Temporal Dynamics of Land Use Land Cover Change and Future Prediction Analysis Using Geospatial Techniques for Tamluk, Purba Medinipur, West Bengal

Sonamoni Mondal[1], Dr. Anindya Basu[2*]

[1]Research Scholar, Department of Geography, Diamond Harbour Women's University, Diamond Harbour, West Bengal, India
[2*]Associate Professor, Department of Geography, Diamond Harbour Women's University, Diamond Harbour, West Bengal, India

Abstract
Land Use Land Cover (LULC) mapping is a fundamental aspect of spatial analysis in fields such as urban planning, environmental management, agriculture, forestry, and climate change studies and the basic information for planning and management at various administrative levels. Research on the temporal changes in LULC patterns and the simulation of future scenarios provides a comprehensive understanding of both current and future development trends, especially for the areas undergoing rapid changes.
The study involving Tamluk Community Development block of Purba Medinipur district, West Bengal, India uses the MOLUSCE plugin of QGIS (Quantum Geographic Information System) for LULC prediction. Digital Elevation Model (DEM), aspect, slope and distance from roads are the spatial variables which are used to learn processes of the artificial neural network and cellular automata (ANN-CA) model within MOLUSCE to project future LULC (i.e. of 2031). LULC maps of 1991, 2001, 2011 and 2021 are used as basic building blocks. Using the 2011 and 2021 LULC maps along with spatial variable maps, the 2031 LULC map was simulated. In the validation phase, the predicted LULC for 2031 achieved 89.43% accuracy and an overall kappa of 0.86, indicating a high degree of prediction accuracy. The predicted LULC for the years 2031 shows notable growth in water bodies (especially fish ponds/bheris) and built-up areas, with increase rates of 22.33% and 10.13% respectively in 2031. The study will probably assist the local administrative bodies and decision-makers in creating optimal land use plans and management strategies ensuring sustainability.

Keywords: LULC, Tamluk, MOLUSCE, CA-ANN, BHERIS

Introduction
Land Use and Land Cover (LULC) mapping is a fundamental aspect of spatial analysis and plays a vital role in geography, environmental management, urban and regional planning, agriculture, forestry, and climate change studies (Anderson et al., 1976; Lambin et al., 2001; Turner et al., 2007). Land use refers to the manner in which human beings utilize and manage land resources for various economic, social, and environmental purposes, including agriculture, settlements, industries, transportation, and forestry, whereas land cover represents the physical and biological features that exist on the Earth's surface, such as forests, croplands, water bodies, wetlands, grasslands, and built-up areas (Di Gregorio & Jansen, 2000; FAO, 1998). Although land use and land cover are distinct concepts, they are closely interrelated because changes in human activities often result in corresponding changes in land cover (Lambin et al., 2003).
Accurate mapping and continuous monitoring of Land Use and Land Cover are essential for understanding the spatial distribution and temporal dynamics of landscapes. LULC information provides a scientific basis for sustainable land resource management, environmental monitoring, biodiversity conservation, disaster risk reduction, agricultural planning, and regional development (Jensen, 2015; Weng, 2012). Rapid population growth, urbanization, industrialization, infrastructure development, agricultural intensification, and climate change have accelerated land use transformations across the world (Foley et al., 2005; Seto et al., 2012). These changes significantly affect ecosystem services, biodiversity, hydrological processes, carbon storage, and the livelihoods of local communities (MEA, 2005; Ellis & Pontius, 2011). Consequently, the assessment of LULC dynamics has become increasingly important for promoting sustainable development and ensuring the efficient utilization of natural resources (Lambin & Geist, 2006).
Recent advances in Remote Sensing (RS), Geographic Information Systems (GIS), and geospatial technologies have greatly improved the accuracy and efficiency of LULC mapping (Jensen, 2015; Lillesand, Kiefer, & Chipman, 2015). Multi-temporal satellite imagery from platforms such as Landsat and Sentinel enables researchers to monitor historical land use changes, detect landscape transformations, and evaluate environmental impacts over time (Wulder et al., 2019; Drusch et al., 2012). Furthermore, predictive spatial modelling techniques, including Cellular Automata (CA), Markov Chain analysis, Artificial Neural Networks (ANN), and integrated models such as Cellular Automata–Artificial Neural Network (CA–ANN), have enhanced the capability to simulate and forecast future land use scenarios (Clarke et al., 1997; Eastman, 2016; Subedi et al., 2013). These models incorporate historical LULC data along with socio-economic, environmental, and infrastructural factors to predict future landscape dynamics, thereby supporting evidence-based planning and sustainable land

management.
In recent decades, Tamluk Community Development Block in Purba Medinipur district of West Bengal has experienced significant changes in its land use and land cover pattern due to both natural and anthropogenic factors. Traditionally, agriculture has been the dominant land use in the region because of its fertile alluvial soils and favourable deltaic environment. However, increasing urban expansion, infrastructure development, population pressure, and the rapid growth of inland aquaculture have gradually transformed the landscape. Large areas of agricultural land, particularly low-lying and waterlogged fields, have been converted into fish ponds owing to the comparatively higher economic returns from aquaculture (Government of West Bengal, 2023; Census of India, 2011). Simultaneously, the region is highly vulnerable to cyclones, flooding, tidal inundation, waterlogging, and soil salinity resulting from its proximity to the Bay of Bengal, particularly following major cyclonic events such as Aila (2009), Amphan (2020), and Yaas (2021) (IPCC, 2022; Government of West Bengal, 2023). These environmental stresses have reduced agricultural productivity, altered land use practices, and accelerated the conversion of croplands into aquaculture.
The changing land use pattern has important implications for agricultural production, food security, water resources, biodiversity, ecosystem stability, and rural livelihoods (Foley et al., 2005; MEA, 2005). Unplanned and uncontrolled land conversion may result in the loss of productive agricultural land and increased environmental degradation. Despite the visible transformation of the landscape, a comprehensive assessment of the spatial and temporal dynamics of LULC in Tamluk Block and its future trajectory remains limited. Understanding the magnitude, pattern, and driving forces of these changes is therefore essential for sustainable land-use planning and environmental management.
The primary aim of this study is to analyze the historical Land Use and Land Cover (LULC) dynamics and predict future land use patterns in Tamluk Community Development Block using Remote Sensing, Geographic Information System (GIS), and spatial modelling techniques. The study seeks to understand the nature, extent, and direction of landscape transformation and to provide scientific information for sustainable land-use planning and environmental management.

Overview of the Study Area
Tamluk Community Development (CD) Block is situated in Purba Medinipur district of West Bengal and is closely associated with Tamluk town, the administrative headquarters of the district. Geographically, the study area lies in the lower Ganges Delta and is located approximately between 22°15′N and 22°24′N latitudes and 87°48′E and 87°57′E longitudes. The region forms an important part of the deltaic landscape of southern West Bengal and has considerable geographical significance because of its close relationship with riverine systems, agricultural land, wetlands, and inland water resources. Tamluk also has considerable historical importance. Historically known as Tamralipta, the area developed as an important ancient port and centre of trade, settlement, and maritime activities in eastern India, particularly during the Mauryan period.
The physical landscape of Tamluk CD Block is predominantly flat and low-lying, with an average elevation of approximately 7 m above mean sea level. The terrain is characterized by extensive floodplains, wetlands, ponds, canals, and agricultural fields. Such a low-lying deltaic setting has played an important role in shaping the land-use structure and livelihood systems of the region. The drainage network is associated with several important rivers and channels, including the Rupnarayan, Haldi, Rasulpur, Bagui, and Keleghai. These river systems contribute significantly to agricultural production, surface-water availability, inland fisheries, aquaculture, and the overall ecological functioning of the region. The interaction between riverine processes and human activities has also influenced the spatial distribution and temporal transformation of land-use and land-cover categories.
The climate of Tamluk is characterized by a tropical monsoon regime, with three broad seasons—summer, monsoon, and winter. Summer temperatures may reach approximately 35–40°C, whereas winter temperatures generally range between 12–25°C. The region receives substantial rainfall, generally concentrated during the southwest monsoon between June and September. The combination of high rainfall, low elevation, and extensive drainage networks contributes to the region's agricultural potential but also increases its susceptibility to waterlogging and flooding. Owing to its geographical position and proximity to the coastal zone of the Bay of Bengal, the area is vulnerable to cyclones, heavy rainfall, flooding, tidal inundation, and storm surges. These hazards periodically affect agricultural land, settlements, water resources, fisheries, aquaculture, and rural livelihoods and consequently contribute to changes in land-use practices and livelihood strategies.
The soils of the Tamluk region are predominantly alluvial in origin, developed through the deposition of sediments associated with the Ganges–Brahmaputra deltaic system and local river processes. The soils are generally deep and fertile, with medium to fine textures, making them suitable for intensive agricultural activities. However, low-lying areas may experience seasonal waterlogging, while flood and tidal processes can contribute to localized salinity problems. Such environmental conditions create a complex relationship between agriculture and aquatic-based activities. In particular, areas affected by persistent waterlogging or other forms of land degradation may become increasingly suitable for fish ponds and aquaculture, thereby influencing the spatial transformation of agricultural land into water bodies.
According to the 2011 Census of India, Tamluk CD Block had a total population of 217,776, comprising 207,064 rural and 10,712 urban residents. The population consisted of approximately 112,458 males and 105,318–105,398 females, with a sex ratio of approximately 937 females per 1,000 males. About 95.1% of the total population lived in rural areas, highlighting the predominantly rural character of the block. The total literacy rate was

approximately 87.06%, with rural and urban literacy rates of about 86.9% and 90.2%, respectively. The block contained two census towns and 99 villages, further emphasizing its predominantly rural settlement structure.

Agriculture has traditionally been the principal economic activity and livelihood base of the population of Tamluk CD Block. However, the rural economy has gradually diversified through the expansion of inland fisheries, aquaculture, trade, transport, small-scale business, agricultural labour, and other non-farm activities. Census-based occupational information indicates that a considerable section of the working population remains associated with cultivation and agricultural labour, although livelihood diversification has become increasingly important in the changing rural economy. The interaction between agricultural practices, water resources, fisheries, settlement expansion, and environmental hazards makes Tamluk an appropriate geographical setting for examining rural transformation.
The physical and socio-economic characteristics of Tamluk CD Block make it particularly suitable for analysing spatio-temporal Land Use and Land Cover (LULC) dynamics, inland fisheries expansion, agricultural transformation, livelihood diversification, and sustainable regional development. Its low-lying deltaic terrain, extensive river and canal networks, fertile agricultural land, growing importance of inland fisheries and aquaculture, and exposure to climatic and hydrological hazards together provide a suitable framework for investigating the interaction between environmental change and socio-economic transformation. Therefore, Tamluk CD Block has been selected as the study area for analysing changes in land use and land cover and their implications for fisheries development, livelihood transformation, and sustainable rural development.

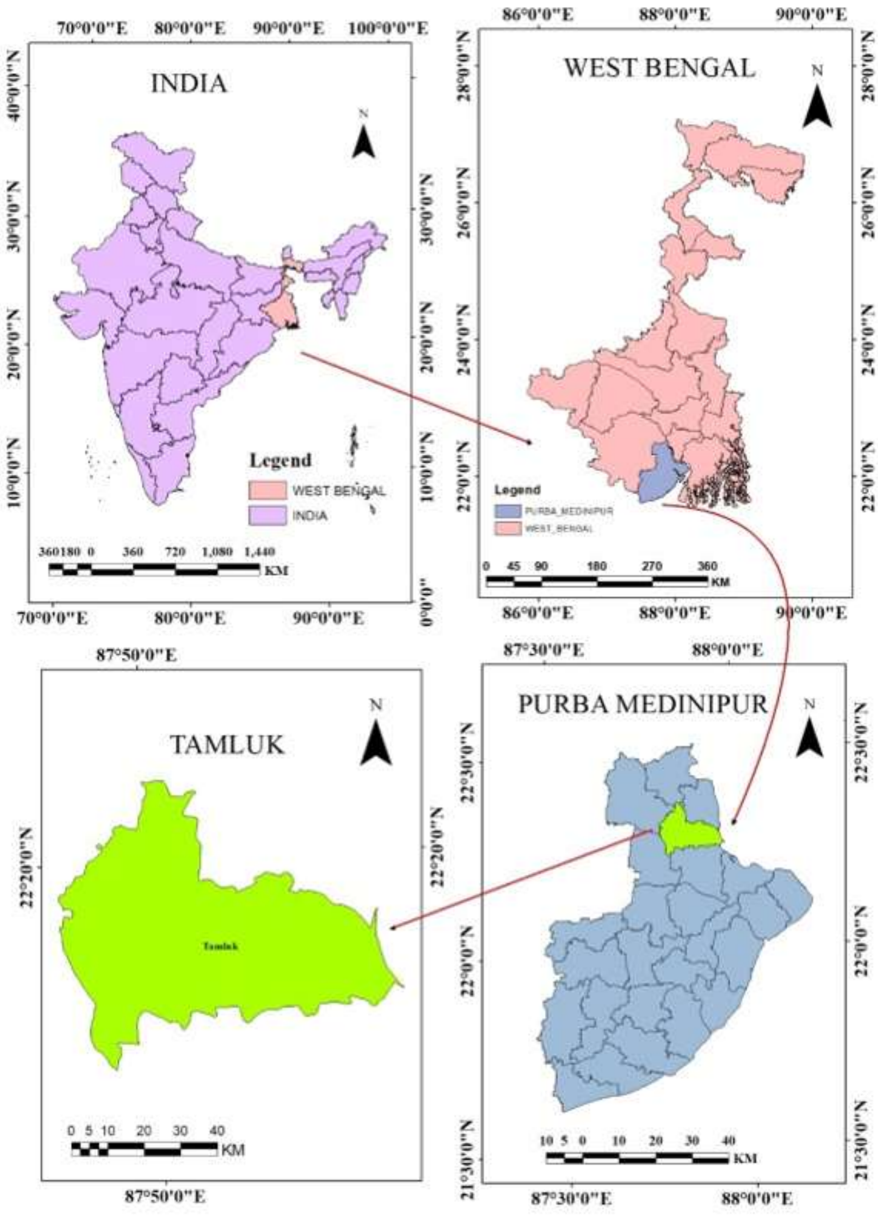

Fig 1: Location map of the study area – Tamluk Community Development Block, Purba Medinipur, West Bengal

Materials and Methods

Data collection

The present study is based entirely on secondary data obtained from reliable government and open-access geospatial databases. Multi-temporal satellite imagery comprising Landsat 5 Thematic Mapper (TM) images for 1991, 2001, and 2011, and Landsat 8 Operational Land Imager (OLI) imagery for 2021, each with a spatial resolution of 30 m, was acquired from the United States Geological Survey (USGS) Earth Explorer. These datasets were used for Land Use and Land Cover (LULC) classification and change detection analysis.
A 30 m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was obtained from the USGS Earth Explorer to generate elevation and slope information for the study area. In addition, road network data were downloaded from OpenStreetMap (OSM) and used as one of the driving factors for future LULC prediction.
Image processing, LULC classification, and change detection analysis were carried out using ArcGIS 10.8. Future Land Use and Land Cover (LULC) scenarios for 2031 were predicted using QGIS (Version 3.34.11) with the MOLUSCE (Modules for Land Use Change Evaluation) plugin based on the Cellular Automata–Artificial Neural Network (CA–ANN) model.

Table 1: Satellite imagery details for the study region, Tamluk Community Development Block, Purba Medinipur, West Bengal (1991 to 2021)

Satellite	Sensor	Path	Row	Cell size	Date of Acquisition	Projection
LANDSAT_ 4-5	ETM	138	44	30	30-Sep-91	WGS-1984-UTM ZONE
LANDSAT_ 4-5	ETM	138	45	30	13-02-01	
LANDSAT _4-5	ETM	138	45	30	8-Nov-11	
LANDSAT_ 8	OLI-TIRS	138	45	30	7-Nov-21	

Source: USGS Earth Explorer

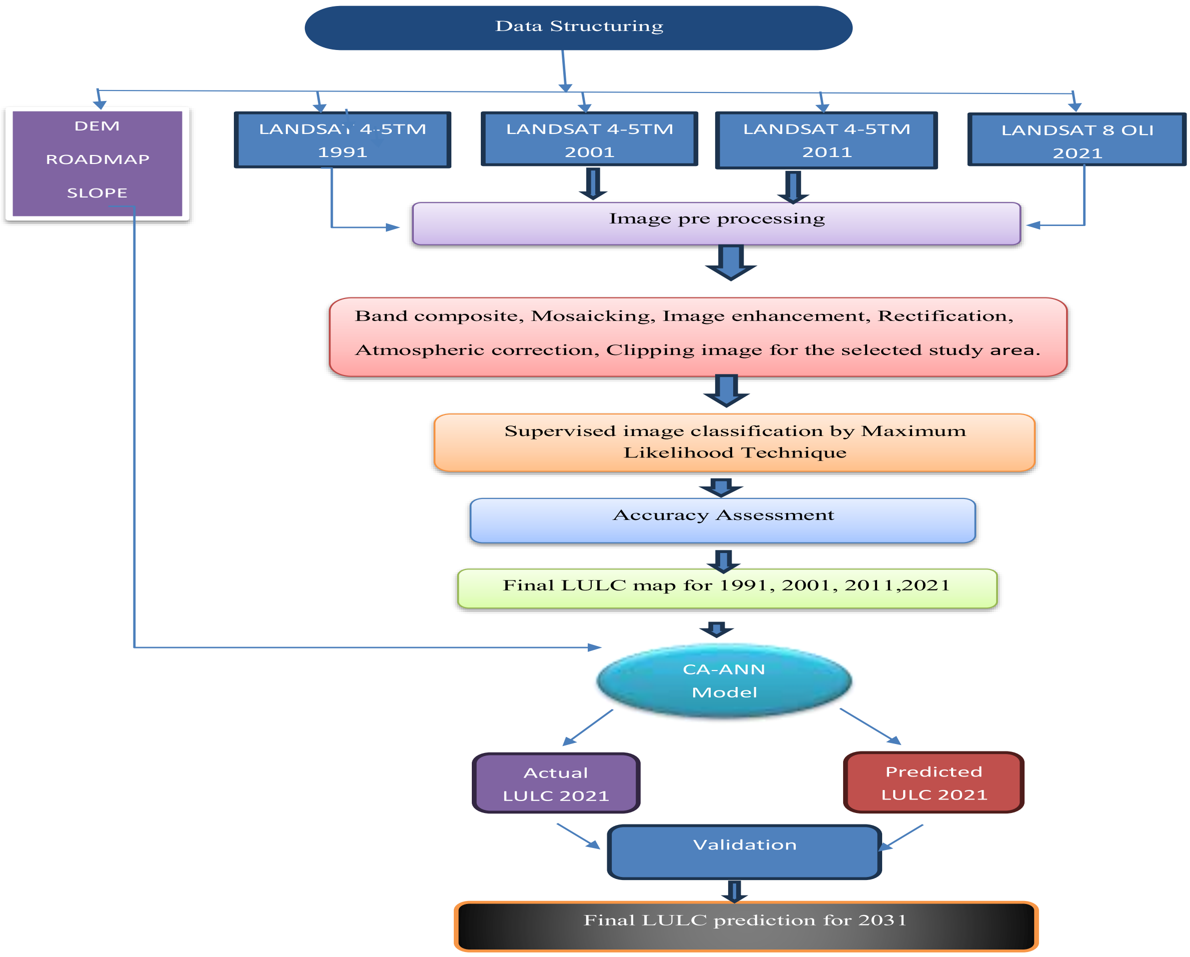

Fig 2: Methodological framework of the work

Image pre- processing
Image-preprocessing means arrange the for further process the downloaded image has spatial referenced in Universal Transverse Mercator (UTM) projection system 45 north with datum world geodetic system (WGS) 1984. The false color composite (FCC) for all images was generated by selecting an appropriate band combination. To eliminate distortions and noise introduced during image processing, both geometric and atmospheric correction methods were applied to all the satellite images. These FCC images were then used to choose training samples for LULC classification.

Image Classification
The classification was carried out using a supervised technique, specifically the maximum likelihood classification (MLC), within the ArcGIS platform for the year 1991, 2001, 2011, and 2021. In this study, five LULC classes were distinguished these are the water bodies, vegetation, agricultural land, built up area, current fallow. For the image classification average 100 above sample (Shikari, 2022) were selected for each class based on the own knowledge and help of the Google Earth engine historical data.
For image classification ground truthing (or ground truth verification) is the process of collecting real-world data or observations to validate or verify the accuracy of remotely sensed data, such as classified satellite or aerial images. Ground truthing ensures that the results of image classification are accurate and correspond to the actual conditions on the ground. (Das, 2018) and for the historical data google earth engine have to be used for the training sample and classification.

Table 2: Details of LULC classes taken into account for Tamluk Community Development Block, Purba Medinipur, West Bengal

LULC classes	Description
Water bodies	surface water found either in lake ponds, or flowing as streams, rivers, and other water bodies.
Vegetation	mixed forest land, grass land, shrub land.
Agricultural land	crop field, horticultural land, vegetation area.
Built up area	settlement area, commercial, industrial, transportation, rail, road.
Current fallow	exposed soil, barren land, uncultivated land.

Source: Compiled by the researcher, 2026

Accuracy Assessment
Accuracy assessment is the process of evaluating how well the classified data matches the actual real conditions. Kappa coefficient test is the appropriate method for accuracy assessment of land use land cover map. kappa test measure by user accuracy and producer accuracy (Shaar, 2020).
User’s accuracy: The probability that a pixel classified as a certain class actually represents that class in reality. This measures the reliability of the classification.
Producer's Accuracy: The probability that a ground truth observation for a particular class is correctly classified. This measures the "correctness" of classification for each class.
Kappa Coefficient (Kappa Index): A statistical measure that accounts for agreement between the classified image and the ground truth, considering random chance. It provides a more robust measure of classification accuracy. (Fan, 2008)
Spatial variables: Spatial variables play a crucial role in improving the accuracy and effectiveness of future predictions, particularly in fields like environmental science, urban planning, climate modeling, economics, and various forms of machine learning. To improve the accuracy of simulations map, we incorporated additional raster layers into the MOLUSCE model, including DEM, distances from roads, slope, aspect. (Muhammad, 2022) These spatial variables significantly influenced the predicted Land Use and Land Cover (LULC) outcomes. Moreover, these factors are particularly relevant to the study area, as water bodies, road infrastructure, and terrain elevation directly affect the expansion of land use classes. Spatial variables map has been made in arc GIS software for the initial year and final year. Cellular automaton (CA), spatial variables would correspond to the positions of cells within the grid, where each cell's state could depend on its position relative to others in the grid. The rules of the CA often involve interactions between neighboring cells at different spatial locations.

Table 3: Information about the spatial variables for future prediction map, Tamluk Community Development Block, Purba Medinipur, West Bengal

Sl. No.	Item	Type	Source
1	Open street map Road	Network (spatial vector data)	http://www.openstreetmap.org

2	Digital Elevation Model (DEM)	SRTM	http://wwwearthexplorer.usgs.gov
3	Slope	SRTM	http://www.earthexplorer.usgs.gov
4	ASPECT	SRTM	http://www.earthexplorer.usgs.gov

Source: Open Street Map and USGS Earth Explorer

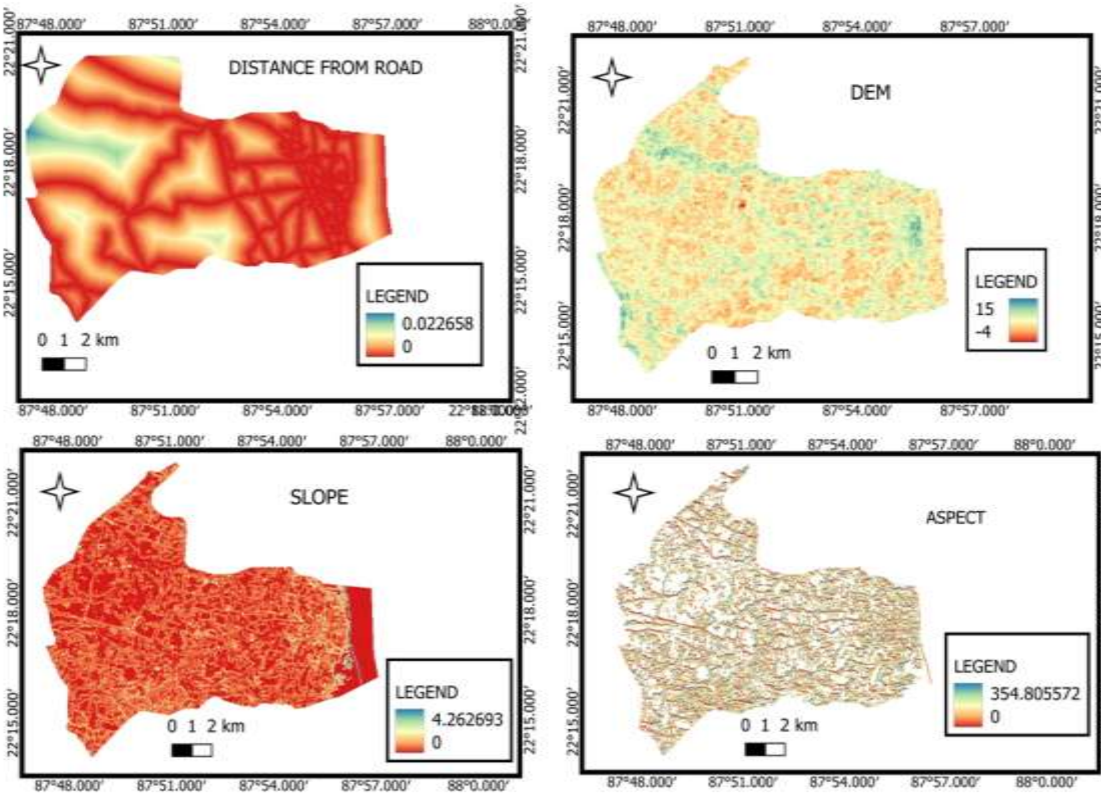

Fig 3: Spatial Driver Variables Used for Future Land Use and Land Cover (LULC) Prediction

Cellular Automata (CA) Artificial Neural Networks (ANN)

The Cellular Automata–Artificial Neural Network (CA–ANN) model is a hybrid spatial modelling approach widely used for predicting future Land Use and Land Cover (LULC) changes. Cellular Automata (CA) is a grid-based model that simulates spatial dynamics by applying transition rules based on the state of neighbouring cells, thereby capturing the spatial patterns of land use change. Artificial Neural Networks (ANN) are machine learning models that learn complex relationships between historical LULC changes and their driving factors, such as elevation, slope, proximity to roads, and other environmental variables (Ahmed, 2013; Voigt, 2016). By integrating the spatial simulation capability of CA with the predictive learning ability of ANN, the CA–ANN model provides reliable forecasts of future land use patterns. Owing to its ability to model both spatial interactions and transition probabilities, it is widely applied in land use planning, urban growth analysis, and environmental impact assessment.

Validation process basically computing the Kappa Statistics i.e. we get to know about Kappa, Kappa Histogram, Kappa Locations. Basically in this process we check, validate and compare the simulation results. For inputs we give two inputs i.e. Reference Land use/Land cover and Simulated Land use/Land cover. After doing this go for map comparison between these maps(Mishra, 2016). The multiple resolution budget method is used in MOLSUCE in this step to decide the number of validation iterations and after doing this one can start the validation process. After this process, have to calculate the overall accuracy of our learning model. Hence, we calculate % Of Correctness, overall Kappa, Histogram Kappa and Locations Kappa (Huang, 2020)

Table 4: Information about the accuracy table of LULC map of Tamluk Community Development Block, Purba Medinipur, West Bengal.

Accuracy name	1991	2001	2011	2021
User’s accuracy (%)	82.4	79.5	80.4	86.5
Producer's Accuracy (%)	83.6	80.3	77.4	89.6

Kappa coefficient	0.81	0.79	0.8	0.88

Source: Compiled by the researcher, 2026

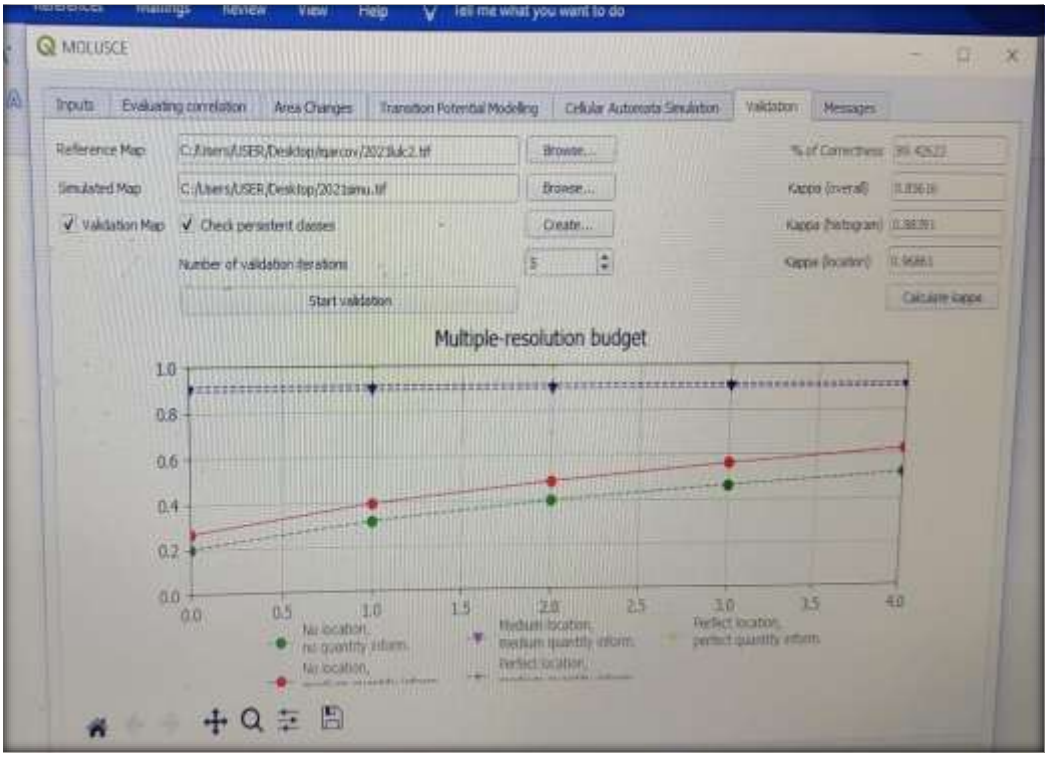

Fig 4: Kappa Value in Molusce Plugin for Validation

Source: Author's own analysis using QGIS–MOLUSCE plugin 2026

Result And Discussion

The land use land cover changes from 1991 to 2021 of Tamluk block

The land use/land cover (LULC) of Tamluk Block was classified into five categories—water bodies, vegetation, agricultural land, built-up area, and current fallow—for the years 1991, 2001, 2011, and 2021 using the Maximum Likelihood Classification method. The results reveal significant decadal changes in land use patterns. Water bodies increased markedly from 5.60 km² in 1991 to 25.29 km² in 2021 (annual growth rate 14.95%), while built-up area expanded from 15.73 km² to 26.33 km² (annual growth rate 8.06%). In contrast, vegetation declined from 35.87 km² to 20.44 km² (annual decline −11.71%), agricultural land decreased from 70.15 km² to 55.76 km² (annual decline −10.90%), and current fallow land showed a slight reduction from 4.30 km² to 3.83 km² (annual decline −0.36%). The rapid increase in water bodies primarily reflects the conversion of agricultural land into aquaculture. This transformation has been influenced by the region's low-lying flat terrain (average elevation 6–7 m), gentle slope (0°–4°), and the hydrological influence of the Rupnarayan River, which connects to the Bay of Bengal via the Hooghly River. Additionally, repeated severe cyclones between 2000 and 2020, including the 2002 Severe Cyclonic Storm, Sidr (2007), Aila (2009), Bulbul (2019), and Amphan (2020), have increased flooding and saltwater intrusion, reducing the suitability of agricultural land and encouraging its conversion to fish farming.

Table 5: Information about the decadal change of LULC category, Tamluk Community Development Block, Purba Medinipur, West Bengal (1991-2021)

LULC Category	**1991-2001**		**2001-2011**		**2011-2021**	
	Area in km2	**%**	**Area in km2**	**%**	**Area in km2**	**%**
Water bodies	6.95	5.28	-0.96	-0.73	13.69	10.4
Vegetation	-16.14	-12.3	-4.02	-3.05	4.73	3.59
Agricultural land	7.71	5.86	1.79	1.36	-23.89	-18.15
Built up area	0.86	0.65	2.55	1.94	7.19	5.46
Current fallow	0.61	0.47	0.63	0.48	-1.72	-1.3

Source: Compiled by the researcher, 2026

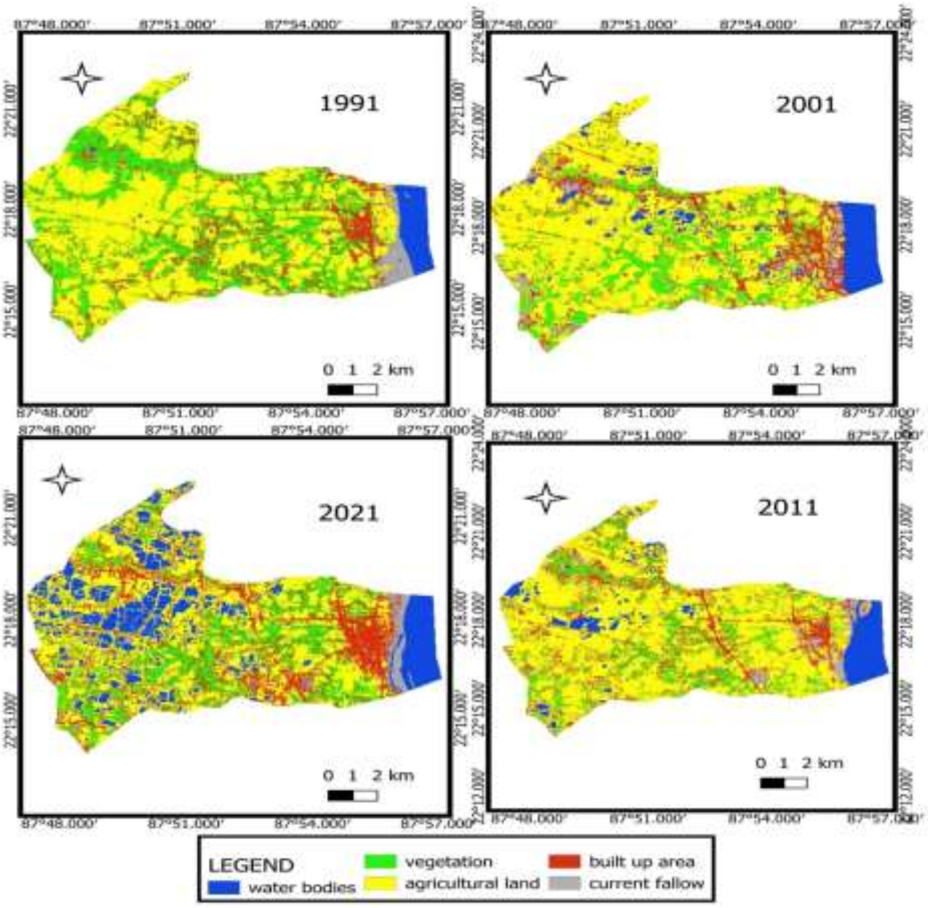

Fig 5. Spatio-Temporal Land Use and Land Cover (LULC) Changes in Tamluk Community Development Block, 1991-2021.
Source: Author's analysis based on Landsat satellite imagery.2026

Transition probability matrix
The transition probability matrix was used to analyse changes in Land Use/Land Cover (LULC) in Tamluk Block between 1991–2001, 2001–2011, and 2011–2021. The matrix shows the probability of each land use class remaining unchanged (diagonal values) or being converted into another class (off-diagonal values), making it useful for understanding land-use dynamics and predicting future LULC patterns.
During 1991–2001, water bodies were the most stable land use class (96%), whereas vegetation experienced substantial conversion to agricultural land (48%). About 76.5% of agricultural land remained unchanged, while current fallow land was the least stable category, with nearly 48.2% converted into water bodies, indicating the initial expansion of aquaculture.
In 2001–2011, agricultural land remained relatively stable (74.6%), although it gained land from vegetation and current fallow areas. Around 34.9% of water bodies were converted into agricultural land, while built-up areas showed moderate stability, reflecting continued urban development.
During 2011–2021, water bodies (76.3%) and vegetation (62.1%) remained largely stable. However, 18.7% of agricultural land was converted into water bodies, indicating the continued expansion of fisheries, while 37.2% of current fallow land was transformed into built-up areas, reflecting rapid urbanization. Agricultural land also shifted to vegetation and fallow land in several locations.
Overall, the transition matrices indicate that agricultural land has been the most dynamic land-use category, undergoing continuous conversion to water bodies, built-up areas, and fallow land. These changes highlight the increasing influence of aquaculture expansion, urban growth, and environmental processes on the changing landscape of Tamluk Block between 1991 and 2021.

Table 8: Information about the Transition Probability Matrix from 1991 to 2001Tamluk Community Development Block, Purba Medinipur, West Bengal

year	2001 (area in sq km)					
1991	LULC category	water bodies	vegetation	agricultural land	built up area	current fallow

	water bodies	0.96	0.001	0.023	0.015	0.001
	vegetation	0.005	0.371	0.483	0.106	0.033
	agricultural land	0.069	0.043	0.765	0.087	0.036
	built up area	0.003	0.21	0.387	0.347	0.051
	current fallow	0.482	0.009	0.144	0.273	0.092

Source: Compiled by the researcher,2026

Table 9: Information about the Transition Probability Matrix from 2001-2011, , Tamluk Community Development Block, Purba Medinipur, West Bengal

YEAR	2011(area in sq km)					
2001	LULC category	water bodies	vegetation	agricultural land	built up area	current fallow
	water bodies	0.558	0.002	0.349	0.028	0.064
	vegetation	0.002	0.415	0.383	0.191	0.011
	agricultural land	0.046	0.083	0.746	0.099	0.024
	built up area	0.044	0.049	0.428	0.385	0.094
	current fallow	0.036	0.044	0.507	0.186	0.228

Source: ‘Compiled by the researcher,2026

Table 10: Information about the Transition Probability Matrix from, 2011-2021, Tamluk Community Development Block, Purba Medinipur, West Bengal

YEAR	**2021(area in sq km)**					
2011	LULC category	water bodies	vegetation	agricultural land	built up area	current fallow
	water bodies	0.763	0	0.126	0.006	0.104
	vegetation	0.002	0.619	0.251	0.124	0.003
	agricultural land	0.189	0.107	0.556	0.135	0.013
	built up area	0.034	0.106	0.241	0.601	0.019
	current fallow	0.132	0.033	0.255	0.372	0.208

Source: ‘Compiled by the researcher,2026

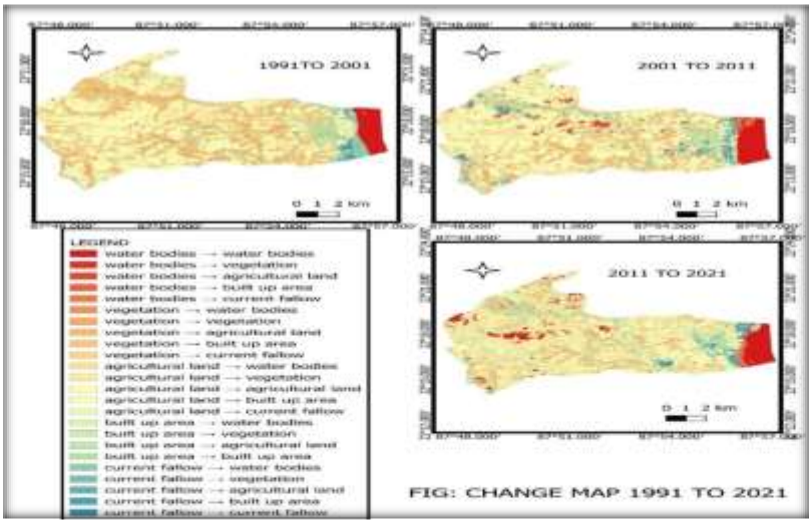

Figure 6. Land Use/Land Cover (LULC) Transition Map of Tamluk Community Development Block1991–2021.

LULC Model Validation

The MOLUSCE (Modules for Land Use Change Simulation) plugin in QGIS provides several advanced algorithms for modelling land use/land cover (LULC) change and predicting future landscape dynamics. These include Artificial Neural Networks (ANN), Weights of Evidence (WoE), Logistic Regression (LR), Multi-Criteria Evaluation (MCE), and Cellular Automata (CA). Among these approaches, the Cellular Automata–Artificial Neural Network (CA–ANN) model was selected for this study because it effectively integrates the spatial neighbourhood effects of Cellular Automata with the learning capability of Artificial Neural Networks, making it well suited for simulating complex land-use transitions.

For model calibration, the LULC maps of 2001 and 2011, together with selected spatial driving factors, were used to estimate transition potentials and simulate the LULC pattern for 2021. The calibrated model achieved a Kappa coefficient of 0.78, indicating substantial agreement and satisfactory predictive performance.

To evaluate the reliability of the simulation, the projected 2021 LULC map was compared with the actual classified LULC map of 2021. The validation results demonstrated a prediction accuracy of 89.42%, with an overall Kappa coefficient of 0.85616, a Kappa histogram value of 0.88391, and a Kappa location value of 0.96861. These high validation statistics indicate that the CA–ANN model accurately captured both the quantity and spatial distribution of land use changes. Therefore, the model was considered reliable for simulating future LULC scenarios and analysing the spatial dynamics of land use change in the Tamluk Block.

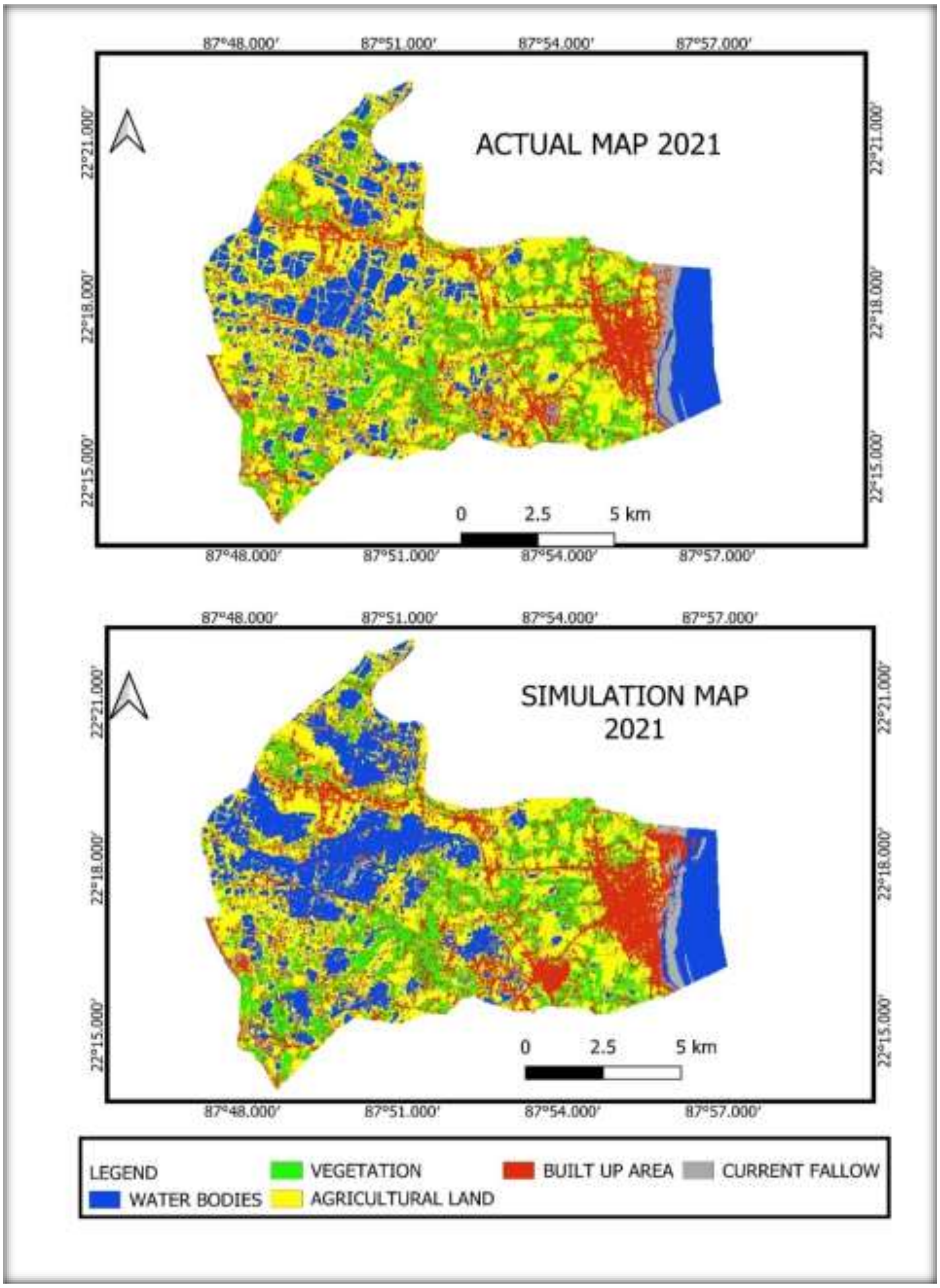

Fig7: Neural Network Learning Curve for LULC Prediction Using the MOLUSCE Plugin.

Source: Author's analysis using the QGIS–MOLUSCE plugin 2026.

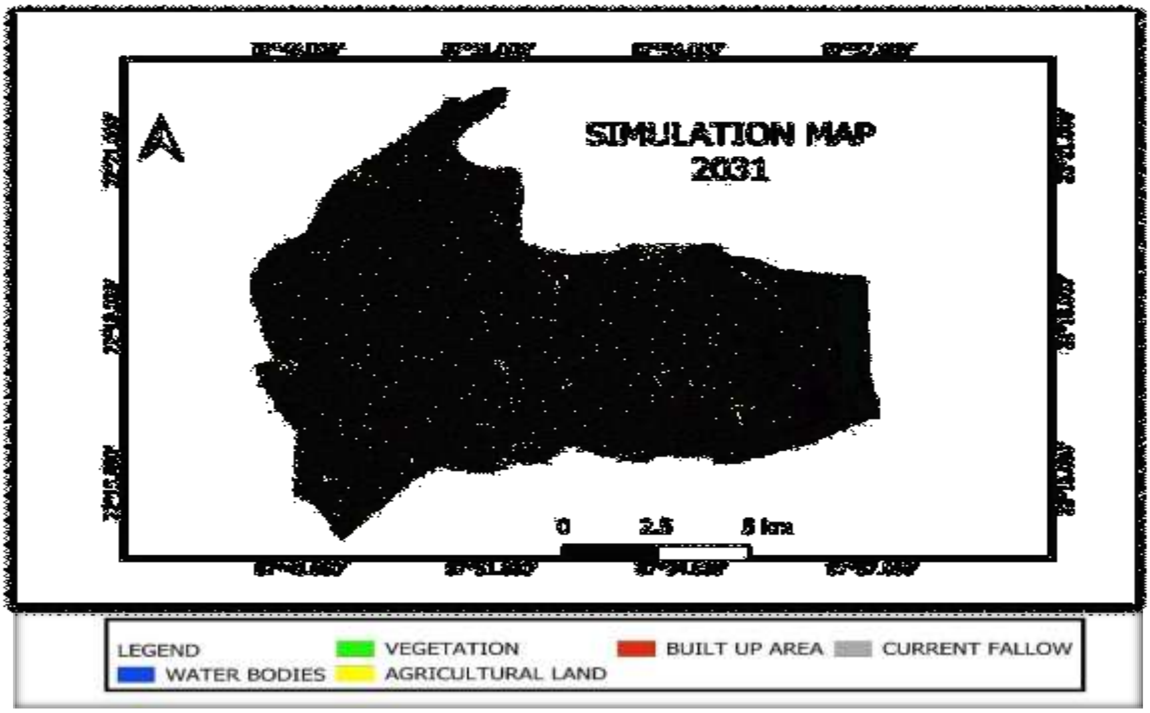

Fig 8. Actual and Simulated Land Use/Land Cover (LULC) Maps of Tamluk Community DevelopmentBlock,2021.
Source: Author's analysis using Landsat-derived LULC data and the QGIS–MOLUSCE plugin 2026.

Future prediction of land use land cover change

After successful validation of the CA–ANN model, the future Land Use/Land Cover (LULC) pattern for 2031 was simulated using the MOLUSCE plugin in QGIS. The prediction was carried out using the 2011 and 2021 LULC maps as temporal inputs, together with selected spatial driving variables to estimate land-use transition probabilities. The model achieved a Kappa coefficient of 0.85, indicating a high level of agreement and strong predictive performance.

The projected LULC map for 2031 represents the expected spatial distribution of different land use classes based on historical land-use trends and neighbourhood interactions. The simulation provides valuable information on the likely expansion or decline of various land use categories and serves as an important tool for sustainable land-use planning, environmental management, and informed decision-making in the Tamluk Block.

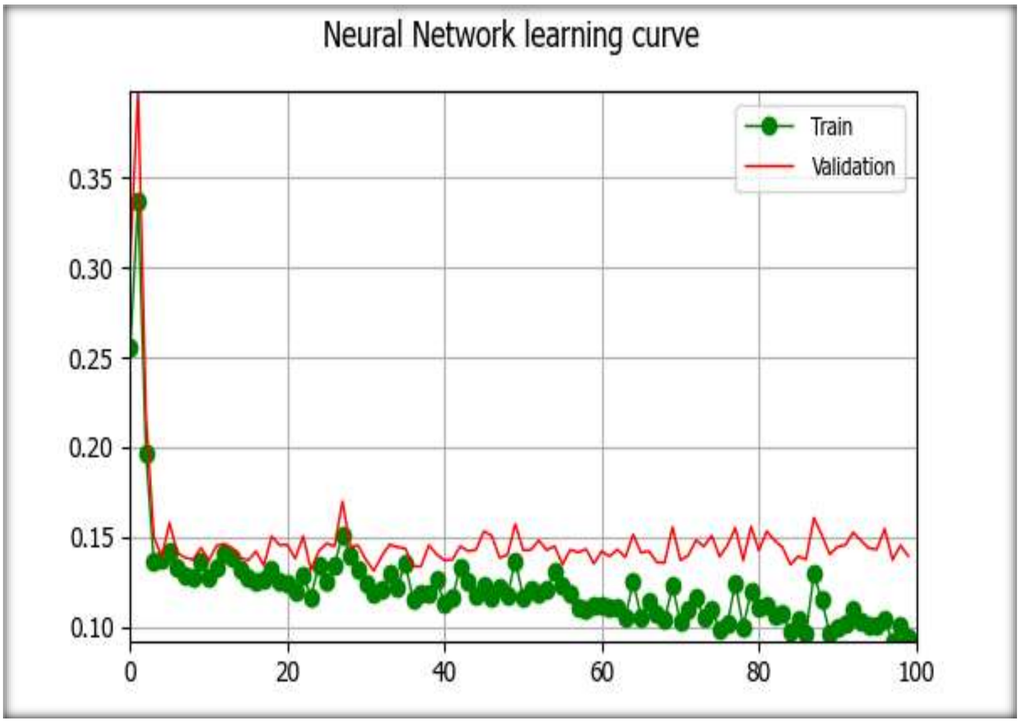

Fig 9. Predicted Land Use/Land Cover (LULC) Map of Tamluk Community Development Block for 2031.
Source: Author's analysis using the CA-ANN model implemented in the QGIS–MOLUSCE plugin.

Conclusion

The spatio-temporal analysis of Land Use/Land Cover (LULC) dynamics in Tamluk Community Development Block during 1991–2021 demonstrates substantial transformation of the landscape. The analysis indicates a consistent increase in water bodies and built-up areas, accompanied by a corresponding reduction in agricultural land, vegetation, and current fallow land. The expansion of water bodies appears to be closely associated with the conversion of agricultural areas into aquaculture ponds and other water-based land uses, while the growth of built-up areas reflects increasing settlement expansion, infrastructural development, and changing socio-economic activities. These transitions signify a gradual shift from a predominantly agriculture-oriented landscape towards a more diversified and increasingly water- and settlement-dominated land-use structure.

The validated Cellular Automata–Artificial Neural Network (CA–ANN) model demonstrates considerable potential for reproducing observed LULC patterns and projecting future land-use configurations. The 2031 simulated LULC scenario indicates that the existing transformation trends are likely to persist in the coming decade, particularly through continued expansion of water bodies and built-up areas and further contraction of agricultural and vegetated land. If these trends continue without appropriate management interventions, they may intensify competition for agricultural land, alter ecological functions, and increase pressure on local natural resources.

The findings highlight that LULC transformation in Tamluk is not merely a spatial phenomenon but also reflects the interaction between agricultural change, aquaculture expansion, population pressure, settlement growth, infrastructure development, and environmental conditions. The CA–ANN-based prediction therefore provides a useful scientific basis for anticipating areas of potential future land-use transition. The study suggests that integrating geospatial modelling with appropriate land-use planning can support the protection of productive agricultural areas, environmentally sensitive zones, and existing vegetation while accommodating necessary development. Consequently, the results can contribute to evidence-based land-use planning, sustainable aquaculture management, agricultural-resource conservation, ecosystem protection, and long-term regional development strategies in Tamluk Community Development Block.

References

1. Agarwal, C., Green, G.M., Grove, J.M., Evans, T.P. and Schweik, C.M. (2002) A review and assessment of land-use change models: Dynamics of space, time, and human choice. Newton Square, PA: U.S. Department of Agriculture, Forest Service.
2. Almeida, C.M., Gleriani, J.M., Castejon, E.F. and Soares-Filho, B.S. (2008) ‘Using neural networks and cellular automata for modelling intra-urban land-use dynamics’, International Journal of Geographical Information Science, 22(9), pp. 943–963.
3. Arsanjani, J.J., Helbich, M., Kainz, W. and Boloorani, A.D. (2013) ‘Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion’, International Journal of Applied Earth Observation and Geoinformation, 21, pp. 265–275.
4. Basu, J. (1921) Medinipurer itihas. Kolkata: Annapurna Prakashani.
5. Bozkaya, A., Balcik, F., Goksel, C. and Esbah, H. (2015) ‘Forecasting land-cover growth using remotely sensed data: A case study of the Igneada protection area in Turkey’, Environmental Monitoring and Assessment, 187, Article 59, pp. 1–18. doi: 10.1007/s10661-015-4322-z.
6. Cabral, P. and Zamyatin, A. (2009) ‘Markov processes in modeling land use and land cover changes in Sintra-Cascais, Portugal’, DYNA, 76, pp. 191–198.
7. Chakraborty, S. and Daspattanayak, P. (2016) ‘Solid waste management of Kolkata Municipal Corporation: A comparative study between Ward No. 115 and 122’, The Indian Journal of Spatial Science, 7(2), pp. 43–48.
8. Chaudhuri, G. and Clarke, K. (2013) ‘The SLEUTH land use change model: A review’, Environmental Resources Research, 1, pp. 88–105.
9. Clarke, K.C., Hoppen, S. and Gaydos, L. (1997) ‘A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area’, Environment and Planning B: Planning and Design, 24(2), pp. 247–261.
10. Fan, F., Wang, Y. and Wang, Z. (2008) ‘Temporal and spatial change detecting (1998–2003) and predicting of land use and land cover in core corridor of Pearl River Delta (China) by using TM and ETM+ images’, Environmental Monitoring and Assessment, 137, pp. 127–147. doi: 10.1007/s10661-007-9734-y.
11. Fu, X., Wang, X. and Yang, Y.J. (2018) ‘Deriving suitability factors for CA-Markov land use simulation model based on local historical data’, Journal of Environmental Management, 206, pp. 10–19.
12. Gao, C., Cheng, D., Iqbal, J. and Yao, S. (2023) ‘Spatiotemporal change analysis and prediction of future land cover changes using QGIS MOLUSCE plugin on a large regional scale and the relationship analysis with mountain hazards: A case study of the Great Yellow River Region (GYRR), China’, Land, 12(2), Article 340. doi: 10.3390/land12020340.
13. Hakim, A.M.Y., Baja, S., Rampisela, D.A. and Arif, S. (2023) ‘Spatial dynamic prediction of land use/land cover change: Case study of Tamalanrea Sub-district, Makassar City’, IOP Conference Series: Earth and Environmental Science, 280(1), Article 012023. doi: 10.1088/1755-1315/280/1/012023.
14. Hu, Y., Raza, A., Syed, N.R., Acharki, S., Ray, R.L., Hussain, S., Dehghanisanij, H., Zubair, M. and Elbeltagi, A. (2023) ‘Land use/land cover change detection and NDVI estimation in Pakistan’s Southern Punjab Province’, Sustainability, 15(4), Article 3572. doi: 10.3390/su15043572.

15. Jiang, W., Yuan, L., Wang, W., Cao, R., Zhang, Y. and Shen, W. (2015) ‘Spatio-temporal analysis of vegetation variation in the Yellow River Basin’, Ecological Indicators, 51, pp. 117–126.
16. Kamaraj, A. and Rangarajan, S. (2021) ‘Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin’, Environmental Science and Pollution Research. doi: 10.1007/s11356-021-17904-6.
17. Liu, X., Li, X., Shi, W., Liu, X., Chen, Y., Yang, J., Zhou, Y. and Zhang, H. (2017) ‘Simulating complex urban development using spatially explicit cellular automata models: A review’, Landscape and Urban Planning, 163, pp. 1–15.
18. Mas, J.F., Kolb, M., Paegelow, M., Camacho Olmedo, M.T. and Houet, T. (2014) ‘Inductive pattern-based land use/land cover change models: A comparison of four software packages’, Environmental Modelling & Software, 51, pp. 94–111.
19. Mondal, M., Paul, S., Bhattacharya, S. and Biswas, A. (2020) ‘Micro-level assessment of rural societal vulnerability of coastal regions: An insight into Sagar Island, West Bengal, India’, Asia-Pacific Journal of Rural Development.
20. Muchová, Z. and Tárníková, M. (2018) ‘Land cover change and its influence on the assessment of the ecological stability’, Applied Ecology and Environmental Research, 16, pp. 2169–2182.
21. Pontius, R.G. Jr., Shusas, E. and McEachern, M. (2004) ‘Detecting important categorical land changes while accounting for persistence’, Agriculture, Ecosystems & Environment, 101(2–3), pp. 251–268.
22. Pontius, R.G. Jr., Boersma, W., Castella, J.C., Clarke, K., de Nijs, A.C.M., Dietzel, C., Duan, Z., Fotsing, E., Goldstein, N., Kok, K., Koomen, E., Lippitt, C.D., McConnell, W., Sood, A.M., Pijanowski, B., Pithadia, S., Sweeney, S., Trung, T.N., Veldkamp, A. and Verburg, P.H. (2008) ‘Comparing the input, output, and validation maps for several models of land change’, The Annals of Regional Science, 42(1), pp. 11–37. doi: 10.1007/s00168-007-0138-2.
23. Rahman, M.T.U., Tabassum, F., Rasheduzzaman, M., Saba, H., Sarkar, L., Ferdous, J., Uddin, S.Z. and Zahedul Islam, A.Z.M. (2017) ‘Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh’, Environmental Monitoring and Assessment, 189. doi: 10.1007/s10661-017-6272-0.
24. Roy, P.S. and Roy, A. (2010) ‘Land use and land cover change in India: A remote sensing & GIS perspective’, Journal of the Indian Institute of Science, 90(4), pp. 489–502.
25. Roy, T. (2006) The economic history of India, 1857–1947: Transition to colonialism. New Delhi: Oxford University Press, pp. 31–72.
26. Sajan, B., Mishra, V.N., Kanga, S., Meraj, G., Singh, S.K. and Kumar, P. (2022) ‘Cellular automata-based artificial neural network model for assessing past, present, and future land use/land cover dynamics’, Agronomy, 12(11), Article 2772. doi: 10.3390/agronomy12112772.
27. Saputra, M.H. and Lee, H.S. (2019) ‘Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton’, Sustainability, 11(11), Article 3024. doi: 10.3390/su11113024.
28. Shikary, C. and Rudra, S. (2020) ‘Measuring urban land use change and sprawl using geospatial techniques: A study on Purulia Municipality, West Bengal, India’, Journal of the Indian Society of Remote Sensing. doi: 10.1007/s12524-020-01212-6.
29. Sohl, T.L., Sayler, K.L., Drummond, M.A. and Loveland, T.R. (2004) ‘The FORE-SCE model: A practical approach for projecting land cover change using a spatially explicit land allocation model’, Ecological Modelling, 179(1), pp. 75–94.
30. Soares-Filho, B.S., Cerqueira, G.C. and Pennachin, C.L. (2002) ‘DINAMICA—A stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier’, Ecological Modelling, 154(3), pp. 217–230.
31. Verburg, P.H., Schot, P.P., Dijst, M.J. and Veldkamp, A. (2004) ‘Land use change modelling: Current practice and research priorities’, GeoJournal, 61(4), pp. 309–324. doi: 10.1007/s10708-004-4946-y.
32. Verburg, P.H. and Veldkamp, A. (2004) ‘Projecting land use transitions at forest fringes in the Philippines at two spatial scales’, Landscape Ecology, 19(1), pp. 77–98. doi: 10.1023/B:LAND.0000018370.57457.58.
33. van Asselen, S. and Verburg, P.H. (2013) ‘Land cover change or land-use intensification: Simulating land system change with a global-scale land change model’, Global Change Biology, 19(12), pp. 3648–3667. doi: 10.1111/gcb.12331.
34. Weng, Q. (2002) ‘Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling’, Journal of Environmental Management, 64(3), pp. 273–284.
35. White, R. and Engelen, G. (1997) ‘Cellular automata as the basis of integrated dynamic regional modelling’, Environment and Planning B: Planning and Design, 24(2), pp. 235–246.
36. Wu, F. (2002) ‘Calibration of stochastic cellular automata: The application to rural-urban land conversions’, International Journal of Geographical Information Science, 16(8), pp. 795–818.
37. Zhang, Q., Ban, Y., Liu, J. and Hu, Y. (2011) ‘Simulation and analysis of urban growth scenarios for the Greater Shanghai Area, China’, Computers, Environment and Urban Systems, 35(2), pp. 126–139.