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Pixel-based and object-based classifications using high and medium spatial resolution imageries in the urban and sub-urban landscapes

Ronald C. Estoque[1,*], Yuji Murayama[1], and Chiaki Mizutani Akiyama[2]

[1] *Faculty of Life and Environmental Sciences, University of Tsukuba, 1-1-1 Tennodai, Tsukuba City, Ibaraki 305-8572 JAPAN*

[2] *National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba City, Ibaraki 305-8506 JAPAN*

* Email: rons2k@yahoo.co.uk; estoque.ronald.ga@u.tsukuba.ac.jp

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With the increasing availability of high spatial resolution remote sensing imageries and with the observed limitations of pixel-based techniques, the development and testing of geographic object-based image analysis (GEOBIA) techniques for image classification have become one of the main research areas in geospatial science. This paper examines and compares the classification performance of a pixel-based method and an object-based method as applied to high (QuickBird satellite image) and medium (Landsat TM image) spatial resolution imageries in the urban and sub-urban contexts. For the pixel-based classification, the maximum likelihood supervised classification approach was employed. And for the object-based classification, the pixel-based classified maps were integrated with a set of image segments produced by using various calibrations. The results show evidence that the object-based method can produce classifications that are more accurate for both high and medium spatial resolution imageries in the context of urban and sub-urban landscapes.

Keywords: GEOBIA; land cover; land use; object-based image analysis; pixel-based image analysis

Introduction

Remote sensing satellite imageries are a major source of data for various government, academic and research undertakings around the world. By processing remote sensing satellite imageries, land-use/cover (LUC) maps can be produced, which can then be used for various purposes in the realms of sustainability, global environmental change, landscape ecology, and urban and geographical studies (Lambin et al. 2003; Turner et al. 2007; Helming et al. 2008; Lambin & Meyfroidt 2011; Weng 2012; Estoque & Murayama 2013; Jones et al. 2013; Weng et al. 2013; Lu et al. 2014; UNEP 2014). However, the quality of information that can be obtained from satellite imageries through the resulting LUC maps relies on the accuracy of the classification, which depends on several factors, including: (a) the type of image to be used – sensor and resolution (e.g. spatial, spectral, and radiometric) and quality (e.g. presence or absence of haze, clouds, and shadows); (b) the area coverage and type of landscape under investigation (e.g. local, regional or global; homogenous or heterogeneous); (c) the number of classes to be extracted; (d) one's own local or expert knowledge of the area of interest, as well as the availability of relevant ground truth information; and (e) the classification method to be used, which is the focus of this study. Thus, in the domain of land-use science (Aspinall 2006; Muller & Munroe 2014), also known as land-change science (Gutman et al. 2004; Turner et al. 2007) and land-system science (Reenberg 2009; Verburg et al. 2013), the accurate extraction of information from satellite imageries is an important aspect of the practical applications of remote sensing technologies.

Although pixel-based image analysis has been, and still is, the basis for thousands of successful applications in remote sensing like LUC mapping, it has its own limitations in regard to context, relative scale, and fuzzy or smooth transitions (Blaschke 2010). The advancement of remote sensing technologies, e.g. the launch of high spatial resolution satellite sensors, has seen the development of methods for GEOBIA (Hay & Castilla 2008; Blaschke et al. 2014) as alternatives to the traditional pixel-based image analysis techniques. Object-based techniques have several advantages over the pixel-based techniques, such as the integration of expert knowledge and feature space optimization in the classification process (Platt & Rapoza 2008). Also, object-based techniques are known by their potential in reducing the 'salt-and-pepper effect' (Blaschke et al. 2000), which is typical in a pixel-based classification (Liu & Xia 2010). It has been observed that GEOBIA has been receiving more recognition compared to traditional pixel-based analysis (Gamanya et al. 2009).

The core of GEOBIA is built on the concept of image segmentation, which is a process of dividing an image into relatively homogeneous and semantically significant groups of pixels, known as image segments (Blaschke 2010; Eastman 2012). The image segments provide the building blocks of GEOBIA (Hay & Castilla 2008; Lang 2008). The concept of image segmentation has long been applied in industrial and medical image processing (Zhang 1996; Blaschke 2010). Its adoption to geospatial science through the integration of contextual information in the classification of remote sensing imageries is believed to have started in the 1970s (Kettig & Landgrebe 1976; Blaschke 2010). Since the turn of the twenty-first century, the development, testing and application of GEOBIA methods in the broad spectrum of geospatial science have been continuously increasing (Blaschke 2010; Baraldi & Boschetti 2012; Blaschke et al. 2014).

It has been proposed that for images with low-to-medium spatial resolutions, where pixels are larger than or of the same size with objects, sub-pixel and per-pixel techniques are appropriate; but for high spatial resolution images, where pixels are smaller than objects, there is a need for regionalization in order to group the pixels into regions and finally into objects (Blaschke 2010). However, in other studies, it has also been shown that object-based techniques can also be applied to medium spatial resolution imageries (e.g. Gao et al. 2006, 2009; Bontemps et al. 2008; Jobin et al. 2008; Myint et al. 2008; Li et al. 2013; Jebur et al. 2014; Tehrany et al. 2014). Apparently, there is still a need for more studies on the comparison of pixel-based and object-based techniques with regard to their applications to various types of satellite imageries.

There is also a growing interest in urban remote sensing, in which the extraction of impervious surfaces or built-up lands and urban green spaces plays an important role in various urban ecological and geographical studies (Weng 2012; Xian et al. 2012; Estoque & Murayama 2012, 2013; Sharma et al. 2013; Li et al. 2014; Huang et al. 2015). In the context of this study, 'urban' refers to a landscape dominated by built-up lands, while 'sub-urban' refers to an urban fringe, which is still dominated by non-built-up lands. The heterogeneity in these landscapes often results in high spectral variation within the same LUC class, especially in high spatial resolution imageries (Moran 2010), posing an important challenge in urban LUC classification and mapping. This study aims to contribute to this endeavour as it examines and compares the classification performance of a pixel-based method and an object-based method as applied to high and medium spatial resolution remote sensing satellite imageries in the context of urban and sub-urban landscapes.

Methodology

Case 1: Using high spatial resolution imagery in a sub-urban landscape

For Case 1, we used high spatial resolution remote sensing satellite image, i.e. a multispectral pan-sharpened QuickBird satellite image of the eastern side of Tsukuba City, Japan. The image has a 0.60 m spatial resolution. It was captured on October 9, 2006, in autumn, after the rice-growing season. For purposes of demonstrating and evaluating the two image classification techniques, a subset measuring 1.5 km × 1.5 km (Figure 1(*a*)) was clipped out from the QuickBird image as part of the pre-processing procedure.

The area is a sub-urban, and contains paddy fields, forests, road network and peri-urban villages. For this case, i.e. sub-urban landscape, we focused on five LUC classes, namely built-up, cropland, forest, other land, and shadow. 'Other land' includes open areas such as grassland and lawns, as well as areas covered with scrubs or bushes.

Case 2: Using medium spatial resolution imagery in an urban landscape

For Case 2, we used medium spatial resolution remote sensing satellite image, i.e. a Landsat TM image of Bangkok, Thailand. The image is a standard data product processed using the Level 1 Product Generation System (http://landsat.usgs.gov). The multispectral bands of this image, which were used in the classification, have a 30 m spatial resolution. It was captured on January 19, 2009, in dry season. For the purpose of this study, a 30 km × 30 km subset of the Landsat TM image was used (Figure 4(*a*)).

Bangkok, a megacity (with population > 10 Million), is located in Chao Phraya River Delta. Its landscape is comprised of urban areas, water body and other mixed landscapes dominated by croplands. But for the purpose of this study, we used the highly urbanized part of the city. For this case, i.e. urban landscape, we focused on the urban land cover (built-up lands), thus classifying only three classes, namely built-up, water and other land. 'Other land' includes all other areas except built-up lands and bodies of water.

Pixel-based and object-based classifications

First, a pixel-based classification employing the maximum likelihood supervised classification approach was performed. At least 60 training samples for each class were digitized from both images and then used in the classification. Second, both images were segmented using the SEGMENTATION module available in IDRISI® GIS and remote sensing software. This module groups the pixels that share a homogeneous spectral similarity together into image segments (Ruefenacht 2011; Eastman 2012). There are five parameters within this module: (1) window width; (2) relative weights of the input bands or images; (3) similarity tolerance or threshold (hereafter referred to as ST); (4) weight mean factor; and (5) weight variance factor.

The module starts by creating a variance image for each input band or image. A window width of '3' means that a 3 × 3 matrix of pixels will be used in the calculation (Ruefenacht 2011; Eastman 2012). In cases where more than one band or image file is used, the final variance image would be a weighted mean of all the variance images (Ruefenacht 2011; Eastman 2012). The module allows the user to define the relative weights of the input bands or images. The values of the pixels within the final variance image are then treated like values in a digital elevation model, where pixels are grouped into watersheds (Ruefenacht 2011; Eastman 2012). Two neighbouring watersheds or segments merge if the difference between the mean and variance values is less than the ST (Ruefenacht 2011; Eastman 2012). The ST parameter (scale in other segmentation programs) controls the generalization level: the larger the value, the lower the number of segments, which leads to more heterogeneous and generalized segmentation results.

In this study, the parameters were calibrated as follows: window width (3 × 3); relative weights of the input bands or images (equal); weight mean factor (0.5); and weight variance factor (0.5). For the ST, two sets of values were used, i.e. 5, 10, 20, 30, 40, and 50 for the QuickBird satellite image (sub-urban landscape), and 1, 5, 10, 15, 20, and 30 for the Landsat TM image (urban landscape). In the implementation of each of the various ST values, the calibrations of the other parameters were not changed.

Finally, the results of the pixel-based method were combined with the results of the object-based segmentation using the SEGCLASS module in the same software. The module uses a majority rule algorithm to assign each segment to the majority class of the pixels within a segment (Eastman 2012). A reference image, i.e. a previously classified LUC map, which is typically a product of a pixel-based classifier, is used to derive the majority class. The pixel-based classified maps or reference images and the generated segments for the QuickBird satellite image and Landsat TM image were used as inputs in the module.

Accuracy assessment

The accuracy assessment approach followed the standard method of comparing a set of sample pixels or points from the classified map with reference data (Congalton 1991; Myint et al. 2011). A total of 620 and 750 randomly selected sample reference points were generated for the QuickBird satellite image and Landsat TM image, respectively. The reference points for the QuickBird satellite image were checked against the image itself and the Google Earth imageries to record and code their respective classes with the same code used for the five classes in the classified maps. The QuickBird satellite image has a high spatial resolution, which allows and aids visual interpretation. The reference points for the Landsat TM image were also checked against the Google Earth imageries. Through an error matrix (Congalton 1991), the user's accuracy (UA) (Equation (1)), producer's accuracy (PA) (Equation (2)), and overall accuracy (OA) (Equation (3)) in terms of proportion correct for each classified map were determined.

$$\mathrm{UA}\ (\%) = \frac{\text{total number of correct pixels in a class}}{\text{sum of pixels in the row}} \times 100 \tag{1}$$

$$\mathrm{PA}\ (\%) = \frac{\text{total number of correct pixels in a class}}{\text{sum of pixels in the column}} \times 100 \tag{2}$$

$$\mathrm{OA}\ (\%) = \frac{\text{total number of correct pixels as summed along the major diagonal}}{\text{total number of pixels in the error matrix}} \times 100 \tag{3}$$

Results

Case 1: Using high spatial resolution imagery in a sub-urban landscape

Figure 1(*b*) presents the results of the object-based image segmentation at various ST values for the QuickBird satellite image in a sub-urban landscape. It can be observed that at a much lower ST value, the image seems to have been over-segmented, as indicated by the presence of many segments for one object. In ST value 5, for example, a single building or a single patch of cropland has been segmented into several parts. In contrast, at a much higher ST value, the image seems to have been under-segmented, as indicated by a fewer number of segments, in which many objects have been grouped within a single segment. For instance, in ST value 50, some buildings have been merged with cropland, and some parts of the forest have been merged with shadow, and so on. In between ST values 5 and 50, i.e. 30, the image seems to have been segmented quite well (Figure 1(*b*)).

Figure 2 presents the classified maps for the QuickBird satellite image in a sub-urban landscape. The results show that the ‘salt-and-pepper effect’ is more evident in the pixel-based classified map than in the object-based classified maps. Through visual inspection of the pixel-based classified map, many pixels of cropland have been found misclassified as built-up and other land, and vice versa, while many pixels that belong to forest have also been misclassified as other land, and vice versa. There were also misclassifications between forest and shadow, and so on. Table 1(*a*) provides some quantitative information about these misclassifications.

In Table 1, the user’s accuracy column provides the accuracy measurement for each class and also quantifies the errors of commission. A pixel is called a commission when it is forest in the classified map but not forest in the reference data. On the other hand, the producer’s accuracy row provides the accuracy measurement for each class and also quantifies the errors of omission. A pixel is called an omission when it is forest in the reference data but not in the classified map.

Meanwhile, in the object-based classified maps (Figure 2), there are indications that the object-based method has been able to reduce the ‘salt-and-pepper effect’. This has resulted to lesser classification errors as can be seen in Table 1(*b*). However, the results also show that as the ST value increases to 50 (Figure 2), the classification becomes more generalized due to the effect of under-segmentation.

Figure 3 shows the comparison between the overall accuracy of the maps classified using pixel-based and object-based methods for the QuickBird satellite image in a sub-urban landscape. The results reveal an overall accuracy of 80.00% for the pixel-based classified map, while the object-based classified maps had an overall accuracy ranging from 77.90% to 85.65%. These results show that, using a high spatial resolution image in a sub-urban landscape, the object-based method has outperformed the pixel-based method. That said, the results also show that the object-based method can also be less accurate than the pixel-based method, depending on the calibration of the segmentation parameters. For example, it can be observed that the map classified by using a ST value of 50 had a much lower overall accuracy (77.90%) than the pixel-based classified map (80.00%) (Figure 3).

Amongst the object-based classified maps for the QuickBird satellite image in a sub-urban landscape, the map classified by using a ST value of 30 obtained the highest accuracy (Figure 3). It can be observed that this ST value also had a relatively better segmentation results (Figure 1). The results also show that in a sub-urban landscape, relatively lower ST values for the QuickBird satellite image seem to produce more accurate results. For example, although ST values 20 and 40 are both 10 units away from the ST value 30, which produced the most accurate result for the QuickBird satellite image, ST value 20 (85.00%) had been more accurate than ST value 40 (82.26%) (Figure 3).

Case 2: Using medium spatial resolution imagery in an urban landscape

Figure 4(*b*) presents the results of the object-based image segmentation at various ST values for the Landsat TM image in an urban landscape. Like in a sub-urban landscape in the case of the QuickBird satellite image, it can be observed that at a much lower ST value, the Landsat TM image in an urban landscape seems to have been over-segmented. In ST value 1, for instance, a contiguous built-up area has been segmented into several parts. In contrast, at a much higher ST value, the image seems to have been under-segmented. For example, in ST value 30, some built-up lands have been merged with some non-built-up lands (Figure 4(*b*)).

Figure 5 presents the classified maps for the Landsat TM image in an urban landscape. Again, like in the case of the QuickBird satellite image in a sub-urban landscape, the results show that the 'salt-and-pepper effect' is also more evident in the pixel-based classified map than in the object-based classified maps. Through visual inspection of the pixel-based classified map, many pixels of non-built-up lands (e.g. cropland) have been found misclassified as built-up, and vice versa. Table 2(*a*) provides some quantitative information about these misclassifications. Meanwhile, in the object-based classified maps for the Landsat TM image, there are indications that the object-based method has also been able to reduce the 'salt-and-pepper effect' as in the case of the QuickBird satellite image in a sub-urban landscape. This has also resulted to lesser classification errors as can be seen in Table 2(*b*). However, as the ST value increases, for example to 30 (Figure 5), the classification also becomes more generalized due to the effect of under-segmentation.

Figure 6 shows the comparison between the overall accuracy of the maps classified using pixel-based and object-based methods for the Landsat TM image in an urban landscape. The results reveal an overall accuracy of 86.92% for the pixel-based classified map, while the object-based classified maps had an overall accuracy ranging from 85.05% to 91.05%. These results show that using a medium spatial resolution image in an urban landscape, the object-based method has also outperformed the pixel-based method. That said and like in a sub-urban landscape, the results also show that the object-based method can also be less accurate than the pixel-based method in an urban landscape depending on the calibration of the segmentation parameters. For example, it can be observed that the map classified by using a ST value of 30 had a much lower overall accuracy (85.05%) than the pixel-based classified map (86.92%) (Figure 6).

Amongst the object-based classified maps for the Landsat TM image in an urban landscape, the map classified by using a ST value of 5 obtained the highest accuracy (Figure 6). The results also show that, like in the case of the QuickBird satellite image in a sub-urban landscape, relatively lower ST values for the Landsat TM image in an urban landscape also seem to produce more accurate results. For example, ST values 1, 5 and 10 had been more accurate than ST values 15, 20 and 30 (Figure 6).

Discussion

Learning and observations

With the increasing availability of high spatial resolution remote sensing imageries and with the observed limitations of pixel-based techniques, the development and testing of GEOBIA techniques have become one of the main research areas in geospatial science (GIScience and remote sensing). Since the 2000s, various studies have shown some evidence that, when applied to high spatial resolution imageries (Guo et al. 2007; Cleve et al. 2008; Platt & Rapoza 2008; Bhaskaran et al. 2010; Myint et al. 2011; Moosavi et al. 2014) and even to imageries with medium spatial resolution (Gao et al. 2006, 2009; Myint et al. 2008; Whiteside et al. 2011; Li et al. 2013; Galletti & Myint 2014; Jebur et al. 2014; Tehrany et al. 2014), object-based methods can produce classification results that are more accurate than those of the traditional pixel-based methods. In our study, the results show that the object-based method has outperformed the pixel-based method for both high and medium spatial resolution imageries in the context of sub-urban and urban landscapes (Figures 3 and 6; Tables 1 and 2). Our results thus support these previous findings.

Image segmentation is central to an object-based classification process. If the quality and accuracy of information that can be obtained from a classified map depends on the accuracy of the classification, the accuracy of the classification depends on, amongst other factors, the parameterization of the segmentation algorithm to be used. As demonstrated by the results (Figures 3 and 6), object-based methods, can also be less accurate than pixel-based methods depending on the calibration of the segmentation parameters (e.g. ST). Therefore, the proper calibration of any given segmentation algorithm is crucial, as it is through the process of segmentation that the core elements for an object-based classification (i.e. the image segments) are produced. In this study, the segmentation algorithm used (i.e. IDRISI's segmentation module) can be considered relatively less sophisticated when compared with the most commonly used ones (e.g. eCognition's segmentation program). Nevertheless, it is amongst the top segmentation algorithms according to the recent evaluation conducted for the most commonly used segmentation programs (Ruefenacht 2011).

In the context of LUC mapping, segmentation errors, i.e. over-segmentation and under-segmentation (Delves et al. 1992), can contribute to classification errors (Moller et al. 2007; Clinton et al. 2010; Liu & Xia 2010). Over-segmentation is characterized by having too many segments in which a single object has been segmented into several parts. In contrast, under-segmentation is characterized by having too few segments in which several objects have been grouped into one segment. Since object-based image segmentation is scale-dependent (Benz et al. 2004), segmentation accuracy, to a certain extent, depends on the scale of the image segmentation (Addink et al. 2007; Kim et al. 2009; Liu & Xia 2010) or the ST in this study. It can be observed that, in Figures 1 and 4, over-segmentation is inversely related with the ST, while under-segmentation is directly related with the ST. Furthermore, in this study, the overall classification accuracy increases to a certain extent at a certain ST value, and then decreases in much higher ST values (Figures 3 and 6). This result is consistent with previously reported findings (e.g. Liu & Xia 2010).

In the comparison of the various ST values for both imageries and landscapes, the results revealed that much lower ST values (greater over-segmentation) seem to produce more accurate classifications than much higher ST values (greater under-segmentation) (Figures 1(*b*), 3, 4(*b*) and 6). This might be because in the case of over-segmentation, there is always a possibility that each of the several segments generated for one object will be classified correctly, but in the case of under-segmentation, the presence of omission and commission errors is guaranteed. For example, if a building is mixed with a patch of cropland within a segment due to under-segmentation and the segment has been classified as built-up, then it is guaranteed that there will be commission errors for the built-up class and omission errors for cropland class, and vice versa. Thus, the possibility of losing crucial details is much higher in the case of under-segmentation than in the case of over-segmentation. In other studies, small-scale segmentation has also been found more accurate (e.g. Myint et al. 2013).

In contrast with the usual ‘segmentation-classification’ process involved in an object-based classification, the object-based method employed in this study uses a reference map, which is typically a pixel-based classified map, together with the generated segments. This provides an important advantage as it enables the user to easily compare the pixel-based classified map with its object-based version. In this study, the use of a pixel-based classified map as input to the object-based classification enabled us to examine the effect of the object-based image segmentations on the same pixel-based classified maps. The combination of the object-based image segments and a pixel-based classified map provides a hybrid object-based classification method (Eastman 2012).

In other several studies, it has been shown that a hybrid object-based method can also outperform both a pixel-based technique and an object-based technique. For example, Wang et al. (2004) found that while the object-based technique yielded a better accuracy than the pixel-based technique in their mapping of mangroves on the Caribbean coast of Panama with high spatial resolution satellite imagery, the hybrid method that combined the two techniques outperformed both individual techniques. Bhaskaran et al. (2010) were also able to improve the accuracy of their urban features mapping in New York City using very high-resolution (VHR) data with a combined pixel-based and object-based approach. They theorize that the combined approach may prove useful in the analysis of VHR satellite data like Ikonos and QuickBird data, since it results in higher per class accuracy. In a more recent study, Li et al. (2013) also compared pixel-based, object-based, and hybrid techniques in their classifications in Budapest, Hungary. They found that the hybrid technique outperformed the object-based technique, while the result of the former was also preferred over the result of the pixel-based technique.

As mentioned earlier, one main advantage of object-based techniques over pixel-based techniques is their potential to reduce the ‘salt-and-pepper effect’, and this has also been observed in this study both in the urban and sub-urban landscapes (Figures 2 and 5). Furthermore, in this study, the flexibility of the object-based method allowed us to calibrate the segmentation parameters to obtain better results both in the urban and sub-urban landscapes (Figures 3 and 6; Tables 1 and 2). And this advantage is related to what has been described as the ‘integration of expert knowledge’ and ‘feature space optimization’ (Platt & Rapoza 2008). However, object-based techniques also have their own limitations, and this poses an important challenge to the GEOBIA paradigm. For example, as the quality and accuracy of object-based image segmentation depends on many factors such as the type of landscape, type of sensor (spatial resolution, radiometric resolution, spectral resolution), and variation of object sizes within each class (Myint et al. 2011), the calibration of any given segmentation algorithm usually takes time. It also involves a trial and error process, as well as a rigorous visual assessment. But since ‘the decision on whether a particular object boundary is correct is subjective’ (Myint et al. 2011, p. 1156), the visual evaluation of object-based image segmentation remains a challenging task, especially for the medium-to-coarse spatial resolution satellite imageries.

Limitations, caveats and outlook

Although the main purpose of this study has been attained, there are some limitations and caveats that need to be considered whenever the results are to be used or interpreted further. For example, the segmentation algorithm used in this study uses only spectral information. Other segmentation programs, such as eCognition’s segmentation algorithm, use texture, shape and contextual information, in addition to spectral information. The absence of these other parameters might have contributed to the relatively poor performance of the object-based method and segmentation algorithm used in this study, particularly in the extraction of linear features, such as roads (Figs. 2 and 5).

Furthermore, there were only three classes considered for the urban landscape (medium spatial resolution), whereas for the sub-urban landscape (high spatial resolution) five classes were considered. Consequently, it was not possible to make an objective comparison between high and medium spatial resolution imageries in terms of overall classification performance. Nevertheless, a class-by-class comparison is possible for the built-up class, although caution should still be exercised because: (1) the number of reference points for the built-up class across the two imageries is different; and (2) the built-up lands were classified from two different landscapes in different geographic location. Based on the results, there seem to be indications that the medium spatial resolution image has been more accurate in the classification of built-up lands than the high spatial resolution image (Tables 1 and 2). It might be because with high spatial resolution imageries, more details of the Earth's surface are revealed, and this increases complexity. In fact it has been observed that while scientists and researchers demanded for higher spatial resolution in recent years (Blaschke 2010; Moran 2010), "fewer and fewer specialists believe that further improvements in the spatial resolution of satellite sensors might yield 'better results'" (Blaschke 2010, p. 11).

In addition, this study focuses only on the comparison of the pixel-based and object-based methods as applied to high spatial resolution image in a sub-urban landscape and medium spatial resolution image in an urban landscape. Other variations that may be worth considering in future studies include: (1) the comparison of pixel-based and object-based methods as simultaneously applied in urban, sub-urban and rural landscapes for both high and medium spatial resolution imageries; and (2) the comparison of pixel-based and object-based methods as applied to high and medium resolution imageries of the same landscape, captured on the same date.

Conclusions

Image processing techniques play a key role in the extraction of valuable information from remote sensing satellite imageries. This study has examined and compared the classification performance of a pixel-based method and an object-based method as applied to high and medium spatial resolution satellite imageries. The object-based method itself helped facilitate the comparison as the same pixel-based classified maps, in combination with the image segments, were used as inputs for this method. The results show that the object-based method – a method that has been relatively less explored– has outperformed the pixel-based method for both high and medium spatial resolution satellite images in the urban and sub-urban landscapes.

The object-based method was able to improve the pixel-based classification results by up to 4% for the medium spatial resolution image in an urban landscape and up to 5% for the high spatial resolution image in a sub-urban landscape. Although these improvements in the accuracy might be viewed as minor, the results show evidence that the object-based method can produce more accurate classifications for both high and medium spatial resolution imageries in the context of urban and sub-urban landscapes. This is despite the limitations of the segmentation algorithm used.

The results also show, however, that an object-based method can also be less accurate than a pixel-based method. This means that in order to achieve the full potential of an object-based method, like the one applied in this study, there is a need to properly calibrate the segmentation algorithm. As discussed above, there are many factors that can affect the quality of object-based image segmentation. And in this context, a trial and error process is inevitable in order to produce the most desired image segments – the so-called building blocks of GEOBIA. However, the evaluation of the accuracy of object-based image segmentation is subjective, and this remains a challenge to the GEOBIA paradigm.

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Table 1. Error matrices for the QuickBird satellite image in a sub-urban landscape.

(*a*) Pixel-based classification

	Reference data						
Classified data	1	2	3	4	5	Total	User's accuracy (%)
Built-up (1)	119	12	1	15	1	148	80.41
Cropland (2)	7	190	0	29	2	228	83.33
Forest (3)	1	0	61	20	5	87	70.11
Other land (4)	3	6	13	96	0	118	81.36
Shadow (5)	5	0	3	1	30	39	76.92
Total	135	208	78	161	38	620	
Producer's accuracy (%)	88.15	91.35	78.21	59.63	78.95		

Overall accuracy (%) = 80.00

(*b*) Object-based classification (ST = 30)

	Reference data						
Classified data	1	2	3	4	5	Total	User's accuracy (%)
Built-up (1)	121	7	1	15	3	147	82.31
Cropland (2)	8	197	0	22	0	227	86.78
Forest (3)	0	0	72	8	8	88	81.82
Other land (4)	2	4	2	116	2	126	92.06
Shadow (5)	4	0	3	0	25	32	78.13
Total	135	208	78	161	38	620	
Producer's accuracy (%)	89.63	94.71	92.31	72.05	65.79		

Overall accuracy (%) = 85.65

Table 2. Error matrices for the Landsat TM image in an urban landscape.

(*a*) Pixel-based classification

Classified data	Reference data 1	2	3	Total	User's accuracy (%)
Built-up (1)	240	35	2	277	86.64
Non-built-up (2)	36	374	10	420	89.05
Water (3)	1	14	38	53	71.70
Total	277	423	50	750	
Producer's accuracy (%)	86.64	88.42	76.00		

Overall accuracy (%) = 86.93

(*b*) Object-based classification (ST = 5)

Classified data	Reference data 1	2	3	Total	User's accuracy (%)
Built-up (1)	251	25	0	276	90.94
Non-built-up (2)	26	394	12	432	91.20
Water (3)	0	4	38	42	90.48
Total	277	423	50	750	
Producer's accuracy (%)	90.61	93.14	76.00		

Overall accuracy (%) = 91.07

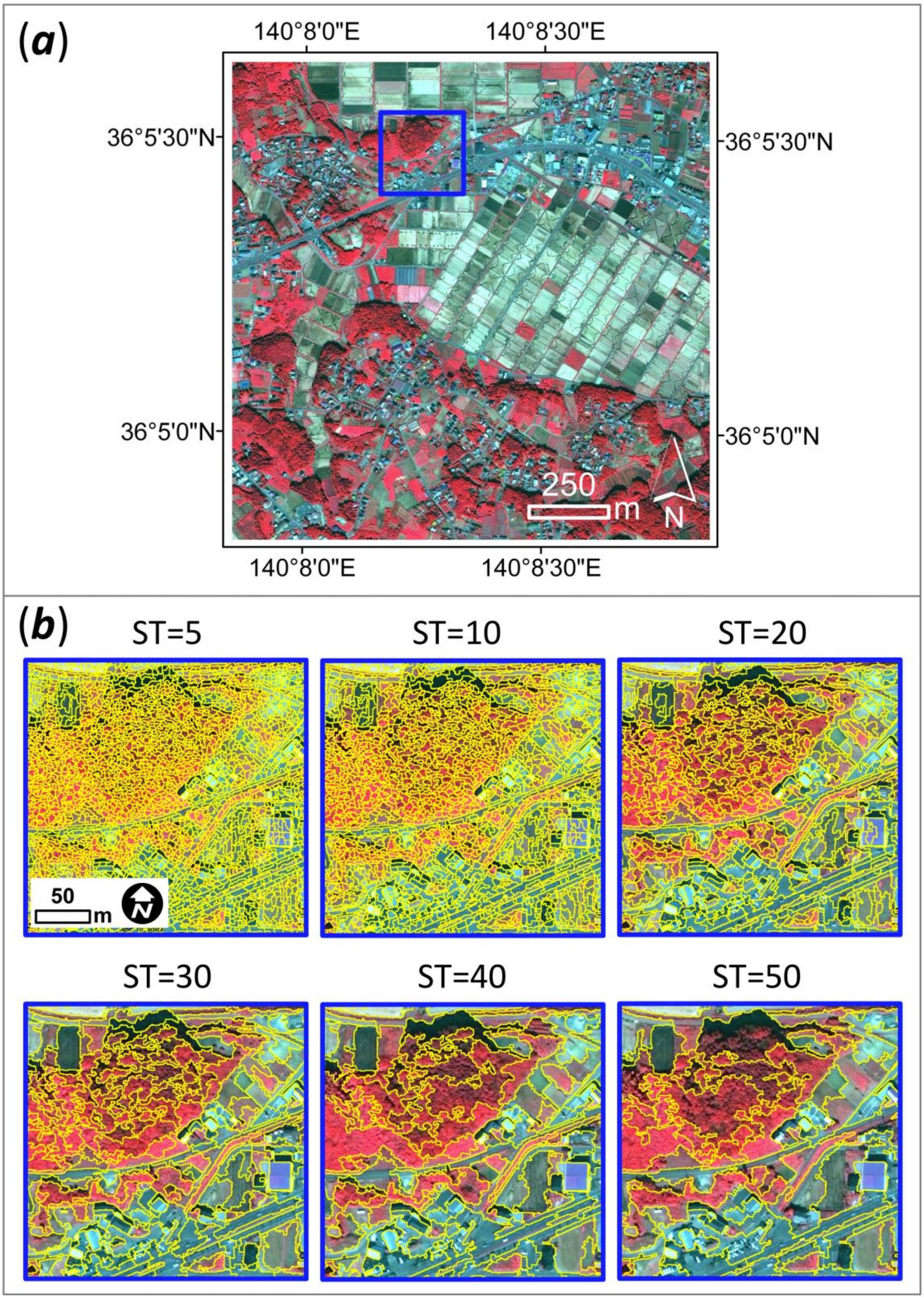

Figure 1. (a) Study area for Case 1: Using high spatial resolution satellite image (i.e. QuickBird satellite image; RGB = 432) in a sub-urban landscape; and (b) Results of the object-based segmentation at various similarity tolerance or thresholds (ST). The maps in (b) show only a portion of the QuickBird satellite image (i.e. blue rectangle inset in Figure 1(a)).

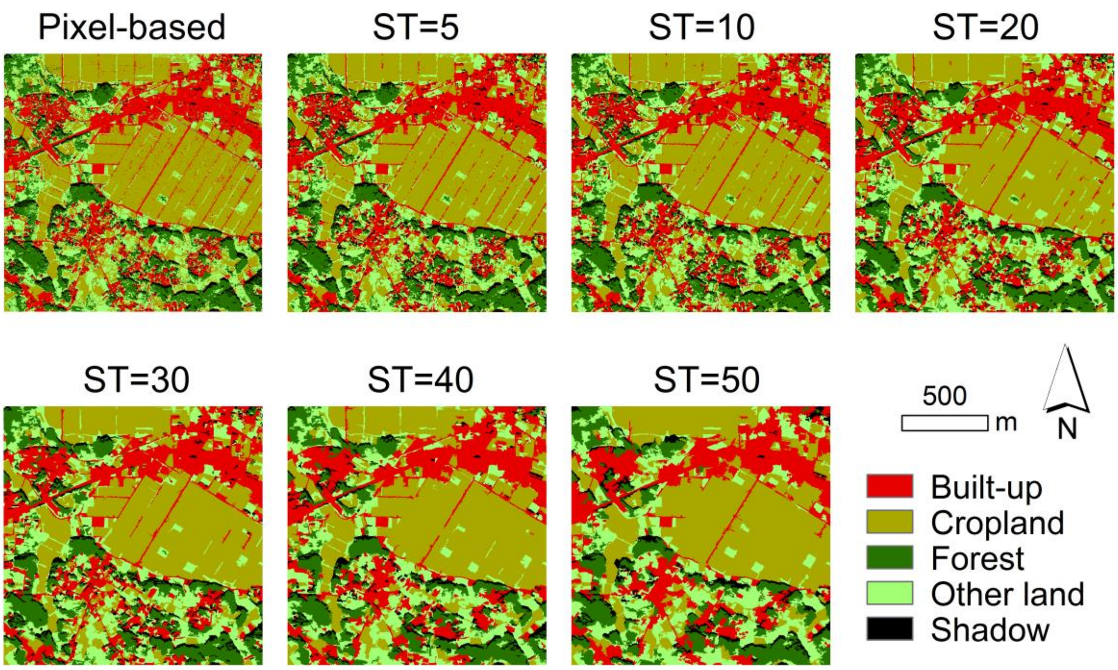

Figure 2. LUC maps produced by the pixel-based and object-based classification methods for the QuickBird satellite image in a sub-urban landscape.

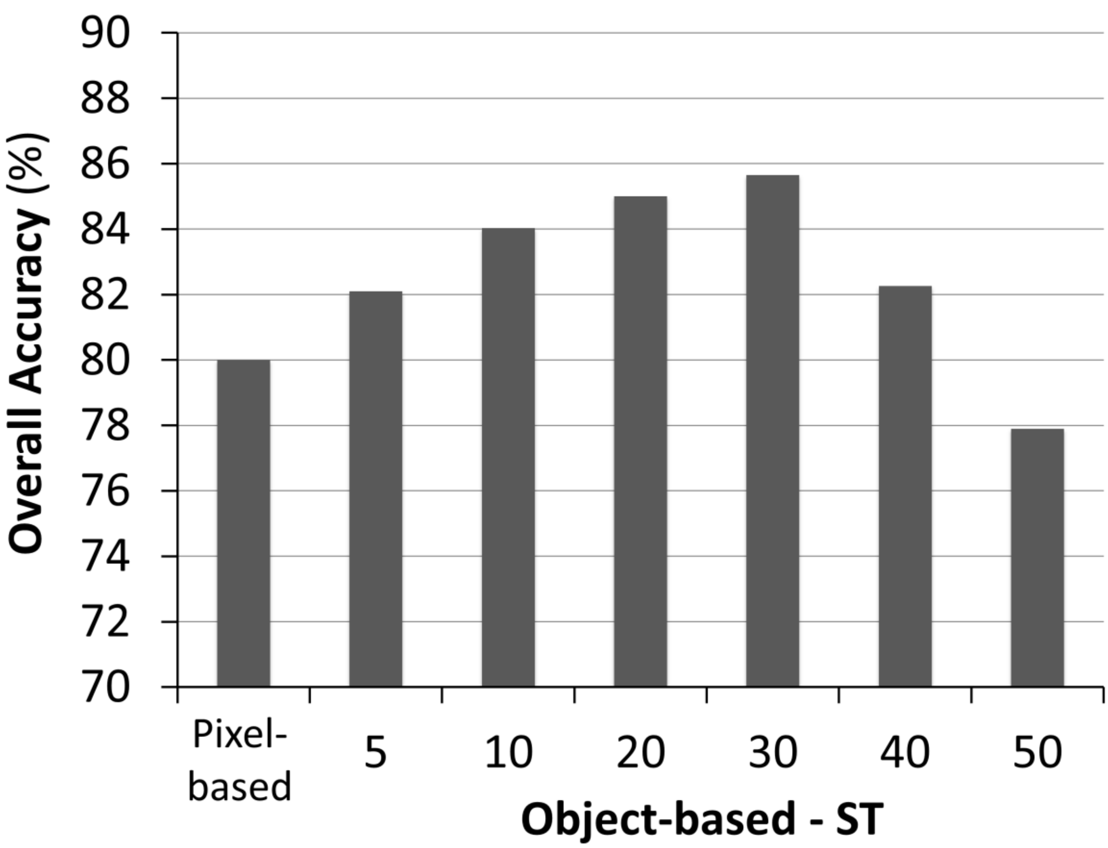

Figure 3. Overall accuracy of the LUC classifications for the QuickBird satellite image in a sub-urban landscape.

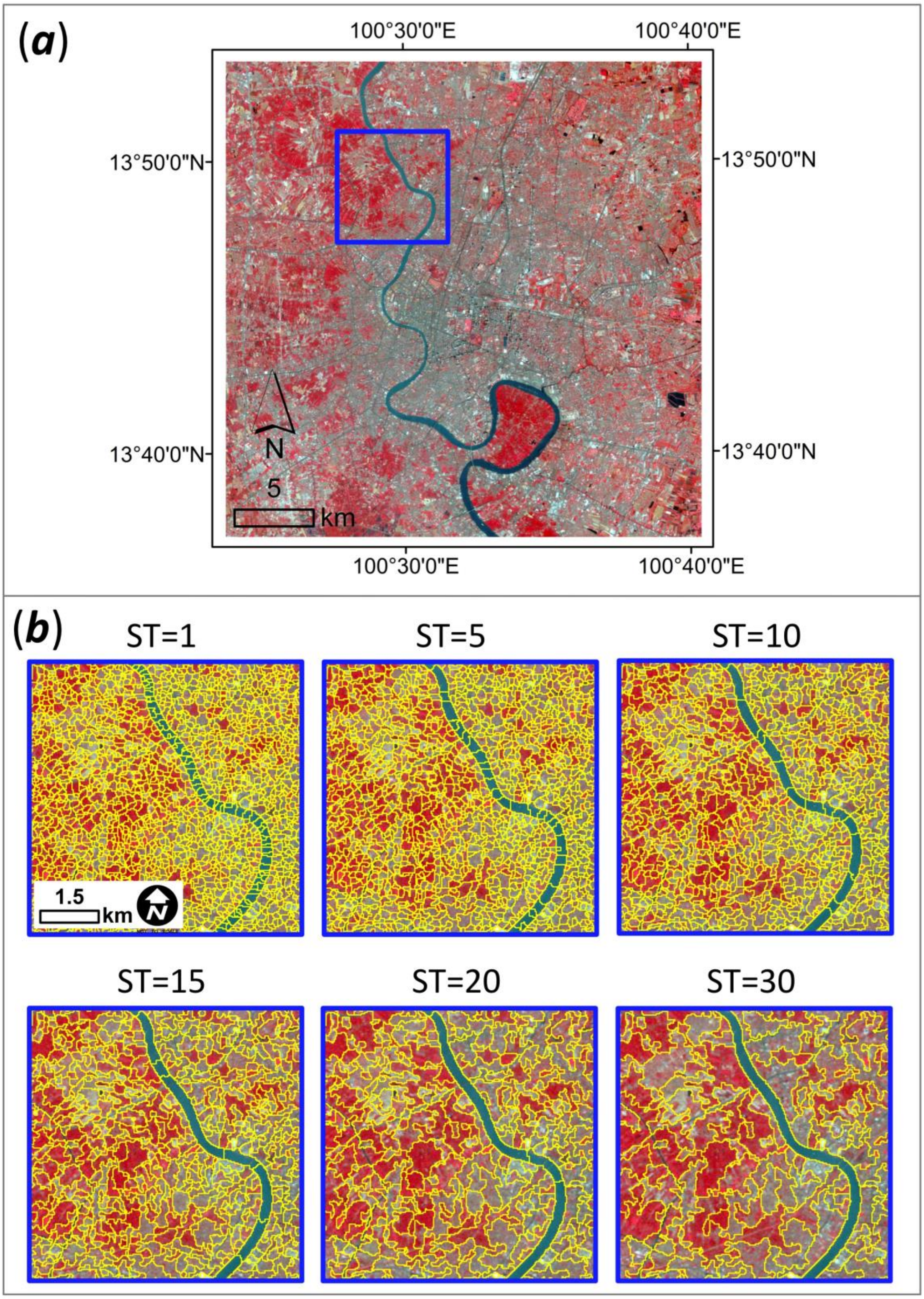

Figure 4. (*a*) Study area for Case 2: Using medium spatial resolution satellite image (i.e. Landsat TM image; RGB = 432) in an urban landscape; and (*b*) Results of the object-based segmentation at various similarity tolerance or thresholds (ST). The maps in (*b*) show only a portion of the Landsat TM image (i.e. blue rectangle inset in Figure 4(*a*)).

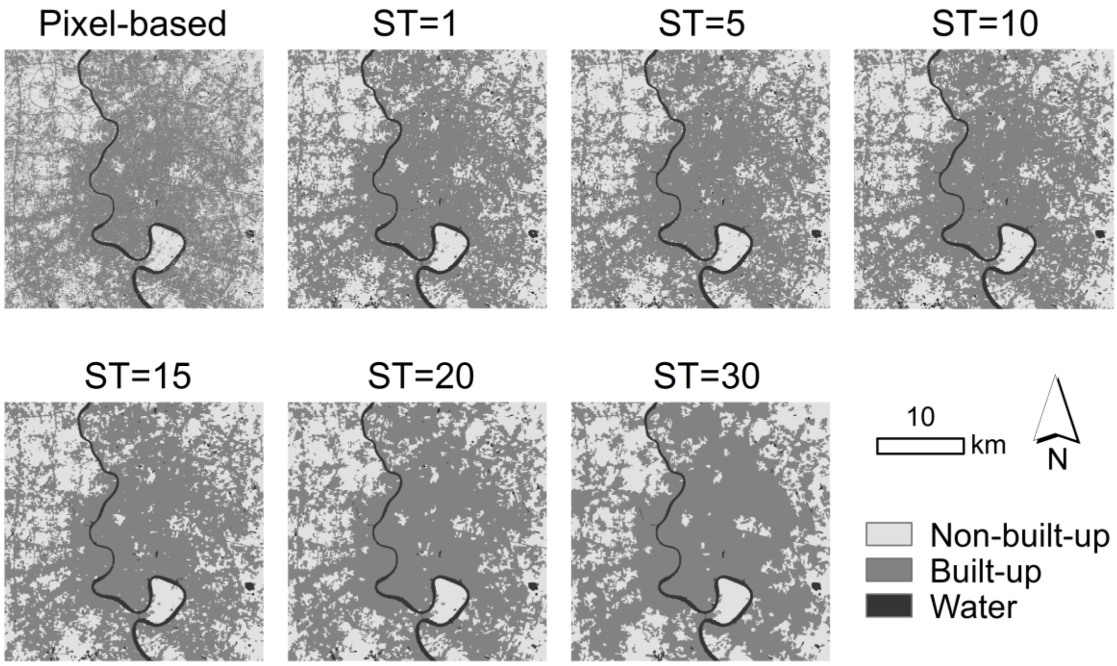

Figure 5. LUC maps produced by the pixel-based and object-based classification methods for the Landsat TM image in an urban landscape.

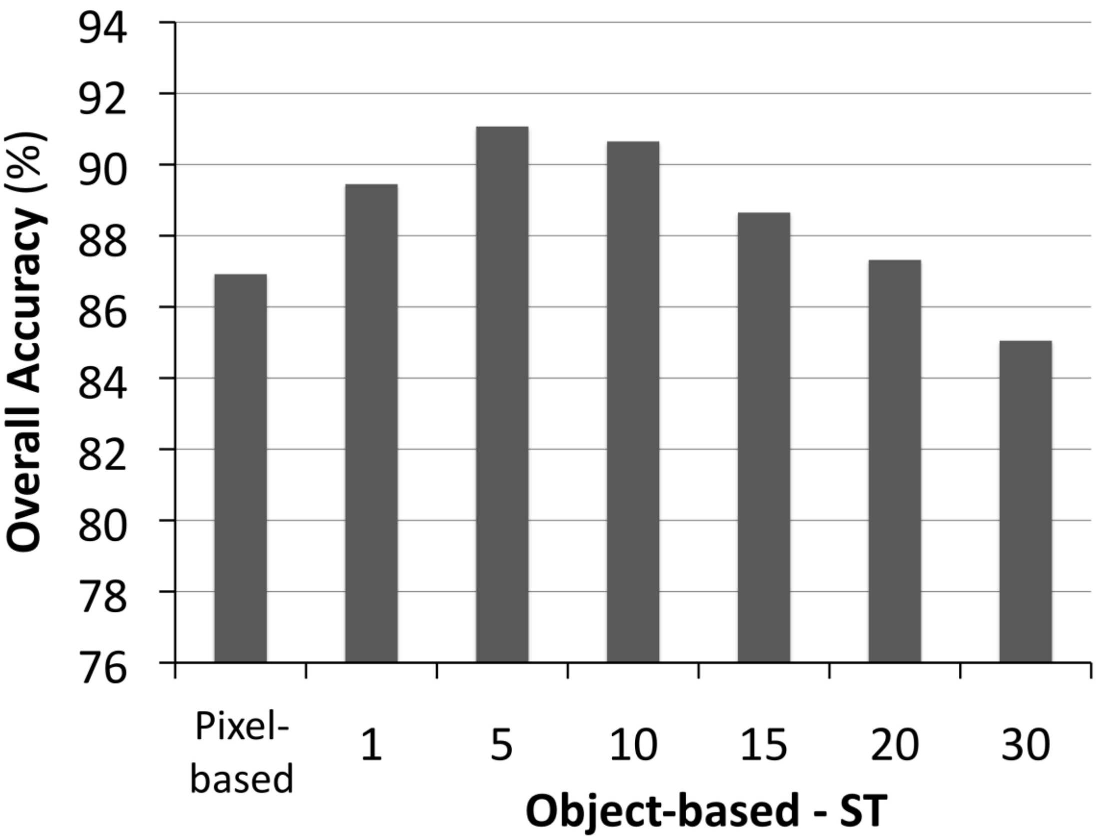

Figure 6. Overall accuracy of the LUC classifications for the Landsat TM image in an urban landscape.