Assessing environmental impacts of urban growth using remote sensing

John Trinder and Qingxiang Liu

School of Civil and Environmental Engineering, University of NSW, Sydney, Australia

ABSTRACT
This paper provides a study of the changes in land use in urban environments in two cities, Wuhan, China and western Sydney in Australia. Since mixed pixels are a characteristic of medium resolution images such as Landsat, when used for the classification of urban areas, due to changes in urban ground cover within a pixel, Multiple Endmember Spectral Mixture Analysis (MESMA) together with Super-Resolution Mapping (SRM) are employed to derive class fractions to generate classification maps at a higher spatial resolution using an Artificial Neural Network (ANN) predicted Wavelet method. Landsat images over the two cities for a 30-year period, are classified in terms of vegetation, buildings, soil and water. The classifications are then processed using Indifrag software to assess the levels of fragmentation caused by changes in the areas of buildings, vegetation, water and soil over the 30 years. The extents of fragmentation of vegetation, buildings, water and soil for the two cities are compared, while the percentages of vegetation are compared with recommended percentages of green space for urban areas for the benefit of health and well-being of inhabitants. Changes in Ecosystem Service Values (ESV) resulting from the urbanization have been assessed for Wuhan and Sydney. The UN Sustainable Development Goals (SDG) for urban areas are being assessed by researchers to better understand how to achieve the sustainability of cities.

1. Introduction

It has been recognized that actions by humans are modifying and altering the energy and mass exchanges that occur between atmosphere, oceans and biota, and researchers now understand that these changes could be beyond the resilience of natural systems to absorb. As well, the growth of cities is causing increasing stress on many aspects of the urban environment. Sustainable development has been proposed for many years as a means of ensuring that human impacts are within the capacity of the Earth’s environment to cope with changes. The UN Economic and Social Council reported in 2017 (United-Nations 2017a) that 54% of world’s population lives in cities; urban population that lives in developing country slums fell from 39% in 2000 to 30% in 2014; cities are becoming less dense; urban sprawl is challenging more sustainable patterns of urban development; from 2000 to 2015 the expansion of urban land outpaced the growth of urban populations; and in 2014, 9 of 10 people who live in cities were breathing air not compliant with World Health Organization (WHO) safety standards. There are various ways to identify patterns of settlement in cities around the world. (Yang et al. 2019), who studied trends in social media in a number of cities in USA and also elsewhere, found similarities in social media responses for regions at similar levels of urban hierarchy. (Chaiyapon 2018) used an Inverse S-shape Rule to analyze urban land density in four towns in North Eastern Thailand in two periods, and compared them with pixel-based classifications. All cities increased in density over time, but the patterns of change varied between the cities. The paper demonstrated that urban density function is useful for studying variations in land densities. (Shao et al. 2019) studied the urban dynamic impact of rainfall and runoff changes over the whole of the urban hydrological environment in Wuhan, China and demonstrated that run-off increases for increasing permeability, leading to significant levels of run-off for high levels of urbanization.

This paper aims to determine the changes in land uses due to urbanization in two cities, Wuhan in China and western Sydney in Australia, by classifying Landsat images over a 30-year period in terms of buildings, vegetation, water and soil and then determine the extent of fragmentation in land uses over the period. A review will be given in Section 2 of methods used for the analysis of urban land cover which involves a large proportion of impervious surfaces, using Landsat medium-resolution remote sensing images. The methods of classification of medium resolution images for urban areas include Spectral Mixture Analysis (SMA) leading to the method used in this paper, Multiple Endmember Spectral Mixture Analysis (MESMA), together with the implementation of Super-Resolution Mapping (SRM) based on Artificial Neural Network (ANN) predicted Wavelet method. Section 3 will review issues of sustainability of
urban areas and the importance of green space for the health and well-being of residents and provide recommendations for minimum levels of green spaces in urban areas. Section 4 will introduce the two cities for consideration of the impacts of urbanization over a 30-year period, Wuhan in China, and western Sydney in Australia, the Landsat data used and describe the implementation of MESMA and SRM methods in detail for the classifications in terms of buildings, vegetation, water and soil. Since urbanization causes fragmentation in vegetation areas, the classified images are analyzed using IndiFrag software to determine the level of fragmentation of land covers in the two cities. Section 5 will compare the indices extracted from the classified Landsat images by IndiFrag software for the two cities, while suggestions are made in Section 6 that Ecosystem Service Values (ESV) could be used to assess the impacts of urbanization in the two cities. The paper concludes that more studies are required to determine how cities can be sustainable in the future, which is proposed to be addressed in the UN Sustainable Development Goals and Agenda 2030 (United-Nations 2017b).

2. Urban land cover classification from Landsat data

Many papers have been published on the topic of urban land cover analysis from remote sensing technologies over the past 40 years. These studies have adopted the best data available at the time, whether it was medium-resolution data, such as that available from Landsat satellites, or high-resolution satellites which became available after the launch of the first high resolution satellite, IKONOS II in 1999. Since Landsat images are the only sources of continuously available images from the 1980s to the present, they have been used by many researchers for long-term studies of land use and urban land use changes, which was demonstrated by (Zhang and Kirby 2000) while (Guobin and Blumberg 2004) used ASTER data combined with GIS data to extract open spaces in urban areas. (Wu et al. 2015) studied the application of the variogram in image classification of high-resolution images at the rural-urban continuum, while (Guan et al. 2017) presented methods of high-resolution image classification in urban areas. Given that urban land cover comprises large sections of impervious surfaces, a comprehensive review of the applications of remote sensing data for analysis of impervious surfaces was given in (Weng 2012), in which it was shown that 184 articles had been published in journals and conferences from 1991–2010 with 2157 citations, the majority of these publications since 2003. Land cover analysis of Landsat data representing impervious surfaces has been widely based on SMA on a single endmember or a combination of two or more endmembers, while multiple endmember methods such as MESMA, as described in more detail below, and some subsequent variations, involve the selection of endmembers which are evaluated according to their ability to model the spectra in the classes. The so-called “per-pixel vs. sub-pixel debate” was also reviewed in (Weng 2012) which arises because mixed pixels occur in medium-resolution images of urban areas. A number of approaches have been developed to resolve the mixed pixels, including neural networks, also studied by (Liu and Jiao 2002) and (Wu and Li 2002) and although more consistent classifications could be obtained by some of these methods, the disadvantages are said to be “black box” technology, slow learning and classifications (Weng 2012). A Multi-Layer Perceptron feed forward network with the back-propagation learning algorithm was employed in (Weng and Hu 2008) as a sub-pixel image classifier to estimate impervious surfaces in Indianapolis USA, and marginally improved accuracies were achieved for classifications of impervious surface mapping for ASTER and Landsat ETM+ images. In (Du et al. 2014) a four-stage process was developed for change detection of Landsat Thematic Mapper and CBERS data, which included: spectral unmixing; differential information generation from endmembers; change determination based on fusion strategies for combining information; and change intensity analysis. The approach led to the overall accuracies of change detection of the order of 90%. An alternative approach to managing mixed pixels in this paper is to undertake SRM.

SRM aims to produce land cover classification maps at a finer scale than the original course-resolution images based on the assumption of spatial dependence, i.e. spatially close pixels/sub-pixels are more likely to be similar than spatially distant ones. Through SRM, each pixel is evenly divided into $S^2$ sub-pixels and each sub-pixel is assigned to a unique class label. $S$ is a scale factor which defines the ratio between the scales of the original image and the target classification map at sub-pixel scale. Given a class fraction map, SRM aims to predict the spatial distribution of pure sub-pixels within each pixel according to their proportions within the pixel. It has been demonstrated in a number of research works (Mertens 2008; Mertens et al. 2006; Tatem et al. 2002) that SRM can produce classification maps at a sub-pixel level. Readers are referred to (Mertens 2008) for more details of SRM. So far a number of SRM models have been developed, such as subpixel/pixel spatial attraction models (Mertens et al. 2006), Hopfield neural networks (Tatem et al. 2002) and Markov random field-based model (Kasetkasem, Arora, and Varshney 2005). In this work the Artificial Neural Networks Predicted Wavelet Transform (ANN WT) method (Mertens et al. 2004) is employed. The experimental
results from (Mertens et al. 2004) indicated that ANN WT method generally performed better than the other two models. This method was also found to be the most accurate SRM method for coastal and shoreline mapping in (Liu, Trinder, and Turner 2016).

There has been limited research on combining a process of endmember selection and super-resolution mapping. Five super-resolution methods were tested in Chan et al. (2010) with the conclusion that super-resolution of 18 m resolution CHRIS/Proba images “might be more effective than the original data in various applications”. An interpolation method of the super resolution was applied to CHRIS/Proba images in Demarchi et al. (2011) to improve the resolution of the images by a factor of 2, then a number of models were used for the selection of endmembers for a MESMA approach. The authors suggested that super-resolution approach may be useful when determining impervious surfaces in an urban environment and that the MESMA model that favors fewer endmembers leads to higher accuracy of unmixing. A Selective Endmember Spectral Mixture (SESM) model was developed in (Wu et al. 2011) Wu et al. (2011) for determining endmembers on hyperspectral images over The Mall in Washington DC and then a backpropagation three layer neural network was applied to the soft classification to achieve super-resolution mapping. The authors claim that there were considerable increases in accuracy by this newly developed method compared with hard classification. Comparisons were made in terms of overall accuracy (improved from about 86% to about 93%), Kappa coefficient (from 0.81 to 0.91), class accuracies and commission errors. From this limited set of papers in which spectral mixture models were applied for endmember selection together with super-resolution, there are indications that the implementation of these procedures for an urban environment should lead to the improved classification of the Landsat images for urban areas studied in this paper. This is the novel aspect of the image classifications presented in this paper, and results below confirm that improved accuracies are achievable by the application of MESMA and SRM.

Some recent studies using medium-resolution images have included (Liu et al. 2016) which used a total of 912 medium-resolution remotely sensed images from various sources, including Landsat TM/ETM+ to determine growth patterns in Chinese cities based on visual interpretation, as was also the case with (Zeng et al. 2015a). Pixel-based Random Forests were used for classifying Landsat andSentinels 1 and 2 images in (Goldblatt, Deininger, and Hanson 2018) for determining urban growth in Ho Chi Minh City in Vietnam with limited accuracy, while (An et al. 2018) used pixel-based SVM to determine rapid changes in Hangzhou, China from 1990 to 2017 and reported high overall accuracy.

### 3. Sustainability of urban environments

A sustainable city, eco-city (also called “ecocity”) or urban area, is stated as being a city designed with consideration of the three pillars of sustainability, namely social, economic, environmental impact, and as a resilient habitat for existing populations, without compromising the ability of future generations to experience the same conditions. Cities themselves are unsustainable according to (Berger 2014) and "built in contradiction to nature, unlike rural living within nature”. The benefits of exposure to green space in urban environments has been described by many authors (Cox et al. 2018; Ekkel and de Vries 2017; Mennis, Mason, and Ambrus 2018; Shanahan et al. 2017; Twohig-Bennett and Jones 2018; van den Bosch et al. 2015; Wolch, Byrne, and Newell 2014). American Forests (Leff 2016b) in the past gave examples of recommended minimum levels of tree cover, but no longer does so. However, it does provide examples of existing tree cover and goals for tree cover varying from 20% to 70%. Leading international city targets for canopy cover include: London – 20% to 25% (Greater-London-Authority 2015) in 2025, Chicago – 17% to 25% by 2040, Toronto – 27% to 40% by 2060, Seattle – 23% to 30% by 2037 (Leff 2016a), although direct comparisons cannot be made between different cities, because each city has different factors affecting its urban forest. The City of Sydney, Australia, plans on a minimum of 15% green space for the central business district (CBD)/City-of-Sydney 2017.

China has experienced rapid and unprecedented levels of urbanization (Yusuf and Saich 2008), the scale of which has never before been seen in history. There are numerous papers describing the development of urban areas in China over the past 30 years. (Chen 2002) described the geo-hazards in China’s urban areas; (Zhang, Zhang, and Na 2009) demonstrated the advantages of applying geostatistics to quantifying uncertainty in classifications; (Nong and Du 2011) studied the pattern of urban growth by logistic regression to understand the drivers for urban growth; (Liu et al. 2016) described the growth of 57 cities (including Wuhan), mainly in the eastern half of China, over the period of 4 decades, where it was stated that urbanization in China from 1987 to 2013 had increased from “17.92% to 52.57%” and is predicted to increase to 70% by 2030. In (Jiang, Deng, and Seto 2013) connections between urban development, agricultural land and agricultural production have been outline, as well as the sustainability of land resources in the presence of urban development and needs for sufficient agricultural land. (Kuang et al. 2016) provided figures on the rapid industrial and urban land-use changes over a period of 20 years. Land-use changes in Wuhan, China, in (Zeng et al. 2015a) and (Sun et al. 2016) revealed a general
deterioration in vegetation cover and growth of impervious areas for the expansion of residential areas over most of the period from 1991 to 2013. In (Zeng, Zhang, and Xu 2016) some of the driving forces for the rapid urbanization in Wuhan have been listed as: urban sprawl; rural migration; socio-economic and transportation developments; and spatial interaction of counties that has been essential for realizing regional urbanization. In the study of changes in urbanization, change detection is often an essential task for decision-makers. Studies such as those of (Sui and Li 2001) described a framework for change detection, and (Li, Sui, and Xiac 2003) who described some procedures for change detection from various data sources. The impacts of land-use changes on food security were raised as early as 2000, when (Li 2000) presented contributions remote sensing data could make for ensuring future food security.

Populations of cities will continue to increase around the world, possibly reaching 8.5 billion by 2030. While green space is clearly not the only measure of sustainability it has been shown that it is an important component of sustainable cities. Consequently, decision-makers in parts of Europe, USA and Australia have concluded on the recommended minimum green spaces for cities given above. A fixed figure would not be relevant for all cities as expressed above, but in the context of decreasing green spaces in cities, based on the above figures, this paper will assume that a desired minimum green cover as recommended for Sydney (City-of-Sydney 2017) should be of the order of 15% to 20% in CBDs and industrial areas, 25% to 30% in residential and light commercial areas, and up to 50% in suburban areas. These figures will be tested against the changes in green spaces, that is vegetation areas, that are measurable by remote sensing technologies, in the rapidly developing city of Wuhan, China, and the expanding western part of Sydney, Australia.

4. Materials and methods

4.1. Study areas and satellite data

Wuhan is the capital of Hubei province in the Central China region at the confluence of the Yangtze and Han Rivers, with an estimated population of over 8 million. It is composed of thirteen administrative districts, seven of which are urban central districts (Figure 1) and the others are suburban and rural districts. The seven central districts, i.e. HanYang, HongShan, JiangHan, JianAn, QiaoKou, QingShan and WuChang, are studied in this work. A dominant feature in the city is the Yangtze River which partially separates the regions such that many of the densely occupied areas are on the western side of the river, while regions on the eastern side of the river are more irregularly shaped, which causes some difficulty in assessing growth of some of the parameters on that side of the river.

The second study site is in the western suburbs of Sydney on the south east coast and the largest city in Australia with a population of over 5 million. The two cities of Sydney and Melbourne have recently been undergoing rapid expansion, due to a large intake of migrants from various parts of the world, a large proportion of whom have settled in these cities. Many Australians have traditionally lived in single dwellings on separate parcels of land which means that most cities spread over large areas. The growth of suburban Sydney extends more than 50 km westwards from the coast, and north and south from the CBD. Many of the recent housing developments in Sydney have occurred in the western suburbs shown Figure 1. The extent of the study site covers 177 suburbs and most parts of five local government areas, i.e. Liverpool, Penrith, Camden, Fairfield and Blacktown.

Seven Landsat scenes acquired between 1987 to 2017 were used for Wuhan and the acquisition dates of these scenes are shown in Table 1, while for Sydney, seven scenes acquired between 1988 to 2017 were used. The images of Wuhan were acquired in September or October for seasonal consistency, when vegetation was likely to be dense and at a similar stage of growth, and there was an absence of cloud. Likewise, for Sydney vegetation was also at a similar stage of early Spring growth. Assessments on an approximately five to 6-year basis were considered adequate for the assessment of land-use changes in both cities, and were similar to frequencies used in (Kuang et al. 2016; Sun et al. 2016; Zeng et al. 2015a, 2015b). Both datasets include five images acquired by Landsat 5 Thematic Mapper (TM) and two by Landsat 8 Operational Land Imager (OLI) sensors. The Landsat Level-2 surface reflectance products were downloaded from the United States Geological Survey (USGS) EarthExplorer website (US-Geological-Survey-(USGS)).

High-resolution images were utilized to assess the classification accuracy of SRM results. Specifically, for Wuhan, a Ziyanu-3 image acquired on 10 October 2013 (a week later than the Landsat image in 2013) and a Gaofen-1 satellite image acquired on 31 October 2017 (only 1 day later than the Landsat image in 2017) were used. Both images have four spectral bands, i.e. red, green, blue and near-infrared. The Ziyanu-3 image covers only the eastern part of the study area, while the Gaofen-1 covers most of the study area except the eastern-most part. Both images have a spatial resolution of 2 m. For Sydney, two aerial images acquired by Nearmap (Nearmap 2018) with a spatial resolution of 2.39 m and visible spectral bands of red, green and blue were utilized. These images were the mosaic of aerial photos acquired at different dates within a month from the acquisition dates of Landsat 8 sensor in 2013 and 2017.
4.2. Landsat data processing

The flow chart of processing Landsat images is shown as Figure 2. Firstly, the images were clipped according to the spatial extent of the study areas. Multiple Endmember Spectral Mixture Analysis (MESMA) (Roberts et al. 1998) was then implemented to derive class fractions within each pixel. Spectral Mixture Analysis (SMA) (Roberts et al. 1998) models each pixel as a spectral combination of “pure” land cover components or endmembers which has been widely used as a solution, based on a commonly used linear spectral model expressed mathematically as (Roberts et al. 1999):

Table 1. Experimental images used for Wuhan and Sydney.

| Satellite mission | Path / Row | Acquisition Date | Satellite mission | Path / Row | Acquisition Date |
|-------------------|------------|------------------|-------------------|------------|------------------|
| Landsat 5         | 123/039    | 26th Sep 1987    | Landsat 5         | 090/083    | 20th Sep 1988    |
|                   |            | 12th Oct 1993    |                   |            | 2nd Sep 1993     |
|                   |            | 27th Sep 1999    |                   |            | 16th Sep 1998    |
|                   |            | 24th Sep 2004    |                   |            | 14th Sep 2003    |
|                   |            | 6th Sep 2009     |                   |            | 9th Sep 2007     |
|                   |            | 3rd Oct 2013     |                   |            | 25th Sep 2013    |
|                   |            | 30th Oct 2017    |                   |            | 20th Sep 2017    |
| Landsat 8         |            |                  | Landsat 8         |            |                  |

Figure 1. (a) Regions of Wuhan studied for changes in land use. (b) Distribution of Local Government Areas (LGA) in western Sydney. Distances shown in Figures 12 and 13 are measured from the crosses in each figure. (c) Location of Wuhan in China (d) Location of Sydney in Australia.
where $R_i$ is the reflectance of band $i$ in a pixel; $f_k$ is the fraction/proportion of endmember $k$; $N$ is the number of endmembers in the pixel; $r_{ik}$ is the known spectral reflectance of endmember $k$ in band $i$; $\varepsilon_i$ is the residual term for band $i$ indicating the difference between the measured and modeled spectra. Normally the fractions are constrained by the unit-sum condition $\sum_{k=1}^{N} f_k = 1$ and the non-negative condition $f_k \geq 0$.

The process of solving Equation (1), which is called linear spectral unmixing, is assessed by the root-mean-square error (RMSE):

$$RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^{M} \varepsilon_i^2}$$

(2)

where $j$ is the number of spectral bands used for the analysis. MESMA, which is an extension of SMA, addresses the concern of using a fixed number of endmembers for the entire scene, by allowing the number and type of endmembers to vary on a per-pixel basis (Roberts et al. 1998).

To implement MESMA, candidate endmembers were firstly selected to build a spectral library. Using Google Earth images as reference, a set of pixels with known class attributes were manually selected from each Landsat image. An optimal set of spectra for all the classes were then selected from the library based on the Endmember Average RMSE (EAR), which was first proposed by (Dennison and Roberts 2003). EAR evaluates each endmember’s ability to model all the other spectra in the same class, which is calculated as the average of the RMSE:

$$EAR_{A_i} = \frac{\sum_{j=1}^{n} RMSE_{A_i,A_j}}{n-1}$$

(3)

where $A$ is an endmember; $A_i$ is the selected endmember and $A_j$ other endmembers within the same class; $n$ is the total number of spectra in the class. The endmembers with the lowest EARs within each class were considered as the optimal endmembers to represent that class. Eight endmembers were selected for built-up and vegetation, while for soil and water five endmembers were selected. The numbers of endmembers were decided primarily based on the resulting percentages of successfully modeled pixels and the maximum numbers of endmembers used in (Sun et al. 2016), which also focused on Wuhan. These numbers of endmembers were also used for western Sydney because the resulting percentages of successfully modeled pixels were also high (above 99% for five out of the seven images) and it was believed increasing the numbers of...
endmembers was unnecessary. In each pixel the optimum combination of two endmembers from the eight were determined by the RMSE (Equation (2)) and used to unmix the pixel. Besides, shadow was included as an additional component for each pixel. Spectral unmixing was then implemented to generate endmember and shadow fractions within each pixel. Shade normalization was implemented to eliminate shade fractions from the unmixing results. The MESMA was realized using Viper Tool (UCSB and Geography 2018), an open-source tool developed for the software Environment for Visualizing Images (ENVI).

Through MESMA, a map containing proportions/fractions of land cover classes within each pixel was derived, which is also called a soft classification map. Nevertheless, the spatial distribution of the classes within each pixel was not decided. In other words, the location of accurate boundaries between land cover patches was unknown, which would cause difficulty in extracting fragmentation metrics. Therefore, a Super Resolution Mapping (SRM) technique, sometimes called sub-pixel mapping was employed following MESMA. The framework is described in Figure 3 and described as follows.

It is known that applying 1D discrete Wavelet Transform decomposes a data set into wavelet coefficients, i.e. approximation and detail coefficients. Similarly, when 2D discrete Wavelet Transform is applied on a 2-D dataset such as an image, the image can be decomposed into a set of coefficient images at a coarser scale. Specifically, the coefficient images include an approximation coefficient image and three-detailed coefficient images containing details over horizontal, vertical and diagonal directions. The four new images are half the size of the original image. Inversely, the original image can ideally be reconstructed using the four coefficient images without information loss. The ANN WT method assumes there is a relationship between an approximation coefficient image and its detail coefficient images, which can be modeled by ANN (Mertens et al. 2004). In Figure 3, F, H, V and D represent the class fractional image, horizontal coefficient, vertical coefficient and

![Figure 3. Framework of ANN WT (adapted from Mertens et al. (2004)).](image-url)
diagonal coefficient images, respectively. The subscripts denote different levels of spatial resolution, i.e. $j$ represents a higher resolution than $j+1$. Firstly, a fractional image for a class $F_j$ was decomposed to a coarser resolution approximation image and coefficient images $F_{j+1}$, $H_{j+1}$, $V_{j+1}$, and $D_{j+1}$.

Secondly, ANNs were trained to model the relationship between the coarser resolution fractional image $F_{j+1}$ and coefficient images $H_{j+1}$, $V_{j+1}$, and $D_{j+1}$ respectively. For example, an ANN was trained given $F_{j+1}$ as input and $H_{j+1}$ as output. Using the trained ANNs and the original fractional image $F_j$, coefficient images $H_j$, $V_j$ and $D_j$ at resolution level $j$ were predicted. Finally the fractional image $F_{j-1}$ at higher resolution $j-1$ was reconstructed through WT using $F_j$ and the previously predicted coefficient images $H_j$, $V_j$ and $D_j$. The whole process was implemented to derive a fractional map $F_{j-1}$ for each class. A finer classification map was then derived by assigning each sub-pixel with the class that has the largest fractional value. The scale factor should be powers of two due to the nature of the ANN WT model. To implement SRM with scale factors larger than two, the described process is repeated. A scale factor of 4 was used in this work, i.e. the pixel size of the SRM results was 7.5 m.

Figure 4 shows the SRM maps in Wuhan (years 1987 and 2017) and in Sydney (years 1988 and 2017). Meanwhile, pixel-based classification maps were also derived from MESMA by assigning each pixel with the class that has the largest fractional value. Pixels with known class attributes were randomly selected from the high-resolution evaluation images referred to above (Ziyuan-3 and Gaofen-1 for the Wuhan assessment, and Nearmap for the Sydney assessment) and the class attributes were compared with those from the derived SRM maps. Class attributes of these validation pixels were obtained by visual judgment. 1000 validation pixels were selected for each of the four classes, i.e. buildings, soil, vegetation and water. Table 2 shows the evaluation measures, i.e. Overall Accuracy (OA) and Kappa coefficient (Kappa).

![Figure 4](image_url)

**Figure 4.** Comparisons of SRM results in Wuhan from year 1987 (a) to 2017 (b) and in Sydney from 1988 (c) left to 2017 (d).
for Wuhan and Sydney. The accuracies of pixel-based classification results are also indicated for comparison. While the overall accuracy and Kappa coefficient were satisfactory for the classifications of images over Wuhan, they were lower than expected for the classifications over Sydney. This could be due to the difficulty in determining endmembers for the Sydney area since buildings over the western suburbs of Sydney are based mainly on individual houses whose dimensions tend to be smaller than a Landsat pixel. Nevertheless, the accuracy of SRM results is consistently higher than pixel-based classification results for both sites.

Figure 5 shows a comparison between SRM and pixel-based classification at fine-scale with pixel-based classification results, derived by directly assigning each pixel with a class that has the largest fraction from MESMA. The locations marked with black circles highlight where the SRM results keep small object shapes better and keep more details than pixel-based results. This is important when determining the effects of fragmentation on green spaces in the two cities.

5. Land-use changes in Wuhan and Sydney from 1987 to 2017

The IndiFrag software (Sapena 2015), implemented by (Sapena and Ruiz 2015), uses data in vector format, and computes a set of fragmentation indices into five-semantic groups and multi-temporal changes. The indices can also be determined for cartographic objects at different hierarchical levels of object, class and super-object. The list of all 48 indices (some from individual classes as well as super-objects) and their formulas in IndiFrag, which were derived from about 20 different sources in the literature, are available on the referenced website. Specific fragmentation indices that were derived for this research from the classified images in terms of the four classes of buildings, soil, vegetation and water as described in the previous section are as follows:

- Objects mean size (m²): the average size of objects (m²) in a class
- Number of objects (no.) in a class or super-object (except road objects)
- Object density (no./m²): the number of objects divided by the area of each region
- Statistics of land-use change and change proportion (m²)
- Percentage growth in sectors (%) and annual growth rates (km²/year) for some of the classes.

5.1. Comparison of land-use change metrics for Wuhan and Sydney from 1987/8 to 2017

As described in Section 3, there have been numerous studies of the expansion of urbanization in China over the period from 1980s to the present decade. The previous study on land-use changes in Wuhan by Sun et al. (2016) demonstrated that Wuhan underwent major expansion from 1990 to 2013 commencing at the city’s geographic center with a circular pattern of development, connecting the separate districts and then rapidly developing areas outside the old town. They showed that the development had a significant effect on the landscape of Wuhan, leading to a loss of water areas in the early years, which was subsequently rectified, and a loss of agricultural land. This study has also revealed similar consequences of urbanization, but a major aim of this paper is to review the sustainability of cities such as Wuhan and Sydney, in terms of the impact on the growth of built-up areas on the percentage of green or vegetation areas. It is noted that China has recently elevated its environmental bureaucracy to the ministerial level in response to social pressures, economic growth, and financial investments. As well, environmental impact assessments are undertaken in Wuhan for major projects as in (Wuhan Municipal Government for the Asian Development Bank 2016). The western suburbs of Sydney are undergoing significant developments, mostly based on separate dwellings, as the population of Sydney grows and expands south westward. The issues of sustainability of the local government areas in Sydney are addressed in comprehensive policies.

Building object mean sizes (Figure 6) in Wuhan have varied across the regions from 20,000 m² to 80,000 m², but they have tended to approximately double over the 30-year period for some regions. Vegetation object mean sizes have decreased for some regions, for example in HongShan region where they decreased by a factor of about 2 to about 20,000 m², while in the JiangHan region vegetation object sizes are small. A comparison of the ratio of sizes of vegetation objects/buildings objects reveals the following decreases over the period of 30 years: QiaoKou from 50% to 15%; JiangHan from 50% to
<10% (for 1993 to 2017); QingShan from 50% to 35%; HanYang from 250% to 30%; JiangAn from 120% to 40%; in Wuchang the ratio remains at about 50%, but it deteriorated in the middle years; in HongShan the ratio decreased from 600% to 125%. Considering the recommendations in Section 3 for minimum levels of green cover, while most areas of Wuhan satisfy these recommendations, the heavily built-up regions of QiaoKou and JiangHan appear to show lower percentages than the recommended minimum of 15%, although Figure 14 demonstrates that some increases in vegetation areas have occurred in QiaoKou and
JiangHan regions since about 2009, thus partly rectifying the deterioration in the amount of vegetation areas in the dense parts of the city. In Sydney building object sizes (Figure 7) were generally smaller than in Wuhan, being of the order of 3000 to 4000 m$^2$ or larger, which is indicative of the detached buildings typical of suburban areas in Australia, while vegetation object sizes tended to decrease especially after about 2007 in the Liverpool and Camden areas. The sizes of vegetation areas were generally larger than in Wuhan, since they tend to represent undeveloped land and playing fields. The ratio of mean sizes of vegetation objects/building objects were very variable and generally above 50% and therefore of the order of the recommended minimum levels of green space for suburban areas in cities.

The numbers of building objects (Figure 8) in Wuhan increased slightly from 1987 to 2017, while vegetation objects tended to increase significantly, especially in regions Hanyang and HongShan, Jianghan where they almost doubled. This is

Figure 6. Objects mean sizes (m$^2$) for four classes of buildings, soil, vegetation and water in Wuhan.

Figure 7. Object mean sizes (m$^2$) for four classes in western Sydney. Class built-up, soil and water are indicated in the left axis and vegetation in the right axis.
indicative of greater levels of fragmentation. In Sydney (Figure 9) the numbers of building and vegetation objects have remained relatively stable in the five districts.

Vegetation objects in Wuhan (Figure 10) have become denser in all cases compared with building object densities, which also suggests a higher level of fragmentation in vegetation areas than in buildings in Wuhan. In Sydney (Figure 11), the density of building objects increased over most districts indicating a greater level of building activity, yet vegetation objects tended to remain stable. There is a significant density of soil objects in the Sydney area.

The growth and loss statistics of vegetation in Wuhan and Sydney are given in Figures 12 and 13 in which the distances are measured from the center of the areas shown in Figure 1, and the orientations of these changes at distances are marked by the circles. Similar graphs can be determined for the growth and loss in building objects but are not shown. In Wuhan significant losses in vegetation have occurred in the east of the city, while in Sydney the losses have been toward the south of the city.

Examples of percentage and areal annual rates of change in vegetation are given in Figure 14 for the more densely populated regions of QiaoKou and JiangHan in Wuhan. The changes have not been
uniform over the period from 1987 to 2017, since small increases in vegetation areas occurred during the period from 2009 to 2017 in QiaoKou and from 2004 to 2013 for JiangHan.

6. Discussion on extracted metrics for Wuhan and Sydney for the period 1987 to 2017

Table 2 and Figure 5 both demonstrate the advantage of using MESMA combined with SRM, compared to pixel-based classification. The classification accuracy was, though not considerably, improved compared to pixel-based classification, which is consistent with the few existing research papers based also on MESMA and SRM. More importantly, SRM results kept more details and better delineated small object shapes.

A consequence of urbanization in China has been the deterioration of agricultural land as outlined above in (Jiang, Deng, and Seto 2013). Agricultural areas and different types of vegetation were all considered as vegetation class in this work. In other words, conversion to agriculture and a change in the type of vegetation were not counted as vegetation loss. Nevertheless, some of these vegetation areas may still have been misclassified as other classes as a result of spectral similarity, e.g. some cultivated agricultural areas without vegetation cover can be misclassified as soil. This

Figure 10. Object density (no./km²) in Wuhan for four classes of buildings, soil, vegetation and water.

Figure 11. Object densities (no./km²) in western Sydney for four classes of buildings, soil, vegetation and water.
Figure 12. Growth and loss in vegetation objects in terms of distance (a) and orientation (b) from the center of Wuhan (km²).

Figure 13. Growth and loss in vegetation objects in terms of distance (a) and orientation (b) from the center of western Sydney.

Figure 14. Areal rates (%) of change of vegetation (a) and annual change (km²/year) (b) in QiaoKou region and JiangHan region in Wuhan from 1987–2017.
misclassification should be considered as a factor affecting the amount of vegetation changes. Climate change might contribute to vegetation loss in the long term, but it is out of the scope of this paper.

Ecosystem Service Values (ESVs), which involve assessing the values of services to humans from the natural environment and properly-functioning ecosystems that benefit humans, have been studied extensively over the past 4 decades, as described in (Costanza et al. 1997) and updated in many research publications, including (Costanza et al. 2014). The availability of GIS technologies has provided important tools to assist the process of mapping ESVs (Schagner et al. 2013). For example, (Sandhu and Wratten 2013) list the farmland and urban ecosystem services provided to humans as “provision of services, regulating services, cultural services, habitat and supporting services”. The descriptions of these services are complex, but the understanding is that if ecosystem services are diminished for any reason, such as detrimental human actions, then human well-being and ability to prosper maybe adversely affected.

In (Wang et al. 2018) the impact of urbanization on the city of Dongying in China was evaluated using Landsat images from 1995, 2004 and 2015 to obtain land cover maps and then land metrics were extracted by FRAGSTATS software (McGarigal, Ene, and Holmes 2015) in a similar manner to the work described in Section 5. A land-use map was also simulated for 2025 by Cellular Automata (CA)-Markov model in (Wang et al. 2018). The relevant ESVs for the years 1995, 2004, 2015 and projected for 2025 for Dongying, were extracted from the 17 global ecosystem services or biomes listed in (Costanza et al. 1997) and values assigned for China by (Xie et al. 2008), where buildings do not provide any ESV. (Wang et al. 2018) showed that building areas increased by 3.5 times in Dongying, while green spaces comprising farmland and grassland were reduced by 29%. Therefore, the most significant reduction in ESVs following the urbanization and the anticipated urbanization to 2025 was in “provision services”, which comprise food production and raw materials, due to losses of grassland, farmland, and water areas. The reduction in ESVs brought about by these changes in land use from 1994 to 2015, was of the order of 13%.

In order to estimate changes in ESVs for Wuhan and Sydney in this study, it was desirable to select the same ecosystems values for both areas. It was stated in (de Groot et al. 2012) that even though croplands and urban areas are human-dominated systems, they do provide ecosystem services, listed as: “provision of services, regulating services, cultural services, habitat and supporting services” (Breuste, Haase, and Elmqvist et al. 2013), and the ESVs croplands and urban areas were provided in (Costanza et al. 2014). Therefore, values in terms of $2007/ha/yr have been extracted from (Costanza et al. 2014) and assigned to the four classifications extracted in this paper in Table 3. Grassland/Rangeland/ Cropland ESVs have been determined from the average of Grassland/Rangeland and Cropland ESVs in (Costanza et al. 2014). Also, the assignment of urban area ESVs for “the buildings areas” extracted in this paper, may not reflect the true ecosystem services of urban areas, since urban areas comprise more features than simply buildings. Therefore, total ESVs for Wuhan and Sydney have been assessed for two cases of (i) vegetation + soil + water, and (ii) vegetation + soil + water + urban and displayed in Figure 15. Since there is uncertainty as to whether the ESVs of urban areas should be included for the assessment of ESVs for Wuhan and Sydney, the ESVs derived for the two cases differ significantly. The differences in the values of the ESVs for Wuhan and Sydney is a function of the sizes of the areas of Wuhan and Sydney. However, the important points to note about Figure 15 are the reductions in ESVs over the period from 1987 to 2017.

There are significant losses in ESVs in Wuhan (about 20%) and in Sydney (3%) if urban areas ESVs are excluded in the assessment of ESVs, but there is a minimum decrease in ESVs if urban areas ESVs are included. It could be concluded therefore, that including ESVs of urban areas for buildings do not recognize the detrimental effects of losses of green spaces in cities and the question remains whether buildings, considered as urban services, can compensate for the loss of green spaces in terms of ESVs, especially in Wuhan, but this is beyond the scope of this paper. The impact on the well-being of humans living in Wuhan and the western suburbs of Sydney, brought about by the reduction in ESVs would require further analysis, based on work undertaken by the many researchers in the multi-disciplinary research field of ESVs as has been undertaken by (Li et al. 2019). (Breuste, Qureshi, and Li et al. 2013) have attempted to assess the ecosystem services of parks and green spaces in several cities in Asia and Latin America and suggest that ecosystem services should become part of urban planning process, including the targets and quantities of required services.

Even though it is generally agreed that compact cities are more efficient for the provision of infrastructure, they concentrate buildings and impervious surfaces with a consequent loss of vegetation and hence green spaces. Increasing compactness beyond a certain limit is undesirable for the health and well-being of the population, as well as fauna and flora. Parts of Wuhan appear to have reached or maybe are beyond

| Ecosystem services | Equivalent classifications in this paper | 2007 $/ha/yr |
|--------------------|------------------------------------------|--------------|
| Grassland/Rangeland/Cropland | Vegetation and soil | 4867 |
| Lakes/ rivers | Water | 12512 |
| Urban areas | Buildings | 6661 |

Table 3. Values of ESV for classifications extracted in Wuhan and Sydney.
a satisfactory limit of compactness. A summary of the results of research (Cox et al. 2018; Ekkel and de Vries 2017; Mennis, Mason, and Ambrus 2018; Shanahan et al. 2017; Twohig-Bennett and Jones 2018; van den Bosch et al. 2015; Wolch, Byrne, and Newell 2014) suggests a minimum size of green space between 0.5 ha and 1 ha, which would mean that the minimum area for Wuhan should be of the order of 750 m$^2$. Likewise, accepting the recommended minimum areas of green space as proposed in Section 3 to be 15% of a region, for the average size of built-up areas in Wuhan of the order of 5000 m$^2$, the minimum size of green space is 750 m$^2$. This is achieved in most of the regions of Wuhan, except QiaoKou or JiangHan. The above listed authors also suggest that a threshold distance of the order of 300 m from green spaces is likely to have better health benefits that longer distances. This could be achievable in Wuhan if built-up areas are interspersed with green spaces, but this has not been assessed. Meanwhile planning for individual houses in western Sydney enables the provision of adequate green spaces, but often presents problems with lengthy commutes and therefore congestion, due to lack of adequate infrastructure and services in some cases. Therefore, from the point of view of impacts on greenhouse gas emissions, efficiency of services, infrastructure and public transport, compact cities are more desirable, provided they include adequate green spaces.

Wuhan is a compact city with many mid-rise and high-rise buildings, whereas Sydney is a large city with a low-density population which includes many one and two-story buildings. Neither the high-density dwellings in Wuhan nor the low-density dwellings of Sydney appear to be ideal densities. However, no absolute index appears to exist to suggest an optimum or ideal urban density of development. Housing density can be defined based on local values, socio-economic drivers, policies, culture and other contextual factors. Further investigation is needed by urban planners to determine appropriate densities of urban areas. In (Gardner 2016) it was claimed that sustainable cities “will only be possible if a new relationship between humans, energy and materials is achieved”. Nevertheless, it is essential for humans to strive for sustainable cities in the future, which should include amongst other facilities, healthy, livable and convenient design of buildings and green spaces, efficient public transport that reduces the use of private vehicles, environmentally friendly generation and efficient use of energy, minimization of impacts of cities on the hinterland and efficient disposal of waste (Alberti 1996) (Freedberg 2010). Achieving sustainable cities will be a challenge for future generations who will also have to contend with the effects of climate change, greater demands on resources as populations increase, especially food and water and many of the resources that humans rely on for their transport, communications and shelter. The assessment of ESVs will be an essential aspect of determining the sustainability of cities. As countries continue to urbanize, there is an urgency in determining how sustainability can be assessed and then achieved. This is not only a task for remote sensing specialists, but
a multi-disciplinary task that should include social scientists as well as environmentalists and urban planners, decision-makers, economists and politicians.

Goal 11 of the UN Sustainable Development Goals and Agenda 2030 (United-Nations 2017b) (Anderson et al. 2017) proposes to overcome poverty and improve the environment for urban areas. Studies in (JRC 2016) (UN-Habitat 2018) have revealed more than was previously known about populations in urban areas, but how urban areas can remain or become more sustainable is yet to be addressed. (Scott et al. 2017) in providing a framework for the development of national policies incorporating geospatial information, comment that there has been inadequate uptake of geospatial information so far, but stress the opportunities for the geospatial community to play a significant role in global sustainable development.

7. Conclusions

- Landsat images acquired over an approximately 30-year period were classified into buildings, water, vegetation and soil for Wuhan in China and western Sydney in Australia, by Multiple Endmember Spectral Mixture Analysis (MESMA), together with Super-Resolution Mapping (SRM), to derive higher spatial resolution images using an Artificial Neural Network (ANN) predicted Wavelet method. It was demonstrated that this approach improved the possibility of obtaining high accuracy classifications of the Landsat images, compared with pixel-based classifications, when evaluated against high-resolution satellite or aerial images.
- The classified images were then processed by the software Indifrag to determine the level of fragmentation of buildings, water, vegetation and soil areas in Wuhan China and western Sydney in Australia over the 30-year period from 1987/8 to 2017.
- Since the populations of cities will increase in the future it is important to determine the level of green space in a city that is appropriate for the health of the city and its inhabitants. Therefore, it was concluded from available examples in cities around the world, that the recommended minimum levels of green space should be: of the order of 15% to 20% of the area of CBD and industrial areas, 25% to 30% of residential and light commercial areas and up to 50% of suburban areas. It was found that the levels of green space in some parts of Wuhan have tended to decrease significantly over the past 30 years to lower percentages than minimum recommended levels presented in this paper, while in Sydney urbanization has increased but percentages of green space have been maintained at suitable levels for residential areas. It has been concluded that neither city has an ideal density of housing.
- The extracted ecosystem service values (ESVs) for Wuhan and Sydney over the period of 1988 to 2017 indicate losses in ESVs of 20% for Wuhan and 3% for Sydney if buildings are not assigned as the urban areas component in assessing ESVs. If ESVs of buildings can be considered the same as for ESVs of urban areas, there would be little of no loss of ESVs due to the urbanization in the two cities. Further work would be required to determine the ESVs contribution of buildings as a component of urban areas.
- Studies are being undertaken by many researchers of Goal 11 of the UN Sustainable Development Goals for determining the sustainability of cities.

Acknowledgments

The authors are indebted to the Institute of Remote Sensing and Digital Earth (RADI), Chinese Academy of Sciences (CAS), for the kind provision of the Gaofen-1 and Ziyuan-3 images for the evaluation of the accuracies of the classifications over Wuhan. We are also indebted to Nearmap Ltd for access to their images over Sydney, as part of the license agreement between UNSW and Nearmap, for the evaluation of the classifications over Sydney.

Author Contributions

John Trinder (JT) suggested the topic and undertook the literature review and conceived the experiments. Qingxiang Liu (QL) undertook the experiments, designed the classification procedures, performed the image analysis and the processing using Indifrag. QL and JT analyzed the data and wrote the relevant sections of the paper.

Notes on contributors

John Trinder PhD (NSW) MSc (ITC) was employed at the University of New South Wales in 2013. He currently holds the position of Visiting Emeritus Professor in the School of Civil and Environmental Engineering at the UNSW. John has undertaken teaching and research at UNSW for about 55 years, specializing in Photogrammetry and Remote Sensing and spatial information. He maintains an interest in these areas, and their contributions to studying environmental impacts. He was President (2000-2004) of the International Society for Photogrammetry and Remote Sensing (ISPRS) and is currently an Honorary Member.

Qingxiang Liu received her PhD degree in Geomatics Engineering from the University of New South Wales in 2018. She finished undergraduate study at Wuhan University in 2013. She has worked on remote sensing for large-scale wetland mapping, shoreline change monitoring, landform geometry and vegetation rehabilitation.
monitoring for mining sites. Her current research interests include remote sensing applications to environmental studies and GIS.

**ORCID**

John Trinder [http://orcid.org/0000-0003-0165-5685 ]
Qingxiang Liu [http://orcid.org/0000-0002-7654-9003 ]

**References**

Alberti, M. 1996. “Measuring Urban Sustainability.” *Environmental Impact Assessment Review* 16: 381–424. doi:10.1016/S0195-9255(96)00083-2.

An, Y., J. Y. Tsou, K. Wong, Y. Zhang, D. Liu, and Y. Li. 2018. “Detecting Land Use Changes in A Rapidly Developing City during 1990–2017 Using Satellite Imagery: A Case Study in Hangzhou Urban Area, China.” *Sustainability* 10: 1–14. doi:10.3390/su10093303.

Anderson, K., B. Ryan, W. Sonntag, A. Kavvada, and L. Friedl. 2017. “Earth Observation in Service of the 2030 Agenda for Sustainable Development.” *Geo-spatial Information Science* 20 (2): 77–96. doi:10.1080/10095020.2017.1333230.

Berger, M. 2014. “The Unsustainable City.” *Sustainability* 6: 365–374. doi:10.3390/su6010365.

Breuste, J., D. Haase, and T. Elmqvist. 2013. “Urban Landscapes and Ecosystem Services.” In *Ecosystem Services in Agricultural and Urban Landscapes*, edited by S. Wratten, H. Sandhui, R. Cullen, and R. Costanza, 83–102. Oxford, UK: Wiley-Blackwell.

Breuste, J., S. Qureshi, and J. Li. 2013. “Scaling down the Ecosystem Services at Local Level for Urban Parks of Three Megacities.” *Hercynia-Ökologie und Umwelt in Mitteleuropa* 46: 1–20.

Chaiyapon, K. 2018. “A Comparative Study on Four Major Cities in Northeastern Thailand Using Urban Land Density Function.” *Geo-spatial Information Science* 21 (2): 93–101. doi:10.1080/10095020.2018.1455320.

Chen, J. 2002. “Geo-environment in the Sustainable Development of Chinese Cities.” *Geo-spatial Information Science* 5 (4): 1–4. doi:10.4006/BJF02826466.

City-of-Sydney. 2017. *Environmental Action 2016 – 2021 Strategy and Action Plan* | Sydney.

Costanza, R., R. d’Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, et al. 1997. “The Value of the World’s Ecosystem Services and Natural Capital.” *Nature* 387: 253–260. doi:10.1038/387253a0.

Costanza, R., R. de Groot, P. Sutton, S. van der Ploeg, S. J. Anderson, I. Ida Kubiszewski, S. Farber, and R. K. Turner. 2014. “Changes in the Global Value of Ecosystem Services.” *Global Environmental Change* 26: 152–158. doi:10.1016/j.gloenvcha.2014.04.002.

Cox, D. T. C., D. F. Shanahan, H. L. Hudson, R. A. Fuller, and K. J. Gaston. 2018. “The Impact of Urbanisation on Nature Dose and the Implications for Human Health.” *Landscape and Urban Planning* 179: 234–244. doi:10.1016/j.landurbplan.2018.07.013.

Chan, C.-W., J. Ma, P. Kempeneers, and F. Canters. 2010. “Enhancement of Hyperspectral CHRIS/Proba Images with a Thin-plate Spline Nonrigid Transform.” *IEEE Transactions on Geoscience and Remote Sensing* 48 (6): 2569–2579.

de Groot, R., L. Brander, S. van der Ploeg, R. Costanza, F. Bernard, L. Braat, M. Christie, et al. 2012. “Global Estimates of the Value of Ecosystems and their Services in Monetary Units.” *Ecosystem Services* 1 (1): 50–61. doi:10.1016/j.ecoser.2012.07.005.

Demarchi, L., J. Yang, X. Li, and P. Gong. 2011. “Mapping Impervious Surfaces Using MESMA From Superresolution Enhanced Chris/Proba Imagery In The Brussels Capital Region...” IEEE conference of International Geoscience and Remote Sensing Symposium (IGARSS 2011), Vancouver, Canada, 1–4.

Dennison, P. E., and D. A. Roberts. 2003. “Endmember Selection for Multiple Endmember Spectral Mixture Analysis Using Endmember Average RMSE.” *Remote Sensing of Environment* 87 (2–3): 123–135. doi:10.1016/S0034-4257(03)00135-4.

Du, P., S. Liu, P. Liu, K. Tan, and L. Cheng. 2014. “Sub-pixel Change Detection for Urban Land-cover Analysis via Multi-temporal Remote Sensing Images.” *Geo-spatial Information Science* 17 (1): 26–38. doi:10.1080/10095020.2014.889268.

Ekkel, E. D., and S. de Vries. 2017. “Nearby Green Space and Human Health: Evaluating Accessibility.” *Landscape and Urban Planning* 157: 214–220. doi:10.1016/j.landurbplan.2016.06.008.

Freedberg, M. 2010. “Pathways to Urban Sustainability: Research and Development on Urban Systems.” In *Summary of a Workshop by Committee on the Challenge of Developing Sustainable Urban Systems*, edited by D. Schaffer and D. Vollmer, p. 124. Washington, DC: National Research Council.

Gardner, G. 2016. “Cities in the Arc of Human History: A Materials Perspective.” In *Can a City Be Sustainable?* 11–25. Washington, USA: World Watch Institute - Island Press.

Goldblatt, R., K. Deininger, and G. Hanson. 2018. “Utilizing Publicly Available Satellite Data for Urban Research: Mapping Built-up Land Cover and Land Use in Ho Chi Minh City, Vietnam.” *Development Engineering* 3: 83–99. doi:10.1016/j.development.2018.03.001.

Greater-London-Authority. 2015. “Measuring Tree Canopy Cover in London: An Analysis Using Aerial Imagery.” Accessed September 2015. [https://www.london.gov.uk/sites/default/files/measuring_tree_canopy_cover_2015.pdf](https://www.london.gov.uk/sites/default/files/measuring_tree_canopy_cover_2015.pdf).

Guam, X., S. Liao, J. Bai, F. Wang, Z. Li, Q. Wen, J. He, and T. Chen. 2017. “Urban Land-use Classification by Combining High-resolution Optical and Long-wave Infrared Images.” *Geo-spatial Information Science* 20 (4): 299–308. doi:10.1016/j.gis.2017.1403731.

Guobin, Z., and D. Blumberg. 2004. “An Urban Open Space Extraction Method: Combining Spectral and Geometric Characteristics.” *Geo-spatial Information Science* 7 (4): 249–254. doi:10.1016/BF02828547.

Jiang, L., X. Deng, and K. C. Seto. 2013. “The Impact of Urban Expansion on Agricultural Land Use/intensity in China.” *Land Use Policy* 35: 33–39. doi:10.1016/j.landusepol.2013.04.011.

JRC European Union. 2016. “Mapping Human Presence on Earth.” Accessed November 2018. [https://ghsl.jrc.ec.europa.eu/documents/Infographics_Key-messages.pdf? t=1522311272](https://ghsl.jrc.ec.europa.eu/documents/Infographics_Key-messages.pdf? t=1522311272).

Kasetkasem, T., M. K. Arora, and P. K. Varshney. 2005. “Super-resolution Land Cover Mapping Using a Markov Random Field Based Approach.” *Remote Sensing of Environment* 96 (3–4): 302–314. doi:10.1016/j.rse.2005.02.006.

Kuang, W., J. Liu, J. Dong, W. Chi, and C. Zhang. 2016. “The Rapid and Massive Urban and Industrial Land
Expansions in China between 1990 and 2010: A CLUD-based Analysis of Their Trajectories, Patterns, and Drivers." Landscape and Urban Planning 145: 21–33. doi:10.1016/j.landurbplan.2015.10.001.

Leff, M. 2016a. "The Sustainable Urban Forest: A Step-by-Step Approach." Accessed 25 September 2018.

Leff, M. 2016b. "Urban Forest Strategy - A Step-by-Step Approach." Accessed February 2018.

Li, D. 2000. "Role of Remote Sensing in Achieving National Food Self-sufficiency and Food Security." Geo-spatial Information Science 3 (3): 1–5. doi:10.1007/BF02866585.

Li, D., H. Sui, and P. Xiac. 2016. "Detection of Geo-spatial Data from Imagery." Geo-spatial Information Science 6 (3): 1–7. doi:10.1007/BF02826885.

Li, Z., Z. Sun, Y. Tian, J. Zhong, and W. Yang. 2019. "Impact of Land Use/Cover Change on Yangtze River Delta Urban Agglomeration Ecosystem Services Value: Temporal-Spatial Patterns and Cold/Hot Spots Ecosystem Services Value Change Brought by Urbanization." International Journal of Environmental Research and Public Health 16 (1): 123. doi:10.3390/ijerph16010123.

Liu, F., Z. Zhang, L. Shi, X. Zhao, J. Xu, L. Yi, B. Liu, et al. 2016. "Urban Expansion in China and Its Spatial-temporal Differences over the past Four Decades." Journal of Geographical Sciences 26 (10): 1477–1496. doi:10.1142/S1009502016339-3.

Liu, Q., J. Trinder, and I. Turner. 2016. "A Comparison of Sub-pixel Mapping Methods for Coastal Areas." ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences III (7), 67–74. XXIII ISPRS Congress Prague, Czech Republic.

Liu, Y., and L. Jiao. 2002. "The Application of BP Networks to Land Suitability Evaluation." Geo-spatial Information Science 5 (1): 55–61. doi:10.1007/BF02863495.

McGarigal, K., E. Ene, and C. Holmes. 2015. FRAGSTATSMetrics. Amherst, USA: University of Massachusetts—Produced Program.

Mennis, J., M. Mason, and A. Ambrus. 2018. "Urban Greenspace Is Associated with Reduced Psychological Stress among Adolescents: A Geographic Ecological Momentary Assessment (GEMA) Analysis of Activity Space." Landscape and Urban Planning 174: 1–9. doi:10.1016/j.landurbplan.2018.02.008.

Mertens, K. 2008. Towards Sub-pixel Mapping: Design and Comparison of Techniques. PhD thesis, Ghent University, Ghent, Belgium.

Mertens, K. C., B. De Baets, L. P. C. Verbeke, and R. R. De Wulf. 2006. "A Sub-pixel Mapping Algorithm Based on Sub-pixel/pixel Spatial Attraction Models." International Journal of Remote Sensing 27 (15): 3293–3310. doi:10.1080/01431160500497127.

Mertens, K. C., P. C. Lieven, T. W. Verbeke, and R. R. De Wulf. 2004. "Sub-pixel Mapping and Sub-pixel Sharpening Using Neural Network Predicted Wavelet Coefficients." Remote Sensing of Environment 91 (2): 225–236. doi:10.1016/j.rse.2004.03.003.

Nearmap. 2018. Current, Clear Aerial Imagery as a Service for Australian Businesses. Nearmap. Accessed September 2018. https://www.nearmap.com.au/

Nong, Y., and Q. Du. 2011. "Urban Growth Pattern Modeling Using Logistic Regression." Geo-spatial Information Science 14 (1): 62–67. doi:10.1007/s11806-011-0427-x.

Roberts, D. A., G. Batista, J. Pereira, E. Waller, and B. Nelson. 1999. "Change Identification Using Multitemporal Spectral Mixture Analysis: Applications in Eastern Amazonia." doi:10.1046/j.1469-1899.1999.6320101.x.

Roberts, D. A., M. Gardner, R. Church, S. Ustin, G. Scheer, and R. O. Green. 1998. "Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models." Remote Sensing of Environment 65 (3): 267–279. doi:10.1016/S0034-4257(98)00037-6.

Sandhu, H., and S. Wratten. 2013. "Ecosystem Services in Farmland and Cities." In Ecosystem Services in Agricultural and Urban Landscapes, edited by S. Wratten, H. Sandhu, R. Cullen, and R. Costanza, 17–31. Oxford: Wiley-Blackwell.

Sapena, M. 2015. "IndiFrag." Accessed 24 March 2018. http://cgat.webs.upv.es/software/.

Sapena, M., and L. A. Ruiz. 2015. "Analysis of Urban Development by Means of Multi-Temporal." 36th international symposium on remote sensing of environment, Berlin, Germany, May 11–15.

Schagner, J. P., L. Brander, J. Maes, and V. Hartje. 2013. "Mapping Ecosystem services’ Values: Current Practice and Future Prospects." Ecosystem Services 4: 33–46. doi:10.1016/j.ecoser.2013.02.003.

Scott, G., and A. Rajabifard. 2017. "Sustainable Development and Geospatial Information: A Strategic Framework for Integrating a Global Policy Agenda into National Geospatial Capabilities." Geo-spatial Information Science 20 (2): 59–76. doi:10.1007/s12665-016-6016-4.

Shanahan, D. F., B. D. Cox, R. Fuller, S. Hancock, B. B. Lin, K. Anderson, R. Bush, and K. J. Gaston. 2017. "Variation in Experiences of Nature across Gradients of Tree Cover Incompact and Sprawling Cities." Landscape and Urban Planning 157: 231–238. doi:10.1016/j.landurbplan.2016.07.004.

Shao, Z., H. Fu, D. Li, O. Altan, and T. Cheng. 2019. "Remote Sensing Monitoring of Multi-scale Watersheds Impermeability for Urban Hydrological Evaluation [J]." Remote Sensing of Environment 232 (October): 111338. doi:10.1016/j.rse.2019.111338.

Sui, H., and D. Li. 2001. "A Framework For Automated Change Detection System." Geo-spatial Information Science 4 (3): 29–34. doi:10.1007/BF02826921.

Sun, A., T. Chen, N. R-q, and J. Trinder. 2016. "Land Use/cover Change and the Urbanization Process in the Wuhan Area from 1991 to 2013 Based on MESMA." Environmental Earth Sciences 75 (2013): 1214: 1–12. doi:10.1007/s12665-016-6016-4.

Tatem, A. J., H. G. Lewis, P. M. Atkinson, and M. S. Nixon. 2002. "Super-resolution Land Cover Pattern Prediction Using a Hopfield Neural Network." Remote Sensing of Environment 79 (1): 1–14. doi:10.1016/S0034-4257(01)00229-2.

Twohig-Bennett, C., and A. Jones. 2018. "The Health Benefits of the Great Outdoors: A Systematic Review and Metaanalysis." Environmental Research 166: 628–637. doi:10.1016/j.envres.2018.06.030.

UCSB and Geography. 2018. "The VIPER Tools Software Package Version 2." Accessed July 2018. https://sites.google.com/site/ucsbviperlab/viper-tools.

UN-Habitat. 2018. Tracking Progress Towards Inclusive, Safe, Resilient and Sustainable Cities and Human Settlements – SDG 11 SYNTHESIS REPORT HIGH LEVEL POLITICAL FORUM 2018. In UN Habitat.

United-Nations. 2017a. Progress Towards the Sustainable Development Goals. New York, USA: United Nations.

United-Nations. 2017b. UN Sustainable Development Goals. New York, USA: United Nations.
van den Bosch, M. A., P. Mudu, V. Uscila, M. Bardahl, A. Kulinkina, B. Staatsen, W. Swart, et al. 2015. "Development of an Urban Green Space Indicator and the Public Health Rationale." *Scandinavian Journal of Public Health* 44(2): 159–167.

Wang, C., Y. Wang, R. Wang, and P. Zheng. 2018. "Modeling and Evaluating Land-use/land-cover Change for Urban Planning and Sustainability: A Case Study of Dongying City, China." *Journal of Cleaner Production* 172: 1529–1534. doi:10.1016/j.jclepro.2017.10.294.

Weng, Q. 2012. "Remote Sensing of Impervious Surfaces in the Urban Areas: Requirements, Methods, and Trends." *Remote Sensing of Environment* 117: 34–49. doi:10.1016/j.rse.2011.02.030.

Weng, Q., and X. Hu. 2008. "Medium Spatial Resolution Satellite Imagery for Estimating and Mapping Urban Impervious Surfaces Using LSMA and ANN." *IEEE Transaction on Geosciences and Remote Sensing* 46 (8): 2397–2406. doi:10.1109/TGRS.2008.917601.

Wolch, J. R., J. Byrne, and J. P. Newell. 2014. "Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities ‘just Green Enough.’" *Landscape and Urban Planning* 125: 234–244. doi:10.1016/j.landurbplan.2014.01.017.

Wu, K., L. Zhang, R. Niu, B. Du, and Y. Wang. 2011. "Super-resolution Land-cover Mapping Based on the Selective Endmember Spectral Mixture Model in Hyperspectral Imagery." *Optical Engineering* 50 (12): 1–14.

Wu, X., J. Peng, J. Shan, and W. Cu. 2015. "Evaluation of Semivariogram Features for Object-based Image Classification." *Geo-spatial Information Science* 18 (4): 159–170. doi:10.1007/10095020.2015.1116206.