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Land use/land cover changes and their impact on land surface temperature using remote sensing technique in Chapai Nawabganj, Bangladesh

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Abstract

Rapid urbanization contributed to changes in land use/land cover (LULC) and had a considerable influence on land surface temperature (LST). Rapid urban growth has greatly changed LULC, which impacts ecosystems, and regional and local weather conditions. Urban LST has risen greatly as a consequence of poor planning and uncontrolled handling of LULC shifts. Remote-sensing is being found to be efficient for a quick study of urban growth and figuring out how the growth affects LST. With the help of multi-temporal and multi-spectral Landsat 8 OLI, this study investigates the effects of LULC variations on LST for 2015 and 2020 in Chapai Nawabganj, Bangladesh. On top of that, cellular automata-based artificial neural network (CA-ANN) model was employed in Chapai Nawabganj to predict LULC and LST for the years 2025 and 2030. According to forecasts, the built-up area would grow 9% from 2015 to 2020, 5% from 2025 to 2025, and 12% from 2025 to 2030. The highest estimated LST jumped from 22 °C to 24 °C in 2020, 24 °C to 29 °C in 2025, and 29 °C to 34 °C in 2030. The CA-ANN model evaluation showed high accuracy with an overall kappa value of over 0.80. This study will be crucial in ensuring sustainable urban growth and limiting the consequences of rapid urbanization by offering useful suggestions for suitable authorities.

Keywords: *Land use/land cover changes; Land surface temperature; Prediction; Cellular automata; Artificial neural network.*

1 Introduction

Cities in emerging nations experience greater urbanization difficulties than those in developed nations. Urban LST is negatively impacted by the expanding urban population, because LULC is significantly changed (Bahi et al., 2016). LST has a negative impact on vegetation, vegetation can specifically lower the LST in urban areas and lessen urban sensitivity to climate change (Mubeen et al., 2021). To examine changes LULC and LST, RS and GIS approaches are effective and powerful tools (Scarano and Sobrino, 2015). When predicting LULC change, CA-ANN models are frequently used. The hybrid CA-ANN model incorporates artificial neural networks with cellular automata (Saputra and Lee, 2019). CA models are frequently used to simulate future LULC utilizing their historical data. The ANN algorithm is regarded as a competent LST forecaster simply because it considers past shifting patterns and uses the LULC indices to foresee future changes (Ullah et al., 2019).

Lately, Chapai Nawabganj has grown noticeably. So far, this sort of study is missing in Chapai Nawabganj. This study will offer useful insights that may be used to lessen the consequences of climate change in this region. This study explores the historical change of LULC and its influence on LST, changes of LST under different LULC classes for 2015 and 2020. MOLUSCE is a free QGIS plugin that analyzes and forecasts land cover shifts. It was utilized to simulate the LULC and LST situation for 2025 and 2030 using CA-ANN model.

2 Study Area

Northwest Bangladesh is home to the Chapai Nawabganj district, which is located between latitudes 24°22' and 24°56'N and longitudes 8°20' to 8°23'E. 5 Upazilas make up the district, which has a total area of 1684.87 km^2 . The weather there is tropically dry and humid. It is surrounded on the north, south, and west by the Indian state of West Bengal. East of it are the districts of Rajshahi and Naogaon. Figure 1 illustrates the study area.

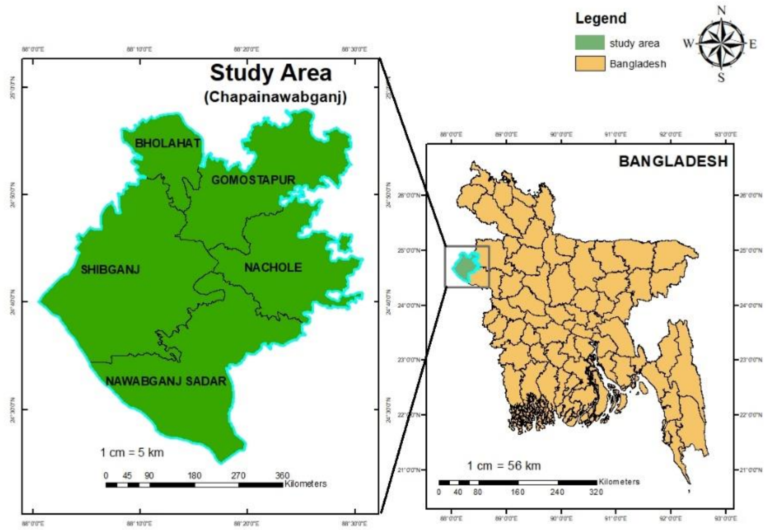

Figure 1. Map of the study area

3 Data and Methodology

3.1 Data Acquisition Information

The study used Landsat 8 Operational Land Imager (OLI) satellite images for the years 2015 and 2020 that were downloaded from the US Geological Survey Earth Exlplorer website (https://earthexplorer.usgs.gov). WGS-84 datum was used to project the Landsat images to UTM zone 45 North projection. Table 1 shows the specification of images used and date of attainment.

Table 1. Downloaded Landsat image information

Years	Date of acquisition	Sensor ID	Cloud cover
2015	October 16, 2015	OLI TIRS	Less than 5%
2020	October 23, 2020		Less than 5%

3.2 LULC Classification

Figure 2 represents methodology used to estimate LULC and LST in flow chart. The LULC was divided into four categories: bare land, built-up areas, water bodies, and vegetation using the Maximum Likelihood Classification (MLC) algorithm in ArcGIS 10.8 (Kafy et al., 2020).

3.3 Accuracy Assessment

The producer accuracy, user accuracy, and overall accuracy were calculated as following (Hussain et al., 2021):

$$\text{Producer, User and Overall Accuracy}=\frac{\text{number of sampling classes classified correctly}}{\text{number of reference sampling classes}} \tag{1}$$

Kappa (K) values are used to assess the classification accuracy, it is expressed as follows (Safder and Babar, 2019):

$$K=\frac{\text{Overall Accuracy- Chance Assessment}}{\text{1- Chance Assessment}} \tag{2}$$

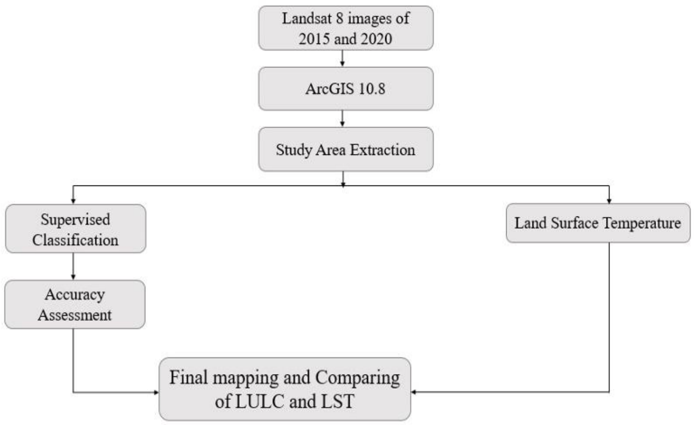

Figure 2. Estimation of LULC and LST

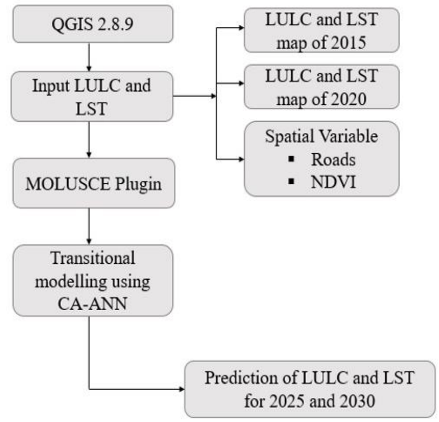

Figure 3. Prediction of LULC and LST

3.4 Land Surface Temperature

LST was calculated using six stage process (Ashwini and Sil, 2022). The following equation is used to calculate LST in degree Celsius:

$$T = \frac{BT}{(1+\left(\lambda\frac{BT}{\rho}\right)\ln(\varepsilon))} \quad (3)$$

Where λ is the wavelength of emitted radiance, BT is brightness temperature and where ρ is calculated using the following equation:

$$\rho = h\frac{c}{\sigma} = 1.438 \times 10^{-2} \text{ mK} \quad (4)$$

Where, σ is the Boltzmann constant (1.38×10^{-23} J/K), h is Planck's constant (6.626×10^{-34} Js), and c is the velocity of light (2.998×10^{8} m/s).

3.5 LULC and LST Prediction

Figure 3 represents methodology used to predict the future LULC and LST. The LULC and LST distribution for 2025 and 2030 were predicted using the MOLUSCE plugin tool in the QGIS program for this study, which is regarded as one of the finest prediction models (Das et al., 2021). The plugin is made up of a number of different parts, including an input module, a study of the changing trend, modeling techniques, prediction, and validation (Kafy et al., 2021).

4 Result and discussion

4.1 Variation of Past Patterns of LULC

Figure 4 and Table 2 shows the changes in LULC classes occurred during the study period. From 2015 to 2020, there was a sharp increase in built-up areas (8.81%) and a marked decline in vegetation (-4.89%) and water bodies (-2.93%). The LULC pattern showed a moderate decline in the amount of barren land (-.99%). Table 3 provides more specific information on accuracy assessment.

4.2 Forecasting of future LULC scenarios

Figure 5 and Table 2 shows further decrease of vegetation cover (-4.65%) and rapid increase of built-up area (13%) from 2015 to 2020. Significant amount of water body (-2.52%) and bare land (-5.83%) have declined during 2015 to 2020. The changes in different LULC classes has also seen in 2020 to 2025. A huge decline in vegetation (-17.35%) and sharp increase in bare land (18.36%) was observed. Further it also demonstrate the increase in built-up area (3.25%) and simultaneous decrease in water body (-4.26%). Figure 9 shows a clear view that how different land cover changing over time from 2015 to 2030. Competitive analysis between various land use classification (vegetation, bare land, built-up area and water body) change and precise visual description has been presented in this radar diagram.

Table 2. Area change in different LULC classes

Year	**2015**		**2020**		**2015-2020**	**2025**		**2020-2025**	**2030**		**2025-2030**
LULC classes	**Area**		**Area**		**Change (%)**	**Area**		**Change (%)**	**Area**		**Change (%)**
	Km^2	**%**	**Km^2**	**%**		**Km^2**	**%**		**Km^2**	**%**	
Vegetation	749.26	44.47	666.87	39.58	-4.89	374.55	22.23	-17.35	296.20	17.58	-4.65
Built-up area	345.73	20.52	494.17	29.33	8.81	548.94	32.58	3.25	767.96	45.58	13
Bare land	373.03	22.14	356.35	21.15	-.99	665.69	39.51	18.36	567.46	33.68	-5.83
Water body	216.84	12.87	167.47	9.94	-2.93	95.70	5.68	-4.26	53.24	3.16	-2.52

Table 3. Accuracy Assessment

Year	**User Accuracy (%)**				**Producer Accuracy (%)**				**Classifica-tion Accuracy**	**Kappa statistics**
	Veget-ation	**Built-up area**	**Bare land**	**Water body**	**Veget-ation**	**Built-up area**	**Bare land**	**Water body**		
2015	92.5	80	82.5	100	85.72	100	83.33	100	88.83	0.87
2020	100	80	82.5	100	91.67	100	83.33	100	89.33	0.88

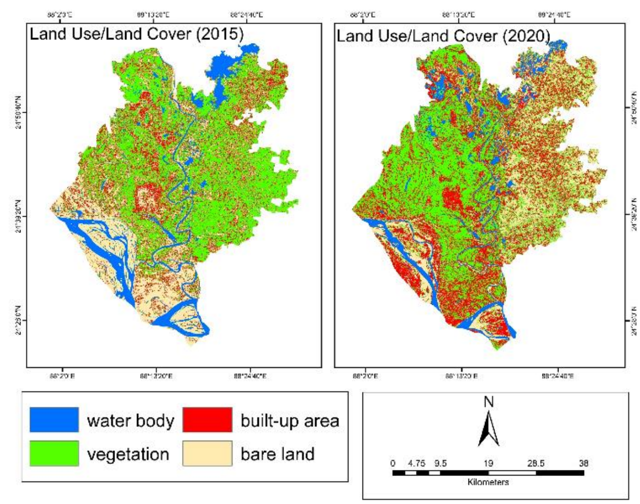

Figure 4. LULC distribution for 2015 and 2020

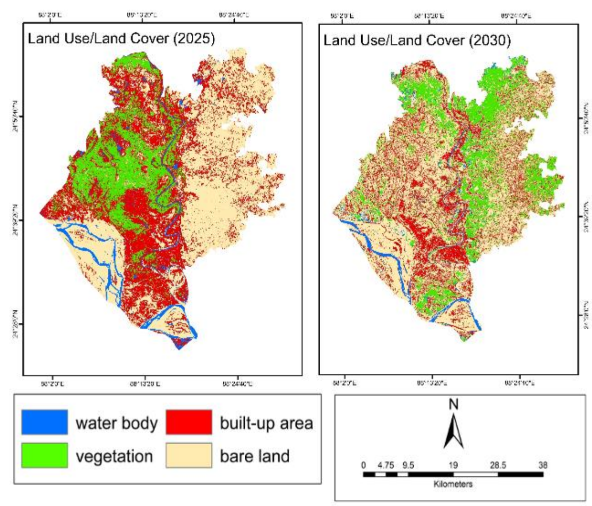

Figure 5. LULC distribution for 2025 and 2030

4.3 Variation of Past Patterns of LST

Figure 6 and Table 4 shows the areal distribution and spatial pattern of LST in two periods, for instance, 2015 and 2020. LST was typically range between 11-22 °C in 2015 and 15-24 °C in 2020. Out of total area, 46.36% area represented temperature from 15-16 ºC in 2015. In 2020 temperature grew, 54.07% area faced 17-18 ºC. The LST was raised as a result of the increased build-up area in the region between 2015 and 2020.

4.4 Forecasting of future LST scenarios

Table 5 and Figure 7 shows simulated LST situations for 2020 and 2030, using historical LST data. The simulated scenario showed that places with greater temperatures will probably occur in the south-western region. According to the projected findings, LST has been rising during years 2025 and 2030, with built-up areas having a dominant role in increased LST. Table 6 shows the acceptance of the forecasted outcomes. Figure 8 illustrates the projected mean LST for each LULC classes.

Table 4. Distribution of historical LST

Ranges of LST in °C	Area (2015)		Area (2020)	
	km^2	%	km^2	%
11-12	0.83	0.05	-	-
13-14	216.39	12.84	-	-
15-16	780.70	46.36	59.98	3.56
17-18	527.76	31.32	910.97	54.07
19-20	158.92	9.41	613.26	36.39
21-22	0.27	0.02	96.65	5.84
23-24	-	-	4.01	0.24

Table 5. Forecasted LST for 2025 and 2030

Ranges of LST in °C	Area (2025)		Ranges of LST in °C	Area (2030)	
	km^2	%		km^2	%
18-19	0.83	0.05	21-22	158.68	9.69
20-21	216.39	12.84	23-24	755.01	44.81
22-23	780.70	46.36	25-26	596.77	34.74
24-25	527.76	31.32	27-28	80.26	4.77
26-27	158.92	9.41	29-30	31.18	1.85
28-29	0.27	0.02	31-32	26.46	1.57
			33-34	36.51	2.57

Table 6. Validation of forecasted LST maps using CA-ANN model

Predicted year	QGIS-MOLUSCE Plugin Module Kappa Parameters					
	K-location	K-no	K-location Strata	K-standard	%-Correctness	Overall Kappa Value
LULC 2025	0.90	0.88	0.89	0.87	87.45	0.83
LULC 2030	0.89	0.87	0.90	0.88	85.75	0.81
LST 2025	0.88	0.88	0.91	0.86	88.77	0.84
LST 2030	0.86	0.89	0.91	0.87	83.34	0.80

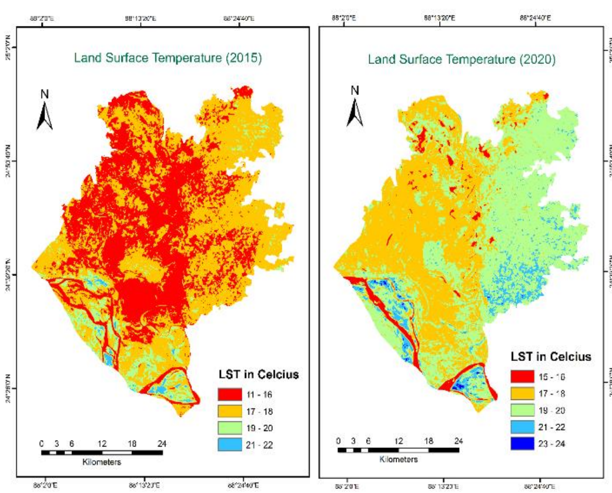

Figure 6. Distribution of LST for 2015 and 2020

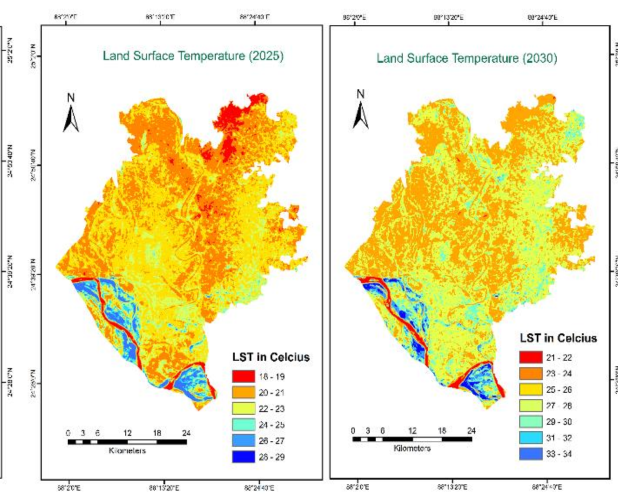

Figure 7. Distribution of LST for 2025 and 2030

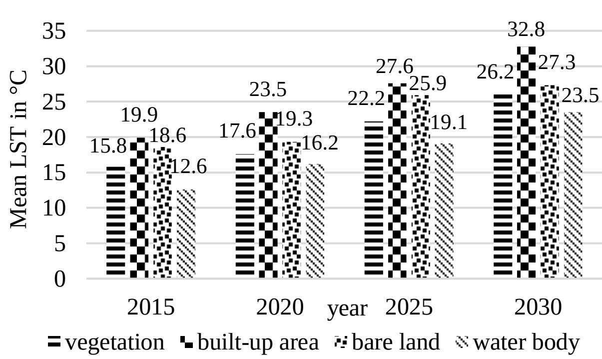

Figure 8. LST distribution for different LULC classes

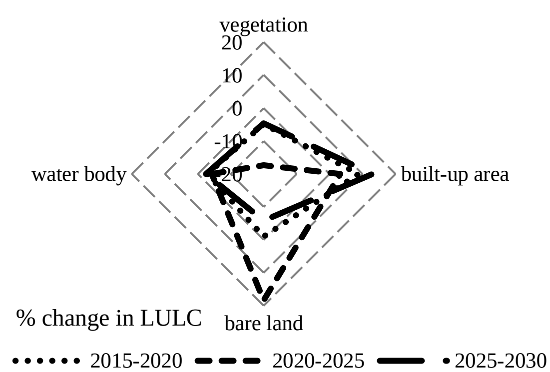

Figure 9. Radar chart of changes in LULC

5 Conclusion

The primary goal of this study is to evaluate and forecast changes in land usage and their effects on alterations in land surface temperature in Chapai Nawabganj. The investigation showed that the study area has an increase in temperature with the growth in built-up area and a loss of vegetation in every coming years. The built-up area has significantly increased, with net growth of 9%, 5%, and 12% through 2015 to 2020, 2025 and 2030, correspondingly. Water bodies as well as vegetation were steadily disappearing in the region. The LST did not crossed 25 °C till 2020. The simulated LULC and LST shifts in 2025 and 2030 which demonstrates alarming outcomes. But maximum LST reached 29 °C and 34 °C, for 2025 and 2030 respectively. For the examined years, maximum temperature was found in built-up areas, while the lowest was found in water bodies.

Taking these findings into account, Chapai Nawabganj will become ecologically sustainable and better prepared to manage the potential effects of changes in the climate. The agricultural productivity and food security will grow by incorporating those analysis into development planning. Authorities along with urban planners could regard unplanned and haphazard growth in and out of the region, as well as the formation of rising LST, as a major problem of this region based on the findings of the study. This information will also help urban planners build inclusive policies with more insight and make it more sustainable in the long run. For a greater grasp on the reasons and effects of urban expansion, LULC alteration, and LST shift, future study may concentrate on interactions between humans and the environment.

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