Case study

Monitoring Urban Green Space (UGS) Changes by Using High Resolution Aerial Imagery: A Case Study of Kuala Lumpur, Malaysia

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ABSTRACT

Urban green space (UGS) in a city is the foundation of natural productivity in an urban structure. It is also known as a natural cooling device that plays a vital role in the city as an urban lung, discharging oxygen to reduce the city heat and as a wall against harmful air pollution. When urbanization happens, UGS, including the gazetted areas, is essentially converted into an artificial surface due to the population's demand for new development. Therefore, identifying its significance is a must and beneficial to explore. The purpose of this study is to identify the 10 years of UGS change patterns and analyze the UGS loss, particularly in the affected gazetted zone. The study used available aerial imagery data for 2002, 2012, and 2017, and database record of green space. The study had classified UGS by using the Support Vector Machine (SVM) algorithm. The training area was determined by visual interpretation and aided by a land use planning map as reference. The result validity was then determined by kappa coefficient value and producer accuracy. Overall, the study showed that the city had lost its UGS by about 88% and the total gain in built up area was 114%. The loss in UGS size in the city could be compared to a total of 2,843 units of football fields, transformed forever in just 10 years. The uncontrolled development and lack of advanced monitoring mechanism had negatively affected the planning structure of green space in KL. The implementation of advance technology as a new mitigation tool

to monitor green space loss in the city could provide a variety of enhanced information that could assist city planners and urban designers to defend decisions in protecting these valuable UGS.

Keyword: Gazetted areas, GIS, high resolution aerial imagery, image segmentation, land cover change, urban green space (UGS)

INTRODUCTION

The importance of urban green space (UGS) is already known for decades. It is demonstrated by many collected reviews whereby most findings claimed that green space can enhance city ambience, improve urban dwellers' well-being and generate a positive monetary asset in a strategic way (Cilliers, 2015; De Ridder & Lefebre, 2003; Wolch et al., 2014). It is not only seen as a natural hardscape to provide a recreational activity space, but is also functioning beyond appraisal. Moreover, many studies have claimed that the presence of UGS could help a city to combat urban heat islands, and thus improve all city body elements, for instance, its heat and air quality, as well as promoting bodiversity growth (Liu & Shen, 2014; Tani & Chang, 2017). However, urbanization process has put more pressure to the city development; thus, it is reflected in the growing city size and change in land use arrangement (Nor et al., 2017). Therefore, some of the UGS are being transformed and converted into hard surface that is fully covered with concrete and asphalt, with no space left for any green space to live in (Jiang & Tian, 2010). Similarly, Malaysia as a developing country also experiences rapid urbanization, especially in Kuala Lumpur (KL) that has an acreage of 243 square km. The hasty development process has attracted population to reside in KL; thus, more land are acquired for new development to meet the urban dwellers' demands (Isa et al., 2017) . Generally, the uncontrolled new economic development, particularly in KL city center, has expanded the city size towards suburbs, and subsequently altering the natural resources (Elsayed, 2012).

Monitoring green spaces within an entire city is important in enhancing information which enable city planners to know the current events and regularly update the green space database. Most of the local councils including Dewan Bandaraya Kuala Lumpur (DBKL) use Geographic Information System (GIS) to track land use changes and as a support tool for controlling urban development. However, the available database is obsolete and outdated, and relyon the manual inventory information (Yusof, 2012). The use of high-resolution aerial imagery has great potential to help city planners in time to extract, update, and detect land changes by applying advance spatial techniques and tools (Noorollahi, 2005). With the capacity and ability to differentiate land cover types at a larger scale, remote sensing is widely used and explored to map and detect green space changes . Available datasets of the USA imaging satellite, such as GeoEye, QuickBird, IKONOS, and WorldView will give a real world imagery with ground accuracy distance up to 15km. It is also often used by

many scholars to study environmental changes (Michel et al., 2015). However, the spatial detail of these datasets is not sufficient to capture, classify and segment the small patches of green space, and thus limits the spatial distribution and classification of green space present in the urban fabric form (Vatseva et al., 2016). Recently, many studies have used aerial photography to measure urban growth and land use changes due to greater accuracy and pixel resolution in the image covers and temporal data. For example, Moskal et al. (2011) used the 1m, 4-band infrared of aerial photography to monitor urban tree cover area in Seattle, USA. The higher spatial resolution used in this study generated a good classification with 79.7% overall accuracy. The significant strength of hyper spatial imagery was that it could map very small urban features, for instance, small patches of green space or shrub clusters. Besides, the limited spectral bands also allowed spatial and spectral comparability, and thus details in land changes detection can be attained (Crommelinck et al., 2016).

Land cover classification is widely used in many fields, such as urban planning, environmental change and land resources mapping. It digitally illustrates on how the land has been developed, conserved and changed through time. To classify the land into beneficial information, a good classifier should be determined. According to Bahari et al. (2014), there were three factors that should be considered when selecting the classification method, such as accuracy, processing speed and efficiency, to handle huge data input. For example, Abebe and Megento (2016) used the maximum likelihood classification (MLC) algorithm to classify land cover into 12 classes. The study had proven that the city of Addis Ababa had UGS loss with an annual rate of 5.9% over 30 years through high detection of changes from an aerial imagery source. However, classifying aerial imagery by using MLC needs a larger training area besides assuming the sample in use to be normally distributed. This can minimize the optimal separating image into various land use classes and affect the accuracy agreement. Beyond the conventional method classifier like MLC, Li and Shao (2014) presented the object-based approach in detecting land changes at Tippecanoe County in Indiana State, USA from 1 m resolution imagery with 5-feet DEM. The study used multi-threshold (MT) segmentation to classify the land use classes. The algorithm was capable to classify three categories of vegetation types, such as trees, grass and crop, through its own spatial distinct and spectral features. However, even though MT segmentation approach was effective in separating an image into meaningful object, its processing time was rather much longer than quadtree-based (QT) and SVM segmentation, and thus requires high hardware performance (Hsu et al, 2010). In recent years, there were efforts to develop and turn out the classification method to be more reliable and efficient in computation time and result accuracy. SVM is an artificial intelligence and novel machine-learning classification algorithm. For example, the method can apply minimal training area within a larger scale study to extract comprehensive information on land cover. SVM also

requires no assumption on data type therefore less tedious (Rudrapal & Subhedar, 2015; Shi & Yang, 2015). Bahari et al. (2014) implemented SVM to classify tropical land cover in Klang Valley, Malaysia. The study successfully classified the high-resolution imagery into 10 classes without any pixels being unclassified in a quick time processing. Furthermore, the study showed that the overall accuracy for Klang Valley tropical land cover classification was 97.1% with kappa coefficient at 0.96. It indicated that the classifier can produce high agreement between sample areas and classified data. Therefore, this study was carried out by using SVM classifier to perform image classification due to its ability to handle the complexity of features and optimal assessment for separating the features into classes with maximum margin. The aim of this study is to present the distribution and analyze the UGS changes in KL with functional classification of SVM based on available high-resolution aerial imagery data and GIS application. Furthermore, the wide range of output generated from the multiple temporal aerial imagery can improve data reliability and develop high performance to interpret the visualized phenomenon in the real world.

STUDY AREA AND DATA SETS

Study Area Boundaries

The study area of Kuala Lumpur is the most populous city in Malaysia with an estimated population of 2.2 million by 2020. It covers an area of about 243km^2 (Figure 1). It is located at the west of Peninsular Malaysia at 3°8.472′ N, 101°41.1918′ E and originally formed at the confluence of Sungai Gombak and Sungai Klang (Dewan Bandaraya Kuala Lumpur, 2018). The city was selected as the ideal test-bed area for green space classification because in the last two decades, KL experienced rapid changes in commercial activities and the resided population into the city center (Elsayed, 2012). Furthermore, the intention to develop KL into a major Asia commercial hub has tremendously changed the green area patterns in this city (Rakhshandehrooet al., 2015). According to Yaakup et al. (2005) KL has boosted its built-up areas since 1950 and has an estimated green space loss of 50% due to the high demand for housing developments, high grade infrastructure and modern public facilities. Since then, KL has received a huge transformation plan in land use activities, including the building of Kuala Lumpur Convention Center (KLCC), and has continued to undergo new rapid mega-project developments. Therefore, it is beneficial to visualize these trends and employ advanced approach in order to analyze the environmental changes in the city.

A definition of UGS was specified as the first task in this study to determine the range of classification assessment based on the objective criteria. This study used the term 'urban green space' that contained the elements of greening area covered in urban setting, including cemeteries and institutional green space. It was comprehensive and covered almost every point in urban area, especially KL whereby reserved forests, undeveloped land, green
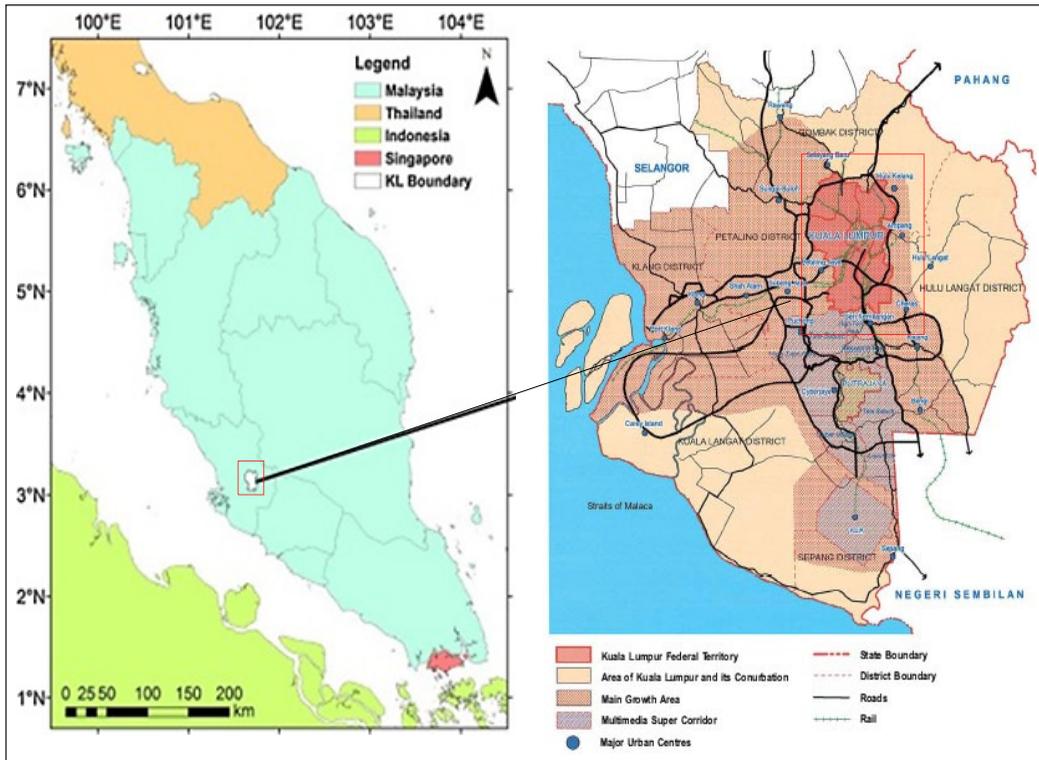
Figure 1. Map of Kuala Lumpur
Source: Dewan Bandaraya Kuala Lumpur, 2013

corridors, recreational areas, open land within the built-up areas, riverside, golf course and public amenity (institutional green areas and cemeteries) were included. This definition also includes water areas that provide greenways that enable people to connect with nature. However, this study did not capture the vertical green space and individual private green area in a housing gated scheme due to access limitation and data availability. Table 1 shows the full extent of green space classification adapted from Kuala Lumpur City Plan 2020 (KLCP 2020) (Dewan Bandaraya Kuala Lumpur, 2018) that were considered in this study.

Table 1
UGS classes for Kuala Lumpur

Main Class	Sub-Classes
Urban Green Space	District Park, City Park and Local Park
	Urban Greenery in Housing Neighborhood
	Playgrounds/Playing Lots/Playing Fields
	Urban Greenery in Public Facilities
	Greenery in Sport Facilities and amenities
	Forest Reserve
	Cemeteries

Table 1 *(continue)*

Main Class	Sub-Classes
Urban Green Space	Green Conservation Area (Hill, River, Lakes)
	Controlled Green Area (Public Open Space, Private Open Space, Transmission Line, Redevelopment Areas, Infrastructure Corridor)
	Open land within built-up areas

Data Sets

In this study, the orthophotography data for 2007, 2012 and 2017 were gathered from the Department of Survey and Mapping Malaysia (JUPEM). The city boundary maps, green area development data and spatial land use map were obtained from the GIS division of DBKL. Detailed information related to the data used is listed in Table 2.

Table 2
Detailed information on the data used

Types of Data	Description	Data Source
Orthophotography	Ground Sample Distance (GSD) = 4cm Scale = 1:15,000 Altitude = 60m/200ft Radiometric Resolution = 8 bit Digital Number Values (DN) = range 0-255 Format = Tagged Image File Format (TIFF)	JUPEM
Planning Map	Land use planning map (year 2007, 2012, 2017) = Shape file Green space database = existing and gazette information inventory KL administrative boundary = Shape file *All data used GDM 2000 reference (Geocentric Datum Malaysia 2000)	DBKL

METHODS

The overall process of green space segmentation and classification that was extracted from orthophoto data is illustrated in Figure 2. The segmentation process with selected parameters and accuracy assessment are described in the following sub-section. The software used for this analysis was ArcGIS Pro due to the capability and enhancement on this application to support the entire classification workflow, such as segmentation, training sample collection, classifier procedure, class merging and editing, and accuracy assessment in one comprehensive image analyst tool (Liedtke & Hu, 2018). The use of this application has received wide attention by many researchers and they claimed that the classification tools provided quick access to the main functionality with consideration of time consuming and the hardware capacity to handle big data processing (Kwak, 2016; Nakata-Osaki et al., 2018; Santos et al., 2016).
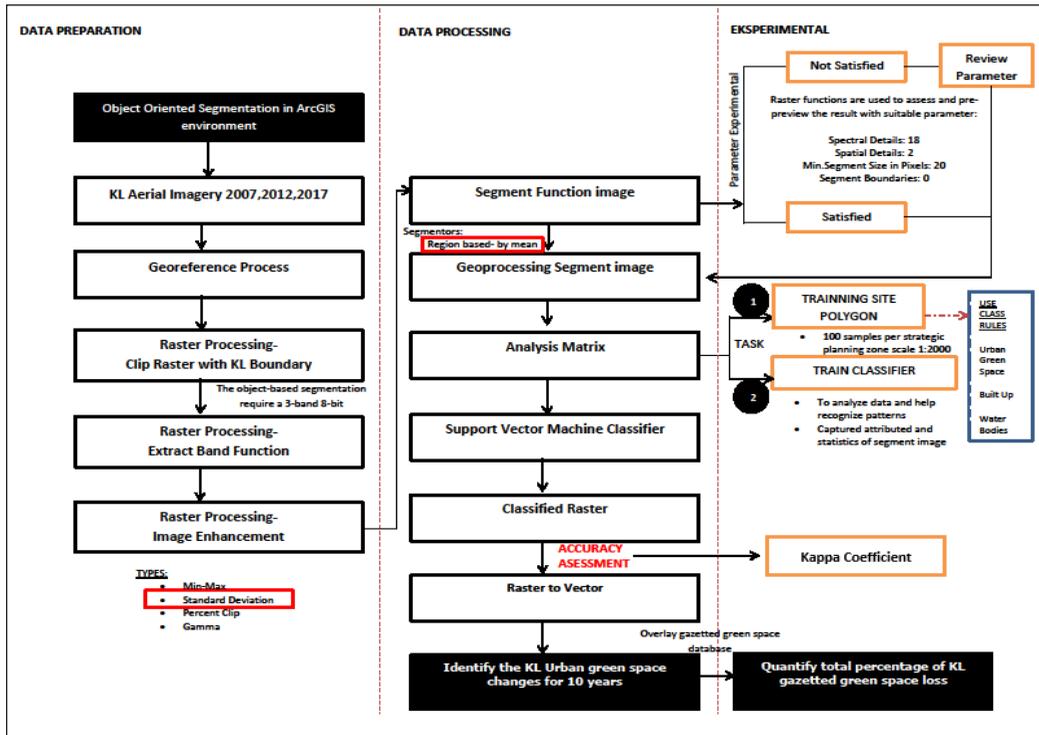
Figure 2. Flowchart of segmentation and classification methodology for quantifying the loss of gazetted green space in Kuala Lumpur by using ArcGIS Image Analyst

Image Pre-Processing

The imagery pre-processing and data management were the initial processes to be conducted. After reprojecting all datasets to the coordinate system of Geocentric Datum Malaysia 2000 (GDM 2000), the image enhancement analysis function was utilized to derive all imagery data having the same resolution conditional of 0.5m with 3-band (RGB) 8 bit-unsigned. The conditional helped to reduce spectral dimension of multivariance images. As a result, it could present three uncorrelated features that simply distinguish vegetation cover and impervious surface contained in RGB bands. Besides, the 0.5m higher resolution data were used to perform high-detection on-screen and recognize individual pixels so as to increase the chance to have the finest object segmentation and processing image classification successfully (Li & Shao, 2014).

Segmentation and Classification

For this study, the object-based segmentation technique was applied to identify KL green space changes in a 10- year time series. The technique comprises two steps. Firstly, the parameter needs to be experimented and tested by using the function of segment-mean shift. This tool allows the output to be generated temporarily and modifies according to

the amount of spatial and spectral smoothing. The parameter input experimentation for spectral, spatial, and segment size per pixel could determine the smoothness, extract color, texture and location of compactness of features from each pixel (Amalisana et al., 2017). Secondly, after recording the suitable parameter that showed the best derivation of features or interests, the geo-processing of segment mean was shifted by using the raster function tools.

In the experiments, the selected segmentation parameters were chosen to balance between spectral and spatial details. The maximum valid value range was from 1 to 20. The spectral detail was dominating the evaluation in achieving the highest segmentation result. The highest value could obtain high homogeneity, and hence to a certain degree could increase the accuracy agreement. Besides, the use of higher spectral value would contribute to greater features discrimination, and thus classify the different land cover classes effectively. Meanwhile, the smaller value in spatial detail could enhance the imagery shape and characteristics of the pixels subsequently creating a smoother segmentation output. In addition, the determination of the maximum segment size parameter was related to the minimum unit of mapping (MMU) or the amount of pixel details. The less detail values will take longer in analysis processing times due to generating a smoothing image segmentation. In a summary, the concept of segmentation parameter sets is illustrated in Figure 3.

In this study the most suitable parameter was successfully identified at Stage 4 (Table 3). The selection of parameter was chosen by using recursive visualization (Figure 4) by the analyst, with the understanding of the segmentation parameter conceptual adapted from Liedtke and Hu (2018).
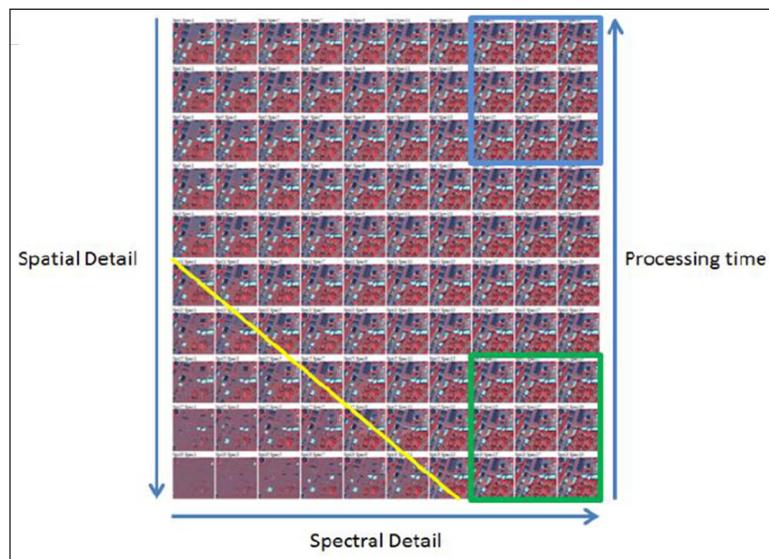

Figure 3. Segmentation parameter conceptual (*Source*: Liedtke & Hu, 2018)

Table 3
Algorithm parameters test and used

Number of Test	Spectral Detail (Max. value 20)	Spatial Detail (Max. value 20)	Min.Segment Size in Pixels (Max. value 20)
1	5	2	10
2	10	10	18
3	18	15	20
4	18	2	20

Figure 4. Image segmentation processing with different parameter testings through segment-mean function algorithm. Test 4 image indicated significant results.

Based on the selected parameter, the spectral details were made larger by 18/20 so that the finest object could be detected, especially for research conducted in urban areas. This was supported by choosing the lower spatial details to create smoother segmented images. According to Kaur and Kaur (2014) there is no specific technique as the best way to do segmentation because the parameter set is developed based on the subject matter to be studied and to suit with the image type. Besides, the requirement to obtain a satisfied complex parameter is crucial and difficult to find (Wężyk et al., 2016).

Image classification can be done by two algorithms that are supervised and unsupervised. The supervised classification was employed in this study and it required training samples that will help to identify the land cover classes. The reference data that included land use map and green space database were used to assist in supervising the training site selection

according to the features of interest. To address the issue of time consumption in doing the sample sites, the image was divided into six zones for effectively managing the classification task. The division of six areas was digitized based on the KL strategic planning zones, as shown in Figure 5. Each zone represented its distinctive spatial pattern and land use activity in order to create more variation segmentations in terms of shape and texture. The zoning also considered the green space distribution patterns to avoid bias in certain dense areas.

This study had at least 200 training areas with a minimum of 10-30 polygons for each strategic zone. To ensure that the training samples were homogenously distributed, this preliminary classification was overlaid with the original image to determine its logical group. SVM classifier was used for classification assessment based on the input generated from the training samples. Besides, the classifier was considered as an easy procedure
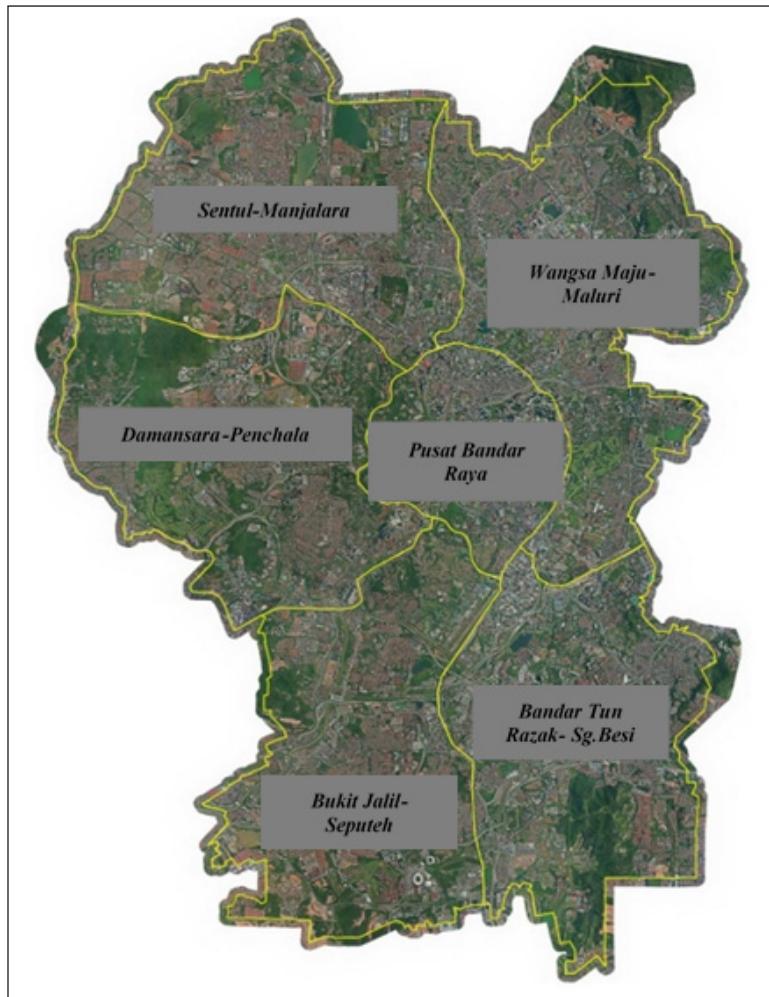

Figure 5. Kuala Lumpur Structure Plan (2004) with six KL administrative boundary zones for more strategic land use and planning distribution
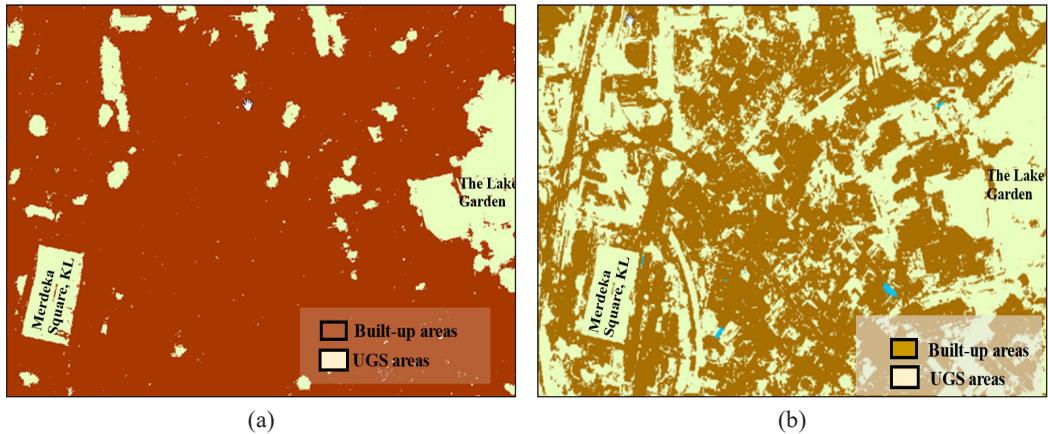
Figure 6. (a) Image representing the classification output using MLC technique and (b) using SVM technique

to operate because it did not require a large sample, and thus can address the issue of processing time. The SVM extraction of each object was more accurate and detailed as compared to the maximum likelihood (MLC) algorithm. Figure 6 shows the classification output by using SVM algorithm as compared to the MLC algorithm.

Generally, SVM is a non-parametric binary linear classifier. It works by identifying the optimal separating hyperplane (such as a dividing line to separate the data into two set) in a high space by using the kernel approach to locate optimal boundaries between classes (Rudrapal & Subhedar, 2015). It can produce a good classification with less amount of sample data and did not require the features selection in the pre-processing assessment because it can independently function based on fully dimensional hyperspectral data. The easier way to work with SVM classifier is by using linearly separable classes. Adapting from the work by Taati et al. (2015), the SVM algorithm is expressed as,

$WXi + b \geq +1$; which is for all y = +1 (member of Class 1)   [1]
$WXi - b \leq -1$; which is for all y = −1 (member of Class 2)   [2]

Based on Equation [1] and Equation [2], the numbers of training data are represented as $\{Xi, Yi\}$, i =1, 2....k, where X $\in$ Rn is denoted by n-dimensional space and Y $\in$ {+1, -1} is a class label. Then, all classes involved are considered as linear and separable if a vector of W is present and perpendicular to the linear hyperplane. For the two classes, Class 1 is represented as +1 while Class 2 as -1. The hyperplane is capable to discriminate the data point into respective classes. The kernel function in the SVM algorithm offers a solution to locate the training sample into one of the two categories, making the decision accurate and error free (Rudrapal & Subhedar, 2015). In additional, Figure 7 illustrates the basic concept on how the SVM functions. They are unlimited numbers of hyperplanes that will be involved in particular areas of study and SVM will consider selecting the hyperplane

with maximum margin. Then, SVM will calculate the gap between the margin range, which is from the reference vector (classifier) and the training point (support vector). The main idea is to maximize the clearance distance for which the gap is large.

Therefore, in this study, after processing the image segmentation and classification procedure, there are three main land covers that were successfully identified, namely urban green space areas, built-up areas, and water bodies (Table 4).
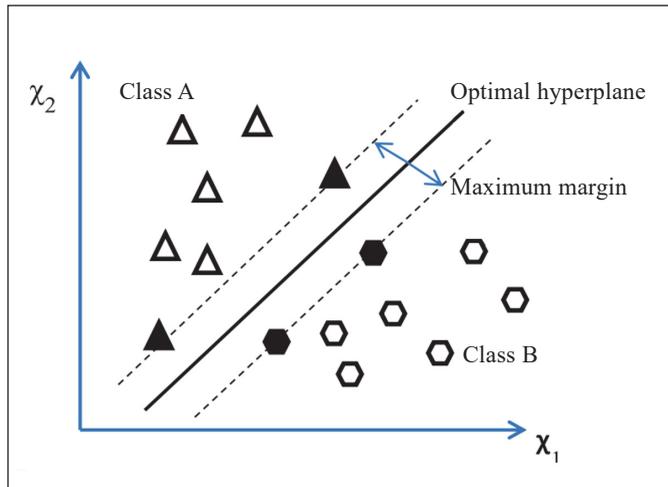

Figure 7. Conceptual of SVM functional (*Source*: Bahari et al., 2014)

Table 4
Identified classes by supervised classification

No.	Land classes	Description
1	Built-up	Residential, commercial, Industrial, Roads, Railway, mixed urban and developed lands
2	UGS	District Park, City Park and Local Park, Urban Greenery in Housing Neighborhood, Playgrounds/Playing Lots/Playing Fields, Greenery in Sport Facilities and amenities, Forest Reserve, Cemeteries, Controlled Green Area (Public Open Space, Private Open Space, Transmission Line, Redevelopment Areas, Infrastructure Corridor), Open land within built-up areas
3	Water Bodies	Lakes and ponds, wetlands

Accuracy Assessment

In this study, test sample areas (pixels) of approximately 50 objects or polygons for each class were selected by visual inspection through the entire images and with consideration the sample are well distributed. Then, error matrix (also known as confusion matrix) statistic was applied to test the degree of difference between the automated classified images with the sample areas. The validation of the output was important to determine the ratio of pixels identified for each category and to find out classification error, whether over-estimation

or underestimation (Shubho et al., 2015). The result was presented in statistical form of producer accuracy and overall accuracy. According to Anderson et al. (1976) 85% is the minimum accuracy value which is acceptable and satisfactory to classify the images. In additional, kappa coefficient value was demonstrated as less than 1 or equivalent to 1. A value near or equal to 1 indicates that variables are in perfect agreement and significant to illustrate the real event.

RESULTS AND DISCUSSION

Classification Accuracy Assessment

Table 5 shows the summary of accuracy result for all three sets of the imagery data while Table 6 illustrates the detailed accuracy of the image classification for 2017 as a sample result. The overall accuracy indicated that the percentage of successful pixels was correctly classified accordingly to their land use classes with the application of SVM classifier. The results also demonstrated that most of the SVM classification and sample areas were in perfect agreement, which were the kappa coefficient for the three set images were recorded near to value 1.

Table 5

Accuracy assessment for supervised classification using SVM classifier

Year of Data (Orthophoto)	Overall Accuracy	Kappa Coefficient	Indicator	Significant Agreement
2007	91.2%	0.84	<0 no agreement	Almost perfect agreement
2012	94.67%	0.89	0 – 0.20 slight	
2017	93.3%	0.83	0.21 – 0.40 fair	
			0.41 – 0.60 moderate	
			0.61 – 0.80 substantial	
			0.81 – 1 almost perfect agreement	

Table 6

Error Matrix (%) comparing image classification for 2017 to the sample areas (pixels) data

		Sample areas (Pixels)				
	Classes	UGS	Built-up	Water Bodies	Total Classified Pixels	User Accuracy (%)
Classification Data (Pixels)	UGS	**40**	3	0	43	93.0
	Built-up	5	**68**	0	73	93.2
	Water Bodies	2	0	**32**	34	94.1
	Total Sample Area	60	80	160	**150**	
	Producer Accuracy (%)	66.7	85	20		
	Overall Accuracy		93.3			
	Kappa Coefficient		0.83			

Referring to Table 6, the automated image classification for 2017 gives 93.3%accuracy. Water bodies were well segmented, and thus recorded the highest accuracy value. UGS and built-up areas delivered slightly misclassified pixels whereby confusion occurred due to similar spectral values and homogenous in spatial form. However, both classes showed a higher accuracy of 93.0% and 93.2%, respectively. Therefore, the accuracy assessment was reliable and derived further significant output.

The Changes of Green Space from 2007 to 2017

The analysis of UGS changes based on the SVM classification method had revealed that in the first period (from 2007 to 2012), KL UGS area had slightly decreased by 191 ha and tremendously reduced by 1515 ha in 2017. Besides, it can be observed from Table 7 that the built-up area had greater increased in 2017 with 12,148 ha, which covered the study area by 50%. Furthermore, water bodies were extremely lost from 2007 to 2012, which was 117.16 ha, and then remained stagnant towards 2017. In summary, the total proportion of UGS loss from 2007 to 2017 was 88%, while a total gain of built up areas was 114%. The result is also visualized in Figure 8.

Table 7
The proportion difference gained and loss for each type of land use classes from 2007 to 2017

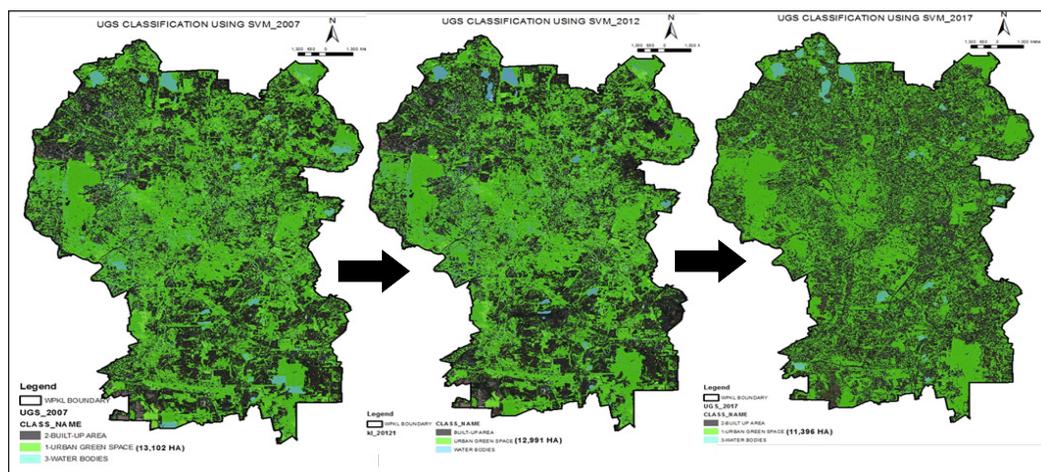| Land Use Class	2007		2012		Difference Gained / Loss from 2007 till 2012		2017		Difference Gained / Loss from 2007 till 2017	
	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%
UGS	13,102	54	12,911	53	191	-99	11,396	47	1515	-88
BUA	10,325	42	10,633	44	308	103	12,148	50	1515	114
WB	873	4	755.84	3	117.16	-87	755.84	3	0	0
SUM	24,300	100	24,300	100			24,300	100		

Figure 8. Changes in the green space in Kuala Lumpur from 2007 to 2017 based on SVM classification method

Generally, the size of UGS loss in KL can be compared to a total of 2,843 units of football fields that has transformed into built up areas. The result also demonstrated that the UGS in KL had struggled to survive in the last 10 years due to the demand of new development that had acquired more lands. Furthermore, this event was related to the intention of KL to become a world class city by 2020 with the provision of various mega developments, such as high grade infrastructure and modern public facilities (Nor et al., 2017; Yusof, 2012). The vision has directed to the uncontrolled land management and land scarcity in KL had pushed the new development to use available green areas.

The Loss of Green Space in the Gazetted Zone Areas

The trend for a 10-year period showed that the net green space loss was randomly located at the northeast and spreading out to the west and south of the city's boundary (Figure 9). Most of the destructed areas were located near or within the gazetted zones. A recent government report (Dewan Bandaraya Kuala Lumpur, 2018) examined the total green space that was legally declared as 'prohibited development areas' and recorded at about 978.42 ha. However, the figure can be argued because through the classification analysis, the potential green space that was identified to be preserved and protected was tremendously transformed into new developments. This can be proven by referring to Figure 9 that demonstrates four samples of the gazetted parks that were allowed to develop into a high-rise affordable housing project. These four sites obviously separated the object features into two classes which were built-up area and gazetted green space zone.

In addition, it can be observed from Table 8 that in Metropolitan Kepong Park, the gazetted zone has lost about 4.04 ha, which covers 4.8% of its total area. Furthermore, Taman Wahyu Park, Tasik Permaisuri Park and Bukit Jalil Technology Park was decreased by 14.49 ha, 3.23 ha and 1.63 ha, respectively.

Table 8
The percentage of green space loss in selected gazetted zone areas

Site	Acreage 2007-2012 (Hectares)	Acreage 2017 (Hectares)	Allocation for affordable housing land (Hectares)	% Loss
A	83.17	79.13	4.04	4.80
B	88.57	74.08	14.49	16.35
C	9.32	6.09	3.23	34.65
D	53.39	51.76	1.63	3.05

Overall, the gazetted green space loss in KL was 1,706 ha, which was 12% out of the total city areas. However, despite the facts showing a small loss, the relatively pint-sized of green spaces throughout the years will lead to higher air temperature (Chejarlaet al., 2016), can harm urban wildlife homes (Karuppannan et al., 2014) , was significant to
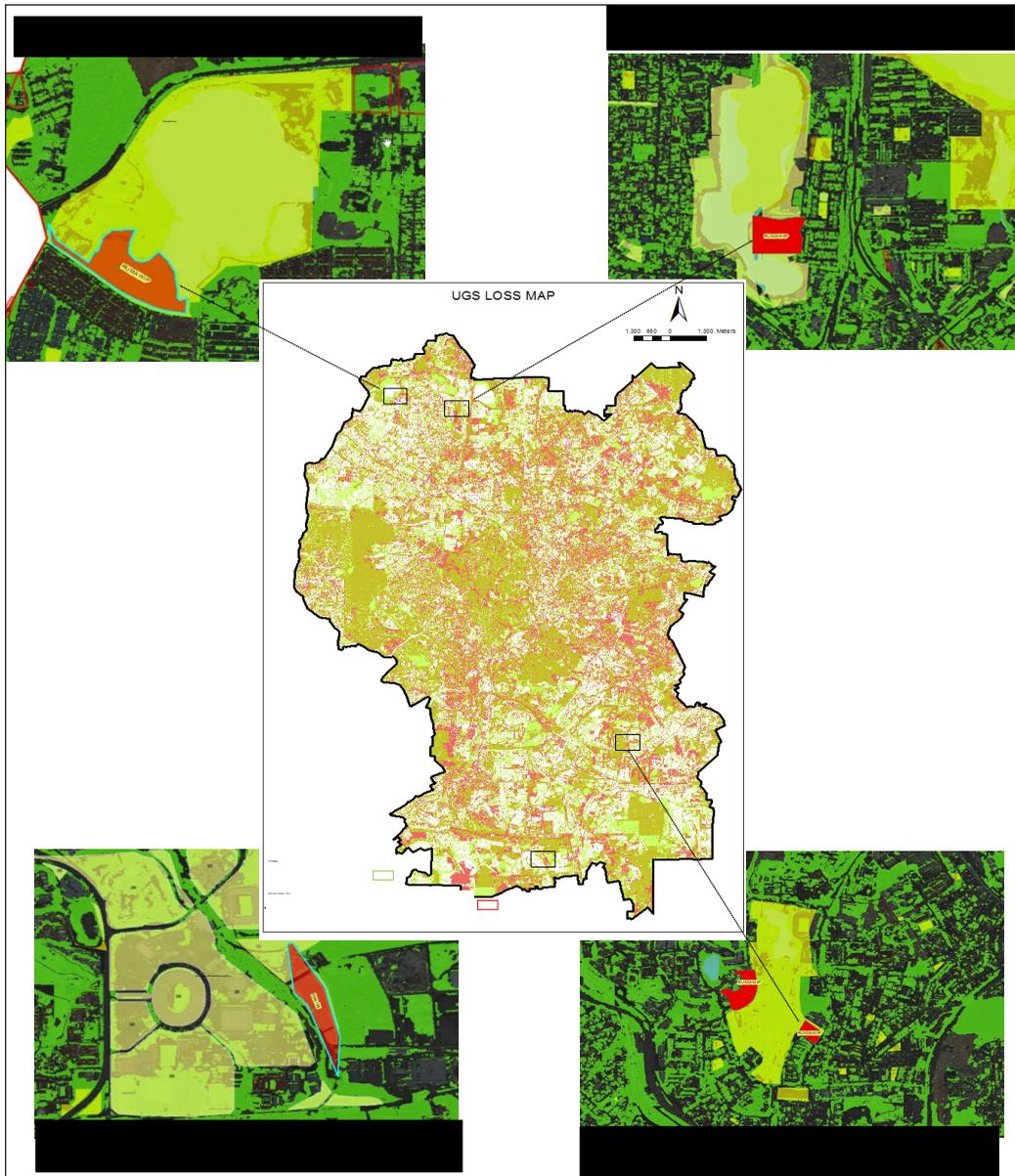
Figure 9. The net loss of green space in Kuala Lumpur and sample sites of four gazetted parks affected by development

increase water volume, and thus causing flood (Kim et al., 2016), erosion and polluted water problems (Mansor & Said, 2008).

In summary, the declining trend of the green space showed that urbanization had continuously occurred without a limit even though there active action plans were strategized, for example, green initiatives that aimed to plant 100,000 trees by 2020 (Government of Malaysia Performance Management and Delivery Unit, 2016). Besides, green space was

tremendously sacrificed for the objective of political force and investment prophecy. New development had aggressively entered the gazetted zone to develop affordable housing projects, for instance, *Rumah Mampu Milik Wilayah Persekutuan* (RUMAWIP), *Perumahan Rakyat 1 Malaysia* (PR1MA) and *Perumahan Penjawat Awam 1 Malaysia* (PPA1M). It can be argued that with the limited land available in the city to cater for the population's demand, the green space is seen as the only space left to be developed. Obviously, the green space was now meant not only for environmental improvement but had to make way for social and economic development too. Therefore, a comprehensive UGS planning framework through various initiatives must be strategied in an effective way and should be aided by visualize monitoring system to ensure that the profits of UGS could dispense to all urban sector developments.

CONCLUSION

Overall, the classification assessment done in this study had revealed the amount of remaining urban green space in KL. The land cover change analysis revealed that the UGS had constant decrease over the last 10 years. In summary, the city had UGS loss of about 88% and the total gain of built up areas was 114%. The rapid development has grown the size of KL city, and thus altered the left-over green space. The integration between GIS and high-resolution aerial imagery can give high accuracy evidence and can play an important role in monitoring and controlling urban development. The presented case study showed the high performance of automatic extraction of green space from three sets of high-resolution aerial imagery data for the year 2007, 2012, and 2017. The accuracy result for all three sets of the imagery data were very high, as recorded at 91.2%, 94.67%, and 93.3%, respectively. Besides, the method applied was significant to map KL green space changes and prove that the event had more accuracy by using a SVM classifier. The outcome generated from this spatial analysis provided an up-to-date information that served genuine green space data, and thus improved the decision-making process. The outcome can also help the Kuala Lumpur City Hall to identify the location where natural preservation areas are threatened. Furthermore, this spatial form analysis would contribute for planning the protection of green space across KL's boundary and prioritizing specific regulation in dealing with this event.

ACKNOWLEDGEMENTS

REFERENCES

Abebe, M. T., & Megento, T. L. (2016). The city of Addis Ababa from 'Forest City' to 'Urban Heat Island': Assessment of urban green space dynamics. *Journal of Urban and Environmental Engineering*, *10*(2), 254–262.

Amalisana, B., & Hernina, R. (2017, September 27-28). Land cover analysis by using pixel-based and object-based image classification method in Bogor land cover analysis by using pixel-based and object-based image classification method in Bogor. In *The 5th Geoinformation Science Symposium 2017 (GSS 2017)* (pp. 1-7). Yogjakarta, Indonesia.

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). *A Land Use and Land Cover Classification System for Use with Remote Sensor Data* (Vol. 964). Washington, D.C.: US Government Printing Office.

Bahari, N. I. S., Ahmad, A., & Aboobaider, B. M. (2014, April 23-24). Application of support vector machine for classification of multispectral data. In *7th IGRSM International Remote Sensing & GIS Conference and Exhibition* (p. 012038). Kuala Lumpur, Malaysia.

Chejarla, V. R., Maheshuni, P. K., & Mandla, V. R. (2016). Quantification of LST and CO_2 levels using Landsat-8 thermal bands on urban environment. *Geocarto International*, *31*(8), 913-926.

Cilliers, E. J. (2015). The Importance of Planning for Green Spaces. *Agriculture, Forestry and Fisheries,* *4*(4-1), 1-5.

Crommelinck, S., Bennett, R., Gerke, M., Nex, F., Yang, M., & Vosselman, G. (2016). Review of automatic feature extraction from high-resolution optical sensor data for UAV-based cadastral mapping. *Remote Sensing*, *8*, 1-28.

Dewan Bandaraya Kuala Lumpur. (2013). *Draft Kuala Lumpur City Plan 2020*. Kuala Lumpur, Malaysia: Author.

Dewan Bandaraya Kuala Lumpur. (2018). *Kuala Lumpur City Plan 2020.* Kuala Lumpur, Malaysia: Author

De Ridder, K., & Lefebre, F. (2003). BUGS, Benefits of Urban Green Space. *MESO WP final report*.

Elsayed, I. S. M. (2012). Mitigation of the urban heat island of the city of Kuala Lumpur, Malaysia. *Middle-East Journal of Scientific Research*, *11*(11), 1602-1613.

Government of Malaysia Performance Management and Delivery Unit. (2016). *National Transformation Programmed Annual Report 2016*. Putrajaya, Malaysia: Author.

Hsu, C. W., Chang, C. C., & Lin, C. J. (2010). *A practical guide to support vector classification* [Lecture PowerPoint slides]. Retrieved February 19, 2019, from https://www.csie.ntu.edu.tw/~cjlin/talks/freiburg.pdf

Isa, N. A., Wan Mohd, W. M. N., & Salleh, S. A. (2017, October 4). The effect of built-up and green areas on the land surface temperature of the Kuala Lumpur City. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* (Vol. XLII, pp 107-112). Kuala Lumpur, Malaysia.

Jiang, J., & Tian, G. (2010, August 27-29). Analysis of the impact of land use / land cover change on land surface temperature with remote sensing. In *International Society for Environmental Information Sciences 2010 Annual Conference (ISEIS)* (pp 571-575). Beijing, China.

Karuppannan, S., Baharuddin, Z. M., Sivam, A., & Daniels, C. B. (2014). Urban green space and urban biodiversity: Kuala Lumpur, Malaysia. *Journal of Sustainable Development, 7*(1), 1-16.

Kaur, D., & Kaur, Y. (2014). Various image segmentation techniques : a review. *International Journal of Computer Science and Mobile Computing*, *3*(5), 809-814.

Kim, H., Lee, D. K., & Sung, S. (2016). Effect of urban green spaces and flooded area type on flooding probability. *Sustainability (Switzerland), 8*(2), 134-150.

Kwak, Y. (2016). *GIS-Base Suitability Analysis and Planning of Green Infrastructure: A Case of the PPCOD, Capitol Hill* (Master thesis). University of Washington, US. Retrieved December 10, 2018, from http://hdl.handle.net/2123/7128

Li, X., & Shao, G. (2014). Object-based land-cover mapping with high resolution aerial photography at a county scale in midwestern USA. *Remote Sensing*, *6*(11), 11372-11390.

Liedtke, J., & Hu, H. (2018). ArcGIS Pro : Image Segmentation , Classification , and Machine Learning (27). *Esri User Conference*. San Diego, California.

Liu, H., & Shen, Y. (2014). The impact of green space changes on air pollution and microclimates: A case study of the Taipei Metropolitan area. *Sustainability, 6*, 8827-8855.

Mansor, M., & Said, I. (2008). Green infrastructure network as social spaces for well-being of urban residents in Taiping , Malaysia. *Jurnal Alam Bina*, *11*(2), 1-18.

Michel, J., Youssefi, D., & Grizonnet, M. (2015). Stable mean-shift algorithm and its application to the segmentation of arbitrarily large remote sensing images. *International Transactions on Geoscience and Remote Sensing*, *53*(2), 952-964.

Moskal, L. M., Styers, D. M., & Halabisky, M. (2011). Monitoring urban tree cover using object-based image analysis and public domain remotely sensed data. *Remote Sensing*, *3*(10), 2243-2262.

Nakata-Osaki, C. M., Souza, L. C. L., & Rodrigues, D. S. (2018). THIS – Tool for Heat Island Simulation: A GIS extension model to calculate urban heat island intensity based on urban geometry. *Computers, Environment and Urban Systems*, *67*, 157-168.

Nor, A. N. M., Corstanje, R., Harris, J. A., & Brewer, T. (2017). Impact of rapid urban expansion on green space structure. *Ecological Indicators*, *81*, 274-284.

Noorollahi, Y. (2005). *Application of GIS and Remote Sensing in Exploration and Environmental Management of Namafjall Geothermal Area, N-Iceland* (Master thesis). University of Iceland, Iceland.

Rakhshandehroo, M., Mohdyusof, M. J., Tahir, O. M., & Yunos, M. Y. M. (2015). The social benefits of urban open green spaces : a literature review. *Management Research and Practice*, *7*(4), 60-71.

Rudrapal, D., & Subhedar, M. S. (2015). Land cover classification using support vector machine. *International Journal of Engineering Research and Technology (IJERT)*, *4*(09), 584-588.

Santos, T., Tenedório, J. A., & Gonçalves, J. A. (2016). Quantifying the city's green area potential gain using remote sensing data. *Sustainability (Switzerland)*, *8*(12), 1-16.

Shi, D., & Yang, X. (2015). Support vector machines for land cover mapping from remote sensor imagery. In J. Li & X. Yang (Eds.), *Monitoring and Modeling of Global Changes: A Geomatics Perspective* (pp. 265-279). Dordrecht, Netherlands: Springer.

Shubho, M. T. H., Islam, S. R., Ayon, B. D., & Islam, I. (2015). An improved semiautomatic segmentation approach to land cover mapping for identification of land cover change and trend. *International Journal of Environmental Science and Technology*, *12*(8), 2593-2602.

Taati, A., Sarmadian, F., Mousavi, A., Pour, C. T. H., & Shahir, A. H. E. (2015). Land use classification using support vector machine and maximum likelihood algorithms by landsat 5 TM images. *Walailak Journal of Science and Technology*, *12*(8), 681-687.

Tani, A., & Chang, J. (2017). Air quality and health effects of biogenic volatile organic compounds emissions from urban green spaces and the mitigation. *Environmental Pollution*, *230*, 849-861.

Vatseva, R., Kopecka, M., Otahel, J., Rosina, K., Kitev, A., & Genchev, S. (2016, June 13-17). Mapping urban green spaces based on remote sensing data: case studies in Bulgaria and Slovakia. In *Proceedings of 6th International Conference on Cartography and GIS* (pp. 569-578). Albena, Bulgaria.

Wężyk, P., Hawryło, P., Szostak, M., & Pierzchalski, M. (2016). Using geobia and data fusion approach for land use and land cover mapping. *Quaestiones Geographicae*, *35*(1), 93-104.

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning*, *125*, 234-244.

Yaakup, A., Zalina, S., Bakar, A., & Bajuri, H. (2005, November 21). GIS based integrated planning assessment for sustainable land use development. In *National Planning Seminar, Selangor, Malaysia* (pp. 1-14). Shah Alam, Malaysia.

Yusof, M. J. M. (2012). Identifying green spaces in Kuala Lumpur using higher resolution satellite imagery. *Alam Cipta*, *5*(2), 93-106.