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An Analyze of Urban Temperature Using Energy Balance Algorithm for Land (SEBAL) in Yogyakarta City

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ABSTRACT

This study examines the Land Surface Temperature (LST) using the Surface Energy Balance Algorithm for Land (SEBAL) model in Yogyakarta. SEBAL is relied upon for its accurate LST predictions because it takes into account the influence of vegetation and soil. This study identified LST in various land cover/land use (LULC) types extracted from Landsat 8 remote sensing images recorded in April 2019 (wet day) and June 2019 (dry day). The LULC classification results in the study area show that built-up land is the dominant land use, with 93.30% of the total area, and the rest is non-developed land (vegetation, open land, and water body). The average LST value on a wet day is 26.79 °C, while on a dry day, it is 30°C. The highest temperature occurs on the dry day, 35.17 °C, and the lowest on the wet day, which is 13.63°C. The correlation between LST and LULC shows the same pattern on the two different days, in which the value of vegetation temperature is lower than that of open and developed land. This research proves that vegetation influences a decrease in land surface temperature. Judging from the dominant land use being the built-up area in Yogyakarta, urban planners need to consider increasing green open spaces.

Keywords: Land surface temperature, SEBAL, Yogyakarta

INTRODUCTION

The density of the urban population contributes to climate change due to pressure on land use (Ilcheva and Yordanova 2019). The advantages of the city as a center of economic activity encourage the acceleration of urbanization, which impacts the complexity of problems in the city (Arif et al. 2019; Chrysoulakis et al. 2018). Conversion of land from non-built into built-up land results in increased air temperature reduces evapotranspiration and causes drought (Tursilowati et al. 2012). On the other hand, if the vegetation cover increases, the temperature will decrease (Goward et al. 2002). The vegetation dynamics are significantly influenced by geographical factors, climate, and the inhabitants' everyday activities (Kalisa et al. 2019). The importance of vegetation land cover in sustaining the urban climatic balance cannot be overstated. As a result, cities with dense populations must factor green space availability into urban design and development.

This study focuses on land surface temperature (LST) in Yogyakarta's various land cover/land use (LULC) categories. Yogyakarta city is an essential part of the Yogyakarta Special Region's development as an Indonesian province since it is one of the most important centers of education and tourism domestically and internationally (Cahya et al. 2017). This fact has allowed the city to grow by expanding the number of built-up areas, such as student boarding houses, apartments, and hotels. This study combined remote sensing technology and geographic information system (GIS). At the micro to macro scale, remote sensing has the advantage of consistency of observation and up-to-date spectral reflectance and land surface radiation (Bastiaanssen et al. 1998a). Remote sensing and geographic information systems (GIS) are essential tools in a range of applications related to this topic, including the study of urban climates (Nwaerema et al. 2019; Pal and Ziaul 2017), fractional vegetation cover mapping (Arif et al. 2020; Timmermans et al. 2007), LST mapping (Arif et al. 2019; Weng 2009), green space area (Chan and Vu 2017; Oliveira et al. 2011) and thermal monitoring city (Zhou et al. 2019; Zinzi and Carnielo 2017).

Land Surface Temperature is essential in urban energy studies and climatology (Khandelwal et al. 2018). LST is used to measure the temperature of the city's surface heat because it takes into account the radiation of the earth's surface (Pal and Ziaul 2017). The characteristics of LULC are closely related to LST (Weng 2009). The temperature characteristics of various types of LULC are investigated in this study on two separate days, namely the rainy day and the dry day. Previous studies have shown a relation between LST and LULC, with vegetation land cover having a lower surface temperature than built-up areas (Weng 2009). The Surface Energy Balance Algorithm for Land (SEBAL) method examined LST. The main objective of SEBAL modeling was to determine how the visible and thermal infrared channels of different surface types, such as dry land and wetlands, interacted (Bastiaanssen et al. 1998a; Bastiaanssen et al. 1998b). By analyzing the effects of vegetation and soil, the SEBAL model can accurately estimate land surface temperature (Song et al. 2016). The objective of the vegetation index analysis was to examine the properties of the vegetation both geographically and temporally. SEBAL estimates canopy radiation as a function of NDVI using a semi-empirical method (Rahimzadegan and Janani 2019; Timmermans et al. 2007). The weighted difference vegetation index (WDVI) and the soil-adjusted vegetation index (SAVI) are two more approaches to estimating the vegetation index that can be utilized in the SEBAL calculation (Clevers 1991). The soil aspect is highlighted using SAVI (Huete 1988). The SEBAL model's different vegetation index formulas are expected to improve accuracy and decrease LST information. Land surface temperature mapping greatly benefits city planners in developing policy designs considering environmental conditions, climate, and citizens' comfort.

MATERIALS AND METHODS

Study Area

The city of Yogyakarta, which is located at 7°48'5" N and 110°21'52" E, is the case study for this study (Figure 1). Yogyakarta is the seat of the Yogyakarta Special Region, one of Indonesia's provinces. Yogyakarta has a tropical monsoon climate, with precipitation below 60 millimeters in August, the driest month.

Data Collection

The USGS Global Visualization Viewer provided the Landsat 8 OLI imagery utilized in this inquiry. The

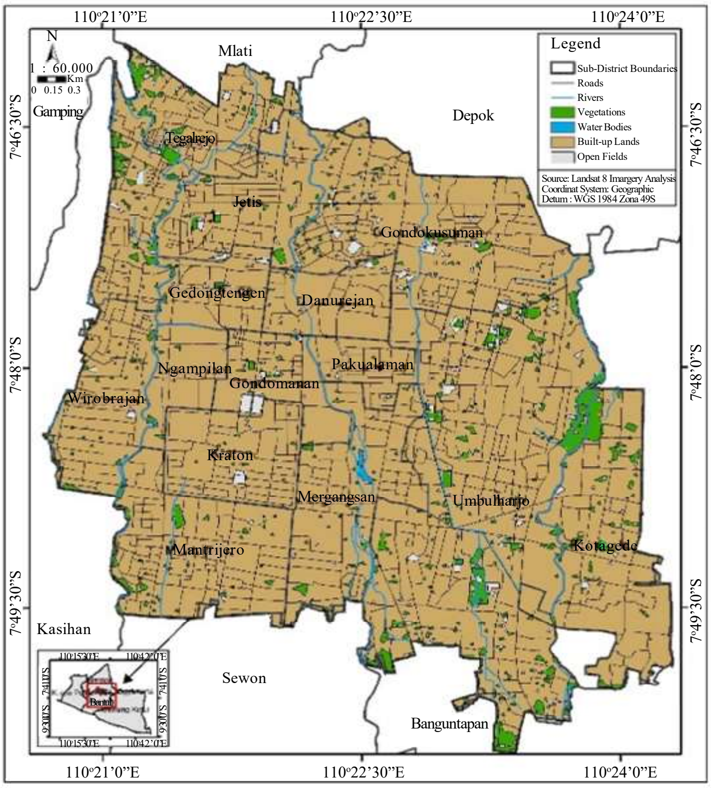


Figure 1. The LULC map of Yogyakarta City.

Table 1. Image data source.

	Data acquisition
Landsat 8 wet day	22 April 2019
Landsat 8 dry day	25 June 2019

(http://earthexplorer.usgs.gov 2019)

Landsat imaging records the earth's surface every 16 days, allowing for regular monitoring of a given area. Each Landsat pixel has a geographical coverage of 30 m and a radiometric resolution of 12 bits. Table 1 shows the Landsat 8 data that were used in this investigation.

Surface Energy Balance Algorithm for Land

In this study, the SEBAL algorithm was used to estimate land surface temperature, and this model uses near-infrared sensors and thermal infrared in Landsat imagery. British et al. (2002) arrange the stages used in SEBAL as follows.

(1). Convert Digital Number (DN) values to radians for thermal bands (bands 10 and bands 11) using the band math according to the following formula:

$$L\lambda = MLQcal + AL$$

Where,
Lλ = spectral radians on the sensor (W / (m2sr. Ìm)
Qcal = pixel value (DN)
ML = rescaling constant (RADIANCE_ MULT_ BAND_x, where x is the band used)
AL = constant (RADIANCE_ADD_BAND_x, where x is the band used

(2).Convert DN values to reflectance for non-thermal bands according to the following formula:

$$\rho\lambda' = M\rho Qcal + A\rho$$

where,
ρλ'= Image reflectance values (min and max values are listed in the image header)
Qcal = pixel value (DN),
Mρ = rescaling constant (REFLECTANCE_ MULT_BAND_x, where x is the band used)
Aρ = adder constants (REFLECTANCE_ ADD_ BAND_x, where x is the band used)

(3).The reflectance value (ρλ') has not been corrected with d = the sun's angle. To get the TOA reflectance value, we need to correct the sun's angle with the equation:

$$\rho\lambda = \frac{\rho\lambda'}{cos(\theta sz)} = \frac{\rho\lambda'}{sin(\theta se)}$$

Where,
ρλ = TOA planetary reflectance (without units),
ρλ'= previous processing results, without correction of the taking angle
θSE = Sun elevation angle when recording (sun elevation) obtained in the image header
θSZ = zenith angle; θSZ = 90° - θSE αtoa

(4).Calculating the value of Albedo. Surface albedo is the ratio of the sun's electromagnetic radiation reflected from the surface of the soil and plants to the incoming radiation (Song et al. 2019). Albedo is calculated from the following equation.

$$\propto = \frac{\propto_{toa} - \propto_{path-radiance}}{\tau sw^2}$$

$$\propto_{toa} = \sum(\omega\lambda \, x \, \rho \, \lambda)$$

$$\omega\lambda = \frac{ESUN_\lambda}{\sum ESUN_\lambda}$$

$$\tau sw^2 = 0.75 + 2\, x 10^{-5} x \, z$$

where,
α = Albedo, the ratio between the rays of the sun that arrives at the surface of the earth and that is reflected into space
$\propto_{toa}$ = Albedo on the surface of the atmosphere (Albedo at the top of the atmosphere)
$\propto_{path-radiance}$= albedo path radiance
ρ λ = reflectivity for band λ
τsw = shortwave transmissivity of air
ωλ = weighting coefficient for band λ

(5). Calculate NDVI values with the formula:

$$NDVI = \frac{\alpha NIR - \alpha RED}{\alpha NIR + \alpha RED}$$

where,
NDVI = NDVI value
αNIR = reflectance at near long-wavelength (band 5)
αRED = reflectance at the length of the infrared band (band 4)

(6). Calculates the *Weighted Life Vegetation Index* (WDVI) value according to the following formula

$$WDVI = NIR - \alpha RED$$

where,
WDVI = WDVI value
NIR = near-infrared band (band 5)
α = coefficient equation of the relationship of the infrared band close to the infrared band
RED = infrared band (band 4)

(7). Calculating the Soil Adjusted Vegetation Index (SAVI) value using the equation:

$$SAVI = \left(\frac{(NIR - RED)(1 + L)}{(NIR + RED + L)}\right)$$

where,
SAVI = SAVI value
NIR = near-infrared band
RED = infrared band
L = Monin-Obukhuv length
L = 1 - 2 × a × NDVI × WDVI, a = 1.6

(8). Calculate LAI values using equations

$$LAI = \left(\frac{\ln\left(\frac{0.69 - SAVI}{0.59}\right.}{0.91}\right)$$

In practice, the LAI value used is adjusted to the following conditions.
LAI = 11 * SAVI ^ 3 (for SAVI ≤ 0.817), or
LAI = 6 (for SAVI> 0.817)

(9). Calculates the object's emissivity value
εNB = 0.97 + 0.0033 * LAI; (for LAI <3)
ε0 = 0.97 + 0.0033 * LAI; (for LAI <3)
εNB = 0.98 and ε0 = 0.98 when LAI ≥ 3
where,
- the εNB value is used in the calculation of surface temperature
- the value of ε0 is used to calculate the total longwave radiation emission from the surface

(10). Calculates the corrected thermal radians (Rc)

$$Rc = \frac{L6 - Rp}{\tau NB} - (1 - \varepsilon NB)Rsky$$

where,
L6 = spectral radians of band 6 corrected
Rp = path radians
Rsky = thermal radiation in a narrow band when the sky is clear
τNB = air transmission in narrowband

(11).Calculate surface temperature (Ts)

$$Ts = \frac{K2}{\ln\left(\frac{\varepsilon NB\ K1}{Rc} + 1\right)}$$

where,
Ts = surface temperature (K)
K1, K2 = constants from Landsat images
Rc = corrected thermal radians value

In the process, the surface temperature calculation is used for each thermal band, namely band 10 and band 11. Then, the value of the surface temperature is actually calculated, i.e., the average value. Next, a calculation is performed to get the temperature value to Celcius (Celcius = Kelvin - 273.15)

Tskelvin = (TsB10 + TsB11) / 2; (Ts in Kelvin)
Tscelcius = Ts in Kelvin-273.15; (Ts in Celsius)

RESULTS AND DISCUSSION

Supervised classification divides pixels into land cover classes based on their pixel values' similarity to the region of interest (ROI). Land cover classification is carried out using the maximum likelihood classification because it shows better results than the unsupervised classification, where several classes are automatically entered, which can lead to possible errors in classification (Gadrani et al. 2018). In the earlier studies, LULC was applied to determine the relationship with LST (Arif et al. 2017; Guha and Govil 2020; Pal and Ziaul 2017; Weng 2009; Weng and Lu 2008). The built-up area takes up 94.19 percent of the total area on the LULC map, while the non-built-up area takes up the rest (vegetation, open land, water body). Yogyakarta is thus a densely populated city with a varied range of functions. Table 2 shows the percentages of each LULC.

Table 3 shows that the higher temperature in the image recorded on a dry day is 35.17°C compared to the image recorded on a wet day, with the highest temperature being 32.11°C. Figure 2 shows the results of the spatial distribution of LST on two different days. The Kraton, Gondomanan, Pakualaman, Danurejan, Jetis, Mergangsan, Gondokusuman, Ngampilan, Wirobrajan, and part of the Kotagede districts have maximum dry day temperatures in the range of 31-33°C. The Tegalrejo districts and Umbulharjo have the highest

Table 2. LULC area.

LULC	Area (%)
Open field	1.88
Waterbody	0.08
Buil up area	94.19
Vegetation	3.86

(analysis 2020)

Table 3. LST value of study area.

	Wet day (°C)	Dry day (°C)
Average	26.79	30
Maximum	32.11	35.17
Minimum	13.63	25.24
Standard deviation	2.44	1.35

(analysis 2020)

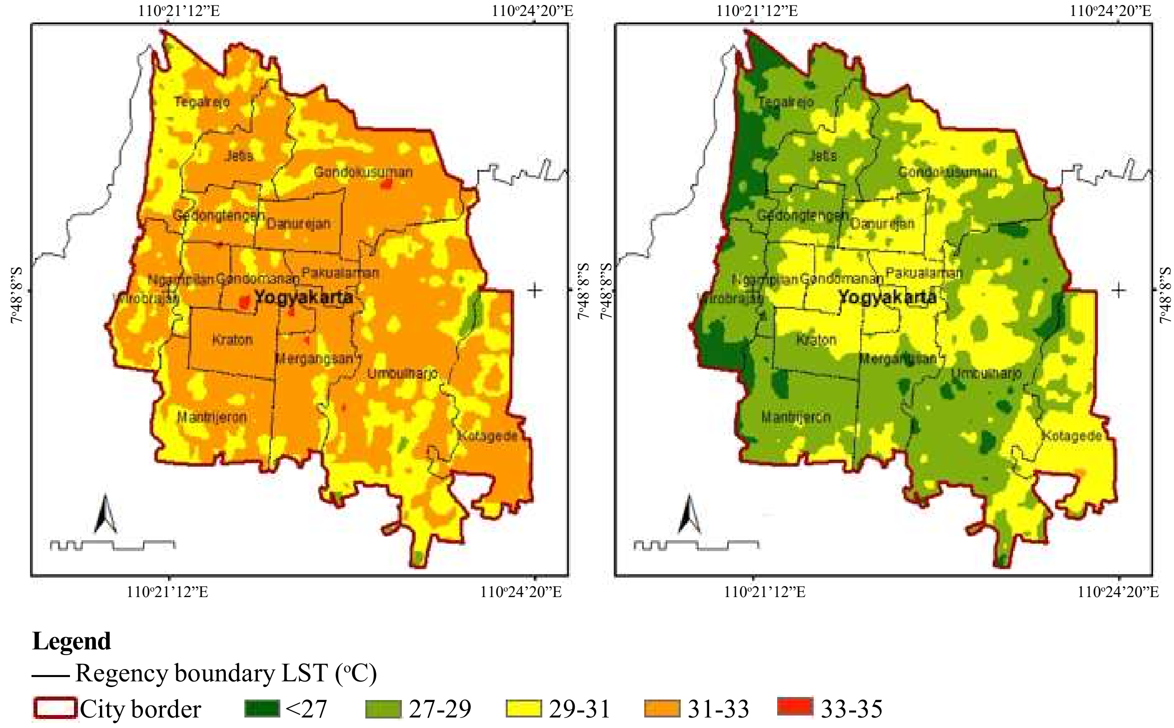


Figure 2. a). The LST on a dry day; b) The LST map on the wet day (analysis 2020).

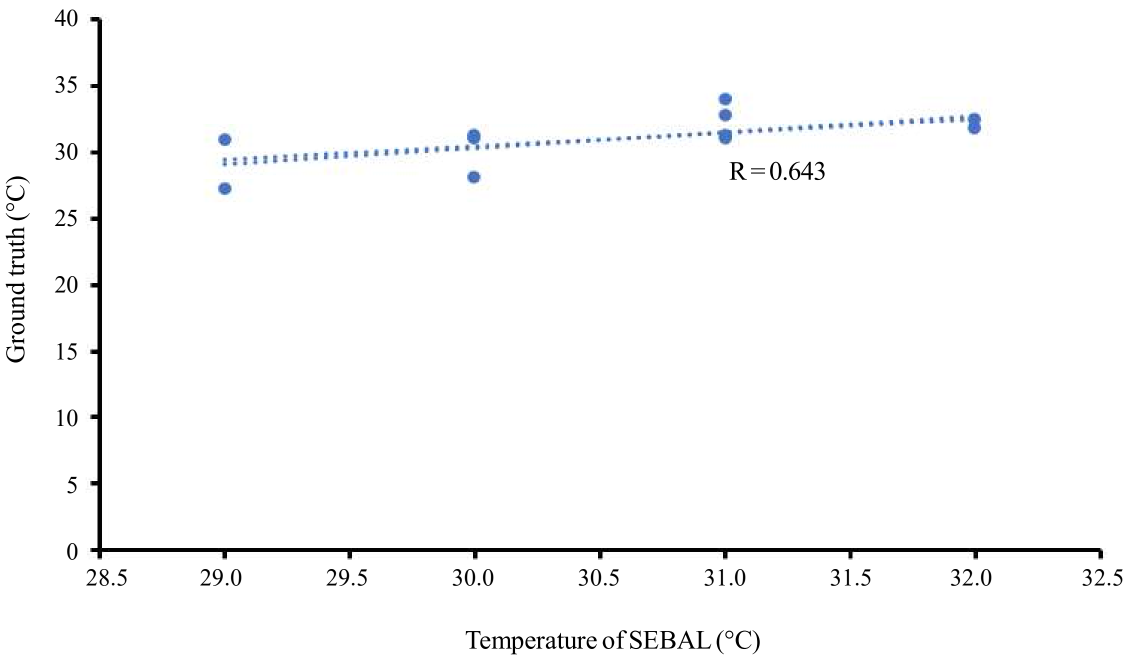
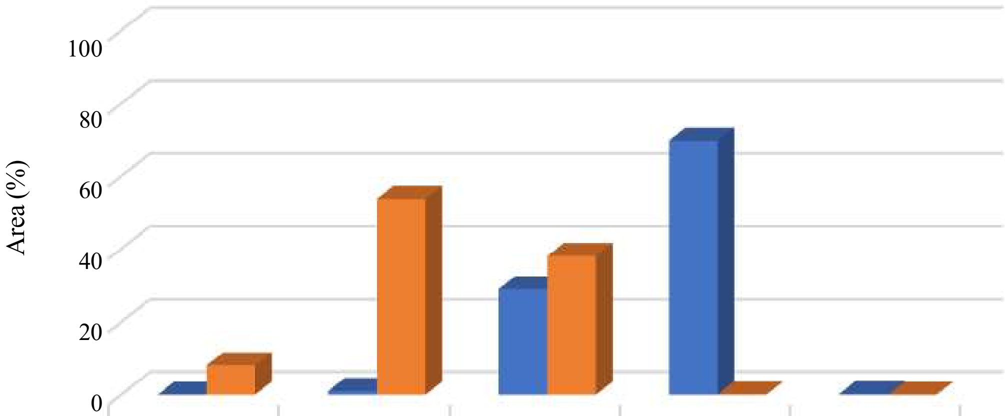


Figure 3. LST and ground truth correlation (analysis 2020).

temperatures, with temperatures ranging from 29 to 31°C. Correlation between LST and ground truth is presented in Figure 3.

Figure 3 shows a high correlation between LST values and ground truth with an R-value of 0.64. Gondomanan, Pakualaman, Danurejan, part of Gondokusuman, Kotagede, region of Kraton, and Mergangsan have high temperatures in the 29-31°C range on rainy days. In the Kotagede district, temperatures in the 31-33°C range are only observed in a small area. On a dry day, LST with a temperature range of 33-35°C can be found in some regions, but not on a rainy day. The highest LST pattern was clustered in the city center, precisely in



	23 - 27	27 - 29	29 - 31	31 - 33	33 - 35
Dry day (%)	0.00	0.98	29.00	69.75	0.26
Wet day (%)	8.02	53.85	38.05	0.09	0.00

Figure 4. Graphic percentage distribution of LST on a dry day and the wet day (analysis 2020)

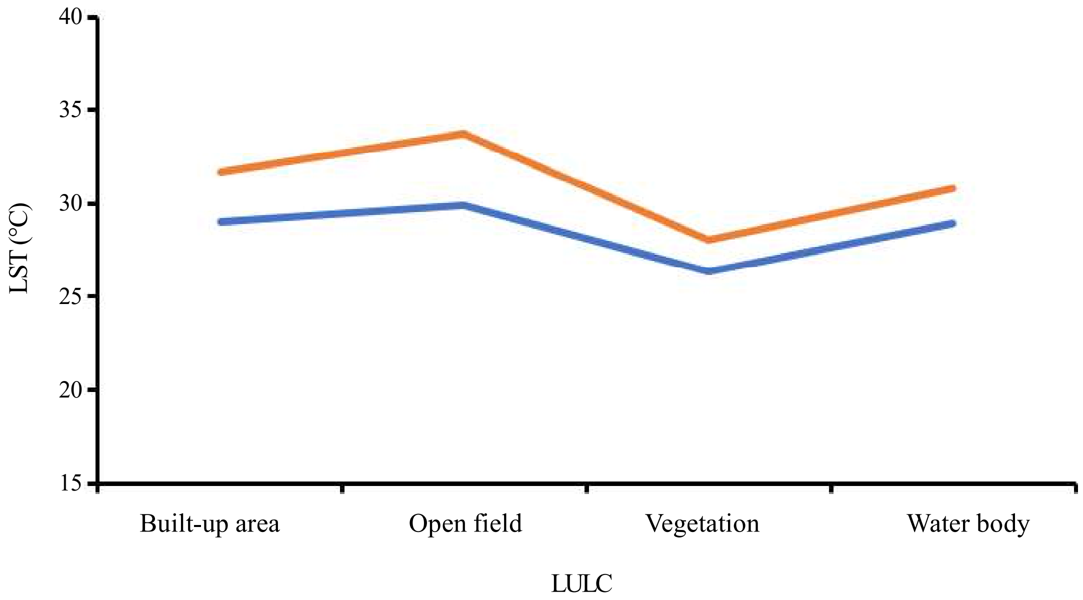


Figure 5. LST values for various LULC types. : LST wet day, : LST dry day.

Danurejan, Gondomanan, and Pakualaman districts, as in Sumunar et al. (2020), with the highest LST pattern, was found in the city center, particularly in Danurejan, Gondomanan, and Pakualaman districts. Sumunar et al. (2020) stated that the land surface temperature in Yogyakarta is clustered in the same area where the area is the center of economic activity with the dominance of built-in land, namely the Danurejan district and its surround. The following Figure 4 shows the details of each temperature range's area.

On a dry day, the highest temperature range is 33-35°C, which is spread over 0.26 percent of the whole area, while the minimum temperature range is 27-29°C, which is distributed in roughly 0.98 percent of the total area, as shown in Figure 4. On a wet day, the maximum temperature range of 31-33°C is found in only 0.09 percent of the whole area, but the maximum temperature range of 27-29°C is found in 53.85 percent. Many factors influence the difference in surface temperature, including city surface roughness (Burakowski et al. 2018), the thermal properties of the city's surface objects, which vary depending on their position and orientation in the form of roof and wall qualities (Voogt and Oke 2003), and the biophysical conditions of the soil (Weng 2009). Figure 5 shows the impact of land use on LST values in this study.

Figure 6 illustrates a similar pattern, namely that the temperature of the vegetation is lower than that of open land and built-up areas. This study's SEBAL processing shows that vegetation causes a low land surface temperature (Khandelwal et al. 2018). Green spaces are essential in urban areas because they create a cooling effect (Oliveira et al. 2011). As a result, based on Yogyakarta's predominant land use, urban planners should consider expanding the green space area.

CONCLUSIONS

The SEBAL approach, which combines remote sensing and GIS, helps map urban land surface temperatures. The results of LST mapping show that the average temperature in the wet day recording image is 26.79°C. While the average temperature on a dry day recorded images are 30°C. The LST value is correlated with LULC, where high temperatures are distributed in open land and built-up land, and lower temperatures are found in vegetation land cover. High LST values are clustered in several sub-districts around the city center, namely Gondomanan, Danurejan, Pakualaman, and surrounding districts.

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