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The Impact of Land Cover Changes on Land Surface Temperature in Klang Valley, Malaysia

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Abstract – The Klang Valley and its suburbs have grown rapidly as metropolitan cities since the 1990s with various infrastructure areas for commercial, residential, transportation, industry, and other purposes. Urban expansion has led to widespread land-use changes due to population growth and economic activity demand. The reduction of green space has affected the Land Surface Temperature (LST) by unbalancing the surface energy budget. Higher LST in urban areas reduces the comfort of urban residents resulting in increased use of air conditioners. This will affect the ozone layer and contribute to global warming. This study used Landsat 8 data for 2014 and 2021 over the Klang Valley area (Kuala Lumpur, Petaling, and Putrajaya districts) to obtain the land cover map, vegetation indices, and LST for the land cover change analysis with temperature. This study aims to examine urban land cover change and its impact on urban temperature and study the relationship between LST and vegetation indices such as NDVI (Normalized Difference Vegetation Index), MNDWI (Modified Normalized Difference Water Index) and NDBI (Normalized Difference Built-up Index) for all three (3) districts. Results show that LST values negatively correlate with NDVI and MNDWI for all three (3) districts for two (2) different years. Whereas NDBI had a positive correlation with LST. Our further analysis focused on urban class temperatures, which revealed that LST did not significantly increase from 2014 to 2021 due to the urban expansion rate of about 3%. The temperature of KL and Petaling is slightly higher than Putrajaya due to urban size, which is more than 80% for KL and 70% for Petaling compared to Putrajaya of only 50%. Mean urban temperature shows that Putrajaya has the lowest temperature compared to Kuala Lumpur and Petaling district, due to an urban percentage of only 50%, and the rest consists of greenery and water area. KL green areas with only 17% left and Petaling area with 25% in 2021 are factors for increasing temperature. Areas with no vegetation covered with impervious surfaces cause a temperature rise. Warmer places mostly consist of impervious surfaces, while those with vegetation cover are associated with lower temperatures. It is noteworthy that the Golden Triangle area in Kuala Lumpur has a lower LST in 2021. This is due to shadows from high-rise buildings affecting the LST values.

Keywords - Land Cover Changes, Land Surface Temperature, Landsat 8, Vegetation Indices

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1. Introduction

Klang Valley has grown rapidly as a metropolitan city since the 1990s with various infrastructures area for commercial, residential, transportation, industry, and other purposes. Urban expansion has led to extensive land-use changes due to population growth and economic activity (Ali and Kamaruzzaman, 2010; Tehrany et al., 2013; Akmar et al., 2020). Recently, many studies have been carried out to understand better the driving factors in changing local and regional climate due to land-use changes (Swades and Ziaul, 2017; Ang and Owi, 2018; Darren et al., 2020; Imran et al., 2021). The reduction of green space has affected the Land Surface Temperature (LST) by unbalancing the surface energy budget. Higher LST in urban areas reduces the comfort of urban residents, resulting in increased use of air conditioners. This will affect the ozone layer and contribute to global warming. Many studies have been conducted to identify the relationship between land-use change and LST using Landsat satellite imagery. Hasnat (2021) perform time series of forest and LST change in Bangladesh using Landsat Imagery. The results show significant forest degradation from 1990 to 2010 and forest restoration from 2010 to 2020 caused increased temperature by almost 2.3°C–3.0°C. Research by Darren et al. (2021) in Cameron Highlands found a temperature rise of 2.0–3.5°C in each decade caused by the conversion of forest and agricultural cover to urban. Similar few studies used remote sensing vegetation indices techniques such as NDVI, NDBI, and MNDWI to evaluate the impact of LST on urbanisation growth (Swedes and Ziaul, 2017; Awuh et al., 2019; Pham 2021; Siddeque 2020; Le 2021).

The objectives of this study are to examine urban land cover change and its impact on urban temperature using Landsat 8 data dated 25 April 2014 and 7 February 2021 and to investigate the relationship between LST and vegetation indices such as NDVI (Normalized Difference Vegetation Index), MNDWI (Modified Normalized Difference Water Index) and NDBI (Normalized Difference Built-up Index) for Klang Valley specifically in Kuala Lumpur, Petaling, and Putrajaya districts. Identifying the characteristics of urban land use and LST for these three districts can give an idea of which areas have lower LST for comfortable urban life.

2. Materials and Methodology

2.1 Study Area

Kuala Lumpur is the national capital, and Putrajaya is the federal administrative capital. Apart from Kuala Lumpur and Putrajaya, Klang valley includes Petaling, Gombak, Klang, and Hulu Langat, as shown in Figure 1. Petaling district, which consists of three municipalities, Shah

Alam, Petaling Jaya, and Subang Jaya, is rapidly developing compared to Klang and Hulu Langat. The study area covers Kuala Lumpur, Putrajaya, and the Petaling district. Kuala Lumpur (Upper left 3° 11’ 37.478” E, 101° 25' 23.123" N and Lower right 2° 52’ 42.78” E, 104° 41' 13.021" N) area is 243.65 km^2 with a population of 1,796,200 and density of 6,891/km^2, Putrajaya area is 49 km^2, population 91,900 and density 1,900/km^2 and Petaling area are 484.92 km^2, population 1,660,869 and density 3,400/km^2. These three areas were chosen because of the main urban areas with different population ranges and densities.

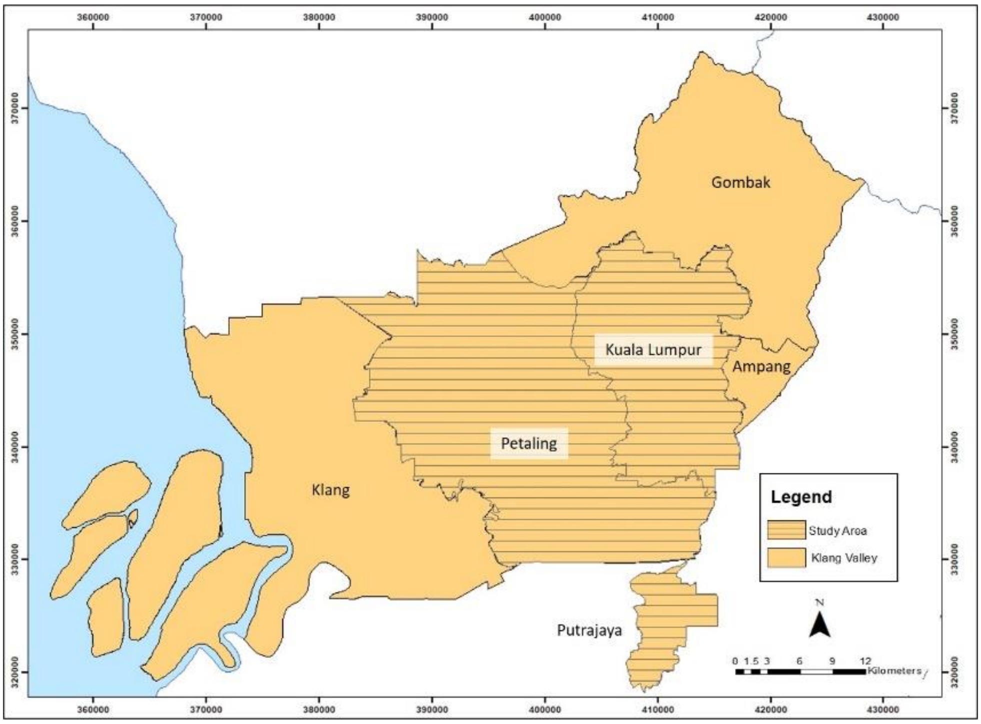


Figure 1. Study area.

2.2 Image Acquisition

The Level 1 Landsat 8 images of Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) were downloaded from the website of the United States Geological Survey (USGS) Earth Explorer (USGS 2013) dated 25 April 2014 and 7 February 2021.

Table 1. The Specification of Landsat 8 bands.

Band Name	Wavelength Range (μm)	Resolution (m)
Band 1 Coastal Aerosol	0.43 - 0.45	30
Band 2 Blue	0.45 - 0.51	30
Band 3 Green	0.53 - 0.59	30
Band 4 Red	0.64 - 0.67	30
Band 5 Near-Infared	0.85 - 0.88	30
Band 6 SWIR 1	1.57 – 1.65	30
Band 7 SWIR 2	2.11 – 2.29	30
Band 8 Panchromatic	0.50 - 0.68	15
Band 9 Cirrus	1.36 – 1.38	30
Band 10 TIRS	10.6 – 11.19	100
Band 10 TIRS	11.5 – 12.51	100

2.3 Methodology

The framework used in this study is shown in Figure 2. First, both imageries were classified into five main land cover classes: Urban, Bare Land, Forest, Vegetation, and Waterbody using the Support Vector Machine Classifier (SVM). For extracting LST and NDVI, TIRS Band 10 was used as the thermal image input for LST calculation due to the larger calibration uncertainty in Band 11 as recommended by USGS (Barsi et al., 2014; Avdan and Jovanovska, 2016). Meanwhile, bands 4 and 5 were used to generate NDVI images. TOA (Top of Atmospheric) spectral radiance was calculated using the following equation (GISCrack, 2018).

$$TOA\ (L) = M_L * Q_{cal} + A_L \tag{1}$$

where:

M_L = Band-specific multiplicative rescaling factor from the metadata

Q_{cal} = Corresponds to band 10

A_L = Band-specific additive rescaling factor from the metadata

The TOA image is converted to a Brightness Temperature Image with the following equation;

$$BT = (K_2 / (\ln (K_1 / L) + 1)) - 273.15 \quad (2)$$

where:

K_1 and K_2 = Band-specific thermal conversion constant from the metadata

L = TOA

NDVI imageries were generated using the following equation;

$$NDVI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4) \quad (3)$$

The proportion of vegetation (P_v) was then calculated.

$$P_v = Square\ ((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})) \quad (4)$$

Emissivity (ε) was calculated using the following equation;

$$E = 0.004 * P_v + 0.986 \quad (5)$$

where:

the value of 0.986 corresponds to a correction value of the equation.

Finally, the LST image was generated with the following equation;

$$LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon))) \quad (6)$$

2.4 Vegetation Indices (VI)

To investigate the relationship between LST and Vegetation Indices, randomly sampled points were extracted, which are 250, 300, and 200 points for Kuala Lumpur, Petaling, and Putrajaya. NDBI is sensitive to the built-up area and is used as an indicator of built-up extent; meanwhile, MNDWI is used to detect water content in vegetation (Imran et al., 2021). The Vegetation Indices were calculated in ArcGIS using the formula as shown below:

$$NDVI = [NIR-RED] / [NIR+RED] \quad (7)$$

$$NDBI = [MID-NIR] / [MID+NIR] \quad (8)$$

$$MNDWI = [Green - SWIR] / [Green + SWIR] \quad (9)$$

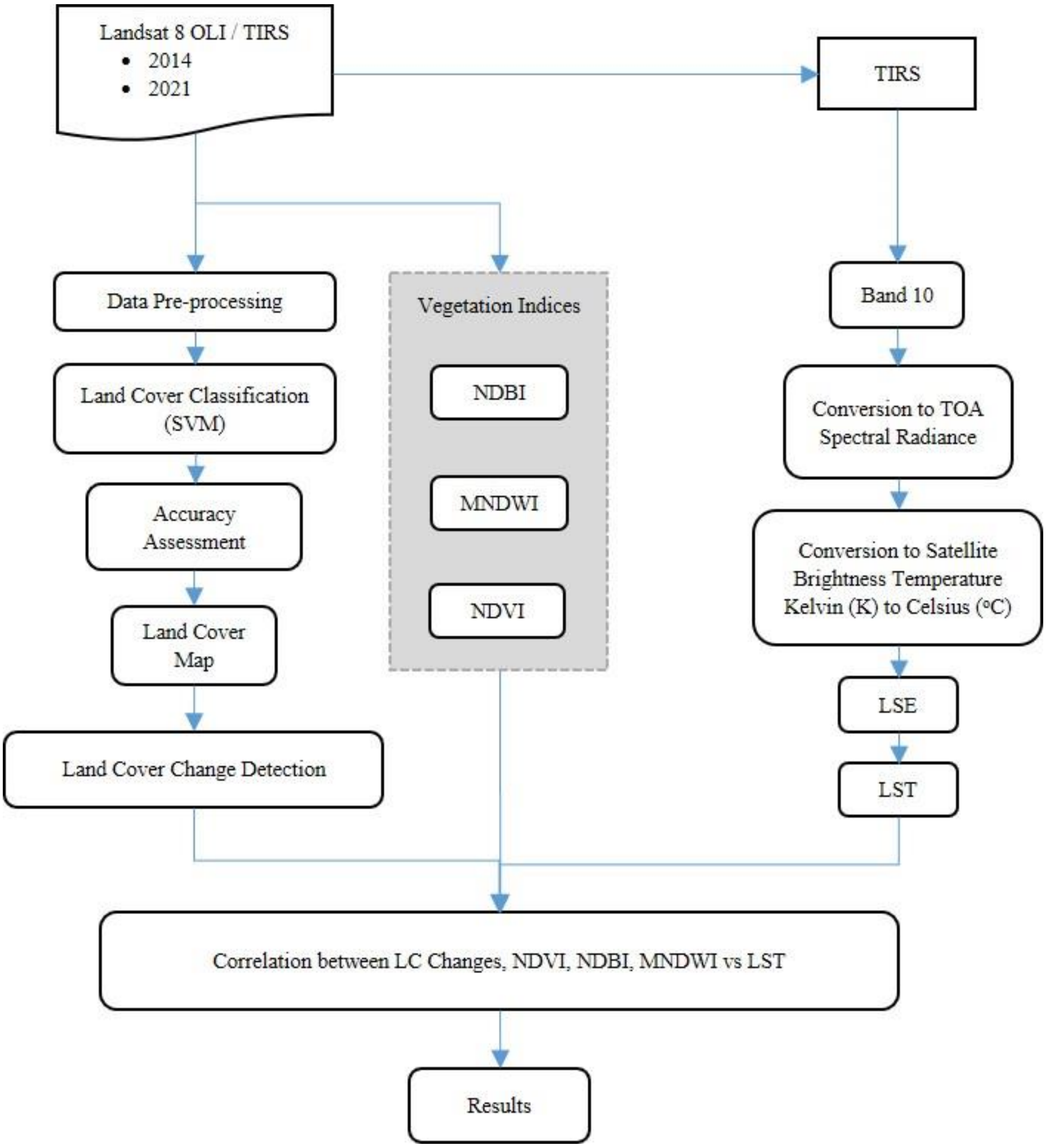
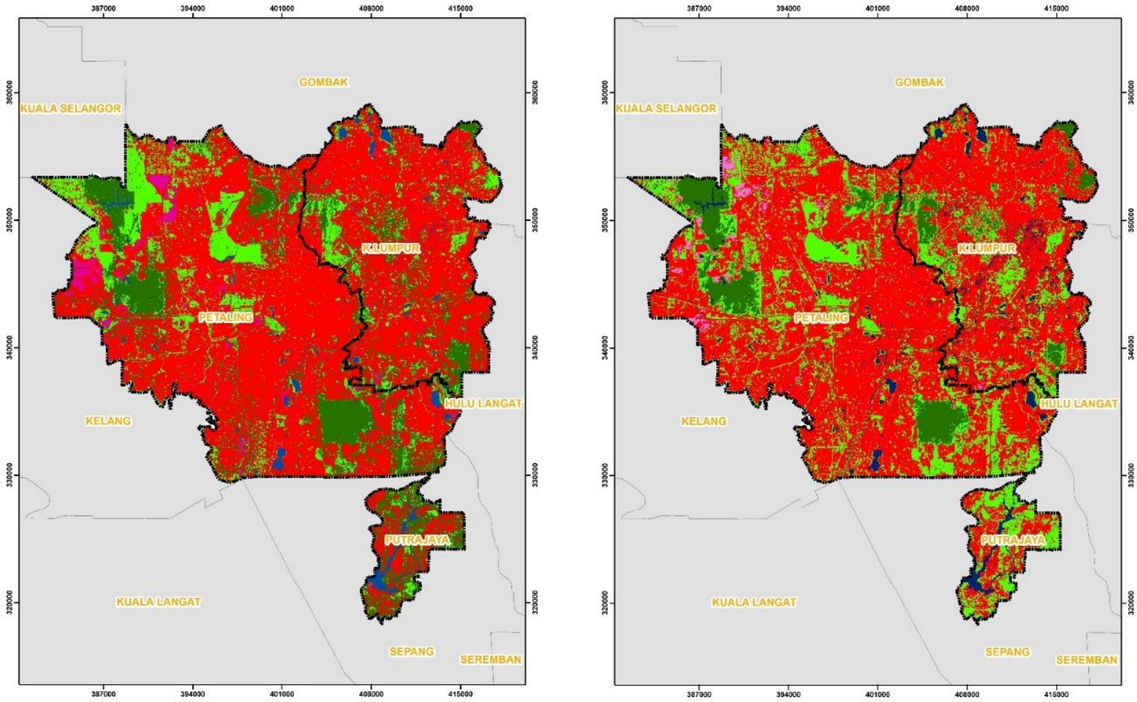


Figure 2. Methodology Framework

3. Results and Discussion

3.1 Land Cover Classification

The classification accuracies are 93.9% and 92.8% for 2014 and 2021, respectively. Meanwhile, kappa statistics values are 0.89 and 0.86. These results (see Table 2 and 3) show that Kappa values are more than 0.80, indicating good classification performance (Lillesand et al., 2004; Jensen 2005).



(a) 25 April 2014 (b) 2 July 2021

Figure 3. Land cover classification results for Kuala Lumpur, Petaling, and Putrajaya Districts.

Table 2. 2014 Confusion Matrix.

Year	:	2014
Overall Accuracy	:	93.9 %
Kappa Statistics	:	0.885

LC	Bare land	Forest	Urban	Vegetation	Water	Total	User Accuracy
Bare land	10.000	0.000	0.000	0.000	0.000	10.000	1.000
Forest	3.000	40.000	3.000	0.000	1.000	47.000	0.851
Urban	2.000	0.000	197.000	5.000	3.000	207.000	0.952
Vegetation	0.000	2.000	0.000	34.000	0.000	36.000	0.944
Water	0.000	0.000	0.000	0.000	10.000	10.000	1.000
Total	15.000	42.000	200.000	39.000	14.000	310.000	0.000
Producer Accuracy	0.667	0.952	0.985	0.872	0.714	0.000	0.939

Table 3. 2021 Confusion Matrix.

Year : 2021							
Overall Accuracy : 92.8 %							
Kappa Statistics : 0.855							
LC	Bare land	Forest	Urban	Vegetation	Water	Total	User Accuracy
Bare land	10.000	0.000	0.000	0.000	0.000	10.000	1.000
Forest	0.000	32.000	3.000	2.000	0.000	37.000	0.865
Urban	0.000	5.000	202.000	5.000	5.000	217.000	0.931
Vegetation	0.000	0.000	1.000	32.000	0.000	33.000	0.970
Water	0.000	1.000	0.000	0.000	9.000	10.000	0.900
Total	10.000	38.000	206.000	39.000	14.000	307.000	0.000
Producer Accuracy	1.000	0.842	0.981	0.821	0.643	0.000	0.928

Table 4. LC Percentage in 2014 and 2021.

LC	LC 2014 (%)			LC 2021 (%)		
	KL	Petaling	Putrajaya	KL	Petaling	Putrajaya
Urban	77.6	67.4	41.5	81.2	70.3	51.9
Cleared	0.4	2.42	0.3	0.7	3.0	0.8
Vegetation	9.2	13.9	5.7	6.2	12.8	17.5
Forest	11.3	14.8	43.5	10.4	12.4	20.4
Water	1.6	1.49	8.95	1.5	1.43	9.4

Table 5. LC changes from 2014 to 2021.

LC	LC Changes 2021-2014 (%)		
	KL	Petaling	Putrajaya
Urban	3.5	3.0	10.3
Cleared	0.4	0.5	0.5
Forest	-0.8	-2.3	-23.1
Vegetation	-3.0	-1.1	11.8
Water	-0.1	-0.1	0.5

Tables 4 and 5 show that urban area increased from 2014 to 2021 for Kuala Lumpur from 78% to 81%, Petaling from 67% to 70%, and Putrajaya from 42% to 50 %. Where urban expansion rate is 3.5% (Kuala Lumpur), 3.0% (Petaling) and 10.3% (Putrajaya). While for green areas (forest and vegetation) areas slightly decreased from 20% to 17% (KL), 29% to 25 % (Petaling) and 49% to 38% (Putrajaya).

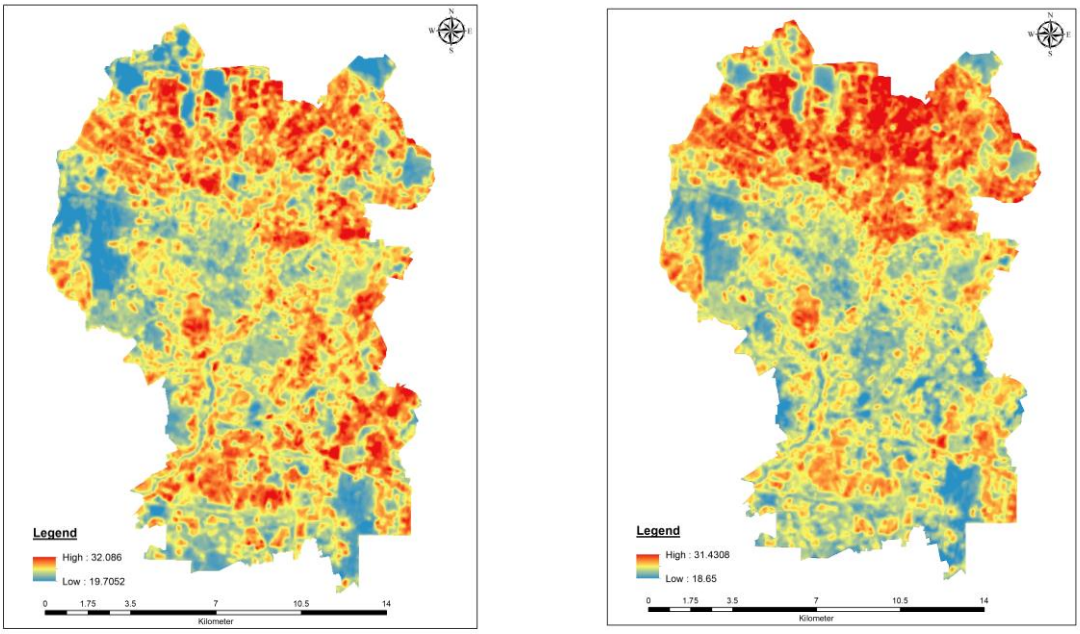
3.2 Land Surface Temperature and Vegetation Indices

VI was produced for the three areas to show their difference in temperature and index. The results of LST and VI were 9 analysed using linear regression, as shown in section C.

3.2.1. Kuala Lumpur

a) Land Surface Temperature

Figure 4 shows LST maps dated 25 April 2014 and 2 July 2021. The LST value for the year 2014 ranges from 19.71°C to 32.09°C, while for the year 2021 is 18.65°C to 31.43°C. We found that in dense high-rise buildings area, a slight drop in temperature is due to shadows from high-rise buildings.

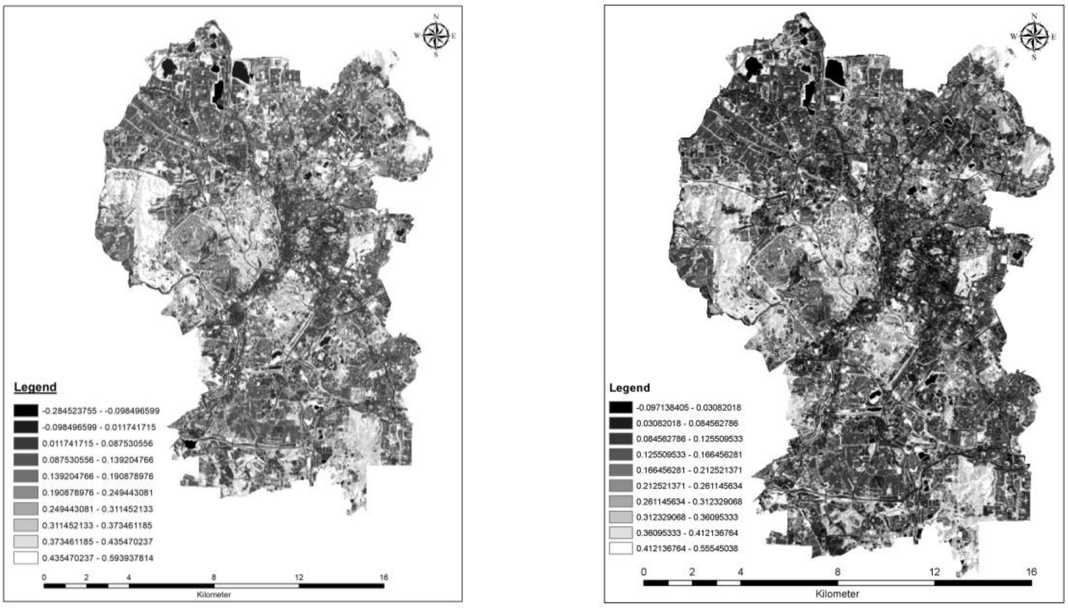


(a) 25 April 2014 (b) 2 July 2021

Figure 4. LST (°C) for Kuala Lumpur district.

b) Vegetation Indices

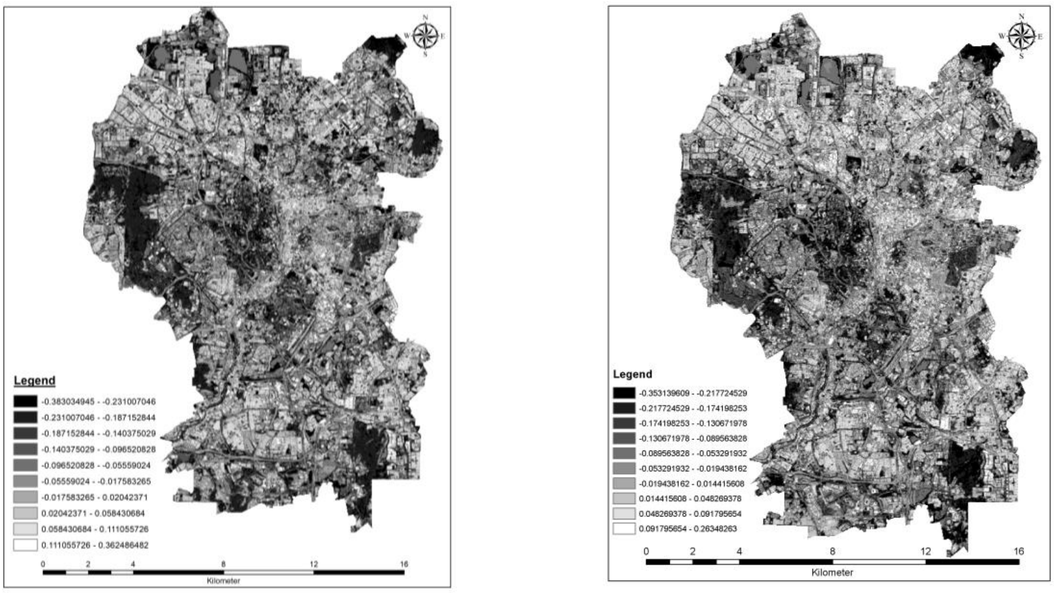
The 2014 and 2021 NDVI maps are shown in Figure 5. 2014 NDVI values range from -0.28 to 0.59, while 2021 NDVI values range from -0.10 to 0.56.



(a) 25 April 2014　　(b) 2 July 2021

Figure 5. NDVI for Kuala Lumpur district.

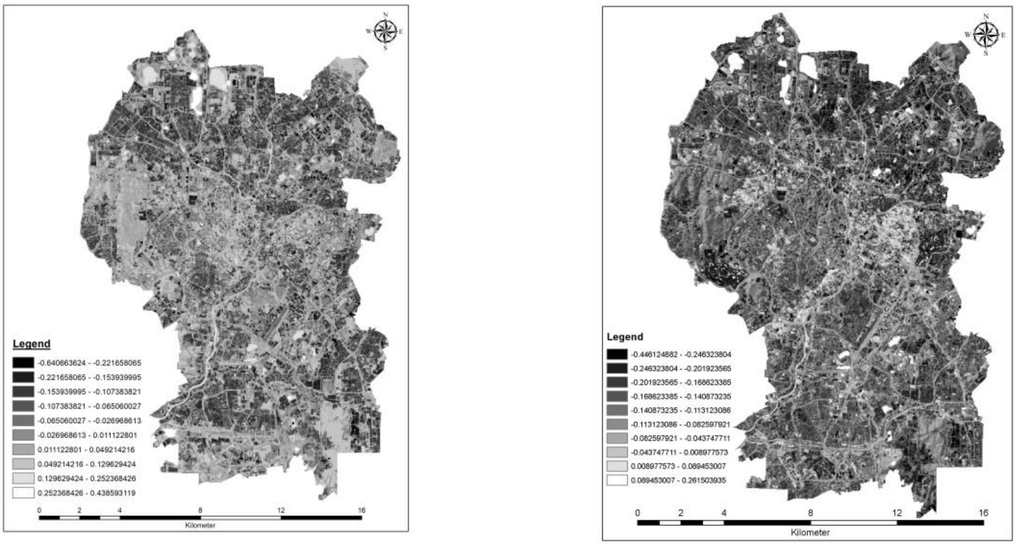
Figure 6 presents 2014 NDBI ranges from -0.38 to 0.36, and NDBI 2021 ranges from -0.35 to 0.26.



(a) 25 April 2014　　(b) 2 July 2021

Figure 6. NDBI for Kuala Lumpur district.

The MNDWI map derived from the imageries is shown in Figure 7. The values range from -0.64 to 0.44 for the year 2014. Meanwhile, for 2021, the MNDWI values range from -0.45 to 0.26.



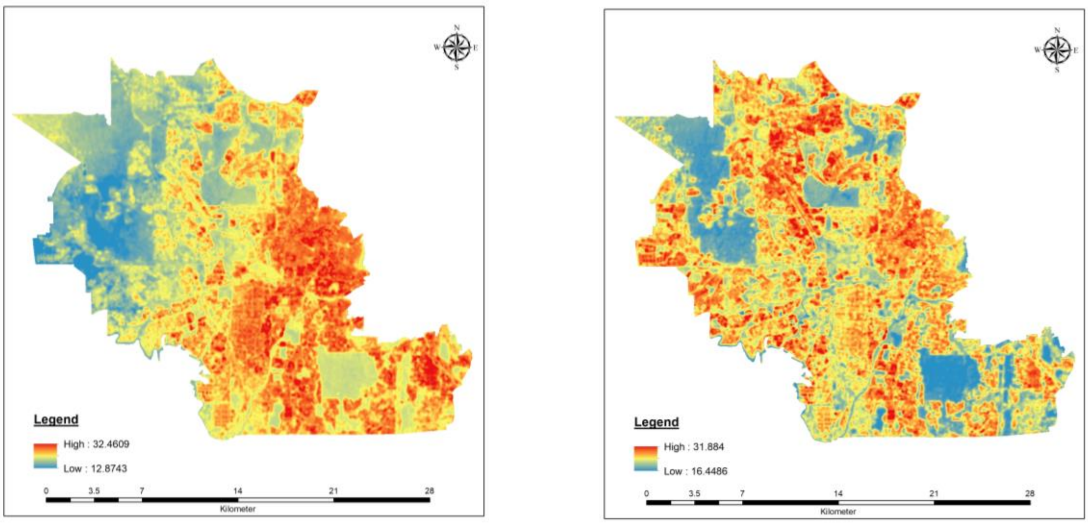
(a) 25 April 2014 (b) 2 July 2021

Figure 7. MNDWI for Kuala Lumpur district.

3.2.2. Petaling

a) Land Surface Temperature

The 2014 LST ranges from 12.87°C to 32.46°C, while the temperature in 2021 ranges from 16.45°C to 31.88°C.

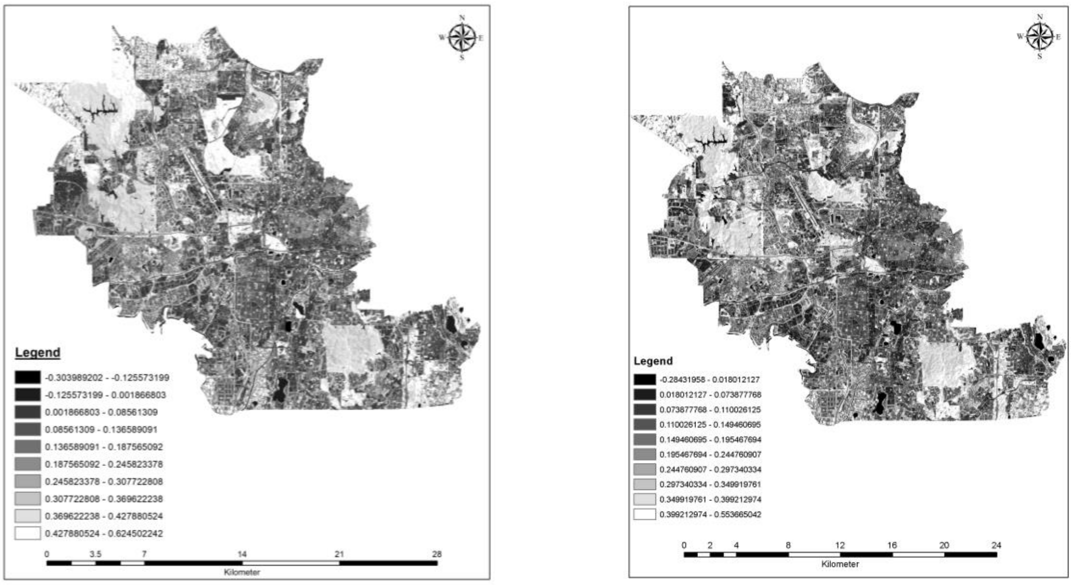


(a) 25 April 2014 (b) 2 July 2021

Figure 8. LST (°C) for Petaling district.

b) Vegetation Indices

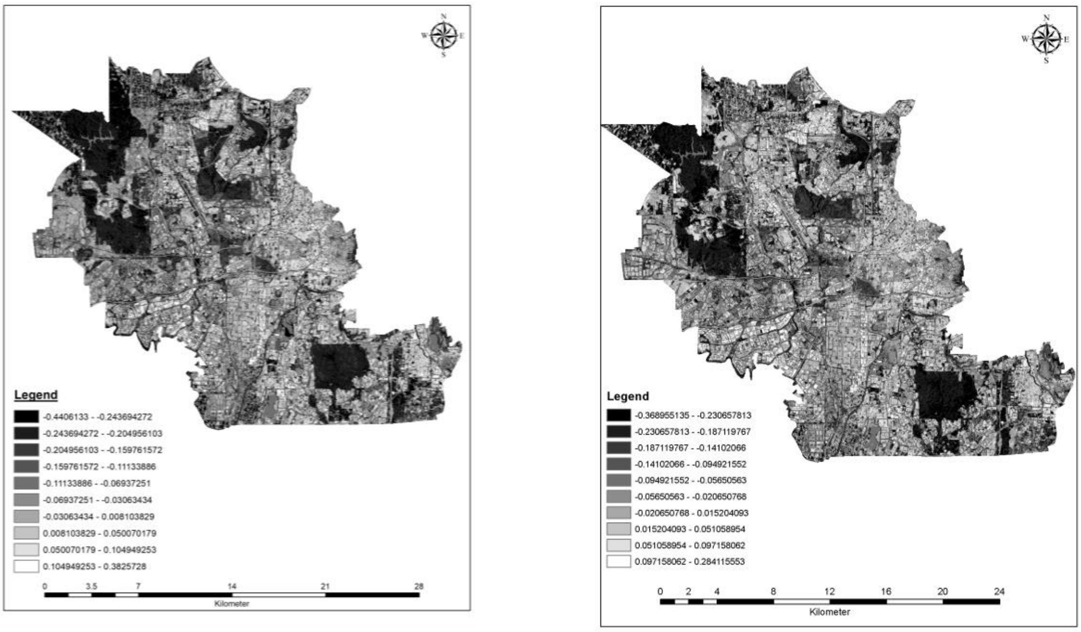
The 2014 NDVI ranges from -0.30 to 0.62, while in 2021, the image varies from -0.28 to 0.55.



(a) 25 April 2014 (b) 2 July 2021

Figure 9. NDVI for Petaling district.

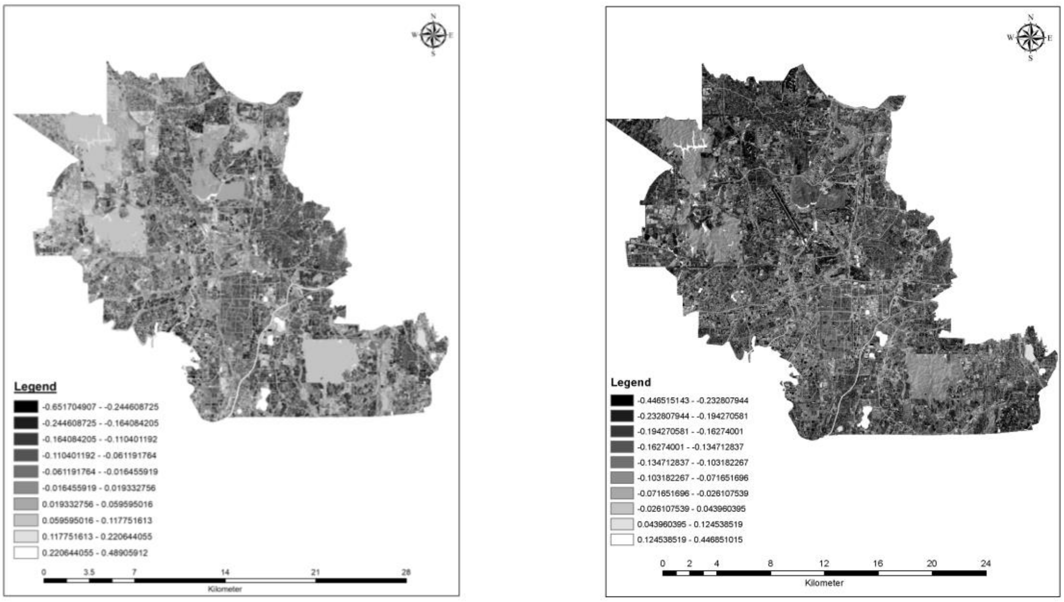
The 2014 NDBI values range from -0.44 to 0.38, while the values in 2021 range from -0.37 to 0.28.



(a) 25 April 2014 (b) 2 July 2021

Figure 10. NDBI for Petaling district.

The 2014 MNDWI values ranged from -0.65 to 0.49, and 2021 MNDWI went from -0.45 to 0.45 in 2021.



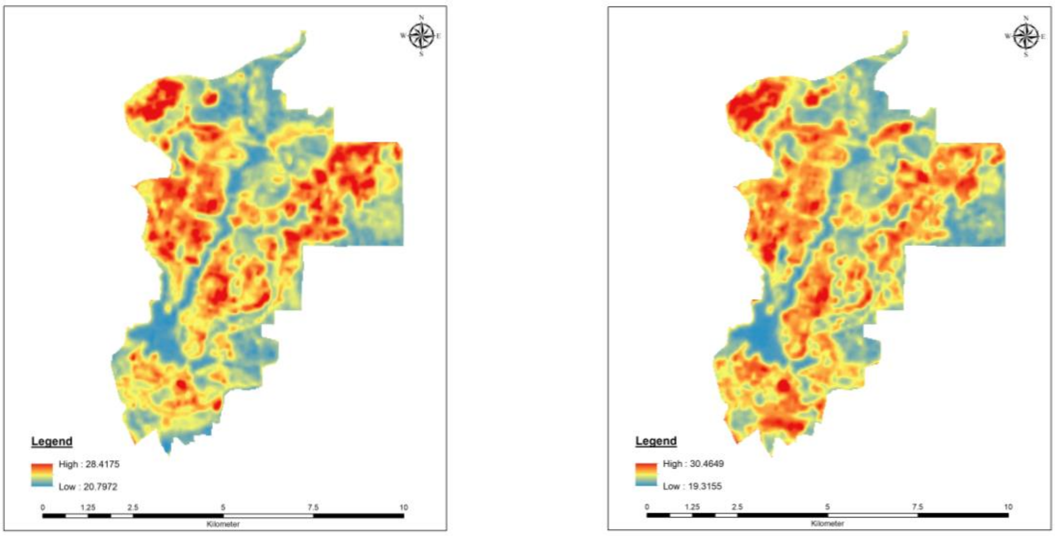
(a) 25 April 2014 (b) 2 July 2021

Figure 11. MNDWI for Petaling district.

3.2.3 Putrajaya

a) Land Surface Temperature

The 2014 LST ranges from 20.80°C to 28.42°C, while the temperature in the 2021 LST ranges from 19.32°C to 30.46°C (see Figure 12).

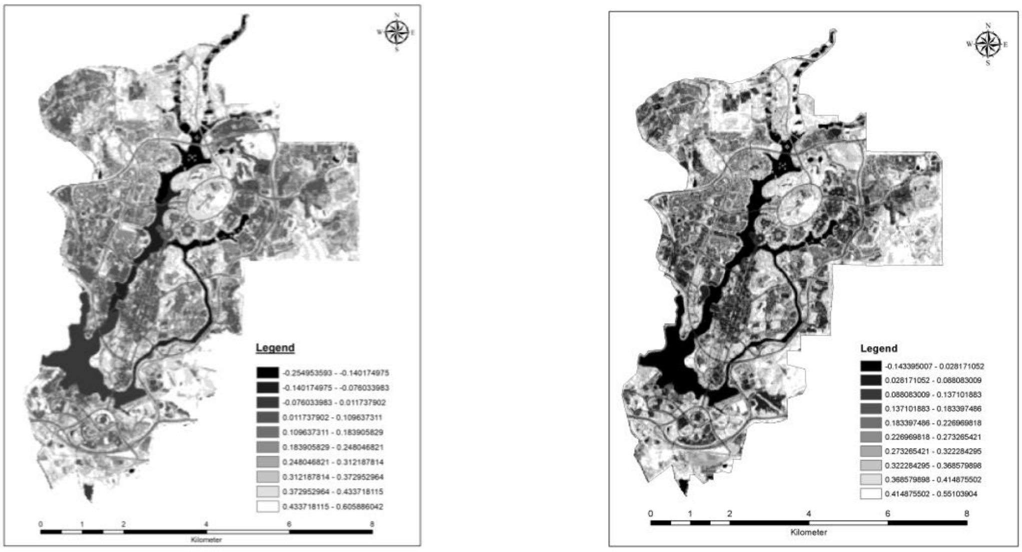


(a) 25 April 2014 (b) 2 July 2021

Figure 12. LST (°C) for Putrajaya district.

b) Vegetation Indices

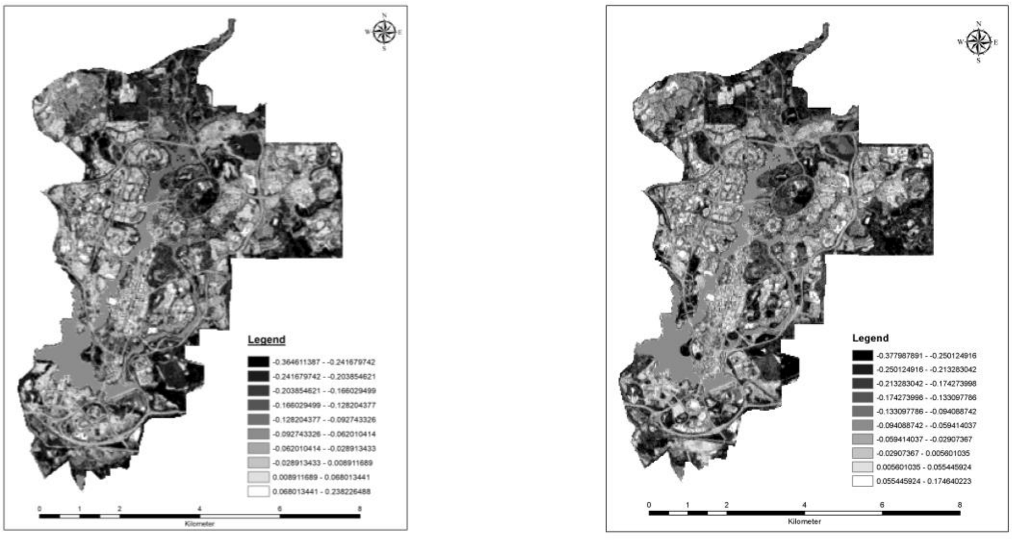
The 2014 NDVI ranges from -0.25 to 0.61, while in 2021, the image varies from -0.14 to 0.55 (see Figure 13).



(a) 25 April 2014 (b) 2 July 2021

Figure 13. NDVI for Putrajaya district.

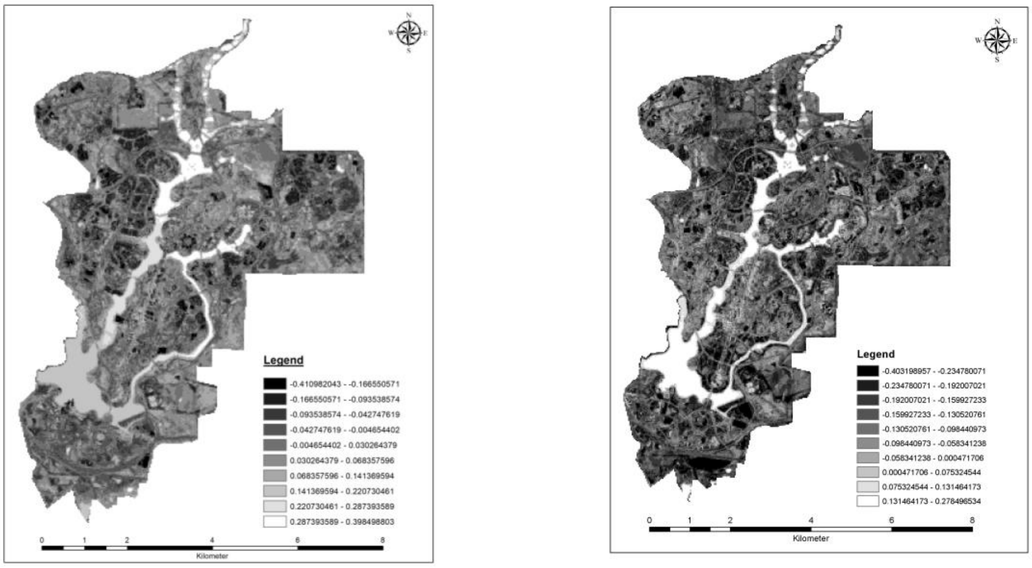
The 2014 NDBI and 2021 NDBI range from -0.36 to 0.24 and -0.38 to 0.17 (see Figure 14).



(a) 25 April 2014 (b) 2 July 2021

Figure 14. NDBI for Putrajaya district.

The 2014 MNDWI values range from -0.41 to 0.40, while the value went from -0.23 to 0.28 in 2021 (see Figure 15).



(a) 25 April 2014 (b) 2 July 2021

Figure 15. MNDWI for Putrajaya district.

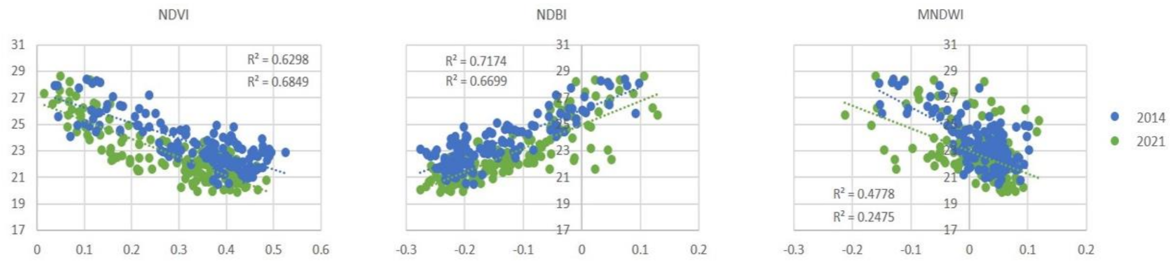
3.3 Relationship between LST and Vegetation Indices

Vegetation indices regression analysis for all three districts was produced to investigate the temperature effect on the urban area. A graph for each district is constructed to show its correlation to temperature. Table 6 summarizes linear regression values of vegetation indices for each location for 2014 and 2021. LST values negatively correlate to NDVI for all three districts for two different years. According to Cohen et al. (2013), the linear regression coefficient is determined based on the strength of the correlation coefficient, where 0.31–0.5 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 strong correlation. Therefore, most results show a negative normal correlation coefficient for Kuala Lumpur and Putrajaya districts. Only the Petaling district has a weak correlation coefficient for 2014 and a normal correlation coefficient for 2021. This study found that NDBI has a positive correlation with LST and MNDWI has a negative correlation with LST. The result obtained also coincides with the literature from Imran et al. (2021).

Table 6. Linear Regression Values of Indices for the years 2014 and 2021.

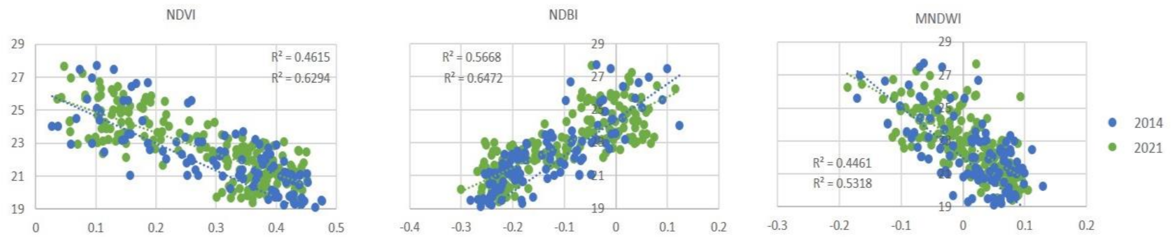
LST	NDVI		NDBI		MNDWI	
	2014	2021	2014	2021	2014	2021
KL	R^2=0.62	R^2=0.69	R^2=0.71	R^2=0.67	R^2=0.48	R^2=0.25
Petaling	R^2=0.46	R^2=0.63	R^2=0.57	R^2=0.65	R^2=0.47	R^2=0.53
Putrajaya	R^2=0.63	R^2=0.68	R^2=0.61	R^2=0.65	R^2=0.31	R^2=0.27

Figures 16, 17, and 18 show good correlation between VI and temperature in Kuala Lumpur, Petaling, and Putrajaya. This results revealed that the temperature in 2014 are slightly higher than in 2021. The temperature difference over seven years (from 2014 to 2021) is not significantly affected by land-use changes and the reduction of green areas.



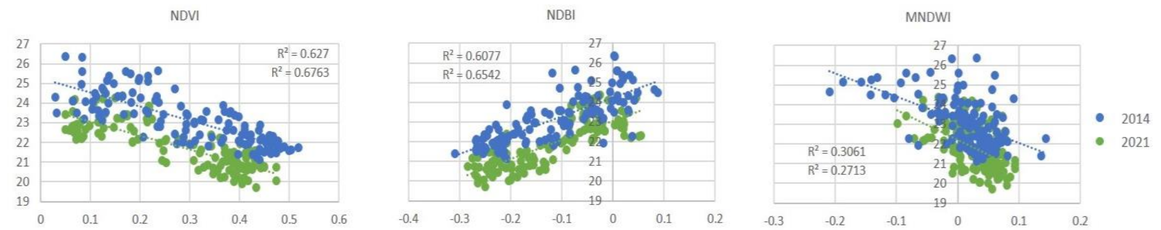
(a) NDVI KL (b) NDBI KL © MNDWI KL

Figure 16. Correlation of LST and VI for 2014 and 2021 (Kuala Lumpur).



(a) NDVI Petaling (b) NDBI Petaling © MNDWI Petaling

Figure 17. Correlation of LST and VI for 2014 and 2021 (Petaling).

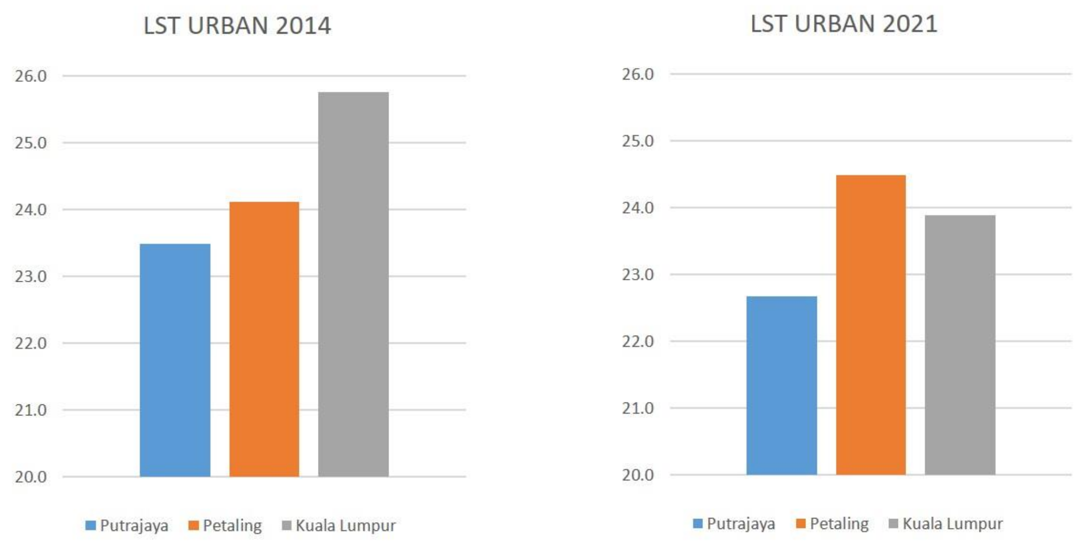


(a) NDVI Putrajaya (b) NDBI Putrajaya © MNDWI Putrajaya

Figure 18. Correlation of LST and VI for 2014 and 2021 (Putrajaya).

3.4 Analysis of Urban LST

Our further analysis focused on urban class, where we plot the 2014 and 2021 temperatures as shown in Figure 19. We found that urban temperature for both Kuala Lumpur and Putrajaya declined, while urban temperature for the Petaling area showed a slight increment (0.5ºC). The result also revealed that urban temperature in 2014 was slightly higher compared to 2021. Mean urban temperature shows that Putrajaya has the lowest temperature compared to Kuala Lumpur and Petaling districts. LU classification result shows that Putrajaya is covered by 50% urban and the rest consists of greenery and water area. These findings coincide with Kaufmann et al. (2003), which stated that areas with no vegetation covered with impervious surfaces cause a temperature rise. According to Cruz et al. (2019), warmer places mostly consist of impervious surfaces, while those with vegetation cover are associated with lower temperatures. In 2021, Kuala Lumpur has a lower LST than in 2014 due to shadows created by high-rise buildings in central urban areas, affecting the mean LST.



(a) Urban LST in 2014 (b) Urban LST in 2021

Figure 19. Urban LST in Kuala Lumpur, Petaling and Putrajaya.

4. Conclusion

Klang Valley land-use change and LST analysis from 2014 to 2021 is divided into Kuala Lumpur, Petaling, and Putrajaya. The urban expansion for these districts is 3.5%, 3%, and 10.3% for Kuala Lumpur, Petaling, and Putrajaya, respectively. The Green area (vegetation and forest) has decreased by 3.9% and 3.5% in Kuala Lumpur and Petaling, respectively, but has expanded by 34.9% in Putrajaya. Meanwhile, for LST analysis, the result shows that

Putrajaya has a cooler temperature versus Kuala Lumpur and Petaling districts. Putrajaya has a cooler climate since it only has around 50% urban area compared to Kuala Lumpur and Petaling, which have 80% and 70% urban areas, respectively, and a percentage of green and water areas of almost 48%. However, Kuala Lumpur has a lower 2021 LST than in 2014 due to shadows created from high-rise buildings in central urban areas, affecting the mean LST.

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