Effect of Urban Sprawl on Temperature Distribution in Semarang

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Abstract. Several environmental and social impacts have emerged from the expansion of the industrial sector, including the high rate of urbanization, which has raised the population density and hence the demand for residential. The density of built-up land affects changes in surface temperature. The greater the urban sprawl, the higher the surface temperature will be. This research examined surface temperature distribution, the density of built-up land in 1999, 2009, and 2019, and the relationship between built-up land and rising surface temperatures. Landsat 5 TM and Landsat 8 OLI TIRS satellite images with remote sensing technology were utilized to map surface temperature distribution and built-up land. This study employed the Google Earth Engine (GEE) platform for temperature transformation and the NDBI, EBBI, BI, and UI transformations for the city propagation influence factors. This study discovered that in 1999, 2009, and 2019, there was a significant relationship between the density of built-up land and the rate at which Semarang's surface temperature changed. The average surface temperature in Semarang rose steadily from 9.1 to 35 °C in 1999 to 11.9 to 35.2 °C in 2009 and a whopping 15.89 to 41 °C in 2019. Correlation coefficients above 0.500 indicate a significant relationship between built-up land and surface temperature based on findings from all-year transformation results. Following the results of the coefficient of determination for each transformation, the impact of built-up land density on surface temperature in the Semarang area was 25% to 50% in 1999, 2009, and 2019.

Keywords: Urban sprawl · Temperature · Semarang Area

1 Introduction

A city is a legally recognized administrative division analogous to a district (Hidayati et al., 2018). A city is a large urban settlement with a complete set of public facilities and infrastructure. Cities serve as governmental centers, residential areas, service centers, economic growth centers, and social centers. Annual infrastructure development across all sectors is essential to addressing this issue. The construction of new facilities within a city, whether they be commercial or residential, is undertaken to enhance the economic and social well-being of its residents (Rahayu & Cahyono, 2021). There is a clear correlation between a city's degree of growth and the scale of its industrial sector,

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settlements, government buildings, shopping centers, and city tourism, among other aspects of urban life (Fauzia, 2019). The interplay between cities and villages, known as urbanization, leads to rapid settlement growth and, in turn, a substantial rise in population (Angin & Sunimbar, 2021).

The provincial capital of Central Java is located in Semarang, which is also one of the largest cities in Central Java. Semarang City is not only a provincial capital but also one of Indonesia's greatest metropolises; therefore, there is a great deal of activity there (Darlina et al., 2018). Semarang City, a major metropolitan in Indonesia, is home to nine industrial zones covering 1,029 ha (or 75% of the city) with a significant concentration of manufacturing and other types of high industry (Junaidi, 2015). The Investment and One-Stop Services Office of Central Java Province (DPMPTSP) in 2019 reported that 29 cross-sectoral industries, both Indonesian and foreign, were located in Semarang's different industrial areas. Because of the high demand for workers in the industrial sector, residential is in short supply in many places (Aprillia & Pigawati, 2018). As a result of urbanization, population density has been growing steadily over the past several years in Semarang; for example, the number of in-migrants was 20,159 in 2018 and increased to 20,267 in 2019 but decreased to 16,535 in 2020. A widespread pandemic is to blame for the rise in migration to 17,613 in 2020 (Dispendukcapil, 2022).

The development of Semarang City has impacted the economies and infrastructure of neighboring communities, including Semarang Regency and Salatiga City, known as hinterland areas. In the same way as the City of Semarang relies on its thriving industrial sector, so does Semarang Regency. In 2021, the Semarang Regency became home to 160 major and medium-sized businesses, including 41 in the garment and other sectors (BPS Kabupaten Semarang, 2022). Tengaran, Pringapus, Susukan, Kaliwungu, West Ungaran, East Ungaran, Bawen, and Bergas are only a few of the sub-districts where industrial areas have been planned following Neighbourhood/Community Association (RT/RW) directions from Semarang Regency for 2011 to 2031.

Salatiga City, the other hinterland area of Semarang, is conveniently placed between Surakarta and Semarang Cities, leading to an uptick in infrastructure development. In contrast to Semarang Regency, which relies on its dominant sector—industry—Saltiga City feels the effect of urban sprawl from both Surakarta and Semarang Cities (Khasanah & Widi Astuti, 2020). Because the spread of urban sprawl necessitates the clearing of non-built-up land, particularly on the city's outskirts, into built-up land, the demand for residential and settlement development has expanded in Salatiga (Apriani & Asnawi, 2015). High population growth contributes to urban sprawl, and the high rate of urbanization in Semarang is reflected in the city's bustling atmosphere (Darlina et al., 2018). An ever-increasing population density in Salatiga City is evidence of this trend since the development of the city affects the number of settlements (Pigawati & Rudiarto, 2011). In 2020, the population density of Salatiga was 3,283 people/km^2; in 2021, it rose to 3,520. Salatiga's development has affected not only its residential neighborhoods but also its municipal institutions and physical infrastructure.

One way in which the development of Semarang and its surrounding hinterland area, including Semarang Regency and Salatiga City, might disrupt the delicate environmental balance of the area is by raising local temperatures (Handayani et al., 2017). Rising surface temperatures in Semarang and its suburbs are exacerbated by the city's rapid urbanization and the accompanying reduction of green spaces and flora. Temperatures in Semarang City hit 38.5 °C on October 18, 2022, and 39.4 °C on October 22, 2019, both records (BKMG, 2021). Similar annual surface temperature increases are noticed in the Semarang Regency and Salatiga City due to land conversion. The air and environment will suffer as a direct result of this.

Learning about the surface temperature and how it fluctuates is crucial. This factor must be considered while assessing regional growth to decide which parts of a region are most suited for the industrial sector. High-temperature values generally occur at points of built-up land such as settlements and industry (Ramdhan et al., 2021). Increasing annual temperature could be traced back to Semarang City, Salatiga City, and Semarang Regency. To determine how much the average surface temperature has increased during a certain period, it is necessary to have a temporal understanding of the phenomena of rising temperature, which might be understood in terms of years. Spatial investigations utilizing remote sensing can help pinpoint these issues (Reddy et al., 2017). It is essential to conduct geographical research on the issue of how the height of the built-up area of Semarang City, Semarang Regency, and Salatiga City influences the surface temperature. One way to accomplish it is through the use of remote sensing technology.

Data benefits in synoptic views and temporal coverage over real-time data acquisition are provided by remote sensing technology (Hegazy & Kaloop, 2015). Studies of land cover and land use mapping, including building density, frequently employ remote sensing with optical sensors (Fikriyah, 2020). Cloud-based processing using Google Earth Engine (GEE) has become a millennial favorite remote sensing technique. Remote sensing with GEE is a cloud-based platform with high computing power and low hardware storage requirements (Gorelick et al., 2017). There are benefits to using the GEE platform over other methods. One of them is the ease with which data can be processed, even at enormous capacities, without the need to download data; instead, it is sufficient to create scripts in Javascript and Python in the browser being used (Nur Wachid & Wido Prananing Tyas, 2022). Extensive studies have been conducted to determine the relationship between Land Surface Temperature (LST) and built-up in Medan City by remote sensing technique, such as the use of the Split Window Algorithm (SWA) with Landsat 8 imagery as the data (Syahputra et al., 2021). The selected Terra acquisition data were compared to further investigations employing the higher resolution thermal bands available in the Landsat 8 data (Hadibasyir et al., 2020). A further examination utilized a remote sensing technique to map out the temperature distribution of land surfaces along Surabaya's northern shore utilizing the GEE platform and a series of contemporary images (Prayogo, 2021). Since the GEE technique is underutilized, its benefits and drawbacks are not well-known. It highlights the critical need to upgrade to a cloud-based remote sensing technique.

Knowing the rise in surface temperature over the past decade is crucial because it can be correlated with the availability of built-up land in the region, which is especially true in Semarang City, Semarang Regency, and Salatiga City, all of which have a relatively high percentage of built-up land. Landsat 4 and 5 TM imagery and Landsat 8 OLI TIRS imagery were utilized on the GEE platform to process temperature distribution mapping because they could provide constant information to demonstrate the distribution of temperature changes and represent temperature classification (Sejati et al., 2019). This research aims to analyze the temperature distribution and urban sprawl in 1999, 2009, and 2019 and the relationship between city propagation and temperature rise with the transformation parameters of NDBI, EBBI, BI, and UI. This study might serve as a useful resource for evaluation and reference for regional development planning, particularly in built-up land areas.

2 Methods

Central Java Province was the focus of this study, specifically the Cities of Semarang and Salatiga, as well as the Semarang Regency. Semarang City had an area of 373.70 km^2, Salatiga City covers 56.78 km^2, and Semarang Regency spans 950.21 km^2, according to BPS statistics for Central Java Province for 2022. This investigation underwent several steps.

2.1 Pre-processing

Tools and Materials

1. Computer/Laptop
2. ENVI 5.3 Software, ArcMap 10.8, Microsoft Excel, and SPSS 16
3. Landsat 5 TM images
4. Landsat 8 OLI/TIRS images

Data Collection
Landsat 5 TM image data from September 6, 1999, and July 31, 2009, and Landsat 8 OLI/TIRS image data from June 25, 2019, have all been geometrically corrected, as indicated by the code L1TP in the image data. Figure 1 displays the metadata of each image.

Clipping Area
The clipping area was intended to cut the image following the study area, making data processing quicker and more accurate by reducing the probability of errors caused by the large region.

```
GROUND_CONTROL_POINTS_VERSION = 5
GROUND_CONTROL_POINTS_MODEL = 809
GEOMETRIC_RMSE_MODEL = 5.297
GEOMETRIC_RMSE_MODEL_Y = 3.880
GEOMETRIC_RMSE_MODEL_X = 3.606
GROUND_CONTROL_POINTS_VERIFY = 108
GEOMETRIC_RMSE_VERIFY = 3.273
```

Fig. 1. Landsat imagery geometric correction metadata

2.2 Processing

GEE platform processing, ENVI 5.3 software on ArcMap 10.8, and Microsoft Excel and SPSS 16 regression testing were the three phases of the image-processing workflow. In ENVI, data processing involved layer stacking of seven bands over each image before cutting off the study area. The ENVI software also performed several other processes.

DN to Radiance

Initial Landsat 5 TM image adjustment was performed using the following formula.

$$\mathrm{L}'_{\lambda} = \mathrm{M_L Q_{cal}} + \mathrm{A_L} \tag{1}$$

Description:

L_{λ}' : ToA Spectral Radiance
Mp : Radiance_Mult_Band_x, with x as the band number
A_L : Radiance_Add_Band_x, with x as the band number
Qcal : Digital Number Value (DN)

Radiometric Correction

A radiometric correction is a method to eliminate or reduce radiometric inaccuracies in pixel values, with atmospheric disturbances being the major source of error (Sitorus et al., 2019). The equation for the radiometric correction is as follows.

$$\rho\lambda' = \mathrm{M}\rho\mathrm{Qcal} + \mathrm{A}\rho \tag{2}$$

Description:

$\rho\lambda$' : ToA reflectance, without sun angle correction
Mp : Reflectance_Mult_Band_x, with x as the band number
Ap : Reflectance_Add_Band_x, with x as the band number
Qcal : Digital Number Value (DN)

The equation for the radiometric correction (ToA) of the sun angle is as follows.

$$\mathrm{P}\lambda = \rho\lambda' \big/ (\cos(\theta \mathrm{SZ})) = \rho\lambda' \big/ (\mathrm{Sin}(\theta \mathrm{SE})) \tag{3}$$

Description:

$P\lambda$: ToA reflectance
$\rho\lambda$' : ToA reflectance, without sun angle correction
θSE : Sun elevation
θSZ : Solar zenith angle, $\theta SZ = 90°$ - θSE

Atmospheric Correction

To facilitate object recognition and interpretation, an atmospheric correction was conducted to improve the image's clarity (Giofandi et al., 2020). This atmospheric correction employed the tools provided by the ENVI software, called the Dark Object Subtraction (DOS) method.

Image Transformation

Image transformation is a way to take advantage of previously unavailable data. This study's parameters regarding the impact of image transformation on temperature rise are as follows.

Temperature

Surface energy, the atmosphere, the thermal properties of the surface, and the subsurface media all work together to maintain a steady temperature (Yatimas Murni et al., 2021). To ascertain the temperature distribution in the research area, Landsat 5 TM and Landsat 8 OLI TIRS images were filtered using the GEE.

The most crucial phase in determining the temperature distribution with the GEE platform, as detailed by (Roy & Bari, 2022), is the provision of a script utilized for the following.

a. Performing radiometric correction (DN to Radiance) on each Landsat 5 TM and Landsat 8 OLI TIRS imagery

Calculating the NDVI index or vegetation availability with the equation (NIR - RED)/(NIR + RED), as well as the Pv value with the transformation of NDVI.

$$Pv = \frac{NDVI - NDVImin}{NDVI - NDVImin} \tag{4}$$

b. Calculating temperature in Kelvin using the transformation of

$$T_B = \frac{K2}{lnln\left(\frac{K1}{L\lambda} + 1\right)} \tag{5}$$

Description:

T_B : Radiant temperature in Kelvin
$L\lambda$: ToA spectral radiance
K1 : K1_Constant_Band_x, where x is the thermal band number
K2 : K2_Constant_Band_x, where x is the thermal band number

c. Converting temperature in radian or Kelvin into Celsius with the following formula T_C: T_B – 273.15

On the GEE platform, converting radian or Kelvin temperature values to Celsius could be codified (script). The following are the mapping transformation implemented by the GEE platform:

Return img.expression ('((1321.08/(log(774.89/((TIR*0.0003342)+0.1)+1)))-273.15)', {'TIR':img})

Normalized Difference Built-Up Index (NDBI)

NDBI is a transformation to analyze urban areas by taking advantage of both the short-wave infrared (SWIR) and near-infrared (NIR) bands of an image, assuming that built-up land and vacant areas reflect a lot of SWIR waves, making the image appear bright. At the same time, bodies of water tend to absorb a lot of NIR waves, making the image appear dark. The following is the NDBI transformation equation.

$$NDBI = \frac{(SWIR_1 - NIR)}{(SWIR_1 + NIR)} \tag{6}$$

NDBI values vary from -1 to 1. The closer the value to 1, the higher the density of buildings in that location (Gascon et al., 2016). Since the NDBI is highly sensitive to built-up and open land phenomena, it became the standard for measuring urbanization density (Hidayati et al., 2018).

Enhanced Built-Up and Bareness Index (EBBI)

Compared to other measures, the EBBI excels in mapping vacant land. However, this index has the limitation of not being able to depict highly populated places (Prakoso et al., 2018). The following is the formula for the transformation algorithm from the EBBI.

$$EBBI = \frac{SWIR_1 - NIR}{10\sqrt{(SWIR_1 + TIRS_1)}} \tag{7}$$

EBBI has a root function beneficial to classify and differentiate identical objects following the reflection of different values ranging from -1 to 1 (As-syakur et al., 2012).

Urban Index (UI)

The UI method can differentiate between built-up and non-built-up areas by assigning a score between -1 and 1, with values closer to 1 indicating densely built-up areas (Sitorus et al., 2019). The following is the UI transformation formula.

$$UI = \frac{(SWIR_2 - NIR)}{(SWIR_2 + NIR)} \tag{8}$$

Built-up land objects will look brighter, and plant objects will appear darker due to the differences in spectrum reflection between dry soil and vegetation captured by the SWIR2 and NIR channels (Sukrisyanti, 2007).

Bare Soil Index (BSI)

Assuming that the vegetation index is less accurate when the plant cover is less than 50%, the BSI/BI is an analytical tool employed in such a situation. The range of BI values is 0 to 200 (Januar et al., 2016). The following equation describes this transformation.

$$BI = \frac{(SWIR_1 + RED) - (NIR + BLUE)}{(SWIR_1 + RED) + (NIR + BLUE)} \times 100 + 100 \tag{9}$$

Higher BSI values indicate open land or non-vegetative objects with a brighter mosaic appearance, whereas lower BSI values, or those closer to 0, represent an area with vegetation (Sitorus et al., 2019).

2.3 Classification and Sampling

After all transformations had been accomplished, the following phases were reclassification, map creation, and random sampling of each transformation using ArcMap 10.8 software. Data were collected using ArcMap 10.8 and stratified random sampling. This sampling technique has become the procedure for each predetermined classification class (Ulya et al., 2018). ArcMap's Create Random Sampling was employed to select 10 sample points randomly for each temperature class, after which the appropriate values were extracted for the NDBI, EBBI, BI, and UI indices using the Extract Value tool.

2.4 Regression Test

This linear regression test was conducted using SPSS 16 and Microsoft Excel to unveil the correlation and percentage relationship between variable X (NDBI, UI, BI, and EBBI) and variable Y (temperature). The variable linkage model and coefficient of determination will display the outcomes of the linear regression test (R2).

2.5 Data Analysis

Maps, range values for each transformation, correlation tests, and regressions were all part of the analysis of processing results at this step. Three paired data were analyzed for differences using spatial analysis to describe the local environment around Semarang. Temperature from 1999, 2009, and 2019 was employed in the testing, with a building density representing urban sprawl.

3 Results and Discussion

Increased population leads to many side effects, including urban sprawl, which boosts the level of built-up land in a region (Putra W. et al., 2022). Since Semarang City follows an urban sprawl structure that naturally produces suburbs, growth in those regions has been evenly distributed. This condition is similar to a study comparing the air temperature in urban and suburban areas, unveiling a 4.325% and 10.062% rise in population density in 2013 and 2017 (Darlina et al., 2018). It transformed the surface temperature distribution to be more uniformly spread out to the city's periphery. The Regencies of Semarang, Demak, Kendal, and Grobogan were just a few neighboring regions witnessing the city's development due to urban sprawl emanating from Semarang, Indonesia's Mega Urban City (Mujiandari, 2014). This situation is pertinent to the findings of this study, representing the growth of the built-up area associated with a certain temperature distribution pattern or urban propagation circumstances.

3.1 Distribution of Temperature in Semarang in 1999, 2009 and 2009

Semarang covers, among others, Semarang City, Semarang Regency, and Salatiga City. Semarang, also known as the Capital City of Central Java Province, has developed rapidly in recent decades to become a major economic and industrial center or metropolitan.

Figure 2 displays the 2022 Semarang Administration Map, outlining the jurisdictional boundaries of the region. The City of Semarang is divided into 16 districts, the Regency of Semarang into 19, and the City of Salatiga into four sub-districts, all located within the Semarang Regency.

Semarang Regency and Salatiga City, for example, have felt significant effects from the rapid development. The City of Semarang, serving as a development corridor in Central Java, is at the island's economic crossroads, with access to districts and cities in all directions (the north, south, east, and west coast corridors).

One of the criteria for built-up land is industrial and residential development density. Asphalt and concrete roads are instances of additional built-up land parameters (Rumihin et al., 2015), and they could be encountered in both manufacturing zones and district or city infrastructure. A growing number of people living and working close to one another and a growth in the number of roads, bridges, and other artificial structures could have serious environmental consequences. The average annual increase in surface

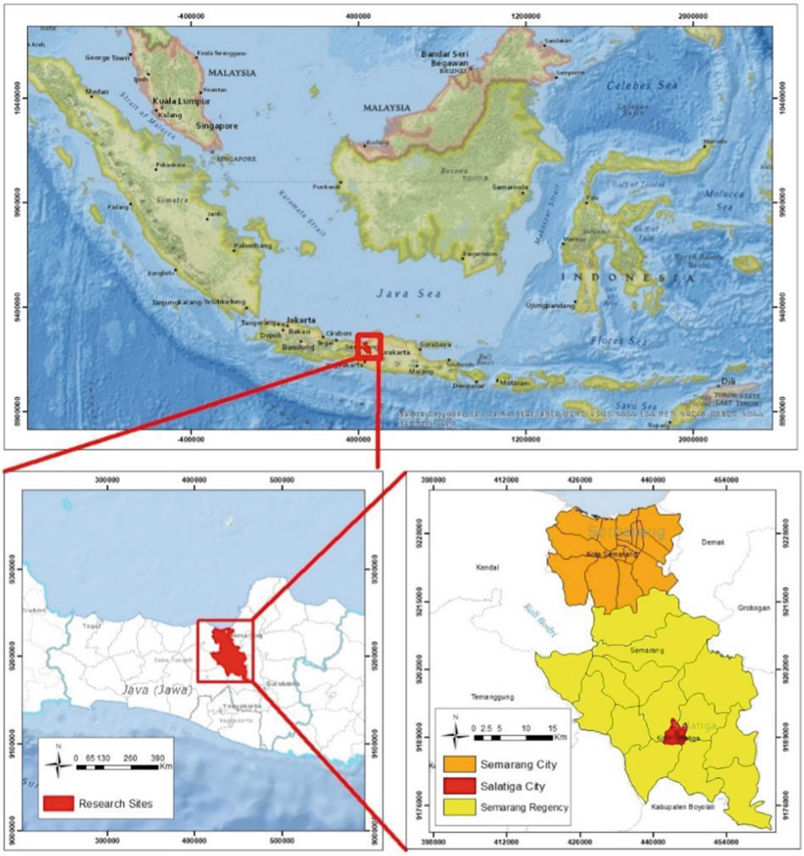


Fig. 2. Semarang administration map for 2022

temperature in Semarang was particularly pronounced. Figure 3 illustrates the pattern of Semarang's temperature increase over the past 20 years, from 1999 to 2009 and 2019.

Figure 3 displays the temperature distribution pattern in Semarang during the past decade. Minimum and maximum surface temperature limits for each of the three time periods (1999, 2009, 2019) were separated into five classifications. The year 1999 saw Semarang's temperature range from a low of 9.1 °C to a high of 35 °C. Semarang saw its largest temperature increase in the recent decade in 2009, when the lowest temperature was 11 °C, and the maximum temperature was 35.2 °C. Figure 2, however, reveals that the green area, representing the coolest surface temperature, shrank and was replaced by the yellow area, signifying a moderate surface temperature. Due to the city's massive development in recent years, Semarang today experienced a year-round temperature ranging from a chilly 15.89 °C to a scorching 41 °C. A similar condition was confirmed in research where Semarang City experienced a high surface temperature of 40.38 °C on October 15, 2019 (Insan & Prasetya, 2021).

Semarang City and the western half of Semarang Regency exhibit the greatest temperature increase (Fig. 4). Figure 3 is a graph depicting the temperature distribution in Semarang from 1999 to 2019, revealing the dynamics of changes in the area based on temperature classification. Area distribution for each temperature class was calculated

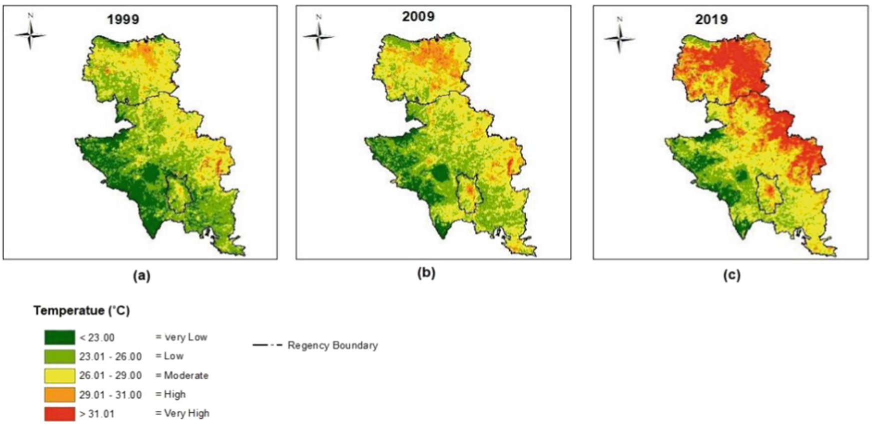


Fig. 3. Temperature map of Semarang in 1999, 2009, and 2019

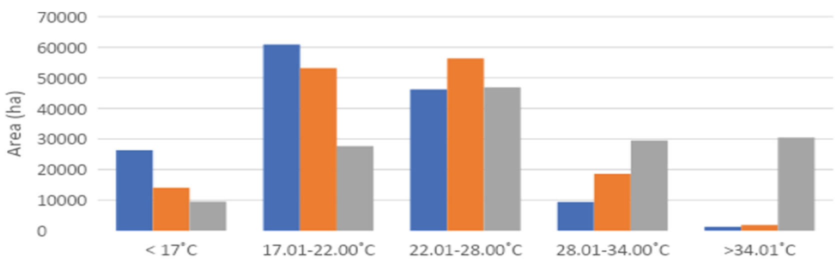


Fig. 4. Graph of temperature distribution in Semarang based on area in 1999–2019

using pixel temperature; for example, in 1999, the area under the lowest temperature class (<23 °C) was 26,307.16 ha. In 2009 it was 14,047.21 ha, and in 2019 it was 9,527.01 ha. High class (29.01–31.00 °C) and extremely high class (>31.01 °C) surface temperature distributions were inversely related to these stipulations. Figure 4 demonstrates that the graph has expanded with time, with the blue region representing 1999, the orange area reflecting 2009, and the gray area signifying 2019. High and extremely high-temperature class areas increased by 9,821.33 ha between 1999 and 2009, then again between 2009 and the present, for a total of 39,475.31 ha. One reason for this issue was converting green open land to built-up land (Walad & Purwaningsih, 2019). Given the preceding, it is crucial to understand Semarang's construction density in 1999, 2009, and 2019. This information is directly tied to the availability of green land for temperature balance.

3.2 Analyzing Changes in Density of Built-Up Land of NDBI, BI, UI, EBBI in Semarang in 1999, 2009 and 2009

Building Density Analysis using the Normalized Difference built-up Index (NDBI) One factor influencing temperature increase was the density of built-up. Table 1 highlights the dramatic rise in Semarang's built-up land density from 1999 to 2019. The classification of the built-up land density index was split into five groups (Trinufi & Rahayu, 2020): non-built-up (-1–0), low (0–0.1), moderate (0.1–0.2), high (0.2–0.3), and extremely high (0.3–1). Following are the processing results of the NDBI for 1999, 2009, and 2019.

Table 1 exhibits the NDBI transformation results in Semarang. The average NDBI value in Semarang grew by 0.0828 between 1999 and 2019, indicating an increase in the density of built-up land. A rise in the density of built-up land is depicted by a pattern in which the spread of average values produced by the NDBI transformation widens with time (Zulkarnain, 2016).

From 1999 on, as depicted in Fig. 5, most of Semarang's built-up land density was yellow, signifying a moderate building density. However, many red dots with an extremely high built-up density index could be detected within Semarang. Semarang City, an industrial center, and numerous places in Salatiga City and Semarang Regency also had increases in built-up land density in 2009. The density of built-up in Semarang increased dramatically in 2019 compared to prior years. Figure 5 depicts the red color

Table 1. NDBI transformation results in Semarang

Years	NDBI Value Range		StdDev	Average
	Minimum	Maximum		
1999	-1	0.6881	0.1589	-0.1753
2009	-1	1	0.1456	-0.1431
2019	-1	1	0.1354	-0.1160

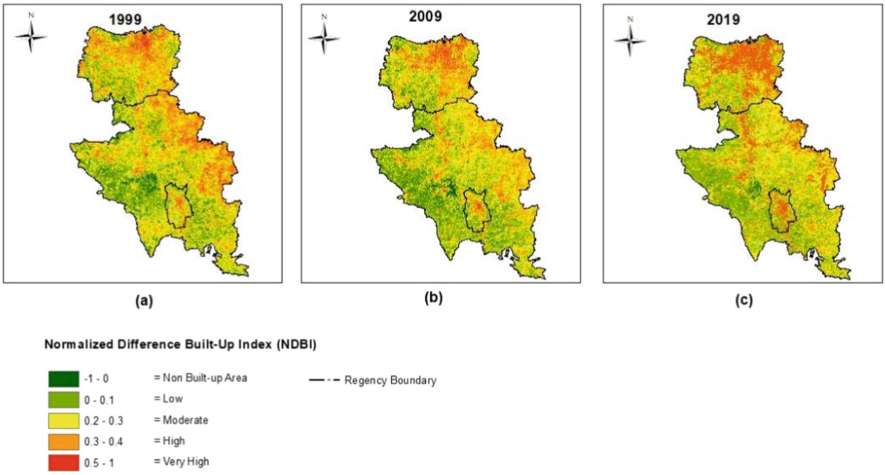


Fig. 5. Normalized difference built-up index (NDBI) map of Semarang

with an extremely high building density index that began to expand. In contrast, the non-built-up land index decreased compared to 1999 and 2009.

Building Density Analysis Using Enhanced built-up and Bareness Index (EBBI)

It is believed that an EBBI transformation can map the distribution of built-up land and open land to an even greater degree than the NDBI index transformation can.

Table 2 displays the results of the EBBI transformation in Semarang, exhibiting a decreasing average value with time and an increasing upper bound on EBBI values. Figure 6 graphically illustrates this phenomenon by displaying how the red density of buildings became denser, particularly in the City of Semarang, indicating a rapid acceleration in the rate of change in land cover.

Figure 6 demonstrates that these EBBI results can be adapted to produce maps of built-up land, open land, and non-built land. While the results of the NDBI transformation indicated that the red visual color classification of built-up land would rise, notably in Semarang Regency, the opposite has been true. Semarang and Salatiga Cities depicted rapid increases in their built-up land areas due to the NDBI transformation. Similar findings were discovered by previous research that the results of the EBBI transformation in Semarang City from 2013, 2015, and 2017 exhibited a rise and decreased vacant land

Table 2. EBBI transformation results in Semarang

Years	EBBI Value Range		StdDev	Average
	Minimum	Maximum		
1999	-0.084	0.1034	0.0138	-0.10534
2009	-0.113	0.1534	0.0163	-0.1515
2019	-0.108	0.0218	0.0218	-0.0229

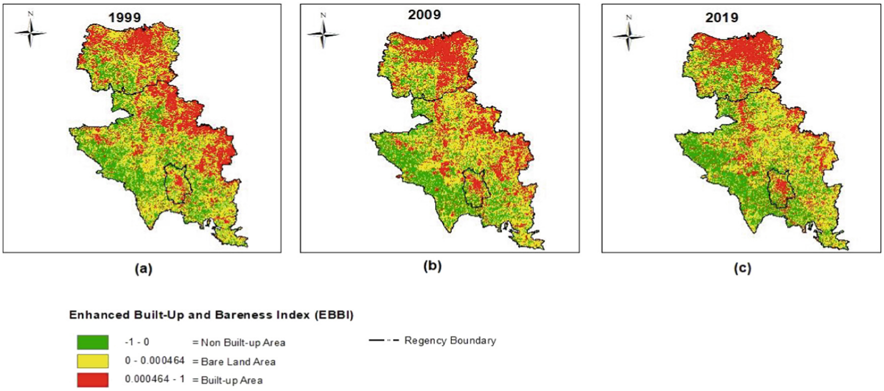


Fig. 6. EBBI map of Semarang

area (Prakoso et al., 2018). However, despite a decline in the yellow vacant land index, the extent of built-up land has decreased at certain sites due to the transformation in this research, including in Semarang Regency.

Building Density Analysis using Bare Soil Index (BSI/BI)

According to a previous study (Sitorus et al., 2019), the BSI/BI class is divided as follows: $0 < BI < 200$, where a BI value closer to 200 indicates an area of built-up land with visual colors ranging from yellow to red, and an index value closer to 0 indicates a vegetation area with a green visual color. The BSI value for Semarang was transformed from 1999 to 2009 to 2019, and the resulting values were higher in 2019 than in 1999 or 2009. Table 3 displays the range of BSI values for Semarang and demonstrates that in 2009 the lowest and maximum BSI values were greater than in 1999. However, in 2019 the minimum BSI results were higher than the 2009 data, despite the maximum BSI values being lower than in 2009.

The rate at which land was converted from vegetation to vacant land or built-up land increased as the BSI's minimal threshold value rose. It is supported by the fact that the maximum value was raised between 1999 and 2009.

Figure 7 depicts a color scale from yellow to red for vacant and built-up land and from dark green to light green for open land and vegetation. Figure 7's visual results reveal an annual transition from green to yellow, indicating a shift in land use. Similarly, the

Table 3. Range of BSI values in Semarang

Years	BSI Value Range	
	Minimum	Maximum
1999	31.62	132.58
2009	43.40	156.60
2019	45.10	143.73

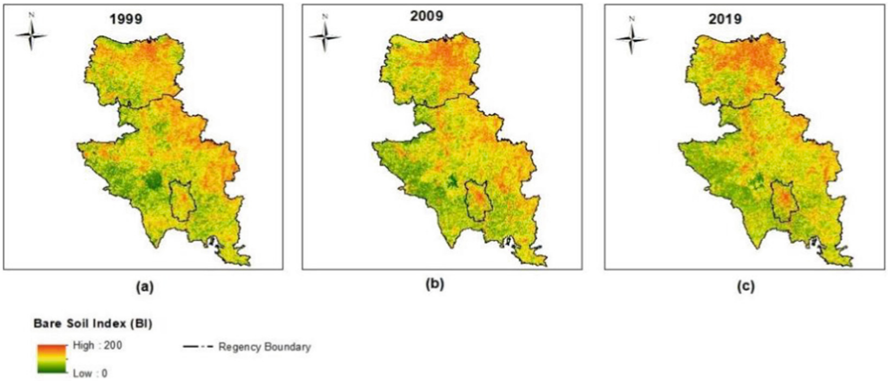


Fig. 7. BSI map of Semarang

area of built-up land with a red color index has increased. The BSI results in Semarang are displayed in Fig. 7. This BSI index has qualities more sensitive when discriminating green open land or vegetation from non-vegetation. Therefore, it is simpler to discern between built-up and open land (Januar et al., 2016).

Building Density Analysis Using Urban Index (UI)

Areas of built-up land and non-built-up land can be calculated using the UI transformation. Table 4 displays the enlarged minimum and maximum limit values that resulted from transforming Semarang's UI in 1999, 2009, and 2019.

Table 4 demonstrates that the maximum and average values of the UI have risen between 1999, 2009, and 2019. It exhibits a rise in Semarang's built-up area. According to the research (Melati et al., 2020), the closer to the value 1 in the UI classification range signifies a higher density of built-up land in an area.

Figure 8 portrays the UI visual results depicting the development of built-up land growing in tandem with the average result of the UI value transformation. The visual results of the UI transformation revealed the high, low, and moderate density of built-up areas with gradations of yellow to red colors. At the same time, densely vegetated regions below the value 0 were visualized with dark green gradations. It was since a high index of built-up land in the image made it appear brighter, and this correlation between the presence of green open space and the UI method for built-up land made it easier to spot. Vegetational cover began to thin out in 2017, and by 2018, the built-up

Table 4. UI Transformation Results

Years	UI Value Range		StdDev	Average
	Minimum	Maximum		
1999	-1	0.684	0.219	-0.41
2009	-1	1	0.201	-0.38
2019	-1	1	0.187	-0.31

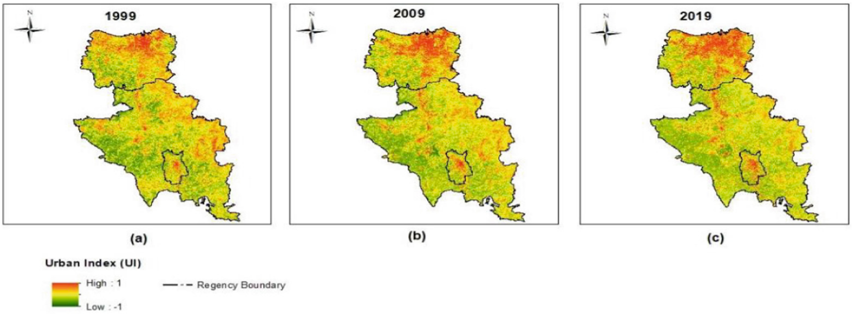


Fig. 8. UI map of Semarang

land cover had expanded to cover more area than any other land cover type. Accordingly, growing populations directly impacted urban sprawl (Darlina et al., 2018).

3.3 Analysis of the Effect of Density of built-up Land on Increasing Surface Temperature

Relationship between Temperature and Building Density (NDBI, EBBI, BI, and UI) in 1999

Extraction of the values of the four building density indices (NDBI, EBBI, BI, and UI) and the temperature value of each classification, i.e., as many as 50 sample points, was employed to determine the relationship between temperature and building density. A total of 50 sample points were utilized to unveil the relationship between temperature and the four building density indices (NDBI, EBBI, BI, and UI).

Table 5 displays the relationship between variables X and Y in 1999 and the relationship between temperature and the index transformation results. The high density of built-up land contributed significantly to the rise in surface temperature in 1999. The results of the relationship between the four indicators suggested a significant association with the temperature surface. The high coefficient of determination over 45% to 52% implies that building density significantly impacted Semarang's temperature rise.

Figure 9 demonstrates a linear relationship between the rise in surface temperature and the density of built-up land in Semarang in 1999. It implies that the higher the density

Table 5. Correlation and Regression of Temperature and Building Density (NDBI, EBBI, BI, and UI) in 1999

Transformation	Correlation (R)	(R^2)	Coefficient of Determination
NDBI	0.670 (strong)	0.449	45%
EBBI	0.675 (strong)	0.456	46%
BI	0.719 (strong)	0.517	52%
UI	0.683 (strong)	0.466	47%

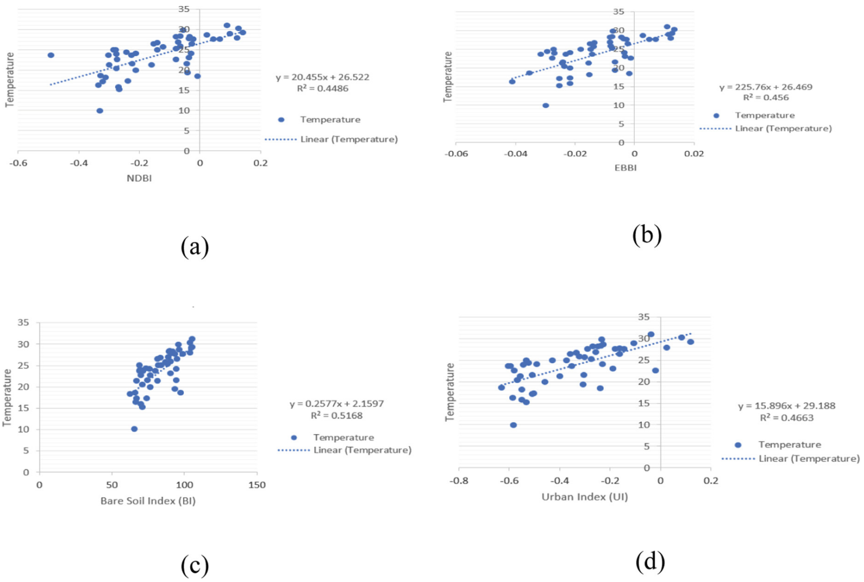


Fig. 9. Relationship graphs of temperature and building density in 1999 with (A) NDBI, (b) EBBI, (c) BI/BSI, and (d) UI

of buildings in Semarang, the larger the increase in surface temperature. However, the value of open green land or vegetation has the opposite effect on temperature: the higher the value of green open land, the lower the temperature.

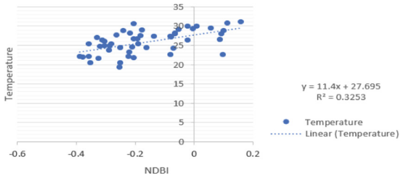
Relationship between Land Surface Temperature (LST) and Building Density (NDBI, EBBI, BI, and UI) in 2009

Table 6 displays a correlation and regression analysis findings between temperature and Semarang's built-up land density. Although the percentage coefficient of determination has reduced, the results of the correlation or association between built-up density and temperature of all strong indicators are still significant.

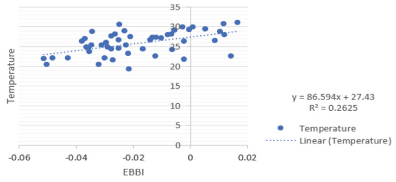
In 2009, the density of buildings had a 25%-34% impact on the temperature in Semarang. Several other elements affected the temperature average, which was not a concern even though the building density level increased higher than in 1999.

Table 6. Correlation and regression of temperature and building density (NDBI, EBBI, BI, and UI) in 2009

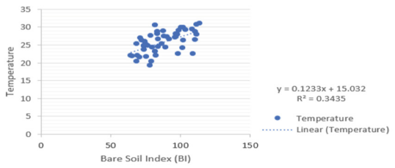
Transformation	Correlation (R)	(R^2)	Coefficient of Determination
NDBI	0.570 (strong)	0.325	32%
EBBI	0.512 (strong)	0.263	26%
BI	0.589 (strong)	0.344	34%
UI	0.500 (strong)	0.250	25%



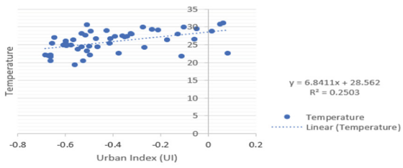
(a)



(b)



(c)



(d)

Fig. 10. Relationship graphs of lst and building density in 2009 with (a) NDBI, (b) EBBI, (c) BI/BSI, and (d) UI

The relationship between rising temperature and urban sprawl, represented by built-up land, is illustrated by the equation and linear line depicted in Fig. 10. This line is precisely proportionate to the influence of the density of built-up land in 1999.

Relationship between LST and Building Density (NDBI, EBBI, BI, and UI) in 2009

Table 7 displays that the correlation results of all indices still had a strong relationship with the coefficient of determination or the percentage effect of building density on the temperature of Semarang in 2019, ranging from 29% to 42%. This figure is quite high in the influence of rising surface temperatures, particularly in industrial areas like Semarang City.

Figure 11 exhibits the findings of the correlation and regression in 1999 and 2009, revealing that building density was directly or linearly related to temperature in Semarang in 2019.

Table 7. Correlation and regression of temperature and building density index (NDBI, EBBI, BI, and UI) in 2019

Transformation	Correlation (R)	(R^2)	Coefficient of Determination
NDBI	0.628 (strong)	0.395	40%
EBBI	0.646 (strong)	0.418	42%
BI	0.540 (strong)	0.291	29%
UI	0.629 (strong)	0.396	40%

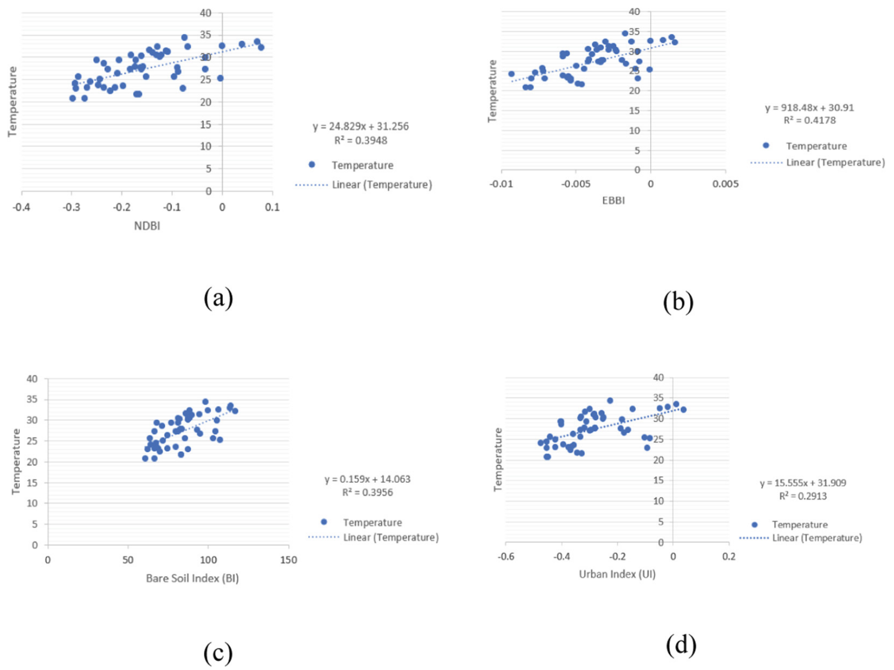


Fig. 11. Relationship graph of LST and building density in 2019 with (a) NDBI, (b) EBBI, (c) BI/BSI, and (d) UI

The density of built-up land was one of several variables affecting the local temperature. Faster development in the region's industrial and residential sectors was highly correlated with greater surface temperature. Several indices, including the Split Window Algorithm (SWA) formula, could be employed to visualize the distribution of built-up land. Each has its benefits and drawbacks depending on the channel adopted. To evaluate the success of the transformation, it is necessary to compare the correlation results of LST and building density with more than one indicator (Ardiansyah et al., 2019). The Semarang regional administration can utilize this research as an evaluation and a reference in regional planning to determine how much of an effect the density of built-up land has on temperature over a given period.

4 Conclusions

Semarang had a considerable rise in surface temperature in 1999, 2009, and 2019, with each year separated into five categories based on the degree of the rise. The distribution of urban sprawl was determined using several index transformations, encompassing the Normalized Difference Built-Up Index (NDBI), the Enhanced Built-up and Bareness Index (EBBI), the Bare Soil Index (BI/BSI), and the Urban Index (UI). The average, as well as the lowest and maximum values, were all on the rise as a result of NDBI, BI, and UI transformation. While the vacant land index has fallen, the built-up land index has declined at several pixel sites in this research. The favorable outcomes of the regression and correlation analyses support this. Limitations in this study provide opportunities for future research; for example, transformation features associated with vegetation density in this case, the Normalize Difference Vegetation Index (NDVI) into spatial LST mapping of urban sprawl might boost its accuracy and balance. The study focused on the spread of urban areas and ignored the role that vegetation density had in the environment.

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References

Angin, I. S., & Sunimbar. (2021). analisis perubahan penggunaan lahan Kota Kupang Nusa Tenggara Timur tahun 2010-2018 (Studi Kasus di Kecamatan Kelapa Lima, Oebobo, dan Kota Lama). *Jurnal Geoedusains*, *2*(1), 36–52.

Apriani, V. I., & Asnawi. (2015). Tipologi tingkat urban sprawl di Kota Semarang bagian selatan. *Jurnal Teknik PWK*, *4*(3), 405–416.

Aprillia, Y., & Pigawati, B. (2018). Urban sprawl typology in Semarang City. *Forum Geografi*, *32*(2), 131–145. https://doi.org/10.23917/forgeo.v32i2.6369

Ardiansyah., et al. (2019). Percent of building density (PBD) of urban environment: A multi-index Approach Based Study in DKI Jakarta Province. *Indonesian Journal of Geography*, *50*(2), 154–161. https://doi.org/10.22146/ijg.36113

As-syakur, A. R., et al. (2012). Enhanced built-UP and bareness index (EBBI) for mapping built-UP and bare land in an urban area. *Remote Sensing*, *4*(10), 2957–2970. https://doi.org/10.3390/rs4102957

Kabupaten Semarang, 2022. Kabupaten Semarang Dalam Angka 2022. Kabupaten Semarang: Badan Pusat Statistik

BMKG. 2021. Pusat Informasi Perubahan Iklim. Badan Meteorologi Klimatologi dan Geofisika. https://www.bmkg.go.id/iklim/buletin-iklim.bmkg. Diakses pada 27 November 2022

Darlina, S. P., Sasmito, B., & Yuwono, B. D. (2018). Analisis fenomena urban heat island serta mitigasinya. *Jurnal Geodesi Undip*, *7*, 109–119.

Dinas Kependudukan Dan Pencatatan Sipil Kota Semarang, 2022. Jumlah Migrasi Penduduk Masuk. Kota Semarang: dispendukcapil

Fauzia, S. (2019). Analisis urban heat island (Pulau Bahang Perkotaan) di Kota Bekasi menggunakan Citra Landsat *8*. 1–23.

Fikriyah, V. N. (2020). Mapping land cover based on time series Synthetic Aperture Radar (SAR) data in Klaten, Indonesia. *Jurnal Geografi Lingkungan Tropik*, *3*(2), 12–21. https://doi.org/10.7454/jglitrop.v3i2.67

Gascon, M., et al. (2016). Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry and Urban Greening*, *19*, 88–94. https://doi.org/10.1016/j.ufug.2016.07.001

Giofandi, E. A., Safitri, Y., & Eduardi, A. (2020). Deteksi keberadaan ekosistem padang lamun dan terumbu karang menggunakan algoritma lyzenga serta kemampuan menyimpan karbon di Pulau Kudingarenglompo. *Jurnal Kelautan: Indonesian Journal of Marine Science and Technology*, *12*(2), 165–174. https://doi.org/10.21107/jk.v12i2.5803

Gorelick, N., et al. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*(2016), 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hadibasyir, H. Z., Rijal, S. S., & Sari, D. R. (2020). Comparison of land surface temperature during and before the emergence of covid-19 using modis imagery in Wuhan City, China. *Forum Geografi*, *34*(1), 1–15. https://doi.org/10.23917/forgeo.v34i1.10862

Handayani, M. N., Sasmito, B., & Putra, A. (2017). Jurnal Geodesi Undip Oktober 2017 Jurnal Geodesi Undip Oktober 2017. *Jurnal Geodesi Undip*, *6*(4), 208–218.

Hegazy, I. R., & Kaloop, M. R. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. *International Journal of Sustainable Built Environment*, *4*(1), 117–124. https://doi.org/10.1016/j.ijsbe.2015.02.005

Hidayati, I. N., Suharyadi, R., & Danoedoro, P. (2018). Kombinasi Indeks Citra untuk Analisis Lahan Terbangun dan Vegetasi Perkotaan. *Majalah Geografi Indonesia*, *32*(1), 24. https://doi.org/10.22146/mgi.31899

Insan, A. F. N., & Prasetya, F. V. A. S. (2021). Sebaran Land Surface Temperature Dan Indeks Vegetasi Di Wilayah Kota Semarang Pada Bulan Oktober 2019. *Buletin Poltanesa*, *22*(1), 45–52. https://doi.org/10.51967/tanesa.v22i1.471

Januar, D., Suprayogi, A., & Prasetyo, Y. (2016). Analisis penggunaan ndvi dan bsi untuk identifikasi tutupan lahan pada citra landsat 8 (Studi Kasus: Wilayah Kota Semarang, Jawa tengah). *Jurnal Geodesi Undip*, *5*(1), 135–144.

Junaidi, M. (2015). Pengembangan kawasan industri dalam memaksimalkan pendapatan asli daerah (Pad) di Kota Semarang suatu perspektif konsep pembangunan berkelanjutan. *Jurnal Dinamika Sosial Budaya*, *17*(1), 57. https://doi.org/10.26623/jdsb.v17i1.503

Khasanah, M., & Widi Astuti, D. (2020). Memahami urban sprawl: analisa perkembangan permukiman Kota Salatiga dengan digitasi arcgis. *Langkau Betang: Jurnal Arsitektur*, *7*(2), 151. https://doi.org/10.26418/lantang.v7i2.41869

Melati, F. S., Sukmono, A., & Bashit, N. (2020). Analisis pengaruh perubahan densifikasi bangunan terhadap fenomena urban heat island menggunakan algoritma urban index dengan citra landsat multitemporal. *Jurnal Geodesi Undip*, *9*(Sistem Informasi Geografis), 166–175.

Mujiandari, R. (2014). Perkembangan Urban Sprawl Kota Semarang pada Wilayah Kabupaten Demak Tahun 2001–2012. *Jurnal Wilayah Dan Lingkungan*, *2*(2), 129. https://doi.org/10.14710/jwl.2.2.129-142

Nur Wachid, & Wido Prananing Tyas. (2022). Analisis transformasi ndvi dan kaitannya dengan lst menggunakan platform berbasis cloud: Google Earth Engine . *Jurnal Planalogi*, *19*(1), 60–74. http://jurnal.unissula.ac.id/index.php/psa/article/view/20199/6864

Pigawati, B., & Rudiarto, I. (2011). Penggunaan citra satelit untuk kajian perkembangan kawasan permukiman di Kota Semarang. *Forum Geografi*, *25*(2), 140. https://doi.org/10.23917/forgeo.v25i2.5041

Prakoso, D. T., Sasmito, B., & Hani'ah. (2018). Pemanfaatan enhanced built-up and bareness index (ebbi) untuk pemetaan kawasan terbangun dan lahan kosong Di Kota Semarang. *Jurnal Geodesi Undip*, *7*(4), 325–333.

Prayogo, L. M. (2021). Platform google earth engine untuk pemetaan suhu permukaan daratan dari data series modis. *DoubleClick: Journal of Computer and Information Technology*, *5*(1), 25. https://doi.org/10.25273/doubleclick.v5i1.8604

Putra W., I. W. C., Dwijendra, N. K. A., & Putra, I. D. G. A. D. (2022). Pola spasial pertumbuhan kawasan permukiman Di Desa Dalung. *PADURAKSA: Jurnal Teknik Sipil Universitas Warmadewa*, *11*(1), 15–23. https://doi.org/10.22225/pd.11.1.3301.15-23

Rahayu, Y. E., & Cahyono, M. S. D. (2021). *Bandara Dhoho Kediri*. *11*(2), 80–85.

Ramdhan, D. M., Satryo, I. F., Cerlandita, K. P., Studi, P., Informasi, S., Indonesia, U. P., & Citra, P. (2021). Analisis perubahan land surface temperature menggunakan citra multi - temporal (studi kasus : Kota Banjarmasin). *Jurnal Pendidikan Dan Ilmu Geografi*, *6*(1), 15–20. http://repository.upi.edu/30417/

Reddy, S. N., Manikiam, B., & Jeevalakshmi, D. (2017). Land surface temperature retrieval from landsat data using emissivity estimation. *International Journal of Applied Engineering Research*, *12*(20), 9679–9687. https://www.ripublication.com/ijaer17/ijaerv12n20_57.pdf

Roy, B., & Bari, E. (2022). Examining the relationship between land surface temperature and landscape features using spectral indices with google earth engine. *Heliyon*, *8*(9), e10668. https://doi.org/10.1016/j.heliyon.2022.e10668

Rumihin, A., Djajadi, R., & Kusumastuti, C. (2015). Analisis banjir di DAS Wai Ruhu Dan Wai Batu Merah, Ambon. *Jurnal Dimensi Pratama Teknik Sipil*, *4*(1), 1–8. https://media.neliti.com/media/publications/78190-ID-analisis-banjir-di-das-wai-ruhu-dan-wai.pdf

Sejati, A. W., Buchori, I., & Rudiarto, I. (2019). The spatio-temporal trends of urban growth and surface urban heat islands over two decades in the Semarang Metropolitan Region. *Sustainable Cities and Society*, *46*(January), 101432. https://doi.org/10.1016/j.scs.2019.101432

Sitorus, W. M., Sukmono, A., & Bashit, N. (2019). identifikasi perubahan kerapatan hutan dengan metode forest canopy density menggunakan citra landsat 8 tahun 2013, 2015 dan 2018 (studi kasus: Taman Nasional Gunung Merbabu, Jawa Tengah). *Jurnal Geodesi Undip*, *8*(1), 338–347. https://ejournal3.undip.ac.id/index.php/geodesi/article/view/22595

Sukrisyanti,. (2007). evaluasi indeks urban pada citra landsat multitemporal dalam ekstraksi kepadatan bangunan. *Jurnal RISET Geologi Dan Pertambangan*, *17*(1), 1. https://doi.org/10.14203/risetgeotam2007.v17.153

Syahputra, A., Jatmiko, R. H., Hizbaron, D. R., & Fariz, T. R. (2021). perbandingan indeks lahan terbangun ndbi dan land surface temperature dalam memetakan kepadatan bangunan di Kota Medan. *Journal of Science, Technology, and Visual Culture*, *1*(1), 16–22. http://journal.itera.ac.id/index.php/jstvc/article/view/540

Trinufi, R. N., & Rahayu, S. (2020). Analisis perubahan kerapatan vegetasi dan bangunan di Kota Banda Aceh pasca bencana tsunami. *Ruang*, *6*(1), 28–37. https://doi.org/10.14710/ruang.6.1.29-39

Ulya, S. F., Sukestiyarno, Y., & Hendikawati, P. (2018). Analisis prediksi quick count dengan metode stratified random sampling dan estimasi confidence interval menggunakan metode maksimum likelihood. *Unnes Journal of Mathematics*, *7*(1), 108–119.

Walad, F., & Purwaningsih, E. (2019). Dinamika lahan terbangun dan vegetasi perkotaan terhadap fenomena iklim mikro uhi (urban heat island) (Studi Kasus Kota Solok Tahun 1997–2018). *Jurnal Buana*, *3*(4), 778. http://geografi.ppj.unp.ac.id/index.php/student/article/view/481

Yatimas Murni, L., Yuliara, I. M., & Windaryoto, W. (2021). Distribusi land surface temperature (lst) menggunakan metode spasial berdasarkan citra landsat 8 di Kabupaten Manggarai Nusa Tenggara Timur Pada Periode Juni-Juli 2015–2019. *Buletin Fisika*, *24*(1), 1. https://doi.org/10.24843/bf.2023.v24.i01.p01

Zulkarnain, R. C. (2016). Pengaruh perubahan tutupan lahan terhadap perubahan suhu permukaan di Kota Surabaya. *Skripsi Institut Teknologi Sepuluh Nopember*, 1–306.