# IDENTIFYING GREEN SPACES IN KUALA LUMPUR USING HIGHER RESOLUTION SATELLITE IMAGERY

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## Abstract

*There is a growing need for municipal councils to map and to monitor the extent and condition of urban green spaces, as one measure of the overall sustainability of a city. In this study, we identify the information about urban green spaces that can be obtained from satellite imagery. This research which is based in the city of Kuala Lumpur tests the ability of IKONOS higher resolution satellite imagery in identifying the different types and the different functions provided by green spaces using both automated methods and manual methods of visual interpretation. Both these methods were found to produce a map of green space for the entire city area that was 70% accurate when validated against ground surveys. In cases where higher resolution satellite imagery exists, we show how it can produce a variety of enhanced information which may enable city planners to monitor green space more regularly and to evaluate consistently which areas of green space within the city ought to be protected in order to maintain its benefits for the city population.*

***Keywords:*** *Urban green spaces, IKONOS satellite imagery, Image classification*

## 1 INTRODUCTION

The importance of maintaining urban green spaces is a matter of global public interest. The need to recognise and protect these spaces is perhaps at its most urgent in the rapidly expanding cities of the developing world. The United Nations estimate for the world's population in 2010 was approximately 6.9 billion and forecast to increase to 9 billion by the year 2050 (United Nations, 2009). Already more than 50% of the world's population is living in urban areas. Even in less developed regions, the number of urban dwellers is expected to rise to equal the number of rural dwellers by 2017. This rapid growth of urban populations is likely to demand and require large quantities of land to be used for providing housing, education, employment, transport and other infrastructure and amenities. Although such urban growth seems inevitable and planning will need to make provision for it, it seems reasonable to argue that there will also be a need to plan more explicitly and proactively to preserve adequate areas of urban green because poorly planned urban expansion can damage existing natural environments that are critical to the good functioning of urban areas.

Despite increasing amounts of digital geographic information now available to support spatial planning, including data from high resolution remote sensing, there is still a widespread public perception that planners are sometimes ‘out of touch’ with the situation on the ground. This perception is reinforced in situations where planners are unable to control developments that appear to pay little regard to the social, cultural or intrinsic environmental values of a land area. Given the pace of land development and the number of land parcels affected, it remains a challenge for urban planning to assemble an overview of the current situation and to make decisions with sufficiently current and comprehensive information. Although planners increasingly make use of GIS to track land use change and support decisions about controlling land development, the basic data does not always exist or is not always provided to them in a timely enough manner. Land parcel data, for example is usually maintained by other government departments, for their own purposes and planning often has to make best use of these data for their purposes.

Remote sensing has great potential to provide synoptic and up to date information on changes in the extent, distribution and condition of urban land uses. To be used by planners, however, the information extracted from the remote sensing imagery has to be easily related to existing land use and strategic mapping and provided in a form that is compatible with other information used for planning functions - e.g. development control purposes. The compatibility refers, for example, to the geographical units used to report the information, the definitions of the classes and the attributes or properties that are recorded. If not well matched, remotely sensed data products will tend to exist separately, rather than being integrated into the information system and the decision making process. The starkest examples are the many remote sensing ‘wall maps’ which adorn office walls, without the information they contain being assimilated into any organisational function. Kuala Lumpur (KL) is a particularly suitable city in which to study this problem. The metropolitan area of KL has almost tripled in area since 1950 and now covers 243 square km. Despite this expansion, it is estimated that since year 1988 until 2012, KL has lost nearly 50% of its green spaces, mainly to residential development to cater for the population increase, together with some industrial development (Yaakup, 2005). To allay public concerns about the loss of green spaces, the Malaysian government has declared its vision to become the ‘most beautiful garden nation’ by 2020 and tasked the planners with devising a strategy to fulfil this vision, particularly for the urban areas where 60 percent of Malaysians now reside. Although KL has initiated a series of high profile tree planting programmes, there is a general view that spatial planning needs to be much more proactive in protecting the remaining open and green spaces from land development. Malaysia generally is a well-mapped country, with the national mapping agency (JUPEM) having completed the conversion to digital format of most of the basic scales of mapping. Within the metropolitan area of KL, the Federal Land Survey Office has provided KL City Hall a complete coverage of all land parcels in digital form.

In this study, we will explore ways in which spatial planning might be able to use remotely sensed imagery, to respond more consistently to proposals to develop individual green spaces, by developing methods to identify and classify remaining green spaces for protection from development in a more holistic and objective manner. We proceed from the pragmatic standpoint that cadastral data will continue to be used as the basis for spatial planning because of its institutional legacy and because these boundaries have legal status and are bound with issues of land title and ownership. Land parcel data however carries a limited set of attributes, which are rarely sufficient to determine the quality and condition of the land parcel. This study explores how far such supplemental information about the quality of the spaces can be obtained from remote sensing.

## 2 RESEARCH METHODOLOGY

An image classification method was employed. Identifying and developing green spaces classification from high resolution IKONOS imagery using an object-oriented image analysis method with secondary manual refinement were carried out. Both of these approaches are summarised in figure 1, how these approaches relate to each other is explained and illustrated in the following section.

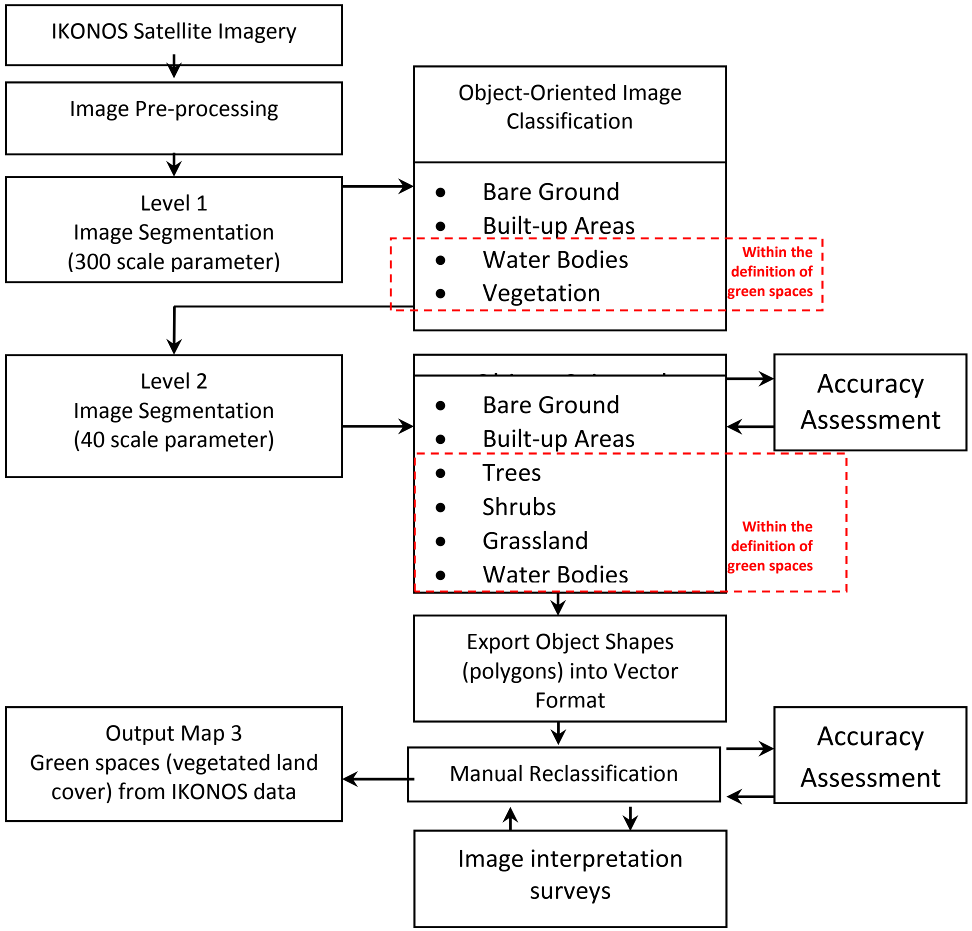


*Figure 1: Flowchart of Methodology for Identifying Kuala Lumpur's Green Spaces using IKONOS Imagery*

### 2.1 *Data Sources*

The data used were 18 IKONOS image tiles acquired in 2002. An attempt has been made during data collection at KL City Hall in August 2007 to acquire satellite images captured in more recent years (i.e.: 2006 or 2007), but only the 2002 IKONOS images were made available by KL City Hall at that point in time. These 18 IKONOS scenes had to be combined into a mosaic to cover the metropolitan area of Kuala Lumpur. These images were then divided into 11 zones for managing the classification task, as shown in Figure 2. The IKONOS images were acquired with initial geo-rectification complete. The multi-spectral images have a spatial resolution of one meter and include the three visible spectral bands (red, green and blue). The lack of the near infra-red (NIR) band did limit the ability to classify land cover of vegetation and also limited the ability to carry out some standard image processing operations, such as atmospheric correction of the images. Some further spectral enhancements of these images were done to increase the ease of visual interpreting and to enable more consistent results from automatically segmenting the images.

### 2.2 *Image Pre-processing*

Initial processing has been carried out on these IKONOS satellite images. Image enhancement and visual inspection was conducted using ERDAS Imagine software. As some haze was found in most of the images, a 3x3 convolution kernel filter for low-haze conditions was applied before any other spectral enhancement was done. Although having only the three visible bands available limited the analysis that can be carried out using these images and according to Cleve et al. (2008), classifying only using the three visual bands of an image may result in high confusion of classes as these three bands tend to have highly inter-correlated values. However, according to Lillesand and Kiefer (2000), decorrelation stretching can be useful to display multi-spectral data that is highly correlated. Therefore, a decorrelation stretch was applied to discriminate features of these three visual bands.

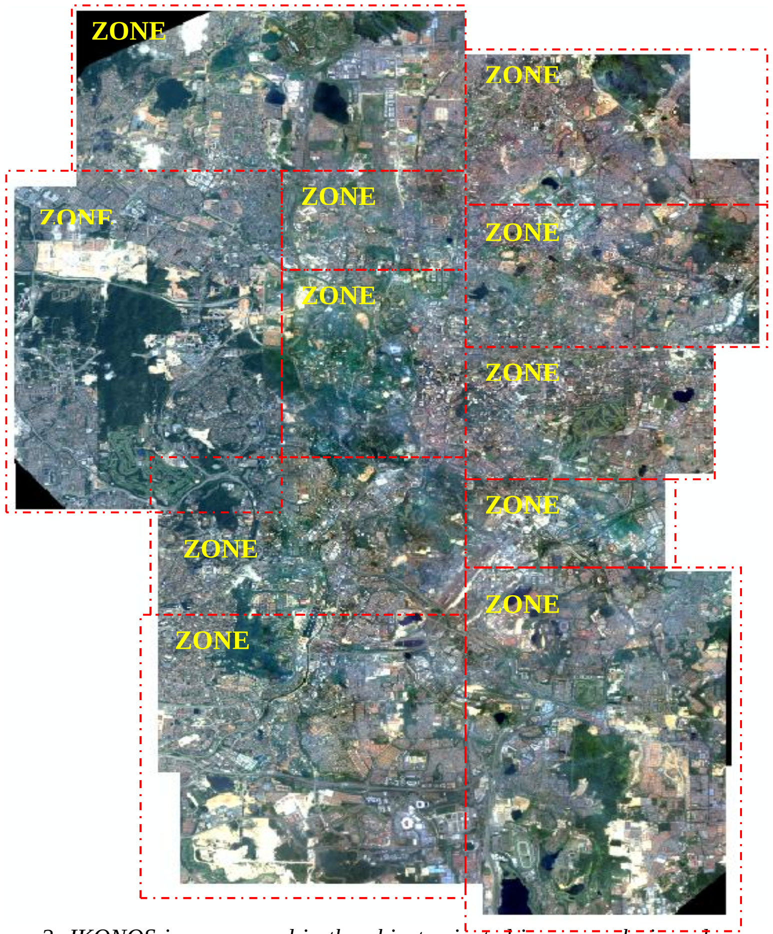


*Figure 2: IKONOS imagery used in the object-oriented image analysis and were classified separately into 11 zones*

### 2.3 *Image Segmentation*

As shown in Figure 1, the object-oriented approach involves two consecutive steps, firstly a segmentation of the image, that breaks it down into a series of smaller image objects and secondly followed by a classification of the objects that were recognised (Baatz et al. 2004). Both of these steps were conducted using Definiens eCognition software. Segmentation is the process of grouping adjacent pixels with similar spectral and textural characteristics. These groups of pixels represent meaningful entities or objects for examples trees, houses, roofs or water (Cleve et al. 2008). In this study, a multi-scale segmentation algorithm was used. This segmentation approach, which is also known as bottom-up segmentation technique merges smaller image objects (starting with one pixel) into bigger image objects until a threshold size is achieved (Definiens, 2004).

There are five parameters influencing the result of image segmentation: scale, colour, shape, smoothness and compactness. The scale parameter is used to define the average size of the objects to be detected in the image. The larger the scale parameter value, the larger the image object detected. Colour determines the spectral homogeneity of the objects whereas shape controls the degree of object shape homogeneity. According to Lackner and Conway (2008) and Fung et al. (2008), colour is generally more effective at differentiating land cover types than shape and shape is controlled by two further parameters, smoothness and compactness. There is some variation as to which is the best value for smoothness and compactness. However, according to Mathieu et al. (2007), Su et al. (2008) and Fung et al. (2008) the best smoothness and compactness value tend to range from 0.5 to 0.7 for smoothness and 0.1 to 0.5 for compactness. Generally, smoothness is given higher value for better extracting longer objects whilst compactness is ideal for image objects that are more contained. Figure 3 shows the concept flow diagram of these five parameters that influencing the results of image segmentation.

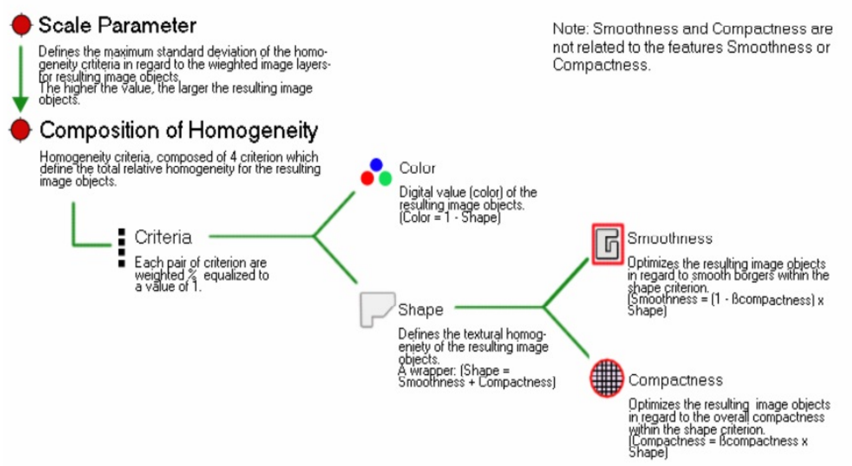


*Figure 3: Concept flow diagram of the five parameters that influence the results of image segmentation. (Source: Definiens, 2007)*

After undergoing several processes of experimentation and after examining numerous segmentations with different scale and shape parameters and also visually comparing these to the original IKONOS images, the following segmentation parameters were chosen based on how clearly and accurately the segments delineated the boundaries of the small and large objects visible in the image. Table 1 summarises the parameters chosen and used in this study.

*Table 1: Segmentation parameters selected and used*

| Segmentation Level | Scale Parameter | Colour | Shape | Compactness | Smoothness |
|---|---|---|---|---|---|
| Level 1 | 300 | 0.7 | 0.3 | 0.8 | 0.2 |
| Level 2 | 40 | 0.7 | 0.3 | 0.8 | 0.2 |

As shown in table 1, the images were segmented at two different scales. The example of this segmentation is shown in Figure 4. The first level of segmentation was produced using a scale parameter of 300 and the second level of segmentation was carried out using a scale parameter of 40. In both level of segmentation, a greater weight given to the colour values (0.7), rather than the shape of features (0.3). This weight value was chosen based on the previous studies carried out which claimed that colour generally is more effective in differentiating land cover type than shape. A value of 0.8 was used for compactness and consequently, a weight of 0.2 was allocated to smoothness in both level of segmentation. The higher value given to compactness due to it might be useful in extracting vegetation patches that mostly in nucleated form and not elongated shape. These two hierarchical levels of segmentation help to facilitate the extraction of meaningful objects. The segmentation workflow proceeded from the top to the bottom layer. This logic permitted the early recognition and subsequent masking out of some types of objects that were not relevant for the research.

(a)

(b)

*Figure 4: An example of segmentation:*

*(a) Segmentation using a scale parameter of 300 (left) leads to large objects that contains considerably variability within them; and*

*(b) Segmentation progressively reducing the scale value to 40 (right) to allow smaller and more spectrally pure objects to be identified from the image.*

### 2.4 *Class Hierarchy and Object-Based Classification*

According to Baatz et al. (2004), image classification is a task to assign image objects recognised during segmentation process into user-defined classes. Hence, a meaningful classes need to be developed before any image classification process can begin. In this study, the class hierarchy were carried out into two levels according to the segmentation level. In each hierarchy there are parent and child classes. Parent classes have been further classified into more detailed child classes. Figure 5 below summarise these two class hierarchical levels at different segmentation level.

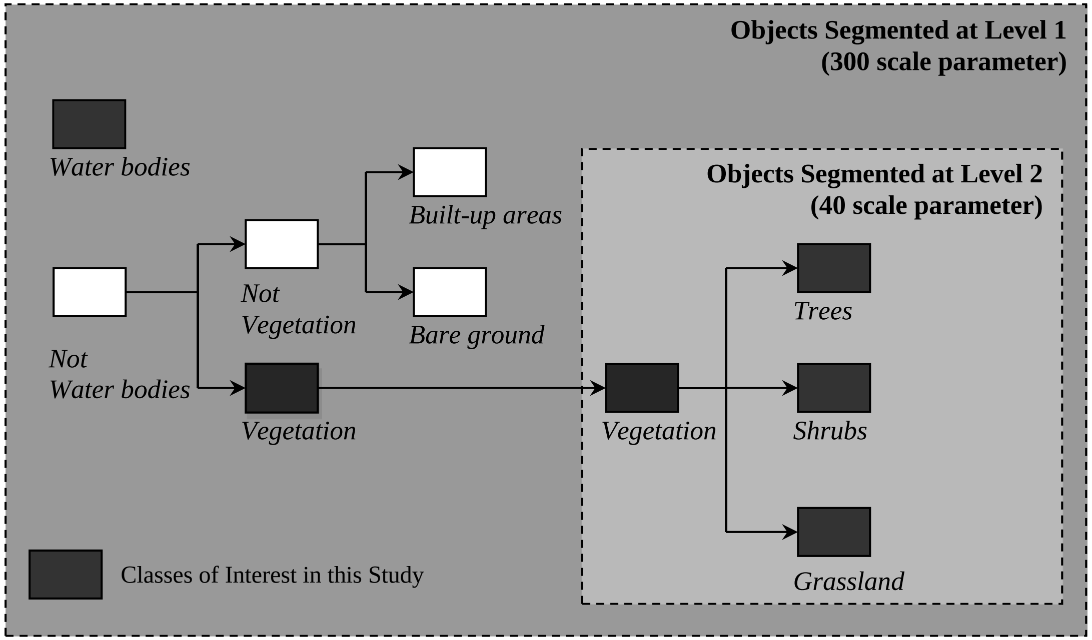


*Figure 5: Example workflow diagram, showing the class hierarchy for segmenting the image into meaningful objects*

As shown in figure 5, in the first level of class hierarchy (in level 1 segmentation), water bodies and 'non-water' bodies are the parent classes. This first level segmentation classified the study area into four broad classes (large image objects) of water bodies, vegetation, built-up areas and bare ground. This would allow some of the large objects to be masked out of the image and not segmented further at the lower levels, for instance water bodies, built-up areas and bare ground. On the other hand, in level 2 segmentation, trees, shrubs and grassland are the child classes. The smaller objects created at this second level permitted smaller patches of vegetation to be extracted. Within the larger class of open vegetated areas, more information was extracted to characterise the mixtures of vegetation occurring internally. For instance, this allowed areas of trees, shrubs and grassland to be separately distinguished. This second level segmentation classified the study area into three classes of trees, shrubs and grassland.

### *2.5 Sampling Design and Accuracy Assessment*

In this research, a stratified random sampling design was used in order to produce a statistically reliable accuracy assessment of the results. One of the most important factors a sampling design is the independence of the reference data that will be used in the accuracy assessment. The need for independent reference data presented a problem since totally independent reference data was not available for the study area. As a result of this constraint, a comparison of the predicted classes as output by the classifier was carried out against samples visually interpreted by the author from the IKONOS imagery in the selected zone areas. To partly overcome the difficulty of the reference samples independence, the sample for the accuracy assessment was chosen and interpreted before the map was classified. This step was done in order to eliminate any potential bias in the classification assessment.

According to Congalton (2008) and Sydenstricker-Neto et al. (2004), it has been proposed that there are three common sampling units for creating reference data for assessing the accuracy of remote sensed data, which are:

- the pixel;
- a group of pixels; and
- a polygon.

In this research, the sample unit selected was in a form of polygon. The image objects that are formed by segmentation were the basic spatial unit in this research, thus these classified units (polygons) were used to build the confusion matrices. Therefore, once the segmentation process finished, the test samples were chosen per class to calculate the accuracy. Approximately 50 objects or polygons (or more) in each class were chosen and according to Green and Congalton (2004) such volumes are required to adequately populate an error matrix. Definiens eCognition software enables users to create a TTA (training or test areas) mask of samples, which can then be used to generate an error matrix of the classification. A TTA mask is generated as a reference to check the classification quality.

Confusion matrix and Kappa statistic were calculated to report the classification accuracy. The error matrix is the most widely accepted format to report remotely sensed data classification accuracy (Congalton 2008). The matrix allows not only the total accuracy to be shown but also the accuracy of each class and thus the confusion between classes (Green and Congalton 2004). These statistics were calculated using a Definiens eCognition software tool, which generates estimations of the overall accuracy, the accuracy per class as well as the Kappa statistic.

## 3 FINDINGS

Figure 6 illustrate the results of the IKONOS classification at level 2 (40 scale parameter) for Kuala Lumpur city. The classification results cover most of the vegetated or visually green spaces without discriminating between privately owned or publicly owned green spaces. However, some problems remain with the classification of this IKONOS imagery. Whilst it was possible to develop a few classes that matched closely with the definitions of green spaces used, most of the detailed classes could not be discriminated, whereas others were misclassified.

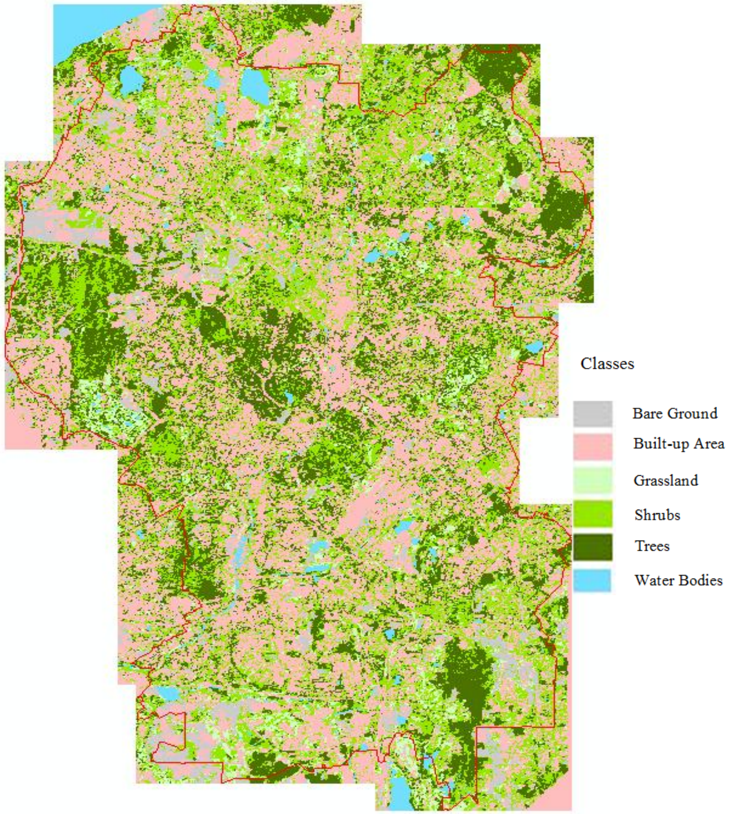


*Figure 6: Image classification result for Kuala Lumpur city (Level Two - 40 scale parameter)*

It can be observed from the classification result that shrubs were over-estimated and misclassified. The shrub class was mainly confused with built-up areas dues to the similar spectral values of these objects, thus affecting the capability of the membership rules to extract them. The result also shows that some areas of bare ground area were not correctly extracted from the image and were mainly confused with built-up areas. Such bare ground areas were under-estimated in this object-oriented classification due to their similar spectral values. Ground checking or ground truth could be used to resolve these misclassifications and possibly determine more effective threshold values for separating these classes.

Similar issues occurred for some water bodies which were under-estimated because a few were misclassified as built-up areas. Confusion on the water bodies' classification is probably due to the shape of these thinner rivers and streams which makes them similar to the pavements found along the river corridors. Furthermore, some of the water bodies such as rivers were also covered by low density tree canopies which may have blocking the water to be extracted in the classification process. In these instances, ground checking might be useful to resolve this misinterpretation or find improved threshold values for such classes.

### *3.1 Manual Reclassification of IKONOS Image Classification*

When the results of the automated IKONOS imagery classification were compared against ground reference data, some of the classes assigned were found to be in error. Therefore, further reclassification task were carried out in order to correct and improve this automated classification results. Post-classification inspection and manual reclassification by visual interpretation is widely practised and as an empirical means of improving the results of image processing when the final required result is a map often for some practical purpose. In the UK, green space mapping is still undertaken by visual interpretation and classification of aerial photography at 25cm resolution (Greenspace Scotland, 2010). In this study, further reclassification was done visually by examining the underlying IKONOS imagery presented as an RGB composite. This process corrected a number of repeated misclassification which occurred.

The exercise of visually reclassifying the automated classification results was carried out based on the author's first-hand familiarity with many parts of the city. Besides that, many of the areas had also been observed recently by the author during travelling across the city on site assessment visits. Furthermore, the author's knowledge of how different land cover types typically appeared on the IKONOS imagery also helped in visually reclassifying the results. This checking exercise and reclassification in certain instances was carried out solely by the author for the entire city area to ensure consistency, so that the resulting reclassification more reliably represented the actual distribution of green spaces known to exist. Although this exercise was a labour intensive process, a number of repeatedly types of misclassified class were identified and corrected. It was found that several cover types which had repeatedly been misclassified by the automatic classifier could be corrected this way.

Figure 7 shows the result of this manual reclassification. It can be observed that the confusion and widespread misclassification between the shrubs and trees classes and between both the trees and shrubs class with the built-up areas class has been largely corrected. Similarly, the confusion between bare ground and water bodies within built-up areas was also corrected. This resulted in a more accurate classification of Kuala Lumpur's green spaces not so much in terms of overall extent but rather by providing a more geographically accurate division of space between the trees, shrubs, grassland and other land cover. As shown in figure 7, in overall, the green space land cover (consisting of trees, shrubs, grassland and water bodies) have decreased from approximately 14490 hectares (before the reclassification task carried out) to approximately 14386 hectares.

To support the overall green space map, it was important that an overall statement of the likely accuracy of the map be produced for the intended users at KL City Hall. Two further accuracy assessments were carried out to evaluate the accuracy of the city-wide green space mapping produced firstly by the automatic classification using Ecognition and secondly as a result of the further manual reclassification which was guided by visual inspection of the raw imagery and comparison with the classified result.

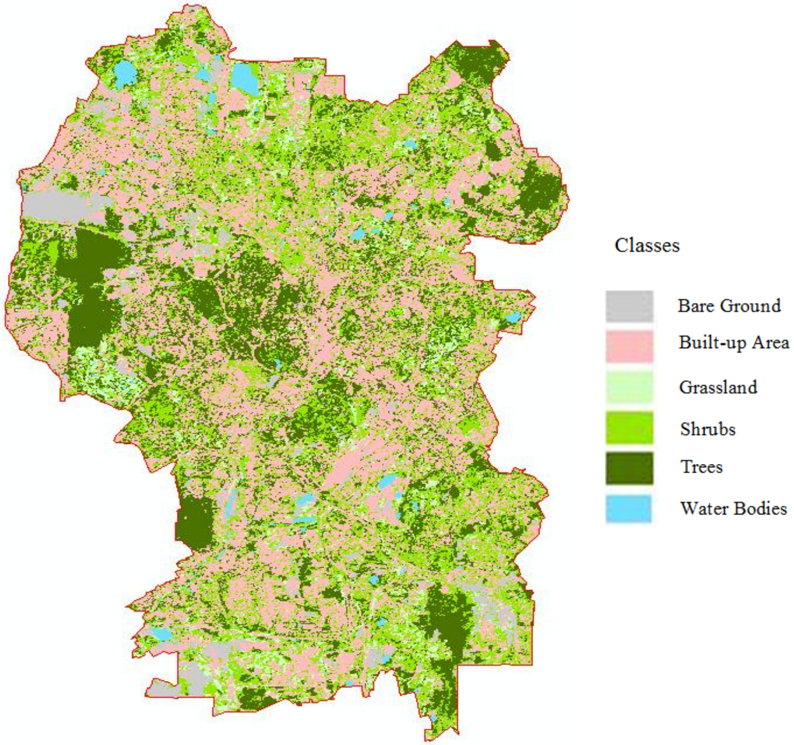


*Figure 7: Result after visual checking and manual reclassification*

| Techniques and data used to map and identify Kuala Lumpur's green spaces | Total area of green spaces identified (in hectare) |
|---|---|
| Automated IKONOS image classification | 14490.61 |
| Manual reclassification of automated IKONOS image reclassification | 14386.45 |

Total area (in hectare) of Kuala Lumpur's remaining green spaces using different techniques

By providing a quantitative estimate of the accuracy of the mapping produced by each technique, the benefit of the additional effort spent on post-classification improvement can be assessed. A stratified random sampling design was used to select reference data from the IKONOS imagery. Where sufficient examples could be identified confidently, 50 or more reference polygons were extracted for each land cover class by visual inspection of the imagery in different areas, well distributed throughout the city. Table 2 presents the accuracy assessment for the automated classification produced for Kuala Lumpur using Ecognition, whilst Table 3 shows the accuracy following the manual reclassification of polygons whose assignment can be seen visually to be incorrect by inspection of the raw imagery and application of local knowledge about the ground conditions.

Table 2 shows that the automated method delivers an overall accuracy of around 70%, which is generally considered a minimum acceptable level for many thematic mapping applications (Foody, 2008). Whilst water bodies are well discriminated, the use of the reference data reveals several instances where areas of trees have been misclassified as shrubs and vice-versa, as well as some less important cases where bare ground has been erroneously classified as a built up area. As a result, the per-class accuracy for the tree and shrub classes is only 62% and 65% respectively. This may limit the use of this result as the basis for deriving further products where the correct differentiation of these two classes is important, such as for example, producing maps of areas where trees provide an important source of shade and shelter.

*Table 2: Classification accuracy for the initial green space map created by automated classification of IKONOS imagery*

| | Automated Classification | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Reference Data** | **Bare Ground** | **Built-up Areas** | **Trees** | **Shrubs** | **Grassland** | **Water Bodies** | **Total** | **Accuracy Percentage** |
| **Bare Ground** | **8** | 11 | | 1 | | | 20 | 40.0% |
| **Built-up Areas** | 6 | **50** | 2 | 5 | | | 63 | 79.4% |
| **Trees** | | 1 | **46** | 27 | | | 74 | 62.2% |
| **Shrubs** | | 2 | 12 | **35** | 5 | | 54 | 64.8% |
| **Grassland** | | 2 | | 7 | **33** | | 42 | 78.6% |
| **Water Bodies** | | | | | | **29** | 29 | 100% |
| **Overall Classification Accuracy** | **70.8%** | | | | | | | |

Table 3 presents the corresponding results for the accuracy of the mapping produced after the manual reclassification task. The accuracy percentages for all classes are now above 85% and the overall accuracy of the mapping following the manual reclassification has increased to 90.2%.

The result of conducting the visual checking and manual reclassification has therefore been to increase the overall accuracy statistic by nearly 20% above that for the automated classification technique. By comparing tables 2 and 3, it can also be observed that the accuracy for all the individual classes has also increased. The bare ground class shows the greatest improvement of accuracy from 40% to 85%. This bare ground class was mostly confused with built-up areas and this had led to a very low accuracy in the automated classification. Similarly, by comparing these two tables it can also be observed that the confusion that had occurred between the tree and shrub classes has mostly been resolved by the visual checking and manual reclassification. The accuracy of both these classes has improved significantly, from 62.2% to 93.2% for the tree class and from 64.8% to 85.2% for shrub class.

The confusion between the tree and shrub classes might have been resolved more easily if the NIR band of the IKONOS sensor had been available, since the two classes might have been more easily differentiated based on their differences in biomass by an index such as the NDVI (Rouse et al. 1974). The accuracy that might potentially be achieved by an automated method alone could be higher than estimated here.

The results in table 2 in part reflect the limitations of the data that was available and the skills of the author as only a novice at image processing. Nevertheless, the manual reclassification task that was carried out was shown to provide an acceptable means by which misclassified areas could be corrected and delivered an acceptable mapping accuracy of over 90% for the final product.

*Table 3: Classification accuracy for the revised green space map produced after manual reclassification*

| | Manual Reclassification | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Reference Data** | **Bare Ground** | **Built-up Areas** | **Trees** | **Shrubs** | **Grassland** | **Water Bodies** | **Total** | **Accuracy Percentage** |
| **Bare Ground** | **17** | 3 | | | | | 20 | 85.0% |
| **Built-up Areas** | 3 | **55** | | 5 | | | 63 | 87.3% |
| **Trees** | | 1 | **69** | 4 | | | 74 | 93.2% |
| **Shrubs** | | | 5 | **46** | 3 | | 54 | 85.2% |
| **Grassland** | | 1 | | 3 | **38** | | 42 | 90.5% |
| **Water Bodies** | | | | | | **29** | 29 | 100.0% |
| **Overall Classification Accuracy** | **90.2%** | | | | | | | |

## 4 DISCUSSION

High resolution imagery is a valuable source of information especially in an urban environment. The spatial resolution (mostly less than five meter) allows different features and objects in an urban setting to be distinguished visually. However, the amount of detail at such image resolutions leads to a large variability of spectral responses from one pixel to the next, due to the complexity of urban surfaces. For an example, a single roof area of the same material could have at least two different spectral responses depending on the illumination angle. Similarly, a patch of grass that could be semantically considered as a single area would be formed from many individual pixels that may each have slightly different spectral responses depending upon factors such as the slope, degree of shadowing and general condition of the grass in different parts of the area. Although visually the human brain may be able to recognise such areas as distinct features by their colour, shape and context, many automatic classifiers may be unable to extract these features from such an image. A further difficulty in this study was that the IKONOS imagery provided to the author by KL City Hall, although it was the only data they had themselves received from Malaysian Remote Sensing Agency (MACRES), contained only three bands (visible red, green and blue-RGB) but lacked the infra-red band that is well-known to be useful for facilitating the extraction of vegetation. Because some types of green spaces could not be reliably differentiated from the high resolution imagery, a complete mapping of all the proposed land cover classes could not be achieved by automated classification approaches. Thus, after careful inspection of the RGB image, a further reclassification was carried out to identify the green spaces in Kuala Lumpur city and manually correcting the misclassified areas that had been assigned to the incorrect class by the automated procedure. This is not entirely unexpected as a number of studies have found that only some types of green spaces can be reliably determined automatically from high resolution imagery. Nevertheless, the automated classification provides a good summary of the extent and quantity of total green spaces in the city, which can be used to derive a further series of indicators about the relative supply of green spaces and the particular contribution of certain spaces.

## 5 CONCLUSION

Overall, this study has suggested and presented a means of producing a more comprehensive and up-to-date inventory of green and open spaces remaining in Kuala Lumpur than is presently held in the KL City Hall's Planning Office. Combining the benefits of a typology adapted for the Malaysian context, digital land parcel data and satellite imagery, city planners can gain a more realistic picture of the distribution of remaining spaces. Adopting a closer approximation to the actual extent of green space creates opportunities for planning the protection and conservation of green space at a city-wide level. It also permits the loss of all types of urban green space to be monitored and measured more objectively. Furthermore, this study suggested that these techniques could offer planners an enhanced understanding of the nature and condition of remaining urban green spaces, allowing them to recognise a greater number of land areas within the city that provide some environmental, social or amenity value, within this wider definition of green space. This information might also allow planners to reach and to defend decisions about protecting different spaces more transparently.

## 6 ACKNOWLEDGEMENT

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## REFERENCES

Baatz, M., Benz, U., Dehghani, S., Heynen, M., Holtje, A., Hofmann, P., Lingenfelder, I., Mimler, M., Sohlnach, M., Weber, M. and Willhauck, G. 2004. eCognition Professional User Guide. Definiens Imaging GmbH. Munchen, Germany.

Cleve, C., Kelly, M., Kearns, F.R. and Moritz, M. 2008. Classification of the wildland-urban interface: A comparison of pixel and object-based classifications using high resolution aerial photography. Computers, Environment and Urban Systems. Vol. 32, Issue 4, pp. 317-326.

Congalton, R.G. and Green, K. 2008. Assessing the accuracy of remotely sensed data. Boca Raton, Florida. Taylor and Francis Group.

Definiens. 2004. Definiens Developer 7 User guide. Definiens Imaging.

Foody, G.M. 2008. Harshness in Image Classification Accuracy Assessment. International Journal of Remote Sensing. 29 (11) pp. 3137-3158

Fung, T., So, L.L.H., Chen, Y., Shi, P. and Wang, J. 2008. Analysis of green space in Chongqing and Nanjing Cities of China with ASTER images using object-oriented image classification and landscape metric analysis. International Journal of Remote Sensing. 29.

Green, K. and Congalton, R.G. 2004. An error matrix approach to fuzzy accuracy assessment: The NIMA geocover project. In Remote Sensing and GIS Accuracy Assessment edited by Lunnetta, R. CRC Press. Chapter 2.

Greenspace Scotland. 2010. Urban Greenspace Mapping and Characterisation Handbook. Greenspace Scotland.

Lackner, M. and Conway, T.M. 2008. Determining land use information from land cover through an object-oriented classification of IKONOS imagery. Canadian Journal of Remote Sensing. 34, pp. 77-92.

Lillesand, M. and Kiefer, W. 2000. Remote sensing and image interpretation. John Wiley and Sons.

Mathieu, R., Aryal, J. and Chong, A.K. 2007. Object-based classification of IKONOS imagery for mapping large-scale vegetation communities in urban areas. Sensor. 7, pp. 2860-2880.

Rouse, J.W., Hass, R.H., Schell, J.A. and Deering, D.W. 1974. Monitoring vegetation systems in the Great Plains with ERTS, in Third ERTS-1 Symposium, Vol. 1, NASA Spec. Publ. NASA SP-351, 309-317.

Su, W., Zhang, C., Li, L., Wang, Y.J. and Li. D.L. 2008. Object-oriented implementation monitoring of zone type land consolidation engineering using SPOT 5 imagery. Wseas: Advances on Applied Computer and Applied Computational Science. Pp. 546-550.

Sydenstricker-Neto, J., Wright, A. and DeGloria, S. 2004. Participatory reference data collection method for accuracy assessment of land cover change map. In Remote Sensing and GIS Accuracy Assessment edited by Lunnetta, R. CRC Press. Chapter 6.

United Nations Population Division. 2009. Urban and rural areas 2007. United Nations.

Yaakup, A., Johar, F., Abu Bakar, S. Z., Sulaiman, S. & Baharuddin, M. N. 2005. Integrated Land Use Assessment: The Case Study of Klang Valley Region, Malaysia.