

Land Use and Land Cover Dynamics in Dinajpur District: Spatio-Temporal Trends and Future Scenario Using Google Earth Engine and CA–Markov Modeling

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Abstract- Investigation on the detection and prediction of changes in land use and land cover (LULC) is essential for reinforcing sustainable management and planning. As a result, the purpose of this research was to discover LULC changes in the Dinajpur area of Bangladesh between 2000 and 2020, as well as anticipate future changes for 2040. Landsat-5, 7, 8, and 9 pictures, as well as vegetation indices and topographic parameters, were used to classify LULCs in 2000, 2005, 2010, and 2020. Classification was performed using the random forest (RF) machine learning method, which is embedded into the cloud-based platform Google Earth Engine (GEE). The classification accuracy evaluation found excellent agreement between the classified maps and the validation dataset, with kappa coefficients of 0.904, 0.919, 0.924, and 0.901 for the LULC maps of 2000, 2005, 2010, and 2020, respectively. The Spatio-Temporal Trends study shows that from 2000 to 2020, built-up land grew by 82.8%, barren land grew by 41.1%, and vegetation and agriculture shrank by 74.1% and 15.1%, respectively. The LULC state in 2040 was simulated using Cellular Automata-Markov. CA-Markov forecasts indicate that agricultural land would decline by 18%, while built-up and barren areas will rise by 27% and 22.6%, respectively. Furthermore, declining forest cover raised concerns about long-term ecological balance. The recent developments in Dinajpur highlight the need for a unified land strategy that balances urban growth and environmental protection.

Keywords- LULC, Dinajpur, GEE, CA–Markov, Spatio-temporal Change.

1. Introduction

A major worldwide environmental issue that has an impact on sustainability over the long run is LULC change. Significant changes in LULC patterns have resulted from increased urban aggregation brought on by rapid population growth and economic development [1]. Neglecting other LULC categories during urban growth has had a negative

influence on the environment, especially in poorer nations [2]. For sustainable land use planning, remote sensing and sophisticated modelling approaches are essential for tracking and organizing LULC changes [3]. In the past thirty years, several techniques for detecting changes using data from remote sensors have been developed. Rogan and Mietkiewicz [4] characterized digital change detection as 'the technique of identifying and delineating changes in land use/land cover

attributes via co-registered multi-temporal remote sensing data.' Numerous strategies exist for evaluating change, including both statistical and rule-based methods. Reviews of these methodologies and their applications are available in Tassi and Vizzari [5], Nasiri et al. [6], and Rahman et al. [7]. Land use change is modeled and predicted using various methods and strategies [8]. A stochastic modeling technique that has been widely utilized to investigate the dynamics of land use change at various scales is Markov chain analysis [9]. It is an easy way to represent changes in land usage, particularly on a large scale. Unlike previous ways that only forecast a one-way transition from one group to another, it can predict all multigroup land-use changes among all accessible land-use categories [10]. Markov chain analysis treats the landscape as an arrangement of discrete states (i.e., land cover classes) with the underlying assumption, called the Markov property, that the future state of a given location is dependent only on its current state, and not on its past states. The main result of a Markov chain analysis is the transition probability matrix (TPM), which is an $n \times n$ matrix where the element P_{ij} represents the probability that a pixel in class i will change to class j within a given time period. Multiplying this matrix by the "state distribution" vector at time t allows the predicted distribution of land cover classes at any future time step to be calculated. This mathematical simplicity, along with the straightforward method for calculating TPMs from any two classified historical maps, also makes the Markov chain analysis a widely used and replicable approach for modelling LULC changes [9]. But a simple Markov chain is not spatially explicit, since it deals with proportions of area and does not consider the spatial pattern of pixels. To address this limitation, Markov chain analysis is often combined with Cellular Automata (CA), which uses transition rules to account for spatial effects of land cover change. Thus, the CA-Markov hybrid model integrates the statistical rigour of stochastic transition probabilities with the spatial realism of cellular automata, and is the most common hybrid model for spatially explicit LULC change prediction [9, 10].

Previous research on LULC change in Bangladesh has examined historical trends and future projections across different regions, emphasizing a range of factors and outcomes. Hassan [11] utilized Landsat imagery to investigate the alterations in land cover and land use across five Bangladeshi cities (Rajshahi, Rangpur, Sylhet, Khulna, and Barisal) from 1973 to 2014. The five cities' built-up area grew from 2,356 hectares in 1973 to 13,435 hectares in 2014, an increase of 468%. This expansion came at a cost to natural cover, with agricultural fields losing 61.91% and vegetation losing 27.77%. Hoque et al. [12] studied changes in LULC and related ecosystem service values in coastal Bangladesh from 1999 to 2019. In general, there was a big drop in agricultural and barren land and a rise in built-up areas, aquatic bodies, saltpan/aquaculture, and mangrove forests. While biodiversity and water management experienced a slight enhancement, the primary objective of this decline was the production of food and raw materials. Alam and Ahamed [13] looked at how LULC changed along Bangladesh's main river systems from 1995 to 2021. The LULC study found that all eight divisions saw a significant 11.68% drop in the amount of land used for farming. But both urban areas (+2.55%) and bodies of water

(+3.65%) grew. Bhattacharjee et al. [14] say that the Lakshmibaur-Nalair Haor wetland got a lot worse between 1989 and 2019. This is shown by an 8.34% drop in plant life and a 37.54% loss of deep water bodies.

The majority of this loss was transformed into farmland (+29.39%) and shallow water (+45.44%), with bare soil also increasing by 28%. The main causes of these significant LULC changes are population pressure and human activities, which allowed agriculture to grow as deep water gave way to shallow water throughout the research period. Abdullah et al. [15] used a new method to map LULC changes in coastal Bangladesh between 1990 and 2017 by using XGBoost feature selection and RF classification on Landsat images. The study found that agricultural land (+5.44%), built-up areas (+4.91%), and river areas (+4.52%) all gained land, while vegetation cover as a whole lost land (-8.26%). But since 2000, government tree-planting programs have led to more plants. This study offers significant insights and a robust methodology for future decisions regarding coastal environmental management and policy. Rahman et al. [16] looked at the LULC changes in Assasuni Upazila, Satkhira District, in the southwest coastal area of Bangladesh, from 1989 to 2015. They found a big change: bare lands went down by 21% and shrimp farms went up by 25.9%. The CA-ANN model says that this trend will keep going until 2028, when more empty land will be turned into shrimp farms. Surveys have shown that this change is a big reason why people are moving to the area. Dewan and Yamaguchi [17] looked at LULC trends in the Dhaka Metropolitan Area from 1960 to 2005 using maps and satellite data. They discovered that built-up areas expanded from 11% to 344% overall, indicating substantial urban growth. Over 45 years, built-up areas grew by about 15,924 hectares, mostly at the expense of natural and agricultural land. Agricultural land shrank by 7,614 hectares, and wetlands and lowlands shrank by 6,385 hectares.

Significant changes in land use have been seen in Bangladesh's northern region of Dinajpur. Satellite imagery is essential for understanding and predicting such shifts in LULC mapping. The purpose of this study is to forecast future LULC change for 2040 and evaluate the spatiotemporal dynamics of LULC in the Dinajpur area from 2010 to 2020. For this study, USGS satellite images were collected, including Landsat-5 (2000), Landsat-7 (2005 and 2010), and Landsat-8/9 (2020). The supervised machine learning technique RF is used to identify spatiotemporal trends of LULC for the years 2000, 2005, 2010, and 2020 using the cloud computing platform GEE. The confusion matrix, generalized accuracy, and Kappa coefficient were used to evaluate the chosen machine learning algorithm's accuracy. This research uses the CA-Markov model to forecast the expected future LULC by 2040 in order to present a realistic picture of land cover change and urban growth. The initiatives would have important ramifications for assessing urbanization patterns and directing land management strategies via the use of remote sensing and modeling techniques. Given the issue of urban growth and land degradation, the findings will aid in bettering land-use planning and policymaking.

2. Study Area

The Rangpur division, which is situated in the northwest of Bangladesh, includes the study area, Dinajpur district (Figure 1). Geographically, it is located between latitudes 25°10' and 26°04' north and longitudes 88°23' and 89°18' east. With 13 upazilas, the region has a total size of 3437.98 square kilometers. Urbanization, aquatic bodies, and agricultural areas dominate the terrain. When it comes to producing and exporting rice and other basic goods, Dinajpur is one of the largest regions. However, due to the rapid pace of urbanization, industrial accretion, and population growth, the district has been experiencing a notable undermining of its LULC pattern [18].

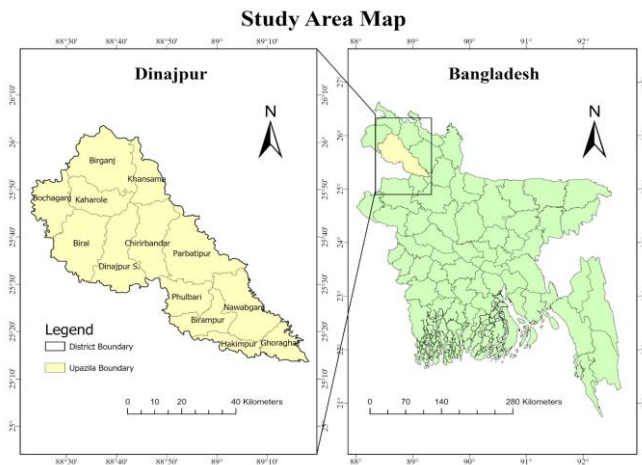


Figure 1. Map of the study region.

3. Methodology

3.1 Data Collection and Preprocessing

Landsat satellite image data from 2000, 2005, 2010, and 2020 were obtained from USGS to fulfill study objectives, as shown in Table 1. GEE, a well-renowned platform, was used to process the gathered image data. GEE and GIS is one of the most widely used powerful platform that used to generate spatial distribution maps from satellite and point data [19-28]. Cloud-free median composites were generated from raw images using a cloud cover threshold of 15%. In particular, we selected all scenes from the entire calendar year with less than 15% cloud cover; pixels affected by cloud and cloud-shadow were then masked using the QA_PIXEL quality band (bits 3 and 4 for cloud and shadow, respectively); finally, the statistical median was calculated across all scenes for each pixel. The result is a single, cloud-free mosaic image in which cloud-contaminated pixels are replaced by the median surface reflectance of cloud-free scenes, producing a representative annual composite image that is not affected by residual clouds and seasonal variations in vegetation. The 30-meter resolution of Landsat was used to identify land cover and its temporal change patterns at a local scale. Atmospheric correction and radiometric recalibration were later performed automatically inside GEE [29].

Table 1. Details of image data

District	Year	Landsat	Date Range	Sensor	Path/Row	GEE Collection ID
Dinajpur	2000	Landsat-5	01 Jan – 31 Dec	TM	138/42	LANDSAT/LT05/C02/T1_L2
	2005	Landsat-7	01 Jan – 31 Dec	ETM+		LANDSAT/LE07/C02/T1_L2
	2010	Landsat-7	01 Jan – 31 Dec	ETM+		LANDSAT/LE07/C02/T1_L2
	2020	Landsat-8/9	01 Jan – 31 Dec	OLI/TIRS		LANDSAT/LC08/C02/T1_L2 / LANDSAT/LC09/C02/T1_L2

3.2 LULC Classification

Multi-temporal LULC maps for the years 2000, 2005, 2010, and 2020 were developed for Dinajpur District using a sequence of Landsat satellite data in GEE. To maintain uniformity across the categorization era, the image for each of these years Landsat 5, 7, 8, and 9 was utilized. To reduce the effects of season and weather, data collections were filtered by acquisition year (January 1–December 31 for each target year) and cloud cover <15%. Each year, median composites were created to create a cloud-free matrix by masking cloud and shadow pixels with the QA_PIXEL picture [30]. The clips of each composite are transported to the administrative boundary of Dinajpur District and analyzed with some significant spectral indices, e.g., Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), Normalized Difference Built-up Index (NDBI), and Soil Adjusted Vegetation Index (SAVI). To improve the separability of classes, topographic features (i.e., elevation and slope) were also derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) and then included in the feature set [31]. Ground truth samples for the five major LULC categories (barren land, vegetated area, built-up area, agriculture, and water body) were manually selected from the image by visual interpretation. In each year of research, a subset of around 150–200 points was selected from the members belonging to each class as a training set. The entire sample population was further divided into a training set (80%) for fitting the RF classifier and a test set (20%) that was held out for the purpose of performance evaluation only. Class-specific sample counts were checked in both subsets using GEE's aggregate_histogram() function and showed a relatively even distribution of samples for all five LULC classes in each of the years. A RF classifier with 200 trees was trained for the findings using 80% of the data and tested for validation using 20% of samples to measure accuracy. The accuracy of classification was checked through the confusion matrix, generalized accuracy, and Kappa coefficient. The ultimate classified images demonstrate the spatiotemporal shift of LULC for the years 2000–2020 on the landscape of Dinajpur district.

3.3 Area Calculation

Each LULC class's total area was calculated using the class maps from 2000, 2005, 2010, and 2020. The total surface area in square meters was calculated using GEE by converting the categorized pictures into binary masks of each LULC type and multiplying the result by the pixel size (30 m × 30 m). Equations 1 and 2 were used to rescale the output pixel areas

gathered across the Area of Interest (AOI) to square kilometers (km²) and % of total area after processing them using the reduceRegion() function. In this case, the reducer parameter defines the reduction operation to be applied to the pixels (in this case a grouped sum (ee.Reducer.sum().group()), which summates pixel areas by class label; the geometry parameter specifies the spatial area over which to perform the reduction (the Dinajpur district boundary); the scale parameter specifies the size of the original pixels in meters (30 m, in this case, to match the Landsat imagery); and the maxPixels parameter specifies the maximum number of pixels to be processed (in this case 1×1013) to avoid memory issues when dealing with large areas.

$$\text{Area (km}^2\text{)} = \frac{\text{Total pixel area (m}^2\text{)}}{1,000,000} \quad (1)$$

$$\text{Percentage (\%)} = \frac{\text{Class area}}{\text{Total AOI area}} \times 100 \quad (2)$$

The total area of each LULC class was then tabulated to assess the proportional distribution and spatio-temporal changes over the study period. The net gain/loss and percentage change were calculated utilizing Equation 3.

$$\text{Percentage change} = \frac{A_t - A_{t-1}}{A_{t-1}} \times 100 \quad (3)$$

where A_t and A_{t-1} denote the area of a particular land cover class at the current and previous time periods, respectively.

3.4 Future LULC Prediction using CA-Markov Model

CA-Markov technique was used to project the future LULC for 2040 in the study area. The CA-Markov model was chosen for its analysis over other models (such as logistic regression, artificial neural network (ANN) or agent-based models) for a number of reasons. First, it only needs two LULC maps and a few driving factors to be input, making it very useful in a data-poor environment. Second, unlike statistical models, it integrates Markov Chain transition probabilities with the spatial neighbourhood rules of Cellular Automata, enabling the capacity to model both the size and spatial pattern of future land cover using historical changes. Third, the CA-Markov model framework is well-tested for Bangladesh and other South Asian agricultural regions [16] and is supported by the TerrSet / Land Change Modeler tool used in this research. The CA-Markov model uses Cellular Automata and Markov Chain analysis to simultaneously predict the quantity and spatial arrangement of future land cover classes, using the observed history of change. We first calculated the transition probability and transition area matrices using a Markov Chain analysis of the classified LULC maps of 2010 and 2020 (Table 2 and Table 3). These matrices show the probability of the conversion of one land cover class into another land cover class over time. The transition probability matrix (TPM) developed from the 2010-2020 classified LULC maps using the Markov Chain analysis in TerrSet is shown in Table 2. The "from" class is in the row and the "to" class in the columns; the row totals equal 1.0,

ensuring the matrix is mathematically correct. The cross diagonal values (self-transitions) show the highest probabilities of retention during 2010-2020 were Agricultural (0.4218) and Barren (0.4694) land. In particular, TPM(Agricultural → Barren) = 0.4300 and TPM(Vegetation → Barren) = 0.4403 suggest the pressures of land conversions from productive land classes to barren land, mirroring the landscape degradation observed in Dinajpur. TPM(Barren → Agricultural) = 0.3624 indicates recovery or seasonal reversal classes of fallow land. These values indicate a rapidly degrading landscape, which the CA-Markov model employs in predicting the 2040 landscape.

Table 2. TPM derived from classified LULC maps of 2010 and 2020 using CA-Markov in TerrSet

From \ To	Water body	Agricultural land	Vegetation area	Built-up area	Barren land
Water body	0.3426	0.1509	0.0414	0.1723	0.2928
Agricultural land	0.0228	0.4218	0.0239	0.1014	0.4300
Vegetation area	0.0563	0.2874	0.0619	0.1540	0.4403
Built-up area	0.0577	0.3160	0.0287	0.2026	0.3950
Barren land	0.0309	0.3624	0.0247	0.1126	0.4694

Table 3. Transition area matrix (cells) corresponding to Table 2, showing the expected number of cells transitioning between classes over the 2010–2020 period

From \ To	Water body	Agricultural land	Vegetation area	Built-up area	Barren land
Water body	191,602	0	0	0	0
Agricultural land	0	1,101,397	0	0	301,694
Vegetation area	0	0	116,086	0	32,775
Built-up area	0	0	0	458,361	0
Barren land	0	299,707	0	93,121	1,261,186

To ensure the CA-Markov model is capable of accurate predictions, before projecting for 2040, it was validated through a back-casting approach. The transition probability matrix was developed from the 2000 and 2010 LULC maps and the model was run to project the expected LULC map for 2020. The cell-by-cell comparison was then used to compare this 2020 map with the classified 2020 map. The overall match between the simulated 2020 and the observed 2020 maps was found to be a Kappa of Accuracy of 0.92 and a Kappa of Quantity of 0.95, which means good spatial agreement between the observed and expected spatial patterns. This suggests that the CA-Markov model has captured the major land change processes in Dinajpur and it is possible to trust the model to generate the 2040 map. Further, the selection of the neighborhood effect was developed using the Cellular Automata module, which introduces spatial effects and allows the model to consider actual spatial drifts. The transition factors, such as elevation, slope, aspect, distance to roads and distance to rivers, were developed using GEE for the study area as predictor variables in the transition potential modelling step of the land change modeler program. The transition probabilities of each of the four major transition sub-models were calculated using a Multi-Layer Perceptron neural network, and the models were validated using Receiver Operating Characteristic (ROC) values. The CA-Markov model was then given the current transition potential maps and

Markov transition probability matrices to predict the LULC map for 2040. The simulation adopted the 5 x 5 cell neighborhood rule, and the time step frequency was between 2020 and 2030 and 2030 and 2040 (every two years). The map is a spatial explicit projection of the pattern of LULC in 2040, based on LULC trends between 2010 and 2020. The flowchart of the methodological process is presented in Figure 2.

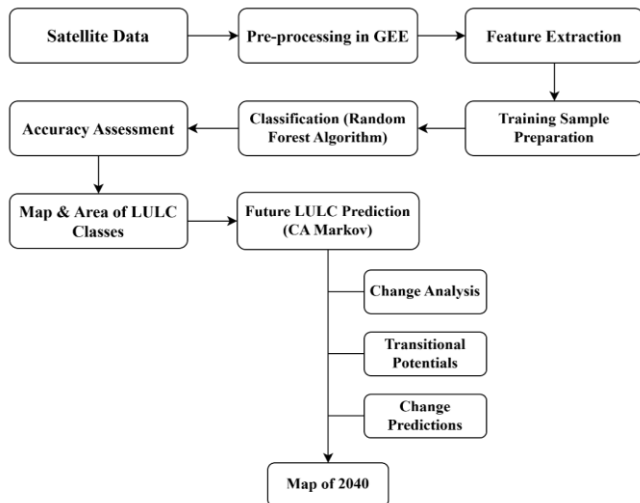
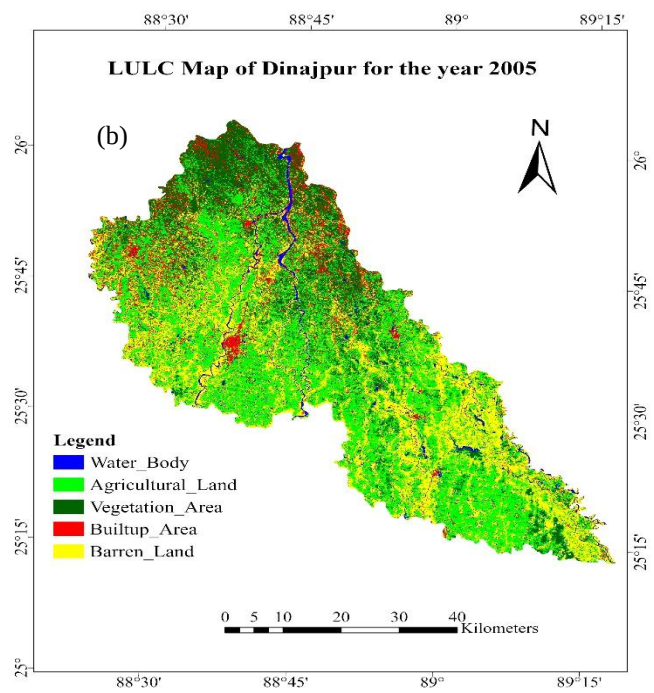
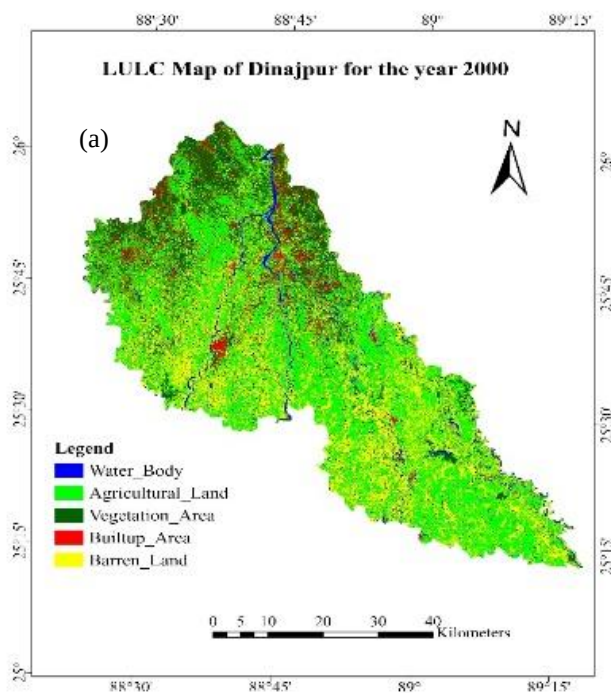


Figure 2. Flowchart of the overall methodology.

4. Results and Discussion

4.1 Accuracy Assessment

Using Google Earth Engin's RF categorization, five primary land cover types—water body, agricultural land, vegetation area, built-up area, and barren land—were identified for the Dinajpur area in the years 2000, 2005, 2010, and 2020. Based on the Kappa coefficient and overall accuracy, the accuracy of the classified image was assessed. The kappa coefficients for the land cover maps of 2000, 2005, 2010, and 2020 were 90.4%, 91.9%, 92.4%, and 90.1%, respectively, while the overall accuracy was 92.5%, 93.6%, 93.9%, and 92.3% (Table 4). Based on a meticulous selection of training data and cloud-free Landsat pictures, the RF classifier effectively caught spatial patterns of land cover types, as seen by the high kappa values. A kappa value of greater than 0.80 is typically defined as "excellent" agreement in classification standards [9], so the LULC maps generated here are likely to be good enough for both change detection and model simulation. The categorized GeoTIFF files were exported from GEE and imported into ArcGIS Pro to produce the final map compositions for enhanced display and cartographic output. Figures 3(a-d) illustrate all land cover categories, including aquatic bodies, agricultural land, vegetated areas, built-up regions, and barren land for the years 2000, 2010, 2015, and 2020.



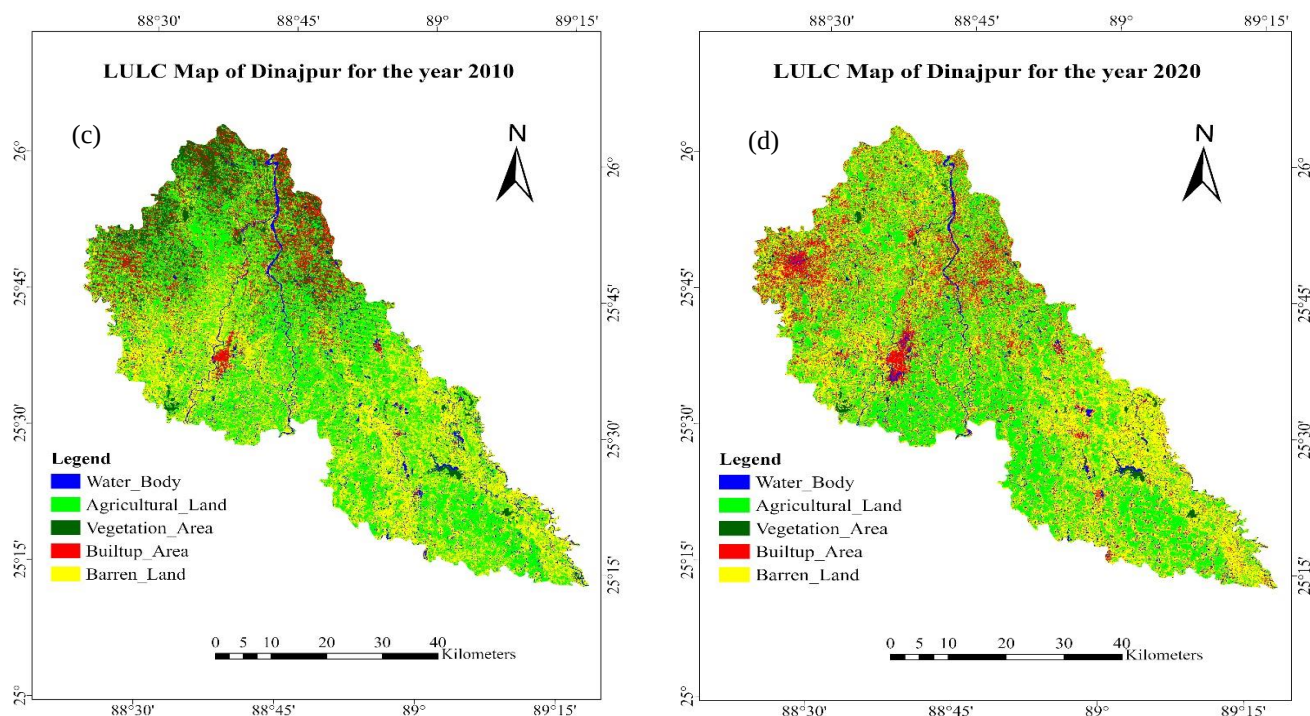


Figure 3. LULC map of Dinajpur district for year (a) 2000, (b) 2015, (c) 2010 and (d) 2020.

Table 4. Accuracy assessment of RF classifier

Year	Overall Accuracy	Kappa Coefficient
2000	0.925	0.904
2005	0.936	0.919
2010	0.939	0.924
2020	0.923	0.901

4.2 Distribution of Samples

Figure 4 shows a comparison of the number of training (80%) and validation (20%) samples used for Land Use and

Land Cover (LULC) classification. The figure illustrates that for each of the years (2000, 2005, 2010 and 2020), the number of samples was kept balanced across various land use categories (water, agriculture, vegetation, built-up, and barren land). The findings show that the number of training samples was much larger than the number of validation samples, which allowed the Random Forest classifier to be properly trained. However, a sufficient number of samples were available for validation.

Moreover, the equal distribution across classes helps avoid classification bias and achieves high overall accuracy and Kappa coefficient observed in this study. The uniform distribution between years also guarantees temporal consistency of classification results.

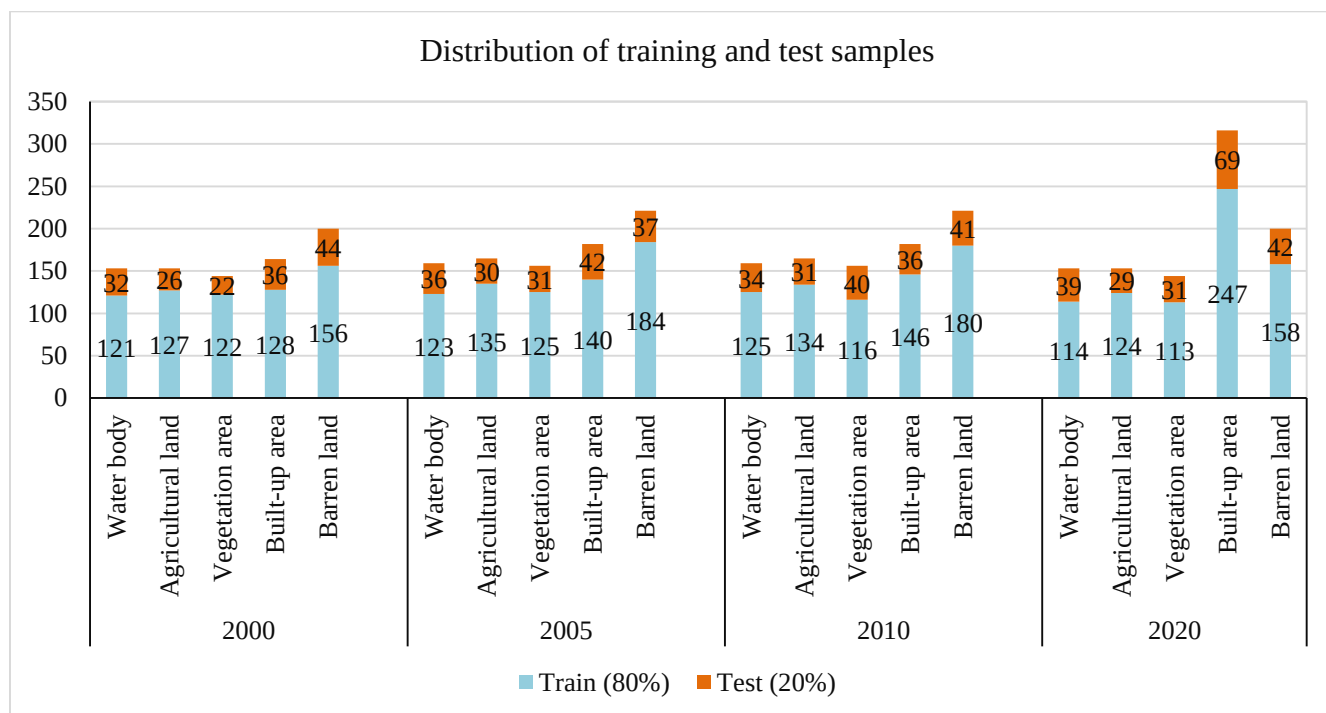


Figure 4. Distribution of training and validation samples across different LULC classes for (2000 - 2020)

4.3 LULC Change Assessment

The classified maps of the study region in Figure 3 depict the temporal fluctuations of the LULC Dinajpur district from 2000 to 2020. The obtained temporal fluctuations of LULC are shown in Tables 5 and 6. All LULC classes saw specific geographic changes, which were connected to urbanization, agricultural intensification, and the loss of natural resources. In the year 2000, agricultural land and vegetation were major classes with areas of 1519.30 km² (43.8%) and 514.21 km² (14.8%), respectively, while the built-up and barren were lesser occupied—224.41 km² (6.5%) and 1030.29 km² (29.7%). Vegetation cover increased to 688.64 km² (19.9%) by 2005, likely as a result of temporally recovering or seasonal dating, whereas agricultural lands decreased to 1,283.99 km²

(37.0%), and built-up area escalated to 304.59 km² (8.8%), indicating urban expansion had begun by this time period. The map of 2010 showed considerable changes, where vegetation reduced dramatically by 311.62 km² (9.0%) and agricultural land increased slightly to 1387.12 km² (40.0%). Sparsely vegetated area increased by 315.94 km² (9.1%) and Bare land by 1267.28 km² (36.5%), indicating the impacts of erosion and depletion of vegetative cover.

Table 5. Changes of LULC area in Dinajpur district for the years 2000, 2005, 2010 and 2020

LULC	Y2000		Y2005		Y2010		Y2020	
	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)
Water Body	169.144	4.876	124.072	3.576	175.396	5.056	172.013	4.958
Agricultural Land	1519.301	43.795	1283.99	37.012	1387.120	39.985	1288.941	37.155
Vegetation Area	514.210	14.823	688.638	19.851	311.620	8.983	132.957	3.833
Built-up Area	224.406	6.469	304.594	8.780	315.939	9.107	410.128	11.822
Barren Land	1030.292	29.699	1056.06	30.442	1267.278	36.530	1453.314	41.893

Urban expansion continued till 2020, with built-up area growing to 410.13 km² (11.8%) and barren land increasing to 1453.31 km² (41.9%). On the other hand, the area of vegetation cover has declined significantly to 132.96 km² (3.8%), and agriculture land was reduced to 1288.94 km² (37.2%). The waterbodies experienced little variation over the

same period, ranging from 169.14 km² in 2000 to 172.01 km² in 2020 (+1.7%). Figure 5, which illustrates the development of built-up and barren areas together with the deterioration of vegetation and agricultural covering, reveals the overall pattern of LULC change between 2000 and 2020. All things considered, these results show how the Dinajpur district's

environmental stability and resource sustainability are being threatened by fast urbanization, deforestation, and unsustainable landscape management dynamics.

These results are broadly comparable to, and in some aspects worse than, other regions of Bangladesh and South Asia. Hassan [11] found that, nationwide, built-up area expanded by 468% between 1973 and 2014 across five Bangladesh cities (Rajshahi, Rangpur, Sylhet, Khulna and Barisal), mostly at the expense of agricultural land and vegetation; the 82.8% built-up increase in Dinajpur over the shorter 2000-2020 period is proportionally in line with this national trend, given that Dinajpur is a secondary district town undergoing rapid transformation. Alam and Ahamed [13] also reported a loss of 11.68% agricultural land across all eight divisions of Bangladesh between 1995 and 2021, which is comparable to the present study's findings of a 15.1% decline in agricultural land in Dinajpur alone, implying that the pace of agricultural land loss in the north-western region is commensurate with, or slightly greater than, the national average. By contrast, Hoque et al. [12] noted an increase in mangrove and aquatic vegetation in coastal Bangladesh, which is not reflected in the inland agricultural zones of Dinajpur, where water bodies were almost unchanged over the period. Comparisons with other regions also provide insights into the Dinajpur trends. In Iraqi Kurdistan, for example, Hamad et al. [9] also observed a decline in vegetation and agricultural land and an increase in built-up areas under CA-Markov projections, with good spatial transitions predicted by the model (similar to the strong back-casting validation, Kappa of Accuracy = 0.92, of the current study). Halmy et al. [1] documented significant increases in barren land in the north-western Egyptian coastal desert due to agricultural degradation and invasion, a pattern similar to the barren land expansion (41.1%) witnessed in Dinajpur, which the present study attributes to soil exposure due to vegetation removal and fallow conversion. These comparative analyses collectively suggest that the LULC trajectories in Dinajpur are not unique but reflect a generalised trend of land degradation and urbanisation in agricultural frontiers across developing economies; however, the alarmingly steep drop in vegetation (74.1%) in Dinajpur demands special attention that may not be needed otherwise.

Table 6. Temporal change of LULC in Dinajpur District (2000–2020)

LULC	Y2000 (km ²)	Y2020 (km ²)	Change (km ²)	Change (%)
Water Body	169.14	172.01	2.87	1.7
Agricultural Land	1519.3	1288.94	-230.36	-15.1
Vegetation Area	514.21	132.96	-381.25	-74.1
Built-up Area	224.41	410.13	185.72	82.8
Barren Land	1030.29	1453.31	423.02	41.1

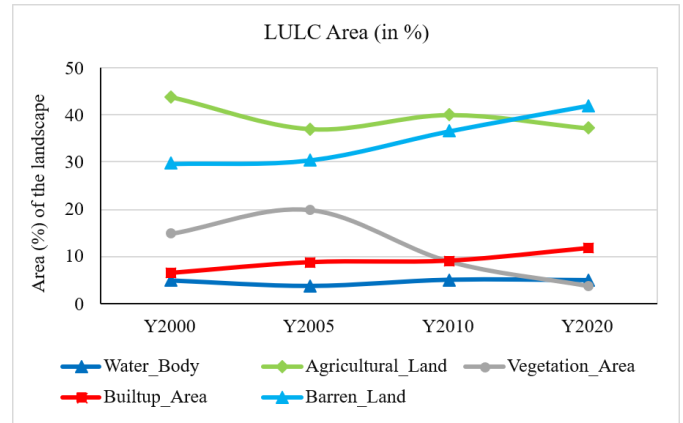


Figure 5. Trend of LULC in Dinajpur district from 2000 to 2020.

4.4 Future Scenario (LULC 2040 Prediction)

The CA-Markov model in TerrSet is used to estimate the LULC status for Dinajpur District in 2040. The net change matrix, which shows the gains and losses among land cover classes between 2010 and 2020, was generated by the model using categorized LULC maps from those two years (Figure 6). The model predicted an LULC distribution for 2040 with a higher likelihood using these data and geographical contiguity constraints. With this data and geographical adjacency restrictions, the model produced the 2040 LULC that was most probable. ArcGIS Pro was used to export the raster map for accurate display. The 2040 LULC map is shown in Figure 7.

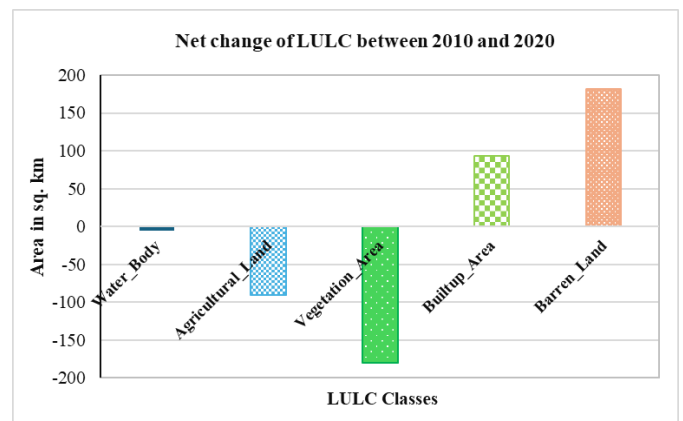


Figure 6. Net change of LULC between 2010 and 2020.

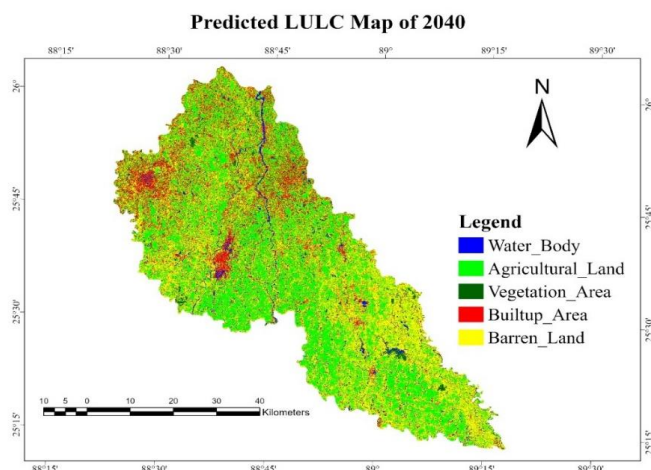


Figure 7. Predicted LULC map of 2040.

TerrSet was used to calculate the anticipated area for each LULC class of 2040. Agricultural Land class will dominate with 1622.23 km², followed by Barren Land with 1781.69 km², according to Table 7, which displays the results we will produce. As the Built-up Areas continue to develop, they will reach 521.35 km². With little changes from the preceding decade, areas like water bodies and vegetation are also anticipated to occupy 150.37 km² and 117.05 km² of the region, respectively.

Table 7. Area calculation of LULC for 2040

Classes	Area (km ²)
Water_Body	150.3702
Agricultural_Land	1622.2266
Vegetation_Area	117.054
Builtup_Area	521.3538
Barren_Land	1781.6913

5. Conclusion

This study used GEE and the CA-Markov model to anticipate the LULC changes in Dinajpur District throughout the period of 2000 to 2020. The data showed a sharp decline in vegetation cover (74.1%) and agricultural land area (15.1%), as well as a notable increase in built-up (82.8%) and barren land area (41.1%), indicating a high level of urbanization processes and overall land degradation. According to the CA-Markov model, agricultural land may decline by 18% during the next two decades (2040), whereas built-up and barren land are expected to grow by 27% and 22.6%, respectively. These patterns show that human strain on the planet's resources is unchecked and point to the possibility of ecological imbalance and soil fertility loss. Therefore, to prevent further deterioration, it is imperative that sustainable land management plans, regulated urban sprawl, and conservation measures be put into place. According to the integrated remote sensing and modeling methodology, the method of integrating remote sensing and modeling offers a valuable way to evaluate land dynamics and planning at the regional level.

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