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Research article

Quantifying forest land-use changes using remote-sensing and CA-ANN model of Madhupur Sal Forests, Bangladesh

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A R T I C L E I N F O

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A B S T R A C T

The conversion of forest cover due to anthropogenic activities is of great concern in the Madhupur Sal Forest in Bangladesh. This study explored the land use changes in the Sal Forest area from 1991 to 2020, with the prediction of 2030 and 2040. This study examined and analyzed the changes in five land use classes viz., waterbodies, settlement, Sal Forest, other vegetation, and bare land, and predict those classes using Cellular Automated Artificial Neural Network (CA-ANN) model. The Sankey diagram was employed to represent the change percentage of Land Use and Land Cover (LULC). The LULC for 1991, 2000, 2010, and 2020 derived from Landsat TM and Landsat OLI images, were used to predict the periods of 2030 and 2040. During the last 30 years, the Sal Forest area decreased by 23.35%, whereas the settlement and bare land area increased by 107.19% and 160.89%. The greatest loss of the Sal Forest was observed from 1991 to 2000 by 46.20%. At the same period of time the settlements were increased by 92.68% indicating the encroachment of settlement in the Sal Forest area. The Sankey diagram revealed a major conversion was found between other vegetation and the Sal Forest area. There was a vis-à-vis between other vegetation and the Sal Forest area from 1991 to 2000 and from 2000 to 2010. Interestingly, there was no conversation of the Sal Forest area to other land use from 2010 to 2020, and the prediction showed that the Sal Forest area will be increased by 52.02% in 2040. The preservation and increment of the Sal Forest area suggested strong governmental policy implementation to preserve the forest.

1. Introduction

Bangladesh has a very low per capita area of forest land (0.0009ha) compared to Asia (0.145 ha) and the world (0.597) [1]. Forest areas in Bangladesh are classified into three categories; (a) tropical evergreen forest; (b) tropical moist deciduous Sal Forest; (c) tidal mangrove forest [2]. With over 0.12 million acres of area, the Sal Forest makes up 4.7% of Bangladesh's total forested land. The Sal Forest's lion section is located in the districts of Mymensingh and Tangail, also known as Madhupur Garh [3]. A flood-prone environment [3] with abundant forest resources makes the Madhupur forest area one of the first human settlements [4]. In the Madhupur Sal Forest, ethnic communities (such as the Garo and Koch) have existed for generations [5].

The Sal Forest is valued as one of the utmost productive and ecologically compelling forest types in Bangladesh facing deforestation

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very quickly [4]. In recent times, Madhupur Sal Forest has been acutely disrupted by both local and indigenous people [6]. Madhupur Forest Area is bordered on all sides by a dense population [7]. led to rapid degradation due to increased energy and wood consumption. Natural Sal Forests are endangered because of shifting cultivation by ethnic people and the introduction of exotic species [8]. KAMRUL and SATO, 2011., found that illegal logging by local syndicates and the conversion of forests into commercial activities are the main cause of forest degradation in the Sal Forest area. In 2015, the Forest Department of Bangladesh reported that only one-third of the Sal Forest remains in the country. In 1985, the Sal Forest's initial cover was around 36%, and according to more recent estimates, it is now barely 10% [9]. The Sal Forest is either empty or has encroachment on more than 66% of its surface. Illegal tree merchants [10] as well as local people are responsible for forest encroachment [11]. In 1962, only 235 Garo families were living in the Madhupur National Park area, whereas in 1990, a total of 3200 Garo and non-Garo families were living in the same area. After the independence of Bangladesh in 1971, about 40,000 local people moved illegally to the Sal Forest for living and agricultural purposes [12]. Increasing jhum cultivation by Garo is a major source of forest degradation [13]. [14], studied human intervention on plant diversity at Madhupur Sal Forest. The forest sites are classified into three groups; low, medium, and high disturbed areas based on the degree of anthropogenic disturbances. These authors reported that the highly disturbed forest is no longer considered a natural forest which has been shifted to agricultural land. Muscle men accounted for grabbing about 70% of the Sal Forest area beside the local people who grabbed nearly 10% for agricultural purposes, especially for bananas [15] [16]. reported that the forest loss was caused by the destruction of migrated people rather than the ethnic communities doing shifting cultivation. These authors also accounted dishonest forest officials helped illegal loggers also responsible for forest loss. [17], reported a 36% decrease in Sal Forest between 1975 and 1993. Satellite images were used to detect the change in Sal Forest cover by Ref. [18]. These authors used Landsat images to detect for over 42 years; from 1972 to 2014. They found that the forest area has increased in recent history (from 2010 to 2014 by 202.4 ha) due to community reforestation programs, however, 7079.4 ha of forest area have been lost from 1972 to 2013. Community involvement in forest conservations reduces their dependence on forest resources with livelihood improvements.

Most of the Madhupur forest degradation studies have been conducted through questionnaire surveys, except [18], which have used satellite images for such studies. The logistic regression model (LRM) and GIS are powerful tools for predicting forest cover dynamics analysis. A number of studies have been conducted in Myanmar and India to detect and project forest degradation (i.e. Myanmar, [19]; India, [20].

However, this study addresses the gap by applying long-term satellite images of the Gazipur district using advanced geospatial tools

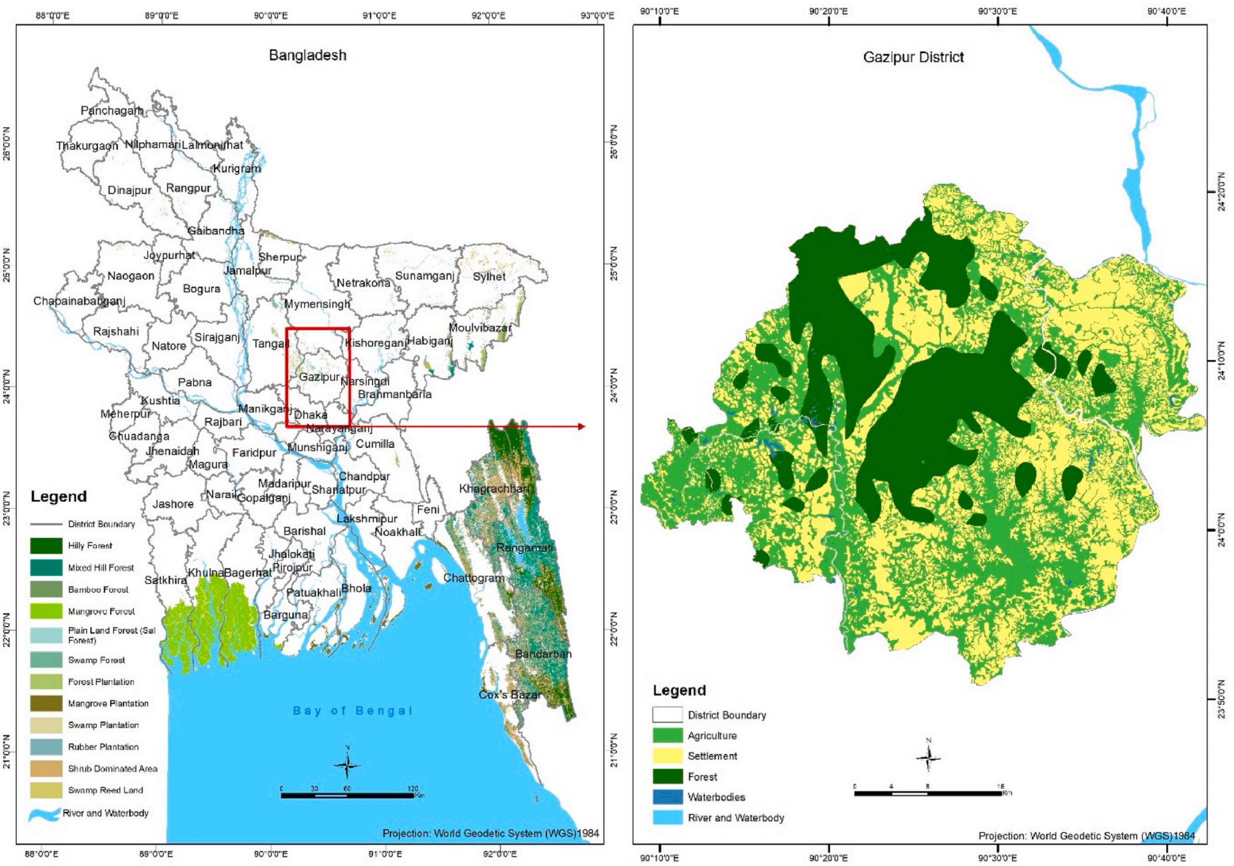

Fig. 1. Location and land use of the study area.

and techniques. Primarily, we extracted land use and land cover of the study area from 1991 to 2020 and predicted for the year 2030 and 2040 using the CA-ANN model.

There are several modeling techniques that investigators used to predict LULC. Future LULC changes have been quantified and predicted using multitemporal RS satellite images from a variety of satellite images [21]. Nowaday's various updated models are used in LULC prediction. For example; ANN model [22]; Markov model [23]; CA-Markov model [24]; CA-ANN model [25,26]; MLP-ANN model [27]; Multi-model ensemble [28–30], CA-ANN MOLUSCE model [31] and to simulate the spatiotemporal changes inside the research region, an integrated CA-artificial neural network (ANN) model using MOLUSCE was adopted for the current investigation. Additionally, we examined spatial driving factors for land surface dynamics in the district using the Geodetector tool.

Monitoring of the forest cover is necessary to inform authorities of any changes to the forest, and correct position and extent information should be provided on forest maps. The government should encourage locals to be aware of the system for protecting forests in order to aid in the Sal forest's restoration.

2. Materials and methods

2.1. Study area

Pleistocene terraces and more recent alluvial floodplains cover the majority of the Sal Forest region [32]. The soil is typically sandy loam to silty loam in texture. Due to its humid tropical environment, Madhupur Forest, which is located in central Bangladesh, has a great amount of flora. The capital of Bangladesh, Dhaka, is about 151 km to the north and nearly 50 km to the south of this location. A 20 m elevation difference from the mean sea level marks the woodland. The Madhupur forest, often referred to as "Madhupur Garh," is raised above the surrounding plains by 1–2 m. The forest is mixed with areas of scrub jungles and is at times thin and at other times thick. The Sal Forest area comprises Tangail, Mymensingh, and Gazipur districts. The Gazipur district is very near to Dhaka city and very much vulnerable to urban and industrial encroachment [33]. The present study revealed the LULC for the Gazipur district (Fig. 1).

2.2. Data acquisition

This study used secondary data such as satellite images, DEM, and spatial vector layers from different sources. Imageries were collected from similar seasons with no cloud cover. Raster layers were acquired in 30 m resolution. The data used in this study are given below in Table-1.

2.3. Data Preparation and Processing

A semi-automatic classification plugin (SCP) in QGIS, which is more reliable and convenient with a free plugin, is used for LULC classification. Landsat L1TP data which are radiometrically calibrated and geometrically corrected using Ground Control Points (GCPs) and digital elevation model (DEM) data, were used in this study [34]. Firstly, acquired Landsat images were converted from DN (Digital Numbers) to TOA (Top of Atmosphere) reflectance. Afterward, atmospheric correction for TOA images was done using the DOS1 method to obtain surface reflectance (SR) images. The flowchart of the methods is given in Fig. 2.

Both natural and anthropogenic factors have a substantial influence on LULC changes. This study considered seven potential factors such as elevation, slope, aspect, population, industry, roads, and railways to observe their influence on LULC in Gazipur (Fig. 3). Population data were converted to raster according to people living in the administrative union/wards in the area. Euclidean distances were measured for industry, roads, and railways to produce continuous raster data. All the produced raster layers were then reclassified into five hierarchical clusters using natural breakpoints in ArcGIS Pro licensed [35].

2.4. Image classification

Multiple unsupervised classification methods such as the Iterative Self-Organizing Data Analysis Technique (ISODATA), and K Means clustering are used for LULC classification [36,37]. This study used K- means clustering for the classification of SR images. It is a

Table 1
Types and sources of data used in this study.

Data Type	Year	Resolution	Source
Landsat-5	December 12, 1991 December 20, 2000 December 16, 2010	30 m	US Geological Survey
Landsat-8	December 27, 2020	30 m	US Geological Survey
National Administration Boundary	N/A	N/A	Survey of Bangladesh (SOB)
Population Data	2011	N/A	BBS,2011
SRTM Digital Elevation Model (DEM) Data	2000-02-11	30	US Geological Survey
Road and Railway Data	N/A	N/A	LGED, BR
Industry Location Data	N/A	N/A	DoE
Forest administration boundary	N/A	N/A	Bangladesh Forest Department (BFD)

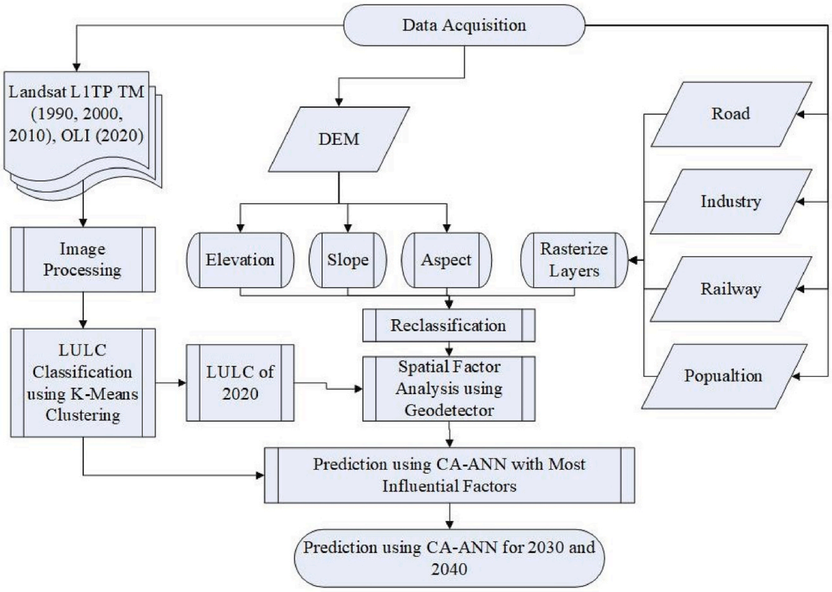

Fig. 2. The flowchart showing the step-by-step analysis of LULC and prediction using CA-ANN from raw image acquisition to Sankey diagram.

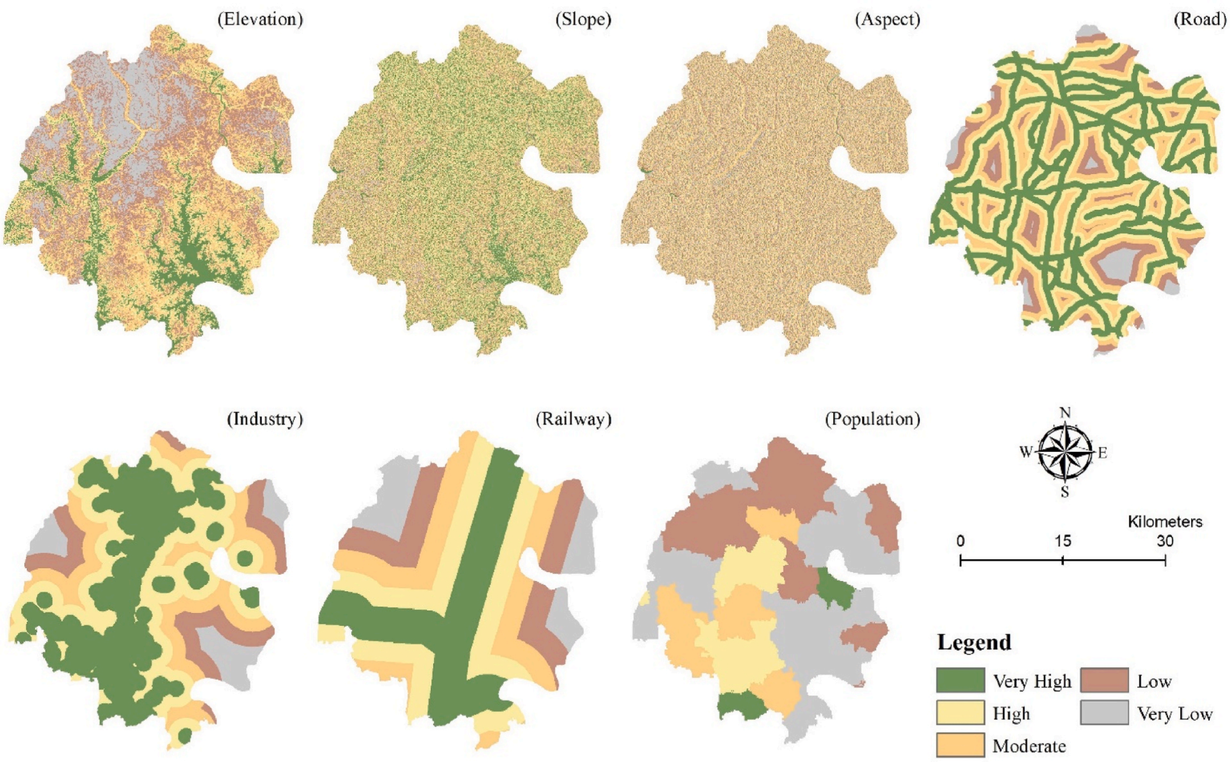

Fig. 3. Potential natural and anthropogenic features influencing spatial distribution of LULC in the study area.

partitional clustering method to classify data in non-overlapping categories [38]. The method is based on the calculation of the average spectral signature of clusters [39]. It is suitable for numerical data as it uses mean values of the attributes [38,40]. A total of five LULC classes such as Water Bodies, Settlements, Sal Forest, Other Vegetations, and Bare Land were extracted in the study area. Post-classification processing such as majority filters and manual editing of misclassified pixels was applied to reduce classification errors. Finally, changes in LULC were obtained by comparing multi-temporal raster layers (1991, 2000, 2010, and 2020).

2.5. Change detection analysis

The Sankey diagram was used to analyze the changing process of LULC in the study area. The LULC transition matrix described changes in the number of land features from the previous year to the later year. The diagram depicts the dynamics between the initial and the final year using transition matrix data [35] It was prepared using R programming [41] with the help of networkD3 package [42].

2.6. Land use degree index

One of the most perceptive characterizations of the degree of human activity and land development in any region can be expressed by the land use degree index [43,44]. The land use degree index (La) comprehensively explains the complex influence of human and natural factors on LULC change [35]. A higher value of (La) indicates a stronger land use intensity with more complex socio-economic interactions [45]. The land use degree index (La) in the study area was calculated by equation (1).

$$La = 100 \times \sum_{i=1}^{n} Ai \times Ci \tag{1}$$

where La is the land use degree index value; Ai is the grading index of land use degree i; and Ci is the percentage of the graded area of the i-th type of land use degree. According to the literature [45,45], the LULC types were divided into four categories and graded by different assigned values in Table-2.

2.7. Geodetector

This study uses the Geodetector package of R programming for analyzing influential factors of LULC in the area. The Geodetector model is a widely used tool to determine spatial heterogeneity (SH) of different factors [35,45–47]. Four SH detecting methods such as factor detector, interaction detector, risk detector, and ecological detector are included in the package. This research utilized a factor detector to analyze the driving forces of LULC change and its quantitative attribution by measuring q-statistic. The q-statistic can be expressed as follows equation (2);

$$q = \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{2}$$

Where q is the determinant power of influential variables and the degree of stratified heterogeneity of LULC; N_h denotes the number of samples in the sub-regions h; N denotes a total number of pixels in the study area; σ and σ_h denotes the total variance and variance in the samples in sub-region h, respectively. The value of q ranges between 0 and 1; q = 0 indicates that there is no association between influential variables and heterogeneity of LULC whereas q = 1 indicates that LULC is completely determined by those variables [47].

2.8. Prediction analysis

This paper uses the MOLUSCE (Modules of Land Use Change Evaluation) plugin in QGIS 20.18 to predict the LULC scenarios in the year 2030 and 2040. MOLUSCE is a widely used plugin that can estimate potential LULC changes built with the CA model and also includes a transition probability matrix [46–50]. There are four established models Artificial Neural Networks (ANN), Logistic Regression (LR), Multi-criteria Evaluation (MCE), and Weights of Evidence (WoE) are operated in this plugin. This plugin includes following steps starting from the input, evaluating correlation, area change, transition potential modelling, CA simulation and validation. For each simulation analysis LULC layers two different years were used as independent parameters and elevation, industrial location, and population were used as dependent parameters. Primarily, correlations of input layers of similar geometries were checked and area change between the time periods were measured to generate a potential transition matrix. In the modelling sections, CA-ANN was employed to predict future LULC scenarios of the study area. The CA-ANN is a hybrid modelling approach which accurately defines nonlinear spatial stochastic LULC change by estimating pixel,s present values based on the initial values and their neighbourhood pixels [46,49]. After inputting two sequential LULC layers with supporting raster layers, model settings were chosen to optimize the accuracy of the model. To account for the spatial interactions among adjacent cells a neighbourhood value of 3 × 3 pixels were chosen for this study. During the training phase, our model underwent 500 iterations at a learning rate of 0.01, with each iteration involving the adjustment of weights and biases of the neural network to reduce the error between the predicted and observed land use

Table 2
Hierarchical grading of land use types.

Land types	LULC classes	Index values
Uncultivated land	Bare land	1
Ecological land	Sal Forest, Water bodies	2
Agricultural land	Other vegetation	3
Construction land	Settlement	4

and land cover (LULC) categories. Based on a thorough consideration of the complexity of the problem and the potential risk of overfitting, we opted to utilize two hidden layers in our model. After predicting LULC for 2030 and 2040, LULC layer of 2020 were produced from 2000 to 2010 to validate the forecasting result with observed classification. The *Kappa* coefficient (0.79) from MOLUSCE plugin were generated for projected LULC (2020) in reference to the actual LULC (2020) layer in the validation stage.

3. Results

3.1. Overall LULC changes

The LULC is represented in Table-3 for the study area over the period of the last 30 years. The water body areas in the study area have increased by nearly 2.88% over the last 30 years. Interestingly, the water bodies decreased nearly 22.99% from 1992 to 2000, and decreased 12.89% from 2000 to 2010. A sharp increase, which was 53.39% of water bodies was found from 2010 to 2020. The settlement area became double from 1991 to 2020 in the study area. The settlement area has been changed by 107.19% from 1991 to 2020. This is the biggest change in the land use of Sal Forest. The largest change which was 92.68% was observed from 1991 to 2000. After 2000, the settlement area increased very slowly, which was 1.61% and 5.83% from 2000 to 2010 and 2010 to 2020, respectively. The Sal Forest area decreased by almost one-fourth of its total area from 1991 to 2020. Nearly 23.35% of the Sal Forest decreased from 1991 to 2020. The largest decrease, which was 46.20%, was from 1991 to 2000. The Sal Forest increased by 36.54% from 2000 to 2010, and 4.35% from 2010 to 2020. Overall, the other vegetation areas have decreased by 30.12% from 1991 to 2020. Interestingly, the other vegetation areas have increased from 1991 to 2000 by 32.39%. Nearly, 11.50% of the vegetation area decreased from 2000 to 2010. The largest decrease, which is 40.35% was observed in the recent past, from 2010 to 2020. The bare land area has increased almost one and a half times from 1991 to 2020. The bare land area increased by 160.89% over the last 30 years. Nearly, 55.56% bare land area increased from 1991 to 2000. Intriguing, there was a dramatic decrease in bare land was observed from 2000 to 2010 by 67.28%. The biggest change in the bare land area occurred from 2010 to 2020. The bare land area increased by 412.33% from 2010 to 2020.

3.2. Changes from 1991 to 2000

Water bodies show a little change from 1991 to 2000 (Table-4 and Fig. 4). Some portion of the water bodies converted to other vegetation. A lion shares of the settlement converted to Sal Forest and other vegetation. The Sal Forest area is mostly converted to other vegetation. A large portion of other vegetation has been converted to Sal Forest and the settlement area. Bare land converted to other vegetation.

3.3. Changes from 2000 to 2010

There were no significant changes were observed in the water bodies from 2000 to 2010 (Table-5). Interestingly, most of the settlements have been converted to bare land and the Sal Forest area. The Sal Forest area also decreased, which was converted to other vegetation and settlement areas. More interestingly, the other vegetations area have been converted into settlement and the Sal Forest area.

3.4. Changes from 2010 to 2020

The water bodies have decreased from 2010 to 2020 (Table-6). The water bodies were mainly converted to settlements. The settlement area also decreased, and converted to other vegetation and the Sal Forest area. The Sal Forest area was invaded by the settlement and other vegetation. Some portion of other vegetation converted to.

3.5. Spatial Factors for LULC in 2020

Among the seven potential factors considered in this study, anthropogenic factors are more influential than natural factors (Table-7). The most influencing drivers of LULC spatial pattern in the area are industry ($q = 0.038$) followed by population ($q = 0.032$), and elevation ($q = 0.017$). Other factors were comparatively less impacting. All the variables showed significant results in geographic factor detection.

Table 3
Changes of Land use for 30 years (1991–2020) with 10 years interval.

Changes	1991–2020	1991–2000	2000–2010	2010–2020
Water bodies	+2.88%	−22.99%	−12.89%	+53.39%
Settlement	+107.19%	+92.68%	+1.61%	+5.83%
Sal Forest	−23.35%	−46.20%	+36.54%	+4.35%
Other vegetations	−30.12%	+32.39	−11.50%	−40.35%
Bareland	+160.89%	+55.65%	−67.28%	+412.33%

Table 4
Land cover change matrix (1991–2000).

Class	Water Bodies	Settlement	Sal Forest	Other Vegetations	Bare Land	Total (1999)
Water Bodies	7721.19	423.54	342.63	3330.54	250.92	12068.82
Settlement	4618.98	5953.5	13694.04	12369.42	1774.08	38410.02
Sal Forest	456.48	1858.41	27586.35	8637.39	377.73	38916.36
Other Vegetations	2679.75	10981.17	29032.47	16647.3	3308.04	62648.73
Bare Land	197.55	718.56	1683.54	6336.72	84.33	9020.7
Total (2000)	15673.95	19935.18	72339.03	47321.37	5795.1	161064.63

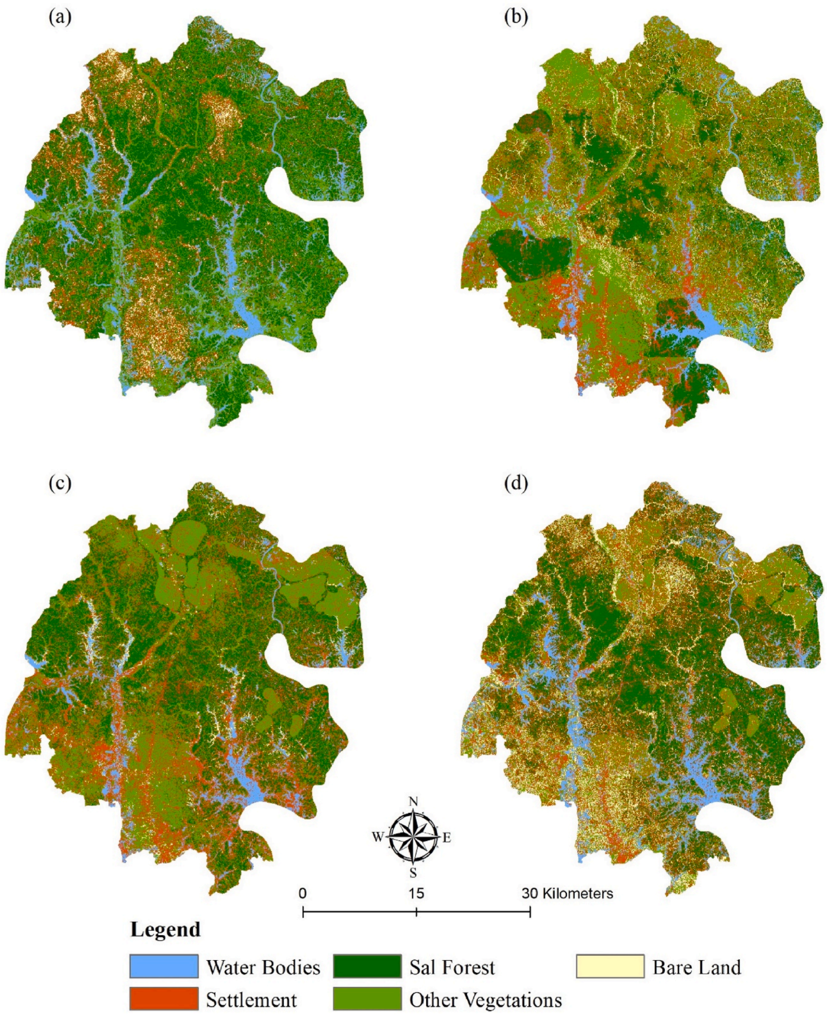

Fig. 4. Landcover change maps (a) 1991, (b) 2000, (c) 2010, and (d) 2020.

Table 5
Land cover changes matrix (2000–2010).

Class	Water Bodies	Settlement	Sal Forest	Other Vegetations	Bare Land	Total (2000)
Water Bodies	6519.06	2410.11	303.03	1199.79	81.18	10513.17
Settlement	3668.04	10719.81	7629.12	14045.49	2968.11	39030.57
Sal Forest	75.6	9618.03	22435.65	19821.78	1183.05	53134.11
Other Vegetations	1073.97	14369.67	8471.7	26790.48	4729.68	55435.5
Bare Land	732.15	1292.4	76.86	791.19	58.68	2951.28
Total (2010)	12068.82	38410.02	38916.36	62648.73	9020.7	161064.63

Table 6
Land cover change matrix (2010–2020).

Class	Water Bodies	Settlement	Sal Forest	Other Vegetations	Bare Land	Total (Ha)
Water Bodies	7106.94	6615.54	176.49	1636.29	590.76	16126.02
Settlement	1729.17	13012.29	9069.66	16547.94	945.09	41304.15
Sal Forest	181.71	6405.57	39461.22	9364.41	32.58	55445.49
Other Vegetations	1109.25	8984.88	3538.98	18546.03	889.92	33069.06
Bare Land	386.1 =	4012.29	887.76	9340.83	492.93	15119.91
Total (Ha)	10513.17	39030.57	53134.11	55435.5	2951.28	161064.63

3.6. *Prediction results for 2030 and 2040*

The prediction result shows that the waterbodies will double (from 6.53% to 10.12%) in 2030 and 2040 (Table-8, Fig. 5). The settlement areas will be almost similar in 2030 and 2040 than those of 2020. Interestingly, the Sal Forest area shows an increasing trend from 2020 (32.99% Sal Forest area) to2030 (44.59% Sal Forest area, and 2040 (52.02% Sal Forest area). There will be a dramatic decrease in the other vegetation area from 34.42% in 2020 to 12.84% in 2030 and 8.70% in 2040. The bare land area shows increasing from 2020 to 2030 by almost three times, although the bare land area also decreased from 2030 to 2040 from 6.09% to 2.80% of the total area.

4. Discussion

Sal Forest (*Shorea roobusta*) in Bangladesh is the most endangered forest due to the expansion of heavy industries, human incursion, and urbanization [51]. Several investigations were found on Sal Forest regarding management [52], agroforestry and livelihood [53], and ecosystems [54]. A multi-temporal image analysis showed that the Bhowal National Park, Gazipur, a part of the Sal Forest increased the water bodies and settlement by 105 and 369%, respectively from 2005 to 2020 [55]. This study area is very near Dhaka city and highly influenced by human activities. The present study shows that the increase of water bodies and settlements by 53 and 6% respectively from 2010 to 2020. The present study area is bigger than the previous study area and also a very remote area with fewer human activities. These reasons might cause different results. However, in both cases, the trends are increasing for both water bodies and settlements. Another remote-sensing based study showed that the Sa forest cover area in Madhupur decreased by 31% from 1972 to 2015 [56]. The present study showed a decrease of 23% in forest area from 1991 to 2020. The Sankey diagram (Fig. 6) showed that a large portion of other vegetation converted to the Sal Forest suggesting the social afforestation in the Sal Forest area implemented by the government.

The transformation of barren ground to other vegetation revealed an expanding tendency of homestead vegetation or agricultural (such as banana, and pineapple) in the research region. The bare land created by the illegal logging of the Sal tree. However, since the 1980s, the Forest Department, Bangladesh government has begun implementing participatory agroforestry schemes in the Madhupur Garh with the aid of programs funded by the World Bank and the Asian Development Bank [57] to incorporate local indigenous people for forest development. The initiatives reflected the land use change from 1991 to 2000. The participatory agroforestry attributed to the conversion of the Sal Forest and other vegetation areas vis-a-vis. A large portion of other vegetations area has been converted to the Sal Forest area by this time due to the participatory agroforestry program. Although, new settlements invaded the other vegetations area in this period. Interestingly, all the bare land area was converted to other vegetation suggesting the impact of the participatory agroforestry program. Agroforestry is a fast-growing land-use practice in the Sal Forest area [58]. From 2013 to 2021, there was a significant increase in paddy (24.7%–27.2%) and urban (3.5%–10.1%) and a significant decline in homestead (67.5%–59.3%) and woodland (4.2%–3.4%) in Kapasia, Gazipur district [33]. Many related factors have contributed to the acceleration of Sal Forest degradation, with illegal rural settlement in Bangladesh's Madhupur tract being the main one [12]. Over the past two decades revealed that 15.42% of Sal Forest land became bare land and 0.37% of Sal Forest land was converted to a built-up area [59] the settlement area showed almost no change over the last three decades, although the land use pattern suggesting that the people have displaced their settlement in the forest area because of illegal settlement. The forest department demolished their present settlement and later on their new settlement in the forest area but not outside the forest area.

One of the main factors which seriously harms the conditions of the forest and accelerates the destruction is rapid industrial

Table-7
Natural and physical factors deploying for LULC and prediction analysis.

Type	Variables	q-statistic	*p-value*
Natural	Elevation	0.017	*<.01*
	Slope	0.001	*<.01*
	Aspect	0.001	*<.01*
Anthropogenic	Population	0.032	*<.01*
	Road	0.002	*<.01*
	Railway	0.012	*<.01*
	Industry	0.038	*<.01*

Table 8
The scenario of land-use of the Sal forests in Bangladesh.

Year	2030		2040	
Class	Area (ha)	Area (%)	Area (ha)	Area (%)
Water Bodies	16307.55	10.12	16307.55	10.12
Settlement	42451.65	26.36	42451.92	26.36
Sal Forest	71820.45	44.59	83788.38	52.02
Other Vegetations	20676.15	12.84	14014.89	8.70
Bare Land	9808.83	6.09	4501.89	2.80

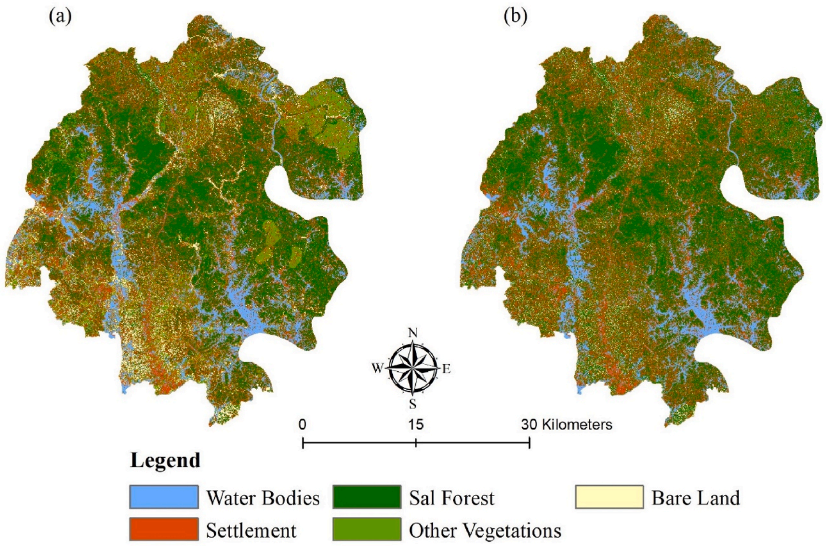

Fig. 5. Land use probability maps (a) 2030, and (b) 2040 based on CA-ANN model.

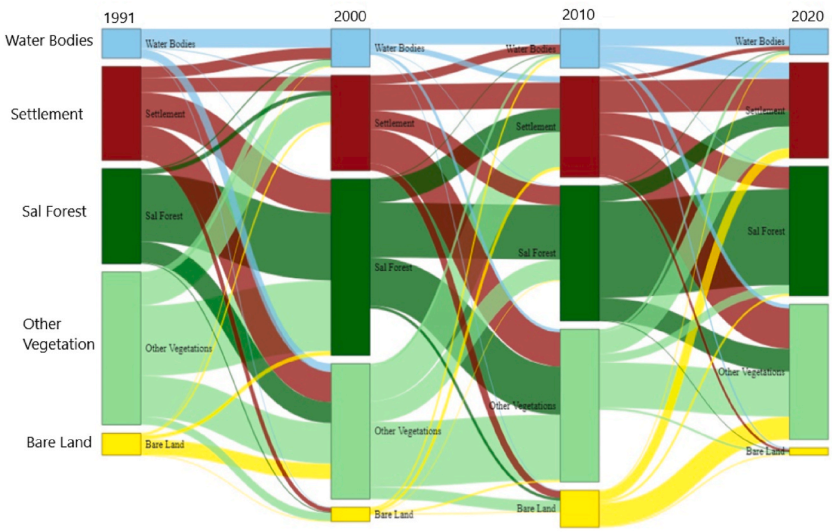

Fig. 6. Sankey diagram showing the interchanges of land-use in Sal forests.

expansion [60]. In the present study, the industrial area was included in the settlement area. The Sal Forest area was continuing to decrease from 2000 to 2020 suggesting the weakness of the government to protect the forest cover. The Linos share of the Sal Forest is being converted to other vegetation suggesting the acceleration of homestead vegetation and agricultural land. The rapid expansion of industries contributes to deforestation by not only cutting trees but also effluent discharges to contaminate the fertile soil, where no trees grown in the future. An ecosystem imbalance results from the open extraction of toxic waste in the forest [61]. Since 1989, the Forest Department (FD) has Prioritized participatory forestry programs (PFP) in areas with degraded Sal Forests, despite the fact that PFP is now seen as a standard practice among donors and the government for managing forests [62].

The waterbodies show an increasing trend from 2020 to 2030 and 2040. The result suggests the increasing commercial fishing in the study area. There might be another cause like; an effluent discharge pond in the study area. The settlements tend to be almost similar up to 2040 indicating the implementation of strict government rules for forest area preservation. Interestingly the Sal Forest area tends to be increased in the future. The increment of the Sal Forest area is attributed to the government initiatives to protect the area through involvement. The other vegetation area seems to become decreasing in the future. There is a possibility of conversion of such other vegetation area into Sal Forest cover. The bare land area also shows a decreasing trend in the future attributed to the homestead vegetation or Sal Forest area.

Using the CA-ANN model to predict LULC offers both benefits and drawbacks. The benefits include better prediction than that of other models and the use of a data-driven model that allows for the simulation of various scenarios by varying input parameters. On the other hand, the drawbacks include the need for a large amount of data, results that are sensitive to input parameters, and a high level of technical expertise [63]. Future land-use trends may be predicted using LULC models, which can also help planners and politicians make well-informed decisions. The approach can assist in identifying places that are appropriate for conservation, agriculture, or development.

5. Conclusions

Settlements were showing internal displacement in the Sal Forest area rather than increasing the area. Homestead gardening and other vegetation were converted to the Sal Forest cover. Dramatic deforestation was observed from 1991 to 2000. A large portion of Sal Forest was converted to other vegetation (e.g. banana, pineapple, spices). The encroachment of other vegetation in Sal Forest and vice versa indicates the loss of Sal Forest in one place and the formation of Sal Forest in other places. A large portion of the Sal Forest was converted to settlements and other vegetation from 2000 to 2010 suggesting the establishment of industries, probably. The settler cut the Sal trees and planted other vegetation for economic purposes because Sal tree takes a long time to gain economic value. The formation of bare land was converted to the other vegetation. The prediction results show the increment of waterbodies in the future. The area of the settlements will be static in the future. The Sal Forest area will be doubled from 2010 to 2040. The other vegetation will be decreased in a very dramatic trend suggesting the increasing Sal Forest area. The bare land area shows both increasing and decreasing trends. The increase of bare land suggests cutting of forest areas, similarly the decrease of bare land suggests the invasion by the homestead forest areas. In order to reduce deforestation, the government should implement some appropriate forest-conserving measures in coordination with other national and international organizations. These measures include limiting commercial logging, establishing monoculture plantations inside of forest areas by removing native trees, and converting native trees into non-forest areas such as agricultural fields. This LULC prediction in this study was based on seven parameters, more parameters and weightage of the parameters could reveal more accurate results.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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