

Analysis of Environmental Criticality Index (ECI) and Distribution of Slums in Yogyakarta and Surrounding Areas Using Multitemporal Landsat Imagery

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Abstract. The environmental challenges arising due to urbanization and population growth have emerged. Reasons for this include rising temperature, high population, and changes in land use to built-up land. Many people prefer to live in cities because they provide better opportunities for work, living standards, and access to facilities like healthcare and education. Yogyakarta and its neighboring areas have witnessed the rise of slum settlements due to these factors. Extreme dense buildings, low building quality, and misaligned land use have all contributed to the environmentally critical status of slum settlements. This study aims to dissect the environmental criticality map of Yogyakarta's slums in 2016 and 2021. Using the Land Surface Temperature (LST) and Built-up Index (BU) methods, this study collected Environmental Criticality Index (ECI) data, to which a Modified Normalized Difference Water Index (MNDWI) was applied to filter out bodies of water. Following the study's findings, the downtown areas fell into the high-criticality zone due to their dense built-up land, low vegetation, and high surface temperature. Slums in Yogyakarta and its suburbs were concentrated in places bordering large waterways, including the Gadjah Wong, Code, and Winongo Rivers. Generally speaking, city centers and their surrounding suburbs contained most settlements. Extremely high critical environmental conditions were present in urban slums, whereas suburban slums have moderate to high critical conditions.

Keywords: LST \cdot BU \cdot MNDWI \cdot ECI \cdot Slum Area

1 Introduction

The city is a center of human activity with a heterogeneous lifestyle and pattern of life, and the economy is not based on agriculture (Bintarto, 1977). The city's high population density and development relying on the non-agricultural sector with high population mobility make it stand out. According to Regulation of the Minister of Home Affairs No. 2 of 1987 on the Guidelines for the Preparation of City Plans, the defining feature of a city is its administrative area boundary, involving the characteristics of urban life, such as population activity and the concentration of settlements subject to specific laws and regulations.

Population increase and urbanization have unintended consequences, chief among them environmental degradation. It occurs due to the high population, the conversion of green land into built-up land, and the rise in average temperature within cities. Dahroni (2008) argued that urbanization occurs when people from the hinterland areas migrate to urban centers. Cities attract people because they provide better living conditions than rural areas, including a wider variety of work opportunities, a more developed and reliable infrastructure, and higher standards of education and healthcare.

Urbanization is the process through which people migrate from rural areas to urban centers due to various influences. Although there are many positive outcomes associated with urbanization, negative consequences affecting the environmental and social aspects of the population also exist. One of these negative outcomes is environmental degradation due to the conversion of natural habitats into buildings, leading to pollution, climate change, and disruptions in ecological cycles (Senanayake et al., 2013).

Building densities in slums are frequently quite high, and the quality of such structures is usually substandard. They often do not even bother to conform to the intended uses of the site. As a result of poor management, such regions suffer from a high level of environmental criticality. Environmental deterioration is a detrimental effect of slum settlements. People who have recently moved from the countryside to the city sometimes live on property developed without regard for environmental concerns by its previous inhabitants (Pigawati, 2015).

Yogyakarta's fast development across several industries has resulted in an average economic growth of 5.45% from 2016 to 2019 (BPS Tahun 2020), making the city a magnet for those hoping to make their fortune. Data from the Population Statistics (BPS) unveil that the population of the Province of the Special Region of Yogyakarta (DIY) kept growing from 2016 to 2021. An expanding population is one element driving urbanization, which in turn increases demand for the residential area. Variations in land conversion to meet residential and industrial demands directly result from the rising demand for land.

According to Dwikorita Karnawati, Head of the Meteorology, Climatology, and Geophysics Agency (BMKG), the average temperature in Yogyakarta increased by 0.7 °C during the previous 30 years. This issue arises because of the rapid acceleration of the pace of land use change, which in turn generates greenhouse gas emissions. As recorded by the BMKG, Yogyakarta has exhibited an upward temperature trend beginning in 2007 due to the correlation between land use and temperature increase (BMKG, 2021). Growing urban temperature is a serious environmental issue caused by the continuing development of green areas to meet land demands. As reported by a previous study, the urban surface temperature rose when vegetation was removed and replaced with construction materials (Khomarudin, 2004). Low albedo has become a common property of the materials used to build buildings. This dark and low albedo surface has a greater absorption of solar radiation, which is then converted to thermal energy (Senanayake et al., 2013).

Previous studies by Fadlin et al., (2020), Sasmito & Suprayogi, (2017), and Alexandra & Pratiwi, (2019) only employed the LST and Normalized Difference Vegetation Index (NDVI) algorithms to calculate ECI values. Additional steps should be taken, such as excluding water bodies and clouds with the MNDWI algorithm to avoid ambiguous

value results (Senanayake et al., 2013). The results of this study need to be refined because of a mistake in categorizing crucial regions, as revealed by previous research. When comparing water bodies unequal to crucial regions, the high ECI value produced from the low ratio of LST and NDVI is inconsistent. The research of Senanayake et al., (2013) was outdated because it utilized Landsat 7. When it comes to drought detection using LST, Landsat 8 is superior to Landsat 7 (Nugraha et al., 2019). Moreover, Roy et al., (2016) discovered that Landsat 8's NDVI algorithm was preferable to Landsat 7. Therefore, the Normalized Difference Built-up Index (NDBI) technique was applied to Landsat 8 OLI/TIRS in this study and MNDWI on the ECI algorithm formula, seeking to enhance the classification accuracy of the distribution of ECI (critical regions) by removing water and clouds as key environmental categories in Yogyakarta and its environs.

In light of this issue statement, studies comparing environmental criticality in slum areas of Yogyakarta in 2016 and 2021 are warranted. These findings can be utilized as input toward a plan to enhance Yogyakarta's urban environment by building better urban spatial designs.

2 Research Method

2.1 Study Area

Yogyakarta has an area of 32.5 km^2 or 1.02% of the total area of the DIY Province (Fig. 1). It is located between $07^{\circ}15'24'' - 07^{\circ}49'26''$ South Latitude and $110^{\circ}24'19'' - 110^{\circ}28'53''$ East Longitude. The greatest distance from north to south is around 7.5 km, while from west to east is about 5.6 km. Yogyakarta is situated at an average elevation of 114 m above sea level (asl), has a slope of between 0 and 2%, an area located at an elevation of fewer than 100 m, has an area of 1,657 ha, and the remainder at an elevation of 100 to 199 m asl. Regosols account for the vast bulk of Yogyakarta's soil types (DPMPTSP Kota Yogyakarta, 2020).

2.2 Data Collection and Processing

To complete this research, secondary data were utilized, containing slum settlement data from the Regency Geoportal (geoportal.jogjaprov.go.id). Slum areas' environmental criticality was examined through these data. The Landsat 8 OLI/TIRS images in 2016 and 2021 were downloaded from the United States Geological Survey (USGS) website at www.earthexplorer.usgs.gov. The coordinates applied for the download were path 120 and row 65. To make the identification results for the parameter of the land criticality index ideal, the recording period was determined based on the state of the images, trying not to be obscured by clouds. The shapefile data for Yogyakarta and its environs were downloaded from the Geospatial Information Agency's website, which could be reached at portal.ina-sdi.or.id. The data were processed using ArcGIS software. Table 1 displays the research data.



Fig. 1. Map of the Study Area

Table 1. Research Data

Data	Source	Utility
Yogyakarta Slum Area Data	Geoportal (Geoportal, 2020)	Distribution of Yogyakarta slums
Landsat 8 OLI/TIRS	USGS (USGS, 2022)	Processed into LST, NDVI, NDBI, MNDWI image transformations
Yogyakarta Administration Map	Geospatial Information Agency (BIG, 2022)	Administrative boundaries of the research area

The data processing stages are as follows. (a) If atmospheric disturbances are the primary cause of inaccuracy in a given image, radiometric correction can bring the pixel values closer to what they will be in the field (Lukiawan et al., 2019). (b) Images captured in 2016 and 2021 were cropped to reflect the scope of the research. Windows Image Analyzer was utilized by the ArcGIS software. (c) The vegetation index is a mathematical formula combining the RED and Near-Infrared Radiation (NIR) bands (Sasmito & Suprayogi, 2017). The Normalized Difference Vegetation Index (NDVI) is a measure of the greenness of a plant, determined using the following algorithm.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$
(1)

Description:

NDVI: Normalized Difference Vegetation Index

NIR: Near Infrared Reflectance Value

RED: Infrared Reflectance Value

(d) The proportion of vegetation (Pv) was calculated by dividing the total area of vegetation by its vertical projection area (including leaves, stems, and branches) above the ground (Deardorff, 1978). The following is the Pv equation.

$$Pv = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2$$
(2)

Description:

Pv: Proportion of Vegetation

NDVImin: Minimum value of the NDVI result

NDVImax: Maximum value of the NDVI result

(e) Land Surface Emissivity (LSE), an intrinsic feature of natural materials, is frequently employed to assess material composition, particularly for silicate minerals, even though it fluctuates with viewing angle and surface roughness (Sobrino et al., 2001). Its equation is as follows.

$$LSE = 0.004 * Pv + 0.986$$
(3)

Description:

Pv: Proportion of Vegetation

LSE: Land Surface Emissivity

(f) The heat level radiated back into space from the Earth's surface due to solar radiation is termed the Land Surface Temperature (LST), obtained through the following equation.

$$LST = \frac{BT}{\left[1 + \lambda * \frac{BT}{c^2}\right]} * \ln(LSE)$$
(4)

Description:

LST: Land Surface Temperature (°C)

BT: Brightness Temperature

LSE: Land Surface Emissivity

(g) The Normalized Difference Built-up Index (NDBI) is the most effective transformation algorithm for highlighting the appearance of built-up land compared to other objects. The NDBI equation is as follows.

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)}$$
(5)

Description:

NDBI: Normalized Difference Built-up Index

SWIR: Shortwave Infrared Reflectance Value

NIR: Near Infrared Reflectance Value

(h) The NDBI and NDVI difference was calculated by the Built-Up (BU) index, an algorithm based on the discrepancies between the two. If vegetation reflections are diminished, urban areas will stand out more clearly. The following formula can be applied to calculate the BU index.

$$BU = NDBI - NDVI$$
(6)

Description:

NDBI: Normalized Difference Built-up Index

NDVI: Normalized Difference Vegetation Index

(i) Because of rising LST and dwindling vegetation density (NDVI), the environment is in a critical state, as measured by the Environmental Criticality Index (ECI). Increases in surface temperature have been proven to correlate directly with ECI. In contrast, decreases in vegetation density have been reported to have an inverse correlation (Senanayake et al., 2013).

$$ECI = LST * BU (1 - 255 \text{ streched})$$
(7)

Description:

ECI: Environmental Criticality Index

LST: Land Surface Temperature (°C)

BU: Built-Up

In this study, the body of water and clouds must be considered non-existent to exclude them from the crucial environment category. The Modified Normalized Difference Water Index (MNDWI) algorithm was employed to extract the body of water through the following equation.

$$MNDWI = \left(\frac{(GREEN - SWIR1)}{(GREEN + SWIR1)}\right)$$
(8)

Description:

MNDWI: Modified Normalized Difference Water Index

Green: Green band reflectance value

SWIR1: Shortwave infrared reflectance value

(j) Regency Geoportal was utilized to obtain data on the distribution of slum settlements, which was then overlaid with the ECI value to produce data on the distribution of the ECI for slum areas in Yogyakarta and its environs.

2.3 Framework

Yogyakarta shapefile data and multitemporal Landsat 8 images in 2016 and 2021 were the starting points for this study's analysis. After using the idea proposed by Russwurm in 1987 (Koestoer, 1997), asserting that the region is a suburb still receiving influence from the city center within a radius of 10 km, the research area was narrowed down to that size. Utilizing Yogyakarta and its environs shapefile, the ArcGIS Buffer tool was applied to delimit the research area.

After obtaining Landsat 8 images from the United States Geological Survey (USGS), a radiometric correction method was employed (Fig. 2). It assisted in rectifying pixel values that atmospheric conditions have altered. Subsequently, the buffered areas of images were cropped and reduced to a circle with a radius of 10 km. ArcGIS' Windows Image Analysis tool was utilized to crop images based on user-specified bounds.

After the images had been cropped to include only the target region of interest, the brightness temperature (BT) algorithm was executed. The surface temperature could not be determined without initially knowing the BT. The rectified images were then converted to NDVI. Calculating the proportion of vegetation (Pv) from the NDVI value was possible. Pv has been beneficial in determining the emissivity value in the NDVI. The roughness of a surface and the authenticity of a landscape's vegetation could be estimated using Land Surface Emissivity (LSE). After completing everything, the temperature of the ground's surface was determined by calculating the LST. Following the radiometric correction, the NDBI and MNDWI conversions were performed. To prevent a pixel value of 0 when calculating ECI, the spectral value of each variable was stretched to 1–255. Following the analysis, a map depicting Yogyakarta and its immediate vicinity's ECI was generated.

3 Results and Discussion

3.1 Land Surface Temperature (LST)

LST is a land surface temperature measurement based on the heat emission from the land surface caused by solar radiation. The use of multitemporal data intends to ease the monitoring of changes in land use across time, facilitating the analysis and producing reliable findings (Wiguna et al., 2022). Figure 3 depicts the change in the surface temperature distribution in Yogyakarta and its environs in 2016 and 2021.

Following the map in Fig. 3, LST has risen in the previous five years. The highest LST rose by 35 °C in 2016 and 42 °C in 2021. The temperature distribution on the map was particularly high in the city center, suggesting that the downtown region lacked vegetation as a canopy, resulting in high surface temperature. The presence of vegetation had a significant impact on the surrounding circumstances. The density of vegetation in urban areas could assist in reducing the danger of climate change (Danardono et al., 2022). The dispersion of high surface temperature spread and approached suburban areas. Pajangan District, Bantul Regency had a comparatively low temperature of 22–24 °C, rising to an extremely high temperature of 25–28 °C in 2021. In other words, the rise in surface temperature significantly impacted environmental quality.

The city center possessed many facilities and infrastructure, thus, having a high temperature. Yogyakarta Palace, Malioboro, Mandala Krida Stadium, Jogja National Museum, Adisutjipto International Airport, health facilities, and universities were only a few examples. According to Yoo et al., (2017), the temperature increase has been driven by population mobility factors. The increase in surface temperature has been caused by human activities such as urbanization, transportation, and settlements.



Fig. 2. Flow Chart of Processing Method



Fig. 3. Land Surface Temperature (LST) Maps of Yogyakarta and its Surroundings in 2016 and 2021

3.2 Built-Up (BU) Index

In the ECI analysis, BU was employed to estimate the distribution of built-up land, one of the crucial environmental indicators. Built-up land refers to transforming the land from green open to built-up. Figure 4 exhibits a variation in the distribution of surface temperature in Yogyakarta and its surrounds in 2016 and 2021.

Figure 4 demonstrates that the built-up area remained the same throughout the two years. However, the development density increased to the north of the city in 2021. It contributed to the depiction of a 42 °C jump in surface temperature in the center of the city, as displayed in Fig. 3. Due to ever-increasing land demands, urban expansion experienced an effect on the neighborhoods bordering city centers.

3.3 Environmental Criticality Index (ECI)

Urban infrastructure projects imposed unintended consequences for society at large, one of which was environmental degradation. Land conversion projects have risen in Yogyakarta because of the city's importance as a cultural, economic, medical, and industrial center. Downtown locations tended to be warmer than their suburban counterparts because built-up land possessed a low albedo value and absorbed more solar heat. Through arithmetic calculations, several variables of the ECI have been uncovered. Figure 5 depicts the shift in environmental criticality in 2016 and 2021.

Because of the high population density, lack of vegetation, and high land surface temperature indicative of environmental degradation discovered in the downtown, this



Fig. 4. Built-up (BU) Index Maps of Yogyakarta and its Surroundings in 2016 and 2021



Fig. 5. Environmental Criticality Index (ECI) Maps of Yogyakarta and its Surroundings in 2016 and 2021

area was classified as having a high criticality level; in contrast, the suburban areas depicted a low criticality level due to the low population density, high vegetation, and low land surface temperature. Critical environments spread, and some formerly stable regions were threatened. The city center and the supporting infrastructure at its periphery have been considered ecologically crucial. Extending a city to its outskirts within a 10-km radius significantly influenced the environment. As can be seen in Fig. 5, most of the city's development has occurred to the north and southwest. The distribution of the ECI matched that of the LST (Fig. 3) and BU values (Fig. 4) (Ranagalage et al., 2017).

3.4 Slum Area Environmental Criticality Index

Critical environmental conditions were brought on by combining a high population density and a low vegetation density. This issue was also associated with slum settlements. Because of the high demand for settlement in the limited land, slums have sprung up all over the area. Figure 6 is a map illustrating the prevalence of slum areas along rivers in and around Yogyakarta, Indonesia, including the Gadjah Wong, the Code, and the Winongo. The city center and its surrounding suburbs, including the southern portion of Sleman Regency and the northern portion of Bantul Regency, were where most people lived. Slums in the city center continued to experience extremely precarious environmental circumstances in 2016 and 2021, while those on the city periphery experienced only moderate to high peril.

Slums in the city center were caused mostly by migrants relocating there due to the long commute between their homes and place of employment. Overpopulation stemming



Fig. 6. ECI in Slum Areas of Yogyakarta and its Surroundings in 2016 and 2021

from this issue led to shabby towns with inadequate infrastructure. Many slum buildings were of poor quality and disorganized since the lower middle class made up most of the slum settlements (Pigawati, 2015). There must be careful land-use planning at the regional level if population densities are to be spread out evenly (Luis et al., 2021).

4 Conclusions

Criticality was likely to be low in places with low surface temperature, dense vegetation, and sparse built-up land and high in places with high surface temperature, sparse vegetation, and densely built-up land. Slums were concentrated primarily near the river in the city center. Slums in and around Yogyakarta were located mostly in areas with extremely poor environmental quality.

Acknowledgment. The authors would like to express their gratitude to the Faculty of Geography, Universitas Muhammadiyah Surakarta, as the organizer of the International Conference of Geography and Disaster Management (ICGDM), for providing them with the opportunity to attend the conference.

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