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Urban Green Connectivity Assessment: A Comparative Study of Datasets in European Cities

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Abstract: Urban biodiversity and ecosystem services depend on the quality, quantity, and connectivity of urban green areas (UGAs), which are crucial for enhancing urban livability and resilience. However, assessing these connectivity metrics in urban landscapes often suffers from outdated land cover classifications and insufficient spatial resolution. Spectral data from Earth Observation, though promising, remains underutilized in analyzing UGAs' connectivity. This study tests the impact of dataset choices on UGAs' connectivity assessment, comparing land cover classification (Urban Atlas) and spectral data (Normalized Difference Vegetation Index, NDVI). Conducted in seven European cities, the analysis included 219 UGAs of varying sizes and connectivity levels, using three connectivity metrics (size, proximity index, and surrounding green area) at different spatial scales. The results showed substantial disparities in connectivity metrics, especially at finer scales and shorter distances. These differences are more pronounced in cities with contiguous UGAs, where Urban Atlas faces challenges related to typology issues and minimum mapping units. Overall, spectral data provides a more comprehensive and standardized evaluation of UGAs' connectivity, reducing reliance on local typology classifications. Consequently, we advocate for integrating spectral data into UGAs' connectivity analysis to advance urban biodiversity and ecosystem services research. This integration offers a comprehensive and standardized framework for guiding urban planning and management practices.

Keywords: urban green areas; urban green spatial patterns; landscape metrics; habitat fragmentation; urban atlas; spectral data; spatial resolution; minimum mapping unit; thematic resolution; urban heterogeneity

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1. Introduction

Urbanization, with its increasing population concentration in cities, poses a substantial challenge amid the global call for sustainable practices [1,2]. Urban expansion has transformed natural landscapes into complex, ever-changing ecosystems shaped by human influence [3]. Within these urban ecosystems, urban green areas (UGAs) are identified as key elements in addressing this challenge and promoting sustainability due to their crucial role in maintaining ecological balance and enhancing the quality of urban life [4]. UGAs encompass a diverse range of typologies and sizes, including native vegetation remnants, urban forests, parks, brownfields, and street trees [5]. This diversity results in rich variation in vegetation composition and structure, creating niche habitats that support a wide range of plant and animal species [6–8]. Additionally, the variety of UGA typologies significantly influences their ecological functions and, consequently, their ability to provide essential ecosystem services that are pivotal for human health and well-being, making cities more livable and environmentally friendly [4,9–11]. These services include mitigating urban heat islands [12], reducing air pollution [13], providing spaces for recreation, exercise, and social gatherings [14], and contributing to the aesthetic appeal of urban landscapes [15].

The effectiveness of UGAs in promoting biodiversity and supporting ecosystem services hinges on three key landscape components. These components include the quantity of UGAs, their quality influenced by vegetation composition and structure, and their spatial relationships with other land cover types (i.e., the permeability of the surrounding matrix). Larger UGAs typically tend to support a greater diversity of plant and animal species by providing a diverse range of favorable habitats and niches [16]. Moreover, high-quality habitats within UGAs can support a broader range of ecosystem functions and services, which can be amplified when the landscape is well-connected and permeable [8,11,17,18]. By understanding the importance of these components and promoting integrated urban green planning, cities can become more resilient in the face of environmental challenges [1,3]. However, in many European cities, UGAs are characterized by their small sizes and fragmented configurations [19], compromising their ecological quality. These fragmented UGAs limit their ability to support diverse species communities and hinder species dispersal and movement within the urban landscape [8,20]. Consequently, these factors affect urban biodiversity and disrupt vital ecological processes [17]. Nevertheless, integrating smaller UGAs with their larger counterparts holds the potential to enhance functional connectivity, facilitate species movement within the urban matrix [3,8], and amplify the myriad services that ecosystems provide [18].

To address these challenges, assessing the connectivity of the urban landscape becomes paramount because green connectivity contributes to the resilience and adaptability of urban ecosystems. Efficient connectivity within the urban landscape promotes the movement of organisms and genetic material, facilitates the flow of essential nutrients, and ensures the overall functionality of ecosystems within and among green patches [20]. Therefore, it is essential to develop specific connectivity indicators to evaluate urban green connectivity comprehensively. Landscape metrics have emerged as powerful and accessible tools for quantifying the spatial arrangement of UGAs within urban settings [18]. These metrics enable quantitative comparisons of UGA connectivity across diverse cities [19,21], offering valuable insights into both localized patch-level and comprehensive landscape-level evaluations. While landscape metrics provide a robust framework for assessing urban green connectivity, the choice of data sources and datasets used in these assessments can significantly impact their accuracy and reliability.

Land cover maps are commonly used for urban connectivity measurements as they allow for the differentiation of land cover classes, including vegetation, built-up areas, and water bodies [22,23]. However, these data, while providing spatial completeness and continuity, have limitations in capturing all urban land cover complexities. This limitation arises from the challenges of interpreting and categorizing the heterogeneous nature of urban settings [22,24]. Consequently, these maps may not adequately represent some UGAs within urban landscapes, where land cover transitions can occur at much finer scales compared to rural settings [24–27]. Additionally, most city-specific land cover maps are developed using distinct classification rules, leading to challenges in standardizing data and making comparisons across different cities and countries [21]. The variations in classification rules, particularly in terms of thematic (number of classes) and spatial resolutions (minimum mapping unit, pixel size, and study area extent), can lead to disparities in connectivity estimates [28–32]. However, the European Environment Agency's Urban Atlas offers a promising solution. This dataset provides a high-spatial-resolution classification of urban land cover for standardized analysis across Europe [33], potentially addressing some of the aforementioned limitations.

Spectral data from Earth observation provide an alternative approach for assessing urban connectivity. These data, which encompass the Normalized Difference Vegetation Index (NDVI), offer several advantages, including reproducibility and standardization on a European scale, thus delivering valuable insights into differentiating land cover, understanding environmental shifts in urban settings, and grasping the spatial patterns of UGA connectivity [34]. Additionally, spectral data's precision allows for the identification and characterization of small patches within the urban landscape [27,35], a critical aspect for accurately estimating urban green connectivity and understanding its role in supporting biodiversity and ecosystem services. This level of precision is particularly important, as small patches and corridors play a crucial role in supporting urban biodiversity and promoting ecological functions [8,34,36]. Despite these advantages, most published studies continue to rely on less precise land cover classifications.

To address this gap in knowledge, our study seeks to examine how dataset choice affects the quantification of urban green connectivity, focusing on three key indicators: (i) green area size; (ii) proximity index; and (iii) the amount of surrounding green area across different spatial scales. We conducted this research in seven European cities, comparing two datasets: (1) the Urban Atlas land cover classification and (2) NDVI spectral data. Although other authors have quantified the impact of using different datasets on the values of urban green connectivity indicators, we used two novel approaches. Firstly, we considered the relative values for connectivity indicators rather than the absolute values by comparing the position in the rank of connectivity. This allows us to partially overcome the problems associated with assuming linear trends: if the absolute values of connectivity change but the relative position of green areas regarding connectivity remains the same, then the ecological value of both data sources would be the same, because we cannot assume a priori that ecological relationships are linear. Secondly, we tested the conditions under which the data source impacts the connectivity indicators the most. For that, we considered a gradient of green area size and climate, testing if specific conditions would result in more impact from using different datasets. Moreover, given the importance of UGAs' quantity, proximity, and quality in supporting ecological functions and services, our goal is to facilitate research in these scientific areas. We aim to identify the most appropriate and reliable dataset for calculating connectivity indicators capable of identifying, quantifying, and monitoring a variety of UGAs on a European scale over time. This insight can inform urban planners and policymakers about the importance of using the most appropriate data sources for making well-informed decisions. These informed choices can boost urban sustainability and resilience while preserving and promoting the benefits of UGAs.

2. Material and Methods

2.1. Study Area

This study was conducted across seven European cities, each chosen to represent a diverse range of urban settings, spanning a climatic gradient and exhibiting varying degrees of spatial heterogeneity (Table 1). These cities included Almada and Lisbon in Portugal, Paris in France, Zurich in Switzerland, Antwerp in Belgium, Poznan in Poland, and Tartu in Estonia. The selection of these cities aimed to encompass a spectrum of urbanization intensities, ranging from cities with well-established urban areas like Paris to those with more recent developments such as Almada. Additionally, these cities vary in size, with Tartu being relatively smaller compared to Antwerp, in population density (for instance, Paris versus Poznan), and in the proportions of urban vegetation (e.g., Zurich in comparison to Antwerp).

Table 1. Overview of each city studied, including its area (in hectares), population density (inhabitants/km^2 in 2021; Census, 2021), size, and percentage of urban green area (in hectares and percentage based on the Urban Atlas, including the following classes: (i) "Green urban areas"; (ii) "Forests"; (iii) "Discontinuous very low-density urban fabric"; and (iv) "Discontinuous low-density urban fabric"), number of UGAs (based on the Urban Atlas and the class "Green urban areas"), climate zone, mean annual temperature (in °C, calculated from WorldClim data), mean annual precipitation (in mm from WorldClim data), and mean aridity index values within the city (calculated from CGIAR-CSI).

City	City Area (ha)	Pop. Density (hab.km^2)	Green Area (ha and %)	No. of UGAs	Climate	Temperature (°C)	Precipitation (mm)	Aridity Index
Almada	6999	3728	1580 (23%)	130	Mediterranean	16.2	685	0.71
Antwerp	22,416	2438	2436 (11%)	111	Temperate maritime	10.5	796	1.09
Lisbon	8687	6429	1393 (16%)	170	Mediterranean	16.7	712	0.73
Paris	10,492	20,238	1706 (16%)	420	Temperate	11.9	649	0.77
Poznan	25,628	2088	4869 (19%)	425	Temperate continental	8.6	505	0.70
Tartu	3882	2240	479 (12%)	128	Hemi-boreal	5.5	617	1.03
Zurich	9200	4867	2774 (30%)	197	Temperate, mild	9.5	1115	1.48

To maintain consistency in this analysis, this study employed the administrative municipal boundaries of each city (see red lines in Figure 1) based on the Local Administrative Units level 2 (LAU-2 level). This approach allowed for standardized and comparable analyses across the different cities, mitigating potential biases introduced by variations in size and spatial scale.

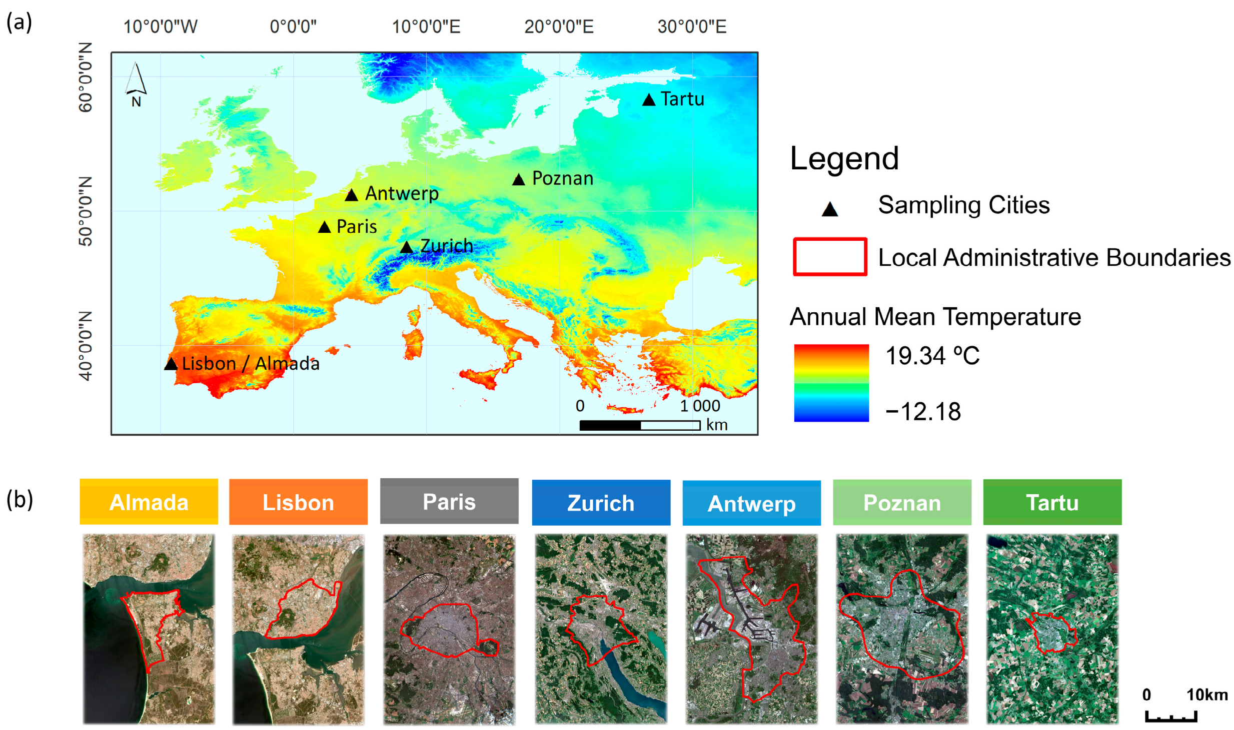

Figure 1. (**a**) Location of the seven European cities studied along a climatic gradient (annual average temperatures extracted from WorldClim). (**b**) Comparison of the research cities' sizes. The city boundaries are represented by the red lines, which correspond to the LAU-2 level. The scale of the city maps is uniform (1:120,000).

2.2. Data Collection

In our comparative analyses, we utilized two primary datasets: (1) the Urban Atlas, a land cover classification, and (2) NDVI spectral data extracted from Sentinel-2A satellite imagery. These two data sources were selected for comparison, as they have been used to support other published [6,37–40] and forthcoming studies that used a sampling approach based on an orthogonal gradient of patch area and connectivity to inventory various taxa in UGA across the seven European cities in 2017. For these data, we used the most concurrent and updated version of the Urban Atlas (2012 edition) and the most updated Earth observation data from Sentinel (2017, as the sensor was only operational since 2016). To ensure comparability between both datasets, adjustments were made to account for their spatial and thematic differences. These adjustments involved aligning the spatial resolution and extent of the datasets, as well as harmonizing the classification schemes. This process allowed for a more accurate and meaningful comparison between these two datasets and facilitated the assessment of their suitability for quantifying urban green connectivity.

2.2.1. Land Cover Classification and Green Area Selection to Sample

The Urban Atlas dataset used in our study encompasses 27 land cover classes, representing various urban features, such as urban fabric, industry and commerce, transportation, open and vegetated areas, and water bodies. This dataset provides consistent and comparable land cover information at a scale of 1:10,000 for all the sampled cities. The 2012 revision of this dataset was employed, which includes minimum mapping units for different land cover categories. Artificial surfaces, including the "Green Urban Areas" class, were mapped with a minimum unit of 0.25 hectares (ha), while natural and semi-natural surfaces had a minimum unit of 1 ha. A minimum mapping width of 10 m (m) between two patches was considered to avoid mapping small, fragmented patches separately [33].

To ensure consistency and comparability across these cities, a standardized approach was adopted to define UGAs within the Urban Atlas dataset. Any patches with a high likelihood of containing trees were considered suitable. We conducted a preliminary analysis, examining the average NDVI values for each land cover class in the Urban Atlas dataset (see Supplementary Table S1), which ensured uniform UGA definitions across the sampled cities. In this way, this analysis provided valuable insights into vegetation density within different land cover classes, facilitated the identification of probable tree-containing areas, and established a consistent framework for assessing the presence and extent of UGAs across the sampled cities. This approach promoted homogeneity in the analysis and simplified straightforward comparisons with NDVI spectral data (Table 2).

Table 2. Overview of the selected Urban Atlas classes and the NDVI threshold.

	Selected Classes	Minimum Mapping Unit	Criteria
Selected urban atlas classes	Green urban areas [a,b]	0.25 ha	Classes with at least 70% of the total class area covered by vegetation and a high probability of having trees.
	Forests [b]	1 ha	
	Discontinuous very low-density urban fabric (soil sealing level (S.L.) < 10%) [b]	0.25 ha	
	Discontinuous low-density urban fabric (S.L. 10–30%) [b]	0.25 ha	
NDVI threshold	NDVI $\geq$ 0.5	0.01 ha or 0.125 ha, depending on the estimated landscape metric	Class characterized by UGAs with high vegetative vigor, including trees and irrigated/fertilized lawns. This class is functionally important throughout the year and has a homogeneous land-use intensity.

[a.] The Urban Atlas class is viewed as focal patches, representing potential sampling sites for urban biodiversity with homogeneous land-use intensity. [b.] All UGAs with the potential for tree presence were used to calculate landscape metrics, considering the neighborhood of sampling sites (proximity index and amount of surrounding green areas at multiple distances).

To select a subset of UGAs for our analysis, we conducted a systematic sampling approach. From a total of 1581 UGAs across all cities, 36 UGAs per city were randomly selected. The selection process considered two key landscape indicators: patch size and connectivity. We used an orthogonal gradient to distribute the selected UGAs across six size classes and six connectivity classes [37]. The size classes were defined as follows: [0–0.4], [0.4–0.8], [0.8–1.6], [1.6–3.2], [3.2–6.4], and >6.4 ha. The connectivity classes were defined based on a proximity index and categorized as follows: [0–5], [5–15], [15–45], [45–135], [135–405], and >405. These classes ensured a diverse representation of UGAs with varying patch sizes and connectivity levels. However, due to the specific characteristics of certain cities (Almada, Paris, and Tartu), it was not possible to find UGAs that met all the defined size and connectivity criteria. As a result, a smaller number of UGAs were selected for these cities: 16 for Almada, 28 for Paris, and 31 for Tartu. Overall, our systematic sampling approach resulted in a final land cover sample of 219 focal patches across the studied cities (Table 3). These samples were used to assess the degree of connectivity using both the Urban Atlas land cover dataset and the NDVI spectral data.

Table 3. A summary of the size and connectivity of the UGAs in the seven European cities.

		Almada	**Antwerp**	**Lisbon**	**Paris**	**Poznan**	**Tartu**	**Zurich**
Number of patches		16	36	36	28	36	31	36
Total patch area (ha)		100.04	334.39	181.56	693.24	252.37	165.04	130.70
Total connectivity		25,103.36	13,026.80	43,339.28	51,271.32	23,718.58	2746.40	38,282.03
Patch size (ha)	Max	43.56	108.59	30.85	588.09	103.34	30.79	27.45
	Min	0.30	0.38	0.33	0.26	0.26	0.31	0.27
	Average	6.25	9.29	5.04	24.76	7.01	5.32	3.63
	Median	1.89	2.66	2.62	1.01	2.34	1.76	1.88
	Standard deviation	10.70	24.03	6.86	110.53	17.96	7.55	5.20
Patch connectivity	Max	23,807.54	3995.62	12,202.27	45,794.28	12,829.47	624.85	26,935.38
	Min	1.30	1.52	0.64	1.77	2.16	1.95	4.87
	Average	1568.96	361.86	1203.87	1831.12	658.85	88.59	1063.39
	Median	10.99	53.03	22.72	6.94	16.40	14.97	42.60
	Standard deviation	5931.57	828.97	3132.94	8634.21	2168.17	161.03	4504.75

2.2.2. Spectral Earth Observation Data

In our study, seven Sentinel-2A images were downloaded from the USGS Earth Explorer archives (https://earthexplorer.usgs.gov (accessed on 4 October 2021)). These images have a high spatial resolution of 10 m, which is ideal for analyzing vegetation in urban landscapes [41]. These images were acquired during the peak tree biomass period, typically in the summer season, with less than 10% cloud cover (see Supplementary Table S2 for a detailed description).

To prepare the Sentinel-2A images for our analysis, we performed atmospheric correction using the Sen2Cor plugin (Sen2Cor, v2.1.2) from the Sentinel-2 toolbox (SNAP, 5.0.7). This correction removes the effects of atmospheric interference and provides accurate and reliable vegetation information. Once the atmospheric correction was applied, we calculated the NDVI for each pixel in these images. The NDVI is calculated using the following equation:

$$NDVI = \frac{\rho\mathrm{NIR} - \rho\mathrm{Red}}{\rho\mathrm{NIR} + \rho\mathrm{Red}}$$

where ρNIR and ρRed are the near-infrared and red band responses, respectively. NDVI values range from −1 to +1, with varying ranges corresponding to different surface types: (i) negative values are usually indicate water bodies or clouds; (ii) values between 0.0 and 0.49 represent mixed surfaces, including barren soils, highly impervious surfaces, sparse vegetation, or areas under water stress like grasslands; and (iii) values above 0.5 indicate areas with dense vegetation and high vitality, such as urban parks and forests. Although the NDVI's insensitivity to changes in biomass at high levels is recognized, this behavior is more pronounced in agricultural and forestry areas than in urban settings, where vegetation tends to be less dense, more heterogeneous, and sparser. Therefore, in urban environments, the NDVI typically does not reach saturation levels as frequently as observed in denser vegetation areas, enabling better differentiation among various types of urban greenery. In our study, a threshold of 0.5 was set to detect similar spectral signatures and identify all patches with a high probability of tree presence (Table 2), ensuring comparability between the two datasets. This threshold minimizes the risk of overestimating green cover using spectral data compared to land cover assessments. Subsequently, the NDVI data were categorized into two groups: UGAs with trees (NDVI $\geq$ 0.5) and other surfaces lacking trees (NDVI < 0.5).

To delineate focal patches with trees (NDVI $\geq$ 0.5), the NDVI data were converted into polygons, representing distinct geometric shapes. This conversion process excluded polygons without trees (NDVI < 0.5), ensuring that only polygons corresponding to UGAs were included in further analysis.

2.3. Landscape Metrics as Urban Green Connectivity Indicators

While there are no universally established guidelines for selecting landscape metrics [42], certain landscape components have been recognized as important for supporting urban biodiversity and enhancing ecosystem services. In this context, three specific indicators were chosen to assess these components: (i) green area size; (ii) proximity index; and (iii) the amount of surrounding green area at multiple distances (Figure 2).

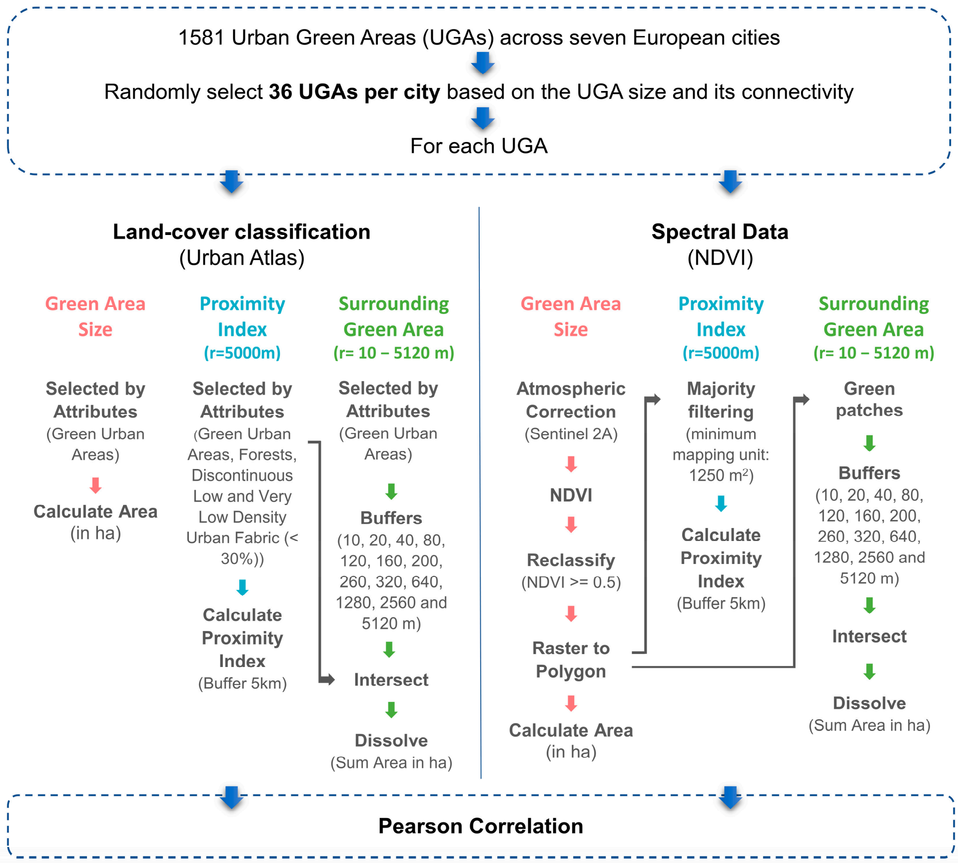

Figure 2. Data processing flowchart considering the two datasets—the Urban Atlas as land cover classification and the NDVI from spectral data—as well as the three estimated landscape metrics.

2.3.1. Green Area Size

The size of individual patches within a landscape matrix affects the overall connectivity of habitats, influencing the quantity and quality of suitable habitat required for maintaining viable populations [23]. Larger UGAs generally provide more space for various plant and animal species to thrive, offering a diverse range of favorable habitats and niches. This encourages the coexistence of different organisms, contributing to a more resilient and balanced ecosystem [16].

In this study, the area or proportion of urban greenery in the cities was calculated. Considering the Urban Atlas dataset, the area of each patch belonging to the "green urban area" class was quantified, typically measured in ha. For the spectral data, the area of greenery was quantified using the polygons described previously (NDVI $\geq$ 0.5). These polygons represent areas with a high likelihood of trees or dense vegetation.

2.3.2. Proximity Index

A well-connected and permeable urban landscape has the potential to create additional habitats, like interconnected green corridors, which offer shelter, food resources, and nesting sites for birds, insects, and small mammalian species [6,17]. This, in turn, can enhance a range of ecological benefits and functions within urban settings. Hence, the proximity index (PROX) plays a crucial role in gauging the permeability of the landscape matrix by facilitating the evaluation of the connectivity or isolation of UGAs within an urban landscape [43].

The PROX metric characterizes the surrounding area of each UGA by considering the area of patches with the same land cover type and the distances to nearby patches with suitable habitat. It is defined as follows:

$$PROX = \sum_{s=1}^{n} \frac{a_{ijs}}{{h_{ijs}}^2}$$

where a_{ijs} represents the area (in m^2) of patch ijs within a specified neighborhood distance (in m) of the patch ij; h_{ijs} is the distance (m) between patches ijs and ij based on the nearest edge-to-edge distance; and n is the number of patches within a given search radius. In this analysis, the search radius for each focal patch was set to 5 km. This value accounts for the limitations of the available mapping data (e.g., the Urban Atlas dataset) and considers potential wildlife mobility ranges. In fact, lower buffer values (from 500 m onwards) had minimal impact on PROX values due to the squaring of distances, which limits the influence of patches beyond a certain distance [37].

The PROX metric was estimated using the ArcGIS extension V-LATE (Vector-based Landscape Analysis Tools), developed by the authors of [44]. Given the large number of patches generated from the NDVI $\geq$ 0.5 data, a reduction in the number of potential neighbors was implemented to simplify data processing, mitigate time and RAM constraints, and enhance computational efficiency. Specifically, UGAs smaller than 0.125 ha (1250 m^2) were removed from consideration. Higher PROX scores are assigned to less isolated patches, indicating larger, more contiguous, and closer UGAs, which can facilitate the movement of organisms and enhance ecological connectivity [42].

2.3.3. Amount of Surrounding Green Area at Multiple Distances

The number of UGAs in the proximity of a focal patch yields valuable insights into the availability and distribution of potentially suitable habitats for promoting biodiversity within urban areas, essentially serving as a critical indicator in assessing the potential of creating and maintaining these habitats. This evaluation encompasses quantifying the total area of all polygons representing UGAs with a high probability of containing trees or dense vegetation within their respective buffer zones, making it an indicator that reflects both the quantity and quality of the urban landscape. This indicator can be measured at multiple distances, thereby avoiding assumptions regarding the maximum influence distance and decay function associated with distance. Unlike PROX, which requires a predefined search radius, the number of surrounding green areas can be calculated over various distances (Figure 2).

Using the Urban Atlas dataset, we measured several buffer zones around the edges of UGAs at different distances (10, 20, 40, 80, 120, 160, 200, 260, 320, 640, 1280, 2560, and 5120 m). These buffer distances were chosen to capture different spatial scales and account for species with varying mobility and dispersal abilities. Only two contrasting distances (80 and 1280 m) were shown to represent species with low and high mobility/dispersity, respectively. Using the Urban Atlas dataset, the total area of UGAs within each buffer distance was computed. This involved measuring the extent of UGAs within the buffer zones created around the focal patches. Additionally, for spectral data, the total area of polygons with an NDVI $\geq$ 0.5 was calculated within each buffer distance.

2.4. Data Analysis

The comparative analysis involved examining the rank correlation between connectivity indicators calculated using two different datasets. To compare the indicators, the sampling sites were ranked based on their values within each dataset. For example, when analyzing the size of green areas within a city with 36 focal patches, the smallest patch was assigned a rank of 1, while the largest patch was assigned a rank of 36. This rank-based approach allowed for the linear comparison of the relative positions of each focal patch in the ranking between the two datasets. As neither dataset is considered the absolute "truth", a perfect regression line with a Pearson correlation coefficient (r) of 1 would indicate that the metrics are not affected by the choice of dataset.

To assess the comparability of information provided by the land cover classification dataset and the NDVI spectral data, a threshold of r = 0.8 was chosen. If the correlation coefficient exceeded this threshold, it suggested that the two datasets yielded similar outcomes regarding connectivity. It is important to note that reaching this threshold does not imply that one dataset is preferable over the other; rather, it indicates that the choice of dataset does not lead to different connectivity outcomes. *p*-values were reported in the analysis, but significance levels were not considered in the Discussion Section. The focus was on achieving the best possible fit between the datasets rather than determining statistical significance. The statistical analysis and plotting were conducted in Excel, while the spatial analysis was performed using ArcMap (v.10.5.1, ESRI).

3. Results

3.1. Green Area Size

When comparing the size of UGAs in seven European cities using ranking positions, the results indicated differences between the two datasets (as shown in Figure 3). Considering all cities collectively, the correlation obtained was below the established threshold (r = 0.39), suggesting a lack of strong agreement between the two datasets in terms of UGA size. This discrepancy implies that smaller UGAs identified in the Urban Atlas land cover classification may be perceived as larger when using NDVI spectral data, and vice versa. Examining individual plots for each city, Almada, Paris, and Lisbon exhibited the strongest correlations (r = 0.76, 0.73, and 0.57, respectively), although still falling below the established threshold. In contrast, Poznan, Tartu, and Antwerp showed weaker linear relationships, indicating significant disparities between the two datasets. In fact, Poznan and Tartu even demonstrated negative correlations (r = $-$0.06 and r = $-$0.18, respectively), indicating that the two datasets calculated different green area values. This discrepancy highlights that the Urban Atlas and NDVI spectral data are not capturing the same extent of UGAs. To explore the potential influence of urban green size on the results, the analysis was repeated after excluding UGAs smaller than 1 ha. This adjustment resulted in an increased correlation for Poznan (r = 0.15) and Tartu (r = 0.34), indicating that the exclusion of smaller UGAs improved the agreement between the datasets. This suggests that the Urban Atlas may underrepresent small UGAs.

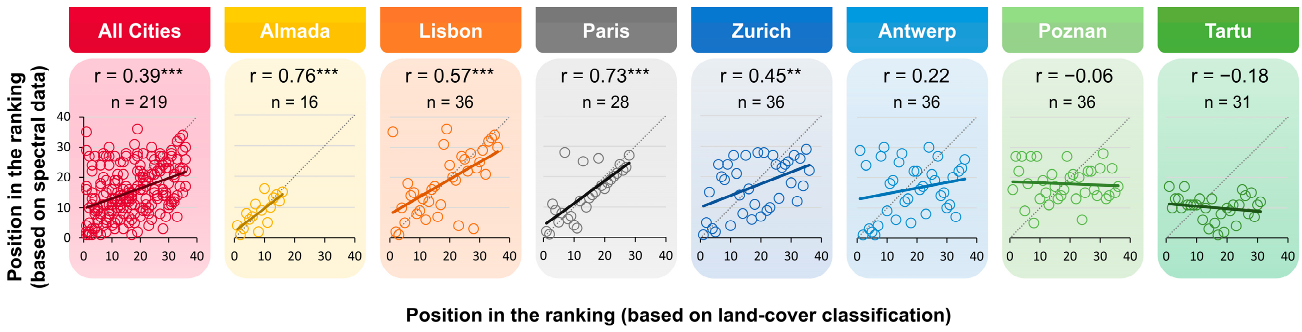

Figure 3. The relationship between patch rankings in a size gradient considers the linear relationship between land cover classification (on the horizontal axis) and spectral data (on the vertical axis) measured by the Pearson correlation coefficient. Small UGAs have a low rank position, while larger UGAs have a high rank position. The dotted line indicates a perfect fit when either dataset would be equivalent (the 1:1 line), while the continuous line represents the actual fit. The significance level is *** at $p < 0.001$ and ** at $p < 0.01$.

3.2. Proximity Index

When examining connectivity using the PROX indicator, our analysis revealed significant discrepancies between the land cover classification and spectral data (Figure 4). The overall analysis across all cities showed a correlation coefficient (r = 0.42) that fell below the established threshold. Upon analyzing each city individually, we found that the behavior of the PROX indicator was more consistent across cities compared to the green area size metric. However, the correlation coefficients still remained below the established threshold, indicating discrepancies between the land cover classification and spectral data in terms of connectivity assessment. The correlation coefficients for individual cities ranged from 0.30 (Antwerp) to 0.64 (Almada), except for Tartu, which exhibited a non-significant negative relationship (r = −0.34). The results in Tartu suggest that patches considered contiguous by one method (NDVI spectral data) are fragmented according to the other method (Urban Atlas land cover classification).

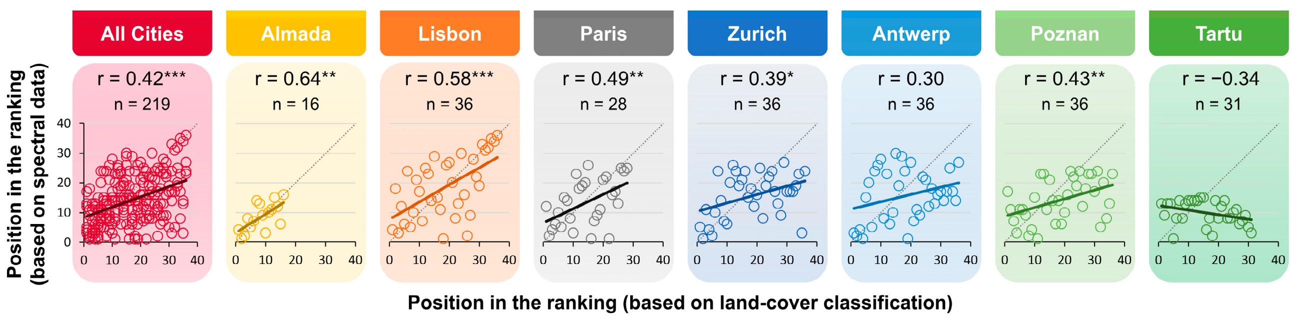

Figure 4. The relationship between patch rankings in a connectivity gradient using the Pearson correlation coefficient to consider the linear relationship between land cover classification (on the horizontal axis) and spectral data (on the vertical axis). Patches with the lowest proximity index values are more fragmented and thus rank lower, while patches with higher proximity index values, which are contiguous and closer, rank higher. The dotted line represents a perfect fit when either dataset would be equivalent (the 1:1 line), while the continuous line shows the actual fit. The significance level is *** at $p < 0.001$, ** at $p < 0.01$ and * at $p < 0.05$.

3.3. Number of Surrounding Green Areas at Multiple Distances

Figure 5 shows the correlation between the two datasets for the surrounding green area when short distances (80 m) are considered. Figure 6 depicts the same correlation but over a longer distance (1280 m). Upon comparing these two figures, it becomes evident that the disparities between the datasets are more significant over short distances, indicating a connection with the spatial extent of the buffers used.

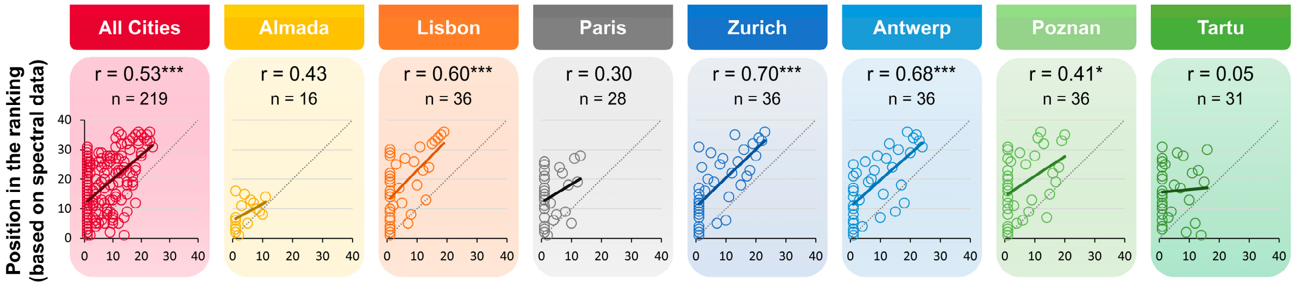

Figure 5. The relationship between patch rankings in a surrounding green area gradient (80 m from the edge), considering the linear relation between land cover classification (on the horizontal axis) and spectral data (on the vertical axis) measured by the Pearson correlation coefficient. Patches without nearby UGAs have the lowest rank, while those with a large number of nearby UGAs have a higher rank. The dotted line indicates a perfect fit when either dataset would be equivalent (the 1:1 line), while the continuous line represents the actual fit. The significance level is *** at $p < 0.001$ and * at $p < 0.05$.

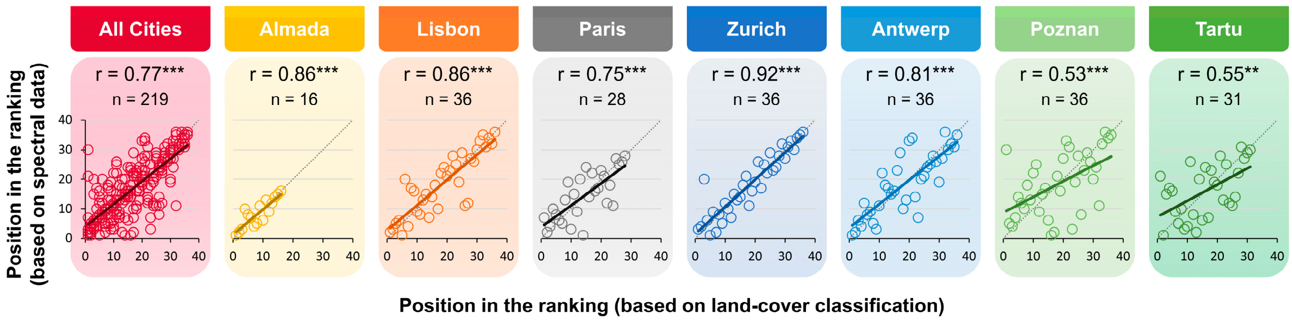

Figure 6. The relationship between patch rankings in a surrounding land cover area gradient (at 1280 m from the edge), considering the linear relationship between land cover classification (on the horizontal axis) and spectral data (on the vertical axis), which was measured by the Pearson correlation coefficient. Patches without nearby UGAs have the lowest rank, while those with a large number of nearby UGAs have a higher rank position. The dotted line indicates a perfect fit when either dataset would be equivalent (the 1:1 line), while the continuous line shows the actual fit. The significance level is *** at $p < 0.001$ and ** at $p < 0.01$.

In Figure 5, the behavior of this indicator varies considerably for short distances, depending on the dataset. When each city was analyzed separately, the correlation coefficients ranged from 0.05 (Tartu) to 0.70 (Zurich), indicating weak to strong linear relationships. Moreover, many focal patches in the Urban Atlas dataset were assigned the same rank position (e.g., 1st = 1) for a short buffer distance. This implies that no UGAs were detected within an 80 m distance from the edge of the focal patch when using the Urban Atlas data. However, this pattern was not observed when ranking was determined using NDVI spectral data, as multiple UGAs were identified at the same distance. These findings highlight that the two datasets exhibit significant discrepancies in terms of detecting surrounding UGAs at short distances. The lack of UGAs identified within 80 m from the focal patch's edge in the Urban Atlas data suggests potential limitations in capturing smaller-scale green features. In contrast, the NDVI spectral data appeared to provide more detailed information, detecting multiple UGAs within the same distance.

When considering longer distances, the correlations between patch rankings showed stronger agreement than over shorter distances (r = 0.77 for all cities). This correlation coefficient was very close to the threshold established, indicating that this indicator was less influenced by the choice of dataset for calculation. Individual plots in Figure 6 demonstrated that four out of the seven European cities exhibited a strong correlation, with r-values exceeding 0.8. Zurich had the highest correlation coefficient of 0.92, followed by Almada and Lisbon with a correlation of 0.86, and Antwerp with a correlation of 0.81. Although the correlations were slightly lower in Paris, Tartu, and Poznan, the behavior of this indicator remained consistent across all cities. These findings suggest that the number of green areas near a focal patch, as measured by the Urban Atlas land cover classification, corresponds to a similar number of UGAs as determined by the NDVI spectral data. The landscape metric assessing surrounding green area over longer distances appears to be less affected by the choice of dataset, exhibiting strong correlations across most cities. This implies that when evaluating larger-scale connectivity and the extent of green areas surrounding focal patches, the choice of dataset has a less significant impact on the outcomes.

4. Discussion

4.1. Impact of Dataset Choice on Urban Green Connectivity Analysis

Although there is no universally prescribed or optimal dataset for quantifying urban landscape connectivity, the choice of dataset can have a significant impact on the outcomes, leading to different connectivity analyses. This observation is consistent with the findings of [45], who emphasized how different datasets can influence ecological analyses, particularly when dealing with geographical or ecological gradients. Our study supports these findings and highlights that the representation of urban green connectivity in various European cities differs based on the chosen dataset and scale of analysis (see Supplementary Figure S1). Specifically, when comparing the Urban Atlas land cover classification to NDVI spectral data, we found that the land cover classification tends to underestimate connectivity, particularly at local scales. However, it is important to note that at a local scale, where individual property owners or smaller UGAs play a significant role, the choice of dataset becomes crucial for accurate and comprehensive assessments of urban green connectivity. In these cases, relying solely on land cover classification data, such as the Urban Atlas dataset, may lead to an underestimation of UGAs and hinder the identification of smaller UGAs that are vital for local biodiversity, ecological connectivity, and community well-being [8,17,20]. Furthermore, this finding gains particular importance because management actions related to green infrastructure, such as tree planting or park creation, often target the local scale. Therefore, it is crucial to consider the limitations of the land cover classification when assessing urban green connectivity. Based on our findings, we recommend using spectral data, such as NDVI, to characterize urban green connectivity at the European scale. Spectral data can more accurately identify the presence of urban vegetation, leading to a more comprehensive and standardized assessment of UGAs, encompassing both their quantity and quality.

4.2. Factors Contributing to Disparities between Datasets

The disparities between the two datasets can be attributed to several key issues: (1) scale effects on the minimum mapping unit; (2) thematic resolution; (3) spatial heterogeneity; and (4) spectral similarity in urban landscapes. In our study, we observed that the absence of small, private, and informal UGAs in the land cover dataset had a significant impact on the outcomes, particularly at the finer spatial scales when assessing urban green connectivity at the patch level (Figures 3–5). This omission primarily stems from differences in the minimum mapping unit and the choices made during the thematic classification process. In the Urban Atlas dataset, the minimum mapping unit is larger compared to the NDVI spectral data (0.25 vs. 0.125 ha, respectively). As a result, small UGAs (<0.25 ha) are often grouped into adjacent, larger, and more abundant non-green land cover types. This phenomenon has been documented in previous studies by [24,25,46,47]. Consequently, small UGAs like tree-lined squares or other small UGAs may be classified as urban fabric and not included in the connectivity indicators as input data. This leads to an underestimation of UGAs in the Urban Atlas dataset (as observed by [47]) and, consequently, an overestimation of urban fragmentation, particularly in the northernmost cities.

These findings support previous research indicating that aggregating different land covers or habitats into broader classes can result in inaccurate estimates of connectivity [22,32,45]. In contrast, spectral data captured many of these small and isolated UGAs that were missed in the land cover classification [47]. It should be noted that special precautions were taken in our study to address differences in thematic resolution between the two datasets. We included all the Urban Atlas classes that could potentially host trees and used a high NDVI threshold ($\geq$0.5) to ensure that we were examining similar types of land cover. Despite these precautions, the discrepancies between the two datasets were even more pronounced in our study compared to the findings of [24,47]. For instance, in Lodz (Poland), Ref. [24] reported variations of 0.1% and 0.2% between the UGAs calculated by the Urban Atlas and Landsat imagery, whereas we observed differences of 1.5% in Lisbon and 52.9% in Tartu. In their study, the authors of [47] found that when employing Landsat image analysis, a particular subset in Brussels contained over 5 km^2 of UGAs, whereas the Urban Atlas indicated less than 1 km^2. In Antwerp, we identified 71 km^2 of UGAs based on Sentinel 2A images, whereas the Urban Atlas suggested approximately 30 km^2. These differences between studies can be partially attributed to the distinct spatial resolutions of Landsat and Sentinel imagery (30 m and 10 m, respectively), with Sentinel images providing more detailed information on UGAs. Interestingly, when examining the two datasets at broader scales, specifically over long distances, the analysis of urban green connectivity yielded comparable results (Figure 6). This observation underscores the significant disparities that can arise between the data used for urban planning purposes at a broad scale (e.g., within a municipality) and the data obtained at a more local scale (e.g., within a parish or city block). This distinction becomes particularly relevant in cities characterized by numerous small, privately owned UGAs, where urban planning interventions and decisions often need to be made at a more fine-grained, local scale.

The discrepancies between these two datasets can also be attributed to the spatial heterogeneity and spectral similarity of various urban land covers, particularly in northern European cities with their distinct characteristics. These cities often feature a less dense urban matrix that is interspersed with small, privately owned UGAs [48]. The presence of a mix of artificial and natural surfaces, each with its own unique spectral signature, poses challenges for accurate land cover mapping, even at high-spatial-resolution classifications [35]. In our analysis using the Urban Atlas dataset, we observed that the average NDVI values for urban classes/surfaces were higher in Tartu and Poznan compared to the other cities (Supplementary Table S1). This finding suggests that the land cover classification within the Urban Atlas dataset is not uniform across European cities. This non-uniformity can affect connectivity indicators since even within the urban classes, the NDVI averages exceeded the defined threshold for distinguishing between the green and gray matrices (Supplementary Table S1). However, it is important to note that using spectral data also has its challenges. Spectral similarities can be observed among different surfaces, even when they possess distinct functional characteristics (e.g., irrigated lawns versus trees), making it challenging to accurately map UGAs. This issue is particularly relevant in wetter biogeographic regions, where UGAs tend to be closer and more contiguous, posing difficulties in differentiating between lawns and trees. On the other hand, in drier biogeographic regions (e.g., Almada and Lisbon), the phenological cycle of lawns and trees may exhibit more pronounced differences, simplifying the distinction between them [49]. Furthermore, it is crucial to consider interannual variations in urban vegetation when calculating landscape metrics [45]. In wetter cities, there is a risk of overestimating urban green connectivity, while in drier cities, it may be underestimated. Therefore, caution must be exercised when interpreting and comparing connectivity results across cities with varying climate conditions.

In addition to the challenges posed by the spatial heterogeneity and spectral similarity of Earth Observation data, it is important to recognize that the modifiable area unit problem can further complicate classification efforts using spectral data. The use of a NDVI threshold to categorize UGAs can oversimplify the variability within this class. This variability includes not only different typologies of green areas but also variations in their management levels, which can impact their spectral signatures. As a consequence of overlooking intra-class variability, there is a potential for misclassification, where areas with distinct vegetation types are inaccurately grouped together under a single class label [50,51]. This limitation can obscure important distinctions and nuances in the urban landscape, leading to less accurate assessments of tree cover and green areas and, consequently, urban green connectivity. To mitigate this challenge, it is advisable to employ complementary techniques that offer a more nuanced understanding of the urban landscape. For example, integrating NDVI thresholds with advanced image segmentation algorithms and texture analysis can improve classification accuracy by capturing finer details and subtle variations in vegetation characteristics. Thus, it becomes possible to identify specific tree attributes and differentiate between various types of vegetation cover and their associated management practices within the urban green category. However, it is important to recognize that the main objective of the study may prioritize the broad-scale identification of UGA, as was the case for us, rather than the detailed characterization of individual features. While limitations in identifying basic entities exist, associated with the modifiable area unit problem, they may not significantly hinder the achievement of the study's primary goals, which focus on broader trends and patterns in urban greenery.

4.3. Advantages of Spectral Data in Urban Green Connectivity Analysis

Based on our findings, our study suggests that spectral data are generally preferable to land cover classification for assessing urban green connectivity across cities with varying climatic and urbanization gradients (but see Section 4.4 on when land cover is important). Spectral data offer several advantages over land cover classification, making them a more efficient, consistent, and standardized approach at a European scale. One significant advantage of spectral data is their ability to identify the presence of greenery, regardless of its typology. This means that smaller, private, and informal UGAs, which may be omitted or misclassified in land cover classification, are more effectively captured [24,47]. Any omission artificially increases fragmentation levels since all UGAs, regardless of their structure, configuration, or composition, have the potential to improve urban connectivity, support biodiversity, and contribute to ecological functions and services [8,17,18]. Using spectral data also helps to reduce biases caused by thematic or spatial issues related to land cover classification, which is particularly important when analyzing short distances or focusing on the patch level. By capturing the continuous and comprehensive nature of spectral data, we can obtain a more accurate and detailed representation of urban green connectivity, especially for organisms with low mobility or ecosystem services provided at local scales [52]. Another advantage of spectral data is their temporal continuity, allowing for the assessment of urban green connectivity over time and the consideration of land-use change dynamics [22]. This is particularly valuable for monitoring and understanding the dynamics of UGAs and their impacts on ecological processes and services. Furthermore, the use of spectral data becomes even more significant in areas where land cover classification products are lacking. Spectral data can be utilized to calculate landscape metrics in remote or low-resource areas where land cover classification data may not be readily available.

4.4. Considerations for Land Cover Classification in Urban Green Connectivity Analysis

While spectral data are generally preferable for quantifying urban green connectivity, land cover classification should not be completely dismissed. There are specific scenarios where land cover classification can still provide valuable insights. Firstly, land cover classification can be useful when seeking homogeneity between patches, especially when focusing on specific types of tree-covered UGAs with similar land-use intensities. It allows for the identification of patches that share similar characteristics, which can be relevant for certain ecological analyses or management strategies. Secondly, when analyzing at a broader scale, land cover classification can provide a more aggregated and simplified representation of urban green connectivity. This can be beneficial for large-scale planning and decision-making processes, where a more general overview is needed. Additionally, it is important to consider species' habitat preferences in ecological analyses. Some species may exhibit specific habitat requirements that are better captured by certain land cover categories in a classification scheme. Therefore, land cover classification can be valuable for understanding species–habitat relationships and supporting targeted conservation efforts. However, it is crucial to improve the available land cover classification for urban ecology applications. This improvement should focus on enhancing the completeness of the classification by including all urban greenness typologies, reducing the minimum mapping unit to capture smaller and more fragmented UGAs, and updating the data more frequently to account for the rapid dynamics of urban environments. Future revisions of the Urban Atlas, in particular, should strive to provide a comprehensive and ecologically meaningful characterization of UGAs across Europe. This would involve considering not only the land cover type but also the spatial configuration, vegetation structural complexity, cultivation degree, and management regime type of the UGAs [41,53,54]. Such improved data would serve as a valuable resource for promoting more sustainable urban planning and management practices, integrating ecological considerations into decision-making processes.

5. Conclusions

Our study focused on seven European cities with varying levels of urbanization to investigate how the choice of dataset influences the analysis of urban green connectivity. We observed that the outcomes of this analysis are heavily influenced by the spatial and thematic resolution of the datasets, particularly when examining connectivity at local scales, such as the patch level. Among the different datasets, high-resolution spectral data emerged as the most suitable and reliable method for studying urban green connectivity.

This preference arises from its ability to provide a more comprehensive depiction of UGAs and yield standardized results applicable across Europe, regardless of specific classification options. In contrast, although a common land cover classification, the Urban Atlas, is available, our findings suggested that it may not exhibit homogeneity at the European scale. This lack of consistency in classification could lead to an underestimation of UGA connectivity, particularly in northern European cities, with potential significant repercussions for urban planning and management practices.

To address these limitations, we highlight the importance of regularly updating land cover classifications. These updates should encompass an ecologically based thematic classification of UGAs, thereby enhancing research on the consequences of urban fragmentation on biodiversity and ecosystem services. By refining the classification scheme and incorporating ecological considerations, future studies can advance our understanding of the impacts of urbanization on urban green connectivity, biodiversity, and ecosystem services. We emphasize that urban planners and decision makers should stay updated on the latest datasets and consider the ecological implications of their choices. This knowledge can lead to more effective urban planning and management strategies that enhance urban sustainability and resilience while ensuring that UGAs are well-preserved, connected, and integrated into the urban landscape.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16050771/s1, Figure S1. Spatial distribution of all urban landscape metrics using land cover classification (the Urban Atlas) and spectral data (NDVI). Note that the spatial scale is different in cities. Table S1. A descriptive analysis of Urban Atlas LULC classes in the studied cities. * LULC classes considered in the study. Table S2. Earth observation data used to determine urban green areas in European cities involved.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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