Analysis of the Correlation Between Urban Development and Population with the Urban Heat Island Phenomenon in South Jakarta City

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Abstract. Urban activities are highly complicated and demand a high level of mobility. The urban area is teeming with diverse activities, such as healthcare, offices, industry, commerce, and services. Those activities are influenced by the number of populations. It is because the populations are a subject that engages in various activities. The greater the population of a city, the more activities can be conducted there. To fulfill the smooth running of various activities, it is necessary to build other supporting infrastructures. Locations are needed to accommodate these activities, so these various infrastructures run smoothly. Urban development is one solution so that various problems for infrastructure can be distributed evenly. However, it will be problematic because numerous lands will be turned into built-up land. The surface temperature has increased so that it can lead to the urban heat island phenomenon. This phenomenon causes the surface temperature in urban areas to be higher than the surrounding temperature. Therefore, this study aims to examine the correlation between population and Urban Development with surface temperature and determine the effect of a land distribution built with the surface temperature that has an impact on the urban heat island phenomenon. The method utilized was image processing Landsat 8 OLI path row 122/064 in 2016 and 2021, with stratified random sampling. Then, it was continued by analyzing it with bivariate Pearson Correlation employing multiple regression analysis. The results showed that the number of populations and built-up land had an impact of 58% on changes in surface temperature.

Keywords: Population · Urban · Temperature · UHI · Jakarta First Section

1 Introduction

The city is a nickname famous for the population's high mobility. This condition causes urban to areas to experience rapid development compared to rural areas. According to Salvati (2018), one of the factors of a developing city is the population growth of the urban area itself, which affects various urban landscapes in the form of clusters and distribution.

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The number of population also affects the dynamics of changes in the development of a city. It is because the needs the population are highly complicated. These needs are supported by adequate facilities and infrastructure, such as street networks, facility of worship, health, education, offices, settlements, and so on. Generally, development in Indonesia has a horizontal pattern. It means that the development of cities in their construction occurs in a sideways direction characterized by a smaller amount of land. As a result, open land is getting minimal.

Based on the definition, horizontal urban development is a model of urban development characterized by increasing the area but constant in height and quantity of built-up land (Martini, 2011). The development of such a model frequently occurs in urban suburbs where there is still a lot of cheaper land with the condition that the location is adjacent to the highway leading to the city. In addition, there is also a vertically upward urban development. The height will increase while the construction area and the quantity of built-up land are constant.

Urbanization is considered to play a role in increasing the number of populations in an area, including the city of South Jakarta. Sato & Yamamoto (2005) suggested that the increase in population in an urban area is in line with increased activity in urban areas that are higher than other areas. More complicated urban areas result in a number of migrants who want to obtain a job because it is considered the need for more workers in the region. The urban area will then become a magnet for those looking for work and housing (Harahap, 2013).

According to Shogo Kayono in Abbas (2002), urbanization will be the driving force behind the social, economic, political, and cultural factors that distinctly affect population concentration and displacement. Increases in population percentage, changes in these percentages' rates of change, and an increase in the number of urban centers are all signs of urbanization.

The goal of the urbanization process is to increase public welfare, as evidenced by the pattern of urbanization that tends to increase year over year. However, urbanization in Indonesia indicates that changes in conditions tend to make the number of populations moving from villages to cities uncontrolled. It will transform the urban area into a metropolitan area. The development of the metropolitan area involves many different financial, governmental, industrial, commercial, and even the center of economic growth on a national and international level, especially in the process of population growth such as urbanization (Silitonga, 2010). South Jakarta is one of the cities that urbanites use as a destination, so South Jakarta is a part of the metropolitan area. As a result of the rapid pace at which various developments took place, issues developed that were characterized by the emergence of numerous new central points that had not previously served as new urban development centers.

Land conversion is the impact of the development process as a logical consequence of the increase in activity and population (Arsyad, 2008). Actually, land conversion is a natural phenomenon, but the problem is that it mostly occurs on productive agricultural land or various land covers that were originally covered in vegetation.

According to Rudiarto (2010), one of the effects of urbanization's speed and pressure is converting open land into developed land. This rapid development of offices, homes, shopping malls, schools, and recreational facilities has led to shrinking green open space

(RTH), reduced water catchment areas, and a food crisis due to declining agricultural productivity.

Other problems also arise because the flow of urbanization will affect the physical and social conditions in an area used as a destination for urbanites. As a result of the socially induced increase in population density, it will be necessary to raise the standard of human resources to compete in many spheres of life, including employment. One of the physical problems is the increase in surface temperature.

Surface temperature changes are impacted by the increasingly condensed distribution of developed land. It may result from diminished vegetation, which lowers the air temperature by using sunlight for photosynthesis. As a result, the temperature beneath the canopy will be lower due to the retained sunlight above the canopy. As a result, it can cool the environment by allowing vegetation or plants to do evapotranspiration. Climate change occurs due to various human activities because humans significantly influence the controlled factors of this climate phenomenon. The rapid growth of the human population and all human interactions with the environment cause an ecological crisis that can result in damage (Subarna, 2017).

One of the damages that occurs is the surface temperature in urban areas that is higher than the surrounding area since there is significantly less vegetation in urban areas than in suburban areas (Nofrizal, 2018). It is because the surface temperature is closely related to human activities and is easily affected by the impact of topography on the environment (Hasler et al., 2015). Land Surface Temperature (LST) functions in identifying changes in climate, air temperature, and urban environment on the local and global scale (Hidayati & Suharyadi, 2019). Through the surface temperature, it can be known whether, in a region, there is a phenomenon of Urban Heat Island (UHI). According to Arifin (2012), surface temperature detection in remote sensing data enables the detection of the UHI phenomenon. Urban areas typically have unevenly distributed LST values, but there is a UHI phenomenon that occurs in parts adjacent to urban districts (Hadibasyir, Rijal, et al., 2020a). In the district, there are numerous interactions, including ecological conditions. The negative impact of UHI is the poor planning of handling areas regarding ecological conditions, so that handling also requires a targeted ecological restoration (Hadibasyir, Fikriyah, et al., 2020b).

Based on the increase in the number of people engaging in social activities, various developments are completed to provide facilities for human needs to conduct all activities. On the other hand, this negatively affects environmental conditions, particularly surface temperatures, which can have an impact on climate change. Uncontrolled social conditions of society can aggravate the phenomenon of climate change. Many people lament the rising surface temperatures and the increasingly erratic weather. Even though humans contribute to the anthropogenic component of the destruction of nature and an increase in surface temperature, many societies experience losses due to uncontrollable weather. Therefore, this study aims to examine the correlation between population and urban development and surface temperature and determine the effect of a distribution of built-up land with a surface temperature that has an impact on the UHI phenomenon.

2 Methods

2.1 Research Area

South Jakarta is one of the cities that is experiencing rapid urbanization. It is in the province of the State Capital of Indonesia, namely the Special Capital Region of Jakarta (DKI Jakarta). The areas covered by the province are expanding and developing very significantly, making up 21.95%, or 141.27 km^2 or 14127 ha, of the total area of DKI Jakarta Province. Astronomically, South Jakarta is located at coordinates between 106°45′ East Latitude and 6°15′ 40.8″ Southern Latitude. South Jakarta is a strategic city for various development activities due to its location in the province that houses the state capital.

Geographically, South Jakarta is bordered to the north by West Jakarta and Central Jakarta, to the south by the city of Depok, to the east by East Jakarta, and to the west by the city of Tangerang and South Tangerang. Based on its geographical location, the city of South Jakarta is included in the Jabodetabek area (Jakarta, Bogor, Depok, Tangerang, and Bekasi). Jabodetabek is renowned as a region whose development center is significantly rapid because it is a national-scale growth center.

There has been a lot of development in the South Jakarta area, which also borders a region with numerous campuses. As one of the major metropolitan areas, South Jakarta is a bustling city in many ways due to complex human activity. Thus, the research was conducted in the South Jakarta City study area based on geographical conditions and the large number of residents who wanted to live there because of the city's rapid development. The study area can be viewed in (Fig. 1).

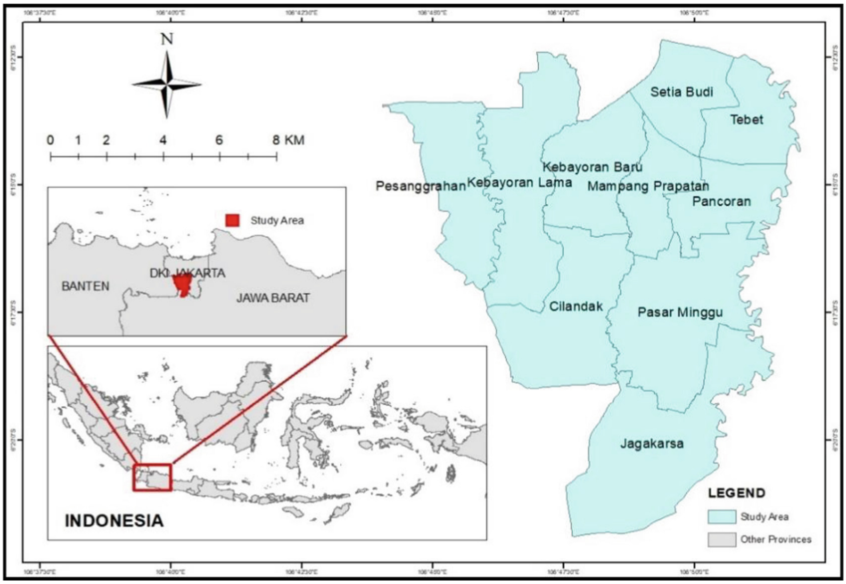


Fig. 1. The Study Area's Map

2.2 Data Collection

Landsat 8 OLI imagery was used in this study because it has two sensors: OLI (*Operational Land Imagery)* and TIRS *(Thermal Infrared Sensor)*. Both have a spatial resolution of 30 m (visible, NIR, and SWIR), 100 m (thermal), and 15 m (panchromatic). High spectral reflection values in Landsat 8 OLI/TIRS enable it to determine the extent of built land distribution in a region (Zulfajri et al., 2019). Landsat 8 OLI/TIRS was used in various image extractions for this study. Some of the data extractions used in Landsat 8 OLI/TIRS are described in (Table 1).

The data that has been obtained was processed, which can be described in (Fig. 2). Research data are first processed by gathering secondary data from sources like Landsat 8 OLI/TIRS imagery and the Indonesian Statistics (BPS). Then, data processing was done based on the goals and results of this study.

Table 1. Research Data

Data	Source	Method
Population	Statistics Indonesia of South Jakarta	Creating population tables and charts for two distinct years
Urban Heat Island Identification	Landsat 8 OLI/TIRS	Land Surface Temperature (LST)
Identification Built-up Land	Landsat 8 OLI/TIRS	NDBI
South Jakarta administration map	Indonesian Geospatial Information Authority	ArcGIS mapmaking

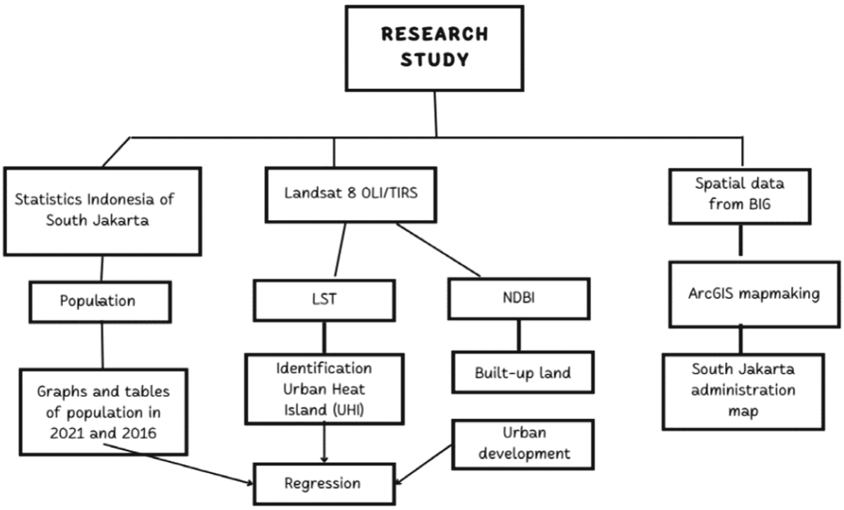


Fig. 2. Research Flow Chart

Developments in each region have an impact on improving human welfare, development, and other aspects of life. The population is a subject/object with qualities and characteristics in a common area (Sugiyono, 2013). As a result, a region's population plays a critical role in determining development characteristics. Following East Jakarta and West Jakarta, which are ranked first and second respectively, South Jakarta has the third-largest population in the province of DKI Jakarta. The population of South Jakarta can be observed in (Table 2).

2.3 Data Analysis Methods

In this study, Landsat 8 OLI/TIRS, which was launched in February 2013, was used to process spatial data. The Landsat imagery with the path/row used was 122/064 based on the study area of South Jakarta. Images without clouds or fog were chosen for image capture because both can lead to distortion, which can lead to errors in data processing or result in inappropriate data.

The images that do not have clouds and fog are found in the images taken on August 17, 2016, and May 11, 2021. Both images were taken in the dry season because the season minimizes the presence of clouds and fog. Changes in populated areas, surface temperatures, and UHI-affected regions were compared to the two years in five years. The need for land to construct facilities and infrastructure for the population is growing along with it. Therefore, in this study, NDBI data was processed *(Normalized Difference Built-up Index).* NDBI processing functions to determine the distribution of built-up land in the city of South Jakarta.

LST can be processed using a variety of calculations, including the ones listed below:

1. Radiometric Correction

   The radiometric value of the image is one area where radiometric correction helps resolve errors caused by atmospheric influences (Sulaiman Hakim Sinaga, Andri Suprayogi, 2018). Value reflectance is an image radiometric value that ranges between 0–1. The value reflectances that are processed include bands 10 and 11.
2. Brightness Temperature

   Brightness temperature is calculated by subtracting the converted value from the image's existing units of °C (Celsius) to determine the brightness temperature of an object (Ayuningtyas, 2015).
3. NDVI (Normalized Difference Vegetation Index)

   NDVI is a value to measure the level of vegetation density by combining the red band with the NIR band (Near-Infrared Radiation) (Prasetyo et al., 2017).
4. PV (Proportion of Vegetation)

   PV is 0.00–1.00 obtained from the NDVI value to inhibit interference from moist soil conditions and surface energy flux. In short, PV is a fraction of a vegetation (Zulkarnain, 2016).
5. Emissivity

   Surface emissivity is the emission of thermal energy possessed by an object (Mallick et al., 2012). The energy is energy in hot or cold conditions depending on the thermal energy possessed by the object (Fawzi, 2014).
6. Land Surface Temperature (LST)

   LST represents all surface energy, the atmosphere, thermal properties of the surface, and subsurface media that are controlled by a condition (Insan & Prasetya, 2021).

Table 2. The population of South Jakarta 2016 and 2021 (Statistics Indonesia of South Jakarta City, 2016 and 2021)

Subdistrict	Village	Population Growth by Village (in Thousand)	
		2016	2021
Jagakarsa	Ciganjur	48,622	47,097
	Cipedak	53,422	47,215
	Jagakarsa	88,311	76,223
	Lenteng Agung	63,941	65,945
	Srengseng Sawah	73,493	71,019
	West Tanjung	51,076	48,558
Pasar Minggu	East Cilandak	28,635	28,853
	Jati Padang	42,114	43,089
	Kebagusan	53,460	50,153
	Pasar Minggu	29,322	28,477
	West Pejaten	42,993	42,770
	East Pejaten	66,991	67,084
	Ragunan	43,728	45,359
Cilandak	West Cilandak	58,596	62,644
	South Cipete	30,330	32,583
	South Gandaria	24,429	26,993
	Lebak Bulus	39,882	44,912
	Pondok Labu	49,535	56,084
Pesanggrahan	Bintaro	54,933	64,797
	Pesanggrahan	24,792	33,973
	South Petukangan	36,860	45,940
	North Petukangan	60,911	66,671
	Ulujami	44,082	50,797
Kebayoran Lama	Cipulir	43,516	49,194
	South Grogol	48,987	54,499
	North Grogol	47,857	52,456
	South Kebayora Lama	45,761	50,407
	North Kebayoran Lama	49,314	52,718
	Pondok Pinang	62,343	68,705

(*continued*)

Table 2. (*continued*)

Subdistrict	Village	Population Growth by Village (in Thousand)	
		2016	2021
Kebayoran Baru	North Cipete	38,960	42,002
	Gandaria Utara	45,805	48,381
	Gunung	10,718	11,262
	Kramat Pela	16,531	17,696
	Melawai	3,109	3,190
	Petogongan	13,643	14,050
	Pulo	6,752	6,803
	Rawa Barat	6,328	6,667
	Selong	3,364	3,314
	Senayan	3,530	3,343
Mampang Prapatan	Bangka	26,308	26,406
	West Kuningan	16.298	15,951
	Mampang Prapatan	25,002	22,824
	Pela Mampang	48,051	53,716
	Tegal Parang	30,470	40,419
Pancoran	Cikoko	12,902	12,973
	Duren Tiga	32,685	34,740
	Kalibata	48,708	52,735
	Pancoran	22,428	24,463
	Pengadegan	24,232	26,742
	Rajawati	22,280	25,849
Tebet	Bukit Duri	38,240	38,640
	Kebon Baru	35,966	36,004
	South Manggarai	23.373	23,422
	Manggarai	29,448	29,457
	Menteng Dalam	42,717	42.810
	West Tebet	22,269	22,275
	East Tebet	18,965	18,986

(*continued*)

Table 2. (*continued*)

Subdistrict	Village	Population Growth by Village (in Thousand)	
		2016	**2021**
Satiabudi	Guntur	4,606	4,598
	Karet Kuningan	18,131	19,541
	Karet Semanggi	3,007	3,192
	Karet	11,718	11,846
	East Kuningan	6.956	7,312
	Menteng Atas	32,758	34,352
	Pasar Manggis	31,011	32,652
	Setiabudi	3,521	3,635
	Total	2,189,026	2,297,463

7. UHI threshold

The threshold value of UHI can be obtained by processing surface temperature, which is obtained from the reduction of LST data (Jatmiko & Hartono, 2016). The calculation is as follows.

$$\mathrm{UHI} = \mathrm{LST} - (\mu + 0.5\alpha)$$

In which:
UHI: Urban Heat Island
LST: Land Surface Temperature (°C)
μ: Mean Land Surface Temperature (°C)
α: Standard deviation value of Land Surface Temperature (°C)

Bivariate correlation is used to test the correlation between the two variables in the correlation testing data. Pearson correlation *(correlate bivariate)* is used to identify the linear correlation between one variable and other variables. The correlation value (r) ranges from 0 to 1, indicating that the closer to 1, the stronger the correlation (Priyanto, 2013).

According to Sugiyono (2013), to interpret the results obtained coefficients can be seen in (Table 3).

Multiple linear regression is a modeling equation that uses two or more independent variables (X1, X2,… Xn) associated with a dependent variable (Y) (Yuliara, 2016). The regression equation is as follows.

$$Y = A + B_1X_1 + B_2X_2 + \ldots + B_nX_n.$$

In which:
Y: independent variable (the value of the variable to be predicted)
A: constants

Table 3. Classification of Correlation Coefficient

Value	Classification
0.00–0.199	Very Low
0.20–0.399	Low
0.40–0.599	Medium
0.60–0.799	Strong
0.80–1.000	Very Strong

$B_1, B_2, \ldots, B_n$: regression coefficient value

$X_1, X_2, \ldots, X_n$: independent variable.

Analysis of built-up land density using NDBI techniques shows that the number of populations utilized the data of each village and surface temperature through LST. Each variable was selected 50 samples with stratified random sampling, in which each class was elected 10 samples for NDBI and LST.

3 Results and Discussion

3.1 Population

The city of South Jakarta will have a population density of 16,262.92 peoples/km^2 in 2021 compared to 15,484.37 peoples/km^2 in 2016 due to the high population mobility and the city's rapid development. From the data, it can be deduced that South Jakarta's population density has grown by 9.52%. The distribution of the population in the city of South Jakarta can be seen in (Fig. 3).

Based on the graph, there are the numbers of people in each district. Jagakarsa subdistrict has the largest population, while Setiabudi subdistrict has the least population. It can be influenced by its geographical location. Many people choose to live in the Jagakarsa subdistrict because of its convenient location next to numerous educational institutions, retail establishments, and theme parks.

3.2 Urban Development

Previous research (Nurul Handayani et al., 2017) employed the parameters of surface temperature and NDBI to determine development in Surakarta. The result demonstrates the impact of weather, which led to a higher surface temperature in 2013 than in 2015. However, other studies state that the value of spectral reflection has little impact on seasonal differences other than on the transformation of urban vegetation (Hidayati et al., 2017). Table 4 shows that the NDBI, population, and LST parameters have increased and decreased over time.

Based on the results of the data processing that has been done on (Table 4), the NDBI value had a maximum value of 0.3 in 2021 and was 0.24 in 2016. Research that has been done by (Syahputra et al., 2021) produces the highest NDBI values ranging from 0.3 to

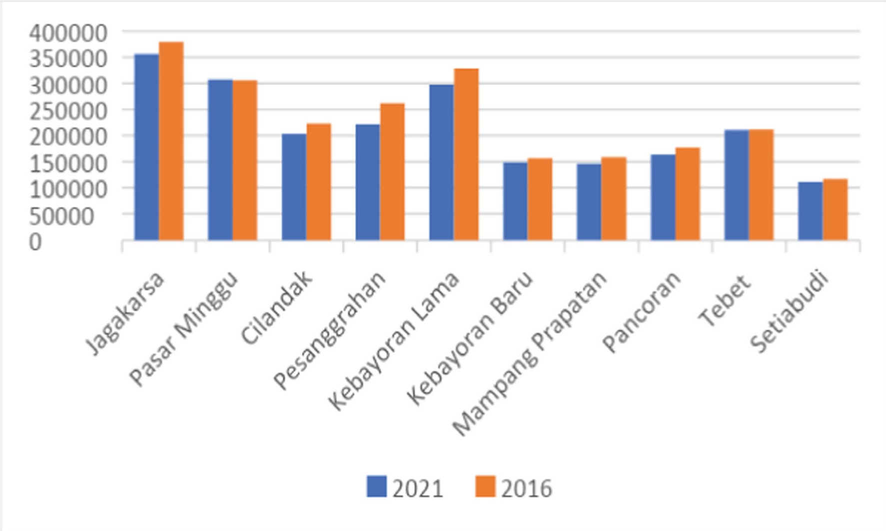


Fig. 3. South Jakarta by Subdistrict (people/sqkm)

Table 4. The Ratio of NDBI, population, and Surface Temperature in South Jakarta in 2016 and -2021

Year	NDBI		Population		LST	
	Min	Max	Min	Max	Min	Max
2016	−0.32	0.24	3,007	66,991	19.05	29.29
2021	−0.41	0.3	3,190	68,705	25.16	32.28

0.5 based on the albedo value due to building roofing material mainly in zinc. The closer the value of 1, the denser the existing built-up land. From 2016 to 2021, there was an increase in both the least and most population, according to the population development. The LST also increased the temperature to the highest temperature value of 3 °C while for the lowest value ranges from 6 °C. It indicates that one of the contributing factors to the higher NDBI value is the growing population and the surface temperature.

The development of the city can be observed in (Fig. 4) regarding the distribution of NDBI values based on building density. NDBI classification is divided into five classes: slightly dense, less dense, dense, moderately dense, and very dense.

Figure 4 illustrates how the building changes are moderately discernible from the minimum and maximum values of NDBI. Although there were only a few districts with a very dense NDBI index, including Mampang Prapatan Subdistrict, Pasar Minggu Subdistrict, and Jagakarsa Subdistrict, the average area that was included in the dense classification class was quite significant in 2016. Meanwhile, there has been a significant amount of land development into built-up land since 2021. Rapid land changes occurred in Kebayoran Lama Subdistrict and Tebet Subdistrict.

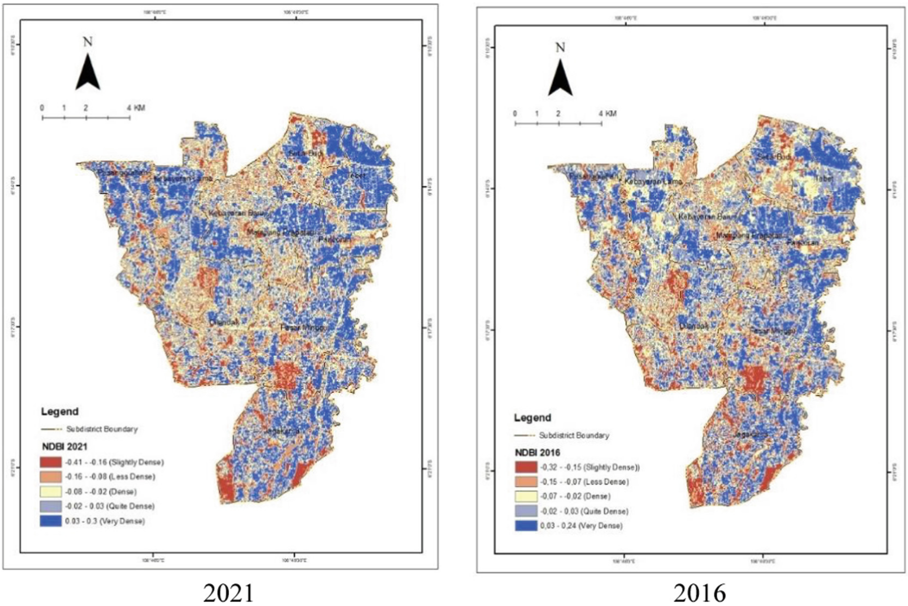


Fig. 4. NDBI in 2021 and 2016

3.3 Surface Temperature

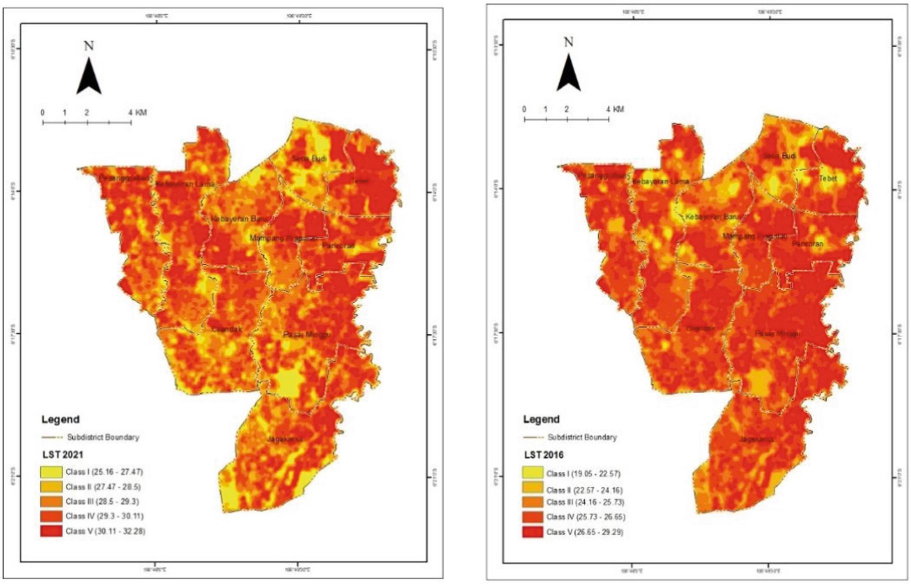
According to research conducted by Liong & Sugiarto Nasrullah (2021), the surface temperature has a correlation with built-up areas because the more built-up land in an area, the higher the surface temperature will be. Figure 5 display the surface temperature distribution between 2016 and 2021.

In 2016, as seen from (Fig. 5), it had a tendency to have a region with surface temperature classification classes into classes III and IV, but Class I did not have a tendency to have one as much as the region of Class I in 2021. The percentage of class I temperatures in 2021 ranged from 25.16 °C–27.47 °C while Class I in 2016 ranged from 19.05 °C–22.57 °C.

Thus, there was an increase in temperature from 2016 to 2021, which initially, the highest temperature was from 29.29 °C to 32.28 °C. Areas that have a change in temperature from high to low were Kebayoran Baru Subdistrict and Tebet Subdistrict. In comparison to the populations in each district, Kebayoran Baru Subdistrict experienced a decline in population, from 156,708 in 2016 to 148,740 in 2021. Tebet District also experienced a decrease in population of 616 people. The less populated it is, the lower the surface temperature.

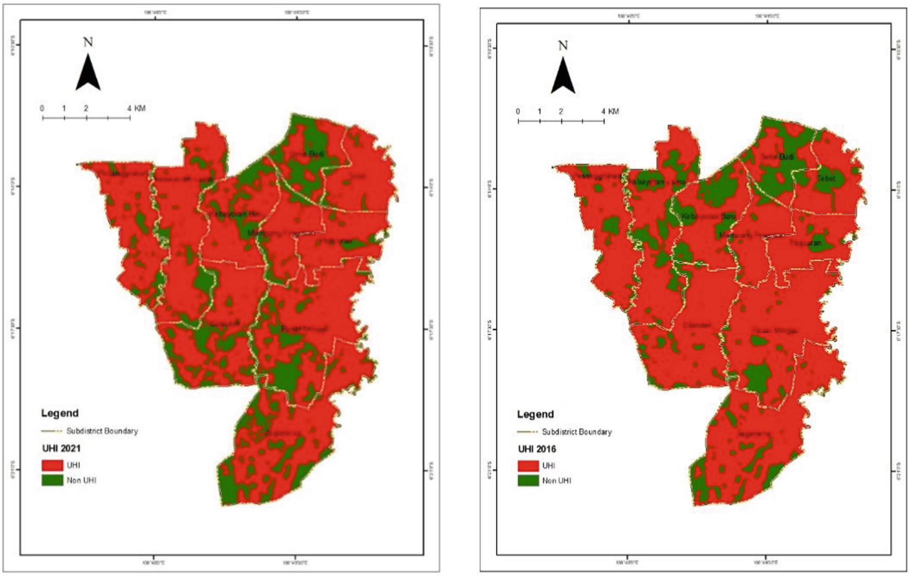
3.4 Urban Heat Island

Identifying regions that are UHI or not is determined by knowing the LST value. The threshold value can be used to identify, which areas are impacted by UHI because the LST value can be calculated. Figure 6 displays the distribution of the geographic areas impacted by UHI in 2016 and 2021.



2021 (°C) **2016 (°C)**

Fig. 5. LST in 2021 and 2016



2021 **2016**

Fig. 6. UHI in 2021 and 2016

Table 5. UHI Area South Jakarta, 2016 and 2021 (Ha)

	2021	**2016**
Non-UHI	3,994.64	3,224.28
UHI	10,547.47	11,316.46

If the results are compared with the results of LST on (Fig. 5), then the regions affected by the UHI phenomenon are those that have LST values between Class IV and Class V, while for other classes, they are included in non-UHI regions. The distribution of non-UHI between 2016 and 2021 shows some differences. The distribution pattern tended to cluster in the eastern area of South Jakarta in 2021 as opposed to the northern part of South Jakarta in 2016.

One of the factors that the changing distribution patterns of non-UHI can control is the movement of people and urban development that occurred in South Jakarta. Through the results of NDBI, changes in urban development can be identified. The distribution of the NDBI value can be used to determine the distribution of built-up land so that it can be known that the center of human activity is primarily in large cities, especially metropolitan areas such as South Jakarta, which relies on office activities, trade, and services. Of course, the activity center needs a building that can accommodate all production processes and workers. Urban development in a region can alter UHI patterns due to rising surface temperatures. Table 5 displays the total area that is UHI and is non-UHI territory.

The growth of a city will have an impact on whether or not a region is affected by the UHI phenomenon. Changing development patterns and the creation of green open spaces can change the UHI phenomenon's distribution. The area affected by UHI in 2021 is less than in 2016, with a total area of 11,316.46 ha to 10,547.47 ha in 2021.

3.5 Correlation Analysis of Built-Up Land Density, Population, and Surface Temperature in 2016 and 2021

Land density, population, and surface temperature are three variables that are interconnected. Humans who constantly interact with nature can change the surface temperature and the various developments of cities. Table 6 and Table 7 display the processing results for the third variable from a bivariate Pearson correlation analysis.

According to correlation results in 2016 and 2021 shown in Table 6 and Table 7, there is a positive correlation between NDBI and LST and the total population with LST. It indicates that in areas with a high NDBI value, the LST value is also high. Similar to the population and LST, if the population is high, there will be an increase in the LST value.

The r-value for the correlation between NDBI and LST increased from 0.272 to 0.770 in 2021 compared to 2016. Although there is a positive correlation value, the correlation is negative. The two variables are, therefore, inversely proportional. If the independent variable (NDBI) increases, then there is a decrease in the dependent variable (LST), and vice versa.

Table 6. Correlation of NDBI, Population, and LST, 2016

2016		NDBI	Population	LST
NDBI	Pearson Correlation	1	.062	.272
	Sig. (2-tailed)		.671	.056
	N	50	50	50
Population	Pearson Correlation	.062	1	.293
	Sig. (2-tailed)	.671		.039
	N	50	50	50
LST	Pearson Correlation	.272	.293	1
	Sig. (2-tailed)	.056	.039	
	N	50	50	50

Table 7. Correlation of NDBI, Population, and LST, 2021

2021		NDBI	Population	LST
NDBI	Pearson Correlation	1	.022	.770
	Sig. (2-tailed)		.878	.000
	N	50	50	50
Population	Pearson Correlation	.022	1	.126
	Sig. (2-tailed)	.878		.385
	N	50	50	50
LST	Pearson Correlation	.770	.126	1
	Sig. (2-tailed)	.000	.385	
	N	50	50	50

Between the two independent variables, namely NDBI and the number of residents, the r-value in the NDBI correlation is the highest in 2021 at 0.770, which means that NDBI and LST have a strong correlation. It results from the value being obtained being far from ideal. However, NDBI has a significantly stronger correlation to the influence of the LST compared with the value of r on the correlation of the number of populations to the LST. Meanwhile, the r-value between the number of populations and LST is weak because the results of the r-value ranged from 0.293 in 2016 to 0.126 in 2021.

Based on the mapping results, it is also obtained how the distribution of land built on LST. It is indicated by the area of built-up land that falls into Class V on the LST mapping also falling into Class V because it is suspected that materials from buildings can affect the value of surface temperature. Meanwhile, the influence of independent dependent variables is obtained from multiple linear analyses. The results of multiple linear analyses can be seen in Table 8, Table 9, and Table 10.

Table 8. Model Summary

Year	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
2016	.38	.151	.11	1.97
2021	.77	.604	.588	.828

Based on Table 8, the obtained correlation value for the independent variable, NDBI, and the number of populations with dependent variables was 0.38 in 2016 and 0.77 in 2021. In 2016, the correlation based on the classification determined by Sugiyono (2013) was included in the low category, while it was included in the strong category in 2021.

In 2016, the coefficient of determination was 0.11, or 11%. It means that the NDBI and the population account for 11% of LST, and the rest are influenced by other factors. Then, the coefficient of determination in 2021 is 0.58, or 58%, which means that the influence of NDBI and the number of populations on LST is 58%, and others are influenced by factors other than these two variables.

a. Predictors: (Constant), NDBI, population
b. Dependent Variables: Surface Temperature

Anova input results on Table 9 show that the F count in 2016 was 4,169 with a significance value of 0,022, while it has a f count value of 35,984 with a significance value of 0 in 2021. From these results, it can be concluded that there was a significant influence between NDBI and the number of populations with LST in 2016 and 2021 because the significance value was less than the alpha value of 0.005.

Based on the results of Table 10, the multiple linear regression equation in 2016 was y = 23.82 + X1 + 5,906 X2, while the multiple linear regression equation in 2021 was y = 29.12 + X1 + 10,479 X2. In research conducted by Satria et al. (2021), the regression equation conducted in his research between LST and Thermo Gun had a positive regression equation. It means that there is a directly proportional correlation between the measurement results and the processing results.

Then, the T-test can be compared with the p-value in the NDBI variable in 2016, which was 0.064, which means that the variable does not significantly affect the LST.

Table 9. Anova

Year	Model	Sum of Squares	df	Mean Square	F	Sig.
2016	1 Regression	32.589	2	16.295	4.169	.022
	Residual	183.706	47	3.909		
	Total	216.295	49			
2021	1 Regression	49.416	2	24.708	35.984	.000
	Residual	32.271	47	.687		
	Total	81.687	49			

Table 10. Coefficients

Year	Model	Unstandardized Coefficient		Standardied Coefficient	t	Sig.
		B	Std. Error	Beta		
2016	1 (Constant)	23.828	.733		35.521	.000
	Population	3.062E-5	.000	.277	2.057	.045
	NDBI	5.906	3.116	.255	1.896	.064
2021	1 (Constant)	29.124	.274		106.431	.000
	Population	6.285E-6	.000	.108	1.183	.243
	NDBI	10.479	1.252	.768	8.372	.000

Meanwhile, the variable population was 0.045, which means that it significantly affects the LST. Similarly, the p-value in the NDBI variable in 2021 was 0.000. The variable population was 0.243. It shows that in 2021 the NDBI variable has a significant influence on the LST. Meanwhile, the variable population had no significant influence on the LST.

4 Conclusion

The South Jakarta area, with an increasing number of populations and an increasing area of built-up land, makes the city act as a metropolitan city where urbanization also occurs on a large scale. The surface temperature of South Jakarta as a city was found to be affected by the growth in population. The complaining attitude is synonymous with humans, who frequently lament the rising surface temperatures that are felt higher and higher each year. It occurred because the land was built based on NDBI values, and the number of people had a significant influence on the increase in surface temperature. The correlation coefficient for NDBI, which compares the amount of land developed in 2016 to 2021, has a higher value, ranging from 11% to 58% of surface temperature. Surface temperatures in South Jakarta experienced a significant change within five years due to a 47% increase.

The real UHI phenomenon occurs in South Jakarta, where the temperature in the city's urban center is higher than the temperature in the surrounding area, as evidenced by the influence of the built-up land distribution. The phenomenon occurs in the middle of the city due to the impact of population mobility, which is concentrated there.

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