

Dynamics of Land Use and Land Cover Changes in Cox's Bazar Municipality Using GIS Based Artificial Neural Network Model

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Abstract: Urban expansion in coastal municipalities has intensified land use and land cover (LULC) transformations, identifying challenges for ecological sustainability. This study explores the spatial and temporal dynamics of LULC change in Cox's Bazar Municipality, Bangladesh, from 2005 to 2025 and predicts future scenarios for 2035 and 2045 using a GIS-based Artificial Neural Network (ANN) model. Multi-temporal Landsat imagery, Shuttle Radar Topography Mission (SRTM) elevation data, and road network layers were processed to classify five major land categories water, built-up, vegetation, agriculture, and bare land using supervised classification. Accuracy assessment specified trustworthy classification performance, with overall accuracies ranging from 78% to 84% and kappa values above 0.8. Results revealed a significant escalation in built-up areas, from 29.7% in 2005 to 39.8% in 2025, largely at the expense of vegetation, agriculture, and water bodies. Change detection underlined urban expansion agglomerated along the coastal belt and road networks, while agricultural and vegetated lands showed fragmentation and decline. ANN-based simulations projected that by 2045, built-up land will account for approximately 47% of the municipality, with vegetation and agricultural land ongoing to shrink, and water bodies fronting gradual reduction. These findings demonstrate that Cox's Bazar is on an unsustainable urban trajectory, driven by tourism, migration, and infrastructural development, which threatens green infrastructure and ecological resilience. The study highlights the potential of GIS-ANN modeling for urban growth prediction and highlights the urgent need for incorporated land management approaches, including zoning, ecosystem conservation, and sustainable tourism planning. By investigating both reflective and predictive understandings, this research offers critical indication for policymakers and planners seeking to balance development with environmental sustainability.

Keywords: LULC; MOLUSCE; Prediction; Artificial Neural Network (ANN Model)

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1. Introduction

Land use and land cover (LULC) change is one of the most noticeable indicators of human-environment interactions, connecting the collective effects of population growth, urbanization, agricultural extension, and climate change (Lambin & Geist, 2006). Monitoring and predicting these changes are essential for sustainable land management, particularly in swiftly urbanizing coastal areas where environmental resources are under rising threats. Remote sensing and geographic information system (GIS) tools and techniques have become widely accepted for LULC monitoring, proposing the capacity to explore spatio-temporal analysis across landscape to regional scale level (Turner et al., 2007; Hassan et al., 2016).

In Bangladesh, the human and natural induced stressors on land resources has strengthened in the last few decades due to fast demographic expansion, economic growth, and the blast of tourism-related infrastructure. Coastal municipalities, such as Cox's Bazar, has been particularly affected as they serve as both ecological hotspots and major tourism targets (Rahman et al., 2020). One of the longest natural sea beaches of the world, located in Cox's Bazar, has made the region a hub of openness and infrastructure growth. But, these activities have come at the cost of agricultural fields, vegetation, and wetlands, leading to extensive ecological deterioration and the damage of green infrastructure (Roy et al., 2022). Prior studies on urban land change in Bangladesh have emphasized the impacts of unplanned expansion, but extrapolative studies focusing on municipal-level dynamics persist limited (Hasan et al., 2021).

Artificial Neural Networks (ANN) provide a rising approach for modeling and predicting LULC changes, as they can incorporate the non-linear and complex interactions between land use drivers and land transformation procedures (Aburas et al., 2017; Guan et al., 2019). Unlike traditional Markov or regression-based models, ANN-based tactics incorporate expounding spatial variables, such as elevation, slope, and distance from road and water, alongside historical land use data to produce more precise predictions of future trajectories. Within the GIS environment, tools such as the MOLUSCE plugin in QGIS have expanded the accessibility of ANN modeling, allowing researchers to apply cross methods like Cellular Automata-ANN (CA-ANN) for urban growth and land transformation simulation. In spite of these methodological progress, very few studies have applied ANN-based LULC prediction specifically to Cox's Bazar Municipality, which encounters exceptional pressures from tourism-driven expansion and coastal vulnerability.

Supporting this background, the present study aims to demarcate, analyze, and predict land use and land cover change in Cox's Bazar Municipality between 2005 and 2025, with predictions for 2035 and 2045 using a GIS-based ANN model. The specific objectives are to: (i) classify multi-temporal LULC maps for 2005, 2015, and 2025 using Landsat imagery; (ii) analyze the accuracy of classifications through confusion matrix and statistical evaluation; (iii) examine LULC transitions across the study period using change detection techniques; and (iv) project future land use scenarios using the CA-ANN method. By combining remote sensing, GIS, and ANN modeling, this study provides both retroactive and predictive understandings into the dynamics of urban expansion including other land use and land covers in Cox's Bazar.

In Bangladesh, most LULC projection studies have depended on CA–Markov models that undertake linear and spatially homogeneous alteration likelihoods, restricting their ability to delineate complex urban change dynamics in swiftly changing environments (Hasan et al., 2021; Islam & Rahman, 2019). Although machine-learning approaches such as Random Forest have been used, they have primarily supported classification rather than long-term simulation of land transformation (Hossain et al., 2022). Very few studies have integrated CA–ANN frameworks, and none has focused specifically on coastal municipal areas like Cox’s Bazar, where tourism-driven expansion, land reclamation, and infrastructure development create highly non-linear land conversion patterns (Rahman et al., 2020; Roy et al., 2022). Traditional models fail to represent these interactions, whereas ANN is capable of learning complex relationships involving slope, elevation, road proximity, and historical transition behavior (Aburas et al., 2017; Guan et al., 2019). This gap underscores the need for an ANN-based predictive approach tailored to Cox’s Bazar’s unique development pressures.

2. Methods and materials

2.1 Study Area

Cox’s Bazar Municipality, located along the southeastern coastal zone of Bangladesh, and has been nominated as the study area due to its swift urban expansion, ecological sensitivity, and importance as one of the country’s most important tourist destinations.

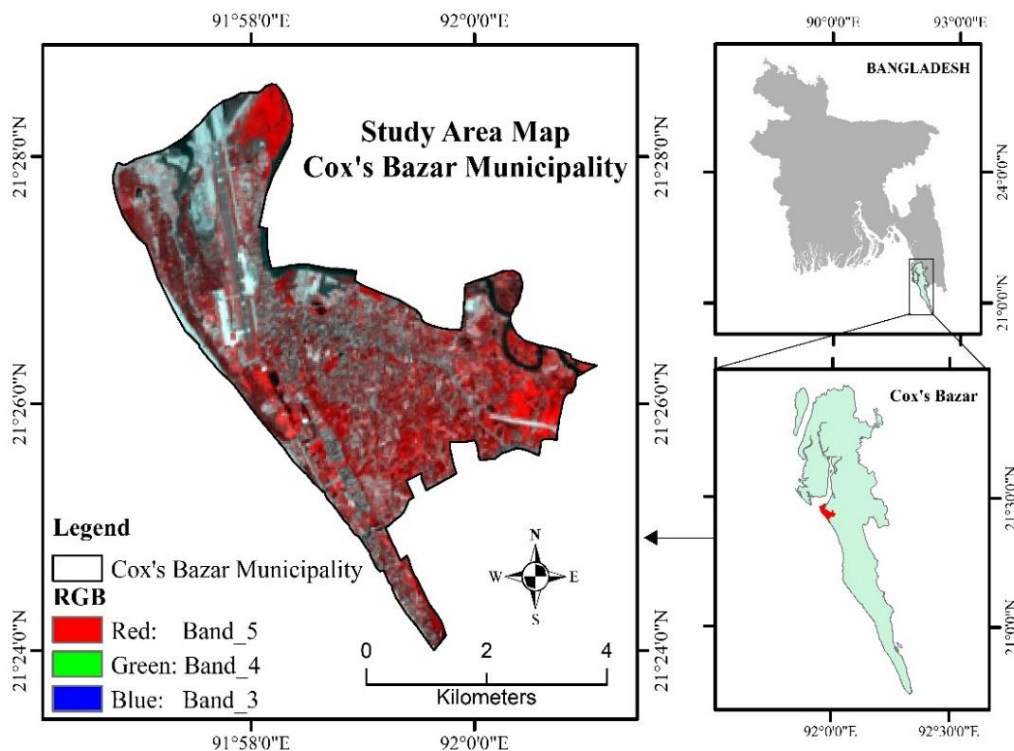


Figure 1: Location map of the study area

Geographically, it lies within the Chattogram Division, bounded by the Bay of Bengal to the west and characterized by sandy beaches, low-lying settlements, and peripheral agricultural lands. The location map (Figure 1) demonstrates the administrative extent of Cox's Bazar Municipality, highlighting its proximity to the world's longest natural sea beach, as well as the surrounding physiographic setting that influences its land use and land cover (LULC) dynamics. The municipality has faced considerable demographic and infrastructural growth over the past few decades, mainly driven by the tourism sector, which has successively accelerated land conversion from vegetation and agricultural lands into built-up areas (Rahman et al., 2020; Roy et al., 2022).

2.2 Data and Methods

This study engaged a multi-source geospatial outline incorporating satellite imageries, ancillary datasets, and an ANN approach to examine and predict LULC change within Cox's Bazar Municipality. The methodological workflow is summarized in the flowchart (Figure 2), which outlines the successive steps of data acquisition, preprocessing, classification, accuracy assessment, and simulation modeling. By coalescing remote sensing and machine learning, the study ensured that both past land alteration patterns and future urban expansion settings were apprehended in a systematic way, a practice consistent with similar land alteration studies in rapidly urbanizing coastal regions (Aburas et al., 2017; Musa et al., 2017).

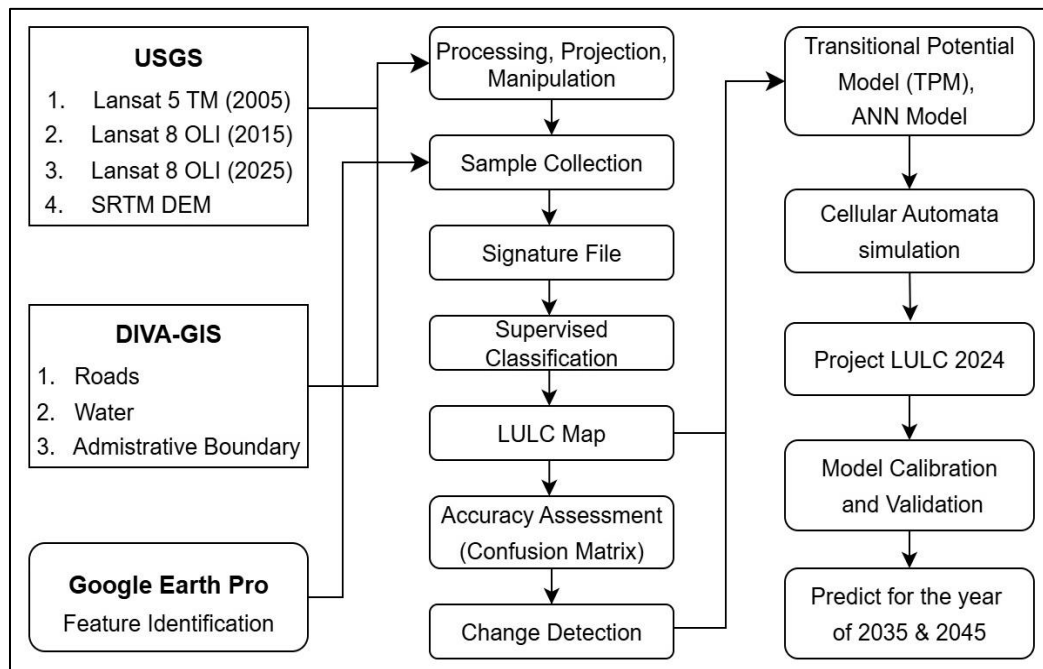


Figure 2: Methodological flowchart for LULC change and simulations

2.3 Data Sources and Classification Outline

Multi-temporal Landsat satellite imagery was the primary dataset utilized to produce LULC maps. Landsat 5 TM (2005) and Landsat 8 OLI/TIRS (2015 and 2025) were selected, each providing 30-meter spatial resolution appropriate for regional-scale urban LULC analysis. The classification trailed a supervised method, trained by training samples collected from high-resolution Google Earth imagery. The classification system was based on five land cover categories: water bodies, built-up areas, vegetation, agriculture, and bare land (Table 2). These classes were resulted from the United States Geological Survey (USGS) Anderson framework (Anderson et al., 1976) but aligned to reflect local land use features, such as shrimp farms within the water class and coastal tourism infrastructure within the built-up class. Prior research in Bangladesh has illustrated the competence of similar schemes in apprehending precise coastal land alterations (Hossain et al., 2022; Rahman et al., 2020).

Table 2: LULC type and its description

LULC Type	Descriptions
Water Bodies	Bay of Bengal shoreline, rivers, canals, wetlands, ponds, lakes, and shrimp farms used for aquaculture.
Built-up	Residential houses, apartments, hotels, resorts, markets, commercial buildings, industrial sites, transport networks (roads, bus terminals), and touristic infrastructures near the sea beach.
Vegetation	Evergreen and semi-evergreen forest patches, coastal mangroves, homestead forestry, orchards, and scattered green vegetation across rural and peri-urban areas.
Agriculture	Croplands (paddy fields, vegetable gardens), plantations (coconut, betel nut, fruits), and other cultivated land located at the periphery of the municipality.
Bare Land	Sandy beaches along the coastline, open soils, vacant land, char land, land under construction, and exposed areas without vegetation cover.

Source: Compile by author after Anderson framework (Anderson et al., 1976)

To smooth interpretation and comparison of different features, false color composites were generated, with both natural color and near-infrared composites (Figure 3). The natural color composite supported identification of urban and bare surfaces, while the infrared composite highlighted vegetation and water bodies.

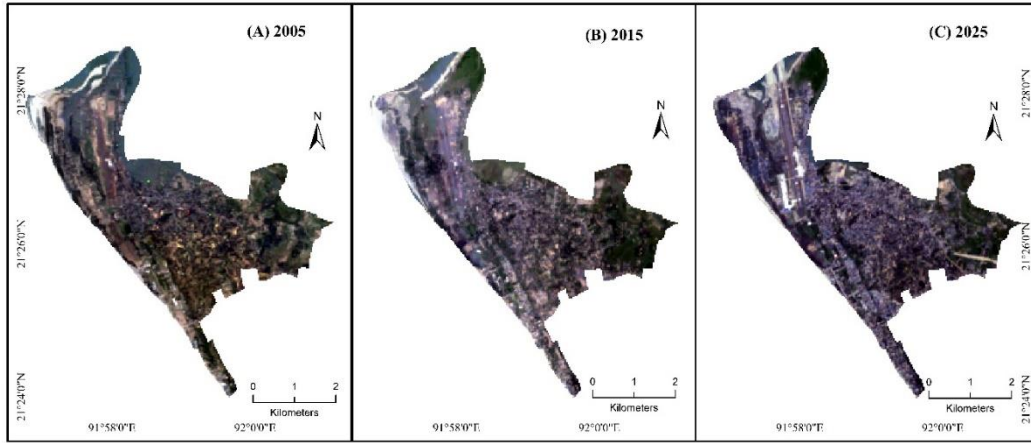
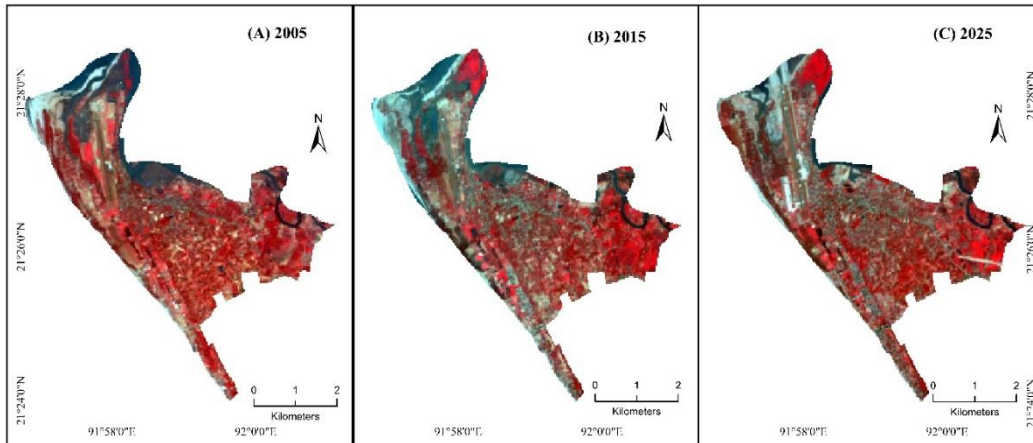
(i) Natural Color**(ii) Infrared Color**

Figure 3: Composite map of Cox's Bazar Municipality (i) Natural Color (ii) Infrared Color

2.4 Ancillary Data for Explanatory Variables

To improve the simulation ability of the ANN model, three explanatory variables were incorporated: elevation, slope, and distance from road (Figure 4). The Shuttle Radar Topography Mission (SRTM) DEM, at 30 m resolution, was processed to extract elevation and slope layers. These topographic variables are suitable in understanding settlement patterns, as low-lying areas in Cox's Bazar are highly suitable for urban development and agriculture (Hasan et al., 2021). Distance from roads was calculated using the DIVA-GIS database of transport networks, which offers open-source global vector data. This variable was involved because road accessibility is a major factor of land conversion, predominantly in tourist-driven municipalities where new resorts and commercial centers develop speedily along major transportation passages (Ahmed et al., 2013).

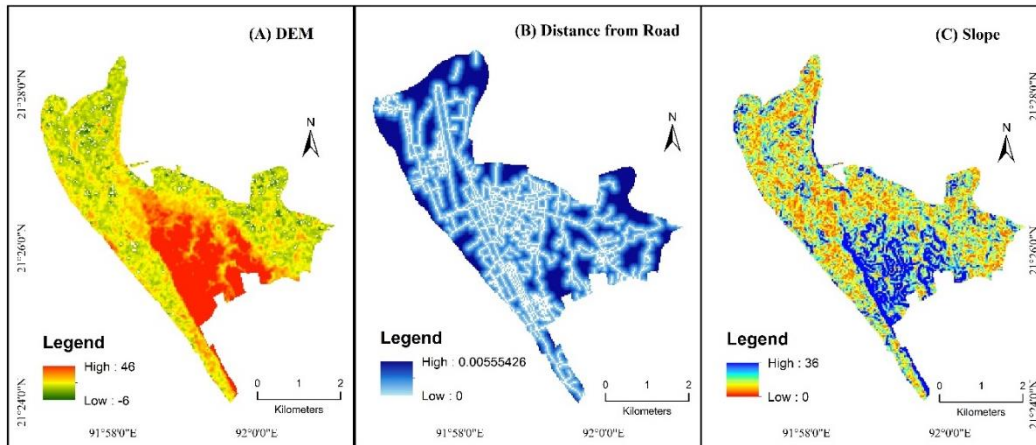


Figure 4: Manipulated datasets for model dependent variables (A) Digital Elevation Model (DEM), (B) Distance from road, (C) Slope

2.5 LULC Classification and Accuracy Assessment

Supervised classification was performed in QGIS using the Semi-Automatic Classification Plugin (SCP). Training samples were manually digitized across the five LULC categories, and maximum likelihood classifier was applied. Post-classification refinement, such as majority filtering, was employed to decrease misclassification noise. Accuracy assessment was performed using error matrices generated from independent validation samples. User's and producer's accuracies were calculated for each class, together with overall accuracy and kappa statistics.

2.6 ANN-Based Change Simulation and Prediction

The ANN model was executed in QGIS through the MOLUSCE (Modules for Land Use Change Evaluation) plugin. This tool incorporates multi-temporal LULC maps with explanatory variables to model transition possibilities and simulate LULC change. In this research, the ANN was trained using the 2005 and 2015 classified maps as initial final layers respectively, combined with Digital Elevation Model (DEM), slope, and distance-to-road variables. The model was then validated against the 2025 classification. After validation, it was utilized to simulate future LULC for 2035 and 2045. The predicted maps focused potential expansion of built-up areas and related declines in vegetation and agriculture, results that align with observed urbanization trajectories in Cox's Bazar. The benefit of the ANN-MOLUSCE approach lies in its ability to handle non-linear relationships among driving factors and to capture the probabilistic nature of land conversion processes. With comparison to traditional Markov chain approaches, ANN-based models have been shown to provide higher accuracy, user friendly, and flexibility in LULC prediction including urban growth (Eastman, 2012; Guan et al., 2019).

Model Parameterization of ANN

Parameter Category	Assigned Value (from ANN Training Panel)
Input Variables	LULC 2005, LULC 2015, DEM, Slope, Distance from Road
ANN Type	Multilayer Perceptron (MLP)
Neighbourhood Size	1 pixel
Number of Training Samples	3,000
Learning Rate	0.100
Maximum Iterations (Epochs)	1,000
Number of Hidden Layers / Neurons	15
Momentum	0.050
Error Function	Root Mean Square Error (RMSE)

A higher learning rate (0.10) and moderate momentum (0.05) ensured faster convergence; 15 hidden neurons allowed the ANN to capture non-linear interactions among topography, accessibility, and past land transitions while preventing model under fitting. The ANN in this study was configured in MOLUSCE as a Multilayer Perceptron (MLP) using six explanatory variables: LULC 2005, LULC 2015, LULC 2025, DEM, slope, and distance from road. A 1-pixel neighborhood was chosen to capture immediate spatial interactions relevant for municipal-scale modelling. The network was trained with 3,000 randomly selected samples, using a learning rate of 0.100 and momentum of 0.050 for stable convergence. Training ran for 1,000 iterations. The model used one hidden layer with 15 neurons, enabling effective learning of non-linear relationships without overfitting. MOLUSCE applied a sigmoid activation function, and RMSE served as the error metric. The minimum validation error (0.13662) indicated satisfactory predictive stability, allowing the ANN to capture complex terrain, accessibility, and historical transition dynamics beyond the capability of CA–Markov models.

3 Results**3.1 LULC classification 2005, 2015 and 2025**

The supervised classification of multi-temporal Landsat imagery delivered a clear picture of LULC dynamics in Cox's Bazar Municipality over the twenty-year period. The classified maps (Figure 5) reveal noteworthy changes between 2005, 2015, and 2025 across the five major land cover types: water bodies, built-up areas, vegetation, agriculture, and bare land. In 2005, built-up areas were concentrated mainly within the middle part of the municipality, while neighboring agricultural fields and vegetation dominated the fringe. By 2015, however, fast expansion of built-up areas became visible, especially along coastal strips and transportation routes, showing the municipality's rapid urbanization and

tourism-led development. The 2025 classification further highlights this trend, with built-up land intensifying to nearly 40% of the municipal area, altering both agricultural land and vegetation.

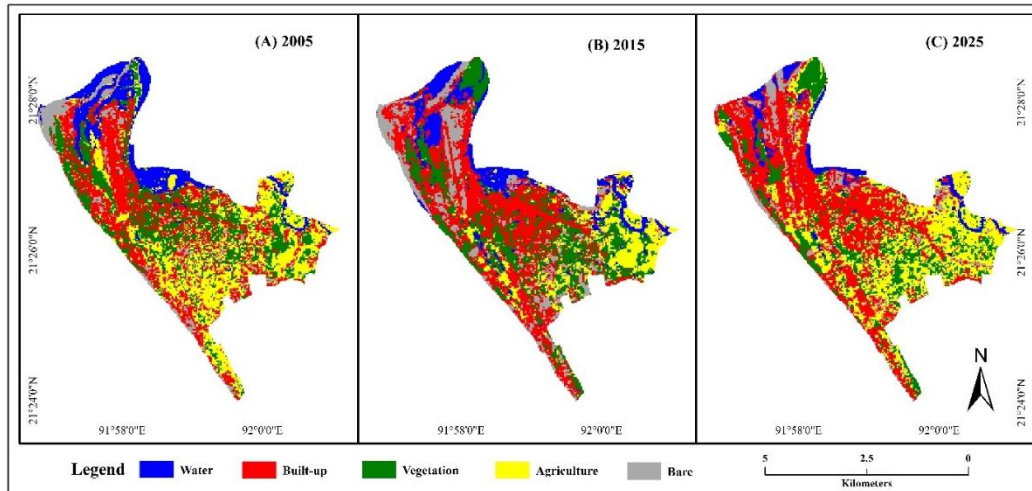


Figure 5: Multitemporal LULC classification (A) 2005 (B) 2015 & (C) 2025

Vegetation cover revealed a gradual decline, lessening from substantial patches in 2005 to fragmented and scattered areas in 2025. Similarly, agricultural land fluctuated, initially decreasing between 2005 and 2015 before recovering partially in 2025, which may be connected to changing cultivation practices and fringe farming creativities. Water bodies, including ponds, rivers, and aquaculture farms, also declined considerably, consistent with land reclamation and infrastructural expansion observed in coastal Bangladesh (Hossain et al., 2022). Bare land, particularly sandy beaches and construction sites, fluctuated moderately, indicating phases of infrastructure growth and subsequent maintenance. These patterns align with broader research on coastal Bangladesh, where tourism and migration have enriched urban expansion at the cost of ecological and agricultural landscapes (Rahman et al., 2020; Roy et al., 2022).

3.2 Accuracy Assessment

The accuracy assessment of the classified maps (Table 3) validates that the classifications for all three time periods achieved acceptable dependability. In 2005, the overall accuracy was 82% with a kappa coefficient of 0.775, representing strong relation between the classified map and reference data. Built-up areas achieved comparatively high user accuracy (90%), although producer accuracy was lower (75%), reflecting some misclassification between built-up and bare land. Agriculture in 2005 recorded lower accuracy (70% user and 61.54% producer), likely due to spectral possibilities with vegetation and bare fields during the dry season.

Table 3: Accuracy assessment for the LULC of 2005, 2015 and 2025

		Waterbody	Built-up	Vegetation	Agriculture	Bare
2005	Commission Error	20%	10%	20%	30%	10%
	Omission Error	6.12%	25%	20%	38.46%	10%
	User Accuracy	80%	90%	80%	70%	90%
	Producer Accuracy	93.88%	75%	80%	61.54%	90%
	Overall Accuracy	82%				
	Kappa Coefficient	0.775				
2015	Commission Error	0%	20%	10%	30%	20%
	Omission Error	0%	20%	10%	30.77%	20%
	User Accuracy	100%	80%	90%	70%	80%
	Producer Accuracy	100%	80%	90%	69.23%	80%
	Overall Accuracy	84%				
	Kappa Coefficient	0.80				
2025	Commission Error	0%	20%	10%	50%	30%
	Omission Error	0%	20%	10%	35.71%	30%
	User Accuracy	100%	80%	90%	50%	70%
	Producer Accuracy	90.91%	66.67%	64.29%	87.50%	70%
	Overall Accuracy	78%				
	Kappa Coefficient	0.725				

The 2015 classification accomplished somewhat better, attaining an overall accuracy of 84% and a kappa value of 0.80. Water bodies and built-up areas were classified with 100% user and producer accuracy, showing improvements from 2005. However, agriculture still exhibited notable commission and omission errors, replicating its transitional nature between other classes. By 2025, classification dependency decreased a little, with an overall accuracy of 78% and a kappa coefficient of 0.725. While water and built-up classes upheld strong accuracies, vegetation and agriculture showed declines in both user and producer accuracy, representing increased fragmentation and spectral overlaps caused by rapid urban encroachment.

Despite the slight decline in accuracy in 2025, all three classifications exceed the minimum 75% accuracy threshold recommended for LULC studies (Foody, 2002). The kappa

statistics further show that the classification outcomes are statistically robust and fit for later change detection and ANN-based simulation modeling.

3.3 LULC change Detection from 2005 to 2025

The spatial dynamics of land transformation between 2005 and 2025 are explained in the change detection maps (Figure 6). These maps depict distinct changes in LULC classes, particularly the slow expansion of built-up areas and corresponding decrease of vegetation and agricultural land. The most prominent pattern is the conversion of agricultural fields and vegetated areas into built-up area, especially along the main roads and coastal belts where tourism-led construction has increased. This transition accentuates the rapid pace of urban sprawl in Cox's Bazar.

Vegetation cover, which was widespread in 2005, shows visible disintegration by 2015 and more distinct reduction by 2025. The reduction of green spaces reveals both deforestation of semi-evergreen patches and clear-cut of homestead forestry to accommodate new settlement and commercial buildings. Agricultural land divulges instabilities, with large-scale delines witnessed between 2005 and 2015, followed by slight recovery in 2025, likely due to re-cultivation of urban peripheral plots. Water bodies also practiced distinguished reduction, as aquaculture ponds and wetlands were domesticated for settlements. These alterations illustrate a broader trend of ecological degradation in Cox's Bazar, consistent with studies that have trailed rapid tourism development with declining ecosystem services in coastal Bangladesh (Hossain et al., 2022; Rahman et al., 2020).

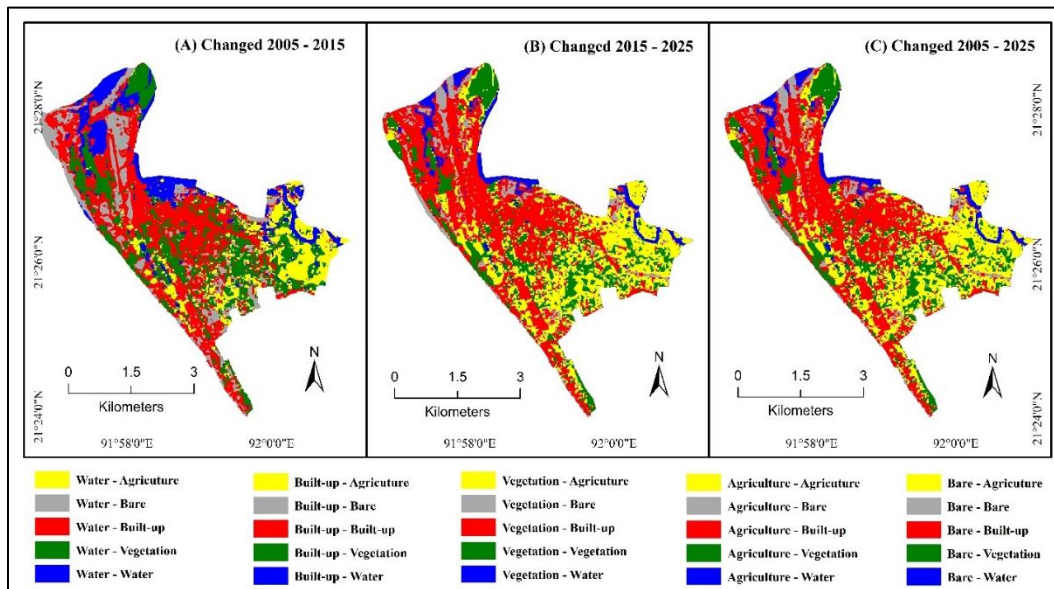


Figure 6: LULC change Detection from 2005 to 2025

Bare land, largely consisting of sandy beaches and construction sites, changed across the study period. Between 2005 and 2015, bare land extended considerably, indicating increased construction activities, but by 2025, some areas transitioned into stable built-up

surfaces. These detected trends together demonstrate that built-up areas have become the prevailing land class, while natural and semi-natural land covers have gradually lessened.

3.4 Multi-year Land Use Monitoring

The quantitative analysis of land cover transformation between 2005, 2015, and 2025 is summarized in the land cover transfer matrix (Table 4). Results designate that built-up areas increased consistently, rising from 610.38 ha (29.73%) in 2005 to 816.75 ha (39.78%) in 2025, demonstrating a net increase of 206.37 ha over two decades. This growth occurred primarily at the cost of vegetation and agricultural land, standing the central role of urban extension in reforming municipal landscapes.

Table 4: Land cover transfer matrix from 2005 to 2025

LULC Types	2005		2015		2025		2005 -2015		2015-2025		2005-2025	
	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Chang ed Area (ha)	(%)	Chang ed Area (ha)	(%)	Chang ed Area (ha)	(%)
Water	251.64	12.26	265.14	12.91	121.32	5.91	13.5	0.65	-143.82	-7.00	-130.32	-6.35
Built-up	610.38	29.73	718.2	34.98	816.75	39.78	107.82	5.25	98.55	4.80	206.37	10.05
Vegetation	466.56	22.72	462.33	22.52	378.81	18.45	-4.23	-0.2	-83.52	-4.07	-87.75	-4.27
Agriculture	563.58	27.45	299.34	14.58	571.77	27.85	-264.24	-12.87	272.43	13.27	8.19	0.4
Bare	161.19	7.85	308.34	15.02	164.7	8.02	147.15	7.17	-143.64	-7.00	3.51	0.17
Total	2053.35	100	2053.35	100	2053.35	100						

Vegetation decayed from 466.56 ha (22.72%) in 2005 to 378.81 ha (18.45%) in 2025, a net loss of 87.75 ha (−4.27%). Similarly, water bodies reduced by 130.32 ha (−6.35%) during the same period, indicating both natural contraction and anthropogenic alteration. Agricultural land showed a more complex trajectory: while it fell precisely between 2005 and 2015 (−264.24 ha, −12.87%), it recovered substantially by 2025 (+272.43 ha, +13.27%), resulting in only a marginal net increase of 8.19 ha over the whole period. This rebound proposes adaptive land use practices, where uncontrolled or bare lands were reintroduced into cultivation. Bare land also varied, increasing by 147.15 ha between 2005 and 2015 before decreasing by 143.64 ha in the following decade, resulting in a marginal net increase of only 3.51 ha.

The transition matrix summarizes the leading flows between classes: large portions of agricultural and vegetated land were absorbed into the built-up type, while water bodies also contributed to urban growth through land reclamation. These findings focus the municipality's urban-led land change pathways, consistent with studies reporting similar dynamics in Chattogram and Sylhet, where built-up growth has outpaced ecological conservation (Hasan et al., 2021; Roy et al., 2022).

Overall, the monitoring results illustrates that Cox's Bazar is facing rapid land transformation driven primarily by tourism-related development and incoming population pressure form surrounding neighborhood. Without effective land management and zoning policies, this path risks aggravating ecological degradation and decline of green infrastructure in one of Bangladesh's most environmentally sensitive coastal zones.

3.5 Land Use Prediction for 2035 & 2045

The prediction of future land use and land cover (LULC) reveals noteworthy alterations in Cox's Bazar Municipality by 2035 and 2045. The simulated maps (Figure 7) illustrate the spatial expansion of built-up areas into previously agricultural and vegetated zones, particularly along the coastal belt and road networks. According to the projections, built-up areas are expected to occupy 941.19 ha (45.84%) in 2035 and further expand to 963.09 ha (46.90%) by 2045 (Table 5). This trajectory underscores the municipality's continuing trend of urban increase driven by tourism, infrastructure development, and population growth.

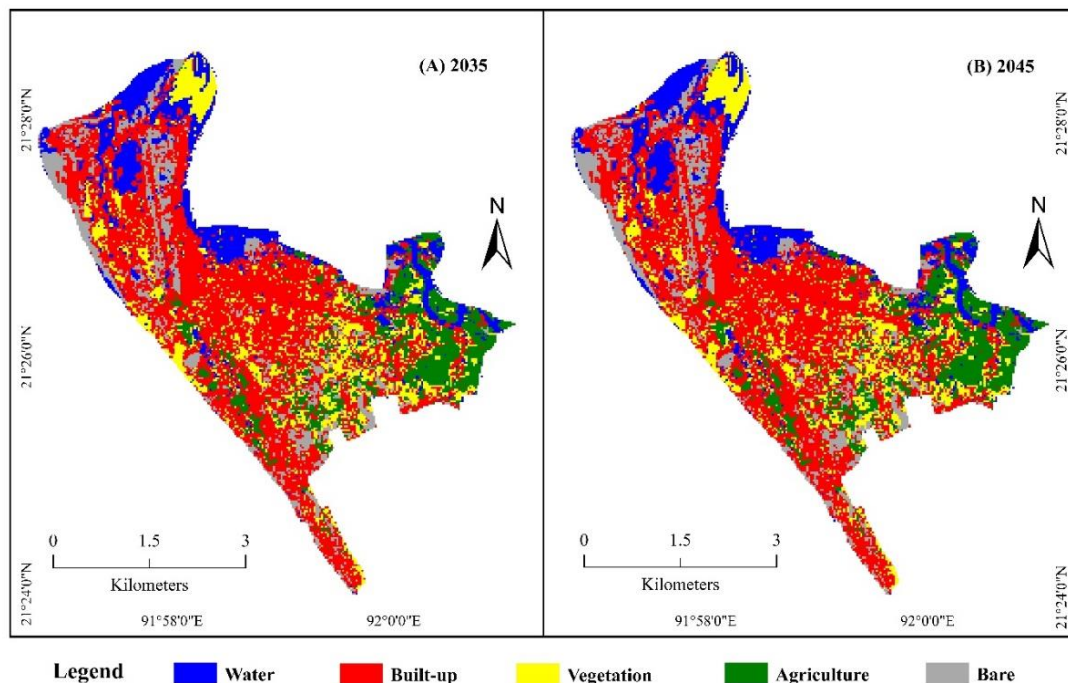


Figure 7: Simulated LULC of Cox's Bazar Municipality (A) 2035 & (B) 2045

Vegetation cover is projected to decline gradually, from 316.08 ha (15.39%) in 2035 to 309.08 ha (15.05%) in 2045. This reduction, though moderate, highlights the persistent conversion of green spaces into urban surfaces, indicating ongoing pressures on local ecosystems. Agricultural land is also expected to decrease from 252.45 ha (12.29%) to 245.67 ha (11.96%) over the same period, as farmland is progressively immersed into residential and commercial uses. Water bodies, including aquaculture ponds and wetlands, are anticipated to decrease slightly, while bare land remains comparatively steady at around 12.5% of the municipal area.

Table 5 Projected LULC areas in 2035 & 2045

LULC Class	Estimated Area (ha)		Estimated Area (%)	
	2035	2045	2035	2045
Water	285.12	279.38	13.89	13.61
Built-up	941.19	963.09	45.84	46.90
Vegetation	316.08	309.08	15.39	15.05
Agriculture	252.45	245.67	12.29	11.96
Bare	258.51	256.13	12.59	12.47
Total	2053.35	2053	100.00	100

These projections collectively acclaim that Cox's Bazar Municipality is likely to experience a consolidation of built-up dominance at the expense of natural and semi-natural land covers. Similar predictive trends have been observed in other urbanizing coastal municipalities of Bangladesh, such as Chattogram and Sylhet, where tourism and industrialization have enhanced the alteration of vegetation and agricultural land by urban growth. Without appropriate land management involvements, the predicted decay of vegetation and agriculture may weaken ecological sustainability and local food security, reliable with apprehensions raised in coastal urbanization studies.

3.6 Prediction of LULC by ANN Model

The Artificial Neural Network (ANN) model provided a robust outline for simulating land cover transitions, incorporating both temporal LULC data and explanatory spatial variables. The transition matrices (Table 6) highlight the probabilities of land conversion between 2005, 2015, and 2025, which formed the basis for ANN calibration and

consequent prediction. For example, agricultural land showed a high probability of transitioning into built-up areas, while vegetation exhibited substantial conversion to both built-up and agricultural categories. Similarly, water bodies were increasingly transformed into built-up and bare land, reflecting the reclamation pressures documented in the region.

The model's predictions align with observed historical patterns of land transformation, confirming that urban growth is the leading trajectory in Cox's Bazar. By including elevation, slope, and distance-to-road variables, the ANN approach apprehended the influence of physical and infrastructural drivers on land use dynamics. The learning curve validated the ANN's performance, with acceptable kappa values indicating strong agreement between predicted and observed classifications.

Table 6: Transition matrices of LULC from 2005 to 2025

LULC Class		LULC 2015				
		Water	Built-up	Vegetation	Agriculture	Bare
LULC 2005	Water	0.601019294	0.166363305	0.136148526	0.022934	0.073535
	Built-up	0.033692922	0.531254618	0.143194917	0.086744	0.205113
	Vegetation	0.064391001	0.328161365	0.48390225	0.067882	0.055663
	Agriculture	0.090501362	0.256287041	0.237385872	0.304661	0.111165
	Bare	0.071428571	0.346456693	0.054555681	0.05793	0.469629
LULC Class		LULC 2025				
		Water	Built-up	Vegetation	Agriculture	Bare
LULC 2015	Water	0.349287	0.249151	0.080787508	0.165988	0.154786
	Built-up	0.024185	0.666165	0.087343358	0.175313	0.046992
	Vegetation	0.009932	0.215744	0.484458341	0.280302	0.009564
	Agriculture	0.004296	0.107403	0.144415069	0.684402	0.059484
	Bare	0.017221	0.445709	0.059252773	0.25394	0.223876
LULC Class		LULC 2025				
		Water	Built-up	Vegetation	Agriculture	Bare
LULC 2005	Water	0.307244266	0.288678558	0.143793	0.109938	0.150345832
	Built-up	0.013890941	0.548692183	0.117925	0.24516	0.074331314
	Vegetation	0.021334368	0.405352987	0.313615	0.228084	0.031613654
	Agriculture	0.035399648	0.262534038	0.18709	0.449463	0.065513375
	Bare	0.028121485	0.453318335	0.118673	0.214848	0.18503937

In the case of Cox's Bazar, the CA-ANN model confirmed the municipality's route toward strengthened urbanization, compact ecological land covers, and increased anthropogenic pressure on coastal resources. Overall, the prediction results highlight the urgent need for urban planning and conservation policies in Cox's Bazar Municipality. If the current trajectory continues, the dominance of built-up areas by 2045 could significantly reduce ecosystem resilience and compromise sustainable development goals in one of Bangladesh's most environmentally concern coastal regions.

3.7 Validation of the ANN model for prediction in LULC changes

Figure 8 illustrates the neural network learning curve, illustrating the variation of training and validation errors over 1,000 epochs. The training error (green line) decreases gradually with increasing epochs, indicating effective learning and improved fitting to the training data.

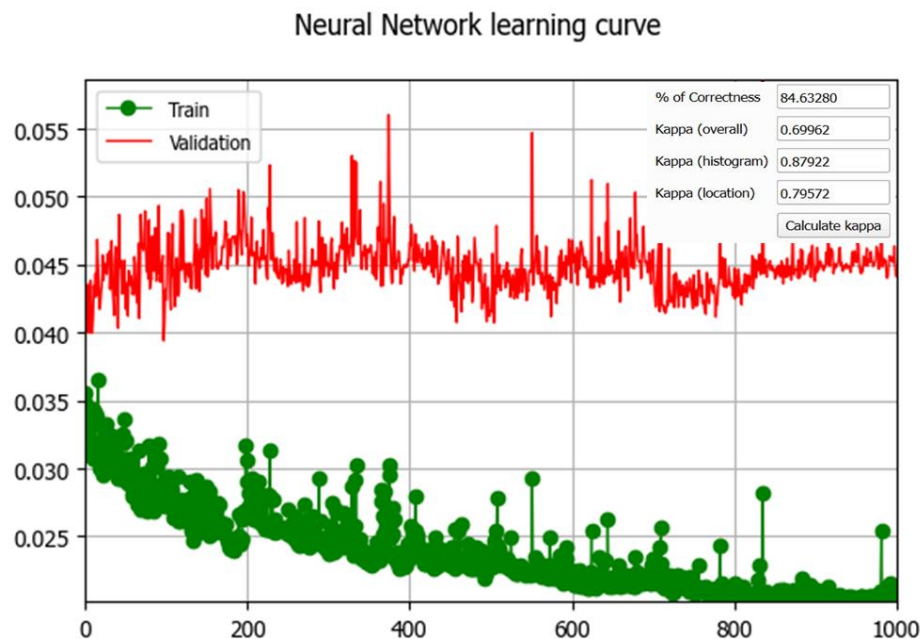


Figure 8: ANN Learning curve with kappa statistics for model validation

In contrast, the validation error (red line) remains relatively higher and fluctuates throughout the training process, signifying a certain degree of overfitting, where the model performs better on the training data than on unseen validation data. The overall classification accuracy achieved is 84.63%, with a Kappa coefficient of 0.70, indicating substantial agreement between the predicted and reference data. The histogram and location Kappa values (0.88 and 0.80, respectively) further confirm good class distribution matching and spatial accuracy of the classification. These results demonstrate that the neural network model is able to learn effectively, although improvements in generalization could be achieved through model regularization or optimization techniques.

4. Discussion

This research reveals the spatial and temporal dynamics of land use and land cover (LULC) change in Cox's Bazar Municipality between 2005 and 2025 and simulated future trajectories for 2035 and 2045 using a GIS-based ANN model. The classification outcomes demonstrated a gradual expansion of built-up areas, rising from less than one-third of the municipality in 2005 to nearly 40% by 2025, while vegetation, agriculture, and water bodies declined or fluctuated. Accuracy assessments confirmed that the classified maps were statistically reliable, with overall accuracies ranging from 78% to 84% and kappa coefficients above 0.70. Change detection analysis revealed that built-up expansion happened largely at the expense of vegetation and agricultural land, with coastal aquaculture ponds and wetlands also being converted. The ANN-based simulations further projected that by 2045, built-up areas will cover nearly half of the municipality's land, while vegetation and agricultural land will continue to shrink, and water bodies will decrease somewhat.

The identified patterns align with wider indication that coastal municipalities in Bangladesh are undergoing rapid, tourism-driven urban development that consistently transforms vegetation, agriculture, and wetland areas into built-up land. Previous studies demonstrates that road accessibility and commercial development hasten this change along major transport strips, strengthening compact and linear urban growth linked to the trends identified in Cox's Bazar. The ANN model effectively captured these clustered transition behaviors and outperformed CA–Markov methods, which often fail to represent non-linear and location-specific dynamics.

The persistent decrease of vegetation and water-related land covers reveals increasing ecological stress, aligning with findings from other coastal districts where unplanned expansion has weakened ecosystem resilience and strengthened land fragmentation (Hossain et al., 2022; Roy et al., 2022). Without strict zoning regulations, ecological protections, and tighter control over land reclamation, these losses are likely to persist and heighten long-term environmental vulnerability in Cox's Bazar. The ANN-based predictions for 2035 and 2045 further indicate a sustained urbanization route formed by terrain suitability, closeness to road networks, and tourism-driven demand. Similar ANN-based LULC research highlights the model's strength in apprehending multifaceted relations among spatial factors, generating more illustrative simulations of future land conversions.

5. Conclusion

In conclusion, the GIS-based ANN framework applied in this study not only provided retrospective insights into LULC dynamics but also offered predictive scenarios that can guide sustainable urban development. By detecting the magnitude, direction, and future route of land change, this research contributes valuable evidence for policymakers,

planners, and conservation practitioners aiming to balance development and ecological sustainability in Cox's Bazar and similar coastal municipalities in Bangladesh. Moreover, the outcomes highlight the significance of integrating ANN-based simulation tools into routine municipal planning, particularly in speedily urbanizing coastal regions where land alteration patterns are highly non-linear and affected by tourism, infrastructure expansion, and road accessibility. The study therefore insights the necessity for coordinated planning approaches that incorporate extrapolative modelling outputs to accomplish urban growth, reserve critical ecological properties, and backing enduring sustainability.

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