BAUET JOURNAL
Published by
Bangladesh Army University of Engineering & Technology (BAUET)
Journal Homepage: https://journal.bauet.ac.bd/
DOI: https://doi.org/10.59321/BAUETJ.V5I1.6

Modeling Carbon Sequestration Dynamics of Sal Forest Area of Bangladesh using the InVEST Carbon Model

Ummul Khayer Salma Keya[1*], Jakia Jannat Fabiha[2], Nahida Rahman[3]

[1,2,3]*Institute of Remote Sensing and GIS, Jahangirnagar University, Savar, Dhaka-1342, Bangladesh*

Abstract: Sal Forest is the third largest forest habitat and is a tropical moist deciduous forest in Bangladesh. Illegal human activities are putting a lot of stress on the forest, making it an endangered ecological resource. This study examined the selected areas of the Sal Forest in Bangladesh, specifically the Madhupur Garh and Bhawal Garh tracts, to assess the effects of changes in forest cover on carbon storage capacity from 1995 to 2025 and to predict future alterations. The research employed spatiotemporal analysis utilizing GIS and Remote Sensing tools, alongside with the InVEST Carbon Model and the Cellular Automata–Artificial Neural Network (CA-ANN) method, to model the dynamics of forest cover and their influence on carbon sequestration. The results show that the Sal Forest cover will drop from 74.26% in 1995 to 49.85% by 2035. This will greatly reduce the forest's ability to store carbon. Sal Forest will lose about 908 square kilometers (24.41%) of its area from 1995 to 2035, over 40 years. Most of this area will be converted into other features, especially built-up areas in the near future. These findings offer significant insights to inform effective management and conservation strategies for the preservation of the Sal Forest ecosystem.

Keywords: *Forest cover; Carbon sequestration; Biomass; CA-ANN; InVEST*

Introduction: Increasing atmospheric carbon dioxide (CO_2) levels are a major factor contributing to the acceleration of climate change on a global scale. Forests function as one of the planet's most vital carbon sinks, absorbing over 16 billion metric tons of CO_2 each year and sequestering an estimated 861 gigatonnes of carbon within their biomass and soils [1]. Thus, conservation of forest is critical for mitigating climate change. However, potential of forests to store carbon is dependent on their ecological health, stability, and resilience against land-use pressures. Recognized for rich biodiversity and ecological productivity, Sal Forest ecosystem is one of the most valuable natural landscapes [2]. The regions are situated mainly in the central part of Bangladesh, within the districts of Tangail, Mymensingh, Gazipur and the Sal forests tract is dominated by Sal (Shorea robusta) trees [3], [4]. The Sal Forest tract commonly referred to as 'Madhupur Garh' primarily encompass the district of Tangail and Mymensing, which are interspersed with residential and agricultural area [5], [6], [7]. 'Bhawal Garh' is located in the Dhaka Forest Division's Gazipur District. There are currently a few sparsely populated patches of Sal forests in the northwest Bangladesh and Comilla district [8]. Sal forests, classified as tropical moist deciduous ecosystem, are presently considered severely endangered due to increasing anthropogenic activity and land-use alterations [9]. According to Khurana [10], Sal forests have a greater carbon retention capacity compared to most other natural forest types in South Asia. Thus, understanding their carbon stock dynamics is critical for conservation planning.

The process of absorbing and holding onto long-term carbon in plants and soils in order to reduce or prevent climate change is known as carbon sequestration [11]. Forest carbon pools are composed of living biomass, dead organic matter, and mineral soils, and fluctuate based on deforestation, afforestation, and land management practices [12], [13]. To achieve the full mitigation potential, these carbon reserves must be accurately estimated using statistically verified, spatially explicit methods [14].

Bangladesh's total primary forest area decreased from 1.494 million hectares to 1.429 million hectares between 1990 and 2015, representing an average yearly deforestation rate of 0.2%. Approximately 2,600 hectares of natural forest were lost annually during this time [15]. Specifically, the Sal woods have lost 36% of their natural cover since 1985 [16]. Overharvesting, excessive litter collecting, and monoculture cultivation of pineapple and banana growing, particularly among nearby Garo people, are among the major of pressures [8], [17], [18]. Both biodiversity and the traditional ways of life of indigenous people have been negatively impacted by this degradation [19]. It is crucial to distinguish between the shift in land use, which refers to how people manage or alter land for social or economic reasons and land-cover change, which is the biophysical alteration of the land, such as vegetation or soil characteristics, in order to analyze these dynamics [20]. Using satellite images and remote sensing to determine these changes can give important non-destructive information about forest loss, regeneration patterns, and changes in carbon stock and sequestration capacity related to these changes [21], [22], [23] .

For effective sustainable forest preservation and management initiatives, a data-driven, spatiotemporal assessment of the alterations in Sal Forest cover is essential [24], [25]. Some studies have used different models to estimate carbon sequestration. These models include the Artificial Intelligence (AI) for Ecosystem Services (ARIES) model [26], [27], the Social Values for Ecosystem Services (SoLVES) model [28], and the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST)

Article history:
Received: 13 June 2025
Received in revised form: 28 August 2025
Accepted: 24 September 2025
Available online: 15 December 2025

Corresponding author details: Ummul Khayer Salma Keya
E-mail address: ummulkhayersalmakeya24@gmail.com
Tel: +8801717183344

model [29], [30], [31], [32], [33]. The SoLVES model has multiple applications for determining the social value of ecosystem services [28], [34]. However, employing the SoLVES requires a longer time for a single evaluation as well as a thorough and complete questionnaire. Additionally, the respondents' subjective variables, their lack of understanding of the types of social values, and the non-standardization of social value points would all have an impact on the model analysis outcomes [35]. ARIES uses the geographical data while taking into account the social, ecological, and economic characteristics of the studied area [36]. Furthermore, in order to construct the ARIES model, a number of particular case study areas were taken into consideration. The model's applicability is restricted because these case study regions are mostly found in North America and Europe [37].

In contrast to these two models, the InVEST model's application studies are more extensive and widespread globally [38], [39]. InVEST is a collection of software models for mapping and economic valuation of sequestration and storage of carbon under various land use or policy scenarios. One advantage of this model over previous spatiotemporal models is that it relies on straightforward, generalized production functions and only needs GIS rather than modeling expertise [40]. Various users employ these models, especially policy-impact analysts, ecological researchers, and land-use managers [31], [32], [41]. Many researchers have used the InVEST carbon model to figure out how much carbon forest ecosystems can store. This let them figure out the carbon stocks change due to land use and land cover change [42], [43], [44]. This method, when coupled with Remote Sensing and machine learning methods like the Cellular Automata Artificial Neural Networks (CA-ANN) model, enables better predictions about how forests will change in the future and how this will affect carbon stocks. This research integrates Remote Sensing, the InVEST carbon model, and CA-ANN methods to examine land cover alterations from 1995 to 2025, evaluating and forecasting their effects on carbon storage capacity up to 2035 in the specified areas of the Sal Forest tract in Bangladesh.

Materials & Method:

Study Area: The Sal Forest is the country's third-largest forest ecosystem, containing pure Sal trees [18], [45]. Covering around 1,200 sq km, the Sal Forest represents approximately 0.81% of Bangladesh's total land area and constitutes 7.5% of the forest land managed by the Forest Department [46]. The study area encompasses both the 'Madhupur Garh' and 'Bhawal Garh' regions. Madhupur Garh is located at 23°50′ to 24°50′ north latitude and 89°54′ to 90°50′ east longitude whereas, the Bhawal Garh is located at approximately 23°58′ to 24°03′ north longitude and 90°17′ to 90°22′ east [2]. The "Madhupur Garh" stands 1-2 meters above the adjacent lowlands [47]. In different locations throughout the Sal Forest tract, the soil is loamy, clay, and sandy loam [48]. The government established national park, known as "Madhupur National Park," with the goal of conserving biodiversity in 'Madhupur Garh' [49]. Figure 1 illustrates the geographic extent and boundary of the study area.

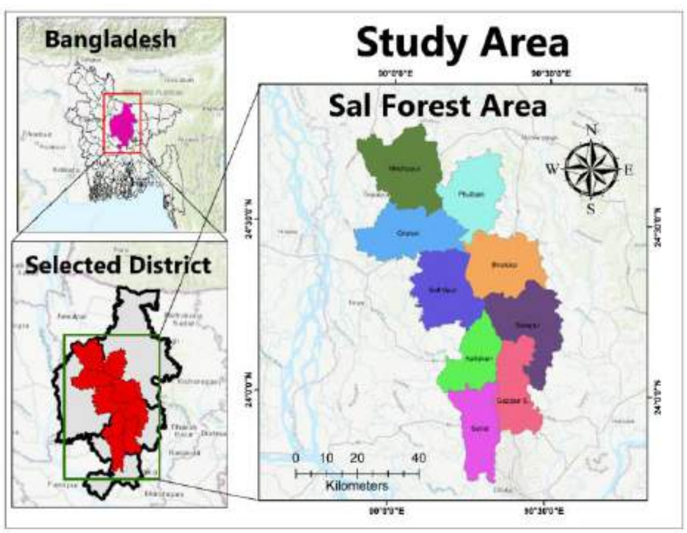

Fig.1. Geographic extent and boundary of the study area.

Data Collection: The data obtained from several organizations and secondary sources was systematically sorted and analyzed in accordance with the specific requirements of the GIS, Remote Sensing and InVEST model approach. Landsat satellite "collection-2 level-2" images were used to explore the forest cover changes of Sal Forest area covering from 1995 to 2025. Table 1 outlines the types of data collected for the study along with their sources.

Table 1. Data collection and sources.

Data Type	Year	Resolution	Source
Landsat 5	October, 1995 October, 2005	30m	US Geological Survey
Landsat 8	October, 2015	30m	US Geological Survey
Sentinel 2	April, 2025	10m	Copernicus Open Access Hub
DEM data	April, 2011	30m	Copernicus Open Access Hub
Road Data	N/A	N/A	Local Government and Engineering Department (LGED)
Railway Data	N/A	N/A	LGED
Industry Location Data	N/A	N/A	Department of Environment (DoE)
Population	2022	N/A	Population and Housing Census, 2022

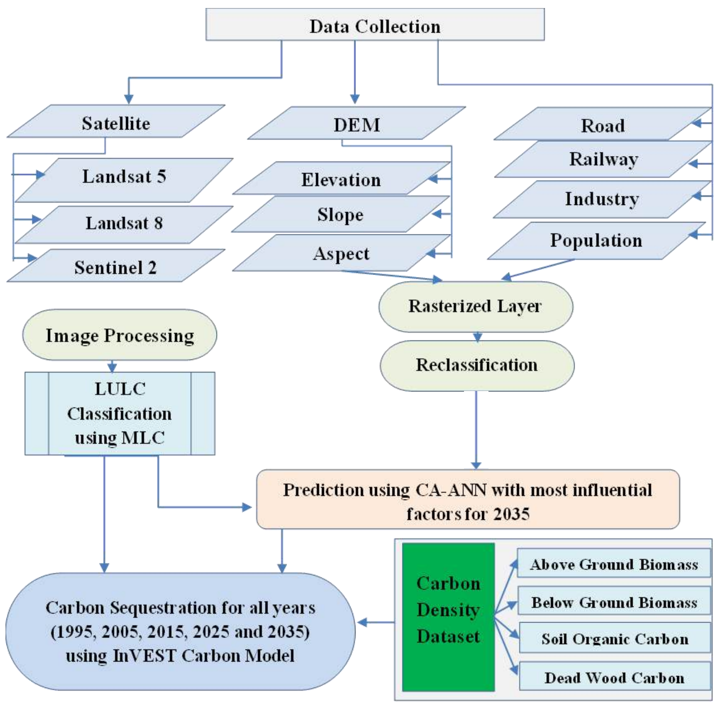

Fig.2. Methodological framework of the study.

Image Classification: Supervised classification was performed using the Maximum Likelihood Classification (MLC) algorithm, which assumes that the statistical distribution of each class in each band is normally distributed and assigns pixels to the class with the highest probability [50]. For this study, five major land use/land cover (LULC) classes were identified: Agriculture, Forest, Waterbody, Settlement, and Barren Land. The land cover classes were categorized using a multispectral image interpretation method called False Color Composite (FCC) imaging. A variety of color combinations can be used to create FCC images. The color scheme selection is determined by the kind of features that must be highlighted in the satellite image. This study used near-infrared (NIR) composite imagery which combines near-infrared, red, and green band of satellite image. When examining vegetations, this band composition is helpful since chlorophyll reflects near-infrared light. Areas in pink to bright red indicate agricultural land, whereas areas in brown to red indicate forest areas and generally have improved vegetation health. Water is dark blue, while bluish green represents built-up areas and barren land appears in white [51], [52].

Accuracy Assessment: The random control points were selected over the classified images for each study year (100 control points for each study year) to assess the accuracy. The points were defined based on the land cover in a 30 m buffer, and in the case of a point falling too close between two different land cover classes, it was slightly modified to represent a complete Landsat pixel. Google Earth Pro historical images and ground truth data were used to verify these control points. Classification accuracy for the classified images was assessed by calculating error metrics (producer, user and overall accuracy) and kappa coefficients (K). According to Congalton, [53] the result of performing a KAPPA analysis is a KHAT statistic and is computed as K with the following equations,

$$\boldsymbol{K} = \frac{\left[n \sum_{i=1}^{r} x_{ij} - \sum_{i=1}^{r} (x_i \, x_j)\right]}{\left[n^2 - \sum_{i=1}^{r} (x_i \, x_j)\right]} \qquad \text{eq.1}$$

Where, n is the total of sample, x_{ij} is the total corrected sample, x_i is the producer total and x_j is the user total. The value of K equal to one means perfect agreement, whereas a value close to zero means that the agreement is no better than would be expected by chance. Therefore, higher value of K indicates the higher the accuracy of land use expectation. Table 2 shows Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy, and Kappa Coefficient for key land use/land cover classes across four years.

Table 2. Accuracy assessment.

	Forest Area		**Agriculture**		**Waterbody**		**Built-up Area**		**Barren Land**			
Year	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**Overall Accuracy**	**Kappa Coefficient (K)**
1995	0.73	0.8	1	1	0.78	0.7	0.78	0.84	1	1	0.88	0.86
2005	0.79	0.79	0.70	1	0.6	0.6	1	0.82	1	1	0.86	0.82
2015	0.86	0.86	0.72	0.93	0.78	0.7	0.97	0.88	1	1	0.90	0.87
2025	0.88	0.82	0.56	0.9	0.8	0.8	0.97	0.81	0.93	1	0.87	0.84

Cellular Automata-Artificial neural network: Following the set of model parameters during the training phase, CA-ANN models, which combine Cellular Automata (CA) and Artificial Neural Networks (ANNs) to simulate land use change, typically in urban and non-urban settings, predict the ultimate land use type of a cell by the highest similarity or likelihood [54]. This approach is implemented in QGIS using the MOLUSCE plugin [55], [56], [57]. This study examined seven predictors elevation, aspect, slope, roads, railroads, industry, and population to investigate how they affected LULC in the Sal Forest Area. While railways, roads, and industry are anthropogenic predictors, elevation, aspect, slope and population are natural. LULC changes are significantly influenced by both natural and man-made influences. Population data was processed and transformed into raster format for spatial analysis according to the number of inhabitants in each upazila. To create continuous raster data, Euclidean distances were measured for railways, roads, and industry. ArcGIS 10.8's natural breakpoints were then used to reclassify each of the generated raster layers into five hierarchical groupings. Area changes were utilized to evaluate changes in different LULC classes, and a number of LULC maps was created. Using the MOLUSCE plugin, land use change maps were generated for the year 2035.

InVEST Model for Carbon Stock Estimation: InVEST, or the Integrated Valuation of Ecosystem Services and Trade-offs, is a tool used to examine the shifts in ecosystems that are likely to affect the advantages that people receive [58]. The four fundamental carbon pools of different land use/cover types, soil and dead organic matter, belowground biomass, and aboveground biomass are incorporated into the carbon density data needed for the InVEST model [59]. By combining the values of carbon pools (aboveground biomass, belowground biomass, dead organic matter, and soil organic carbon) from different ecosystem units, the InVEST-carbon model, which is based on the natural carbon cycle, finally calculates the amount of static carbon that has been stored [40]. The LULC map has been utilized as the main input for estimating the carbon density of each grid cell. The Bangladesh Forest Inventory database provided the carbon pool information for the Sal Forest area. The fundamental idea of the carbon cycle, the overall quantity of carbon storage (static), and the amount of carbon sequestration based on the aforementioned carbon pool and storage data are all taken into account by the InVEST carbon model [60]. The carbon storage of each grid cell has been estimated using the carbon density of each land use and land cover type (from the carbon pool table) as the raw data [61]. Finally, the sum of the carbon pool values allocated to each LULC type has been used to calculate the overall quantity of carbon storage [40][59].The static density of carbon (kg/m2) per individual land use land cover type can be calculated using the equation below according to the InVEST model,

$$\mathbf{C_i = C_{i(above)} + C_{i(below)} + C_{i(dead)} + C_{i(soil)}} \qquad \text{eq.2}$$

Here, $C_{i(above)}$, $C_{i(below)}$, $C_{i(dead)}$ and $C_{i(soil)}$ indicate aboveground carbon density, belowground carbon density, dead organic material and soil organic material carbon density respectively. However, the total carbon storage of the area can be determined by the following formula,

$$\boldsymbol{C_{total} = \sum_{i}^{n} C_i * A_i} \qquad \text{eq.3}$$

Here, $\boldsymbol{C_{total}}$ signifies the total carbon storage in the study area. A_i indicates the area of individual classes.

For example, for the forest area within the study area with a spatial resolution of 30 × 30 m per pixel,

C_i = (31.36 + 5.09 + 0.44 + 84.05) ton/ha (Table 6)
=120.94 ton/ha
So, C_{total} = (120.94*0.09) ton/ha
= 10.34 ton/ha for each pixel

Result and Discussion:

Land Use and Land Cover Change (LULC) (1995-2025): The Sal forests of Bangladesh, especially in Madhupur Garh and Bhawal Garh, represent ecologically significant landscapes that have undergone notable alterations over the past few decades. The study area's land use and land cover trends from 1995 to 2025 can be observed in Figure 3and 4, demonstrating a steady pattern of forest degradation triggered by increased human intervention.

A distinct pattern of forest loss coupled with agricultural and urban growth can be seen in the land use and land cover (LULC) changes in the Sal Forest areas between 1995 and 2025 as illustrated in Table 3 and Table 4. The once-dominant land cover, forests, saw a sharp decline, particularly in the first ten years. Plantation and reforestation initiatives, such as the introduction of rubber cultivation by the Bangladesh Forest Industries Development Corporation (BFIDC) in formerly deforested areas, may have contributed to a brief increase in 2015 [62]. Nevertheless, this improvement was not maintained in the subsequent years.

Due to population-driven forest conversion, agricultural land increased significantly in the early period before gradually declining. Consistent urban growth was indicated by the built-up areas' ongoing rise across all years. Waterbodies fluctuated, and the amount of barren land rose sharply in the last decade after initially declining, indicating abandonment or land degradation. These trends indicate growing ecological stress and highlight why the Sal Forest landscape needs to be protected through conservation and sustainable land-use planning.

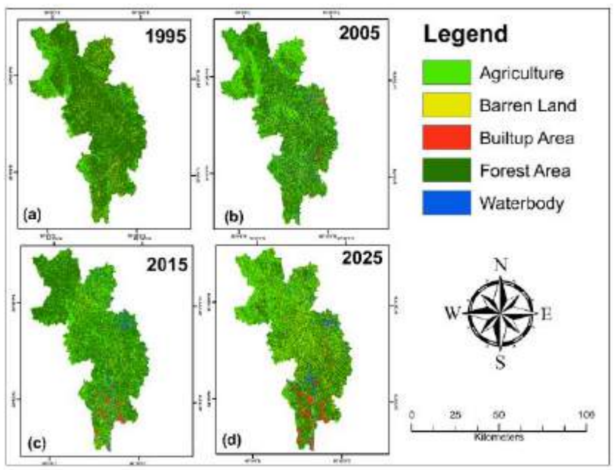

Fig. 3. Land use and land cover (LULC) of the study area (1995-2025).

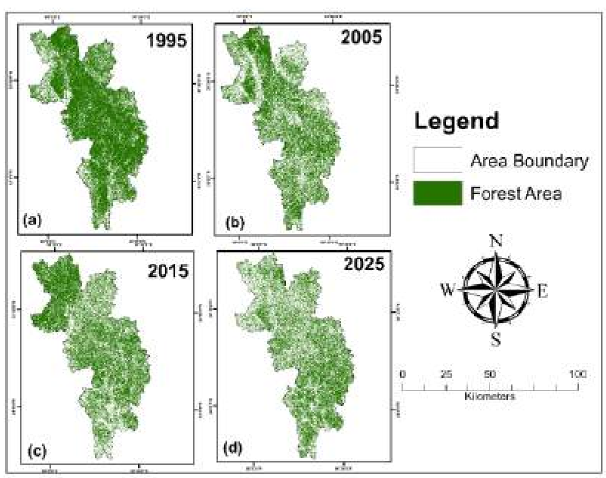

Fig.4. Forest cover changes of the study area (1995-2025).

Table 3. The scenario of land-use of the Sal forests area in Bangladesh (1995-2025).

Class Name	1995		2005		2015		2025	
	Area (sq.km.)	Area (%)	Area (sq.km.)	Area (%)	Area (sq.km.)	Area (%)	Area (sq.km.)	Area (%)
Agriculture	648.10	17.43%	1225.48	32.96%	1154.86	31.06%	1103.25	29.68%
Forest Area	2761.05	74.26%	2061.17	55.44%	2213.77	59.55%	1872.60	50.37%
Waterbody	23.43	0.63%	176.50	4.75%	126.85	3.41%	115.41	3.10%
Builtup Area	42.92	1.15%	58.73	1.58%	84.90	2.28%	153.95	4.14%
Barren Land	242.10	6.51%	195.74	5.27%	137.23	3.69%	472.41	12.71%

Table 4. Changes of Land use for 30 years (1995–2025) with 10 years interval.

Changes	1995-2005	2005-2015	2015-2025	1995-2025
Agriculture	+15.53%	-1.90%	-1.39%	+12.24%
Forest Area	-18.82%	+4.10%	-9.18%	-23.90%
Waterbody	+4.12%	-1.34%	-0.31%	+2.47%
Builtup Area	+0.43%	+0.70%	+1.86%	+2.99%
Barren Land	-1.25%	-1.57%	+9.02%	+6.19%

LULC Prediction (2035): Following the identification of LULC class changes, the study aimed at forecasting the LULC for 2035 using historical LULC maps. Future LULC prediction was done using the elevation, slope, aspect model, distance from main roads, distance from railway, distance from industry and population of the study area as spatial variables. These factors have been selected based on their capacity to drive changes in land use patterns and their impact on land cover dynamics.

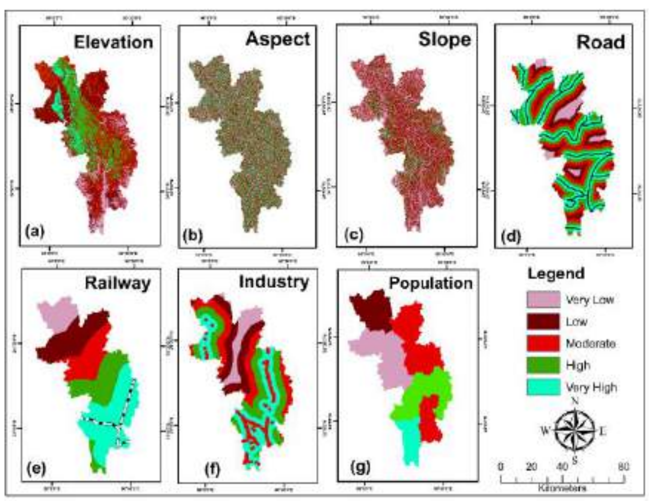

Fig.5. Spatial variables influencing land use and land cover of the study area.

Initially, the CA-ANN method was used to predict the LULC for 2015 based on data from 1995 and 2005. The model was then validated by comparing the 2015 classified image with the predicted image. After the model was validated, the LULC for 2035 was projected from 2015 to 2025. This technique could be used to accurately forecast future land cover scenarios, providing crucial data for land management and regional planning. The main spatial variables used in the analysis are shown in Figure 5.

The projected land use and land cover (LULC) scenario for the Sal Forest areas of 2035 (Figure 6) indicates continued transformation, with forest cover expected to decline further while agricultural, built-up, and barren lands expand. Both direct forest eradication and the slow erosion of protected areas are reflected in these patterns [63][64]. The continued existence of these pressures suggests that forest fragmentation is accelerating, which could upset the natural equilibrium and have a negative impact on the local ethnic communities. Furthermore, the region's biodiversity may be seriously hampered by the ongoing loss of natural forest habitat, endangering native plants and animals that depend on this special ecosystem.

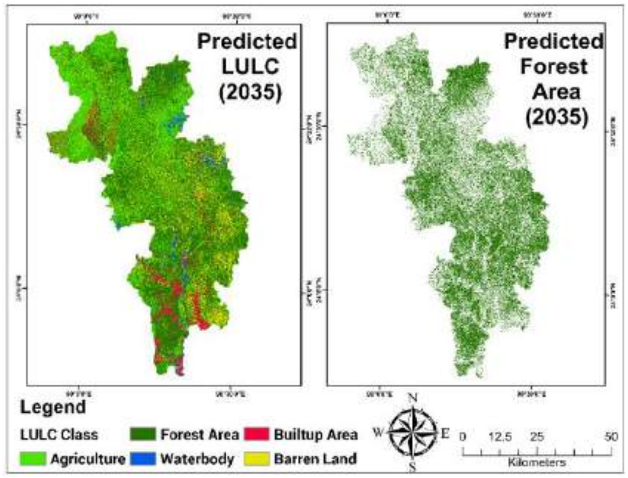

Fig. 6. Predicted LULC and forest cover of the study area (2035).

The forest area, which accounted for 74.26% of the landscape in 1995, is expected to drastically decline to 49.85% by 2035, indicating a significant decline in forest cover (Table 5). The projected increase in agricultural land from 17.43% to 28.17% reflects a steady conversion of forest areas into agricultural land. Rapid urbanization is highlighted by the significant growth that is expected to occur in built-up areas, which are expected to nearly fivefold from 1.15% to 5.60%. All things considered, the projected scenario points to a significant shift away from natural forest landscapes and toward land uses that are more dominated by humans.

Table 5. Predicted land use scenario of the Sal Forest area in Bangladesh (2035).

Class Name	2035	
	Area (sq.km.)	**Area (%)**
Agriculture	1047.22	28.17%
Forest Area	1853.23	49.85%
Waterbody	96.31	2.59%
Builtup Area	208.24	5.60%
Barren Land	512.62	13.79%

Carbon Sequestration of Study Area: Depending on the unique characteristics and environment, forests can play a variety of roles in the carbon cycle, from net emitters to net sinks of carbon. The forest stores carbon dioxide (CO_2) in biomass after absorbing it from the atmosphere during photosynthesis, which process is known as carbon sequestration [65]. By reducing the amount of greenhouse gases in the atmosphere, this function helps to slow down climate change. However, different land uses have different potentials for sequestering carbon.

Table 6. Carbon pool data [66].

LUCODE	LULC Name	C_above	C_below	C_soil	C_dead
1	Agriculture	12.63	1.82	78.025	0.11
2	Forest Area	31.36	5.09	84.05	0.44
3	Waterbody	0	0	24.07	0
4	Builtup Area	25.95	17.35	55.15	0.64
5	Barren Land	0	0	0	0

C_above = Above Ground Biomass; C_below = Below Ground Biomass; C_soil = Soil Organic Carbon; C_dead = Dead Wood Carbon

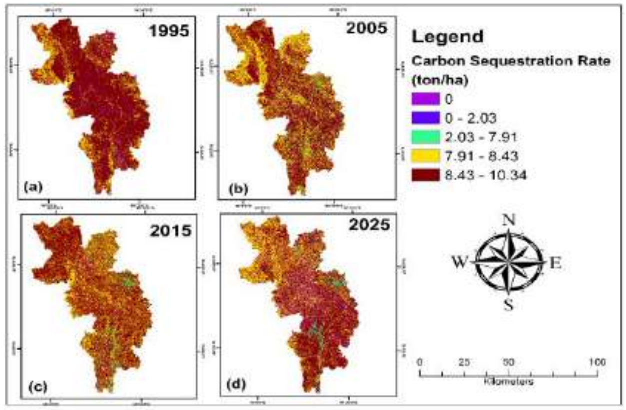

Fig.7. Carbon density map of the study area (1995-2025).

Together with the varied understory vegetation, the dense Sal trees play a significant role in storing carbon. In 1995, widespread forest cover and robust vegetation indicated the region's high to very high carbon sequestration potential in Figure 7. However, between 2005 and 2015, there was a noticeable decrease in high carbon density zones and an increase in low to moderate sequestration areas, indicating a degradation in land cover transformation. The 2025 map shows a further increase in the presence of lower carbon sequestration zones, particularly in the 'Bhawal Garh' area. The decline in carbon sequestration is marked by an initial sharp drop of 7,236.76 tons in 2005, followed by a modest recovery in the amount of carbon sequestered in 2015 (Table 7). The total carbon sequestration declines of 32.17% by 2025 points to a substantial and sustained decline in the forest's ability to store carbon. This decline is closely linked to the ongoing reduction in forest cover that has been noted throughout the study period. As deforestation and land conversion for agriculture, settlements, and other purposes increased, the amount of dense vegetation that could absorb and store carbon decreased. Therefore, the region's capacity to store carbon was directly impacted by the loss of mature forest stands and the deterioration of vegetative biomass.

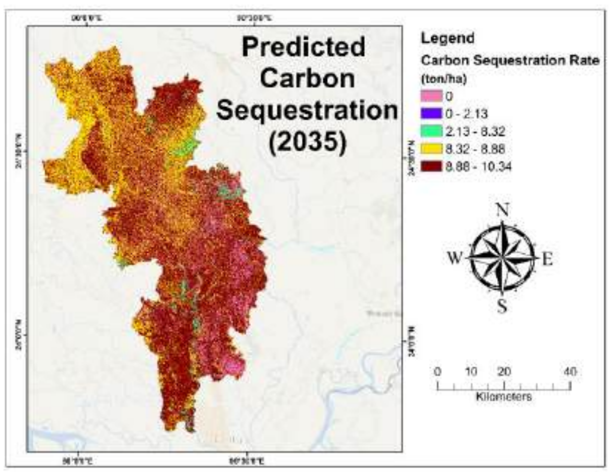

Fig.8. Predicted carbon density map of the study area (2035).

Sal forests are expected to sequester 19,162.40 tons of carbon in 2035, which is a further decrease from the historical values recorded between 1995 and 2025 (Figure 8). It is clear that unless additional preventative measures are implemented, the downward trend in carbon storage is anticipated to continue.

Table 7. Carbon Sequestration by Sal Forest Cover (Forest area only) in Bangladesh (1995–2035).

Year	**Amount (tons)**
1995	28549.26
2005	21312.5
2015	22890.38
2025	19362.68
2035	19,162.40
Total Change	**9386.86 (-32.8%)**

Once lush and thriving, the Madhupur Sal forest is now under growing threat of encroachment. The changing patterns of land usage demonstrate the interaction between ecological condition and socioeconomic factors. These patterns may cause by a number of factors, such as shifting land use pattern, expansion of agricultural activity, which may further worsen by failure to enforce of laws [63]. According to Local Forest Department the illegal concession of more than 8307 acres of Madhupur Sal Forest land has been facilitated by the unapproved occupation of forest land by non-ethnic settlers and organizations, such as political offices, educational and religious institutions, non-governmental organizations [64]. A significant dependence on forest resources, an inadequate amount of available land, and high unemployment have all contributed to the forest's declining condition [67], [68]. Community participation is crucial and should be prioritized because effective conservation requires inclusive planning, teamwork, and active stakeholder engagement [69], [70]. Reforestation efforts can play a vital part in restoring these areas' ability to store carbon in addition to reducing the effects of climate change [71]. Predictive modeling of the study area's future land cover scenarios serves to emphasize the need for proactive planning further. Without targeted conservation and sustainable management strategies, the rate of degradation of forests and landscape change is predicted to accelerate, potentially leading to irreversible ecological consequences. Sustainable forest management involves finding a balance between ecological integrity and economic sustainability in order to cause the least amount of ecological disturbance possible. Establishing governance frameworks and forest policies is also essential to the success of management initiatives for the Sal Forest. The preservation of the Sal forests must be a top national priority due to the growing population pressure and demands on it.

Conclusion: This study proficiently demonstrated the dynamics of carbon sequestration of Sal Forest cover within the Madhupur and Bhawal tracts of Bangladesh using the InVEST Carbon Model. The findings reveal a notable reduction in capacity of carbon storage over the past three decades, with further reductions expected in the upcoming years. This decline also emphasizes the prolonged anthropogenic pressures on Sal forests, including deforestation, land use alterations, and forest decline. The study aids in the understanding of carbon dynamics in tropical forest ecosystems by exhibiting the utility of spatially explicit models like InVEST in quantifying and mapping carbon storage. Moreover, these estimations can guide decision-making processes associated with carbon storage capacity. The government should protect Sal forests by imposing conservation regulations, engaging local inhabitants, planting more trees, and utilizing carbon data during land-use planning to accelerate carbon storage. However, the study is confined by the use of secondary datasets, as well as the absence of field-based validation, which generate uncertainty in the results. To improve model calibration, spatial accuracy, and predictive performance, future research may utilise higher-resolution remote sensing and machine learning strategies, consider socio-economic and policy factors, and involve ground-based biomass and soil carbon measurements.

References:

[1] D. G. N. Harris, Forest Carbon Stocks (Indicators of Biodiversity and Ecological Services), In: Global Forest Review, World Resources Institute. [Online]. Available: accessed Jul. 07, 2025.

[2] K. K. Islam, S. Jose, M. Tani, K. Hyakumura, M. Krott, and N. Sato, Does actor power impede outcomes in participatory agroforestry approach? Evidence from Sal forests area, Bangladesh, Agrofor. Syst., 89 (2015) 885–899.

[3] K. K. Islam and N. Sato, Protected Sal forest and livelihoods of ethnic minorities: Experience from Bangladesh, J. Sustain. For., 32(4) (2013) 412–436.

[4] M. N. Hossain, M. Rokanuzzaman, M. A. Rahman, M. Bodiuzzaman, and M. A. Miah, Causes of deforestation and conservation of Madhupur Sal forest in Tangail region, J. Environ. Sci. Nat. Resour., 6(2) (2013) 109–114.

[5] I. B. C. Office, Bio-ecological zones of Bangladesh, IUCN, 2002.

[6] A. K. Paul, M. M. Mian, M. B. Khan, and M. T. Islam, Study on biodiversity conservation practice in Madhupur Sal forest, Bangladesh, J. Environ. Sci. Nat. Resour., 6(1) (2013) 187–193.

[7] Banglapedia, Sal Forest. Bangladesh National Encyclopedia. [Online]. Available: accessed Jul. 07, 2025.

[8] M. Alam, Y. Furukawa, S. K. Sarker, and R. Ahmed, Sustainability of Sal (Shorea robusta) forest in Bangladesh: past, present and future actions, Int. For. Rev., 10(1) (2008) 29–37.

[9] M. A. Hena, H. Rahman, and M. S. Ali, Satellite Based Approach for Assessing Land Cover Changes of Modhupur Sal Forest Regions in Bangladesh: Its Dynamics and Impacts on Surface Temperature, Indian J. Environ. Eng., 3(1) (2023) 14–21.

[10] P. Khurana, A study on carbon sequestration in natural forests of India, J. Appl. Nat. Sci., 4(1) (2012) 132.

[11] K. Gallant, P. Withey, D. Risk, G. C. van Kooten, and L. Spafford, Measurement and economic valuation of carbon sequestration in Nova Scotian wetlands, Ecol. Econ., 171 (2020) 106619.

[12] S. T. Ahmed et al., Valuation of Madhupur Sal Forest Ecosystem Services and Carbon Sequestration Potency in Bangladesh: an Avenue for Mitigating Climate Change Impact, Contemp. Probl. Ecol., 17(3) (2024) 450–459.

[13] K. Dhanwantri, P. Sharma, S. Mehta, and P. Prakash, Carbon sequestration, its methods and significance, Environ. Sustain.: Concepts, Principles, Evidences Innov., 151(2) (2014) 151–157.

[14] H. Mahmood, M. R. H. Siddique, and M. Akhter, A critical review and database of biomass and volume allometric equation for trees and shrubs of Bangladesh, in: IOP Conf. Ser.: Earth Environ. Sci., IOP Publ., 2016, p. 012057.

[15] Food and Agriculture Organization of the United Nations, Global Forest Resources Assessment 2015: How are the World's Forests Changing?, FAO, 2015.

[16] K. M. Masum, M. N. Islam, N. Saha, M. Z. Hasan, and A. Mansor, Assessment of land grabbing from protected forest areas of Bhawal National Park in Bangladesh, Landsc. Res., 41(3) (2016) 330–343.

[17] S. Dey, The commercialisation of the indigenous economy and its impact on the environment of Modhupur Garh, Bangladesh, Int. J. Green Econ., 1(3–4) (2007) 465–477.

[18] M. S. Islam, T. R. Tusher, M. H. Kabir, M. R. Hassan, and M. N. H. Khan, Carbon storage and sequestration potentiality of tree species in Madhupur Sal Forest of Bangladesh, Bangladesh J. Environ. Sci., 30 (2016) 33–39.

[19] S. Saha, S. S. Hasan, S. Hasan, R. S. Sadi, M. T. R. Labib, and S. Saha, Ecosystem service preference of forest people: a study in Madhupur Sal Forest of Bangladesh, Eur. J. Agric. Food Sci., 4(6) (2022) 20–25.
[20] S. K. Patel, P. Verma, and G. S. Singh, Agricultural growth and land use land cover change in peri-urban India, Environ. Monit. Assess., 191 (2019) 1–17.
[21] P. Leimgruber, D. S. Kelly, M. K. Steininger, J. Brunner, T. Müller, and M. Songer, Forest cover change patterns in Myanmar (Burma) 1990–2000, Environ. Conserv., 32(4) (2005) 356–364.
[22] J. K. Mani and A. O. Varghese, Remote sensing and GIS in agriculture and forest resource monitoring, in: Geospatial Technol. Land Resour. Mapping, Monitoring Manage., 2018, pp. 377–400.
[23] S. Tadese, T. Soromessa, A. B. Aneseye, G. Gebeyehu, T. Noszczyk, and M. Kindu, The impact of land cover change on the carbon stock of moist afromontane forests in the Majang Forest Biosphere Reserve, Carbon Balance Manag., 18(1) (2023) 24.
[24] M. Minta, K. Kibret, P. Thorne, T. Nigussie, and L. Nigatu, Land use and land cover dynamics in Dendi-Jeldu hilly-mountainous areas in the central Ethiopian highlands, Geoderma, 314 (2018) 27–36.
[25] M. Townsend, C. Henderson-Wilson, H. Ramkissoon, and R. Weerasuriya, Therapeutic landscapes, restorative environments, place attachment, and well-being, 2018.
[26] K. J. Bagstad, F. Villa, D. Batker, J. Harrison-Cox, B. Voigt, and G. W. Johnson, From theoretical to actual ecosystem services: mapping beneficiaries and spatial flows in ecosystem service assessments, Ecol. Soc., 19(2) (2014).
[27] B. Zank, K. J. Bagstad, B. Voigt, and F. Villa, Modeling the effects of urban expansion on natural capital stocks and ecosystem service flows: A case study in the Puget Sound, Washington, USA, Landsc. Urban Plan., 149 (2016) 31–42.
[28] H. Duan and N. Xu, Assessing social values for ecosystem services in rural areas based on the SolVES model: A case study from Nanjing, China, Forests, 13(11) (2022) 1877.
[29] X. Li et al., Spatio-temporal patterns of carbon storage derived using the InVEST model in Heilongjiang Province, Northeast China, Front. Earth Sci. (Lausanne), 10 (2022) 846456.
[30] J. Mallick, M. K. Almesfer, M. Alsubih, M. Ahmed, and N. Ben Kahla, Estimating carbon stocks and sequestration with their valuation under a changing land use scenario: a multi-temporal research in Abha city, Saudi Arabia, Front. Ecol. Evol., 10 (2022) 905799.
[31] F. Adelisardou, W. Zhao, R. Chow, P. Mederly, T. Minkina, and J. S. Schou, Spatiotemporal change detection of carbon storage and sequestration in an arid ecosystem by integrating Google Earth Engine and InVEST (the Jiroft plain, Iran), Int. J. Environ. Sci. Technol., 19(7) (2022) 5929–5944.
[32] L. Nel et al., InVEST soil carbon stock modelling of agricultural landscapes as an ecosystem service indicator, Sustainability, 14(16) (2022) 9808.
[33] Z. Xu, Z. Zhao, and C. Lu, The contribution of land use and land cover on carbon storage in the north Tibet Plateau, China, J. Anim. Plant Sci., 31(6) (2021).
[34] B. C. Sherrouse, J. M. Clement, and D. J. Semmens, A GIS application for assessing, mapping, and quantifying the social values of ecosystem services, Appl. Geogr., 31(2) (2011) 748–760.
[35] Z. Zhang, H. Zhang, J. Feng, Y. Wang, and K. Liu, Evaluation of social values for ecosystem services in urban riverfront space based on the SolVES model: A case study of the Fenghe river, Xi'an, China, Int. J. Environ. Res. Public Health, 18(5) (2021) 2765.
[36] K. L. Vigerstol and J. E. Aukema, A comparison of tools for modeling freshwater ecosystem services, J. Environ. Manage., 92(10) (2011) 2403–2409.
[37] S. Willcock et al., Machine learning for ecosystem services, Ecosyst. Serv., 33 (2018) 165–174.
[38] Y. Hu and M. Gao, Evaluations of water yield and soil erosion in the Shaanxi-Gansu Loess Plateau under different land use and climate change scenarios, Environ. Dev., 34 (2020) 100488.
[39] Z. Zhao, G. Liu, N. Mou, Y. Xie, Z. Xu, and Y. Li, Assessment of carbon storage and its influencing factors in Qinghai-Tibet Plateau, Sustainability, 10(6) (2018) 1864.
[40] R. Sharp et al., InVEST 3.8.7 user's guide, The Natural Capital Project, 2020.
[41] J. W. Redhead et al., Empirical validation of the InVEST water yield ecosystem service model at a national scale, Sci. Total Environ., 569 (2016) 1418–1426.
[42] D. Babbar, G. Areendran, M. Sahana, K. Sarma, K. Raj, and A. Sivadas, Assessment and prediction of carbon sequestration using Markov chain and InVEST model in Sariska Tiger Reserve, India, J. Clean Prod., 278 (2021) 123333.
[43] M. Z. Hoque, S. Cui, I. Islam, L. Xu, and S. Ding, Dynamics of plantation forest development and ecosystem carbon storage change in coastal Bangladesh, Ecol. Indic., 130 (2021) 107954.
[44] H. Joloro, G. A. Dianati Tilaki, H. Memarian, and Y. Kooch, Spatial–temporal assessment of land use changes and forest restoration on carbon sequestration using the InVEST model in Central Alborz, Iran, Model. Earth Syst. Environ., 11(4) (2025) 277.
[45] S. H. G. Champion, S. K. Seth, and G. M. Khattak, Forest types of Pakistan, 1965.
[46] Bangladesh Forest Department, Bangladesh wildlife conservation master plan 2015-2035 – BFIS e-Library, [Online]. Available: https://bfis.bforest.gov.bd/library/bangladesh-wildlife-conservation-master-plan-2015-2035/, accessed Jul. 07, 2025.
[47] M. Y. Islam, N. M. R. Nasher, K. H. R. Karim, and K. J. Rashid, Quantifying forest land-use changes using remote-sensing and CA-ANN model of Madhupur Sal Forests, Bangladesh, Heliyon, 9(5) (2023).
[48] M. J. B. Green and M. J. B. Green, IUCN directory of South Asian protected areas, IUCN, 1990.
[49] Bangladesh Forest Department, Tropical Moist Deciduous Forest (Sal Forest), 2025. [Online]. Available: https://bforest.gov.bd/site/page/6c336d56-9484-442d-81e1-7f47bf44cab9/, accessed Jul. 07, 2025.
[50] P. S. Sisodia, V. Tiwari, and A. Kumar, Analysis of supervised maximum likelihood classification for remote sensing image, in: Proc. Int. Conf. Recent Adv. Innov. Eng. (ICRAIE-2014), IEEE, 2014, pp. 1–4.
[51] "Landsat 8 Bands and Band Combinations," GIS Geography, [Online]. Available: https://gisgeography.com/landsat-8-bands-combinations/, accessed Oct. 29, 2025.
[52] "What Is False Color Composite (FCC) and How Its Work in Remote Sensing?," GISRSStudy, [Online]. Available: https://gisrsstudy.com/false-color-composite/, accessed Oct. 29, 2025.
[53] R. G. Congalton, A review of assessing the accuracy of classifications of remotely sensed data, Remote Sens. Environ., 37(1) (1991) 35–46.
[54] T. Li and W. Li, Multiple land use change simulation with Monte Carlo approach and CA-ANN model, a case study in Shenzhen, China, Environ. Syst. Res., 4 (2015) 1–10.

[55] M. T. U. Rahman et al., Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh, Environ. Monit. Assess., 189 (2017) 1–18.
[56] A. S. Değermenci, Spatio-temporal change analysis and prediction of land use and land cover changes using CA-ANN model, Environ. Monit. Assess., 195(10) (2023) 1229.
[57] P. Lukas, A. M. Melesse, and T. T. Kenea, Prediction of future land use/land cover changes using a coupled CA-ANN model in the upper Omo–Gibe river basin, Ethiopia, Remote Sens. (Basel), 15(4) (2023) 1148.
[58] "InVEST | Natural Capital Project," InVEST 3.16.0, Stanford University, University of Minnesota, Chinese Academy of Sciences, The Nature Conservancy, World Wildlife Fund, Stockholm Resilience Centre and the Royal Swedish Academy of Sciences, [Online]. Available: https://naturalcapitalproject.stanford.edu/software/invest, accessed Jul. 07, 2025.
[59] Y. Wang, D. Liang, J. Wang, Y. Zhang, F. Chen, and X. Ma, An analysis of regional carbon stock response under land use structure change and multi-scenario prediction, a case study of Hefei, China, Ecol. Indic., 151 (2023) 110293.
[60] L. Fu, L. Zhang, and C. He, Analysis of agricultural land use change in the middle reach of the Heihe river basin, northwest China, Int. J. Environ. Res. Public Health, 11(3) (2014) 2698–2712.
[61] Y. Liang, L. Liu, and J. Huang, Integrating the SD-CLUE-S and InVEST models into assessment of oasis carbon storage in northwestern China, PLoS One, 12(2) (2017) e0172494.
[62] M. A. Salam and M. A. T. Pramanik, Forest cover change analysis using remote sensing techniques in Madhupur Sal Forest of Bangladesh, J. Environ. Sci. Nat. Resour., 10(2) (2017) 73–78.
[63] R. H. Sojib, Hassan Md. R., Evaluation of Environmental Changes of Sal Forest Land Cover Using GIS and Remote Sensing Techniques: An Empirical Study on Arankhola, Madhupur Sal Forest in Bangladesh, J. Mater. Environ. Sci., 14(10) (2023) 1197–1212.
[64] K. K. Islam and K. Hyakumura, Forestland concession, land rights, and livelihood changes of ethnic minorities: The case of the Madhupur Sal forest, Bangladesh, Forests, 10(3) (2019) 288.
[65] K. Lorenz, Carbon sequestration in forest ecosystems, Springer, 2010.
[66] BFI, BFI Data – Bangladesh Forest Inventory, [Online]. Available: https://bfis.bforest.gov.bd/bfi/bfi-data/, accessed Jul. 07, 2025.
[67] H. M. Abdullah, M. G. Mahboob, M. M. Rahman, and T. Ahmed, Monitoring natural Sal forest cover in Modhupur, Bangladesh using temporal Landsat imagery during 1972–2015, Int. J. Environ., 5(1) (2015) 1–7.
[68] M. S. Iftekhar and A. K. F. Hoque, Causes of forest encroachment: An analysis of Bangladesh, GeoJournal, 62 (2005) 95–106.
[69] F. Berkes, Rethinking community- based conservation, Conserv. Biol., 18(3) (2004) 621–630.
[70] A. Wali, D. Alvira, P. S. Tallman, A. Ravikumar, and M. O. Macedo, A new approach to conservation: using community empowerment for sustainable well-being, Ecol. Soc., 22(4) (2017).
[71] R. Bandara et al., Carbon Stock Assessment in Peat Soil and Mangrove Regrowth Phase of Shrimp Ponds: A Case Study of Ecosystem Restoration in the Indian Sundarbans.