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Review

Urban Ecosystem Services Quantification through Remote Sensing Approach: A Systematic Review

Paulo Amador Tavares [1,*], Norma Beltrão [1], Ulisses Silva Guimarães [2], Ana Teodoro [3] and Paulo Gonçalves [1]

[1] Postgraduate Program in Environmental Sciences, State University of Pará (UEPA), 66095-100 Belém, Brazil; normaely@uepa.br (N.B.); paulogoncalves@uepa.br (P.G.)

[2] Operations and Management Center of the Amazon Protection System (CENSIPAM), 66617-420 Belém, Brazil; ulisses.silva@sipam.gov.br

[3] Earth Sciences Institute (ICT) and Faculty of Sciences (FCUP), University of Porto, 4169-007 Porto, Portugal; amteodor@fc.up.pt

* Correspondence: paulo.tavares@uepa.br; Tel.: +55-919-8070-6429

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Abstract: Urban ecosystem services (UES) is an essential approach to the development of sustainable cities and must be incorporated into urban planning to be able to improve humans' life quality. This paper aimed to identify remote sensing (RS) data/techniques used in the literature in five years (2013–2017) for UES investigation and to analyze the similarity between them. For this purpose, we used the Scopus database of scientific journals, and a set of appropriate filters were applied. A total of 44 studies were selected, being 93.18% of them located in the Northern Hemisphere, mostly in Europe. The most common dataset used was the secondary data, followed by the Landsat family products. Land use and land cover (LULC) was the most common approach utilized, succeeded by radiometric indexes and band related. All four main classes (provision, regulation, supporting, and cultural) of ecosystem services (ES) were identified in the reviewed papers, wherein regulating services were the most popular modality mentioned. Seven different groups were established as having 100% of similarity between methods and ES results. Therefore, RS is identified in the literature as an important technique to reach this goal. However, we highlight the lack of studies in the southern hemisphere.

Keywords: urban planning; urban land cover; spatial analysis; urban forest; satellite data; human well-being; urbanization

1. Introduction

Ecosystem services (ES) are described as the processes, conditions, and benefits provided by nature to maintain and fulfil the human needs and are commonly subdivided into four main classes of services: (i) Provision; (ii) Regulation; (iii) Supporting and; (iv) Cultural [1–3]. All these classes can be represented by at least 17 different types of ES with a total estimated value of about $33 trillion on average [1].

The ES supply depends on biophysical factors and their modifications over time and space [4–7]. Since ES are the benefits that humans acquire directly or indirectly through nature [2,8], the urban environments are important study areas for ES supply and demand analysis, once it is where most of the users and beneficiaries of the ES live [7,9–11]. The incorporation in quantity, quality, and diversity of ES increases the socioecological resilience of urban areas, changing the spatial distribution of the main natural coverages that produce ES [12]. In this context, the preservation and restoration of natural environments within urban areas is socio-environmentally necessary and, commonly, economically viable [13]. Thus, mapping urban ecosystem services (UES) is described in the literature as an opportunity to monitor natural and anthropized areas that provide ES (its identification and classification), verify how this provision changes according to time and space [5,6,9,14,15], and assess how human-driven changes impacted the urban areas, positively or negatively [7,16,17].

Previously literature reviews on UES have found key challenges and insights for future research [18,19]. These papers agreed that the current studies about this subject have some lacks when they are analyzed under the interdisciplinary context and usually have limitations when interpreted under spatial coverage. Some other reviews that consider the remote sensing (RS) of the ES variables, showed that even though RS is not the perfect solution for understanding and monitoring ES, it has the potential to comprehend and improve the quality of the work anywhere in the world, as long as the correct tool is chosen [20,21]. However, all reviews acknowledged here, which considered the spatial distribution of the papers assessed, show that the main part of RS studies of ES and UES variables are concentrated in the Northern Hemisphere [10,18,22].

A key aspect of UES mapping is to locate and identify environmental variables responsible for ES functioning. Aspects related to the temporal dynamics of UES have also been mentioned in the literature, such as the vegetation structural attributes [23] and the change in provision of UES [15,23,24]. Existing research [25–27] has already emphasized the role played by RS data/techniques in enhancing ecological studies given the number of open access data and software available for this purpose [27]. Its potential is still greater when considering data sources with daily images [28], especially for tropical regions with high cloud coverage [29]. Furthermore, RS is highlighted for several authors as an efficient method for urban green spaces [30,31], land use land over (LULC) [32–36], and urban heat islands analyses [24,37,38]. However, current RS methods can vary greatly. For instance, different applications include the LULC change detection [39] and forest disturbance history [40], data fusion of optical and radar data for precisely machine learning supervised mapping of LULC [41,42], the evaluation of water quality index with machine learning algorithms [43], the use of ALOS-2 PALSAR-2 and Sentinel-2A imagery to estimate aboveground biomass [44], and the use of synthetic aperture radar (SAR) and light detection and ranging (LiDAR) data to evaluate the flood depth through the application of a normalized difference index [45].

Understanding how ecological studies involving RS data/techniques can relate different areas and apply different methodologies is; therefore, an issue of great interest in UES identification, classification, and modeling. Conceptually, the outcomes obtained from UES studies are linked to the human well-being and its close relationship with nature [46,47]. From a global point of view, researchers must contribute to the efforts of United Nations (UN) to promote the development of sustainable cities and communities (Sustainable Development Goal, SDG 11) until 2030 [48–52]. Thus, RS data/techniques turns the findings of ES studies more relevant [53], more adequate to urban planning, and able to guide for sustainable development in these areas [13,54–57].

Therefore, by considering the importance of identifying, classifying, and modeling ES in urban environments, as well as the recent developments achieved by the RS data/techniques, the objectives of this work are: (i) To analyze, through a literature review, how researchers are interpreting results from RS data/techniques under a UES perspective; (ii) to identify the methodologies and databases used and; (iii) to analyze the similarities and differences between the studies.

2. Materials and Methods

In order to evaluate and interpret the available and relevant research developed under the topic UES by using RS data/techniques, a systematic literature review was carried out [58,59]. Thus, to present the state of art of the suitability of RS data/techniques to identify, classify, and model UES, a was conducted survey covering five full years of research on this topic, starting from January 2013 until December 2017.

Scopus bibliographic database was chosen to identify these papers. Scopus has a broad coverage with more than 22,000 titles from over 5000 international publishers. This indexer has functional tools for acquiring relevant documents, besides providing them in different ways and covering research areas that are relevant to the keywords chosen [60]. The Scopus platform contains results refinement tabs that offers several types of filtering options, which are (i) Access type; (ii) Year; (iii) Author name; (iv) Subject area; (v) Document type; (vi) Source title; (vii) Keyword; (viii) Affiliation; (ix) Funding sponsor; (x) Country/territory; (xi) Source type; and (xii) Language. These options support the appropriate choice of relevant scientific articles. For these reasons, Scopus is mentioned in the literature as a trustable tool for identifying relevant papers [60–63].

In this work, we chose published scientific journals and relevant conference papers, both were selected using the Scopus database, as it was provided by the education institute where this analysis was carried out. We selected three different sets of keywords, which were chosen in previous analysis of relevant articles to the UES study. These sets of keywords were (a) "Satellite," "Ecosystem Service," and "Urban"; (b) "Mapping," "Ecosystem Service," and "Urban"; and (c) "Remote Sensing," "Ecosystem Service," and "Urban." Moreover, this literature survey considered the following subject areas: (1) Environmental science; (2) agricultural and biological science; (3) social science; (4) Earth and planetary science; (5) decision science; (6) engineering; (7) physics and astronomy; and (8) economics, econometrics, and finance. These subjects were selected as they can be related, in some level, to the scope of this work.

We have further defined some exclusion criteria, which are mentioned, in order, as follows: (i) Removal of duplicate results in the identification section; (ii) in the screening segment, by reading the abstracts, we removed studies that did not use RS applications, nor were UES studies, and studies that did not involve only urban areas; (iii) in the eligibility section, we verified, by assessing the full body of the text, the information described in the exclusion criteria number (ii).

The results found were arranged in three main classes: (1) Database; (2) method; and (3) types of ES considered. To better understand the similarity between the techniques used and the types of results found in each study, we performed a multivariable statistical analysis, and a dendrogram was produced for visualizing the result, as mentioned by Booth et al. [64] as an important approach for systematic reviews.

Figure 1 illustrates the flowchart of the processing analyses performed. In the identification step, only duplicated data were removed. For screening, we read the abstracts and excluded the ones not related to our scope. Then, the full-text analysis was done, and 44 studies from the initial 215 were included in both qualitative and quantitative analysis.

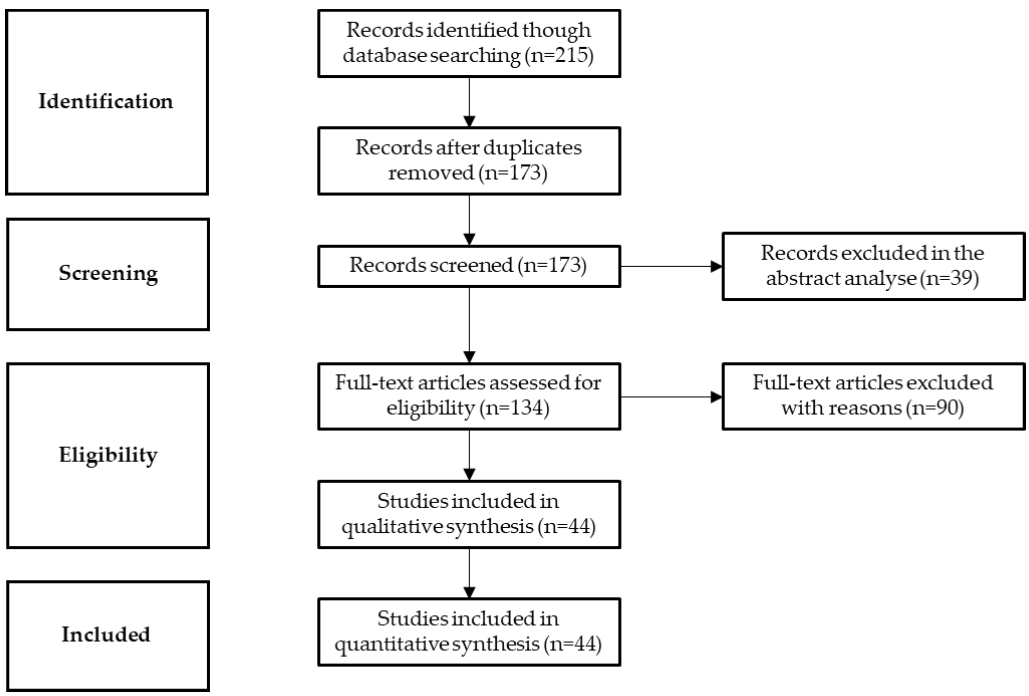

Figure 1. Steps adopted for this research purpose.

3. Results

A total of 44 (20.46% of the total) papers were analyzed in both quantitative and qualitative investigation. This number is considered a low quantity for systematics literature reviews. Hence, we highlight that a small amount of studies relating RS data/techniques with UES approaches were produced during the period analyzed. All these articles were manually reviewed in order to ensure that they were truly applications of RS data/techniques for UES approaches.

The Earth's Northern Hemisphere accounted for most of the studies (93.18%), mainly located in Europe (52.27%), followed by China (15.90%), and USA (13.63%). The South America countries represented the Southern Hemisphere with 6.81% of the total. The Asian countries were also important contributors to the overall number of studies (25%)—as mentioned, mainly located in China (63.63% of Asia's contribution). The map in Figure 2 illustrates the spatial distribution of the papers assessed.

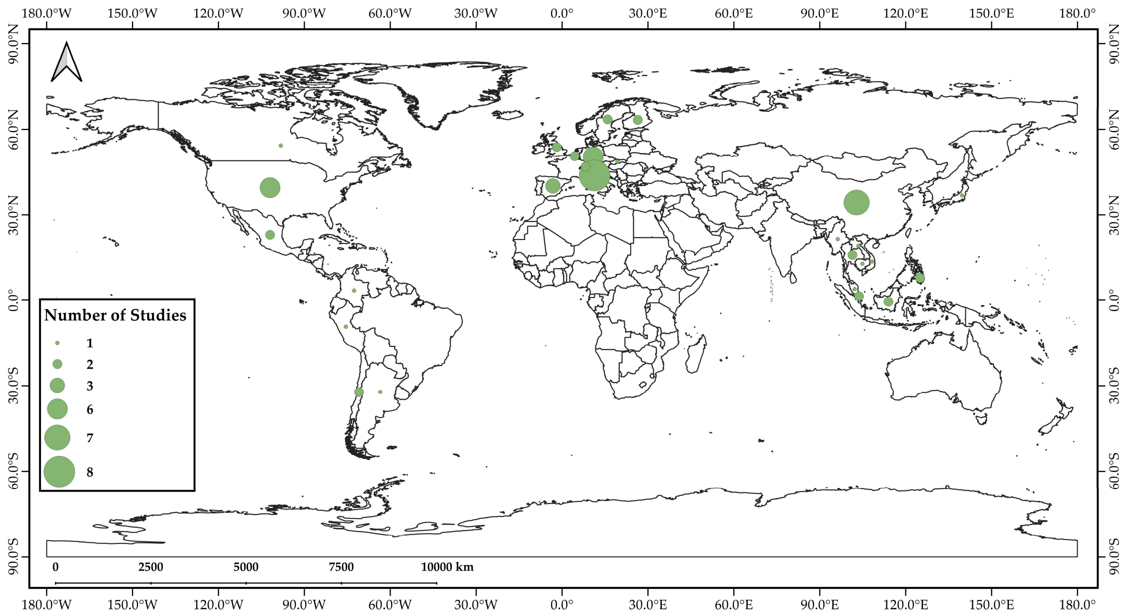

Figure 2. Spatial distribution of the papers considered in our study. Some of the papers assessed used more than one country as a study area, so we added one value for each country.

The studies assessed were distributed along six years according to the following percentages: 2013 (4.55%), 2014 (18.18%), 2015 (9.09%), 2016 (22.73%), and 2017 (45.45%). In this range, it is possible to identify a slight tendency in the increase in the numbers of UES papers published during these years, something that did not happen only in the year 2015, when the number of published articles was lower than in 2014. Largely, 2017 was the major contributor, indicating an increasing trend for research involving ES for urban areas sustainable development.

Figure 3 illustrates that, for the selected studies, the most used primary data (Landsat family) were costless. Usually, secondary data are also costless and appear to be widely employed in UES studies, especially those related to LULC mapping, which were highly mentioned.

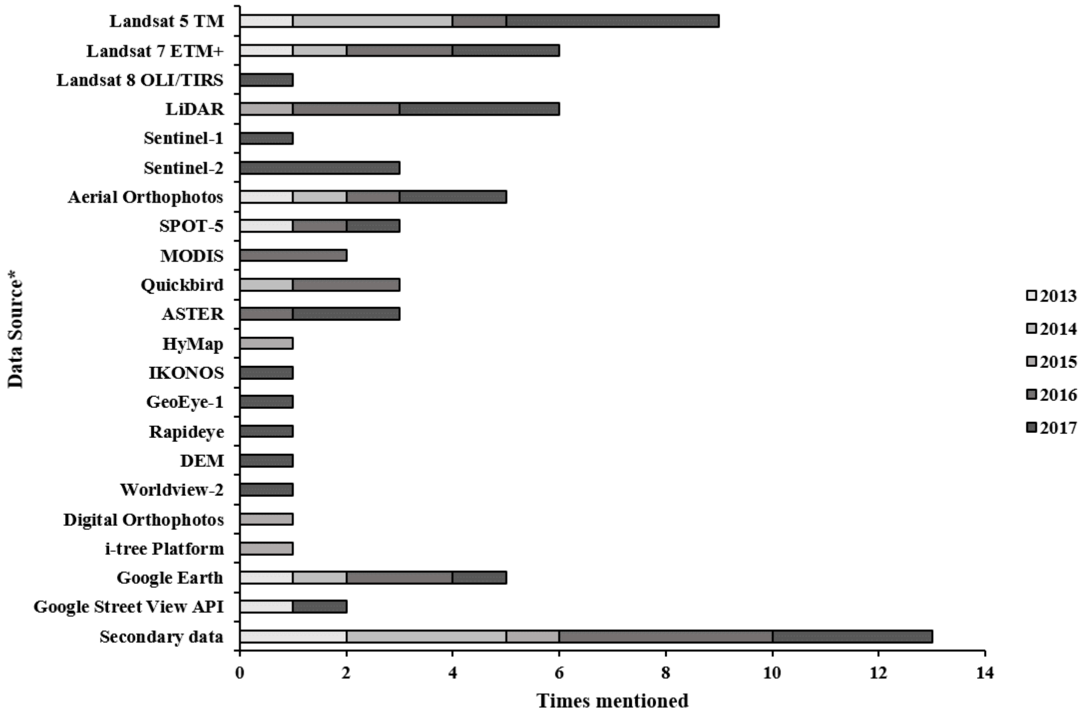

Figure 3. Identification of data source used by the authors, separated by year (2013–2017). * Abbreviations mentioned in the data source axis stands for TM, thematic mapper; ETM+, enhanced thematic mapper plus; OLI/TIRS, operational land imager/thermal infrared sensor; SPOT, satellite pour l'observation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

With regards to LULC secondary data, the information extracted from these were related with zoning plans [65], urban atlas [16], soil maps [66], high ecological resolution classification for urban landscape and environmental systems (HERCULES) [33], census data [67], and information regarding naturalness and natural protected areas [68].

The Google Earth images, another free and open access data source, were used by the UES authors for LULC purposes and for validation analysis of supervised and unsupervised classification algorithms [33,69–71]. Similarly, the Google Street View API was used for understanding the urban green canopy cover, while Google Street View photos, for instance, were used to determine the green canopy cover in different locations of Singapore [72].

In the methodological analyses (Figure 4), the most cited methodology was the LULC (75%), followed by the normalized difference vegetation index (NDVI) with 15.91%, leaf area index (LAI) (11.36%), and land surface temperature (LST) (11.36%). Some methods were mentioned only once (2.27%): normalized difference green-building volume (NDGB), green canopy cover, ES Index, modified normalized difference water index (MNDWI), and visible red and NIR-based built-up index (VrNIR-BI). The biomass estimation in urban areas, the species mapping, and the modeling of carbon assessment (MOCA) flux model were cited in 4.55% of the papers selected.

Urban trees mapping methodology was mentioned as one useful approach for understanding and regulating services [73–76] and supporting services [76]. Such mapping usually uses high-quality images as aerial orthophotos [73,74] and LiDAR [75], since its accuracy is essential to identify the tree coverage in urban areas.

The UES index methodology was mentioned only once in the selected papers [32]. However, it is important to highlight that results found in that study delivered a more consistent approach on UES importance as well as ES supply and demand in the urban scenario. Such finding seems to be a robust tool to instantly propose suggestions for urban planning and development of sustainable cities.

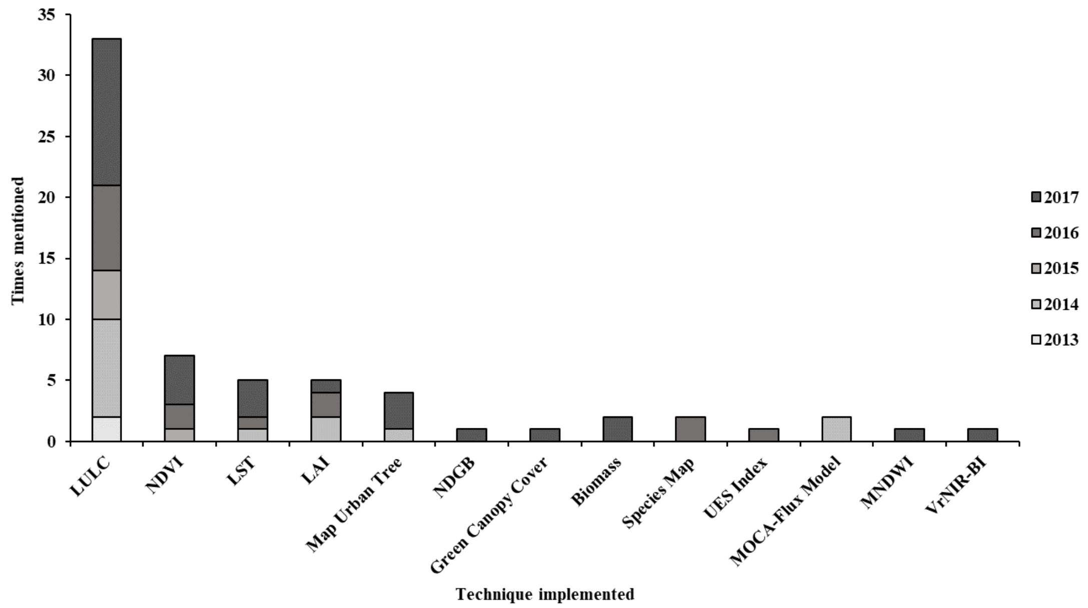

Figure 4. Methods implemented by the authors to infer UES results, separated by year (2013–2017).

Figure 5 summarizes the four main ES groups (Provisioning, Regulating, Supporting, and Cultural) identified in the literature review and their ES subtypes. Additionally highlighted, in a separated category, is the urban green spaces.

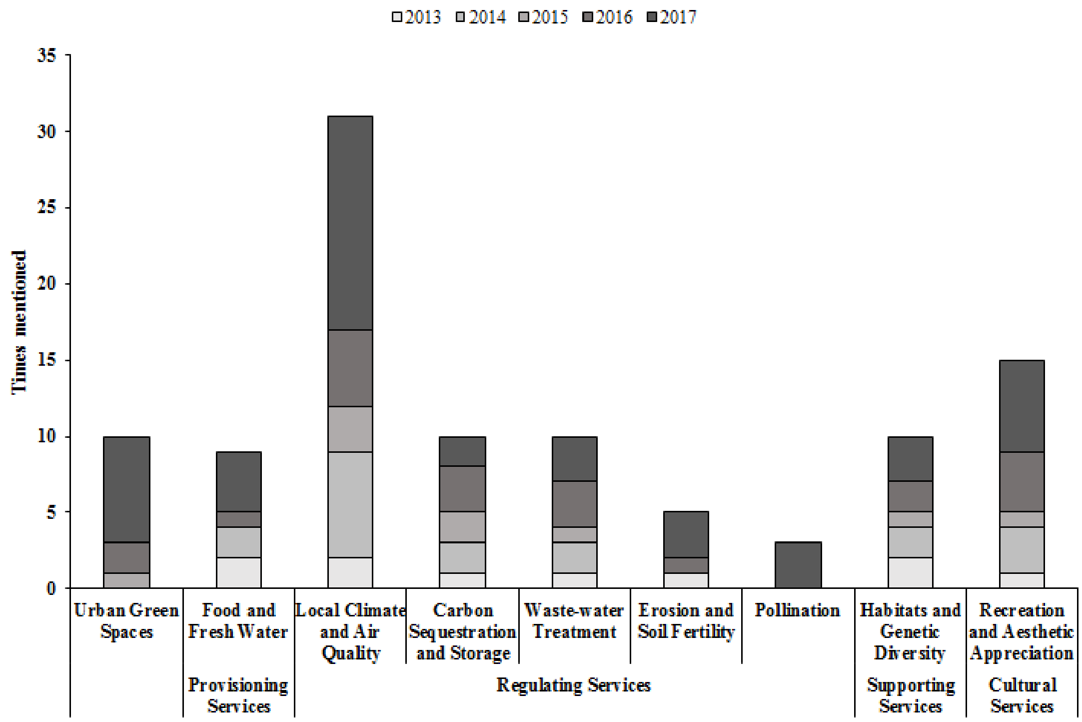

Figure 5. UES identified in the literature reviewed, separated by year (2013–2017).

All the four main classes of ES described by Costanza et al. [1] and TEEB [2] were found in the selected studies. The ES types mentioned in all five years considered were: local climate and air quality (70.45%), carbon sequestration and storage and wastewater treatment (22.73%) for regulating types of services habitats and genetic diversity (22.73%) for supporting services, and recreation and aesthetic contemplation (34.09%) representing cultural services.

The most mentioned regulating services identified were, generally, extracted by the direct interpretation of spectral indexes related to ecological components [77]. In contrast, other regulating services, such as erosion, soil fertility, and pollination, would only be estimated using factors and coefficients throughout data interpretation [67,71].

Supporting services (habitats and genetic diversity) and cultural services (recreation and aesthetic contemplation) were generally obtained by interpreting urban green coverage and identifying significant localities for maintenance of local species of fauna and flora, as well as social interactions and social life, respectively [76,78,79]. The provision services were only related to fresh water and food supply which were identified through water bodies and urban agriculture in urban and peri-urban localities and mainly related to urban green coverage [9,16,33,65,67,79–82].

Urban green spaces were considered in a different column, because its presence (natural or human-made) can be related to the provision of bundles of ES, having positive effects on people's living and buildings' monetary values situated in the neighborhood [9,23,69,70,83–88].

Another parameter considered in this literature review was the similarity of methodologies and the UES estimated in the selected papers. The dendrogram shown in Figure 6 illustrates the findings of cluster analysis. In Figure 6, two main clusters were created (which had 0% of similarity between them and were divided in the components A and B. The difference between them was mostly related to the type of UES identified. In group B, there was a higher number of UES types identified, when compared with group A. Group B was the only one with recreation and aesthetic appreciation services, food and fresh water provision, and pollination services identified. On the other hand, group A had their researchers mostly considering local climate regulation and urban green cover. By dissociating the groups from the methods used, we noticed that group A was more diverse than group B, but LULC was the most common methodology implemented.

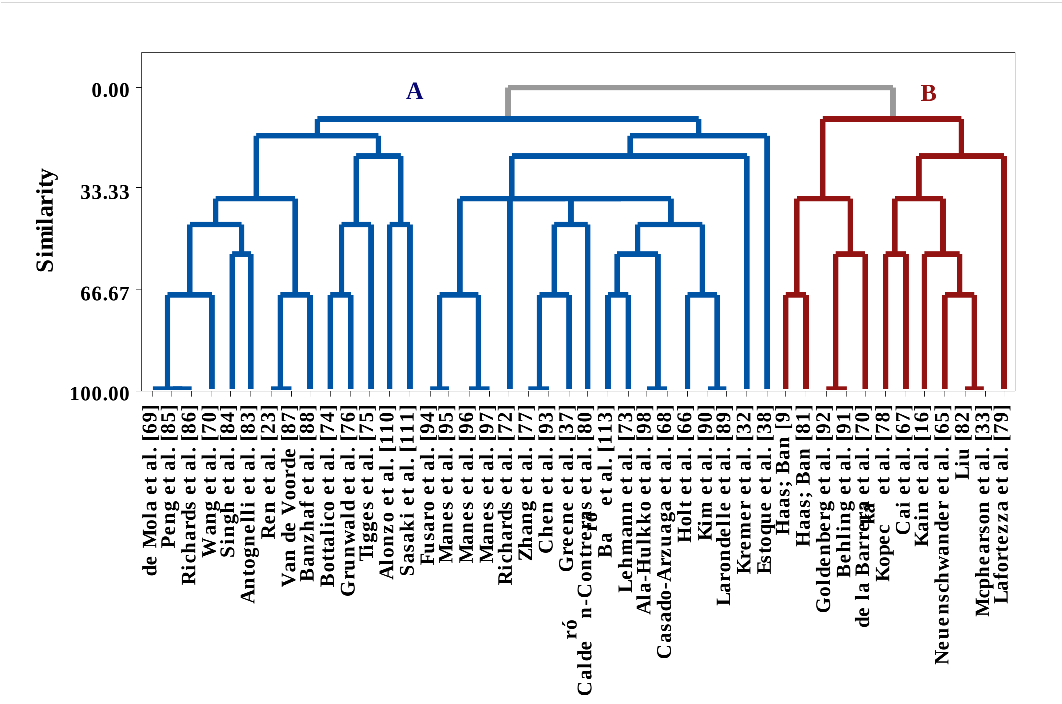

Figure 6. Cluster analysis of the similarity between the methodologies used and the UES identified, the full body papers investigated are expressed according to the order of appearance in the body of the text Clusters were divided into two groups with more than 0% of similarity, group A (blue interactions) and group B (red interactions).

De Mola et al. [69], Peng et al. [85], and Richards et al. [86] developed LULC methodologies for mapping urban green spaces. It is noteworthy the different approaches of obtaining LULC information, since all authors used different data sources in their studies: Google Earth data [69], ASTER, Landsat 7 ETM+ and Landsat 5 TM imagery [85], and only Landsat 7 ETM+ imagery [86].

The papers published by Van de Voorde [87] and Ren et al. [23] used NDVI to identify urban green spaces. However, findings from [86] suggest that its results, using Quickbird high spatial resolution satellite imagery, were more accurate than those obtained by [23], which used a 30 m resolution free data source Landsat 5 TM.

Larondelle et al. [89] and Kim et al. [90] studied the same type of UES by using the same method, as noticed in Figure 6. These authors chose the LULC method and had their results based on regulating services–local climate and air quality, and carbon sequestration and storage. Similarly, Behling et al. [91] and Goldenberg et al. [92] also chose the same type of methodology to identify the same range of UES. In their method, regulating services were the focus of the study, but LULC was also selected. Nonetheless, the services considered were local climate, air quality, and wastewater treatment.

For the estimation of local climate and air quality regulation services only, three 100% similar groups were identified: (i) Chen et al. [93] and Zhang et al. [77], both studies used LST and LULC (similarly to them, Greene et al. [37] used the same techniques plus NDVI (commonly used for LST estimation purposed) to derive the same UES estimative); (ii) Fusaro et al. [94] and Manes et al. [95] used LULC and LAI; and (iii) Manes et al. [96,97], used the same types of methods of Fusaro et al. [94] and Manes et al. [95] and added the MOCA (modeling of carbon assessment) and flux model to identify local climate and air quality regulating services.

Ala-Hulkko et al. [98] and Casado-Arzuaga et al. [68] also chose LULC as methodology. These papers found the cultural services of recreation and aesthetic opportunities as results. The data source selected by these authors was the secondary data, since, for recreation and aesthetic purposes, to understand the local objectives and concerns is important as the feature's identification.

From all papers assessed with 100% of similarity, Liu [82] (China) and Mcphearson et al. [33] (USA) were the ones with more UES estimations. Both studies used LULC as the only methodology. They estimated the four main classes of ES: (i) Provision (food and fresh water); (ii) Regulating (local climate and air quality, carbon sequestration and storage and waste-water treatment); (iii) Supporting (habitats and genetic diversity), and iv) Cultural (recreation and aesthetic appreciation).

4. Discussion

A large concentration of UES studies in the Northern Hemisphere was also found by Haase et al. [10] for UES and for ES in Barbosa et al. [22]. The results concentrated in the Northern Hemisphere confirm that a lack of studies exist in the Southern Hemisphere for sustainable development of cities, when compared with the ones in developed countries [48,51,99], and we could confirm that in our systematic review. However, the number of studies in Asia exceeding the number of studies in the USA, contrasts with what was presented by Haase et al. [10], which shows an interesting trend in the region in terms of UES.

We found that secondary data was the most used data source close agreement with the literature concerning the idea that RS facilitates ecological studies given the low-cost investments needed to study natural phenomena [27,100]. The Landsat and Sentinel satellite families are some of the most cited satellite source images. These are related to the easy access and availability in platforms such as the United States Geological Survey (USGS) and the Copernicus Sci-Hub from the European Space Agency (ESA) [101]. The data aggregation of Landsat and Sentinel constellation provides an Earth observation status with a revisit interval of 2.9 days, which is a perfect scenario for monitoring environments and their ES [102].

High resolution imagery, such as SPOT-5 [70,80], aerial and digital orthophotos [73,74,88] Worldview-2 [79], RapidEye imagery [75], GeoEye, IKONOS [81], Quickbird [70,87,93], and HyMap [91] are considered more trustable and accurate resources for UES evaluation. However, these data are generally related to the researcher level of data access and research funding, since this type of high-quality imagery usually has a high acquisition cost.

Recently, the United States (US) Government started to consider charges introduction to USGS data acquisition, including the Landsat family [103]. This might bring impacts on the LULC studies and deforestation monitoring in critical ecosystems in the world and consequent effects on UES studies, since most have used free source data up to now. The combination of different datasets is also an important alternative to the monitoring of difficult areas, such as the rainforest where the cloud coverage is commonly elevated [104,105], which may be a good alternative for tropical countries, facilitating further studies of UES for many countries in the Southern Hemisphere.

Among several methodologies surveyed, LULC was the only cited in all years. As mentioned, LULC is obtained from several types of techniques and different data sources, including data extracted directly from secondary data. Machine learning (ML) techniques, such as random forest (RF), support vector machine (SVM), and artificial neural networks (ANN) are tended towards for the LULC classification and identification of ecological variables. The accuracy of the methods is increasing along with the diversity in its modes of application, this is because of the popularization of the techniques [41,42,106–109], even for UES studies [9,69,81,82].

One factor that stimulates researchers to use LULC techniques to UES identification and classification purposes is that some authors describe the evaluation of each land use type. For instance, the work of Burkhard et al. [7], and the ESMERALDA project [6], is highly mentioned since it comprehends a description of how to evaluate ES from the CORINE land cover classification, which by itself considers 44 different types of land use and cover. From the interpretation of this paper, it is possible to perform the evaluation and modeling of other classifications simpler or that derivate from the CORINE land cover map [9,16,73,81,82,98].

LULC has the advantage of being a product that is more easily understood by readers; however, radiometric indexes calculation (such as NDVI, LAI, NDGB, and MNDWI), and methodologies directly related with interpretation of sensor's data, produces more accurate and well-defined results, strictly based on band math, irrespective of human interpretation [38,78,94]. These indexes have been used in some papers to increase the LULC accuracy from ML techniques [42,108].

Unlike the studies with 100% similarity presented in the results section, and by comparing the studies of Tigges et al. [75], Alonzo et al. [110], and Sasaki et al. [111], we observe that their results were not in line with those from the other papers reviewed, but all of them produced satisfactory results in their analysis. Tigges et al. [75] suggested the use of the urban trees mapping methodology to identify carbon sequestration and storage services. To this end, Alonzo et al. [110] used LAI and species maps, whereas Sasaki et al. [111] used species maps to assess carbon sequestration and storage, and habitats and genetic diversity results, respectively. This diversity of applications shows that there is a range of RS applications that can be used to reach similar products, demonstrating the importance of RS to the ecological variables, as Kwok [27] proposed it.

The UES index provided by Kremer et al. [32] was the only study, to present, no similarity with others. An explanation would be that their study incorporates a vast range of ES to produce a result reasoned in one value per pixel. Despite its unique methodology, this paper suggests an impressive simulation for urban scenarios by identifying precisely what city areas have more supply or demand for ES. An UES index was also proposed for Alam et al. [112], where several ES were selected as indicators and weighted through a SWOT (strengths, weaknesses, opportunities, threats) analysis; however, this paper was not found in the scope made for this systematic literature review. Baró et al. [113] also considered several indicators of ecosystem services to have a greater understanding of the UES capacity, flow, and demand; however, they do not develop an index to include all these results in one value.

5. Conclusions

In this work, the range of RS applications from the UES perspective was analyzed. Most of the UES studies examined here were concentrated in Northern Hemisphere sites, drawing attention to the need for additional UES studies and scenarios analysis in developing countries. In such regions, science investments are scarce, and; therefore, the use of RS methods with free and open data sources is an option, since the data source most mentioned in the surveyed studies are available for free. As a result, we highlight the importance of free data access for RS purposes, especially from the perspective of developing countries.

Among the benefits of using secondary data for UES studies, it appears as being the cheapest and most accessible alternative to estimate ES per area unit using trustable data. For instance, most of the studies, which considered cultural services, were able to estimate the provision of ES with a high degree of quality. In addition, official data previously validated can reduce costs related to ground truth observations and measurements.

LULC was the most mentioned methodology from those surveyed. Radiometric indexes and data able to be extracted directly from bands math, such as NDVI and LST, were also mentioned a few times. These indexes and band derived estimations are a way of having reliable data (once images are correctly pre-processed) without human interference.

All core classes of ES, described in the classic literature of ES, were mentioned for urban environments in the sample assessed. Regulating services showed a vast range of methodologies used to identify the benefits that urban green areas have to regulate local climate, as well as to estimate the amount of carbon captured and stored in the urban forest.

The similarity test for the studies assessed demonstrated that there is no standard procedure for producing or reproducing RS techniques in UES analyses, because the methods can vary according to the dataset used and their quality, the type of ES evaluated, and the researcher's experience.

In summary, it was possible to identify a vast range of data sources, techniques employed, and ES classification. The findings indicated plenty of opportunities for reproducing methodologies for UES, suggesting that the RS methods still have, in all countries, a valuable perspective for people to work with. Finally, this review found evidences that UES identification through RS data/techniques provides opportunities for scientists to conduct an array of environmental studies able to help countries to achieve, by 2030, the SDG 11 related to the development of sustainable cities. Countries, states, and municipalities in the development of more environmentally friendly public policies could discuss results from these studies.

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