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Review

Remote sensing for the assessment of ecosystem services provided by urban vegetation: A review of the methods applied

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ABSTRACT

The study and assessment of ecosystem services through remote sensing has increased substantially over the last two decades, as evidenced by the publication of studies that have applied it. The technological development of satellite images has improved in terms of spatial, spectral, radiometric, and temporal resolution, allowing the space-time observation, classification and monitoring of vegetation on the surface of the Earth. However, there are remaining methodological challenges for assessing ecosystem services due to the diversity of applications, the resources used, and its study in complex environments such as cities. This systematic review is based on identifying and analysing the variety of methods concerning the application of remote sensing for the assessment of ecosystem services provided by vegetation in cities, through a classification of these methods according to the data collection source (passive sensors, passive and active sensors and the fusion of other data sources with sensors). The classification of methods has been applied to a selection of existing articles in indexed scientific databases based on a non-statistical meta-analysis that make a direct reference to the topic of interest. The results show the approaches found in every method classified, their relationships with the geographical scale and the image resolutions used, and the advantages and limitations from the data processes that comprise remote sensing. We conclude from this analysis with three key factors to consider in the selection of remote sensing methods for the assessment of ecosystem services provided by urban vegetation: the definition of the approach (es), the urban scale to be assessed, and the image resolution available.

1. Introduction

The Millennium Ecosystem Assessment (MA) study carried out in 2001–2005 led to the recognition and classification of the benefits provided by nature, identified as “ecosystem services”, when evaluating the impact of anthropogenic activity on ecosystems (MA and Millennium Ecosystem Assessment, 2005). The importance of recognising ecosystem services has focused on quantifying their values and in particular their complex relationship with ecological and socio-economic systems, and how trade-offs in this relationship affect human well-being at present (Johnston, 2018). The assessment of these services has seen a rise in interest (Fisher et al., 2009) in the last two decades (2000–2020), with an exponential increase in the application of technologies to observe the Earth’s surface via remote sensing (Sishodia et al., 2020).

Remote sensing can be applied to study land cover, as sensors can measure the radiation reflected from the surface, thus allowing its properties to be assessed (De Araujo Barbosa et al., 2015). The relationship between the study of ecosystem services and remote sensing arises with the characterisation of soil type (Feng et al., 2010), biomass (Wu, 2019), tree canopy (O’Neil-Dunne et al., 2014, Leaf Area Index (LAI) Zeng and Moskal, 2009), space-time monitoring of vegetation (De Beurs et al., 2003), among others, which, through models, spectral indices, merging different sources and other processes, enable us to identify and map the contribution and loss of ecosystem services from natural elements on the surface (Andrew et al., 2014).

The improvement of remote sensing in terms of spatial, spectral,

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radiometric and, temporal resolution (Chandra Padney et al., 2020; Grove et al., 2006) has enhanced its application by allowing the assessment of ecosystem services in one of today's most complex ecosystems as cities (Gaston et al., 2013; McPhearson, 2016). In the assessment of ecosystem services and their relationship to urban decision-making, a wide variety of methods and approaches have been identified which makes it particularly challenging, resulting in a lack for a concrete basis to be applied in specific contexts (Cortinovis et al., 2021).

This assessment is important in cities, where surface changes are more accelerated than in other ecosystems, as they are open and dynamic systems (Bottalico et al., 2016), mainly due to population growth (Ritchie and Roser, 2018), land use change (Shulz et al., 2010), and excessive consumption of energy from fossil fuels (UN-Habitat, 2018).

Therefore, remote sensing represents a set of tools for cities and the assessment of ecosystem services provided in them, where the comparison of ground-based assessments and remote sensing frequently appears (Wu and Bauer, 2012); (McGee et al., 2012; Hostetler et al., 2013; Huang et al., 2016; Melaas et al., 2016) with remote sensing primarily being found to be more practical and cost-effective (Alonzo et al., 2016).

However, there are gaps identified in the study, observation, and assessment of ecosystem services in cities using remote sensing (Yang, 2011), such as the challenges within the physical conditions and properties of the urban environment that influence the scattering and emission of radiation from sensors (Small et al., 2018), the need to integrate information for more accurate results due to financial issues, making it difficult to acquire higher resolution images (Zaman-ul-Haq et al., 2022), the processes that have to be put into place for image correction, and to combine information from different sources, the data availability (Qin et al., 2017; Shi and Yang, 2017; Pilant et al., 2020; Richards and Wang, 2020), among others. These gaps result in a diversity of methods that have been proposed (de la Barrera et al., 2016) and may lead to confusion in the selection of a remote sensing method or to the loss of the potential that remote sensing offers at present.

Through this systematic review the methods for the assessment of ecosystem services provided by urban vegetation were analysed to identify the approaches, the diversity of geographical scales and image resolutions used, and the advantages and limitations from data processes when using remote sensing.

For this purpose, the following remote sensing methods based on the resources used to obtain data were classified in remote sensing with passive sensors, the combination of passive and active sensors, and the fusion of other data sources with sensors.

By classifying the methods, we aim to determine the main relevant factors to select a suitable remote sensing method. As to contribute to the current lack of defined methods when assessing ecosystem services provided by urban vegetation.

2. Methods

2.1. Search and selection of the literature analysed

The search for papers was carried out through indexed scientific journals in the Web of Science, Science Direct and Scopus databases, which, according to their search engines, included the set of the following concepts in the title, abstract and key words:

- Remote sensing, multispectral imagery, hyperspectral imagery, geospatial tools, satellite data or imagery,
- urban, city or metropolitan,
- ecosystem services or ecosystem goods; and
- vegetation, green infrastructure, urban green space, urban forests or vegetation cover.

This was followed by the selection of articles within the 13-year period between 2008 and 2021. The selection of the year 2008 corresponds to the United States Geological Survey's (USGS) decision in October of 2008 to make Landsat data (images acquired by Landsat satellites of Earth's surface) open access (Woodcock et al., 2008; Qin et al., 2017), increasing the number of studies carried out using remote sensing. A second selection was made from these articles based on a non-statistical meta-analysis, which included the classification of these articles according to their quality (number of citations). We also included articles by leading authors and research teams on the subject according to their constant referencing (D Nowak, L Zhang, T Elmqvist, B Burkhard, D Geneletti, C Cortinovis, Gómez-Baggethun, O'Neil-Dunne J, D. H. Locke, USDA Forest Service, PLAN S, etc.), in order to have a broader framework for the review.

2.2. Aspects to identify and analyse from the literature

To analyse the literature, we proposed specific aspects to identify in the studies and, subsequently, the applied methods were classified.

The specific aspects to be identified were: ecosystem service(s) assessed, remote sensing resources used (sensors, satellite image sources, etc.) as well as other data resources, vegetation assessment methods, vegetation typology assessed, space-time scale and resolution used, and programmes or software employed for the data acquisition process.

The classification of remote sensing methods was thus determined according to the type of sensors and the combination of other resources used, as this was a variable identified in the studies. Therefore, sensors were defined as the devices or instruments used to acquire data in remote sensing, which can be passive or active depending on the source of radiation, being classified as follows for the present study:

- Remote sensing with passive sensors: Methods based on the use of information acquired exclusively with passive sensors that detect natural energy (radiation) that is emitted or reflected from the objects on the surface depending on an external radiation source (sunlight) (Schowengerdt, 2007). From these methods it is possible to classify objects on the surface, determine temperatures (thermal imagery with FLIR), etc.
- Remote sensing with passive and active sensors: This classification considers studies that have used data from both passive and active sensors. In contrast to passive sensors, active sensors have their own radiation source, which sends a pulse to objects on the earth's surface and measures the backscatter reflected back to the sensor (GIS Geography, 2021).

For this type of sensor, there are systems called Radio Detection and Ranging (Radar), which is the most common type of active microwave remote sensing, but these may or may not provide images (HSU Geospatial sites). Another radar is the Synthetic Aperture Radar (SAR) that makes waves and uses different bands that can provide information about vegetation types, standing biomass of forests, etc. (Van Erik, 2011).

In remote sensing and forestry, the use of Light Detection and Ranging (LiDAR) active sensors has been identified more frequently, which allows to measure the distance to the ground by calculating the time it takes for the light from its source to be reflected back to the sensor, thus allowing us to obtain the vertical dimensions of objects, such as vegetation (Van Leeuwen and Nieuwenhuis, 2010).

- Fusion of other data sources with sensors: Including methods that not only use data from passive or active sensors, but also geographic data (maps), ground-based measurements, weather and atmospheric data, socio-demographic and socio-economic data, and in the most recent period, data from social networks. It is relevant to classify this applied method, given that studies in cities include other factors that can have an impact on the provision or loss of ecosystem services.

The methods are illustrated in Fig. 1, which shows the criteria for the

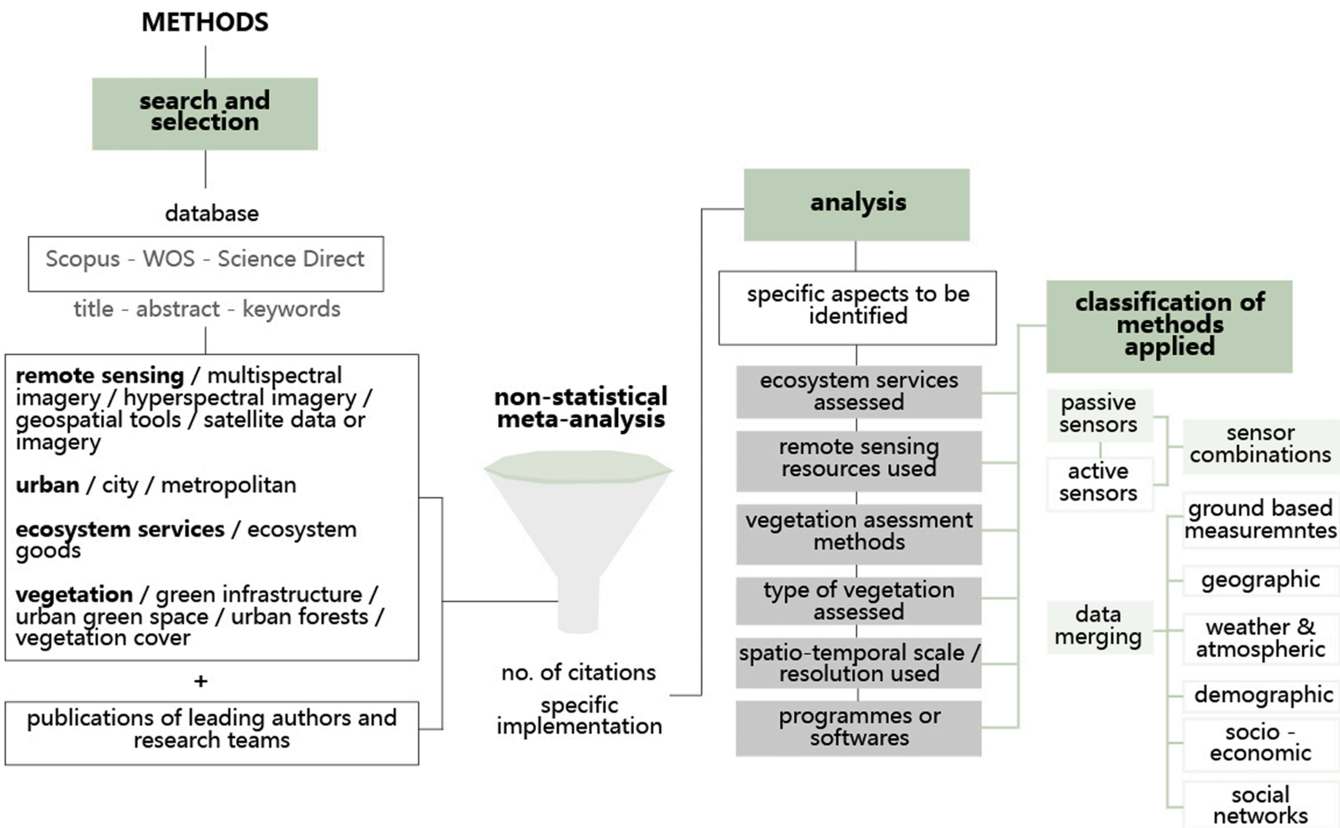

Fig. 1. Methods for the search, selection and analysis of the literature.

indexed scientific databases, the non-statistical meta-analysis, the specific aspects to be identified and, the classification of the applied methods.

3. Results

3.1. Remote sensing with passive sensors

The studies related to the use of remote sensing by means of passive sensors show some similar approaches due to the information that can be obtained from imagery. The approaches in this classified method use the images to identify the type of land and its use in the studied area, known as Land Use / Cover (LULC), analysing through methods such as the pixel-based approach (McGee et al., 2012), the object-based method (Locke et al, 2017; Zhang et al., 2017a; Zhang et al., 2017b), and multiple classifier systems (Shi and Yang, 2017) allowing to make a classification of clusters or pattern recognition with determined values to identify the land use or cover, as in the study of Yang et al. (2015) and de la Barrera et al. (2016). However, this method has not only been able to classify LULC, there are also assessments of land change, known as Land Cover Change (LCC) studied in periods and a given area, where the purpose is to know the environmental impact of the area over time (Trinder and Liu, 2020; Nowak et al., 2016) or the urban growth and its impact on the surrounding natural environment (Richards and Belcher, 2020).

Among similar approaches we find the quantification of urban tree cover or Urban Tree Canopy (UTC) (McGee et al., 2012; O'Neil-Dunne et al., 2014; Kokubu et al., 2020), and in other cases also the assessment of its loss (Hostetler et al., 2013). For studies intended to evaluate and specifically observe the condition of urban vegetation, the application of parameters (Tian et al., 2014; Carlan et al., 2020a), formulas and vegetation indices (VIs) is noted after obtaining imagery to determine the health of vegetation (Carlan et al., 2020b) and in other cases to evaluate the quality of vegetated spaces existing in the study area (Tian et al., 2014).

The study by Richards and Wang (2020) has a different approach to the previous ones, as it considers the values obtained from satellite images and street level photography to determine the Leaf Area Index (LAI). The value of LAI in the study of vegetation and ecosystem services is of utmost importance (Zheng and Moskal, 2009), as it corresponds to one of the main requirements to know the net primary production (Bréda, 2008), evaluate evapotranspiration (Fang and Liang, 2014), atmospheric deposition, biogenic volatile organic emissions (Aboelghar et al., 2010), radiation absorption (Nowak, 1996), among other vegetation processes. This is an alternative for the passive sensor method to obtain the vertical dimensions for LAI when information from active sensors is not available.

Fig. 2 shows the approaches identified in the use of passive sensors for vegetation assessment in the urban environment, representing the previously mentioned and grouped into five main approaches: land use / cover (LULC), land cover change (LCC), urban tree canopy (UTC), vegetation condition, and Leaf Area Index (LAI).

3.2. Remote sensing combining passive and active sensors

For the review of studies utilising data from passive and active sensors, LULC is identified as one of the approaches first approaches to be carried out, found also in the previous method (passive sensor). However, the studies present an in-depth analysis of the vegetation previously classified in LULC, where, complemented with data from active sensors, a Geographic-Object Based Image Analysis (GEOBIA) has been applied for identifying tree canopy (O'Neil-Dunne et al., 2014), the typology of vegetated spaces is determined (Degerickx et al., 2020), as well as the ecosystem services provided by each plant species (Tigges et al., 2013). This also contributes to the estimation of certain ecosystem services from vegetation in an urban area, as it allows us to specifically

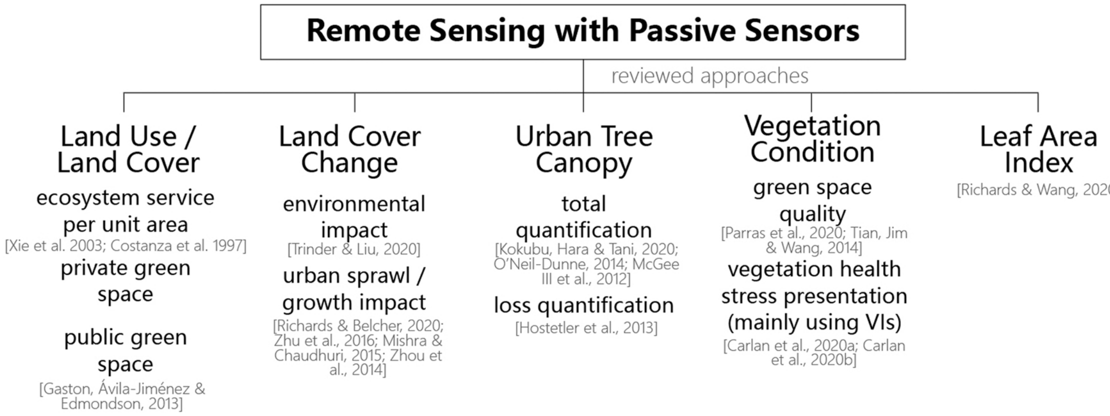

Fig. 2. Identified approaches in remote sensing with passive sensors.

detail the species that conform its urban vegetation cover (Alonzo et al., 2016; Barbierato et al., 2020).

Other conditions studied within the urban environment are identified apart from the in-depth study of vegetation, such as in the study by Lin et al. (2016), where the relationship of vegetation cover with temperatures on road surfaces, park interiors and rooftops are assessed. This is due to the use of hyperspectral and thermal imagery from Forward Looking InfraRed (FLIR), which represents the spatial distribution of different temperatures of a scene with a thermal camera, converting infrared (IR) radiation (heat) into an image (Havens, 2016) and then combined with Light Detection and Ranging (LiDAR).

The assessment of the ecosystem services of invasive plants is another identified approach (Potgieter et al., 2019), which is also linked to the possibility to classify existing vegetation in detail.

The most used active sensor tool within this method classification and in the studies reviewed is LiDAR. With data provided with LiDAR, it is possible to perform a three-dimensional analysis of vegetation and capture land surface features (Qin et al., 2017), in contrast to the majority of approaches in the passive sensor method. By obtaining other dimensions with LiDAR, not only can the surface or vegetation cover be estimated, but also its volume, due to its ability to measure the vertical extent. In the study by Jung and Pijanowski (2012), the importance of knowing the volume of vegetation is recognised, as this can vary also within the same LULC classification.

In the fusion of passive sensor and LiDAR imagery, a dependency between the two is identified for certain vegetation assessments, as LiDAR dimensions can detect other elements in the urban environment that are not only vegetation (Potgieter et al., 2019) and require merging with complementary spectral data for detailed mapping of the elements (Degerickx et al., 2020).

Fig. 3 presents the approaches identified for this method, set out in two main approaches: first, those based on land use classification and temperature measurement by passive sensors (LULC and thermal imagery), and in-depth vegetation analysis using active sensors. From these two, more specific approaches are derived than those in the passive sensors' method on the quantification of ecosystem services from vegetation.

3.3. Fusion of other data sources with sensors

A greater number of approaches are identified in this method, as evidenced by the data integration, and a deeper interest in other urban factors that affect the provision or loss of ecosystem services from vegetation. As in the previously classified methods, the application of remote sensing for the classification of LULC is observed like a main step in the studies, once classified, the studies are directed towards different assessments.

Within the selection of studies, one of the most relevant types of data is related to socio-economic data. We find studies that evaluate the socio-economic relationship with vegetation cover (Grove et al., 2006; Fernández and Wu, 2016), the Tree Canopy Change over time depending on the lifestyle using geodemographic segments and to optimize decision for urban forest investments (Locke et al., 2010; Locke et al., 2017), the distribution of public or private green spaces (Pham et al., 2012; Lin et al., 2015), the location of green spaces inequalities through the measurement of average inhabitant proximity (Van De Voorde, 2016), the quality and diversity in green spaces (Calderón-Contreras and Quiroz-Rosas, 2017) and on a national scale, as in the study of Chi et al. (Chi et al., 2015), the LCC based on different economic regimes.

According to the fusion of weather and atmospheric data resources

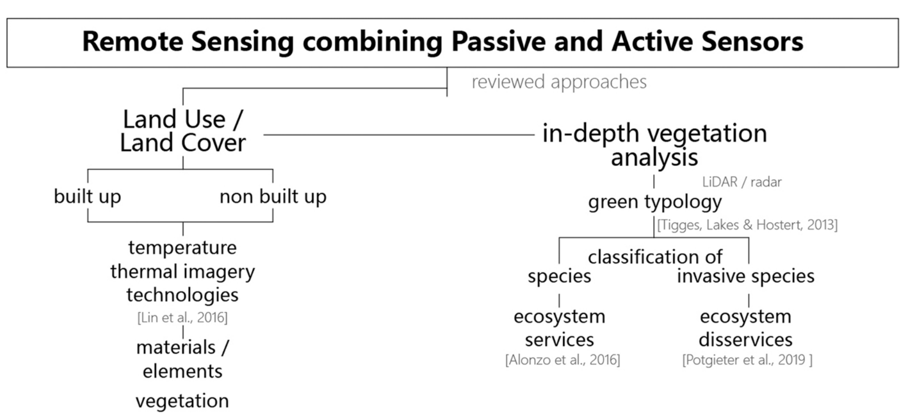

Fig. 3. Identified approaches in remote sensing combining passive and active sensors.

with remote sensing, a more direct link with the assessment of specific ecosystem services is noted, especially for those classified as regulatory ecosystem services, based on Haines-Young and Potschin (2010) classification framework for ecosystem services. The capacity of vegetation to reduce atmospheric pollutants (Manes et al., 2016; Bottalico et al., 2016) or the impact of drought on vegetation (Miller et al., 2020) is assessed. A condition mostly evaluated with weather and atmospheric information is the urban heat island effect (UHI) or the relationship of surface temperature with the existence of vegetation, where, in addition, information from thermal imagery is integrated. In the study by Zhang et al. (2017a), the integration of this data is observed to evaluate the best locations for vegetated spaces to achieve a cooling effect, in others it is done to evaluate the risk of heat exposure (Venter et al., 2020), and in the study case of Schneider et al. (2012) to determine the impact of LCC on urban heating and human discomfort.

On the other hand, more recent studies identify the fusion of information from social networks to complement assessments of ecosystem services. The use of this information is determined through images (where the condition of existing natural elements can be documented), texts, and, furthermore, the relationship of humans with the ecosystem based on metadata (geographic references). In Ghermandi and Sinclair (2019) review of the state of the art on crowdsourcing in environmental research, a constant growth in the use of social media sources in the literature between 2011 and 2017 is found, where, in addition, they classify the approaches of these studies resulting in a “data on nature” category, where LULC, physical monitoring of water, air, species, and invasive species are included.

Furthermore, data from social networks are used to assess urban expansion over time, generating an Urban Expansion Twitter Model (UET) as in the study by Shao et al. (2020), where data is geo-located through GPS of devices and obtained from a Twitter Application Programming Interface (API). Zhang et al. (2017a), merged remote sensing with social media to provide a more accurate classification of urban land use.

Finally, data acquisition related to population health are identified to demonstrate the impact of vegetation on psychological disorders and air pollution (Engemann et al., 2020a; Engemann et al., 2020b) and the association of tree canopy cover with childhood asthma, wheeze, rhinitis, and allergic sensitization studied by Lovasi et al. (Lovasi et al., 2013). Other data is integrated for the verification of values through ground-based measurements (GBM) and vector maps elaborated by entities according to local, regional, and other geographical scales like in Cochran et al. (2020) where interactive maps of environmental and socio-economic data combined with LiDAR are analysed for ecosystem services indicators.

According to maps, cadastral data is also combined with hyperspectral imagery and LiDAR data to map vegetation conditions at a local scale, where Bartesaghi-Koc et al. (2019) proposed a replicable workflow to be applied in other geographical locations.

Fig. 4 illustrates the approaches based on data fused with sensors, underlining the use of socio-economic information, weather and atmospheric data, social networks data, demographic data, ground-based measurements, and vectorial maps.

3.4. Relationship between the methods applied and the geographic scale

Following the previous review of the methods classified, we consider of importance to analyse the relationships of the applied methods and the case studies, considering; the geographical scale (global, national, regional and local) and the image resolution used. The intention behind the identification of this relationship is to respond to the lack of currently defined methods and guide towards an appropriate remote sensing method according to the case study.

For the relationship of the methods applied and the geographical scale, a classification of the case studies was made based on the area of study and its urban character, defining; the global scale (G), the national scale (N - per country), the regional scale (R - covering various states or districts of a country), the regional-metropolitan scale (RC – considering metropolitan areas), the city scale (C), and the local scale (L - neighbourhoods and areas within cities).

From the 83 different cases studied, the most common are the studies carried out on the regional metropolitan scale classified as RC with 30 case studies. In the city scale (C), 22 case studies were identified and in the local scale (L), 20 cases. For the remaining classified scales, a smaller

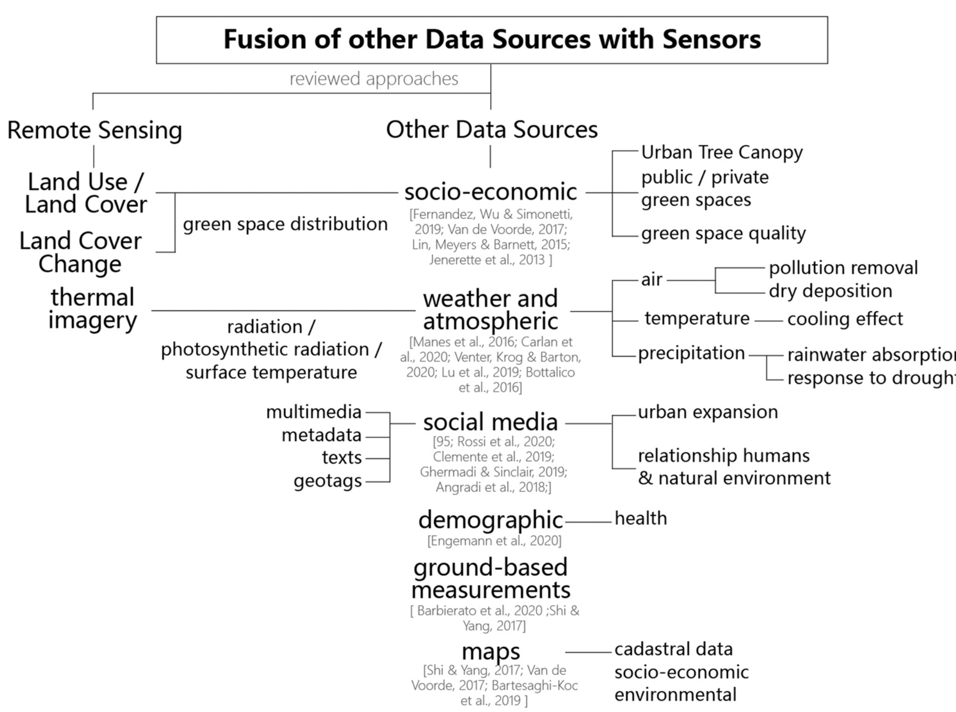

Fig. 4. Identified approaches in fusion of other data sources with sensors.

number of case studies were found; in the global scale (G) one case, in the national scale (N) four and in the regional scale (R) six, this relates to the fact that the method in this review is addressed primarily to the urban context, selecting mostly those at metropolitan, city and local scales.

The relationship between the methods and the geographical scales points out that; at the global scale (G), data from passive sensors were used, while at the national scale (N) the majority of cases have opted for the fusion of other data sources and sensors in order to generate more specific results for the countries evaluated (Spain, Denmark, Singapore and China). Regarding the regional scale (R), the relationship between the greater number of studies carried out with the methods applied has to do with the acquisition of affordable or open access images.

For those scales that are of particular interest to this review, we find that for the regional-metropolitan scale (RC), the most applied methods are the fusion of other data sources with sensors. From this method, approaches of the quantification of ecosystem services can be observed, such as the absorption of atmospheric pollution and the study of the quality of vegetation in order to estimate the ecosystem services provided. The rest of the studies at this scale are not focused on the evaluation of ecosystem services using remote sensing but on the quantification of existing vegetation (Jung and Pijanowski, 2012), the classification and characterization of vegetation according to the elements that are part of the metropolitan context (Chi et al., 2015; Shi and Yang, 2017), the impact that these elements on vegetation (Melaas et al., 2016) and the relationship of the availability of vegetation according to income segregation (Jenerette et al., 2013).

For the city scale (C), the methods of passive sensors and the fusion of other data with sensors are applied with equal concurrence, observing a greater focus on the study of ecosystem services in the method that fuses information with sensors. It is at this scale that more ecosystem services are evaluated than at the other scales, including quantification of food production, raw material, soil formation and conservation, waste regulation, cultural recreation, water regulation and purification, temperature regulation, soil production, flood regulation and removal of atmospheric pollution (Schneider et al., 2012; Li et al., 2014; Yang et al., 2015; Chang and Clay, 2016; Bottalico et al., 2016). This has been of great interest because it includes the quantification of various ecosystem services found in different types of classifications (provisioning, regulating, cultural) according to Haines-Young and Potschin (2010) framework.

For the local scale (L), the most applied method corresponds to the fusion of other data sources and sensors, but it is only at this scale that the other two methods are applied with the same frequency (passive sensors and combining active and passive sensors). It is important to mention that at this scale is where more information from active sensors is used than at the other scales, this may be related to the fact that at this scale it is more suitable to use instruments such as Radar, LiDAR, laser altimeters, ranging instruments, sounder or scatterometers, due to the area assessed, allowing the desired detail or resolution to be reached in each study case. In addition, studies at this scale are mostly related to the evaluation and assessment of vegetation and the provision of its services when both passive and active sensors data is used, including quantification of biological carbon filtration, climate regulation, net primary production and water provision (Wu and Bauer, 2012; Alonso et al., 2016; Hung et al., 2016; Lin et al., 2016).

Fig. 5 shows the application of the methods classified in this review (remote sensing with passive sensors, remote sensing combining passive and active sensors and fusion of other data sources with sensors) at each geographical scale. The RC, C, and L scales have been highlighted due to the particular interest for this review, where the RC scale shows the highest application of data fusion methods with sensors, the C scale shows an equal concurrence of application of data fusion methods with sensors and the method that only uses passive sensors, and finally the L scale shows the highest use of the method that combines passive and active sensors from the rest of the scales.

3.5. Relationship between the methods applied and the image resolution

The image resolution or spatial resolution determines the size of the smallest object that is coherently detected, which can change considerably. For the analysis of this relationship, we have taken as a reference the classification of the spatial resolutions from Small et al. (2018), where the metric prefixes are used: submeter ($\lambda < 1.0$ m), meter ($1.0 \leq \lambda < 10$ m), decametre ($10 \leq \lambda < 100$ m), hectometre ($100 \leq \lambda < 1000$ m), and kilometre ($1000 \text{ m} \leq \lambda < 10\,000$ m).

An overall review of the images acquired by remote sensing in the studies shows a variation in the selection of the image resolution. In this case 26 image resolutions were identified, ranging from submeter to hectometre resolutions (0.2 m x 0.2–1000 m x 1000 m per pixel). The

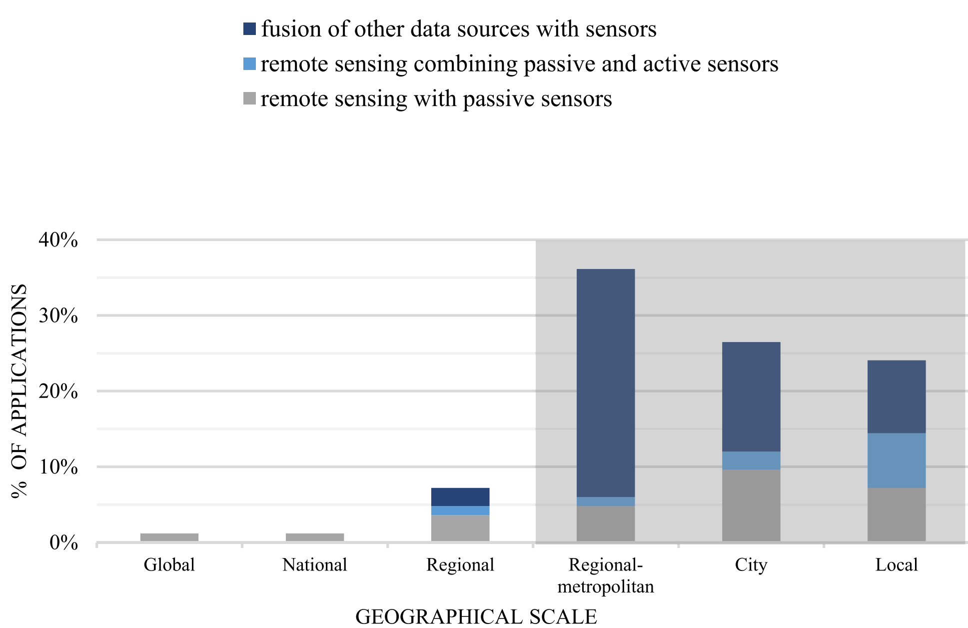

Fig. 5. Percentage of the application of classified methods by geographical scale, where scales RC, C and L are highlighted due to the interest for this review on the urban context.

most used image resolution is 30 m x 30 m per pixel obtained mainly from the Landsat Satellite (Land Remote-Sensing Satellite System), followed by 1 m x 1 m per pixel acquired using LiDAR. Resolutions show in general a greater use of images from passive sensors than from active sensors.

For the method using only data from passive sensors, we can observe the application of 13 different image resolutions ranging from submeter to hectometre (0.25 m x 0.25 m: GeoSpace International, to 250 m x 250 m per pixel: MODIS and Landsat). The most frequently used resolution in this method is decametre (30 m x 30 m per pixel: Landsat and ETM images, Terra Advanced Spaceborne Thermal Emission, and Reflection Radiometer ASTER and Global Digital Elevation Model GDEM), followed by 15 m x 15 m per pixel: ASTER, Landsat 8 Operational Land Imager OLI. The resolutions used for the specific assessment of ecosystem services range from submeter to decametre (2.5 m x 2.5 m: Advanced Land Observing Satellite ALOS, to 15 m x 15 m and 30 m x 30 m per pixel).

When using only data from passive and active sensors, 10 different image resolutions ranging from submeter to decametre (0.2 m x 0.2 m: UltraCam Xp, to 30 m x 30 m per pixel). The most commonly used resolution is submeter (1 m x 1 m per pixel: LiDAR, National Agriculture Imagery Program NAIP, followed by the resolution of 0.5 m x 0.5 m: Hong Kong Map Service, FLIR camera, and WorldView. The resolutions used that approximate the assessment of ecosystem services are submeter and meter (0.5 m x 0.5 m, 1 m x 1 m, 2.8 m x 2.8 m: Quickbird, and 3.7 m x 3.7 m per pixel: WorldView 3 SWIR). This method, compared to the others, shows the importance of using submeter and meter resolutions that could be linked to a more in-depth vegetation analysis.

For the method of fusion of other data and sensors there are more image resolution variations, in total 17, with resolutions ranging from submeter to kilometre (0.2 m x 0.2 m: HRV/SPOT5, to 10000 m x 1000 m per pixel: Mediterranean Extended Daily One Km AVHRR Data Set MEDOKADS and MOD15A2 v005). The most used resolution in this method is decametre (30 m x 30 m: Landsat, followed by 10 m x 10 m: ALOS, Satellite pour l'Observation de la Terre SPOT 5 and Sentinel, and 1000 m x 1000 m per pixel). The resolutions more approximate to the assessment of ecosystem services are very diverse, ranging from meter to kilometre (2.5 m x 2.5 m: ALOS, SPOT 5, 2.4 m x 2.4 m: Quickbird, 5 m x 5 m: SPOT 5, 10 m x 10 m, 30 m x 30 m, 90 m x 90 m: TM images from Shuttle Radar Topography Mission SRTM, and Thermal Emission and Reflection Radiometer ASTER, 500 m x 500 m: MODIS Spectroradiometer albedo data, and 1000 m x 1000 m per pixel).

The three methods show variation in the use of submeter, meter, decametre, hectometre and kilometre spatial or image resolution. Therefore, it was necessary to analyse both resolutions used and approaches for each case. Thereby, we found that for the specific assessment of ecosystem services, submeter resolutions and active sensors have been used more frequently. For the cases of vegetation cover quantification such as Urban Tree Canopy, and surface classification and identification such as Land Use Land Cover and Land Cover Change, the use of decametre and hectometre resolutions were more frequent, where Landsat (30 m x 30 m per pixel) was widely used.

However, the frequency of the 30 m x 30 m resolution does not indicate that this is the most appropriate and may be more linked to its ease of acquisition (open access) than to the characteristics of the site and the ecosystem services to be assessed.

Concerning the previously mentioned, we identify conclusions by authors such as Dong-Binh Tran et al. (2011) who proposed optimal spatial resolutions (OSR) for the identification of spaces with vegetation (decametre or <8 m x 8 m per pixel) and for tree identification (submeter or <1 m x 1 m per pixel) when analysing different resolutions for the characterization of urban elements and districts; they also supported this by finding that the urban environment is closely related to the local variance (dimensions of the objects of interest) giving its heterogeneity. Browning and Locke (Browning and Locke, 2020) concluded that Landsat's 30 m x 30 m per pixel resolution can produce biased results if the vegetation to be studied in the site is concentrated in few pixels, emphasizing that high resolution (submeter or meter) presents less vulnerability because pixels are calculated from binary values.

Walton and Nowak (2008) indicated that the resolution of the National Land Cover Dataset NLCD (30 m x 30 m) provides informative assessments of tree cover but lacks the specific assessment needed for a neighbourhood scale assessment. O'Neil-Dunne et al. (2014) further identified that an ideal approach to mapping tree canopy cover would be accuracy at the scale of individual trees so that municipalities could be analysed at scales ranging from city to individual parcels. Powell et al. (2007) mentioned in a review of Landsat and Landsat-like sensors, that data from lower resolutions can be enhanced by fusing it with various sensors that include higher resolutions in other bands. More recently Neyns & Canter (2022) reviewed vegetation mapping from high-resolution remotely sensed data in which they noted that the mapping of functional green types or green infrastructure does not necessarily require very high spatial resolution (submeter) as vegetation clusters allows its mapping. However, for the mapping of individual species they found that it is necessary to use higher resolution images considering that the elements that make up the urban environment obstruct the image.

Fig. 6 shows the 26 different resolutions applied in all the studies reviewed, where the resolution decametre (30 m x 30 m per pixel) is the most used and it is classified in the passive sensor and fusion of other data sources with sensors methods. There is a particular change in the method that uses information from passive and active sensors where the submeter resolution (1 m x 1 m per pixel) is used more frequently. It also shows a greater variety of resolutions for the meter resolution classification and a less variety for the hectometre resolutions.

3.6. *Data processing in remote sensing for the applied methods*

From the different methods that where classified and their approaches, specific points were highlighted and correlated concerning; image processing, fusion of data and the overall accuracy of the results obtained.

In image processing, attention is given to atmospheric correction (Zhu et al., 2016; Venter et al., 2020; Carlan et al., 2020a, 2020b), radiometric correction (Jenerette et al., 2013), topographic correction (de la Barrera et al., 2016), geometric correction or orthorectification (Lin et al., 2016; Kokubu et al., 2020; Wang et al., 2020), and pansharpening. The relevance of these corrections is associated with the time and conditions under which the images have been captured. Moreover, we find processes to differentiate trees from buildings and other anthropogenic structures (O'Neil-Dunne et al., 2014), to discard the shadows cast by the elements of the cities, where shadows of the buildings (Wu and Bauer, 2012); (Richards and Belcher, 2020) and those generated by the surface (Shi and Yang, 2017), influence the values of the pixels to be analysed in the images.

Regarding the fusion of data, a problem of processing results in LCC studies is identified due to the variation in the image resolution (Chi et al., 2015), which for these studies require different images to be compared over time and as there has been a technological development in the acquisition of images there are often variations in resolutions and information perceived by the sensors.

Furthermore, the need to use more than one software (Tian et al., 2014) to process the various factors that are studied, as in the case of socio-economic factors (Stellmes et al., 2013) and to avoid data redundancy (Qin et al., 2017). However, as indicated in Section 3.3., the fusion of data can have more extensive approaches because it can identify factors and dynamics with vegetation in cities (Carlan et al., 2020a). In addition, some studies use Geographical Information Systems (GIS) for processing diverse data, which allow multisource data analysis (Hostetler et al., 2013).

For the overall accuracy of the studies, a point of concern is the

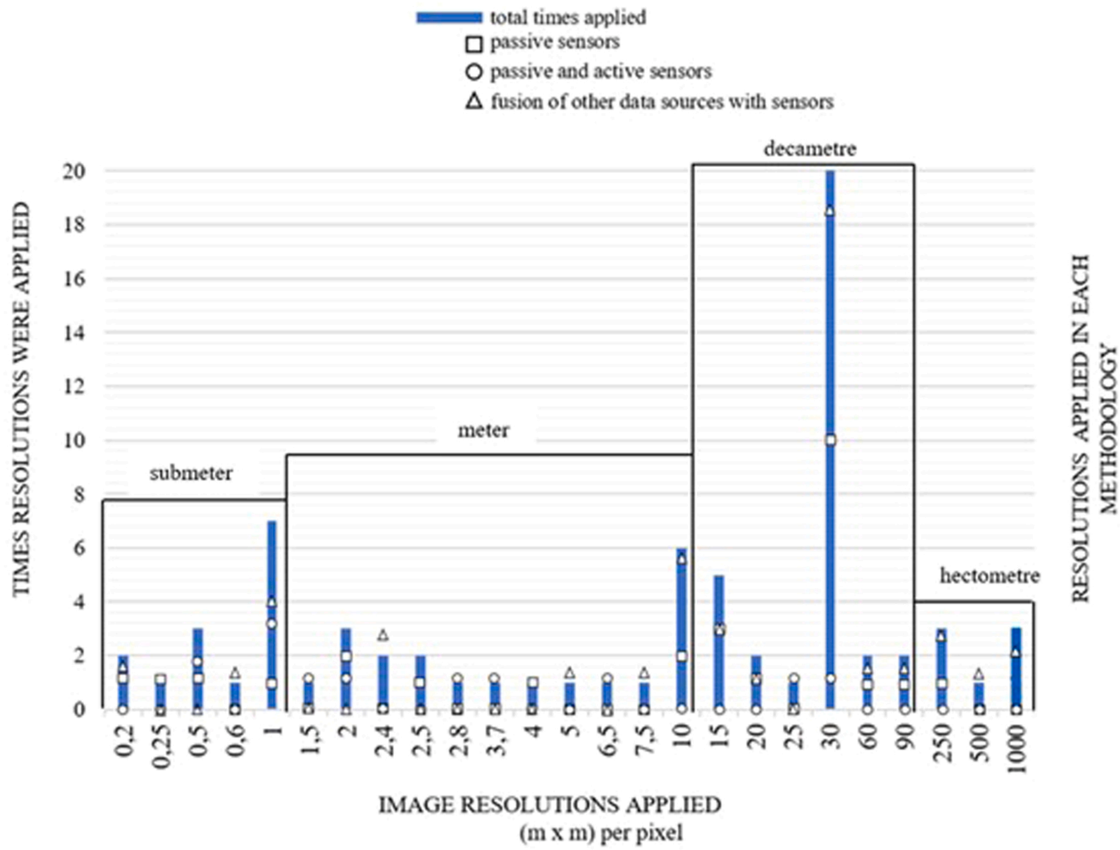

Fig. 6. Image resolutions applied in studies, total number of times the resolutions were applied (left) and times the resolutions were applied in each method classified in this review (right).

process and time needed to verify the results and validate accuracy with the site studied. Among these processes are: the sampling points or random selected points within the studied area (Wu and Bauer, 2012; Tigges et al., 2013; Li et al., 2014; Van de Voorde, 2017; Banzhaf et al., 2020; Pilant et al., 2020; Kuang and Dou, 2020), the Quality Assurance and Quality Control (QA/QC) (Habib et al., 2019), the manual controls that depend mostly on the verification of the results from the site studied (Tigges et al., 2013); (Degerickx et al., 2020; Kokubu et al., 2020; Mugo et al., 2020), and the orthorectification or georeferencing (Beibler and Hack, 2019; Venter et al., 2020) to make a cross-check of the results. An additional precision is found in the LULC classification, which has led to the creation of multiple classification systems after its extensive study and assessment (Shi and Yang, 2017). These processes may be repeated depending on each case study.

Finally, the large number of methods, data and processes can influence accuracy and increase errors (de la Barrera et al., 2016), although it is important to highlight the common reasons found for using remote sensing as a tool in the assessment of ecosystem services of urban vegetation, such as cost efficiency (Grove et al., 2006; Hostetler et al., 2013; Kokubu et al., 2020), the coverage of a large study area (Tigges et al., 2013; Mishra and Chaudhuri, 2015; Zhu et al., 2016; Kuang and Dou, 2020), the possibility of repeated measurements (Stellmes et al., 2013; Qin et al., 2017; Venter et al., 2020), the fine detail achievable (Wu and Bauer, 2012; Alonso et al., 2016; Van de Voorde, 2017; Beibler and Hack, 2019; Degerickx et al., 2020), the efficiency (McGee et al., 2012; Shi and Yang, 2017), and the possibility of assessing private and

Table 1
Advantages and limitations found for data processing in remote sensing.

	Image processing	Fusion of data	Overall accuracy
Advantages	– Development of models, algorithms and methods for pixel classification (Alonzo et al., 2013) – Higher resolutions that reduce errors in the classification of elements in the urban environment (O'Neil-Dunne et al., 2014)	– Local open Databases and formats available for processing in GIS software – Allows comparison of values to get more accurate results (Calderón-Contreras and Quiroz-Rosas, 2017) – Development of multisource data analysis (Hostetler et al., 2013)	– Diversity of methods for carrying out overall accuracy (Xie et al., 2008) – Provides insight into the approximation of the results to reality
Limitations	– Image correction (atmospheric, radiometric, topographic and geometric) (Lin et al., 2016; Kokubu et al., 2020; Wang et al., 2020) – Shadow exclusion or urban contamination (built up and surface) (Neyns and Canters, 2022)	– Spatial misalignment and image resolution variation (LCC) (Chi et al., 2015); (Neyns and Canters, 2022) – Abundant information to process which requires more time and can lead to data redundancy. (Qin et al., 2017) – Analysis and collection of information requires specific knowledge and experience (Chang and Clay, 2016)	– Cross-check processes (random or sampling points, QA/QC, etc.) (Wu and Bauer, 2012);(Tigges et al., 2013; Li et al., 2014; Van de Voorde, 2017; Habib et al., 2019; Banzhaf et al., 2020; Pilant et al., 2020; Kuang and Dou, 2020) – Orthorectification or georeferencing (Beibler and Hack, 2019; Venter et al., 2020)

inaccessible locations (Barbierato et al., 2020).

Table 1 shows the advantages and limitations identified for data processing in remote sensing, where the image processing, fusion of data and overall accuracy are highlighted within the analysis of the selected studies.

4. Discussion

Remote sensing can be used for the assessment of ecosystem services using passive and active sensors and its fusion with other data. These methods have also been found to be the most used for these studies shown in the review by Stroud, Peacock y Hassall (2022), where they also identified existing gaps in geographical discrepancies and information available, especially on vegetation at the local urban scale.

By analysing the approaches and the relationships with the geographical scale, image resolutions, and data processing for each of the methods classified in this review, it has been possible to generate a discussion intended to respond to the lack of specifically defined remote sensing methods for the assessment of ecosystem services provided by urban vegetation.

We have noted that the methods applied depend primarily on the intended approaches. In the reviewed studies we identify five main approaches: i) the identification of the elements within the urban area followed by a classification of the vegetation, ii) the observation of changes in vegetation over time, iii) the quantification of the area and volume of vegetation, iv) the acquisition of specific dimension of vegetation for particular ecosystem services assessment, and v) the identification and assessment of the relationships between socio-economic urban dynamics and vegetation condition.

This dependency is evident because it indicates the data to be collected and used. For the classification and observation of vegetation change, we observe that the passive sensors method is the most frequent because this data can be processed for the intended results without requiring, in the majority of studies, the fusion of other data. Therefore, by applying this method the results might be closer to an estimate rather than specific ecosystem services quantification, however, it is useful for conducting a site-specific diagnosis that would serve as a basis for identifying problems or weaknesses in the vegetation.

When the approaches are related to the quantification and assessment of ecosystem services of vegetation and the study of the relationship of vegetation with specific socio-economic factors, we noted that it is necessary to resort to other sources of data, beyond the passive sensors themselves, meaning that the methods of passive and active sensors and fusion of other data with sensors are more convenient to achieve the intended results.

Apart from the relationship of the approaches with the selection of methods, we found a key element to be considered, the selection of appropriate image resolution to be utilized, given that it has an important influence on the results and their accuracy. We observed the diversity in the selection of resolutions in all the studies, which is precisely one of the problems in remote sensing we identified previous to this review.

From the diversity of resolutions, we noted that for the study of ecosystem services of vegetation in the urban environment, it is essential to consider meter and submeter resolutions, as specific dimensions of the vegetated elements are required, beyond the knowledge of the surface area they cover in the study. We substantiate this with the similarity of authors' conclusions in which they mention the important link between the size of the objects to be analysed with the pixel size to be considered.

The aforementioned does not indicate that lower resolutions are not useful to study and assess urban vegetation, except that it is important to note that the results may have gaps and further accuracy processes may need to be carried out.

Regarding data processing, we identified it is more conditioned by the specific characteristics of the moment in which the data is retrieved, the geographical location, and the software to be used, beyond the remote sensing methods themselves. We do not discard that processing in remote sensing methods is relevant, because we found that it has an important impact on the results obtained, but based on the studies reviewed, there are several processes that seem to be more related to time, experience with the tools and the intended accuracy, rather than to a specific remote sensing method.

Table 2 shows a general review of the approaches, the relationship of the geographical scale and the image resolution, and the data processing of the studies reviewed.

Therefore, we address three key elements for the selection of remote sensing methods: the approach (es), the geographical scale, and the resolution. We found complex to describe a specific methodology using remote sensing methods for the assessment of ecosystem services provided by urban vegetation because of the diversity in information and its sources, in the methods for ecosystem services calculations, in the software features that seem to be updated rapidly, and above all in the particularities of each site. However, the review of studies over a period of time provides us with an understanding of these key elements by which we intend to contribute to narrowing the gap in remote sensing.

From Fig. 7 we intend to show the link between the resolution of the images, the geographical scales and the approaches identified in the studies. In this way we aim to highlight that the higher the image resolution used, the more approaches can be obtained, particularly for the city (C) and local (L) scales, which are the ones of greatest interest in this review.

5. Conclusions

The study and assessment of ecosystem services is a topic pertaining to the urban context which should be discussed and analysed precisely because of the diversity of methodologies and their complexity.

This review focused on relating the application of remote sensing and the current lack of defined methods for a specific urban area and condition to assess as case study. It was found that this gap is evident mainly from the specificity of the approaches and the characteristics of the urban context, in addition to the other gaps identified in the introduction to this review.

From the analysis of remote sensing methods and the identification of their relationship to the identified gap, we consider that the three key factors mentioned in the discussion could guide towards the selection of a suitable remote sensing method, the reasons for these are synthesized promptly as follows.

As a first key factor, approaches were identified because, based on the publications analysis, the choice of using remote sensing derived information is varied, resulting in the use of different sensors or integrating information from other types of sources and from different entities (local, state, national or international).

The second factor is the geographical scale to be addressed, although considering the assessment of specific ecosystem services of vegetation in the urban environment for the purposes of this review, differences were found in the application of the remote sensing methods that are more closely linked to the surface areas of the case studies and their character (metropolitan, city, district, neighbourhood, etc.).

The third factor is image resolution, where we find greater diversity due to the sources available for each study. We note that the choice of resolution is closely linked to the possibilities to acquire the images leading in the majority of cases to the selection of open access. However, based on the results of the studies, we identified that the image resolution needs to be related to the dimensions of the elements to be assessed (single tree, group of trees, shrubs, lawn surface, etc.), in order to obtain results closer to reality. For this factor, we consider that resolutions close to submeter are more viable for the study in urban environments due to the heterogeneity that exists in these.

Based on these three key factors it is possible to select the data to be used leading to the consideration of the potential in remote sensing tools. The purpose of identifying these does not suggest that they are the

Table 2
General approaches, geographical scales, image resolution, and data processing of the studies reviewed.

Approaches	Remote sensing method	Geographical scale	Image resolution	Processes to be carried out
– Identification and classification of vegetation – Assessing changes in vegetation – Quantification of vegetation – Socio-economic dynamics and vegetation	Passive sensors	Metropolitan (RC)	decametre ($10 \leq \lambda < 100$ m)	– Analysis and collection of information – Image correction (atmospheric, radiometric, topographic and geometric) – Shadow exclusion or urban contamination (built up and surface) – Cross-check results (random or sampling points, QA/QC, etc.) – Orthorectification or georeferencing
– Identification and classification of vegetation – Assessing changes in vegetation – Quantification of vegetation – Ecosystem services – Socio-economic dynamics and vegetation	Active sensors /Passive and active sensors	City (C)		
– Identification and classification of vegetation – Assessing changes in vegetation – Quantification of vegetation – Ecosystem services – Socio-economic dynamics and vegetation	Active and passive sensors / Fusion of other data with sensors	Local (L)	Meter and Submeter ($1.0 \leq \lambda < 10$ m) / ($\lambda < 1.0$ m)	

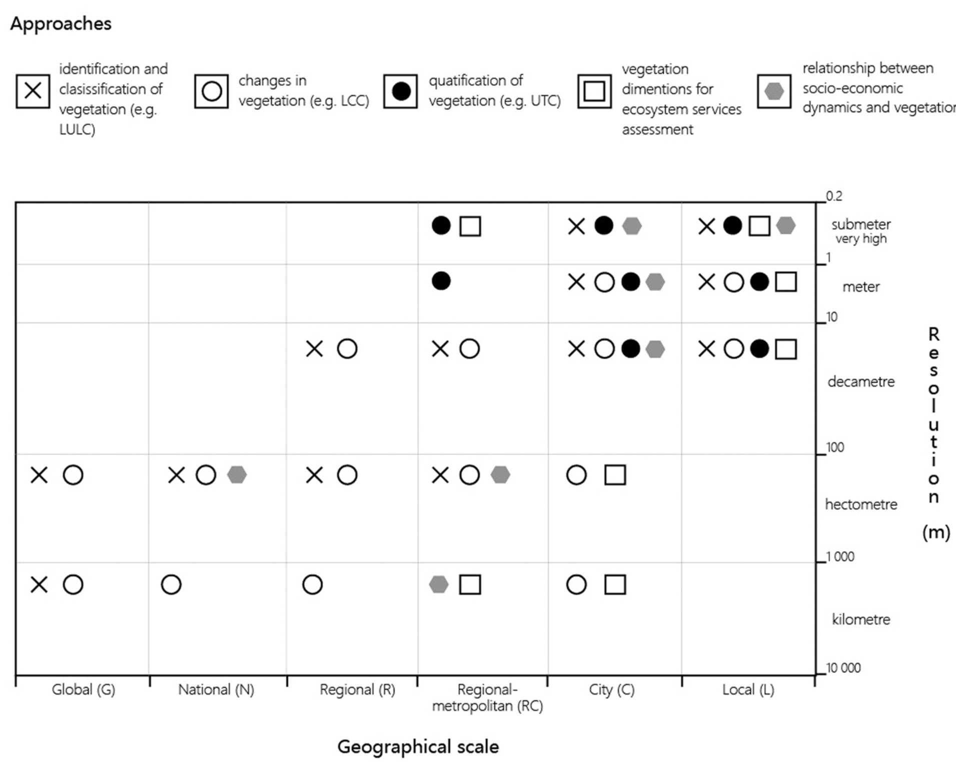

Fig. 7. Overview of the three key elements discussed to guide towards the selection of a remote sensing method based on the studies reviewed. Five general approaches found with their application for the geographical scales and resolutions classified based on Small et al. (2018) in the results Section (3).

only factors to be taken into account, but rather those that have been the most referenced in the publications.

With the input of this review, we believe that a specific assessment at an urban scale can be generated where remote sensing is really optimised in a cost- and time-efficient way. This is also sustained by the diversity of remote sensing data available that shows the possibility to diagnose and estimate vegetation impacts in the environment without the need for ground-based monitoring, leading to decision making in urban management and planning.

On the other hand, the specific assessment and quantification of the ecosystem services provided by urban vegetation still implies the need for more information beyond what can be obtained by remote sensing, as vegetation performance varies according to numerous factors, including individual species, weather conditions, etc.

Finally, we believe that an important step in the research community on the use of data from remote sensing for the assessment of ecosystem services provided by vegetation in cities, would be to include further application in other case studies, by extending the field of remote sensing and data integration. Furthermore, it is worth noting that the evaluation of the services provided by vegetation should be carried out in a transdisciplinary framework, where not only specialists in urban planning or vegetation carry out the assessments, but also, depending on the factors to be considered and the information to be processed, a professional team can be created to obtain results that are closer to reality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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