Hindawi
International Journal of Forestry Research
Volume 2022, Article ID 2585719, 12 pages
https://doi.org/10.1155/2022/2585719

Research Article

The Effect of Built-Up Area Density and Vegetation Density on Surface Temperature in Banjarmasin City

Sidharta Adyatma, Muhammad Muhaimin, Deasy Arisanty, and Karunia Puji Hastuti

Geography Education Department, Faculty of Teacher Training and Education, Lambung Mangkurat University, Banjarmasin, Indonesia

Correspondence should be addressed to Karunia Puji Hastuti; karuniapuji@ulm.ac.id

Received 2 August 2022; Revised 18 October 2022; Accepted 22 October 2022; Published 8 November 2022

Academic Editor: Ranjeet Kumar Mishra

Banjarmasin City continues to develop rapidly. Malls and settlements are the newly built-up area that has reduced vegetation cover leading to changes in surface temperature in Banjarmasin City. Analysis of temperature changes is needed to determine the effect of increasing built-up areas and decreasing vegetation cover. The surface temperature can be detected and analyzed using satellite imagery. The study aimed to analyze the built-up area and vegetation density index and their effect on changes in surface temperature in Banjarmasin City from 2015 to 2019. We employed remote sensing and surveys to monitor and detect regional changes in urban areas due to rapid development. Built-up areas can be mapped using the Normalized Difference Built-Up Index (NDBI) algorithm, and vegetation density can be mapped using the Normalized Difference Vegetation Index (NDVI) algorithm. The correlation value between building density and surface temperature in 2015 was 0.826, and in 2019, it was 0.969. This means that the NDBI of the built-up area density in 2015 and 2019 strongly correlates with surface temperature. Correlation values between the vegetation density score and the surface temperature were -0.860 in 2015 and -0.949 in 2019. All correlation results are negative, which means that the vegetation density has an inverse ratio to surface temperature; in other words, high vegetation density causes low surface temperature.

1. Introduction

Increasing temperature has been a concern in urban areas, mainly during the daytime, since it reached 38.8°C in October 2019. The rapid population growth in urban areas due to natural growth and urbanization has led to changes in natural characteristics, which are changes in land use or land cover; this phenomenon then causes changes in surface temperature [1–4] because of changes in the wavelength of solar radiation reflected into the atmosphere. As a result, urban areas are now marked by higher air temperature and surface temperature compared to rural areas [5–13].

Changes in land cover affect ecosystem functions, biodiversity, and climate, increasing or decreasing ambient surface temperature due to the different responses of each object or material in receiving, absorbing, and re-emitting sunlight. The surface temperature of materials in built-up areas differs from the ones in nonbuilt-up areas; thus, there is a relationship between land cover and surface temperature. Built-up surface areas have a positive exponential relationship with the land surface temperature rather than a simple linear one. As such, an ecological evaluation index can be calculated to reveal the impact of overgrown land surface and built-up surface areas on urban heat island [14–17].

Decreasing vegetation and built-up areas full of overlapping high buildings in urban areas have reduced solar radiation and carbon dioxide absorption, which poses a risk of increasing air temperature. In addition to the increasing number of solar heat-reflecting elements, the heat from human activities also produces greenhouse gases, such as carbon dioxide, carbon monoxide, and methane. Increased air temperature in urban areas forms heat islands compared to suburban air temperatures, so urban warming contributes to global warming [18–21]. Vegetation can provide microclimate control and thermal comfort because trees help to create more thermally comfortable environmental conditions or lower air temperature [22]. Vegetation cover reduces thermal discomfort duration by more than half and limits excess heat from solar radiation. Vegetation can reduce the effect of urban heat islands and improve air quality and quality of life [23–25].

Remote sensing techniques can identify changes in land cover to surface temperatures [26]. Landsat satellite imagery can be used to determine the effect of land cover on surface temperature [27]. Landsat 8 OLI TIRS is widely used to observe land use changes and build models to monitor soil surface biophysical features, including ground surface temperature (ESG) [28]. The Landsat satellite series has the potential to provide ESG estimates at a high spatial resolution, which are particularly suitable for local or small-scale studies [29], including also heterogeneous and dynamic urban areas [30].

Banjarmasin City covers an area of 98.46 km^2. It is the government center and the city of trade, industry, tourism, and harbor. In October 2019, the city reached a temperature of 39°C. The Central Bureau of Statistics of Banjarmasin City reported a population density of 7,118 people per km^2, with a total population of 700,870 people and an average growth rate of 1.38% per year from 2011 to 2018. Built-up land continues to increase due to higher population growth. Meanwhile, vegetation cover has decreased significantly [31–33]. These changes have the opportunity to increase the temperature of the soil surface. The existence of the Banjarmasin city government's policy regarding the increase in green open space or urban forests in Banjarmasin can have the opportunity to reduce the temperature of the land surface. Therefore, this study examined the effect of the built-up area and vegetation density index on changes in surface temperature in Banjarmasin City in 2015 and 2019. The study aimed to analyze the built-up area and vegetation density index and their effect on changes in surface temperature in Banjarmasin City from 2015 to 2019.

2. Materials and Methods

This research was carried out in Banjarmasin City, South Kalimantan, Indonesia. Banjarmasin City is South Kalimantan Province's capital, with the highest population density compared to other cities in South Kalimantan. This city is a wetland area with a tidal swamp [34, 35].

This study used Landsat 8 OLI TIRS imagery. This study used Landsat 8 OLI TIRS on August 19, 2015 , and on August, 14, 2019. The extracted image data consisted of 11 separate channels; bands 1, 2, 4, 5, 6, and 10 were combined for research purposes. Bands 4, 5, 6, and 10 were used for processing vegetation index, built-up area density index, and land surface temperature (LST). In addition, bands 1 and 2 were used to determine the bias (offset) of the atmosphere influence. Geometric correction of Landsat 8 OLI TIRS images was performed using the ground control point (GCP) transformation method with a polynomial interpolation order 3, so coordinates in the image had field coordinates. Image radiometric correction included the histogram adjustment method, calibration of digital number values to radiance values, calibration of object values to reflectance values, correction of sun position, and atmospheric correction (dark subtract). The corrected image underwent a spectral transformation, including NDVI, NDBI, and LST.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}. \tag{1}$$

Note: red represents the red spectral band in the Landsat 8 OLI TIRS image, and NIR is the near-infrared band in the Landsat 8 OLI TIRS image [36, 37].

$$\mathrm{NDBI} = \frac{\mathrm{SWIR\,1} - \mathrm{RED}}{\mathrm{SWIR\,1} + \mathrm{RED}}. \tag{2}$$

Note: red represents the red spectral band in the Landsat 8 OLI TIRS image, and SWIR 1 is the short-wave infrared band in the Landsat 8 OLI TIRS image [38, 39].

$$L\gamma = \mathrm{ML} * \mathrm{QCal} + \mathrm{AL}. \tag{3}$$

Note: $L\gamma$ represents the TOA spectral radiance (watts/(m^2 * srad * μm)), ML is the band-specific (Radiance_Mult_Band_x, where x is the band number), AL is band-specific (Radiance_Mult_Band_x, where x is the band number), and QCal is the image pixel value of DN (digital number) [40].

$$T = \frac{K2}{In(K1/L\lambda + 1)}. \tag{4}$$

Note: T represents the TOA brightness temperature (K), $L\lambda$ represents the TOA spectral radiance (watts/(m^2 * srad * μm)), $K1$ represents the band-specific thermal conversion constant, and $K2$ represents the band-specific thermal conversion constant [40].

$$\mathrm{LSE} = \varepsilon s * (1 - \mathrm{FVC}) + \varepsilon v * \mathrm{FVC}. \tag{5}$$

Note: LSE refers to land surface emissivity, FVC represents the FVC value obtained previously, εs represents the emissivity of the soil surface of band 10, and εv represents the emissivity of the vegetation of band 10.

$$\widehat{Y} = a - bX. \tag{6}$$

Note: $\widehat{Y}$ is the subject in the predicted dependent variable, a is the value of Y when $X = 0$ (constant), b is the regression coefficient, which shows the increase or decrease in the dependent variable based on changes in the independent variable, (+) means an increase and (−) represents a decrease, and X is the subject of the independent variable with a specific value [41].

Prefield visits aimed to find locations of vegetation density, built-up area density, and surface temperature on the map resulting from the NDVI, NDBI, and LST spectral transformations. During the field visit, 100 samples of vegetation density were measured, consisting of 50 samples to build the model and 50 samples to test the accuracy using a camera to analyze the density of the vegetation canopy;

measurement of surface temperature on the field employed a digital thermometer and laser thermometer. In addition, we examined the density of the built-up area using a tentative NDBI map validated by the number of buildings in Banjarmasin City. Furthermore, the 2015 and 2019 surface temperature maps were normalized using the maximum and minimum temperature parameters and then classified into 4 (four) classes of surface temperature based on the average value and standard deviation [31, 42]. Finally, GPS was used to analyze the distribution of sample plots in the area; the extracted scores of the analysis were regressed through NDVI, NDBI, and LST maps, resulting in vegetation density maps, built-up area density maps, and surface temperature maps. Using the maps, we chose 21 samples randomly to extract the score of vegetation density, built-up area density, and surface temperature. The extraction results were analyzed using Pearson correlation to reveal (a) the relationship between surface temperature and built-up area density and (b) the relationship between surface temperature and vegetation density.

3. Results and Discussion

3.1. Built-Up Area Density of the Study Sites. We obtained the built-up area density from the NDBI classification results on the image of Landsat 8 OLI TIRS on August 19, 2015, and the idea of Landsat 8 OLI TIRS on August 14, 2019. The higher the NDBI score or close to 1, the higher the density of the built-up area. The results of the NDBI image of Landsat 8 OLI TIRS on August 19, 2015, and the image of Landsat 8 OLI TIRS on August 14, 2019, are presented in Figure 1.

The NDBI spectral transformation shows that the built-up area density of Banjarmasin City in 2015 has a score of −0.72954 (blue) to 0.43045 (red) centered in the downtown area of the city, which was Banjarmasin Tengah District, and marked with reddish yellow color; the built-up area density of Banjarmasin City in 2019 has a score of −0.760237 (blue) to 0.42407 (red). Higher scores on NDBI represent a denser built-up area. The built-up area density spatial pattern did not change significantly between 2015 and 2019. The built-up area density is inversely proportional to vegetation density because every pixel with a low built-up area density will have a high vegetation density. Changes in the built-up area density between 2015 and 2019 from NDBI spectral transformation were analyzed using image analysis (difference) to determine the significant changes in the built-up area density over five years. The image analysis (difference) results show that the lowest score is −0.759919 and the highest is 0.752987; higher scores indicate a significant change in the built-up area density in five years, as depicted in red in Figure 2.

3.2. Vegetation Density of the Study Sites. We obtained the vegetation density from the image interpretation results classified by NDVI. The image analysis of Landsat 8 OLI TIRS in 2015 and 2019 resulted in four classes of vegetation density, as presented in Table 1. The classification results of the vegetation density and the area of each classification are shown in Figure 3 and Table 2.

Table 2 shows that the area of nonvegetation land cover increases by 250.11 hectares or 2.54%, and the area of low vegetation density increases by 264.42 hectares or 2.69%. However, the area of medium vegetation density decreases by 499.32 hectares or 5.07%, and the area of high vegetation density reduces by 15.21 hectares or 0.16%. The low vegetation density dominated the vegetation density in 2015 and 2019 because the built-up area dominated Banjarmasin City. In addition, high vegetation density was only found in specific areas, such as the city forest and the suburban regions.

Image analysis (difference) is needed to analyze changes in vegetation density between 2015 and 2019 from the NDVI transformation. The research study helped to spatially reveal the areas experiencing significant changes in vegetation density within five years. The image analysis results are presented in Figure 4.

Figure 4 presents the image analysis results; the lowest score is −0.41284, and the highest score is 0.3970; the higher value indicates a significant change in vegetation density in five years, depicted in green.

3.3. Surface Temperature of the Study Sites. The surface temperature in the study sites was known from the LST spectral transformation, which was applied to the Landsat 8 Oli TIRS image on August 19, 2015, and the Landsat 8 Oli TIRS image on August 14, 2019, as presented in Figure 5.

Figure 5 shows the LST results of Banjarmasin City in 2015 and 2019. Figure 5 confirms the high surface temperature centered in the city's downtown area (Banjarmasin Tengah District), which is reddish. The LST ranged from 20.6031°C (blue) to 38.1345°C (red) in 2015 and from 21.746°C (blue) to 30.4851°C (red) in 2019. The highest surface temperature happened in the densely populated downtown area with many high buildings and public activities with low vegetation cover. On the other hand, the suburbs of Banjarmasin City had a relatively lower surface temperature than the downtown area, and this was because the suburbs had lower built-up area density and fewer public activities added with high vegetation cover.

Image analysis (difference) is needed to analyze changes in surface temperature between 2015 and 2019 from the LST transformation. The research study helped to spatially reveal the areas experiencing significant changes in surface temperature within five years. The image analysis results are presented in Figure 6.

Figure 6 shows the LST results of Banjarmasin City in 2015 and 2019. Figure 6 confirms that the surface temperature has the lowest score of −3.27682 and the highest score of 9.34878, and higher scores show significant changes in surface temperature within five years, represented by red color. The most significant changes in surface temperature happened in the city's downtown area (Banjarmasin Tengah District) because the area is the center of public activities with densely packed buildings. LST results confirm surface temperature within four classes [42], as presented in Table 3. The classification results of surface temperature in 2015 and 2019 are shown in Figure 7, and each classification area is presented in Table 4.

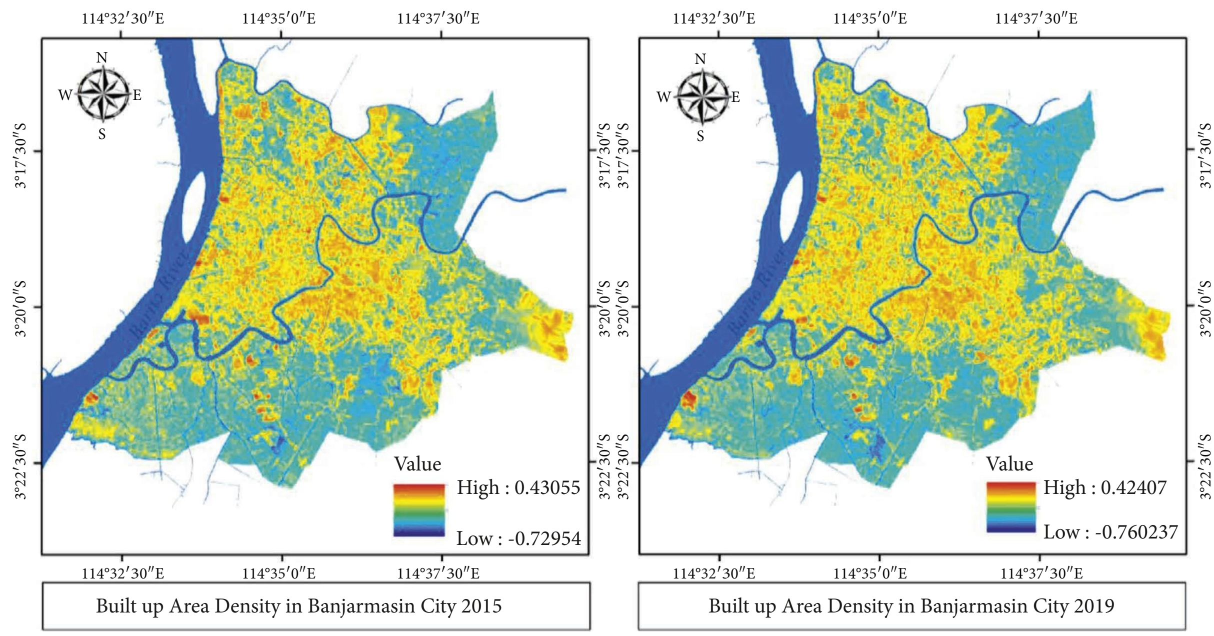

Figure 1: Built-up area density of Banjarmasin City in 2015 and 2019.

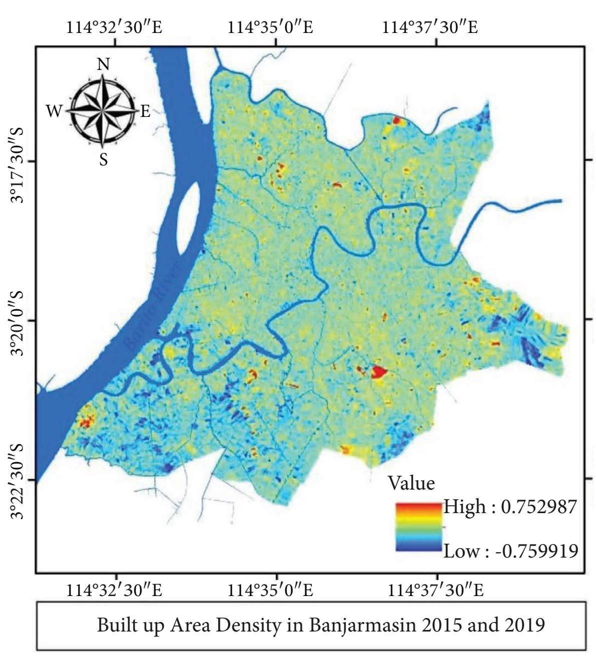

Figure 2: Changes in the built-up area density in Banjarmasin City in 2015 and 2019.

Table 1: NDVI classification based on vegetation density.

No.	Class	Score	Note
1	1	>0.2	Nonvegetation
2	2	0.2–0.35	Low vegetation density
3	3	0.36–0.5	Medium vegetation density
4	4	>0.5	High vegetation density

Table 3 shows that within five years, the class of very low temperature has decreased by 124 hectares or 1.26%, the low temperature class has increased by 885 hectares or 8.98%, the medium temperature class has reduced by 116 hectares or 1.22%, and the high temperature class has decreased by 642 hectares or 6.5%.

3.4. Spatial Analysis of Surface Temperature. We employed Pearson correlation analysis to find the relationship between surface temperature and vegetation density and built-up area density based on the sample sites' scores on surface temperature, vegetation density, and built-up area density.

3.4.1. The Relationship of Surface Temperature and the Built-Up Area Density in 2015 and 2019. Maps on the built-up area density and surface temperature showed that high temperature occurred in areas with high built-up density, which was in the city's downtown. In addition, there were differences in surface temperature of the built-up areas in the city's downtown and suburbs because the city's downtown had low vegetation density than the suburbs (such as Banjarmasin Utara, Selatan, Timur, and Barat District).

The built-up area density was concentrated in the city's downtown (Banjarmasin Tengah District), causing the area's surface temperature to be higher than its surrounding areas. The farther the area from the city's downtown, the lower the surface temperature of the area, following the pattern of the built-up area density. The correlation between surface temperature and built-up area density in Banjarmasin City in 2015 and 2019 is presented in Tables 5 and 6.

Tables 5 and 6 show that in 2015, the average temperature in the study sites was 30.02°C, and the average NDBI for the built-up area was −0.784; with a 99% significance level, we obtained an r-value of 0.826. This means that the NDBI of the built-up area density in 2015 strongly correlated with surface temperature. Then, in 2019, the average temperature in the study sites was 26.68°C, and the average

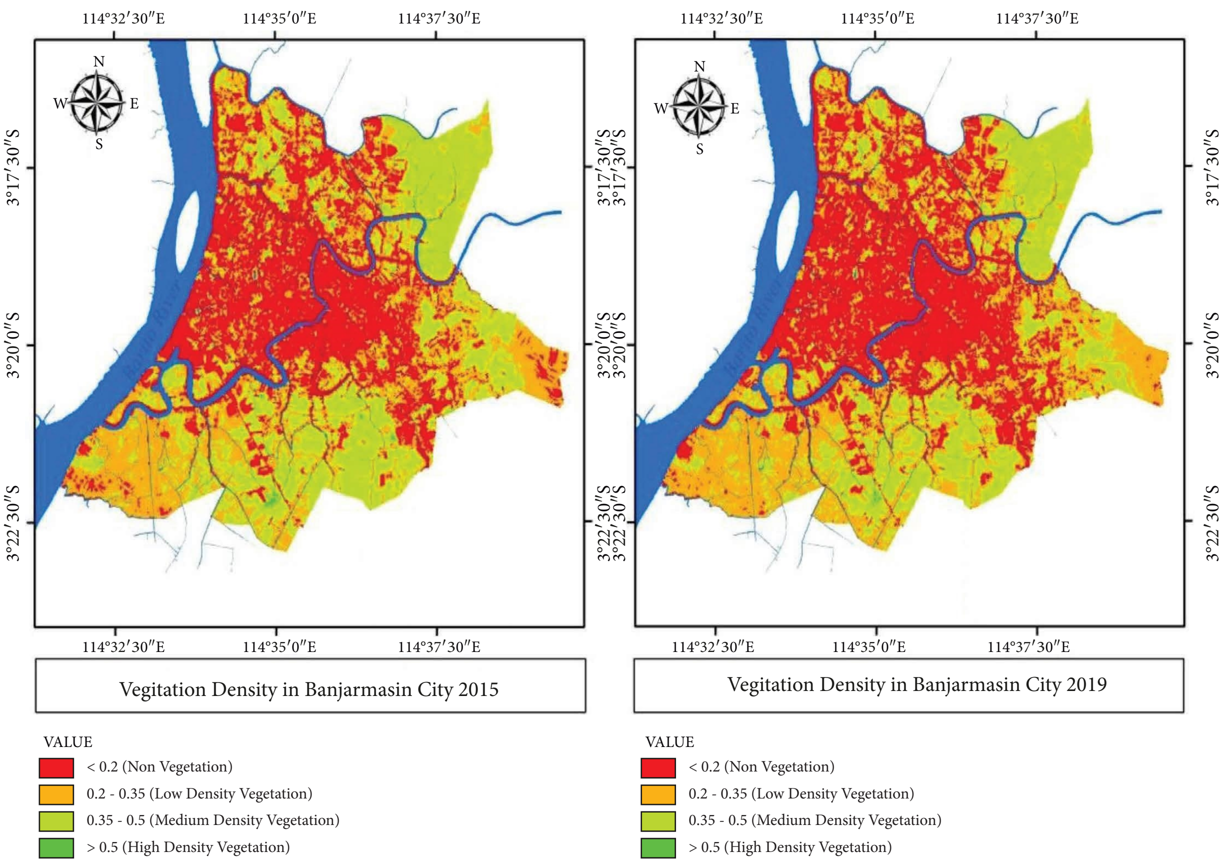

Figure 3: Vegetation density in Banjarmasin city in 2015 and 2019.

Table 2: The area of vegetation density in Banjarmasin City in 2015 and 2019.

No.	Types of land cover	Year			
		2015		2019	
		Area (hectares)	Percentage (%)	Area (hectares)	Percentage (%)
1	Nonvegetation	3842.55	39.02	4092.66	41, 56
2	Low vegetation density	3215.07	32.65	3479.49	35, 34
3	Medium vegetation density	2769.66	28.13	2270.34	23, 06
4	High vegetation density	19.62	0.20	4.41	0, 04
	Total	9849.33	100	9849.33	100

NDBI for the built-up area was −0.1150; with a 99% significance level, we obtained an r-value of 0.969. Again, this means that the NDBI of the built-up area density in 2019 strongly correlated with surface temperature.

The built-up area density index is the opposite of the vegetation density index. If the built-up area density index is high, the vegetation density index will be low or vice versa. The Pearson product-moment correlation results show that the surface temperature and the built-up area density were 0.826 in 2015 and 0.969 in 2019. All the correlation results were positive, meaning a very strong relationship existed between surface temperature and the built-up area.

The development of the built-up area in Banjarmasin City has significantly increased surface temperature. Building materials that cannot reduce emissions from the sun cause the temperature to be higher in the city's downtown than suburbs. Ultimately, this increasing temperature causes the urban climate to be more uncomfortable and hotter, leading to urban heat islands in Banjarmasin City.

3.4.2. The Correlation between Surface Temperature and Vegetation Density in Banjarmasin City in 2015 and 2019.

Vegetation can reduce the daily temperature amplitude; vegetation canopy can reduce solar radiation, and the humidity resulting from vegetation transpiration affects the surrounding environment. Banjarmasin City has a higher temperature than the surrounding area because it has fewer vegetated areas. A city government policy regarding adding green open space in the form of city parks is expected to increase the city's vegetation density and reduce the city's

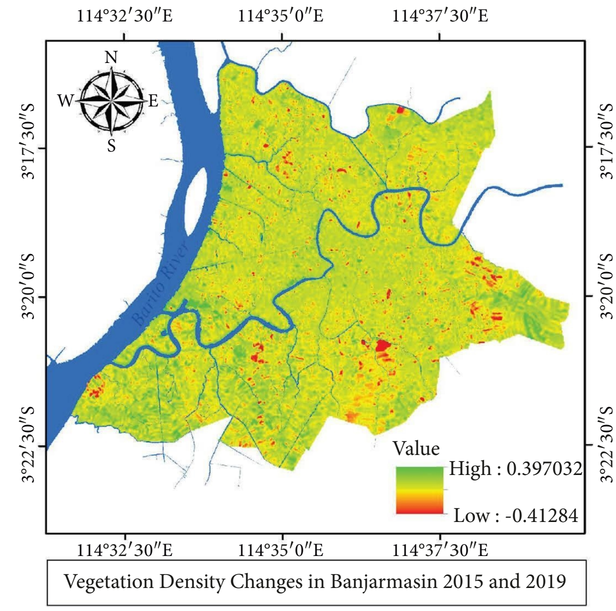

Figure 4: Changes in vegetation density in Banjarmasin City in 2015 and 2019.

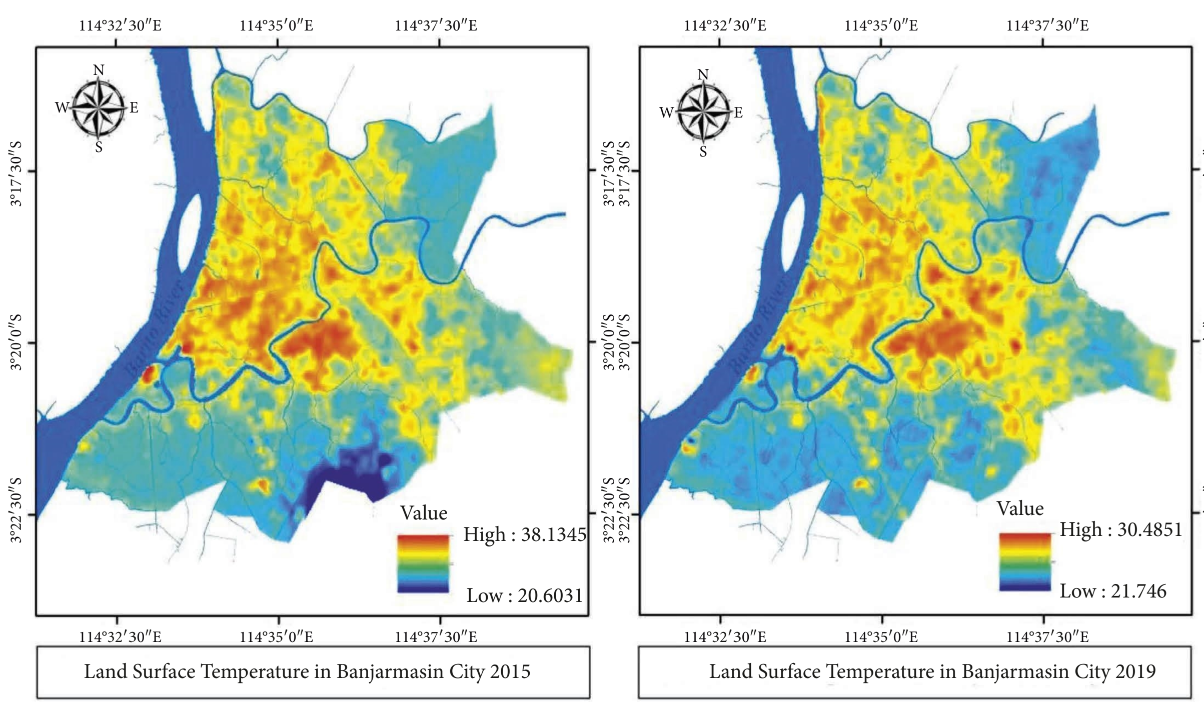

Figure 5: LST of Banjarmasin City in 2015 and 2019.

surface temperature [31]. The list of city parks in Banjarmasin City in 2013 is presented in Table 7.

Table 7 shows that Banjarmasin City has a narrow park area and the total area is below the minimum standard; this causes discomfort during the daytime because of the low amount of vegetation that can reduce heat. Maps of vegetation density and surface temperature confirm that high surface temperature occurs in nonvegetated areas in the city's downtown. In contrast, low surface temperature occurs in highly vegetated areas in the city's suburbs.

The Pearson product-moment correlation examined the correlation between surface temperature and vegetation density in 2015 and 2019. The correlation results are presented in Tables 8 and 9.

Tables 7 and 8 show that in 2015, the average temperature in the study sites was 30.02°C, and the average vegetation index was 0.2619; with a 99% significance level, we obtained an r-value of −0.86. This means that the vegetation density in 2015 had a strong negative correlation with surface temperature. Then, in 2019, the average temperature

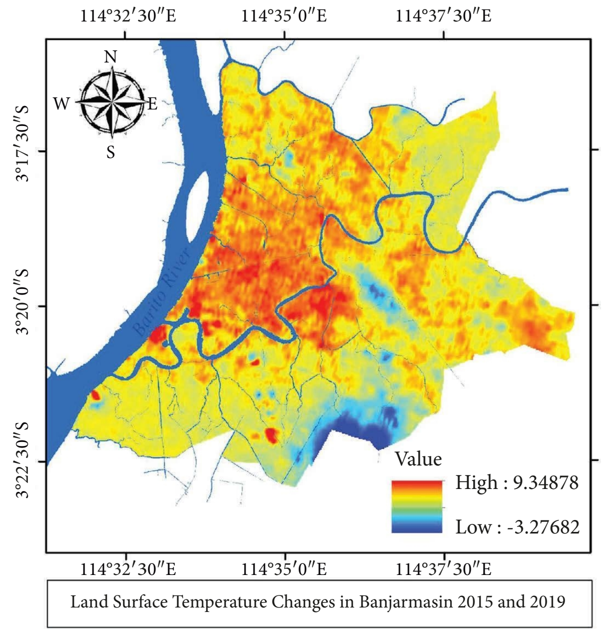

Figure 6: Changes in LST of Banjarmasin City in 2015 and 2019.

Table 3: Classification of the surface temperature.

No.	Temperature classes	Class ranges
1	Very low temperature	$T \leq T_{mean} - 1.5STD$
2	Low temperature	$T_{mean} - 1.5STD < T \leq T_{mean} - STD$
3	Medium temperature	$T_{mean} - STD < T \leq T_{mean} + STD$
4	High temperature	$T_{mean} + STD < T \leq T_{mean} + 1.5STD$

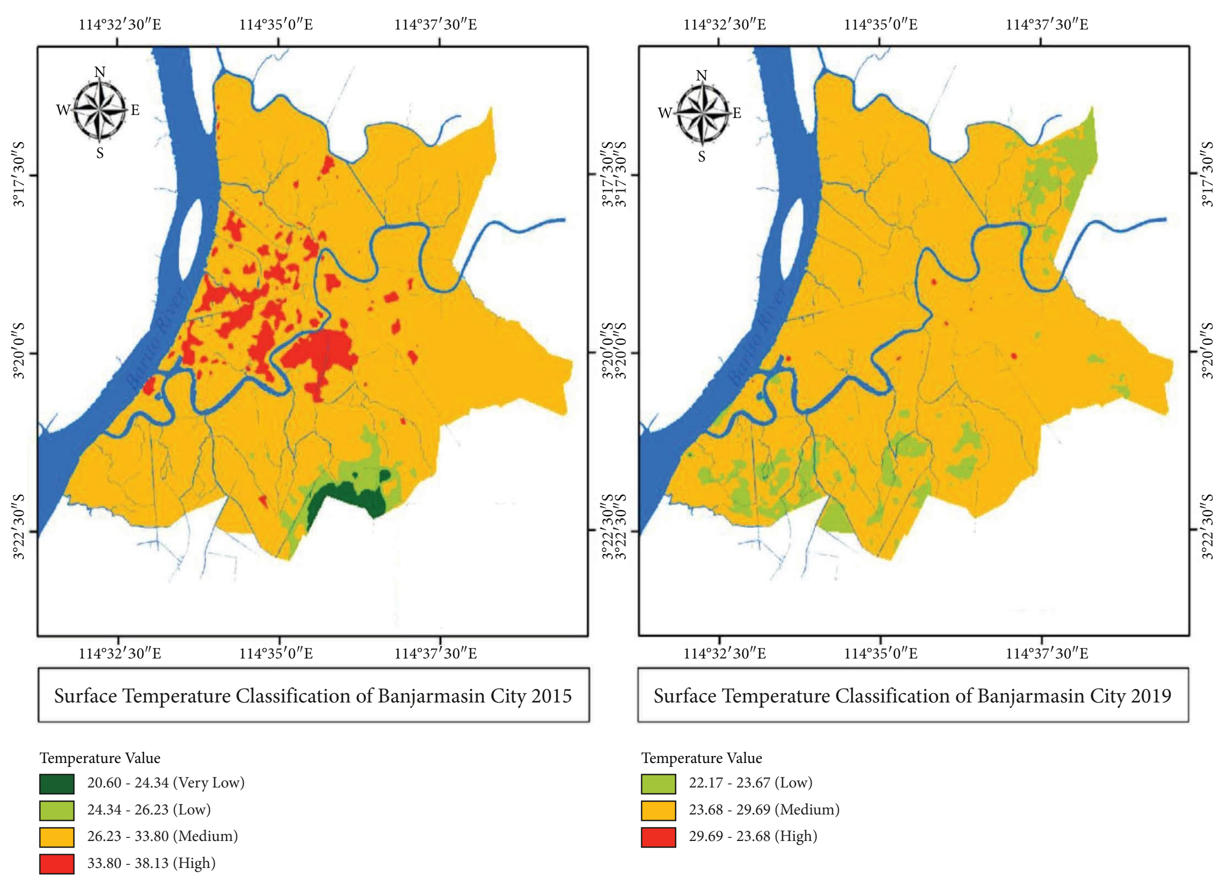

Figure 7: Surface temperature classification results in 2015 and 2019 in Banjarmasin city.

Table 4: Area of surface temperature classification in Banjarmasin City in 2015 and 2019.

No.	Temperature classes	Year			
		2015		2019	
		Area (hectares)	Percentage (%)	Area (hectares)	Percentage (%)
1	Very low temperature	124	1.26	0	0
2	Low temperature	327	3.32	1212	12.3
3	Medium temperature	8745	88.82	8626	87.6
4	High temperature	650	6.60	8	0.1
	Total	9846	100	9846	100

Table 5: The correlation between surface temperature and built-up area density in Banjarmasin City in 2015.

Descriptive statistics	Mean	Std. deviation	N
Temperature	30.0173	3.78176	21
Built-up area density	−0.0784	0.31567	21

Correlations		Temperature	Built-up area density
Temperature	Pearson correlation	1	0.826**
	Sig. (2-tailed)		0.000
	Sum of squares and crossproducts	286.035	19.717
	Covariance	14.302	0.986
	N	21	21
Built-up area density	Pearson correlation	0.826**	1
	Sig. (2-tailed)	0.000	
	Sum of squares and crossproducts	19.717	1.993
	Covariance	0.986	0.100
	N	21	21

**Correlation is significant at the 0.01 level (2-tailed).

Table 6: The correlation between surface temperature and built-up area density in Banjarmasin City in 2019.

	Mean	Std. deviation	N
Temperature	26.6834	3.00599	21
Built-up area density	−0.1150	0.28174	21

Correlations		Temperature	Built-up area density
Temperature	Pearson correlation	1	0.969**
	Sig. (2-tailed)		0.000
	Sum of squares and cross-products	180.720	16.417
	Covariance	9.036	0.821
	N	21	21
Built-up area density	Pearson correlation	0.969**	1
	Sig. (2-tailed)	0.000	
	Sum of squares and cross-products	16.417	1.588
	Covariance	0.821	.079
	N	21	21

**Correlation is significant at the 0.01 level (2-tailed).

in the study sites was 26.68°C, and the average vegetation index was 0.2431; with a 99% significance level, we obtained an r-value of −0.949. Again, this means that vegetation density had a strong negative correlation with surface temperature.

The Pearson product-moment correlation results show that the surface temperature and vegetation density score was −0.860 in 2015 and −0.949 in 2019. All correlation results are negative, which means that the vegetation density has an inverse ratio to surface temperature; in other words, high vegetation density causes low surface temperature.

Vegetation cover is very influential in reducing the heat of Banjarmasin City because the vegetation can reduce heat through the absorption of solar radiation and transpiration, which increases humidity for the surrounding environment. Vegetation covered 60.9% of the area in Banjarmasin City in

Table 7: The list of city parks in Banjarmasin city in 2013.

No.	Names of city parks	Location	District	Area (m^2)
1	Taman sabilal	Jl. Jend. Sudirman	Banjarmasin Tengah	30,100
2	Taman ULM	Jl. H. B Kayu Tangi	Banjarmasin Utara	5,000
3	Taman Kota Korem	Jl. Lambung Mangkurat	Banjarmasin Tengah	2,000
4	Taman Kamboja	Jl. H. Anang Adenansi	Banjarmasin Tengah	15,216
5	Taman Percontohan PKK	Jl. Djok Mentaya	Banjarmasin Tengah	4,460
6	Taman Jahri Saleh	Jl. Jahri Saleh	Banjarmasin Utara	14,000
7	Taman Tower PDAM	Jl. Sutoyo S	Banjarmasin Tengah	1,430
8	Taman Basirih	Jl. Tembus Mantuil	Banjarmasin Selatan	360

Table 8: The correlation between surface temperature and vegetation density in Banjarmasin city in 2015.

	Mean	Std. Deviation	*N*
Temperature	30.0173	3.78176	21
Vegetation density	0.2619	0.19264	21

Correlations

		Temperature	Vegetation density
Temperature	Pearson correlation	1	−0.860**
	Sig. (2-tailed)		0.000
	Sum of squares and crossproducts	286.035	−12.538
	Covariance	14.302	−0.627
	N	21	21
Vegetation density	Pearson correlation	−0.860**	1
	Sig. (2-tailed)	0.000	
	Sum of squares and crossproducts	−12.538	.742
	Covariance	−0.627	.037
	N	21	21

**Correlation is significant at the 0.01 level (2-tailed).

Table 9: The correlation between surface temperature and vegetation density in Banjarmasin City in 2019.

	Mean	Std. Deviation	*N*
Temperature	26.6834	3.00599	21
Vegetation density	0.2431	0.18561	21

Correlations

		Temperature	Vegetation density
Temperature	Pearson correlation	1	−0.949**
	Sig. (2-tailed)		0.000
	Sum of squares and crossproducts	180.720	−10.591
	Covariance	9.036	−0.530
	N	21	21
Vegetation density	Pearson correlation	−0.949**	1
	Sig. (2-tailed)	0.000	
	Sum of squares and crossproducts	−10.591	0.689
	Covariance	−0.530	0.034
	N	21	21

**Correlation is significant at the 0.01 level (2-tailed).

2015, yet it decreased by 58.4% in 2019. The decrease in the vegetated areas and their uneven distribution happens much in the suburbs.

Findings confirmed that the built-up area density and surface temperature were highly correlated. Our results support the study in Huabei, China, and Dhaka, India, stating that urban areas can affect LST with a strong correlation [43–45]. Increased built-up areas lead to surface physical characteristics that ultimately cause surface and air temperature changes [46].

Vegetation density and surface temperature were found to be highly correlated. The finding supports the study in Sardinia, Italy. In Songnen, China, it is stated that forests are the most effective vegetated areas to reduce LST, and vegetation density tends to become a crucial factor in reducing air and surface temperature [47, 48]. In addition, decreased vegetated areas can lead to changes in surface physical characteristics that ultimately cause changes in surface temperature and air temperature [46].

Several studies show that increased surface temperatures happen due to changes in the urban environment, namely, more built-up areas [49–53]. However, our findings contradict the previous studies. We found that the surface temperature in 2015 was higher than in 2019, although more built-up areas and less vegetated areas were found in 2019; this happened because of El Nino. The 2015 El Nino in Indonesia was very strong and happened at the worst scale throughout history [54], yet the 2019 EL Nino was weak [55]. Thus, an increase or decrease in land surface temperature in Indonesia, especially in Banjarmasin City in 2015 and 2019, was strongly affected by El Nino, not by changes in the built-up area density and urban vegetation density;the latter was only at a micro level.

4. Conclusions

The built-up area density index and vegetation index affected the surface temperature of Banjarmasin City in 2015 and 2019 at a micro level. Building density increased in the 2015–2019 period while vegetated areas decreased. The density of the building correlates with surface temperature. The higher the strength of the building, the more the surface temperature will increase. The correlation value between building density and ground surface temperature in 2015 was 0.826; in 2019, it was 0.969. Meanwhile, the density of vegetation with surface temperature has a negative correlation, meaning that the higher the density of vegetation, the lower the surface temperature. The existence of a city government policy by increasing green open space or urban forests can reduce the surface temperature in the city. However, it turns out that the green open space in Banjarmasin City is still not widespread. Furthermore, efforts to control the surface temperature of urban areas in Indonesia are urgently needed by implementing land cover arrangements that allocate 30% of the urban area for green open spaces.

Data Availability

The data supporting this article are from datasets that have been cited.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

The authors thank the Faculty of Teacher Training and Education, Lambung Mangkurat University, for supporting and funding the research. The research was funded by the Faculty of Teacher Training and Education, Lambung Mangkurat University.

References

[1] A. R. As-Syakur, I. W. S. Adnyana, I. W. Arthana, and I. W. Nuarsa, "Enhanced built-up and bareness index (EBBI) for mapping built-up and bare land in an urban area," *Remote Sensing*, vol. 4, no. 10, pp. 2957–2970, 2012.

[2] L. Chu, F. Oloo, H. Bergstedt, and T. Blaschke, "Assessing the link between human modification and changes in land surface temperature in hainan, China using image archives from google earth engine," *Remote Sensing*, vol. 12, no. 5, p. 888, 2020.

[3] W. Hu, W. Zhou, and H. He, "The effect of land-use intensity on surface temperature in the Dongting lake area, China," *Advances in Meteorology*, vol. 2015, Article ID 632151, 11 pages, 2015.

[4] X. Yang, Y. Zhang, L. Liu, W. Zhang, M. Ding, and Z. Wang, "Sensitivity of surface air temperature change to land use/cover types in China," *Science in China Series D: Earth Sciences*, vol. 52, no. 8, pp. 1207–1215, 2009.

[5] A. J. Arnfield, "Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island," *International Journal of Climatology*, vol. 23, no. 1, pp. 1–26, 2003.

[6] F. Fujibe, "Detection of urban warming in recent temperature trends in Japan," *International Journal of Climatology*, vol. 29, no. 12, pp. 1811–1822, 2009.

[7] M. N. Handayani, B. Sasmito, and A. P. Wijaya, "Analisis hubungan antara perubahan suhu dengan indeks kawasan terbangun menggunakan citra landsat (studi kasus: kota Surakarta)," *Jurnal Geodesi Undip*, vol. 6, no. 4, pp. 208–2018, 2017.

[8] L. Howard, Harvey, J. Darton, A. Arch, H. Longman, S. Highley, and R. Hunter, *The Climate of London: Deduced from Meteorological Observations Made in the Metropolis and at Various Places Around it*, Climatology, 1833.

[9] C.-H. Huang, H.-H. Tsai, and H. C. Chen, "Influence of weather factors on thermal comfort in subtropical urban environments," *Sustainability*, vol. 12, no. 5, p. 2001, 2020.

[10] E. Kalnay and M. Cai, "Impact of urbanization and land-use change on climate," *Nature*, vol. 423, no. 6939, pp. 528–531, 2003.

[11] T. R. Oke, "City size and the urban heat island," *Atmospheric Environment*, vol. 7, no. 8, pp. 769–779, 1967.

[12] B. Stone Jr, "Urban and rural temperature trends in proximity to large US cities: 1951–2000," *International Journal of Climatology*, vol. 27, no. 13, pp. 1801–1807, 2007.

[13] J. A. Voogt and T. R. Oke, "Thermal remote sensing of urban climates," *Remote Sensing of Environment*, vol. 86, no. 3, pp. 370–384, 2003.

[14] F. Bektaş Balçik, "Determining the impact of urban components on land surface temperature of Istanbul by using remote sensing indices," *Environmental Monitoring and Assessment*, vol. 186, no. 2, pp. 859–872, 2014.

[15] J. P. Connors, C. S. Galletti, and W. T. L. Chow, "Landscape configuration and urban heat island effects: assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona," *Landscape Ecology*, vol. 28, no. 2, pp. 271–283, 2013.

[16] M. Sahana, R. Ahmed, and H. Sajjad, "Analyzing land surface temperature distribution in response to land use/land cover change using split window algorithm and spectral radiance model in sundarban biosphere reserve, India," *Modeling Earth Systems and Environment*, vol. 2, no. 2, pp. 1–11, 2016.

[17] J. Southworth, "An assessment of Landsat TM band 6 thermal data for analysing land cover in tropical dry forest regions," *International Journal of Remote Sensing*, vol. 25, no. 4, pp. 689–706, 2004.

[18] E. N. Adinna, I. C. Enete, and T. O. Arch, "Assessment of urban heat island and possible adaptations in Enugu urban using Landsat-ETM," *Journal of Geography and Regional Planning*, vol. 2, no. 2, pp. 30–36, 2009.

[19] A. Mohajerani, J. Bakaric, and T. Jeffrey-Bailey, "The urban heat island effect, its causes, and mitigation, with reference to the thermal properties of asphalt concrete," *Journal of Environmental Management*, vol. 197, pp. 522–538, 2017.

[20] M. Nuruzzaman, "Urban heat island: causes, effects and mitigation measures-a review," *International Journal of Environmental Monitoring and Analysis*, vol. 3, no. 2, pp. 67–73, 2015.

[21] A. Synnefa, A. Dandou, M. Santamouris, M. Tombrou, and N. Soulakellis, "On the use of cool materials as a heat island mitigation strategy," *Journal of Applied Meteorology and Climatology*, vol. 47, no. 11, pp. 2846–2856, 2008.

[22] S. Adyatma, M. Muhaimin, D. Arisanty, and I. Rajiani, "The Role of the urban green space density in determining the temperature humidity index of an Indonesian main city|international business information management association (IBIMA). international business information management association (IBIMA)," 2019, https://ibima.org/accepted-paper/the-role-of-the-urban-green-space-density-in-determining-the-temperature-humidity-index-of-an-indonesian-main-city/.

[23] D. Armson, *The Effect of Trees and Grass on an Urban Area's Thermal and Hydrological Performance*, The University of Manchester (United Kingdom), Manchester, UK, 2012.

[24] M. A. Irmak, S. Yilmaz, H. Yilmaz, S. Ozer, and S. Toy, "Evaluation of different thermal conditions based on thi under different kind of tree types-as a specific case in ata botanic garden in eastern Turkey," *Global NEST Journal*, vol. 15, no. 1, pp. 131–139, 2013.

[25] L. Shashua-Bar, D. Pearlmutter, and E. Erell, "The influence of trees and grass on outdoor thermal comfort in a hot-arid environment," *International Journal of Climatology*, vol. 31, no. 10, pp. 1498–1506, 2011.

[26] K. J. Gohain, P. Mohammad, and A. Goswami, "Assessing the impact of land use land cover changes on land surface temperature over Pune city, India," *Quaternary International*, vol. 575-576, pp. 259–269, 2021.

[27] S. Ullah, A. A. Tahir, T. A. Akbar et al., "Remote sensing-based quantification of the relationships between land use land cover changes and surface temperature over the lower himalayan region," *Sustainability*, vol. 11, no. 19, p. 5492, 2019.

[28] A. Liaqut, I. Younes, R. Sadaf, and H. Zafar, "Impact of urbanization growth on land surface temperature using remote sensing and GIS: a case study of Gujranwala city, Punjab, Pakistan," *International Journal of Economic and Environmental Geology*, pp. 44–49, 2019.

[29] S. L. Ermida, P. Soares, V. Mantas, F.-M. Göttsche, and I. F. Trigo, "Google earth engine open-source code for land surface temperature estimation from the landsat series," *Remote Sensing*, vol. 12, no. 9, p. 1471, 2020.

[30] N. Kabisch, P. Selsam, T. Kirsten, A. Lausch, and J. Bumberger, "A multi-sensor and multi-temporal remote sensing approach to detect land cover change dynamics in heterogeneous urban landscapes," *Ecological Indicators*, vol. 99, pp. 273–282, 2019.

[31] S. Adyatma, M. Muhaimin, D. Arisanty, and I. Rajiani, "The density of the urban green space effect on thermal comfort," in *Proceedings of the ADVED*, pp. 344–353, Istanbul, Turkey, October 2019.

[32] M. Muhaimin, A. N. Saputra, P. Angriani, S. Adyatma, and D. Arisanty, "Mapping of shifting cultivation (gilir balik) patterns in dayak meratus tribe," in *Proceedings of the 2nd International Conference on Social Sciences Education (ICSSE 2020)*, pp. 475–482, September 2020.

[33] M. Muhaimin, J. Jumriani, D. Arisanty, K. P. Hastuti, and P. Angriani, "Landscape metrics analysis in the proboscis monkey habitat in kuala lupak wildlife reserve," *Jurnal Pengelolaan Sumberdaya Alam Dan Lingkungan (Journal of Natural Resources and Environmental Management)*, vol. 12, no. 2, pp. 301–316, 2022.

[34] D. Arisanty, M. Muhaimin, D. Rosadi, A. N. Saputra, K. P. Hastuti, and I. Rajiani, "Spatiotemporal patterns of burned areas based on the geographic information system for fire risk monitoring," *International Journal of Forestry Research*, vol. 2021, Article ID 2784474, 10 pages, 2021.

[35] D. Arisanty, M. Feindhi Ramadhan, P. Angriani et al., "Utilizing sentinel-2 data for mapping burned areas in banjarbaru wetlands, South Kalimantan province," *International Journal of Forestry Research*, vol. 2022, Article ID 7936392, 12 pages, 2022.

[36] H. A. Barbosa, A. R. Huete, and W. E. Baethgen, "A 20-year study of NDVI variability over the Northeast region of Brazil," *Journal of Arid Environments*, vol. 67, no. 2, pp. 288–307, 2006.

[37] J. W. Rouse Jr, R. H. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, "Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation," Technical ReportRemote Sensing Center, Texas A&M University, College Station, Texas, TX, USA, 1974.

[38] S. Guha, H. Govil, N. Gill, and A. Dey, "A long-term seasonal analysis on the relationship between LST and NDBI using Landsat data," *Quaternary International*, vol. 575-576, pp. 249–258, 2021.

[39] Y. Zha, J. Gao, and S. Ni, "Use of normalized difference built-up index in automatically mapping urban areas from TM imagery," *International Journal of Remote Sensing*, vol. 24, no. 3, pp. 583–594, 2003.

[40] V. Ihlen, "Landsat 8 data users handbook, U.S. geological survey," 2019, https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8-data-users-handbook.

[41] D. S. Susanti, Y. Sukmawaty, and N. Salam, *Analisis Regresi Dan Korelasi*, IRDH, Indonesia, 2019.

[42] H. Xu, Y. Chen, S. Dan, and W. Qiu, "Spatial and temporal analysis of urban heat Island effects in Chengdu city by remote sensing," in *Proceedings of the 2011 19th International Conference on Geoinformatics*, Shanghai, China, June 2011.

[43] M. M. Rahman, R. Avtar, A. P. Yunus et al., "Monitoring effect of spatial growth on land surface temperature in Dhaka," *Remote Sensing*, vol. 12, no. 7, p. 1191, 2020.

[44] J. A. Sobrino, N. Raissouni, and Z.-L. Li, "A comparative study of land surface emissivity retrieval from NOAA data," *Remote Sensing of Environment*, vol. 75, no. 2, pp. 256–266, 2001.

[45] T. Sun, R. Sun, and L. Chen, "The trend inconsistency between land surface temperature and near surface air temperature in assessing urban heat island effects," *Remote Sensing*, vol. 12, no. 8, p. 1271, 2020.

[46] N. D. Andani and B. Sasmito, "Pengaruh perubahan tutupan lahan terhadap fenomena urban heat island dan keterkaitannya dengan tingkat kenyamanan termal (temperature

humidity index) di kota semarang," *Jurnal Geodesi Undip*, vol. 7, no. 3, pp. 53–65, 2018.

[47] S. Lai, F. Leone, and C. Zoppi, "Spatial distribution of surface temperature and land cover: a study concerning Sardinia, Italy," *Sustainability*, vol. 12, no. 8, p. 3186, 2020.

[48] Y. Song, D. Zhou, H. Zhang, G. Li, Y. Jin, and Q. Li, "Effects of vegetation height and density on soil temperature variations," *Chinese Science Bulletin*, vol. 58, no. 8, pp. 907–912, 2013.

[49] P. Fu and Q. Weng, "A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with landsat imagery," *Remote Sensing of Environment*, vol. 175, pp. 205–214, 2016.

[50] Y. Liu, J. Peng, and Y. Wang, "Diversification of land surface temperature change under urban landscape renewal: a case study in the main city of Shenzhen, China," *Remote Sensing*, vol. 9, no. 9, p. 919, 2017.

[51] M. Morabito, A. Crisci, A. Messeri et al., "The impact of built-up surfaces on land surface temperatures in Italian urban areas," *Science of the Total Environment*, vol. 551-552, pp. 317–326, 2016.

[52] S. K. Alavi Panah, M. Kiavarz Mogaddam, and M. Karimi Firozjaei, "Monitoring spatiotemporal changes of heat island in babol city due to land use changes," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 42, pp. 17–22, 2017.

[53] K. Zhang, R. Wang, C. Shen, and L. Da, "Temporal and spatial characteristics of the urban heat island during rapid urbanization in Shanghai, China," *Environmental Monitoring and Assessment*, vol. 169, no. 1-4, pp. 101–112, 2010.

[54] BBC, "El Nino 2015 samai rekor 1998 sebagai "yang terkuat dalam sejarah"-BBC News Indonesia," 2015, https://www.bbc.com/indonesia/majalah/2015/12/151231_majalah_elnino.

[55] D. Wardani, "BMKG: siklus el nino jadi lebih cepat karena pemanasan global-satu harapan," 2019, https://www.satuharapan.com/read-detail/read/bmkg-siklus-el-nino-jadi-lebih-cepat-karena-pemanasan-global.