Spatial dynamic of land surface temperature in ciliwung watershed

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Abstract. Land surface temperature (LST) is one of critical element in urban climatology study, especially on urban heat island (UHI) mitigation and water balance. Urbanization in Ciliwung watershed continuously erodes open areas and considerably significant affect the surface temperature within watershed area. Therefore, the purpose of the study is to explore the potential contribution of land surface rising between elevations, vegetation and built-up index. Landsat 8/OLI satellite images use to derive LST, normalize differences vegetation index (NDVI) and normalized differences built-up index (NDBI) in study area on 2014 and 2018. Furthermore, elevation derive from DEMNAS raster provide by Geospatial Information Agency (BIG). In summary, there were LST increases from means temperature from 28.52 Celsius (2014) to 29.10 Celsius (2018) along with land cover changes (LCC). Meanwhile, LST spatial distribution is very closely related to the distribution of NDVI and NDBI. Statistical test results show high correlation (R-squared = 0.89 - 0.91) between LST, elevation, NDVI and NDBI. This indicates elevation, NDVI and NDBI factor play a significant role in LST dynamics.

1. Introduction
Land surface temperature (LST) is key parameter of surface energy balance and urban climatology study. LST is one of the factors that influence urban climate changes where its role relates to Urban Heat Island (UHI) mitigation. LST changes is a complex spatial phenomenon caused by various factors such as land cover (LC)[1], elevation [2], vegetations [3][4] and building density [5].

LC is related to human activity on a particular plot of land [6], where LC changes have an impact on climate change stronger than pollution [7]. In terms of elevation, differences in altitude also significantly affect surface temperature changes in an area [8]. Vegetation and building density also have an impact on LST changes because correlation between surface temperature and vegetation density have an inversely relationship [9] and building index have a positive relationship [10].

Ciliwung Watershed is one of the largest watersheds with watershed total area around 370.8 km2 and the main river length reaches 124.1 Km. Recently, incessant urbanization within Ciliwung watershed area continuously erodes pervious surfaces and convert it into impervious surfaces. Land surface conversion would cause soil absorb and reflect more solar radiation, which periodically increase land surface temperature [8].

Over the past 5 years, population growth and the urbanization in the Ciliwung watershed are in line with the increasing needs of residential land and supporting facilities. Conversion of pervious surface into built-up land around the Ciliwung watershed rapidly happens every year, more than 40% of residential area within the Ciliwung upstream is not in line with government spatial masterplan. The
rapid development of urban areas has an impact on decreasing the carrying capacity of the environment, includes the LST increase.

The LCC pattern show spatial dynamic of land surface temperature changes happens in the Ciliwung watershed. LST changes in Ciliwung watershed have an impact on the ecological, economic and hydrological systems of the region. As a result of rapid population growth and increases 27% of residential area, following decreases 16.62% forest area [11] is a trend of an increase in extreme rainfall and aerosol concentrations in the downstream region of the impact of the UHI phenomenon in the upstream region [12]. The increase in aerosols in the downstream region as an indication of the increase in extreme rain that has caused the intensity of floods in the Jakarta area has increased since 1986 [13].

In this study remote sensing technologies uses to determine LST through Landsat 8/OLI image and perform statistical analysis to correlation between elevation, NDVI and NDBI. The objective of this study is to analyze the spatial dynamic of LST in relation to elevation, NDVI and NDBI value in Ciliwung watershed. To have understanding on LST changes that will be caused due to change in the elevation, NDVI and NDBI in space over a large area along different surface characteristics.

2. Methods
This study uses remote sensing methods to derives LST, NDVI, NDBI data from Landsat 8/OLI, meanwhile elevation data derives through DEMNAS raster where obtained from BIG. By using certain algorithms on red reflectance, near infrared, short wave infrared, and thermal bands, in Landsat 8/OLI images, the value of surface temperature, vegetation index and built-up index can be determined. Landsat 8/OLI image used in this could be seen on Table.1. Linear regression performs to understanding how correlation between LST, elevation, NDVI and NDBI.

### Table 1. Landsat 8/OLI data used for the study.

| No | Date       | Path/ROW |
|----|------------|----------|
| 1  | 13-Sep-2014| 122/64   |
| 2  | 13-Sep-2014| 122/65   |
| 3  | 06-Jul-2018| 122/64   |
| 4  | 06-Jul-2018| 122/65   |

2.1. Study Area
Ciliwung watershed, geographically located between 6 ° 11’ 54” - 7 ° 01’ 27” S latitude and 106 ° 42'12” - 106 ° 55’20” E longitude. Its pass through 4 mayor cities i.e. DKI Jakarta Province in downstream part and Bogor City, Bogor Regency and Depok City in mid-upstream. Topography in downstream area have varies elevation between 0-100 m, meanwhile the midstream have hilly topography with height variation between 100-300 m. In the upstream part, the area covered by mountain topography with height variation between 300-3,000m. The distribution of elevation of Ciliwung watershed has presented in figure 2. Ciliwung watershed itself has a total area of 370.8 km2 and the main river length measured from upstream to downstream reaches 124.1 Km.
Based on its function, the upstream watershed is based on a conservation function that is managed to maintain the environmental conditions of the watershed so that it is not degraded, which can be indicated by watershed land cover vegetation conditions, water quality, the ability to store water (discharge) and rainfall. Midstream part is managed to be able to provide benefits for social and economic interests, which can be indicated from the quantity of water, water quality, ability to channel water, and groundwater level, and related to irrigation infrastructure such as river management, reservoirs and lakes. Furthermore, the downstream part is managed to be able to provide social and economic benefits, which is indicated by the quantity and quality of water, the ability to channel water, the height of rainfall, and related to agricultural needs, clean water and waste water management [14].

**Figure 1.** Extent of study area.

**Figure 2.** Surface elevation of the study area as derived from DEMNAS raster.
2.2. Land Surface Temperature
LST retrieve from thermal band (Band 10) of Landsat 8/OLI image using radiometric calibration to convert digital number (DN) which store in pixel image into spectral radiance (SP). SP value would be process into Kelvin and Celsius unit using following algorithm [15]:

\[ L_\lambda = M_P \times Q_{cal} + A_L \]  

(1)

Where \( L_\lambda \) is spectral radiance in Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\), \( M_P \) is scale factor, \( Q_{cal} \) is DN and \( A_L \) is an adding factor on thermal band.

\[ T_B = \frac{K_2}{\ln((K_1/L_\lambda)) + 1} \]  

(2)

Where \( T_B \) is brightness temperature or radiance temperature which represent surface temperature in Kelvin (K), \( L_\lambda \) is spectral radiance in Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\), \( K_1 \) and \( K_2 \) is calibration constants which obtained from Landsat 8/OLI metadata (\( K_1 = 774.89 \) and \( K_2 = 1321.08 \)).

\[ ^\circ C = K - 273.15 \]  

(3)

Where \( ^\circ C \) is temperature in Celsius unit, \( K \) is temperature in Kelvin unit and -273.15 is constants.

2.3. Vegetation Index
Normalized difference vegetation index (NDVI) is used as indicator of biomass and greenness [16]. NDVI derives from Landsat 8/OLI images using DN value in Near Infrared Reflectance (NIR) and Red Reflectance (RED) with following algorithm:

\[ NDVI = \frac{(NIR - RED)}{(NIR + RED)} \]  

(4)

Where \( NDVI \) is vegetation indexes the value ranges from -1 to +1, where positive value indicates a vegetated area and a negative value indicates a non-vegetated area. \( NIR \) is DN stored in pixel value on Band 5 and \( RED \) is DN stored in pixel value on Band 4.

2.4. Built-up Index
Normalized difference building index (NDBI) is widely used for the extraction of urban built-up areas and to map it automatically [17]. NDBI derives from Landsat 8/OLI images using DN value in Short Wave Infrared (SWIR) and Near Infrared Reflectance (NIR) with following algorithm:

\[ NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \]  

(5)

Where \( NDBI \) is used to extract built-up features and have indices range from -1 to +1, where negative value of NDBI represent water bodies where as higher value represent build-up areas. NDBI value for
vegetation is low. \textit{SWIR} is DN stored in pixel value on Band 6 and \textit{NIR} is DN stored in pixel value on Band 5.

3. Results and discussions

3.1. Results

Based on the results of the study, figure 3a and b show the spatial distribution of LST in the study area produced from Landsat 8/OLI in 2014 and 2018. In general, temperature profile of the study area from both LST images indicate that the temperature was high in the north and low in the south. Overall downward trend from north to the southern part of the study area along with the increases of topography profile. In addition, both LST image show that there were increases on maximum and minimum temperature from 37.45 $^\circ$C and 11.95 $^\circ$C in 2014 to 39.29 $^\circ$C and 16.11 $^\circ$C in 2018.

![Figure 3a. LST spatial distribution of the study area in 2014 derived from Landsat 8/OLI](image1)

![Figure 3b. LST spatial distribution of the study area in 2018 derived from Landsat 8/OLI](image2)

Figure 4a and b, show that the maximum and minimum NDVI in 2014 is 0.417 and -0.278, while in 2018 is 0.407 and -0.320. According to the NDVI image, both NDVI in 2014 and 2018 exhibited opposite spatial distribution pattern with LST pattern. NDVI spatial pattern low in the north and high in the south, similar to elevation rising pattern from north to the southern part of study area. Increasing NDVI value indicate that vegetation coverage in the southern area is higher than northern area of Ciliwung watershed.
Figure 4a. NDVI spatial distribution of the study area in 2014 derived from Landsat 8/OLI

Figure 4b. NDVI spatial distribution of the study area in 2018 derived from Landsat 8/OLI

Figure 5a and b, show that the maximum and minimum NDBI in 2014 is -0.399 and -0.791, while in 2018 is -0.383 and -0.783. Both NDBI show similar spatial distribution pattern with the LST, there were high in the north and low to the south. Although the NDBI value is questionable because the overall NDBI are showed as negative value. However, the spatial distribution show reasonable pattern where highest NDBI value mostly found in the urban area (City of Jakarta, Depok and Bogor).

Figure 5a. NDBI spatial distribution of the study area in 2014 derived from Landsat 8/OLI

Figure 5b. NDBI spatial distribution of the study area in 2018 derived from Landsat 8/OLI
3.2. Discussions
In order to have further understanding correlation between LST, elevation, NDVI and NDBI, statistical analysis was performed at the pixel level. Approximately 200 observation point were generated randomly and value acquired uses to perform ordinary least square (OLS) test. Table 2a and b show that LST has negative relationship with Elevation and NDVI (-0.004770 and -5.685089), but has positive relation ship with NDBI (18.833869). Probability value indicate correlation between LST with elevation, NDVI and NDBI is statistically significant (p < 0.05) without redundancy among explanatory variables (VIF < 7.5). In statistical analysis R² use to measure of model fit/performance, OLS result show R² value in 2014 is 0.94 and 2018 is 0.89. Thus, regression analysis in 2014 is 94% fit and 2018 is 89% fit.

| Variable | Coefficient | Probability | VIF  |
|----------|-------------|-------------|------|
| Intercept| 43.164141   | 0.000000*   |      |
| Elevation| -0.004770   | 0.000000*   | 1.708060 |
| NDVI     | -5.685089   | 0.000966*   | 6.427027 |
| NDBI     | 18.833659   | 0.000001*   | 5.524176 |

Table 2a. Summary of OLS Result in 2014.

Furthermore, the coefficient between LST and elevation exhibited negative relationship. It’s shown in spatial distribution image in Figure 2 and 3. Elevation in study area tend increase from north to the south, while LST colour change from red to blue from north to south of study area. Therefore, LST gradually decrease with increases in altitude.

| Variable | Coefficient | Probability | VIF  |
|----------|-------------|-------------|------|
| Intercept| 44.619199   | 0.000000*   |      |
| Elevation| -0.005570   | 0.000000*   | 2.491551 |
| NDVI     | -5.344916   | 0.048184*   | 3.198885 |
| NDBI     | 19.252238   | 0.000003*   | 2.023071 |

Table 2b. Summary of OLS Result in 2018.

Interesting fact in the table 2 is show that LST distribution very closely related to the distribution of NDVI and NDBI. Coefficient between LST, NDVI and NDBI is relatively higher than elevation coefficient. In normal condition high NDVI values indicate the presence of green vegetation, however high NDBI value indicate the presence of dense built-up area and wide bare area. According to the spatial distribution image in 2014 and 2018, LST increase along with increases built-up area and decreases forest/vegetation area.

Over 5 years, population growth and rapid urbanization in Ciliwung watershed area erodes open area continuously. Figure 6a and b show that land cover changes occurs in 2014 to 2018, it’s exhibited that built-up area in the midstream expanding to the north following decreases of vegetation land area. LC change may influence LST value caused by built-up area and bare land area would absorb and reflect more solar radiation, where temporally followed by land surface temperature increases. According to LST image in figure 3a and b, show that there were increases on maximum and minimum temperature from 37.45 °C and 11.95 °C in 2014 to 39.29 °C and 16.11 °C in 2018.
4. Conclusions

In this study, Landsat 8/OLI were used to analyse spatial distribution of LST in Ciliwung watershed and to interpret dynamic relationship between elevation, NDVI and NDBI. Spatially, LST distribution pattern similar with NDBI spatial distribution pattern where downward trend from north to south of Ciliwung watershed area. Meanwhile elevation and NDVI pattern has opposite spatial distribution where low in the north and high in the south.

Temporally, maximum and minimum LST value in 2014 is 37.45 °C and 11.95 °C were increase to 39.29 °C and 16.11 °C in 2018. The differences of LST value may cause by increases built-up and bare area in mid-upstream area of Ciliwung watershed. The presence of built-up and bare area absorb and reflect more solar radiation, which periodically increase land surface temperature in 2018.

Furthermore, LST in Ciliwung watershed significantly correlate between elevation, NDVI and NDBI value. The relationship between LST with elevation, NDVI and NDBI quantitatively interpreted using linear regression. Ordinary least square test result show high correlation indicate by R-square ($R^2$) value in 2014 and 2018 is 0.91 and 0.89. Elevation and NDVI show negative correlation ($-0.004770$, $-0.005570$, $-5.685089$, $-5.344916$), while NDBI show positive correlation ($18.833659$, $19.252238$) with LST value. LST would gradually decrease with the increases elevation and NDVI value, conversely LST would gradually increase with the increases NDVI value.

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