Remote sensing of urban green spaces: a review

Abstract

A knowledge of the characteristics of urban green spaces (UGSs) such as their abundance, spatial distribution and species composition, has an important role in a range of fields such as urban geography, urban planning and public health. Remote sensing technologies have made great contributions to the analysis of UGSs. However, a comprehensive review of the current status, challenges and potential in this area is lacking. In this paper, we scrutinize major trends in remote sensing approaches for characterising UGSs and evaluate the effectiveness of different remote sensing systems and analytical techniques. The results suggest that the number of studies focusing on mapping UGSs and classifying species within UGSs have increased rapidly over recent decades. However, there are fewer examples of non-tree species mapping, change detection, biomass and carbon mapping and vegetation health assessment within UGSs. Most studies have focused on UGSs (mainly trees) which cover large areal extents, with fewer studies of smaller patches such as street trees, urban gardens, recreational spaces and public parks, even though collectively such patches can cover substantial areas. Hence, we encourage future investigations to focus on a wider variety of different UGSs, particularly small-scale UGSs. We also recommend that research focuses on developing more effective image time series analysis techniques, methods to capture the complexity of UGSs and the use of SAR in studies of UGSs. At the same time, further research is needed to fully exploit remote sensing data within thematic applications such as monitoring changes in UGSs over time, quantifying biomass and carbon mapping and assessing vegetation health.

Keywords: urban green spaces; remote sensing; mapping; species classification; urban trees

1. Introduction

Urban inhabitants are expected to reach 70% of the world population by 2050 (Chang *et al.*, 2015) which is likely to lead to an array of environmental problems in cities such as increasing air pollution and climatic perturbations. In response, there is a growing recognition that urban green spaces (UGSs) have a role in mitigating such environmental pressures. UGSs are defined as all natural, semi-natural, and artificial systems within, around and between urban areas of all spatial scales (Chang *et al.*, 2015). UGSs promote multiple effects such as health, wellbeing and aesthetic benefits to urban dwellers (Ossola and Hopton, 2018). To maintain these positive effects, there is an acute need for protecting and improving existing UGSs, and at the same time developing new urban green infrastructure. Therefore, data on UGSs are crucial to a range of issues in urban science such as planning, management and public health.

Historically, various approaches have been employed to collect information about UGSs. Field campaigns can offer precise information on UGSs (Shojanoori and Shafri, 2016) but they are costly and time consuming (Pu and Landry, 2012). Visual interpretation and manual digitizing from hard-copy maps or aerial photographs have also been carried out for mapping UGSs. For example, Nowak *et al.* (1996) identified four different approaches for determining urban tree cover using aerial photos, namely, using a crown cover scale, and the transect, dot and scanning methods. Using these methods aerial photography was the main source of information for mapping UGSs between the 1970s and 1990s. Although visual interpretation and manual digitizing are one of the most accurate techniques, they can be subjective and difficult to replicate, leading to inconsistent results (Morgan and Gergel, 2013; Shojanoori and Shafri, 2016)

In the past decades, remote sensing technologies have occupied an important place in the study of UGSs as they can generate repeated and complete coverage at different spatial scales and for different seasons (Pu and Landry, 2012). Based on recent advances such as high spatial resolution imagery and free data access policies, remote sensing is providing a valuable set of tools which are able to minimize the need for field survey, even in highly heterogeneous and complex urban settings. For instance, remote sensing has proven to be effective for mapping street trees (Parmehr *et al.*, 2016), detecting species within UGSs (Shojanoori *et al.*, 2018), mapping invasive shrubs in UGSs (Chance *et al.*, 2016) and assessing vegetation health within UGSs (Nasi *et al.*, 2018). Furthermore, current remote sensing programs such as Copernicus (Harris and Baumann, 2015) and Landsat (Zhu *et al.*, 2019) not only provide historical time-series data but also facilitate access to recently acquired data.

Owing to these benefits, many researchers and managers have utilized remote sensing to study UGSs (Shojanoori and Shafri, 2016). However, whilst remotely sensed data has become part of existing planning and management systems for UGSs, a comprehensive review of the current status, challenges, and future potential in this area is absent. It is noteworthy that most relevant review papers on UGSs have focused on the specific topics such as urban forests (Shojanoori and Shafri, 2016), mapping urban trees species distributions (Fassnacht *et al.*, 2016), assessing the composition of urban settings (Patino and Duque, 2013) and mapping the social functions of UGSs (Chen *et al.*, 2018). Driven by the growing concerns over urban environmental problems and the overarching benefits of UGSs, it is now important to systematically scrutinize the remote sensing of UGSs as a whole.

This paper fulfills this requirement by providing knowledge that will enable better utilization of remotely sensed data and to stimulate wider interest in researchers for analyzing relationships between such data and studies of UGSs. The review begins by establishing key research questions related to the remote sensing of UGSs, with a particular interest in trends, data characteristics, analytical approaches and potential applications. Next, the methodological design for the review is presented. In the results section, we present the evidence to answer the key research questions while the discussion section covers future outlooks and recommendations. In order to keep the paper succinct, we have not included general background material on remote sensing (e.g., electromagnetic radiation principles and image quality), analytical techniques (e.g., mathematical explanations and computer programming) and UGSs (e.g., UGSs design and characteristics). Many technical textbooks and review papers have covered these topics. However, where necessary, we refer readers to relevant papers for further details. Four key research questions are addressed in this review:

- How and why has the use of remote sensing in studies of UGSs varied over time and space?
- What are the main technical considerations when using remote sensing to study UGSs?
- Which analytical techniques have been used in the remote sensing of UGSs?

- What are the major thematic application areas for remote sensing of UGSs?

The contributions of this review on remote sensing of UGSs are to:

1. Present general trends in remote sensing research concentrating on UGSs;
2. Examine requirements for remote sensing of UGSs, with a particular interest in the effects of remote sensed sensor types (e.g, optical and LIDAR), characteristics (i.e., spatial, spectral and temporal resolutions), cost and pre-processing in the context of UGSs;
3. Assess various techniques for extracting and estimating UGSs;
4. Provide a detail overview of the use of remote sensing in studies focused on UGSs;
5. Identify research gaps and future trends for remote sensing of UGSs.

2. Methodology

The evidence on which this paper is based was acquired using the guidelines for a systematic literature review methodology according to Pullin and Stewart (2006) and Viana *et al.* (2017). The collection and analysis of the published papers was performed according to these steps (Fig.1):

Fig.1. Flowchart of the systematic review method

(1) Collection: articles were gathered from the Web of Science, Bing and Google search engines using a range of keywords (Table 1) within the time span between January 1980 and August 2019. This period was selected as we hypothesized that the year 1980 could be considered as the beginning of medium spatial resolution remotely sensed data era (Landsat 4 TM, launched 1982) which might promote the application of remotely sensed data in the study of UGSs. While this research was conducted during 2019, we also wanted to know the major differences between early studies on UGSs and the contemporary studies.

The Web of Science was used for finding Science Citation Index Expanded (SCIE)/ Social Science Citation Index (SSCI) peer-reviewed journals in the English language while Google and Bing were employed to source data on any conferences, workshops and international activities on remote sensing of UGS. In order to minimize the risk of missing any literatures, the search was also conducted within the digital library of Zhejiang University, China. This library includes a range of databases such as Scopus, Elsevier ScienceDirect, and Nature.

(2) Optimization: More than 1500 studies were found to satisfy the conditional search as shown in Table 1. The collected papers were then screened independently by nine reviewers to identify eligible studies for review. The identification was conducted based on the following criteria:

1. Remote sensing data and techniques: the research must consider application of remotely-sensed data and techniques within their methodological frameworks to study UGSs.

2. Requirements: the research must investigate the influence of spatial, temporal, spectral, pre-processing and cost-efficiency on studies of UGSs.

3. Thematic applications: the research must present thematic application areas for remote sensing of UGSs.

It is worth emphasizing that all sections of the papers (including keywords and highlights, if available) were screened by reviewers under above criteria: three reviewers conducted the review under the methodological perspective, another three reviewers under the requirements aspect and other three under thematic applications. The detailed examination yielded 136 eligible papers for this review (these are listed are in the Supplementary Data1) and the final number of cases was 159 (references of all studies are presented in the reference list). Although 23 out of 159 papers did not fulfill all criteria, they offered very relevant information on the topic of UGSs for certain time periods, such as prior to 2000,and for certain remote sensing systems, such as synthetic aperture radar(SAR), where eligible papers were sparse. We observed that the rest of these studies (4 papers out of 23) used medium spatial resolution satellite sensors to study UGSs with the similar research directions to 136 eligible papers. However, the main difference lay in application of Google Earth Engine (GEE) platform which was employed in the aforementioned studies. For the sake of clarity, these papers were therefore placed in the new subsection named as Google Earth Engine.

(3) Thematic applications: In order to informatively present the thematic areas of studies focused on UGSs, studies within which remote sensing has been used, the papers were allocated to one of seven application areas. The allocation to an application area was based on the topics covered, keywords, objectives and analytical approaches of the reviewed papers (e.g., change detection, species classification, vegetation mapping). In the small number of cases where a single paper was related to more than one application area, it was allocated to the dominant area of interest. Furthermore, we mined the methodology section of each paper to identify the core of the analytical approach that was used in the research. The extracted thematic applications were as follows:

(a) Inventory and assessment: includes studies that evaluate the biophysical properties of UGSs, such as leaf area index, and the health of vegetation in UGSs.

(b) Biomass and carbon: includes studies that estimate these variables within UGSs.

(c) Change detection: includes studies that monitor change in UGSs.

(d) Ecosystem services: includes studies of the role of UGSs in delivering urban ecosystem services.

(e) Overall UGSs mapping: includes studies of the spatial distribution of UGSs which can be at the categorical (i.e. UGSs and non-UGSs) or fractional (per cent of UGSs within each pixel) levels.

(f) Species mapping: includes studies that identify vegetation species within UGSs.

(g)Three-dimensional modeling: includes studies that establish three-dimensional models of UGSs.

(4) Statistical analysis: All papers that were included in the review were analyzed by publication year, country, remotely sensed data requirements, names of satellites, analytical methods and thematic groups. The extracted information was organized in a Microsoft Excel environment (www.microsoft.com) while R statistical software (www.r-project.org) was employed to plot charts. It is important to note that this study was exempted from ethical approval as no human individuals, institutes and government departments were included and only publicly available electronic information was used for investigation.

(5)Presenting results and discussion

Table 1

Criteria used to select publications for review in this research

3.Results

For the presentation of the main findings, each of the research questions referred to in Section 1 of this paper will be addressed:

3.1. How and why has the use of remote sensing in studies of UGSs varied over time and space?

The results showed that there were no relevant eligible publications on remote sensing of UGSs prior to 2001. Between 1980 and 2000, most studies focused on demonstrating the environmental importance of UGSs and used data from visual interpretation of aerial photographs (Nowak *et al.*, 1996) and field campaigns (Shojanoori and Shafri, 2016). This could be largely because of the lack of appropriate remote sensing technology for detecting and mapping UGSs, immature digital image processing and pattern recognition algorithms, limited computing power and lack of open access remotely-sensed data (Jensen and Cowen, 1999; Shojanoori and Shafri, 2016). Moreover, it is worth noting that while some high spatial resolution satellite sensors (e.g., IKONOS) were launched prior to 2001, lack of appropriate image processing techniques could have hindered progress towards applications of these data in UGSs (Blaschke, 2010). At the beginning of the 21st century, the use of remote sensing to study UGSs increased rapidly, as evidenced by an exponential increase in publications (Fig. 2(a)).

Although many remote sensing milestones have occurred during 2001-2019, we selected four major developments which have promoted the remote sensing of UGSs (Fig.2(a)). Firstly, the increased availability of high spatial resolution remote sensing technology (e.g., QUICKBIRD (launched in 2001), OrbView (launched in 2003)) has made fine scale monitoring of UGSs possible, which is important in most UGS investigations. Additionally, high spatial resolution imagery has become available at a global scale through Google Earth, in the form of different products such as aerial photographs, satellite imagery and street views. Secondly, there has been an increasingly wide spread deployment of two data sources either stand-alone or combined together: Light Detection and Ranging (LiDAR) and hyperspectral remote sensing technologies. LiDAR sensors are able to generate precise information on the vertical structure of vegetation within UGSs by using discrete returns and waveform data. Hyperspectral sensors facilitate the identification of vegetation species within UGSs via spectroscopic analysis(Jensen *et al.*, 2009). Stand-alone or combined use of LiDAR and hyperspectral sensing have become important in many practical studies of UGSs. Thirdly, prior to 2008, the cost of access to Landsat imagery (medium spatial resolution) had constrained our ability to monitor UGSs. Since 2009, however, all archived Landsat scenes have become available to all users at no charge via several web sites. This has revolutionized the use of the Landsat archives in establishing new science, algorithms and data products in urban geography. Fourthly, the European Space Agency's has implemented the Copernicus program with a free and open access policy for imagery from the Sentinel satellites since 2015 (medium spatial resolution optical and radar data) which has been beneficial in many studies of UGSs (Dennis *et al.*, 2018). The combined effects of these four key developments in remote sensing can be seen via the increasing number of publications that have exploited these technical capabilities to study UGSs (Fig.2(b)).

A further reason for the surge in remote sensing-based studies of UGSs has been the calls by international organizations for more extensive investigations of UGSs in recent years. For instance, the World Health Organization (WHO) has devoted a special report to UGSs which demonstrates their multiple benefits for public health(WHO, 2016).

Fig. 2, (a) number of publications using remote sensing to study UGSs, annually from 2001 to 2019. Annotations show four key developments in remote sensing; (b) number of publications exploiting the key developments in remote sensing. Note that Google refers to Google Earth products; High spatial resolution (Hig); High spatial resolution & Medium spatial resolution (Hig_Med); Hyperspectral (Hyp); LiDAR(Li); LiDAR & High spatialresolution (Li_Hig); LiDAR & Hyperspectral (Li_Hyp); Medium spatial resolution(Med).

The selected publications on remote sensing of UGSs were also classified according to the country in which the study was conducted, journal publication and thematic application area. The results showed that most studies were conducted within China (37 cases) and the U.S.A (36 cases) (Fig.3a). The remaining studies were undertaken in Europe (Total:25; study per country:1-4), Africa (1 case-Rwanda), Asia (Total:18; study per country:1-4) and Canada (10 cases) (Fig.3a).The majority of the studies were published in the 10 top-ranking journals (covered by SCIE or SSCI) in the categories of remote sensing, urban geography and forestry. The three main journals were: Urban Forestry & Urban greening (Number of studies:17), Remote Sensing of Environment (12), and Landscapeand Urban Planning (15). Moreover, the results showed that frequency of publications on remote sensing of UGSs was limited between 2001 and 2007. Since 2008, remote sensing of UGS has been considerably gaining attention in the UGSs and remote sensing research communities (Fig.3b).

In terms of thematic application areas, overall UGSs mapping accounts for 39 of the papers, followed by species mapping (25 cases), inventory and assessment (18 cases), change detection (19 cases) and ecosystem services (15 cases). A smaller proportion of papers focus on biomass and carbon estimation (11 cases) and three-dimensional modeling (8 cases). Additionally, a growing interest has been observed for the use of remote sensing of UGSs in thematic application areas since 2008. In particular, the number of studies on change detection and biomass and carbon estimation has increased considerably, likely due to the addition of advances in remote sensing such as new sensors and image processing techniques which have prompted such research topics.

Fig.3. (a)World map presenting where the 136 selected articles has been conducted in the world(per country publication);(b) frequency of publication according to the year; Ecological Indicators (EI); Geocarto International (GI);International Journal of Applied Earth Observation and Geoinformation (IJAEO); International Journal of Remote sensing (IJRS); ISPRS Journal of Photogrammetry and Remote Sensing(ISPRS); Landscape and Urban Planning(LULP);Remote sensing (RS);Remote Sensing of Environment(RSE); Science of the Total Environment (STE);Urban Forestry&Urban Greening(UFUG); (c) frequency of use of thematic application area to year; Inventory and assessment (Inv_Ass);Biomass and carbon (BC);Change detection (CD); Ecosystem services (ES):Overall UGSs mapping (OUGS);Species mapping (Spe);Three-dimensional modeling (TDM)

3.2. What are the main technical considerations when using remote sensing to study UGSs?

3.2.1. Importance of technical considerations in UGSs classes and thematic areas

UGSs classes and thematic areas have an important impact in remote sensing-based investigation. UGSs can be broadly divided into two classes (Wang *et al.*, 2018; Haase *et al.*, 2019): (a) Medium to large-scale UGSs such as parks and urban forests and (b) small-scale UGSs such as gardens or backyard green of private houses and scattered patches of trees. It bears emphasis that while small-scale UGSs each occupy a limited area, when considered in their totality, they can represent a significant amount of urban space. Moreover, thematic application areas of remote sensing UGSs can be classified as overall UGSs mapping, species mapping, inventory and assessment, change detection and ecosystem services. Although many research endeavors have been oriented towards the remote sensing of UGSs, the relationship between technical considerations of remote sensing, thematic areas and UGSs classes is unclear.

The motivation for using remote sensing arises from the potential to extract information about UGSs precisely (e.g., detecting location of UGSs, identifying UGSs' vegetation cover species and estimating fraction of UGSs), quickly and at minimum cost. However, the demands on remote sensing may vary according to the UGSs classes and thematic application areas and it is hard to define general standards or optimal characteristics for remote sensing of UGSs. In particular, the cost-effectiveness of using remote sensing may be dependent on the balance between data and processing costs and the benefits provided to a particular application. For example, urban tree species information might be desirable for precision management of UGSs, while land cover mapping (e.g. vegetation and impervious surfaces) at the landscape scale may be sufficient for the management of UGSs across an entire city. In this context, mapping of urban street tree species can be carried out using hyperspectral and LiDAR data which is likely to incur considerable costs (Jensen *et al.*, 2009) while Landsat or Sentinel imagery can be used for large-scale UGSs mapping at a minimal cost (Rosina and Kopecka, 2016). Hence, there are a series of technical issues which need to be considered when determining the most appropriate remote sensing approaches in studies of UGSs, and evidence is drawn from the literature to highlight these issues in the remainder of this section.

3.2.2. Spatial resolution

Cities are incredibly complex and heterogeneous landscapes where vegetation is often present as very small patches or even scattered trees (Mitchell *et al.*, 2018). Also, a portion of UGSs may be on private properties, which may be difficult to access in the field and relatively small in size, but numerous in quantity. Thus, the analysis of UGSs often demands high spatial resolution remotely sensed imagery, as demonstrated in many studies (Li *et al.*, 2015b; Tigges and Lakes, 2017; Mitchell *et al.*, 2018; Sun *et al.*, 2019). Fig.2(b) also confirms this, as 38% of published studies utilized high spatial resolution imagery, followed by medium spatial resolution imagery (17%), and a combination of high and medium spatial resolution imagery (9%) (also see Supplementary Data1:Table 2).

Our investigation showed that most studies using high spatial resolution imagery focused on the application areas of overall UGSs mapping (12 cases), inventory and assessment (9 cases), species mapping (9 cases) and ecosystem services (9 cases) (Supplementary Data 2: Table 1). There were seven studies which focused on change detection and four on biomass and carbon estimation, with only two studies using high spatial resolution imagery for three-dimensional modelling. Only one paper has explicitly identified the impacts of spatial resolution on the uncertainty of mapping UGSs using WorldView-2 (Sun *et al.*, 2017). They synthesized a range of spatial resolution from 2m to 40m based on the WorldView-2.The results of this study demonstrated that UGSs can be captured successfully using imagery with spatial resolutions between 2m and 16m, with less effective results at lower resolutions. Moreover, it is worth noting that some studies employed high spatial resolution sensors on board of unmanned aerial vehicles (UAVs) (Liang *et al.*, 2017) and aircraft (Mozgeris *et al.*, 2018) (Supplementary Data 1: Table 2)

High spatial resolution imagery, however, possesses three major drawbacks: (a) They are not freely available to researchers; (b) There are unique problems with these data, more importantly, shadow. Shadow is widely present in urban environments and covers a large amount of vegetation in avenues, backyards and beside high buildings. With high spatial resolution imagery a significant proportion of pixels may be under deep and complete shadow and this hinders image interpretation, for example by reducing classification accuracy (Jensen *et al.*, 2012); and (c) High spatial resolution can generate high within class and low between class variability in urban areas due to the complex and heterogeneous environment (Pu and Landry, 2012; Geiss *et al.*, 2016).

The availability of medium spatial resolution imagery (e.g., Landsat and Sentinel archives) may compensate for some of the challenges of high spatial resolution imagery. Although these data cannot map UGSs at fine scales, they can be used to assess the overall pattern of UGSs and delineate major parks and patches of vegetation within cities (Small, 2001). The majority of published studies using medium resolution imagery have focused on overall UGSs mapping (12 cases) (Supplementary Data 2: Table 2). Other studies have used medium spatial resolution imagery for change detection of UGSs (4 cases), quantifying ecosystem services (4 cases), biomass and carbon estimation (3 cases) and inventory and assessment (1 case). However, we did not identify any studies where medium spatial resolution imagery has been applied to species mapping and three-dimensional modelling. This result is supported by previous studies which showed that medium spatial resolution imagery may not be sufficient for extracting such information (Pu and Landry, 2012; Alonzo *et al.*, 2014; Tigges and Lakes, 2017).

Our review showed that some studies have used combinations of data from satellite sensors of differing spatial resolution (Kong and Nakagoshi, 2006; Rafiee *et al.*, 2009; Solange, 2015; Zoran *et al.*, 2015; Chen *et al.*, 2017a; Zhou *et al.*, 2018). For instance, information on night time lights from coarse resolution imagery (Defense Meteorological Satellite Program) has been used for detecting boundaries of urban regions, within which medium resolution multispectral imagery (Landsat) were used for monitoring changes in UGSs (Chen *et al.*, 2017a). Similarly, UGSs have been quantified using a combination of low spatial resolution (Terra MODIS) and high spatial resolution (IKONOS) imagery (Zoran *et al.*, 2015).

3.2.3. Spectral resolution

The spectral response of UGSs is generated by radiation interacting with a mixture of vegetation and urban materials, both of which can be very heterogeneous. Thus, in order to discriminate UGSs from other urban features and characterize the vegetation within UGSs, remotely-sensed data of sufficient spectral resolution is required. The spectral resolution of remote sensing instruments can generally be divided into two groups: multispectral and hyperspectral. Multispectral sensors typically include 4-8 bands that span the visible, near infrared, short wave infrared spectral, and thermal infrared domains whereas hyperspectral sensors typically have many hundreds of bands which cover these spectral domains. Both types of instruments can provide useful information for characterizing UGSs. Multispectral systems tend to be capable of discriminating vegetation within urban areas and mapping UGSs, while hyperspectral sensors are usually required for identifying vegetation species within UGSs (Voss and Sugumaran, 2008; Alonzo *et al.*, 2014). Nevertheless, improving the spectral resolution of multispectral system can have a significant impact, for example, it has been shown that the addition of four new bands to World View 2 improves the capabilities for species discrimination compared to IKONOS (Pu and Landry, 2012). Only one study has conducted a comparison between the use of hyperspectral data at high spatial resolution and multispectral data with similar resolution when studying UGSs (Pu and Landry, 2012). A detailed review of the effects of spectral resolution on detecting urban vegetation can be found in Fassnacht *et al.* (2016). Some studies using hyperspectral systems have identified important wavelength regions for classifying urban forests and trees, notably the green edge, green peak, yellow edge, red and near infrared (Xiao *et al.*, 2004; Alonzo *et al.*, 2013; Liu *et al.*, 2017). Moreover, it has be argued that urban tree species can be classified using the blue region due to their relatively lower photosynthetic activity in this region (Pu and Liu, 2011). Despite the potential value of hyperspectral sensors, we observed that only 5% of studies have used these sensors in investigations of UGSs, while the rest rely on multispectral remote sensing mainly at the medium spatial resolution (Fig 1(b) and Supplementary Data 1: Table 2). This is likely due to the limited accessibility to hyperspectral data which are collected from airborne platforms and few satellite sensors that have limited spatial coverage and relatively high acquisition costs. It is important to note that while EO-Hyperion data can make a contribution in analyzing UGS due to their hypespectral sensing capability and free access (Lv and Liu, 2009), their medium spatial resolution(30m), limited spatial coverage and coarse temporal resolution have hampered frequent use of this satellite sensor in such studies.

3.2.4. Timing of image acquisition

Timing of image acquisition is a very important consideration in remote sensing of UGSs because of vegetation phenological cycles which cause changes in leaf biochemistry and canopy structure of vegetation (Voss and Sugumaran, 2008; Tigges *et al.*, 2013; Li *et al.*, 2015a; Pu *et al.*, 2018). Such phenological cycles lead to temporal variations in the remotely-sensed response of vegetation. In general, fall and spring have been found to be the most appropriate seasons for mapping UGSs and identifying vegetation species (Voss and Sugumaran, 2008; Jensen *et al.*, 2012; Zhang and Qiu, 2012; Duarte *et al.*, 2018) . However, there are a variety of findings on this issue. For example, Liu *et al.* (2017) reported that for a species diverse area, the presence of a mixture of trees with leaf-on and leaf-off conditions could reduce classification accuracy when mapping urban tree species. Another study indicated an improvement in accuracy of tree species mapping in late spring (April) (Pu *et al.*, 2018). Voss and Sugumaran (2008) reported no improvement in overall accuracy when applying hyperspectral data from fall as compared to a summer dataset, yet the fall dataset provides more consistent results for all tree species while the summer dataset had a few higher individual class accuracies. It is likely that the variability in results related to the timing of acquisition may be explained by variations in species composition of the study sites used across different studies and the varying physiological responses of species to the different climatic contexts of the study sites.

To minimize such conflict, an alternative way is to use multi-date imagery rather than single date for studies of UGSs (Tigges *et al.*, 2013; Li *et al.*, 2015a; Pu *et al.*, 2018; Yan *et al.*, 2018). For example, using remotely sensed imagery acquired in summer and winter seasons can facilitate the discrimination of deciduous and ever green trees (Xiao *et al.*, 2004).

3.2.5. LiDAR

Light detection and ranging (LiDAR) systems offer one of the most accurate techniques for characterizing vegetation covers from local to regional scales (Liu *et al.*, 2017). The main mechanism of LiDAR is that laser pulses are emitted at the measured object and back scattered returns are recorded and analyzed in order to characterize the 3-dimentional(D) properties of the vegetation surface and canopy structure(Tanhuanpaa *et al.*, 2014). Therefore, LiDAR can reduce influence of shadow, measure structural attributes and biophysical parameters, and provide three-dimensional information (Voss and Sugumaran, 2008; Jiang *et al.*, 2017; Liu *et al.*, 2017). Our results showed that 8% of papers used LiDAR to study UGSs (Supplementary Data 1:Table 2) and of these three cases focused on inventory and assessment, followed by four cases on overall UGSs mapping and four cases on three-dimensional mapping (Supplementary Data 2: Table 3).

Several studies have demonstrated the benefits of combining LiDAR with hyperspectral data and high spatial resolution imagery (Zhang and Qiu, 2012; Alonzo *et al.*, 2013; Dian *et al.*, 2016). For instance, combination of LiDAR and hyperspectral data can aid in the detection of invasive vegetation in urban environments (Chance *et al.*, 2016). Combined LiDAR and hyperspectral data were used in 7.1% of studies while the integration of LiDAR data and high spatial resolution imagery was observed in 10% of studies. At the applications level, the combination of LiDAR with hyperspectral data was mainly employed in UGSs species mapping (8 cases) and inventory and assessment (2 cases) (Supplementary Data 2: Table 4). Moreover, integrated LiDAR data and high spatial resolution imagery were used in UGSs species mapping (4 cases), three-dimensional modeling (2 cases), biomass and carbon analysis (3 cases), change detection (2 cases), ecosystem services (1 case) and overall UGSs mapping (2 cases) (Supplementary Data 2: Table 5).

3.2.6. Synthetic aperture radar (SAR)

SAR sensors actively send microwave signals to the Earth's surface and detect the back scattered energy. Therefore, SAR sensors detect Earth's surface day or night and under all weather conditions. Transmitted microwave signals can also penetrate vegetation canopies and soil surface layers which may be of value in some assessments of UGSs. However, despite these advantages of SAR sensors, the literature pays scant attention on the use of SAR data in studies of UGSs. Our investigation showed that a range of studies have demonstrated a potential role for SAR, mainly through fusion with optical sensor data, in the classification of broad urban land cover types i.e. without a specific focus on UGSs (e.g.,Ban *et al.*, 2010; Niu and Ban, 2013; Werner *et al.*, 2014; Zhang *et al.*, 2018; Zhang and Xu, 2018) as well as through the acknowledged contributions of SAR data in forestry (Fassnacht *et al.*, 2016). Therefore, the use of SAR data in studies of UGSs appears to be a valuable area for future investigations.

3.2.7.Google Earth products- Google Street View

Satellite sensors imagery may not provide information on the visual effects of UGSs on citizens (Yang *et al.*, 2009; Jiang *et al.*, 2017; Li *et al.*, 2018). To compensate for this problem, a range of studies (3.5%) have used Google Earth products, including Google Street View. For instance, Yang *et al.* (2009) developed the Green View Index which is based on assessing vertical profiles from Google Street View imagery to analyze urban forest structures. Likewise, Li *et al.*(2018) calculated the Sky View Factor using Google Street View imagery to measure the proportion of sky that is obstructed by buildings and tree canopies. Jiang *et al.* (2017) pointed out that Google Earth imagery and the software i-Tree street can be used to objectively calculate tree cover density at little or no cost to user. Richards and Edwards (2017) demonstrated that hemispherical canopy photographs taken from Google Street View could be used to assess the shading of diffuse and direct radiation by the canopy at a particular location. Hence, there is growing evidence that Google Earth products can have a role to play in understanding UGSs.

3.2.8. Google Earth Engine(GEE)

Google Earth Engine (GEE), a cloud-based geospatial processing computing platform, offers satellite data processing and geographic information system(GIS) analysis from local to global scale (Gorelick *et al.*, 2017). GEE employs medium spatial resolution satellite sensors such as Landsat and

Sentinel for monitoring land use and land cover in an efficient way. Our findings illustrated that a range of studies have highlighted a potential role for GEE in UGSs (Huang *et al.*, 2017; Huang *et al.*, 2018b; Zhang *et al.*, 2019). For example, Huang *et al.* (2018b) assessed the influence of urban form on the structure of UGSs in 262 cities in China based on the GEE. Huang *et al.* (2017) quantified the change in health benefits generated by urban green spaces in 28 megacities worldwide between 2005 and 2015 by using GEE. Zhang *et al.* (2019) estimated the spatial accessibility of urban forests based on the GEE. Thus, although the spatial resolution of remotely sensed data in GEE may not be sufficient for capturing details of UGSs, there is growing evidence that GEE can play a central role in analyzing UGSs at regional and global scales.

3.2.9. Pre-processing-Atmospheric correction

Earth's atmosphere influences surface-reflected radiation recorded by satellite sensors; this can be detrimental to the remote sensing of surface characteristics and the effect can be amplified over urban regions because of the polluted atmosphere. Consequently, the quality of satellite images usually needs to be improved by using atmospheric correction algorithms (Pu and Landary, 2012). Our results showed that 38 of the studies used atmospheric correction techniques while the remaining majority of the studies did not mention atmospheric correction in their pre-processing section (Supplementary Data 1:Table 3).The most common atmospheric correction methods were Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH; 13 cases) and Atmospheric and Topographic Correction (ATCOR; 7 cases) (Supplementary Data 1:Table 3). Other techniques such as QUick Atmospheric Correction (QUAC) (Shojanoori *et al.*, 2016), dark object subtraction (Asmaryan *et al.*, 2013), and Second Simulation of a Satellite Signal in the Solar Spectrum Vector (6SV)(Li *et al.*, 2015a) were employed in the rest of UGSs studies (18 cases).

While atmospheric correction was used as a pre-processing step in several studies, less attention has been devoted to revealing the specific contributions of atmospheric correction in the remote sensing of UGSs. In this respect, only Pu *et al.*(2015) evaluated the effects of atmospheric correction for identifying urban tree species with WorldView-2 imagery. This study provided two major conclusions: (1) there is uncertainty around the assumed surface reflection model and atmospheric parameters for using atmospheric correction models; and (2) atmospheric correction is not necessary for single date imagery as it may result in a reduction of the signal-to-noise ratio. Hence, it seems that there is scope for more explicit consideration of the impacts of atmospheric effects in remote sensing studies of UGSs, with more judicious use of correction methods for the preprocessing of imagery time series where the detection of real changes in UGSs characteristics is required.

3.2.10. User demands and cost-efficiency

The main rationale behind using remotely sensed imagery in studies of UGSs is to reduce the costs associated with field data collection campaigns. To the best of our knowledge, detailed evaluations of the financial benefits or detriments of using remotely sensed data in measurements of UGSs have not been presented. Among the 136 papers reviewed, the results showed that only two articles conducted comprehensive investigations on the cost efficiency of remotely sensed data in studies of UGSs. Li *et al.*(2015) showed that high spatial resolution images offer fine scale information on UGSs though they are expensive compared to the moderate spatial resolution (30m). Furthermore, Jensen *et al*. (2009) found that modeling urban leaf area index using hyperspectral imagery is cost-effective, accurate and practically feasible. Although the cost of remotely sensed imagery could be an obstacle for detailed, large scale and repetitive measurement of UGSs, it is contended that such costs are outweighed by the value derived from such work in improving UGSs and delivering multiple benefits and services (Jensen *et al.*, 2009; Chen *et al.*, 2017b).

3.3.Which analytical techniques have been used in the remote sensing of UGSs?

Remote sensing-assisted mapping of UGSs can play an important role in characterizing the spatial distribution of vegetation cover within urban regions (e.g., Puissant *et al*. 2014) and several analytical techniques have been suggested for mapping UGSs. Our results show that the techniques are hybrid methods (37 cases), followed by object-based image analysis (29 cases), land cover indices (20 cases) and fraction methods (16 cases) (Supplementary Data1:Table 4). Further details on these techniques are provided below. Fig.4 (a) and (b) outlines the different techniques that have been used to characterize UGSs according to different types of remotely sensed data and thematic application areas, respectively.

Fig.4. Different techniques to characterize UGSs: (a) frequency of use of techniques according to type of remotely-sensed data, and (b) frequency of use of techniques according to application area.

As seen in Fig.4 hybrid methods are popular for characterizing UGS. This is because combining the strengths of various algorithms into a single framework tends to increase the performance of the technique. A standard architecture for hybrid methods consists of combining per pixel classification, soft classifiers and object-based classification. Hybrid techniques can be dependent, whereby the output of one technique is used to inform the next classifier, or independent, whereby each technique is run independently and the outputs are combined. For example, Liu and Yang (2013) first partitioned the entire landscape into rural and urban subsets according to road network density, thereby each subset can be analyzed independently to reduce spectral confusion between some urban landscapes and agricultural land covers. Then the combination of a soft classifier and a supervised classification were employed to generate a map of UGSs. Pontius *et al.* (2017) used the combination of a mixture-tuned match filtering (MTMF)-based spectral unmixing, watershed segmentation and image multiresolution segmentation to map urban ash trees. In this research, MTMF was used for species detection while multiresolution segmentation was used to differentiate forest/non-forest and watershed segmentation to delineate tree crowns. This hybrid method facilitated the synthesis of information from LiDAR and hyperspectral data and this type of hybrid approach is frequently used in this context (Fig. 4(a)). For instance, Liu and Wu (2018) developed a hybrid technique to map vegetation species within UGSs. This method consisted of three steps (Liu and Wu, 2018): (1) delineating individual trees using local maxima (LM) and linear regression based on the relationship between the height of the trees and their crown sizes; (2) extracting crown spectra from hyperspectral imagery using linear spectral mixture analysis; and (3) classifying tree species from crown spectra by applying a support vector machine. In general, hybrid methods have been used in all application areas, but are more frequently observed in UGSs species mapping (14 cases) and overall UGSs mapping (7 cases) (Fig. 4(b)).

Many authors have applied object-based image analysis (OBIA) for mapping UGSs. Fig. 4(a) shows that OBIA approaches are dominant in studies using high spatial resolution imagery. OBIA techniques are generally based on segmentation algorithms which use auxiliary information, such as image texture and context, in tandem with spectral information. For example, Pu and Landry (2012) mapped urban vegetation species by employing texture information from IKONOS and WorldView imagery within an integrated analysis using linear discriminant analysis and regression trees. Likewise, Yan *et al.*(2018) used OBIA to map vegetation functional types within urban regions. It is noteworthy that most studies employing OBIA (either individually or within a hybrid method) mainly used segmentation algorithms in the eCognition software. Among the different application areas, OBIA was used extensively in UGSs species mapping (9 cases) and overall UGSs mapping (8 cases) (Fig. 4(b)).

One large stream of studies employs land cover indices to characterize UGSs from satellite imagery. These techniques typically use combinations of different wave bands from multispectral satellite sensors. Among the land cover indices, the normalized difference vegetation index (NDVI) is the most well-known and most widely applied index for mapping UGSs (Jensen *et al.*, 2012). For example, Chen *et al*.(2017a) employed NDVI to differentiate green and non-green regions within urban areas. Land cover indices have been used in different application areas such as change detection (6 cases) and ecosystem services (5 cases) (Fig. 4b)). For example, Lwin and Murayam (2011) quantified UGSs using NDVI in order to model the accessibility of UGSs and for assessing the implications for environmental quality and health of residents. The popularity of these methods is attributed to their simple estimation techniques, easy interpretation of results, and because they can provide a continuous spatial variable (as opposed to a classified map) which can be integrated in modeling and simulations.

Fraction methods have been used in a number of studies. Mapping urban green spaces at the fraction level (sub-pixel level) provides information on the density of vegetated areas in urban regions (Van de Voorde *et al.*, 2008). In urban geography, fraction estimation is mainly based on the vegetation-impervious surface-soil (V-I-S) model which considers a pixel an urban area as being covered by these three surface types in variable proportions(Van de Voorde *et al.*, 2008). Fraction techniques facilitate overall mapping of vegetation and are particularly effective when using medium spatial resolution imagery. For example, Lu *et al. (*2017) employed an unmixing technique to map urban vegetation fraction across 25 cities using Landsat imagery. Likewise, Hasse *et al. (*2019) used a combination of spectral unmixing and random forest regression to map front and back yard vegetation in residential areas using Rapideye imagery. Fraction methods are much more widely used in overall UGSs mapping compared to other application areas.

Per-pixel analysis (conventional classification techniques) has also been employed for mapping UGSs. For example, Kopecka *et al*., (2017) extracted urban vegetation from Sentinel-2A imagery using a supervised maximum likelihood classification, while Thaiutsa *et al*.(2008) classified UGSs using an unsupervised classification. It is also noteworthy that researchers have employed point sampling and visual interpretation to characterize UGSs from remotely-sensed imagery. A number of studies have also used pre-existing maps as a tool for extracting thematic UGSs datasets (Supplementary Data 1:Table 4).We found that only one study used deep learning algorithm, Dense Convolutional Network (DenseNet), to map USGs from remotely-sensed data (Hartling *et al.*, 2019).

3.4 What are the major thematic application areas for remote sensing of UGSs?

In this section we focus on the variety of thematic application areas related to UGSs that have been supported using remote sensing and the specific approaches within each application area that have been used (Table2). It is worth nothing that providing the details of analytical methods is beyond the scope of this paper and it is suggested that readers consult the corresponding cited literature for further information on the approaches used.

3.4.1 Inventory and assessment

In inventory and assessment applications, researchers have focused on measuring different aspects of UGSs which is also reflected in the context or title of their studies (Table 2). We found that studies assessing the health of vegetation in UGSs (Xiao and Mcpherson, 2005; Asmaryan *et al.*, 2013; Nasi *et al.*, 2018; Nouri *et al.*, 2018) and geospatial modeling were dominant within this group (Table 2). The rest of the studies concentrated on other aspects such as leaf area modeling, vegetation phenology and economical investigations. Among this group, Nouri *et al. (*2018) quantified impacts of salinity on UGSs while Asmaryan*et al. (*2013) monitored effects of pollution on the urban vegetation.

3.4.2 Biomass and carbon estimation

Remotely sensed data have been used in monitoring carbon and biomass within UGSs. This research has mainly used regression modeling between carbon/biomass and remotely sensed variables (Table2). For instance, Yao *et al. (*2015) established regression models between above ground carbon stock in UGSs and several vegetation indices. The Difference Vegetation Index (DVI), Ratio Vegetation Index (RVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI) and Renormalized Difference Vegetative Index (RDVI) were all less well correlated with carbon than NDVI. In another study, carbon stock within UGSs was estimated using guidelines from the Intergovernmental Panel on Climate Change (IPCC) and employing a point sampling approach to analyze aerial photographs (McGovern and Pasher, 2016).

3.4.3 Change detection

An important topic for urban policy makers is the objective measurement of UGSs changes through an approach that takes into account not only major changes between land cover types (e.g., urban brownfields to green spaces) but also information on more subtle changes within UGSs (e.g., changing species composition). Various techniques for monitoring UGSs have been developed using medium and high spatial resolution imagery (Table2). Most change detection studies have employed landscape metrics. For instance, Zhou *et al.*(2018) used landscape shape index (LSI) complexity, mean patch size (MPS), patch density (PD), and edge density (ED) to quantify changes in UGSs of nine Chinese cities. Some studies have employed GIS-based spatial analysis to quantify change in UGSs within concentric buffer zones (e.g., Gan *et al.*, 2014). One study focused on developing maximum information-based nonparametric exploration (Yang *et al.*, 2014). This study calculated maximum information coefficients between the trend of urban green coverage and changes in socio-economic and climate variables. Wang *et al.*(2018) introduced new metrics for UGSs at the patch level in order to quantify the process of growth, shrinkage, creation or disappearance of patches. Moreover, several models have been developed to quantify change in UGSs. For example, Ossola *et al.* (2018) used multi-temporal airborne LiDAR and multi-spectral imagery collected at a 5-year interval to measure urban tree loss dynamics. Multivariate regression models were then established to relate the number and height of tree stems lost in residential parcels in each census tract to a range of urban morphological and socio-economic variables.

3.4.4. Ecosystem services

In this thematic application area, we found three major groups of studies: modeling, policy investigation, and morphological spatial pattern analysis (MSPA) (Table2). A range of models have been constructed to evaluate different aspects of UGSs. For example, Jensen *et al.* (2004) built a neural network model to estimate urban leaf area using field measurements and satellite remote sensing data for studying urban quality of life and urban forest amenities. Some studies have employed a hedonic model for UGSs evaluations (Franco and Macdonald, 2018; Mei *et al.*, 2018). The hedonic method is an indirect approach to valuing public goods and has been widely used in environmental economics studies (Franco and Macdonald, 2018; Mei *et al.*, 2018). This is the best known and most widely accepted method for valuing urban forest amenities. A number of studies have focused on policy and planning evaluations, mainly using GIS or Google Street View analysis. For instance, Richards *et al.*(2017) analyzed hemispherical photographs extracted from Google Street View to quantify the proportion of green canopy coverage and the proportion of annual radiation that is blocked from reaching ground level by the canopy along Singapore's road network. They showed that there was significant variation between different urban land use types, with trees providing more shade in parks and low-density low-rise areas than in industrial and higher-density residential areas. Mapping the provision of street tree ecosystem services could help to prioritize areas for new planting by identifying streets or street sections with low shading. Moreover, MSPA was also employed in two studies (Table2) with the aim of quantifying urban sustainability in the context of the planning and management of UGSs.

3.4.5 Overall UGSs mapping

Our review showed that previous studies have examined a wide range of aspects of overall UGSs mapping (Table2). Studies have concentrated upon urban vegetation mapping (all types of vegetation covers) and urban tree mapping. This is consistent with previous research showing the importance of establishing a database on the spatial distribution and abundance of UGSs which could play a significant role in supporting existing sustainable urban regulations and may emerge as an indicator of the degree of urban quality (Van de Voorde *et al.*, 2008).

Beyond mapping, characterizing biophysical parameters and types of UGSs are of central importance in the smart management of UGSs (Jensen *et al.*, 2009). However, there are only a small number of studies making use of remote sensing technology for such purposes (Table2). For example, Ren *et al.* (2015) estimated canopy density, basal area and leaf area index using remotely sensed vegetation indices. Despite gardens being important urban ecosystems, there were only two studies which focused specifically on this type of UGS (Baker *et al.*, 2018; Haase *et al.*, 2019). This may imply that there are difficulties in extracting detailed information on the precise land use characteristics of UGSs from remotely sensed imagery.

3.4.6. Species mapping

Managers of urban areas are interested to know about vegetation species to maintain UGSs appropriately and more importantly to protect UGSs from invasive species. Previously, species mapping in UGSs species was challenging and costly because it was based on field surveys. However, urban managers and scientific communities are now able to identify vegetation species within urban regions in an accurate and timely way through remote sensing technology. As shown in Table 2, the dominant research focus has been to identify urban tree species. The popularity of this topic could be attributed to the dominance of tree cover in almost all cities. Therefore, tree covers can be detected readily compared to other types of vegetation. Shrub detection has also been studied (Table 2). Such research was mainly conducted for detecting invasive vegetation within urban regions. It is also noteworthy that some studies have quantified atmospheric and phenological effects on species detection from remote sensing.

3.4.7.Three-dimensional modeling

This group of studies covers the analysis of the vertical characteristics of UGSs, and using such information to establish three-dimensional models. Such studies are based on LiDAR data and a combination of LiDAR and high spatial resolution imagery. For example, Caynes *et al*. (2016) quantified the relative density of vegetation within different vertical strata using LiDAR data. They also calculated the foliage height diversity for each raster cell to characterize the vertical complexity of vegetation in UGSs. Moreover, several models using vertical information derived from remote sensing were developed to estimate the volume of UGSs. For instance, Hetch *et al*.(2008) developed a model based on fuzzy logic techniques and LiDAR point clouds to estimate UGS volume.

Table 2

Thematic areas of application of remote sensing in the context of UGSs

4. Discussion

4.1 Future technical requirements

The findings of this review showed that the amount of scientific literature relevant to remote sensing-assisted analysis of UGSs has been increasing rapidly since 2000. This trend demonstrated the significant contribution of the science of remote sensing to the monitoring, planning and management of UGSs. The review revealed that the analysis of fine scale remotely sensed data lies at the core of much work on UGSs. Fine scale remotely sensed data offer a wealth of detailed information that may be used to answer a wide range of critical questions related to UGSs. In addition, LiDAR data, ultra-high spatial resolution imagery, hyperspectral data and Google Earth Products provide a spectrum of useful information which can be used stand alone or in combination. Although the remote sensing of UGSs has matured considerably, there is scope for significant further development. The key concerns that have been identified based on the review are presented below.

- Presence of shadow in high spatial resolution imagery can reduce the accuracy of UGSs mapping (Zhang and Qiu, 2012; Merry, 2014). Considerable further research is therefore needed for recovering information from areas under shadow or at least to minimize the effects of shadow.
- Compared to species detection (Table 2), studies on the use of hyperspectral information in UGSs such as public parks and urban gardens are currently still in an early experimental stage. Spectra of UGSs respond to a mixture of different types of vegetation species and urban materials (Jense, 2012). Future research should improve the understanding of the reflectance characteristics of vegetation covers in such environments. Ultimately, this could facilitate accurate species mapping, invasive plant detection, health assessment, and above all, smart management of UGSs.
- There is a need to develop methods for extracting informative and intelligent information from Google Street View, for example, species characteristics and the quality of UGSs as might be perceived by users of the spaces.
- Existing mapping approaches may not be sufficient to capture the complexity of the UGSs such as mapping private gardens and yards. More advanced techniques such as fractional approaches (Haase *et al.*, 2019), deep learning algorithms (e.g., DenseNet (Hartling *et al.*, 2019)) and hybrid frameworks (Liu and Wu, 2018) could be used as alternative methods for achieving this.
- Copernicus, Landsat and Google Earth data policies guarantee continuous data acquisition and dissemination for decades. This capability is triggering a shift from single image analysis to time series processing. Novel approaches must be established to optimally analyze the temporal characteristics jointly with spatial and spectral information within these images.
- Since GEE is composed mainly medium spatial resolution imagery, developing new approaches for quantifying small UGSs patches based on GEE platform should be addressed in future studies.
- While this review covered the contributions of remote sensing in studies of UGSs, we did not review the detailed technical aspects. A robust evaluation of all algorithms used in the reviewed studies would require a standardized setting with respect to targeted topics which is beyond the scope of this research. Future research should, therefore, review the analytical approaches used in the application of remote sensing in USGs studies, such as the techniques used to model leaf area in urban regions or to detect changes in UGSs.
- Although several studies have indicated that SAR imagery could be of value in urban land cover mapping (e.g.,Ban *et al.*, 2010; Niu and Ban, 2013; Werner *et al.*, 2014; Zhang *et al.*, 2018; Zhang and Xu, 2018), the potential of such data specifically in studies of UGSs seems to be under-examined. Given the increasing availability of high quality SAR data, notably Sentinel-1A data from the Copernicus programme, there is now a timely opportunity to explore the contributions of these data in studies of UGSs.
- Although many research endeavors have been oriented towards applications of GEE in study of UGSs, there is a great need for providing a comprehensive comparison (e.g. systematic review) among a range of techniques in GEE in terms of analyzing UGSs.

- Small-scale UGSs, when considered in their totality, can represent a significant amount of urban spaces. In this view, the result of the present review was consistent with previous research (Wang *et al.*, 2018; Haase *et al.*, 2019) showing that remote sensing of UGS has tended to overlook the analysis of small-scale UGS. Therefore, more research is needed to quantify small-scale UGSs.

4.2 A potential framework for future applications of remote sensing in the context of UGCs

The utility of remotely sensed data for investigating UGSs has been explored in this paper. It has been demonstrated that the remotely sensed data offer a valuable source of information that allows researchers and managers working with UGSs to move beyond traditional methods and tackle large scale problems. However, for this potential to be realised it will be crucial to follow a suitable framework in order to appropriately conduct scientific or engineering projects based on remote sensing of UGSs. For example, Fig. 5 presents the potential nested architecture for designing projects that apply remote sensing to UGSs. In this architecture, forging a link between research or management objectives and satellite sensors is essential and this could be obtained through a thorough understanding of user demands. Accordingly, if a project focuses on large scale UGSs mapping with less details (e.g., UGSs and non-UGSs) medium spatial resolution imagery such as Landsat and Sentinel data are worth exploring for the initial step. However, if a project demands fine scale details, other remotely sensed data can be integrated. This architecture ends with obtaining ultra-detailed maps, which offer information such as documenting the number of urban trees, number of gardens and their health status, which may demand the use of detailed imagery from sensors on board UAVs (Liang *et al.*, 2017).This architecture holds potential as a means of maximizing the efficiency of using remotely sensed data to analyze UGSs whilst minimizing costs, and potential errors; thereby achieving sustainable management of UGSs.

Fig.5. A possible nested architecture for remote sensing of UGSs

5. Conclusion

Monitoring the overall magnitude, trends and spatial patterns of UGSs is critical for designing effective schemes to improve the environmental conditions within cities, and for the sustainable management of urban vegetation. This review aimed to highlight the role of remote sensing technology in this respect, and thereby, serve as a potential guide to managers and researchers. A systematic review of the literature was established to succinctly summarize and analyze: trends in the remote sensing of UGSs over space and time, remotely sensed data considerations in the context of UGSs, methods for extracting information on UGSs from remotely sensed data and the different thematic application areas for remote sensing of UGSs.

The review indicated that studies have employed various types of remotely sensed imagery to extract key parameters necessary to analyze UGSs regions. The data used were found to consist of two main classes. Firstly, satellite imagery at medium spatial resolution. Here, sensors such as Landsat, and Sentinel (optical sensors) have contributed significantly to the capabilities in overall mapping of UGSs and change detection using time series archives. Such data offer the benefits of requiring less complex of image processing techniques and being free to access. However, the spatial resolution of these sensors hinders the process of detecting fine scale characteristics of UGSs in complex urban regions. In contrast, sensors with high and ultra-high spatial resolution (e.g., IKONOS) have offered fine scale information (e.g., urban street tree detections (Tanhuanpaa *et al.*, 2014), monitoring subtle change within USGs (Wang et al., 2018)) in studies of USGs. A number of studies have employed LiDAR, hyperspectral and other data sources in order to determine specific characteristics of UGSs.

The review also undertook in-depth analysis of the image processing approaches employed to derive information on UGSs. The techniques used include hybrid approaches, fraction analysis, land cover indices, per pixel classification, point sampling, visual interpretation, analysis of pre-existing maps and deep learning. The review suggested that researchers selected their methodologies based on the complexity of the project. For example, land cover indices may be sufficient to obtain information on the general pattern of UGSs while mapping street trees may need a hybrid approach. Thus, in this respect, project demands determine remotely sensed data types and corresponding processing requirements.

A critical part of the review was to consider the different thematic applications of remote sensing in the context of UGSs. The findings showed that overall UGSs mapping and species mapping are the dominant applications while less attention has been given to other aspects. It is likely that the aforementioned applications can be handled easily, for example by being less reliant on field campaigns and having easy access to the data sources, compared to other application areas such as biomass and carbon estimation where data for calibrating and validating remote sensing techniques is more difficult to acquire.

Although the remote sensing of UGSs has matured considerably, some major considerations remain:

(1) Further work is needed to develop processing techniques that overcome or reduce the effect of shadow in urban images.
(2) Research efforts towards developing temporal approaches to analyze changes in a range of different properties of UGSs should be increased.
(3) There is a great need to develop more effective analytical approaches for the use of remote sensing across a range of thematic applications related to USGs, such as change detection, ecosystem services and species mapping.
(4) Despite small-scale UGSs such as gardens being important in urban ecosystems, there were only few studies which focused specifically on this type of UGSs. Therefore, further research is needed to quantify small-scale UGSs.

Standing on the edge of a paradigm shift from remote sensing science to application level, it is important that those with expertise in UGSs bring their expertise into remote sensing science so as to introduce innovative approaches for solving UGSs problems. Moreover, we encourage efforts within the UGSs community to share data and techniques for dealing with the challenges presented by UGSs for the years to come.

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Figures

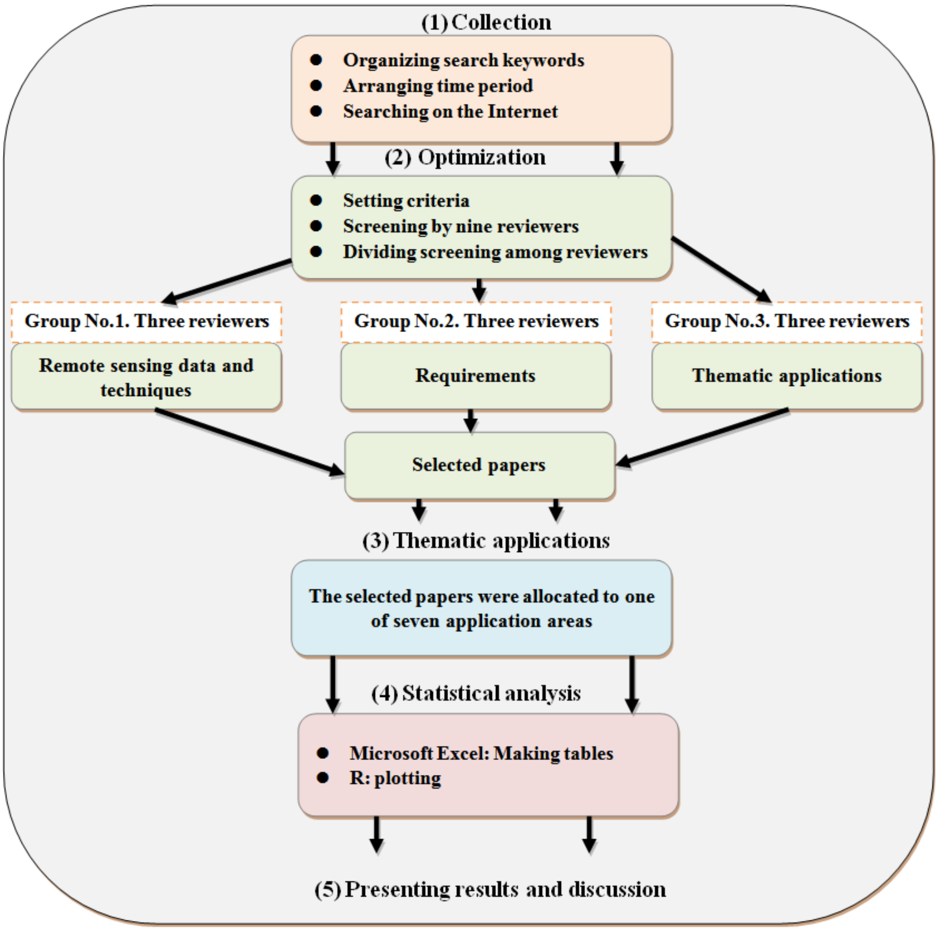

Fig.1. Flowchart of the systematic review method

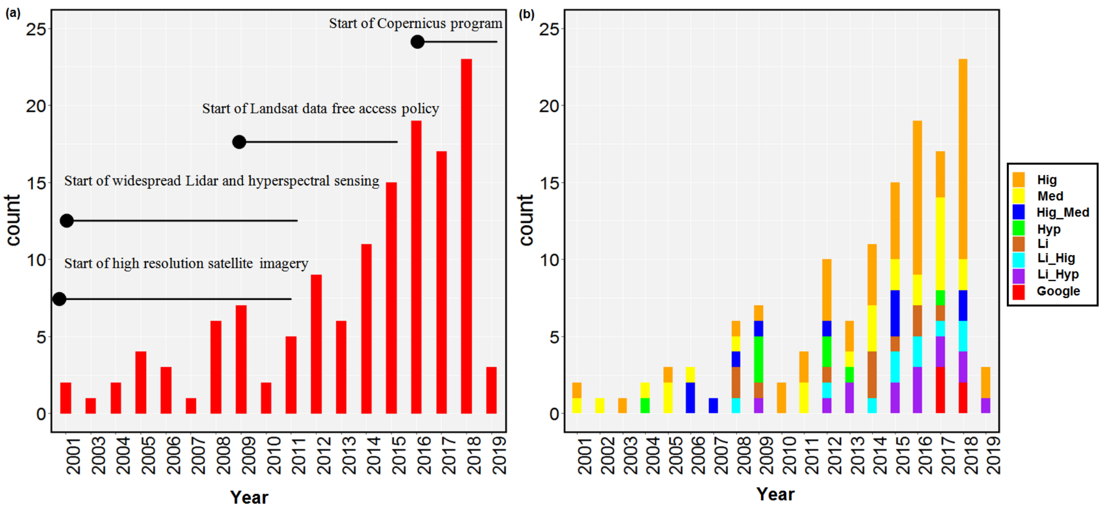

Fig. 2, (a) number of publications using remote sensing to study UGSs, annually from 2001 to 2019.Annotations show four key developments in remote sensing; (b)number of publications exploiting the key developments in remote sensing. Note that Google refers to Google Earth products; High spatial resolution (Hig); High spatial resolution & Medium spatial resolution (Hig_Med); Hyperspectral (Hyp); LiDAR(Li); LiDAR & High spatialresolution (Li_Hig); LiDAR & Hyperspectral (Li_Hyp); Medium spatial resolution(Med).

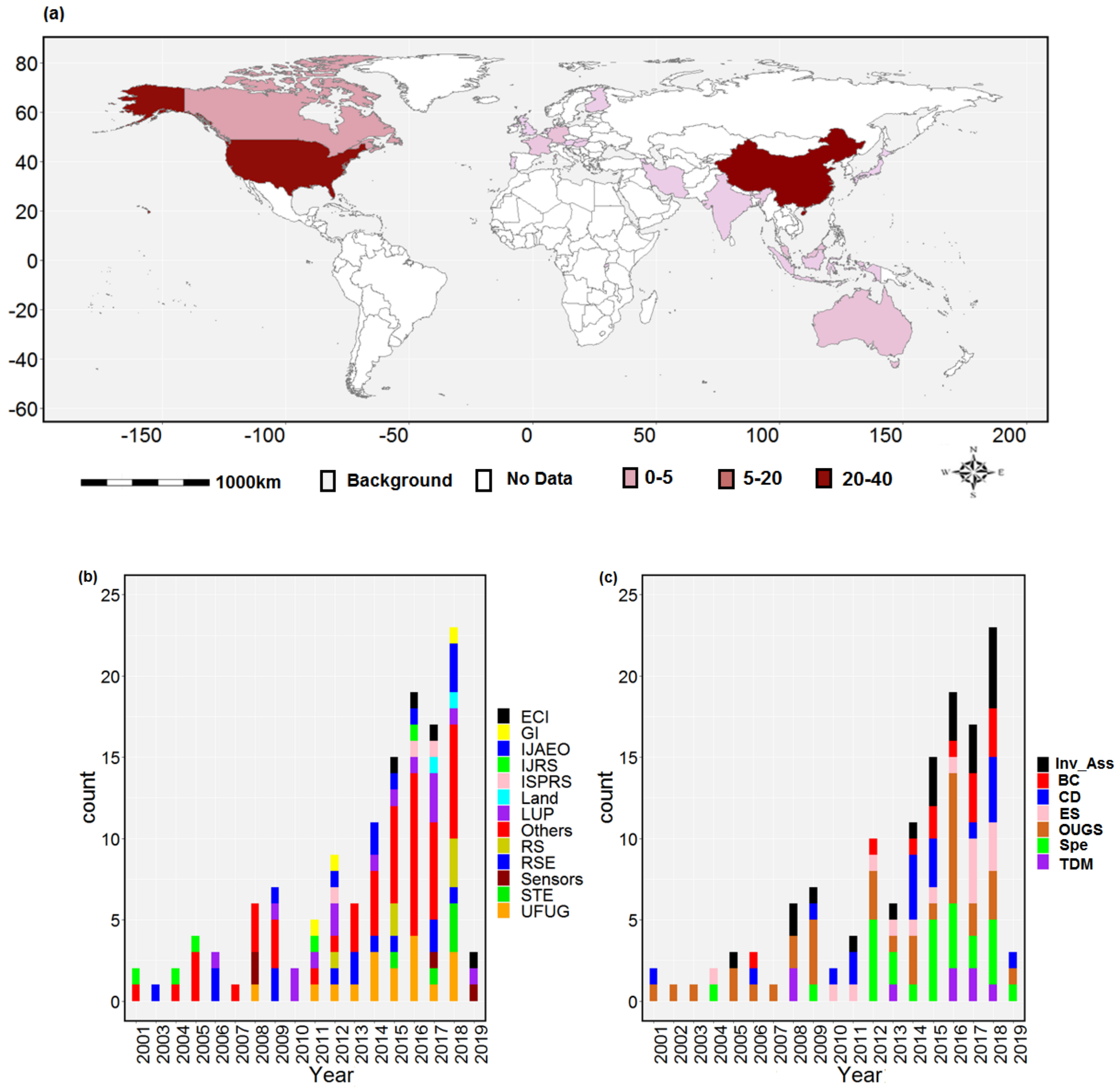

Fig.3. (a)World map presenting where the 136 selected articles has been conducted throughout the world(per country publication);(b) frequency of publication according to the year; Ecological Indicators (EI); Geocarto International (GI);International Journal of Applied Earth Observation and Geoinformation (IJAEO); Internationa Journal of Remote sensing (IJRS); ISPRS Journal of Photogrammetry and Remote Sensing(ISPRS); Landscape and Urban Planning (LULP);Remote sensing (RS);Remote Sensing of Environment(RSE); Science of the Total Environment (STE);Urban Forestry&Urban Greening (UFUG); (c) frequency of use of thematic application area to year; Inventory and assessment (Inv_Ass);Biomass and carbon (BC);Change detection (CD); Ecosystem services (ES):Overall UGSs mapping (OUGS);Species mapping (Spe);Three-dimensional modeling (TDM)

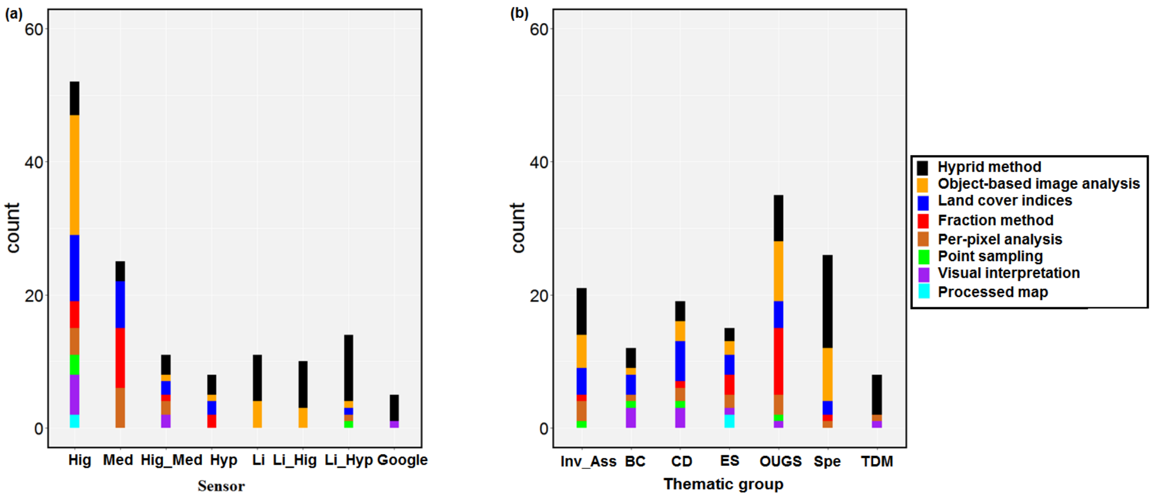

Fig.4.Different techniques to characterize UGSs: (a) frequency of use of techniques according to type of remotely-sensed data, and (b) frequency of use of techniques according to application area

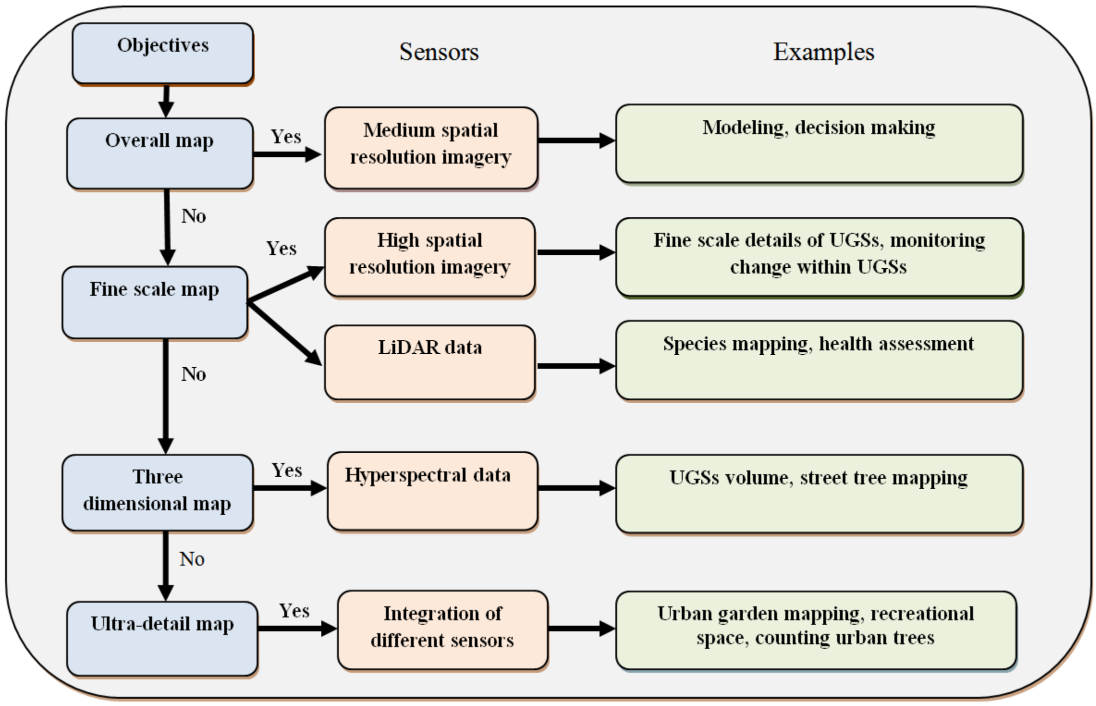

Fig.5. A possible nested architecture for remote sensing of UGSs

Tables

Table 1

Criteria used to select publications for review in this research

Key words within abstract	"Urban forest" OR "Urban vegetation" OR "Urban green space" AND "Satellite sensor image" OR "Remote sensing" AND "Review"
Document Type	Journal papers, conference proceedings, book chapters
Peer-review status	Only peer-reviewed material
Language	English
Publication date range	1980-2019
Publication status	SCIE, SSCI

Table 2

Thematic areas of application of remote sensingin the context ofUGSs

Thematic application area	Core of analytical approach	Number of studies	Literaturesources
Inventory and Assessment	Models based on LiDAR information	3	Mak and Hu (2014),(Plowright *et al.*, 2015), Plowright *et al.* (2016)
	Modeling chlorophyll content and leaf area index	1	Degerickx *et al.* (2018)
	Geo-spatial modeling	4	Yang *et al.* (2009), Bardhan *et al.* (2016),Ucar *et al.* (2016),Huang *et al.* (2018a)
	Phenological evaluation	1	Dhami *et al.* (2011)
	Mapping the health of UGSs	4	Xiao and Mcpherson (2005), Asmaryan *et al.* (2013),Nasi *et al.* (2018),Nouri *et al.* (2018)
	Assessment of spatial resolution	1	Sun *et al.* (2017)
	Other type of assessment	4	Heritage tree assessment,Thaiutsa *et al.* (2008); UGS benefits, Li *et al.* (2015b); Tree measurement density,Jiang *et al.* (2017); Measurement of tree shade provision,Li *et al.* (2018)
Biomass and carbon estimation	Modeling	11	Myeong *et al.* (2006),Liu and Li (2012),Pasher *et al.* (2014),Yao *et al.* (2015),McGovern and Pasher (2016),Raciti *et al.* (2015),Zheng *et al.* (2017),Chen *et al.* (2017b),Mitchell *et al.* (2018),Lv *et al.* (2018),Amoatey *et al.* (2018)
Change detection	GIS and Landscape metrics analysis	14	Zhou and Wang (2011),Gan *et al.* (2014),Kong *et al.* (2010),Tian *et al.* (2011),Qian *et al.* (2015),Rafiee *et al.* (2009),Zhou *et al.* (2018),Kong and

			Nakagoshi (2006),Zoran *et al.* (2015),Solange (2015),Fung and Siu (2001),Sun *et al.* (2019),Merry *et al.* (2014),Kord *et al.* (2014)
	Maximum information-based nonparametric exploration	1	Yang *et al.* (2014)
	Object metrics	1	Wang *et al.* (2018)
	Model	3	Ossola and Hopton (2018),Handayani *et al.* (2018b),Chen *et al.* (2017a)
Overall UGSs mapping	Classification(Street tree mapping)	6	Tanhuanpaa *et al.* (2014),Goodwin *et al.* (2009),Puissant *et al.* (2014),Ardila *et al.* (2012),Seiferling *et al.* (2017),Parmehr *et al.* (2016)
	Classification(Urban vegetation mapping)	27	Hofle *et al.* (2012),Behling *et al.* (2015),Van de Voorde *et al.* (2008),Zhu *et al.* (2005),Dennis *et al.* (2018),Liu and Yang (2013),Rosina and Kopecka (2016),Small (2001),Lu *et al.* (2017),Kopecka *et al.* (2017),Small (2005),Vatseva *et al.* (2016), Lv and Liu (2009),Franke *et al.* (2009),Iovan *et al.* (2008),Li *et al.* (2016),Santos *et al.* (2016),Zylshal *et al.* (2016),Yan *et al.* (2018),Rougier *et al.* (2016), Feng *et al.* (2015),Small (2003),Yu *et al.* (2016),Liu *et al.* (2016),Gupta *et al.* (2012),Small and Lu (2006),Zhang *et al.* (2007)
	Classification(Charaterizing UGSs)	4	Jensen and Hardin (2005),Jensen *et al.* (2009),Han *et al.* (2014),Ren *et al.* (2015)
	Classification(Urban garden mapping)	2	Baker *et al.* (2018), Haase *et al.* (2019)
Ecosystem services	Model	6	Jensen *et al.* (2004),Mei *et al.* (2018),Kanniah (2017),Franco and Macdonald (2018),Lwin and Murayama (2011),Wang *et al.* (2016),
	Policy investigation	7	Yu *et al.* (2017),Senanayake *et al.* (2013),Van de Voorde (2017),Landry and Pu (2010),Tian *et al.* (2014),Richards and Edwards (2017),Sung (2012)

	Morphological spatial pattern analysis	2	Chang *et al.* (2015),Wei *et al.* (2018)
Species mapping	Classification(Gradient analysis)	1	Gu *et al.* (2015)
	Classification(Tree species)	20	Liu *et al.* (2017),Zhang and Qiu (2012),Dian *et al.* (2016),Alonzo *et al.* (2014),Liu and Wu (2018),Alonzo *et al.* (2013),Jensen *et al.* (2012),Pu and Liu (2011), Pontius *et al.* (2017),Pu and Landry (2012),Shojanoori *et al.* (2016),Zhang and Hu (2012),Zhou *et al.* (2016),Mozgeris *et al.* (2018),Pu *et al.* (2018),Tooke *et al.* (2009),Tigges *et al.* (2013),Hartling *et al.* (2019),Shojanoori *et al.* (2018),Li *et al.* (2015a)
	Classification(Shrub mapping)	2	Chance *et al.* (2016),Singh *et al.* (2015)
	Classification(Effects of atmospheric correction on species detection)	1	Pu *et al.* (2015)
	Classification(Seasonal effect)	1	Voss and Sugumaran (2008)
Three-dimensional modeling	Quantification	4	Cheng *et al.* (2017),Caynes *et al.* (2016),Liang *et al.* (2017),Omasa *et al.* (2008)
	Green Volume	4	Yu *et al.* (2016),Huang *et al.* (2013),Hecht *et al.* (2008),Handayani *et al.* (2018a)