Ecological Network Analysis in Urban Areas Through Graph Theory and Remote Sensing

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Abstract

Urban green areas play a crucial role in supporting the provision of ecosystem services, and are pivotal in urban landscape planning and in enhancing the ecological connectivity of cities. However, urban sprawl poses challenges to urban vegetation connectivity and biodiversity, being one of the main causes of landscape fragmentation and degradation. Our paper aimed to introduce a standardized and comparable approach for evaluating the connectivity of green urban areas across Europe. The goal was to evaluate the landscape connectivity of urban areas in 28 European Capital cities and to establish rankings based on two key criteria: the percentage of vegetation and overall landscape connectivity. First, we implemented data from the European Union Earth Observation program—Copernicus—to construct the European Urban Vegetation Maps (EUVMs). EUVMs referred to 2018, had a spatial resolution of 10 m, and categorized dominant vegetation cover into trees, shrubs, and grass across 28 European Capital cities at two official geographical levels: Local Administrative Unit (LAU) and Urban Core areas (UC). Based on the EUVMs, the percentage of vegetation was calculated per each Capital city in Europe. The accuracy assessment against field surveys conducted under the Land Use and Coverage Area Frame Survey confirmed the EUVMs' potential, with an overall accuracy of 83.57%. Further, to evaluate the connectivity of green urban areas we conducted a landscape network analysis using Graphab software. Our analysis examined three global metrics—Probability of Connectivity (PC), Integral Index of Connectivity (IIC), and Equivalent Connected Area (ECA)—as well as networks' nodes and links features within each city. Results showed a mean urban vegetation percentage of 49.43% within the LAU areas, with Southeast European Capitals, such as Sofia, Ljubljana, and Zagreb, exhibiting over 75%. The network analysis showed how Stockholm, despite having the highest average patch capacity and ECA, exhibited an uneven distribution of patch capacity (Gini coefficient 0.96), while Ljubljana recorded the largest values in PC and IIC metrics (0.131 and 0.098, respectively). In conclusion, future research should (i) consider species-specific habitat requirements to develop effective conservation strategies, (ii) investigate public accessibility and urban green area utilization, and (iii) identify standardized methodologies for city boundaries identification to improve international comparability. In this context, Copernicus data can be leveraged for urban planning and ecological connectivity analysis.

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Urban forestry · Remote sensing · Ecosystem services · Landscape connectivity · Biodiversity conservation

1 Introduction

With the world population rapidly increasing, cities and urban areas represent the ecosystems where most of the global population is expected to live by 2050 (United Nations 2018). Urban ecosystems were a central focus in recent global research activities, due to the goods and services vegetation provides to people (Konijnendijk 2023; Nieuwenhuijsen et al. 2022), especially in highly anthropized environments. Indeed, preserving urban vegetation against fragmentation and degradation is crucial for maintaining its functions, including carbon removal and pollutant sequestration (Nowak et al. 2006; Russo et al. 2015; Shafique et al. 2020), temperature regulation (Duncan et al. 2019) and biodiversity conservation (Afrifa et al. 2022; Seto et al. 2012).

In this perspective, the network theory—a mathematical concept dealing with the study of interconnected elements (Bollobás 1998)—can be efficiently implemented in assessing the connectivity of urban green areas (Caldarelli 2007), contributing to shaping sustainable and environmental-friendly cities (Barthelemy 2016). Indeed, the network theory focuses on (i) how landscape elements (i.e., nodes and links) are connected, (ii) how information and resources flow through them, and (iii) how they can be optimized to achieve specific objectives (Caldarelli et al. 2023). While larger cities often track urban vegetation through extensive and expensive field surveys, these efforts primarily focus on public green spaces (Neyns and Canters 2022). Private properties, despite their substantial contributions to ecosystem services, generally lack monitoring (Baker et al. 2018). In this context, the creation of a high-resolution, remote sensing-based urban vegetation cover map can contribute to the establishment of an empirical foundation for supporting urban vegetation management, where private green areas also play a central role. With the recent advancements in temporal, spectral, and spatial resolution of the free available products (Jutz and Milagro-Pérez 2020; Wulder and Coops 2014), along with the surge in computational power of cloud platforms such as Google Earth Engine (Gorelick et al. 2017), the role of remote-sensing technologies in urban green areas monitoring have been emphasized. For instance, Light Detection and Ranging (LiDAR)—the most used active remote sensing tool in urban environment analysis (García-Pardo et al. 2022)—was efficiently used in vegetation types and species identification (Matasci et al. 2018), especially when combined with optical imagery (Katz et al., 2020; Liu et al., 2017), or with very high resolution ($\leq$1 m spatial resolution) technologies. However, one of the main limitations of this approach is the scattered availability of LiDAR data across Europe (Kakoulaki et al. 2021), which hampers the ability to make meaningful comparisons of urban vegetation across different areas. Moreover, financial constraints make it challenging to acquire high-resolution images to integrate information for more precise results (Zaman-ul-Haq et al. 2022). Hence, there is an increasing demand for more accessible and efficient approaches that rely on freely accessible, timely, and widely available remote sensing products—multi-spectral imagery, above all—to accurately produce estimates of urban green areas at the international level (Yan et al. 2018). The Sentinel-2 satellite mission—as part of the European Union (EU) Earth Observation program, Copernicus—offers highly detailed multi-spectral optical observations in 13 wavelengths with a spatial resolution of up to 10 m. These observations are available every 5 days (Drusch et al. 2012), surpassing the frequency of other openly accessible satellite missions like Landsat (spatial resolution up to 30 m and 16 days of revisit time).

In this paper, we presented a methodology for assessing the connectivity of green urban areas in the Capital cities of the EU28 countries, in a standardized and comparable way. The analysis employed an innovative method to implement spatial information sourced from the Copernicus database by using ready-to-use, validated products (Gascon et al. 2017) available at the international level, at the European level. Indeed, Sentinel data and Sentinel-based products are considered a benchmark for quality and reliability (Szantoi et al. 2020), and their application is well-known in urban vegetation monitoring (e.g., Krüger et al. 2018; Kuc and Chormański 2019; Mudele and Gamba 2019). First, the European Urban Vegetation Map (EUVM) was developed for 28 European Capitals separately, with a 10 m spatial resolution for the year 2018. EUVMs identified three main types of vegetation: trees, shrubs, and grassland. To ensure EUVMs accuracy, we exploited field surveys conducted under the Land Use and Coverage Area Frame Survey (LUCAS). Further, the network connectivity of green urban areas in EU28 Capital cities was assessed, and three global network metrics were calculated: the Probability of Connectivity (PC), the Equivalent Connected Area (ECA), and the Integral Index of Connectivity (IIC). The results of the network analysis, coupled with the assessment of green urban areas, were utilized to rank European Capital cities based on their level of green urban coverage and network connectivity.

2 Materials and Methods

2.1 Study Area

The study examined 28 European Capital cities (Fig. 1) defined using two different official geographical datasets: Local Administrative Unit (LAU) and Urban Core areas (UC). LAU represents areas where at least 50% of the population, based on the Degree of Urbanization assessment, as defined by Eurostat (Eurostat 2021), while UC boundaries were defined using the Urban Atlas of the Copernicus Land Monitoring Service (ESA 2018).

In 15 cities, UC and LAU have minor differences, while in 12 cities, LAU was within UC boundaries. Lastly, in Sofia, UC was within LAU boundaries. A 1-km buffer was applied around both LAUs and UCs to account for vegetation patches crossing boundaries, still contributing to the ecological network connectivity analysis of the city. Overall, the total investigated area was 1,531,096 ha across Europe, comprising 969,058 ha of LAU.

2.2 The European Urban Vegetation Map

The European Urban Vegetation Map (EUVM) was developed for the year 2018 at a 10 m spatial resolution, categorizing dominant vegetation cover into trees, shrubs, and grass. The map was created by aggregating data from five Copernicus Land Monitoring Service layers, available for the year 2018: Urban Atlas (UA), Street Tree Layer (STL), High-Resolution Layers (HRL) for Grassland (HRL-GRA), Tree Cover Density (HRL-TCD), and Small Woody Features (HRL-SWF). The EUVM was then generated by reclassifying data from these layers into three vegetation categories according to the relations reported in Table 1.

During the reclassification, classes not included in the three vegetation categories were classified as (0), "other". Reclassification and dataset elaboration were performed in the Google Earth Engine (GEE) environment (Gorelick et al. 2017).

2.3 Data Validation

To assess the accuracy of the European Urban Vegetation Maps (EUVM) in identifying urban vegetation classes, a validation process was conducted using data from the Land Use and Coverage Area Frame Survey (LUCAS) for the reference year 2018 (d'Andrimont et al. 2020). Initiated in 2006 and conducted every three years, LUCAS operates as an in-situ area frame survey primarily based on field observations. LUCAS is based on a two-phase approach, with a systematic sample with points spaced on the 2 × 2 km grid, which are then photo-interpreted and assigned to a land cover class (Gallego and Bamps 2008). From the stratified first phase sample, a second phase sample of points is investigated on the field (Ballin et al. 2018). In detail, the survey points are situated at the intersections of a 2 × 2 km grid, totaling approximately 1 million points across the EU.

Fig. 1 European Capital cities are reported in red, while Copernicus built-up areas are shown in orange (2018 reference year)

Table 1 Copernicus database reclassification categories, according to the classes reported in the European Urban Vegetation Map (EUVM)

Input	Output—EUVM		
Layer	[1] Trees	[2] Shrubs	[3] Herbaceous
UA—Urban Atlas	31000 (Forest)	32000 (Herbaceous vegetation associations) 33000 (Open spaces with little or no vegetation)	21000 (Arable land (annual crops)) 22000 (Permanent crops) 23000 (Pastures) 24000 (Complex and mixed cultivation)
STL—Street Tree Layer	1	–	–
HRL TCD—Tree Cover Density	>10% Coverage	–	–
HRL GRA—Grassland	–	–	1
HRL SWF—Small Woody Features	1	–	–

In the LUCAS 2018 survey, about 240,000 of the second phase points were physically visited by 750 field surveyors, while an additional 98,000 points were interpreted through photointerpretation. Hence, LUCAS provides unique statistics, offering standardized definitions and methodology, ensuring comparability of data across EU countries and the database is openly available in GEE as a harmonized version of yearly surveys (d'Andrimont et al. 2020). In the 2018 LUCAS dataset, 2,210 s-phase sample points were located within 1 km of the UC boundaries of European Capitals. These points were then utilized to validate the EUVM's performance in landscape network analysis. Both the EUVM and LUCAS datasets (ESTAT 2018) were converted into binary maps, with a value of 1 assigned to categories representing forests and shrubs (LUCAS codes C00* and D00*) and a value of 0 applied to all other categories. Finally, the overall accuracy (OA) was calculated using a 2 $\times$ 2 confusion matrix, which provides a summary of the performance of a classification model by showing the number of true positive, true negative, false positive, and false negative predictions.

2.4 Ecological Network Analysis and Landscape Connectivity

Within the different approaches to transforming complex systems into a network, the framework proposed by Foltête et al. (2012)—the Graphab package—recently emerged as a promising operational tool. First presented in 2012 and further updated since (Foltête et al. 2021), Graphab is a free-to-use tool that was successfully applied to different scenarios in urban landscape analysis (e.g., Kohler et al. 2016; Kim and Kang 2022; Lumia et al. 2023). Here, the network analysis was conducted using the R package "Graph4lg" (Savary et al. 2021) which incorporates principles of graph theory (Urban and Keitt 2001) with the functionality of the Graphab software for landscape connectivity, producing nodes and links representing habitat patches and ecological corridors, respectively (Baranyi et al. 2011; Rayfield et al. 2011). The analysis used the EUVMs as input, designating pixels classified as "trees" (code 1) and "shrubs" (code 2) as target habitat categories. Pixel aggregation into patches followed the 4-neighbor method, grouping pixels based on adjacency. A habitat patch was formed when the cumulative area of adjacent pixels reached or exceeded the minimum patch area threshold of 0.1 hectares. Planar links between habitat patches were computed based on Euclidean distance, assuming uniform resistance values for landscape categories. The graph was pruned with a maximum distance threshold between patches set at 200 m.

Various metrics were then calculated for each graph, including (i) the total number of patches (nodes), (ii) their mean capacity (area), (iii) the GINI index, (iv) the number of links equal to or smaller than 200 m, and (v) their mean distance. Further, three global metrics were computed, per city: the Probability of Connectivity (PC), the Equivalent Connected Area (ECA), and the Integral Index of Connectivity (IIC). In detail, PC represents the probability that two individuals, randomly placed within the landscape, fall into interconnected habitats (Saura et al. 2011; Saura and Pascual-Hortal 2007), and varies from 0 to 1, increasing with habitat connectivity. On the other hand, ECA is the size of the single maximally connected habitat patch that would yield the same PC value as the actual habitat pattern (Pascual-Hortal and Saura 2006), while IIC indicates the probability that individuals randomly located within a patch can access each other, ranging from 0 (lack of habitat) to 1 (complete landscape occupation by habitat). Finally, the Pearson correlation coefficient (r) and statistical significance for all possible pairs of metrics were calculated, to understand how these metrics collectively influence overall urban network connectivity.

3 Results

3.1 Data Validation and Urban Vegetation Coverage

For the entire dataset, we achieved an OA of 83.57%. At the city level, the highest OAs were observed in Athens and Ljubljana, both exceeding 90%, followed closely by Sofia at 88.89%. Conversely, Brussels, Tallinn, and Madrid recorded OAs below 75%.

According to the EUVM (Fig. 2), on a European scale, the average vegetation percentage within the LAU boundaries was 49.43%, which increased to 57.80% within the UC areas. Among the 28 European Capital cities analyzed within their UC, 13 cities had vegetation coverage below this threshold: Nicosia, Paris, Valletta, London, Athens, Brussels, Amsterdam, Bucharest, Budapest, Lisbon, Copenhagen Berlin, and Riga (listed from the lowest to the highest vegetation coverage). Similarly, when considering the LAU boundaries, 12 cities fell below the EU threshold: London, Valletta, Athens, Paris, Lisbon, Nicosia, Brussels, Copenhagen, Amsterdam, Dublin, Stockholm, and Bucharest.

Within LAU boundaries, Sofia and Ljubljana registered the highest proportion of vegetation over the total urban area among European Capitals, at 84.36% and 78.73%, respectively. Zagreb and Bratislava followed closely, with 76.27% and 73.72%, respectively. Similar trends were observed within UC boundaries, where Ljubljana, Zagreb, and Stockholm recorded the highest proportion of vegetation over the total UC area. Conversely, London and Valletta exhibited less than 10% vegetation coverage of the total LAU (2.47% and 3.16%, respectively). In UCs, Nicosia, Paris, and Valletta recorded a vegetation coverage below 40% (25.97%, 32.27%, and 26.36%, respectively).

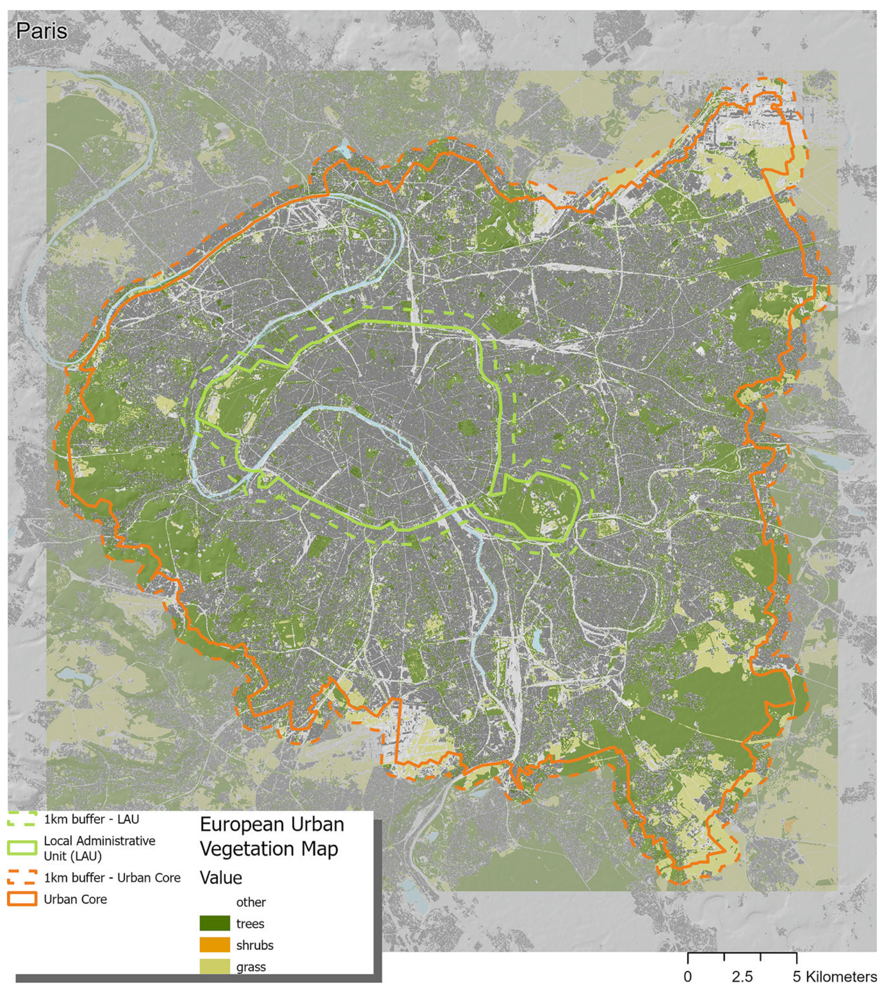

Fig. 2 European Urban Vegetation Map in Paris Urban Core (in orange) and Local Administrative Unit (in green, bottom right panel)

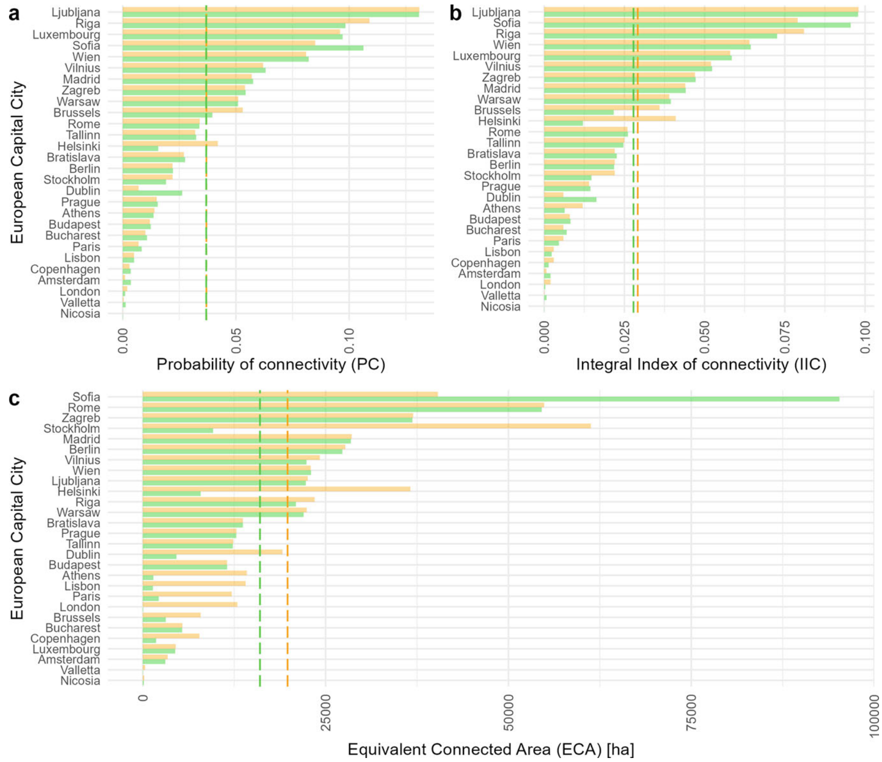

Fig. 3 Global metrics calculated in 28 European Capital cities, in both Urban Core (in orange), and Local Administrative Units (in green) boundaries. Dashed lines indicate the mean value assessed at the European level considering the two boundaries separately

3.2 Landscape Connectivity

The distribution of mean distances of the landscape networks showed how Stockholm recorded the largest mean patch capacity across European Capital cities' UC, with 10.55 ha, and one among the largest Gini index (0.96) on patch capacity. On the other hand, the network comprised in Brussels LAU boundaries showed the largest ratio of trees and shrubs patches in the landscape (0.94 per hectare). Further, the smallest ratio of patches per hectare was recorded in Sofia (0.10), Zagreb (0.13), and Nicosia (0.14).

Within European Capital city boundaries, a positive correlation pattern emerged among the three global metrics, the patch capacity and the number of patches per hectare—especially between PC and IIC—both in LAU and UC ($r = 0.98$ and $p < 0.01$). Similarly, a positive correlation was observed between ECA and the mean patch capacity ($r = 0.70$). The same occurred between IIC and the mean patch capacity ($r = 0.84$, $p = 0$). On the other hand, strong negative correlations were identified between the mean patch capacity and the number of trees and shrubs patches per hectare ($r = -0.62$, and $r = -0.73$ in UC and LAU, respectively).

The analysis of global metrics for each European Capital city provided information about the connectivity of their urban landscape network at the international level. When observed in the UC, the IIC index (Fig. 3, panel b), which provides insights into the habitat network's connectivity, indicated that Ljubljana, Riga, and Sofia have the highest levels of connectivity, with scores of 0.098, 0.081, and 0.079, respectively. Furthermore, these cities also showed high PC values (Fig. 3, panel a), with scores of 0.131, 0.109, and 0.085, respectively. Regarding ECA (Fig. 3, panel c), Stockholm had the highest estimate with 61269.18 ha, followed closely by Rome with 54880.59 ha. When analyzing global metrics within LAU boundaries, the highest IIC values were obtained in Ljubljana, Sofia, and Riga, with scores of 0.098, 0.095, and 0.073, respectively. These cities also recorded the highest PC values, with 0.13, 0.11, and 0.10, respectively. On the other hand, the highest ECA values were obtained in Sofia, Rome, and Zagreb, with 95261.79 ha, 54546.74 ha, and 36872.07 ha, respectively.

4 Discussions and Conclusions

Over the past two decades, Europe has experienced a consistent urbanization trend, which is projected to continue, anticipating a growth of up to 30 million more people in European urban areas by 2050 (UN Habitats 2011; United Nations 2018). In this context, the positive impact of vegetation on human well-being in urban areas is well-documented (Venter et al. 2020), and its effectiveness is based on its structural and functional connectivity (Beninde et al. 2016). Therefore, evaluating landscape connectivity indicators is crucial for effective urban planning and management (Von Thaden et al. 2021), especially in the context of climate change and efforts to enhance urban sustainability (MacGregor-Fors et al. 2020).

In this study, we developed the European Urban Vegetation Map (EUVM) based on Copernicus data, providing harmonized, cost-effective information on discrete vegetation elements in European urban environments for the year 2018 at a 10 m spatial resolution. The quantitative accuracy assessment against LUCAS field sampling confirmed the EUVM's potential, with an overall OA of 83.57%. According to EUVM analysis, the mean urban vegetation percentage in European LAU was slightly below 50% (49.43%) of the total urban area. However, twelve of the analyzed European Capital cities fall below this threshold: City of London and Valletta ranking the lowest. In contrast, Southeast European Capitals, including Sofia, Ljubljana, and Zagreb, showed more than 75% of the total urban area covered by vegetation. Analyzing landscape network structural features in European Capitals UCs, Stockholm emerged with the highest average patch capacity (10.55 ha) and ECA (61269.18 ha). However, Stockholm also displayed an uneven distribution of patch capacity among European Capitals, with a Gini coefficient of 0.96. Hence, while larger patches are ecologically valuable in supporting substantial and enduring wildlife populations, small vegetation patches should not be disregarded as they play the "stepping stones" role for connectivity, particularly in heavily modified urban environments. On the other hand, Ljubljana's UC stood out for achieving the largest PC (0.131) and IIC (0.098) scores (Fig. 3), highlighting remarkable vegetation connectivity. Nevertheless, the intrinsic characteristics of these metrics should be considered while involved in urban planning, as IIC assigns higher values to patches at short and intermediate distances compared to PC (Bodin and Saura 2010).

Although the presented study offered valuable insights into urban vegetation and connectivity, it is important to acknowledge limitations and identify future steps. First, in order to formulate effective urban biodiversity conservation strategies, future research should delve into species-specific habitat requirements related to landscape and network connectivity. In this study, a uniform network resistance was utilized. However, future steps may involve evaluating the habitat and movement suitability requirements of different species, with a focus on network connectivity related to key species behavior, such as pollinators (Biella et al. 2022) or ground-dwelling animals (Braaker et al. 2014). Second, there is a need for more comprehensive research to evaluate the accessibility and utilization of urban green areas by the public, considering their role in promoting valuable services for physical and mental health (Nieuwenhuijsen et al. 2022), while social aspects of research gained prominence in the planning of more sustainable cities (Farkas et al. 2023). In this context, future studies could explore the integration of social science research methods with existing remote-sensing-based approaches. This may include the collection of social media data (Plunz et al. 2019; Roberts et al. 2018), and the processing of mobile phone GPS data to map how and when people utilize public green areas (Ladle et al. 2018; Vich et al. 2019). Finally, the diverse geographical definitions of "cities" across different scales present a challenge to comparing studies among European cities. These variations may largely stem from historical, topographical, and socio-economic factors, as well as the city's geographic location, climatic conditions, and urban planning considerations (Farkas et al. 2023). Therefore, it is essential to develop and adopt a harmonized and standardized methodology for city boundaries identification, to improve comparability of future studies at the international level. In this context, the Copernicus data has proven to be an asset in the creation of comprehensive maps of urban vegetation throughout Europe and could support further detailed research at the city level.

References

Afrifa, J. K., Monney, K. A., & Deikumah, J. P. (2022). Effects of urban land-use types on avifauna assemblage in a rapidly developing urban settlement in Ghana. Urban Ecosystems. https://doi.org/10.1007/s11252-022-01281-0.

Baker, F., Smith, C., & Cavan, G. (2018). A Combined Approach to Classifying Land Surface Cover of Urban Domestic Gardens Using Citizen Science Data and High Resolution Image Analysis. Remote Sensing, 10(4), 537. https://doi.org/10.3390/rs10040537.

Ballin, M., Barcaroli, G., Masselli, M., & Scarnó, M. (2018). Redesign sample for Land Use/Cover Area frame Survey (LUCAS) 2018.

Baranyi, G., Saura, S., Podani, J., & Jordán, F. (2011). Contribution of habitat patches to network connectivity: Redundancy and uniqueness of topological indices. Ecological Indicators, 11(5), 1301–1310. https://doi.org/10.1016/j.ecolind.2011.02.003.

Barthelemy, M. (2016). The structure and dynamics of cities. Cambridge University Press.

Beninde, J., Feldmeier, S., Werner, M., Peroverde, D., Schulte, U., Hochkirch, A., & Veith, M. (2016). Cityscape genetics: structural vs. functional connectivity of an urban lizard population. Molecular Ecology, 25(20), 4984–5000. https://doi.org/10.1111/mec.13810.

Biella, P., Tommasi, N., Guzzetti, L., Pioltelli, E., Labra, M., & Galimberti, A. (2022). City climate and landscape structure shape pollinators, nectar and transported pollen along a gradient of urbanization. Journal of Applied Ecology, 59(6), 1586–1595. https://doi.org/10.1111/1365-2664.14168.

Bodin, Ö., & Saura, S. (2010). Ranking individual habitat patches as connectivity providers: Integrating network analysis and patch removal experiments. Ecological Modelling, 221(19), 2393–2405. https://doi.org/10.1016/j.ecolmodel.2010.06.017.

Bollobás, B. (1998). Modern graph theory (Vol. 184). Springer Science & Business Media.

Braaker, S., Moretti, M., Boesch, R., Ghazoul, J., Obrist, M. K., & Bontadina, F. (2014). Assessing habitat connectivity for ground-dwelling animals in an urban environment. Ecological Applications, 24(7), 1583–1595. https://doi.org/10.1890/13-1088.1.

Caldarelli, G., Arcaute, E., Barthelemy, M., Batty, M., Gershenson, C., Helbing, D., Mancuso, S., Moreno, Y., Ramasco, J. J., Rozenblat, C., Sánchez, A., & Fernández-Villacañas, J. L. (2023). The role of complexity for digital twins of cities. Nature Computational Science, 3(5), 374–381. https://doi.org/10.1038/s43588-023-00431-4.

Caldarelli, Guido. (2007). Scale-free networks: complex webs in nature and technology. Oxford Finance.

d'Andrimont, R., Yordanov, M., Martinez-Sanchez, L., Eiselt, B., Palmieri, A., Dominici, P., Gallego, J., Reuter, H. I., Joebges, C., Lemoine, G., & van der Velde, M. (2020). Harmonised LUCAS in-situ land cover and use database for field surveys from 2006 to 2018 in the European Union. Scientific Data, 7(1), 352. https://doi.org/10.1038/s41597-020-00675-z.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. Remote Sensing of Environment, 120, 25–36. https://doi.org/10.1016/j.rse.2011.11.026.

Duncan, J. M. A., Boruff, B., Saunders, A., Sun, Q., Hurley, J., & Amati, M. (2019). Turning down the heat: An enhanced understanding of the relationship between urban vegetation and surface temperature at the city scale. Science of the Total Environment, 656, 118–128. https://doi.org/10.1016/j.scitotenv.2018.11.223.

ESA. (2018). Copernicus Urban Atlas. https://land.copernicus.eu/local/urban-atlas/urban-atlas-2018.

ESTAT. (2018). LUCAS2018-C3-Classification.

Eurostat. (2021). Applying the Degree of Urbanisation. In Applying the Degree of Urbanisation.

Farkas, J. Z., Hoyk, E., de Morais, M. B., & Csomós, G. (2023). A systematic review of urban green space research over the last 30 years: A bibliometric analysis. Heliyon, 9(2), e13406. https://doi.org/10.1016/j.heliyon.2023.e13406.

Foltête, J.-C., Clauzel, C., & Vuidel, G. (2012). A software tool dedicated to the modelling of landscape networks. Environmental Modelling & Software, 38, 316–327. https://doi.org/10.1016/j.envsoft.2012.07.002.

Foltête, J.-C., Vuidel, G., Savary, P., Clauzel, C., Sahraoui, Y., Girardet, X., & Bourgeois, M. (2021). Graphab: An application for modeling and managing ecological habitat networks. Software Impacts, 8, 100065. https://doi.org/10.1016/j.simpa.2021.100065.

Gallego, J., & Bamps, C. (2008). Using CORINE land cover and the point survey LUCAS for area estimation. International Journal of Applied Earth Observation and Geoinformation, 10(4), 467–475. https://doi.org/10.1016/j.jag.2007.11.001.

García-Pardo, K. A., Moreno-Rangel, D., Domínguez-Amarillo, S., & García-Chávez, J. R. (2022). Remote sensing for the assessment of ecosystem services provided by urban vegetation: A review of the methods applied. Urban Forestry & Urban Greening, 74, 127636. https://doi.org/10.1016/j.ufug.2022.127636.

Gascon, F., Bouzinac, C., Thépaut, O., Jung, M., Francesconi, B., Louis, J., Lonjou, V., Lafrance, B., Massera, S., Gaudel-Vacaresse, A., Languille, F., Alhammoud, B., Viallefont, F., Pflug, B., Bieniarz, J., Clerc, S., Pessiot, L., Trémas, T., Cadau, E., … Fernandez, V. (2017). Copernicus Sentinel-2A Calibration and Products Validation Status. Remote Sensing, 9(6), 584. https://doi.org/10.3390/rs9060584.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Jutz, S., & Milagro-Pérez, M. P. (2020). Copernicus: the European Earth Observation programme. Revista de Teledetección, 56. https://doi.org/10.4995/raet.2020.14346.

Kakoulaki, G., Martinez, A., & Florio, P. (2021). Non-commercial Light Detection and Ranging (LiDAR) data in Europe. https://doi.org/10.2760/212427.

Katz, D. S. W. D. S. W. S. W., Batterman, S. A. A. S. A., & Brines, S. J. J. S. J. (2020). Improved Classification of Urban Trees Using a Widespread Multi-Temporal Aerial Image Dataset. Remote Sensing, 12(15), 2475. https://doi.org/10.3390/rs12152475.

Kim, J., & Kang, W. (2022). Assessing Green Roof Contributions to Tree Canopy Ecosystem Services and Connectivity in a Highly Urbanized Area. Land, 11(8), 1281. https://doi.org/10.3390/land11081281.

Kohler, M., Blond, N., & Clappier, A. (2016). A city scale degree-day method to assess building space heating energy demands in Strasbourg Eurometropolis (France). Applied Energy, 184, 40–54. https://doi.org/10.1016/j.apenergy.2016.09.075.

Konijnendijk, C. C. (2023). Evidence-based guidelines for greener, healthier, more resilient neighbourhoods: Introducing the 3–30–300 rule. Journal of Forestry Research, 34(3), 821–830. https://doi.org/10.1007/s11676-022-01523-z.

Krüger, T., Hecht, R., Herbrich, J., Behnisch, M., & Oczipka, M. (2018). Investigating the suitability of Sentinel-2 data to derive the urban vegetation structure. Proceedings of SPIE-The International Society for Optical Engineering, 10793. https://doi.org/10.1117/12.2325337.

Kuc, G., & Chormański, J. (2019). SENTINEL-2 IMAGERY FOR MAPPING AND MONITORING IMPERVIOUSNESS IN URBAN AREAS. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-1/W2, 43–47. https://doi.org/10.5194/isprs-archives-XLII-1-W2-43-2019.

Ladle, A., Galpern, P., & Doyle-Baker, P. (2018). Measuring the use of green space with urban resource selection functions: An application using smartphone GPS locations. Landscape and Urban Planning, 179, 107–115. https://doi.org/10.1016/j.landurbplan.2018.07.012.

Liu, L., Coops, N. C., Aven, N. W., & Pang, Y. (2017). Mapping urban tree species using integrated airborne hyperspectral and LiDAR remote sensing data. Remote Sensing of Environment, 200, 170–182. https://doi.org/10.1016/j.rse.2017.08.010.

Lumia, G., Praticò, S., Di Fazio, S., Cushman, S., & Modica, G. (2023). Combined use of urban Atlas and Corine land cover datasets for the implementation of an ecological network using graph theory within a multi-species approach. Ecological Indicators, 148, 110150. https://doi.org/10.1016/j.ecolind.2023.110150.

MacGregor-Fors, I., Gómez-Martínez, M. A., García-Arroyo, M., & Chávez-Zichinelli, C. A. (2020). A dead letter? Urban conservation, management, and planning strategies from the Mexican urban bird literature. Urban Ecosystems, 23(5), 1107–1115. https://doi.org/10.1007/s11252-020-00970-y.

Matasci, G., Coops, N. C., Williams, D. A. R., & Page, N. (2018). Mapping tree canopies in urban environments using airborne laser scanning (ALS): a Vancouver case study. Forest Ecosystems, 5(1), 31. https://doi.org/10.1186/s40663-018-0146-y.

Mudele, O., & Gamba, P. (2019). Mapping vegetation in urban areas using Sentinel-2. 2019 Joint Urban Remote Sensing Event, JURSE 2019, 1–4. https://doi.org/10.1109/JURSE.2019.8809019.

Neyns, R., & Canters, F. (2022). Mapping of Urban Vegetation with High-Resolution Remote Sensing: A Review. Remote Sensing, 14(4), 1031. https://doi.org/10.3390/rs14041031.

Nieuwenhuijsen, M. J., Dadvand, P., Márquez, S., Bartoll, X., Barboza, E. P., Cirach, M., Borrell, C., & Zijlema, W. L. (2022). The evaluation of the 3-30-300 green space rule and mental health. Environmental Research, 215. https://doi.org/10.1016/j.envres.2022.114387.

Pascual-Hortal, L., & Saura, S. (2006). Comparison and development of new graph-based landscape connectivity indices: towards the priorization of habitat patches and corridors for conservation. Landscape Ecology, 21(7), 959–967. https://doi.org/10.1007/s10980-006-0013-z.

Plunz, R. A., Zhou, Y., Carrasco Vintimilla, M. I., Mckeown, K., Yu, T., Uguccioni, L., & Sutto, M. P. (2019). Twitter sentiment in New York City parks as measure of well-being. Landscape and Urban Planning, 189, 235–246. https://doi.org/10.1016/j.landurbplan.2019.04.024.

Rayfield, B., Fortin, M.-J., & Fall, A. (2011). Connectivity for conservation: a framework to classify network measures. Ecology, 92(4), 847–858. https://doi.org/10.1890/09-2190.1.

Roberts, H., Resch, B., Sadler, J., Chapman, L., Petutschnig, A., & Zimmer, S. (2018). Investigating the Emotional Responses of Individuals to Urban Green Space Using Twitter Data: A Critical Comparison of Three Different Methods of Sentiment Analysis. Urban Planning, 3(1), 21–33. https://doi.org/10.17645/up.v3i1.1231.

Saura, S., & Pascual-Hortal, L. (2007). A new habitat availability index to integrate connectivity in landscape conservation planning: Comparison with existing indices and application to a case study. Landscape and Urban Planning, 83(2–3), 91–103. https://doi.org/10.1016/j.landurbplan.2007.03.005.

Saura, S., Estreguil, C., Mouton, C., & Rodríguez-Freire, M. (2011). Network analysis to assess landscape connectivity trends: Application to European forests (1990–2000). Ecological Indicators, 11(2), 407–416. https://doi.org/10.1016/j.ecolind.2010.06.011.

Savary, P., Foltête, J., Moal, H., Vuidel, G., & Garnier, S. (2021). graph4lg: A package for constructing and analysing graphs for landscape genetics in R. Methods in Ecology and Evolution, 12(3), 539–547. https://doi.org/10.1111/2041-210X.13530.

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109.

Szantoi, Z., Lafrance, B. B., Aznay, O., Chambrelan, B. A., Lebreton, D. T., Defence, A., Marion, B., Malle, N. Van, & Sterckx, B. S. (2020). Copernicus Sentinel-2 Mission: Calibration and Validation activities. https://doi.org/10.25923/enp8-6w06.

UN Habitats. (2011). Hot Cities: battle-ground for climate change.

United Nations. (2018). The World's Cities in 2018. World Urbanization Prospects: The 2018 Revision, 34.

Urban, D., & Keitt, T. (2001). Landscape Connectivity: A Graph-Theoretic Perspective. Ecology, 82(5), 1205. https://doi.org/10.2307/2679983.

Venter, Z. S., Krog, N. H., & Barton, D. N. (2020). Linking green infrastructure to urban heat and human health risk mitigation in Oslo, Norway. Science of the Total Environment, 709. https://doi.org/10.1016/j.scitotenv.2019.136193.

Vich, G., Marquet, O., & Miralles-Guasch, C. (2019). Green exposure of walking routes and residential areas using smartphone tracking data and GIS in a Mediterranean city. Urban Forestry & Urban Greening, 40, 275–285. https://doi.org/10.1016/j.ufug.2018.08.008.

Von Thaden, J., Badillo-Montaño, R., Lira-Noriega, A., García-Ramírez, A., Benítez, G., Equihua, M., Looker, N., & Pérez-Maqueo, O. (2021). Contributions of green spaces and isolated trees to landscape connectivity in an urban landscape. Urban Forestry & Urban Greening, 64, 127277. https://doi.org/10.1016/j.ufug.2021.127277.

Wulder, M. A., & Coops, N. C. (2014). Satellites: Make Earth observations open access. Nature, 513(7516), 30–31. https://doi.org/10.1038/513030a.

Yan, J., Zhou, W., Han, L., & Qian, Y. (2018). Mapping vegetation functional types in urban areas with WorldView-2 imagery: Integrating object-based classification with phenology. Urban Forestry & Urban Greening, 31, 230–240. https://doi.org/10.1016/j.ufug.2018.01.021.

Zaman-ul-Haq, M., Saqib, Z., Kanwal, A., Naseer, S., Shafiq, M., Akhtar, N., Bokhari, S. A., Irshad, A., & Hamam, H. (2022). The Trajectories, Trends, and Opportunities for Assessing Urban Ecosystem Services: A Systematic Review of Geospatial Methods. Sustainability, 14(3), 1471. https://doi.org/10.3390/su14031471.