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Multi-Temporal LULC Change and Future Urban Expansion in Faridpur Municipality, Bangladesh: A CA-ANN Based Simulation

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ABSTRACT

The study examines land use and land cover (LULC) conversions and forecasts future urban growth in Faridpur Municipality, Bangladesh. Despite substantial urbanization in recent years, smaller cities such as Faridpur have been largely absent from LULC studies. Using Landsat data from 2004, 2014, and 2024, the research employed Maximum Likelihood Supervised Classification (MLSC) to identify land cover changes. It used an Artificial Neural Network (ANN) with Cellular Automata (CA) to anticipate LULC trends for 2034, 2044, and 2054. Findings indicate that urbanized areas grew from 2.18% in 2004 to 7.31% in 2024, initially replacing vegetation and cropland, and are projected to expand further to 15.04% by 2054. An R^2 of 0.9164 represents a strong statistical fit of the plotted built-up-area trend; however, for greenspace, farmland, and water, such expansion into the projected future is not promising. Geospatial analysis suggests the most developed areas are in the northeast and southwest regions, which offer greater connectivity and are the two growth magnets. Validation of the model consistently showed an accuracy of 92.56%, Kappa of 0.878, Kappa (histogram) of 0.9829, and Kappa (location) of 0.8940, which indicates that the model reproduces the observed spatial pattern reasonably well. Thus, the findings suggest that urban planners need to pay attention to trends in sustainable expansion and in the creation of agricultural space. By conveying practical understandings into growth patterns, it supports policymakers, local authorities, and urban planners in monitoring and predicting future urbanization in Faridpur Municipality.

Keywords: LULC; Urban Expansion; Modules for Land Change Simulation (MOLUSCE); Prediction; Artificial Neural Network (ANN)

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1. Introduction

For centuries, urban growth has been related to population changes, economic structuring, and cultural evolution, which have subsequently adjusted human existence worldwide^[1]. Recently, urban growth has reached unprecedented levels as urban land cover increased approximately 168% from 2001 to 2018^[2]. According to the United Nations, urbanized regions have housed a majority of the global population, and by mid-century, 68% more will be housed in such areas^[3]. This is primarily because urban areas offer the majority of economic opportunities, advanced infrastructure, and public resources. So far, unplanned urban growth has contributed to a wide variety of environmental stresses, from microclimatic changes to ecosystem disruptions^[4]. These land use and land cover (LULC) changes caused by urbanization contribute to biodiversity damage and intensify warming trends in urban areas^[5]. Thus, without spatially planned intervention, unplanned growth continues to convert natural regions into sprawling urbanized metropolises, which boast irreversible implications for global ecological sustainability^[6]. This is in addition to changed land-use patterns that require adjustments to infrastructure for resource acquisition, allocation, and sustainability. In Bangladesh, an urbanizing nation, increasing LULC change has been noted as development has increased, especially vegetation cover changes, agricultural land transformation, and urban settlement expansions^[7, 8]. Population pressures and rural-to-urban migration have led to increasingly stronger land attachments, which exhibit extensive levels of LULC change^[1, 9]. This intensified vulnerability is mainly due to inadequate capacity to manage the ecological and social outcomes of such growth^[10]. As a result, monitoring and examining urban development has become a critical issue for ensuring global urban sustainability^[11].

By using remote sensing and GIS-based geoinformation tools, researchers can now identify, classify, and predict settlement patterns with greater precision^[12, 13]. Earlier studies have efficiently used GIS and remote sensing to derive LULC maps and monitor urban extension over time. Simulation models have also been widely accepted for understanding possible future land-use scenarios. Among the most general models are the Markov Chain, Artificial Neural Networks (ANN), and Cellular Automata (CA), which are often

used in combination to increase predictive power^[14, 15]. Hybrid methods, such as Markov-ANN and Markov-CA models, offer strong ways to model how settlements change under different plans^[16–18]. Several mapping and forecasting methods have been used to understand how cities grow. A multi-spatial and sequential study examines LULC changes using satellite imagery and a Markov model to predict urban expansion. Using Landsat-based classification and the Modules for Land Change Simulation (MOLUSCE) model in Purwokerto, Indonesia, significant increases in built-up areas over time were identified^[15, 19]. A similar method was applied in the Gopalganj, Pabna district of Bangladesh, where Landsat 5 and 8 data were considered, applying Maximum Likelihood Supervised Classification (MLSC), and using ANN combined with CA simulation, to anticipate urban growth^[20, 21]. At the same time, CA-Markov and logistic-regression approaches remain valuable alternatives, particularly where transition probabilities or interpretable statistical relationships are central to the research question. The present study therefore positions CA-ANN as a spatially explicit, data-driven approach rather than assuming that it is universally superior to other models.

Faridpur Municipality provides an important case because it combines a rapidly changing secondary-city landscape with agricultural land, vegetation, river-connected lowlands, and expanding transport connections. The municipality expanded from 19.07 km² and nine wards to 66.72 km² and 27 wards, while the population reached 237,172 according to the 2022 census^[22, 23]. The Padma Bridge, opened in 2022, has strengthened regional connectivity and is expected to influence accessibility, economic activity, and development pressure in southwestern Bangladesh. Existing research also indicates directional urban development in Faridpur, particularly toward the northeast and southwest^[24, 25]. Its expanding urban area and recent development projects make it an important case for studying land use changes with geospatial modeling. The city is an important business center in the region, known for making jute, textiles, and farm products, because its rich soils are good for farming. These characteristics make Faridpur municipality suitable for examining how accessibility, topography, hydrological constraints, and land-cover conditions interact with observed urban expansion.

The contribution of this study is methodological as

well as geographical. It is not limited to documenting LULC change in Faridpur; it integrates historical LULC classification, six spatial driving variables, CA-ANN transition-potential modelling in MOLUSCE, transition-probability analysis, ward-level urban-density assessment, and directional expansion analysis within one municipal-scale framework. The combined analysis of transition probabilities, ward-level density, and directional expansion provides an additional planning-oriented interpretation of the simulated urban footprint. Accordingly, the study aims to (i) quantify LULC change in Faridpur Municipality between 2004 and 2024, (ii) identify the principal spatial directions and locations of urban expansion, (iii) simulate plausible LULC configurations for 2034, 2044, and 2054 using CA-ANN, and (iv) interpret the implications of the projected expansion for agricultural land, vegetation, and water body protection. The projections are intended to support scenario-aware planning rather than to represent fixed predictions of future develop-

ment.

2. Methods

2.1. Study Area

This study considers the Faridpur municipality of Bangladesh as the subject region, which is administratively located within the Dhaka Division, Faridpur District, and Faridpur Sadar Upazila. The municipality of Faridpur is located 116 km from Dhaka. It is a rapidly expanding city on the banks of the Padma River. With convenient road, water, and rail connections, Faridpur is one of the nation's oldest towns, having been designated an 'A' class municipality in 1986. It is one of 53 district-level municipalities in the country^[22]. A river named Kumar runs alongside the municipality. **Figure 1** displays the geographic location of the study area map, which lies between 23°31'55" N and 23°36'58" N and 89°46'50" E and 89°51'53" E.

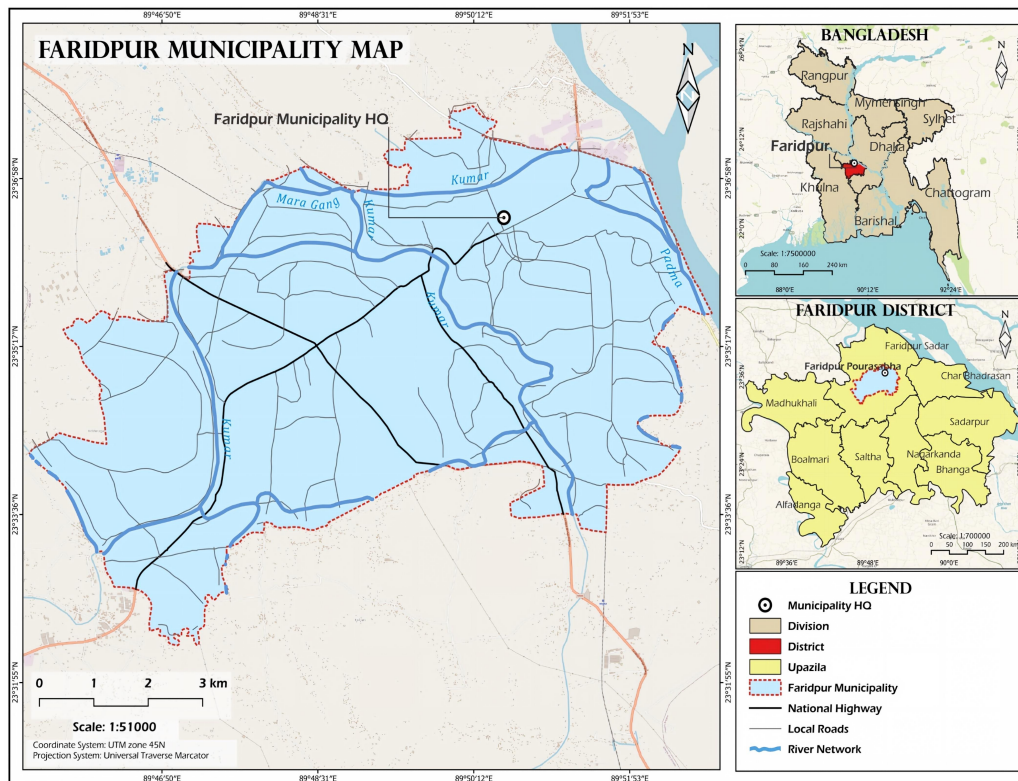


Figure 1. Location map of the study area.

The Municipality covered an area of 66.72 km² with 27 wards. It is housing a total population of 237,172^[23]. The current study area spans 66.72 km². According to the Bangladesh Bureau of Statistics (BBS) report, Faridpur mu-

nicipality has a higher population density than other municipalities, with 3,564 people per square kilometer and a population growth rate of 2.27%. According to the Bangladesh Meteorological Department, the average annual temperature

is between 21.3 °C and 30.6 °C, and there is an average of 154 mm of rainfall. The region experiences a tropical monsoon climate, characterized by hot, humid summers and cool winters^[26, 27]. The area lies on a mostly flat plain, with an average elevation of 43 ft. The eastern part of the municipality is predominantly used for residential and commercial purposes^[21]. The central business zone is situated in the eastern and central parts.

2.2. Data Collection

Figure 2 shows the methodological outline for the LULC investigation and future simulation in an organized framework. Landsat scenes were obtained from the United States Geological Survey (USGS) archive for 2004, 2014, and 2024. Ancillary vector data, including roads and administrative boundaries, were obtained from LGED; the river network was obtained from DIVA-GIS, and Google Earth Pro was used for visual reference during accuracy assessment. All datasets were brought into the UTM Zone 45N/WGS 84 spatial reference used for the analysis. The Landsat scenes were acquired from path 137, row 44, with 30 m spatial resolution and cloud cover below 0.1% (**Table 1**).

2.3. Radiometric Calibration

The effects of the atmosphere on the satellite images were fixed using the DOS1 algorithm through the Semi-Automatic Classification Plugin (SCP) in Quantum GIS (QGIS) software^[21, 28, 29]. The Dark Object Subtraction (DOS) algorithm is designed to identify pixels with minimal or zero reflectance values, representing dark objects within the imagery^[30]. The lowest digital number (DN) value corresponds to the removal of atmospheric scattering effects from the image. Performing the DOS correction automatically generates adjusted multispectral images. The same atmospheric-correction workflow was applied to the selected Landsat scenes before classification. Because Landsat 5 TM and Landsat 8/9 OLI/TIRS differ in sensor characteristics and radiometric resolution, the study did not perform an additional empirical cross-sensor radiometric normalization. Instead, consistency was promoted through the common preprocessing workflow, common projection, common spatial resolution, the same five-class legend, and a consistent supervised-classification procedure. This choice is explicitly treated as a source of uncertainty in the interpretation of inter-annual class differences.

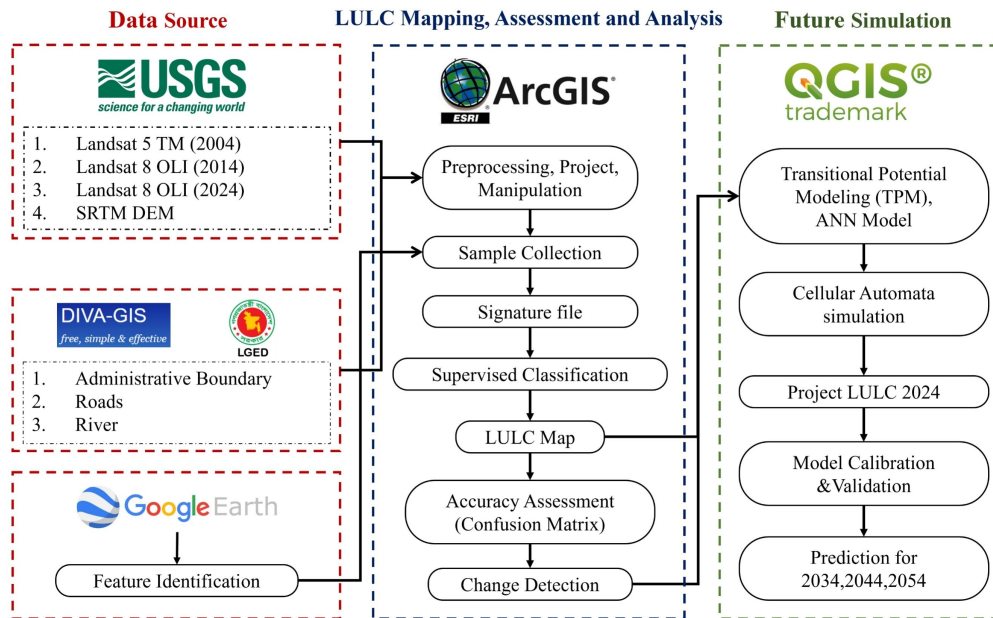


Figure 2. Methodological flowchart for LULC and simulation.

Table 1. Landsat data used for mapping LULC.

S/N	Landsat	Sensor	Row	Path	Spatial Resolution	Acquisition Date
1	L5	TM	137	44	30 m	January 19, 2004
2	L8	OLI/TIRS	137	44	30 m	December 24, 2013
3	L8	OLI/TIRS	137	44	30 m	January 10, 2024

2.4. LULC Classification Scheme

During the classification stage, a signature file needs to be created. To achieve this, the digitized polygon measures the signature value based on the image band composition. The resulting spectral signatures were used by the Maximum

Likelihood classifier. The classification legend contains five classes: water body, built-up, vegetation, cropland, and bare land (**Table 2**). Maintaining the same five-class legend across the three dates was necessary for subsequent change detection and CA-ANN simulation.

Table 2. LULC type description.

Land Cover Types	Descriptions
Water body	Rivers, lakes, ponds
Built-up	Residential, commercial, industrial, and road network and settlement
Vegetation	Park, homestead vegetation, play area, trees
Cropland	Cropland, cultivated land, and unplanted land
Bare land	Unoccupied land, bare soils, landfill site, development land, and chars

2.5. Band Composition

Figure 3 presents the image composites used to support visual interpretation and training-sample selection. For Landsat 5, the natural-color composite used bands 3-2-1, while the corresponding Landsat 8/9 natural-color composite used bands 4-3-2. Infrared and false-color combinations

were selected to improve discrimination among vegetation, built-up surfaces, water bodies, and bare land. The same classification legend was maintained for all dates. Because the purpose of these composites was visual discrimination and training-sample support, the composites themselves were not treated as independent classification outputs.

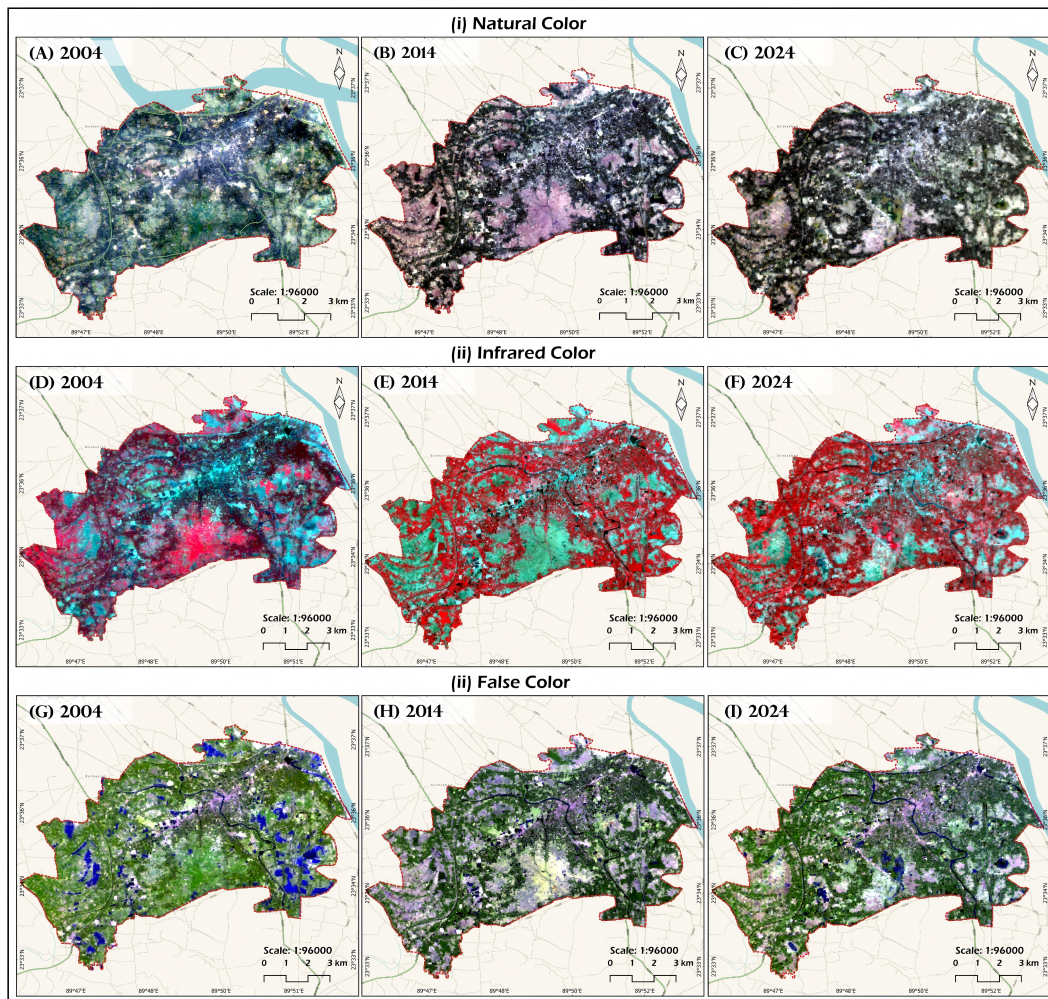


Figure 3. Composite map of Faridpur Municipality.

2.6. Data Manipulation

To prepare the dependent variables for the CA-ANN model, six spatial driving variables were collected, such as Digital Elevation Model (DEM), road network, and river network from the Shuttle Radar Topography Mission (SRTM), Local Government Engineering Department (LGED), and DIVA-GIS, respectively. **Figure 4** shows the processed and manipulated datasets. These variables were used as inputs in the ANN model. The DEM was processed to generate slope

data using the hydrology tool. The DEM value ranges from -21 m to 24 m from the mean sea level. The slope ranges from 0 to 22.95° . The road network within the municipal area was analyzed using multiple buffer rings of 100 m, extending up to 1 kilometer. Similarly, the distance from rivers was calculated using 200 -m buffer intervals, extending up to 2 km. The satellite image is used to measure the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI).

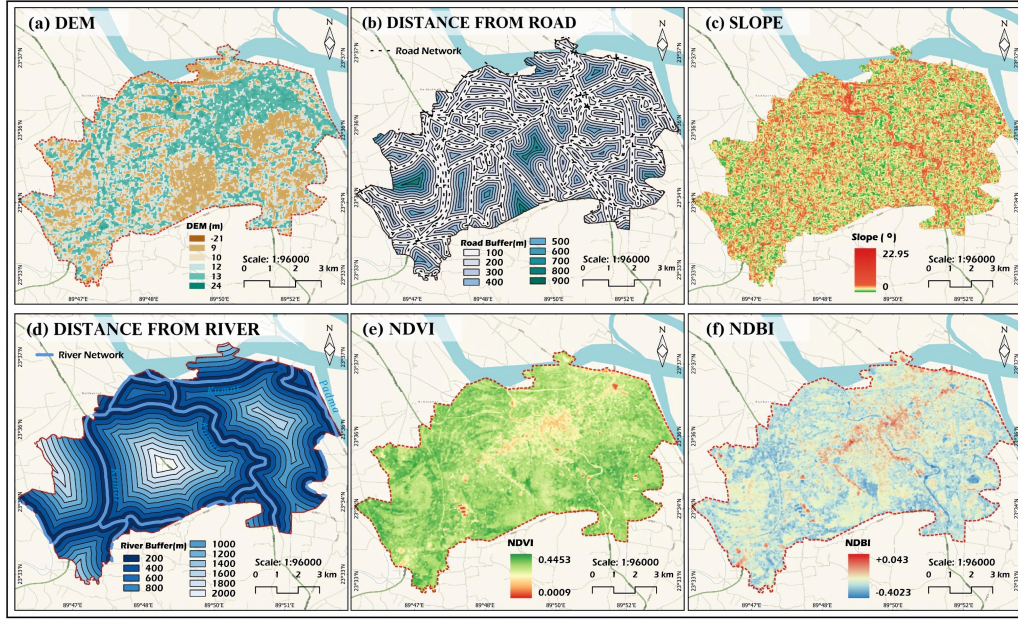


Figure 4. Manipulated datasets for model dependent variables: (a) Digital elevation model (DEM); (b) Distance from road; (c) Slope; (d) Distance from river; (e) NDVI; (f) NDBI.

2.7. NDVI and NDBI

This research used several spatial drivers, including NDVI and NDBI, to comprehensively understand the biophysical characteristics and anticipate urban development in the Faridpur municipality. These indices are vital for predicting urban environmental trends. To achieve this, we have used multiple spectral indices to assess the effects of biophysical parameters as dependent variables. A thorough description of these indices is provided in the following Equations (1) and (2) for biophysical indices.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (1)$$

$$\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}} \quad (2)$$

The NDVI values in the prepared dataset range from approximately 0 to $+0.4453$, while the NDBI values range from

approximately -0.4023 to $+0.043$. The indices were used as spatial predictors rather than as independent measures of future urbanization. In particular, higher NDVI generally indicates stronger vegetation cover, whereas relatively higher NDBI values are associated with more impervious or built-up surfaces^[31–34].

2.8. Multi-Temporal Data Processing and LULC Classification

The spectral signatures were used to classify the Landsat scenes with the Maximum Likelihood classifier into five LULC classes: water body, built-up, vegetation, cropland, and bare land for 2004, 2014, and 2024 (see **Table 2**). False Color Composite (FCC) images, merging mid-infrared, near-infrared, and blue bands, were used to generate training data. The resulting maps were assessed using confusion matrices,

user accuracy, producer accuracy, overall accuracy, and the Kappa coefficient. The same class definitions were retained for 2004, 2014, and 2024 so that the mapped differences represented changes in the same thematic categories.

2.9. Accuracy Assessment

Classification accuracy was assessed separately for 2004, 2014, and 2024 using 250 reference points, with 50 points allocated to each of the five LULC classes. Reference interpretation relied on available historical imagery in Google Earth Pro and visual assessment of the corresponding Landsat locations. The resulting confusion matrices were

used to calculate user accuracy, producer accuracy, overall accuracy, and Kappa statistics^[35, 36]. The 250-point design provides balanced class representation, but the historical reference data are less certain in heterogeneous urban–rural transition zones than contemporary field observations. The reported accuracies should therefore be interpreted as evidence of useful thematic discrimination rather than as error-free land-cover maps. Kappa statistics and an uncertainty matrix, expected among the most dependable quantitative methods, were used to evaluate map consistency.

To verify classification accuracy, the following Equations (3)–(5) were applied:

$$\text{User precision} = \frac{\text{Number of correctly classified pixels for a class}}{\text{Total number of pixels classified as that class (column total)}} \times 100 \quad (3)$$

$$\text{Producer precision} = \frac{\text{Number of correctly classified pixels for a class}}{\text{Total number of reference pixel for class (row total)}} \times 100 \quad (4)$$

$$\text{Overall precision} = \frac{\text{Number of correctly classified pixels}}{\text{Total of all reference pixels}} \times 100 \quad (5)$$

2.10. Change Forecasting with ANN Process

Future LULC was predicted using the MOLUSCE 4.1.0 tool, which combines methods like CA, ANN, Logistic Regression (LR), and Multi-Criteria Evaluation (MCE). These methods help study and predict how land use changes over time. Transitional Potential Modeling (TPM) and ANN were

used to predict LULC changes based on historical data due to their high accuracy. As illustrated in **Figure 5**, the ANN structure is like the human brain. It has a network of interrelated nodes that can recognize patterns and relations within data. By using the interrelationships, it can create complex spatial distribution analysis and change estimation^[28, 37].

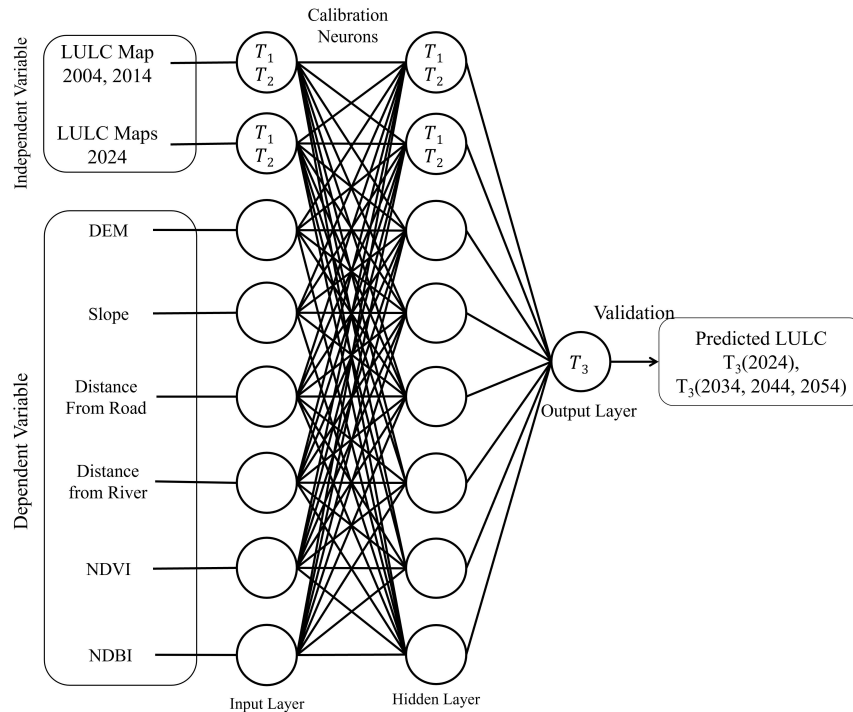


Figure 5. LULC prediction process in ANN model.

The ANN process begins with an input layer, where LULC maps from 2014 and 2024 are combined with six driving variables, such as DEM, slope, distance from road, distance from river, NDVI, and NDBI^[38–41]. The DEM in the study area ranges from a minimum of –21 m to a maximum of 24 m above mean sea level (MSL). Most of the area drops within the 12–24-m range, representing a mostly flat landscape. The closeness to major roads and the river network was examined using vector layers originating from LGED. Access to road networks is important for urban growth because it shapes where people settle and how infrastructure spreads. This district surrounds many waterbodies, and seasonal flooding occurs during the rainy season when rivers overflow into low-lying areas. As a result, people often choose higher ground to avoid flood risks. Slope is also important for predicting changes in land use and land cover, since elevation affects where people live and how the landscape changes^[42, 43].

To forecast land use for 2034, 2044, and 2054, the LULC maps from 2014 and 2024 serve as the primary references. The LULC conversions between two time points (T1 and T2) are added, deriving transition matrices and modification maps (see **Figure 5**). In the modeling phase, the number of hidden neurons was considered over the range of 5 to 20, and 10 was chosen as the optimal value in order to maximize accuracy without causing overfitting. Learning rates were tested across the range from 0.01 to 0.20, and a value of 0.10 was finally adopted in order to secure efficient and stable convergence. A momentum factor of 0.05 was selected from the range of 0.01 to 0.10 since it helped to reduce oscillations during the weight updates and kept the training stable. The maximum number of iterations was fixed at 200 (having been tested between 50 and 500) because the model errors levelled off by about 100 iterations. With regard to the dataset, a training-to-validation split of 70:30 was picked from a possible range of 60:40 to 80:20, as this provided the best compromise between model generalization and learning capacity. Lastly, the Sigmoid activation function was preferred to both ReLU and Tanh because of its reliable way of handling nonlinear relationships, and Mean Squared Error (MSE) was used as the loss function to make sure that the predictions remained consistent for the continuous environmental variables. The projected result at time T3 is fixed based on differences between the start and end years, allow-

ing the model to predict LULC changes over the next 10-year interval. The resulting outputs represent a continuation of the transition patterns learned from 2004–2024 and are therefore best interpreted as trend-based scenarios for 2034, 2044, and 2054 rather than forecasts that incorporate future policy or market shocks.

2.11. Model Calibration and Validation

Model validation was conducted within the MOLUSCE workflow by comparing a simulated LULC map with an observed reference map for a historical time step. **Figure 6** shows the learning curve of the ANN model, including the training and validation curves. The validation output includes overall agreement and Kappa statistics, such as the Kappa histogram and Kappa location. The reported overall agreement is 92.56%, with Kappa = 0.878, Kappa histogram = 0.9829, and Kappa location = 0.8940. These metrics indicate good agreement between the simulated and reference spatial patterns. However, they should not be interpreted as a guarantee that the 2054 scenario will have the same accuracy. Long-term projections accumulate uncertainty, and the future driving environment may differ from the historical period^[44, 45]. This distinction is important when interpreting the 2034–2054 scenarios.

2.12. Limitations and Uncertainty of Data

Several limitations affect the interpretation of the results. The Landsat 5 TM and Landsat 8/9 OLI/TIRS sensors have different radiometric characteristics. The study applied the same DOS1 atmospheric-correction workflow, common projection, common five-class legend, and consistent classification procedure, but did not apply a dedicated cross-sensor radiometric normalization^[46–48]. Therefore, some apparent changes may reflect residual sensor or preprocessing differences in addition to genuine land-cover change^[49–51]. The 30 m spatial resolution can mix land-cover types within a single pixel, especially along narrow roads, small ponds, fragmented vegetation, and peri-urban plots. This may cause underestimation or overestimation of small features and can contribute to confusion among built-up, bare land, cropland, and vegetation classes. The overall classification accuracy of 84.8–88.0% is reasonably useful for municipal-scale change analysis, but the lower 2024 accuracy and the relatively

weaker vegetation performance indicate that fine-scale transitions should be interpreted cautiously. Future work should combine field-based GPS observations, very-high-resolution

imagery, stratified reference sampling, and repeated independent validation to quantify class-specific uncertainty more rigorously^[52–55].

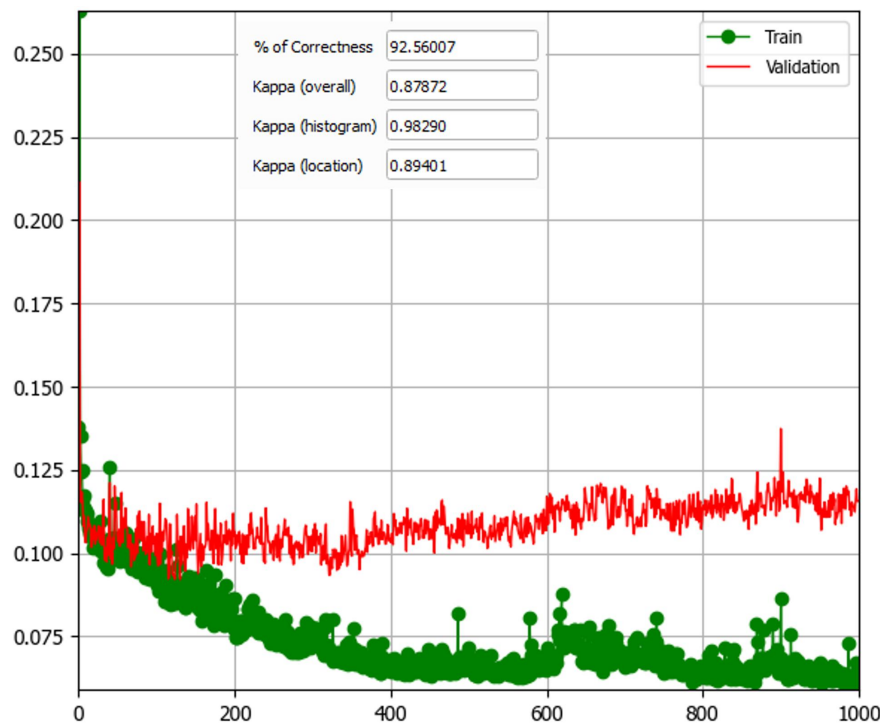


Figure 6. ANN learning curve with kappa statistics.

2.13. Scenario Interpretation for Long-Term Projections

The 2034–2054 outputs represent a continuation-of-trends scenario based on the transition relationships learned from 2004–2024. They do not explicitly simulate alternative policy, infrastructure, population, or land-market scenarios. Consequently, the projected maps should be interpreted as a baseline spatial scenario that identifies locations potentially exposed to continued development pressure. Alternative scenarios could be developed in future work by adding population density, land value, zoning, planned transport projects, industrial locations, flood-risk restrictions, and agricultural-protection rules.

0.835) for 2014, and 84.8% (Kappa = 0.81) for 2024. Producer accuracy is lowest for vegetation in 2004 (81.48%) and 2014 (79.63%), while vegetation and bare land also show greater confusion in 2024. This pattern is plausible for a heterogeneous municipality where homestead vegetation, small agricultural plots, exposed soil, and built-up surfaces can occur within or adjacent to the same 30 m pixel. The results are comparable with recent LULC studies using Landsat and machine-learning or hybrid approaches, but the present study should not claim that the maps are equivalent to global standards^[56–58]. Rather, the accuracy range indicates that the maps are sufficiently reliable for broad municipal-scale change analysis while retaining uncertainty at fine spatial scales.

3. Result and Discussion

3.1. Accuracy Assessment

The classification results in **Table 3** show overall accuracies of 88.0% (Kappa = 0.85) for 2004, 86.8% (Kappa =

3.2. Tracking Land Use Dynamics across Years

Figure 7 depicts substantial shifts in land-use patterns and advancing environmental dynamics. The LULC data from 2004, 2014, and 2024 show big changes in how land is used. The LULC changes are the result of internal transitions

rather than territorial expansion. More people, new buildings, and increased commercial activity were the main causes of the overall 7.31% increase. From **Table 4**, the built-up area increased from 2.18% in 2004 to 7.31% in 2024. The cropland decreased from 29.30% to 26.89%, and vegetation decreased from 55.97% to 53.84%. This indicates that land previously used for agriculture or covered by natural vegetation is being changed into urban or semi-urban landscapes.

By testing land cover over multiple years, it becomes apparent that land use dynamics are particularly evident in the post-2014 decade, underscoring the strong need for sustainable development and strategies. These outcomes clearly demonstrated that agricultural and vegetated lands are being transformed into urban or semi-urban areas. The trend became particularly robust after 2014, when urbanization accelerated.

Table 3. Accuracy assessment for the LULC of 2004, 2014, and 2024.

		Water Body	Built-Up	Vegetation	Cropland	Bare Land
2004	Commission Error	8%	14%	12%	14%	10%
	Omission Error	6.12%	12.24%	18.52%	12.24%	8.16%
	User Accuracy	92%	86%	88%	86%	90%
	Producer Accuracy	93.88%	87.76%	81.48%	87.76%	91.84%
	Overall Accuracy (%)			88%		
	Kappa Coefficient			0.85		
2014	Commission Error	16%	8%	14%	18%	10%
	Omission Error	4.55%	11.54%	20.37%	16.33%	11.76%
	User Accuracy	84%	92%	86%	82%	90%
	Producer Accuracy	95.45%	88.46%	79.63%	83.67%	88.24%
	Overall Accuracy (%)			86.80%		
	Kappa Coefficient			0.835		
2024	Commission Error	14%	10%	20%	14%	18%
	Omission Error	6.52%	15.09%	20.00%	17.31%	16.33%
	User Accuracy	86%	90%	80%	86%	82%
	Producer Accuracy	93.48%	84.91%	80.00%	82.69%	83.67%
	Overall Accuracy (%)			84.80%		
	Kappa Coefficient			0.81		

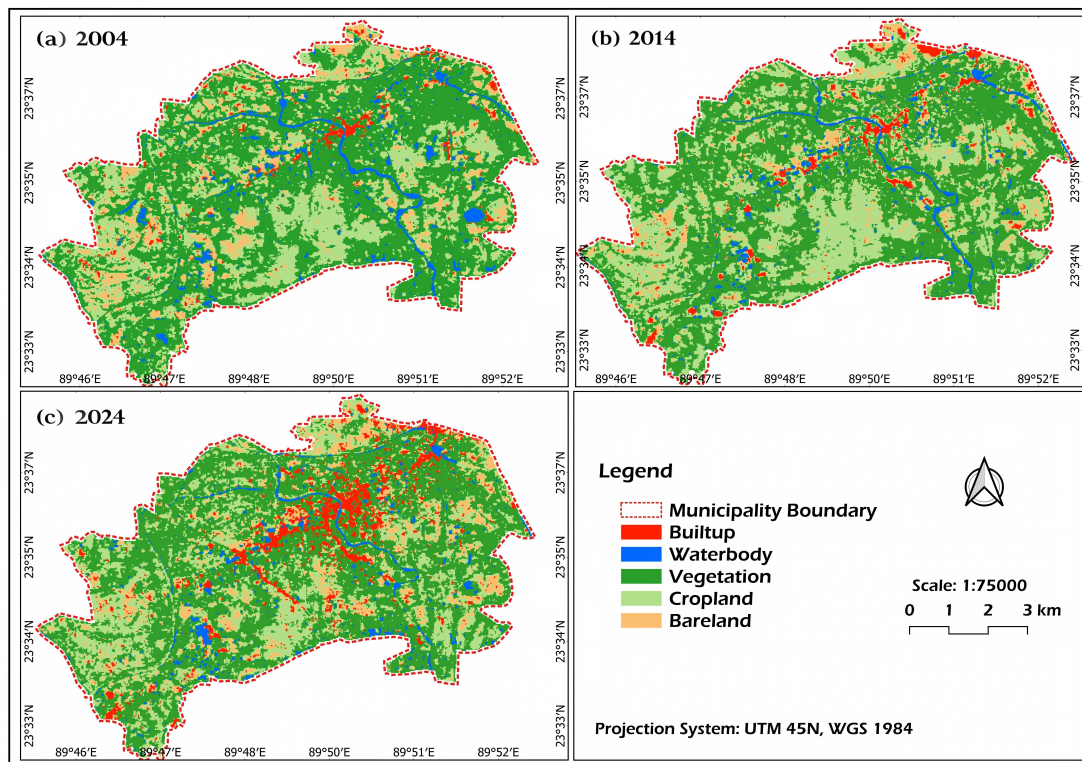


Figure 7. Multitemporal LULC classification: (a) 2004; (b) 2014; (c) 2024.

Table 4. Land cover distribution matrix (2004–2024).

Land Cover Types	2004		2014		2024		Change (%) (2004–2014)	Change (%) (2014–2024)	Change (%) (2004–2024)
	Area (km ²)	(%)	Area (km ²)	(%)	Area (km ²)	(%)			
Built-up	1.46	2.18	2.03	3.03	4.88	7.31	+0.85	+4.28	+5.13
Water body	2.86	4.29	2.14	3.20	2.25	3.37	−1.09	+0.17	−0.93
Vegetation	37.34	55.97	35.9	53.81	35.92	53.84	−2.15	+0.03	−2.12
Cropland	19.55	29.30	22.78	34.15	18.00	26.98	+4.85	−7.17	−2.32
Bare Land	5.51	8.26	3.87	5.80	5.67	8.49	−2.46	+2.69	+0.23
Total	66.72	100%	66.72	100%	66.72	100			

The observed conversion of cropland and vegetation to built-up and other transitional classes is consistent with findings from rapidly urbanizing cities in Bangladesh and elsewhere, where accessibility and development pressure can increase the demand for peripheral land^[59, 60]. In Faridpur, the pattern is particularly relevant because agricultural land and vegetated areas remain substantial components of the municipal landscape. The results therefore support planning approaches that direct new development toward already accessible and serviced areas while limiting fragmented conversion of productive agricultural and ecologically sensitive land.

3.3. LULC Multi-Temporal Change Assessment

The three maps from 2004, 2014, and 2024 provide a thorough comparison of LULC dynamics over two decades. In particular, the built-up area has changed the most, both in total size and percentage. It grew from 1.46 km² in 2004 to 4.88 km² in 2024, which is a 234.25% increase. The growth was slower between 2004 and 2014, with only 39.04% more built-up area, but much faster between 2014 and 2024, when it grew by 140.39%. In contrast, cropland and vegetation have gone down. Cropland shrank from 19.55 km² to 18.00 km² (a drop of 2.32%), and vegetation went down from 37.34 km² to 35.51 km² (a drop of 2.12%). These changes indicate that the urban footprint expanded rapidly after 2014 and that part of the expansion occurred on land previously classified as cropland or vegetation. Similar conversion patterns have been reported in other growing South Asian cities^[60–62].

The results should be interpreted as evidence of increasing land-use pressure rather than proof that every observed

class transition was caused by urbanization. Some transitions among cropland, vegetation, and bare land may reflect seasonal conditions, cropping cycles, construction phases, or classification uncertainty. The combination of increasing built-up land, declining cropland, and directional expansion nevertheless indicates a clear planning concern. Protection of productive agricultural land, retention of connected vegetation, and preservation of waterbodies should therefore be considered alongside infrastructure and housing demand in future municipal land-use planning.

3.4. Prediction of LULC for 2034, 2044, and 2054

ANN and CA were combined in the MOLUSCE plugin to derive the expected LULC scenarios for 2034, 2044, and 2054. It shows that Faridpur Municipality's urban growth has a steady pattern. Over the next three decades, there will be significant changes in built-up, vegetation, cropland, and other land types. The projected LULC changes presented in **Table 5** are spatially consistent with the patterns shown in **Figure 8**, which illustrates the corresponding distribution of future land-cover changes across the municipality. The polynomial trend shown in **Figure 9** has $R^2 = 0.9164$, indicating a strong statistical fit to the plotted built-up-area sequence; however, this R^2 should not be interpreted as a validation statistic or as proof that future urban growth is highly predictable. The CA-ANN validation statistics provide separate evidence of model agreement. Spatially, the simulated growth is concentrated around existing developed areas and accessible corridors, particularly toward the northeast and southwest. These patterns are broadly consistent with reported transport-oriented expansion in South Asian cities^[63–67].

Table 5. Projected LULC areas in 2034, 2044, 2054.

LULC Class	Estimated Area (km ²)			Estimated Area (%)		
	2034	2044	2054	2034	2044	2054
Built-up	6.52	8.23	10.03	9.77	12.34	15.04

Table 5. Cont.

LULC Class	Estimated Area (km ²)			Estimated Area (%)		
	2034	2044	2054	2034	2044	2054
Water body	2.64	2.34	2.28	3.96	3.50	3.42
Vegetation	34.97	34.26	33.55	52.41	51.34	50.28
Cropland	15.35	14.58	12.84	23.01	21.85	19.24
Bare Land	7.24	7.32	8.02	10.85	10.97	12.02
Total	66.72	66.72	66.72	100	100	100

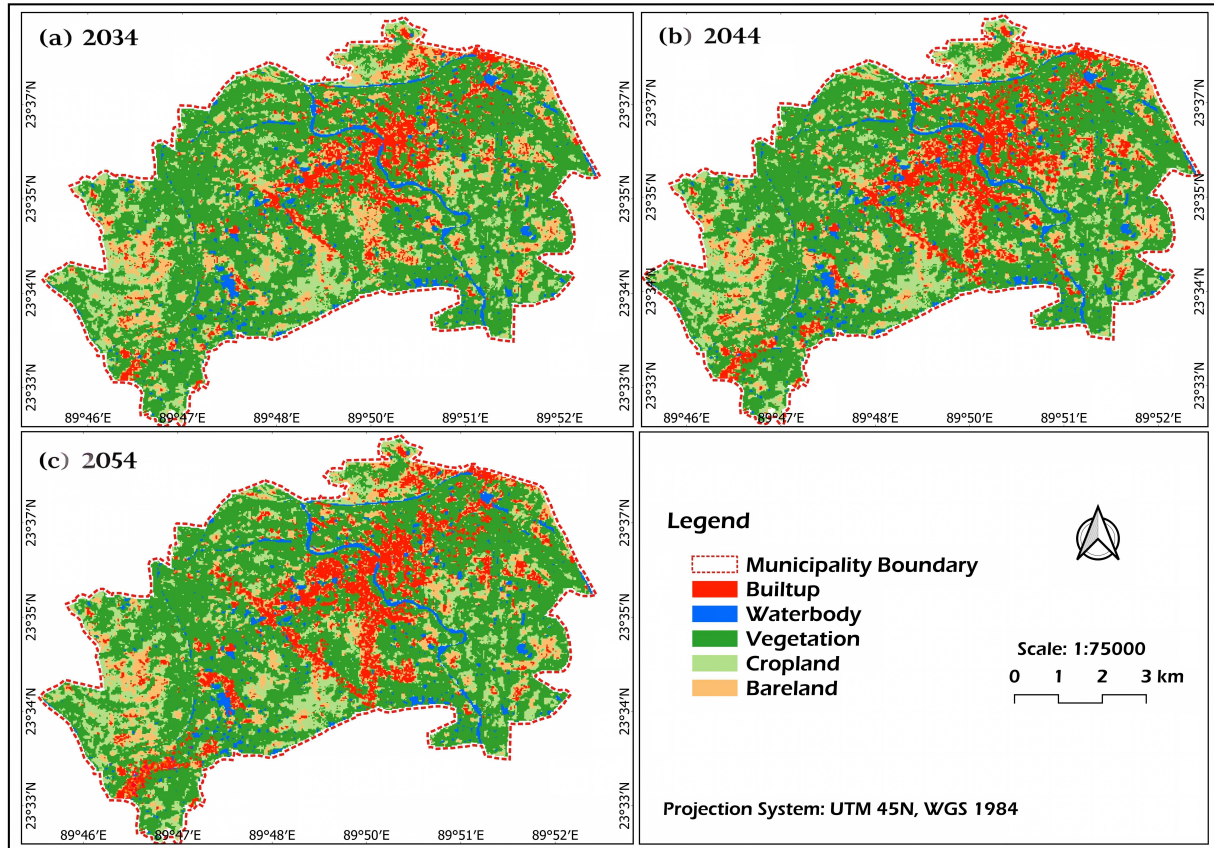


Figure 8. Simulated LULC of Faridpur Municipality: (a) 2034; (b) 2044; (c) 2054.

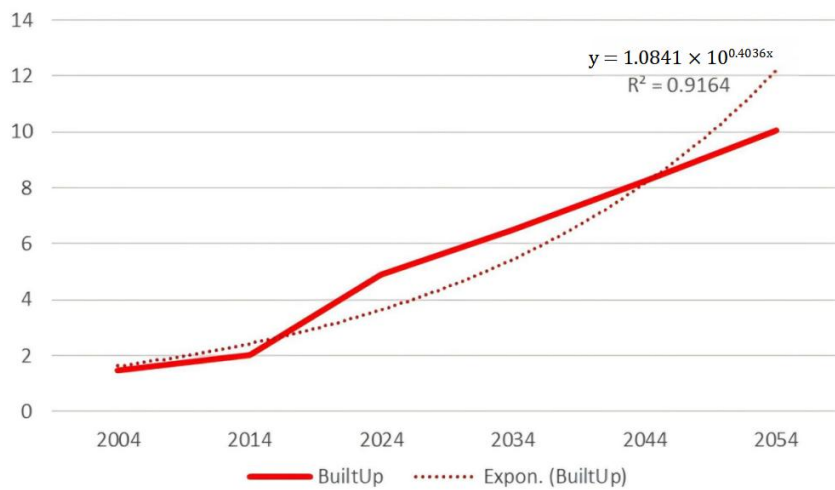


Figure 9. Urban area growth trendline with R^2 value.

It is expected that the municipality's vegetation cover, which was 52.41% in 2034, will drop to 50.28% by 2054. The percentage of cropland converted to built-up areas has decreased more sharply, from 23.01% (15.35 km²) in 2034 to 19.24% (12.84 km²) in 2054. This pattern is similar to findings by other researchers who described that cropland loss is a primary result of unplanned urban growth in developing countries, with long-term implications for food security and ecosystem services^[59, 64, 68]. Water body exposure is projected to contract somewhat from 3.96% in 2034 to 3.42% in 2054. Such falls have significant ecological impacts even though they are relatively small in spatial terms, especially in areas where surface water resources are essential for domestic and agricultural use. Growing from 10.85% in 2034 to 12.02% in 2054, bare land may be considered a transitional land state as it transitions from agricultural or vegetated land to urban use. The maps show how transportation infrastructure affects urban morphology and how built-up growth is concentrated around existing urban centers and transportation networks. In practice, a major transport investment, a new industrial or institutional development, a change in zon-

ing, a sudden increase in housing demand, or a land-market shift could accelerate, redirect, or suppress growth. Conversely, stronger agricultural protection, greenbelt policies, flood-risk zoning, or infrastructure restrictions could reduce conversion pressure. The 2054 map should therefore be used as a baseline trend scenario against which alternative policy scenarios can be evaluated.

3.5. Temporal LULC Transitions: 2024–2034

The expected dynamics of LULC between 2024 and 2034 are shown in the transition probability matrix in **Table 6**. The likelihood that a land cover class in 2024 will change into a different class by 2034 is indicated by each cell. While the off-diagonal values show changes between classes, the diagonal values stay the same. According to the results, built-up areas have a high persistence probability of 0.798, meaning that roughly 80% of the land that is urbanized in 2024 will still be urban in 2034. Significant shifts from cropland (0.037) and bare land (0.157) to built-up areas, however, highlight how urban areas are constantly growing at the expense of farming and undeveloped areas.

Table 6. Transition matrices of LULC from 2024 to 2034.

LULC Class		Land Use 2034				
		Built-Up	Water Body	Vegetation	Cropland	Bare Land
Land Use 2024	Built-up	0.798036466	0.001227209	0.043653576	0.059607293	0.097475456
	Water body	0.006092917	0.93335872	0.052170602	0.007616146	0.000761615
	Vegetation	0.02916875	0.014001	0.898207015	0.042884016	0.015739219
	Cropland	0.037487528	0.001425381	0.313203782	0.515845489	0.13203782
	Bare Land	0.157457729	0.000452899	0.039402174	0.129981884	0.672705314

With a probability of 0.933, water bodies are stable and are rarely transformed into other types of land. Seasonal land use or invasions may be caused by slight changes in cropland (0.008) and vegetation (0.052). Though small areas are expected to become cropland (0.043), built-up areas (0.029), or bare land (0.016), the vegetation is also stable (0.898). This pattern shows a slow fragmentation of vegetative cover, similar to what has been seen in peri-urban areas of Bangladesh^[69]. Cropland is the least stable (0.516), and it will change. Nearly half of the cropland is expected to shift to other types, mainly vegetation (0.313), bare land (0.132), and built-up areas (0.038). This conversion creates pressure on agricultural land, raising food insecurity and unsustainable land management^[59]. Bare land shows moderate (0.673) but substantial changeovers toward built-up

(0.157) and cropland (0.130). This underlines its role as a transitional zone that is highly susceptible to urban invasion and agricultural expansion^[70]. Based on the transition matrix, urban extension in the study area will continue to occur mainly at the expense of agricultural land and bare land. At the same time, water bodies and vegetation remain relatively unchanged. These findings suggest that without policy-making, the current transformation of productive croplands into built-up areas may have adverse implications for regional sustainability.

3.6. Analysis of Municipal Urban Development

The analysis of urban development patterns suggests a spatial and temporal strengthening of built-up land, mostly in the last decade of the study period. **Figures 10 and 11**

illustrate the ward-wise urban area density from 2004 to 2034 in Faridpur Municipality, which shows a clear trend of advancing urban extension, with changing rates of development across the municipality. Most of the wards have faced a continuous increase in urban cover from 2004 to 2014, followed by faster growth from 2014 onwards, showing strengthened development activities in the last decade. Jhiltuli (Ward No. 20), Goalchamat (Ward No. 16), and East Khabaspur (Ward No. 15) are seen with higher growth rates. These are located centrally, and Jhiltuli shows the highest estimated urban percentage of 69.38% by 2034. It also serves as a central commercial and residential hub. Goalchamat and East Khabaspur also show substantial expansion, hav-

ing 59.39% and 45.05% of urban density, respectively, by 2034. This has happened due to the housing structures in this city. Some other wards, including Badarpur (Ward No. 06) and Raghunandanpur (Ward No. 09), depict swift late-stage growth, proposing current urban sprawl towards the municipal fringe. Gopalpur (Ward No. 19) and Bil Mamudpur (Ward No. 21) are moderately growing and show stable expansion, with Gopalpur reaching 26.87% in 2024. On the contrary, slowly growing wards, such as Kafura (Ward No. 27) and Bil Mamudpur (Ward No. 26), uphold slight urban coverage, possibly due to environmental limits, agricultural land retention, accessibility, rurality, or lower infrastructure investment.

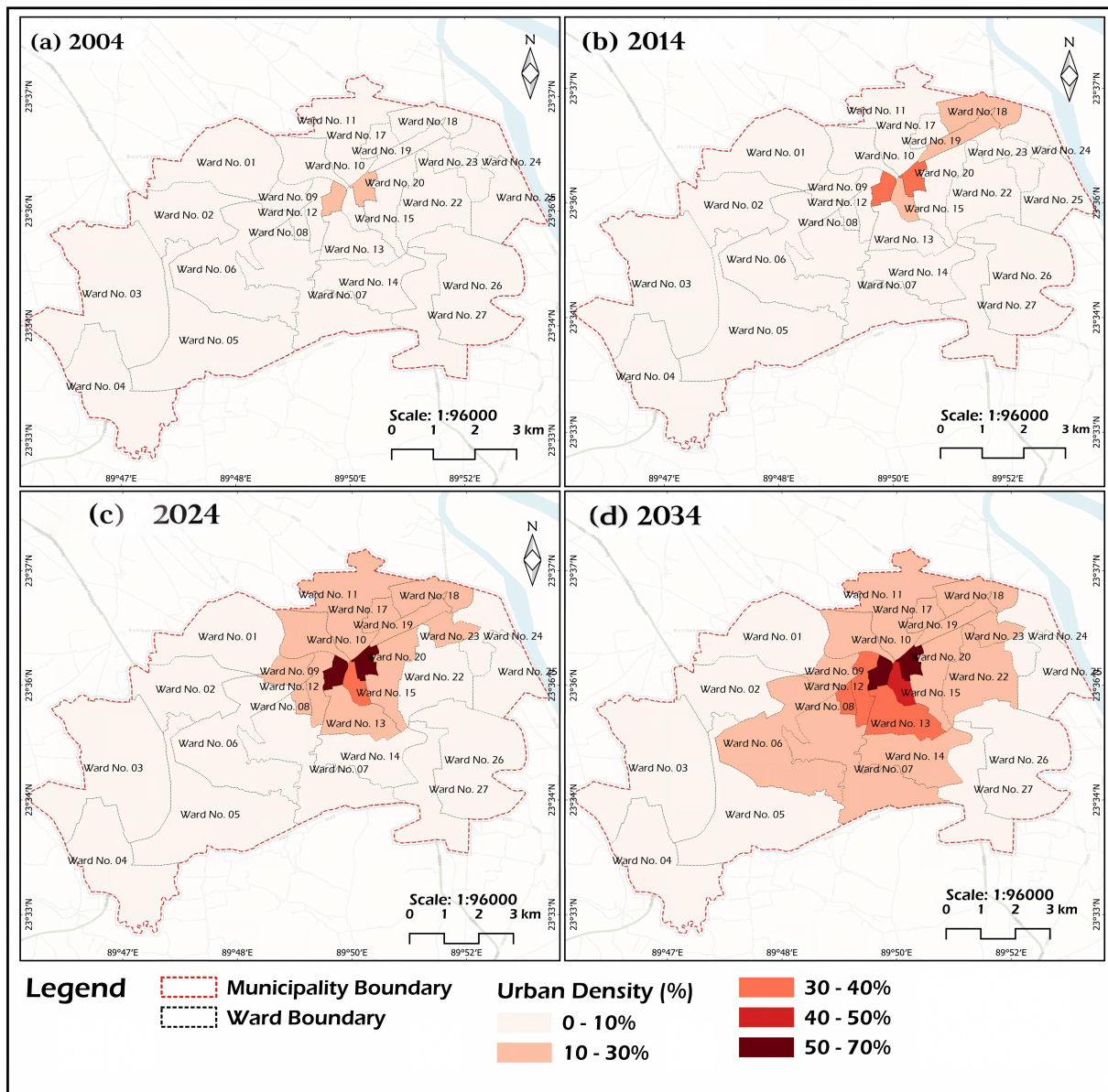


Figure 10. Municipality ward wise urban density map.

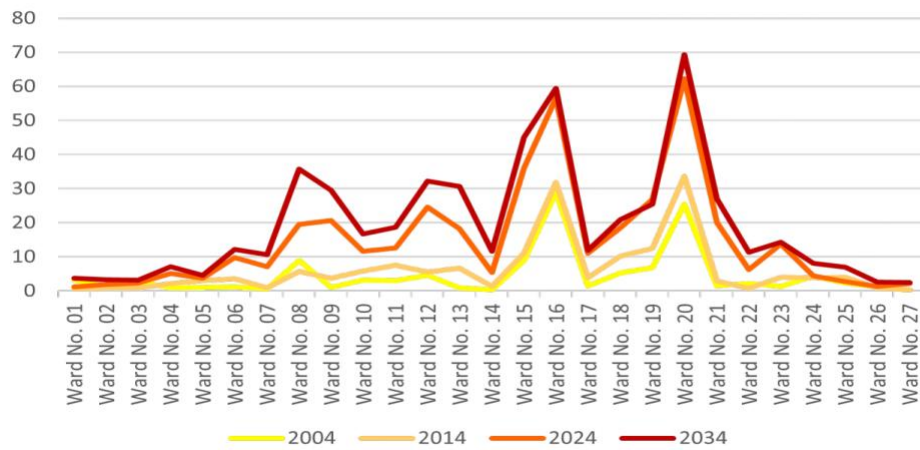


Figure 11. Percentage of urban density of 27 wards of Faridpur Municipality.

Between 2004 and 2024, the built-up area grew from 1.46 km² to 4.88 km², making up 5.13% of the total municipal area. Most of this growth replaced cropland and vegetation. Cropland decreased from 19.55 km² to 18.00 km², a net loss of 2.32%. Vegetation also fell by 2.12%. Water bodies show a small net loss of 0.93%, likely due to development. Bare land changed over time, ending with a 0.23% increase, possibly from ongoing construction. The city center is now densely built, with new growth in the north and northeast. Losing water bodies and green spaces reduces opportunities for recreation, mental well-being, and cooling, and limits groundwater recharge. Unplanned urban growth can cause traffic congestion, air pollution, and noise pollution that negatively affect respiratory health, increase stress, and reduce work efficiency. In addition, inadequate urban services can result in poor housing conditions, inefficient waste management, and limited access to healthcare^[71, 72]. If these trends continue in this municipality, shrinking farmland, less vegetation, and a growing population will likely make these issues worse.

3.7. Directional Dynamics of Urban Development

The directional study of the municipality's urban growth from 2004 to 2034 in **Figure 12** and **Table 7** exposes an extremely irregular spatial distribution of extension. The built-up area expanded from 1.45 km² in 2004 to 6.89 km² in 2034, which resulted in a fivefold growth over thirty years. The vital extension happened in the northeast (NE), southwest (SW), and east (E) sectors. The NE direction grew from

0.25 km² in 2004 to 1.04 km² in 2034, while the SW direction increased from 0.44 km² to 2.01 km². In the same way, the E direction increased from 0.22 km² to 0.86 km². This indicates that these areas became growth hotspots, which are generally affected by transportation networks, access to open space, and new development plans. Such sectoral growth along preferred axes is relevant to outcomes in other Asian cities, where transport routes play a serious role in creating expansion. So, the land development along major transportation corridors should be carefully regulated to protect agricultural land and direct urban growth. Moderate but stable growth was seen in the north (N) and south (S). The N sector grew from 0.10 km² in 2004 to 0.42 km² in 2034, while the S increased from 0.02 km² to 0.92 km². The post-2014 hastening in these directions proposes that urbanization pressure steadily expanded externally as the core and high-demand sectors became saturated. This pattern reveals the “leapfrog expansion” process described in urban sprawl studies, where new settlements arise in marginal zones as central areas become compactly developed^[73–75].

On the other hand, the northwest (NW) and west (W) faced comparatively limited growth. The NW increased from 0.08 km² to 0.29 km² during 2004–2034, while the W direction only extended by 0.71 km² by 2034. The limited growth in these areas results from physical barriers, which include water bodies and flood-prone areas, and incomplete infrastructure development. Parallel constraints have been recognized in Dhaka, Jakarta, and Karachi, where natural and socio-economic factors formed the unequal urban footprint^[2, 65, 76]. The spatial arrangement of the extension shows a sectoral rather than a concentric growth pattern. Cities often

grow in certain areas where transport networks and business centers push development in particular directions. This kind of growth is a sign of unplanned sprawl, which leads to scattered neighborhoods and uneven access to services^[67, 77]. The rapid growth in NE, SW, and E areas creates strain on infrastructure, but the slow growth in NW and W areas results

in underused land resources. The distance between urban and rural areas will create greater socioeconomic disparities, lead to traffic jams, and accelerate the destruction of agricultural land and natural environments. Sustainable growth needs the combination of these trends through land zoning, greenbelt strategies, and transit-oriented growth.

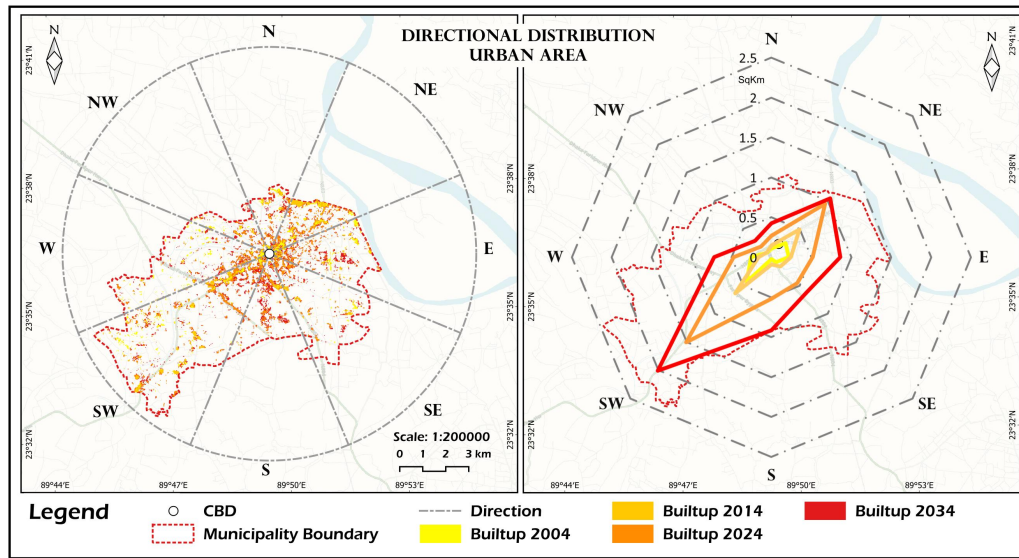


Figure 12. Left: Built-up area expansion between 2004 and 2034; Right: Expansion patterns of built-up areas in km².

Table 7. Directional urban expansion rate of Faridpur Municipality.

Year	Direction of Urban Expansion (km ²)								Total
	N	NE	E	SE	S	SW	W	NW	
2004	0.107232	0.249413	0.219806	0.083788	0.021939	0.440383	0.253653	0.0795	1.45
2014	0.149201	0.494614	0.242334	0.160204	0.089823	0.640464	0.160411	0.085725	2.02
2024	0.268807	0.948798	0.517066	0.456855	0.517518	1.509553	0.47196	0.188052	4.87
2034	0.42411	1.042958	0.86389	0.623463	0.916248	2.010893	0.718594	0.290966	6.89

3.8. Justification of CA-ANN Simulation

The CA-ANN model validation overall classification accuracy reached 92.56%, which is relatively good for urban growth prediction. Moreover, the Kappa coefficient (0.878) indicates a robust level of agreement between the predicted and observed maps. According to Mas et al.^[44], Kappa values between 0.81–1.00 represent “almost perfect agreement”, which indicates the strength of the simulation results. Beyond the overall accuracy, the Kappa (histogram) value of 0.9829 indicates that the model was very accurate in regenerating the quantitative distribution of land cover categories. In the same way, the Kappa (location) value of 0.8940 focuses on the model’s robust ability to handle the spatial distribution of land use change, confirming that anticipated urban

extension closely ties to the real observed growth patterns. These indicators indicate that the CA-ANN model not only envisages the right quantity of LULC conversions but also assigns them in spatially representative arrangements, which is a critical constraint for urban growth simulation.

The better performance of the model can be attributed to its incorporation of neural network learning with the spatial dynamics of cellular automata. The ANN constituent efficiently recognizes complex, nonlinear relationships between dynamic factors, e.g., closeness to roads, river, elevation, slope, NDVI, NDBI, while the CA outline integrates neighborhood effects, taking the transmissible nature of urban extension^[78, 79]. This hybrid approach has been broadly documented as superior to outdated CA or regression-based models^[58, 80]. Some studies accept the efficiency of

CA-ANN in urban and regional growth simulation. For instance, Pijanowski et al. (2002)^[81] illustrated that CA-ANN outperformed logistic regression models in predicting land use change in the United States. Likewise, Tayyebi et al. (2011)^[82] found that CA-ANN produced more representative spatial patterns than CA-Markov in Iran. These findings are consistent with the current results and support the use of CA-ANN for long-term LULC predictions. This model's strengths lie in its performance and its ability to generate realistic projections of urban development. It produces reliable spatial results by following past growth trends. However, as with most machine-learning methods, the accuracy of CA-ANN is dependent on the quality and the realistic level of input variables^[83]. The six predictors were chosen to capture accessibility, topographic suitability, hydrological constraints, and existing land-cover conditions. The absence of consistent historical population-density and land-price data limits the socioeconomic representation of the model. Insufficient or biased driving variables may border transferability throughout the regions. The strong statistical performance of the CA-ANN model supports its use for LULC prediction in this study.

4. Conclusions

This study examined LULC transformations in Faridpur Municipality from 2004 to 2024. The CA-ANN model was used to predict urban development patterns through 2054. The results showed that the municipal area experienced major changes because built-up areas expanded from 2.18% in 2004 to 7.31% in 2024 through the loss of agricultural land and vegetation. Cropland and vegetation face the highest risk of conversion to built-up areas. Also, the directional analysis indicates that the northeast and southwest areas will experience the most development due to their better infrastructure and connectivity. This model produced reliable predictions and was able to achieve 92.56% overall accuracy and a 0.878 Kappa coefficient. The model predicts that built-up land expansion will continue until 2054, reaching 15.04%. These trends indicate rising human activity, which aligns with the urban development patterns observed in other secondary cities across Bangladesh. The uncontrolled spread of built-up areas threatens to damage both food production and environmental health and climate adaptation capabilities. The expected

reduction in cropland and vegetation loss and water body decline will make urban heat islands worse while decreasing groundwater replenishment and increasing flood susceptibility. The uncontrolled urban expansion within the city will create more traffic congestion while producing worse air quality and increased noise pollution, which will negatively affect resident health through respiratory problems, heat-related illnesses, and waterborne diseases.

The strategic position of Faridpur, along with its rising economic value, requires strategic urban planning to protect long-term social and economic stability. The study highlights the urgent need for local administrations such as Faridpur Pouroshava, LGED, and the Government to devise sustainable urban planning, develop green infrastructure, check population increase, and implement agricultural land protection policies in Faridpur. To protect cropland, vegetation, and waterbodies, land-use zoning regulations are essential for achieving sustainable urban development. Using the CA-ANN geospatial tools in municipal planning will enable local authorities to predict future land-stress points, develop master plans, and implement preventive measures. The city will transform into a sustainable, inclusive urban center that will serve as a model for other secondary cities in Bangladesh through data-based decision systems and modern geospatial planning tools.

Author Contributions

Conceptualization, R. and E.K.; methodology, R.; software, R.; validation, R., E.K. and A.A.S.; formal analysis, R.; investigation, E.K. and A.A.S.; resources, R.; data curation, R.; writing—original draft preparation, R. and E.K.; writing—review and editing, R. and E.K.; visualization, R.; supervision, E.K.; project administration, E.K. and A.A.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this work, the authors used the Grammarly tool in order to improve grammar and language readability. No AI tools were used for data analysis, interpretation, or generation of scientific content. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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