A Multiscale Quantification of Leaf Area Index with Unmanned Aerial Vehicle and SPOT-7 Satellite Imageries: A case of Kuala Lumpur, Malaysia

On, C. L., Kanniah, K. D.* and Lau, A. M. S.
Department of Geoinformation, Faculty of Built Environment & Surveying, Universiti Teknologi Malaysia, Lingkaran Ilmu, Universiti Teknologi Malaysia, 81310 Skudai, Johor Bahru, Johor, Malaysia
E-mail: onlee@graduate.utm.my, kasturi@utm.my*, alvinlau@utm.my
Corresponding Author

DOI: https://doi.org/10.52939/ijg.v20i5.3231

Abstract
The statutory planning of the urban landscape of Kuala Lumpur (KL) has been solely relied on a rigid and fixed quantitative specification without ecological evaluation, resulting in the loss of biodiversity, degradation of urban ecosystem services and liveability. Past research in the area of quantitative urban green space (UGS) planning and ecology were mainly concentrated in the provision, accessibility, and connectivity of UGS, but lacking in the ecological quality dimension. This paper intends to fill the knowledge gap by quantifying the ecological quality of UGS in multiple scales from tree, park, to city level with unmanned aerial vehicle (UAV) to map the leaf area index (LAI) in the city of KL. The estimation of KL LAI involves a two-step processes. In the first step, 9 UGSs under the management of local authority were selected for the mapping of the distribution of Normalized Differential Vegetation Index (NDVI) with Unmanned Aerial Vehicle (UAV). Concurrently, rigorous field works are conducted to sample field LAI of selected trees in all of the UGSs with AccuPAR LP-80 Ceptometer. UGS LAI are estimated with regression of UAV NDVI and field LAI. Analysis of the result shows that there is a moderately strong relationship (R^2 = 0.56, RMSE =0.33) between UAV NDVI and field LAI and the established statistical equation is used for the estimation of UGS LAI covering all the parks. In the second step, the statistical relationship was upscaled to the entire city level with UGS LAI and SPOT-7 NDVI data (R^2 =0.50, RMSE = 0.94). The multiscale estimation of LAI provides an effective indicator of the landscape ecological performance among the different electoral area where targeted landscape enhancement and remediation policies can be formulated to improve urban sustainability.

Keywords: Landscape Ecological Quality, Leaf Area Index, Remote Sensing, Urban Green Space, Unmanned Aerial Vehicle

1. Introduction

In Malaysia, current statutory landscape planning by the Department of Town & Country Planning (JPBD) required a certain fixed percentage of 10% of open green space for all development projects across the country [1]. One of the issues with this standard is that the policy made no differences of the different types of urban green space (UGS) in terms of biophysical quality with different ecological, environmental, and social functions. For example, there are differences in ecosystem services provided by open spaces in high-density built-up areas with sparse and low vegetation composition and distribution, and open spaces in low-density built-up with dense and high variation of vegetation composition and distribution. With this statutory requirement of percentage of green spaces as the sole policy intention, the denegation of ecological dimension meant that landscape planning and design are solely devoted to the meeting of the standard and only in the consideration of aesthetic factors. Past studies on open space standard have highlighted various weaknesses in its implementation such as lack of scientific basis, differences in interpretation, and weak enforcement, which resulted in the decreasing and imbalanced development of UGS [2] [3] and [4]. Searches on quantitative open space studies in the literature similarly revealed that most of the research on quantitative open space evaluation are based on open space standards such as percentage of green area and/or green area per capita [5] [6] [7] [8] [9] [10] [11] and [12] which did not evaluate the vegetational structural variables.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

For past research studies that were based on qualitative open space evaluation, most of these studies were mainly conducted from landscape ecological perspective [13] [14] [15] [16] and [17].

The landscape ecological methodology of these studies did not capture the variation of vegetative canopy structures distributed within the individual UGS and is difficult to be implemented as the methodology is not in line with existing urban landscape planning convention. In the tropical region like Malaysia where regulation of urban temperature and water are important ecosystem services, UGS canopy structures are important parameter consideration for the provision of urban ecosystem services [18] and [19].

The vegetation canopy structural index such as Leaf Area Index (LAI) is potentially able to overcome this limitation of existing quantitative open space evaluation and hence provides a complementary decision tool in the ecological dimensions for landscape planning. LAI is defined as one half of the total green leaf area per unit of ground surface area [20]. LAI provide a measurement for the total amount of leaf area in an ecosystem and is a valuable and critical plant parameter for the mapping, evaluating, and monitoring of terrestrial ecological, environmental, hydrological, and biogeochemical processes, such as net primary production and carbon cycle [21]. The LAI as one of the important ecological qualities of UGS is critical in the provision of urban ecosystem services. Previous studies on the effect of LAI on microclimate and photosynthetic rate in urban forest and urban park have reported positive correlation between LAI and ecological and environmental parameters [22] [23] and [24].

The use of remote sensing technologies has been instrumental in contributing spatially explicit mapping and assessment in a timely manner on ecosystem research [25] [26] [27] [28] and [29] and LAI estimation [30] and [31]. In the case of LAI, reviews of past studies of LAI retrieval indicated that studies were generally based on satellite data such as Landsat-8, Sentinel-2, MODIS, and Rapideye [32] [33] [34] and [35] for LAI and vegetation indices on large analysis scale. However, these satellite data with coarse resolution might not be suitable for the mapping of UGS in a much smaller scale and scattered throughout the heterogenous urban matrix. There are currently no readily available fine resolution LAI data for UGS. The accurate estimation of LAI in UGS thus required a specific targeted area and a finer data resolution which can be derived from Unmanned Aerial Vehicle (UAV). UAV has gained widespread uses for its fine spatial and temporal resolution, deployment flexibility, cost efficiency, and targeted area coverage and is well suited for the survey and mapping in a spatial confined area of urban, forest, and agricultural studies.

For the estimation of LAI, one of the indirect approaches is using vegetation index such as Normalized Differential Vegetation Index (NDVI). NDVI is one of the commonly used and stable indices to estimate LAI. Past review of NDVI-LAI conversion has been conducted mostly for agricultural crops in the temperate regions [36] and [37]. As far as the authors are aware, there is currently no studies on developing NDVI-LAI studies specifically on UGS in the tropic. The methodology presented in this study is thus the first attempt to estimate LAI in high resolution for UGS and contribute to the knowledge gap by expanding the NDVI-LAI relationship to the discipline of urban landscape planning in the tropic which until now only rely on quantitative planning standard.

2. Materials and Methods

2.1 Study Area

Kuala Lumpur (KL) is the capital of Malaysia located at the west coast of Peninsular Malaysia. The capital city has 100% urbanization rate in a land area of 242 km^2 with a population of 1.98m and has the highest population density among Malaysia’s cities with 8157 people per square kilometre as of 2020 [38]. The capital city is divided into 11 electoral division as show in Table 1. All the planning, development, and maintenance of public parks in the city are under the jurisdiction of the local authority, Dewan Bandaraya Kuala Lumpur (DBKL). There are 15 major recreational public parks and urban forest of various categories with a total area of 523 hectares administered by DBKL in KL [39]. For this study, a total of 9 UGS scattered around the city are identified with a variation of age, location, size, vegetation type and cover, and water bodies for sampling collection and analysis. Figure 1 shows the locations of the parks within KL and Table 2 provides their areal coverage. The percentage of total area of selected parks to total park area is 87% and 1.8% of total land area in KL.

2.2 Data and Methodology

2.2.1 Methodology

The study’s methodology is divided into 2 stages. For the first stage, the NDVI-LAI relationship is modelled at the park level. For the second stage, based on the results of the first stage, the result is expanded and upscaled for the modelling of LAI to the entire KL city area. The analysis followed the methodological flowchart as shown in Figure 2.

Table 1: Kuala Lumpur electoral division and its respective area

	Electoral Division	Area (Km^2)
1)	Kepong (KP)	12
2)	Batu (BT)	20
3)	Wangsamaju (WM)	16
4)	Segambut (SGB)	51
5)	Setiawangsa (STW)	16
6)	Titiwangsa (TTW)	15
7)	Bukit Bintang (BB)	21
8)	Lembah Pantai (LP)	20
9)	Seputeh (SPT)	31
10)	Cheras (CHR)	16
11)	Bandar Tun Razak (BTR)	25
	Total	243

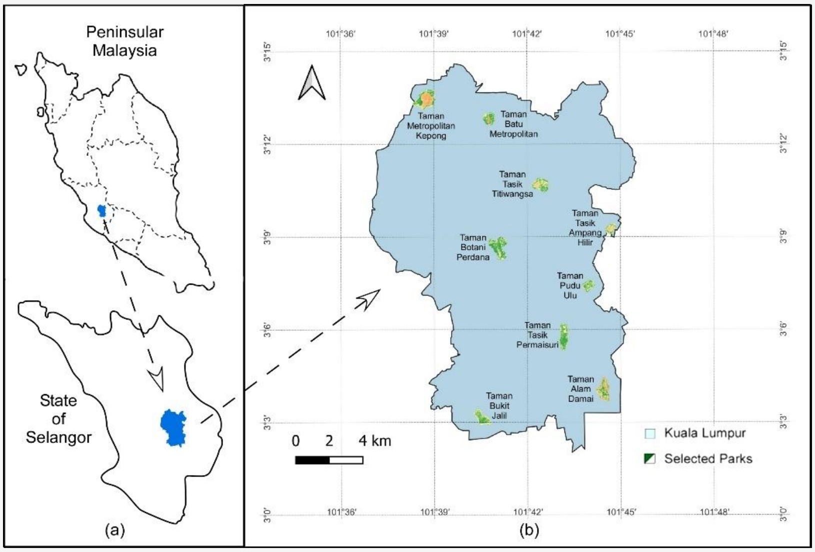

Figure 1: (a) Index map showing the location of Kuala Lumpur (b) The selected parks in Kuala Lumpur

Table 2: List of selected parks and their respective area

	Park	Area (Hectare)
1)	Taman Metropolitan Kepong (TMK)	88
2)	Taman Metropolitan Batu (TMB)	113
3)	Taman Tasik Titiwangsa	46
4)	Taman Botani Perdana (TBP)	92
5)	Taman Tasik Ampang Hilir (TAH)	12
6)	Taman Pudu Ulu	26
7)	Taman Tasik Permaisuri	49
8)	Taman Alam Damai (TAD)	10
9)	Taman Bukit Jalil (TBJ)	20
	Total	456

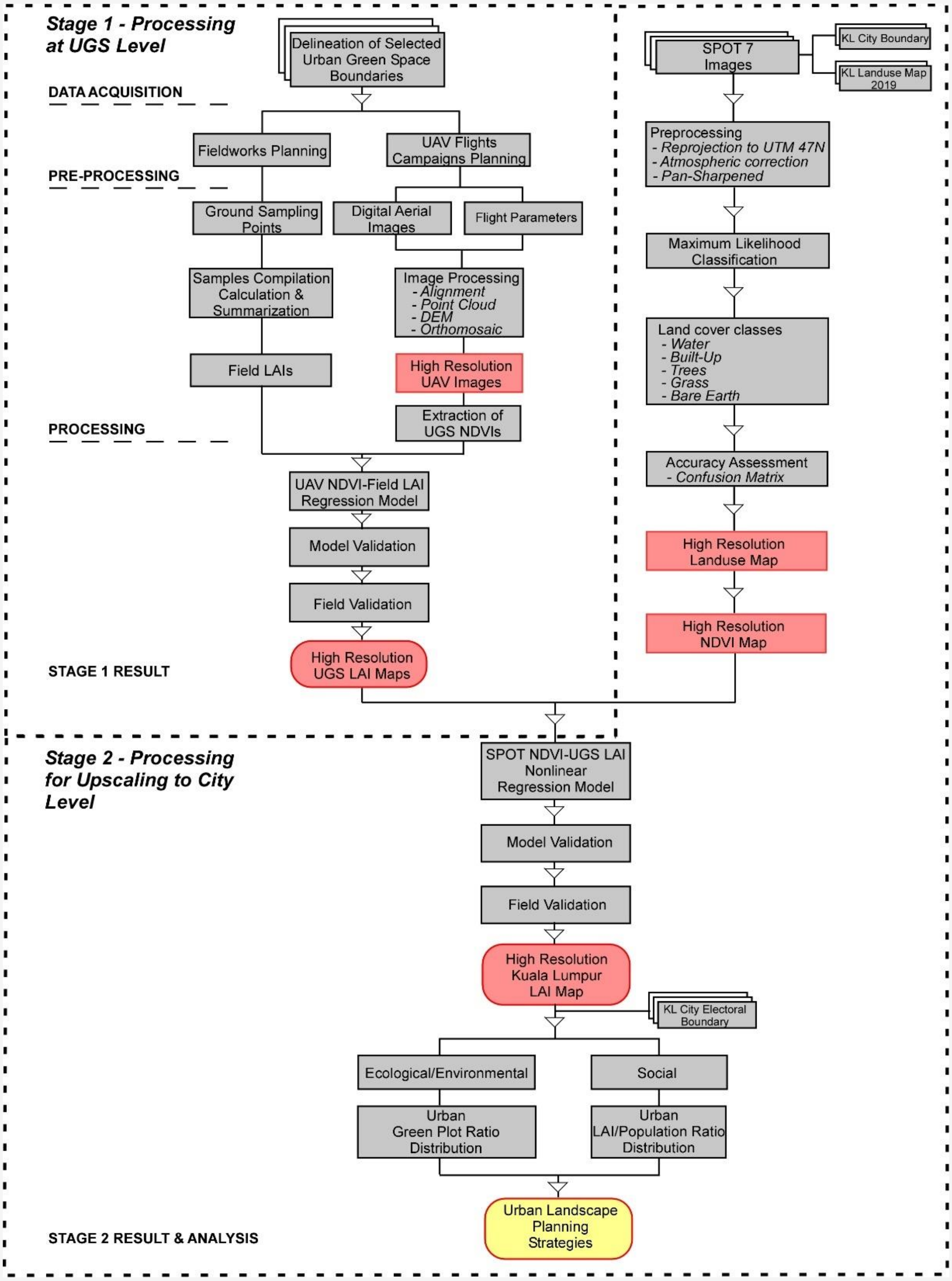

Figure 2: Methodological flowchart of the study

2.2.2 Dataset

a) Leaf Area Index

The main data used in the study are the LAI estimated in the field. Field sampling collection on the selected UGS (trees) is based on random sampling procedures whereby the location of each tree in each park is identified and selected randomly using Google Earth to demarcate clear tree canopy for the sampling of LAI at the field. The location coordinate of each tree was marked. To determine the sufficiency of sampling points, a pilot study was conducted to randomly sample the LAI of selected trees around the city of KL to gauge the sample parameters' statistical distribution for the determination of sample size. A total of 110 sampling was collected in the pilot study with mean and standard deviation of 2.22 and 0.91.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Based on this, the required sample size is determined using the remote sensing ground sampling formula [40] Equation 1:

$$n = (\sigma * t/e)^2$$

Equation 1

where n is the sample size, Σ is the standard deviation of measured value, T is the two-tailed t value test with n-1 degree of freedom at 95% confidence level, and E is the acceptable error in the same unit as σ.

Based on the pilot study data statistical value, it is estimated that the minimum required sample is 324, based on acceptable error of ±0.15 (or minimum accuracy criteria of 85%) and a 95% of confidence level [41]. For the first stage of study, a total of 327 sample points were identified and collected successively over the period of the sampling months from the period of Aug'2022 – Mar'2023. For the second stage of the study, a total random generated sample points of 4,500 points (500 points per park) over the selected parks area was used for the study. The proportion of division of sample points used for the 2 stages of study is as shown in Table 3.

Field samplings are carried out in the morning in clear sunny day from 8am to 12pm over the sampling period. Before the field sampling, the maps of the selected parks are checked to identify the location of each individual tree and the location coordinates of the tree are marked. At the field, LAI samplings are carried out directly under the marked tree canopy with a LAI Ceptometer LP-80 AccuPAR [42]. The LP-80 Ceptometer is a model of line quantum sensor consists of 80 sensors embedded in a meter long probe and a control unit. It measures the Photosynthetically Active Radiation (PAR) in the wave bands of 400 – 700nm and invert the PAR to estimate the LAI value. A major assumption underlying this indirect method of LAI measurement is that the foliage is black and randomly distributed. This assumption thus does not take into consideration the influence of foliage clumping, woody shoots, stems, and branches. However, for measurements focused on individual tree or small patches of green, this technique is commonly used [43] and [44]. The LP-80 Ceptometer is a cost effective and efficient LAI meter used for non-destructive sampling of LAI and has a relatively long history of 15 years uses that are supported by research studies [45].

The ceptometer has been used extensively in past studies in the estimation of LAI for agricultural crops [46] and [47]. At each of the tree location, multiple readings are recorded outside the canopy coverage and directly below the canopy at breast height facing the north direction. All readings are repeated for 3 times to capture the variation of lighting conditions around the canopy and to minimize foliage clumping effects.

b) Aerial Images

Concurrently with the field sampling, several UAV flights mission are planned and carried out to fly over the selected parks boundary with DJI Mavic 3 Enterprise drone with a RGB resolution of 20MP and 4-bands camera (Green: 560 ± 16nm; Red: 650 ± 16nm; Red Edge: 730 ± 16nm; Near infrared: 860 ± 26nm) for the mapping of park vegetation for the extraction of NDVI distribution within the parks. The flights plans are made during clear sky at a height of 200m above mean sea level with approximate 10cm ground resolution. Following this, the NDVI value are extracted for all the tree locations at each of the park. All the data from the UAV flights were processed using DJI Terra and QGIS 3.22 to align, build dense cloud and Digital Elevation Model (DEM), mosaic images, and the generation of the map of orthomosaic. The orthorectified images were processed to extract NDVI values for each pixel covering the parks (Equation 2):

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$

Equation 2

Where NDVI is Normalized Different Vegetation Index, NIR is near infra-red band, and Red is red band. At each tree location, the extracted NDVI value is regressed against the corresponding value of the field LAI surveyed during the sampling using Microsoft Excel. The regression model result is interpreted quantitatively and used for the upscaling of NDVI map to LAI map for the whole area of the selected parks. A total of 242 points are used for the analysis, in which the data is further divided into 124 points (50%) for the model building, 63 points (25%) for model validation, and 55 points (25%) for field validation.

Table 3: Division of sample points for the 2-stage of study

Area of Study	Modelling Points	Model Validation Points	Field Validation Points	Total Sample Points
Park Level	124	63	55	242
City Level	2449	2048	85	4582

c) SPOT-7 Satellite Data

For upscaling of LAI to the city level, SPOT-7 data is used for the modelling of NDVI-LAI relationship. The SPOT-7 satellite data spatial resolution is 6m for multispectral and 1.5m for panchromatic consists of 5 bands (Red: 0.625-0.695nm; Green: 0.530-0.590nm; Blue: 0.450-0.520nm; Near Infrared: 0.760-0.890nm; Panchromatic: 0.450-0.745nm) [48]. As the upscaling of LAI were based on the high-resolution UAV images, the potential of information loss was minimised while maximizing the reliability of LAI estimation at the city level using SPOT-7 data.

The SPOT-7 image, which was acquired on 15 January 2022, was pan-sharpened with the panchromatic band to increase the spatial resolution to 1.5m and reprojected to WGS 84/UTM 47N projection coordinate system and clipped to the boundary of KL city. Following this, the image was classified into 6 classes of land cover, namely, water, tree, grass, built-up, road, and bare earth with Maximum Likelihood Classification (MLH) algorithm. MLH, as one of the commonly used supervised classification methods, calculates and assign each of the pixel based on Bayes' classification of the probability the pixel belongs to a particular class with a discriminant function [49]. Past study on MLH has concluded that MLH is a robust technique and has minimum chance of misclassification [50]. A set of training samples in each of the land cover classes were randomly collected for computation of mean vector and covariance metric as a basis for training the model. After the classification, the model was subjected to validation with another set of validation samples drawn independently from each class and the confusion matrix was calculated to measure the accuracy of the classification.

For upscaling to city level, a total of 4500 random sample points (500 sample points per park) is generated to extract the selected parks' LAI from the UAV images and corresponding SPOT-7 NDVI value to model the NDVI-LAI relationship for the entire city level. Out of the 4500 sample points, 2449 sample points (55%) are used for the modelling and 2048 sample points (45%) are used for model validation (Table 3). The model is further validated with 85 field sample points. All the regression analysis and validation are carried out using Microsoft Excel.

2.3 Analysis

The estimation of LAI is used for the assessment and analysis of landscape ecological quality at city level. Statistical ratios of Green Plot Ratio (GnPR) and LAI per capita are computed and analysed for each of the electoral area.

a) Green Plot Ratio

The comparison of the urban built-up area and its quantitative and qualitative vegetation availability provide an insight as to the adequacy and quality of the vegetation in supporting urban socio-ecological processes for sustainable development. This can be derived with a calculation of the ratio of LAI as the volume of greenery to the total built-up area. This ratio, defined as Green Plot ratio (GnPR) [51], quantify and optimize the quantity and quality of greeneries necessary in an urban environment for the delivery of urban ecosystem services by measuring the amount of leaf areas of all the vegetative plantings in proportion to total site area which can be obtained from land classification image. Higher ratio indicates higher potential ecological processes and environmental performance of the landscape (Equation 3):

$$\mathrm{GnPR} = \frac{\text{Total leaf area of greenery}}{\text{Total Built} - \text{Up area}}$$

Equation 3

b) LAI/Population Ratio

While the GnPR measured the potential ecological and environmental performance of the landscape, the LAI per capita ratio (Equation 4), as an indicator of environmental equity, provides an estimation of the availability of LAI in the social dimension. Compared to the area per capita and percentage of green cover as used in the current UGS quantitative standards, LAI per capita assess the amount of leaf volume per capita which provides more insights in addition to the current standards. For example, two areas with similar percentage of green cover and area per capita but with different LAI per capita would indicate the different type of vegetative cover in these areas. As trees provide the highest LAI value, areas with high LAI per capita would indicate higher density of trees and its associative services like sun shading, nature experience, etc. for the local population.

LAI per capita complements the GnPR by balancing the ecological and social functionalities of the landscape. High GnPR and high LAI per capita ratio indicate optimum landscape socio-ecological services, while low GnPR and low LAI per capita indicate insufficiency in ecosystem services in both the ecological and social dimensions.

$$\text{LAI per capita} = \frac{\text{Total leaf area of greenery}}{\text{Population}}$$

Equation 4

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

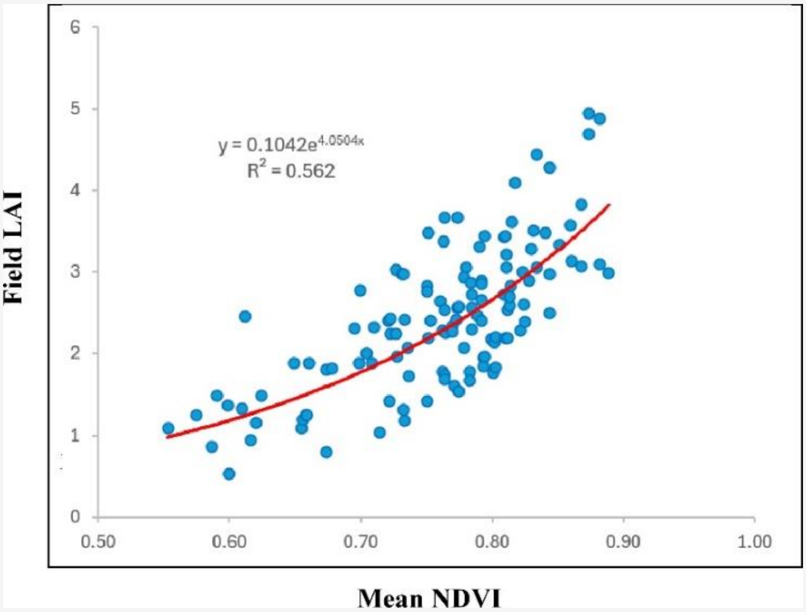

Figure 3: Exponential NDVI-LAI regression model for selected parks in Kuala Lumpur

Table 4: Exponential regression analysis for mean NDVI and field LAI

Regression Summary								
Multiple R	0.75							
R Square	0.56							
Adjusted R Square	0.56							
Standard Error	0.11							
Observations	124							
ANOVA								
	Degree of Freedom	*Sum of Square*	*Mean Square Error*	*F-test*	*Significance F*			
Regression	1	2.06	2.06	156.58	0.00			
Residual	122	1.61	0.01					
Total	123	3.67						
	Coefficients	*Standard Error*	*t-Stat*	*P-value*	*Low 95%*	*Up 95%*	*Low 95%*	*Up 95%*
Intercept	-0.98	0.11	-9.14	0.00	-1.19	-0.77	-1.19	-0.77
Mean NDVI	1.76	0.14	12.51	0.00	1.48	2.04	1.48	2.04

3. Results and Discussion

Commensurate with the nature of data distribution in the scatter plot and in line with previous study [36], the NDVI-LAI exponential regression model was chosen to fit the data (Figure 3 and Table 4). From the regression analysis, the R^2 is moderately high at 0.56 with RMSE of 0.33. The Anova Significance F test value and P-value for both intercept and independent variable indicate that there is a direct correlation relationship between field LAI and mean NDVI at 95% confidence level, and NDVI is a valid independent variable for the prediction of LAI. The analysis from the result indicates that vegetation index like NDVI is an acceptable predictor for LAI. Following this, the model is subjected to validation test with the validation and field data set. The validation test indicated that the model could achieve a reasonable fitting with a R^2 of 0.51 with RMSE of 0.7.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

The field validation test achieved a R^2 of 0.63 with RMSE of 0.7. The model and validation test fitness conformed largely to previous study [52] and thus is accepted as a reasonable and valid regression equation of the NDVI-LAI relationship. To estimate the LAI for the entire park, the model was upscaled to the park level and the distribution of LAI in each park was generated.

Following the derivation of high-resolution LAI maps at the park level, the maps were upscaled to the city level using the landuse classification map of KL. The confusion matrix achieved an overall classification accuracy of 94.65% and Kappa Coefficient of 0.92 (Table 5).

Both the Producers' and Users' accuracy for vegetation of tree and grass have high accuracy of well above 92%. The high accuracy of the classification is accepted for the generation of landuse map (Figure 4) and the estimation of NDVI in KL (Figure 5). In contrast to the park level sample points trajectory, the trajectory of the city level sampling points exhibited a polynomial relationship in the scatter plot. The polynomial model, as one of the commonly used models for the modelling of NDVI-LAI relationship [36], is thus chosen to model the NDVI-LAI relationship with polynomial 2nd degree regression equation (Table 6 and Figure 6).

Table 5: Confusion matrix for the land cover classification

	Ground Truth (Percent)								
Class	**Water**	**Tree**	**Grass**	**Building**	**Road**	**Bare Earth**	**Total**	**Users' Accuracy (%)**	**Errors of Commision (%)**
Water	76.23	0.00	0.00	1.70	0.00	0.00	10.49	98.00	2.00
Tree	0.00	99.11	1.22	0.01	0.00	0.00	55.90	99.87	0.13
Grass	0.00	0.81	98.68	0.00	0.00	0.33	6.45	92.65	7.35
Building	23.77	0.09	0.10	91.25	5.71	2.16	14.99	75.13	24.87
Road	0.00	0.00	0.00	5.87	94.29	0.00	6.36	88.60	11.40
Bare Earth	0.00	0.00	0.00	1.17	0.00	97.50	5.81	97.52	2.48
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00		
Producers' accuracy (%)	76.23	99.11	98.68	91.25	94.29	97.50		Overall Accuracy =	94.65%
Error of omission (%)	23.77	0.89	1.32	8.75	5.71	2.50		Kappa Coefficient =	0.92

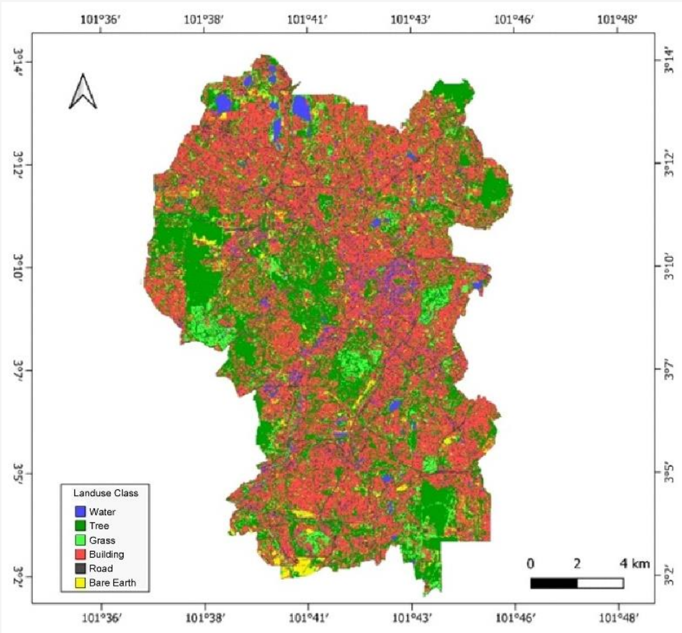

Figure 4: Kuala Lumpur landuse classification map

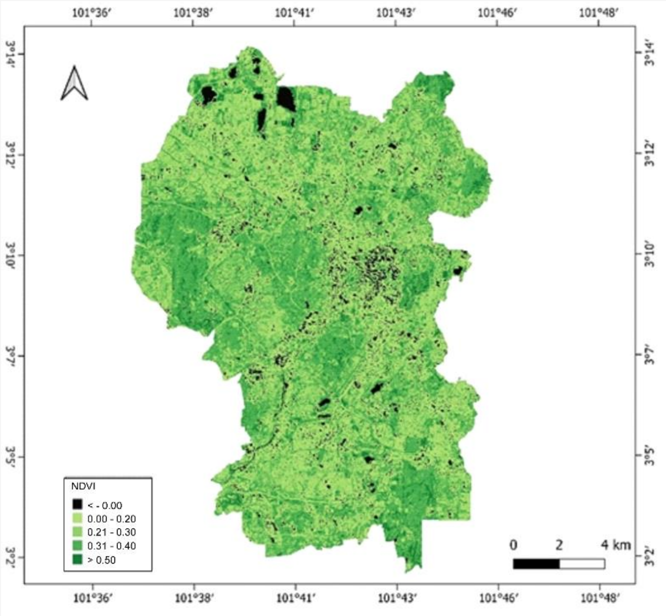

Figure 5: Kuala Lumpur NDVI distribution

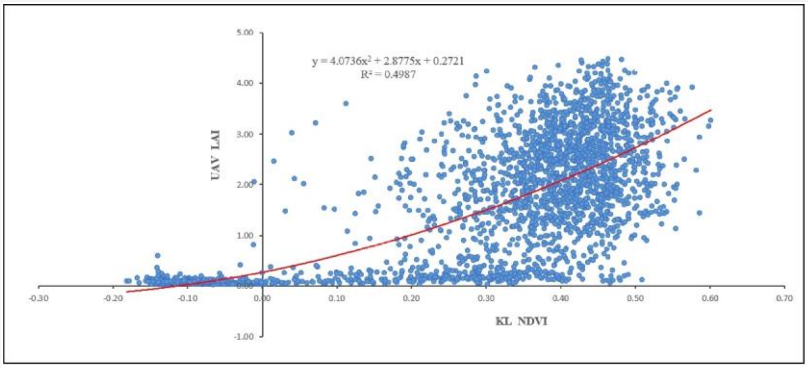

Figure 6: Polynomial 2nd degree NDVI-LAI regression model for Kuala Lumpur

Table 6: Polynomial 2nd degree regression analysis for KL NDVI and UAV LAI

Regression Summary									
Multiple R	0.71								
R Square	0.50								
Adjusted R Square	0.50								
Standard Error	0.90								
Observations	2449								
ANOVA									
	Degree of Freedom	*Sum of Square*	*Mean Square Error*	*F-test*	*Significance F*				
Regression	2	1959.04	979.52	1216.64	0.00				
Residual	2446	1969.28	0.81						
Total	2448	3928.32							
	Coefficients	*Standard Error*	*t-Stat*	*P-value*	*Low 95%*	*Up 95%*	*Low 95%*	*Up 95%*	
Intercept	0.27	0.03	8.26	0.00	0.21	0.34	0.21	0.34	
KL-NDVI	2.88	0.23	12.41	0.00	2.42	3.33	2.42	3.33	
KL-NDVI^2	4.07	0.56	7.27	0.00	2.97	5.17	2.97	5.17	

As in the exponential regression at the park level, the polynomial regression also achieved a moderately high R^2 of 0.50 and RMSE of 0.94. The Anova Significance F test value and P-value for both the intercept and independent variables also indicated that there is a direct correlation relationship between field LAI and mean NDVI at 95% confidence level, and NDVI-LAI model is reasonable and valid for upscaling to the larger city scale. The validation of the model achieved a R^2 of 0.51 and RMSE of 0.91. To further test the model fitness, the model is field validated with field sample points collected around different areas of KL and achieved a R^2 of 0.30 and RMSE of 0.63. The moderately low R^2 can possibly be attributed to the wider variation of indirect reflected radiation environment surroundings the urban environment from surrounding hard surfaces such as buildings, glasses, roofs, roads, cars, etc. [53]. As the LP-80 Ceptometer take into consideration the ambient radiation as one of the input values to estimate LAI, sampling readings in the urban built-up environment is likely to be more unstable compared to inside UGS. As this urban effect cannot be avoided, the moderate achievement of the model in field validation is reasonable in view of the lower RMSE, and the high fitness already achieved by the model in the model validation stage.

Based on this, the LAI map for the entire KL was generated. In contrast to NDVI which indicates the health and vigour of the vegetation, the LAI reflect the structure and density of tree canopy. Higher value of LAI indicates denser tree canopy and vice versa [52]. Based on this, the KL LAI map was reclassified into density categorization with LAI value of less than 1 classified as no vegetation, LAI value of between 1 to 2 as low-density vegetation, LAI value of between 2 to 3 as medium- density vegetation, LAI value of 3 to 4 as high-density vegetation (Figure 7) [54]. The image was clipped to the electoral boundaries and indicator statistics are calculated to analyse the landscape ecological quality at the city level in each electoral area in more details (Table 7). Total LAI value sums up all the LAI of all the vegetation pixels in each electoral area regardless of vegetation types. Compared to vegetation area, Total LAI captured the multi-layered variation of the tree canopy and provide more insights compared with vegetation cover. For example, electoral areas that have similar green cover but with different mean LAI has different vegetation composition and landscape ecological quality.

Conversely, electoral areas with similar mean LAI but with different vegetation cover implied the different efficiency of the vegetation in contributing to landscape ecosystem services in each of the area. At the city scale level, in assessing the urban landscape ecological and environmental functions, it is essential not only to compare the percentage of green cover but also to relate to other urban socio-ecological parameters, such as urban built-up surfaces which could exert considerable influence on the ecological performance of vegetation [55].

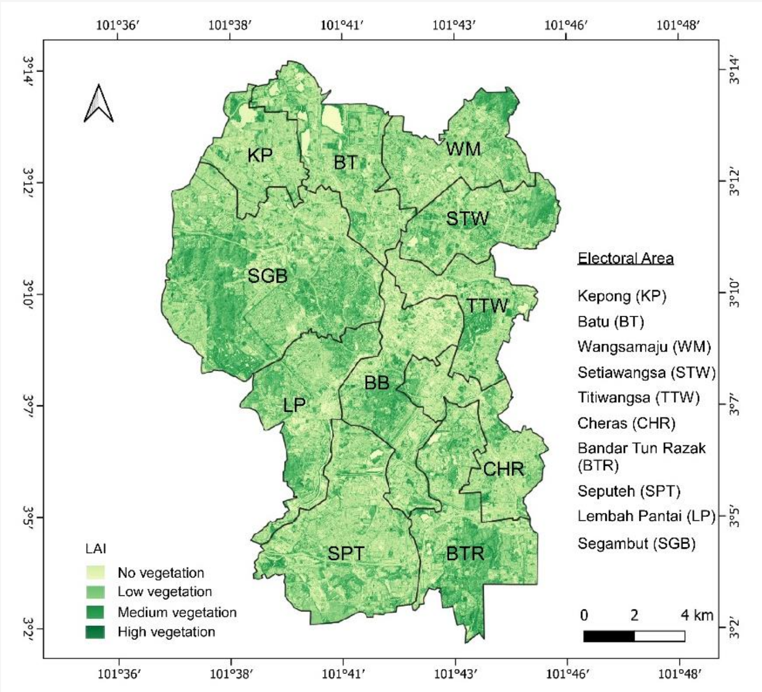

Figure 7: Kuala Lumpur LAI distribution map in each electoral area

Table 7: Detailed statistical breakdowns of Green Plot Ratio and LAI per capita in Kuala Lumpur

Name	Population	Built-Up		Vegetation		Total LAI	Green Plot Ratio	LAI per Capita
		(Sq.m)	(%)	(Sq.m)	(%)	(Sq.m)		
Kepong	104,200	8,670,623	72.26	2,700,011	22.50	9,110,430	1.05	87.43
Batu	215,100	12,212,278	61.06	6,403,225	32.02	16,548,622	1.36	76.93
Wangsa Maju	211,600	10,592,477	66.20	5,844,289	36.53	14,146,763	1.34	66.86
Segambut	249,000	22,964,979	45.03	25,118,575	49.25	46,374,063	2.02	186.24
Setiawangsa	144,400	8,250,415	51.57	6,573,977	41.09	13,671,356	1.66	94.68
Titiwangsa	119,800	9,011,250	60.08	4,215,028	28.10	11,100,366	1.23	92.66
Bukit Bintang	118,300	11,884,577	56.59	7,183,502	34.21	16,291,957	1.37	137.72
Lembah Pantai	145,300	9,792,495	48.96	8,675,289	43.38	16,863,802	1.72	116.06
Seputeh	316,500	18,827,789	60.73	9,736,861	31.41	24,764,383	1.32	78.24
Cheras	133,300	10,785,998	67.41	4,176,078	26.10	11,668,621	1.08	87.54
Bandar Tun Razak	187,800	11,232,764	44.93	11,922,124	47.69	22,492,073	2.00	119.77

Large built-up area would attenuate the amelioration of temperature and water interception by the vegetation [56] [57] and [58]. As urban areas are centre of socioeconomic activities, it is also necessary to include the social parameters such as population as a measure for vegetational socio-ecological processes. The effects of urban built-up density and population on the functionalities of UGS are captured by the GnPR and LAI per capita ratio respectively. The GnPR and LAI per capita enable an accurate assessment of the quantity and quality of vegetation necessary to achieve the balance of development and ecosystem functionalities.

Comparison of GnPR among the electoral areas, the highest electoral areas are Segambut 2.02 and Bandar Tun Razak 2.00. The electoral areas with intermediate GnPR are Setiawangsa 1.66, Lembah Pantai 1.72, Batu 1.36, Bukit Bintang 1.37, Wangsamaju 1.34, and Seputeh 1.32. And the electoral areas with the lowest GnPR are Titiwangsa 1.23, Kepong 1.05, and Cheras 1.08. The comparison revealed that Segambut and Bandar Tun Razak areas have higher vegetational quantity and quality compared to the rest of the electoral areas in supporting the urban built-up and indicated the higher landscape ecological and environmental functionalities. This could be a result of the urban forest parcels located within these electoral areas. This is followed by areas having intermediate GnPR, which indicate lower vegetation density, like Setiawangsa, Lembah Pantai, Batu, Bukit Bintang, Wangsamaju, and Seputeh. Areas with lowest GnPR near to 1 like Kepong and Cheras would indicate virtually no vegetation and thus have poor ecological quality for the provision of urban ecosystem services. The findings revealed that vegetation coverage area doesn't equate to ecological performance. For example, both Setiawangsa and Lembah Pantai has vegetation coverage of more than 40% of its area, but the GnPR are not the highest. This is possibly due to high development intensity and more grasses are planted compared to trees. Conversely, built-up area doesn't necessarily decrease ecological performance. Titiwangsa and Lembah Pantai have quite similar built-up area, but Lembah Pantai's GnPR 1.72 is much higher compared to Titiwangsa 1.23. In terms of LAI per capita ratio, the electoral areas with the highest are Segambut 186.24, Bukit Bintang 137.72, Bandar Tun Razak 119.77, and Lembah Pantai 116.06. The high LAI per capita ratio is a result of the existence of high vegetation areas such as urban forests and low population level within these electoral areas, indicating high cultural ecosystem services provision. The electoral areas with the lowest LAI per capita ratio are Wangsamaju 66.86, Batu 76.93, Seputeh 78.24, Kepong 87.43, and Cheras 87.54, as these areas generally are more developed with higher population concentration.

The findings revealed that the increase in urban built-up would generally lead to the decline of urban landscape ecological quality [59]. For example, Kepong and Cheras are among the highest in terms of percentage of built-up of 70%, but both of these areas achieved the lowest GnPR of near to 1, indicating the insufficiency of vegetation for ecological functions. Areas which retained the urban forests would generally fare better in term of landscape ecological quality and environmental performance. This points to the importance of conservation of urban forest resources, and proper landscape planning and management for urban sustainable development. However, in comparison to the GnPR standard in other countries such as Singapore, KL still fared poorly.

As reference, in Singapore the specified minimum effective GnPR range is 3 - 4 and vegetation coverage is 30 - 40% for sustainable urban development [60]. As presently there is no regulation and guidelines on the use of GnPR for landscape planning in KL, this leaves much room for DBKL to improve the landscape planning and management standards.

4. Conclusion

In the estimation of LAI in the urban context, this study's methodology bridged the gap between utilisation of UAV for its high-resolution image but limited in arial coverage with the wide coverage of satellite imageries but in coarser resolution to expand the NDVI-LAI relationship for urban landscape planning. The findings attest to the importance of differentiation between vegetation green cover and LAI and delve deeper into the understanding of urban landscape ecological quality. The findings implied the ineffectiveness of relying only on green area targets for landscape planning to achieve urban sustainability as larger green area doesn't equate to higher ecological functionalities. Urban areas with high density of development generally have low ecological quality unless the LAI is increase in tandem. The multiscale approach at tree, UGS, and city scale represent the first approach for UGS LAI estimation and contribute to the knowledge gap in the remote sensing literature. The significance of the study is important for urban landscape assessment and planning, providing scientific, objective, and evidence-based methodology for the ecological performance of UGS. This is especially relevant in the context of compact urban development to meet the challenges of climate change.

5. Recommendation

As this study focus on the derivation of LAI with statistical relationship, there are few improvements future studies can contribute to the study model. First, future studies can include more factors which affects the LAI value, such as type of vegetation, species, age, maintenance regime, etc. Second, more advanced remote sensing technique such as LIDAR for the 3D mapping of vegetation can be employed to further improve the model. Third, future model developments are needed for a deeper understanding of the relationship between the GnPR and various urban ecosystem services.

Acknowledgement

The authors would like to thank the local authority, DBKL, for granting the permission for the survey of the UGS during the study period, and the Malaysian Space Agency (MYSA), for providing the SPOT 7 data. This study would not be possible without the assistance of the above agencies.

Funding

The authors would like to gratefully acknowledge and declare that this study is funded by Malaysia Ministry of Higher Education and Universiti Teknologi Malaysia (Grant number - Q.J130000.2452.08G51)

References

[1] Jabatan Perancangan Bandar Dan Desa., (2013). *Garis Panduan Perancangan Tabah Lapang dan Kawasan Rekreasi, Jabatan Perancangan Bandar Dan Desa Semenanjung Malaysia*. Kementerian Perumahan Dan Kerajaan Tempatan. 1-43, https://mytownnet .planmalaysia.gov.my/ver2/gp/GPPKL_Format %20Baru.pdf.

[2] Maryanti, M. R., Khadijah, H., Uzair, A. M. and Ghazali, M. A. R. M. M., (2017). The Urban Green Space Provision Using the Standard Approach: Issues and Challenges of its Implementation in Malaysia. *Sustainable Development and Planning VIII*. *WIT Transactions on Ecology and the Environment*, Vol. 210. https://doi:10.2495/SDP160311.

[3] Ibrahim, P. H., Dali, M. M. and Yusoff, S. Y. M., (2013). Implementation of Open Space: The need for Uniform Policy. *Journal of Sustainable Development*, Vol 6(7). http://dx.doi.org/10 .5539/jsd.v6n7p16.

[4] Veal, A. J., (2009). Alternatives to Standards: A Review of Leisure Planning Guidelines: U-Plan Project Paper 2. 4th edition. *School of Leisure, Sport and Tourism Working Paper 12*. Lindfield NSW. University of Technology Sydney. Available: www.business.uts.edu.au/lst/resea rch/research_papers.html and www.leisuresour ce.net.

[5] Shahfahad, K. B., Tayyab, M., Hoang, T. H., Khan, M. F. and Rahman, A., (2019) Assessment of Public Open Spaces (POS) and Landscape Quality Based on Per Capita POS index in Delhi. India. *SN Appl. Sci*. Vol. 1. https://doi.org/10.1007/s42452-019-0372-0.

[6] Sathyakumar, V., Ramsankaran, R. A. A. J. and Bardhan, R., (2020) Geospatial Approach for Assessing Spatiotemporal Dynamics of Urban Green Space Distribution among Neighbourhoods: A Demonstration in Mumbai. *Urban Forestry & Urban Greening*, Vol. 48. https://doi.org/10.1016/j.ufug.2020.126585.

[7] Zhu, Z., Lang, W., Tao, X., Feng, J. and Liu, K., (2019). Exploring the Quality of Urban Green Spaces Based on Urban Neighbourhood Green Index - A Case study of Guangzhou City. *Sustainability*, Vol. 11. http://doi:10.3390/su1 1195507.

[8] Liu, Y., Meng, Q., Zhang, J., Jancso, T. and Vatseva, R., (2015). An Effective Building Neighborhood Green Index Model for Measuring Urban Green Space. *International Journal of Digital Earth*, Vol. 9(4). https:// doi.org/10.1080/17538947.2015.1037870.

[9] Addas, A. and Alserayhi, G., (2020). Quantitative Evaluation of Public Open Space Per Inhabitant in the Kingdom of Saudi Arabia: A Case Study of the City of Jeddah. *Sage Open*, Vol. 1. https://doi.org/10.1177/21582440209 20608.

[10] Lahoti, S., Kefi, M., Lahoti, A. and Saito, O., (2019). Mapping Methodology of Public Urban Green Spaces Using GIS: An Example of Nagpur City, India. *Sustainability*, Vol. 11(7). https://doi.org/10.3390/su11072166.

[11] Jafrin, M., and Beza, B. B., (2018). Developing an open space standard in a densely populated city: A Case Study of Chittagong City. *Infrastructures*, Vol. 3(3). https://doi.org/10.33 90/infrastructures303004.0.

[12] Gupta, K., Kumar, P., Pathan, S. K. and Sharma, K. P., (2012). Urban Neighbourhood Green Index - A Measure of Green Spaces in Urban Areas. *Landscape and Urban Planning*, Vol. 105, 325–335. https://doi.org/10.1016 /j.landurbplan.2012.01.003.

[13] Tian, Y., Jim, C. Y. and Wang, H., (2014). Assessing the Landscape and Ecological Quality of Urban Green Spaces in a Compact City. *Landscape and Urban Planning*, Vol 121, 97-108. https://doi.org/10.1016/j.landurbplan.2 013.10.001.

[14] Dennis, M., Scaletta, K. L., and James, P., (2019). Evaluating Urban Environmental and Ecological Landscape Characteristics as a Function of Land-Sharing-Sparing, Urbanity and Scale. *PLoS ONE*, Vol. 14(7). https://doi.org/10.1371/journal.pone.0215796.

[15] Liang, H., Chen, D. and Zhang, Q., (2017). Assessing Urban Green Space Distribution in a Compact Megacity by Landscape Metrics. *Journal of Environmental Engineering and Landscape Management*, Vol. 25(1), 64-74. https://doi.org/10.3846/16486897.2016.121015 7.

[16] Luo, M. and Li, T., (2021). Spatial and Temporal Analysis of Landscape Ecological Quality in Yulin. *Environmental Technology & Innovation*, Vol. 23. https://doi.org/10.1016/ j.eti.2021.101700.

[17] Soltanifard, H. and Jafari, E., (2018). A Conceptual Framework to Assess Ecological Quality of Urban Green Space: A Case Study in Mashhad City Iran. *Env. Dev. and Sus*., Vol. 21, 1781–1808. https://doi.org/10.1007/s10668-01 8-0103-5.

[18] Rakoto, P. Y., Deilami, K., Hurley, J., Amati, M. and Sun, Q. C., (2021). Revisiting the Cooling Effects of Urban Greening: Planning Implications of Vegetation Types and Spatial Configuration. *Urban Forestry & Urban Greening*, Vol. 64. https://doi.org/10.1016/j.uf ug.2021.127266.

[19] Sheikhi A., and Kanniah K. D., (2018). Impact of Land Cover Change on Urban Surface Temperature in Iskandar Malaysia, *Chemical Engineering Transactions*, 63, 25-30. https://doi.org/10.3303/CET1863005

[20] Fang, H. and Liang, S., (2008). Leaf Area Index Models. *Encyclopedia of Ecology*. 2139-2148. https://doi.org/10.1016/B978-008045405-4.00 190-7.

[21] Liang, S., Li, X. and Wang, J., (2012). Chapter 11 - Leaf Area Index. *Advanced Remote Sensing*. Academic Press. 347-381. ISBN 9780123859549. https://doi.org/10.1016/B978-0-12-385954-9.00011-3

[22] Hardwick, S. R., Toumi, R., Pfeifer, M., Turner, E. C., Nilus, R. and Ewers, R. M., (2015). The Relationship between Leaf Area Index and Microclimate in Tropical Forest and Oil Palm Plantation: Forest Disturbance Drives Changes in Microclimate. *Agricultural and Forest Meteorology*, Vol. 201, 187-195. https://doi. org/10.1016/j.agrformet.2014.11.010.

[23] Kimm, H. and Ryu, Y., (2015). Seasonal Variations in Photosynthetic Parameters and Leaf Area Index in an Urban Park. *Urban Forestry & Urban Greening*, Vol. 14(4), 1059-67. https://doi.org/10.1016/j.ufug.2015.10.003.

[24] Guo, T., Zhao, Y., Yang, J., Zhong, Z., Ji, K., Zhong, Z. and Luo, X., (2023). Effects of Tree Arrangement and Leaf Area Index on the Thermal Comfort of Outdoor Children's Activity Space in Hot-Humid Areas. *Buildings*, Vol. 13(1). https://doi.org/10.3390/buildings 13010214.

[25] Andrew, M. E., Wulder, M. A. and Nelson, T. A., (2014). Potential Contributions of Remote Sensing to Ecosystem Service Assessments. *Progress in Physical Geography*, Vol. 38(3), 328–353. https://doi.org/10.1177/0309133314 528942.

[26] Ayanu, Y. Z., Conrad, C., Nauss, T., Wegmann, M. and Koellner, T., (2012). Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications. *Environmental Science and Technology*, Vol. 46(16), 8529–8541. https://doi.org/10.1021/es300157u.

[27] Araujo Barbosa, C. C. D., Atkinson, P. M. and Dearing, J. A., (2015). Remote Sensing of Ecosystem Services: A Systematic Review. *Ecological Indicators*, Vol. 52, 430–443. https://doi.org/10.1016/j.ecolind.2015.01.007.

[28] Homolová, L., Malenovský, Z., Clevers, J. G. P. W., García-Santos, G. and Schaepman, M. E., (2013). Review of Optical-Based Remote Sensing for Plant Trait Mapping. *Ecological Complexity*, Vol. 15, 1–16. https://doi.org/10.1016/j.ecocom.2013.06.003.

[29] Tavares, P. A., Beltrão, N., Guimarães, U. S., Teodoro, A. and Gonçalves, P., (2019). Urban Ecosystem Services Quantification through Remote Sensing Approach: A Systematic Review. *Environments – MDPI*, Vol. 6(5), 9–11. https://doi.org/10.3390/environments6050051.

[30] Fang, H., Baret, F., Plummer, S. and Schaepman-Strub, G., (2019). An Overview of Global Leaf Area Index (LAI): Methods Products Validation and Applications. *Reviews of Geophysics*, Vol. 57, 739-799. https://doi.org/10.1029/2018RG000608.

[31] Zheng, G. and Moskal, L. M., (2009). Retrieving Leaf Area Index (LAI) using Remote Sensing: Theories, Methods, and Sensors. *Sensors*, Vol. 9, 2719-2745. https://doi.org/10.3390/s90402719.

[32] Meyer, L. H., Heurich, M., Beudert, B., Premier, J. and Pflugmacher, D., (2019). Comparison of Landsat-8 and Sentinel-2 Data for Estimation of Leaf Area Index in Temperate Forests. *Remote Sensing*, Vol. 11. 1160, https://doi.org/10.3390/rs11101160.

[33] Dube, T., Pandit, S., Shoko, C., Ramoelo, A., Mazvimavi, D. and Dalu, T., (2019). Numerical Assessments of Leaf Area Index in Tropical Savanna Rangelands, South Africa using Landsat 8 OLI Derived Metrics and In-Situ Measurements. *Remote Sensing*, Vol. 11(7. https://doi.org/10.3390/rs11070829.

[34] Qiao, K., Zhu, W., Xie, Z. and Li, P., (2019). Estimating the Seasonal Dynamics of the Leaf Area Index using Piecewise LAI-VI Relationships Based on Phenophases. *Remote Sensing*, Vol. 11(6). https://doi.org/10.3390/rs11060689.

[35] Neinavaz, E., Darvishzadeh, R., Skidmorem A. K. and Abdullah, H., (2019). Integration of Landsat-8 Thermal and Visible-Short Wave Infrared Data for Improving Prediction Accuracy of Forest Leaf Area Index. *Remote Sensing*, Vol. 11(4). https://doi.org/10.3390/rs11040390.

[36] Bajocco, S., Ginaldi, F., Savian, F., Morelli, D., Scaglione, M., Fanchini, D., Raparelli, E. and Bregaglio, S. U. M., (2022). On the Use of NDVI to Estimate LAI in Field Crops: Implementing a Conversion Equation Library. *Remote Sensing*, Vol. 14. https://doi.org/10.3390/rs14153554.

[37] Ma, J., Zhang, J., Wang, J., Khromykh, V., Li, J. and Zhong, X., (2023). Global Leaf Area Index Research Over the Past 75 Years: A Comprehensive Review and Bibliometric Analysis. *Sustainability*, Vol. 15(4). https://doi.org/10.3390/su15043072.

[38] Department of Statistics Malaysia. (2022). *Key Findings Population and Housing Census of Malaysia 2020 Local Authority Area*. Available https://www.dosm.gov.my/portal-main/release-content/key-findings-population-and-housing-census-of-malaysia-2020-administrative-district.

[39] Dewan Bandaraya Raya Kuala Lumpur. List of Public Parks in Kuala Lumpur. Available https://portal-staging2.dbkl.gov.my/en/perkhidmatan/kemudahan-awam/taman-taman-awam/.

[40] Curran, P. J. and Williamson, H. D., (1986). Sample Size for Ground and Remotely Sensed Data. *Remote Sensing of Environment*, Vol. 20, 31-41. https://doi.org/10.1016/0034-4257(86)90012-X.

[41] Anderson, J. R., Hardy, E. E., Roach, J. T. and Witmer, R. E., (1976) A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *Geological Survey Professional Paper*. United States Department of Interior. Vol. 964, 1-40.

[42] Meter Group. The researcher's complete guide to Leaf Area Index (LAI). Available https://metergroup.com/education-guides/the-researchers-complete-guide-to-leaf-area-index-lai/.

[43] Fang, H. and Liang, S., (2014). Leaf Area Index Models. *Reference Module in Earth Systems and Environmental Sciences*. Available https://doi.org/10.1016/B978-0-12-409548-9.09076-X.

[44] Tan, C. W., Zhang, P. P., Zhou, X. X., Wang, Z. X., Xu, Z. Q., Mao, W., Li, W. X., Huo, Z. Y., Guo, W. S. and Yun, F., (2020). Quantitative Monitoring of Leaf Area Index in Wheat of Different Plant Types by Integrating NDVI and Beer-Lambert Law. *Scientific Report*, Vol. 10. https://doi.org/10.1038/s41598-020-57750-z.

[45] Pokovai, K. and Fodor, N., (2019) Adjusting Ceptometer Data to Improve Leaf Area Index Measurement. *Agronomy*, Vol. 9. https://doi.org/10.3390/agronomy9120866.

[46] Finzel, J. A., Seyfried, M. S., Weltz, M. A., Kiniry, J. R., Johnson, M. V. V. and Launchbaugh, K. L., (2012). Indirect measurement of Leaf Area Index in Sagebrush-Steppe Rangelands. *Rangeland Ecology & Management*, Vol. 65(2), 208-212. https://doi.org/10.2111/REM-D-11-00069.1.

[47] Garrigues, S., Shabanov, N. V., Swanson, K., Morisette, J. T., Baret, F. and Myneni, R. B., (2008). Intercomparison and Sensitivity Analysis of Leaf Area Index Retrievals from LAI-2000, AccuPAR, and Digital Hemispherical Photography Over Croplands. *Agricultural and Forest Meteorology*, Vol. 148(8–9), 1193-1209. https://doi.org/10.1016/j.agrformet.2008.02.014.

[48] Earth Online. European Space Agency. Spot 7 Instrument. Available https://earth.esa.int/eogateway/missions/spot-7.

[49] Richards, J. A., (1999). *Remote Sensing Digital Image Analysis*. Springer-Verlag, Berlin, Germany, 1-240. https://doi.org/10.1007/978-3-662-03978-6.

[50] Sisodia, P. S., Tiwari, V. and Kumar, A., (2014). Analysis of Supervised Maximum Likelihood Classification for Remote Sensing Image. *International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014)*, 1-4. http://doi.org/10.1109/ICRAIE.2014.6909319.

[51] Ong, B. L., (2003). Green Plot Ratio: An Ecological Measure for Architecture and Urban Planning. *Landscape and Urban Planning*, Vol. 63(4). 197-211. https://doi.org/10.1016/S0169-2046(02)00191-3.

[52] Klingberg, J., Konarska, J., Lindberg, F., Johansson, L. and Thorsson, S., (2017). Mapping Leaf Area of Urban Greenery Using Aerial LiDAR and Ground-Based Measurements in Gothenburg, Sweden. *Urban Forestry & Urban Greening*, Vol. 26, 31-40. https://doi.org/10.1016/j.ufug.2017.05.011.

[53] Wang, S., Wu, M., Hu, M., Fan, C., Wang, T. and Xia, B., (2021). Promoting Landscape Connectivity of Highly Urbanized Area: An Ecological Network Approach. *Ecological Indicators*, Vol. 125. https://doi.org/10.1016/j.ecolind.2021.107487.

[54] Asner, G. P., Scurlock, J. M. O. and Hicke, J. A., (2003). Global Synthesis of Leaf Area Index Observations: Implications for Ecological and Remote Sensing Studies. *Global Ecology & Biogeography*, Vol. 12, 191–205, http://www.blackwellpublishing.com/journals/geb.

[55] Chapman, S., Thatcher, M., Salazar, A., Watson, J. E. M. and McAlpine, C. A., (2018). The Effect of Urban Density and Vegetation Cover on the Heat Island of a Subtropical City. *Journal of Applied Meteorology and Climatology*, Vol. 57(11), 2531-2550. https://doi.org/10.1175/JAMC-D-17-0316.1.

[56] Guo, L., Liu, R., Men, C., Wang, Q., Miao, Y. and Zhang, Y., (2019). Quantifying and Simulating Landscape Composition and Pattern Impacts on Land Surface Temperature: A Decadal Study of the Rapidly Urbanizing City of Beijing, China. *Science of the Total Environment*, Vol. 654, 430-440. https://doi.org/10.1016/j.scitotenv.2018.11.108.

[57] Serdar Yakut, E. S., Cenani, S. and Cagdas, G., (2022). Assessment of Urban Surface Performance of Open Spaces with Multi-Criteria Decision-Making Method. *Megaron*, Vol. 17(4), 658–672. https://doi.org/10.14744/MEGARON.2022.47827.

[58] Zhang, Y., Yuchen W. and Nan, D., (2022). Spatial Effects of Landscape Patterns of Urban Patches with different Vegetation Fractions on Urban Thermal Environment. *Remote Sensing*, Vol. 14(22). https://doi.org/10.3390/rs14225684.

[59] Kanniah, K. D., (2017) Quantifying green cover change for sustainable urban planning: A case of Kuala Lumpur, Malaysia. *Urban Forestry & Urban Greening*, Vol 27, 287-304. https://doi.org/10.1016/j.ufug.2017.08.016

[60] Urban Redevelopment Authority, (2017). Updates to the Landscaping for Urban Spaces and High-Rises (LUSH) Program: LUSH 3.0. Circular No: URA/PB/2017/06-DCG. Available https://www.ura.gov.sg/Corporate/Guidelines/Circulars/dc17-06.