allowing more detailed categorisation of urban land covers, therefore improving the characterisation of albedo and model accuracy (Trlica et al. 2017), enabling finer-scale evaluation of albedo variation, for instance among different roof types (Ban-Weiss et al., 2015). High-resolution geospatial data has been used to quantify urban summertime albedo at 30 m resolution for the city of Boston, although clear trends in albedo and urbanisation emerged only after aggregating data to 500 m resolution (Trlica et al. 2017).

As remote sensing instruments do not directly measure surface albedo, the albedo must be inferred through a series of manipulations to the raw remote sensing data. Firstly, a method for determining which pixels are cloud-free within the data is necessary so that they are not used in the measurements of surface albedo (step: applying cloud-free mask to get cloud-free pixel – DN (digital numbers)). Secondly, remote sensing data are originally stored as digital numbers which must be calibrated in order to represent geophysical units of radiance, or $W{\cdot}m^{-2}{\cdot}sr^{-1}$ (calibration step to get DN radiance). The third step involves atmospheric corrections when satellite instruments measure radiance-reflectance at the top of the atmosphere (TOA). Since we are concerned with albedo at the Earth's surface, a correction must be made to account for the effects of the intervening atmosphere (step: anisotropic correction). The data can then be divided by the Planck irradiance curve to derive the surface reflectance. However, there is difficulty that most satellite instruments only take measurements at one or a few viewing angles. Thus, a computation must be made to estimate albedo from reflectance, which requires an understanding of the bidirectional reflectance distribution function (BRDF) of the surface being measured. Finally, satellites normally measure the Earth's radiation in a number of separate narrowband channels, but albedo must represent the total broadband region of solar radiation of approximately 0.3-3.0 µm. A conversion is necessary, therefore, to extrapolate the narrowband albedo values inferred from remote sensing instruments to broadband values (step: narrowband-to-broadband (NTB) conversion).

For albedo calculations, Landsat imagery has to be converted from digital numbers to Top of Atmosphere (TOA) reflectance. Liang (2000) developed a series of algorithms for calculating albedo from various satellite sensors. His Landsat formula to calculate Landsat shortwave albedo was normalized by Smith (2010) and is presented below:

$$\alpha_{short} = \frac{0.356\rho_1 + 0.130\rho_3 + 0.373\rho_4 + 0.085\rho_5 + 0.072\rho_7 - 0.0018}{0.356 + 0.130 + 0.373 + 0.085 + 0.072}$$

where ρ represents Landsat bands 1,3,4,5, and 7. Note that Landsat band 2 (green) is not used. This formula can be implemented in ENVI using Band Math as:

((0.356*B1) + (0.130*B2) + (0.373*B3) + (0.085*B4) + (0.072*B5) -0.018) / 1.016.

In-situ measurements are typically used to ground-truth and corroborate satellite data, for instance from fixed tower-mounted instruments. Whilst these provide accurate data, this is limited in terms of spatial range and may not accurately represent landscape variation. Pyranometers mounted on Unmanned Aerial Vehicles (UAVs) have been used to capture more site-to-site variation in albedo and provide finer-scale data caused by local landscape heterogeneity than satellite measurements, and provide a bridge between in-situ (tower) measurements (Levy et al., 2018). Cao et al. (2018) developed an UAV method for determining the landscape albedo which was tested at two sites typical of urban landscapes consisting of impervious and vegetated surfaces. They compared the visible and shortwave band albedo derived from their method with those of Landsat 8 and confirmed that this method can save labour costs and can be applied to landscape albedo estimations where direct field measurement may be difficult.

Public participation in measuring albedo has been successfully trialled in a pilot citizen science project in the USA. This used an existing volunteer network - Community Collaborative Rain, Hail & Snow (CoCoRaHS) - that measure and map precipitation (rain, hail and snow) in their local communities, to measure surface albedo (https://www.cocorahs.org/; Burakowski et al., 2013). Equipped witha low-cost toolkit including a pyranometer, the volunteers collected high-quality albedo data for research and education applications, that will be combined with a network of tower, aircraft, and satellite albedo measurements to investigate the climate response to historical and future land cover change in North-eastern USA (Burakowski et al., 2013; Amaral et al., 2017).

An albedo app is available online that could potentially be used as a public engagement tool https://play.google.com/store/apps/details?id=com.h2optics.albedo&hl=en.

Data on changes to albedo by nature-based solutions collected in these ways can be used to:

- Provide baseline data and prediction of albedo for planning and design processes (e.g. construction materials/geometrical configurations);
- Establish targets in relation to changing of surface albedo;

- Quantify the contribution of NBS to albedo in terms of providing thermal comfort zones for residents and reducing cooling energy use;
- Quantify changes to UHI on a city-wide scale;
- Contribute towards health and well-being evaluation linked to UHI.

Scientific solid evidence: Satellite remote sensing has been widely used for the determination of land surface albedo (Ban-Weiss et al., 2015; Cescatti et al., 2012; Liang, 2000; Smith, 2010; Trlica et al., 2017). An advantage of satellite monitoring is that it provides global coverage. New satellites can provide albedo measurements at reasonably high frequencies (2–3 days in the best case for Sentinel 2) and spatial resolutions (pixel size 10 m in the case of Sentinel 2, and several cm in the case of DigitalGlobe) to provide useful information for studies on ecosystem (tens of meters) to landscape (several kilometers to tens of kilometers) scales. However, all satellite measurements are biased towards cloud-free sky conditions. In urban landscapes with heavy haze pollution, retrieval of the true surface albedo from satellite imageries must remove signal contamination caused by particle scattering. Lightweight unmanned aerial vehicles (UAVs) as an alternative for albedo monitoring may be able to overcome these limitations. UAVs can cover areas ranging from 0.01 km^2 to 100 km^2, depending on battery life and type of UAV (Cao et al., 2018; Watts et al., 2012), can provide measurements at sub-decimeter spatial resolutions, and can be used to obtain data under both clear sky and cloudy conditions (Salamí et al., 2014; Watts et al., 2012). UAV experiments can be conducted at almost any time, and at any locations (Cao et al., 2018). Finally, UAVs can measure albedos at locations that are not accessible by ground-based instruments, such as steep rooftops in cities.

Whilst there are uncertainties related to albedo measurements from satellite remote sensing, there are however methods for validating coarse spatial resolution albedo products. Field measurement accuracy will depend on the precision class of instruments used and the conditions under which measurements are taken but, typically, field measurements are used to validate satellite data and refine model predictions.

Level of expertise: This represents a technical indicator with expertise required for interrogating satellite data, modelling and use of technical instruments in the field. As previously mentioned, due to its repetitive global coverage, remote sensing provides the most promise for estimating regional and global albedo. There are already many algorithms used operationally for the retrieval of surface albedo from remote sensing data, however there are still many difficulties that must be taken into consideration when measuring surface albedo from space. Thus, expertise is required to create and validate the satellite retrieval methods in order to avoid the difficulties inherent to satellite albedo measurements and the many potential errors that can occur.

Cost: Many remotely sensed EO products are freely available, however, EO data at finer resolutions can be expensive to obtain (Ban-Weiss et al. (2015) estimate as of 2014, minimum costs for fine resolution data (~1 m) are roughly US$15 per km^2, so acquiring imagery for only the City of Los Angeles would cost circa $20,000, and for the entire metropolitan area of Los Angeles approximately $200,000). Field instruments vary in cost, depending on the precision required. Burakowski et al. (2013) quoted US$700 for their citizen science toolkit, including a pyranometer. The labour and financial expense of UAVs are much lower than those of aircraft (Cao et al., 2018; Yang et al., 2017)).

Effort: Effort is directly related to the methodology used. Participatory processes can represent lower effort in terms of data collection, but can still require a substantial input in terms of establishing and managing the scheme. When using remote sensing, the role of radiation forcing versus atmosphere forcing requires a thorough knowledge of the surface albedo. Moreover, the following aspects should be considered: mapping from patch, impact of directional sampling, surface radiation modelling, spectral albedo conversion, satellite data merging, environmental monitoring, criteria for quality and uncertainty assessment, link with land cover and land use classification, data assimilation, thematic applications, satellite missions, field campaigns, ground observation networks, and validation.

Participatory process: Opportunities are available for a participatory process if members of the public can be provided with the necessary instruments to measure albedo (Burakowski et al., 2013).

Data availability: Can use existing satellite data or generate new data through in-situ field measurements.

Geographical scale: Can be measured at various geographical scales. At larger (city-wide) scales, analysis of satellite data is the most appropriate metric. Remote sensing measurements have high potential to provide valuable information regarding the mapping of land surface albedo at various spatial and temporal scales.

Temporal scale: monitoring could be used to establish a baseline and to capture impacts following an NBS project implementation. If satellite imagery is used, it may be possible to establish a historical baseline using archived data. Remote sensing measurements have high potential to provide valuable information regarding the mapping of land surface albedo at various spatial and temporal scales.

Synergies: There are synergies in relation to UHI and relevance to health & well-being indicators associated with exposure to heat.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: UnaLab

Metric reference(s):

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2.2.3 Air Temperature – Energy Demand (Env17)

Umbrella: Temperature reduction

Indicator: Air temperature – Energy Demand

Code: Env17

Description: The use of vegetation/wetlands in urban areas to reduce peak air temperatures with the objective of reducing energy demand for cooling.

Metric(s): The metrics are based on quantifying a percentage reduction in energy demand for cooling under different landscape management strategies. As such, this indicator comes under the umbrella of greenspace management and corresponds to a modelling urban planning/landuse approach. This indicator has particular relevance in hot arid situations where air conditioner energy use is high but can have relevance in most cities. For instance, since most cities today experience some level of urban heat island (UHI) from urbanisation, the problem of air cooling is an issue for settlements of all sizes in all climatic regions (Leal Filho et al., 2017). UHI defined as a metropolitan area, which is significantly warmer than surrounding rural areas, can occur year-round, during the day or night, but generally the UHI reaches its peak during the summer nights in temperate cities.

Cooling is typically achieved by reducing the internal temperature of buildings directly through thermal insulation provided by vegetation added onto a building envelope (e.g. green roof or green wall), or indirectly though shading (e.g. tree canopy or green curtains shade). A similar effect can also be achieved by reducing external peak temperatures by changing external landscaping from hard surfaces to permeable vegetated surfaces that increase evapotranspiration. In particular, the implementation of green roofs can help decrease the use of energy for cooling and heating buildings by between 20% and 25%, depending on the construction materials used and whether or not green roofing is being used (Leal Filho et al., 2017; Sahnoune and Benhassine, 2017; Susca et al., 2011). Trees and vegetation lower surface and air temperatures by providing shade and through evapotranspiration (EPA, 2020). As such, shaded surfaces, may be 11–25°C cooler than the peak temperatures of unshaded materials, and evapotranspiration, alone or in combination with shading, can help reduce peak summer temperatures 1–5°C. When planted in strategic locations around buildings or to shade pavements in parking lots and on streets, trees and vegetation planted to the west is typically most effective for cooling a building, especially if they shade windows and part of the building roof (EPA, 2020).

An applied approach for implementing this indicator would be to monitor internal building temperatures relative to external temperatures before and after the NBS implementation or compared to a control building that is not being similarly impacted by the NBS (D'Orazio et al. 2012; Hunter et al. 2014; Olivieri et al. 2017). An alternative approach is to monitor changes in building energy demand, particularly associated with air conditioner use, before and after nature-based solution implementation (Jim 2014; Skelhorn et al. 2016). Again, this can also be carried out in comparison with a control building with a similar thermal signature but without the nature-based solution intervention.

A general methodology for measuring the impact of green-roofs on the UHI, and defining a decision model that helps calculate the best green-roof/green-infrastructure ratio, includes: a) measurement instruments to gather on-site temperatures, and data from the local weather-station; b) ArcGIS analysis tools and effective ways of converting complex measurement data in simple charts and graphics that can be easily readable by decision makers or the general public; c) probabilistic and comparative approaches, which can be evaluated using different green-roof models (to calculate the contribution of flat roofs in regulating the imbalance between mineral and natural surfaces), in most cases ENVI-met 4.02, which provides many simulation features and models. In addition to direct measurement, predictive impact of nature-based solutions applied to buildings on building energy performance can be modelled. This can be done on a building scale, for example using the Energy Plus calculation engine of the Design Builder interface to optimise the envelope energy performance of buildings (Zinzi and Agnoli 2011; Sailor et al. 2012), or can be evaluated based on the implementation of NBS on buildings across regions or city scales (Langemeyer et al. 2020).

Sailor et al. (2012) also used modelling (the EnergyPlus building energy simulation program) to study the building energy impacts of green roof design decisions in four distinct climates, complete with an integrated green roof simulation module. They concluded, that in all cases, a baseline green roof resulted in heating energy cost savings compared to the conventional black membrane roof. The effect of green roofs in office building districts for mitigating the UHI effect and reducing CO_2 emissions have been measured using a simulation-based evaluation method (Hirano et al., 2019). To calculate energy consumption, they proposed a technique that combines intensity and temperature sensitivity methods and a simulation-based evaluation using an air-conditioning load calculation. A coupled urban canopy/building energy model (CM-BEM) was utilized to simulate the effectiveness of green roofs. The amount of water needed for evapotranspiration was calculated by using latent heat flux, which was derived from the results of roof surface heat balance calculations. The effect of green roofs on CO_2 emissions was determined based on their effectiveness to reduce the energy demand for space cooling, calculated by air-conditioning load simulation (Hirano et al., 2019).

A methodical approach for measuring the effects of facade greening (in particular cooling towards the greened structures through shadowing, transpiration cooling and thermal insulation) has been described and applied by Hoelscher et al. (2015), who conducted outdoor experiments during hot summer periods on three building facades in Berlin, Germany. They determined transpiration rates (sap flow) and surface temperatures of greened and bare walls as well as of plant leaves (temperature probes) of several climbing plants, and measured air temperature, relative humidity and incoming short-wave radiation. They found that surface temperatures of the greened exterior walls were up to 15.5 ◦C lower than those of the bare walls, and concluded that greening can be an effective strategy to mitigate indoor heat stress as long as the plants are sufficiently irrigated with up to 2.5 L m^{-2} d^{-1} per wall area.

Modelling metrics can also be applied to other types of greenspace beyond NBS directly incorporated into building envelopes. This includes the prediction of the impact of urban trees to reduce building energy use (Akbari, 2002; Skelhorn et al. 2016) using tools such as iTree Design (iTree 2020), and the evaluation of the greening of street canyons (Alexandri and Jones 2008).

Decisions regarding different types of NBS implementation across a city scale can also be carried out in relation to predicted thermal benefits (Derkzen et al. 2015). Such mapping of air temperature improvements can be carried out as part of a broader ecosystem service evaluation associated with greenspace design/distribution (Derkzen et al 2015).

ENVI-MET (Bruse 2007) is emerging as a commonly used tool to evaluate the impact of vegetation implementation on both microscale simulations on building envelopes (López-Cabeza et al. 2018) and on larger scales across street canyons (Zhao et al. 2018) and neighbourhoods (Wu et al. 2019; Ziaul and Pal 2020). Consideration must be given, however, to the precision of results from modelled scenarios as they might not capture some of the nuances of real-world implementation (López-Cabeza et al. 2018; Crank et al. 2018; Salata et al. 2016).

The STAR tools (STAR, 2020) allow users to assess the potential of green infrastructure in adapting their areas to climate change. They include a surface temperature tool and a surface runoff tool which can be used at a neighbourhood scale (in the North West of England and beyond) to test the impact of different land cover scenarios of greening and development on surface temperatures and runoff, under different temperature and precipitation scenarios.

Earth observation data from space-borne sensors have been widely exploited to examine UHI effects (Bonafoni et al., 2017). Unlike in situ measurements, providing uneven distributed data, satellite observations have the advantages of covering large areas at the same time, and during different temporal intervals, ensuring a more effective analysis of the intra-urban UHI spatial variability, closely related to building distribution, surface materials and vegetation density. Different space-borne platforms, such as AVHRR (which use advanced very high-resolution radiometers), MODIS (use moderate resolution imaging spectrometers), and medium-resolution sensors such as ASTER and Landsat can be used to retrieve the UHI. Furthermore, satellite sensor measurements of surface reflectivity make it possible to retrieve albedo maps, both at the local and global spatial scale.

Most studies applied the retrieval from Landsat satellite data of urban land surface temperature. The 60 m pixel size of Landsat 7 ETM+ thermal channel proved to be suitable to monitor SUHI changes at the district level, making it possible to point out if urban construction changes move towards an urban sustainable criterion. Based on combined technology, using Landsat and Thematic Mapper (TM) images at a city scale, several studies examined the relationships between the effect of vegetation on the land surface temperature in different contexts (Wang et al., 2019). Studies by Sobrino et al. (2008) and Wang et al. (2019) applied the radiative transfer equation to acquire land surface temperatures, using measured atmospheric sounding data synchronized with satellite transit time. Santos et al. (2016) estimated the potential of green cover at rooftop level using 3D data obtained by Light Detection and Ranging (LiDAR) data and Very High Resolution (VHR) images. This approach allows for a detailed estimation of available roof areas since the physical aspects, such as slope, orientation, and shadows cast by surrounding buildings and topography, are calculated for each building in the area. Results can be presented in scenarios: on the one hand, taking into consideration the current vegetation cover at the ground level; and on the other, estimating the potential cover area on rooftops, according to different geographical and planning criteria. In a similar study, Mallinis et al. (2014) proposed a methodology based on GEographic Object-Based Image Analysis (GEOBIA) to estimate green roof retrofitting areas using VHR orthoimages and a Digital Surface Model (DSM). Several studies confirmed the possibility of using unmanned aircraft systems (UAS) for remote building inspection and monitoring (Eschmann et al., 2012; Morgenthal and Hallermann, 2014), especially for visual identification of areas of thermal anomalies using UAS equipped with thermal cameras, and detailed inspection applied to areas of high interest to quantify envelope heat-flow using computer vision techniques.

Data on the reduction of air temperature in relation to NBS implementation assessed in this way can be used to:

- Identify areas where NBS is needed;
- Plan NBS delivery to ensure social justice in relation to thermal stress on buildings;
- Establish thresholds for strategic NBS delivery;
- Support the planning of nature-based solutions for built infrastructure (e.g. green roofs and walls);
- Form part of a strategy to reduce building energy use;
- Compare modelled predictions with indicators that deliver air temperature quantifications.

Scientific solid evidence: Assuming that suitable comparable controls can be found, solid scientific evidence can be generated using applied metrics. This will, however, depend upon the accuracy of monitoring equipment and the level of replication. In relation to modelling, robustness of evidence depends upon the precision and accuracy of the method adopted. Precision of automated tools like i-Tree and ENVI-MET can be increased through greater understanding of local conditions through ground-truthing. Finally, remote sensing techniques and UAVs can measure air temperature reduction by vegetation at locations that are not accessible by ground-based instruments, such as steep rooftops in cities.

Level of expertise: For methods such as monitoring building energy use or internal and external temperature, expertise is required for experimental design of the monitoring. Following this, data analysis can be relatively straightforward. For tools such as i-Tree and ENVI-MET a basic level of expertise is required for using the software. Dependent upon the i-Tree resource utilised, field skills in surveying and measuring vegetation may also be required. Similarly for ENVI-MET, expertise can be required for field survey. Expertise is required to create and validate the satellite retrieval methods in order to avoid the difficulties inherent to satellite measurements of surface temperature and the many potential errors that can occur.

Cost: Use of basic automated tools such as i-Tree Canopy and ENVI-MET basic can be very low cost and just involve the time required to input and analyse the data. Costs for other i-Tree and ENVI-MET resources can become more expensive the greater the volume of sample sites and complexity of information required. Thermal sensors and energy monitoring can also be relatively low cost, although cost increases proportionally with sophistication of sensors. Cost of both applied and modelling approaches can be reduced by partnering local universities to carry out laboratory analyses, for example as student research projects. The selection of remotely sensed imagery depends on acquisition costs, scale, the extent of analysis, amount of detail (spatial and temporal resolutions), and type of information (number of bands) required. Most remotely sensed studies employed medium and low spatial resolution imagery acquired from Landsat 5TM, Landsat 7ETM+, ASTER and MODIS satellites as this was freely accessible. Contrastingly, the use of high-resolution satellite imagery (IKONOS, WORLD-View 2 and QuickBird) and very high-resolution airborne-based imagery is still less common due to the complex logistics and prohibitive costs for most users.

Effort: Automated tools such as i-Tree Canopy are relatively low effort with reports generated automatically after minimal data input. More complex tools such as i-Tree Eco and ENVI-MET as well as use of remote sensing require more involved data generation and input. Direct monitoring can involve some effort installing sensors, but analysis can be relatively low effort. For this installation, data analysis and equipment maintenance are the only inputs required. The only onerous aspect can be the volume of data generated.

Participatory process: Participatory processes are not typical for this indicator, although citizens can be included in data analysis/reporting to raise awareness of benefits. Citizens can also be involved in ground surveys for modelling methods like i-Tree and ENVI-MET.

Data availability: Generates new data. Baseline data prior to NBS installation is essential unless a similar control building can be identified. Energy usage can be calculated from past energy records, although there needs to be certainty in relation to any other variables that could have affected energy usage.

Geographical scale: Can be applicable across scales, from a single room to networks of buildings. The typical unit, however, is on a building scale.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with current status and impacts immediately following NBS implementation (or predicted impacts as part of planning). However, longer-term in-situ monitoring is generally more effective in terms of capturing a more comprehensive overview of how temperature/energy usage changes over time in relation to maturing of the vegetation of the NBS and potential impacts from NBS management.

Synergies: Strong synergies with other air temperature and climate change adaptation evaluation indicators. Also, potential overlap with social justice and health & wellbeing heat stress indicators

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Eklipse; Akbari 2002

Metric reference(s):

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2.2.4 Flood damage (economic) (Env20)

Umbrella: Reduction of flood risk

Indicator: Flood damage (economic)

Code: Env20

Description: Evaluating the change in economic impact of flood damage due to nature-based solution implementation. For example, estimation of avoided damages and costs from flooding (stage-damage curves relating depth and velocity of water to material damages £).

Metric(s): Adequate management of floods is reliant on *a priori* assessments of flood events and their consequences. Such assessments give insights into what can be expected, and thereby open up the discussion on how to tackle such situations, for instance by using nature-based solutions. Such assessment frameworks can be used to evaluate (or predict) the effectiveness of measures in a standardised way. This supports decision-making on possible measures that can be taken and prioritisation of areas where action is required (IPCC 2012).

Flood risk and damage is commonly associated with economic cost. Cost is linked to aspects such as damage to property, disruption of transport networks, lost work hours due to unsafe/inaccessible workspace, etc (IPCC 2012). Various approaches exist regarding damage appraisals, such as financial and economic valuation based on market values (i.e. based on historical values or replacement values), and scales of analysis (micro-, meso- or macro-scale) (Pistrika, 2010; World Bank 2017). Today the typical approach is economic estimation of direct damage, mostly by applying depth-damage functions. An integrated, unifying approach is, however, missing. For consistent decision making it is desirable to have a more or less standardized approach for damage estimation at least at higher aggregation levels, such as a river basin or a complete region. As such, impact on the economic cost of flood damage can be an integral component of evaluation of the performance of nature-based solutions implemented to reduce the impact of floods. Nevertheless, the economic cost of flood damage (Env20) indicator is strongly linked with the indicator Env19 (Reduction of inundation risk for critical urban infrastructures - probability), as quantifying risk typically comprises a necessary precursor step in understanding the economic impacts of flood damage. Therefore, it is recommended that Env 19 is also read as an introductory foundation when reading this indicator review.

Nature-based solutions for flood risk management need to be tested, designed, and evaluated using quantitative criteria (World Bank 2017). There are international standards and guidelines for engineered flood management structures, e.g. the International Levee Handbook (CIRIA 2013) and the Coastal Engineering Manual, which not only provide guidance for implementation but also for evaluating the effectiveness (especially economic) of such measures. EC FP7 project CONHAZ developed guidance for assessing flood losses (Green et al., 2011), which include evaluating the losses of productive and consumption assets. The first stage is to estimate the shock to the systems; the second stage, how the trajectories of the systems will consequently be affected. In assessing the shock, it is appropriate to differentiate between resources, production durables, productivity durables, and consumption durables. The most frequently used procedure for the assessment of direct monetary flood damage comprises three steps described in detail by Green et al. (2011):

1) classification of elements at risk
2) exposure analysis and asset assessment by describing the number and type of elements at risk and by estimating their asset value

3) susceptibility analysis by relating the relative damage of the elements at risk to the flood impact.

In terms of considering the economic impact of flood damage, damage assessments are typically based on metrics such as depth-damage curves, stage-damage curves or other multi-variable models (de Moel et al. 2015; Oubennaceur et al. 2019). These estimate the flood event in terms of flood extent and inundation depth, how probable such an event is, and the possible consequences. The conceptual framework is that risk is a function of hazard, exposure and vulnerability.

For the de Moel et al. (2015) metric, the economic impact assessment starts with an assessment of the flood hazard, based on observed hydrological data/simulation models (e.g. observed rainfall data input into a hydrological catchment model). The hazard data (i.e. inundation depth/extent) can be combined with information on exposure – the people, property and other assets present in the hazard zone. Datasets on population, land use, etc, or remotely sensed data can be used and assessed in a binary (i.e. affected/not affected) way, or by gradations (e.g. relative to water depth). Cultural values can also be incorporated (monuments, heritage sites, etc) and indirect effects such as GDP production.

For evaluation, direct consequences are usually expressed in a single monetary figure (£/Euros), allowing comparison with evaluations of other measures (de Moel et al. 2015). Water depth is typically the main indicator of hazard, but also duration/flow velocity can be used, by estimating stage-damage curves (de Moel et al. 2015). Most commonly, direct damages are based on depth-damage curves (Huizinga et al. 2017). Assessment of different damage probabilities are estimated as the monetary risk per year, or expected annual damage (EAD, or average annual loss (AAL)) (de Moel et al. 2015).

Such risk-based damage assessment models can suffer from uncertainties and need validation to ensure the accuracy and precision of their outputs (Gerl et al. 2016). For more applied/participatory approaches to this indicator, it is possible to generate empirical data on flood damage before and after nature-based solution implementation. For example, telephone or face-to-face interviews can be held that use questionnaires with individuals whose properties and/or business premises have been affected by flooding to estimate damages (Booysen et al. 1999; Bubeck et al. 2012).

Alternatively, feedback from experts on damage reconstruction costs, cost of clean-up, and cost of assistance can be used for economic damage assessments prior to and following nature-based solution interventions (Wind et al. 1999). Such approaches can be particularly useful for categories that are very heterogeneous and need specific details (such as industrial land-use) (de Moel et al. 2015). In addition, de Moel et al. (2015) present some multi-parameter models that have been developed: this includes a conceptual model in the UK (Nicholas et al. 2001), a multi-variate regression model to estimate losses in private households in Japan (Zhai et al. 2005), and rule-based models for loss estimation to companies and private households in Germany (Kreibich et al. 2010; Elmer et al. 2010). Multi-parameter probability methods such as these have the advantage of being able to incorporate additional factors into decision-making and evaluation processes. This can include factors such as contamination issues and warning times (de Moel et al. 2015). They can also provide quantitative information about model uncertainty.

In order to assess the ability of the NBS to protect the surrounding area from flooding, it is essential to value the benefits of improved flood protection using Cost-Based Methods. This can help in valuing the flood protection services of the particular NBS, especially when a budget available for a valuation study is not large. The method can be applied in 2 steps:

- Step 1: to conduct an ecological assessment of the flood protection services provided by the NBS. This assessment would determine the current level of flood protection, and the expected level of protection if the NBS is implemented.
- Step 2: The Damage Cost Avoided method might be applied using two different approaches. One approach is to use the information on flood protection obtained in the first step to estimate potential damages to property / ecosystems / humans if flooding were to occur. In this case, the researcher would estimate, in monetary value, the probable damages to property / ecosystems / humans if the NBS will be not implemented. A second approach would be to determine whether nearby property / ecosystems' owners have spent money to protect these from the possibility of flood damage, for example by purchasing additional insurance or by reinforcing their basements. These avoidance expenditures would be summed over all affected properties to provide an estimate of the benefits from increased flood protection. However, one would not expect the two approaches to produce the same estimate. One might expect that, if avoidance costs are expected to be less than the possible damages, people would pay to avoid those damages.

The replacement cost method is applied by estimating the costs of replacing the affected ecosystem services. In this case, flood protection services cannot be directly replaced, so this method would not be useful. The substitute cost method is applied by estimating the costs of providing a substitute for the affected services. For example, in this case a retaining wall or a levee might be built to protect nearby properties from flooding. The researcher would thus estimate the cost of building and maintaining such a wall or levee and compare them with the costs of the planned NBS. The monetary values of the damages avoided, or of providing substitute flood protection services, provide an estimate of the flood protection benefits of particular NBS, and can be compared to the implementation costs to determine whether it is worthwhile to strengthen the flood protection services of the planned NBS.

According to Johnson et al. (2020), the flooding costs could be reduced through the acquisition and conservation of natural land in floodplains, also through NBS. They quantify the benefits and costs of reducing future flood damages in the United States by avoiding development in floodplains. They find that by 2070, cumulative avoided future flood damages exceed the costs of land acquisition for more than one-third of the unprotected natural lands in the 100-yr floodplain (areas with a 1% chance of flooding annually). Large areas have an even higher benefit–cost ratio: for 54,433 km^2 of floodplain, avoided damages exceed land acquisition costs by a factor of at least five to one. As such, strategic conservation of floodplains and implementing NBS related to flood mitigation would avoid unnecessarily increasing the economic and human costs of flooding, while simultaneously providing multiple ecosystem services.

Several models (Dutta et al., 2003; Win et al., 2018; Zhai et al., 2005) based on survey results were developed to estimate flood damage cost caused in cities, which investigate such factors as the influence of income, inundation duration and inundation depth, slope, population density and distance to major roads on the loss costs. Surveyed data can be analysed using Excel and ArcGIS 10 software. Ordinary least square and the geographically weighted regression analyses can be used to predict flood damage costs. Estimates should then be delineated using geostatistical map tools. In addition, these models should be applied and validated using actual official records as reference data. Finally, the use of a calculation-based approach is suggested to determine flood damage costs in order to reduce subjectivity during surveys.

Evaluation of the reduction of the economic impact of flood damage by nature-based solutions simulation can be used to:

- Support the development of strategic plans for nature-based solution implementation to reduce the economic impact of flooding;
- Predict the impact of individual nature-based solutions projects;
- Quantify the impact of implemented nature-based solutions;
- Promote stakeholder engagement in nature-based solution planning;
- Support the leveraging of finances necessary for delivering nature-based solution projects through cost-benefit analysis;
- Underpin decision-making about insurance values associated with flood damage risk.

Scientific solid evidence: Robustness of evidence depends upon the level of precision of the simulation software and the data analysed. Typically, simulations requiring the most basic data input are associated with the least precise results. This is not always the case, however, and model validation (either through real-world testing or validation against other models) is recommended. Empirical methods that use direct questionnaires can provide scientifically robust outputs, particularly if delivered in partnership with reconstruction experts. Again, however, validation can be required in relation to increasing certainty that quantified impacts are related to the nature-based solution implemented rather than due to different rainfall, ground conditions, and/or other catchment changes between flooding events.

Level of expertise: Expertise required is very much based on the complexity of the method implemented. Damage curve assessment requires complex analysis and inclusion of numerous data sets requiring a significant level of expertise. Questionnaire-based approaches can require a lower level expertise, particularly at more local scales, but expertise is still required in relation to correlating responses with flooding event scales. Model-based approaches need expertise in modelling and use of related software.

Cost: With complex analyses and multiple datasets, costs can be relatively high. Costs can be reduced by working with specialists that have predeveloped processes for delivering such analyses. Questionnaire methodologies can be cheaper, but this is typically dependent upon the scale of the area in question with damage-curve/modelling approaches potentially more cost-effective over larger scales.

Effort: Similar to the level of expertise required, effort is directly related to the method adopted and the associated data requirements. For small-scale survey-based approaches, effort can be low, particularly if online surveys with automated data analyses are adopted.

Participatory process: Participatory processes are possible through questionnaire-based approaches. Similarly, participation can be incorporated into damage-curve/modelling approaches for some aspects of data generation (e.g. flood extent/damage mapping). For more details on participatory approaches to modelling see Env19.

Data availability: Baseline data is required from multiple sources. Some of this can be obtained through open source data (e.g. digital terrain models), but other aspects need to be generated or modelled.

Geographical scale: These metrics are applicable over a range of spatial scales. Typically, the larger the scale the more complex the analyses. Questionnaires tend to be more applicable on smaller scale assessments.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with single extreme events. They can also be adopted for long-term strategic simulations in relation to city-wide rollout programmes over long time periods and for predicting changes in the economic cost of flood damage with future climate change predictions.

Synergies: Due to the multiple datasets required for assessing this indicator, there are synergies with several other indicators. Principle to this is flood risk prediction. Flood risk & flood damage can also be related to health & wellbeing indicators associated with the stress caused by flood damage to properties, businesses and other infrastructure.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Eklipse

Metric reference(s):

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2.2.5 Community accessibility (Env26)

Umbrella: Greenspace accessibility

Indicator: Community accessibility

Code: Env26

Description: Measure of distance to and use of greenspace to evaluate/inform viable strategies to increase the use of green space

Metric(s): To achieve the benefits of urban green spaces supporting the activities of various social groups, urban green spaces must be accessible to the public, as accessibility is a key indicator used to evaluate the effective social and ecological functioning of cities (Chen and Chang, 2015). Accessibility is defined as "relative ease" of approach to specific attractive locations from certain places (Kazmierczak et al., 2010; So, 2016) and how visible the site is to the public. Accessibility usually refers to the non-linear distance travelled in the specific time unit without the use of means of transportation, from the user's location to the closest green space (So, 2016). Although the definition of accessibility is relatively simple, its implementation can be quite challenging, due to the characteristics of city's transport networks (Comber et al., 2008). Size and distance (from home) criteria have typically been used as a metric for evaluating greenspace accessibility, but determining whether greenspace is accessible can also involve physical and social aspects that can constrain the extent to which sites are accessed (as much as legal site ownerships and access rights). Physical constraints include factors such as: distance from home; factors that sever access such as busy roads, private land, steep gradients linked to the potential users' degree of independent mobility, etc (Harrison et al., 1995). Social and cultural factors that can impact accessibility include: personal safety, fear of crime, social and cultural stigmas/preferences (Cronin-de-Chavez et al. 2019). Mapping greenspaces provides information on their extent and distribution in a city, but this data alone does not necessarily capture the contribution these greenspaces have as accessible places for city residents to use and enjoy.

Measures of distance to and use of greenspace can provide data to evaluate which factors influence their use and metrics related to this have been reviewed in Env41 (accessibility of greenspaces).

A model for greenspace (GS) accessibility can be developed in the ModelBuilder environment of ArcGIS, where the actual proximity of GS can be calculated and can be enriched using a proximity sub-model based on theoretical functional levels (TFLs) and GS quality and sub-quality information based on a quality assessment (Stessens et al., 2017). GS quality can be described as a weighted linear combination of *inherent* (e.g. naturalness and biodiversity, spaciousness, quietness) qualities based on publicly available GIS data, and user-related sub-qualities (e.g. feeling of safety) based on ratings given by a sample of GS visitors (Stessens et al., 2017). This provides data on the provision of public GSs, and their quality and sub-qualities for each urban block, and each of the sub-qualities can then be separately used to evaluate alternative design scenarios (Stessens et al., 2017). This approach gives a clear overview of inequalities in the quality and accessibility of GS, and maps can be produced that facilitate well-informed design and policy interventions not only on GS and the path network connecting residents and GS, but also on densification and general planning strategies (Stessens et al., 2017).

Alternatively, three aspects of urban greenspace (UGS) provision can be distinguished to make the common claim of "access to UGS" more specific (Biernacka and Kronenberg, 2018):

- *Availability* – greenspace exists within a suitable distance;

- *Accessibility* – the user feels welcome, can freely reach enter GS and safely use at any time;
- *Attractiveness* – the user willingly wants to use/spend time in GS because it corresponds with the individual's needs, expectations and preferences

The above three aspects represent a hierarchical order and can be connected to proximity to where the user lives, and are important to operationalising 'universal access' commitments (Biernacka and Kronenberg, 2018). Cities should consider performing an analysis of institutional barriers preventing UGS availability, accessibility and attractiveness as part of any urban planning initiative (Biernacka and Kronenberg, 2018). Whilst availability is typically represented during most UGS mapping exercises, attention needs to be paid to different UGS types as some are only rarely considered as greenspaces, for instance informal GS and brownfields (Feltynowski et al., 2018). To verify whether specific UGS are accessible, investigations should examine local zoning plans, as well as collate detailed maps of UGS (e.g., using orthophotomaps or local land surveying resources) with data and maps related to property rights, new investments (a UGS may be closed, at least temporarily, due to construction), schools and kindergartens (educational garden), tree felling and road traffic, etc (Biernacka and Kronenberg, 2018). UGS attractiveness involve participatory GIS or questionnaires to reflect the perceptions of urban inhabitants (e.g. Kothencz & Blanschke, 2017). Accessibility and attractiveness can best be investigated through field research to check which UGS are fenced, abandoned or in poor condition, who uses which UGS (e.g., using participant observations, time-use surveys), or where there is not enough park furniture and leisure equipment (Biernacka and Kronenberg, 2018). Once key barriers are identified policy makers or other interested stakeholders can create a comprehensive inventory of UGS and visualize UGS availability, accessibility and attractiveness on a map, which can be used to improve the current situation (Biernacka and Kronenberg, 2018).

Le Texier et al. (2018) argued that urban green space accessibility must be defined from different land use data types. They propose to compare UGS indicators measured from an imagery source (NDVI from Landsat), an official cadastre-based map, and the voluntary geographical information provided by OpenStreetMap (OSM). Pafi et al. (2016) suggest a methodology to calculate accessibility to urban green areas using the Green European Settlement Map 2016, and outline input data, tests and tools plus the results of running tests for some European cities. The spatial analysis of this workflow has been implemented using ESRI ArcGIS tools, including the toolbox Network Analyst, and script using Python language and the ArcPy library for ArcGIS.

Multi-dimensional models can measure both objective (geographic) accessibility and subjective (perceived) accessibility (Wang et al. 2014). These use socio-economic data, questionnaires and GIS to map data. Bivariate correlations and regression models can measure the relationship between distance and perceived access and the various relationships of dimensions of perceived and physical accessibility (Wang et al. 2014). Kabisch & Haase (2014) and Kabisch (2015) use a multi-method approach that examines the distribution and provision of UGS as well as the distribution of different population groups to establish possible relationships between UGS provision and socio-demographic indicators of population density, immigrant status and age, and calculated the percentage of immigrants and individuals aged ≥65 years within specific distances from park entrances to quantify potential accessibility. By using this multi-method approach, two levels can be addressed: a district level for the whole city including all sub-districts, and a site level with the focus on a large urban green space in a particular city. A number of different GIS and statistical methods can be applied, including hierarchical cluster analysis to identify clusters of districts with significantly different socio-demographic characteristics and simultaneously differing urban green space distribution. The standardized variables share of UGS, population density, percentage of immigrants and percentage of addresses situated in a residential area classified as "simple residential area" (defined as areas with continuous urban fabric and rather bad building conditions with nearly no renovation). The selection of these variables is based on their importance of indicating possible areas with diverging land uses and demographics. Cluster analysis can be conducted in SPSS (or other statistical programs), based on the WARD-Method with squared Euclidian distance (Kabisch, 2015).

In general, accessibility analysis of urban green spaces (UGS) includes the development of a spatial database as the first step in generating UGS accessibility indicator. Data can be collected using supervised classification methods of multispectral LANDSAT images and manual vectorization of high-resolution digital orthophoto (DOP). An analysis of UGS accessibility can be conducted according to Accessible Natural Greenspace Standards (ANGst) proposed by English Nature (2003) and further developed by Natural England (2010). Accessibility indicators can be generated based on seven objective measures which include the UGS per capita and accessibility of six UGS functional levels. It can be beneficial for UGS accessibility indicators to be compared with subjective measures that can be obtained by field survey of respondents within statistical units. The collected data reflect an individual assessment and subjective evaluation of UGS accessibility. The importance of using such objective and subjective measures in the process of understanding UGS accessibility has been confirmed by several studies (Kabisch and Haase, 2014; Natural England, 2010). Often, while evaluating accessibility, residents emphasize the immediate residential environment, neglecting the UGS of higher functional levels. The outputs from measuring this indicator may serve as guidelines for further development of the functional UGS city network.

Large-scale questionnaire campaigns provide opportunities for public participatory processes, and can be used to capture data on a variety of variables including distance and type of greenspace, frequency of use, main reasons for visiting GS (e.g. to enjoy the weather, observing flora and fauna, to exercise etc), socio-demographic/economic status (Schipperijn et al 2010). Multiple logistic regression analysis can be used to investigate the relationships between these variables and obtain a thorough analysis of a neighbourhood or city, its population, and the available green spaces, to inform viable strategies to increase the use of green space (Schipperijn et al 2010). For instance, the results from the Schipperijn et al 2010 Danish study highlighted that distance to green space was not a limiting factor.

Public Participation GIS methods such as 'Maptionnaire' (Raymond et al., 2016) and 'By the Water' (Laatikainen et al., 2015) can be used to collect activity and user data in green/blue spaces. Users can mark on a map the sites they use and identify activities they undertake there (e.g. recreational activities, relaxing and spending time together; sports activities and nature activities) as well as data regarding the location of their home, places they perceive as inaccessible, modes of transport used and visiting frequency (Raymond et al., 2016; Laatikainen et al., 2015). Raymond et al.'s (2016) tool also collected demographic and socio-economic data about the user, users then map their experiences based on a range of options (the options listed are related to barriers regarding perceived accessibility). Cluster analysis and Shannon Diversity Index calculations can be applied to the data to understand different components of activity and user diversity, so that landscape planners can use the tool to spatially identify barriers/opportunities regarding perceived accessibility (Raymond et al., 2016).

Glasgow's Place Standard tool https://www.placestandard.scot/ could also potentially be used as a citizen science tool to determine community perceptions of accessibility to greenspaces and how they could be improved to increase use.

An Australian pilot project has developed a citizen science smartphone tool for auditing how and why older people engage with public greenspaces, to gather evidence beyond mere utilisation of greenspace (Barrie et al., 2019). The tool provides a geocoded data on the location and perceived quality of the greenspace, duration of visit, etc, and the data can be used to inform how urban greenspaces can become enablers of ageing well from the perspective of older people. This project followed a co-creation process, with citizens participating in data collection, analysis, and feedback on the design of the tool and the wider project. The tool could be used with different population groups.

Refer to other metrics detailed in 'Env41 - Accessibility of Greenspace' indicator review regarding mapping accessibility in relation to distance/travel time.

Data on community accessibility to greenspace generated in these ways can be used to:

- Improve the design of new nature-based solution greenspaces to enhance perceived and actual accessibility and achieve equitable distribution;
- Prioritise sites for interventions and increase the use of existing greenspaces;
- Support the planning of new nature-based solution greenspace initiatives;
- Promote community engagement in nature-based solution planning;
- Underpin other indicators that require an understanding of greenspace distribution and accessibility as a foundation.

Scientific solid evidence: Greenspace accessibility based on measures of distance to greenspace alone can miss other important factors, but when coupled with complementary data such as reasons/frequency of use, ratings from visitors etc., can provide solid evidence for evaluating accessibility strategies for nature-based solutions planning.

Level of expertise: Expertise in relation to mapping and modelling will be necessary. Also, expertise in leading participatory processes would be of value to maximise the quality of outputs.

Cost: Some map datasets and satellite imagery are freely available online, others involve a licence fee. There can be costs associated with acquiring GIS software and GIS specialists if not already available in-house. Also costs for questionnaires to capture qualitative data if not already known and participatory GIS can also involve costs in relation to designing a portal, hosting the webpage, generating engagement, and analysing data.

Effort: The level of effort involved would be dependent on the scale of the project, the amount of data to be captured and analysed and expertise already available.

Participatory process: PPGIS tools such as Maptionnaire and/or questionnaires on GS accessibility and The Place Standard Tool or a similar mechanism could provide a participatory element.

Data availability: some GS map data is likely to be available for mapping distance to GS but factors relating to use might not be available and new data would need to be generated. Participatory data can be obtained in the form of already available data from local authorities, land managers, and non-government organisations, or generated through participatory engagement processes with organisations and individuals.

Geographical scale: Most published studies examine the city-scale, but a local accessibility analysis is also possible.

Temporal scale: Evaluation methods can be adopted for short-term snapshots for strategic greenspace accessibility planning, or can represent a baseline for long-term evaluation of change in accessibility/use.

Synergies: The diversity of data captured to enable assessment under this indicator means there are potential synergies with other greenspace and land-use indicators (e.g. Env41 and Env43), as an index for other environmental and health and wellbeing indicators, and/or to investigate the relationship between greenspace accessibility and health (e.g. Tamosiunas et al. 2014).

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

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2.2.6 Mapping ecosystem services and spatial-temporal biodiversity legacies (Env38)

Umbrella: Greenspace distribution mapping

Indicator: Mapping ecosystem services and spatial-temporal biodiversity legacies

Code: Env38

Description: Biodiversity mapping (in a temporal context) and ecosystem services (ES) mapping to identify where nature-based solutions efforts should focus (to maximise conservation/ES outcomes and minimise costs).

Metric(s): Approaches to mapping urbanisation impacts on biodiversity have typically used an urban to rural gradient, but this can be too simplistic to capture the spatial-temporal characteristics of contemporary urbanisation, which tends to be more dispersed and non-linear (Ramalho & Hobbs, 2012). It is important to understand how implemented NBS along with the environmental conditions and heterogeneity affect the distributions of species and how do the spatial-temporal dynamics of heterogeneity affect ecological and evolutionary drivers of biodiversity? Past land-uses strongly shape remnant ecosystems and time-lags can mask remnant biodiversity response to ongoing fragmentation and environmental change, which an explicit temporal measure could capture (Ramalho & Hobbs, 2012). A more comprehensive 'Dynamic Urban Framework' (DUF) has been proposed that uses a temporal perspective and records land-use legacies, past remnant configurations, urbanisation age, local environment, and socio-economics and urban land use (Ramalho & Hobbs, 2012). For urban planning this can provide guidance on the selection of remnant sizes and landscape configurations that will allow reasonable conservation outcomes in the future, help prioritise remnants for conservation, help understand thresholds for restoration and identify interventions to improve quality of remnants (Ramalho & Hobbs, 2012). The DUF can be used to identify the drivers controlling remnant ecosystems and elucidate where management and restoration efforts should focus in cities, helping to formulate meaningful management guidelines and tailor strategies of action for urban planners (Ramalho & Hobbs, 2012). The spatiotemporal context of biodiversity, e.g. individual organisms, populations and species defines their environmental and biotic setting. This setting, in turn, drives ecological processes and provides the arena for micro- and macro-evolutionary mechanisms (Jenz, 2011).

Methods for ecosystem services mapping can be found in core indicator review guidelines for **Env85** (Change in ecosystem service provision – remote sensing and applied). De Groot et al. (2010) provides a list of potential indicators that can be used to determine the capacity of landscapes/nature-based solutions to provide ES, based on two main indicator categories: state indicators describing what ecosystem process or component is providing the service and how much (e.g. total biomass or Leaf Area Index), and (2) performance indicators describing how much of the service can potentially be used in a sustainable way (e.g. maximum sustainable harvest of biomass or the effect of Leaf Area Index on air-quality). Various integrated and multicriteria ES assessment/evaluation frameworks and modelling tools have been proposed that can help identify and prioritise nature-based solutions implementation in order to boost ES provision in cities (i.e. Nelson et al., 2009; De Groot et al., 2010; Haase et al., 2012; Pedersen Zari, 2015 & 2019; Kremer et al., 2016). As with mapping biodiversity, land-use legacies that influence the structure, function and biota of ecosystems can affect ES supply and time-lags may influence predictions of ES provision and should therefore be considered when evaluating indicators of current ES supply (Dallimer et al., 2015; Ziter et al., 2017).

The third European Commision report on mapping and assessing the condition of Europe's ecosystems (EU, 2016) provides an overview about available information on ecosystem condition and proposes a flexible methodology for assessment of ecosystems and their services building on the outcomes of previous work undertaken mainly by the European Environment Agency and based on existing data flows, especially from reporting obligations. A systematic process is outlined in the report, consisting of the following steps (EU, 2016):

1) mapping which involves identifying and delineating the spatial extent and temporal dynamics of different ecosystems through the spatio-temporal integration of a wide range of data sets on land/sea cover and environmental characteristics;
2) assessment of ecosystem state/condition based on analysing the major pressures on ecosystems and the impact of these pressures on the condition of ecosystems in terms of the health of species, the condition of habitats and other factors including soil, air and water quality. If impacts or condition cannot be quantified, the pressures are also used as indicators of ecosystem condition;
3) assessment of ecosystem service delivery which include assessing the links between ecosystem condition, habitat quality and biodiversity, and how they affect the ability of ecosystems to deliver ecosystem services, and then evaluating the consequences for human well-being.

The mapping and assessment process can be coherently structured using the well-established DPSIR (Drivers, Pressures, State, Impact and Response) framework. This is used to classify the information needed to analyse environmental problems and to identify measures to resolve them (EEA, 2015; Maes et al., 2013; Turner et al., 2010). Drivers of change (D), such as population, economy and technology development, exert pressures (P) on the state (condition) of ecosystems (S), with impacts (I) on habitats and biodiversity across Europe that affect the level of ecosystem services they can supply. If these impacts are undesired, policymakers can put in place the relevant responses (R) by taking action that aims to tackle negative effects. This framework is particularly useful, as it can be adapted and applied for any ecosystem type at any scale (EU, 2016).

Several European Union FP7 projects such as OPERAs (OPERAS, 2015) and OpenNESS (OPENNESS, 2015) have undertaken a critical review of these mechanisms and their application, and along with the EU H2020 project ESMERALDA (ESMERALDA, 2015) provide a flexible methodology for European, national and regional integrated mapping and assessment of ecosystem services and their biophysical, economic and social values at different scales. H2020 project Eklipse has published the report from its first request from policy makers for synthesizing available knowledge and provided an impact evaluation framework to support planning and evaluation of nature-based solutions projects (Raymond et al., 2017). Indicators of ecosystem service supply and demand are also developed by Burkhard et al. (2012), Haines-Young et al. (2012), Maes et al. (2013).

Mapping biodiversity and ecosystem services in these ways can be used to:

- Evaluate how land-use legacies and configuration can influence nature-based solutions designs/outcomes;

- Help planners target nature-based solutions strategies to improve conservation outcomes and boost ES provision;
- Assess the effects of different scenarios of design/management change on sites.

Scientific solid evidence: (from Env85 review) The integration of RS technologies into ES concepts and practices leads to potential practical benefits for the protection of biodiversity and the promotion of sustainable use of Earth's natural assets. The last decade has seen the rapid development of research efforts on the topic of RS for ES (especially, in the context of spatially explicit RS and valuation of ES), which has led to a significant increase in the number of scientific publications. Remote sensing can be used for ecosystem service assessment in three different ways: direct monitoring, indirect monitoring, and combined use with ecosystem models. Some plant and water related ecosystem services can be directly monitored by remote sensing. Most commonly, remote sensing can provide surrogate information on plant and soil characteristics in an ecosystem. For ecosystem process related ecosystem services, remote sensing can help measure spatially explicit parameters. We conclude that acquiring good in-situ measurements and selecting appropriate remote sensor data in terms of resolution are critical for accurate assessment of ecosystem services.

The assessment of ES is often limited by data, however, a gap with tremendous potential can be filled through Earth observations (EO), which produce a variety of data across spatial and temporal extents and resolutions. Despite widespread recognition of this potential, in practice few ecosystem service studies use EO. There are some challenges and opportunities to using EO in ecosystem service modelling and assessment which we can identify:

- technical - related to data awareness, processing, and access (these challenges require systematic investment in model platforms and data management)
- other challenges – more conceptual but still systemic; they are by-products of the structure of existing ecosystem service models and addressing them requires scientific investment in solutions and tools applicable to a wide range of models and approaches.

As stated by variety of research, more widespread use of EO for ecosystem service assessment will only be achieved if all of these types of challenges are addressed. This will require non-traditional funding and partnering opportunities from private and public agencies to promote data exploration, sharing, and archiving. Investing in this integration will be reflected in better and more accurate ES assessment worldwide.

Remote sensing (RS) provides a useful data source that can monitor ecosystems over multiple spatial and temporal scales. Although the development and application of landscape indicators (vegetation indices, for example) derived from remote sensing data are comparatively advanced, it is acknowledged that a number of organisms and ecosystem processes are not detectable by remote sensing. The potential for applying remote sensing for analysis and mapping of ES efforts has not been fully realised due to concerns about ease-of-use and cost. Historically, RS data have not always been easy to find or use because of specialised search and order systems, unfamiliar file formats, large file size, and the need for expensive and complex analysis tools. That is gradually changing with increasing implementation of standards, web delivery services, and the proliferation of free and low-cost analysis tools. Although data cost used to be a common prohibitive factor, it is no longer a big stumbling block for most users except where high resolution commercial images are needed.

Remote sensing is generally most useful when combined with in situ observations, and these are usually required for calibration and for assessing RS accuracy. RS can provide excellent spatial and temporal coverage, for example, though its usefulness may be limited by pixel size which may be too coarse for some applications. On the other hand, in situ measurements are made at very fine spatial scales but tend to be sparse and infrequent, as well as difficult and relatively expensive to collect. Combining RS and in situ observations takes advantage of their complementary features (Geller et al., 2016).

Level of expertise: (from Env85-RS review) It is important to clarify the resources that are needed to carry out ecosystem services assessments, such as technical and human resources, and the time needed for certain analyses. The methods vary greatly depending on the required expertise, availability of the data and its coverage, available software, time, and financial costs. The most suitable approach will depend on the research questions which need to be addressed, whether the study will be an assessment, or if maps are also required. For mapping methods, the level of scale should be considered. The limitations are often set by the availability of the data. For small research areas more detailed data sources, or even opportunities to conduct field measurements, may be available. However, for larger studies Earth Observation products may offer a solution for areas of poor data coverage. In addition to scale, it is also important to pay attention to the purpose of which the assessment is aimed at: Which biophysical units can and should be used to gain information on ecosystem services? Do we want to know if sufficient ecosystem service potential is available, or do we wish to quantify the rate at which the ecosystem service is delivered? Also, do we wish to deliver spatially explicit information for the chosen locations? The most suitable methods should be identified and selected according to the answers to these questions. Using a mixture of remote sensing and field methods appears to deliver the best results (e.g Mikolajczak et al., 2015; Vihervaara et al., 2017). Yet, this requires ecologists and remote sensing experts to collaborate closely with the newest methods and capabilities.

Cost: (from Env85 RS review) If the data and GIS expertise is already available in-house then should be fairly low cost. If not, many remotely sensed EO products, including those from MODIS (250 m+), Landsat (30 m), and Sentinel's Ocean Land Color Instrument (OLCI, 300 m), are freely available. However, EO data at finer resolutions (< 3 m) can be expensive to obtain. Obtaining GIS expertise can also be costly, if none is available in house.

Effort: (from Env85 RS review) The level of effort involved would be dependent upon the amount of data and expertise already available. According to Andrew et al. (2014), efforts to map the distribution of ESS often rely on simple spatial surrogates that provide incomplete and non-mechanistic representations of the biophysical variables they are intended to proxy. However, alternative datasets are available that allow for more direct, spatially nuanced inputs to ES mapping efforts.

Remote sensing data acquisition and processing requires financial, technological, and professional capacity. Even though there are some freely available data sets, the quantification of broad categories of ecosystem services cannot be achieved with these datasets alone. Acquiring the commercially available satellite images (e.g., QuickBird) incurs higher costs which also applies to the current hyperspectral, RADAR, and LiDAR sensors. Data acquisition from these sensors is usually upon request by the users which creates inconvenience in obtaining data from a specific area. Besides the acquisition, processing and analysis of data like hyperspectral images demands a very high technical capacity and computers with storage capacities up to tens of Terrabytes or even Petabytes.

As stated by Ayanu et al. (2012), the quantification of ESs can be better and more correctly achieved by linking remotely sensed information to a limited number of in-situ observations using semi-empirical linear or nonlinear regression models. For example, vegetation indices derived from the near-infrared and red proportion of the electromagnetic spectrum can be linked to in-situ biomass measurements to derive a proxy for timber production. Irrespective of the regression type, the statistical relationship between the sensor signal and the data derived from field observations is affected by the sensor characteristics like spectral, spatial, and temporal resolution. Moreover, multiple boundary conditions like time of the day and year, actual state of ecosystem components, and the atmosphere also affect the statistical relationship and reduce its validity for monitoring and spatial transfers to other study areas.

The properties of remote sensing systems vary significantly among each other making selection of the sensor system and the optimal methodology prerequisites for an accurate delineation of the proxies for ecosystem services. For instance, many indicators can be delineated for extensive areas within a clearly defined range of uncertainty based on operationally available data and well-established methods. Other indicators useful for exact quantification of ecosystem services can be only derived experimentally at local scale. The success of remote sensing application therefore depends on careful selection of the data from which the relevant parameters are derived for the chosen indicators of ecosystem services.

The quantification of ecosystem services is limited by the respective resolution of the remote sensing system. While multispectral data (e.g., Landsat, MODIS) have been widely used, the retrieval of some variables is limited by the rather poor combination of spatial and spectral resolution. Thus, utilizing high resolution hyperspectral, radar and LiDAR sensors would be desirable. With respect to the current status of these sensors, the derivation of ecosystem parameters such assoil clay mineralogy, belowground biomass, or water quality indicators like chlorophyll-a content, nitrogen, and phosphorus loading is primarily restricted to experimental landscape scale studies. Therefore, in situ measurements are needed for validation when using remote sensing data.

Participatory process: (from Env85 RS review) Participatory activities can be combined with remote sensing analysis into an integrated methodology to describe and explain land-cover changes and changes in ES provision caused by them. In doing so, semi-structured interviews, focus group discussions, transect walks and participatory mapping can be used to identify and assess priority ES. Local community members and experts can together discuss which (positive) impact (benefits) the implemented NBS will have on various ES for local, regional, national and international users. This participatory process can help to identify priority ES (e.g. air purification, carbon sequestration, water regulation, soil protection, landscape beauty, biodiversity, etc.). The approach will reveal if there any strong variations in the valuation of different ES between local people and experts who apply RS techniques, between genders and between different status and income classes in the local communities. Scientific evidence has demonstrated that participatory tools, combined with free-access satellite images and repeat photography are suitable approaches to engage local communities in discussions regarding ES and to map and prioritise ES values (Brown & Donovan, 2014; Brown et al., 2012). A review of several citizen science projects found they can provide opportunities to support ecosystem service assessments, although are predominantly applied in relation to assessing regulating and cultural services (Schröter et al., 2017). Citizen science participation formats mostly comprised volunteered data collection as the most successful employing approaches for ecosystem service assessments, meanwhile direct assessments of ecosystem services remain rare (Schröter et al., 2017).

Data availability: (from Env85 RS review) Once ecosystem service analysts have identified a useful EO product and have the capacity to process it, they may still be unable to access it. Though many remotely sensed EO products, including those from MODIS (250 m+), Landsat (30 m), and Sentinel's Ocean Land Color Instrument (OLCI, 300 m), are freely available, EO data at finer resolutions (< 3 m) can be expensive to obtain (Schaeffer et al., 2013). While many assessments can be done at coarser resolutions, high resolution data are important for precise assessments, such as delineating urban canopies. Data producers could collaborate with public agencies to make EO data and products available at low or no cost for non-commercial research purposes. Since Landsat archives were released for free to the public, there has been a dramatic uptake and use of the data worldwide (Engel-Cox et al., 2004; Popkin, 2018; Wulder and Coops, 2014).

Data access may also be limited by restricted use permissions or lack of public availability, particularly derived data products that are not available in data archives. Many new EO products are generated through one-off analyses that are novel (and therefore seen as worthy of publication) but result in data products that quickly become outdated or that cannot be regenerated due to technical and resource limitations. Producing regularly updated EO products requires ongoing funding to operationalize such products and to allow for algorithm and product improvement to meet the continually evolving needs of end users. This does not align with traditional time-limited calls for research innovation, yet in the absence of such funding, the ecosystem services and broader geographic science community loses the value created by initial research outputs.

Geographical Scale: (from Env85 RS review) Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change at various geographical scales. However, the higher the resolution required, the more expensive would be RS data needed. In some cases, it would be better to use images provided by drones, but in this case permissions for survey mapping will be required and depends on the local and national / government regulations. Methods can be applied from small to large geographical scales but are linked to the limitations of the data sources.

Temporal scale: (from Env85 RS review) Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change over time, at various temporal scales.

Synergies: (from Env85 RS review) In comparison to conventional sources of information on urban environment, remotely sensed data are inherently suited to provide information on urban land cover characteristics and ecosystem services provisioning, and their change over time, at various spatial and temporal scales. Synergies and trade-offs between the type and quantity of UGS and ES supply can also be identified e.g. cooling, carbon storage and air purification demonstrate synergies as these are primarily being supplied by the same UGS types. The method can reveal differences between neighbourhoods in terms of amount and type of ES supplied, and can highlight possible ES shortages in neighbourhoods.

Original reference(s) for indicator: Eklipse

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2.2.7 Accessibility of greenspaces (Env41)

Umbrella: Greenspace accessibility

Indicator: Accessibility of greenspaces

Code: Env41

Description: Distance from/or time to public greenspaces as a measure of accessibility

Metric(s): Greenspace accessibility has become an important issue for sustainable urban planning, particularly in relation to public health and social justice. It is widely acknowledged that access to greenspace may be particularly beneficial for children, socio-economically deprived groups and those with physical/mental illness. Distance-based metrics are often used to investigate relationships between greenspace availability and accessibility and health and wellbeing outcomes because studies have tended to indicate usage declines with increased distance to greenspace. A review to test the World Health Organisation's urban greenspace indicator for public health suggests everyone should live within 300 metres of a greenspace (with a minimum size of 1 hectare), equivalent to a five-minute walk, and this has been recommended as an indicator of greenspace accessibility (Van den Bosch et al., 2016). The decision of where to create greenspace and nature-based solutions should ideally be based on criteria related to maximising its accessibility (among other factors), so that it is easier for it to be accessed by the highest number of people, across social groups, and particularly those already lacking access. Feature indicator Env26 (Community accessibility) includes metrics that also capture public perception and use of greenspaces as a measure of accessibility. As these are important factors in evaluating accessibility, ideally both indicator reviews should be consulted for a detailed accessibility study.

Greenspace accessibility will require a mapping exercise. However, different urban green space (UGS) datasets are based on different definitions and parameters, which can result in large differences in the total amount of UGS depicted in cities (Feltynowski et al., 2018). A Polish study comparing data from five publicly available sources: 1) public statistics, 2) the national land surveying agency, 3) satellite imagery (Landsat data), 4) the Urban Atlas, and 5) the Open Street Map revealed that the most commonly used data source - public statistics (1) - excluded many types of greenspace (i.e. informal greenspaces and brownfields) creating inaccuracies in spatial extent, whereas the most comprehensive dataset was from the national land surveying agency (Feltynowski et al., 2018). Resources typically used for creating spatial datasets of urban green spaces include: Open Street Map (OSM); satellite imagery (Landsat, Sentinel etc.); orthophotomaps; LiDAR; Urban Atlas; and CORINE which are then typically geoprocessed in a GIS environment (Feltynowski et al., 2018). Core indicator review Env56-RS has further detailed information on mapping using remotely sensed data. To differentiate private and public green space, data sources are again an important concern because, for instance, Landsat data cannot distinguish private from public UGS, while OSM data does not depict private UGS (Le Texier et al., 2018). It may therefore be necessary to undertake a manual exercise in order to evaluate and define public versus private greenspaces, for instance consulting land ownership maps (Feltynowski et al., 2018).

Two common approaches used for measuring greenspace (GS) accessibility (La Rosa, 2014) comprise:

- the number of green areas within a fixed distance/time from a user's origin point, i.e. number of greenspaces within a fixed distance of residential areas, people within a fixed distance, minimum distance to closest greenspaces, or average distance to greenspaces (GS).

This does not account for the actual spatial distribution of the population that can use certain GS and the relative distance of the population to GS; calculate proximity measures based on users/members of population in relation to specified distance/time to GS; or

- calculate proximity measures based on users/members of population in relation to specified distance/time to GS.

Users/population data can be georeferenced from census data. The location of the GS will differ in relation to the selected destination place in the GS (i.e. geometric centroids, boundaries, access points, entrances) which must therefore be considered.

Three types of distance measures are typically used:

- Euclidean (straight line),
- Manhattan (distance along the two sides of a right-angled triangle opposed to the hypotenuse); and
- network distance (shortest time and distance).

The first two are easily calculated in GIS, the latter requires more detailed GIS layers (i.e. the city's street network). Depending on the needs of the accessibility analysis, two approaches can be used (La Rosa, 2014):

1. to understand the geographical distribution or supply of urban greenspaces, indicators such as the number/area of GSs within a fixed distance from population, or the minimum distance from GSs would be preferable;
2. to understand the potential demand of greenspaces for planning, indicators need to quantify a characteristic of the potential users in an urban context and then attribute it to a greenspace, then the number of people living within a fixed distance from a greenspace is a typical measure.

'Simple' indicators account for the number of people or users that can have access to a particular greenspace, while 'proximity' indicators weight people or users with the distance from their location to the greenspaces (La Rosa, 2014). The choice of metric used as an indicator of accessibility will depend on the aim of the project and the number and type of geo-datasets available. If the aim is to chose specific types of GS for high-accessibility areas, with high proximity to residential settlements, e.g. allotments, playgrounds and other informal green areas, understanding the spatial configurations of the most accessible spaces to create this nature-based solution would be the most suitable metric to use.

Measurement methods used to calculate distance to/accessibility of greenspace can have implications for determining the strength of relationships between access and health (Higgs et al., 2012). When network-based metrics are used to measure distance to greenspace they can result in different findings to Euclidean distance, similarly whether the destination point at the greenspace is the nearest centroid, nearest boundary point or nearest actual access point. If a uniform approach is not used, then different greenspaces can be identified as 'closest' and this in turn could influence the strength and accuracy of associations. The 'gold standard' for measuring potential accessibility to the nearest greenspace using proxy measures would be to measure from individual households to public entrances (or other actual physical access points) of greenspaces using network distance (based on as detailed path or road network as is available) (Higgs et al., 2012). A range of different accessibility techniques should be considered when providing objective measures of access to GS as analysis of the relationships between access measures, health variables, and the attributes of such green spaces may be fundamentally flawed unless the consequences of alternative methodological approaches are at least highlighted and sensitivity analyses conducted.

De la Barrera et al. (2016) propose a range of indicators for measuring GS accessibility related to quantity of GS (i.e. per inhabitant, per built up area, etc, at the municipal scale), quality of GS (e.g. mean size of GS, vegetation cover, etc) and spatial distribution and accessibility to GS (e.g. aggregation index, share of blocks served by GS >0.5 ha, etc). Accurate measurement of accessibility requires the most refined demographic data available (e.g. population per block) combined with the location of the GS, so that the population supplied by GS can then be derived from the population living in each block (De la Barrera et al., 2016). This gives a socio-spatial differentiation of GS accessibility making it possible for planners to compare different neighbourhoods to steer and evaluate public investment toward the more deprived sectors (De la Barrera et al., 2016).

Geocoded land-use data from the European Atlas can be merged with national census data and a set of variables measuring provision of GS at household level then defined (Wüstemann et al., 2016). For instance, the distance to the nearest GS measured as the Euclidean distance between the household and the border of the GS provides a proxy for how long it takes to reach the nearest GS (Wüstemann et al., 2016). The coverage of GS can be measured as the square meters covered by GS in a predefined buffer area of 500 m around households and grid centroids respectively to allow estimation of a per capita GS provision (Wüstemann et al., 2016). Ideally both should be measured because distance can be short, but coverage can be low, therefore the two do not represent substitutes (Wüstemann et al., 2016). To analyse for provision of GS in relation to socioeconomic background, household must be controlled for in terms of age, income, employment, etc, and then distance and coverage can be tested against household data using Welch's t-tests (i.e. to show differences in GS provision for income) (Wüstemann et al., 2016). There can be inconsistency in findings using these metrics depending on the minimum size of GS used in the study, for instance, Wüstemann et al. (2016) use 0.25 ha as a minimum, whereas Kabisch et al. (2016) use 2 ha as a minimum, resulting in a considerably different GS provision value.

Provision of, and access to, UGS can also be examined with respect to the spatial distribution of the following four indicators: (i) availability (share of land dedicated to urban green space divided by a reference surface), (ii) fragmentation (the ratio of the total perimeter of UGS over their total area), (iii) privatisation (the ratio of private (i.e. residential gardens) to total UGS cover, and (iv) accessibility (the average distance, per neighbourhood, from each cell to the nearest public UGS through the road network (Le Texier et al., 2018).

Given the varied methodologies available for assessing greenspace accessibility, results reported can be inconsistent (Mears & Brindley, 2019). The heterogeneity in the types of objects included and the minimum mapping units used in different datasets (e.g. Landsat, OSM) must therefore be controlled for if data is to be used for comparative purposes (Le Texier et al., 2018). Straight-line distances can over-estimate accessibility by failing to consider actual routes available for travel, therefore network-based distance calculations can be more accurate. Other factors such as neighbourhood size and aggregation levels, local context and the complexities of relationships between deprivation and greenspace must be considered to avoid bias and understand reasons behind observed patterns and improve GS distribution equity (Mears & Brindley, 2019).

A PPGIS tool called 'By the Water' has been used to gather data on actual access patterns, providing not only a public participation opportunity but also revealing that proximity and availability did not always correlate with utilisation, and that measuring distance to the nearest blue/greenspace available alone is not enough to evaluate the true multidimensional nature of greenspace accessibility (Laatikainen et al., 2015). PPGIS approaches can therefore provide valuable information to accessibility research and provide additional approaches for the planning of public greenspaces (Laatikainen et al., 2015).

Data on greenspace accessibility generated in these ways can be used to:

- Achieve more equitable greenspace accessibility;
- Prioritise areas with limited accessibility for nature-based solution initiatives;
- Support the planning and design of new greenspaces;
- Track trends in public greenspace accessibility and set targets for equitable greenspace distribution (environmental justice);
- Underpin other environmental, health and wellbeing and economic indicators that require an understanding of greenspace distribution and accessibility as a foundation.

Scientific solid evidence: Greenspace accessibility based on measures of distance to greenspace can vary based on the methodologies used but represent a sound broad base for urban planning. However, it is critically important that a consistent methodology is used by a city to avoid overstating/underestimating actual greenspace availability/accessibility.

Level of expertise: Expertise in GIS tools, spatial analysis methods and processing of sensor data are needed

Cost: Some map datasets and satellite imagery are freely available online, more comprehensive data needed for network-based measures potentially can involve a licence fee. Typically, the higher the resolution of the data required, the greater the cost. Potentially, there are also costs for acquiring GIS software and GIS specialists if not already available in-house.

Effort: The level of effort involved would be dependent on the scale of the project, the amount of data to be captured and analysed and expertise already available.

Participatory process: PPGIS tools can provide valuable supplementary information to accessibility research and provide additional approaches for the planning of public greenspaces.

Data availability: some GS map data is freely available for mapping distance to GS but the quality and resolution can still be variable.

Geographical scale: Most published studies examine the city-scale, but local analyses are also possible.

Temporal scale: Evaluation methods can be adopted for short-term snapshots for strategic greenspace accessibility planning, or can represent a baseline for long-term evaluation of change in accessibility in relation to nature-based solution project implementation.

Synergies: The diversity of data captured to enable assessment under this indicator means there are potential synergies with other greenspace and land-use indicators (e.g. Env41 and Env43), as an index for other environmental and health and wellbeing indicators, and/or to investigate the relationship between greenspace accessibility and health (e.g. Tamosiunas et al. 2014).

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Eklipse (the original indicator description has been exchanged with Env26 'Community accessibility' Env26 for improved coherence with indicator title).

Metric reference(s):

De la Barrera, F., Reyes-Paecke, S. and Banzhaf, E. (2016) Indicators for green spaces in contrasting urban settings. *Ecological Indicators*, 62:212-219.

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Higgs, G., Fry, R. and Langford, M. (2012) Investigating the implications of using alternative GIS-based techniques to measure accessibility to green space. *Environment and Planning B: Planning and Design*, 39(2): 326-343.

Kabisch, N., M. Strohbach, D. Haase, and J. Kronenberg (2016). Urban green space availability in European cities. *Ecological Indicators*, 70: 586-596.

Laatikainen, T., Tenkanen, H., Kyttä, M. and Toivonen, T. (2015) Comparing conventional and PPGIS approaches in measuring equality of access to urban aquatic environments. *Landscape and Urban Planning*, 144, 22-33.

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Le Texier, M., Schiel, K. and Caruso, G. (2018) The provision of urban green space and its accessibility: Spatial data effects in Brussels. *PloS one*, 13(10): e0204684.

Mears, M. and Brindley, P. (2019) Measuring urban greenspace distribution equity: the importance of appropriate methodological approaches. *ISPRS International Journal of Geo-Information*, 8(6), 286.

Van Den Bosch, M.A.; Egorov, A.I.; Mudu, P.; Uscila, V.; Barrdahl, M.; Kruize, H.; Kulinkina, A.; Staatsen, B.; Swart, W.; Zurlyte, I. (2016) Development of an urban green space indicator and the public health rationale. *Scand. J. Pub. Health*, 44, 159–167.

Wüstemann, H. and Kalisch, D. (2016) *Towards a national indicator for urban green space provision and environmental inequalities in Germany: Method and findings* (No. 2016-022). SFB 649 Discussion Paper.

Synergies:

Tamosiunas, A., Grazuleviciene, R., Luksiene, D., Dedele, A., Reklaitiene, R., Baceviciene, M., Vencloviene, J., Bernotiene, G., Radisauskas, R., Malinauskiene, V. and Milinaviciene, E. (2014) Accessibility and use of urban green spaces, and cardiovascular health: findings from a Kaunas cohort study. *Environmental Health*, *13*(1): 20.

2.2.8 Ratio of open spaces to built form (Env43)

Umbrella: Greenspace distribution mapping

Indicator: Ratio of urban spaces to built form

Code: Env43

Description: Measures change in urban densification by recording the ratio of green (open) space to built form

Metric(s): The success of urban regeneration projects partly depend on integrating biodiversity, urban greenery and ES with the built form. With the rise in high density developments, ensuring adequate open space provision can be a challenge but is crucial to promoting a high-quality urban environment. Open spaces should be considered in conjunction with the built form as together they influence air movement and modify the microclimate. The size and scale of open spaces should therefore be optimised as part of city planning. Evaluating and increasing understanding of the relationship between the urban population and the quality and amount of open and green space in cities is vital to creating sustainable, healthy and resilient urban areas.

The basic methodologies of applying geostatistical approaches to spatial data for recording and assessing land use and land cover needed for this indicator have been covered in other indicator reviews (for instance refer to Env55 (Greenspace area) for metrics related to spatial recording of urban green (open) spaces), and Env63 (Land use mix) for metrics related to recording other urban morphologies). The European Urban Atlas provides free and reliable, inter-comparable, high-resolution land use maps for over 300 Large Urban Zones, available at: https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-urban-atlas, with a minimum mapping unit of 0.25 hectare. Alternatively, OpenStreetMap (OSM) (https://www.openstreetmap.org/) is a freely-licensed, global geospatial database built by a community of volunteer mappers that can provide an up-to-date Land Use Land Cover (LULC)

Wherever possible studies of urban form should cover different scales as most cities are composed of a nested network of scales with inter and intra-scale relationships (Sharifi, 2019a). The scale hierarchy ranges from:

- Macro: overall structure of the city and some major elements and aspects such as city size, development type (i.e., compact, dispersed, etc.), distribution pattern of people and jobs, degree of clustering, and landscape connectivity (Sharifi, 2019a);
- Meso: the structure and layout of neighbourhoods, blocks, lots, open spaces and streets (Sharifi, 2019b); and
- Micro: the granular design and structure of buildings, and their position with respect to neighbouring buildings, open spaces, and pathways individual buildings (Sharifi, 2019a).

Bottom-up development where the lower-scale components support/reinforce the higher scales strengthen the self-organisation capacities cities and can promote resilience (Sarafi, 2019a). The following metrics tend to concern the meso-scale level, however as part of upscaling and out-scaling, meso and micro-scale nature-based solutions interventions can have a cumulative macro-scale impact. Sharifi (2019b) provides a review of how various open space parameters such as their design, configuration, size, spatial distribution and connectivity can influence their performance in terms of microclimate regulation, supporting biodiversity, stormwater management, urban food production, accessibility and resilience, and note that optimal distribution of open space tends to be context specific (therefore no one-size-fits-all perfect configuration).

A commonly used density metric at the macro-scale level is Floor Area Ratio (FAR), also known as floor area density or floor-space index, typically defined as the amount of floor space of building divided by that building's plot area (Krehl et al., 2016). This is often used as a regulatory mechanism for new development to ensure density regulations are met. For use as a density indicator, determining the floor area ratio can be a complex task, since official surveys of building metrics (e.g., floor number, volume or height data) may not be available (Krehl et al., 2016). Stereo images acquired by the Remote Sensing Satellite, which employs the Cartosat-1 stereo sensor on board, provides the spatial and the geometric requirements for an area-wide and cost-effective derivation of height information from various large urban regions, enabling analysis at the spatial level of individual buildings and generation of 3D building models using digital surface models (DSMs) (Wurm et al., 2014; Krehl et al., 2016). Alternatively, an optical image and a DSM can be acquired by the same platform, with the concurrent utilization of the Advanced Land-Observing Satellite (ALOS) to generate urban volume which can be divided up into built-up volume and green volume (Handayani et al., 2018).

Alternatives measures that focus on estimates of greening/landscaping are Landscape Surface Ratio (LSR) or Green Area Ratio (GAR). For LSR, the area of designated landscaping/open space area on development is divided by the area of the site proposed for development. Keeley (2011) provides an overview of the Green Area Ratio (GAR) calculation used in Berlin. It is composed of three adaptable, interconnected components: (1) a set of ratings; (2) a set of targets; and (3) the final ratio determined for each parcel (Table 1). The first two are established by municipal planners and determine the scope and stringency of the metric (Keeley, 2011). Their development is time intensive, but then requires only periodic review (Keeley, 2011). The third value is generated by the property owner and involves a simple calculation of how each parcel meets these standards (Keeley, 2011).

Table 1. Descriptions of Green Area Ratio Components (Keeley, 2011)

Green Area Ratio components	Description
Environmental Performance Ratings	Planners rate the environmental services provided by each green technique; these numbers are used to weight or prioritise each technique
Greening Targets	Planners set the minimum percentage of each parcel to be comprised of green infrastructure
Parcel Achieved GAR	The weighted sum of green techniques actually implemented on a property

Some planning initiatives have set minimum targets for open (or green) space per resident e.g. 75 m^2 green space per dwelling in the Netherlands. Other studies have shown that open space *within* the built-up city can be considerably more important to urban populations than open space at the urban fringe (Wagtendonk & Koomen, 2019). To understand the impacts of urban development on the remaining open spaces within an area, rather than looking at urban sprawl, Wagtendonk & Koomen (2019) propose two spatial metrics:

- Open Space Ratio (OSR) = Open Area/Total Area; and
- Total Unit Density (TUD) = (Number of Built = up area units Number of Open Spaces) 100 + /Total Area - where Open Area represents the summed area of all open space units within the analysis area (both in km^2) and Total Area the size of the analysis area in km^2.

OSR is expressed as a dimensionless fraction, while TUD is presented as the number of units per 100 km^2 to arrive at values ranging from 0 to 50 (depending on the characteristics of the area and applied data sets) and these can be used to show the temporal dynamics of open space and built-up areas at different spatial scales and shed light on different urban development processes (Wagtendonk & Koomen, 2019).

Scottish Natural Heritage have published a 'Wayfinder Guide' for the preparation of open space audits and strategies (https://www.nature.scot/wayfinder-guide-preparation-open-space-audits-and-strategies) that provides an overview on identification, classification and mapping of open spaces, and advice on developing accompanying open space strategies that take account of quantity, quality, value and accessibility of the open space resource . Glasgow City Council's Open Space Strategy (https://www.glasgow.gov.uk/CHttpHandler.ashx?id=47093&p=0) and accompanying Open Space Map (https://glasgowgis.maps.arcgis.com/apps/webappviewer/index.html?id=a968a2a7fa514eb1ac66abc571949c2e) provides an exemplar for setting out a long-term vision to ensure that urban open spaces meet the City's needs for years to come. As part of their open space assessment process, Glasgow City Council used a 'Quality Matrix' to evaluate whether a site could meet their quality standard considerations.

Remote sensing methodologies are well-suited to detecting spatial-temporal changes at the urban scale, enabling the assessment of green space development and the outcome of the interplay between land-use policies focussing on densification and green space. Giezen et al. (2018) proposed the use of remote sensing technologies to monitor and analyse the resultant effects of opposing and conflicting urban policies for densification and protection and improving of urban green space in Amsterdam. High-resolution satellite images from 2003 and 2016 from Worldview 2 (0.46 m pixels) and Quickbird (0.64 m pixels) were used to measure land-use changes, which were assessed by applying landscape metrics for each land-use i.e. the percentage share of land use and their changes over the period measured (Giezen et al., 2018). This revealed a decrease of green space and an increase in the built-up environment, as well as strong fragmentation of green space, indicating that green space was increasingly available in smaller patches (Giezen et al., 2018). The findings highlighted that urban green space policies can be insufficient to mitigate the negative outcomes of a city's densification on urban green space, and that this should be looked at using more detailed metrics of changing spatial patterns, e.g. both "patch density" and "shape index" to indicate the overall level of fragmentation of the land-use and shape complexity (Giezen et al., 2018).

Krehl et al. (2016) underlined the analytical opportunities that recent remote sensing data offers with regard to an objective and transparent measurement of built density patterns of city regions.

Dennis et al. (2018) propose a new approach using open-source, high spatial and temporal resolution data with global coverage to measure and represent the landscape qualities of urban environments. The presented landscape approach employs remote sensing, GIS and data reduction techniques to map urban green infrastructure elements in a city region and how they relate to the built environment, and demonstrates considerable improvement in terms of coverage and thematic detail (Dennis et al., 2018). By going beyond simple metrics of quantity, such as percentage green and blue cover, it is possible to explore the extent to which landscape quality helps to unpick the mixed evidence from previous research on the benefits of urban nature to human well-being and provides a promising basis for developing further insight into processes and characteristics that affect human health and well-being in urban areas (Dennis et al., 2018).

Data on the ratio of open space to built form can be used to:

- Ensure that increasing density is not achieved at the expense of open/green space provision;
- Enhance the design of compact cities to ensure integration of nature-based solutions to deliver a balance of social, economic and environmental benefits;
- Track trends in open/green space provision and set targets for equitable provision and distribution;
- Prioritise areas with limited open/green space for nature-based solution initiatives.

Scientific solid evidence: Accuracy will be influenced by the resolution of land use/land cover data that is used. The variety of published methodologies and approaches to data collection mean there is a lack of consistency for comparative analyses nationally and internationally, and the use of density indicators often suffers from an imprecise definition of the reference area (Krehl et al., 2016). A city-scale ratio measure could mask distribution inequities.

Level of expertise: Expertise in relation to mapping and modelling/statistical analysis will be necessary and knowledge regarding applicable data sources and appropriate methods/measures for processing data will be needed. Processing remote sensing data requires advanced expert knowledge.

Cost: Increasingly high resolution, high-quality data is becoming freely available (i.e. OpenStreetMap (OSM)) and the main costs would be associated with employing suitably experienced specialists/technology to analyse data if this is not already available in-house. High resolution data to accurately characterise small land parcels can be expensive. See indicator review for Env_42_RS for some commercial costs for newly acquired high resolution RS imagery.

Effort: More detailed studies will be more data-intensive and time-consuming and effort will be directly related to the level of expertise available. Much of the effort associated is required upfront and especially when using remote sensing techniques, however, once a land use map has been developed, updating it can be relatively low effort if links to good processes are established with planning departments.

Participatory process: Projects such as OSM and LandSense offer a mechanism for community participation in the process of recording and/or verifying land cover/uses (see Env63 (Land use mix) for further information on these platforms). Chen et al. (2018) introduced a novel methodological framework for integrating social sensing and remote sensing data sources to conduct 'social functional' mapping of urban green spaces and land use structure.

Data availability: Land use and land cover data is widely available in the EU, depending on the resolution required, and some data can be accessed for free (e.g. OSM). The extensive and increasingly affordable availability of remote sensing data, with which not only land use, but also the height of built structures can be modelled, offers entirely new opportunities. Large-scale volume calculations can be made, from which density measures, such as the floor area ratio, can be derived (Krehl et al., 2016). Further benefits ensue as a result of: (i) the objectivity of the density calculation, since building heights and volumes can be reliably determined; (ii) the high spatial resolution of the data and the possibility to aggregate them at will into spatial reference systems (such as ring zones or grid cells) that are independent of local administrative units; (iii) the extensive availability at comparatively moderate costs; and (iv) the ability to easily link data with demographic and socioeconomic data at the sub-municipal level.

Geographical scale: Typical metrics such as FAR/GAR tend to examine data at the project/neighbourhood scale, however macro and micro-scale analyses are possible.

Temporal scale: Suitable for various temporal scales, although the availability of high-resolution historical data can sometimes be a barrier to studying past trends. Wagtendonk & Koomen (2019) propose a methodology that can model future trends.

Synergies: Strong synergies with other land use and mapping indicators (e.g. Env63, Env42, Env55 etc), also, other environmental indicators (e.g. UHI, air quality, flooding etc.) and health and wellbeing indicators (i.e. open spaces provide opportunities for social encounters).

Original reference(s) for indicator: Eklipse

Reference (s):

Chen W., Huang H., Dong J., Zhang Z., Tian Y., Yang Y. (2018) Social functional mapping of urban green space using remote sensing and social sensing data. ISPRS Journal of Photogrammetry and Remote Sensing 146, 436–452. https://doi.org/10.1016/j.isprsjprs.2018.10.010

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Wagtendonk, A.J. and Koomen, E. (2019) An indicator set for capturing long-term open space fragmentation and urban development dynamics. *Computers, Environment and Urban Systems*, 76, 178-193.

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2.2.9 Green space area (Env55)

Umbrella: Greenspace distribution mapping

Indicator: Greenspace area

Code: Env55

Description: Measures green area (publicly or privately owned that is publicly accessible) in relation to population (e.g. ha/100k) as an indicator of environmental benefits provided by green areas in urban settings (reducing UHI and health benefits)

Metric(s): greenspaces provide a range of ecosystem services in urban areas including reducing the urban heat island, capturing particulates and social and health benefits through contact with nature. More green and blue space also reduces vulnerability to extreme weather events like flooding by heavy rainfall. Greenspace area can be used as an indicator of these environmental, social and economic benefits. An important metric for evaluating urban green space is determining its area per capita, where population and urban area are the two main parameters. However, one of the difficulties in using the measure of square metres of green space per capita is that it can count all green space, including private green space which is largely inaccessible. The EU, through Eurostat and other agencies, has collected data on accessibility and green infrastructure gain/loss over time, which are also useful standards to apply.

Greenspace area information has typically been collected from high-resolution satellite images and then mapped and measured (area) in a GIS environment. Different urban green space (UGS) datasets are based on different definitions and parameters, which can result in large differences in the total amount of UGS depicted in cities (Feltynowski et al., 2018). A Polish study comparing data from five publicly available sources: 1) public statistics, 2) the national land surveying agency, 3) satellite imagery (Landsat data), 4) the Urban Atlas, and 5) the Open Street Map found that the most commonly used data source - public statistics (1) - excluded many types of greenspace (i.e. informal greenspaces and brownfields) creating inaccuracies in spatial extent, whereas the most comprehensive dataset was from their national land surveying agency (Feltynowski et al., 2018).

Resources typically used for creating spatial datasets of urban green spaces include: Open Street Map (OSM); satellite imagery (Landsat, Sentinel etc.); orthophotomaps; LiDAR; Urban Atlas; and CORINE which are then typically geoprocessed in a GIS environment (Feltynowski et al., 2018). However, it is important to note, that extracting green space polygons from OSM using GIS software will be successful only if the case study area has been well drafted by OSM users. These polygons identify, generally, urban green public spaces, parks, pitches and their perimeters are not dependent on the availability of trees, grass and other vegetated surfaces. Core indicator review Env56-RS has further detailed information on mapping using remotely sensed data. To differentiate private and public green space, data sources are again an important concern because, for instance, Landsat data cannot distinguish private from public UGS, while OSM data does not depict private UGS (Le Texier et al., 2018). It may therefore be necessary to undertake a manual exercise in order to evaluate and define public versus private greenspaces, for instance consulting land ownership maps (Feltynowski et al., 2018). Calculation of green space per capita depends on the spatial resolution of the data used (e.g. Landsat). With ArcGIS or QGIS it is possible to make a supervised classification. Another option is to use Normalized Difference Vegetation Index (NDVI), which is not as complicated as supervised classification, but provides useful data. When using open LANDSAT image gallery, NDVI is one of the simplest algorithms and enables calculation of green space in ArcGIS, where it is possible to extract surfaces having $0{,}3 < \text{NDVI} < 0{,}8$. This will define all the "vegetated surfaces", however permeable surfaces and unsealed soils not covered by trees, bushes and shrubs will not be identified as green spaces.

An example method published by the European Commission (Pafi et al., 2016), extracts green areas >0.25ha in a city from the European Settlement Map (2016 release but a 2019 release is now available) at 10 metre resolution, and takes the total population of the city and number of inhabitants data from the 'EU 100m pop mosaic Global Human Settlement Layer' (GHSL), along with the best available input census data for a city. This data can then be used to estimate green area in relation to population. Greenspace per capita can be calculated as the total green area in hectares in the city divided by one 100,000th of the city's total population (Bosch et al., 2017; Wendling et al., 2019), or green area per capita in m^2 (Pafi et al., 2016). Kabisch et al. (2016) undertake a number of greenspace availability analyses in relation to city population using the European Urban Atlas land cover dataset (https://www.eea.europa.eu/data-and-maps/data/urban-atlas).

Alternatively, the Integrated Landscape Map (ILM) methodology uses open-source, high spatial and temporal resolution data with global coverage (e.g. the OS Mastermap Greenspace layer (see link below) and Sentinel S2A data) to generate a composite spatial dataset that can classify land cover in a way that produces a more refined green infrastructure map for cities (Dennis et al., 2018). This method has the capacity to include public and private green (and blue) spaces and overcomes some of the shortcomings of the large minimum mapping units of other datasets (Dennis et al., 2018). ILM uses a classification system involving seven thematic land-use types coupled with five land cover values which can be used to more accurately investigate social-ecological relationships and measure and represent the landscape qualities of urban environments (Dennis et al., 2018).

Examples of publicly available mapped greenspace data include UK public greenspace datasets, available (under licence) from https://www.ordnancesurvey.co.uk/business-and-government/products/os-mastermap-greenspace.html and Scotland's Greenspace Map (a mapping project of public greenspaces) available from https://www.greenspacescotland.org.uk/greenspace-map.

Mears and Brindley (2019) provided several methodological recommendations for measuring green space distribution and provision, including taking steps to capture the relevant neighbourhood, as experienced by residents, as accurately as possible. They defined greenspace provision as the total area of greenspaces with at least one access point within a specified distance of each address point or population centroid. For their methodology, the whole area of greenspaces with an access point within the distance were included, rather than just the area within that distance, as the distance bands were determined considering how far people will travel *to* greenspaces, rather than *within* them. Provision was assessed at the same distance buffers and using the same buffer construction methods (network, straight-line) as for accessibility and the areal coverage provision measure was calculated using the area of the intersect between urbanised output levels and greenspaces (Mears and Brindley, 2019).

Public participation opportunities to engage with greenspace area mapping include the freely available GLOBE observer app https://observer.globe.gov/about/get-the-app. This enables citizen scientists to photograph the landscape with their smartphones, identify the kinds of land cover they see around them, and then match their observations to available satellite data. Users can also share the knowledge of the local environment around them and how it has changed. The "Adopt a Pixel" initiative is designed to fill in details of the landscape that are too small for global land-mapping satellites to see. Manchester City's citizen science project 'My Backyard Survey' http://mybackyard.org.uk/index.php was used to provide data on the extent of greenery in private residential gardens as part of a scheme to map citywide greenspaces. This involved an online questionnaire gathering data on the proportion of greenspace in gardens and how residents value their gardens. This improved estimates of actual greenspace in the city, although much of this would probably not be publicly accessible (a target for this indicator). Brown et al. (2018) provided an evaluation of participatory mapping methods to assess urban park benefits, designing an internet-based public participation GIS (PPGIS) survey and using household and volunteer sampling to identify the type and locations of urban park benefits.

Data on greenspace area collected in these ways can be used to:

- Quantify the distribution of greenspace across target areas and prioritise nature-based solutions implementation for areas deficient in public greenspace;
- Track trends in public greenspace availability in relation to nature-based solutions implementation;
- Support the equitable distribution of greenspace through urban planning for environmental, social and economic benefits;
- Provide underpinning data for other indicators such as ecosystem service mapping, stormwater management, biodiversity mapping, etc.

Scientific solid evidence: Relatively comprehensive and accurate greenspace datasets provide solid evidence, although there can be limitations in terms of capturing areas smaller than 0.25ha. It is important that a consistent methodology for evaluating greenspace area is used by a city to avoid overstating/underestimating actual greenspace availability. A weakness of this indicator is it does not capture the quality/health of the greenspace which would influence ES benefits.

Level of expertise: Accessing the public datasets should be relatively straightforward. Experience of working with large datasets related to remotely sensed, climatic and environmental parameters as well as their statistical analysis using tools is important. Knowledge of GIS techniques such as multi-criteria evaluation and sensitivity analysis are also desirable.

Cost: Some map datasets and satellite imagery are freely available online, others involve a licence fee and higher resolution imagery comes at increasing cost. There would be costs associated with acquiring GIS software if not already available, and GIS specialists if not available in-house.

Effort: Would depend on the level of in-house expertise available and the scale of area being analysed, availability of suitable data, and level of automation of analysis.

Participatory process: Citizen participation could be through a PPGIS tool such as the GLOBE app or a study such as Manchester's My Back Yard which can provide more detailed greenspace data to augment RS data.

Data availability: There can be existing greenspace map data available (for example in the UK under licence - OS Mastermap Greenspace Layer) as well as in open-access format (OS Open Greenspace Layer), and international satellite data available online from the Copernicus Scientific Data Hub (scihub.copernicus.eu/dhus). There may be variation in terms of spatial resolution available.

Geographical scale: City-scale typically, due to the per capita component of the indicator, but also possible to use the data to monitor local-level changes in greenspace in relation to local population levels.

Temporal scale: Depending on the data available and the purpose of the exercise, could produce a current snapshot or a temporal view of change, although analysis of past trends can be a challenge if historical data is not available in a suitable resolution.

Synergies: Synergies with other greenspace mapping indicators, and the data can be used as an index for other environmental and health/wellbeing indicators, for instance proportion of greenspace and health and wellbeing (Van den Berg & Van den Berg, 2015); UHI reduction by greenery (Heusinkveld et al., 2014).

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches. However, this feature indicator can utilise metrics detailed for core indicator Env56 (Bluespace area) as well as methods described for other mapping/accessibility indicators such as Env41 (Greenspace accessibility). For more detail on relevant earth observation, remote sensing and modelling approaches, including those used on past and current EU projects, see: Env56_RS on Documenta.

Original reference(s) for indicator: Eklipse

Reference (s):

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Synergies

Heusinkveld, B.G., Steeneveld, G.J., Hove, L.V., Jacobs, C.M.J. and Holtslag, A.A.M. (2014) Spatial variability of the Rotterdam urban heat island as influenced by urban land use. *Journal of Geophysical Research: Atmospheres*, *119*(2), 677-692.

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2.2.10 Local food production (Env58)

Umbrella: Food production

Indicator: Local food production

Code: Env58

Description: A measure of the share of food consumption produced within a 100 km radius.

Metric(s): Local food production is a provisioning ecosystem service in cities. Food production can take place in peri-urban fields, residential gardens, and in community gardens and allotments (Gómez-Baggethun et al. 2013). Though only a small proportion of food consumed is produced in cities, localising food production can make cities more sustainable and resilient (McPhearson et al. 2014). Urban agriculture (UA) and community gardening can potentially decrease food miles measured as the distance between production and consumption, thus lowering fossil fuel use and transportation costs (McClintock 2010). Urban food production can also strengthen a sense of community, reconnect consumers with food producers, increase awareness of the environment and human health (McPhearson et al. 2014), and keep money circulating locally (McClintock 2010). Evidence of the value of own-grown fruit and vegetable production in terms of ecosystem services is increasing (e.g. Edmondson et al. 2014; Speak et al. 2015; Kortright & Wakefield 2010), although quantitative data to enable realistic estimates of the contribution own-grown food is lacking (Edmonson et al. 2019).

Short food supply chains and local food systems have been gaining interest in the EU and one definition given states they are ‘a food system in which foods are produced, processed and retailed within a defined geographical area' (depending on the sources, within a 20 to 100 km radius approximately) (Augere-Granier 2016).

The CITYkeys indicators document defines local food production as ‘production within 100 km of the city to which the project is related’ and the recommended metric for measuring this is: (food produced in 100 km radius (tons) / total food demand within city (tons)) * 100. Food consumption values have been estimated as 770 kg per person a year in Europe (EEA, 2005). The food demand can then be calculated by multiplying the number of citizens with 770 kg. Food production values can be extracted from crop statistics and animal populations, but this is only available at NUTS2 level (Eurostat 2015) and has to be disaggregated from the database. There are overlaps with metrics for Env59, therefore if resources allow a city specific GIS analysis of UA land, as detailed in Env59, this could be used to provide a measure of food produced within 100 km radius.

Foodshed analyses attempt to capture the feasibility for a local region to be able to provide enough agricultural products to feed its population (Butler, 2013). The matrix below (Figure 1), taken from Butler (2013) provides an overview of attributes used in key research publications on conducting foodshed analysis (Blum-evitts 2009; Peters et al. 2008; Desjardins et al. 2010; Giombolini et al. 2011). A further method for estimating local food capacity proposes: 1) calculating local production and consumption for aggregated categories of food products, to determine overall local capacity, then 2) conducting more detailed assessments of local production of specific, locally significant foods (Timmons et al. 2008). A criticism of the foodshed analyses approach is the tendency to simplify understanding of localization feasibility to matching supply with demand within an area, without considering mediating factors like trade and transportation linkages (O’Sullivan 2012).

	Peters et al.	Giombolini et al.	Blum-Evitts	Desjardins et al.
Area of Study	New York State (1 state)	Willamette Valley, OR (1 watershed)	Pioneer Valley, MA (3 counties)	Waterloo Region, Canada (1 regional municipality)
Goal of Study	Determine the *potential* ability of NYS agriculture to feed NYS pop.	Determine the *current* ability of WV agriculture to feed WV pop.	Determine current and potential ability for PV agriculture to feed PV pop.	Estimate capacity to improve nutrition of pop. through local agriculture
Measure of Food Production	Model using soil and landuse data	Last 5 years of agricultural yields (OSU Extension)	Current production: Census of Agriculture (USDA) Potential production: model using soils and landuse data	Estimate based on soil, climate, amount of available land
Measure of Food Consumption	Complex equation accounting for 42 different diets to produce per capita area of land required	USDA "Dietary Guidelines for Americans"	Consumer Expenditure Survey (stats on household purchasing habits)	Optimal food consumption based on Canada's Food Guide (Health Canada). Focus on foods currently under-consumed
Calculation of Distance travelled	Euclidean Distance between production zones and population centers	none	none	none

Figure 1. Matrix of attributes of the Foodshed Analysis studies taken from Butler, 2013.

A Metropolitan Foodshed and Self-sufficiency Scenario (MFSS) model has been developed, which combines regional food consumption and agricultural production parameters in a data-driven approach to assess the spatial extent of foodsheds, as well as the theoretical self-sufficiency of the communities they serve (Zasada et al., 2019). The model differentiates between food groups, food production systems, levels of food loss and waste as well as food origin. The authors propose that the tool enables the ex-ante assessment of the consequences of spatial changes within metropolitan food systems, on both demand and supply sides.

To more accurately quantify yields achieved by own-growers, Edmonson et al. (2019) have proposed a citizen science approach, in conjunction with Geographic Information Systems (GIS) and fieldwork. This involves mapping allotments/potential allotment space using GIS, ground-truthing for food cultivation, and development of a citizen science app called MYHarvest (https://myharvest.org.uk/) to collect yield data. This will provide the first comprehensive UK dataset on own-grown production for use by research scientists, policy-makers and the public.

Questionnaires followed by face-to-face interviews have been used to gather qualitative data on food growing in residential gardens to assess how edible backyards can contribute to community food security (Kortwright and Wakefield 2010).

Bristol City carried out a baseline study of the food systems that serve Bristol, including 'local food supply' – how much food comes from within a 50-mile radius (Carey 2011). This includes a detailed account of the data used to assess local food provision.

Methodologies for gathering accurate data on local food consumption are limited. Conner et al. (2013) collect data from a variety of sources to estimate current local consumption of food (e.g. U.S. Census non-employer data for food manufactured in Vermont by small-scale businesses, USDA National Agricultural Statistics Service figures measuring food sales direct to consumers, and direct inquiries to several types of stakeholders to fill data gap) but they acknowledge a lack of data from certain sources was a significant constraint in their study.

In order to reveal the spatial distribution of urban farming in cities, remote sensing provides spatially consistent data sets that cover large areas with both high spatial detail and high temporal frequency. Remotely sensed satellite data can provide an alternative to more limited traditional ground-based systems of production estimation and offer timely, objective, economical, and synoptic information for crop monitoring (Calvão and Pessoa, 2015). Remote sensing to estimate vegetation quantity and condition for the development of physiology-based plant growth models can be used, however the lack of available data means this has had limited application at scales larger than field scale. Instead, remote sensing vegetation characterization has developed using empirical or semi-empirical relationships between plant biophysical parameters and arithmetic combinations of reflectance from different spectral bands into a single metric, the so called “vegetation indices” (Calvão and Pessoa, 2015). Vegetation indices (VIs) have been found to be related to a number of vegetation biophysical parameters such as biomass, Leaf Area Index (LAI, the total one-sided area of photosynthetic tissue per unit of ground surface area), percent vegetation cover, fraction of absorbed photosynthetically active radiation and crop yield (Brown and McCarty, 2017). A major weakness of VIs is that relationships are often site-specific and thus their extrapolation to new areas is not always feasible or recommended. Nonetheless, remote sensing provides an efficient tool to monitor long term farmland changes in urban/ peri-urban areas, while the GIS environment provides a framework for spatial analysis and modelling based on geographic principles and seeks to integrate the analytical capabilities to broaden the understanding of the real-world system.

Some of the metrics in indicator Env59 ‘cultivated crops’ may overlap with this indicator.

Data on the performance of nature-based solutions in relation to local food production collected in these ways can be used to:

- Quantify the amount of food production within a city;
- Quantify the proportion of food consumption in a city produced locally (within a set distance);
- Assess performance in relation to targets for increasing the proportion of food consumed from local sources;
- Assess local food production potential to reduce carbon footprints associated with transport costs;
- Assess social equality in relation to locally produced food;
- Support the development of new food growing sites to support local food sourcing.

Scientific solid evidence: Figures based on Unalab’s calculation represent a coarse estimation rather than solid scientific evidence. Apps such as MYHarvest can help quantify local food production. Nonetheless, Conner et al. (2013) highlight the difficultly of gathering more accurate ‘actual’ figures of consumption of locally produced foods. The extents of foodsheds used in foodshed analyses have often been constrained by data availability rather than being driven by key variables such as geography, distribution/transport or markets and can over-simplify networks of food production and consumption (Blum-evitts 2009; O’Sullivan 2012). Satellite remote sensing techniques have been widely used in detecting and monitoring land cover change, including urban farming, at various scales with useful results (Atzberger, 2013; Bégué et al., 2015; Brown and McCarty, 2017; Parece and Campbell, 2017; Saha and Eckelman, 2017; Schollaert et al., 2019; Stefanov et al., 2001; Russo et al., 2017). Recently, remote sensing has been used in combination with Geographical Information Systems (GIS) and Global Positioning Systems to assess land cover change more effectively than by remote sensing data only. It has already proved useful in mapping urban areas, and as data source for the analysis and modelling of urban growth and land use/land cover change (Herold et al., 2003). In the meantime changes in urban farming in developing nations can be quantified by coupling remote sensed data with available historic information from archival area photography and other sources in a GIS environment.

Level of expertise: No specialist expertise for applied approaches is needed, unless GIS is used. The interpretation of remote sensing data requires knowledge of the spectral properties of different constituents of the Earth's surface as well as their variation caused by external factors. The spectral characteristics of different plant species must be known for accurate estimation of biophysical parameters such as biomass and productivity from remote sensing methods (Calvão and Pessoa, 2015; Camacho-De Coca et al., 2004). Training is an integral component to bridge the gap between remote sensing professionals and end users. Remote sensing involves sophisticated technology, and specialized training is required to process the data, convert it into information, and interpret the results. Many agencies and organizations either lack the financial resources to provide such training or do not understand the importance of periodic retraining for technical staff.

Cost: For applied approaches costs are largely related to hiring someone to gather the data from various sources if this cannot be covered by staff in-house. Remote sensing techniques provide spatially consistent data sets and allow the current size of city farmlands to be rapidly determined and mapped at relatively low cost. Remote sensing can be less expensive than field-based mapping efforts, however, the cost of some high resolution remote sensed data can still be prohibitive.

Effort: Trying to calculate actual consumption of locally produced food can be a fairly labour-intensive task. Remote sensing approaches must consider the technical limits on feature discrimination, the requirement of high levels of technical expertise, and the need for information to calibrate and verify remote sensing results, which can require effort and represent a limitation (Turner et al. 2003).

Participatory process: Engagement with 'locavores' could be embedded into the indicator to deliver a form of public participation that could data on locally produced and consumed food. The MYHavest app engages local own-growers. Hodbod et al. 2019 propose an approach for combining participatory methods with remote sensing to provide a more holistic understanding of ES change, including local food production. Participatory mapping in focus group discussions can identify traditional ecological knowledge regarding what ES were present, where, and their value to communities. Obtained traditional ecological knowledge can then be integrated with satellite imagery to extrapolate to the landscape-scale.

Data availability: Data availability on actual local food production/consumption is likely to be limited (Conner et al. 2013) and therefore based on data disaggregated from national/regional figures. A large volume of remotely sensed images at different temporal and spatial resolutions are available in many countries and international agencies (Huang et al., 2018). LiDAR and radar sensors pose other constraints to availability such as cost and lack of analytical monitoring standards. When classifying remote sensing data to produce a map of vegetation, the individual features belonging to a particular class of interest must be large with respect to the resolution of the imagery. For example, a stream that is 10 metres wide could not be detected in an image composed of cells of 1-kilometre spatial resolution. In addition, and crucially, the feature being observed must have a sufficiently unique spectral signature to be separated from other types of features. For example, it may be difficult to distinguish secondary from primary forest without additional supporting data.

Atmospheric phenomena, mechanical problems with sensors, and numerous other effects can distort the input data and therefore the results, although algorithms and models to correct these distortions are improving continuously. Cloud cover is the most common impediment to seeing the earth's surface with optical sensors and is particularly problematic in some regions of the world where cloud cover is common. Haze and thin clouds are less problematic, but can result in distortions of feature spectral signatures, resulting in greater error or more expensive and complex processing.

Geographical scale: Applied methods typically examine patterns at the city scale, although these approaches could be carried out on a neighbourhood scale if there was reason to target a specific development or area. Remote sensing allows the acquisition of data in areas difficult to reach and at different resolutions (Calvão and Pessoa, 2015; Wang et al., 2013), and agricultural monitoring from space has historically been extensively utilized (as early as the 1930s) over a wide range of geographic locations and spatial scales (Atzberger, 2013). Thus, remote sensing can provide a detailed insight into the spatial dynamics of the processes of urban growth and land use change.

Temporal scale: Applied methods can be used to generate a snapshot (baseline) ads well as monitoring change over time following nature-based solution implementation. Remote sensing can provide consistent historical time series data. Future repeated observations will, over time, allow detailed quantification of changes in farmland sizes and types of crops produced. Thus, remote sensing can also provide a detailed insight into the temporal dynamics of the processes of urban growth and land use change.

Synergies: This indicator has strong synergies with health and wellbeing indicators, for instance through education about nature and healthy food, and environmental indicators measuring greenhouse gas emissions from food miles. Combining remote sensing and GIS for urban/peri-urban farmland mapping enables data overlay, which is significant for effective urban land management.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: UnaLab

Metric reference(s):

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2.2.11 Cultivated crops (Env59)

Umbrella: Food production

Indicator: Cultivated crops

Code: Env59

Description: Vegetables produced by urban allotments and in the commuting zone (ton or per kg/ha^{-1}/year^{-1})

Metric(s): Cultivated crops offer a provisioning ecosystem service in cities. Fruit and vegetables can be produced in urban allotments, on green roofs, and in the rural-urban fringe (Gómez-Baggethun et al., 2013). Metrics typically measure the surface area of allotments and food production statistics, most often yield (Maes et al., 2016). Cultivated crops produced in cities are broadly defined in Maes (2016) as 'vegetables produced by urban allotments and in the commuting zone', and the service providing units include crop fields, fruit trees, private and public gardens. Recommended metrics in Maes (2016) are:

- production of food in tons or kilograms (kgs) per hectare (ha)/year
- surface of community gardens/small plots for self-consumption (ha)

Manual analysis of high-resolution images in Google maps in conjunction with GIS can be used to identify and map public and private spaces of food production (Taylor & Lovell, 2012). This involves two strategies: (1) the visual analysis of aerial images of previously documented allotments and community gardens; and (2) the manual extraction and classification of undocumented sites from high-resolution aerial images of the city in Google Earth. Known sites can be geocoded and reference images used to identify and digitise previously undocumented food growing sites. Visual markers - orthogonal garden layout, vegetation planted in rows or in beds separated by paths, bare earth or mulch between individual plants or rows of plants – provide indicators of food production (this was confirmed by ground-truthing a large number of accessible sites). Once all sites have been digitised as polygons in Google Earth, they can be imported into a GIS environment for calculation of food production area in m^2 or ha.

Formal institutions such as the Food and Agriculture Organization (FAO) of the United Nations and the U.S. Department of Agriculture (USDA) are using online, self-registration techniques to gather information about urban agriculture across different cities. Data mining techniques can be used to identify UA locations in cities and then remote sensing techniques such as NDVI, NDWI and EDI, once UA locations are known, can be used to monitor UA, but RS data alone can have limitations in terms of accurately detecting UA from other vegetation types (Brown & McCarty, 2017). A free platform called OneSoil was recently launched online, providing an interactive digital map of agriculture data detected using AI. The map provides data on hectarage, crop and field score for the three years between 2016 and 2019 for 55 countries in Europe and USA. On a smaller scale, initiatives like Fruit City can provide a more informal mechanism for community mapping of city food production.

The National Society of Allotment and Leisure Gardeners Ltd (NSALG) states an expected yield value of 31.28 tonnes of vegetable per ha on an average allotment plot (based on average size of an allotment plot being 30 x 100 feet, or 0.0278 ha for 259 days growing season), although a more labour-intensive study suggested a yield of 40 tonnes per ha can be achieved (Tomkins, 2006). Once spatial data has been collated, these metrics could be used as a proxy for yield in the UK. A modelling study in Boston in North America used more conservative average yield values of 13.5

tonnes/ha^{-1}/year^{1} for conventional urban garden food growing and 195 tonnes/ha^{-1}/year^{1} for hydroponic rooftop food growing (Saha & Eckleman, 2017). Research for Oakland California in the US used calculations based on average yields under three different management practices: conventional at 24.71 tons/ha); low-biointensive at 37.07 tons/ha; and medium-biointensive at 61.78 tons/ha (McClintock et al., 2013). Weidner et al. (2019) give the following yield figures: average by community gardens 12-26 t/ha; horticulture in developed countries 25-33 t/ha; professional and intensive UA 54-71 t/ha. A new citizen science app called MYHarvest (https://myharvest.org.uk/) was developed and launched to enable the collection of more accurate yield data from own-grown food.

Knowing where food is grown and in what form can help planners and local authorities identify gaps in the spatial distribution of existing food growing sites, where urban agriculture is not occurring but possibly should be because of poverty, lack of food access, or public health problems and can also help to identify valuable local resources for the development of new sites and the enhancement of existing sites (Taylor & Lovell, 2012).

Metrics that only concern measuring yield in weight/surface area of plots may not necessarily be capturing the quality of the food produced or the quality of the allotment system producing the food (for instance in environmental terms management practices such as pesticide/fertiliser use and emissions, water use, soil erosion, and biodiversity etc). Moreover, there might be strong links with social and health & wellbeing indicators that are missed by adopting a yield-only approach.

In terms of evaluating a city's capacity for UA, a study of vacant lots, open space, and underutilized parks with agricultural potential using GIS and aerial imagery can be undertaken to calculate the potential contribution of these sites to a city's vegetable production needs (McClintock et al., 2013). Other city level estimations can be undertaken looking at various other urban landcovers, including rooftops (Kremer & Liberty, 2011; Ackerman et al., 2014 and Grewal & Grewal, 2012). A geospatial methodology can be used for estimating maximum food crop production capacity (MFCPC) of a city using remote sensed data and Object-Based Image Analysis (Richardson & Moskal, 2016). A study of urban agriculture in the city of Milan (Italy) provides an example of a spatiotemporal quantification for assessing food self-provisioning potential (Pulighe & Lupia, 2019).

Recent developments in remote sensing technologies coupled with GIS have significantly increased the capability of conducting farmland mapping. There are a variety of methods used for farmlands mapping that could potentially be applied to urban food production (Table 1). Remote sensing techniques can also be used to distinguish between farmlands and farmlands use. Satellite images facilitate the estimation over a wide area the impact of farmlands change on nearby facilities. Land-cover classification can be derived through remote sensing for all allotments in the city and show structural and morphological diversity for allotment gardens. A study by Dongus and Drescher (2006) used remote sensing and GIS to map out vegetable production in open spaces.

Table 1. Summary of farmlands mapping methods (Source: Addo, 2010; Seto et al., 2002)

Methods	Types	Data sources	Advantages	Disadvantages
Photogrammetric	Analog/ Analytical	Aerial photos	Relatively fast	Expensive
	Digital	Aerial photos/ Multispectral imagery	Accurate Wide coverage	Photo distortions
Digitising	Manual/Scanning	Historic maps	Ability to correct errors	Labour intensive Slow

			Correct distortions Reliable	Depend on map accuracy
Physical survey	Planetable	Field measurement	Higher accuracy	Very tedious Time consuming Expensive

Studies (Addo, 2010; Clinton et al., 2018; Nduati et al., 2019) show advances in the use of remote sensing technology to develop an integrated monitoring technique for urban farmlands. Normalized Difference Vegetation Index (NDVI) can be used as an environmental metric to track changes in vegetation phenology, assess vegetation stress and health, and, in urban areas, to separate vegetation from impervious surfaces. NDVI has a positive relationship with net primary production. Parece and Campbell (2017) used NDVI product from U.S. satellites (Landsats 5, 7, and 8) to assess urban community garden sites. They confirmed that this approach can be applied by conducting a time series analysis over the growing seasons (May–September) for several cities in the USA. Their results show that establishment of community gardens alter seasonal NDVI trajectories, sometimes with initial declines, but then increasing over time. Furthermore, NDVI profiles reveal the vigorous character of urban agriculture.

Nduati et al. (2019) show that daily MODIS 250 m NDVI and intermittent Landsat NDVI images can be fused, to generate a high temporal frequency synthetic NDVI data set. In their study, the identification and distinction of upland croplands from other classes (including paddy rice fields), within the year, was evaluated on the temporally dense synthetic NDVI image time-series, using Random Forest classification. As result, they achieved overall classification accuracy of 91.7%, with user and producer accuracies of 86.4% and 79.8% respectively, for the cropland class. Cropping patterns were also estimated, and classification of peanut cultivation based on post-harvest practices was assessed. Image spatiotemporal fusion provides a means for frequent mapping and continuous monitoring of complex urban and peri-urban agriculture in a dynamic landscape.

As vegetables and fruits are the most commonly grown crops in urban and peri-urban agriculture (UPA). Mapping of major staples such as rice, wheat, maize, and soybeans using remote sensing has been successful due to the spatial scale of production and the relatively uniform regional cultivation and management practices. However, varied crop types, crop varieties, tillage practices, and planting times characterize UPA crop production, resulting in misaligned phenological development and thus necessitating multi-temporal classification approaches which utilize time-series data. Cropland mapping approaches that use time-series data have been shown to perform better than single-date methods.

Nonetheless, one of the main challenges of time-series analysis and classification for cropland mapping requires timely a priori knowledge of the cropland landscape for labelling of clusters (in the case of unsupervised classification), and derivation of the signature files to guide supervised classification models (Belgiu et al., 2018; Gómez et al., 2016; Matton et al., 2015; Nduati et al., 2019). Generally, satellite images are, for most applications, processed and analyzed retrospectively unless the data acquisition and processing are real-time or near real-time, as is the case for meteorological monitoring and prediction applications. The most reliable source of reference data is in-situ field observations, collected through farmer surveys and field campaigns (Matton et al., 2015). However, the acquisition of this data, especially for large areas and heterogeneous croplands, is an expensive and time-consuming exercise (Matton et al., 2015). The collection of ground-truth information for urban and peri-urban agriculture croplands, therefore, remains a daunting task that requires an investigation into the application of novel approaches, such as crop-specific post-harvest practices, for reference data acquisition.

Another challenge of time-series analysis is missing data due to atmospheric artefacts, which results in an irregular sampling frequency of the phenomena of interest (Belgiu et al., 2018; Gómez et al., 2016). At any one time, approximately 35% of the global land surface is under cloud cover, thus limiting information retrieval and meaningful interpretation of optical satellite data (Shen et al., 2015). Various techniques have been developed to deal with cloud cover and other causes of missing data, such as sensor failures (Gómez et al., 2016). Shen et al. (2016) broadly classified these methods into spatial, spectral, temporal, and hybrid categories, which vary by the type of images they can be applied to, and the sources of information used to fill the missing data. The synthesis of multisource data with complementary information; data integration in the spatial, spectral, and temporal domains; and development of efficient, accurate, and task-oriented algorithms are areas of potential improvement for missing data reconstruction. The last decade has seen a proliferation in the development of multi-sensor image fusion or blending methods that exploit redundant and complementary information in the spatial and temporal dimensions of remote sensing data, to enhance interpretation and classification accuracy (Zhao et al., 2018). Fusion of high spatial–low temporal resolution images (e.g., Landsat 30 m) with low spatial–high temporal resolution satellite images (e.g., MODIS 250 m or 500 m), to generate synthetic high spatial–high temporal resolution data, can enable mapping of small, fragmented, and spatially and temporally heterogeneous UPA croplands at a regular frequency (e.g., seasonally or annually).

In any case, the generation of comprehensive crop classification maps is usually hampered by limits in the technical capabilities of remote sensing systems (e.g. spectral or radiometric resolution), with regard to high spectral similarities of certain crop types (Waldhoff et al., 2017). Varying crop development (e.g. winter/summer crops) or weather conditions (Whitcraft et al., 2015) are additional aspects, which hinder the crop differentiation. These factors necessitate multitemporal observations to capture and differentiate all crop types. Such approaches are often enhanced by integrating expert-knowledge in the form of production rule-based methods.

As-syakur et al. (2010) have also used NDVI from remotely sensed imagery to quantify primary production in an urban area, but again the spatially fine-scale and heterogeneous nature of urban agriculture plots adds complexity to NDVI (As-syakur et al., 2010; Parece and Campbell, 2017). In large agriculture plots, an individual pixel will typically represent a single crop species but urban agriculture generally involves polyculture, i.e. multi-cropping, and intercropping. Multi-cropping is defined as two or more crop species cultivated within the same unit area and intercropping as two or more species grown at the same time in close proximity (Parece and Campbell, 2017). Such practices are commonly used in community gardens as documented in studies by Yadav et al. (2012) and Li et al. (2013). Thus, any application of remote sensing to examine urban agriculture will likely encounter multi-cropping and intercropping, and record plots as mixed pixels (pixels representing integration of several different spectral features), preventing direct application of conventional remote sensing analyses.

Some of the metrics in indicator Env58 ‘food production’ may overlap with this indicator.

Data on the performance of nature-based solutions in relation to food production collected in these ways can be used to:

- Quantify the amount of food production within a city;
- Support the identification of existing sites with potential to support urban agriculture;

- Assess local food production potential to reduce carbon footprints associated with transport costs;
- Assess social equality in relation to access to grow-your-own schemes;
- Support the targeting of urban allotments to the communities with the greatest need.

Scientific solid evidence: For more applied methods, the robustness of evidence will be biased by how detailed existing data is on CGs in a city and the accuracy of census data. Similarly the accuracy of distance to CGs will vary based on the distance measure used. They can however represent a useful indicator basis for urban planning. Using ground-based survey methods to map urban farmlands can be inherently problematic and prohibitively expensive, influencing accurate assessment of the future role of urban farming in enhancing food security. Remote sensing, however, allows areas being used as urban farmlands to be rapidly determined at relatively low cost. Due to the propensity for multi-cropping/polyculture practices in urban farming, remote sensing approaches such as NDVI may not accurately discriminate such fine-scale heterogeneity, but can provide a time series analysis over growing seasons (As-syakur et al., 2010; Parece and Campbell, 2017), although the accuracy of this can be impacted by atmospheric artefacts and reliable reference data for labelling and classification (Belgiu et al., 2018; Gómez et al., 2016; Matton et al., 2015; Nduati et al., 2019). Both remote sensing and participatory approaches will have inaccuracies based on the quality and resolution of aerial photos and level of participation. A combination of the two approaches may provide the most reliable data.

Level of expertise: Participatory approaches typically require expertise in relation to development of an online platform and experience in organising community engagement projects. GIS expertise is needed for remote sensing approaches as well as technical expertise in handling and interpreting remotely sensed data. Managing even small quantities of satellite imagery requires specialized software, hardware, and training. The expertise and equipment often exist in-country, but not necessarily within the agencies interested in undertaking a monitoring programme. Fortunately, new software tools are making remote sensing data more accessible to non-specialists, and the possibilities for training are growing rapidly. Some remote sensing platforms (for example, hyperspectral, LiDAR, and radar) are largely or exclusively in the research phase of development and may not be in common use for some years. The number of experts who can work with these platforms is likely to grow in the future.

Cost: Some map datasets and satellite imagery are freely available online, but the comprehensive data needed for network-based measures potentially can involve a licence fee. Higher resolution satellite imagery can have a cost associated. There also would be costs associated with acquiring GIS software if not already available, and GIS specialists. The analysis of satellite remote sensing data can be a cost-effective way to generate up-to-date crop classification maps for larger areas at various scales (Atzberger, 2013; Waldner et al., 2015), however if this needs reliable reference data from in-situ field observations, the acquisition of this data can be expensive (Matton et al., 2015).

Effort: Manual feature extraction and classification required approximately 40 minutes per square kilometer of land area, and mapping the entire city of Chicago required approximately 400 hours of effort (Taylor & Lovell, 2012). Time-series analysis and classification for cropland mapping requires timely a priori knowledge of the cropland landscape for labelling of clusters (in the case of unsupervised classification), and derivation of the signature files needed to guide supervised classification models (Belgiu et al., 2018; Gómez et al., 2016; Matton et al., 2015; Nduati et al., 2019). In-situ field observations can be the most reliable data and necessary for calibrating/validating remote sensing approaches, but the acquisition of this data can be time-consuming (Matton et al., 2015).

Participatory process: Online portals for voluntary mapping of urban allotment distribution represent a potential participatory approach. Complementing remote sensing analysis using participatory mapping can help provide information for an initial land cover assessment (including food production), gain better understanding of how local land use might affect changes, and provide a way to engage local communities. Jacobi et al. 2019 and Zaehringer et al. 2018 propose an approach for combining participatory methods with remote sensing to provide a more holistic understanding of local food production by cultivated crops. Participatory mapping in focus group discussions can identify traditional ecological knowledge. Obtained traditional ecological knowledge can then be integrated with satellite imagery to extrapolate to the landscape-scale.

Data availability: Some greenspace map data is freely available for mapping distance within a commuting zone. Spatio-temporal data on crop types and on crop rotations at the field level for regional scales are rarely available. A rare example of multiannual crop maps are the Cropland Data Layers (CDL) for the Unites States, provided by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (Boryan et al., 2011). However, in most European countries, such information is not available to the general public, due to data protection laws. The lack of this information is a major drawback for regional agro-ecosystem modelling, since large uncertainties concerning management and site-specific matter fluxes arise. To reduce these uncertainties, usually only a few different prototype crop rotations are considered, which are based on expert-knowledge or designed according to good farming practice.

By combining the precise multiannual crop type data, a database for the spatio-temporal identification of crop sequences and crop rotations can be built. For crop mapping on a regional scale (larger than 1000 km^2), usually multispectral remote sensing data of moderate spatial resolution (ca. 10–30 m) is still the most reasonable choice. Nevertheless, many studies also demonstrate the potential of satellite-borne synthetic aperture radar (SAR) data (Bargiel and Herrmann, 2011, Hütt et al., 2016, Koppe et al., 2013, McNairn et al., 2014) and their combination with optical data (Blaes et al., 2005, Forkuor et al., 2014, McNairn et al., 2009, Lussem et al., 2016) for land use/land cover mapping.

Geographical scale: Typically analyses would be carried out at a city-scale, but could potentially be targeted at other administrative/neighbourhood scales. Remote sensing provides spatially consistent data sets that cover large areas with both high spatial detail and high temporal frequency to analyse the spatial distribution of urban farming in cities. Satellite remote sensing techniques have been widely used in detecting and monitoring land cover change, including urban farming, at various scales with useful results.

Temporal scale: Ideally assessment should be carried out before and after nature-based solution implementation. Following this, assessment should be carried out a regular intervals (e.g. annual, 5 yearly). Remote sensing provides spatially consistent data sets that cover large areas with high temporal frequency to analyse the spatial distribution of urban farming in cities. Remote sensing can also provide consistent historical time series data. Future repeated observations will, over time, allow detailed quantification of changes in the farmland sizes and types of crops produced. Thus, remote sensing provides a detailed insight into the spatial and temporal dynamics of the processes in urban growth and land use change.

Synergies: Strong synergies with health and wellbeing indicators and social cohesion indicators in terms of physical activity, bringing together people from different backgrounds, education about nature and healthy food. Also, synergies with other environmental indicators (e.g. biodiversity measures, water regulation and air temperature) and possibly economic indicators if enterprises emerge selling produce. Recently, remote sensing has been used in combination with Geographical Information Systems (GIS) and Global Positioning Systems to assess land cover change more effectively than by remote sensing data only. Combining remote sensing and GIS for urban peri-urban farmland mapping enable data overlay, which is significant for effective management.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: UnaLab

Metric reference(s):

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2.2.12 Intensity of landuse (Env61)

Umbrella: Land use mapping

Indicator: Intensity of land use

Code: Env61

Description: Measure of artificial area per inhabitant (m^2/person) - implement nature-based solutions to minimise artificial areas

Metric(s): The land take assessment produced by the European Environment Agency (2017) for 2006–2012 reports that "based on the average for the EU-28, 52% of all areas that changed to artificial surfaces were arable land or permanent crops in 2006". This means that several land cover types change to impervious cover, which in turn compromises the provision of important services provided by vegetation and soils, namely the storage and filtering of water, and the transformation of nutrients and contaminants —a direct call for the phenomenon to be monitored at proper spatial and temporal scales (European Environment Agency, 2017). Moreover, the latest assessment of Maes et al. (2019) revealed that now 22% of the surfaces in European cities are sealed; if only soil sealing in artificial areas is considered, 58% of urban surfaces are sealed (average values, in many cities the proportion of the impermeable surfaces is higher). This measure provides a state indicator of urban ecosystems in terms of built infrastructure intensity and can be used as an indicator of the condition of urban ecosystems by determining the ratio of built and green infrastructure (Maes et al., 2016). This includes metrics that quantify urban sprawl. Methods will largely concern identification of land cover and land use, therefore, the same metrics outlined for feature indicator Env63 (Land use mix) will apply here and should be reviewed in the first instance. Also relevant is core indicator Env81 (Soil sealing).

From mapping land use and land cover, land use intensity calculations can be derived as set out in the MAES Urban technical report (Maes et al., 2016):

- artificial area per inhabitant (m^2/person using latest city population statistics) or artificial surfaces as a percentage of the total municipal area;
- land annually taken for built-up areas per person (m^2/person);
- proportion of urban green space (%) (synergies with support of human health and well-being as well as connectivity of urban green infrastructure);
- proportion of impervious surface (%) (synergies with flooding – infiltration capacity, UHI);
- proportion of natural area (%) (synergies with support of urban biodiversity);
- proportion of protected area (%) (synergies with support of urban biodiversity);
- proportion of agricultural area (%); and
- proportion of abandoned area (%).

Other calculations related to land use that may be significant attributes for measuring urban form in relation to land use intensity include (from Wendling et al., 2019):

- Residential density: number of residents divided by their residential area (number/km^2) based upon population (census) and land use data (EEA, 2006; Siedentop & Fina, 2010);
- Percent of built-up area to describe urban sprawl pattern: built up area divided by total urban area, based on land use data (EEA, 2006; Siedentop & Fina, 2010);
- Share of low/dense residential areas (low density areas are areas with less than 80% of built-up areas i.e. buildings, roads and other structures): calculate as dense (low density) area /

total residential areas using land use data with dense and low density areas specified (EEA, 2006; Siedentop & Fina, 2010);
- Scattering Index to differentiate urban sprawl from compact urban expansion and characterize how urban patches are dispersed in the landscape (patches = urban areas laying less than 200 m apart): measure as number of patches / total area or number of patches / number of inhabitants using land use data with the urban patches delimited (Arribas-bel et al., 2011).

Loss of environmentally fragile land or gain due to nature-based solutions adding ecologically valuable spaces to cities can also be derived from land use data (Johnson, 2001).

The European Commission provide a database: UDP – artificial areas per inhabitant, 2010 – 2050, JRC LUISA Trend Scenario (European Commission, 2016) that includes an index measuring the surfaces of artificial area per inhabitant (in square meters) for a specific year, comprising built-up areas, which correspond to land classified as urban, industrial and abandoned urban and industrial. In addition to built-up areas, artificial areas include infrastructure and green urban leisure land classes which also should be included in the assessment of this indicator.

The increased quality and availability of satellite map data has given a better view of the form and extent of artificial areas, for example there are a number of algorithms and indices which can be used to distinguish the colours and patterns on maps, to discern between built-up areas and natural ground cover or water-covered surfaces (e.g. suggested by Faridatul and Wu, 2018). Moderate Resolution Imaging Spectroradiometer (MODIS) provides medium resolution maps (with resolutions of about 500m) that can be used to map urban built-up areas across regions. Higher resolution maps such as Quickbird (around 2m or less and) can be used at the city level to estimate different land use types, based on the colours, shapes, and ground cover. Alternative maps do not even necessarily rely on daylight, for instance night-time light data using Defense Meteorological Satellite Program Optical Line Scanner (DMSP-OLS) at a higher resolution and greater electromagnetic spectrum coverage, Visible Infrared Radiometer Suite (VIIRS), allow for distinguishing the form and brightness of built-up areas by recording ambient light. These maps have not only been used to track urban form and expansion, but also to estimate the intensity and location of economic activity within cities.

In order to classify urban land covers, various image classification approaches can be used (Doustfatemeh and Baleghi, 2016; Le and Wan, 2015; Faridatul and Wu, 2018). Use of different spectral indices has proved to be an effective alternative means of mapping land covers. For example, the normalized difference vegetation index (NDVI), developed by Rouse et al. (1973), extracts vegetation and biomass information. The soil-adjusted vegetation index (SAVI) proposed by Huete (1988) separates vegetation and water in urban areas. The normalized difference water index (NDWI) developed by McFeeters (1996) delineates open water features in remote sensing images. The modified normalized difference water index (MNDWI) (Xu, 2005) enhances accurate water detection. And finally, the normalized difference built-up index (NDBI), developed by Zha et al. (2003) is widely used to map built-up urban areas. The indexed-based built-up index (IBI) (Xu, 2008; Zhang et al., 2016) delineate urban built-up features. In addition to the individual indices, different combinations of indices or modified indices have been developed and used to map land covers and define artificial areas (Li et al., 2015; Patel and Mukherjee, 2015). However, as confirmed by Faridatul and Wu (2018), the existing approaches have limitations in terms of classifying urban land covers, for instance separating impervious and bare land is still a challenge. Thus, they proposed three novel indices: the modified normalized difference bare-land index (MNDBI), tasseled cap water and vegetation index (TCWVI), and shadow index (ShDI) and addressed the above-mentioned limitations of existing methods and enabled automated classification of land cover.

Population-based estimates of urban artificial areas aim to refine the application of available population census data. This approach uses known population centres and applies a grid across administrative boundaries (usually of about 1 km^2). It enables an estimated distribution of the population within built-up and non-built-up areas within each grid cell.

Evaluating the intensity of land use can generate data on:

- Patterns of urban densification/sprawl;
- Changes in relation to loss/increase of permeable surfaces;
- The importance of land use configuration for shaping urban climate conditions;
- The design of cities to ensure integration of nature-based solutions to deliver a balance of social, economic and environmental benefits.
- Targeting of nature-based solutions in areas with greatest land use intensity.

Original reference(s) for indicator: UnaLab

Scientific solid evidence: Accuracy will be influenced by the quality of land use and land cover data that is used and the mix of measures that are used, but can provide robust and useful data on land use intensity (Siedentop & Fina, 2010).

Level of expertise: Expertise in relation to mapping and modelling/statistical analysis will be necessary and knowledge regarding applicable data sources (especially those related to remote sensing and GIS) and appropriate methods/measures for processing data will be needed.

Cost: Increasingly high resolution, high-quality data is becoming freely available (i.e. Open Street Map (OSM)) and the main costs would be associated with employing suitably experienced specialists/technology to analyse data if this is not available in-house. See indicator review for Env_42_RS for some commercial costs for newly acquired high resolution RS imagery.

Effort: More detailed land use intensity studies will be more data-intensive and time-consuming and effort will be directly related to the level of expertise available. Much of the effort associated is required up front, however. Once automated methods such as NDVI have been developed, re-running them on new aerial photos can be relatively low effort. Similarly, once a land use intensity map has been developed, updating it can be relatively low effort if links to good processes are established with planning departments. Although various land cover classification approaches are available (Doustfatemeh and Baleghi, 2016; Le and Wan, 2015; Faridatul and Wu, 2018), the selection of the best classifier is difficult because each of the methods has its own strengths and limitations and requires the related expert knowledge.

Participatory process: As described in Feature Indicator Review Env63, projects such as OSM and LandSense offer a mechanism for community participation recording land use.

Data availability: Land use and land cover data is widely available in the EU, depending on the resolution required (e.g. CORINE Land Cover data).

Geographical scale: Most studies reviewed examine data at the city scale, however more fine-scale analyses are possible for local planning contexts.

Temporal scale: Suitable for various temporal scales, although the availability of high-resolution historical data can sometimes be a barrier to studying past trends.

Synergies: Strong synergies with other land use and mapping indicators (e.g. Env63, Env42, Env55 etc) and soil sealing (Env81). Also, other environmental indicators (e.g. UHI, air quality, flooding etc.) and health and wellbeing indicators (i.e. active travel).

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2.2.13 Landuse mix (Env63)

Umbrella: Land use mapping

Indicator: Land use mix

Code: Env63

Description: Mapping the diversity of land uses in an area by measuring urban morphology and composition. This can include using a 'self-organising map' algorithm to visualise and map urban form and mix of land uses.

Metric(s): Land use mix refers to the heterogeneity of land uses in urban areas, with land use often simplified into categories such as residential, commercial, industrial, recreational, and agricultural uses (Croucher et al., 2012). Complementary land use in cities has been regarded as a sustainable development model that limits urban sprawl and can potentially benefit health and wellbeing by encouraging active travel. Nonetheless, as cities densify this can pose a threat to greenspace (ergo nature-based solutions) provision (Fuller & Gaston, 2009). Whilst a number of strategies to overcome this have been identified (Haaland & van Den Bosch, 2015), ensuring provision of sufficient, well-functioning greenspace/nature-based solutions as part of urban land use mix remains a major challenge. For this indicator to adequately address this challenge, it is crucial that greenspace/nature-based solutions are accounted for as accurately as possible when using metrics to measure land use mix. Some of the studies set out below use a very simplified range of land use categories that do not always explicitly include a greenspace category (for instance transport related studies) but have been included here as they provide indicative methodologies for evaluating land use mix.

A mixture of land uses has been shown empirically to encourage non-automobile-based modes of travel such as walking and bicycling, which in turn are seen as having a positive impact on public health and well-being (Tallen, 2008). Land use diversity is a key component of compact liveable communities where everything is within reasonable distances. This can range anywhere between 5 to 20 minutes of walking distance to a park, public space or a cluster of services. Exploring land use data supports the process of determining access to public spaces and institutions, parks or even vacant land for future development. This is helpful for establishing the number of potential destinations in a neighbourhood and for drawing a more general conclusion on walkability. While public spaces and local centres act as anchors that allow people to meet and socialize, housing is the key to population density that actually brings people together.

The input data sets for land use/land cover classification studies typically use aerial data such as remotely sensed images acquired by sensors such as Landsat. The European Urban Atlas service offers a high-resolution land use map of urban areas (https://land.copernicus.eu/local/urban-atlas). In the UK, Digimap offers a collection of Ordnance Survey Products for free to academic institutions, and the land cover data can be supplemented with government land use data for instance via the Generalised Land-Use Database (GLUD), which allocates all identifiable land features on Ordnance Survey's OS MasterMap® into nine simplified land categories: domestic buildings, domestic gardens, non-domestic buildings, roads, paths, rail, greenspace, water, other land uses (largely hardstanding) and unclassified (DCLG, 2007). OpenStreetMap (OSM https://www.openstreetmap.org/) is a freely-licensed, global geospatial database built by a community of volunteer mappers that can provide an up-to-date Land Use Land Cover (LULC) resource free, and that for some cities can be considered as complete as a commercial data set (Gervasoni et al., 2016). Where data coverage is incomplete, it can be merged with a high-resolution product such as GlobeLand 30 (GL30) to generate LULC maps that are more accurate and up-to-date and have a more detailed nomenclature (e.g. more detailed urban classes) (Fonte et al., 2017). OSM provides a community driven participatory process to LULC mapping processes. Yang et al. (2017) in their study of mapping land-use and management practices, developed a robust regional land-use mapping approach by integrating OSM data with earth observation remote sensing imagery. This novel approach incorporates a vital temporal component to large-scale land-use mapping while effectively eliminating the typically burdensome computation and time/money demands of such work.

High-resolution remotely sensed images have the spectral and textural properties suitable to extract urban land use maps, using, for instance, object-based (Voltersen et al., 2014) or scene classification (Zhong et al., 2015) methods, although it can still be difficult to distinguish urban land use mix accurately using classification algorithms based on physical characteristics alone. For example, remotely sensed spectral and spatial features of business and commercial land uses are similar, consequently a combination of remote and socially sensed data can be advantageous in terms of distinguishing 'social' land use classes (Jia et al., 2018). Using high-resolution remotely sensed data and social features data derived from mobile phone positioning data (MPPD), Jia et al. (2018) generated a 'fused', six-class land use map of Beijing to increase accuracy: 1) residential, 2) business; 3) entertainment; 4) scenic areas; 5) open (including parks, outdoor locations etc.); 6) other (areas with limited human activities). The method was applied in two steps: first, a support vector machine was adopted to classify the RSI and MPPD; second, classification results were fused using a decision fusion strategy to generate the land use map. This method is also helpful for analysing the activity density in key zones during day-time and night-time to illustrate the volume and variation of people working and living across different regions.

Gervasoni et al. (2016) present a GIS-based land use mix analysis framework for urban planners using OpenStreetMap crowd-sourcing data and Kernel Density Estimation, with the degree of land use mix measured using the Entropy Index calculation. In terms of potential land use mix measures, the literature is extensive, particularly in relation to active transport (Manaugh & Kreider, 2013). Whilst a variety of different approaches are available, most contain two concepts either implicitly or explicitly – distance and quantity – and reflect how the quantity and proximity of one type of land use influences the utility of another (Song, Merlin & Rodriguez, 2013). Song, Merlin & Rodriguez (2013) reviewed a range of common measures of urban land use mix to understand their differences and identify their strengths and limitations, including landscape ecology metrics such as Percent/Proportion; Balance Index; Entropy Index; Herfindahl-Hirschman Index and so on. They categorise these as:

- 'integral' measures – which measure area-wide totals of land use types tend to reflect land use balance, or whether various land uses are present in equal proportion in the area as a whole (e.g. Percentages, the Balance Index, the Entropy Index and the Herfindahl–Hirschman Index); or
- 'divisional' measures – that examine at the finer level of district and tend to reflect evenness, or whether one district tends to look like another (Song, Merlin & Rodriguez, 2013).

Whilst integral measures are relatively easy to compute and understand, they have some significant limitations in terms of masking micro-scale variation and being sensitive to the size of area under analysis (Song, Merlin & Rodriguez, 2013). Divisional measures are sensitive to variations of land use patterns within an area, but not to variations of land use pattern within district boundaries, or typically to the spatial arrangement of districts relative to each other, and depending upon the geography of the division (i.e. the size and shape of the districts), the same mixed use measure will produce different measurement results (Song, Merlin & Rodriguez, 2013). The results of applying 14 mixed use measures to both simulated and real-world data suggest that integral mixed-use measures provide measures of overall land use balance, whereas divisional measures provide measures of evenness (Song, Merlin & Rodriguez, 2013). Selection of the appropriate mixed-use measure requires knowledge of the number of land use dimensions of interest and the approximate scale(s) at which land use mix influences the outcome of interest (Song, Merlin & Rodriguez, 2013).

Manaugh & Kreider (2013) provide a novel land use interaction method for measuring land use mix that accounts for the extent to which complementary land uses adjoin one another, and which can potentially improve the explanatory power of land use mix when modelling walking and cycling. The results of this study suggest that the focus that the entropy index places on the balance of land uses is misplaced, and that equal proportions of land uses are somewhat arbitrary in predicting travel outcomes. Moreover, the authors concluded that area-based measures of land use mix do not adequately capture the subtleties of land use mix. Thus, the degree to which an area shows fine-grained patterns of land use is shown to be more highly correlated with behaviour outcomes than indices based solely on the proportions of land use categories (Manaugh & Kreider, 2013). Gehrke & Clifton (2016) identify some of the conceptual and methodological shortcomings of current land-use interaction and geographic-scale representations, and outline why a mix measure that includes a spatial-temporal element is needed to better understand land-use mixing and travel behaviour.

As a method for measuring different aspects of urban sprawl, Arribas-Bel et al. (2011) propose measuring:

- 'urban morphology' - which includes variables such as the scattering of urban development, the connectivity of the area, and the availability of open space, and
- 'internal composition' - which includes density, decentralisation and land-use mix (measured using the Simpson's Index (Torrens, 2008)).

Using land cover data derived from EEA datasets (Urban Audit, Corine, and UMZ), the above indices were calculated for a sample of European cities and the information analysed using a 'self-organising map' algorithm, that can visualise and map urban form and the mix of land uses and be used to differentiate urban sprawl from compact development and identify hot-spots of urban sprawl in Europe (Arribas-Bel et al. 2011). Local policy makers may find the approach useful to view their cities or regions in the supra-national context and in comparison with other European areas (Arribas-Bel et al. 2011).

LandSense (https://landsense.eu/) is an EU project that aims to engage citizens in monitoring change in the urban landscape that can be integrated into local authorities databases to improve urban planning (Olteanu-Raimond et la., 2018). The LandSense observatory collects data both actively (through citizens) and passively (from authoritative, open access, and other citizen-based initiatives) and integrates them into an open platform that provides valuable quality-assured in-situ data for SMEs, larger businesses, government agencies, NGOs and researchers. The LandSense Engagement Platform will become a marketplace where citizens can participate in Land Use and Land Cover (LULC) campaigns and can register new or reuse existing services. Citizens use a mobile app to validate current land use and add new information for land use changes (under the name PAYSAGES in France). Campaigns can be opportunistic or guided, and contributors would typically either: edit a feature, add new information about a feature, report of change or an error in existing data, take pictures of features depicted on the map (Olteanu-Raimond et la., 2018).

At a site or project level, a Green Space Factor score (between 0 and 1) can be calculated based on score assigned (by a planning authority) to any particular surface-cover type (e.g. asphalt, lawn, green roof etc) as a measure of land use mix at a microscale. The area for each surface cover type is calculated and multiplied by its factor, and the overall total score is divided by the total area of the project. The project score can then be compared to targets set by local authorities. GSF can provide certainty for developers regarding expectations for urban greening for new developments. It can identify planning proposals with insufficient quantity and functionality of greening, encourage improvements in greening, and compare and evaluate proposals for a site. Examples are Malmo's Green Space Factor and Green Points system (Kruuse (2011), the City of London's Urban Greening Factor Study (Grant, 2018)and Southampton City Council's GSF guidance available at: https://www.southampton.gov.uk/policies/green-space-factor-guidance-notes-2015_tcm63-371696.pdf.

Evaluation of land use mix can be used to:

- Ensure better urban design in the context of scarce land resources and the potential benefits of using nature to address the challenges of cities (European Commission, 2018);
- Enhance the design of compact cities to ensure integration of nature-based solutions to deliver a balance of social, economic and environmental benefits;
- Address the challenge of urban sprawl, limit land take and help build compact liveable;
- Support 'no net land take by 2050' targets (European Commission, 2016).

Scientific solid evidence: Remote-sensing techniques on satellite images have been effective at capturing land cover patterns and high-resolution aerial and satellite images can provide accurate land use maps when augmented with detailed and up-to-date auxiliary data on land use. Methodological inconsistencies in measuring land use mix have hindered generation of more generalizable and comparable results and imperfect conceptual assumptions can result in misunderstandings regarding true associations between land-use mixing and, for instance, travel behaviour (Gehrke & Clifton, 2016). Selection of appropriate measures for the study project is critical (see Song, Merlin & Rodriguez, 2013). There can be missing data to some degree with remotely-sensed and crowd-sourced tools such as OSM, however it is of sufficient quality for most cities (Gervasoni et al., 2016).

Level of expertise: Expertise in relation to mapping (especially those based on remote sensing and GIS techniques) and modelling will be necessary and knowledge regarding applicable data sources and appropriate methods/measures for processing data will be needed.

Cost: Increasingly high resolution, high-quality data is becoming freely available (i.e. OSM) and the main costs would be associated with employing suitably experienced specialists/technology to analyse data if this is not available in-house. The resolution needed to capture land use mix in very high density areas and accurately characterise small land pockets can be expensive. See indicator review for Env_42_RS for some commercial costs for newly acquired high resolution RS imagery.

Effort: More detailed land use mix studies will be more data-intensive and time-consuming and effort will be directly related to the level of expertise available.

Participatory process: Volunteered Geographic Information Projects such as OSM and LandSense offer a mechanism for community participation in the process of recording land use mix, contributing not only to road network distribution information but also to the potential for using these data to justify and delineate land patterns.

Data availability: Land use and land cover data is widely available in the EU, depending on the resolution required.

Geographical scale: Most studies reviewed examine data at the city scale, however more fine-scale analyses are possible for local planning contexts.

Temporal scale: Suitable for various temporal scales, although the availability of high-resolution historical data can sometimes be a barrier to studying past trends

Synergies: Strong synergies with other land use and mapping indicators (e.g. Env61, Env42, Env55 etc) and health and wellbeing indicators (Barton, 2009; Fallon and Neistadt, 2006; Hajna et al., 2015; Hajrasoulih et al., 2018; Pineo and Rydin, 2018; Wu et al., 2016) particularly in terms of active travel (e.g. Gehrke & Clifton, 2017) and land use diversity as a key component of compact liveable communities where everything is within reasonable distance.

Original reference(s) for indicator: UnaLab

Reference (s):

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2.2.14 Air quality change (Env66)

Umbrella: Air Quality

Indicator: Air quality change

Code: Env66

Description: Measurement of change in air quality through nature-based solution implementation. Typically, such evaluation will be linked to the strategic planning of nature-based solutions to intercept atmospheric pollutants through the use of street trees, urban woodlands, green walls, green roofs, hedgerows, etc. Scale and location are critical components of this indicator as, whilst localised nature-based solution interventions could reduce overall air pollution on a city-scale, poorly planned nature-based solutions have been reported to exacerbate localised air pollution by vegetation releasing volatile organic compounds (VOCs) and/or disrupting wind flows and trapping poor quality air increasing public exposure (Vos et al. 2013; Shaneyfelt et al. 2017). This localised effect should be considered, particularly when adopting spatial modelling-based metrics for this indicator.

Metric(s): Urban nature-based solutions can affect local and regional air quality through several different mechanisms (Escobedo and Nowak 2009). This includes:

- Removing atmospheric pollutants (Dochinger et al. 1980; Scott et al. 1989);
- Emitting atmospheric chemicals from the vegetation and emissions through nature-based solutions maintenance (Calfapietra et al. 2013);
- Lowering urban microclimate temperatures through shading and evapotranspiration (Nowak et al. 2000; Moss et al 2019);
- Changing wind patterns (Wang et al. 2001; Shaneyfelt et al. 2017);
- Modifying boundary layer heights (Beckett 1998);
- Reducing building energy use and consequent emissions from power plants (Castleton et al. 2010; Lee and Jim 2019).

Due to this diversity of potential impacts of nature-based solution implementation on air quality, the first step to establishing evaluation indicators is to determine those that are relevant to the specific project. For this, it is important to consider which air quality impacts the nature-based solution project is being implemented to deliver (benefits), and which other impacts are likely to be delivered incidentally (co-benefits). It is also useful to consider any negative impacts that might occur (disbenefits). By identifying these, it is possible to develop a theory of change to determine which aspects of air quality are most relevant and should be evaluated.

Basic measurements in relation to air quality have tended to either focus on measuring change in local air quality before and after an nature-based solution intervention, improvement in air quality behind or within the nature-based solution (Yin et al. 2011), or measurement of the pollutants directly absorbed or intercepted by the vegetation. The difference between absorption and interception is a critical factor in relation to air quality improvement. Absorption corresponds to a direct reduction in pollutants like sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3) through leaf stomata and the dissolving of water-soluble pollutants on moist leaf surfaces (Nowak, 1994). Interception represents a more temporary removal of particulate matter from the air through sedimentation/impaction on leaves (Beckett et al. 1998). This comprises temporary removal as, unless the particulates are washed off the vegetation and locked away in soils or storm drain systems, the possibility of resuspension still exists (Przybysz et al. 2014).

A strong link has been established between particulate air pollution and poor health. As a result of this, the PM_{10} value is typically used as a measure of particulate matter pollution in relation to causing illness (Beckett et al. 1998).

Other parameters used to measure air quality have included:

- $PM_{2.5}/PM_{0.2}$ (Sæbø et al. 2012);
- Total Suspended Particles (TSP) (Monn et al 1995)
- Ozone (O_3) (Cardelino and Chameides 1990)
- Sulphur dioxide (SO_2) (Zhan et al. 2018)
- Nitrogen dioxide (NO_2) (Zhan et al. 2018)
- Volatile organic compounds (VOCs) (Calfapietra 2013)
- CO (Zhan et al. 2018)
- Lead (Pb) (Mage et al. 1996)
- Carbon flux (See Env_01)

Selection of pollutants to evaluate in relation to nature-based solutions implementation tends to be related to the local/regional problems in relation to air quality where the nature-based solution is being implemented and the type of nature-based solution being implemented.

To measure change in local air quality, quantification of pollution reduction is typically done using system modelling combining hourly meteorological data and air pollutant concentrations, with canopy cover data (Scott et al. 1998). Direct sampling to quantify air pollution concentrations typically uses either passive sampling (based on diffusion) or active sampling using pumps. Generally, in-situ continuous monitoring is used to generate averages over set time periods (IARF 2016a). A comprehensive review of measurement methods for different pollutants has been carried out by IARF (2016b). This includes information on practicality, precision, and costs of different methods for each pollutant. Such monitoring is commonly carried out formally across populated areas in many cities to comply with air quality standards. These monitoring networks are typically implemented across a series of fixed points covering the city to continuously measure key pollutants: SO_2 (sulfur dioxide), NOx (nitrogen oxides), CO (carbon monoxide), O_3 (ozone), PM_{10} (coarse particles) and $PM_{2.5}$ (fine particles), C_6H_6 (benzene), and Pb (lead) (Năstase et al. 2018). If nature-based solution projects are located in the vicinity of such monitoring stations, or are implemented on a scale considered sufficient to have wide-ranging impact across cities or city regions, these data sources can be used to monitor nature-based solution impacts before and after implementation.

If accurate measurements are required but with greater flexibility on location (e.g. at a finer spatial scale to fixed point monitoring stations), stationary portable monitors are available that retain a relatively high level of accuracy, but that can be easily moved between locations. A comprehensive literature is now available in relation to the systems available and the opportunities for implementation (Morawska et al. 2018). Miniaturisation of these systems through the development of microsensors is enabling greater flexibility in terms of monitoring location. Such sensors have greater flexibility than fixed stations and stationary portable monitors in terms of where they can be placed, including being carried by subjects (Marć et al., 2012; McKercher et al. 2017). This enables more effective assessment of exposure levels. Such sensors provide an opportunity for more personal monitoring, enabling exposure in more precise locations related to nature-based solution implementation to be monitored, and also providing an excellent opportunity for citizen science approaches (McKercher et al. 2017). It has been recognised, however, that such democratisation of air quality monitoring can lead to issues related to comparability of data when common protocols are not adopted for data collection across studies (Hubbell et al. 2018; Morawska et al. 2018). This should be a critical consideration when planning air quality evaluation indicators across and between cities.

Examples of use of low-cost monitoring methodologies to promote community participation include:

- Wearable sensors for monitoring PM levels in London Underground stations (Zhang et al. 2017);
- Crowd sourced air quality monitoring programmes (Thompson 2016);
- Personal ozone monitoring (Cao and Thompson 2016);
- Use of smartphones to collect air quality data (Pereira et al. 2018);
- Use of low-cost sensors to cover new pollutants and new areas (Commodore et al. 2017);
- Toolboxes of monitoring systems to support citizen science (Barzyk et al 2016);
- Nitrogen dioxide passive diffusion tubes for ambient measurement (Kirby et al. 2000).

Such studies have demonstrated that low-cost sensors can make a valuable contribution to understanding and awareness-raising in relation to air pollution exposure (Jerrett et al. 2017).

Biological monitoring of air quality using plant/lichen growth patterns in relation to the presence of air pollutants has also been used as a mechanism for assessing air quality (Matos et al. 2019, Limo et al. 2018), including for promoting a participatory approach (Nali and Lorenzi 2007).

For the measurement of the pollutants directly absorbed or intercepted by the vegetation, methods adopted have focused on the physical removal and analysis of samples of vegetation, or the 'washing' of material from foliage (Dzierzanowski et al. 2011; Weerakkody et al. 2017). For air pollution deposition sampling over known time periods, vegetation is washed at the beginning of the study to establish a baseline (Weerakkody et al. 2018). Once samples are obtained, standard laboratory analytical methods and/or scanning electron microscopy are used to identify accumulation rates (Weerakkody et al. 2017).

Results from these absorption/interception studies, combined with more controlled studies under laboratory conditions (Blanus et al. 2015), has typically been fed into the development of a series of modelling tools designed to predict the impact of nature-based solution implementation on air quality level (e.g. Hirabayashi et al. 2012). These include iTree (Hirabayashi et al. 2012), UFORE (Nowak et al. 1998) and the FRAME models (MacDonald et al. 2007). Examples of the implementation of such tools are widespread (Nowak et al. 2016; Rogers et al. 2018) with numerous resources listed on the iTree website (https://www.itreetools.org/resources/reports.php). Recent studies have, however, questioned the reliability of some of the long-held assumptions behind these models (Xing and Brimblecombe 2019), including the lack of consideration of disservices of nature-based solution implementation (Pataki et al. 2011).

In addition to direct sampling of air pollutants, various methods have been employed that use modelling or remote sensing methods to quantify the impact of nature-based solutions on air quality. This includes the use of emerging predictive tools such as iTree (2019) and long-established multilayer models (e.g. for sulphur dioxide) (Baldocchi 1967). Open-access tools such as i-Tree (Tools for Assessing and Managing Community Forests; https://www.itreetools.org/tools) provide a valuable database on tree species, as well as options to quantify benefits and ecosystem services of community trees and forests. While the chemistry is fairly well understood, the quantification of emissions generated by nature-based solutions in specific cities and their contribution to airborne particles is still a grey area in research. In addition, the World Urban Database and Access Portal Tool (WUDAPT; http://www.wudapt.org/wudapt/) is another type of complementary database that provides climate-relevant information on urban centres across the world in the form of local climate zones using remote sensing imagery (Hammerberg et al., 2018; Kumar et al., 2019). It also captures variations across urbanised landscapes (Hammerberg et al., 2018). Such a database could complement dispersion modelling, which together with the deposition component in the i-Tree model, could support the multidisciplinary assessment of nature-based solutions impact on pollutant concentrations at a city scale.

Remote sensing can be used to measure the scattering and absorption of infrared, visible, and ultraviolet radiation at different wavelengths along a sight path. Path lengths may range from a few metres, used for in-plume monitoring, to thousands of kilometres for geostationary satellites (Hidy et al., 2009; Hoff & Christopher, 2009). Satellite remote sensing estimates for PM, NO_2, SO_2, and some other pollutants often correspond to urban and industrial areas, but spatial resolution is limited to about 10 km.

As stated by Martin (2008), satellite remote sensing of air quality has evolved dramatically and global observations are now available for a wide range of parameters including aerosols, tropospheric O_3, tropospheric NO_2, CO, HCHO, and SO_2. Satellite retrievals can add synoptic and geospatial context to ground-based air quality measurements and can be applied to qualitative, quantitative and numerical modelling analyses of events that affect air quality (Martin 2008). Nonetheless, the review highlights the need for improvements in the capability for satellite remote sensing of air quality in the boundary layer, particularly in relation to focusing on pollution gradients within cities, because spatial resolution of satellite observations can be insufficient to resolve intra-urban scales (Martin 2008).

In the study of Bagheri et al. (2017), land use maps including 6 classes of green space, urban areas, roads, river, agriculture lands, and barren land were produced using maximum likelihood algorithm and the landscape metrics were analyzed using FRAGSTATS software. Then, a partial least square (PLS) model was applied to assess the effects of changes in the pattern of green space on air pollution. The model results indicated that reduction in the area of large green space patches promote air pollution, suggesting that there is a direct relation between increases in the area of large green space patches and air pollution reduction. Similarly, Vatseva et al. (2016) mapped urban green spaces based on remote sensing data and confirmed the positive impact of urban green spaces on air quality. Schöpfer et al. (2005) present an approach that uses remote sensing data sets and GIS layers to provide spatially disaggregated information of green space. Their approach is to combine image processing, GIS and spatial analysis tools to quantify urban structures in terms of greenness, generating a spatially disaggregated ‘green index’ from classified orthophotos (with additional weighting factors), which can form part of an indicator set for Salzburg city and can be used for assessing impacts to air quality.

Other studies using remote sensing techniques for air pollution assessment include:

- regression models to analyse and map the relationship between Air Pollution Index (API) indicators, remote sensing and ground-based measures of NO_2 and $PM_{2.5}$ in several cities of Ukraine (Putrenko and Pashynska, 2017);
- an algorithm to provide a reliable and cost effective technique for estimating and mapping PM_{10} using Landsat satellite images (Lim et al. 2009)
- estimating air quality in the form of aerosol optical depth (AOD) from Landsat ETM+ images as part of a study to develop an integrated index of urban environmental quality (UEQ) which can be used by planning and environmental authorities as an objective measure of

environmental quality over a whole city, for comparisons between places and cities and for monitoring changes over time (Nichol and Wong, 2009).

Microscale simulations are also becoming more commonly employed for street-scale evaluation (Wania et al. 2012), with software such as ENVI-MET (Bruse 2007) commonly being adopted (Simon et al. 2019).

Further detail on current understanding on the links between nature-based solutions and urban air quality can be found in recent reviews (e.g. AQEG 2018, Ferranti et al. 2019).

Data on the air quality performance of nature-based solutions collected in these ways can be used to:

- Quantify the benefits of nature-based solutions in terms of air quality improvement;
- Assess any negative impact on air quality of implementing nature-based solutions;
- Underpin evaluation of the health impacts of air quality;
- Assess compliance with Ambient Air Quality Directives;
- Provide easily accessible data to communities and decision-makers to promote the uptake of nature-based solutions to provide clean air spaces.

Scientific solid evidence: Robustness of evidence depends upon the precision and accuracy of the method adopted. Frequency and design of sampling is also linked to the strength of evidence. For example, regular interval sampling may provide long-term and seasonal patterns but may miss significant short-term events. Modelling impacts of nature-based solutions might be the most cost-effective mechanism for generating usable data but there may be a trade-off with accuracy if local context is not incorporated. The properties of satellite data are highly complementary to ground-based in-situ measurements, and whilst remotely sensed data have distinct benefits, the interpretation is often less straightforward compared to traditional in-situ measurements. Integrated approaches using satellite data, ground-based data and models combined with data assimilation, could provide improved characterisation of air quality. Maps of air pollution measured from space can have a strong impact on the general public and the policy makers (Veefkind et al. 2007).

Level of expertise: Some expertise required for installation of equipment and/or sampling methodology. Expertise required for sample analysis depends on the level of automation of the sampling equipment. For example, samplers that include automated analysis generally only require calibrating. Samples than are not automatically analysed generally require specialist analytical methods, these are typically carried out through an accredited laboratory. Biological monitoring methods can be simpler, sometimes only requiring species identification skills. Data analysis/interpretation against statutory guidelines can be very basic once systems are in place.

Applying remote sensing technique requires expert knowledge. According to Martin (2008), aerosol remote sensing at visible wavelengths exhibits high sensitivity to boundary layer concentrations. Although atmospheric scattering and surface emission of thermal radiation generally reduce instrument sensitivity to trace gases near the surface, a strong boundary layer signal in NO_2 arises from its large boundary layer concentrations relative to the free troposphere. Recommendations are presented including (1) additional dedicated validation activities, especially for tropospheric NO_2 and HCHO; (2) improved characterization of geophysical fields that affect remote sensing of trace gases and aerosols; (3) continued development of comprehensive assimilation and inversion capabilities to relate satellite observations to emissions and surface concentrations; (4) development of satellite instruments and algorithms to achieve higher spatial resolution to resolve urban scales, facilitate validation, and reduce cloud contamination that increases remote sensing error; and (5) support for the next generate of satellite instrumentation designed for air quality applications.

Cost: Can be low cost, but this is very dependent upon the level of sophistication, frequency of sampling, and automation of the equipment. The financial requirements associated with this indicator tend to be associated with a sliding scale of cost. Cost increases with: greater numbers of air quality parameters; greater numbers/frequency of sampling; and greater levels of precision and accuracy. Cheapest solutions are generally represented by the use of citizen science, particularly in relation to monitoring biological indicators. In-situ continuous monitoring equipment can have relatively large up-front costs, but can represent value for money compared to repeated laboratory analysis for long term studies and costs for labour for collecting/changing samples.

Remote sensing data for monitoring air quality in cities and countries can provide a wide territorial coverage at relatively low cost, but typically the use of RS data necessary to conduct complex work requires verification and comparison with ground-based measurement tools. The following are freely accessible RS data that can be used for air quality assessment:

- Glovis - Global Visualization Viewer, with easy-to-go navigation tools (http://glovis.usgs.gov/);
- NASA (http://reverb.echo.nasa.gov);
- Hyperspectral Unmixing, Ground Truths (http://www.escience.cn/people/feiyunZHU/Dataset_GT.html);
- http://openremotesensing.net provides access to MATLAB codes of different remote sensing fields, and other invaluable free data;
- http://freegisdata.rtwilson.com provides a categorised list of links to over 300 sites providing freely available geographic datasets all ready for loading into GIS.

For downloading users have to register. The images are provided as jpg for a quick preview, but also as the complete spectral-data set. There are the manuals to explain how to use the portal.

Effort: Automated in-site data-gathering and analysis is very low effort, with installation, data analysis and equipment maintenance the only inputs required. The only onerous aspect can be the volume of data generated. If samples are taken manually, or auto-sampling does not include analysis, effort can be substantially more with container preparation and site visits required plus post-collection analysis. Effort under this scenario will be strongly linked with frequency of sample collection. Effort can also be linked to the duration of the monitoring, with short-term analysis of impact relatively low effort compared to long term monitoring schemes that evaluate change in nature-based solution performance over time (linked to changing performance with maturation/management of the nature-based solution). For remote sensing approaches, the level of effort involved would be dependent on the scale and amount of data to be analysed, the level of automation of data processing, and the level of technical expertise already available. With the availability of high-resolution remote sensing images and multi-source geospatial data, there is a great need to transform Earth observation data into useful information necessary for urban planning and decision making related to air quality improvement.

Participatory process: Participatory processes represent a key part of air quality monitoring as they are directly linked to assessing exposure, raising awareness, and behaviour change. Air quality analysis can be linked to local schools/universities through the use of microsensors, and biological indicators. Automated sampling and analysis equipment offer less opportunity for such participation with participation limited to observing and/or processing the data produced. Several studies revealed the success of incorporating remote sensing and citizen's perception of green space and especially their role for air quality improvement (Chen et al., 2018; Schöpfer et al., 2005).

Data availability: Many ground-based measurement approaches generate new data, or it is possible to use existing city-wide air quality monitoring station data if available. Baseline data prior to intervention is not always necessary as it may be possible to measure air quality across the nature-based solution (from pollution source to leeward side) to get a measure of air quality change. If comparison to a previous green or grey space is required, establishing baseline data prior to installation can be of benefit. Alternatively, a control space without a nature-based solution but with a high likelihood to be experiencing the same air pollution levels as the nature-based solution site could also be used for comparative purposes. Remote sensing data is widely available free of charge (see Cost section above for examples). According to Vatseva et al. (2016), recently available Sentinel-2A (S2A) multispectral satellite imagery are provided free of charge in the frame of European Copernicus Earth observation program, and the target minimum mapping unit presents a five-fold improvement compared to Urban Atlas, i.e. 500 m^2 as well as more frequent and timely data updates compared to Urban Atlas.

Geographical scale: Implementation scale can be very different depending on indicator metrics used. Direct sampling tends to be focused on a component or site scale. Spatial modelling can be carried out on all scales including city and region scales. Evaluating over a range of scales can be critical as local impacts can vary substantially compared to larger-scale impacts. Both low and medium spatial resolution remote sensing products have been be applied to the identification of vegetation types and their role for air quality improvement at the city and regional scale.

Temporal scale: Monitoring methods can be adopted for short-term snapshots associated with impacts immediately following implementation. However, long-term in-situ monitoring is generally more effective in terms of capturing a more comprehensive overview of the performance of the nature-based solution over a range of environmental conditions. Long-term monitoring is also recommended as nature-based solution performance could be expected to change over time.

Existing satellite applications can suffer from poor temporal resolution. Pollution clouds e.g. gas, smoke from a fire or invisible gas, move at (roughly) the same speed as normal clouds and therefore remote sensing is not always appropriate if there are scattered clouds but is better if cloud cover is consistent. A long-term daily average will give typical background levels, however, air quality (i.e. short-term exposure) is more concerned with the magnitude and duration of temporal maxima during air quality events. The trade-off is usually between temporal and spatial resolution, and the size of the domain. Using high temporal resolution remote sensing images together with vegetation phenological features can achieve more accurate identification of vegetation types and thus better predict the effects of urban green for air improvement through implementation of particular nature-based solutions.

Synergies: Strong synergies with health & wellbeing benefits in relation to the health impacts of air pollution. Weather data collected for analysis also has relevance for other indicators such as stormwater management and thermal stress.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Eklipse; Baró et al., 2014

Metric reference(s):

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2.2.15 Tree shade for local heat change (Env88)

Umbrella: Temperature reduction

Indicator: Tree shade for local heat change

Code: Env88

Description: Trees as nature-based solutions to create shade in neighbourhoods measured by °C or K per spatial unit (m^2)

Metric(s): Thermal comfort in cities has increased in importance due to impacts from global warming and high-density urbanisation. Metrics to measure the shading services provided by trees are largely based on quantifying differences in local air temperature from unshaded areas. The effect of tree shade on local temperature may be upscaled to a citywide impact if modelled and assessed cumulatively. This indicator principally concerns measuring how tree shade effects urban microclimates, in particular by intercepting solar radiation preventing warming of the ground and thereby reducing surface temperature. Other basic measures of air temperature covered in Env03 (Air temperature reduction) such as apparent temperature (the temperature equivalent perceived by humans – based on air temperature, relative humidity and wind speed), and Physiological Equivalent Temperature (thermal perception of an individual including thermal physiology) can also be used to evaluate the human thermal comfort conditions associated with tree shade (e.g. Kàntor et al., 2018). Various factors such as tree species (size, shape, leaf type, seasonality etc), tree age, distance between trees, type of surface beneath the tree, surrounding environment and climate will impact the degree of shade provided.

The classical methodical approach for measuring tree shading was developed by Barlow and Harrison (1999) and considered different factors affecting shading, such as topography, time of day and year and geographical location. They provided mathematical descriptions and procedures used to calculate the length of the shadow and its duration (Barlow & Harrison, 1999).

The shade from tree canopies can generate significant surface cooling in cities, particularly over impervious surfaces such as asphalt, where a temperature reduction of about 6°C has been recorded (Rahman et al., 2019). This study examined the vertical temperature gradient beneath two common urban street tree species *Tilia cordata* and *Robinia pseudoacacia*, recording a range of morphological measurements (e.g. diameter at breast height (DBH), tree height, crown projection area (CPA) and leaf area index (LAI) derived from hemispherical photographs), as well as air and surface temperature and various other meteorological data, collected using a combination of temperature loggers at 3 different heights and weather stations installed at the study sites (Rahman et al., 2019). Surface cooling was strongly correlated with LAI, and the relationship was found to be stronger over asphalt than grass, indicating therefore that tree species with higher canopy density might be preferential when planted over asphalt surfaces in cities, but low water using species with lower canopy density could be chosen over grass surfaces (Rahman et al., 2019).

In a meta-analysis of the characteristics of urban tree species that influence cooling potential, a total of 13 studies were analysed that reported on cooling by shading (as measured by surface temperature difference ΔST), and consensus from the review in terms of surface cooling was that the following parameters contributed to ΔST in order of relative importance: climate > below canopy surface > growing size > leaf thickness > LAI > crown shape > plant functional type > habitat > wood anatomy > leaf shape > leaf colour (Rahman et al., 2020). LAI was again reported as the most influential driver of cooling benefits in terms of human thermal comfort, although vertical leaf area densities can also be influential, and species with higher leaf density at the lower crown may ensure better cooling benefits (Rahman et al., 2020). Studies reviewed in the meta-analysis used various methods for gathering data on tree shade effects on surface temperature, for example:

- ***Field measurements***: empirical microclimate measures using for instance temperature sensors attached to dataloggers, infrared thermometers/thermal cameras, globe thermometers (to measure radiant temperature as a determinant of physiological equivalent temperature (PET) which is used to assess human thermal comfort), in combination with weather station data and tree species morphology (i.e. height, canopy spread and LAI (using a LAI analyser/ceptometer or hemispherical images) (Lin & Lin, 2010; Armson et al., 2012 & 2013; Devia & Torres, 2012; Berry et al., 2013 (building walls rather than ground level); Millward et al., 2014; Gillner et al., 2015; Napoli et al., 2016; Rahman et al., 2018; Stanley et al., 2019); also leaf colour (using colorimeter), leaf thickness (using thickness gauge) canopy coverage area (using handheld GPS and walking a transect round the tree canopy edge) and canopy thickness from photographs of individual trees (Lin & Lin, 2010); hemispherical photographs to measure tree shade cover on walls (Berry et al; 2013);
- ***statistical/modelling techniques***: linear mixed model and/or regression analyses of field data (Lin & Lin, 2010; Armson et al., 2012; Milward et al., 2014; Gillner et al., 2015; Rahman et al., 2018; Stanley et al., 2019), shade area analysis (Armson et al., 2013), vertical shading coefficient of walls (Berry et al., 2013); a heat transfer model, which was found to be effective at predicting surface temperatures of pavements and lawn under different trees (Napoli et al., 2016);

Rötzer (2019) presents different techniques for greening cities, particularly through planting trees in all climate zones, as effective tools to mitigate climate change and the Urban Heat Island (UHI), and provides empirical as well as modelling studies of urban tree growth and their services and disservices in cities worldwide, including the dynamics, structures, and functions of urban trees, as well as the influence of climate and climate change on urban tree growth, urban species composition, carbon storage, and biodiversity.

Stanley et al. (2019) analysed urban tree growth and regulating ecosystem services along an urban heat island (UHI) intensity gradient in Salzburg (Austria). For the phenological monitoring in spring March – May (and later verification in autumn), they used the well-established method presented by Wesolowski and Rowinski (2006). They developed a scale of point values from 0 to 2 for assessing the development status of a leaf bud. For each observation day, ten randomly selected apical buds in the upper, south-exposed part of the crown are evaluated and their sum is calculated. The monitoring starts when all buds are closed and thus evaluated as having zero points. As soon as all ten leaves are completely developed and each scores two points, the monitoring is finished. Moreover, for all observation trees, the height, trunk circumference at breast height, and leaf area index (LAI) were measured. Using these data, the tree age, crown area, and crown volume were further calculated. The tree height was measured using a Leica DISTOTM D810 Touch (Leica Geosystems); LAI was determined based on LAI-2200C Plant Canopy Analyzer from LI-COR (Lincoln, NE, USA). The measured values were then edited in the FV2200 software from LI-COR (2.1.1, Lincoln, NE, USA). The microclimate was measured using the difference of the surface temperatures between the crown-shaded area and the full sun-exposed area using an Infrared Radiometer, Model MI-220. Data were assessed using statistical analysis similar to those applied by Gillner et al. (2015). They found out, after leaves have developed, trees cool the surface throughout the whole growing season by casting shadows. On average, the surfaces in the crown shade were 12.2 ◦C cooler than those in the sun. Thus, the tree characteristics had different effects on the cooling performance. In addition to tree height and trunk circumference, age was especially closely related to surface cooling. They conclude, if a tree's cooling capacity is to be estimated, tree age is the most suitable measure, also with respect to its assessment effort. Practitioners are advised to consider the different UHI intensities when maintaining or enhancing public greenery. The cooling capacity of tall, old trees is needed especially in areas with a high UHI intensity. Species differences should be examined to determine the best adapted species for the different UHI intensities. The results of such studies can be the basis for modelling future mutual influences of microclimate and urban trees.

An alternative methodology to those above used a high-resolution thermal imaging camera to record the crown temperature of trees from above (using a helicopter), and determined that urban tree temperatures are species-specific due to traits such as leaf size, stomatal conductance and canopy structure, and that foliage temperature was mostly influenced by the location of the tree (i.e. park or pavement) (Leuzinger et al., 2010). Generally small-leaved trees were cooler, but this trend did not always hold at temperature extremes (40°C), indicating that the cooling effect of urban trees could be species *and* context specific, which may be useful information for future urban tree planning projects (Leuzinger et al., 2010).

Thermal imaging (in combination with a range of other field measurements and photographic records) has also been used to record the surface temperatures of three common urban surfaces – asphalt, porphyry, and grass – in the shade of 332 single tree crowns, of 85 different species, during the peak temperature period of summer days, to evaluate which tree traits play an important role in cooling (Speak et al., 2020). Measurements at three locations within the shadow of individual trees revealed higher cooling in the centre and at the western edge and cooling was related to a multitude of tree traits, of which Leaf Area Index estimate (LAIcept) and crown width were the most important (Speak et al., 2020). Median average cooling of 16.4, 12.9 and 8.5 °C was seen in the western edge of the tree shade for asphalt, porphyry and grass, respectively (Speak et al., 2020). Tree traits recorded were modelled using descriptive and predictive multiple linear regression models and were able to predict cooling with some success from several of the predictor variables (LAIcept and gap fraction), which has implications for the selection of trees within urban design schemes by altering the weight given to certain tree traits if high shade provision is a desired outcome (Speak et al., 2020).

ENVI-met (a three dimensional microclimate simulation software) can be used to generate a microscale model simulating various tree canopy scenarios under various climate conditions and investigate the relationship between percentage tree canopy cover and temperature reduction at the neighborhood scale (Middel et al., 2015). The study findings suggested the relationship between percent canopy cover and air temperature reduction was linear, with 0.14 °C cooling per percent increase in tree cover for the neighborhood under investigation, although they highlight Envi-met has various shortcomings, for instance in terms of estimating nocturnal cooling under trees and accounting for anthropogenic heat (Middel et al., 2015). Beyond the local scale, the Weather Research and Forecasting (WRF) model has been coupled with urban land surface processes parameterized by urban canopy models (UCMs) to investigate the radiative shading effect of trees over the contiguous United States (Wang et al., 2018). This WRF-urban modelling framework can be informative to researchers and policy makers, but as it omits other biophysical functions of trees such as evapotranspiration, more work is needed to produce a more comprehensive and realistic representation of urban tree shade cooling effects (Wang et al., 2018).

Remotely sensed tree canopy cover has been widely used to estimate the amount of trees in an area. However, where this is limited to two-dimensional calculations, it may not fully evaluate the shading service of trees as the vertical structure and density of trees can also influence the solar radiation reaching ground level (Li et al., 2018). Google Street View (GSV) provides publicly available, high spatial resolution photographs of vegetation along streetscapes, which can be used to quantify the degree of shading under street trees (Richards & Edwards, 2017). The GSV panoramas can be transformed into hemispherical images and pixels classified into classes (i.e. sky, trees, buildings), and combined with remotely sensed data (i.e. LiDAR) to enable estimation of canopy cover provided by street trees (Li et al., 2018). A sky view factor (SVF) calculation - the ratio of sky hemisphere visible from the ground that is not obstructed by buildings, trees and terrain - can been applied to these images to quantify the shading effectiveness of street trees alone (SVF ranges from 0 to 1, indicating totally enclosed and totally open street canyons respectively) (Li et al., 2018). The quantitative information and spatial distribution of shade provision by street trees generated by this method can be used as a reference for urban planners and city officials for urban greening projects, for instance so they can target critical areas for urban heat island (UHI) mitigation (Li et al., 2018).

The influence of vertical and horizontal tree canopy structure on land surface temperature (LST) can also be measured using a combination of a high-resolution vegetation map, Light Detection and Ranging (LiDAR) data and various statistical analysis methods (Chen et al., 2020). Results from this method indicated that composition, configuration and vertical structure of tree canopy were all significantly related to both daytime LST and night-time LST, highlighting the important contribution measuring the vertical structure of tree canopies can have in determining LST in cities (Chen et al., 2020).

The influence of patch size of trees (from 500 m^2 – 80,000 m^2) on shading has been modelled, using a variety of field measurements (e.g. DBH, distance between trees, temperature, weather etc) and simulated using the solar radiation tool embedded in ArcGIS, and found that multiple small patches can provide more total area of shade than a single large one (Jiao et al., 2017). However, they also found a non-linear relationship between patch size and transpiration, both of which are key cooling services provided by trees, therefore there may be a trade-off between shading and transpiration at certain patch sizes, and with different tree species (Jiao et al., 2017).

A study of the effects of street trees in three contrasting street canyon environments found the cooling and human thermal comfort benefits of street trees were localised and highly variable both spatially and temporally, based on factors such as the amount of shading, street geometry, and the local meteorological conditions (Coutts et al., 2015). Thus, depending on their position in the street canyon, the prevailing conditions, and time of day, trees can have either a cooling or warming effect, highlighting the importance of strategic placement of trees to maximize their shade area whilst spacing them sufficiently to allow some nocturnal longwave cooling and ventilation, and reduce potentially detrimental impacts on urban cooling at night (Coutts et al., 2015).

i-Tree Canopy (https://canopy.itreetools.org/) is a web browser application that offers a quick and easy way to produce a statistically valid estimate of land tree canopy cover using aerial images available in Google Maps. This can be used as an easy to understand concept for communicating messages about tree cover to policy makers and the public, and can be linked to shading provision in terms of percentage cover/m^2 gained/lost in an area being an index of potential shading benefits gained/lost. i-Tree Canopy could also be used to map existing canopy cover in order to determine tree-less areas that may benefit from shade. The package i-Tree Design (https://design.itreetools.org/) can be used to evaluate the cooling benefits of shade from individual trees on building energy demand.

Mobile sensors (a fast-response, high-accuracy temperature probe, GPS device and data logger) mounted to bicycles have been used to measure temperature variability along urban transects in relation to tree canopy and impervious cover, both of which can interact to influence both daytime and nighttime summer air temperature (Ziter et al., 2019). In this study, generalised additive models were used to test the effect of percentage canopy and impervious cover and distance to nearest lake at 4 scales (10-90 metre radius) surrounding each temperature measurement (Ziter et al., 2019). This fine-scale method detected that canopy cover >40% can counter the warming effect of impervious surfaces during the daytime within a radius of 60-90 m (the scale of a city block). However, the impact at night-time was much less pronounced, indicating that reducing impervious cover as well as tree planting could be key to reducing UHI (Ziter et al., 2019). This method may also be suitable for citizen science projects (Ziter et al., 2019). Citizen science has also been successfully used to collect temperature data in cities using vehicle-mounted temperature sensors and global positioning system devices (GPS), with volunteers undertaking one-hour 'traverses' through study areas in a city to provide a snap-shot of temperatures, which can then be modelled against land use and land cover data to evaluate the role of trees in reducing/amplifying local temperatures and create a heat map for city planners (Shandas et al., 2019). Other participatory methods include the use of wearable sensors to detect human thermal stress (Sim et al. 2018), which could potentially be used to deliver a citizen science project on the effects of urban tree shade.

Berland et al. (2019) also confirmed that inventories relying on citizen scientists or virtual surveys conducted remotely using street-level photographs may greatly reduce the costs of street tree inventories since those ones conducted in the field by trained professionals are expensive and time-consuming. However, they pointed here several fundamental uncertainties regarding the level of data quality that can be expected from these emerging approaches to data collection. In particular, 16 volunteers were asked to inventory street trees in suburban Chicago using Google Street ViewTM imagery, and later this was assessed by comparing their virtual survey data to field data from the same locations conducted by experts. The findings suggest that virtual surveys may be useful for documenting the locations of street trees within a city more efficiently than field crews and with a high level of accuracy. However, tree diameter and species identification data were less reliable across all expertise groups, and especially analysts. Based on this analysis, virtual street tree inventories are best suited to collecting very basic information such as tree locations, or updating existing inventories to determine where trees have been planted or removed.

It should be noted that measuring shade alone will not fully capture cooling services provided by trees, since evapotranspiration also plays a role in regulating temperatures. Also, if tree planting is poorly designed, it can lead to disruption of airflows, causing trade-offs such as localised increases in air pollution concentrations (e.g. Vos et al., 2013) and night-time temperatures (Bowler et al., 2010; Coutts et al., 2015).

Data on the reduction of air temperature by tree shade collected in these ways can be used to:

- Quantify the benefits of trees as nature-based solutions in terms of cooling the local microclimate, reducing building energy use and providing thermal comfort zones for residents (synergies with Env17);
- Target tree planting in areas prone to temperature extremes/UHI and/or to provide optimal shade benefit to commuting pedestrians (see also Langenheim et al., 2020);
- Contribute towards other environmental and health and well-being indicators linked to temperature, air pollution, carbon storage, flooding and biodiversity.

Scientific solid evidence: Robustness of evidence depends upon the level of precision of the equipment, the spatial design of the monitoring and the duration of temperature recording. Generally, direct measurement in the field can provide greater confidence than microclimate simulations, and it can be hard to accurately scale-up local measurements to the whole city. Photographic methods yield good results, but they typically require manual acquisition and processing of fisheye images, which is time consuming and not feasible at the neighborhood or city-scale (Middel et al., 2018). To accurately simulate the thermal performance benefits that trees provide, it is necessary to account for growth and phenological changes in tree shade amount and quality and the influence of street canyon geometry.

Level of expertise: Some expertise may be required in relation to appropriately designing studies and with respect to the selection/use of specialist instrumentation and software such as ENVI-met. Expertise in relation to mapping (especially those based on remote sensing and GIS techniques) and modelling will be necessary.

Cost: Cost would be linked to the scale of monitoring and the complexity of equipment used. Basic digital thermometers and thermocouples are relatively cheap, but cost increases when these are linked to dataloggers. However, this could be offset by decreased staff costs for data collection. Overall cost also tends to be linked to the level of precision of equipment and the number of sampling points. Li et al.'s (2018) study provides a fully automatic workflow for quantifying the shade provision of street trees without much cost and computational burden.

Effort: With field measurements, effort is related to frequency of visits and number of sampling points/measurements. If feasible, automated in-situ data gathering is very low effort, with installation, data analysis and equipment maintenance the only inputs required. Li et al. (2018) state that the datasets required in their proposed method of study are easily accessible for most cities, and that all the data collection and image processing procedures could be done on a personal computer. In this study, for all 11,451 GSV panoramas in Boston, it took about 48 h to collect all GSV panoramas, process synthetic hemispherical images, and generate the shade estimation result on a 64-bit desktop computer with 8G RAM and 3.7 GHz processor (Li et al., 2018).

Participatory process: Opportunities are available for participatory processes in relation to collecting temperature measurements using mobile dataloggers or wearable sensors (Shandas et al., 2019), as well as collecting very basic information such as tree locations, or updating existing inventories to determine where trees have been planted or removed (as based on the findings of Berland et al. (2019).

Data availability: This indicator mostly involves generating new data. However, it is also possible to use publicly available data such as Google Street View to estimate canopy cover. Baseline data prior to intervention is not always necessary as it may be possible to measure temperature at increasing distances away from nature-based solutions to quantify effect. If comparison to a previous green or grey space is required though, establishing baseline data prior to installation can be of benefit.

Geographical scale: Typically, tree shade effects on temperature are measured in terms of the local microclimate impact. Wang et al. (2018) propose a modelling framework for the shading effect of trees that can be used at the city and regional scale with moderate accuracy.

Temporal scale: Monitoring methods tend to be adopted for short-term snapshots, for instance to show benefits on days of extreme heat. Monitoring should be undertaken at repeated intervals to capture a more comprehensive overview of the performance of trees and account for change over time and under different climatic conditions. Establishing a network of sensors across the city could provide a useful baseline as tree-planting is upscaled across the city to a scale that impacted city-wide temperatures, if this was planned.

Synergies: Strong synergies with health and wellbeing indicators in relation to heat stress. Reducing temperatures in a specific location could also have links to social cohesion and accessibility as people may be more likely to use a space. Where weather stations are utilised, there are synergies in relation to capturing additional environmental parameters of relevance for other indicators (e.g. total rain fall for stormwater management indicators). This indicator has synergies with Env03 (Air temperature reduction).

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: Haase et al. (2014), Andersson et al. (2014), Kremer et al. (2018)

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2.2.16 Community garden area per child capita and in a defined distance (Env90)

Umbrella: Greenspace accessibility

Indicator: Community garden area per child capita and in a defined distance

Code: Env90

Description: A measure of per child capita garden area per target distance - public community gardens provide places of active learning in nature and opportunities for healthy play.

Metric(s): Measuring community gardens as part of the greenspace network in cities provides evidence on a wide range of services provided by such spaces. This includes: accessible greenspace provision and preservation, diversity of land use for humans and biodiversity, sustainable use of vacant land, climate regulation (cooling, stormwater, reduced GHG emissions associated with food transportation), food security, physical activity, access to healthy food/fruit and vegetable consumption, community cohesion and empowerment. Community gardening projects promote healthy lifestyles with educational initiatives such as a community garden club, exercise and nutrition lessons, and environment and recycling education which encourage and enable children and parents to learn collectively about sustainable living in cities. Ultimately, community gardens deliver a social function. In addition to mapping evidence, mapping exercises can also be used to identify areas where future community garden (CG) projects should be targeted (i.e. need for CGs).

Metrics will largely concern identification of CGs as part of the city's greenspace provision and then quantification in relation to population census data and an assessment of accessibility in relation to proximity measures. This indicator differs from Env89 (Community garden area per capita and in a defined distance) in that it is specifically in relation to per **child** capita. Therefore, the same metrics as for Env89 are provided below, but census data would need to be interrogated to extract figures relating to the population of children (typically under 16 years old) in the survey area.

Identification of CGs within a city will involve data gathering from land use plans on location, extent and characteristics, analysing official websites to identify additional CGs not included in planning documents, interrogating available satellite imagery provided on regional geoportals, and ground truthing by field observation/surveys (Senes et al., 2016). The collated data can then be entered into a GIS database for digitisation. From this, it would be possible to generate metrics regarding average CG area within the city (m^2), and distance from urban centres by overlaying a land use map and mapping buffer areas of 330 and 660 m (which correspond to a walking distance of 5 and 10 min respectively at a speed of 4km/h) (as outlined in Senes et al, 2016).

Alternative metrics that have been calculated in a GIS environment include: stratified spatially diverse and representative sampling design based on measuring the district area (ha) and the area of CGs (ha) and calculating a CG area proportion for the city as a % of the overall district area (Speak et al., 2015). Measuring the proportion of households within 0.25 miles of a CG, or a measure of the acreage used for CG per 1,000 residents as measures of accessibility and density (Jakubowski & Frumkin, 2010). Metrics outlined in the indicator review for Env41 (Accessibility of greenspaces) can also be applied here, to provide a 'defined distance' measure for this indicator. For instance La Rosa's (2014) 'simple distance indicators' which measure the Euclidean distance or Network distance to a greenspace, in this case CGs, at a fixed threshold distance of 300 m or 600 m. Within GIS, the total population present (taken from census data) within the considered distance thresholds can be calculated in relation to each CG.

In general, GIS analysis of urban gardens needs the following data to be utilized: community garden outlines (by City Municipality), biotope and land-use survey, and authoritative topographic-cartographic information systems. City-wide VHR hybrid remote sensing comprising Digital Orthophotos (DOP) at 20 cm resolution and LiDAR elevation data at 2 m resolution can be applied. From this, distance to roads, distance to edge of built-up area (urbanity), as well as types and proportion of surrounding structure types can then be analysed. Moreover, it is essential to consider here to the concept of 'walkability' as a measure of how safe/friendly an area is for walking, in particular when evaluating use of community gardens by children. Thus, the following factors influencing walkability should additionally be analysed: the presence or absence and quality of footpaths, sidewalks or other pedestrian rights-of-way, traffic and road conditions, land use patterns, building accessibility, and safety, among others (Speck, 2012).

Another important issue to reflect is to analyse how 'child-friendly' is the particular community garden, as it has been confirmed by several studies (ACT, 2013; Shallue 2014) that community gardens can play a powerful role in shaping a child-friendly city. In a physical context, CGs provide children with the opportunity to engage with and explore their natural environment, and the chance to learn about flora, fauna and gardening. Children can also develop new skills and learn about healthy lifestyle choices and nutrition through helping to grow food. This indicator has direct relevance to the objectives of the 'Child Friendly Cities Initiative' of UN Habitat II (https://childfriendlycities.org/), where it was declared "...the well-being of children is the ultimate indicator of a healthy habitat, a democratic society and good governance". In this regard not only provision per child capita, but also the ability of community gardens to give children the opportunity for exploring and learning nature, to connect with their community and foster a sense of belonging should be evaluated. Additionally, community gardens can be assessed from the perspective of how, through playing an active role in the tending of the gardens, children can develop a sense of responsibility, self-confidence and cooperation, all important parts of their social development (ACT, 2013).

As well as providing metrics for calculating existing CG provision, Senes et al. (2016) also provide a methodology for identifying possible sites suitable for CG projects. They identify areas potentially suitable for new CGs on the basis of the following criteria: i) proximity to residential road network, because the accessibility to the CGs is a fundamental requirement for a public service (considers only the residential road network, usually not characterized by heavy traffic); ii) compatible land-use, in order to exclude areas with a land-use that doesn't allow a future transformation to CG; iii) identify areas with soils with land capability class 1 and 2 and exclude from the possible conversion into CG to allow the preservation of agriculture. The data is mapped in a GIS environment to generate a plan of potentially suitable and available areas for new CGs (Senes et al., 2016).

'Incredible Edible Lambeth' (IEL) have created an online map of community garden projects in the borough https://www.incredibleediblelambeth.org/map/ which can be updated by citizens who become a member (for free) online. As well as connecting citizens to CGs in the borough, this also provides a public participation mechanism for generating a comprehensive map of CGs in an area.

A study by Ramirez-Andreotta et al. (2015) illustrates the benefits of a community-academic co-created citizen-science program in addressing the complex problems that can arise for community garden projects neighbouring a contaminated site. This place-based, community-driven project was designed where academics and community members maintained a reciprocal dialogue, and together: 1) defined the question for study, 2) gathered information, 3) developed hypotheses, 3) designed data collection methodologies, 4) collected environmental samples (soil, irrigation water, and vegetables), 5) interpreted data, 6) disseminated results and translated results into action, and

7) discussed results and asked new questions (Ramirez-Andreotta et al., 2015). Such a project can increase the community's involvement in communication and decision-making, which ultimately has the potential to help mitigate environmental exposure, reduce associated risks and increase the provision of community gardens. It also demonstrates that community members can successfully participate in environmental science investigations. Pollard et al. (2017) also demonstrates that a citizen science approach offers a unique method to investigate provision as well as the inputs (labour, costs and water use) and outputs (produce yields and value) of urban community gardens. Citizen science enables a large cohort of gardeners to identify and measure urban agriculture, notably the sheer number of geographically separated gardens, the enormous diversity of garden sizes and types, as well as highly variable cultivation and management techniques (Pollard et al., 2017).

Mapping community garden accessibility in these ways can be used to:

- Identify deficits and inequalities in relation to community garden access specifically for children;
- Assess changes in access for children in relation to new projects/sites;
- Inform strategic planning decisions in relation to community garden provision for children;
- Assess different types of accessibility;
- Set targets in relation to community garden provision for children and monitor progress towards targets.

Scientific solid evidence: Robustness of evidence will be determined by how detailed existing data is on CGs in a city and accuracy of census data in relation to child capita. Similarly, the accuracy of distance to CG will vary based on the distance measure used. They can, however, represent a useful indicator basis for urban planning.

Level of expertise: some mapping/GIS expertise is likely to be needed, in particular when: using remotely sensed imagery and field observations to identify community gardens; applying geographic mapping software to analyse data layers; understanding how the distribution of community gardens relates to children as well as demographic data on race, ethnicity, and socio-economic conditions.

Cost: Some map datasets and satellite imagery are freely available online, more comprehensive data needed for network-based measures potentially can involve a licence fee. Could be additional costs associated with acquiring GIS software and specialists if not already available in-house.

Effort: The level of effort involved would be dependent on the amount of data already recorded by the city on community garden distribution, and the expertise available in terms of GIS. Public participation in organised research efforts (citizen science) could be beneficial in terms of reducing the amount data collection needing to be undertaken by in-house personnel.

Participatory process: The project Incredible Edible Lambeth demonstrates it may be possible to validate CG distribution using a PPGIS-type citizen science exercise. The studies by Ramirez-Andreotta et al. (2015) and Pollard et al. (2017) show that establishing a community-academic partnership, and building a co-created citizen science program in urban community gardens can confirm the role of local knowledge in scientific research.

Data availability: Some GS map data is freely available for mapping distance, aerial data is increasingly available but the quality and resolution can still be variable. This indicator can also be used to generate new data, for instance CG per child capita before and after nature-based solutions project implementation.

Geographical scale: Typically used at city-scale, but other scales such as region/neighbourhood scale are possible.

Temporal scale: Can provide a snapshot or a temporal view of change over time if adequate historical data is available.

Synergies: Strong synergies with health and wellbeing indicators and social cohesion indicators in terms of physical activity, bringing together people from different backgrounds, education about nature and healthy food. Also, synergies with other environmental indicators (e.g. biodiversity measures, water regulation and air temperature) and possibly economic indicators if enterprises emerge selling produce.

Modelling: The Feature indicator reviews are combined for applied metrics and earth observation/remote sensing/modelling approaches.

Original reference(s) for indicator: SDG11; Kabisch et al., 2016; Eklipse

Metric reference(s):

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