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Analysis of Land Use/Land Cover Change And Their Effects On Spatiotemporal Patterns Of Urban Heat Islands (UHI) In The City Of Makassar, Indonesia

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ABSTRACT

Warming in the climate system is undisputable, which has received increasing global attention since the global mean surface temperature was reported to be increasing in the late 19th century. As more than 50% of the world population prefers to live in cities, urbanization has become a trigger of global warming. This research will explore the effects of changes in land use land cover (LULC) to find out the effects of urban heat islands (UHI). Makassar City in South Sulawesi is one of the cities in Indonesia that is experiencing rapid urbanization, and is expected to experience significant Urban Heat Island (UHI), which may inevitably affect regional climate, the environment, and socio-economic development. This study aims to determine and analyze the relationship between LULC changes and land surface temperature (LST) patterns. UHI and LULC maps were obtained from Landsat data for the years 1989, 1999, 2007, and 2018 from USGS to show their spatiotemporal patterns. To analyze the relationship between LULC and UHI changes, this study used a quantitative approach to explore the relationship between LST, LULC classification and several indices. The results showed that: (1). During the period of study (1989 – 2018), there were significant changes in LULC. The highest percentage was built up areas, which rose by 73.83% from 4849.21 ha in 1989 to 8429.21 ha in 2018; (2). The spatiotemporal pattern in LST shows an upward trend in all parts of the city, especially in the western part of the city. (3). It was found that the highest temperatures were in built up areas, and the lowest was discovered near waterbodies.

Key words: *Urbanization, urban heat islands (UHI), land use changes, Makassar, Indonesia*

1. INTRODUCTION

Urbanization is a global issue, especially for many developing countries (Golden, 2014). Urbanization is defined as population movement from rural to urban areas. Globally, the percentage of people who lived in urban areas was approximately 30 percent in 1950, and that proportion rose to 54 percent, or over half of the world's poopulation decided to live in the city in 2014 [1].

The main problem of rapid urbanization is that it can cause urban sprawl, which is a trigger for the conversion of agricultural land or wetlands into built up areas. As a result, the built zones are denser, buildings are taller than before, or coastline expansion projects that change urban morphology. In addition to environmental changes, rapid urbanization is considered a major factor causing the phenomenon of urban heat island (UHI), which refers to the temperature difference between urban areas and the surrounding rural areas.

The term of urban heat island (UHI) was first introduced by Luke Howard in 1808 in England, which later became known throughout the world. UHI is the most serious problem related to the climate of the urban environment. Urban areas have surfaces that mostly use waterproof materials, so they have the ability to withstand more heat. Compared to rural areas, building structures in cities are denser and rougher, which causes a lot of reflection and absorption of heat. These characteristics cause a large amount of heat to remain trapped and accumulated. In addition, anthropogenic activity, which generates a lot of heat, further aggravates the quantity of heat trapped in urban areas.

Several studies show the factors that influence UHI.A study conducted by Imhoff [2] stated that more than 45% of the world's population choose to live in urban areas, and facts show that human effects on the environment are the most severe. This study also showed that the UHI effect can increase the air temperature from 2 to 8ºC. Senanayake [3] explains that various factors can affect climate in the city. These factors include changes in land use and cover, reduction in green areas, increased land impermeability, and heat production generated by human activities. Rapid development, which is often associated with urbanization, can influence the formation of UHI due to a lack of proper urban development planning. Other researchers examine the relationship between UHI and urban morphology, such as building density, building height, orientation and road width can affect urban temperatures [4]. The increase of urbanization, the UHI phenomenon is becoming more severe with the intensity of urban heat islands continuing to increase, especially in the major cities of the world [5][6].

During hot periods, the UHI phenomenon impacts on the urban thermal environment, with the use of air conditioners that are more intense than before. This dependence on air conditioning actually exacerbates the negative effects of UHI because it will further increase the amount of anthropogenic heat released into the air. Therefore, it is clear that a well-planned city can greatly improve the quality of the urban thermal environment and alleviate the UHI phenomenon [4]. To prevent the development of cities that are not environmentally friendly, cities must be planned carefully before they are totally built, and this planning must be based on quantitative calculations and analysis.

Conventionally, UHI studies have been conducted by ground-based identification [8]. Recently, with the development of remote sensing technology, image satellite has become common in urban climate and environment studies. It has become a powerful research tool for UHI studies [8-10]. Rao [11] was the first authorto demonstrate that UHI could be identified from the analyses of thermal infrared data acquired by a satellite. Gallo [9] analysed and illustrated the use of satellite aquired data on the analysis of UHI. In recent years, Landsat Thermatic Mapper (TM) and Enhanced Thermatic Mapper Plus (ETM+) data with spatial resolutions at 120 m and 60 m, respectively, have also been employed for local-scale research of UHI [12][13].

Since 1972, the Landsat series of satellites have provided multi temporal records of earth surface observations, and have become more popular among UHI studies [13]. UHI intensity has correlation with patterns of land use/land cover (LULC), such as the distribution of vegetation, water bodies and built-up areas. LULC have had negative environmental, social and economic impacts on many cities in the world. Land use types with different thermal properties and radiation features make different contributions to the UHI study. Qualitative studies on the relationship between LULC and UHI will help cityplanners in land use planning. [14].

As a certainty, various indices gained from remote sensing images can be used in the assessment of LULC, qualitatively and quantitatively [15]. For example, Normalised Differential Vegetation Index (NDVI) is conventionally used as the indicator of vegetation distribution to estimate the UHI-vegetation correlation [16][17], Normalised Difference Water Index (NDWI) can be used for analysing water body content purpose [20], and Normalised Different Built-up Index (NDBI) for identification of urban and built-up areas.

The main objective of this study is to quantitatively analyse the impact of LULC change, in a rapidly changing area of Makassar City, on the intensity and spatial pattern of UHI impact in the region. LULC information is obtained from remote sensing images using NDVI, NDBI and NDWI equations for different time periods and then thermal infrared bands are used to analyze land surface temperatures. The specific goals of this study are: (1) to examine the spatial pattern of the land use/land cover, index values, and their changes from 1989 to 2018; (2) to obtain land surface temperature from the Landsat TM/ETM+ thermal band over the study period; and (3) to explore the correlation between land surface temperature and land use/landcover patterns in Makassar city, South Sulawesi, Indonesia.

2. METHODOLOGY

A. Studi area and data

Makassar City, along the southwest coast of Sulawesi island, has been selected as the study area because of its accelerated rate of urbanization in the past 20 years. Makassar is the capital city of the Indonesian province of South Sulawesi. It is the largest city in the eastern part of Indonesia and the fifth largest urban centre in Indonesia. Landsat 4 TM imagery (12 December 1990), Landsat 7 ETM + (20 September 1999), Landsat-5 TM (1 August 2007) and Landsat-8 OLI/TIRS (14 July 2018) collected from US Geological Survey (USGS) data, for the years 1990 to 2018, were used to construct time series imagery to analyse the information of LULC and to characterize the thermal environment in this study area. All of the images were of good quality. nearly free of clouds, or less than 10% cloud coverage.

B. Image Preprocessing & LULC Classification

Prior to interpretation of LULC and LST retrievals, both radiometric calibration and rectification were applied to these images. Radiometric calibration is a prerequisite for making high-quality scientific data, and consequently, producing a final product that has a high level of quality. After atmospheric correction, all images are corrected and geo-referenced to UTM map projections before interpretation. This study requires the detection of fine changes in surface reflectance and LULC.

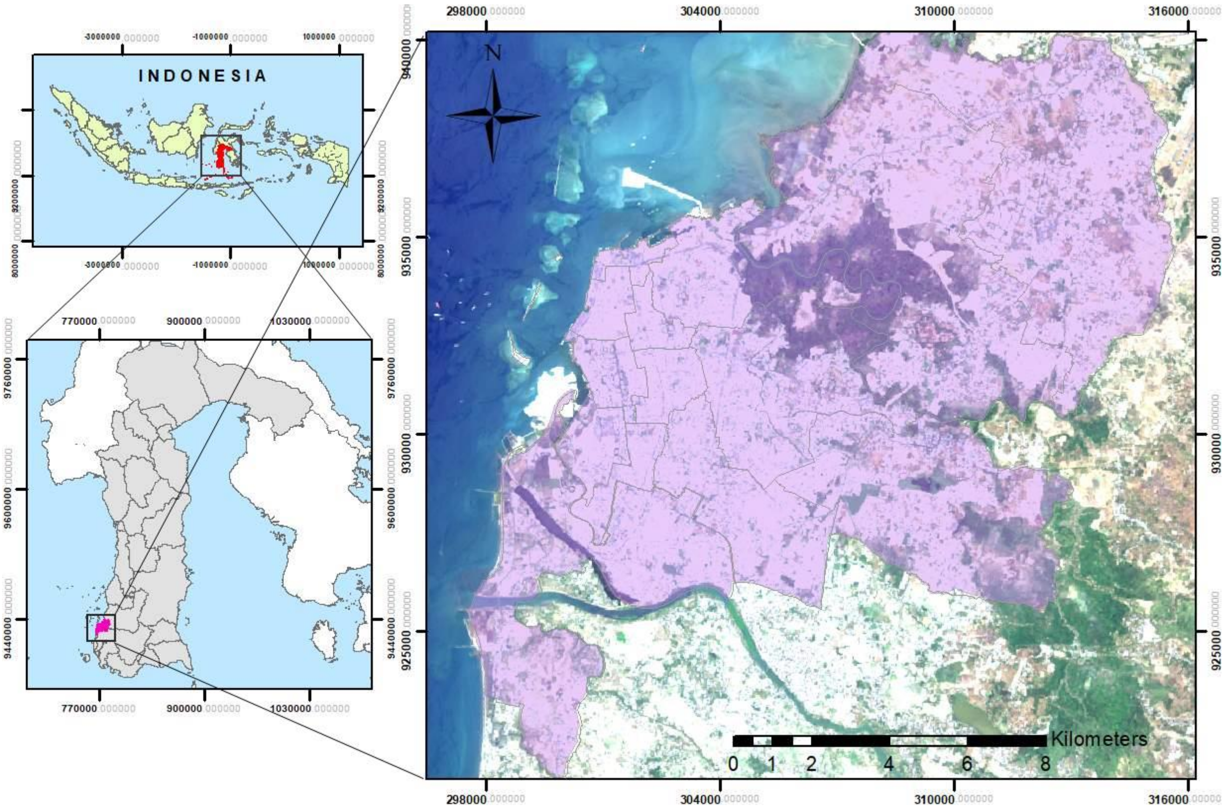

Figure 1. The study area.

Based on the characteristics of the study area, prior knowledge, and previous studies, five land use/land cover types, as defined in Table 2, were identified by maximum likelihood method on supervised classification and combined with visual interpretation from false-color Landsat images in 1990, 1999, 2007 and 2018 using ArcGIS 10.4.1. Comparing to the automatic interpretation, or computer based interpretation, of remote sensing images, visual interpretation usually takes more time and effort, but yields a more accurate result. The land use type of each patch was identified according to the shape, size, shadow, height, tone or color, texture, pattern, association, and site. During this process, when it comes to an unknown type because of cloud cover or other barrier, Google Earth with high spatial resolution images and other auxiliary data including visual transformation indices (NDVI, NDWI and NDBI) were combined to help identify the land use type.

*C. **Accuracy assessment***

Accuracy assessment was carried out with the following procedure. Firstly, for each classified map, at least 30 samples for each land use class were selected using a random stratified method to represent different land cover classes of the study area. Therefore, 150 samples for each classified map were used to check the accuracy of the classified maps. Secondly, the reference data and the results of visual interpretation were combined with the classification results to improve the classification accuracy of the classified images. Overall, the total accuracy of the land use map in 1989, 1999, 2007 and 2018 achieves 88.27%, 89.33 %, 88,67% and 91.30%, respectively, meet the recommended value of accuracy assessment [19].

D. ***Derivation of NDVI, NDBI and NDWI***

The NDVI, NDWI, NDBI and NDBaI [18] [14] indices were used to quanitatively describe the land use/cover types in the study area and to study the relationship between land use/cover types and UHI. NDVI in Equation (1), is the most popular index in remote sensing systems for vegetation cover analysis [18] and the most widely used vegetation index to monitor greening worldwide [20].

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

Where ρRED is the radiance of a red channel near 0.66 μm, and ρNIR is the radiance of a near-IR channel around 0.86 μm [18].

NDBI in Equation (2), will be used in this study, because it is sensitive to the built-up area.

$$NDBI = \frac{(\rho SWIR - \rho NIR)}{(\rho SWIR + \rho NIR)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

NDWI in Equation (3) is proposed for remote sensing of water from outer space. This index is used for the analysis of water bodies, which use green and near infra-red bands from satellite images.

$$NDWI = \frac{(\rho Green - \rho NIR)}{(\rho Green + \rho NIR)} \ldots\ldots\ldots\ldots\ldots \ldots (3)$$

E. ***Land surface temperature (LST) retrieval***

Due to the difficulty in acquiring the spatial distribution of land surface temperatureand near real-time atmospheric profile data, an image-based method was applied. This method was successfully used in other case studies to analyse the LST and its effects on LULC.

In this study, a single-channel algorithm was used because of its simplicity and validity [20] compared to other methods such as image-based methods [21] and mono-window algorithm methods [22]. The conversion process is done through 4 transitions [20]:

E.1. Convert the digital number (DN) into radiant temperatures (L_λ)

$$L_\lambda = gain * DN + offset \ldots\ldots\ldots\ldots\ldots (4)$$

Where L_λ is the radiance of thermal band pixels in W/(m^2 ster μm), gain is the slope of the radiance/DN conversion function, and offset the slope of the radiance/DN conversion.

E.2. Spectral radiance into satellite brightness temperature

$$T_B = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda}+1\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where T_B is the effective at-satellite temperature in ^oK, both K_1 and K_2 are pre-launch calibration constants (K_2 = 1282.71 K, K_1= 666.09 mW cm^{-2} sr^{-1} μm−1).

E.3. Calculation of land surface temperature

The land surface temperature was computed as follows:

$$Ts = \frac{T_B}{1+(\lambda\ x\ T_B/\rho)\ln\varepsilon} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where Ts is the radiant surface temperature in Kelvin (K), T_B the black body temperature in Kelvin (K), λ the wavelength of emitted radiance, λ=11.5 μm, α=*hc/K* (1.438 × 10−2 mK),

h=Planck constant (6.626×10^{-34}Js−1), and c=velocity of light (2.998×10^{8}ms^{-1}), K=Boltzman constant (1.38×10^{-23} JK^{-1}), and ε=surface emissivity.

*F. **Correlation Analysis***

To find out the relationship between LULC and LST, a simple statistical analysis was performed, whereas for the relationship between NDVI, NDWI, NDBI and LST, Pearson correlation analysis was used. The study area is divided into 500 x 500 m^2 grids with a total of 694 grids. Determination of 500 m distance is based on everyone's need for comfort [23]. One sample point is taken from each grid, so we get 694 points that were used to extract values from each parameter. Furthermore, the values obtained are processed using Microsoft Excel 2016 ®application to obtain descriptive statistics and a correlation coefficient.

3. RESULT AND DISCUSSION

*A. **Spatiotemporal patterns of LULC***

Figure 3 illustrates the pattern of LULC in the study area for the past 30 years. It is clear that Makassar has experienced a rapid process of urbanization, and LULC patterns have conversed substantially. Among the five land use classes, the water area changed little; the vegetation and built area had a continuously expanding trend, while open land and wetland area had been decreasing continuously.

In 1989, the percentage of vegetation was the highest among others by 28.55%, followed by built up area at 27.64%, which was spread on west part of Makassar. The proportion of wetland area was about 23% of total LULC followed by open land (18.92%), while water was the smallest portion at 1.89%.

Overall, in the period 1989 to 2018, the built-up area increased by 73.83%. Approximately all of the newly emerging developed land was converted from vegetation (46.35%), openland (33.58%), wetland (19.97%) and water body (0.11%). The net increase in built up area is clearly at the expense of vegetation area. Developed landwas the main LULC types in the LULC structure of the city. Vegetationand openland area also played an important role as it occupied more than 20% of the total land use structure. The study results showed that LULC in the study area changed considerablyfrom 1989 to 2018. The main LULC change driver was transformation of vegetation and openland to built up area due to urbanization and industrialization.

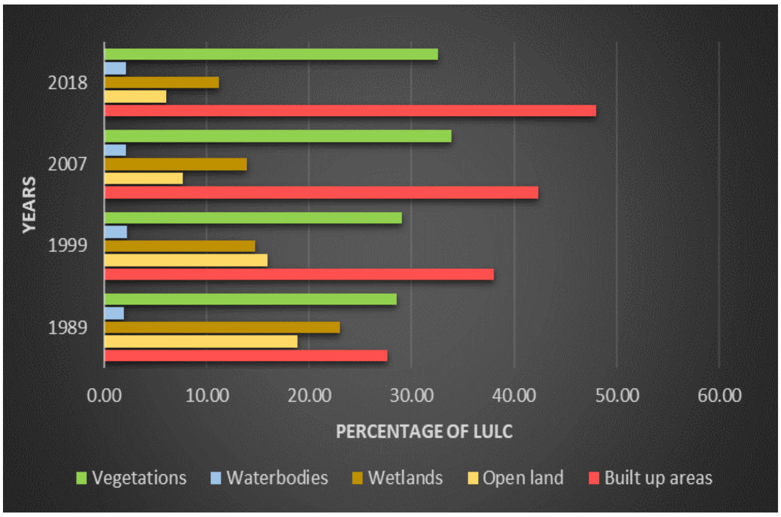

Figure 2. The proportion of LULC on study area in 1989, 1999, 2007 and 2018

B. ***Spatiotemporal patterns of NDVI, NDWI, and NDBI***

B.1. Spatiotemporal Pattern of NDVI

NDVI values in 1989 were in the range between -0.28 and 0.76, from -0.80 to 0.65 in 1999, between -0.94 and 0.78 in 2007 and during 2018, the range is between -0.79 and 0.89. Maps show a gradual decline in overall vegetation trends over the years. It was observed that despite an increase in urbanization, the total amount of vegetation cover did not change significantly. This is because the development trend in the city of Makassar is more directed to the coastal areas.

On the other hand, although there was a reduction in vegetation cover, replanting activities continue to be carried out by the government, the community and the private sector, particularly in the districts of Tamalate, Tamalanrea and Biringkanaya which still have relatively large open land.

B.2. Spatiotemporal Pattern of NDBI

NDBI values in 1989 were in the range of -0.836 and 0.045, from -0.549 to 0.021 in 1999, between -0.300 and 0.666 in 2007, and during 2018, the range was between -0.757 and 0.552. From the NDBI map, areas with values greater than zero represent built-up areas with NDBI values indicating maroon-colored areas while values below zero or close to zero represent non-built up area features such as open land, vegetation and water.

B.3. Spatiotemporal Pattern of NDWI

The minimum and maximum NDWI values in 1989 were in the range of -0.654 to 0.433, from -0.467 to 0.885 in 1999, between -0.671 and 0.959 in 2007, and during 2018, the range was between -0.885 and 0.964.

Wetland conversion is a popular trend in Makassar, including conversion of coastal wetlands through reclamation projects. This is because the price of wetlands is relatively cheap. Although the developer still has to spend a lot of money to get the wetlands ready for use, the conversion of these areas remains high due to their strategic position. The same pattern is shown by the map of interpretations of changes in LULC where the wetland area in Makassar city decreased significantly over the years between 1989 and 2018.

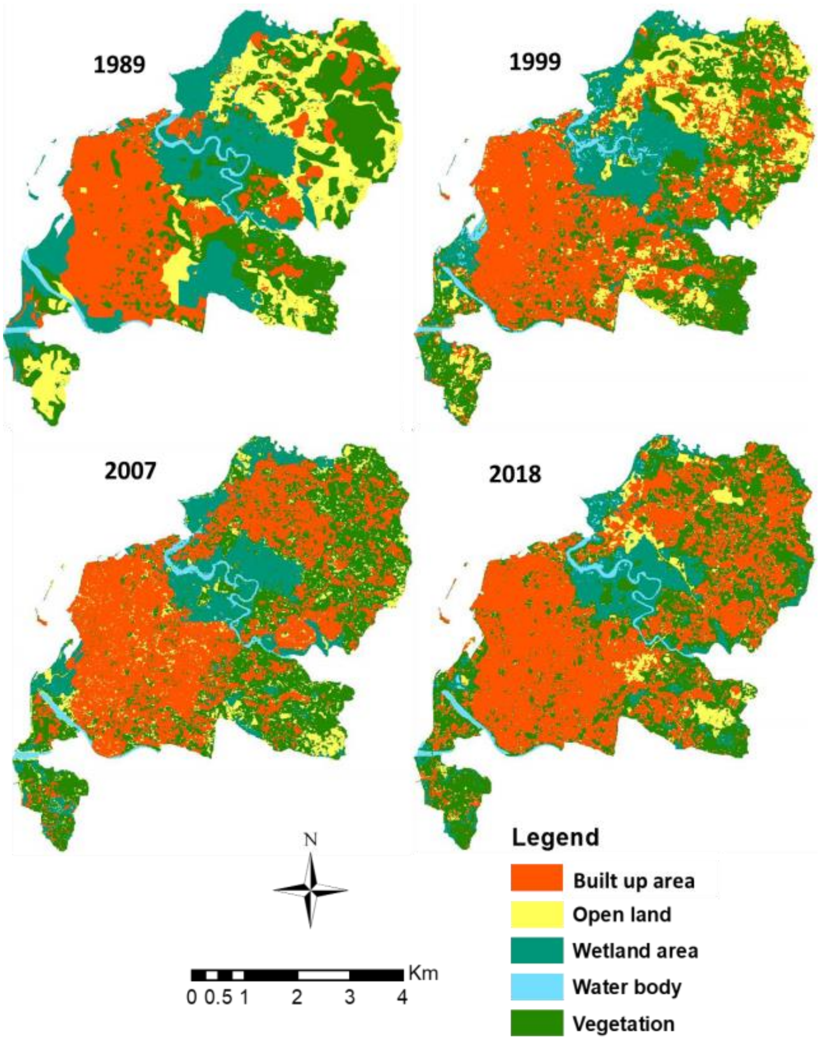

Figure 3. LULC Maps in Makassar city during the period from 1989 to 2018

B.4. Spatiotemporal pattern of land surface temperature

From the calculations, we obtained several important findings as a result of this study. According to Figure 4a - d, the highest LST distribution in Makassar in 1989 was in the western part. In 1999, besides the northwest area, the highest LST Values were seen spreading to the eastern part. This high value could be a reflection of dry open land value, because in reality, during those years, there were no high density urban area in northeast part of Makassar. In 2007 and 2018, the distribution of the highest LST Value was not only in the western part, but had spread to the western and southwestern parts of Makassar city. This region is considered as the heart of Makassar because shopping centers, markets, head offices, large hotels and large banks can be found in this region. Therefore, this area has a high building density. Areas with high or higher LST zones are scattered in the eastern part of the city. The pattern is to form spot areas that are spread evenly. Over time, if there are no preventive measures, these zones will merge and create a new urban heat island. As expected, in all images analyzed, the low, the lower and the lowest LST were found near water bodies, vegetation and wetland areas.

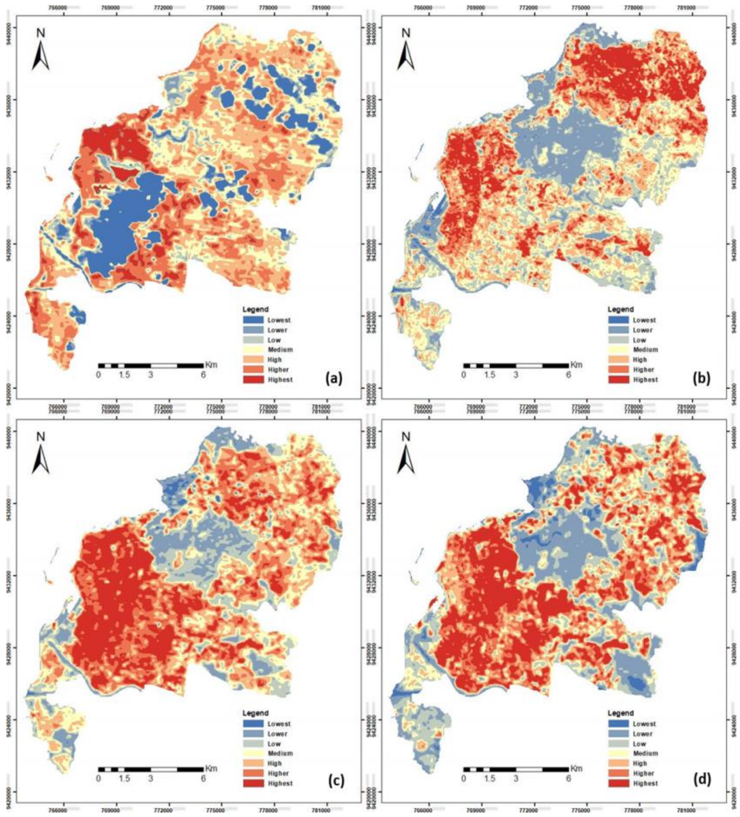

Figure 4. LST values map in Makassar city during study period,
(a). 1989, (b). 1999, (c). 2007, and (a). 2018.

Table 1. Temporal patterns of LST Classes in Makassar city during study period in 1989, 1999, 2007, and 2018.

LST Classes	1989		1999		2007		2018	
	Area (Ha)	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**
Lowest	2355.22	13.42	100.21	0.57	101.97	0.58	394.54	2.25
Lower	699.98	3.99	2568.87	14.64	1694.14	9.66	2621.91	14.94
Low	1109.81	6.32	2791.29	15.91	2196.95	12.52	2822.80	16.09
Medium	3762.34	21.44	3558.28	20.28	2723.42	15.52	2296.88	13.09
High	4926.90	28.08	3900.57	22.23	3541.83	20.19	2776.85	15.83
Higher	3589.91	20.46	2159.41	12.31	3685.08	21.00	2896.21	16.51
Highest	1103.38	6.29	2467.03	14.06	3601.81	20.53	3737.37	21.30

B.5. Correlation between UHI and LULC

The characteristics of surface area are the most influential factor on the distribution of UHI in the study area. These characteristics are influenced by materials that show the properties such as radiation, water content, aerodynamics and heat capacity, which is strongly influenced by the surrounding environment. Heat capacities and radiation are the most influential properties of UHI distribution, because they affect how wave radiation is reflected, emitted, absorbed and stored. In addition, anthropogenic activities can significantly influence the microclimate and specifically enhance the UHI phenomenon. From the results of the LULC in Figure 5, it is known that the areas that have high temperature are mostly built up areas. Conversely, wetland areas, water bodies and vegetation clearly show their effects as cooling areas. Because the decrease of vegetation cover and wetland areas and increasing LST have a negative impact on public health and the surrounding environment, it is important to know the distribution of LST.

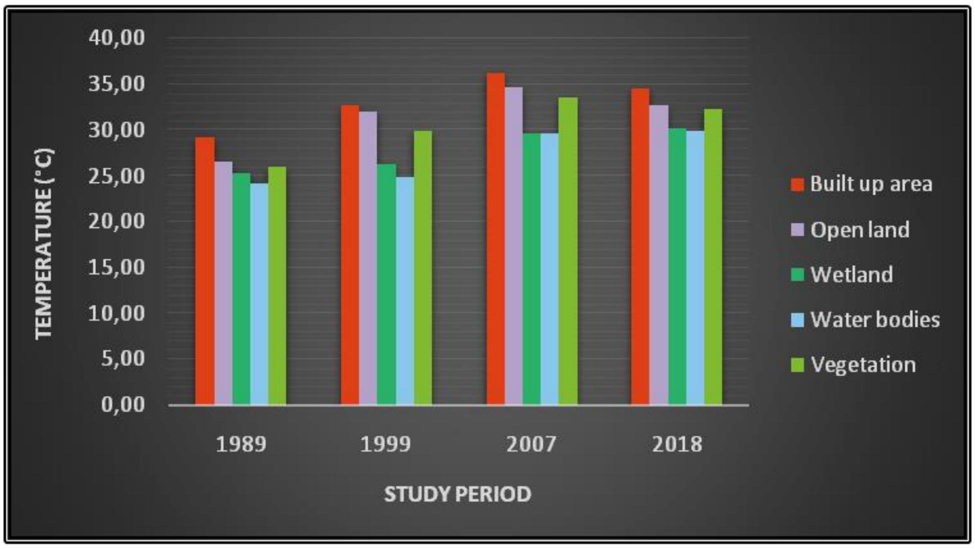

Figure 5. Mean temperature of five type of LULC in 1989, 1999, 2007 and 2018.

Figure 5 provides information on average temperatures in several LULC classes in different years. Overall, it can be seen that during this period there was an upward trend of temperatures in all LULC classes. The lowest average temperature is found near waterbody and wetland areas with averages ranging from 24.21° C to 30.21° C. This result implies the importance of waterbody and wetland area as a cooling effect to the Makassar city, compare to vegetation, wetland areas has higher capacity of heat.

B.6. Correlation between temperature and NDVI, NDWI and NDBI

Correlation analysis between several indices, namely NDWI, NDVI, NDBI, and LST was conducted to find their relationship. The results show a strong positive correlation between NDBI and LST. In other words, as NDBI increases, the LST will also increase. Table 12 provides information that the lowest NDBI-LST correlation was in 1999 with 0.31, followed by 2007, 2018 and 1989 with 0.44, 0.56, and 0.68, respectively. The results obtained for the correlation between NDVI, NDWI and LST show a negative correlation where regions with high NDVI and NDWI values are found to have lower temperatures compared to regions with low NDVI and NDWI values.

The results obtained from this study imply important conclusions about the undoubtable role of vegetation and wetland in UHI mitigation. Urban planning that considers the presence of vegetation and wetland areas will help in controlling urban temperatures. In the city of Makassar a lot of land changes in the name of development that is not environmentally friendly. Some examples are, the road widening project on Jalan Pettarani, which cut more than 1000 trees that are in the median strip of the road, a coastal wetland reclamation project along the coastal area, and luxury residential developments in several wetland spotsin the eastern part of the city. In the future, the local government in Makassar city must seriously consider regulating land use land cover changes from vegetation or wetland areas to built up areas. This regulation maybe the most effective solution to reduce the effects of UHI in the city.

B.7. Future Study Recommendation

Based on the study limitations mentioned above, it is recommended that several aspects need to be improved in future studies. Firstly, it is better to use the year to year image satellite data or several short periods of data to provide more effective information about the pattern of LULC and LST changes in the study area, although it will be very difficult to find image data that has the same quality in short periods of time.

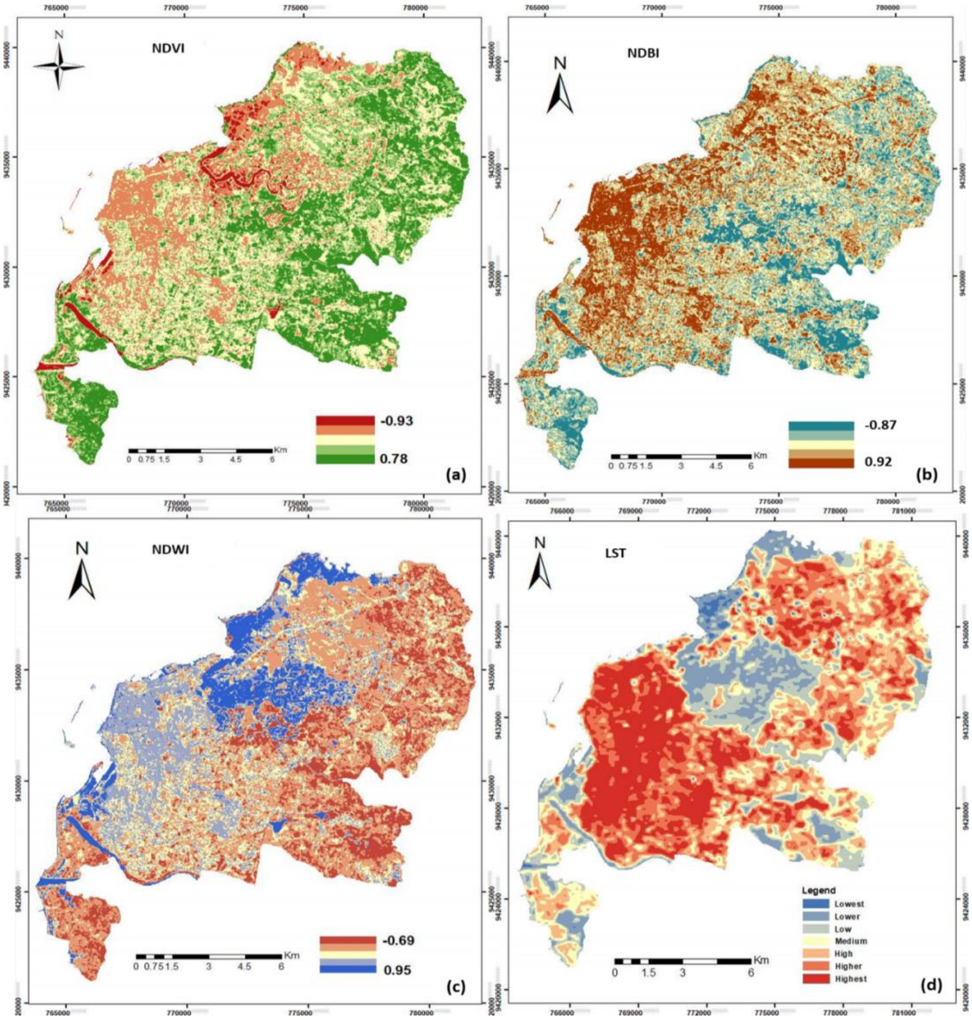

Figure 6. Maps of NDVI (a), NDBI (b), NDWI (c), and LST (d) in Makassar city derived from Landsat 5-TM image on August. 1, 2007.

Secondly, satellite images with high spatial resolution will result in better analysis of LULC changes and LST retrieval, therefore further research will be better when using high-resolution images because the city of Makassar is a small area or just in the local level. Finally, it is highly recommended for future researchers to emphasize the impact of coastal wetlands and inland wetlands conversion to the temperature distribution in the city of Makassar.

4. CONCLUSION

Three main conclusions can be made from the results of this study. First, both of the patterns of LUCC and LST have had significant changes in the past 30 years. The urban area in Makassar city increased 73.83%, from 4849.21 Ha in 1989 to 8429.21 Ha in 2018. The highest percentage of developed area was on the western part of the study area. This pattern is predicted to expand in the eastern part of the city, because urbanization rate shows an upward trend in that area. Second, LULC change has a great influence on LST. In other words, the spatiotemporal changes in LST were consistent with the rate of urbanization, because anthropogenic activities tend to transform the environment based on people's needs. Third, based on the average LST value of various types of land use, the built uparea has the highest LST, while the lowest is water body and wetland areas. Thus, the average LST in the study area has steadily increased because other LULC categories have been changed to develop the area. The UHI effect will be a challenge because the city will continue to urbanize and grow in size and density. This effect is getting worse because of the high land conversion in both coastal wetland and inland wetland areas.

All the analyses in this study were based on remote sensing image analysis, which is not only analyzing the phenomenon of UHI, but also the relationship with other factors. The spatiotemporal relationship of LULC and LST has been studied by analyzing multitemporal remote sensing data. Although remote sensing data were useful for UHI analysis, it is difficult to find the proper images that have the same condition in all study periods, including cloud cover, season, sensor error factor and atmosphere condition. If UHI analysis is to work on a local level, it is necessary to use high quality images that have high spatial resolution. The improvement of UHI studies is a great challenge for researchers from multiple discipline to contribute in order to advance the analytical capacity in analyzing UHI phenomenon. Thus, results and conclusions attained in this study will provide better consideration for local government to create sustainable regional planning strategies.

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