

Modelling future land use/land cover and seasonal land surface temperature changes based on CA-ANN algorithm to assess its impacts on Chennai Metropolitan Area (CMA), India

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Abstract

Urbanization may cause huge amount of Land use and land cover (LULC) changes, which creates a significant influence on land surface temperature (LST) in fast developing megacities. This study first analyzed the pattern of LULC changes and then evaluated their implications on LST in the Chennai Metropolitan Area (CMA) for the years 2000, 2010, and 2020 using Landsat TM/EMT+/OLI satellite images. The study ultimately predicted the future LULC and LST scenarios for the years 2030 and 2040 using Artificial neural network and cellular automata algorithms based on previous predicted change maps of LULC and LST. The study then used correlation analysis to examine the relationship between LULC, LST, and other vital spectral indices such as NDVI, NDWI, and NDBI for both the summer and winter seasons. Overall accuracy assessment of 91% in 2000, 89% in 2010 and 92% in 2020, with Kappa coefficients more than 85% for LULC. The results indicated a considerable decrease in agricultural land (40.91 %), Forest land (51.60 %) and an increase in built-up area (64.39 %) from 2000 to 2020, respectively. Maximum LST increases from 34.29°C in 2000 to 41.51°C in 2020 and 35.06°C in 2000 to 41.26 in 2020 during summer and winter seasons respectively and with substantial LST differences seen among different LULC classes. The predicted outcomes for 2030 and 2040 show considerable losses of agricultural land, forest land by 4.69 % and 38.95 %, respectively, as well as increases in built-up areas by 16.96 %. The predicted seasonal LST revealed that in 2030 and 2040, more than 70% and 80% of the summer and 22% and 13% of the winter seasons will likely have LSTs in the 32-34 °C range. The study shows that LST with NDVI and NDWI are negative correlation and on the other hand, LST with NDBI are positive correlation. This study can help urban planners, environmental engineers and agricultural officers design successful policy efforts to protect agricultural and forest areas for sustainable development.

1. Introduction

Urbanization has a challenge for many countries. Developed nations have less daunting issues than underdeveloped countries, because of fast and unplanned urbanization . Population expansion and industrialization have also worked as a stimulant in the process of urban in-migration. In 1950, 30 percent of the world's population lived in cities , a rate that increased to 54 percent in 2014 and is predicted to rise to 66 percent by 2050. India's urban population was 217 million in 1991, but it increased to 377 million in 2011. According to Census of India 2011 statistics, India's urban population has grown considerably during the previous two decades. According to a United Nations assessment, India's urban population would grow by approximately 500 million during 2010 and 2050 (United Nations 2012). Tamil Nadu has experienced significant urbanization, for the last two decades. Chennai, India's fourth biggest metropolis, is the greatest accomplishment of Tamil Nadu's urbanization. According to 2011 Census statistics, more individuals in Tamil Nadu have relocated from rural to urban regions in the past ten years than in other states.

The use of Remote Sensing (RS) and Geographic Information Systems (GIS) has made it possible to estimate LULC variations and LST distribution in a given region. Several studies have used multi-temporal Landsat imagery to characterize the LULC change and its effects on LST. Several studies used Logistic Regression

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(LR), Cellular Automata (CA), Markov Chain (MC), and Artificial Neural Network (ANN) to predict LULC and LST changes. Each approach has its own set of advantages and disadvantages. The CA-ANN model, which predicts the future LULC and LST change matrix by integrating the previous pattern of change, is extensively used for prospective LULC and LST simulation. CA-ANN, in connection with related LULC indices like as NDVI, NDWI, and NDBI, can accurately predict LST. As a result, CA-ANN is often considered as the most accurate approach for forecasting the LULC and LST consequences.

The study makes use the advantage of the geospatial technologies and the historical record of Landsat Satellite imagery data to analyse land use change in CMA. The objectives of this study to (i) Map and examine the different changes in CMA LULC pattern during the past 20 years (i.e., 2000–2020); (ii) analyse the distribution of LST, NDVI, NDWI, and NDBI in the city; (iii) To determine the relationship between LST and other spatial indices (i.e., NDVI, NDWI, and NDBI); (iv) In addition, CA-ANN algorithms were employed in this work to predict future LULC and LST scenarios for CMA in 2030 and 2040.

2. Study area and datasets

2.1 Study area

The Chennai Metropolitan Area (CMA), seen in Figure 1, is India's fourth largest metropolitan region. It is Asia's 22nd most populous city and the world's 40th most densely populated city. CMA covers an area of 1189 km² and includes Chennai district, parts of Kancheepuram and Tiruvallur districts, with Chennai district covering an area of 176 km2. Chennai is situated on the southeastern coast of India, at 13.04° N 80.17° E, in the northeastern side of Tamil Nadu. According to the Chennai Metropolitan Development Authority (CMDA), the CMA encompasses 176 km2 of Chennai district, 637 km2 of Thiruvallur district (including Ambattur, Tiruvallur, Ponneri, and Ponnamallee taluks), and 376 km2 of Kancheepuram district (including Tambaram. Sriperumbudur, and Chengalpattu taluks). It is located on the eastern sea side fields, a coastal plain. The city has a typical elevation of 6 m (20 ft), with the highest point being 60 m (200 ft).

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Figure.1 Location map of the study area

2.2 Datasets

The study focuses on multi-temporal satellite images Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) acquired from the US Geological Survey (USGS) website (https://earthexplorer.usgs.gov) where path is 141 and row is 51 for the years 2000, 2010, and 2020. The images all have a spatial resolution of 30m. Using the WGS-84 datum, the Landsat images (Level 1 Terrain Correction product) was projected to UTM zone 44 North projection. Satellite images of the summer and winter seasons from the time series 2000, 2010, and 2020 were downloaded at ten-year intervals to assess the variance in LULC and LST in the study area. Landsat images from March to May were collected in order to predict the summer season LST of the study area for the mentioned years. Landsat images from January to February were used for winter season LST.

3.Methodology

3.1 Method for calculating NDVI, NDWI, NDBI and LST

The NDVI value ranges from -1 (negative) to +1 (positive). Values ranging from 0 to +1 (positive) indicate vegetation cover, whereas values near to 1 indicate dense vegetation.

$$NDVI = \frac{NIR_{Band} - RED_{Band}}{NIR_{Band} + RED_{Band}}$$
(1)

The NDWI value ranges from -1 (negative) to +1 (positive). Water bodies are represented by values ranging from 0 to +1 (positive), with values near to 1 indicating a high density of water bodies

$$NDWI = \frac{Green_{Band} - NIR_{Band}}{Green_{Band} + NIR_{Band}}$$
(2)

The NDBI ranges from -1 to +1, with negative values indicating water bodies and vegetation, positive values indicating built-up areas, and low positive values indicating barren soil types.

$$NDBI = \frac{MIR_{Band} - NIR_{Band}}{MIR_{Band} + NIR_{Band}}$$
(3)

LST was estimated using the Digital Number (DN) of a thermal band. Thermal band 6 was taken into account for Landsat 5 TM and Landsat 7 EMT+. LST was calculated for Landsat 8 OLI utilizing bands 10 during the summer and winter seasons. The DNs in the downloaded data were transformed to LST. However, the extraction of LST from Landsat TM, EMT+, and OLI is slightly different in terms of calculating spectral radiance.

3.2 LULC Classification

In this study, LULC types were classified into five categories in the years of 2000, 2010 and 2020 respectively (Water bodies, Urban/Built-up land, Open land, Forest land and Agricultural land. To categorize

LULC for the various study periods, we used Maximum Likelihood (ML) and the supervised classification technique. The categorized maps were validated using random sample ground truth data from 100 Google Earth images. For accuracy assessment, user accuracy, producer accuracy, the overall accuracy, and kappa statistics were computed, and one of the best quantitative techniques for image classification accuracy was used.



Figure 2. Methodological flow chart of the study

3.4 LULC and LST predictions for 2030 and 2040

For this study, the MOLUSCE plugin tool in QGIS software was used to predict the 2030 and 2040 LULC and LST distributions, which is considered as one of the best prediction models. This study's input module includes dependent variables such as LULC maps and LST distribution and independent variables such as Distance from Road, Railways, Rivers, Slope, Aspect and elevation (for LULC prediction) and NDBI, NDVI, and NDWI (for LST prediction). The validation step provided several kappa statistics such as percent of correctness, kappa histogram, standard kappa, and kappa location for the accuracy validation of the predicted LULC map.

4. Results and discussions

4.1 Variation in past LULC patterns and Accuracy Assessments

The LULC classification maps for the years 2000, 2010, and 2020 are shown in Figure 4. The ML classifier showed good overall accuracies for Chennai, with evaluations of 91 percent (2000), 89 percent (2010) and 92 percent (2020), respectively, and Kappa accuracies of 88% (2000), 86% (2010), and 90% (2020). The accuracy study showed that the verification rates for all years were more than 85%, suggesting an excellent accuracy match.



Figure 3. Factors contributing to LULC change and urban growth a) DEM, b) Slope, c) Aspect, d) Dist from major roads e) Dist from major railways f) Dist from rivers



Figure. 4 Land use land cover map of a)2000, b)2010, c)2020

4.2 Changing pattern of seasonal LST

The summer season LST distribution for the years of 2000,2010, and 2020 are shown in Figure 5. In 2000, 0.5% (6.28 km) of the study area was experienced temperatures between 30-<32°C. Also, 1% (1 km^2) of the study area came under the range of 32- <34 °C in 2010 and was increased to 41.61 % (511.23 km^2) in 2020.



Figure 5. Spatial distribution of summer LST a)2000, b)2010, c)2020

For the study area, zone-wise winter LST variation is shown in Figure 6. In 2000, 2010, and 2020, around 7.47% (91.77km²), 17.63% (216.58 km²) and 17.43% (214.09 km²) of the area in study region were recorded temperatures from 28-<30°C.

4.3 Impact of NDVI, NDWI and NDBI on LST

According to the literature, a greater degree of LST is related with a lower NDVI in this study. The lowest NDVI is observed in built-up areas that dominate the residential areas in chennai. NDVI is found to be a negative regulator of LST.



Figure 6. Spatial distribution of winter LST a)2000, b)2010, c)2020



Figure 7. Spatial distribution of Summer NDVI a)2000, b)2010, c)2020



Figure 8. Spatial distribution of winter NDVI a)2000, b)2010, c)2020



Figure 9. Spatial distribution of summer NDWI a)2000, b)2010, c)2020



Figure 10. Spatial distribution of Winter NDWI a)2000, b)2010, c)2020



Figure 11. Spatial distribution of summer NDBI a)2000, b)2010, c)2020

Water has a lower temperature than other patterns of land usage. In lower NDWI, the LST was increasing.NDWI is found to be a negative regulator of LST.

The NDBI value steadily increased, resulting in a larger LST value. It demonstrates a positive relationship between LST and built-up regions. According to the results, lower LST values associated with lower NDBI, whereas higher LST values correlated to densely built-up regions.



Figure 12. Spatial distribution of Winter NDBI a)2000, b)2010, c)2020

4.4 Predicted LULC for 2030 and 2040

According to the predicted LULC map, if the current trend of expanding built-up area continuing without any planned steps, the increasing urban areas will be 53.73 percent in 2030 and 62.84 percent in 2040, with bare land and forest land being displaced by built-up areas. Forest land and agricultural land were also reduced by 12.71 percent in 2030 and 7.76 percent in 2040,

compared to 13.19 percent in 2020. The predicted LULC scenario of 2040 would confront a 121.58 percent rise in built-up areas, followed by a significant decline in open land, forest land, and agricultural land by 35.19 percent, 71.52 percent, and 44.19 percent, respectively, compared to the initial year 2000.

Reduced forest cover and increasing urbanization may have an impact on the ecosystem services, urban health, and thermal features of a city. If the unplanned urban growth trend continues, the effects of UHI will be exacerbated, leading to an increase in environmental, economic, and medical issues in the study region. Appropriate land-use planning, water-body preservation, and an increase in urban greeneries will all help to make the CMA more ecologically sustainable by minimizing the consequences of UHI.



Figure 13. LULC prediction for the year a) 2030 b) 2040

4.7 Predicted Seasonal LST for 2030 and 2040

As a result, increased LST will have a direct influence on air temperature. In the summer of 2030, around 69.74 percent of the study area would be in the high temperature zone (32 - 34 °C), while just 0.01 percent will be in the low temperature zone (26 - 28 °C). For winter LST, the years 2029 and 2039, respectively, only 21.79 percent and 13.47 percent of the study area would likely be in the high-temperature zone (32-34°C), whereas 0.03 percent and 2.92 percent will be in the 36-28 °C. Because the forecast LST was calculated using the trends of past years' LST patterns (2000-2020), the forecast findings also indicated a substantial probable increase in the LST value for the years 2030 and 2040.



Figure 14. Summer LST prediction for the year a) 2030 and b) 2040



Figure 15. Winter LST prediction for the year a) 2030 and b)2040

5.Conclusion

The study's aim is to assess changes in LULC and LST in the CMA from 2000 to 2020. Finally, this analysis predicted the LULC and LST for the years 2030 and 2040 using CA-ANN model. The investigation indicated that the study region has seen enormous agricultural land loss, with more to emerge in the future years. This study also looked at the effects of land cover change, temperature rise, and climate change in the study area. Finally, this study suggested a sustainable land use management plan for the Chennai Metropolitan Area based on expert viewpoints and taking into account the implications of unplanned infrastructure expansion, loss of green cover, and climate change

The study's findings will be useful to Chennai City authorities, government officials, policymakers, and urban planners, who will be able to use the study's findings for future planning and decision making. City officials can also develop rules, restrictions, and initiatives to help minimize LST in the city. Furthermore, incorporating the study's findings will make Chennai more ecologically and environmentally sound, inclusive, and sustainable. Future study may concentrate on the effects of LST change as seen by city inhabitants. Furthermore, human-environment interactions must be explored in order to have a better understanding of the causes and effects of LST change. Other Tamil Nadu cities' urban expansion, changes in LULC, and spread of LST should be evaluated and simulated to determine that they develop in a sustainable manner. The research concluded by suggesting a variety of solutions for mitigating the negative impact of LULC changes through sustainable land-use practices.

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