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SPATIAL ANALYSIS OF LAND SURFACE TEMPERATURE AND ITS RELATIONSHIPS TO LULC INDICES IN SURIGAO CITY

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ABSTRACT: The integration of Remote Sensing and statistical analysis method became broadly used to assess and mitigate urban problems, such as thermal environment cases. The most evident effect of urbanization in the City of Surigao is the Land Use/Cover (LULC) Change, which produces pollution and changes in the atmospheric properties that lead to the formation of Land Surface Temperature (LST). This study used the generated LULC map of Landsat imageries (i.e. 1996 Landsat 5 TM, 2006 Landsat 7 ETM+, and 2016 Landsat 8 OLI/TIRS) to correlate with the LST through linear regression analysis. Indices such as NDVI, NDBI, and NDBaI were used to analyze the relationship between LST and LULC qualitatively, and NBEM was used to retrieve LST. The results showed that maximum values of LST were experienced in the built-up and barren areas, while minimum values were in the water and dense vegetation areas. It also revealed that LST has a negative correlation with NDVI and a positive correlation with NDBI and NDBaI. Spatial change analysis was also used to assess the variations of LST changes in the study area. This study would serve as an essential mechanism for monitoring LST trends in relation to LULC dynamics in the study area.

1. INTRODUCTION

One of the apparent effects of urban developments is the increased surface temperature on the Earth's surface due to the conversion of vegetated surfaces to impervious surfaces (J. Mallick, Y. Kant, B.D. Bharath, 2008). The transformation of vegetated wetlands into agricultural land or bare wasteland (S.Pal and O.C. Akoma, 2009). Pollution and changes in the atmospheric properties and surface land cover could result in the formation of Urban Heat Island (UHI), the increase in urban temperatures compared to its surrounding rural areas (Q. Weng, 2001). A considered reliable indicator of UHI is the Land Surface Temperature (LST), since, generally, it has a high relationship to the air temperatures in any surface area.

The rapid urban expansion has caused land use/land cover (LULC) changes, affecting the local and regional ecological and environmental processes, especially on the urban heat island (K.P. Gallo, T.W. Owen, 1998). The NDVI, NDBI, and NDBaI indices help calculate the LULC change about the LST.

Remote Sensing approaches are broadly used and proven to have an essential role in studies like monitoring LULC changes. It also has a complete package which makes it more suitable, especially in large areas with the need for high-resolution images since it costs less in terms of time, effort, and financial matters.

Due to the developments, the presence of LST has become higher and more extreme in the City of Surigao. The spatial analysis of Land Surface Temperature and its relationship to the Land Use/Cover Change were conducted through linear regression analysis. NDVI, NDBI, and NDBaI were used to correlate it with the LST qualitatively, and the Maximum Likelihood

Classification (MLC) was used in the generation of LULC maps. In the retrieval of LST, NDVI- the based emissivity method (NBEM) was used. Random point sampling was also used to assign multi-values to the LULC Maps to determine the correlation.

This study aimed to estimate Land Surface Temperature using NBEM and generate LULC maps of 1996, 2006, and 2016. Assess the LULC through the Indices (NDVI, NDBI, and NDBaI); evaluate the spatial changes of LST, and determine using linear regression the relationships of LST and LULC based on the Indices used.

The analysis of Land Surface Temperature and its relationship to the Land Use/Cover Change using Landsat Images could help the local government of Surigao City to obtain information and awareness regarding the existing physical conditions of the province in terms of urban heat. It could become helpful for urban planning and development since it is a developing city. It is also valuable for individuals, communities, and organizations based on other studies that could help improve the communities and their environment.

2. MATERIALS AND METHODS

2.1 LULC Map Generation Using Landsat Images

2.1.1. Data Sources and Image Pre-processing

The data needed in this study were downloaded at USGS website (http://www.earthexplorer.USGS.gov) from the years 1996, 2006, and 2016. All Landsat Images are raw datasets that are required to undergo first pre-processing. 1996 Landsat 5 TM, 2006 Landsat 7 ETM+, and 2016 Landsat 8 OLI were used to generate LULC and LST maps and analyze their spatial changes.

Pre-processing is a fundamental process for raw datasets such as Landsat Images. It is vital since captured satellite images compensate for errors due to radiometric and atmospheric influences; thus, pre-processing could make the image normalized. The environment of Visualizing Images (ENVI) application was used to pre-process the data.

2.1.2. Maximum Likelihood Image Classification

Classification of images is a process of categorizing pixels into different land cover classes such as built-up, dense, and sparse vegetation, bare land, water bodies, and many other classes. The classified image was utilized to make thematic maps by the objectives of any study.

In this study, the Supervised Classification, the Maximum Likelihood Classification (MLC), was used. It was employed to generate the Land Cover Map of the year 1996, 2006, and 2016 of the study area with land cover classes; built-up, dense vegetation, sparse vegetation, barren, water, and pond. It was processed in the ENVI Classic application.

2.2 Indices Calculation

2.2.1. Normalized Difference Vegetation Index (NDVI) Calculation

To measure the NDVI values of the data, it uses the equation:

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad \text{Equation 1}$$

Where **NDVI** is the Normalized Difference Vegetation Index, **NIR** is the Near Infrared Spectral Band, and **RED** is the Red Spectral Band.

2.2.2. Normalized Difference Built-up Index (NDBI) Calculation

NDBI Calculation is the extraction of built-up areas in the Landsat images. It uses the equation:

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \qquad \text{Equation 2}$$

Where **NDB**I is the Normalized Difference Built-up Index, **MIR** is the Middle Infrared Spectral Band and **NIR** is the Near Infrared Spectral Band.

2.3.3. Normalized Difference Bareness Index (NDBaI) Calculation

This index calculation extracts the bare areas of the Landsat Image. It uses the equation:

$$NDBaI = \frac{MIR - TIR}{MIR + TIR} \qquad \text{Equation 3}$$

Where **NDBaI** is the Normalized Difference Bareness Index, **MIR** is the Middle Infrared Spectral Band, and **TIR** is the Thermal Infrared Spectral Band. All Indices Maps were generated using the Band Math tool in the ENVI 5.0 software.

2.4 Land Surface Temperature (NDVI-based emissivity method) Calculation

The Metadata of the Landsat Images was loaded in the ENVI 5.0 software for the process of calculating the LST. The Band Math tool was used as the primary tool for each significant procedure to derive the LST as shown in Figure 1.

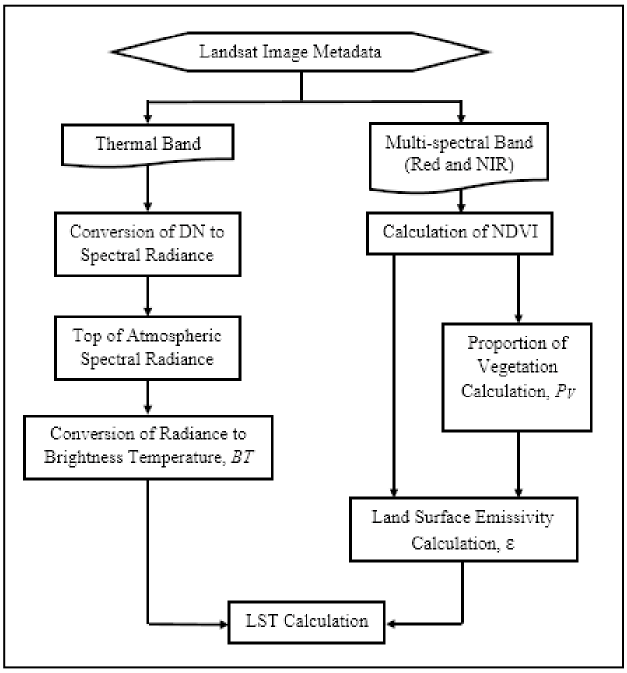

Figure 1. LST Calculation (NBEM)

2.5 Random Points Sampling on the Study Area

After the Land Cover map generation, random points were then created in each land cover class. Multi values were then assigned on the random points (LST, NDVI, NDBI, NDBaI). In the attribute table, all the values were displayed. Each indices value of the random points was then correlated to its LST values.

2.6 Linear Regression Analysis

This process was executed in Microsoft Excel to determine the relationships between the LST and Indices values. Each value of NDVI, NDBI, and NDBaI was inputted on different columns paired with the LST values. The independent variables are the Indices values, while the dependent variables are the LST values. Graphs were inserted to visualize the relationship between the two variables and the linear regression line's equation and coefficient (R^2).

2.7 Spatial Change Analysis

In determining the spatial changes on LST, the generated LST Maps in 1996, 2006, and 2016 were reclassified in ArcGIS and categorized into six classes. The number of pixels per category conformed to the areas of each land cover class. This category ranges from less than 8 ºC, 8-12 ºC, 12-16 ºC, 16-20 ºC, 20-24 ºC, and more than 24 ºC.

2.8 Accuracy Assessment

Accuracy assessment is essential to determine the accuracy of the generated land cover maps. The samples of pixels were created in the classified image and compared with the reference data. Two sets of pixels sampling or ROI's would be designed for comparison, training, and ground truth ROI's.

3. RESULTS AND DISCUSSION

3.1 Land Cover Maps and Accuracy Assessment

Land Cover Maps of 1996, 2006, and 2016 were generated. The 1996 Land Cover has a kappa coefficient equal to 0.8924 and overall accuracy of 91.2214%, 2006 Land Cover has a kappa coefficient equal to 0.9055 and overall accuracy of 92.2840%, and 2016 Land Cover has a kappa coefficient equal to 0.9500 and overall accuracy of 95.8781% (Figure 2).

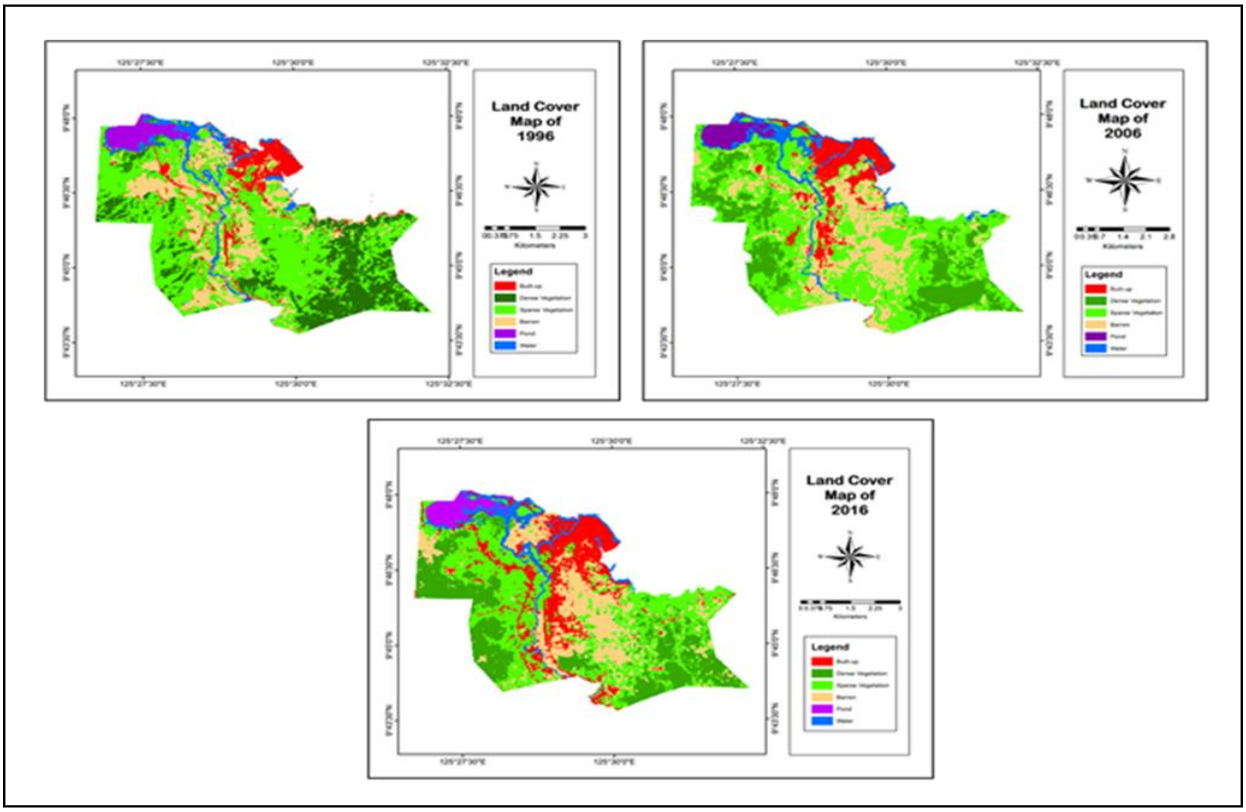

Figure 2. LULC Maps (1996, 2006, 2016)

3.2 Change Detection Assessment on Land Cover Maps

Change detection assessment on land cover maps is shown in Figure 3. It shows that the water area has maximum changes from 1996 to 2006 with a change rate of 56.26 %, while the dense vegetation area has negative changes with a change rate of -11.51%, which implies that the dense vegetation area became smaller for a 10-year interval. From 2006 to 2016, the built-up area had a maximum change rate of 49.01% compared to 2006. While the sparse area has a negative change rate of -20.32% from 2006 to 2016.

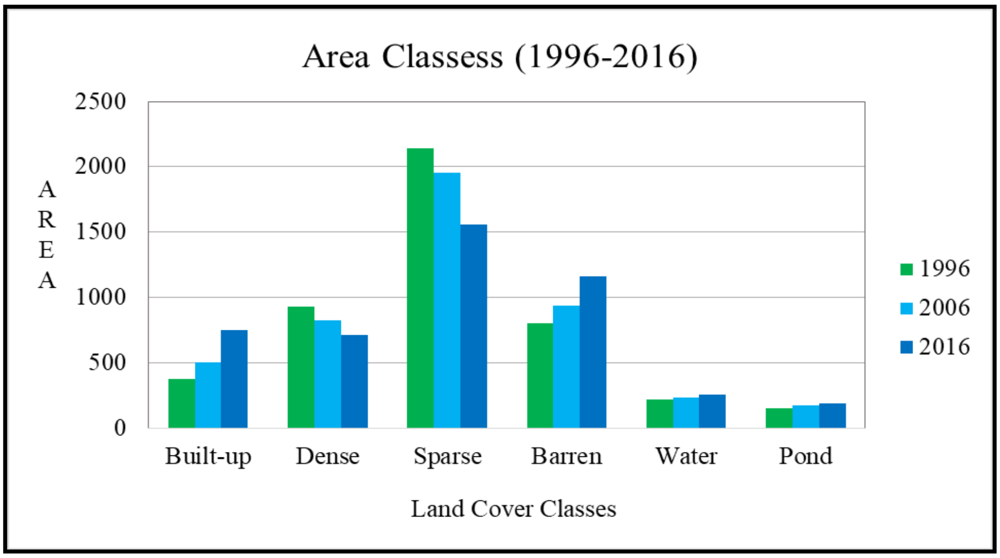

Figure 3. Area of classes (1996-2016)

3.3 Indices Maps

Through indices, the relationship between the LST and LULC could be determined. Three indices were used to correlate in LST values: NDVI, NDBI, and NDBaI. Indices have the same ranges of values which starts from -1 to +1. NDVI Maps, as shown in Figure 4, depict the green or vegetation areas; those areas that are dark green have the highest values of NDVI. However, those areas, especially in the city areas, have a reddish color which signifies lower NDVI values. It could be observed that there is a massive difference between the NDVI maps of 1996 to 2016.

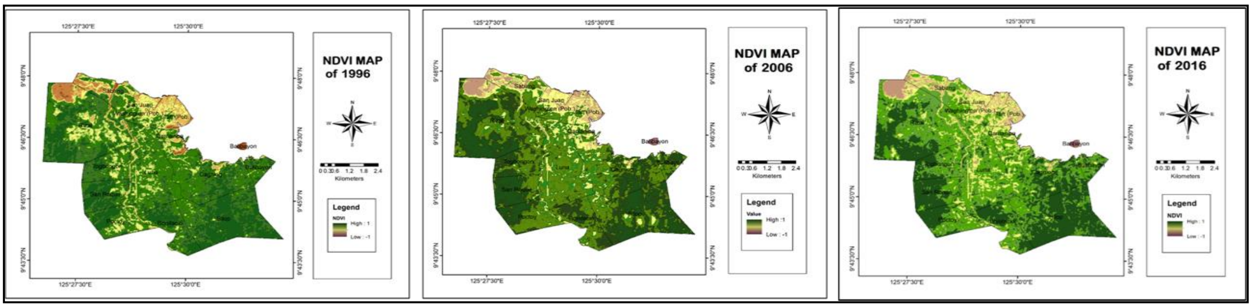

Figure 4. NDVI Maps (1996, 2006, 2016)

NDBI Maps depict the built-up areas, including road networks. It also has minimum values of -1 and maximum values of +1. The reddish areas correspond to the highest values of NDBI, while the yellow areas represent a lower value of NDBI. It could be seen that the reddish part clustered in the city area of the map signifies the highest values of NDBI as shown in Figure 5.

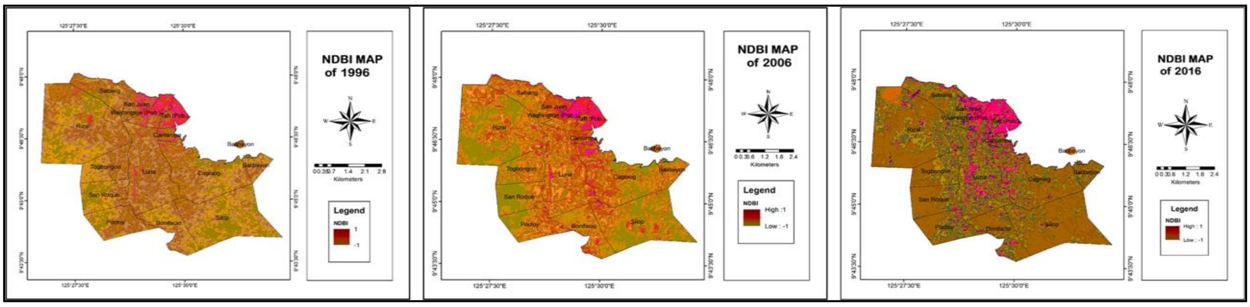

Figure 5. NDBI Maps (1996, 2006, 2016)

Barren areas have the highest values of NDBaI since this index detects areas with a lesser value of vegetation. Like the other indices, it ranges from -1 to +1. Figure 6 is the NDBaI Maps derived from the Landsat images. The red-orange areas mean the highest values of NDBaI, and the green areas correspond to the lower values of NDBaI.

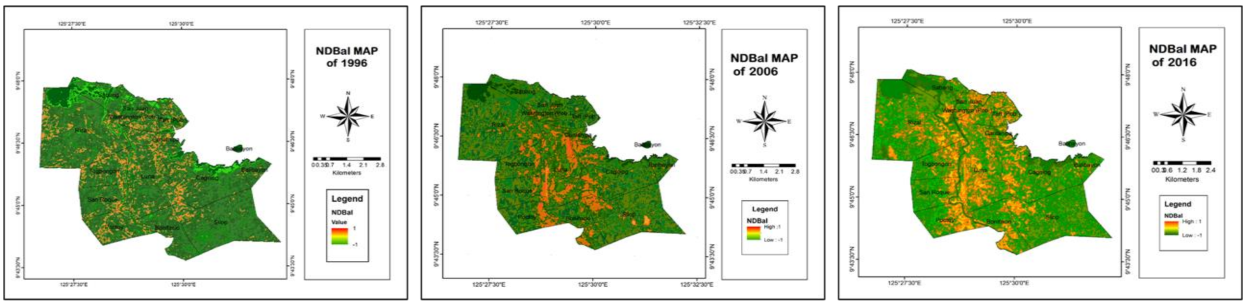

Figure 6. NDBaI Maps (1996, 2006, 2016)

The differences between each indices were determined through Compute Difference Map in ENVI 5.0. It has a concept of subtracting the Final State from the Initial State, which could result in a new image, displaying the degree of changes in the whole area image. The results were labeled as Change (+1) and Change (-1) thresholds. Positive change signifies the positive transformation of the two inputted indices map (Initial State and Final State), while the negative change corresponds to the negative transformation values. Three Index Differencing were produced, the NDVI, NDBI and NDBaI Change Detection Map from 1996 to 2016 (Figure 7).

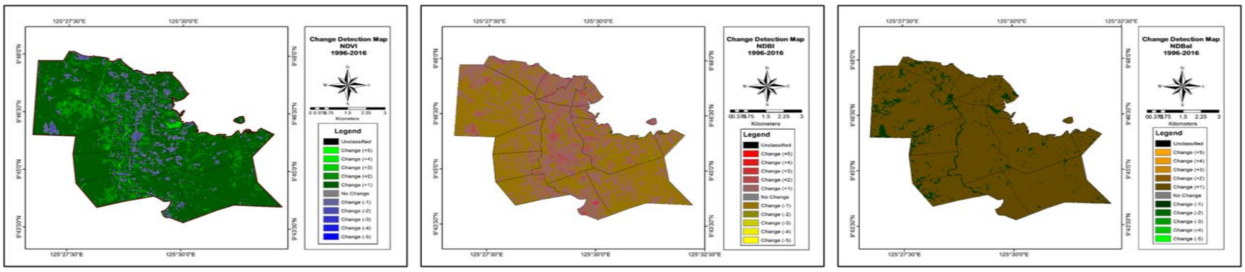

Figure 7. . Indices Differencing

3.4 Derived Land Surface Temperature (LST) Maps

Figure 8 shows the derived Land Surface Temperature (LST) maps. The red color corresponds to the highest values of LST, which are clustered in the City area. It could be concluded that those parts experienced an intense degree of Surface Temperature compared to their surrounding areas. On the contrary, the yellow part of the classified image experienced warmer temperatures in the west and some in the east part of the study area.

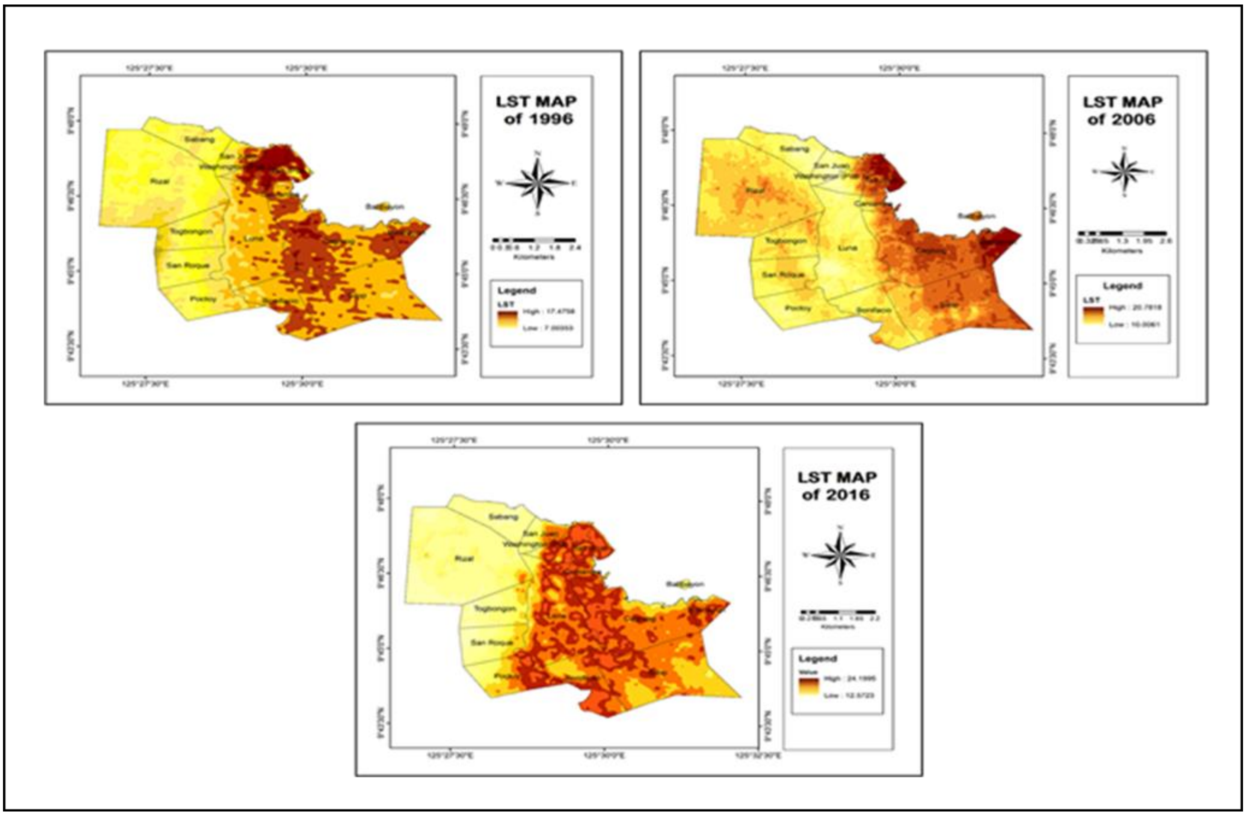

Figure 8. Derived LST Maps (1996, 2006, 2016)

The LST Map of 2006 has the highest value of 20.7818 ºC, with a mean value of 15. 2825 ºC and the lowest value of 10.0061 ºC. Still, the maximum values were in the city areas and started to disperse in the east. The rising temperature resulted in much intense temperature experienced in the center of the city. For a 10-year interval, the Land Surface Temperature in the study area is slightly different. For 2016, the derived LST Maps determined the maximum value of LST as 24.1995 ºC and a minimum value of 12.5723 ºC. For a 20-year interval from 1996 to 2016, there was a drastic temperature change. The areas with higher temperatures are scattered almost the entire study area. The yellow areas became fewer and could only be observed in the western part of the classified image

3.5 Relationship of LST with LULC

This part presents the relationships between the LST and the LULC through linear regression analysis. Random point sampling was used to extract samples from each indices. The correlation coefficient (R^2) indicates an excellent statistical measurement of how close the examples are in the inputted regression line.

Figure 9 displays the graph indicating the relationship between LST and NDVI for all years used in this study. It could be observed that the equation has a negative slope which implies a negative relationship between the two. In 1996, the coefficient of NDVI had a negative value of 16.231. It means that the value of LST will increase by an average of 16.231 per value of NDVI. It has a correlation coefficient of 0.9942. The nature of the correlation of NDVI with the LST is the same in the years 2006 and 2016.

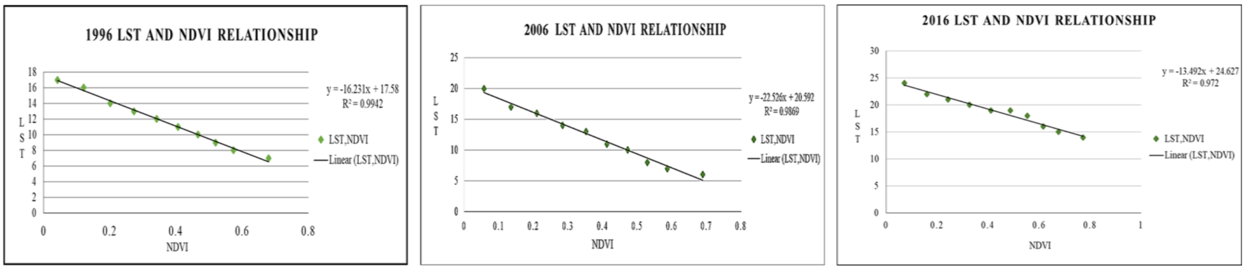

Figure 9. . LST and NDVI Relationship (1996, 2006, 2016)

LST and NDBI relationships are shown in Figure 10. It depicts a positive relationship since LST increases as impervious areas expand. It could be noticed that there is a positive inclination of the linear regression line, implying a directly proportional relationship. The coefficient of NDBI in 1996 has a positive value of 14.502. It indicates that the value of LST will increase by an average of 14.502 for each value of NDBI. The linear regression line fitted in the values signifying a good association. The correlation coefficient in 1996 is 0.9529, in 2006 is 0.9461, and in 2016, is 0.9215.

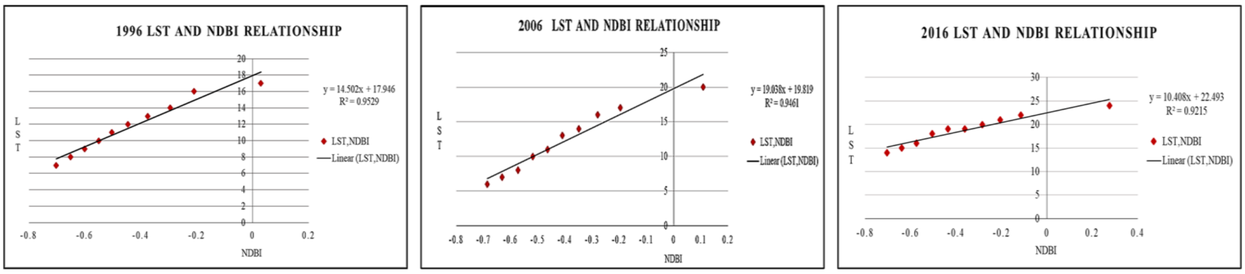

Figure 10. . LST and NDBI Relationship (1996, 2006, 2016)

The NDBaI-LST relationship is the same as the NDBI-LST relationship. Figure 11 also displays a positive correlation. The NDBaI coefficient has a positive value of 221.95 which means that the value of LST will increase by an average of 221.95 for each value of NDBaI. It could be concluded that the LST values also increase due to the expansion of barren areas. The correlation coefficient is 0.9311 in the year 1996, 0.9252 in the year 2006, and 0.9246 in the year 2016. The linear regression line also fits well, implying a good correlation.

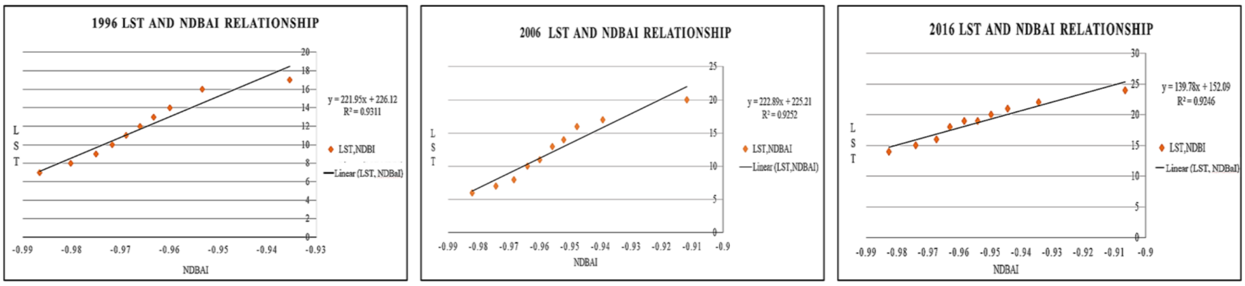

Figure 11. . LST and NDBaI Relationship (1996, 2006, 2016)

3.6 Spatial Change Analysis of LST

Table 1 presents the changes in the spatial-temporal context of LST. In 1996, 32.82% of the area had LST ranges from 8-12 ^{o}C, while 65.49% had LST ranges from 12-16 ^{o}C. However, the maximum values of LST ranges in 16-20 ^{o}C have only 1.38% of the study area. But in 2006, these values changed to 39.45% and 45.565, respectively. There were also 14.27% areas with LST ranges from 16-20 ^{o}C and 0.72% of 20-24 ^{o}C. This result indicates the remarkable increase of areas with high values of LST, which might lead to increased UHI situations. The fact is proven to be severely expanded in 2016, as shown in Table 1. There were drastic changes in areas of 47.25 % with LST ranges from 20-24 ^{o}C and 0.043% of areas with LST above 24 ^{o}C.

Table 1. Spatial Change Analysis of LST

LST Category (^{0}C)	1996		2006		2016	
	Area (has)	Percent Area (%)	Area (has)	Percent Area (%)	Area (has)	Percent Area (%)
< 8	14.4	0.31	-	-	-	-
8 - 12	1518.9	32.82	1825.4	39.45	-	-
12 - 16	3030.5	65.49	2108.5	45.56	863.2	18.66
16 - 20	63.7	1.38	660.3	14.27	1575.8	34.05
20 - 24	-	-	33.3	0.72	2186.5	47.25
> 24	-	-	-	-	2	0.04
Total	4627.5	100	4627.5	100	4627.5	100

4. CONCLUSION

Maximum Likelihood Classification (MLC) was used to produce the LULC Maps of 1996 with a kappa coefficient equal to 0.8924 and overall accuracy of 91.2214%. In 2006, a kappa coefficient equaled 0.9055, with an overall accuracy of 92.2840%. In 2016, a kappa coefficient equaled 0.9500 and an overall accuracy of 95.8781%. NDVI, NDBI, and NDBaI maps were also generated in ENVI 5.0 software to correlate the LULC with the LST maps. It was found that in 1996, the maximum LST value was 17.4758 ^{o}C, the minimum value was 7.0035 ^{o}C, and the mean value of LST was 13.0228 ^{o}C. In 2006, the ultimate value was 20.7818 ^{o}C, the minimum value was 10.0061 ^{o}C, and the mean value of LST was 15. 2825 ^{o}C. Lastly, in 2016, the maximum value was 24.1995 ^{o}C, the minimum value was 12.5723 ^{o}C, and the mean value of LST was 18.9801 ^{o}C.

Spatial change analysis was executed to assess the variation of LST changes in all areas in the city proper of Surigao. It was revealed that there were drastic changes in the areas with LST values ranges from 12-16 ^{o}C. And in 2016, there were 34.05% from 14.27% in 1996 of areas with LST ranges from 16-20 ^{o}C. Through linear regression analysis, the relationship of LST with the LULC was determined qualitatively. In the indices, the correlations were identified. It was revealed that the LST had a negative relationship with the NDVI, and a positive correlation with the NDBI and NDBaI.

Generally, this study ascertained that LST has been rising over time since the expansion of built-up areas has been prominently happening in the city proper of Surigao. Remote Sensing techniques and applications have also proven to be effective methods in extracting the desired values such as LST, NDVI, NDBI, and NDBaI and generating LULC maps. NDVI- based emissivity method (NBEM) was also provenly effective in retrieving the LST values.

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