Correlation Analysis of Normalised Difference Built-Up Index (NDBI) and Land Surface Temperature (LST) from 2013 to 2023 Landsat 8 Imagery: A Case Study in Makassar City, Indonesia

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Abstract
Land use change dynamics exert a complex and varied impact on ecological factors. The expansion of metropolitan areas and developed land induces numerous environmental issues, notably a rise in Land Surface Temperature (LST). The correlation between built-up area and LST is crucial for comprehending the urban heat island phenomenon. This study conducts a spatiotemporal analysis of LST and normalised difference built-up index (NDBI) in Makassar City, Indonesia, selected for its fast urbanization. Ten years of Landsat 8 Operational Land Imager (OLI) data (2013-2023) were analysed on the Google Earth Engine (GEE) platform to derive the NDBI and LST. The outcomes were statistically examined utilizing SPSS and represented in ArcGIS. The findings indicated that substantial growth in the built-up area results from population expansion and urbanisation in the study area. The average land area in Biringkanya and Tamalanrea District expanded significantly due to urbanisation and infrastructural development. The land surface temperature in Makassar City rose from 26°C to 35°C, peaking at 43°C in 2014 and 40°C in 2023. The correlation between developed land and land surface temperature is robust, with built-up density markedly influencing temperature elevations. The linear regression also indicated a positive correlation between NDBI and LST, suggesting that heightened urbanisation and alterations in built-up land contribute to elevated LST. Subsequent investigations should incorporate high-resolution data, employ sophisticated remote sensing techniques, and analyse urban heat dynamics. Predictive modelling and socio-economic consequences of temperature fluctuations can guide policy measures.

Keywords: Built-up land growth, Land use change, LST, Makassar City, Urbanization

1. Introduction

Urbanisation poses significant environmental issues, including increased urban temperatures and the Urban Heat Island (UHI) effect [1][2][3]and[4]. The conversion of natural landscapes into built environments disrupts the natural water flow, reduces green spaces, contributes to habitat loss, and leads to a fall in biodiversity. The Urban Heat Island (UHI) effect occurs when urban areas experience higher temperatures than rural regions due to human activities and changes in land cover. Urbanisation profoundly affects environmental systems, leading to phenomena such as the UHI effect, habitat destruction, and a decline in biodiversity due to elevated temperatures and the alteration of natural landscapes. The impacts are closely linked to human activity and climate change, as demonstrated by the above studies. For example [5] emphasises the essential function of evapotranspiration in affecting the hydrological cycle, wherein intensified agricultural practices and ecological advancements lead to augmented recycled moisture and precipitation in arid areas. This diminishes water storage, highlighting the fragile equilibrium between urbanisation and natural resource management.

Study of [6] illustrates that the expansion of Urban green-blue spaces in Nanjing, influenced mainly by natural variables such as radiation and elevation, mitigates certain adverse effects of urbanisation by safeguarding biodiversity and improving ecological resilience. Nevertheless, such mitigation is constrained since swift urban expansion frequently leads to diminished vegetation and elevated surface temperatures [7], where the Greater Accra Region had substantial land use and land cover alterations, intensifying urban heat island areas from 2000 to 2020.

Furthermore, urbanisation intensifies habitat fragmentation and pesticide use, directly affecting biodiversity [8]. In Africa, climate change and urban expansion exacerbate the hazards of zoonotic diseases by altering ecosystems and enhancing human-wildlife interactions [9]. The interrelated dynamics necessitate sustainable urban design and environmental policy to mitigate the cascading effects of urbanisation. Between 2013 and 2023, Makassar City's developed land underwent significant transformations due to population expansion and urbanisation. As a result, energy consumption increases, leading to heightened greenhouse gas emissions and degraded air quality [10] and [11]. Simultaneously, the transformation of green spaces into developed areas and the rise in greenhouse gas emissions impact urban comfort [12] and [13].

Land use transition is vital in developing regional policies and preserving ecosystems at different spatial scales [14]. Moreover, land use change processes exert a complicated and multifaceted impact on ecological factors [15]. Since gaining independence, Indonesia has undergone substantial changes in land usage, particularly in developed areas, with rapid urbanisation. This phenomenon is defined by the migration of individuals from rural areas to urban centres, a trend that has intensified since 1970. During this period, Indonesia initiated a systematic national development program that substantially accelerated urbanisation in metropolitan areas, resulting in extensive conversion of developed land [16]. The development of Makassar City in South Sulawesi Province, particularly in Wajo District, Panakkukang, Ujung Pandang, Tamalete, and Tamanlanrea, is attributed to educational, governmental, and economic influences. As a result, Makassar City exhibits more accelerated development than other areas in South Sulawesi [17]. The development has induced alterations in land use from previously undeveloped areas to constructed land. The processing of developed land expressed as NDBI focuses on the representation of land in satellite imagery to effectively differentiate between land cover and built-up areas [18]. Alterations in urban land utilisation induce a rise in LST.

LST is a critical measure for comprehending climate change and environmental dynamics. It is defined as the temperature recorded on an object's surface, and this parameter offers significant insights into the physical properties of the Earth's surface. These features are crucial in the processes that govern thermal variations in average surface temperature in the environment [9] and [20]. The study examines the relationship between built surfaces and LST in Makassar City over ten years (2013 to 2023), utilizing geospatial and statistical methodologies. The GEE platform facilitated the acquisition and processing of Landsat 8 OLI images from 2013 to 2023. The research also employed ArcGIS for spatial analysis and visualization, and SPSS 16.0 for regression analysis. Further details of the methods are presented in the following section. Subsequently, the results and discussion are presented, culminating in the conclusion of the findings.

2. Methods

2.1 Study Area

This research was conducted in Makassar (Figure 1), the capital city of South Sulawesi Province, with an area of 175.77 km^2, and the fourth largest city in Indonesia [21]. Makassar City has seen substantial urbanisation due to population increase, economic advancement, and the proliferation of constructed areas. Makassar, a significant metropolitan hub in eastern Indonesia, has experienced economic expansion and urbanisation that draws rural inhabitants in search of improved livelihoods and educational prospects. Since 2001, the city's population has experienced significant growth, alongside a rising migration rate. In 2015, the population reached 1,449,401, with urbanization serving as a significant influence on land-use changes. Urban areas have increased considerably, converting agricultural and green spaces into urban zones. Urbanisation fosters economic development but also introduces issues such as congestion, the proliferation of informal settlements, and environmental deterioration. Efforts to regulate Makassar’s spatial planning are essential for sustaining development and reconciling urban requirements with environmental sustainability.

2.2 Overview of Research Framework

This study examines the correlation between NDBI and LST in Makassar City. This study employed a multi-faceted method integrating geospatial and statistical techniques (Figure 2).

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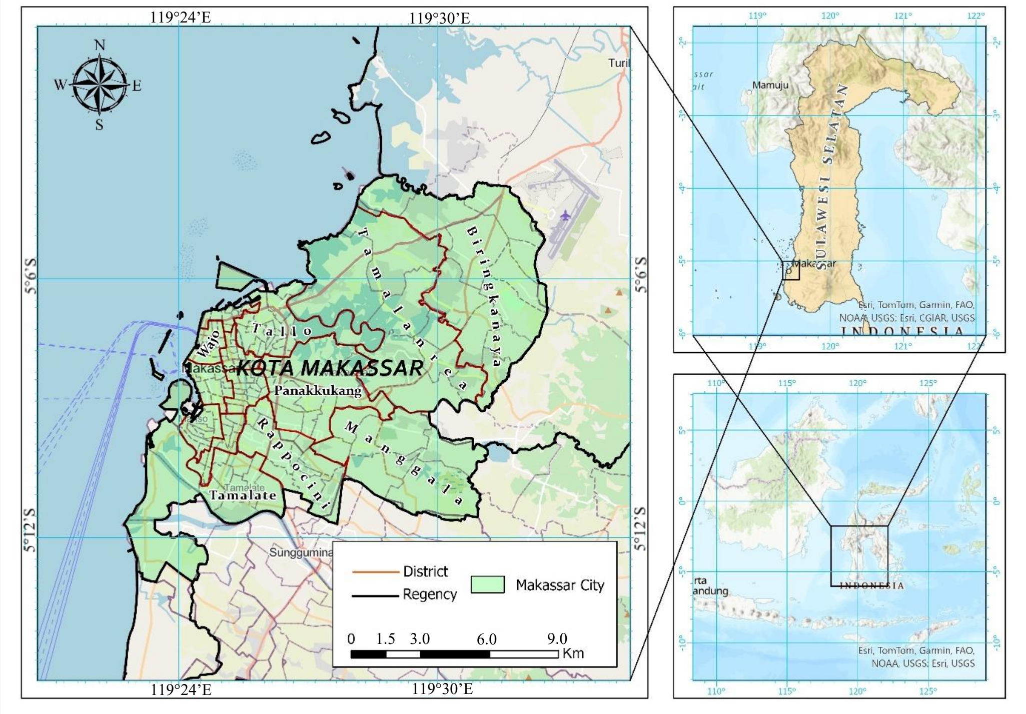

Figure 1: Makassar, South Sulawesi province, Indonesia

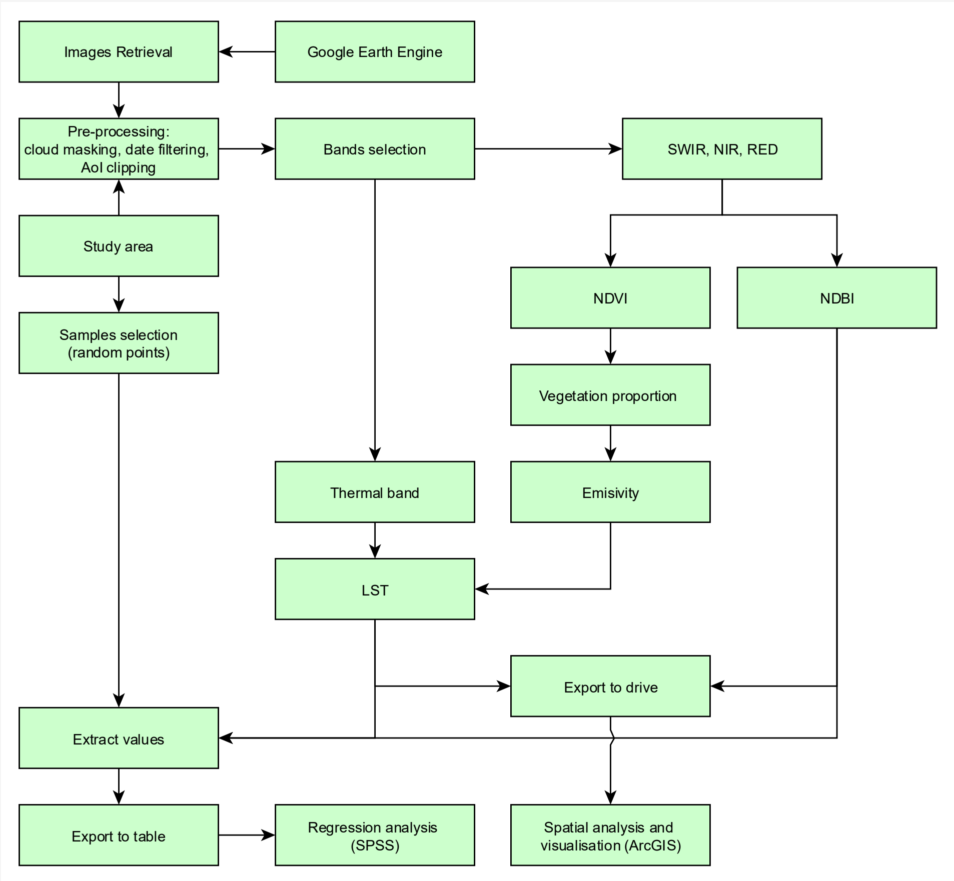

Figure 2: Research framework

Table 1: Acquisition date

No	Year	Acquisition date	No	Year	Acquisition date
1.	2013	March	7.	2019	September
2.	2014	May	8.	2020	August
3.	2015	August	9.	2021	September
4.	2016	July	10.	2022	July
5.	2017	August	11.	2023	August
6.	2018	July			

The GEE platform facilitated the acquisition of Landsat 8 OLI images spanning from 2013 to 2023 through a decade-long spatiotemporal analysis (Table 1). Pre-processing encompasses cloud detection and elimination, image filtering to choose particular dates, and image cropping to align with the administrative borders of the study region. The investigation will concentrate on particular bands, including Shortwave Infrared (SWIR), Near Infrared (NIR), Red, and Thermal bands. The NDBI assesses built-up areas, whereas the Normalized Difference Vegetation Index (NDVI) quantifies vegetated areas. NDVI values are computed to determine vegetation density, which is then employed to obtain emissivity values for accurate LST estimations. The LST computation entails modifying temperature bands under their respective emissivity values. This data is then transmitted to ArcGIS, where 91 random sample locations are produced. The LST and NDBI data are extracted and exported as CSV files for use in regression analysis with SPSS. This research utilised spatial analysis and visualisation methods through ArcGIS to produce comprehensive maps.

2.3 Processing Tools and Techniques

This study employs GEE, ArcMap 10.8, and SPSS 16.0 for data processing and interpretation. GEE was used in Landsat 8 OLI acquisition and processing. It provides a user-friendly interface for working with large amounts of image datasets [22]. The application is renowned for its ability to manipulate geographic data, enabling the creation of maps that reveal NDBI and LST for the study period. ArcMap 10.8 was used to analyse and visualise the spatial datasets exported from GEE. In addition, SPSS version 16.0 functions as a regression processing tool that incorporates statistical analytical features for investigating the correlation between built-up surfaces and LST. SPSS software version 16.0 is a statistical programming application based on the highest standard calculations to perform data analysis with various statistical tools [23]. The linear regression tool in this software was used to analyse the relationship between two variables [24], namely NDBI and LST.

2.4 Data Processing Technique

2.4.1 Transformation of Landsat 8 OLI into NDBI

NDBI is a built-up land indicator derived from the use of near-infrared wavelengths (NIR and SWIR). Bands 5 and 6 of the Landsat 8 OLI image were explicitly used to process built-up land through the *NDBI* algorithm. Digital Number (DN) data were converted to *NDBI* to classify the density of settlements or buildings (Equation 1).

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

Equation 1

Where:

NDBI = Normalised Difference Built-Up Index
NIR = Near Infra-Red band
SWIR = Short Wave Infra-Red band

2.4.2 Classification of NDBI

After transforming NDBI, NDBI classification is done using ArcMap, which becomes four classifications: namely, $-1 < NDBI < 0$ is undeveloped land, $0 < NDBI < 0.1$ is less dense built-up land, $0.1 < NDBI < 0.2$ is dense built-up land, and very dense built-up land $NDBI > 0.2$. [25]

2.4.3 NDVI and emissivity analysis

Emissivity values are processed in relation to Land Surface Temperature. NDVI is a commonly used standard for comparing the greenness of plant vegetation based on satellite image data. This parameter is calculated by taking the ratio between the red (Band 4) and Near Infrared (NIR, Band 5) bands on Landsat 8 OLI imagery, using Equation 2.

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

Equation 2

Where:

NDVI = Normalised Difference Vegetation Index
NIR = Near Infrared band
RED = Red band

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The calculation of vegetation proportion (P_v), which indicates the percentage of area covered by vegetation, is crucial in various environmental analyses. NDVI was previously used to estimate Pv values. The minimum and maximum NDVI values were obtained from the categorisation of data with GEE processing using Equation 3.

$$P_v = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \right]$$

Equation 3

Where:

P_v = Proportional of Vegetation
$NDVI_{min}$ = minimum $NDVI$ value
$NDVI_{max}$ = maximum $NDVI$ value

P_v values are used in the emissivity equation (Equation 4) to calculate the properties of the Earth's surface, as well as the ability to convert thermal energy (heat) into radiation [26]. This equation is applicable for various applications, such as climate change, land cover changes, and natural resource management.

$$\varepsilon = 0.004P_v + 0.986$$

Equation 4

Where:

ε = Emissivity
P_v = Proportional of Vegetation

2.4.4 LST and Brightness Temperature (BT)

In thermal infrared measurements based on remote sensing, it is common to convert the brightness temperature (BT) Equation 5, which represents the emission temperature. After determining the Top of Atmosphere (TOA) value, BT conversion is performed. After stating the resulting BT in Kelvin (K), 273.15 is subtracted from 273.15, resulting in the following formula in Celsius (°C)[27].

$$BT = \frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)} - 273.15$$

Equation 5

Where:

BT = Brightness temperature (ºC)
L_λ = TOA *Spectral Radiance* (Watts/(m^2·srad·µm)
$K1$ = Band-specific thermal coversion contant form the metadata (K1_CONSTANT_BAND_x, Where x is the thermal band number.
$K2$ = Band-specific thermal coversion contant form the metadata (K2_CONSTANT_BAND_x, where x is the thermal band number)

The Land Surface Temperature distribution is obtained from processing the Thermal band in the Landsat 8 Image, namely in band 10 or "BT", which has been converted to Kelvin and Emissivity obtained from the derivative of Pv and NDVI Pv (Equation 6).

$$LST = \frac{BT}{1 + \left[\left(\lambda \frac{BT}{\alpha} \right) \ln(\varepsilon) \right]}$$

Equation 6

Where:

LST = Land Surface Temperature
λ = Length of radiation emitted (11.5 µ*m* Landsat 5 and 10.8 µ*m* Landsat 8)
α = 143.888 µ*mK*

2.4.5 Regression test

A simple linear regression test was conducted using SPSS 16 to determine the correlation (Multiple R), percentage relationship (R2 or Determination (%)) between variable X, Built-up Land (NDBI), and Variable Y, Land Surface Temperature (LST). The simple linear regression test model displays the correlation relationship (Multiple R), the coefficient of determination (R^2 or Determination (%)), and the P-value or Significance (Sig.)

3. Results and Discussion

3.1 Built-Up Land Area Changes in Makassar City (2013-2023)

Built-up land in Makassar City from 2013 to 2023 underwent rapid changes, as indicated by the processing results shown in Figure 3. Built-up land in Makassar City has experienced significant changes, primarily due to an increase in population. This is in accordance with Surakarta City, where the value of built-up land increased with a rise in population each year [28]. However, conversion into uncontrolled built-up land will have a negative impact on the environment [29]. The results showed that from 2013 to 2023, Makassar City experienced rapid changes starting from the city centre, as shown in Table 2. The urban growth of Makassar City has exhibited considerable fluctuation over the previous decade, with built-up areas ranging dramatically among different districts. Nevertheless, certain districts, such as the Sangkarrang Islands, display distinctive patterns where there are no developed areas for several years. This phenomenon can be attributed to natural changes in land use or specific governmental or environmental initiatives. Tamalanrea and Tallo districts displayed distinct changes in their built-up areas. Based on the results of the study, every year there is an increase in built-up land, as described in Table 2 and Figure 4. The increase can be attributed to population growth and urbanisation factors. The growth of built-up land started from the city centre and extended to the periphery. A similar incidence was observed in Tangerang Regency, where the process of development extended to the periphery of Cisauk Subdistrict [30]. The growth of Makassar City was influenced by many factors, namely the economy, education, employment, and infrastructure, triggering the phenomenon of urbanisation [14]. The continued development has increased built-up land, namely in Biringkanya and Tamalanrea District. This is because the Biringkanya sub-district is included as a suburban area in Makassar City, which is experiencing changes in the impact of changes in the city area on the periphery or peri-urban area [31]. This increase is the phenomenon of peripheral growth in Makassar City. Based on Table 2, the average built-up land area of the Biringkanaya sub-district in 2013 was 3560.47 Ha, which increased rapidly due to urbanisation factors and supporting infrastructure to 3580.87 Ha in 2023. Meanwhile, for the Tamanlanrea sub-district, the average built-up land area increased to 3495.62 ha in 2023.

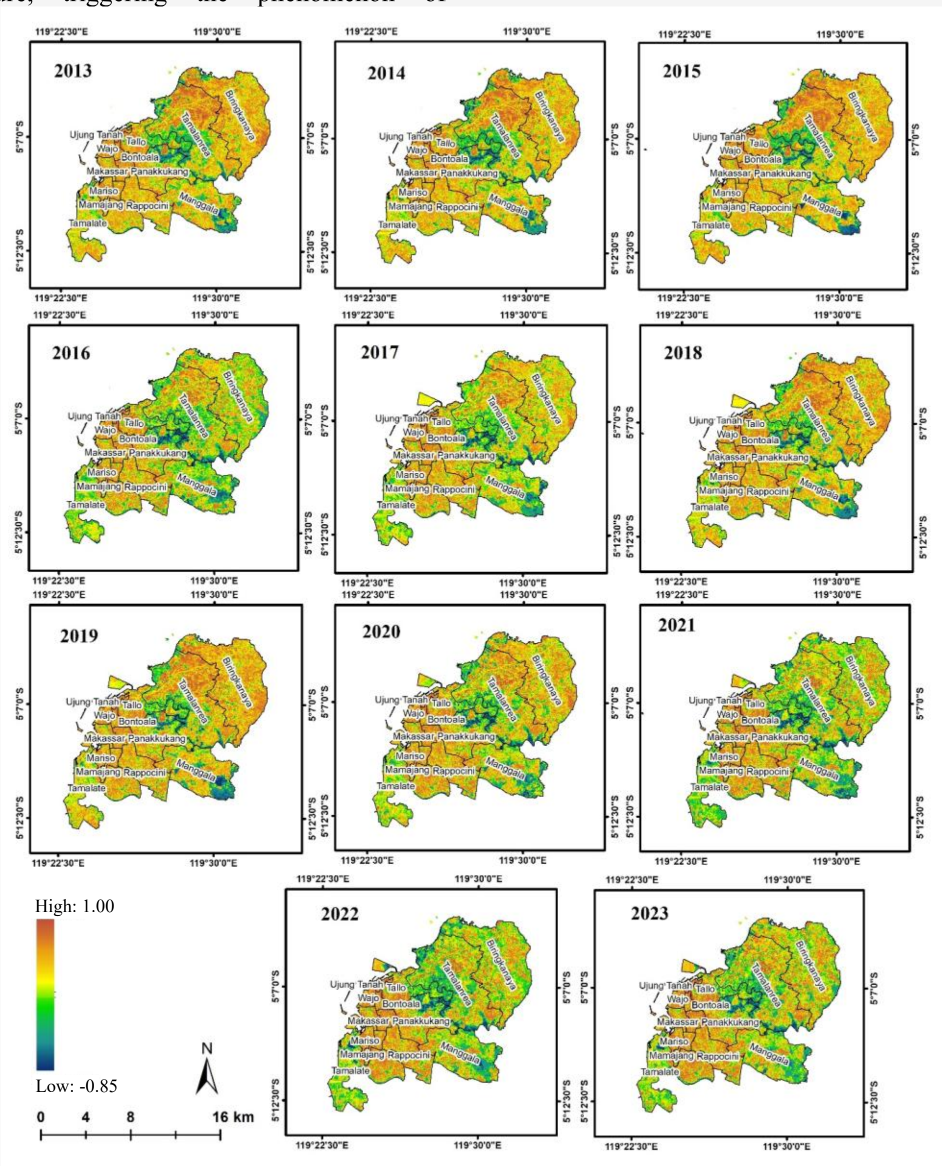

Figure 3: Spatio-temporal changes of NDBI in Makassar city

Table 2: Average spatiotemporal built-up area (ha)

District	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Biringkanaya	3,560.47	3,560.16	3,623.65	3,614.74	3,560.29	3,572.92	3,619.25	3,617.95	3,444.65	3,598.24
Bontoala	173.79	173.79	173.79	173.79	1,432.99	173.75	173.79	173.79	173.44	173.79
Sangkarrang Islands	25.19	36.59	47.59	47.25	47.43	47.84	47.35	47.43	47.65	47.88
Makassar	263.24	263.42	265.3	265.18	263.96	264.1	265.23	265.3	263.95	265.36
Mamajang	254.75	254.67	255.41	255.25	254.56	254.35	255.56	255.56	254.28	255.56
Manggala	1,849.13	1,823.14	2,011.67	2,095.90	1,772.45	1,751.43	2,025.77	2,097.63	1,730.60	2,181.07
Mariso	269.38	269.39	270.32	269.8	267.82	268.14	269.89	269.88	262.41	269.87
Panakkukang	1,247.14	1,248.83	1,360.23	1,316.76	1,488.17	1,252.71	1,338.52	1,345.76	1,240.60	1,346.27
Rappocini	1,077.05	1,074.97	1,092.61	1,091.61	1,061.10	1,061.30	1,093.73	1,094.57	1,061.38	1,094.80
Tallo	839.72	829.52	868.59	889.83	1,092.12	977.89	1,026.42	1,020.04	968.01	1,009.10
Tamalanrea	3,283.19	3,259.16	3,548.98	3,507.72	3,352.14	3,335.13	3,560.48	3,539.39	3,162.13	3,345.60
Tamalate	2,055.57	2,095.57	2,131.86	2,125.43	2,082.49	2,162.90	2,236.41	2,232.45	2,023.50	2,184.74
Ujung Pandang	283.16	281.67	284.64	284.69	279.8	281.16	284.58	284.9	280.12	284.92
Ujung Tanah	145.12	145	144.29	144.45	144.8	145.11	144.26	144.28	144.6	144.45
Wajo	205.62	205.86	205.65	205.64	205.66	205.36	205.8	205.19	205.47	205.7

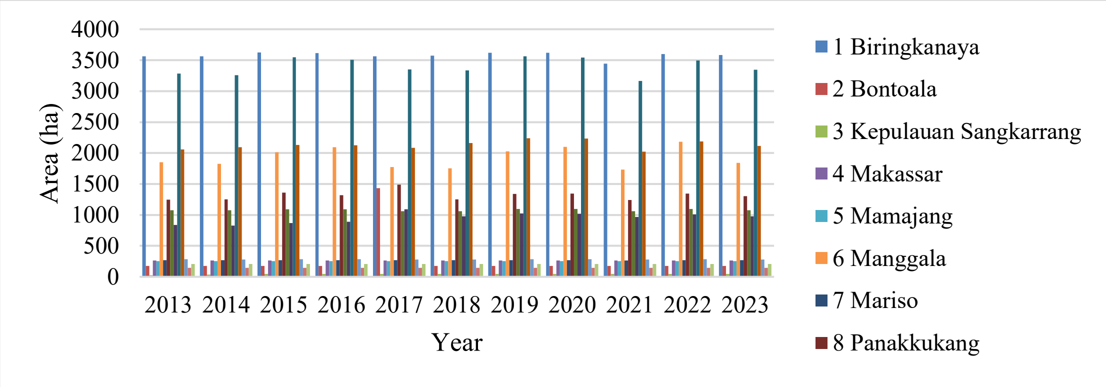

Figure 4: Built-up land area from 2013 to 2023

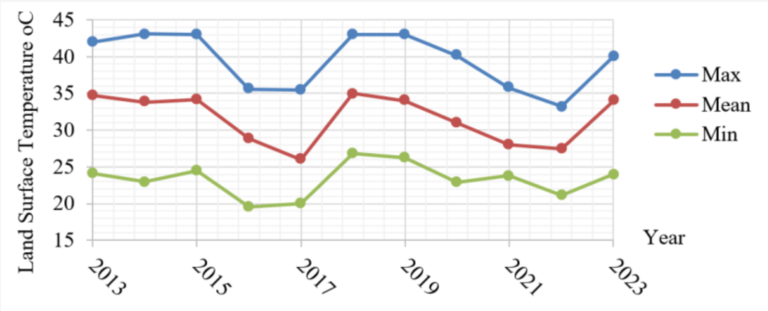

Figure 5: Variation in land surface temperature from 2013 to 2023

3.2 Distribution of LST in Makassar City from 2013 to 2023

Visualisation of the LST dynamics is presented in Figure 5. Based on the results, Makassar City experienced rapid changes in built-up land and temperature fluctuations, as shown in Figure 6. Land Surface Temperature of Makassar City from 2013 to 2023 averaged 26°C - 35°C. The highest value was observed in 2014 and 2015 at 43° C, followed by 40°C in 2023. Meanwhile, the lowest value occurred in 2022, amounting to 33°C. The average Land Surface Temperature decreased quite significantly in 2016 and 2017 by 1°C, but increased in 2018 by 5°C. In 2021 and 2022, the temperature decreased by 2°C, but a considerable increase of 8°C occurred in 2023. The rise in temperature every year has a significant impact on the Urban Heat Island (UHI) phenomenon.

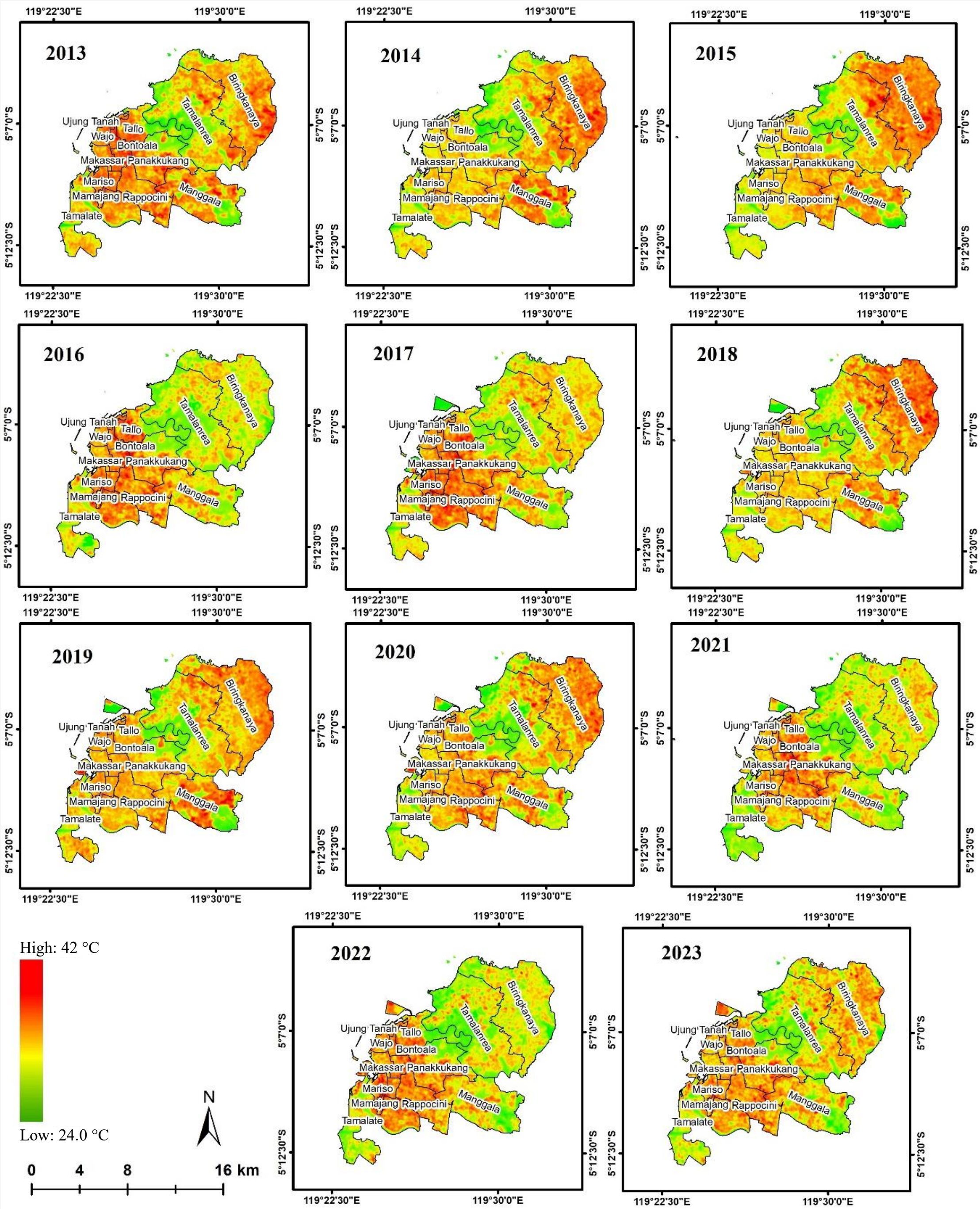

Figure 6: Land surface temperature 2013 – 2023

Changes in LST in Makassar City are visually observed in the city centre, namely Makassar City and spread to peripheral areas such as Bringkanaya and Tamalanrea sub-districts shown in red and orange colours where they have high to moderate surface temperatures, as shown in Figure 5 this is in the 2017 to 2018 timeframe there is a toll road construction project in the center of Makassar city [32]. Green areas indicate low land surface temperature values in Panakukang District and Manggala District, where green open spaces and water bodies are still present. The change in distribution each year is influenced by the reduction of green open space and the conversion of land use to built-up land [33].

3.3 Spatiotemporal Relationship between Built-up Land and Land Surface Temperature in Makassar City

The relationship between built-up land and Land Surface Temperature was assessed using *a* simple linear regression with two variables. Linear regression was carried out using data extracted from the values of both variables, each with a total of 90 points.

3.3.1 Relationship between built-up land and land surface temperature from 2013 to 2023

Extraction of built-up land and Land Surface Temperature values from 90 sample points in each of 10 consecutive years was conducted to determine the relationship between built-up land and land surface temperature. The simple linear regression table of built-up land and land surface temperature during the period 2013 to 2023 shows a relationship that varies from year to year, both in terms of the strength of the relationship (R^2) and the size of the regression coefficient (Table 3). The coefficient of determination (R^2) indicates that the influence of built-up land on surface temperature is not constant, but tends to increase in certain years. The highest R^2 values were recorded in 2015 (0.662) and 2020 (0.599). This indicates that 66.2% of the variation in land surface temperature in 2015 and 59.9% in 2020 can be explained by changes in built-up land, showing that the increase in built-up areas strongly influences land surface temperature in both years [34]. Conversely, 2016 shows the lowest (R^2) of 0.324, which indicates that only 32.4% of the variation in surface temperature is influenced by built-up land, and the rest is influenced by other factors. This fluctuating pattern indicates that the relationship between built-up land and land surface temperature is highly dependent on the dynamics of land use in line with the finding that the observation of the relationship between built-up land and land surface temperature can change depending on local conditions [35], although in 2023 Makassar city recorded a high regression coefficient of 19.125. Still, the R^2 value was only 0.445 (44.5%), indicating that although the effect is mathematically strong, there are still many other variables that affect significant land surface temperature, such as vegetation and the presence of surface water, that moderate the relationship [35].

In general, the simple linear regression of the relationship between built-up land and land surface temperature in 2013 to 2023 has a positive trend and in other words the significance coefficient value of 0.000 is smaller than (α) 0.005 can be seen in Table 4, which can be interpreted from 2013 to 2023 the increasing value of built-up land, it tends to be followed by an increase in surface temperature such as in Semarang City [36].

Table 3: Regression built-up area and land surface temperature 2013 – 2023

Year	Relationship between NDBI (x) and LST (y)	R^2
2013	y = 17.060x + 35.186	0.487
2014	y = 15.873x + 34.359	0.366
2015	y = 4.498x + 38.826	0.662
2016	y = 2.731x + 31.407	0.324
2017	y = 15.081x + 24.351	0.512
2018	y = 18.202x + 37.569	0.511
2019	y = 2.376x + 31.160	0.466
2020	y = 2.564x + 33.111	0.599
2021	y = 9.446x + 29.717	0.366
2022	y = 1.383x + 28.648	0.420
2023	y = 19.125x + 33.369	0.445

Table 4: P-values built-up area and land surface temperature 2013 – 2023

Year	B (NDBI)	Std. Error	Beta	t	Sig. (p)
2013	17.06	1.865	0.698	9.149	0.00
2014	15.873	2.226	0.605	7.130	0.00
2015	4.498	0.343	0.813	13.117	0.00
2016	2.731	0.421	0.569	6.493	0.00
2017	15.081	1.568	0.716	9.618	0.00
2018	18.202	1.897	0.715	9.596	0.00
2019	2.376	0.268	0.683	8.867	0.00
2020	2.564	0.221	0.774	11.588	0.00
2021	9.446	1.326	0.605	7.123	0.00
2022	1.383	0.171	0.648	8.079	0.00
2023	19.125	2.276	0.667	8.405	0.00

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The highest coefficient was recorded in 2023; before that, in 2018, a coefficient value of 18.202 was recorded. In 2013, a coefficient value of 17.060 was recorded, indicating that development, urbanization, and urban sprawl dominated in Makassar City during this period. This is in line with the findings of the expansion of built-up areas, especially the central growth area [2].

4. Discussion

The main findings of this study show that Makassar City has undergone significant changes in terms of land and infrastructure development from 2013 to 2023. These changes were caused by various factors, including the process of urbanization and population growth, especially in the suburban areas such as Tamalanrea and Biringkanaya. These two areas experience rapid expansion of built-up land. The data shows that land surface temperature peaked in 2014 and 2015 at 43°C, followed by a slight decrease and then a sharp increase in 2023 at 40°C. These findings are in line with previous studies in major world cities that show a close relationship between built-up land density and increased surface temperature. For example, a study in Bhopal City revealed a strong positive correlation between the standardized built-up land index (NDBI) and land surface temperature (LST), indicating the significant role of urbanization in triggering temperature increases [37]. Similarly, it was reported that a 21.10% expansion of built-up area in Aligarh City over 20 years was directly proportional to an 11.35°C increase in temperature, indicating an increasing urban heat island (UHI) phenomenon [38].

Specifically for Makassar City, the results of simple linear regression analysis between NDBI and LST for 11 years showed a consistent positive trend, although the coefficient of determination (R^2) fluctuated each year. The year 2015 recorded the highest R^2 value of 0.662, indicating that about 66.2% of the variation in surface temperature can be explained by changes in built-up land. In contrast, 2016 recorded the lowest R^2 value of 0.324, indicating the influence of other factors on temperature dynamics, such as the presence of vegetation, water cover, or local conditions.

This phenomenon does not only occur in Indonesia, but also in other countries. For example, [39] found that the conversion of green open spaces into built-up areas in Kolkata had a significant impact on increasing LST and increasing UHI. Meanwhile, a study in Kayseri City, Turkey, confirmed a strong positive relationship between NDBI and LST, reinforcing similar findings in Makassar [40]. This phenomenon does not only occur in Indonesia, but also in other countries. For example, the conversion of green land to built-up land in Kolkata has a significant impact on increasing LST and UHI. Meanwhile, a study by [40] in Kayseri City, Turkey, confirmed a strong positive relationship between NDBI and LST, reinforcing similar findings in Makassar [39].

5. Conclusion

During the study period, built-up land in Makassar City experienced considerable changes due to population growth and urbanization. The average area of built-up land in the Tamalanrea and Biringkanya sub-districts increased due to urbanization and infrastructure development. This led to a rapid expansion of built-up land in these two areas. The data shows that land surface temperature peaked in 2014 and 2015 at 43°C, followed by a slight decrease and then a sharp increase in 2023 at 40°C. The simple linear regression relationship between built-up land and land surface temperature over the period 2013 to 2023 shows a variable relationship in terms of the strength of the relationship value R^2 as well as the magnitude of the regression coefficient, the highest R^2 values were recorded in 2015 and 2020 with magnitude values of 66.2% and 59.9%, while 2016 showed a low R^2 value of 32.4%. This fluctuating pattern indicates that the relationship between built-up land and surface temperature is highly dependent on the dynamics of land use and changes in local conditions. Notably, in 2023, Makassar City recorded a high regression coefficient of 19.125. However, the R^2 value of 44.5% indicates a mathematically strong influence, but there are still many other variables that affect the relationship, including vegetation and human activities.

6. Limitation

The limitation of this study lies in its reliance on satellite data, which does not directly consider local environmental elements such as the type of building materials, humidity, or wind patterns that affect temperature fluctuations. In addition, other elements such as air pollution that contribute to the increase in temperature in urban areas, the aspect of vegetation as a temperature control factor has also not been discussed in depth. However, it is generally known that vegetation loss in urban areas is closely related to an increase in surface temperature. Land use change, especially the conversion of green regions into built-up land, has the potential to accelerate temperature increase. To improve the accuracy of future analysis, the use of high-resolution spatial-temporal data and field verification approaches are recommended to identify local variables that influence temperature in more detail. Future research should also include indicators of urban morphology, vegetation index, and other meteorological variables to provide a more comprehensive understanding of temperature dynamics in urban areas. In addition, predictive modeling approaches can be a useful tool to simulate urban development scenarios.

7. Future Direction

On the other hand, further research is also needed to assess the socio-economic impacts of increasing temperatures in urban areas, such as impacts on public health, energy consumption, and quality of life. This will support the development of policies that are more responsive to urban environmental issues. Sustainable spatial approaches, such as the development of green open spaces and heat-resilient urban design, are essential to mitigate the impacts of UHI. Finally, a comparative approach across major cities in Indonesia and Southeast Asia, such as Jakarta and Surabaya, will provide a broader regional perspective. This enables the identification of common patterns and collaborative solutions to the challenge of microclimate change resulting from massive urbanization.

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