Tools4LDN Project Roadmap for Trends.Earth Data Enhancements

A Review of Publicly Available Geospatial Datasets and Indicators In Support of Land Degradation Monitoring

Gabriel Antunes Daldegan, Monica Noon, Alex Zvoleff, Mariano Gonzalez-Roglich

Moore Center for Science, Conservation International

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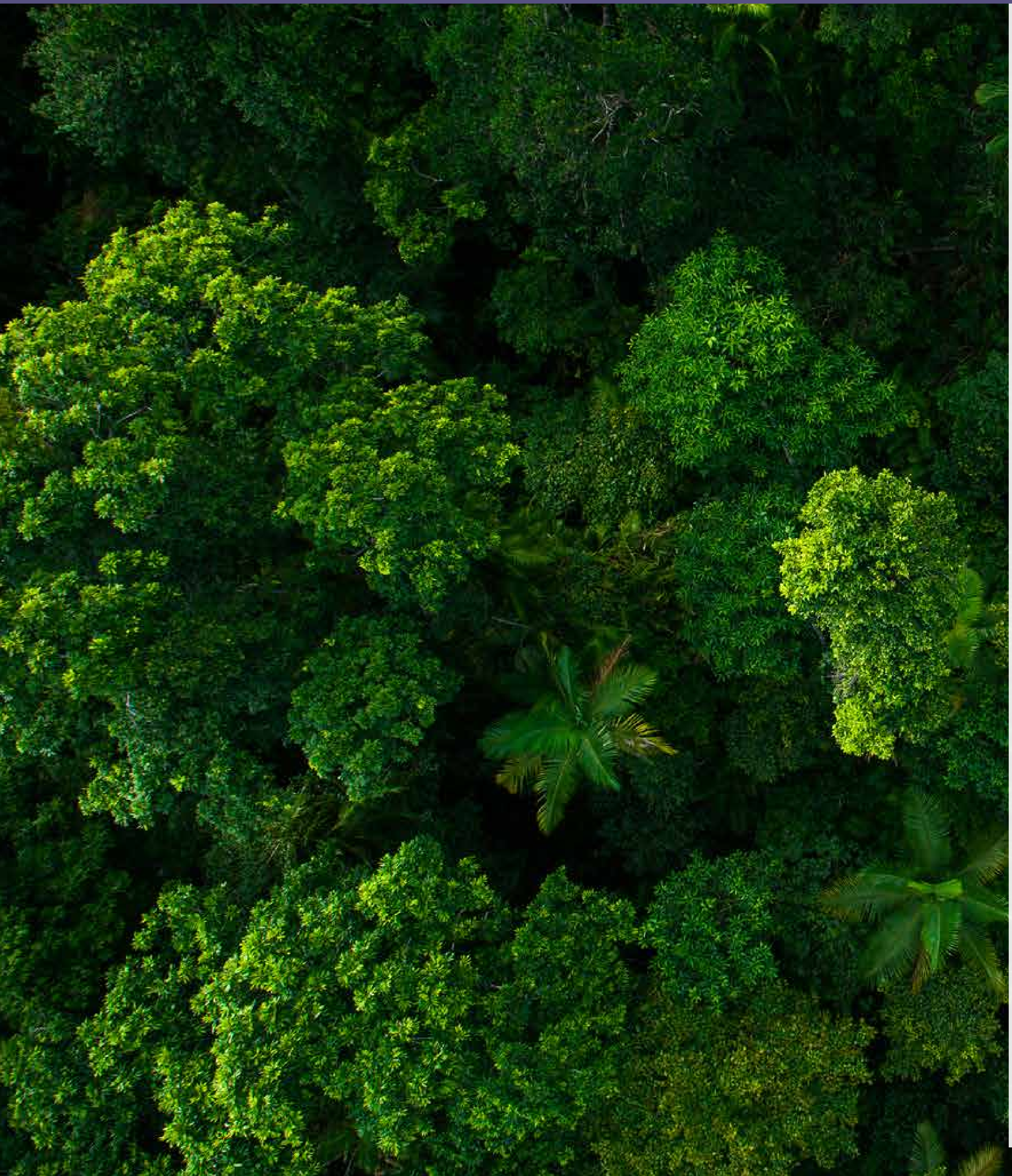

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1 This report was produced as an output of the Global Environment Facility (GEF)-funded project "Strengthening Land Degradation Neutrality data and decision-making through free and open access platforms". For additional information on the project see https://www.tools4ldn.org/. This project is a collaboration of Conservation International, Bern University, University of Colorado, and the University of California Santa Barbara.

Acronymns

ANPP	Annual Net Primary Productivity
ARD	Analysis Ready Data
AVHRR	Advanced Very High-Resolution Radiometer
BRDF	Bidirectional Reflectance Distribution Function
CBERS-4	China-Brazil Earth Resources Satellite
CCI	Climate Change Initiative
CEOS	Committee on Earth Observation Satellites
CGLS	Copernicus Global Land Service
CI	Conservation International
CIAT	International Center for Tropical Agriculture
COP	Conference of the Parties
DVI	Difference Vegetation Index
EO	Earth Observation
ETM+	Enhanced Thematic Mapper Plus
ESA	European Space Agency
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
GEE	Google Earth Engine
GEF	Global Environment Facility
GEO	Group on Earth Observation
GEO LDN	Group on Earth Observations Initiative on Land Degradation Neutrality
GFW	Global Forest Watch
GIMMS	Global Inventory Monitoring and Modeling System
GLAD	Global Land Analysis and Discovery
GLC	Global Land Cover
GPG	Good Practice Guidance
GPP	Gross Primary Productivity
GSOC	Global Soil Organic Carbon
INPE	National Institute of Space Research (Brazil)
ISRIC	International Soil Reference and Information Centre
LAI	Leaf Area Index
LandPKS	Land Potential Knowledge System
LDN	Land Degradation Neutrality
LP DAAC	Land Processes Distributed Active Archive Center
LPD	Land Productivity Dynamics
LUE	Light Use Efficiency
MODIS	Moderate Resolution Imaging Spectroradiometer
MSAVI	Modified Soil-Adjusted Vegetation Index
MSI	Multispectral Instruments
NASA	National Aeronautics and Space Administration (USA)
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
NPP	Net Primary Productivity
NOAA	National Oceanic and Atmosphere Administration (USA)
OLI	Operational Land Imager
PAR	Photosynthetically Active Radiation
PPI	Plant Phenology Index
SATVI	Soil-Adjusted Total Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
SDG	Sustainable Development Goals
SEEA	System of Environmental and Economic Accounting
SO	Strategic Objectives
SOC	Soil Organic Carbon
STAP	Scientific and Technical Advisory Panel
SWIR	Short Wave-Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
TSP	Target Setting Programme
UN	United Nations
UNEP	United Nations Environment Programme
UNCCD	United Nations Convention to Combat Desertification
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United States Geological Survey
VI	Vegetation Indices
VIIRS	Visible Infrared Imaging Radiometer Suite
WCMC	World Conservation Centre
WHRC	Woods Hole Research Center
WOCAT	World Overview of Conservation Approaches and Technology

Executive Summary

Land degradation affects the livelihoods of millions of people worldwide. Diminished overall productivity and reduced resilience in the face of climate and environmental change, have made addressing land degradation a global priority formalized by the United Nations Convention to Combat Desertification (UNCCD) and the Sustainable Development Goals (SDGs), in particular Target SDG 15.3 on Land Degradation Neutrality (LDN).

The LDN scientific framework provides the conceptual underpinning for how to achieve LDN, while the SDG 15.3.1 Good Practice Guidance (GPG) outlines a set of methodological options countries can follow to perform the land degradation assessments based on their local capacities. However, for many countries, limited resources and human capacity have hindered their ability to implement such recommendations. To address this need, Trends.Earth was developed as a free and open source platform which provides standardized methods, following SDG 15.3.1 GPG, and curated global datasets for the development of land degradation assessments. Over 130 countries were trained to use Trends.Earth for the 2018 SDG 15.3 reporting cycle, significantly lowering the technical barriers for providing robust assessments of land degradation. Country representatives, the UNCCD, scientists, and the Group on Earth Observations (GEO) acknowledged the significant contribution of Trends. Earth to supporting the achievement of land degradation neutrality, while at the same time identifying numerous areas for improvement which would allow for more robust monitoring. The objective of this report is to review currently available geospatial datasets which could be used in support of monitoring the three SDG 15.3.1 sub-indicators: trends in land cover, trends in land productivity, and trends in carbon stocks, in order to enhance Trends.Earth functionalities before the 2022 SDG 15.3 reporting cycle.

Remote sensing offers the most cost-effective approach to monitor and evaluate large scale Earth surface change. Several spatially-explicit datasets at relatively fine spatial resolution (i.e. 10 – 30 m) have become available in recent decades at no cost to end users; these data, combined with cloud-based computing power processing, have enabled the assessment of natural and anthropogenic forces that modify land structures and process over long time-series. Based on the review of currently available global geospatial datasets, we have identified datasets at fine spatial resolution (i.e. 10 – 30 m) with significant potential for contributing to the assessment of land degradation complementing products at moderate to coarse spatial resolution that have already been successfully used so far. The Harmonized Landsat-Sentinel collection is the most promising of those datasets, given its high spatial resolution (10 – 30 m) combined with high revisiting frequency (3 to 4 days). For the assessment of changes in land productivity, the Normalized Difference Vegetation Index (NDVI) is the most studied and accepted vegetation index making it the preferred option, although limitations on some conditions would indicate that other better suited vegetation indices could provide better insights on the productivity trends. We have identified two other vegetation indices which can enhance assessments in particular conditions: for areas with high biomass, the two-band Enhanced Vegetation Index (EVI2), and for areas with low biomass, the Modified Soil-Adjusted Vegetation Index (MSAVI). Based on the review, we suggest developing processing capabilities in Trends.Earth to compute productivity indicators using the Harmonized Landsat-Sentinel collection with NDVI, EVI2, and MSAVI for improving monitoring of changes in land condition to complement the current assessment produced with MODIS NDVI long term series data. Detailed user guidance on conditions in which each indicator should be used should also be added. For land cover and soil organic carbon, no new finer spatial resolution global resolution datasets were identified as currently available. Trends.Earth will continue then supporting current global datasets and will regularly check with data providers to incorporate any new relevant dataset which could be added into the tool if they meet the recommendations and quality requirements determined by the SDG 15.3.1 GPG and the GEO LDN Initiative.

Contents

Trends.Earth and the Tools4LDN Project

The Land Degradation Monitoring Project (LDMP), a project funded by the Global Environment Facility (GEF) under the sixth replenishment, was designed to provide guidance on robust methods and a toolbox for assessing, monitoring status, and estimating trends in land degradation using remote sensing and other datasets. The project was inspired by a review commissioned by the Scientific and Technical Advisory Panel (STAP) of the GEF on the use of NDVI to monitor land degradation.

Numerous international processes, including the United Nations Convention to Combat Desertification (UNCCD), the Convention on Biological Diversity (CBD), the United Nations Framework Convention on Climate Change (UNFCCC), and the Sustainable Development Goals (SDGs) have highlighted land degradation as a key development challenge, and that a lack of reliable information and cost-effective methods for collecting and analyzing data hampers the development of policies to address that challenge. The STAP approached Vital Signs, the National Aeronautics and Space Administration (NASA), and the European Space Agency (ESA) to develop a proposal to address the land degradation issue, ultimately resulting in the LDMP project.

A major output of the project included a free and open-source tool – Trends.Earth (Trends.Earth, 2018) – for monitoring land degradation trends, and the creation of a set of guidance documents to support its use. Trends. Earth allows non-technical users to integrate national data and information with global datasets to track changes in indicators of land degradation. The Project's guidance and tools can be employed to inform land management and investment decisions, as well as to improve reporting to the UNCCD and to the GEF. Trends.Earth is an open data platform that is freely available as a global public good.

A novel feature of Trends.Earth is its use of cloud-computing – by using Google Earth Engine (GEE) the toolbox makes it possible for users with limited computing capacity and without expert knowledge of cloud computing to perform complex calculations on large datasets (enabling analyses of land degradation on national-global scales) in minutes. While the benefits of the cloud-based approach are clear (and to date over 3,000 users have registered to use the tool), the project team also recognized that in many regions' internet connectivity limits the use of cloud-based tools. For that reason, Trends. Earth also supports offline computation of indicators (for areas where internet connectivity may be limited). This two-pronged approach allowed the project to maximize its reach by meeting the needs of most stakeholders. Trends.Earth supports the calculation of all three of the indicators (changes in land productivity, land cover and soil carbon stocks) for monitoring the achievement of Land Degradation Neutrality (LDN), allowing the use of a set of standardized, recommended methods for estimating the indicators of land degradation, while providing the flexibility for users to customize the methods depending on local circumstances and the availability of national data.

Trends.Earth is a tool which has proven valuable for facilitating the assessment of land condition at national scale using Earth observation (EO) data, with potential to inform at sub-national scales. Based on feedback received from users, stakeholders, and partners it was possible to identify key areas of improvement of the tool, which would greatly benefit planning and monitoring for LDN. Those areas of improvement include: 1) enhance spatial resolution of the geospatial data, 2) increase capabilities for linking remote sensing analysis with field and in-situ data for verification purposes, 3) link remote sensing with participatory assessment processes to include local knowledge and increase the sense of ownership over the outcomes, and 4) incorporate decision support tools to assess the trade-offs in different proposed activities and inform LDN planning. In order to address these needs, Conservation International partnered with the University of Colorado (Land Potential Knowledge System - LandPKS), Bern University (World Overview of Conservation Approaches and Technologies - WOCAT) and University of California Santa Barbara (Planetary

Health Institute) to design and implement the GEF-funded project "Strengthening Land Degradation Neutrality data and decision-making through free and open access platforms" (henceforth referred as Tools4LDN).

The objective of the Tools4LDN project is to provide improved methods for assessing land degradation and understand the socio-economic conditions of vulnerable communities in affected areas through the integration of free and open platforms to support country level reporting to the UNCCD (project execution period: October 2019-September 2021). The project has four main components:

- **Component 1:** Improve land degradation biophysical indicators to support monitoring towards land degradation neutrality: Trends.Earth currently provides global datasets at resolutions of 250-300 m. Even though Trends.Earth supports the usage of higher spatial resolution datasets provided by the user, the majority of the UNCCD parties used default data to report on the land-based progress indicators, underscoring the utility, suitability and need for data prepared in a globally consistent manner, lowering the barriers to reporting for many countries. Under this component, new datasets and algorithms will be added to Trends.Earth to provide enhanced spatial resolution (10-30 m) indicators for the three land-based indicators: changes in primary productivity, land cover, and soil organic carbon. Fine spatial resolution data will be critical for tracking changes in land condition from on-the-ground activities and to facilitate monitoring of different land management activities implemented to support LDN.
- **Component 2:** Understand the socio-environmental interactions between drought, land degradation, and poverty to support development of monitoring frameworks for the UNCCD Strategic Objectives (SO) 2 and 3: Under this component we will evaluate, in close collaboration with the UNCCD, the World Meteorological Organization, and other key stakeholders, datasets and approaches for evaluating the socio environmental interactions between drought, land degradation and poverty. Global datasets (representing biophysical and socioeconomic variables) and approaches will be integrated into Trends.Earth to allow users to run national level assessments to understand the risks that drought and poverty could pose to the most vulnerable communities in order to enhance their resilience and wellbeing. Global datasets to support reporting of SO 2 and SO 3 will be evaluated and made available to users through Trends.Earth.
- **Component 3:** Support planning and monitoring of LDN priorities from field to national scales: Up to now, Trends.Earth has provided functionalities for assessing historical changes in land condition. Relating those satellite-based assessments to on-the-ground information is key; however, many users have indicated that they lack the knowledge and resources to perform such analyses. Trends.Earth is partnering with WOCAT and LandPKS to facilitate the integration of remotely sensed analysis with land management information collected through a mobile application for this project. This will enable systematic verification of degradation trends and monitoring of progress made under the LDN Target Setting Programme (LDN-TSP), while also collecting land condition and management information on the ground which will be critical for posterior planning processes. Other freely available tools to assess land condition and change, such as Collect Earth (OpenForis, 2020), will be evaluated and integrated workflows will be developed to support user uptake. These assessments will be the input for a simple decision support tool which will allow users to identify priorities for interventions at national and subnational scales. These tools and approaches will be tested in different geographies within a pilot country, developing case studies that will provide example applications for scaling the tool to a larger user base. A capacity building workshop with equitable participation by women and men focused on the integrated assessments using Trends.Earth, WOCAT, and LandPKS will take place in the pilot country.
- **Component 4:** Assist the UNCCD and its signatory countries by building capacity to support planning, monitoring, and reporting: since it was launched in late 2017, Trends.Earth has supported a user base of over 3,000 registered participants. With the enhancements and new modules to be added to the tool under the current proposed project, we expect that number to at least triple in the next three years. For that reason, it is critical to update and maintain documentation and training resources available through the project website, and to provide users with the required support and training, allowing for equitable participation by women and men. Updated documentation and online training courses will include guidelines for integrated assessments using Trends.Earth, LandPKS, WOCAT, and Collect Earth maximizing the utility of remotely sensed data, field data, and local expert knowledge. To support the UNCCD signatory countries on their reporting needs for the cycle 2021-2022, we will host a capacity building technical workshop on tools and methods for monitoring strategic objectives progress at a UNCCD parties meeting.

Before implementation of the technical enhancements under Component 1, a review of geospatial datasets and indicators relevant for SDG 15.3.1 was completed. This report focusses on reviewing datasets and indicators that have been published and/or made publicly available since the released of the SDG 15.3.1 Good Practice Guidance (Sims et al., 2017) until July 2020. Consulted websites include: European Space Agency - ESA, Food and Agriculture Organization - FAO, GitHub, Global Forest Watch – GFW, Google Earth Engine – GEE, Google Scholar, Group on Earth Observation – GEO, National Institute of Space Research - INPE, International Center for Tropical Agriculture – CIAT, International Soil Reference and Information Centre - ISRIC, National Aeronautics and Space Administration - NASA, National Oceanic and Atmosphere Administration – NOAA, Global Land Analysis & Discovery – GLAD, UN Environment Programme World Conservation Centre – UNEP/WCMC, United States Geological Survey - USGS, Web of Science, Woodwell Climate Research Center - WCRC, World Agroforestry Centre. All datasets listed in this report need to meet the following criteria for implementation:

- Follows the SDG 15.3.1 Good Practice Guidance (Sims et al, 2017)
- Follows the GEO LDN Working Group 2 guidance on data quality standards (GEO LDN, 2020a)
- Feature global coverage
- Available at no cost for the end user
- Provides publicly available and detailed documentation on data sources, processing, and quality.

Although we performed a thorough research on scientific journals, websites and publicly available data repositories aiming for this report to be as comprehensive as possible, new datasets and methods are constantly developed and/or updated. Thus, we acknowledge that other spatially explicit datasets that meet these criteria may be available and are not listed here. If you are aware of geospatial products that could potentially be added to the toolbox to enhance land degradation assessments, please contact us at trends.earth@conservation.org.

SDG Indicator 15.3.1: Proportion of land degraded over total land area

The United Nations (UN) published in 2015 the document "Transforming Our World: The 2030 Agenda for Sustainable Development" (UN, 2015) in which it launches a set of 17 Sustainable Development Goals (SDG) that would guide the international community on the social, environmental and economic challenges that need to be addressed by 2030 (SDGs, 2020).

Designed to safeguard life on land, SDG 15 aims to "protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss". The SDG 15 has specific targets for addressing different components of land sustainability; target 15.3 aims to "by 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world."

The UNCCD, custodian agency of the SDG 15.3, defines LDN as "a state whereby the amount and quality of land resources, necessary to support ecosystem functions and services and enhance food security, remains stable or increases within specified temporal and spatial scales and ecosystems." Specific indicators are used to estimate the progress of each SDG; in the case of SDG target 15.3 the progress towards a land degradation neutral world is being assessed by indicator 15.3.1 "proportion of land that is degraded over total land area". To estimate land degradation, the proposed approach is based on three biophysical sub-indicators: changes in land productivity, in land cover, and in soil carbon stocks (UNCCD, 2016).

To monitor progress towards the achievement of LDN by 2030, countries estimated baseline levels of land degradation for the period 2000-2015. These analyses were performed by using a combination of global and national data, depending on country resource availability. The UNCCD highlighted that for the first round of LDN reporting it was key to provide globally consistent and readily available default geospatial data to enable country Parties to efficiently assess land-based progress indicators (UNCCD, 2018). The UNCCD also highlighted that Trends.Earth has considerably helped the reporting process by enabling country Parties to adapt the default set of data to official country boundaries, and by allowing them to take advantage of nationally generated datasets while maintaining alignment with the suggested methodological framework proposed by the LDN-TSP (UNCCD, 2018). The use of Trends.Earth improved the pursuit of methodological harmonization on assessing and combining sub-indicators towards SDG 15.3.1 Indicator, and at the same time enhanced the potential for country ownership in monitoring and analyzing data. In November 2018, the Group on Earth Observations Initiative on Land Degradation Neutrality (GEO LDN) was launched with the mission of "promoting the collaborative development, and support the provision and use, of EO datasets, quality standards, analytical tools and capacity building to avoid, reduce, and reverse land degradation with the aim of achieving LDN in all countries by 2030. The Initiative will help connect data providers to data users, including researchers, decision-makers, land use planners, commercial sector, donors/investors and other stakeholders in order to optimize the use of EO datasets for LDN assessment, planning, implementation, monitoring and reporting" (GEO LDN, 2020b). The GEO LDN is organized in three working groups, one on capacity building, one on data quality standards and a third one on data analytics. Conservation International and the Trends.Earth team actively participate in the GEO LDN initiative, to secure alignment between country data and processing needs and technical developments in the tool.

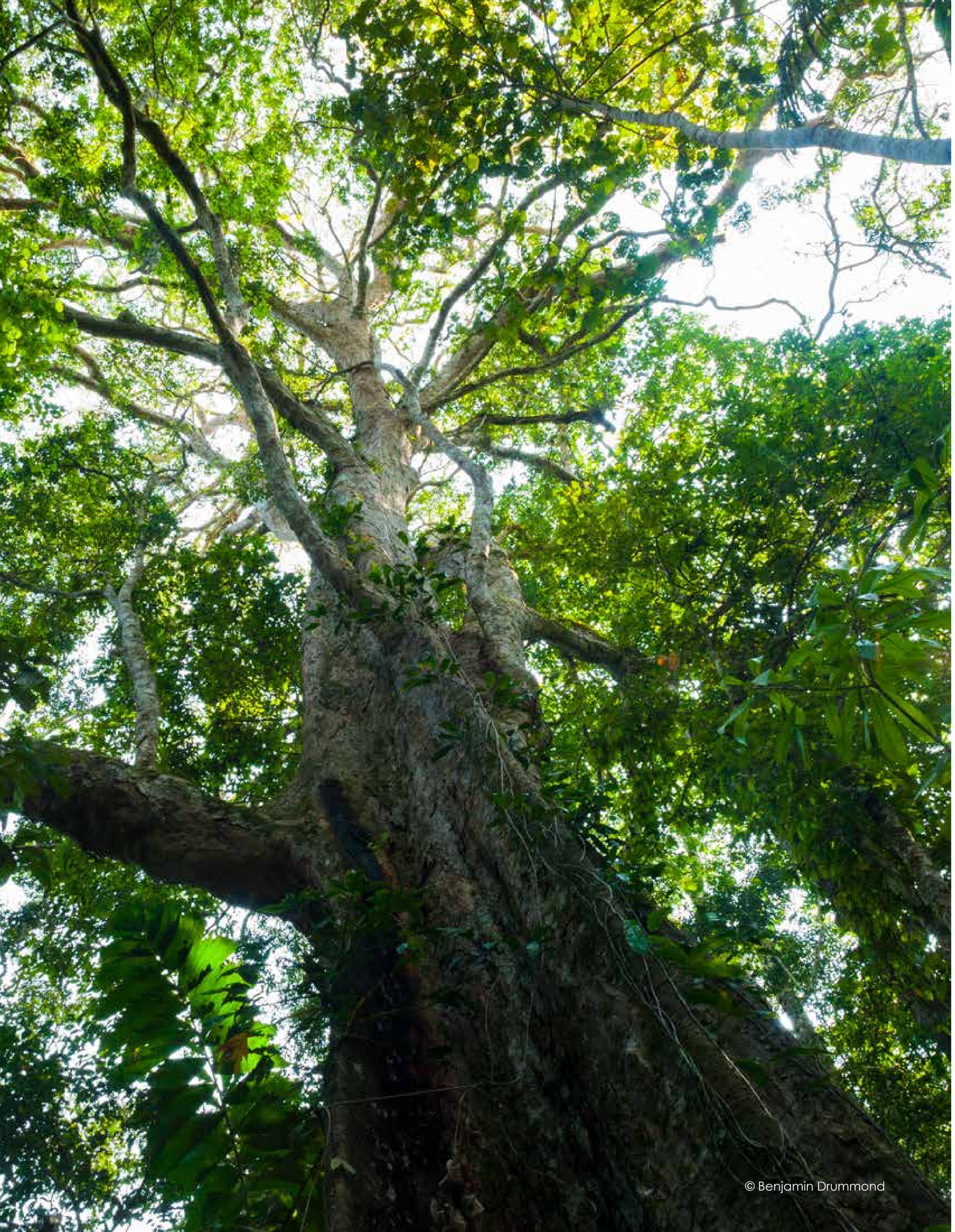
Global datasets currently available in Trends.Earth

Currently, Trends.Earth supports moderate to coarse geospatial datasets representing each of sub-indicators necessary to calculate the SDG 15.3.1 (Table 1).

For changes in land productivity, users have the choice to apply either the Advanced Very High Resolution Radiometer Global Inventory Monitoring and Modeling System (AVHRR GIMMS) or the Moderate Resolution Imaging Spectroradiometer (MODIS) 13Q1 datasets, both representing the Normalized Difference Vegetation Index (NDVI); changes in land cover are estimated using the European Space Agency Climate Change Initiative (ESA CCI) datasets; and to estimate changes in carbon stocks, the SoilGrids layer representing soil organic carbon (SOC) is combined to the ESA CCI land cover, accounting for carbon conversion coefficients for changes in land use (Trends.Earth, 2020). In the following section, we present a review of currently available datasets to be considered for inclusion into Trends.Earth in support of assessments of land degradation at finer spatial resolution.

Table 1 – Geospatial datasets representing the sub-indicators required to estimate SDG 15.3.1 currently supported in Trends.Earth.

Sub-indicator	Name	Source	Spatial Resolution	Temporal Coverage	Temporal Frequency	Extent
Land Productivity	NASA/USGS MODIS Terra MOD13Q1 v006 (Collection 6) NDVI	NASA-USGS	250 m	February 18, 2000 - Present	16-Day Composite	Global
	NASA AHVRR GIMMS 3g.v0 NDVI	NASA – GIMMS 3g.v0	8 km	July, 1981 – December, 2015	Monthly	Global
Land Cover	ESA CCI land cover	ESA CCI land cover	300 m	1992-2018	Annually	Global
Carbon Stocks	SoilGrids	ISRIC	250 m	2010	NA	Global



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Measuring changes in land productivity

Land productivity is the biological productive capacity of the land, which is the source of all the food, fiber, and fuel that communities rely on (Sims et al., 2017).

Generally, land productivity is assessed through methods designed to estimate the amount of biomass produced over a fixed period and area. Net primary productivity (NPP), the net amount of carbon assimilated by vegetation after photosynthesis and autotrophic respiration over a given period of time (Clark et al. 2001), is normally used to estimate land productivity over large extents, typically represented in units such as kg/ha/year. NPP is a fundamental ecological variable given its importance in revealing the condition of the vegetated land and the status of ecological processes, ecosystem services and human wellbeing. Remote sensing is the most effective way to estimate land productivity biophysical variables at varying scales through known correlations between the fraction of absorbed photosynthetically active radiation and plant growth, vigor, and biomass (Yengoh et al., 2016). Vegetation indices (VIs) derived from satellite imagery are known surrogates applied to estimate NPP, since they measure the amount of photosynthetically active vegetation at particular points in time, and through integration over the growing season, they can be used to estimate annual net primary productivity (ANPP).

Gross Primary Productivity - GPP

Gross primary productivity (GPP) estimates the portion of the incident energy that is assimilated by autotrophic organisms, directly resulting in the carbon fixation rate through the photosynthetic process. Estimating GPP is key to understanding the efficiency of assimilation at which primary producers capture the electromagnetic energy incident from the sun and convert it to sugar molecules through photosynthesis (Odum, 1968). GPP can be measured on the ground by modeling the gain on biomass and the respiration rate – net CO2 exchange measured using eddy covariance (EC) techniques. However, field work measurements using EC have a very strict spatial footprint that depends on the EC tower height, physical characteristics of the canopy and wind velocity (Wu et al., 2010). Direct observation of GPP at the global scale is not available. When assessing GPP over large extents, remote sensing techniques offer a more cost-effective approach through consistent and systematic observations of the vegetation-light biophysical interactions. The light use efficiency model (LUE: Monteith, 1977, 1972) – Equation 1 - is assumed to be the most adequate approach to predict spatial and temporal variations on GPP (Wu et al., 2010). GPP units are normally reported as energy flux (j $m^{-2}day^{-1}$) or as mass per area (t ha^{-1}).

$$GPP = LUE * fAPAR * PAR \qquad (1)$$

where LUE is the light use efficiency and fAPAR is the fraction of absorbed photosynthetically active radiation (PAR).

Data review conclusion: Global spatially explicit datasets of GPP exist at relatively coarse spatial resolution (Table 2). However, remote sensing GPP products are normally derived from the LUE model; thus, their estimates are subject of great uncertainty given their direct relationship to the LUE rate, which need to be rigorously calibrated across the diversity of vegetation types over time, therefore, it requires ground-based meteorological measurements (Wu et al., 2010). Given the coarse spatial resolution and the uncertainties associated with the modeling of GPP, currently available datasets of GPP are not suitable for supporting estimation of changes in the land productivity indicator.

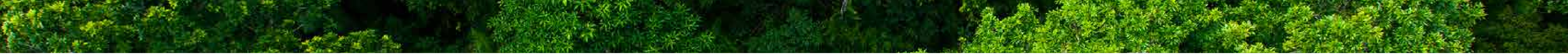


Table 2 – Global publicly available geospatial datasets that model Gross Primary Productivity based on remotely sensed data.

Name	Source	Spatial Resolution	Spectral Resolution	Temporal Coverage	Temporal Resolution	Analysis Ready?[2]	Extent
PML_V2: Coupled Evapotranspiration and Gross Primary Product	Penman-Monteith-Leuning (PML)	500 m	5 bands representing derived products: Gross Primary Product (GPP); Vegetation Transpiration (Ec); Soil Evaporation (Es); Interception from vegetation Canopy (Ei); Water body, snow and ice evaporation (ET_water)	July 04, 2002 – August 29, 2019	8 days	Yes	60°S to 90°N
MOD17A2H v006: MODIS/Terra Gross Primary Productivity	NASA/USGS LP DAAC	500 m	3 bands representing derived products: Gross Primary Production (Gpp); Net photosynthesis (GPP minus the maintenance respiration (PsnNet); Quality control bits (Psn_QC)	March 05, 2000 - Present	Cumulative 8-day composite	Yes	Global
MOD17A2HGF v006: MODIS/Terra Gross Primary Productivity Gap-Filled	NASA/USGS LPDAAC	500 m	3 bands representing derived products: Gross Primary Production (Gpp_500m); Net photosynthesis (GPP minus the maintenance respiration (PsnNet_500m); Quality control indicators (Psn_QC_500m)	January 1st, 2000 - Present	Cumulative 8-day composite	No[3]	Global
MYD17A2H v006: MODIS/Aqua Gross Primary Productivity	NASA/USGS LP DAAC	500 m	3 bands representing derived products: Gross Primary Production (GPP); Net photosynthesis (GPP minus the maintenance respiration (PsnNet); Quality control bits (Psn_QC)	July 04, 2002 - Present	Cumulative 8-day composite	Yes	Global
MYD17A2HGF v006: MODIS/Aqua Gross Primary Productivity Gap-Filled	NASA/USGS LPDAAC	500 m	3 bands representing derived products: Gross Primary Production (Gpp_500m); Net photosynthesis (GPP minus the maintenance respiration (PsnNet_500m); Quality control indicators	January 1st, 2002 - Present	Cumulative 8-day composite	No[3]	Global

2 Analysis ready indicates satellite data that have been processed to a minimum set of requirements and organized into a form that allows immediate analysis with a minimum of additional user effort and interoperability both through time and with other datasets.

3 The MODIS GPP and NPP Gap-Filled products are currently not available as Analysis Ready Data, given that they are provided scene-by scene in HDF format, which require users to spend considerable amount of time pre-processing these datasets.

Net Primary Productivity - NPP

Net primary productivity (NPP) estimates GPP minus the energy dissipated due to metabolism and maintenance of autotrophic organisms, representing the actual rate of biomass production that is available for consumption to heterotrophs organisms (Clark et al., 2001). NPP as defined above cannot be directly assessed in the field due to transformations such as decomposition and consumption during the measuring period. Though, it can be estimated by applying a set of assumptions based on a suite of measurements (Clark et al., 2001). Estimating NPP through remote sensing is more cost-effective and allows for spatiotemporal analysis.

Table 3 – Global publicly available geospatial datasets that model Net Primary Productivity scale based on remotely sensed data.

Name	Source	Spatial Resolution	Spectral Resolution	Temporal Coverage	Update Frequency	Analysis Ready?	Extent
MOD17A3H v006: MODIS/Terra Net Primary Productivity	NASA/USGS LP DAAC	500 m	2 bands representing derived products: Net Primary Production (Npp_500m); Quality control bits (Npp_QC_500m)	December 26, 2000 - Present	Annually	Yes	Global
MOD17A3HGF v006: MODIS/Terra Net Primary Productivity Gap-Filled	NASA/USGS LPDAAC	500 m	2 bands representing derived products: Net Primary Production (Npp_500m); Quality control bits	February 18, 2000 - Present	Annually	No[4]	Global
MYD17A3H v006: MODIS/Aqua Net Primary Productivity	NASA/USGS LP DAAC	500 m	2 bands representing derived products: Net Primary Production (Npp_500m); Quality control bits (Npp_QC_500m)	December 27, 2002 - Present	Annually	Yes	Global
MYD17A3HGF v006: MODIS/Aqua Net Primary Productivity Gap-Filled	NASA/USGS LPDAAC	500 m	2 bands representing derived products: Net Primary Production (Npp_500m); Quality control bits (Npp_QC_500m)	July 04, 2002 - Present	Annually	No[4]	Global

4 The MODIS GPP and NPP Gap-Filled products are currently not available as Analysis Ready Data, given that they are provided scene-by scene in HDF format, which require users to spend considerable amount of time pre-processing these datasets.

Conclusions on the GPP and NPP data review:

Global geospatial datasets modeling NPP based on remotely sensed data are of coarse spatial resolution (Table 3). Global direct observation of NPP is not available and estimating NPP through satellite imagery involves considerable uncertainties given the amount of assumptions and variables that need to be calibrated regarding vegetation spatiotemporal variations (i.e. type and phenology), atmospheric effects, temperature, water balance (Fensholt et al., 2006; Shabanov et al., 2015). Given the need, identified by decision makers and geospatial experts, for supporting finer spatial resolution data (finer than the current 250 m resolution global data) and the limitations of currently available NPP and GPP datasets, it does not seem appropriate to include them into Trends.Earth as part of the current upgrade cycle. Vegetation indices are able to overcome several of the limitations, and as such, further development will explore the inclusion of finer remote sensing data and a suite of vegetation indices, to provide options suitable for assessment of productivity under different local conditions (see sections below for review and conclusions).

Remote sensing derived vegetation indices

Measuring land productivity is essential to better understand vegetation dynamics and for assessing and monitoring its responses to natural and human-induced disturbances. Observation-based measurements of primary productivity provide results that more realistically reflect biophysical processes of the ground biomass accumulation per unit of time and area, which are useful for decision making such as informing fodder availability in grasslands, for instance. However, objective land productivity estimations are restricted to small extents and therefore are not applicable for global land degradation assessments. Spatially explicit datasets representing GPP and NPP are based on models accounting several variables and assumptions, and given the complexity involved in getting the parameters necessary to model Gross Primary Productivity (GPP) and Net Primary Productivity (NPP) and their inherent uncertainties (Anav et al., 2015; Tucker and Pinzon, 2017) surrogates of photosynthetic activity such as remote sensing derived vegetation indices are generally applied when estimating land productivity over regional to national scales.

Vegetation indices (VIs) are broadly used proxies to estimate land productivity. VIs are based on the well-documented biophysical interaction between primary producers and narrow wavelengths of the electromagnetic spectrum (Gao et al., 2020; Gausman, 1974; Huete, 1988; Jiang et al., 2008; Kong et al., 2019; LeVine and Crews, 2019; Qi et al., 1994; Tucker, 1979; Yengoh et al., 2016). Chlorophylls are responsible for major absorption rates in the visible part of the spectrum (400—680 nm), while palisade mesophyll cells account for the considerable increase in reflectance rates in the near-infrared (700—1,300 nm: Gausman, 1974; Tucker, 1979). Several Earth observation sensors feature spectral resolution covering such wavelengths (e.g. Sentinel 2 MSI, Landsat 5 TM/7 ETM+/8OLI, CBERS 2/2B/4/4A, MODIS Aqua/Terra, AVHRR). VIs are commonly used as a reliable way to assess the state of vegetation cover, photosynthetic capacity, and vegetation structure, among other variables (Yengoh et al., 2016). Moreover, VIs can be readily derived from imagery covering large extents and over long time-series, and can be used as one of the indicators to map and monitor land degradation (Cowie et al., 2018; Sims et al., 2019). NDVI is the most widely used VI given its simple computation, ease of interpretation and broad range of application, however, some limitations have been identified. Below we provide a review of commonly used broadband VIs that can be derived from most satellite imagery publicly available at the present and that are routinely produced and/or applied globally, which could be considered for inclusion into Trends.Earth to support land degradation assessments at national and subnational scales. The VIs included in this report were selected based on a thorough review of peer-reviewed scientific papers and specialized technical reports and on recommendations made by experts and partners of the Tools4LDN project.

a. Normalized Difference Vegetation Index - NDVI

The Normalized Difference Vegetation Index (NDVI: Tucker, 1979) is based on the red (~680 nm) and near-infrared (~860 nm) wavelengths and is defined as the ratio of the difference between the near-infrared (NIR) band and the red band over the sum of these two bands.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad (2)$$

where NIR is reflectance measured in the near-infrared band, and Red is the reflectance measured in the red band. NDVI values vary from -1 to 1, with vegetated areas normally returning values ≥ 0.2.

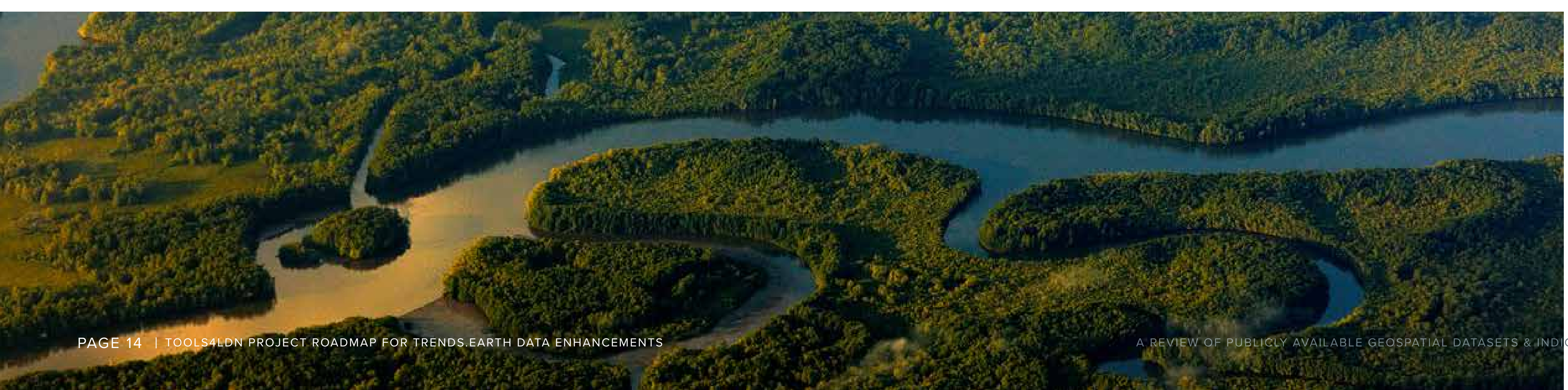
NDVI is one of the first proposed remote sensing-based proxies to assess potential photosynthesis activity and it is the most used vegetation index around the globe. Given its simpler equation when compared to other more sophisticated VIs, it can be computed using most of the currently available satellite imagery. NDVI has been widely implemented virtually in all regions around the world, given that it works relatively well in most areas (Tucker and Pinzon, 2017; Tucker, 1979; Yengoh et al., 2016). However, several studies affirm that NDVI tends to saturate in densely vegetated areas, where reflectance of the Red band is reduced, and the NIR/Red ratio asymptotically approaches 1. Moreover, NDVI response varies with viewing geometry and substrate reflectance (Jiang et al., 2008; Neinavaz et al., 2020; Yengoh et al., 2016) and it is sensitive to soil brightness influences (Huete, 1998).

b. Enhanced Vegetation Index - EVI

Enhanced Vegetation Index (EVI: Liu et al., 1995) is a vegetation index that further explores the relationship between the near-infrared (~860 nm) and the red (~680 nm) bands and adds the blue (~465 nm) band.

$$EVI = 2.5 * \frac{(NIR - RED)}{(NIR + C_1 * RED - C_2 * BLUE + L)} \qquad (3)$$

where NIR is reflectance measured in the near-infrared band, Red is the reflectance measured in the red band, Blue is the reflectance measured in the blue band, 2.5 is a gain factor, L is a variable to adjust for canopy and soil background signals, and C1 and C2 are coefficients derived using the blue band to correct the red band sensitivity to aerosol scattering.



EVI was developed to improve sensitivity to densely vegetated tropical forests characterized by high biomass where NDVI tends to saturate, and to correct for noises derived from the atmospheric additive path and canopy background. Nevertheless, EVI has been shown to be relatively inefficient in assessing vegetation globally. That is because its coefficients C1 and C2 were developed for assessing vegetation across temperate latitudes, returning biased estimates for non-temperate regions of the globe (Jiang et al., 2008; Yengoh et al., 2016). Additionally, EVI uses the Blue band (~465 nm), which limits its consistency across different sensors (Jiang et al., 2008) and makes it highly sensitive to Raleigh scattering effects, diminishing its effectiveness due to problems with sub-pixel clouds, aerosols, and snow-covered surfaces (Tucker & Pinzon, 2017).

c. Enhanced Vegetation Index 2- EVI2

The Enhanced Vegetation Index 2 (EVI2: Jiang et al., 2008) is a reformulation of EVI that eliminates the use of the Blue (~465 nm) band, given its characteristic sensitivity to atmospheric aerosols.

$$EVI2 = 2.5 * \frac{(NIR - RED)}{NIR + (2.4 * RED) + 1} \tag{4}$$

where NIR is reflectance measured in the near-infrared band, and Red is the reflectance measured in the red band.

Yengoh et al. (2016) claims that EVI2 is very similar to NDVI, arguing that NDVI is more sensitive to primary production and that EVI2 is more sensitive to very dense plant canopies. In a comparison of NDVI and EVI2 to solar-induced chlorophyll fluorescence (SIF), which is an observation more closely related to photosynthetic activity, Tucker & Pinzon (2017) found that EVI2 exceeds NDVI as a proxy for potential photosynthesis. NASA is implementing EVI2 as the new standard VI product for the Visible Infrared Imaging Radiometer Suite (VIIRS) program, which is expected to extend the lifespan of VI products similar to those being generated from MODIS imagery. Nevertheless, EVI2 is sensitive to snow cover and thus this type of surface needs to be accounted in mid to high latitudes (Moon et al., 2019; Zhang et al., 2020).

d. Soil-Adjusted Vegetation Index – SAVI

The Soil-Adjusted Vegetation Index (SAVI: Huete, 1988) was developed to account for influences from factors external to the vegetation structure, such as soil background variations (Huete, 1988).

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} * (1 + L) \tag{5}$$

where NIR is reflectance measured in the near-infrared band, Red is the reflectance measured in the red band, and L factor is a variable that accounts for soil adjustment. Generally, it is recommended that L equals to 1 in areas featuring low green vegetation, and equals 0 in areas with high green vegetation, in which case SAVI is equivalent to NDVI.

SAVI is recommended for arid regions with sparse vegetation, given that the soil adjustment factor L was introduced aiming to minimize the influence from background soil brightness due to soil color, and moisture, variability. Albeit, having to adjust for the influence of soil backgrounds makes SAVI less sensitive to vegetation coverage and variability (Jiang et al., 2008) and more sensitive to atmospheric artifacts. Moreover, the soil-adjusting factor needs to be empirically determined (Gilabert et al., 2002).

e. Modified Soil-Adjusted Vegetation Index – MSAVI

The Modified Soil-Adjusted Vegetation Index (MSAVI: Qi et al., 1994) is a modified version of the Soil-Adjusted Vegetation Index (SAVI) that replaces the soil-adjusting L variable by a self-adjusting L factor, even though this factor is not explicit within the equation.

$$MSAVI = \frac{\left(2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - RED)}\right)}{2} \tag{6}$$

where NIR is reflectance measured in the near-infrared band and Red is the reflectance measured in the red band.

MSAVI was developed to increase the vegetation signal and decrease soil-induced external variations, particularly in areas with high degree of exposed bare soils. Jiang et al. (2007) found that MSAVI reduces soil background influences and that values estimated with MSAVI closely approximate field-measured and modeled canopy biophysical over varying canopy structures and a broad range of vegetation fraction, LAI, and soil conditions, concluding that MSAVI is a robust VI for sparsely vegetated lands.

f. Soil-Adjusted Total Vegetation Index – SATVI

The Soil-Adjusted Total Vegetation Index (SATVI: Marsett et al., 2006) is a vegetation index designed to be applied over rangeland areas, given its sensitivity to green and senesced vegetation fractions.

$$SATVI = \frac{SWIR1 - RED}{SWIR1 + RED + L} * (1 + L) - \frac{SWIR2}{2} \tag{7}$$

where SWIR1 is reflectance measured in the Short Wave-Infrared #1 band (~1,660 nm), Red is the reflectance measured in the red band (~680 nm), SWIR2 is reflectance measured in the Short Wave-Infrared #2 band (~2,250 nm), and L is a constant related to the slope of the soil-line in a feature-space plot.

Unlike another VIs, SATVI has a lower limit equal to 0.0 and its upper limit boundary is undetermined. SATVI was developed to be applied over rangelands mostly composed of grasses, and its applicability across areas featuring combinations of grasses with shrubs and trees are still to be further explored (Marset et al., 2006). SATVI is also sensitive to rock outcrops that have high reflectance on the shortwave infrared band, returning these types of surfaces as vegetated, potentially limiting its applications.

g. Plant Phenology Index – PPI

The Plant Phenology Index (PPI: Jin and Eklundh, 2014) is a physically based vegetation index that was proposed for improving plant phenology monitoring and that provides an operational and efficient approach for retrieving canopy growth.

$$PPI = -K * \ln\left(\frac{M - DVI}{M - DVI_S}\right) \tag{8}$$

where K is a gain factor that is estimated from 1/k (k being the light extinction coefficient per unit of LAI); DVI is the Difference Vegetation Index (DVI = NIR – Red); DVIs is the DVI of the background soil; and M is a site-specific canopy maximum DVI. DVI is computed from sun-sensor geometry corrected Red and NIR reflectance, such those implemented in bidirectional reflectance distribution function (BRDF) adjusted products such MODIS/MCD43.

PPI has been demonstrated to work well for monitoring evergreen needle-leaf forests over bright soil background, such as snow in northern boreal forests. Contrary to NDVI and EVI, PPI is less sensitive to background influences from snow. PPI is also based on the Red and Near-Infrared (NIR) wavelengths and has a strong correlation with canopy green leaf area index (LAI). It requires a standardized high-quality reflectance imagery as input, which can be a downside when trying to implement it globally.

Given the complexity of the equation and the number of required standardized inputs, PPI does not seem to be a feasible vegetation index that could be easily implemented. Moreover, as the authors stressed, PPI was designed specifically to be applied over evergreen needleleaf forests that are more common in the high latitudes of the northern hemisphere (Jin and Eklundh, 2014).

Tables 4 and 5 below provide a review of readily available and commonly used VIs derived using broadband multispectral sensors at regional to global scales.

Table 4 –Summary of the reviewed Vegetation Indices (VIs).

Vegetation Index	Spectral Bands Required to Calculate VI	Parameters Required	Pros	Cons
NDVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Simple equation; ease to calculate; most used VI; works relatively well in most areas, very widely used.	Saturates at high biomass areas; sensitivity to background influence - soils, non-photo-synthetic vegetation structure; viewing geometry dependent
EVI	Blue (~ 465nm, Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	Gain factor (G), variable to adjust for background influence (L); Coefficients to adjust for aerosol scattering (C1 & C2)	Improved response to high biomass areas; accounts for influences from atmosphere and background	Coefficients to adjust for aerosol scattering (C1 & C2) are region specific; high sensitivity of the blue band (~465 nm) to Raleigh scattering.
EVI2	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Improved response to areas with dense plant canopies; simple equation; does not use the blue band (~465 nm)	Sensitivity to snow cover at mid to high latitudes
SAVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	Variable to adjust for background influence (L Factor)	Improved response to areas with sparse vegetation	Decreased response to vegetation coverage and variability; sensitivity to atmospheric artifacts; L Factor is empirically determined
MSAVI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	None	Low sensitivity to soil background; Improved response to areas with sparse vegetation; high correlation to field measurements over varying canopy structures, LAI and soil conditions	Relatively complex equation
SATVI	Red (~680 nm) and Shortwave InfraRed (SWIR: ~1,660 nm) and Shortwave InfraRed #2 (SWIR2 ~2,250 nm)	Constant to account for the slope of the soil-line in a feature-space plot (L)	Improved response to areas with sparse vegetation; high correlation to field measurements over varying canopy structures, LAI and soil conditions	Sensitivity to rock outcrops; not thoroughly tested for areas featuring mixture of grasses, shrubs and woodlands
PPI	Red (~680 nm) and Near-InfraRed (NIR: ~860 nm)	Gain factor (K) derived from 1/k (k being the light extinction coefficient per unit of LAI); site-specific canopy maximum Difference Vegetation Index (DVI	Improved response over boreal forests; decreased sensitivity to snow; strong correlation to leaf area index (LAI)	Complex equation; high parameterization level;

Table 5 – Readily and publicly available global geospatial datasets representing Vegetation Indices (VIs).

Name	Source	VI	Spatial Resolution	Temporal Coverage	Temporal Frequency	Analysis Ready?	Extent
Landsat 8 32-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	April 7, 2013 – May 9, 2017	32-day Com-posite	Yes	Global
Landsat 8 8-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 2013 – Jan 1, 2018	8-day Composite	Yes	Global
Landsat 8 Annual EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 2013 – Jan 1, 2018	Annually	Yes	Global
Landsat 8 32-Day NDVI Composite	NASA-USGS-GEE	NDVI	30 m	April 7, 2013 – May 9, 2017	32-day Composite	Yes	Global
Landsat 8 8-Day NDVI Composite	NASA-USGS-GEE	NDVI	30 m	Jan 1, 2013 – Jan 1, 2018	8-day Composite	Yes	Global
Landsat 8 Annual NDVI Composite	NASA-USGS-GEE	NDVI	30 m	April 7, 2013 – May 9, 2017	32-day Composite	Yes	Global
Landsat 5 32-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984 – May 8, 2012	32-day Composite	Yes	Global
Landsat 5 8-Day EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984 – May 8, 2012	8-day Composite	Yes	Global
Landsat 5 Annual EVI Composite	NASA-USGS-GEE	EVI	30 m	Jan 1, 1984 – May 8, 2013	Annually	Yes	Global
Landsat 5 8-Day NDVI Composite	NASA-USGS-GEE	NDVI	30m	Jan 1, 1984 – May 8, 2012	8-day Composite	Yes	Global
Landsat 5 32-Day NDVI Composite	NASA-USGS-GEE	NDVI	30m	Jan 1, 1984 – May 8, 2012	8-day Composite	Yes	Global
Landsat 5 Annual NDVI Composite	NASA-USGS-GEE	NDVI	30m	Jan 1, 1984 – May 8, 2012	8-day Composite	Yes	Global
NASA/USGS MODIS Terra MOD13Q1 v006 (Collection 6)	NASA-USGS	NDVI & EVI	250 m	February 18, 2000 - Present	16-Day Composite	Yes	Global
NASA/USGS MODIS Terra MOD13A1 v006 (Collection 6)	NASA-USGS	NDVI & EVI	500 m	February 18, 2000 - Present	16-Day Composite	Yes	Global
NASA/USGS MODIS Terra MOD13A2 v006 (Collection 6)	NASA-USGS	NDVI & EVI	1 km	February 18, 2000 - Present	16-Day Composite		
NASA/USGS MODIS Aqua MYD13Q1 v006 (Collection 6)	NASA-USGS	NDVI & EVI	250 m	July 04, 2002 - Present	16-Day Composite	Yes	Global
NASA/USGS MODIS Aqua MYD13A1 v006 (Collection 6)	NASA-USGS	NDVI & EVI	500 m	July 04, 2002 - Present	16-Day Composite	Yes	Global
NASA/USGS MODIS Aqua MYD13A2 v006 (Collection 6)	NASA-USGS	NDVI & EVI	1 km	July 04, 2002 - Present	16-Day Composite	Yes	Global
NASA VIIRS Vegetation Indices 16-Day 500m -EVI, EVI2, NDVI (VNP13A1)	NASA-USGS	NDVI; EVI & EVI2	500 m	January 17, 2012 - Present	16-Day Composite	Yes	Global
NASA AHVRR Global Inventory Monitoring and Modeling Systems (GIMMS) 3g.v1	NASA – GIMMS 3g.v1	NDVI	8 km	July 01, 1981 – December 31, 2015	Monthly	Yes	Global

Conclusions on the vegetation indices review:

To date, global land degradation monitoring frameworks have been relying on NDVI products derived from moderate to coarse spatial resolution imagery – 250 m (MOD13Q1) to 8 km (AVHRR GIMMS), due to the fact that NDVI has been one of the most consistently used proxies for assessing vegetation health globally given its ease of implementation and popularity (Yengoh et al., 2016). For instance, the land productivity dataset generated by Trends.Earth and the Land Productivity Dynamics (LPD) dataset generated by Joint Research Centre of the European Commission (Ivits and Cherlet 2016) are derived using NDVI at moderate resolution. Currently, there are readily available datasets derived from Landsat 5TM and Landsat 8OLI that deliver NDVI and EVI products at relatively high spatial resolution (Table 5). Nevertheless, several studies claim that NDVI tends to asymptotically reach a plateau over high-biomass lands, and the 3-band version of EVI does not seem to be reliable to be applied globally given its use of the Blue band (Sims et al., 2017; Tucker and Pinzon, 2017). Yet, another limitation of these commonly used VIs is their capacity to cope with background soil influences in sparsely vegetated areas (Huete, 1988; Qi et al., 1994).

NDVI is undoubtedly the most widely used VI given the multiple advantages previously outlined. However, for specific locations with biomass on the two extremes of the spectrum, either very high or very low, other vegetation indices could provide improved sensitivity for measuring land productivity, and as such could be useful for assessing changes in land degradation. Considering that, we recommend implementing two other VIs into Trends.Earth that will provide users further options when performing land degradation assessments: the two-band Enhanced Vegetation Index (EVI2) and the Modified Soil-Adjusted Vegetation Index (MSAVI). EVI2 is particularly helpful for users analyzing lands featuring high biomass, given that it does not tend to saturate over highly vegetated areas. MSAVI has been shown to be a robust VI for sparsely vegetated lands and will be helpful in lands presenting large influence from soil background, conditions such as those present in degraded lands in need for restoration. Besides adding vegetation indices better suited for specific area, clear guidance on when each of the indicators is best suited should be included in the user manual of Trends.Earth.

Publicly available multispectral imagery

There are a multitude of Earth observing sensors designed to acquire data globally featuring different spatial, temporal, and spectral resolutions, that allow analysis of changes in land condition, as those required for land degradation assessment. Here, we provide a comprehensive summary of publicly available multispectral imagery collections (Table 6). This table includes only imagery collections that can be accessed without any direct costs to the end user; most of the imagery database offer a global scope, although this worldwide coverage is not thoroughly consistent across time, especially for those sensors that were launched prior to 2010. Countries that have historically had the technological infrastructure (i.e. downlink antenna to receive imagery, storage capacity and highly trained personnel) feature a more extensive imagery collection throughout time; whereas most regions around the globe do not have historical data that would allow annual time-series analysis going back to the 1980's and 1990's, or even to the 2000's (Wulder et al., 2016).

Working with satellite imagery is not a trivial task, not only given the volume of data to be treated but also the level of technical details involved to access, download, and perform necessary adjustments on each scene individually. Before the relatively recent developments in methods, technology, and capacity building, constructive and coherent applications of Earth observation techniques and products had significant challenges. Not long ago, analyses of remote sensing data required trained users to invest extensive time pre-processing data, a set of technical procedures which could lead to delays and inconsistencies in results if users applied different pre-processing workflow or parameters. This could also mean that a substantial number of potentially interested organizations would not have access to the usefulness of EO data due to their limited personnel, knowledge and physical resources (i.e. computers, processing capacity, data storage) to handle the data. To overcome these expensive pre-processing steps, there is a demand from end-users and major organizations interested in geospatial data to have access to Analysis Ready Data (ARD).

The Committee on Earth Observation Satellites (CEOS) defines ARD as "satellite data that have been processed to a minimum set of requirements and organized into a form that allows immediate analysis with a minimum of additional user effort and interoperability both through time and with other datasets." The minimum set of requirements being: General Metadata, Quality Metadata, Measurement-based/Radiometric Calibration, and Geometric Calibration. For optical sensors, specifically, CEOS also adds Solar and View Angle Correction and Atmospheric Correction, and Radiometric Correction for Topography and Radiometric Correction for Incidence Angle for active sensors (CEOS, 2020). Nevertheless, the definition of the ARD concept is still under active development and not all imagery providers deliver their ARD products following the CEOS definition. For instance, the United States Geological Survey (USGS) defines the U.S. Landsat ARD as "pre-packaged and pre-processed bundles of Landsat data products that make the Landsat archive more accessible and easier to analyze, and reduce the amount of time users spend on data processing for time-series analysis", given that U.S. Landsat ARD are tiled, georegistered, top-of-atmosphere and atmospherically corrected products (Dwyer et al., 2018). Most datasets shown in Table 6 meet the CEOS definition of ARD, however some of the imagery are not delivered as surface reflectance products.

Regarding the continuity of future medium spatial resolution imagery availability, a partnership between the NASA and the USGS known as the Landsat Mission, is planning to launch the Landsat 9 satellite in early 2021 with a design life of 5 years. Landsat 9 will carry enhanced replicas of the Operational Land Imager (OLI) sensor and Thermal Infrared Sensor (TIRS) currently orbiting the Earth onboard of Landsat 8, and will image the Earth every 16 days in an 8-day offset, increasing the availability and temporal resolution of imagery with similar characteristics (NASA Landsat 9, 2020). The Multispectral Instruments (MSI) sensors onboard of Sentinel-2A and Sentinel-2B were designed with an initial nominal mission of 7.5 years and potential to be extended to a maximum of 12 years (ESA Sentinel 2, 2020) with imagery featuring medium spatial resolution expected to be available for assessing changes on the Earth surface at least until mid-2020's.

Table 6 – Global publicly available multispectral imagery collections.

Satellite/Sensors	Source	Spectral Resolution	Spatial Resolution	Temporal Coverage	Temporal Resolution	Analysis Ready?	Extent
ESA Sentinel 2 Multispectral Instrument (MSI) Level-1C Top-of-Atmosphere (TOA) Reflectance	ESA/Copernicus	13 bands covering visible-NIR-SWIR wavelengths (443—2190 nm)	10 m (Vis-NIR bands) 20 m (Red-Edge and SWIR bands) & 60 m (Aerosols, Water Vapor and Cirrus bands)	Jun 23, 2015 - Present	5 days	No	Global
ESA Sentinel 2 Multispectral Instrument (MSI) Level-2A Surface Reflectance	ESA/ Copernicus - GEE	13 bands covering visible-NIR-SWIR wavelengths (443—2190 nm)	10 m (Vis-NIR bands) 20 m (Red-Edge and SWIR bands) & 60 m (Aerosols, Water Vapor and Cirrus bands)	March 28, 2017 - Present	5 days	Yes	Currently limited geography. Conversion to SR occurs based on opportunistic cases.
NASA Harmonized Landsat 8 OLI Sentinel-2	NASA Goddard	Product dependent	10 m and 30 m Product dependent	April 19, 2013 -Present (Landsat 8 OLI)October 22, 2015 – Present (Sentinel-2)	2 to 3 days	Yes	No - limited geography
China-Brazil Earth Resources Satellite (CBERS) Multispectral (MUX) and PanMUX 4	INPE – Brazilian National Institute for Space Research	4 bands covering visible-NIR wavelengths (510—890 nm)	5 m (Panchromatic band) & 10 m (Vis-NIR bands)	January 1, 2015 – Present	26 days	No	Global
China-Brazil Earth Resources Satellite (CBERS) Multispectral (MUX) and PanMUX 4A	INPE – Brazilian National Institute for Space Research	4 bands covering visible-NIR wavelengths (510—890 nm)	5 m (Panchromatic band) & 10 m (Vis-NIR bands)	December 27, 2019 – Present	26 days	No	Global
China-Brazil Earth Resources Satellite (CBERS) Coupled Charged Device (CCD) Multispectral	INPE – Brazilian National Institute for Space Research	5 bands covering visible-NIR wavelengths (450—890 nm)	20 m (Vis-NIR bands)	October 28, 2003 – October 1, 2009	26 days	No	Global
China-Brazil Earth Resources Satellite (CBERS) Coupled Charged Device (CCD) Multispectral and Panchromatic (HRC) 2B	INPE – Brazilian National Institute for Space Research	5 bands covering visible-NIR wavelengths (450—890 nm)	2.7 m (HRC Pancromatic band) & 20 m (Vis-NIR bands)	September 9, 2007 – May 12, 2010	26 days	No	Global
GLAD Landsat Analysis Ready Data (ARD)	GLAD - Global Land Analysis & Discovery	7 bands covering the visible-NIR-SWIR-TIR wavelengths plus 1 Observation Quality band	27.83 m	January 1st, 1997 - Present	16 days	Yes	Global
USGS Landsat 8 Operational Land Image (OLI) / Thermal Infrared Sensor (TIRS) Surface Reflectance Tier 1	USGS	11 bands covering visible-NIR-SWIR-TIR wavelengths (430—1251 nm)	15 m (Panchromatic band); 30 m (Vis-NIR-SWIR bands) & 60 m (TIRS bands)	April 11, 2013 - Present	16 days	Yes	Global
USGS Landsat 7 Enhanced Thematic Mapper + (ETM+) Surface Reflectance Tier 1	USGS	8 bands covering visible-NIR-SWIR-TIR wavelength (455—1250 nm)	15 m (Panchromatic band); 30 m (Vis-NIR-SWIR) & 60 m (Thermal Infrared band)	July 1, 1999 – Present (to be decommissioned in 2020)	16 days	Yes	Global
USGS Landsat 5 Thematic Mapper (TM) Surface Reflectance Tier 1	USGS	8 bands covering visible-NIR-SWIR-TIR wavelength (455—1250 nm)	30 m (Vis-NIR-SWIR) & 120 m (Thermal Infrared band)	Jan1, 1984 – May 5, 2012	16 days	Yes	Global
Moderate Resolution Imaging Spectroradiometer (MODIS) Terra/Aqua Surface Reflectance Daily Global Version 6 (MOD09GQ.006)	NASA	2 bands covering the Red (620—670 nm) and NIR (841—876 nm)	250 m (Red & NIR bands)	February 24, 2000 – present	Twice daily	Yes	Global
Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Surface Reflectance Daily L2G Global Version 6 (MOD09GA.006)	NASA	7 bands covering Visible-NIR-SWIR wavelengths (459—2155 nm)	500 m & 1 km (Visible-NIR-SWIR bands)	February 24, 2000 – present	Twice daily	Yes	Global
Visible Infrared Imaging Radiometer Suite (VIIRS) Surface Reflectance Daily VNP09GA	NASA	3 bands covering the Red-NIR-SWIR wavelengths (600—1640 nm) at 500m	500 m (Red-NIR-SWIR)	January 19, 2012 -- present	Daily	Yes	Global
Visible Infrared Imaging Radiometer Suite (VIIRS) Surface Reflectance Daily VNP09GA v001– 1km	NASA	9 bands covering the visible-NIR-SWIR wavelengths 402—2280 nm) at 1km	1 km (visible-NIR-SWIR)	January 19, 2012 -- present	Daily	Yes	Global
Advanced Very High-Resolution Radiometer (AVHRR) Climate Data Record (CDR) Surface Reflectance Version 5	NOAA	5 bands covering Visible-NIR-TIR wavelengths (640—1200 nm)	5 km (Visible-NIR-TIR band)	June 26, 1981 – present	Daily	Yes	Global

Conclusions on the imagery data review:

Assessment and monitoring of land degradation at regional and national scales have been done using geospatial data derived from moderate to coarse spatial resolution imagery (Bai et al. 2008, 2010; Cherlet et al. 2018). Trends.Earth currently offers its users access to datasets ranging in spatial resolution from 250 m to 8 km. Given the availability of global and open access imagery at finer spatial resolution (i.e. 10 – 30 m – Table 6) we see a huge potential for these datasets to inform monitoring of land degradation to assess progress towards LDN. Incorporating these datasets would improve the spatial detail of observations, significantly enhancing land degradation evaluation and monitoring at local scales, and better inform decision making. It will also increase the range of countries which would benefit from these analyses, notably in small islands. Based on this review, generating the land productivity sub-indicator globally is viable nowadays, given that it is measured by applying proxies of potential photosynthetic activity that can be implemented based on vegetation indices.

Considering the set of technical specifications (spatial, temporal, spectral resolutions) in addition to the historical archive and plans to continue image acquisition in the future, the Landsat and Sentinel family of sensors provide the best imagery collections to monitor land degradation at fine scales. These would not replace the moderate resolution geospatial datasets that have been successfully applied to develop land degradation baselines but complement them to bring further details that can only be observed with imagery featuring finer spatial resolution. For instance, NASA and ESA are developing a set of algorithms to produce a Harmonized Landsat and Sentinel-2 Virtual Constellation of surface reflectance imagery acquired from Landsat 8 OLI and Sentinel-2 MSI sensors. These datasets are designed to deliver seamless products that will feature atmospheric correction, cloud and cloud-shadow masking, spatial co-registration shared gridding, normalization of the viewing and illumination geometry and adjustments of the spectral bands (Claverie et al., 2018). The Harmonized Landsat OLI/Sentinel-2 will offer an excellent opportunity for deriving the SDG15.3.1 sub-indicators given its relatively high spatial resolution (10 – 30 m) combined to a high revisiting frequency (3 to 4 days) that will significantly increase the number of observations at any part of the world. Nevertheless, it is important to note that these datasets will not be useful for estimating LDN baselines due to their limited temporal coverage, given that Sentinel 2 MSI was first launched in 2015.

Measuring changes in Land Cover

Land cover refers to the biophysical material that composes the surface of the Earth, rendering the actual coverage of a given region in thematic classes (Di Gregorio, 2005; ESA, 2017). To assess changes in land cover under the LDN framework, it is necessary to utilize land cover maps for the baseline period and target years.

Moreover, these maps would ideally have a 100 m or finer pixel size, be of acceptable accuracy (>85%), must use a hierarchical class structure, and should include region specific and standardized classes that would allow for a valid comparison over time (GEO-LDN Initiative, 2020a). Considering that, geospatial datasets representing land cover classes ideally should be generated in a way to allow regrouping into standardized thematic classes (i.e. System of Environmental and Economic Accounting: SEEA) to be considered in the process of assessing land degradation neutrality. Geospatial datasets shown in Table 7 were selected because they represent land cover and land cover change at global extent. There are other publicly available datasets providing finer spatial resolution for land cover, but these are currently delivered for limited parts of the globe in a consistent manner.

Table 7 – Readily and publicly available global geospatial datasets representing land cover.

Name	Source	Spatial Resolution	Temporal Coverage	Update Frequency	Accuracy	Analysis Ready?	Extent
Global Land Cover at 30m	GlobeLand30	30 m	2000 & 2010	NA	~80%	No	Global
Copernicus Global Land Service (CGLS)	ESA-Copernicus	100 m	2015	Land Cover Change maps planned to be updated annually	80.2%	Yes	Global
ESA CCI land cover	ESA-CCI	300 m	1992-2018	Annually	73%	Yes	Global
Global Land Cover Map (GlobCover)	ESA	300 m	2009	Only for 2009	67.5%	Yes	Global
NASA/USGS MODIS Land Cover Type MCD12Q1 v006 (Collection 6)	NASA-USGS	500 m	2001-2018	Annually	73.6%	Yes	Global
Global Land Cover (GLC) SHARE Database	FAO	1 km	2013	NA	80.2%	Yes	Global

Conclusions on the land cover data review:

The European Spatial Agency (ESA) leads the development of most of the spatially explicit datasets representing land cover at global scale. Currently, the ESA Climate Change Initiative (ESA-CCI) geospatial dataset representing global land cover is still the most appropriate global dataset to be applied when assessing the land cover sub-indicator to monitor land degradation, given its global coverage, its spatial resolution and the fact that it has been consistently updated at annual basis across a long time-series.

The Copernicus Land Cover product, also under ESA leadership, has produced a land cover dataset covering the entire world for 2015, but plans to deliver annual land cover datasets in the same fashion is still not clear now. Nevertheless, ESA is also currently developing the World Cover project (ESA WorldCover, 2020) which aims to deliver to the public a land cover map of the entire globe at 10m resolution based on its Sentinel-1 and 2 data with an overall accuracy of 75%. While the release of this global product is only expected for mid-2021, a prototype 10 m land cover product covering 10% of the world is expected for the end of August 2020, and this will provide a great opportunity to further explore how fine scale maps representing land cover and land cover change under the LDN framework, especially for small island state and national to local relevance and implementation.

New datasets representing land cover will be evaluated to be added into Trends.Earth when they become available. The selection criteria for addition are that datasets must have global coverage, be publicly available at no cost to end users, have licensing allowing sharing, and meet the SDG 15.3.2 Minimum Data Quality Standards Technical. These standards outline datasets with 100 m or finer pixel size, an accuracy higher than 85%, and cover a period of at least 10 years or plan to be produced for 10 years (GEO LDN Initiative, 2020a).

Measuring changes in Soil Organic Carbon Stocks

The third sub-indicator for monitoring land degradation as part of the SDG 15 process quantifies changes in carbon stock over the reporting period.

Country Parties of the UNCCD agreed to use soil organic carbon (SOC) for assessing land degradation, with the understanding that this variable will be replaced by total terrestrial system carbon stocks when global datasets accurately representing this variable become operational (UNCCD 22/COP.11). Soil organic carbon is the sub-indicator featuring the least amount of spatially explicit datasets, given the complexities required to generate such dataset. Estimating soil carbon stocks requires an exhaustive amount of soil sampling around the globe that could be compiled in an interpolated model that would represent this continuous variable as accurate as possible (FAO, 2018). Currently, there is no globally consistent spatially explicit time series dataset of soil organic carbon. There are a series of modeled products which combine historically available field data on SOC to produce one-time global maps (Table 8). Those maps, when combined with a time series of land cover data and following the guidelines described in the SDG 15.3.1 GPG, allow for estimation of changes in SOC over time.

Table 8– Readily and publicly available datasets representing soil organic carbon (SOC)

Name	Source	Spatial Resolution	Temporal Coverage	Update Frequency	Analysis Ready?	Extent
SoilGrids V 2.0	ISRIC	250 m	2015	NA	Yes	Global
SoilGrids	ISRIC	250 m	2010	NA	Yes	Global
OpenLandMap Soil Organic Carbon Content	EnviromentriX Ltd	250 m	One-time composite that covers January 1, 1950-January 1, 2018	NA	Yes	Global
Global Soil Organic Carbon on Cropland – Derived from Soilgrids	CIAT	250 m	2010	NA	Yes	Global
Global Soil Organic Carbon Map -GSOC map (v1.5.0)	FAO	1km	1990 (Baseline)	NA	Yes	Global

Conclusions on the soil organic carbon data review:

As defined in the LDN conceptual framework, land degradation would ideally be assessed considering carbon stocks in biomass and soil. New datasets representing soil carbon and biomass are constantly developed, but we have not reached the point of producing annual datasets of soil organic carbon (Table 8) nor biomass (Table 9). Hence, the approach presented in the SDG 15.3.1 Good Practice Guidance (Sims et al., 2017), which combines land cover maps and transition coefficients to estimate the change in SOC from a baseline level, are still the most relevant. The SoilGrids V 2.0 is the best dataset for assessing changes in soil organic carbon, given that it features the finer spatial resolution among the datasets reviewed here. When new and/or updated datasets representing carbon stocks become available, they will be evaluated against the SDG 15.3.1 Minimum Data Quality Standards, and if they meet them, will be considered for inclusion into Trends.Earth (GEO-LDN Initiative, 2020a). Table 9 (Appendix) shows currently available datasets that represent above and below ground biomass.

Conclusions

The review of currently available global geospatial datasets which could be used for computing SDG 15.3.1 sub-indicators shows that some promising datasets are becoming available to complement moderate resolution datasets assessments of land degradation. The Harmonized Landsat-Sentinel collection is the most promising dataset to monitor progress on land degradation neutrality, given its relatively high spatial resolution (10 – 30 m) and high revisiting frequency (3 to 4 days) that will significantly increase the number of observations at any part of the world. Nonetheless, these datasets will not be useful for estimating LDN baselines due to limited temporal coverage, so guidance on how to harmonize for such differences will need to be developed and provided to users.

NDVI is undoubtedly the most widely used vegetation indicator due to its simplicity of usage and flexibility, although we have identified two other vegetation indices which can help assessing primary productivity in lands where the use of NDVI has been shown to not perform optimally. For tropical forest with high biomass, the two-band Enhanced Vegetation Index (EVI2) has been proven to outperform NDVI; and for sparsely vegetated areas with low biomass, we recommend the Modified Soil-Adjusted Vegetation Index (MSAVI). We suggest developing computational capabilities in Trends.Earth to derive productivity indicators using the Harmonized Landsat-Sentinel imagery with NDVI, EVI2, and MSAVI for improving monitoring of changes in land condition to complement the current assessment produced with MODIS NDVI long term series data. Detailed user guidance on recommended use of each indicator under different conditions will be provided.

For land cover and soil organic carbon sub-indicators, the review did not identify new or updated datasets at fine spatial resolution and global coverage, highlighting the importance of local land cover and SOC data for accurate and relevant land degradation assessments. Functions to use local land cover and SOC data, as well as local land productivity indicators, are already available in Trends.Earth and will be critical for future reporting cycles. Trends.Earth will continue to support current global datasets and will regularly check with data providers to incorporate any new or updated relevant datasets that could be added into the tool if they meet the recommendations and quality requirements determined by the SDG 15.3.1 GPG and the GEO LDN Initiative.

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Appendix

Table 9 – Readily and publicly available datasets representing above and below ground biomass.

Name	Source	Spatial Resolution	Temporal Coverage	Update Frequency	Analysis Ready?	Extent
Aboveground Live Woody Bio-mass Density	Global Forest Watch	30 m	2000	NA	Yes	Global
GlobBiomass	ESA/ GlobBiomass	100m	2010	NA	No	Global
Harmonized global maps of above and belowground biomass carbon density in the year 2010	NASA DAAC	300 m	2010	NA	No	Global
WCMC Above and Below Ground Carbon Density	UNEP/WCMC	300 m	2010	NA	Yes	Global
Woodwell Climate Research Center - WCRC Above-Ground Live Woody/ Pantropical National Level Carbon Stock Dataset	WCRC	500m	January 29, 2012	NA	Yes	No – Tropics Only
Geocarbon	Wageningen University & Research	1km	2000	NA	Yes	No – Pan-Tropical
Global Tree Cover and Biomass Carbon on Agricultural Land	World Agroforestry Centre	1 km	2000 & 2010	NA	Yes	Global
Global Forest Above Ground Biomass	Guo-Lab	1 km	2004 (Baseline)	NA	Yes	Global