Exploiting Copernicus Core Services for Assessing the Surface Urban Heat Island Intensity

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***Abstract*— The rise in human activity accompanying urbanization has led to a noticeable increase in temperature in urban areas compared to rural ones, which is commonly known as the urban heat island (UHI) phenomenon. UHI can have negative effects on various aspects of urban life, such as environmental conditions, human health, water and energy consumption, and citizens' comfort. Traditionally, UHI is linked to air temperature differences and it requires *in-situ* climatology data for assessing its intensity, which are seldom available. Hence, a scalable proxy often used in the literature is the so-called surface UHI (SUHI), which is measured by exploiting satellite-based land surface temperature (LST) information. The presented work introduces a novel framework to objectively quantify the SUHI intensity (SUHII) through regression analysis of LST and the density of impervious areas. In particular, this has been implemented in the context of the H2020 CURE (Copernicus for Urban Resilience in Europe) project, whose main goal has been the development of cross-cutting city-scale applications for urban resilience that synergistically exploit the Copernicus Core Services. The proposed method was successfully applied to all 10 targeted CURE cities and has the potential to be scaled at the pan-European level.**

Keywords*— *Surface Urban Heat Island Intensity, Urban Resilience, H2020 CURE project, Copernicus Core Services, Land Surface Temperature, Imperviousness

I. INTRODUCTION

The steady increase and variability in temperature driven by the ongoing climate change has significant impacts on the well-being of the population living in urban areas. In particular, cities tend to be warmer compared to nearby rural surroundings mostly because of the thermal characteristics of the built environment and the heat generated by human activities. Scientists commonly refer to this phenomenon as the urban heat island (UHI) effect [1]. The growing number of urban dwellers is also commonly associated with an expansion of impervious surfaces at the cost of formerly vegetated areas. In consequence, urban temperature rises, which has a direct impact on human health, increasing the risk of heat stress and associated mortality. Additionally, higher temperatures lead to increased energy consumption for air conditioning, resulting in higher greenhouse gas emissions. Warmer water also flows into streams and water quality decreases, while the remaining urban vegetation is put under stress [2]-[5]. Efforts to mitigate the UHI effect are manifold, still often costly. On the one hand, solutions include the expansion of vegetated areas like parks or green roofs within cities, which exhibit a cooling effect through the process of evapotranspiration. On the other hand, attempts include structural construction planning, targeting improved ventilation and, hence, heat exchange with the surroundings (e.g., through ventilation corridors such as straight roads) or the employment of thermally reflective surfaces (e.g., light-colored materials), which reflect more solar irradiation and absorb less heat.

Variations in the intensity of the UHI effect across cities can be attributed to the complex interplay between regional and local climatic factors, as well as the composition and arrangement of the specific urban fabric (including grey, green and blue infrastructures). The UHI effect is typically quantified in terms of UHI intensity (UHII), which denotes the difference in air temperature measured between two different *in situ* stations located in the urban and adjacent rural areas, respectively. Similarly, remote sensing techniques are employed to assess the so-called surface UHII (SUHII) over selected pixels located in the rural and urban regions separately. [6]. However, fixed pixels only provide a partial representation of SUHI characteristics (particularly in cities with more than a single UHI center) and solely represent the micro-climate of the local area which they refer to. Moreover, the lack of internationally agreed standards in defining the boundaries between urban and rural regions makes it challenging to compare SUHII among different cities.

To address these shortcomings, we implemented a novel solution in the framework of the Horizon 2020 (H2020) funded project CURE (Copernicus for Urban Resilience in Europe), whose main goal has been the development of 11 cross-cutting city-scale applications for urban resilience that synergistically exploit the Copernicus Core Services and assess their added value in supporting analyses related to climate change mitigation and adaptation, urban health, and economic development [7], [8]. In particular, CURE has demonstrated that, by integrating products from the Copernicus Climate Change Service (C3S), Copernicus Atmospheric Monitoring Service (CAMS), Copernicus Land Monitoring Service (CLMS) and Copernicus Emergency Service (EMS), it is possible to derive enhanced environmental information supporting the implementation of urban resilience plans at the local scale.

All details describing the dedicated CURE AP02 specifically designed to reliably estimate the SUHII are provided in the following sections. Moreover, results are

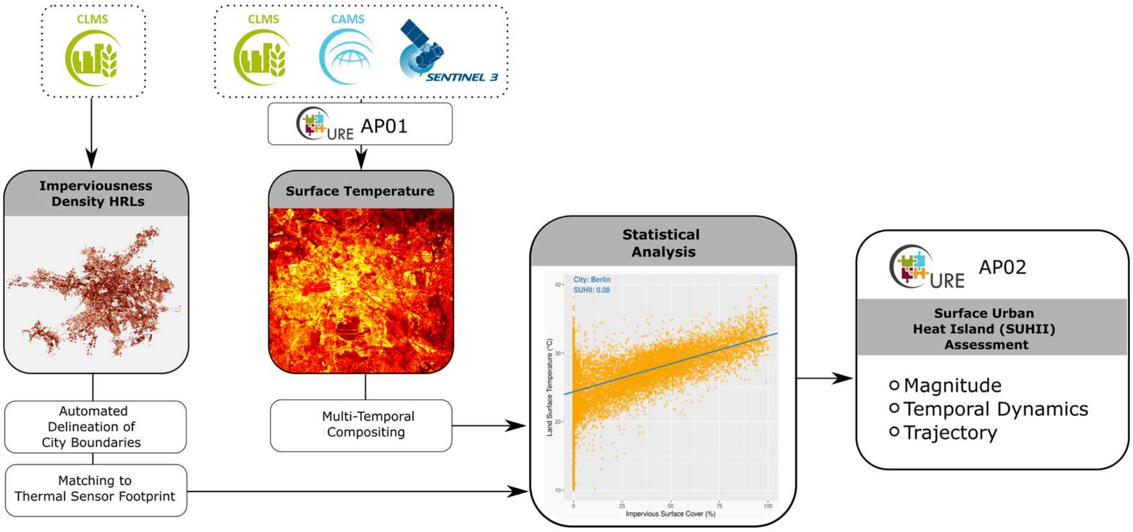


Fig. 1. Simplified flowchart of the CURE AP02 SUHII processor.

presented for all CURE test sites, which included 4 "front-runner" cities – i.e., Heraklion (Greece), Sofia (Bulgaria), Copenhagen (Denmark) and Berlin (Germany) – and 6 "follower cities" – i.e., Basel (Switzerland), Bristol (United Kingdom), Munich (Germany), Ostrava (Czech Republic), as well as Vitoria-Gasteiz and San-Sebastian (Spain).

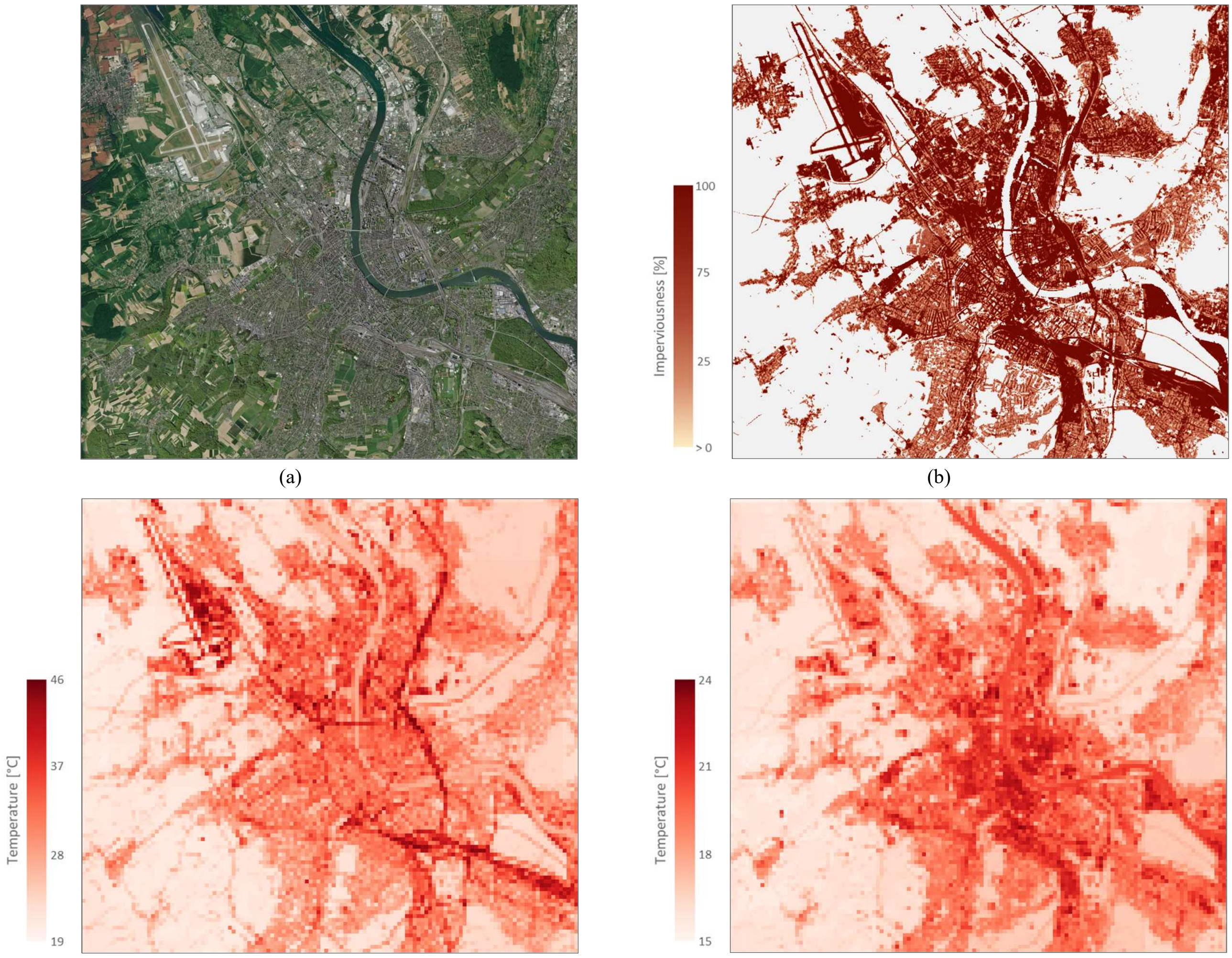
II. METHODOLOGY

The CURE AP02 leverages the solution recently proposed in the literature by Li et al. [9]. In particular, the approach aims at computing the SUHII and its temporal dynamics by exploiting the linear relationship between LST and the impervious surface area (also commonly referred to as imperviousness), which denotes all "human-produced surfaces that are essentially impenetrable by rainfall" [10] (typically streets, parking lots or buildings made of materials such as asphalt, concrete or stone, whose albedo is lower than that of natural unsealed surfaces). Indeed, several studies in the literature have proven a strong positive correlation between the two variables, where the imperviousness is the major driver of LST variation both during day- and night-time, especially for cities located in biomes dominated by forests and grasslands as in the case of Europe [11]-[13]. Accordingly, the basic idea is to estimate the SUHII as the slope of the first order linear regression between LST and imperviousness. A simplified flowchart of the corresponding processor is reported in Fig. 1.

Concerning LST, the currently existing CLMS product is not suitable for supporting analyses at the city level; indeed, it assumes land surface to be solely composed of vegetation and bare soil and it is generated at 5 km spatial resolution. To overcome this limitation, local LST information at 100m spatial resolution has been derived through the dedicated CURE AP01, which implemented the approach developed by Mitraka et al. [14] further improved by adapting it to the Copernicus Core Services for deriving coherent estimates across different cities. In particular, a downscaling has been developed that exploits the Sentinel-2 (S2) and Sentinel-3 (S3) synergy, along with atmospheric information from CAMS and surface cover information from CLMS, and it is capable of providing 100m resolution LST at S3 temporal frequency. Detailed surface cover fractions are first derived by exploiting S2 imagery in combination with CLMS data. On the one hand, these are used for downscaling the 1km resolution S3 thermal infrared (TIR) radiance to generate high-resolution TIR information. On the other hand, they are combined with openly available spectral libraries [15], [16] to estimate surface emissivity [14], [17]. Local-scale LST is finally estimated by combining the high-resolution TIR and emissivity data with atmospheric information from CAMS through a split window approach [18]. CURE AP01 LST products are generated on a S3 per-scene basis. Examples of the day/night LST products generated for the city of Basel are reported in Fig. 2. Nevertheless, individual acquisitions are subject to the natural variability of temperature due to weather conditions, as well as gaps due to cloud-cover. Therefore, to enhance the robustness of LST characterization, multi-temporal compositing is performed by calculating for each pixel its median value over a given timeframe (e.g., bi-monthly, quarterly).

As regards the imperviousness, the corresponding CLMS high-resolution layer (HRL IMD) for the year 2018 has been used, which is available at 10m resolution for entire Europe. Imperviousness refers to the fraction of a pixel's land surface that is impermeable to water, resulting in heightened surface runoff and is represented on a scale of 0-100% (see Fig. 2). Specifically, this has been estimated by semi-automated classification of remote sensing imagery. Previous releases of the HRL IMD product were generated at 20m resolution for the years 2006, 2009, 2012 and 2015. Over time, the degree of automation in the production process has gradually increased as a result of the improved spatial resolution of Earth observation (EO) imagery and the availability of more accurate reference data [19]. To match the 100m spatial resolution of the CURE AP01 LST layer, a regionalized imperviousness is ultimately calculated by convolving the 2018 product with a Gaussian kernel of 50m width.

To define up to which extent to consider the rural surrounding around a given city for the computation of the corresponding SUHII, the technique presented in [20] has been employed, which allows to automatically delineate its boundaries. Specifically, a preliminary urban boundary is first determined from the 2018 HRL IMD layer by means of a combined approach of Cellular Automata (CA) [21] based



(a) (b)

(c) (d)

Fig. 2. Basel (Switzerland): Google Earth very high resolution imagery (a); 10m-resolution Copernicus 2018 HRL IMD (b); day (c) and night (d) LST estimated for 18th July 2019 at 100 spatial resolution by CURE AP01.

urban growth modelling and Kernel Density Estimation (KDE) [22]. Next, morphological dilation and erosion are applied in fringe areas. Finally, based on extensive empirical analysis, a buffer of 2km is considered, which generally allows to include a representative number of pixels located in rural areas characterized by the absence of impervious surfaces.

Within the resulting study region defined above, pixel values are then sampled from both the LST composite and regionalized imperviousness (IMP) by using a regular grid. To mitigate the impact of outliers on the analysis, these are employed to fit a robust linear model as:

$$LST = \beta_0 + \beta_1 \cdot IMP \qquad (1)$$

where finally β_1 defines the SUHII.

III. RESULTS

Ultimately, the output of the CURE AP02 are estimated SUHII values per city, per targeted temporal interval, whose interpretation enables a comparison and relative ranking of cities by their thermal characteristics. In the framework of CURE, experiments have been carried out for all 10 targeted cities. In particular, Fig. 3 shows the day and night SUHII temporal profiles obtained at bi-monthly time steps by exploiting LST data from the years 2018 and 2019 generated by CURE AP01. High SUHII values indicate a pronounced heating effect of the city core as opposed to its rural surroundings. This clearly occurs at day time for most of the cities, especially in the summer months. In particular, very high values are reported for Basel, Berlin, Copenhagen, Ostrava, San Sebastian and Sofia, for which the difference with respect to the night values is generally quite remarkable. Here, the case of Sofia is also specific, as the city exhibits the highest night SUHII, which in the winter months is even greater than during the day. Munich, Vitoria-Gasteiz and Bristol look less impacted by the UHI phenomenon, with relatively lower and rather similar day and night SUHII. Instead, given its specific structure and position (facing the Mediterranean Sea at North), Heraklion constantly exhibits among the highest SUHII values at night; on the contrary, during day the city body is actually cooler than its surroundings (especially in summer) as it clearly emerges from the negative SUHII.

IV. CONCLUSION

The presented solution implemented in the framework of CURE AP02 provides a quantitative way to assess the SUHII at the city level and its temporal development by exploiting existing Copernicus Core Services. Thanks to its high degree of automation, the approach has the potential in the future to

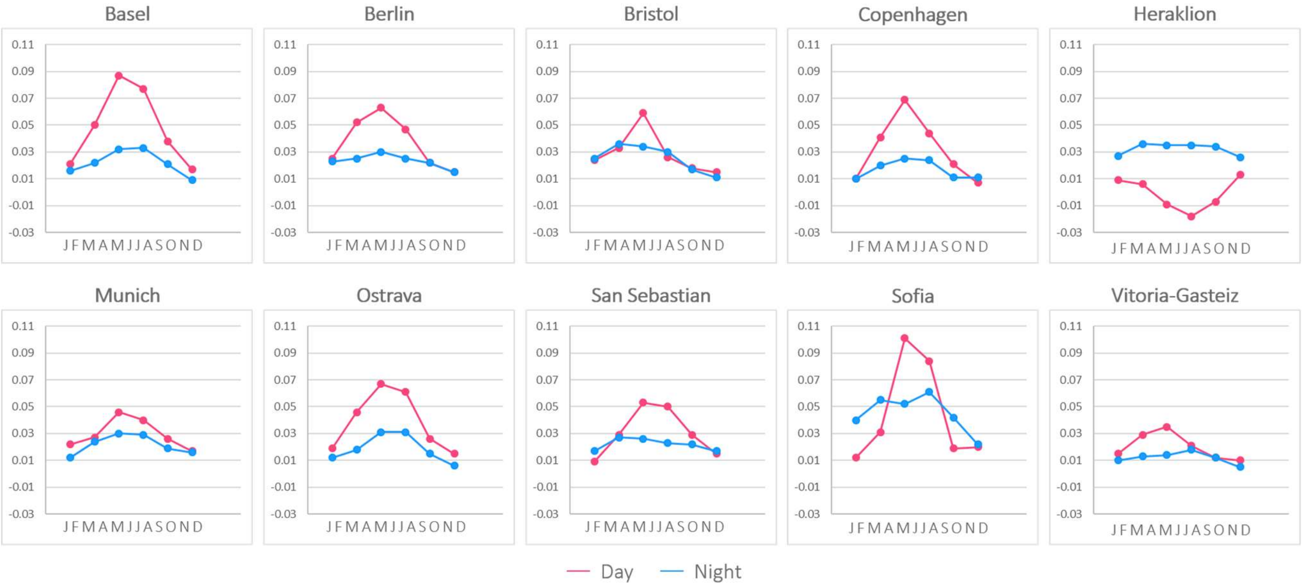


Fig. 3. Bi-monthly day and night SUHII estimated for the 10 CURE targeted cities derived exploiting 2018-2019 LST data from CURE AP01.

systematically monitor the UHI effect for all European cities, hence contributing to identifying those most affected by the phenomenon, evaluating the potential heat risks as well as guiding the planning of resilient urban development in the face of global climate change.

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