Urban Built-Up Effects to Land Surface Temperature

[1]Nur Adilla Nordin, [2]Zaharah Mohd Yusoff, [3] Nor Aizam Adnan, [4]Ainon Nisa Othman

[1]Nur Adilla Nordin, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia

[2]Zaharah Mohd Yusoff, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia;

[3]Nor Aizam Adnan, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia

[4]Ainon Nisa Othman, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia

[1] nurdillanordin@gmail.com, [2]zmy1208@salam.uitm.edu.my

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Abstract

Shah Alam is one of the regions which has a dense population and high level of urbanization in Malaysia. The study assumed high urbanization leads to the increase of temperature. The aim is to study the trend and relationship between Land Surface Temperature (LST) with built-up areas and Normalized Difference Vegetation Index (NDVI) in three different years (1997, 2007, 2017) in Shah Alam, Selangor. This study used Geographical Information System (GIS) and Remote Sensing software to process satellite imagery data (Landsat 5 TM, 7 ETM+, 8 OLI). Built-up area was processed using Principal Component Analysis (PCA) from Landsat 8 (OLI) while the land use land cover was processed using Supervised Classification method. The results were analyzed using linear regression analysis in the Statistical Package of the Social Science (SPSS) to describe the relationship of the LST with built-up area and NDVI. The highest LST distribution of 35.717ºC is recorded in 2017. This indicates that built-up area gives more impact to the increase of LST in Shah Alam despite NDVI having the highest correlation relationship as shown by the values of R^2 which are 0.557, 0.533, and 0.585 for year 1997, 2007, and 2017 respectively. This paper focused on the changes of land use land cover for built-up area (i.e. residential and industrial area) which have increased from year 1997 to 2017. In year 1997, the percentage of built-up area is 36.69% and it has increased to 44.36% in year 2017. The study can conclude that urban built-up is one of the major factors in the increasing LST.

Keywords *:* Built-up, LST, Land use land cover, Linear regression

I. Introduction

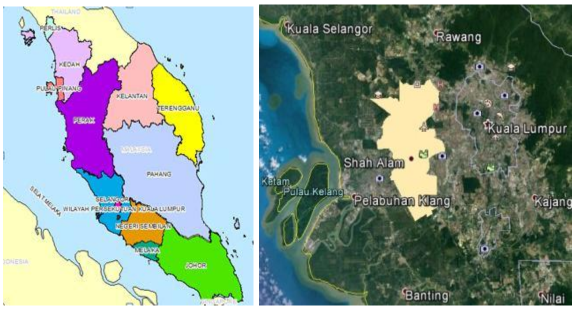
The heat concentrations can be defined as one of serious climate phenomenon that occurred in the urban area. When the urbanization is growing rapidly, the excess heat produced from built-up areas is trapped and the heat accelerates to high level of temperature (Ibrahim et al., 2016). Urbanization can be defined as an expansion process of urban related area, or the process where natural physical landscape is converted to human-made environment (Shaharuddin et al., 2014). An average heat temperature of 31º C to 33ºC is recorded in February and March which have been known to be the warmest months in Kuala Lumpur as stated by Ahmad et al., 2014 and Elsayed, 2012. The lowest temperature in Kuala Lumpur is approximately 23ºC to 30ºC which often occurs in December during the monsoon season, making it the coldest month every year (Dasimah and Bo, 2009). Brian (2001), stated that the temperature over the next century will rise between 3.5ºF and 6ºF after he compared the elevation of temperature caused by high heat temperature and global warming phenomenon. He also stated that from 1990 to 2025, roughly 2.9 billion of new residents are estimated to migrate to urban regions. It signifies that the rural areas will undergoing rapid developments in order to establish a high density population in the areas.

According to Salleh et al. (2013), the main factors that lead to high heat concentrations in Putrajaya are not only urbanization but also by climate change effects. The statistics of surface temperature in 1999,
2006, and 2009 increased, especially in 2006 due to the growth of urban activities. Human activities modified the materials, energy-balance and structure of the urban environment compared to sub-urban and rural environment (Ahmad et al., 2010).

By referring to Ibrahim et al. (2013), green space is one of the open spaces that is essential to enhance the lifestyle of the surrounding community because it acts as a green belt area and buffer zone to attune the nature and the developments for a sustainable environment.

Study Area

This study covered Shah Alam as the study area which is located in Petaling District, Selangor Darul Ehsan, Malaysia. The study area is selected based on the high heat temperature of the district, in addition to the location of Malaysia near to the equator where it is common to experience the humid and warm climate change condition. Furthermore, Selangor is the second most urbanized state in Malaysia (Jamaludin et al., 2015).



(a) **(b)**

Fig. 1. **(a)** Peninsular Malaysia **(b)**Boundary of Shah Alam in Petaling District, Selangor (source: Google Earth, 2017)

II. Methodology

The study used different types of Landsat satellite imagery data in three different years, which are Landsat 8 OLI (year 2017), ETM+ (year 2007), and TM (year 1997). Supervised classification is processed using ERDAS 2013 while LST and other analysis were processed and analyzed using ArcGIS 10.4 and SPSS software.

The supervised classification is one of the concepts in segmenting a spectral domain into regions which is associated with the class of ground cover interest in a particular application (Richards, 2013). The class of land use land cover had been recorded to five classes (industrial area, residential area, water bodies, green area, and barren land) for each year. Tan et al. (2010), concludes that if the overall accuracy exceeded 80%, then the classification for all classes was done in the highest accuracy.

All bands that will be used to retrieve LST must undergo a radiometric calibration. Mono-window algorithm techniques were used to retrieve Landsat 8 OLI, 7 ETM+, and 5 TM. The requirement of the mono-window algorithm is to extract other parameters such as vegetation value (NDVI) and land surface emissivity. These two parameters were retrieved using an algorithm. For Landsat 8 OLI, a thermal band used is band 10, 7 ETM+ used thermal band 6 1 (low) while 5 TM used band thermal 6 to retrieve LST. LST was retrieved based on Equation 1 where BT is an At-Satellite Temperature, W is a Wavelength of emitted radiance (11.5µm), P is a h*c/s (1.438*10^-2mK), h is a Plank's constant (6.626*10^-34Js), s is a Boltzmann constant (1.38*10^-23J/K), and c is a velocity of light (2.998*10^8 m/s).

$$LST : \frac{BT}{1 + W * [(BT / P) * / Ln(e)]} \tag{1}$$

According to Bhatti and Tripathi (2014) and Isa et al. (2017), the results for extraction of built-up area of Landsat 8 OLI can be improved using Principal Component Analysis (PCA). Bhatti and Tripathi (2014) also describes that thermal band 10 and 11 in Landsat 8 contributes high temperature rather than water and vegetation because it removed redundancy of every pixel in dataset whereas PCA preserved all the correlated data. Built-up area for Landsat 8 OLI was extracted using

Equation 2 which utilized PCA while built-up area for Landsat 7 ETM+ and 5 TM were extracted using Equation 4 which is a normal algorithm for built-up area. NDVI was extracted using Equation 3. NIR in the equations stand for Near Infrared. Then, NDWI of Landsat 8 OLI and Landsat 7 ETM+ was extracted using Equation 5. Lastly, the extraction of built-up area is calculated using Equation 6.

$$NDBI = \frac{[PCA\rho SWIR1, \rho SWIR2 + PCATOATIRS1, TIRS2] - \rho NIR}{[PCA\rho SWIR1, \rho SWIR2 + PCATOATIRS1, TIRS2] + \rho NIR} \tag{2}$$

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \tag{3}$$

$$NDBI = \frac{\rho SWIR1 - \rho NIR}{\rho SWIR1 + \rho NIR} \tag{4}$$

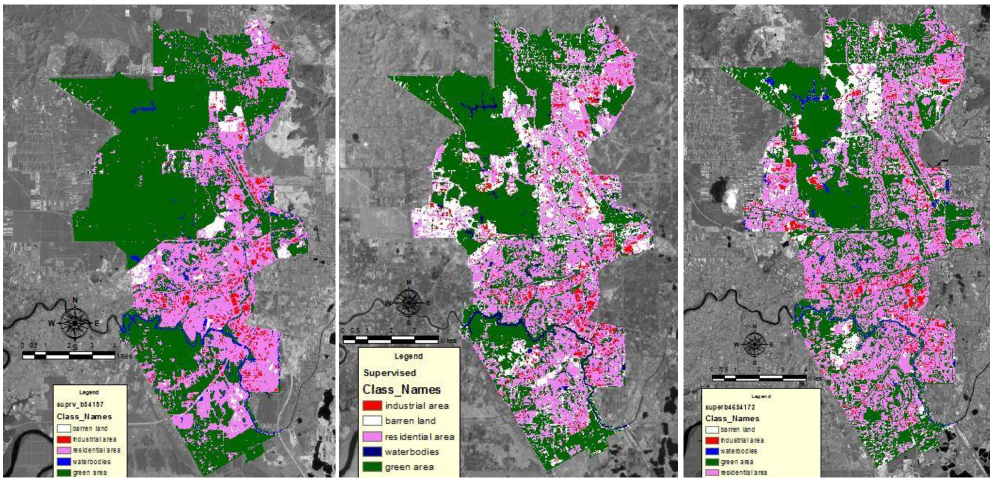
$$\frac{\rho GREEN - \rho NIR}{\rho GREEN + \rho NIR} \; NDWI = \tag{5}$$

$$BUILT - UP = NDBI - NDVI - NDWI \tag{6}$$

III. Results and Discussion

Trend of land use land cover for Year 1997, 2007 and 2017

The overall accuracy assessment of year 1997 is 96.00% and can be validated as a classification was done with highest accuracy. Land use land cover for each year were analyzed based on their area for each land use class. Based on Fig. 3. (a), (b), and (c) the study found that built-up area (i.e. industrial and residential area) increased from year to year by 1.32% from year 1997 to year 2007, although the percentage from year 2007 to year 2017 increased dramatically by 6.35%. It is supported by the significant change of total built-up area between year 1997 and year 2017 which are 27081.92 acres and 32750.3 acres respectively. This indicates that there is a rapid development from year 2007 to year 2017. In contrast to the increase of built-up area, land use for green area is shown to gradually decrease from year 1997 with 1637.94 acres to 1009.01 acres in year 2017. It is also notable that the total area of Shah Alam is 73825.8 acres.

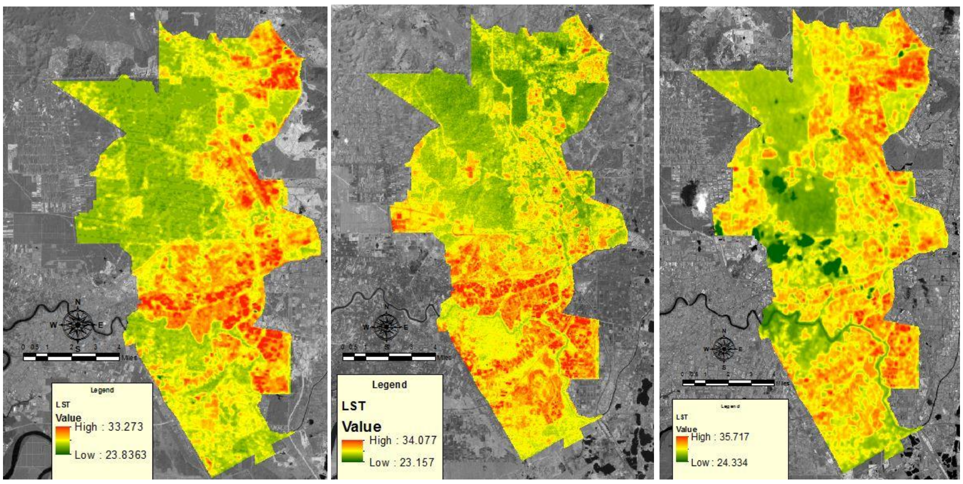


(a) (b) (c)

Fig. 3. (a) Trend of Land Use Land Cover of Shah Alam in Year 1997; (b) Trend of Land Use Land Cover of Shah Alam in Year 2007; (c) Trend of Land Use Land Cover of Shah Alam in Year 2017

Land Surface Temperature (LST) Retrieval

Based on Fig. 4 (a), the highest LST distribution for year 1997 is 33.273ºC and the lowest is 23.836ºC. The study found that the highest LST was distributed in the highest built-up area, while the lowest LST was distributed in vegetated areas. Section 7, Section 13, Section 16, Section 25, and Subang, Selangor are determined to have the highest LST because these areas are dense with residential and industrial area. Fig.4. (b) shows the highest LST of 34.077ºC in year 2007 while the lowest LST is 23.157ºC. Fig.4. (c) shows the distribution of LST in the year 2017. The study found that the highest LST in year 2017 is 35.717ºC and the lowest is 24.334ºC. Some of the distribution of LST in built-up area in this year does not present the correct value because the built-up area has the lowest LST. Theoretically, built-up area would have high LST due to the variation of urban activities. Moreover, the results differed each year and may be affected by environmental factors during the imagery acquisition, which in turn would affect the LST retrieval during data processing. One of the factors is satellite imagery data is captured on unclear sky-view such that the sky is covered with thick clouds. To obtain the best results, the satellite data should have clear view of the sky and cloud-free.



(a) (b) (c)

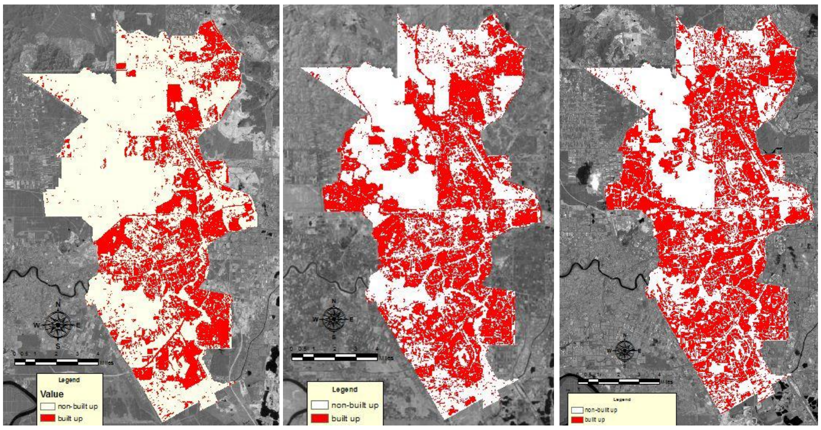
Fig. 4. (a) Distribution of LST in Shah Alam in Year 1997; (b) Distribution of LST in Shah Alam in Year 2007; (c) Distribution of LST in Shah Alam in Year 2017

Built-up area

Built-up area of Shah Alam in year 1997 was shown in Fig. 5 (a) and non built-up area predominated Shah Alam with the largest covered area. Built–up area is referred to as residential area and industrial area while non-built up area consists of waterbodies, green area, and barren land. By referring to Table 1, the study found that the built-up area increased roughly by 2% from year 1997 to 2007. Contrary to this, non-built up area is shown be decreasing moderately from year to year. Therefore, the study can conclude that built-up area gives positive values when derived using an algorithm and gives high LST value. Although the percentage of built-up area is 2% from year 1997 to year 2007, the built-up area increased approximately 6% from year 2007 to year 2017.

Table 1. Percentage of built-up and non built-up area in Shah Alam

	1997	2007	2017
Built-up	36.68%	38.00%	44.36%
Non-built up	63.32%	62.00%	55.64%

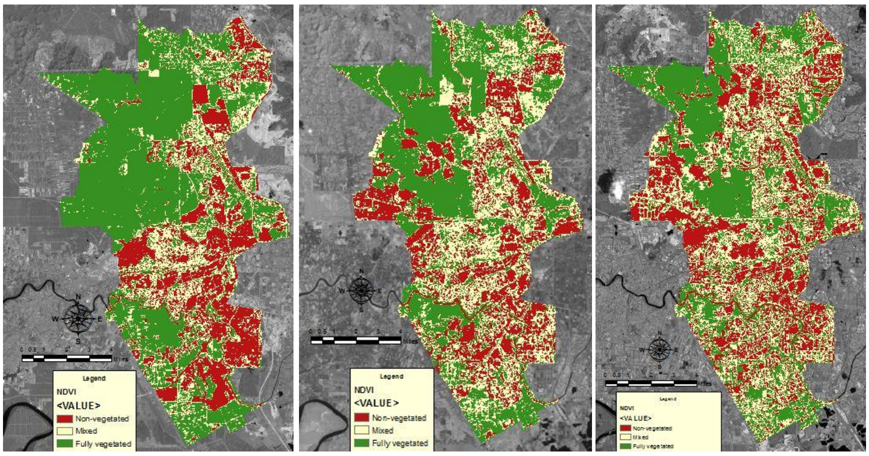


(a) (b) (c)

Fig. 5. (a) Built-up area of Shah Alam in Year 1997; (b) Built-up area of Shah Alam in Year 2007; (c) Built-up area of Shah Alam in Year 2017

Vegetated area

Vegetation is classified based on the range of NDVI values. The value that is less than 0.2 will be classified as non-vegetated area, whereas value of more than 0.2 but is less than 0.5 is classified as mixed area. Basically, the mixed area is referred to the are with vegetation, bared soil, and hard surfaces. Lastly, if the NDVI value is more than 0.5, then it will be classified as fully vegetated area (Isa et al., 2017). Fig. 6 shows the trend of vegetation area from year 1997 (a), 2007 (b) and 2017 (c). It is apparent that the vegetation area gradually decreased each year as illustrated by Fig. 6. The value of NDVI and LST is inversely proportional to each other. For example, when the NDVI value is low, the LST value will be high and vice versa.



(a) (b) (c)

Fig. 6. (a) Vegetated area of Shah Alam in Year 1997; (b) Vegetated area of Shah Alam in Year 2007; (c) Vegetated area of Shah Alam in Year 2017

Relationship between LST with Built-up area and vegetation index

This study determines the relationship between LST with built-up area using linear regression by utilizing SPSS to produce the graph. 50 points were selected randomly and distributed evenly across the study area to extract the values of LST and built-up area on each point. LST is chosen as a dependent variable while built-up area is chosen as an independent variable since the value of LST depends on the value of built-up area. R^2 was analyzed in terms of percentage to describe the relationship of LST with built-up area. In reference to Fig.7, the highest correlation between LST and built-up area in year 2017 as R^2 is 0.585. The R^2 can also be expressed such that 58.5% of LST can be predicted using the built-up area as the relationship is in positive correlation. If the value of built-up increases, so does the value of LST.

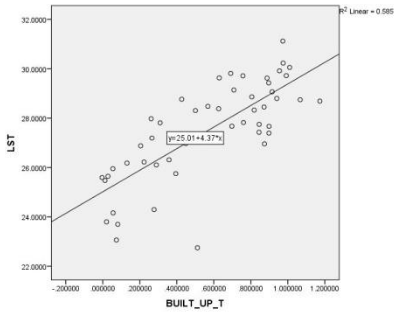


Fig. 7. Relationship between LST with built-up area in Year 2017

If the NDVI is high, then the LST will be low, hence there is a negative correlation between LST and NDVI. Fig. 8 shows the correlation between LST with vegetation indices in year 2017, with 0.153 of R^2 value. It shows that only 15.3% of LST can be predicted using the vegetated area.

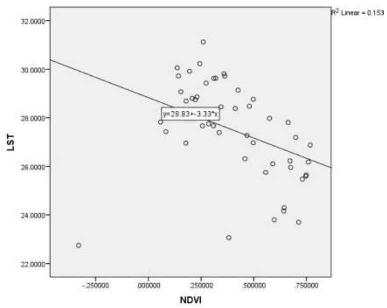


Fig. 8. Relationship between LST with vegetated area in Year 2017

IV. Conclusions

This study concludes that built up area gives significant impact on LST compared to using NDVI as presented by the positive correlation in year 2017 with the R^2 value of 0.585. R^2 of more than 0.5 signifies that LST value of more than 50% can be predicted using built-up parameters. On the other hand, there is a weak correlation between LST and vegetated area as indicated by R^2 of less than 0.5 in year 2017, which the R^2 is 0.153. The low value implies that only 15.3% of LST can be predicted using vegetated area as a parameter. This study will not be able to achieve result with sufficient accuracy if less than 50% of correlation instead of more than 50% result is used. The trend for land use land cover has been continuous as shown by the satellite imagery in 1997, 2007, and 2017. The changes are evident by the developments in Shah Alam particularly with the increase of built-up area from 1997 to 2017. The accuracy of land use land cover is validated using accuracy assessment in which the land use land cover used in this study is able to produce more than 80% accuracy during the assessment. Thus, the result for the accuracy of land use land cover can be accepted. Then, the trend of LST is positively correlated to built-up area since the LST increased when built-up area increased as shown by the findings of this study for year 1997, 2007, and 2017. In the future, it is suggested that SPOT data is used instead because it has better spatial resolution than Landsat to achieve higher quality result.

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References

I. S. A. A. I.Ibrahim, R. Fauzi and N. M. Noor. (2016)."The Land Surface Temperature Impact To Land Cover Types," *The International Achieves of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* pp. 871-876.

II. Shaharuddin, M. H. Noorazuan, W. Takeuchi and A. Noraziah. (2014). "The Effects of Urban Heat Islands on Human Comfort : A case of Klang Valley Malaysia," *Global Journal on Advances in Pure & Applied Science,* pp. 1-8.

III. S. Ahmad, N. M. Hashim, Y. M. Jani, K. Aiyub and M. F. Mahmod. (2010). "The Effects of Different Land Uses on Temperature Distribution in Urban Areas," in *SEAGA*, Hanoi.

IV. S. Elsayed. (2012). "Mitigation of the Urban Heat Island of the City of Kuala Lumpu, Malaysia," *Middle-East Journal of Scientific Research ,* pp. 1602-1613.

V. Dasimah and BO. (2009)., "Urban Form and Sustainability of Hot Humid City of Kuala Lumpur," *European Journal of Social Sciences,* pp. 353-359.

VI. S. J. Brian. (2001). Remote Sensing Analysis of Residential Land Use, Forest Canopy Distribution and Surface Heat Island Formation in Atlanta Metropolitan Region, Georgia, Atlanta: Georgia Institute of Technology.

VII. S. A. Salleh, Z. A. Latif, W. M. Mohd and A. Chan. (2013). "Factors Contributing to the Formation of an Urban Heat Island in Putrajaya, Malaysia," *Procedia Social and Behavioral Sciences*, pp. 840-850.

VIII. W. Y. Wan Ibrahim, A. Long and A. S. Permana. (2013). "Green Spaces Audits on its Accessibility in Pasir Gudang," *Planning Malaysia Geospatial Analysis in Urban Planning,* vol. II, pp. 39-56.

IX. N. M. Jamaludin, N. Izma, M. F. Khamid and S. N. Wahab. (2015). "Thermal Comfort Residential Building in Malaysia at Different Micro-Climates," *Procedia Social Behavioral Sciences,* pp. 613-623.

X. J. A. Richards. (2013). Remote Sensing Digital Image Analysis, New York: Springer-Verlag.

XI. K. C. Tan, H. S. Lim, M. Z. MatJafri and K. Abdullah,. (2010). "Landsat Data to Evaluate Urban Expansion and Determine Land Use / Land Cover Changes in Penang Island, Malaysia," *Environ Earth Sci,* pp. 1509-1521.

XII. S. S. Bhatti and N. K. Tripathi. (2014). "Built-up Area Extraction using Landsat," *GIScience & Remote Sensing,* pp. 445-467.

XIII. N. A. Isa, W. N. Wan Mohd and S. A. Salleh. (2017). "The Effects of Built-up and Green Areas on the Land Surface Temperature of the Kuala Lumpur City," *The International Archieves of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* vol. XLII, pp. 107-112.