Assessment of the Comfort Level of Cilegon City Communities Based on Surface Temperature, Vegetation Density, and Built-Up Land

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Abstract. Cilegon's appeal as an industrial city is heavily influenced by urbanization. The most important impact of urbanization is the increasing need for residential, commercial, and industrial buildings, resulting in the rapid conversion of green land into built-up land. Reduced vegetated areas that function to absorb solar heat causes surface temperatures to increase so that the comfort of city residents decreases. This study aims to analyze the comfort level of the people of Cilegon City based on land surface temperature, vegetation density, and built-up land. The approach used was based on remote sensing based on Landsat-5 TM and Landsat 8 OLI/TIR image data using the Normalized Different Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Enhanced Built-up and Bareness Index (EBBI) index transformations, Land Surface Temperature (LST), and Temperature Humidity Index (THI). The results showed that developments in LST, NDVI, NDBI, and EBBI result in changes in THI. LST experienced an increase in temperature until it reached an average LST of 30.65 °C in 2019. This condition increased in temperature, causing a decrease in the comfort level of Cilegon City, where in 2019, most of the area was uncomfortable with a little comfort. Comfortable conditions were only felt in densely vegetated areas, while discomfort was felt in densely built-up areas. The correlation results showed a positive relationship between LST, NDBI, EBBI, and THI. There was a negative relationship between NDVI and THI. That is, an increase in LST, NDBI, and EBBI caused an increase in THI, while an increase in NDVI caused a decrease in THI and vice versa.

Keywords: Industry · Urbanization · NDVI · NDBI · EBBI · LST · THI · Cilegon · Indonesia

1 Introduction

Urban areas, including public facilities, health services, education, employment, and the economy, are the main attraction for people to move from villages to cities to obtain better welfare (Furoida, 2021). Based on the World Urbanization Prospects in the United

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Nations (United Nations, 2015), the United Nations (UN) estimated that around 66% of the world's population will live in urban areas in 2050. The proportion of urban residents in Indonesia as a result of the 2010 population census has increased by 27.3%, so the proportion is 49.7%, higher than the results of the population census thirty years earlier (in 1980), which was only 22.4%. The number of urban residents in the future will continue to increase to more than 200 million people, with a proportion of nearly 70% of Indonesia's total population in 2035 (Statistics Indonesia (BPS), 2021). Cilegon City is one of the cities that has experienced a rapid increase in population. 441,761 people occupied 175.51 km^2 of Cilegon City in 2021, which was greater than the proportion of Cilegon's population in 2010 (BPS, 2021).

Migration is the dominant factor for the high rate of population growth because Cilegon is known as a large industrial city that plays an important role both nationally and internationally in the development of industry, economy, and trade in Banten Province, thus helping to strengthen its attractiveness as a migration destination (BPS, 2021). The increase in the city's population has driven high demand for commercial, industrial, and residential areas such as apartments, roads, and infrastructure, as well as other facilities and infrastructure to support the socio-economic activities of urban residents (Kumari et al., 2018). As a result, the green land, which functions to absorb heat, decreases, replaced by an increase in the built-up area which causes the surface temperature to increase (Zhang et al., 2010).

Land Surface Temperature (LST) or land surface temperature is the heat of the earth's surface touching a certain location (when viewed from a satellite, the surface visible through the atmosphere can be grass, roofs of buildings, and leaves on forest plant canopies), so that heat is stored and becomes a source of longwave radiation (Risalah, 2011). Reducing vegetation cover and increasing built-up areas contribute to an increase in the Urban Heat Island (UHI) phenomenon, which impacts aspects of comfort (Kumari et al., 2018). Based on Statistics Indonesia of Cilegon City in 2008, the maximum air temperature for Cilegon was 32 °C, then in 2015, it was 34 °C and 37 °C. This increase in temperature affected the comfort of the people living in the area (Fahmi, 2013). It changed the microclimate, which had a major impact on the health and welfare of living things in Cilegon City. Hot weather and dry air in summer affect thermal comfort, especially for pedestrians (Tulandi et al., 2012).

Uncomfortable environmental conditions that last a long time and can continuously reduce productivity levels, health levels, life expectancy, and intelligence can even increase criminality and horizontal conflict between community groups (Hawa, 2016). Therefore, the need for a study that discusses the level of comfort of the people of Cilegon City because it will affect the quality of life of the people. Temperature Humidity Index (THI) is commonly used to assess comfort levels in an area (Fahmi, 2013). This method produces an index that determines the effect of hot conditions on human comfort based on elements of temperature and humidity (Hawa, 2016).

Weather/climate information can be obtained using remote sensing systems (Wardhani, 2006). The advantage of using remote sensing is that it allows the measurement of natural conditions via satellite with a wide area coverage without direct contact with the area under study (Lillesand and Kiefer, 1987). Compared with in situ measurements, traditionally considered the most reliable observations (Dubovik et al., 2002), but have limitations on the number of weather stations, the resulting data is limited (Wardhani, 2006). Therefore, remote sensing is needed to minimize the limitations of these data. This study aims to analyze the impact of land surface temperature on the comfort level of the people of Cilegon City based on the level of vegetation density and built-up land in 1997 and 2019 using Landsat Imagery.

2 Method

2.1 Research Location

Figure 1 shows the research location displayed with 543 composite Landsat imagery so that the built-up area can be observed clearly. Cilegon is located between 5°52′24″ North Latitude and 6°04′07″ South Latitude and between 105° 54′05″–106°05′11″ East Longitude. A total of 441,761 people occupy an area of 175.51 km^2 with an altitude between 0–500 masl. Cilegon is divided into 8 sub-districts: Cibeber, Citangkil, Ciwandan, Gerogol, Cilegon, Jombang, Pulomerak, and Purwakarta Districts. It has a tropical climate with annual rainfall ranging from 1,374–5,716 mm/year. The highest temperature is 35.6 °C, while the lowest is 21 °C (Observation Data for Climatic Elements of the Maritime Meteorological Station, Serang).

This study used remote sensing data of Landsat imagery obtained through the site https://earthexplorer.usgs.gov/, located at Path/Row P123/R64. Landsat imagery was chosen because this image has channels supporting obtaining the information needed in this study, namely the RED, NIR, SWIR, and Thermal channels (USGS, 2013). Table 1 shows the Landsat imagery used in the study.

2.2 Data Processing and Analysis Techniques

The data in Table 1 is layer stacked and extracted based on the Area of Interest (AOI) using the Cilegon City administrative boundaries at a scale of 1:25,000. Indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Enhanced Built-up and Bareness Index (EBBI), Land Surface Temperature (LST), and Temperature Humidity Index (THI) were calculated for 1997 using Landsat 5-TM (Thematic Mapper) imagery and in 2019 using Landsat 8 OLI-TIRS (Operational Land Imager-Infrared Sensor) imagery so that changes can be identified during that period. Community comfort level assessment based on land surface temperature and its relationship to vegetation density and built-up land was analyzed with SPSS using pearson bivariate correlation and simple linear regression with scatter plots. The stages of image processing are as follows.

Radiometric and Atmospheric Corrections

Radiometric and atmospheric image correction is used to correct pixel values that do not match the actual object's reflection or spectral emission values and suppress the effects of atmospheric disturbances reaching the sensor (Widyatmanti et al., 2021). The Landsat-5 and Landsat-8 image correction process uses QGIS in one of its features, namely the Semi-Automatic Classification Plugin (SCP) with the Dark Object Subtraction (DOS)

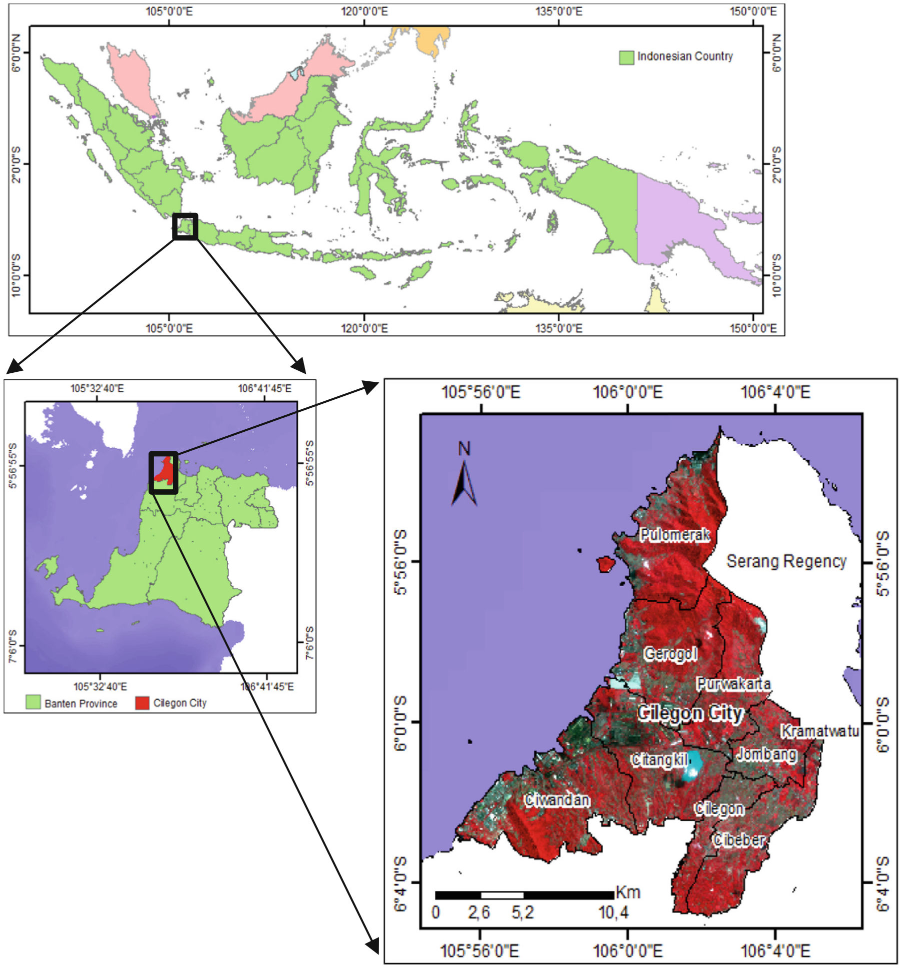

Fig. 1. Map of Cilegon City as a study area presented with the imagery of Landsat-8 composite 543

method to convert the corrected TOA reflectance into reflectance values on the surface. The SCP feature can also be used in the thermal band to convert radiance to a Brightness Temperature (BT) value.

Built-Up Land Extraction

Built-up land can be identified through various building index transformations such as NDBI, Urban Index (UI), BI, IBI, and NDbaI [16]. This study compared built-up land resulting from NDBI extraction and built-up land from EBBI extraction. The NDBI was chosen as one of the indices often used in mapping built-up areas (Hidayati et al., 2017), while the EBBI was chosen because it is more accurate for built-up mapping areas and vacant land (Abd Rahman As-syakur et al., 2012). The built-up land indices are less effective in distinguishing between the two simultaneously, so they are often mapped

Table 1. Landsat Imagery Used

Date of Image Acquisition	Sensor	Bands for Vegetation Density Classification	Bands for the Classification of Constructed Land	Thermal Bands
19 July 1997	Landsat 5 TM	4 and 3	4,7, and 6	6
16 July 2019	Landsat 8 OLI/TIRS	5 and 4	5, 6, and 10	10

into one class (Prakoso & Sasmito, 2018). NDBI and EBBI are calculated using Eq. 1 and Eq. 2.

$$\mathrm{NDBI} = \frac{(SWIR - NIR)}{(SWIR + NIR)} \tag{1}$$

$$\mathrm{EBBI} = \frac{SWIR - NIR}{10\sqrt{SWIR + TIRS}} \tag{2}$$

Vegetation Density Extraction

The level of vegetation density can be calculated using the Normalized Different Vegetation Index (NDVI) algorithm, which uses a combination of near-infrared and red bands. The NDVI value is calculated using Eq. 3 (Kristian, 2014).

$$\mathrm{NDVI} = \frac{(NIR - Red)}{(NIR + Red)} \tag{3}$$

Land Surface Temperature Extraction

The land surface temperature value is extracted from the thermal band radiance value and converted into Brightness Temperature by integrating the emissivity value (Eq. 4). Table 2 shows the NDVI threshold values for calculating emissivity.

Table 2. Emissivity for Each NDVI Value

NDVI Value	Emissivity Value
<-0.18	0.985
$-0.18 \leq \mathrm{NDVI} < 0.157$	0.955
$0.157 \leq \mathrm{NDVI} < 0.727$	$1.0094 + 0.047 * \mathrm{Ln(NDVI)}$
≥ 0.727	0.990

Furthermore, the Brightness Temperature and emissivity values are integrated into Eq. 4 to obtain land surface temperature values.

$$\mathrm{LST} = \frac{\boldsymbol{BT}}{\{1 + [\left(\frac{\boldsymbol{WxBT}}{\boldsymbol{\rho}}\right)\boldsymbol{ln\varepsilon_{\lambda}}]\}} \tag{4}$$

Information:
LST: Land Surface Temperature (K)
BT: brightness temperature (K)
W: average wavelength of radian beam or band 10
P: the value of the equation 1.438×10^{-2} mK
ε_{λ}:emissivity

The results of LST calculations in Kelvin units (K) are then converted into Celsius units (°C) to facilitate later analysis.

City Community Comfort Level Assessment

The comfort level of city residents can be calculated based on the Temperature Humidity Index (THI). This comfort index value is obtained by processing the parameters of air temperature and relative humidity values (Arifah & Susetyo, 2018; Fardani & Yoslian-syah, 2022). The comfort index is calculated using Eq. 5, which was introduced by Nievwolt in 1975 (Tulandi et al., 2012).

$$\mathrm{THI} = 0.8\mathrm{T} + \frac{T\ x\ RH}{500} \tag{5}$$

Information:
THI: Thermal-Humidity Index
T: air temperature (°C)
RH: relative humidity (%)

This study used LST as T/temperature (°C) for several reasons. First, LST is the temperature recorded by satellite imagery due to the radiant temperature of objects on the earth's surface (Astuti & Nucifera, 2021). Second, LST is influenced by the human ability to change nature, which tends to sacrifice green open areas to become built-up areas so that surface temperatures increase. Third, LST is statistically correlated with NDVI and NDBI (Kumari et al., 2018). The results of the comfort index were then validated based on an assessment survey with human respondents obtained from Tulandi et al. (2012). Comfort is defined as:

$21 \leq$ THI ≤ 24 defined 100% of the subject feels comfortable
$24 \leq$ THI ≤ 26 means that 50% of the subjects feel comfortable
THI > 26 is defined as 0% of subjects feeling uncomfortable (or the equivalent of 100% saying they are uncomfortable).

3 Results and Discussion

3.1 Analysis of the Leisure Level of Cilegon City in 1997 and 2019

The level of human comfort is often associated with the warm sensation received by humans or thermal comfort (Tulandi et al., 2012). The comfort level assessment of Cile-gon City is based on the Temperature Humidity Index (THI) combining land surface temperature values obtained from Landsat image thermal bands and daily average relative humidity values from the Climatic Element Observation Points of the Maritime Meteorological Station, Serang.

Spatial-Temporal LST in 1997 and 2019

Table 3 presents descriptive statistics for ESGs for 1997 and 2019. During the two selected study periods, LST experienced a significant increase. The LST value in 1997 was in the range of 21 °C to 24.8 °C. The temperature was lower than the LST in 2019, reaching 24 °C to 40 °C.

The distribution of LST in Cilegon City spatially and temporally is illustrated in Fig. 2. The distribution of LST in 1997 and 2019 has the same pattern. The highest LST peak is located in the center of Cilegon, where the area is fairly densely built-up, followed by commercial and industrial areas. Further outside the center of Cilegon, the temperature decreases until the minimum LST peak is above the vegetated land (Fig. 2). Nurgiantoro and Aris (2019) stated that land surface temperature will always be concentrated in built-up land areas, bare soil, and areas with sparse vegetation levels and will continue to increase with population growth in an area. Figure 3 displays a graph of the average surface temperature for each sub-district in Cilegon City in 1997 and 2019.

Based on Fig. 3, the highest surface temperatures are often found in the city center (Cibeber District, Cilegon District, Citangkil District, and Ciwandan District). The further away from the city center, the temperature decreases gradually towards the city's outskirts. This condition occurs because the center of Cilegon City functions as a center for large-scale processing industries, namely the Kratau Steel (KS) area as a trade and service center. After all, it is located at the main gate that connects the Java Island and Sumatra Island systems. This factor triggers high urbanization, which results in changes in the conversion of vegetation cover into built-up areas, thereby significantly affecting temperature increases in urban areas (Fardani & Yosliansyah, 2022). The impact of high

Table 3. Descriptive Statistics of LST at the Sub-district Level in 2019 and 1997

No	District	LST 1997 (°C)			LST 2019 (°C)		
		Min	Mean	Max	Min	Mean	Max
1	Cibeber	24.39	27.99	30.63	27.42	31.48	34.67
2	Cilegon	24.39	28.08	31.46	27.48	31.81	37.32
3	Citangkil	24.39	28.37	35.53	26.69	31.86	38.97
4	Ciwandan	22.64	27.96	32.70	25.50	31.05	40.14
5	Gerogol	21.15	26.71	31.87	24.64	29.73	37.20
6	Jombang	23.96	27.49	30.22	28.29	31.33	34.59
7	Pulomerak	21.76	25.66	31.87	24.10	29.03	36.76
8	Purwakarta	23.08	27.50	31.87	25.36	30.07	35.58

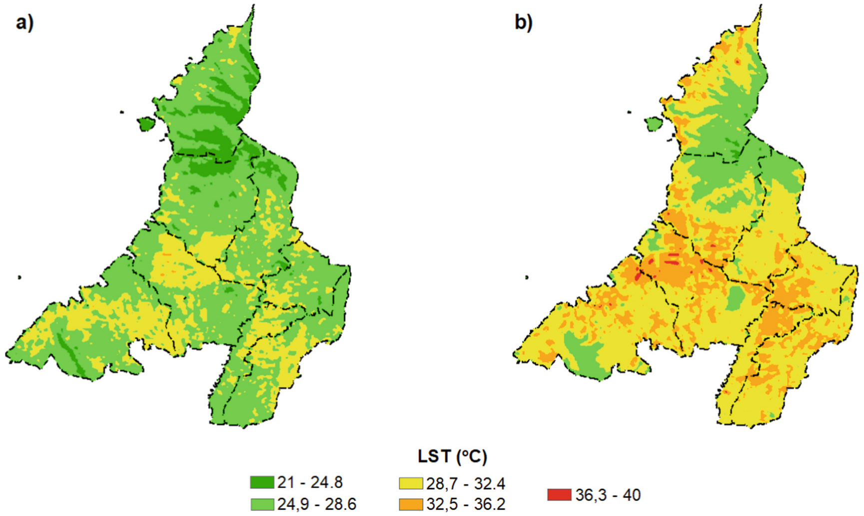

Fig. 2. Temporal spatial comparison of LST 1997 to 2019 (a) 1997, and (b) 2019

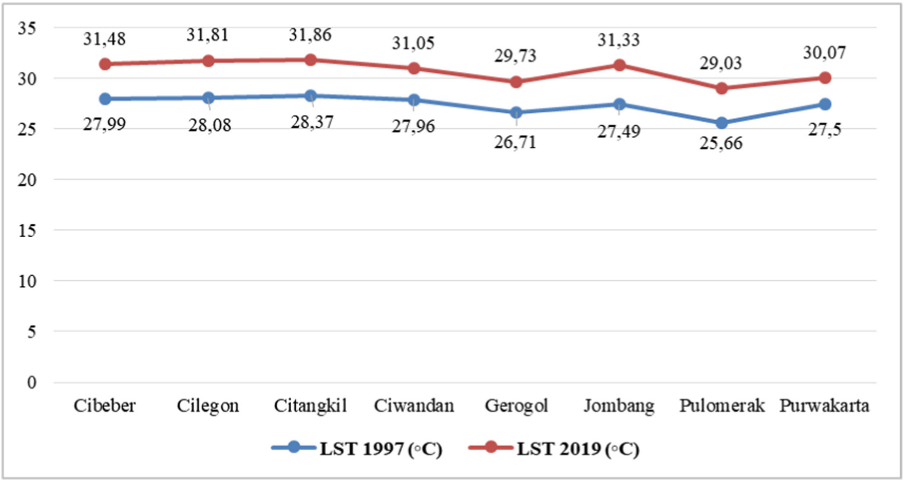

Fig. 3. Graph of average LST for each sub-district in Cilegon City in 1997 and 2019

temperatures in an area can disrupt human activities and reduce the comfort of urban communities (Wardhani, 2006).

Assessment of the Comfort Level of the Cilegon City Communities in 1997 and 2019

The community's comfort level is assessed based on the accumulated LST value and the area's relative humidity. Table 4 compares average LST values, daily average relative humidity, and average THI in each study period.

The THI index shows that the average THI value increased in 2019 to 29.12, which was only 26.30 in 1997. According to Tulandi et al. (2012), a THI index of >26 is

Table 4. The Average LST, Average RH, and Average THI Values for Cilegon City in 1997 and 2019

Year	LST (°C)	RH (%)	THI
1997	27.40	80	26.30
2019	30.65	75	29.12

interpreted as an uncomfortable condition, so in 1997 and 2019, most of the Cilegon area had a comfortable level of discomfort. A comparison of the spatial distribution of THI and changes in the area of THI over the study period can be seen in Fig. 4 and Table 5.

The distribution of THI in 1997 compares comfort levels between comfortable, somewhat comfortable, and uncomfortable classes with a proportion of the area that is not too far away. Nevertheless, the uncomfortable class still dominates. In contrast to THI

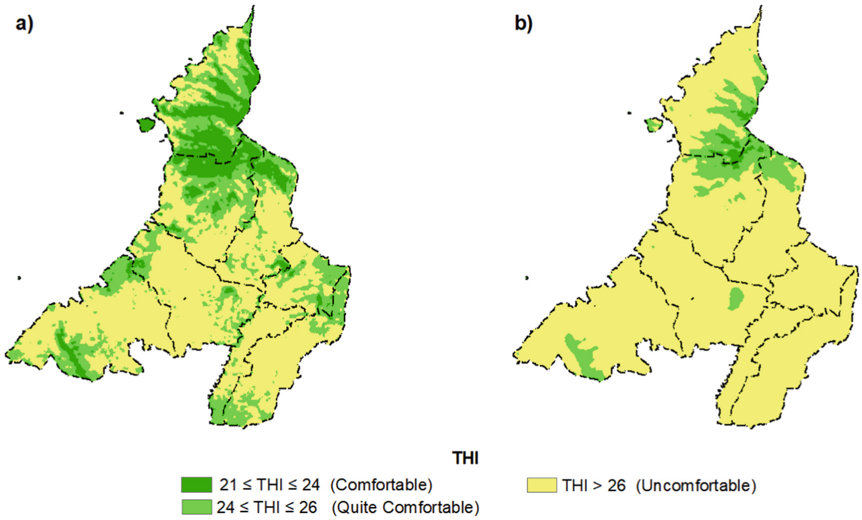

Fig. 4. Temporal Spatial Comparison of THI 1997 to 2019 (a) 1997 and (b) 2019

Table 5. THI Area of Cilegon City in 1997 and 2019

THI	Community Comfort Level	Area (1997)		Area (2019)	
		Km^2	%	Km^2	%
$21 \leq THI \leq 24$	Comfortable	20.31	12.42	1.95	1.19
$24 \leq THI \leq 26$	Quite Comfortable	44.65	27.29	16.75	10.24
> 26	Uncomfortable	98.63	60.29	144.93	88.57

in 2019, the entire area is almost evenly distributed at an uncomfortable comfort level, 144.93 km^2 of the total area of Cilegon, except for the northern part of Cilegon, which has a comfortable level of comfort. This condition can be influenced by the physical condition of the Cilegon area, where the northern part of Cilegon has a relief of plateaus/mountains, so it has a lower temperature than the surrounding area. Meteorological conditions in mountainous areas (high elevation) are different from those in lowland areas, where mountainous areas have diurnal temperature variations (Masitoh & Rusydi, 2020). In contrast to humidity, air temperature conditions will decrease along with increasing elevation (Fu & Shen, 2016). In addition, the characteristics of mountainous areas are still dominated by dense vegetation and have visual comfort related to the aesthetics/beauty of natural scenery.

The Impacts of LST on THI Cilegon City in 1997 and 2019

Table 6 compares the land surface temperature and comfort level for each sub-district of Cilegon City, which was obtained based on the 1997 and 2019 LST and THI values. Table 6 shows the average trend of high LST values in each sub-district and a high average THI value. According to Tulandi et al. (2012) the THI value limit that is quite comfortable is 26. A THI value of more than 26 is considered uncomfortable. That is, descriptively, an increase in surface temperature can reduce the comfort of city people, strengthened by the LST and THI correlation tests so that the relationship between the two can be identified. The results of the LST and THI correlation tests for the study period are shown in Table 7.

The statistical test in this study resulted in a significance value (Sig.) of less than 0.005 and a correlation value of 1 with a positive relationship in both 1997 and 2019 (Table 7). According to Sugiyono (2013), the correlation value at 0.800–1.00 has a very close relationship level. There is a very strong relationship between LST and THI. If LST increases, it will be followed by an increase in THI so that an increase in land surface temperature can reduce the comfort level of urban residents. Hot temperatures and dry air due to microclimate changes affect thermal comfort and significantly impact

Table 6. The Average LST and THI for Each Sub-district of Cilegon City in 1997 and 2019

No	District	1997			2019		
		LST (°C)	THI	Comfort Level	LST (°C)	THI	Comfort Level
1	Cibeber	27.99	26.87	Uncomfortable	31.48	29.90	Uncomfortable
2	Cilegon	28.08	26.96	Uncomfortable	31.81	30.22	Uncomfortable
3	Citangkil	28.37	27.24	Unconfortable	31.86	30.27	Uncomfortable
4	Ciwandan	27.96	26.84	Uncomfortable	31.05	29.50	Uncomfortable
5	Gerogol	26.71	25.64	Quite comfortable	29.73	28.24	Uncomfortable
6	Jombang	27.49	26.39	Uncomfortable	31.33	29.77	Uncomfortable
7	Pulomerak	25.66	24.64	Quite comfortable	29.03	27.58	Uncomfortable
8	Purwakarta	27.50	26.40	Uncomfortable	30.07	28.57	Uncomfortable

Table 7. Correlation of LST and THI in 1997 and 2019

1997		LST	THI	2019		LST	THI
LST	Pearson Correlation	1	1.000**	LST	Pearson Correlation	1	1.000**
	Sig. (2-tailed)		0.000		Sig. (2-tailed)		.000
	N	100	100		N	100	100
THI	Pearson Correlation	1.000**	1	THI	Pearson Correlation	1.000**	1
	Sig. (2-tailed)	0.000			Sig. (2-tailed)	0.000	
	N	100	100		N	100	100

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

the health and welfare of humans, animals, and plants in cities (Tulandi et al., 2012). Heat conditions, besides being able to reduce health, in extreme situations, heat stroke in unfavorable cases will cause death (Iizuka & Akiyama, 2020).

3.2 The Impacts of Vegetation Density on Community Comfort in Cilegon City

The level of vegetation density can be calculated based on the Normalized Different Vegetation Index (NDVI) transformation, which uses a combination of the near-infrared band and the red band in Landsat imagery. NDVI will produce a range of values between -1 to $+1$, which illustrates that the closer to $+1$, the denser the vegetation density. Identification of NDVI in the study area using Landsat imagery shows a difference in vegetation density between 1997 and 2019 (Fig. 5).

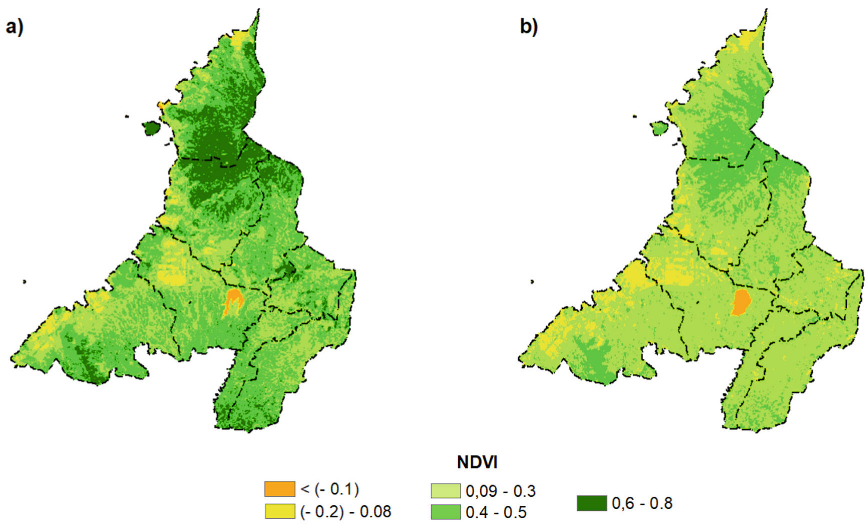

Fig. 5. Spatial-Temporal Comparison of NDVI from 1997 to 2019 (a) 1997 and (b) 2019

Table 8. NDVI Area of Cilegon City in 1997 and 2019

Vegetation Density	Area (1997)		Area (2019)	
	Km^2	%	Km^2	%
Non-vegetation	1.80	1.10	1.85	1.13
Sparse	35.69	21.82	131.35	80.29
Medium	56.98	34.83	26.95	16.48
Haigh	69.11	42.25	3.44	2.10

Temporarily, the NDVI in 1997 showed a higher value than in 2019 which was shown by many dark green areas with NDVI class groups of 0.6 to 0.8. NDVI value $\geq$0.5, according to Sobrino et al. (2008), is considered a fully vegetated plant. In 1997, the study area had fairly good vegetation. In the last 22 years, the amount of NDVI has decreased. NDVI in 2019, most of them are in the NDVI 0.4 to 0.5 class group. Changes in vegetation density during the study period can also be observed based on Table 8.

Table 8 shows that the biggest change in vegetation area occurred in the sparse vegetation density class, where in 1997, sparse vegetation was only 35.69 km^2. In 2019 it expanded to 131.35 km^2, 80.29% of the total area of Cilegon. In addition to the sparse vegetation density class, significant changes were also shown in the high-density class. The area of vegetation with a high-density level in 2019 only remained at 2.10% of Cilegon's area. The rest was dominated by sparse vegetation density. Changes in NDVI can be caused by changes in green land into built-up land along with the development of an area (Aprilia et al., 2021). As a result, urban areas have hotter temperatures than surrounding non-urban areas. According to Hadibasyir et al. (2020), the lower the level of vegetation density, the higher the land surface temperature, except for bodies of water. Tree vegetation has a big role in reducing air temperature and can overcome UHI (Rushayati et al., 2018). In addition, vegetation can change the state of the surrounding environment by affecting air quality, reducing pollutant emissions, reducing the effects of heat radiation reflection from buildings, and reducing noise levels (A Rahman As-syakur, 2005). Therefore, the comfort level of urban residents is also determined based on the condition of the vegetation.

Table 9 displays the level of community comfort from the THI index based on the level of vegetation density from the NDVI index in each sub-district in Cilegon. The results show that sub-districts with sparse vegetation density have a low comfort level. On the other hand, sub-districts that have dense vegetation density have a high comfort level. Masitoh and Rusydi (2020) proved comfortable and rather comfortable areas separated into medium and high-density levels, while uncomfortable to very uncomfortable in areas of sparse vegetation.

Table 10 and Fig. 6 show the relationship between vegetation density and the comfort level of the people of Cilegon City based on NDVI and THI values.

The correlation results in Table 9 show a negative correlation between NDVI and THI with a correlation value of 0.7. This figure illustrates the form of a strong relationship between the two. Meanwhile, a negative correlation indicates that areas with high NDVI

Table 9. The Average NDVI and THI for Each Sub-district of Cilegon City in 1997 and 2019

No	District	1997			2019		
		NDVI	THI	Comfort Level	NDVI	THI	Comfort Level
1	Cibeber	0.37	26.87	Uncomfortable	0.21	29.90	Uncomfortable
2	Cilegon	0.39	26.96	Uncomfortable	0.20	30.22	Uncomfortable
3	Citangkil	0.30	27.24	Unconfortable	0.17	30.27	Uncomfortable
4	Ciwandan	0.33	26.84	Unomfortable	0.20	29.50	Uncomfortable
5	Gerogol	0.44	25.64	Quite comfortable	0.26	28.24	Uncomfortable
6	Jombang	0.35	26.39	Uncomfortable	0.19	29.77	Uncomfortable
7	Pulomerak	0.48	24.64	Quite comfortable	0.27	27.58	Uncomfortable
8	Purwakarta	0.42	26.40	Uncomfortable	0.26	28.57	Uncomfortable

Table 10. Correlation of NDVI and THI in 1997 and 2019

1997		NDVI	THI	2019		NDVI	THI
NDVI	Pearson Correlation	1	-0.79^{**}	LST	Pearson Correlation	1	-0.71^{**}
	Sig. (2-tailed)		0.000		Sig. (2-tailed)		0.000
	N	100	100		N	100	100
THI	Pearson Correlation	$-.079^{**}$	1	NDVI	Pearson Correlation	-0.71^{**}	1
	Sig. (2-tailed)	0.000			Sig. (2-tailed)	0.000	
	N	100	100		N	100	100

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

values have low THI values, and an increase in NDVI causes a decrease in THI or vice versa. This result is also proven by the regression test between NDVI and THI, which produces linear lines that are inversely proportional (Fig. 6). The coefficient of determination is 0.63 and 0.51 in 1997 and 2019, which means that 63% and 51% of NDVI can explain THI, and the remaining 37% and 49% are influenced by other variables not counted in the regression model. However, it should be underlined that the higher the THI value, the lower the comfort level of urban residents. Discomfort conditions can be reduced by increasing the density of vegetation (Suwasono et al., 2013). Urban vegetation, besides contributing to ecological aspects, also plays a role in maintaining beauty and increasing environmental comfort, which can stimulate the creativity and productivity of urban communities (As-syakur, 2005).

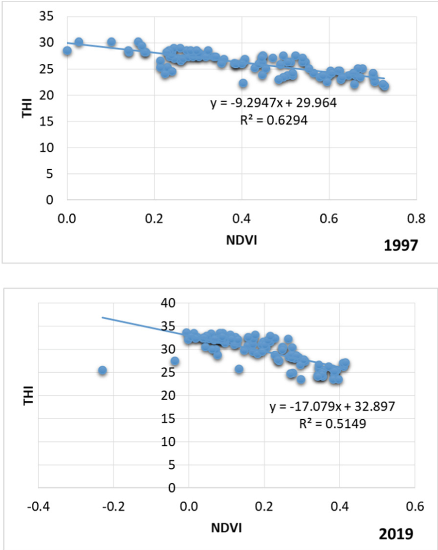

Fig. 6. Simple Linear Regression Statistics Between NDVI and THI in 1997 and 2019

3.3 The Impacts of Built-Up Land on the Cilegon City's Community Comfort

Built-up land in an area can be identified using the Normalized Difference Built-up Index (NDBI) and Enhanced Built-up and Bareness Index (EBBI) transformations. A comparison of the calculation results of the two indices in mapping the built-up area based on Landsat imagery data can be seen in Table 11 and Fig. 7.

The results showed that the total built-up area obtained from the NDBI transformation was 18.10 km^2 in 1997 and then increased in 2019 to 57.44 km^2. This result is greater than the result of the EBBI transformation in 1997, which was only 16.90 km^2; in 2019, it was 56.25 km^2 (Table 11). In contrast, the vacant land resulting from the NDBI transformation is smaller in area than the vacant land resulting from the EBBI transformation. In line with the results of research from As-Syakur et al. (2012), which resulted in a higher level of accuracy for EBBI than NDBI in built-up mapping land, the built-up land resulting from the EBBI transformation was smaller than the built-up land resulting from NDBI because vacant land is easy to detect compared to NDBI which often vacant land is mapped into built-up land. EBBI includes a thermal channel in its equation with low

Table 11. Comparison of Built-up Area and Vacant Land for Each Type of Transformation Index

		NDBI			EBBI	
Year	Built-up Land (km^2)	Bare Land (km^2)	Non-Built Land (km^2)	Built-up Land (km^2)	Bare Land (km^2)	Non-Built Land (km^2)
1997	18.10	1.00	144.55	16.90	2.08	144.66
2019	57.44	1.70	104.46	56.25	2.76	104.58

albedo, which can eliminate the effects of shadows and water bodies so that it is more effective in distinguishing built-up land from vacant land and increases the accuracy of the percentage of building density compared to other built-up land indices (Abd Rahman As-syakur et al., 2012). The spatial distribution of built-up areas and vacant land based on NDBI and EBBI is shown in Fig. 7.

Figure 7 shows a change in the built-up land area which increased in intensity during the study period. In 1997 there were fewer built-up areas than in 2019. Most of the distribution of built-up land was in the southwestern, western, and northwestern parts of Cilegon along the coastline and the center of Cilegon, with a pattern that tends to be clustered in the industrial zone area of the study area. Along with the changing times followed by population growth, built-up land is increasing. Urban areas and impervious

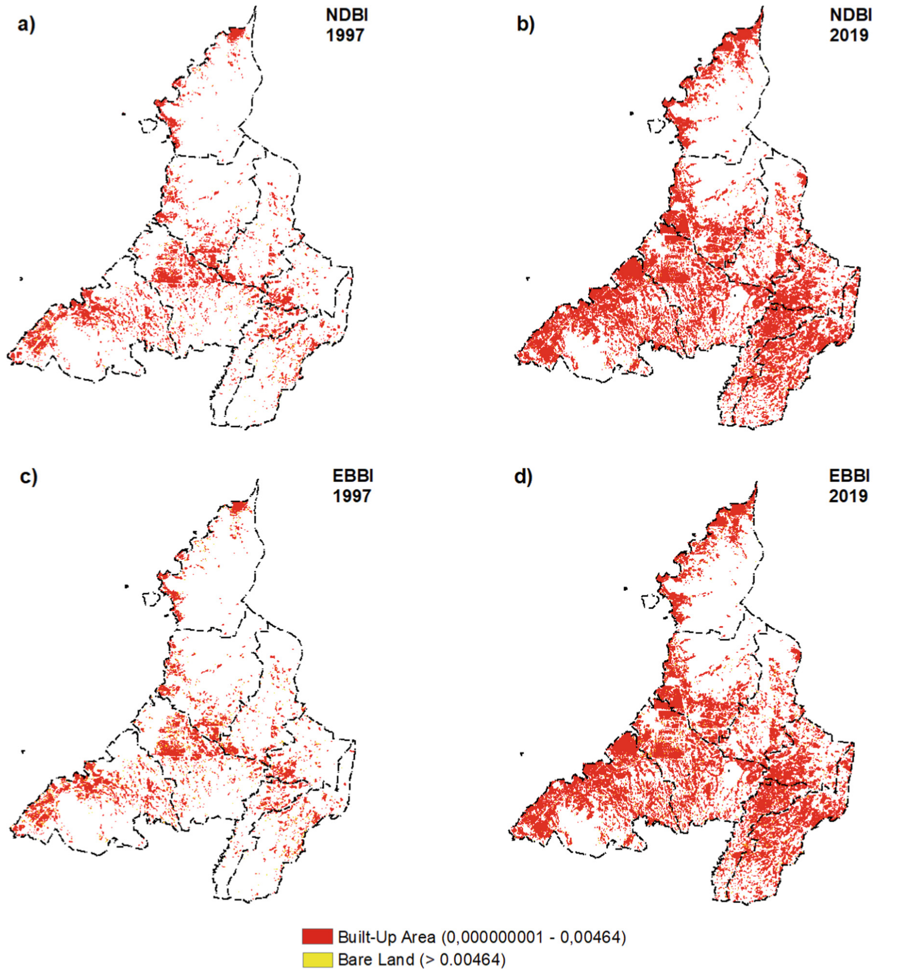

Fig. 7. The Spatial Distribution of Built-up and Vacant Land Areas are Shown for the 1997 and 2019 Remote Sensing Transformation Indices, Respectively

surfaces have been expanded in industrial zones, settlements, and buildings. In addition, thermal energy from industrial activities in industrial areas makes the surface temperature in this area higher than the surrounding temperature (Nguyen et al., 2019).

The rapid increase in urban population and expansion of urban areas caused an increase in built-up land and a decrease in vegetation cover (Kumari et al., 2018). Urbanization causes the conversion of green land and agricultural land, especially those on the outskirts of cities, into built-up areas (Kumari et al., 2018). Reduced green land that serves to absorb the sun causes surface temperatures to rise. Fikriyah et al. (2022) examined the relationship between NDBI and LST and concluded that an increase in a built-up area causes an increase in surface temperature. This increase in surface temperature causes a decrease in the comfort level of the city. Table 12 shows the comfort level of urban residents from the THI index based on built-up land from the NDBI and EBBI indexes in each sub-district in Cilegon.

Based on Table 12, districts with high NDBI scores have high THI. On the other hand, districts with low NDVI also have low THI, so areas with dense built-up land have a low comfort level, while areas with sparse built-up land have a high comfort level. Masitoh dan Rusydi (2020) stated that most inconveniences were felt in built-up areas. Table 13 and Fig. 8 illustrate the relationship between built-up land resulting from NDBI extraction and THI. In contrast, the relationship between built-up land resulting from EBBI and THI is shown in Table 14 and Fig. 9.

The correlation test between NDBI and THI produces a correlation coefficient (r) of 0.8 with a positive relationship (Table 13). Hence, between NDBI and THI, there is a strong relationship, and an increase in NDBI causes an increase in THI or vice versa. Based on the scatter plot of the regression test between NDBI and THI, the coefficient of determination in the study period was 0.75 and 0.70, respectively. That is, NDBI of 75% and 70% can explain THI, and the rest is influenced by other variables that are not counted in the regression model.

Table 12. The Average NDBI, EBBI, and THI for Each Sub-district of Cilegon City in 1997 and 2019

No	District	1997				2019			
		NDBI	EBBI	THI	Comfort Level	NDBI	EBBI	THI	Comfort Level
1	Cibeber	−0.20	−0.09	26.87	Uncomfortable	−0.04	−0.02	29.90	Uncomfortable
2	Cilegon	−0.19	−0.08	26.96	Uncomfortable	−0.02	−0.01	30.22	Uncomfortable
3	Citangkil	−0.18	−0.07	27.24	Unconfortable	−0.05	−0.02	30.27	Uncomfortable
4	Ciwandan	−0.18	−0.08	26.84	Uncomfortable	−0.03	−0.02	29.50	Uncomfortable
5	Gerogol	−0.31	−0.13	25.64	Quite comfortable	−0.14	−0.09	28.24	Uncomfortable
6	Jombang	−0.23	−0.10	26.39	Uncomfortable	−0.05	−0.02	29.77	Uncomfortable
7	Pulomerak	−0.36	−0.14	24.64	Quite comfortable	−0.17	−0.10	27.58	Uncomfortable
8	Purwakarta	−0.24	−0.11	26.40	Uncomfortable	−0.11	−0.07	28.57	Uncomfortable

Table 13. Correlation of NDBI and THI in 1997 and 2019

1997		NDBI	THI	2019		NDBI	THI
NDBI	Pearson Correlation	1	0.86**	LST	Pearson Correlation	1	0.83**
	Sig. (2-tailed)		0.000		Sig. (2-tailed)		0.000
	N	100	100		N	100	100
THI	Pearson Correlation	0.86**	1	NDBI	Pearson Correlation	0.83**	1
	Sig. (2-tailed)	0.000			Sig. (2-tailed)	0.000	
	N	100	100		N	100	100

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

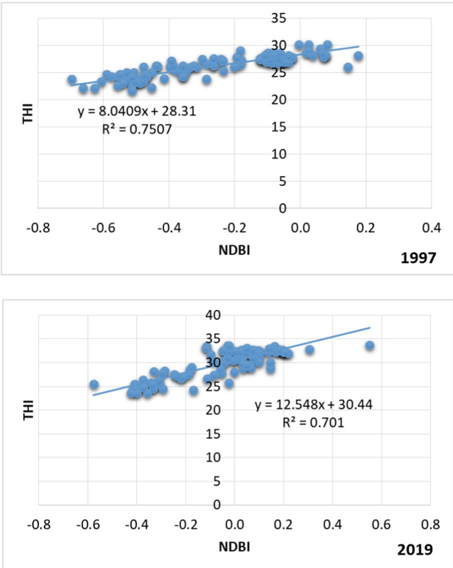

Fig. 8. Simple Linear Regression Statistics Between NDBI and THI in 1997 and 2019

Meanwhile, the correlation test between EBBI and THI produced a correlation coefficient (r) of 0.7 in 1997 and 0.8 in 2019, with a positive relationship (Table 14). Hence, between EBBI and THI, there is a strong relationship, and an increase in EBBI results in an increase in THI and vice versa. Based on the scatter plot of the regression test between EBBI and THI, the coefficient of determination in the study period was 0.62 and 0.67, respectively. Therefore, 60% and 67% of EBBI can explain THI, and the rest are influenced by other variables that are not counted in the regression model.

Table 14. Correlation of EBBI and THI in 1997 and 2019

1997		EBBI	THI	2019		EBBI	THI
NDBI	Pearson Correlation	1	.789**	LST	Pearson Correlation	1	.819**
	Sig. (2-tailed)		.000		Sig. (2-tailed)		.000
	N	100	100		N	100	100
THI	Pearson Correlation	.789**	1	NDBI	Pearson Correlation	.819**	1
	Sig. (2-tailed)	.000			Sig. (2-tailed)	.000	
	N	100	100		N	100	100

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

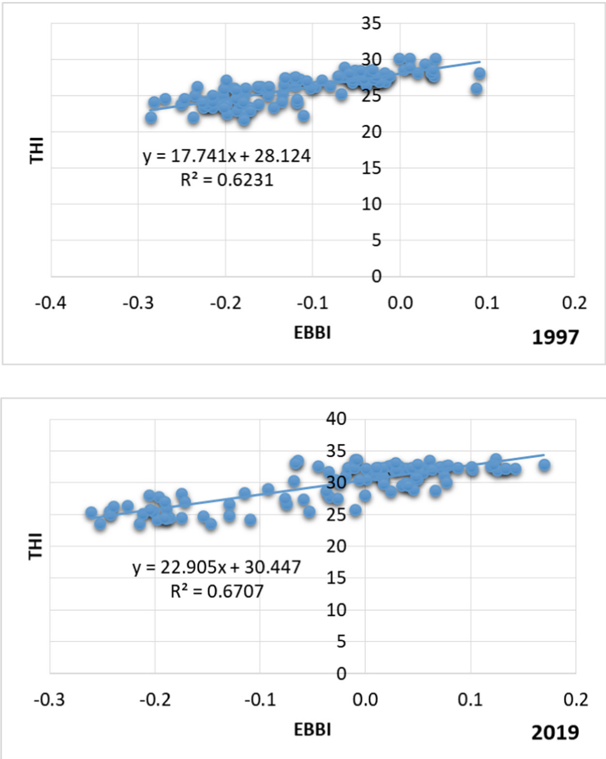

Fig. 9. Simple Linear Regression Statistics between EBBI and THI in 1997 and 2019

4 Conclusion

The comfort level of city residents could be assessed using the Temperature Humidity Index (THI). This study has explained the development of community comfort levels based on land surface temperature, vegetation density, and built-up land in 1997 and 2019. The results showed that developments in LST, NDVI, NDBI, and EBBI during the research period resulted in changes in THI. In general, LST experienced an increase in temperature until it reached an average LST of 30.65 °C in 2019. This increase in temperature resulted in a decrease in the comfort level of Cilegon City, where in 2019, most of the areas were uncomfortable with a little bit comfortable. Comfortable conditions are felt in densely vegetated areas, while discomfort is felt in densely built-up areas or vice versa. The correlation results showed a positive relationship between LST, NDBI, EBBI, and THI, while a negative relationship occurred between NDVI and THI. When LST, NDBI, and EBBI increased, THI also increased, and when NDVI increased, THI would decrease, and vice versa. THI is directly proportional to LST, meaning that in areas with a high surface temperature, THI is also of high value, so the comfort level is low. Meanwhile, the regression analysis showed a directly proportional relationship between NDBI, EBBI, and THI, while NDVI and THI produced an inverse relationship. An increase in NDBI and EBBI would affect an increase in THI, while an increase in NDVI would affect a decrease in THI or vice versa.

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