The influence of land-use/land-cover changes on land surface temperature: a case study of Kuala Lumpur metropolitan city

Ang Kean Hua* and Owi Wei Pingb

*Department of Environmental Sciences, Faculty of Environmental Studies, Universiti Putra Malaysia (UPM), Serdang, Malaysia; bDepartment of Mathematic, Faculty of Science and Mathematics, Universiti Pendidikan Sultan Idris, Tanjung Malim, Malaysia

ABSTRACT
This paper evaluates the impact of land-use and land-cover (LULC) changes on land surface temperature (LST) in the Kuala Lumpur metropolitan city using multi-spectral and multi-temporal satellite data. The spectral radiance model was used to extract the LST from Landsat 8 OLI and Landsat 5 TM. The analysis on LULC changes revealed a phenomenal increase in the urban (high built-up area) areas and a decrease in the forest land area. The distribution of average changes in LST shows that urban (high built-up area) areas recorded the highest increase in temperature followed by urban (low built-up area) areas, grass land area, forest land area and waterbodies. The LST and normalised difference vegetation index (NDVI) were computed based on changes in LULC which indicates that a strong correlation value was observed between LST and NDVI for urban (high and low built-up areas) areas, grass land area and forest land area. This study demonstrated that an increase in non-evaporating surfaces and a decrease in the vegetation area have increased the surface temperature and modified the temperature of the study area. Remote-sensing techniques were found to be efficient, especially in reducing the time for analysis of urban expansion, and are useful tools to evaluate the impact of urbanisation on LST.

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INTRODUCTION

Human activities continuously decrease the vegetation cover of the earth’s surface to cause environmental changes, especially the terrestrial ecosystem at local, regional, and global scales (Kikon, Singh, Singh, & Vyas, 2016; Sahana, Ahmed, & Sajjad, 2016; Zhang et al., 2016). Major causes of environmental changes are due to the various anthropogenic activities that are integrated not only with the present but also with the past (BokaieZarkesh, Arasteh, & Hosseini, 2016; Singh, 1996; Weng, 2001; Xiao & Weng, 2007; Zhang, Odeh, & Ramadan, 2013). These problems, especially the urbanisation, had indirectly increased the surface temperature due to the conversion of vegetation surfaces into impervious surfaces (Zhang et al., 2013), agricultural land (Sahana et al., 2016) and bare land (Sun, Wu, & Tan, 2012). According to Pal and Ziaul (2017), the changes in land use will affect the degree of absorption of solar radiation, surface temperature, evaporation rate, transmission of heat soil, heat storage and wind turbulence. Also, this will result in an alteration in the near-surface atmospheric energy, water balance, as well as environmental processes in the cities (Buyadi, Mohd, & Misni, 2013; Kikon et al., 2016; Zhang et al., 2016). Including various pollutants, land surface temperature (LST) is expected to rise rapidly and will expose 69% to the world population in the year 2050 (United Nations, 2010). There is no exception for the urbanisation process to stop occurring, especially in a developing country like Malaysia.

The urbanisation of land-use and land-cover (LULC) changes has become major issues of debate in human history (Pal & Ziaul, 2017; Zhang et al., 2013). Population and economic growth are among the listed issues that caused urbanisation to occur rapidly. Improper planning and uncontrolled management of LULC changes in the urban areas will have a great impact on the climate and local environment, which can contribute to the development of urban heat island. Therefore, previous studies on LULC changes, in particular areas, can help to understand the spatial extent and the degree of changes, as well as other human-related environmental changes (Buyadi et al., 2013; Kikon et al., 2016). Although Malaysia has widely used the satellite images for analysis, more studies are still required to focus on multi-temporal LULC in the Kuala Lumpur metropolitan city (Balakeristanan & Md Said, 2012; Tehrany, Pradhan, & Jebur, 2013), especially using Landsat data which have benefits in multi-spectral, multi-resolution and multi-temporal forms of analysis and monitoring the land-cover and vegetation.
density (Sahana et al., 2016; Zhang et al., 2013). Therefore, Landsat programme is not only readily accessible and available free of charge, but has also provided invaluable information through the Landsat 8 OLI, Landsat 7 +ETM and Landsat 5 TM satellite images for the past few decades until presently (Pal & Ziaul, 2017).

LST is the key parameter to estimate the surface energy budget in assessing the land-cover changes and other characteristics of the earth surface (Kikon et al., 2016; Pal & Ziaul, 2017). Various scholars had demonstrated that LULC had impacted LST in various research articles (Kikon et al., 2016; Pal & Ziaul, 2017; Sahana et al., 2016; Zhang et al., 2013), especially using Geographic Information System (GIS) and remote-sensing methods to measure and analyse both the drastic changes. Yusuf, Pradhan, and Idrees (2014) explained that more study on LST is required in evaluating and monitoring the metropolitan area to maintain the Greater KL city, particularly involved with LULC changes in the city. Hence, this paper aims to analyse how LULC changes impact the LST in the Kuala Lumpur metropolitan city. The specific objectives of this study are (1) to examine the LULC changes, (2) to assess the LST changes and (3) to establish the relationship between LULC and LST in the metropolitan city area.

Study area

This study was carried out in the Kuala Lumpur city which is located in the Selangor state, Malaysia, with the geographical coordinate of 3°8′N and 101°41′E (Figure 1). The total study area is 243 km² and is surrounded by Titiwangsa Mountains in the north and east, the Straits of Malacca in the west and Port Dickson in the south. Kuala Lumpur metropolitan city becomes the hub of Malaysia’s industrial and commercial activities as reported in the 2014 project: “ Developing Greater Kuala Lumpur/Klang Valley as an Engine of Economic Growth (ETP (Economic Transformation Programme), 2014)”. With approximately 7.5 million population, the majority are foreign workers from Indonesia, India, Bangladesh, Nepal and Myanmar, and it is one of the fastest growing metropolitan regions in the country, in terms of population and economic perspective. The development of Kuala Lumpur regions appeared to have grown south towards the Negeri Sembilan border and to the north towards Rawang (Tehrany, Pradhan, & Jebuv, 2014). Kuala Lumpur city experienced equatorial climate throughout the year, which have an annual temperature ranging between 17°C and 38°C and an average daily mean of 28°C with a minimum and maximum temperature range between 23°C and 32°C. Meanwhile, the average annual relative humidity is between 70% and 90%, with an average annual rainfall of about 223 cm (Yusuf et al., 2014). During the monsoon wind periods, the population will experience sunshine during the day but rainfall in the evening. The wettest periods are generally expected to occur from April to June and from October to December.

Materials and methods

In evaluating land-use changes, and to gauge the effects of these changes on LST, the Kuala Lumpur metropolitan city adopted the Landsat satellite images (Landsat TM and OLI) (Figure 2). From 1990 to 2015, a range of satellite images of Landsat data chosen for this study was highlighted in Table 1. The chosen images have to conform to the following set of criteria (Tan, San Lim, MatJafri, & Abdullah, 2010): (1) satellite images of cloud coverage should be <10% or cloud free in the study area and (2) the availability of selected satellite images should be in long time series for at least 5 years and above between two imageries to maximise the separability and differentiate their different land-use classes. For this study, only the imageries data that have complied to both criteria will be chosen for use.

The US Geological Survey (USGS) Global Visualization Viewer provided the satellite imageries of Landsat data from 1990 to 2015. But, before the data can be accepted for use in this study, it must be co-registered with the UTM zone 47 North projection using WGS-84 datum in ArcGIS 10.1 and ENVI 4.7 (Table 1). The following steps describe the technique on how to extract surface temperature from the thermal band of Landsat data. Basically in Landsat 5, the wavelength use for LST is band 6, while Landsat 8 will involve with TIRS of band 10 and band 11, as well as OLI sensor band 2 to band 5.

LST extraction from thermal band

Conversion of the digital number (DN) into spectral radiance $(L_s)$

As every item is capable of discharging thermal electromagnetic energy, accordingly the signals received by thermal sensors can, therefore, be transformed into the sensor radiance. The following equation explains how the spectral radiance $(L)$ can be arrived at (Grover & Singh, 2015; Lee, Lee, & Wang, 2012; Nichol & To, 2012):

$$L = M \times Q_{CAL} + A$$  \hspace{1cm} (1)

where $M$ is the band-specific multiplicative rescaling factor (radiance mult band 6 October 2011); $Q_{CAL}$ is the DN of a given pixel (the images of band 6 or band 10 or band 11); and $A$ is the band-specific additive rescaling factor (radiance add band 6 October 2011).
Conversion of spectral radiance ($L_\lambda$) into at-satellite brightness temperatures (TB)

Based on the nature of land cover, any rectifications for emissivity ($\varepsilon$) would be applied to the radiant temperatures. In practice, vegetation areas are assigned a value of 0.95 and non-vegetation areas a value of 0.92 (Grover & Singh, 2015; Lee et al., 2012; Nichol & To, 2012; Siu & Hart, 2013). The emissivity-corrected surface temperature was derived by using Grover and Singh’s (2015) analysis:

$$TB = \frac{K_2}{\ln(K_1 + 1)}$$

where TB is the at-satellite brightness temperature (K); $L_\lambda$ is the spectral radiance in W.m$^{-2}$.sr$^{-1}$.µm$^{-1}$; and $K_1$ and $K_2$ are the two calibration constants prior to launching. In Landsat 8 OLI/TIRS, the constant values of $K_1$ and $K_2$ in band 10 are 774.88 and 1321.08, as well as in band 11, $K_1$ and $K_2$ values are 480.88 and 1201.14, respectively. Meanwhile, in band 6 of Landsat 5, the $K_1$ and $K_2$ values are 607.76 and 1260.56.

**LST for Landsat 5TM**

Subsequently, it is essential to rectify the spectral emissivity ($\varepsilon$) in order to obtain the temperature values with a black body. Such rectifications can be achieved based on the nature of land cover or by referring to emissivity values from the normalised difference vegetation index (NDVI) values for each pixel (Grover & Singh, 2015; Lee et al., 2012; Nichol & To, 2012; Siu & Hart, 2013). The emissivity-corrected LSTs were calculated based on Grover and Singh (2015):

$$LST = \frac{TB}{1 + \left(\frac{\lambda}{TB/\rho}\right) \ln \varepsilon}$$

where LST is the land surface temperature in Kelvin; $\lambda$ is the wavelength of emitted radiance in metre (for the peak response and the average of the limiting wavelengths ($\lambda = 11.5$ µm)) (Grover & Singh, 2015; Lee et al., 2012; Nichol & To, 2012); $\rho = h \times c/\sigma$ (1.438 x 10$^{-2}$ mK), where $\sigma$ is the Boltzmann constant (1.38 x 10$^{-23}$ J/K), $h$ is the Planck’s constant (6.626 x 10$^{-34}$ Js) and $c$ is the velocity of light (2.998 x 10$^8$ ms); $\varepsilon$ is the emissivity (range between 0.97 and 0.99) which can be referred in Equation (5); and the $P_v$ is the proportion of vegetation.

Land surface emissivity ($\varepsilon$)

$$\varepsilon = 0.004 \times P_v + 0.986$$

$$P_v = \left(\frac{NDVI_{fr} - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2$$
Figure 2. Methodological framework adopted for analysing variation in land surface temperature distribution influenced by the land-use and land-cover changes using spectral radiance model (TIRS, Landsat 8 and TM, Landsat 5) on Kuala Lumpur metropolitan city.

Table 1. The specification of Landsat data selected for the study.

| Satellite  | Sensor                        | Path/row | Year | Resolution (m) | Wavelength (µm)                                    |
|-----------|-------------------------------|----------|------|----------------|---------------------------------------------------|
| Landsat 5 | TM (Thematic Mapper)          | 127/58   | 1990 | 30             | Band 1: 0.45–0.52  
                          |                    | 1995     |      |                | Band 2: 0.52–0.60  
                          |                    | 2000     |      |                | Band 3: 0.63–0.69  
                          |                    | 2005     |      |                | Band 4: 0.76–0.90  
                          |                    | 2010     |      |                | Band 5: 1.55–1.75  
                          |                    |          |      |                | Band 6: 10.40–12.50 (Thermal Band)  
                          |                    |          |      |                | Band 7: 2.09–2.35  |
| Landsat 8 | OLI (Operational Land Imager)  | 127/58   | 2015 | 30             | Band 1: 0.435–0.451  
                          | and TIRS (Thermal Infrared Sensor) |          |      |                | Band 2: 0.452–0.512  
                          |                    |          |      |                | Band 3: 0.533–0.590  
                          |                    |          |      |                | Band 4: 0.636–0.673  
                          |                    |          |      |                | Band 5: 0.851–0.879  
                          |                    |          |      |                | Band 6: 1.566–1.651  
                          |                    |          |      |                | Band 7: 2.107–2.294  
                          |                    |          |      |                | Band 8: 0.50–0.68  
                          |                    |          |      |                | Band 9: 1.363–1.384  
                          |                    |          |      |                | Band 10: 10.60–11.19 (Thermal Band)  
                          |                    |          |      |                | Band 11: 11.50–12.51 (Thermal Band) |
**LST for Landsat 8 OLI/TIRS**

Since Landsat 8 is involved with two thermal infrared sensors (band 10 and band 11), the process to extract the information of LST by applying the calculation of structural mathematical algorithm, which is split-window (SW) algorithm (Figure 3).

In other words, these techniques use brightness temperature of two TIRS bands, the means and the differences in land-surface emissivity in estimating LST for particular area. The algorithms can be explained in detail in Equation (7):

\[
\text{LST} = TB_{10} + C_1(TB_{10} - TB_{11}) + C_2(TB_{10} - TB_{11})^2 + C_0 + (C_3 + C_4 W)(1 - \epsilon) + (C_5 + C_6 W)\Delta \epsilon
\]

where LST is the land surface temperature in K; TB\text{10} and TB\text{11} are the brightness temperatures of band 10 and band 11 in K; \(\epsilon\) is the mean of land surface emissivity (LSE) of TIR bands; W is the atmospheric water vapour content; \(\Delta \epsilon\) is the difference in LSE; and \(C_0\) to \(C_6\) are the SW coefficient values \([C_0 = -0.268; C_1 = 1.378; C_2 = 0.183; C_3 = 54.300; C_4 = -2.238; C_5 = -129.200; C_6 = 16.400]\) (Skoković et al., 2014; Zhao, Qin, Yang, Xiong, & Qiu, 2009). To determine the LST, it is compulsory to calculate the LSE for the study area. The LSE can be extracted using NDVI threshold method.

\[
\text{LSE} = \epsilon_s(1 - \text{FVC}) + \epsilon_v \times \text{FVC}
\]

where \(\epsilon_s\) and \(\epsilon_v\) are the soil and vegetative emissivity values of the corresponding bands. In band 10, the \(\epsilon_s\) and \(\epsilon_v\) are 0.971 and 0.987, respectively. Meanwhile, in band 11, the \(\epsilon_s\) and \(\epsilon_v\) are 0.977 and 0.989. Simultaneously, the FVC is the fractional vegetation cover which is used to estimate for a pixel of an image by using Equation (9):

\[
\text{FVC} = \frac{\text{NDVI} - \text{NDVI}_S}{\text{NDVI}_V - \text{NDVI}_S}
\]

where NDVI\text{S} – NDVI are reclassified for soil and NDVI\text{V} – NDVI are reclassified for vegetation. The calculation for OLI of bands 2, 3, 4 and 5 as well as NDVI are using ENVI software. To obtain the NDVI\text{S} and NDVI\text{V}, the images of NDVI were reclassified into soil and vegetation, where the classified data were used to find out FVC. Apart from generated LSE for bands 10 and 11 of TIRS, the last step is to identify the mean and difference of LSE by using Equations (10) and (11) as:
Figure 4. The spectral signature curves for LULC classes from 1990 to 2015 in the study area.

Figure 5. Classification map for LULC changes in Kuala Lumpur city of 1990.
\[ \epsilon = (\epsilon_{10} - \epsilon_{11})/2 \]  
\[ \Delta \epsilon = \epsilon_{10} - \epsilon_{11} \]

where \( \epsilon \) means LSE; \( \Delta \epsilon \) means LSE difference; and \( \epsilon_{10} \) and \( \epsilon_{11} \) are the LSE of band 10 and band 11.

**Conversion of LST from Kelvin into degree Celsius**

To transform into degree Celsius, a thorough analysis on LST can be conducted by using the relation of 0°C equals 273.15 K.

**Method for LULC classification**

Landsat 5 TM for 1990, 1995, 2000, 2005 and 2010, as well as Landsat 8 OLI/TIRS for 2015 from USGS Earth Explorer, are used for image classification, and ENVI v.4.7 software is selected for image classification. For this study, a supervised image classification of nonparametric rule based on parallelepiped, minimum distance-to-mean and maximum likelihood has been applied. When classifying the Landsat data, one can adopt the parallelepiped classification method which uses a simple decision rule (Pal & Ziaul, 2017), having this approach as an advantage to use in this study. The decision boundaries form an \( n \)-dimensional parallelepiped in the image data space (Sahana et al., 2016). Furthermore, the defining of the dimensions of a parallelepiped classifier depends on the standard deviation threshold which is derived from the mean of each selected class (Bokaie et al., 2016; Kikon et al., 2016). Assuming that the pixel value is higher than the low threshold but is below the high threshold for all the classified \( n \) bands, this is the class which will be assigned to. At the same time, maximum distance are applied in the study is due to the mean vectors for each end member applies the shortest distance method are required to calculate using the Euclidean distance from

![Classification map for LULC changes in Kuala Lumpur city of 2000.](image-url)
each unknown pixel to the mean vector for each of the class (Pal & Ziaul, 2017). Unless a standard deviation or distance threshold is stated, most of the pixels are classified according to the nearest class. However, should any pixels fail to meet the chosen criteria, very likely it will then be de-classified. Generally, the training pixels used to cover various LULC types in the study of Kuala Lumpur metropolitan city are 1990 \((970 + 223 + 1107 + 448 + 20)/3129 = 0.88\%\); 1995 \((915 + 130 + 1118 + 395 + 85)/3084 = 0.86\%\); 2000 \((778 + 177 + 1324 + 485 + 107)/3079 = 0.93\%\); 2005 \((376 + 103 + 1985 + 354 + 77)/3188 = 0.91\%\); 2010 \((435 + 222 + 2422 + 179 + 43)/3628 = 0.91\%\); and 2015 \((597 + 167 + 2025 + 177 + 18)/3177 = 0.94\%\). Furthermore, the pixel with maximum likelihood classification is used because of the capability to assume the statistics for each class in each band is normally distributed which, in turn, calculates the probability that a given pixel belongs to a specific class (Pal & Ziaul, 2017). All pixels are classified only when a probability threshold is selected. Every pixel with the highest probability will be assigned to the class.

In addition, there is still one important issue that needs to be highlighted, namely the proper classification of rules and method used is dependent on the scale in which the classification is carried out. According to the findings of Pal and Ziaul (2017), the spectral variability or heterogeneity within a land class at a larger scale will, no doubt, effect the pixel-based approach, making it less robust and causing it to creating an error when classifying the pixels. The problem of spectral variability can be prevented by using an object-based classification, which utilises not only the spectral details but also the topological relationships between image objects, as well as the advantages in the resolution of image which is the prime concern here. Pal and Ziaul (2017), Bokaie et al. (2016), Kikon et al. (2016) and Sahana et al. (2016) unanimously proposed using the Landsat-based higher image classification accuracies.

Figure 7. Classification map for LULC changes in Kuala Lumpur city of 2010.
Method used for accuracy assessment

In order to test the confusion or error matrix with information on the actual and predicted classifications completed during classification process, it is recommended to use the accuracy assessment for supervised technique (Sun et al., 2012; Yusuf et al., 2014; Zhang et al., 2013, 2016). The pixel derived from the image is used to compare the same site in this field. In a way, the results of the accuracy assessment will give the users an overall accuracy of the map and an accuracy for each class in the map. The total accuracy in the form of percentages can be computed using the following formula:

![Classification map for LULC changes in Kuala Lumpur city of 2015.](image)

**Figure 8.** Classification map for LULC changes in Kuala Lumpur city of 2015.

| Time series | Classification method          | Maximum likelihood | Minimum distance-to-mean | Parallelepiped |
|-------------|--------------------------------|--------------------|--------------------------|----------------|
| 1990        | OC                             | 89.47              | 83.23                    | 53.19          |
|             | KC                             | 0.857              | 0.812                    | 0.418          |
| 1995        | OC                             | 88.03              | 85.41                    | 45.83          |
|             | KC                             | 0.861              | 0.809                    | 0.331          |
| 2000        | OC                             | 93.24              | 89.73                    | 50.72          |
|             | KC                             | 0.902              | 0.850                    | 0.371          |
| 2005        | OC                             | 93.00              | 90.51                    | 67.23          |
|             | KC                             | 0.866              | 0.847                    | 0.229          |
| 2010        | OC                             | 91.68              | 89.84                    | 34.10          |
|             | KC                             | 0.862              | 0.839                    | 0.809          |
| 2015        | OC                             | 95.02              | 92.18                    | 78.79          |
|             | KC                             | 0.891              | 0.856                    | 0.282          |

**Table 2.** The overall classification accuracy and Kappa coefficient for the land-cover map of 1990, 1995, 2000, 2005, 2010 and 2015.
Table 3. Error matrix of the 1990 LULC map.

| Classified data | Reference data |
|-----------------|----------------|
| FLA             | GLA            | UHA | ULA | WB | Total | UA (%) | Kc |
| FLA             | 970            | 1   | 0   | 0  | 0     | 971    | 99.90| 0.951|
| GLA             | 102            | 223  | 69  | 3  | 0     | 397    | 89.17| 0.829|
| UHA             | 7              | 51   | 1107| 12 | 0     | 1177   | 95.26| 0.911|
| ULA             | 0              | 8    | 11  | 448| 0     | 467    | 95.93| 0.935|
| WB              | 97             | 0    | 0   | 20 | 0     | 117    | 86.88| 0.853|
| Total           | 1176           | 283  | 1187| 463| 20    | 3129   | 100.00|    |
| PA (%)          | 87.48          | 88.80| 96.76|   | 100.00|        |    |    |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; UA: user accuracy; PA: producer accuracy; Kc: Kappa coefficient.

Table 4. Error matrix of the 1995 LULC map.

| Classified data | Reference data |
|-----------------|----------------|
| FLA             | GLA            | UHA | ULA | WB | Total | UA (%) | Kc |
| FLA             | 915            | 50   | 1   | 0  | 33    | 999    | 91.59| 0.896|
| GLA             | 120            | 130  | 139 | 1  | 11    | 401    | 88.42| 0.872|
| UHA             | 12             | 5    | 118 | 6  | 6     | 1147   | 98.34| 0.920|
| ULA             | 0              | 0    | 33  | 395| 0     | 428    | 92.29| 0.875|
| WB              | 0              | 21   | 3   | 85 | 109   | 189    | 87.98| 0.864|
| Total           | 1047           | 206  | 1294| 402| 135   | 3084   |      |    |
| PA (%)          | 87.39          | 86.11| 90.71|   | 94.69  |        |    |    |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: Waterbodies; UA: User Accuracy; PA: producer accuracy; Kc: Kappa coefficient.

Table 5. Error matrix of the 2000 LULC map.

| Classified data | Reference data |
|-----------------|----------------|
| FLA             | GLA            | UHA | ULA | WB | Total | UA (%) | Kc |
| FLA             | 778            | 0    | 0   | 0  | 0     | 778    | 100.00| 0.989|
| GLA             | 46             | 177  | 72  | 0  | 6     | 301    | 85.80 | 0.811|
| UHA             | 8              | 17   | 1324| 8  | 0     | 1357   | 97.57 | 0.898|
| ULA             | 0              | 8    | 27  | 485| 0     | 520    | 93.27 | 0.932|
| WB              | 15             | 0    | 1   | 107| 123   | 135    | 89.99 | 0.857|
| Total           | 847            | 202  | 1424| 493| 113   | 3079   |      |    |
| PA (%)          | 91.85          | 87.62| 92.98|   | 94.69  |        |    |    |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; UA: user accuracy; PA: producer accuracy; Kc: Kappa coefficient.

Table 6. Error matrix of the 2005 LULC map.

| Classified data | Reference data |
|-----------------|----------------|
| FLA             | GLA            | UHA | ULA | WB | Total | UA (%) | Kc |
| FLA             | 376            | 0    | 4   | 0  | 0     | 380    | 98.95| 0.910|
| GLA             | 22             | 103  | 55  | 0  | 10    | 190    | 87.31 | 0.836|
| UHA             | 2              | 17   | 1985| 17 | 23    | 2044   | 98.06 | 0.928|
| ULA             | 0              | 1    | 110 | 354| 0     | 465    | 90.13 | 0.857|
| WB              | 3              | 0    | 29  | 0  | 77    | 109    | 87.46 | 0.872|
| Total           | 403            | 121  | 2183| 371| 110   | 3188   |      |    |
| PA (%)          | 93.30          | 91.12| 93.78|   | 95.42  |        | 87.00|    |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; UA: user accuracy; PA: producer accuracy; Kc: Kappa coefficient.

Table 7. Error matrix of the 2010 LULC map.

| Classified data | Reference data |
|-----------------|----------------|
| FLA             | GLA            | UHA | ULA | WB | Total | UA (%) | Kc |
| FLA             | 435            | 17   | 0   | 0  | 1     | 453    | 89.53| 0.865|
| GLA             | 15             | 222  | 113 | 0  | 6     | 356    | 85.02| 0.851|
| UHA             | 5              | 25   | 2422| 0  | 0     | 2452   | 88.96| 0.884|
| ULA             | 0              | 0    | 87  | 179| 0     | 266    | 87.79| 0.847|
| WB              | 42             | 4    | 12  | 43 | 101   | 133    | 83.60| 0.873|
| Total           | 497            | 268  | 2634| 179| 50    | 3628   |      |    |
| PA (%)          | 90.76          | 94.81| 89.96|   | 83.14  |        |    |    |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; UA: user accuracy; PA: producer accuracy; Kc: Kappa coefficient.
Table 8. Error matrix of the 2015 LULC map.

| Classified data | FLA | GLA | UHA | ULA | WB | Total | UA (%) | Kc |
|-----------------|-----|-----|-----|-----|----|-------|--------|----|
| FLA             | 597 | 1   | 0   | 0   | 0  | 598   | 99.83  | 0.957 |
| GLA             | 59  | 167 | 39  | 0   | 32 | 297   | 86.23  | 0.851 |
| UHA             | 2   | 10  | 2025| 0   | 1  | 2038  | 99.53  | 0.922 |
| ULA             | 0   | 0   | 45  | 177 | 0  | 222   | 89.73  | 0.867 |
| WB              | 0   | 1   | 3   | 0   | 18 | 22    | 85.82  | 0.835 |
| Total           | 658 | 179 | 2112| 177 | 51 | 3177  |         |     |
| PA (%)          | 90.73 | 93.30 | 96.91 | 100.00 | 89.29 |        |        |     |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; UA: user accuracy; PA: producer accuracy; Kc: Kappa coefficient.

Table 9. Statistical analysis for the differential LULC changes for 1990, 1995, 2000, 2005, 2010 and 2015.

| Classes | FLA 1990 | FLA 1995 | FLA 2000 | FLA 2005 | FLA 2010 | FLA 2015 |
|---------|----------|----------|----------|----------|----------|----------|
|         | A        | P        | A        | P        | A        | P        |
| FLA     | 41.91    | 27.84    | 15.16    | 13.94    | 12.47    | 9.70     | 16.15    | 6.64    |
| GLA     | 62.14    | 26.64    | 45.07    | 29.27    | 19.93    | 13.00    | 27.23    | 11.21   |
| UHA     | 114.49   | 109.52   | 121.18   | 132.87   | 145.26   | 161.93   | 66.64    |         |
| ULA     | 21.33    | 12.05    | 14.39    | 48.44    | 31.58    | 15.00    | 27.23    | 11.21   |
| WB      | 3.13     | 2.71     | 2.95     | 1.21     | 3.29     | 1.35     | 3.44     | 1.42    |
| Total   | 243      | 100      | 243      | 100      | 243      | 100      | 243      | 100     |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; A: area in km²; P: percentage (% of satellite image).

Table 10. Results of land-use classification from 1990 to 2015 images showing area changes of each class.

| Classes | 1990 to 1995 | 1995 to 2000 | 2000 to 2005 | 2005 to 2010 | 2010 to 2015 |
|---------|--------------|--------------|--------------|--------------|--------------|
| FLA     | −5.06        | −2.08        | −1.22        | −3.59        | −1.47        | −6.72        | −2.77        | −7.42        | −3.06        |
| GLA     | 2.6          | 1.07         | −14.48       | −5.96        | −21.81       | −8.97        | 10.85        | 4.46         | −5.05        | −2.08        |
| UHA     | −4.97        | −2.05        | −11.66       | 4.8          | 11.69        | 4.81         | 12.39        | 5.1          | 16.67        | 6.86         |
| ULA     | 7.94         | 3.27         | 5.7          | 2.34         | 13.47        | 5.54         | −16.86       | −6.93        | −4.35        | −1.79        |
| WB      | −0.51        | −0.21        | 0.09         | 0.04         | 0.24         | 0.09         | 0.34         | 0.14         | 0.15         | 0.07         |
| Total   | 0            | 0            | 0            | 0            | 0            | 0            | 0            | 0            |

FLA: forest land area; GLA: grass land area; UHA: urban high area; ULA: urban low area; WB: waterbodies; NC: net changes; %: percentage.

Overall Accuracy = Total no. of correct samples
X 100% Total no. of samples
(12)

In addition to the overall accuracy, the correct classification of individual classes is also being computed in the similar manner involving the user’s accuracy and producer’s accuracy. The producer’s accuracy can be achieved by dividing the number of correct pixels in a class divided by the total number of pixels taken from reference data. That is to say, the producer’s accuracy is gauged based on how great a certain area is being classified. One has to take into account the error of omission which refers to the proportion of observed features on the ground that is not classified in the map. Similarly, the user’s accuracy is calculated by dividing the number of correct classified pixels in each category with the total number of pixels that were classified in that category (Pal & Ziaul, 2017). To gauge the commission error and indicate the possibility of a pixel classified into a given category that actually presents the category at ground level, very often the user’s accuracy is used (Pal & Ziaul, 2017; Sun et al., 2012; Yusuf et al., 2014; Zhang et al., 2013, 2016). Hence, the producer’s and user’s accuracy are performed in the following formulae:

\[\text{Comission Error} = \frac{\text{off. diagonal.row elements}}{\text{Total.of.row}}\]

\[\text{Comission Error} = \frac{\text{off.dia.gnom.column.elements}}{\text{Total.of.column}}\]

\[\text{Producer’s Accuracy} (%) = 100% - \text{error of omission} (%)\]

\[\text{User’s Accuracy} (%) = 100% - \text{error of commission} (%)\]

In addition to the overall accuracy, Congalton (1991) proposed the Kappa coefficient \((K)\) as an alternative measurement that can also be utilised for this study. The K technique is computed by increasing the total number of pixels in all the ground verification classes \((N)\) with the sum of the confusion matrix diagonals \((X_{kk})\) and subtracting the sum of the ground verification pixels during the class time. The sum of the
classified pixels in that class is summed up over all classes (ΣXkΣ YkΣ), where XkΣ is the row total and YkΣ is the column total, and divided by the total number of pixels squared minus the sum of the ground verification pixels in that class times the sum of the classified pixels in that class summed over the classes. In general, the Kappa value (in percentage) lies between 0 and 1, where 0 represents the agreement due to chance only and 1 represents a complete agreement between two sets of data (Congalton, 1991). However, should there be a negative value, it will be considered as spurious. The Kappa statistic can be explained in equation as follows:

\[ k = \frac{N \sum_{i=1}^{c} x_{ii} - \sum_{i=1}^{c}(x_{i} + y_{i})i}{N^2 - \sum_{i=1}^{c}(x_{i} + y_{i})i} \]  

(17)

and

\[ k = \frac{\text{(Total Sum of correct)} - \text{Sum of the all the (row total column total)}}{\text{Total squared} - \text{Sum of the all the (row total column total)}} \]  

(18)

In general, the Kappa value will always be less than or equal to 1. A value that is equal to 1 means a perfect agreement, whereas a value less than 1 is considered as less perfect agreement. However, very seldom researchers can have a perfect agreement, as different people will have different understanding as to what is a good level of agreement. Precisely, the Kappa value of less than 0.4 represents poor or very poor agreement, values from 0.4 to 0.55 represent fair agreement, values
from 0.55 to 0.7 represent good agreement, values from 0.7 to 0.85 represent very good agreement and values higher than 0.85 represent excellent agreement between the images (Bokaie et al., 2016; Kikon et al., 2016; Pal & Ziaul, 2017; Sahana et al., 2016; Sun et al., 2012; Yusuf et al., 2014; Zhang et al., 2013, 2016).

Methods for change detection
In order to evaluate the qualitative and quantitative aspects of the changes for the periods from 1990 to 1995, 1995 to 2000, 2000 to 2005, 2005 to 2010 and 2010 to 2015, the classified images of two different time phases are compared using cross-tabulation. The quantitative area data for the overall LULC changes including the net changes for loss and gain in each category from 1990 to 2015 are assembled.

Results and discussion
LULC changes and analysis
For this study, a total of five classes of land area have been selected for the LULC analysis, namely forest land area, grass land area, highly built-up area or urban high area, low built-up area or urban low area and waterbodies. Specifically, the high built-up area is referred to the area which built-up with residential, industrial and commercial activities, while the low built-up area is likely to be involved with residential activities (Figure 4). Figures 5–8 illustrate the map after classification of different LULC changes for the Kuala Lumpur metropolitan city from the year 1990 to 2015. The total accuracy and Kappa coefficients for LULC maps for 1990, 1995, 2000, 2005, 2010 and 2015 were compared with each of the classification methods of maximum likelihood, minimum distance-to-mean and parallelepiped (Table 2).
Normally, to conduct an LULC analysis, a supervised classification technique-based maximum likelihood method is employed. The overall accuracy and Kappa coefficient, as illustrated in Table 2, stipulate that the maximum likelihood of 1990, 1995, 2000, 2005, 2010 and 2015 is above 85% or 0.85 which signifies the excellent agreement of the classified images. Concurrently, the producer’s and user’s accuracy for all the classes from 1990 to 2015 exceeded 80% (Tables 3-8). This suggests that the classification was done with the highest accuracy. However, some of the classification processes are repeated for the year 2010 due to the confusion which arose between the waterbodies with the grassland area, but still the producer’s and user’s accuracies of the waterbodies are still greater than 0.8.

Table 9 shows the statistical analysis of LULC changes in the Kuala Lumpur metropolitan city from the year 1990 to 2015. Obviously, from 1990 to 1995, the results indicated that the majority of the forest land area was converted into grass land and urban low areas of 2.6 and 2.46 km², resulting in 36.85 km². Supported by Kanniah and Ho (2017) as well as Nor, Corstanje, Harris, and Brewer (2017), the green covers in the city are subjected to have rapid net loss than the net gain of forested area due to the demand for development activities. Simultaneously, the same situation happens to the urban high area, which was reduced from 114.49 to 109.52 km² to transform into grass land of 2.05%, before it is converted into other classes of area. Reported by Kanniah (2017), implementation of “Greening KL” program which aims to plant at least 100 thousand trees in the city along the streets and recreational parks will indirectly contribute to an increment in green spaces within the developed city in Kuala Lumpur. Nevertheless, the forest land area was detected to have changed drastically for 20 years starting from 1995, whereas the area declined from 36.85 to 16.15 km² for −8.52% (Table 10). These changes are suspected to transform into urban low area, which has a great increase in
the coverage area from 1995 to 2005 of 7.88%. The urban low area has been converted into high built-up area for the next 10 years from 48.44 to 27.23 km² of −8.72%. Simultaneously, the grass land area is also decreasing in the area of about −12.55% to reduce about −30.49 km² for transforming into high and urban low areas, as well as the waterbodies coverage. The waterbodies show an increase from 1995 to 2015 of 0.34% after the decline from 1990 to 1995 of −0.21% for the coverage area. Lastly, the urban high area is detected continuously increasing from 1995 for 20 years due to drastic changes from 109.52 to 161.93 km², which consists of 21.29% area that was converted from forest land area, grass land area and urban low area.

Overall, the development in the Kuala Lumpur city is found to have occurred rapidly and continuously from 1990 to 2015. Based on statistics, the major development is involved with the urbanisation, where most of the forest and grass land area are transformed into urban low area, before it is converted into urban high area. The main issue to cause uncontrolled rapid urbanisation is the demand for land use for human activities like residential, industrial, commercial and other concrete buildings. Since industrial and commercial activities provide job opportunities, this situation will attract people to centralise themselves in urban low area which is surrounded by forest and grass land area. Hence, migration from local and

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**Table 11.** Average land surface temperature (LST) in °C for different land covers.

| Land cover | 1990 | 1995 | 2000 | 2005 | 2010 | 2015 |
|------------|------|------|------|------|------|------|
| FLA        | 22.84| 23.85| 25.23| 26.46| 27.00| 29.83|
| GLA        | 24.71| 25.92| 26.83| 28.11| 29.02| 31.50|
| UHA        | 27.78| 29.58| 30.64| 32.91| 33.70| 35.58|
| ULA        | 26.25| 26.25| 27.94| 29.62| 31.18| 34.06|
| WB         | 21.79| 22.91| 23.42| 24.84| 26.63| 29.16|
non-local residents into the Kuala Lumpur city has increased the development activities which boosted from sub-urban area to urban area in providing activities (e.g. residential, industrial, etc.) for the people. Therefore, the majority of the urban low area are developed and converted into urban high area, which indirectly increased pollution to impact the environment in the Kuala Lumpur city.

**Urbanisation impact on LST**

When examining the characteristics of LULC changes and LST of particular areas, the satellite images can prove to be beneficial. It is easy for the satellite images to understand the impacts of LULC changes on the LST when using the Landsat data (Figures 9–12). The average of LST data for each LULC type in 1990, 1995, 2000, 2005, 2010 and 2015 are outlined in Table 11. The result shows that the urban high area exhibits the highest LST compared to other land cover types (Bokaie et al., 2016; Pal & Ziaul, 2017) (27.78°C in 1990, 29.58°C in 1995, 30.64°C in 2000, 32.91°C in 2005, 33.70°C in 2010 and 35.58°C in 2015), followed by the urban low area (26.25°C in 1990, 26.59°C in 1995, 27.94°C in 2000, 29.62°C in 2005, 31.18°C in 2010 and 34.06°C in 2015) (Fu & Weng, 2016). Furthermore, the grass land area also demonstrates a high LST (24.71°C in 1990, 25.92°C in 1995, 26.83°C in 2000, 28.11°C in 2005, 29.02°C in 2010 and 31.50°C in 2015). These circumstances show that urbanisation has brought about an increase in LST since the change in the forest area to non-affected surface materials like concrete, stone, tars, etc. The lowest LST detected was in the forest land area (22.84°C in 1990, 23.85°C in 1995, 24.78°C in 2000, 25.23°C in 2005, 25.92°C in 2010 and 26.25°C in 2015). The main idea to have forest land area as low as LST when compared with other land cover type is because the forest contains a variety of overgrown vegetation, which becomes important for the processing of photosynthesis and transpiration that helps to reduce heat in particular area. Comparative between forest land area and grass land area, where forest land areas are being converted into grass land to carried out human activities such as agriculture, would indirectly had cause the nature of photosynthesis and transpiration to be reduce as well as increase the possibility of temperature in surrounding environment. These circumstances could be occur when the heat (temperature) from the ground (soil structure) is directly expose into the environment. Nevertheless, comparing forest land area with other built-up areas, these changes in land surface properties could bring about a large share in LST due to the dryness of non-evaporate materials. As Kuala Lumpur city is experiencing a relatively high annual humidity within the range of 70–90%, it is possible that urbanisation did not impact the LST in the urban area.

![Table 11. Linear regression correlation coefficients between LST and NDVI by land use and land cover types.](image-url)
Figure 13. The bar chart of relationship between LST and NDVI. Based on the sequences of FLA, GLA, UHA, ULA and WB, the NDVI values for 6 years are 1990 (−37.14; −2.49; −17.84; −7.99), 1995 (−35.79; −3.23; −19.02; −15.16; −4.67), 2000 (−34.12; −4.75; −20.62; −16.36; 6.89), 2005 (−32.29; −7.86; −21.97; −17.43; −7.78), 2010 (−29.48; −8.39; −22.17; −18.32; −9.64) and 2015 (−25.98; −10.21; −25.85; −21.97; −6.91), respectively.

Figure 14. The maps generated based on NDVI computation of 1990.
areas between 1990 and 2015. However, an enormously high humidity could generate the heat from the urbanisation process naturally and effectively.

**Relationship between LST and NDVI**

The relationship between LST and NDVI was investigated, and the linear regression correlations between five elements are shown in Table 12. From the result, it indicated that LST values tend to correlate negatively with the NDVI values for all LULC types for six different years. According to Cohen, Cohen, West, and Aiken (2013), the linear regression coefficient is determined based on the strength of the correlation coefficient, where 0.31–0.7 represents a weak correlation, 0.51–0.7 represents a normal correlation, 0.71–0.90 represents a strong correlation and 0.91–1.0 represents a strongly correlation. Therefore, the majority of the results show the highest negative strong correlation coefficient in urban high area, urban low area, grass land area and forest land area. Only waterbodies have a normal correlation coefficient in 1990 (0.626), 2000 (0.699), 2010 (0.634) and 2015 (0.694), including a strong correlation coefficient (0.731) in 1995 and a weak correlation coefficient (0.576) in 2005. The main reason for waterbodies to have a low possibility of correlation with LST and NDVI is because the water characteristic has a lower percentage of vegetation index. Therefore, the strong negative correlation between LST and NDVI (Figure 13) indicates that the higher the surface temperature, the lower the values of land cover of vegetation within all types of LULC. The NDVI map is shown in Figures 14–17 for 1990, 1995, 2000, 2005, 2010 and 2015.

This study applied the remote-sensing approach to determine the LULC changes which influences the LST in the Kuala Lumpur metropolitan city between 1990 and 2015. The results obtained from LULC changes are beneficial for providing essential information for decision-making in land management and policymaking. In other words, the result from
Landsat multi-temporal image provides an accurate map and offers detailed description of LULC changes from the study area. LULC changes indicate that urban (high built-up area) areas increased by 19.52%, followed by urban (low built-up area) areas increased by 2.43%, and waterbodies are at 0.13%, for 1990–2015. Meanwhile, the forest area has detected a continuous decrease from 1990 to 2015 at −10.6%, as well as grass land area that declined at −11.48%.

Simultaneously, the average LST from 1990 to 2015 detected that urban (high built-up area) areas increased drastically from 27.78°C to 35.58°C, followed by the urban (low built-up area) areas which increased from 26.25°C to 34.06°C; grass land area from 24.71°C to 31.50°C; and forest land area from 22.84°C to 29.83°C. The main reason for the retrieved higher LST values than the actual values is the effect of the surface roughness which is not taken into consideration when retrieving the LST value (Pal & Ziaul, 2017). In other words, LST is influenced by the land surface structure, water content and chemical composition (Siu & Hart, 2013). According to Bokaie et al. (2016), who stated that, in order to improve the result of LST, the temperature of every part of the vegetation-ground system must be taken into account. Additionally, the different canopy structures may also react as a factor in affecting the surface temperature.

**Conclusion**

In general, urbanisation is the main driving force of LULC changes which consequently increases the LST. A steady increase in LST could harm the habitat for the human and the other ecosystem members. Therefore, considering this trend is unstoppable, immediate transformation policies should be reviewed, especially when transforming the forest and grass land area into urban (built-up area) areas. It has been noted that to stop and reverse the

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**Figure 16.** The maps generated based on NDVI computation of 2010.
urbanisation process is almost impossible, unless a radical decentralisation policy plays a role to avoid further scatter development in the medium and small cities. Apart from providing information on LULC changes, this study also suggested the growth management policies which contain the growth policies that consequently could help to reduce LST as suggested by Nichol and To (2012) as well as Lee et al. (2012) by implementing the new urbanism (or green building) concepts by planning the development stages that would help to reduce the LST as reported by Kibert (2012). Lastly, by developing a free zone of less concrete structure can help to minimise raising the temperature effect.

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No potential conflict of interest was reported by the authors.

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Figure 17. The maps generated based on NDVI computation of 2015.
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