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Research Article

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Spatiotemporal Dynamics and Projection of Forest Cover Using Remote Sensing and Machine Learning in Baishari Bangdopa, Bangladesh

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Abstract

Forest ecosystems in Bangladesh are increasingly threatened by shifting cultivation, agricultural expansion, logging, and infrastructure development, resulting in widespread degradation and fragmentation. The Baishari Bangdopa forest landscape in the Chittagong Hill Tracts represents a critical biodiversity corridor, yet remains poorly studied at the local scale. This study integrates multitemporal Landsat (1988–2014) and Sentinel-2 (2025) imagery with machine learning classifiers—Random Forest, Support Vector Machine, and Long Short-Term Memory (LSTM) networks—to quantify forest cover dynamics, assess fragmentation, and project future scenarios. Results show forest cover declined sharply from 4,867 ha in 1988 to 1,270 ha in 2025, a ~74% reduction, while shrubland and bare land expanded substantially. Fragmentation analysis revealed increasing patch density, declining mean patch size, and a reduction in core forest area from 72% to 22%, underscoring heightened vulnerability to edge effects and biodiversity loss. Classification accuracy was consistently high (overall accuracy > 89%, $\kappa = 0.81\text{--}0.89$), validating the framework. LSTM forecasting achieved strong predictive performance ($R^2 > 0.91$), enabling credible scenario modeling. Projections highlight divergent futures: under business as usual (BAU), forest cover stabilizes at ~8% (~8.5 km²) by 2050; under strict protection, forest cover stabilizes at ~33% (~35.1 km²), nearly tripling forest area compared to BAU; under high deforestation, near-total collapse (~0.2%) is projected by 2050. This study demonstrates forest futures in Baishari Bangdopa are contingent on management choices. By combining remote sensing, machine learning, and scenario analysis, it provides a replicable framework for monitoring and projecting forest dynamics, underscoring the urgent need for strict protection, community-based management, and restoration programs in southeastern Bangladesh.

Keywords: Forest cover dynamics; Remote sensing; Machine learning; Landscape fragmentation; Scenario modeling; Community-based forest management

1 Introduction

Forests underpin ecological stability, biodiversity conservation, and climate resilience worldwide. They provide essential ecosystem services such as carbon sequestration, soil stabilization, and water regulation, while supporting rural livelihoods through timber, fuelwood, and non-timber forest products [7]. Globally, forest loss is driven by agriculture, logging, fire, and urban expansion [11]. Bangladesh reflects many of these pressures, with agricultural expansion and settlement growth being particularly acute.

Bangladesh has experienced substantial forest degradation due to shifting cultivation, agricultural expansion, illegal logging, and infrastructure development [24]. Modeling assessments suggest that forest cover declined by nearly 2,000 km² between 2012 and 2023, underscoring the urgency of robust monitoring and management [21]. These losses threaten ecological stability and climate resilience, highlighting the need for evidence-based conservation strategies.

The Baishari Bangdopa forest landscape, located in the Chittagong Hill Tracts (CHT), is particularly significant as a biodiversity hotspot and ecological corridor, yet remains under-studied compared to other forest regions [2]. In the CHT, forest loss has been especially pronounced, with large tracts converted to shrubland and bare land, reflecting both anthropogenic pressures and weak enforcement of conservation policies [34]. This makes the region an ideal case for analyzing forest fragmentation, scenario modeling, and conservation interventions.

Remote sensing has revolutionized forest ecology by enabling consistent, large-scale monitoring of forest cover dynamics. Satellite platforms such as Landsat,

Sentinel-2, and MODIS provide multi-temporal datasets that allow researchers to detect land cover transitions, assess fragmentation, and quantify vegetation decline [34, 40]. The advent of Google Earth Engine (GEE) has further transformed this field by offering cloud-based access to global satellite archives and scalable computational resources, facilitating long-term, landscape-scale analyses [22]. In Bangladesh, remote sensing has been successfully applied to track mangrove degradation, hill forest dynamics, and Sal forest fragmentation [7, 24].

Traditional classification methods often struggle with heterogeneous forest landscapes. Machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting have demonstrated superior performance in land cover mapping [3, 30]. More recently, deep learning approaches such as Long Short-Term Memory (LSTM) networks have shown promise in capturing temporal dependencies and improving predictive accuracy [1, 21]. These advances enable not only retrospective analysis but also projection of future forest cover scenarios, which is critical for proactive management.

Climate change compounds anthropogenic pressures by altering rainfall patterns, increasing cyclone frequency, and intensifying dry seasons in hill forest ecosystems [24]. The Baishari Bangdopa landscape faces risks from prolonged droughts, shifting cultivation, and soil erosion. Integrating climate variables into spatiotemporal forest cover models enhances predictive capacity and relevance for adaptive management strategies.

Despite growing literature on forest cover dynamics in Bangladesh, localized studies focusing on specific forest landscapes remain limited. The Baishari Bangdopa forest, with its unique socio-ecological context, has not been extensively studied using integrated spatiotemporal analysis and predictive modeling. Most existing studies

emphasize national or regional scales, leaving a gap in site-specific assessments that can inform local management and conservation planning [14, 24]. Addressing this gap is crucial for evidence-based forest management and policy development.

This study aims to assess and project forest cover dynamics in the Baishari Bangdopa Forest Landscape using remote sensing and machine learning approaches. Specifically, it seeks to:

- 1) Quantify spatiotemporal changes in forest cover over recent decades.
- 2) Apply machine learning models to predict future forest cover scenarios.
- 3) Provide insights for sustainable forest management and conservation planning in Bangladesh.

By integrating remote sensing data with advanced machine learning techniques, this research contributes to the growing field of forest ecology and management, offering a methodological framework that can be replicated in other forest landscapes facing similar pressures.

2 Materials and Methods

2.1 Study Area

The Baishari Bangdopa Forest Landscape (10,580 ha) is located in southeastern Bangladesh (21°28'38.35"N, 92°05'31.26"E), spanning the borders of Ramu, Eidgaon, and Naikhongchhari (Fig. 1) [2]. This contiguous forest ecosystem comprises unclassified state forests, reserve forest beats (e.g., Baghkhali), community-managed buffer zones, and local rubber plantations. The terrain is rugged and hilly, with valleys interspersed by agriculture and settlements [17]. Forest types are predominantly tropical evergreen and semi-evergreen, with patches of deciduous vegetation in

disturbed areas [34]. The climate is monsoonal, with annual rainfall exceeding 2,500 mm and mean temperatures ranging between 20–30 °C [2].

At its core lies the Baishari Bangdopa Wildlife Sanctuary (2,233 ha), officially gazetted on 16 April 2023 under Section 13(1) of the Bangladesh Wildlife Act [2]. This legally protected zone is managed by the Bangladesh Forest Department, which prohibits human entry, timber logging, and resource collection to safeguard habitats for flagship species such as Asian elephants and leopards. Ecologically, the Baishari Bangdopa region serves as a biodiversity hotspot and a critical wildlife corridor, supporting species including Clouded leopards, Hornbills, Bears, Sambar deer, and Spotted deer. However, anthropogenic pressures—illegal logging, shifting cultivation, and plantation expansion—have led to fragmentation, habitat loss, and degradation [24, 33]. This dual framework of a strictly protected sanctuary embedded within a multi-use forest landscape makes the area an ideal case study for spatiotemporal forest cover analysis, fragmentation assessment, and projection modeling.

2.2 Data Sources

The primary dataset comprised multitemporal Landsat imagery (Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI) covering the period 1988–2014 (Table 1). Landsat was selected due to its 30 m spatial resolution, global coverage, and long historical archive, which make it particularly suitable for monitoring forest cover dynamics [35, 40]. To enhance classification accuracy in recent years, Sentinel-2 MSI imagery (10–20 m resolution) covering the period 2025 was incorporated, providing finer spatial detail and improved spectral bands for vegetation analysis [16]. These datasets have been widely used in forest ecology studies across South Asia, including Bangladesh, for detecting land-cover transitions and forest fragmentation [24, 34].

Climate, topographic, socioeconomic, and ground truth datasets are summarized in Supplementary Table S1. Climate variables such as rainfall, temperature, and humidity were obtained from the Bangladesh Meteorological Department (BMD). Topographic data were sourced from the Shuttle Radar Topography Mission (SRTM) [18]. Socioeconomic datasets, including population density, agricultural expansion, and settlement growth, were obtained from the Bangladesh Bureau of Statistics (BBS). Historical land-use maps from the Bangladesh Forest Department were also used to validate classification outputs and identify areas of forest management interventions. Field surveys conducted in 2025 collected 350 stratified random validation points across forest, shrub, agriculture, and bare land classes, supported by GPS measurements and participatory mapping with local communities [8, 19].

2.3 Derived Indices

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) were derived from Landsat (1988, 2001, 2014) and Sentinel-2 (2025) imagery to improve vegetation discrimination. NDVI has been widely applied in forest monitoring due to its sensitivity to chlorophyll content and vegetation density [38]. However, NDVI tends to saturate in dense canopy conditions, limiting its ability to detect subtle spectral differences. To address this, EVI was also calculated, as it provides improved performance in areas with dense canopy cover and reduces atmospheric and soil background effects [26]. Both indices were incorporated into the classification framework to strengthen accuracy. For clarity, only NDVI maps are presented in figures, while EVI was primarily used to support classification and predictive modeling.

2.4 Preprocessing

Preprocessing of satellite imagery was a critical step to ensure the reliability of forest cover classification and change detection. Radiometric and atmospheric correction was applied to all datasets. Landsat imagery (1988, 2001, 2014) was corrected using the Dark Object Subtraction (DOS) method to reduce atmospheric scattering and enhance vegetation signal quality [5, 37]. Sentinel-2 imagery (2025) was corrected using the Sen2Cor processor, which generates surface reflectance products suitable for ecological applications [29]. Geometric correction was carried out to align imagery with ground control points, ensuring spatial consistency across multitemporal datasets [35]. To address cloud contamination, the Fmask algorithm was employed to detect clouds, shadows, and snow [41], and annual cloud-free composites were generated using median pixel selection. Following correction and cloud masking, images were mosaicked and subsetting to the Baishari Bangdopa forest landscape. Vegetation indices were then derived to improve discrimination between forest and non-forest classes. NDVI was used to capture general vegetation trends.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$EVI = \frac{2.5 \times (NIR - Red)}{(NIR + 6 \times Red - 7.5 \times Blue + 1)}$$

While EVI provided improved sensitivity in dense canopy conditions [26]. All preprocessing steps were performed using GEE, ENVI 5.6, and ArcGIS Pro 3.0, ensuring methodological robustness and reproducibility. All area values are reported in hectares; change matrices and projections are expressed in km² (1 km² = 100 ha). This unit convention was applied consistently across all analyses and tables.

2.5 Classification and Change Detection

Forest cover classification was performed using supervised machine learning algorithms, which have proven effective in complex tropical landscapes. Training samples were collected through field surveys, high-resolution Google Earth imagery, and forest department maps, ensuring representative coverage of forest, shrubland, agricultural, and bare land classes (Table 2). Three classifiers were employed to strengthen the analytical framework. Random Forest, an ensemble learning method, constructs multiple decision trees and aggregates their outputs, providing high accuracy and resilience against overfitting [3, 4]. Support Vector Machine, a kernel-based classifier, excels in separating complex, non-linear data distributions, particularly when training data are limited [32]. Finally, Long Short-Term Memory networks, a deep learning model capable of capturing temporal dependencies in sequential data, were applied to forecast future forest cover scenarios based on historical classification outputs [25]. To quantify forest cover change, a post-classification comparison approach was adopted. Classified maps from 1988, 2001, 2014, and 2025 were compared to identify areas of forest gain, loss, and persistence. This method is widely recognized for its accuracy in detecting land-cover transitions, as it minimizes spectral confusion by relying on independently classified maps [9, 36]. Change matrices were generated to calculate transition probabilities between classes, providing insights into the drivers of forest dynamics and the spatial patterns of change across the Baishari Bangdopa landscape.

2.6 Accuracy Assessment

Classification accuracy was evaluated using confusion matrices. Metrics included Overall Accuracy (OA), Kappa coefficient, and F1 score. OA was calculated as:

$$OA = \frac{\sum_{i=1}^n x_{ii}}{N}$$

Kappa (κ) as:

$$k = \frac{OA - P_e}{1 - P_e}$$

and F1 score as:

$$F1 = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

where x_{ii} = correctly classified samples for class i , N = total samples, and P_e = expected agreement by chance [8]. Cross-validation (70:30 train-test split) was applied to machine learning models to ensure robustness against overfitting [27]. The integration of field-based validation with statistical accuracy measures strengthened the credibility of remote sensing and machine learning outputs.

2.7 Fragmentation Analysis

Landscape metrics were computed using FRAGSTATS [32]. Edge Density (ED), Mean Patch Size (MPS), and Landscape Shape Index (LSI) were calculated as:

$$ED = \frac{E}{A}$$

$$MPS = \frac{\sum_{i=1}^n a_i}{n}$$

$$LSI = \frac{0.25 \times E}{\sqrt{A}}$$

where E = total edge length, A = landscape area, and a_i = area of patch i . In addition, Patch Density (PD) and Core Area Index (CAI) were computed to provide a more comprehensive understanding of fragmentation. PD measures the number of patches per unit area, while CAI quantifies the proportion of forest area unaffected by edge effects. Together, these metrics allowed us to assess both structural and functional

aspects of forest fragmentation. By integrating fragmentation analysis with classification outputs, we evaluated not only the extent of forest loss but also the spatial configuration of remaining forest patches, which is critical for biodiversity conservation and habitat integrity.

2.8 Projection Modeling

To forecast future forest cover dynamics, we employed LSTM networks, a variant of recurrent neural networks specifically designed to capture temporal dependencies in sequential data [25]. LSTM has proven effective in ecological applications, particularly in modeling land-cover change where historical patterns strongly influence future trajectories. The general model formulation is:

$$y_t = f(y_{t-1}, y_{t-2}, \dots, X_t; \theta)$$

where y_t = forest cover at time t , X_t = external drivers (climate, socio-economic factors), and θ = model parameters [21, 25].

2.9 Projection Scenarios

Three projection scenarios were simulated for the period 2025–2050. The business-as-usual (BAU) scenario assumed continuation of current land-use trends, including agricultural expansion, settlement growth, and limited enforcement of conservation policies. The strict protection (SP) scenario assumed implementation of strong conservation measures, including community-based forest management, restrictions on logging, and expansion of protected areas. In addition, a high deforestation (HD) scenario was modeled, representing accelerated forest loss driven by intensified agricultural expansion, infrastructure development, and weak

enforcement of forest laws. Scenario-based land-use modeling has been applied in the Chittagong Hill Tracts to assess future vegetation coverage [24, 34].

2.10 Model Training and Validation

Historical forest cover data (1988–2025) were used as input sequences for the LSTM forecasting model. External drivers included rainfall, temperature, population density, and settlement expansion. The dataset was split into training (70%) and testing (30%) subsets to ensure robust validation. The model was trained using the Adam optimizer with mean squared error as the loss function. Hyperparameters such as learning rate (0.001–0.01), batch size (32–128), and number of epochs were tuned through grid search to optimize performance. LSTM networks have proven effective in capturing temporal dependencies in land-use forecasting [1, 21].

2.11 Analytical Framework

The methodological framework combined several complementary components to provide a holistic understanding of forest cover dynamics. First, multitemporal remote sensing data were used for spatiotemporal analysis, allowing detection of forest gain, loss, and persistence across intervals (1988–2001, 2001–2014, 2014–2025). Preprocessing of Sentinel-2 imagery was conducted using the Sen2Cor L2A processor [29], while Landsat-based change detection has been widely applied in Bangladesh [24]. Second, predictive modeling was applied using machine learning algorithms (RF, SVM, and LSTM) to classify forest cover and forecast future trends. Third, fragmentation analysis was conducted to evaluate structural and functional changes in forest landscapes through metrics such as edge density and patch size [17, 31].

Finally, scenario analysis was employed to assess potential outcomes under contrasting land-use and management strategies for the period 2025–2050.

2.12 Software and Tools

The analysis was conducted using a combination of software platforms. Google Earth Engine was used for preprocessing, atmospheric correction, and vegetation index derivation [22]. ENVI 5.6 was employed for radiometric correction, mosaicking, and subsetting. ArcGIS Pro 3.0 supported spatial analysis and visualization. FRAGSTATS v4 was used for landscape fragmentation metrics [31]. Python (TensorFlow 2.10, Scikit-learn 1.2) was applied for machine learning classification and LSTM modeling. Classification accuracy was assessed following established protocols [8].

2.13 Methodological Justification

The choice of methods was guided by the need to balance accuracy, reproducibility, and ecological relevance. Multitemporal Landsat imagery provided a long-term perspective on forest cover dynamics, while Sentinel-2 imagery enhanced recent classification accuracy [24, 29]. NDVI and EVI were used together to overcome limitations of individual indices, ensuring reliable vegetation discrimination across varying canopy densities. RF and SVM were selected for their robustness in handling high-dimensional datasets [1, 10], while LSTM was employed for its ability to capture temporal dependencies and project future scenarios [1, 21]. Post-classification comparison minimized spectral confusion and provided reliable change detection. FRAGSTATS metrics allowed for a nuanced understanding of fragmentation [17, 31, 40]. Scenario modeling provided actionable insights for policymakers, highlighting the consequences of different management strategies [24, 34].

3 Results

3.1 Classification Accuracy

Classification outputs demonstrated consistently high reliability across all years (Table 3; Fig. 7). Overall accuracy exceeded 85% in every case, with RF and LSTM outperforming SVM. LSTM achieved the highest accuracy in 2025 (OA = 93.6%, $\kappa = 0.89$, F1 = 0.90), reflecting its strength in capturing temporal dependencies in forest cover dynamics. The 2025 confusion matrix (Supplementary Table S2) further confirmed robustness, with user's accuracies ranging from 87–96% and producer's accuracies from 80–95%. These consistently strong metrics validate the reliability of the classification framework and provide confidence in subsequent change detection and projection analyses.

3.2 Spatiotemporal Forest Cover Dynamics (1988–2025)

Analysis of Landsat and Sentinel imagery revealed substantial forest decline in the Baishari Bangdopa landscape (Table 4; Fig. 3). Forest cover remained stable between 1988 and 2001 (4,867–4,973 ha), but declined sharply thereafter, reaching only 1,270 ha in 2025. Shrubland expanded concurrently, nearly doubling from 5,078 ha to 7,723 ha, while bare land increased steadily from 635 ha to 1,269 ha. Agricultural land appeared only in 2025, covering 318 ha.

Change detection matrices (Table 5; Fig. 4) highlight the severity of forest loss. Forest persistence dropped from 48 km² (1988–2001) to only 12 km² (2014–2025). The most severe decline occurred between 2001 and 2014, when 28 km² transitioned to shrubland and 3.4 km² to bare land, resulting in a net loss of 34.9 km². Losses slowed between 2014 and 2025 but continued, with a net decline of 2.1 km².

Annual change rates (Table 8; Fig. 5) confirm this trajectory: modest gains (+8.2 ha/year) between 1988–2001, severe losses (–268.6 ha/year) between 2001–2014, and slower decline (–19.2 ha/year) between 2014–2025.

3.3 NDVI Derived Classification

NDVI maps (Fig. 6) corroborated classification outputs, showing progressive decline in dense vegetation signatures and expansion of degraded shrubland. NDVI saturation in dense canopy areas was mitigated by incorporating EVI, though NDVI maps are presented for clarity. Together, NDVI and EVI strengthened the classification framework by capturing both general vegetation trends and subtle variations in dense canopy conditions, providing independent validation of classification results.

3.4 Fragmentation Trends

Landscape metrics revealed progressive fragmentation of forest patches (Table 6; Fig. 8). Patch density increased from 0.45 patches/100 ha in 1988 to 1.10 patches/100 ha in 2025, while mean patch size decreased from 12.5 ha to 4.8 ha. Edge density more than doubled (45 m/ha to 120 m/ha), and the Core Area Index declined from 72% to 22%. These results indicate severe reduction of interior forest habitat, with forest persistence replaced by smaller, more isolated patches. The decline in core area is particularly significant, as it reflects the loss of habitat critical for species sensitive to edge effects.

3.5 Projection Scenarios (2025–2050)

LSTM forecasting achieved high predictive performance (Supplementary Table S3), with R^2 values above 0.91 and mean absolute percentage errors below 8%. Scenario

analysis revealed divergent futures (Table 7; Fig. 9). Under Business as Usual, forest cover is projected to decline to ~8% (~8.5 km²) by 2050, leaving only scattered patches dominated by shrub and agriculture. Under Strict Protection, forest cover could stabilize at ~33% (~35.1 km²), supported by regeneration programs and community-based management. The HD scenario projects near-total collapse, with forest reduced to ~0.2% (~2.15 km²) by 2050. Scenario assumptions (Supplementary Table S4) emphasize the critical role of enforcement, regeneration, and community involvement in shaping outcomes.

Therefore, these results demonstrate that forest cover in Baishari Bangdopa has undergone severe decline and fragmentation since 2001, with shrubland expansion dominating the landscape. Without intervention, projections suggest continued degradation under BAU and catastrophic collapse under HD. However, strict protection measures could stabilize forest cover and maintain ecological integrity, underscoring the importance of conservation policy and community-based management in safeguarding biodiversity and ecological resilience.

4 Discussion

4.1 Spatiotemporal Forest Cover Dynamics

Forest cover in Baishari Bangdopa declined by ~74% between 1988 and 2025, shrinking from 4,867 ha to 1,270 ha (Table 4; Fig. 5). This trajectory mirrors broader deforestation trends in Bangladesh, particularly in the CHT, where shifting cultivation, logging, and settlement expansion are major drivers [24, 33]. Losses concentrated along forest edges highlight the vulnerability of peripheral habitats to agricultural conversion and infrastructure development [28].

Fragmentation metrics further underscore degradation: patch density more than doubled, mean patch size declined by over 60%, edge density nearly tripled, and the core area index fell from 72% to 22% (Table 6; Fig. 8). These changes reflect the replacement of continuous forest with smaller, isolated patches, increasing susceptibility to edge effects and biodiversity loss. Similar patterns have been documented globally, where fragmentation reduces species richness, alters ecological processes, and compromises ecosystem functioning [15, 23].

4.2 Drivers of Forest Change

Change detection analysis revealed forest-to-shrub transitions as the dominant pathway of deforestation (Table 5; Fig. 4), reflecting the persistence of jhum cultivation in the CHT. Shortened fallow cycles exacerbate degradation [17], while forest-to-bare land transitions highlight erosion and unsustainable land use. Agricultural expansion after 2014 further intensified conversion.

Limited regeneration was observed in abandoned jhum plots, suggesting secondary succession potential, but insufficient to offset ongoing losses. Assisted natural regeneration and community forestry programs could accelerate recovery, as documented in tropical Asia [6]. In Bangladesh, agroforestry systems demonstrated that proper pruning regimes and optimum fertility management significantly improve yields and farmer income [12]. Incorporating such sustainable land-use practices into forest-adjacent landscapes can reduce reliance on shifting cultivation, complement forest conservation, and provide viable livelihood alternatives for local communities.

4.3 Machine Learning Model Performance

The comparative performance of classifiers revealed that LSTM networks significantly outperformed RF and SVM, achieving overall accuracy above 93% and R^2 values exceeding 0.91 (Table 3; Supplementary Table S3). This aligns with recent studies demonstrating the superior predictive capacity of LSTM in forest cover modeling [21]. LSTM's ability to capture temporal dependencies makes it particularly suitable for spatiotemporal forest dynamics.

RF and SVM, while widely used in remote sensing, showed lower accuracy. RF's ensemble approach provides robustness against noise but lacks temporal modeling capacity [3]. SVM, though effective with limited training data, struggled with complex non-linear transitions [32]. These findings highlight the importance of selecting algorithms aligned with data characteristics and study objectives.

4.4 Forest Cover Projections

LSTM-based projections indicated that forest cover could decline to ~8% (~8.5 km²) by 2050 under BAU conditions (Table 7; Fig. 9). Scenario analysis revealed that stricter forest protection policies could stabilize forest cover at ~33% (~35.1 km²), while unchecked agricultural expansion could reduce it below 1% (~0.2 km²). These projections underscore the urgency of policy interventions to prevent irreversible ecological damage, consistent with regional predictive modeling studies [20].

The stark contrast between BAU and strict protection scenarios highlights the decisive role of governance, enforcement, and community involvement. Under BAU, forest cover stabilizes at fragmented remnants dominated by shrub and agriculture. Under strict protection, however, forest cover stabilizes and regenerates, preserving ecological corridors and biodiversity. The high deforestation scenario illustrates catastrophic consequences, with near-total collapse projected by 2050.

442

443 **4.5 Ecological Implications**

444 The decline and fragmentation of forest cover in Baishari Bangdopa have profound
445 ecological implications. Reduced forest area diminishes carbon sequestration
446 capacity, undermining Bangladesh's climate resilience [7]. Fragmentation disrupts
447 habitat connectivity, threatening species such as elephants, leopards, and hornbills in
448 the CHT [24]. Edge effects further alter microclimates, increase vulnerability to
449 invasive species, and reduce regeneration potential [28].

450 Observed regeneration in abandoned jhum plots offers a glimmer of hope, but
451 without active interventions such as assisted natural regeneration or community
452 forestry, these gains may be insufficient. Limited regeneration is strongly influenced
453 by microclimatic factors such as light intensity, which shape seed germination and
454 seedling establishment [13]. Studies in tropical Asia show that combining natural
455 regeneration with targeted restoration enhances biodiversity and ecosystem services
456 [6].

457

458 **4.6 Policy and Management Implications**

459 The findings have direct implications for forest management in Bangladesh.
460 Regulating shifting cultivation through sustainable alternatives such as agroforestry
461 could reduce pressure on forests while maintaining livelihoods [24]. Infrastructure
462 development must be carefully planned, with environmental impact assessments
463 integrated into project approvals.

464 Community-based forest management offers a promising approach, as
465 demonstrated elsewhere in Bangladesh where local participation improved forest
466 protection [8]. Empowering local communities in Baishari Bangdopa could enhance

stewardship and reduce illegal logging. Integrating remote sensing and machine learning into monitoring systems would provide timely data for decision-making, enabling early intervention in deforestation hotspots. The superior performance of LSTM underscores the potential of deep learning in ecological monitoring and predictive management.

4.7 Contribution to Forest Ecology and Management

This study demonstrates the utility of integrating remote sensing with advanced machine learning models for spatiotemporal forest analysis. The superior performance of LSTM underscores the potential of deep learning in ecological modeling, particularly for predictive applications. By providing both retrospective insights and future projections, the study offers a comprehensive framework for evidence-based forest management.

Focusing on Baishari Bangdopa fills a critical gap in localized forest studies in Bangladesh. While national assessments are valuable, site-specific analyses are essential for tailoring management strategies to local socio-ecological contexts. The findings provide actionable insights for policymakers, forest managers, and conservation practitioners in the CHT. Ultimately, the study demonstrates that forest futures in Baishari Bangdopa are contingent on management choices, emphasizing the urgency of proactive interventions to safeguard biodiversity and ecosystem services.

5 Conclusion

This study provides clear evidence of severe forest decline and fragmentation in the Baishari Bangdopa landscape, with forest area shrinking by nearly three-quarters

between 1988 and 2025. The expansion of shrubland and bare land, coupled with intensifying fragmentation, highlights the vulnerability of remaining patches to edge effects, biodiversity loss, and reduced ecological resilience. These findings underscore the urgent need for conservation interventions in southeastern Bangladesh, particularly in the Chittagong Hill Tracts.

By integrating multitemporal Landsat and Sentinel imagery with advanced machine learning classifiers (RF, SVM, LSTM), this study achieved robust classification outputs validated by accuracy metrics. Fragmentation analysis using FRAGSTATS provided critical insights into landscape changes, while LSTM forecasting enabled credible scenario projections. Together, these methods present a comprehensive framework for monitoring, analyzing, and projecting forest dynamics in complex tropical landscapes.

Scenario modeling revealed that forest futures are highly contingent on management choices. Under business-as-usual trajectories, forest cover is projected to decline to ~8% by 2050, leaving scattered remnants dominated by shrub and agriculture. Strict protection could stabilize forest cover at ~33%, nearly tripling the area compared to BAU and preserving ecological corridors essential for biodiversity. A high-deforestation scenario illustrates catastrophic consequences, with near-total collapse projected by 2050. These contrasting outcomes emphasize the decisive role of enforcement, regeneration, and community-based management in shaping forest resilience.

Finally, this study demonstrates that forest futures of Baishari Bangdopa are not predetermined but depend on proactive management. Strengthening legal protection, expanding community-based forest management, and investing in restoration programs are essential to safeguard biodiversity and ecosystem services.

The methodological framework applied here offers a replicable approach for forest monitoring and scenario planning across tropical regions, supporting evidence-based policy and management decisions.

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Author Contributions

N.D. conceived and designed the study, collected and processed the data, performed the analyses, interpreted the results, and wrote the manuscript. All aspects of the research, including study design, data acquisition, methodology development, statistical analysis, and manuscript preparation, were completed solely by the author.

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Data Availability Statement

All data underlying the results presented in this study are available from the corresponding author upon reasonable request for verification and further analysis.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The author declares no competing interests.

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714 **Table 1.** Description of satellite datasets used- in the study, including sensor type,
715 spatial resolution, acquisition year, and source.

Satellite / Sensor	Platfor m	Spatial Resolution (m)	Spectral Bands Used	Acquisition Years	Purpose / Application	Source
Landsat 5 TM	NASA / USGS	30	Visible, NIR, SWIR	1988	Historical forest cover baseline	USGS EarthExplorer
Landsat 7 ETM+	NASA / USGS	30	Visible, NIR, SWIR, Panchromatic	2001	Mid period forest cover and change detection	USGS EarthExplorer
Landsat 8 OLI	NASA / USGS	30	Visible, NIR, SWIR	2014	Recent forest cover mapping and trend analysis	USGS EarthExplorer
Sentinel 2 MSI	ESA	10–20	Visible, NIR, Red Edge, SWIR	2025	High resolution vegetation analysis and classification refinement	Copernicus Open Access Hub
SRTM DEM	NASA / JPL	30	Elevation	2000	Terrain correction and topographic analysis	USGS EarthExplorer

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725 **Table 2.** Land-cover classification scheme and spectral characteristics.

Class	Description	Spectral Characteristics (NDVI / Reflectance)	Examples / Indicators
Forest Land	Dense tree cover, natural or managed forest	Typically, high NDVI (> 0.6), strong NIR reflectance, low SWIR	Evergreen forest, mixed deciduous stands
Shrub Land	Sparse woody vegetation, degraded forest patches, transitional areas	Moderate NDVI (0.3–0.5), moderate NIR, higher SWIR than forest	Bushes, scrub, regenerating forest
Agricultural Land	Cropland, plantations, shifting cultivation	Variable NDVI (seasonal), moderate NIR, distinct spectral cycles	Paddy fields, jhum cultivation, plantations
Bare Land	Exposed soil, rocky terrain, degraded land	Low NDVI (< 0.2), high reflectance in visible and SWIR	Eroded hillsides, barren soil

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740 **Table 3.** Accuracy assessment of classification results for 1988, 2001, 2014, and 2025.

Year	Classifier	Overall Accuracy (OA, %)	Kappa Coefficient	F1 Score (Macro Average)
1988	RF	87.4	0.83	0.85
	SVM	85.7	0.81	0.83
	LSTM	89.2	0.85	0.87
2001	RF	88.9	0.84	0.86
	SVM	86.3	0.82	0.84
	LSTM	90.1	0.86	0.88
2014	RF	90.3	0.86	0.88
	SVM	87.2	0.83	0.85
	LSTM	91.5	0.88	0.89
2025	RF	92.4	0.88	0.90
	SVM	88.1	0.84	0.86
	LSTM	93.6	0.89	0.90

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Table 4. Area statistics of major land-cover classes for 1988, 2001, 2014, and 2025.

Land cover Class	1988 (ha)	2001 (ha)	2014 (ha)	2025 (ha)
Forest	4867	4973	1481	1270
Shrub	5078	4761	8041	7723
Agriculture	0	0	0	318
Bare Land	635	846	1058	1269

Note: 1 km² = 100 ha

775 **Table 5.** Forest cover change matrix (km²) for 1988–2001, 2001–2014, and 2014–
776 2025.

Interval	Forest Persistence	Forest Loss → Shrub Land	Forest Loss → Agriculture	Forest Loss → Bare Land	Forest Gain (Regeneration)	Net Change (km ²)
1988–2001	48.0	0.8	0.0	0.2	1.3	+1.1
2001–2014	14.0	28.0	0.0	3.4	0.9	–34.9
2014–2025	12.0	1.5	0.3	0.3	0.0	–2.1

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796 **Table 6.** Fragmentation metrics for forest patches in Baishari Bangdopa (1988–2025).

Year	Patch Density (no./100 ha)	Mean Patch Size (ha)	Edge Density (m/ha)	Core Area Index (%)
1988	0.45	12.5	45	72
2001	0.50	11.8	52	70
2014	0.85	6.2	95	28
2025	1.10	4.8	120	22

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817 **Table 7.** Projection results of forest cover under Business-as-Usual, Strict Protection,
818 and High deforestation scenarios to 2050.

Scenario	Forest Cover (%)	Forest Area (km²)	Trend Description
Business as Usual (BAU)	~8%	~8.5 km²	Continued decline; forest reduced to scattered patches, dominated by shrub/agriculture expansion.
Strict Protection (SP)	~33%	~35.1 km²	Stabilization; forest cover maintained through strict enforcement, regeneration programs, and community co management.
High deforestation (HD)	0.2%	~2.15 km²	Accelerated decline; near-complete forest loss driven by intensified agriculture, infrastructure expansion, and weak enforcement.

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Table 8. Annual forest cover change rates (ha/year and %/year) for 1988–2001, 2001–2014, and 2014–2025.

Period	Forest Cover Change (ha/year)	Forest Cover Change (%/year)
1988–2001	+8.2	+0.17
2001–2014	–268.6	–5.40
2014–2025	–19.2	–1.30

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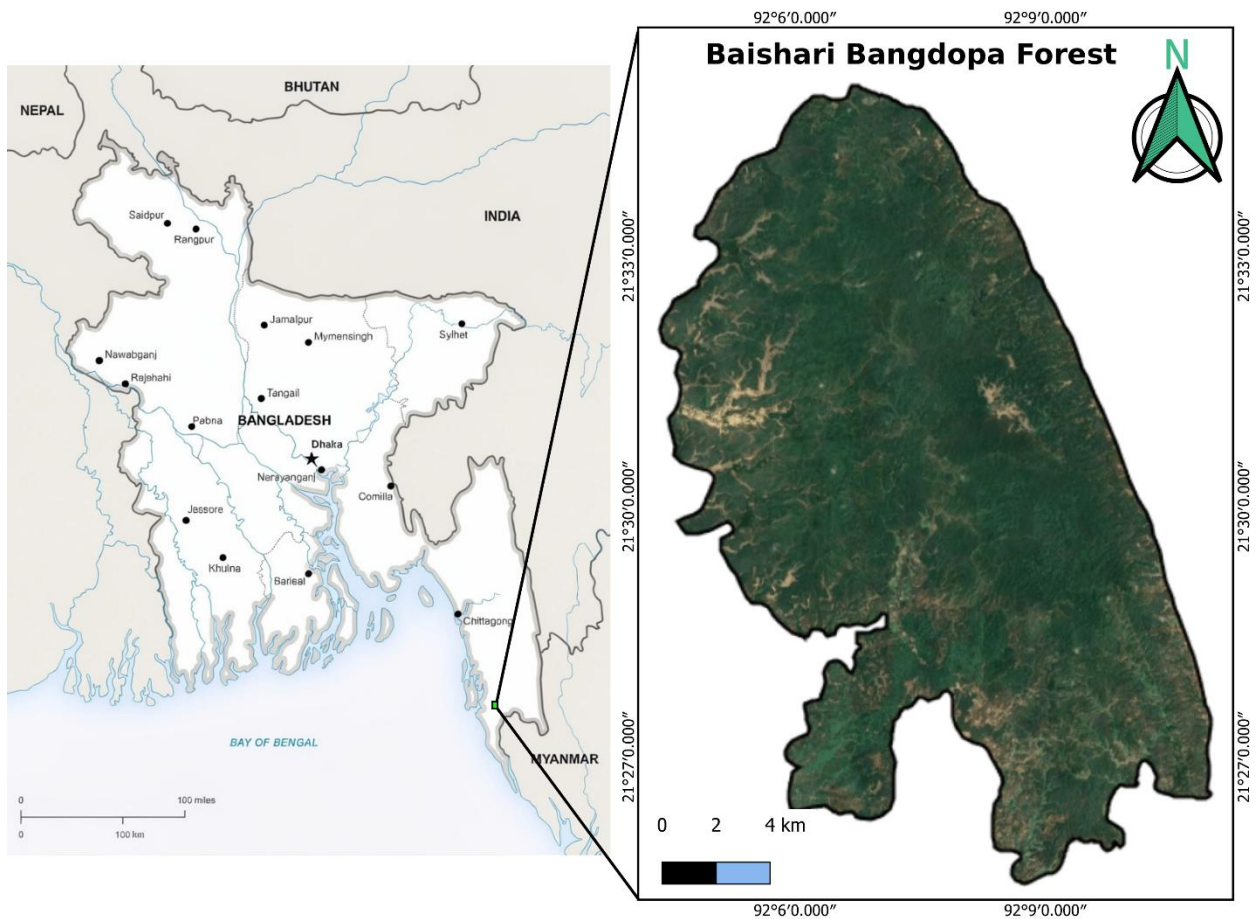


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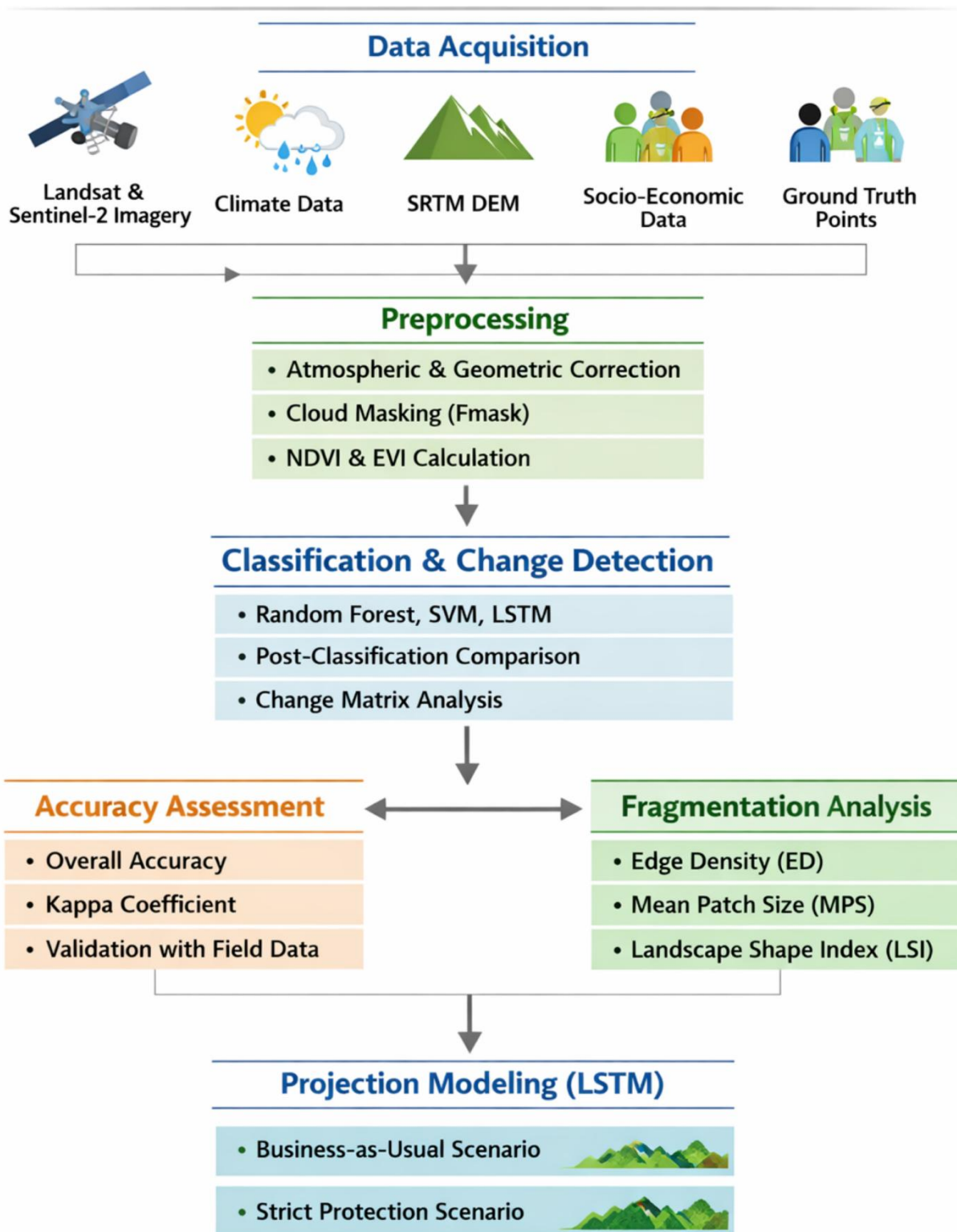


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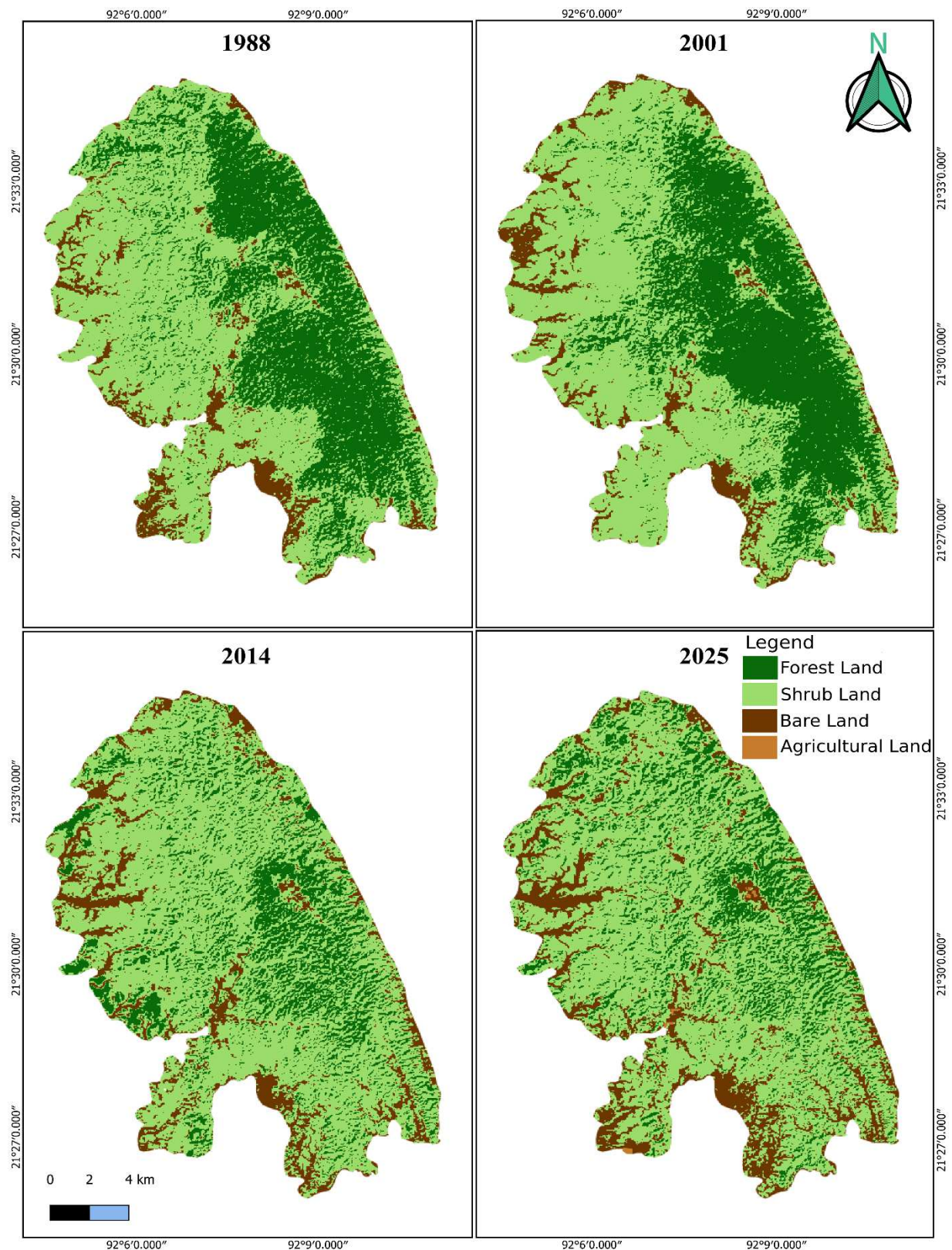


Fig. 3. Land-cover classification maps for 1988, 2001, 2014, and 2025.

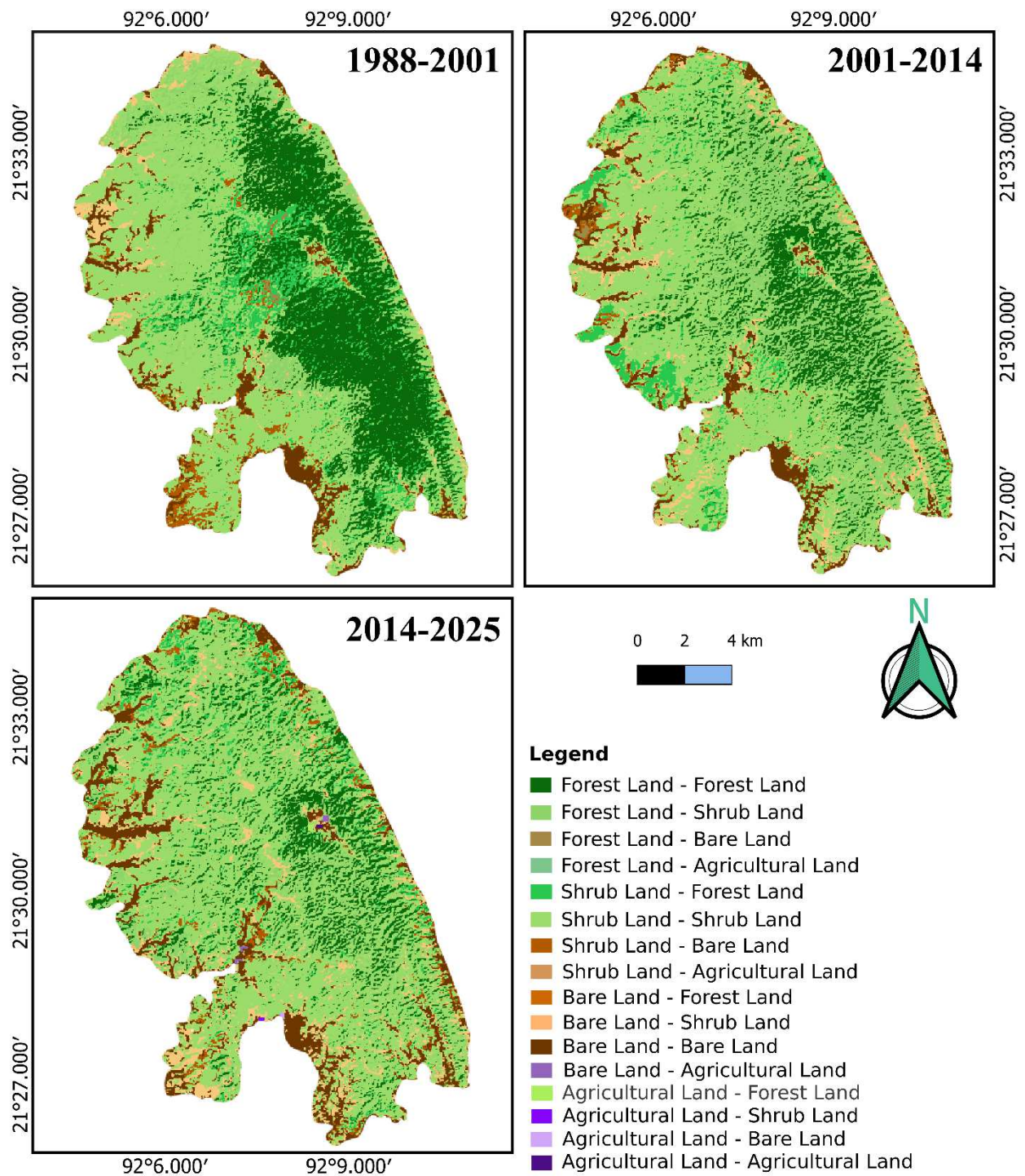


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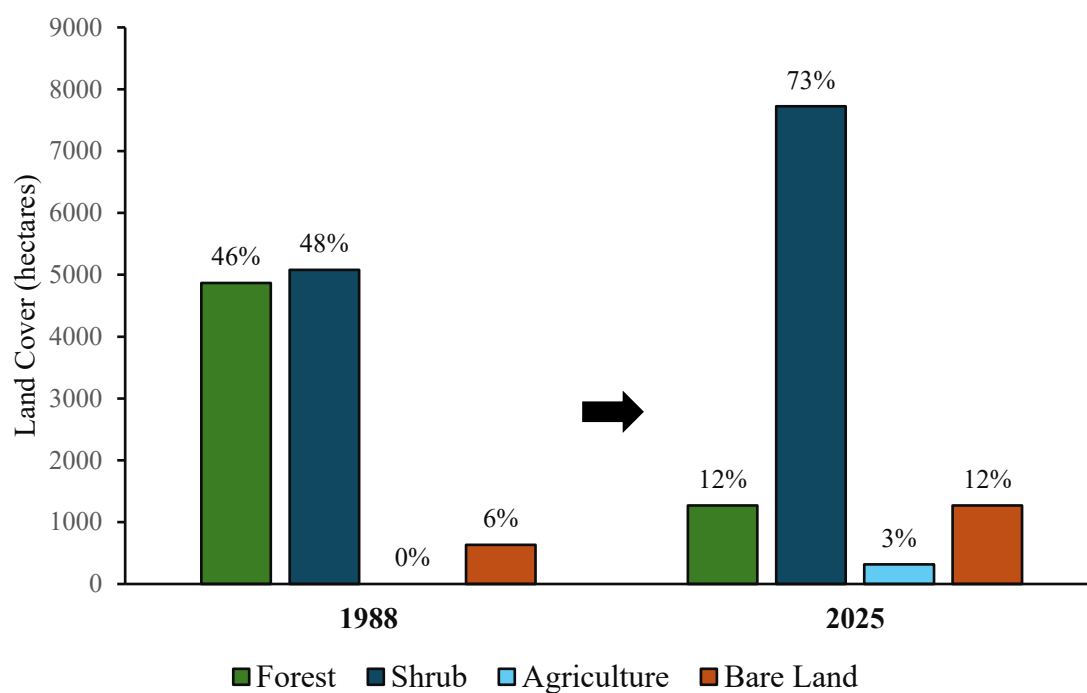


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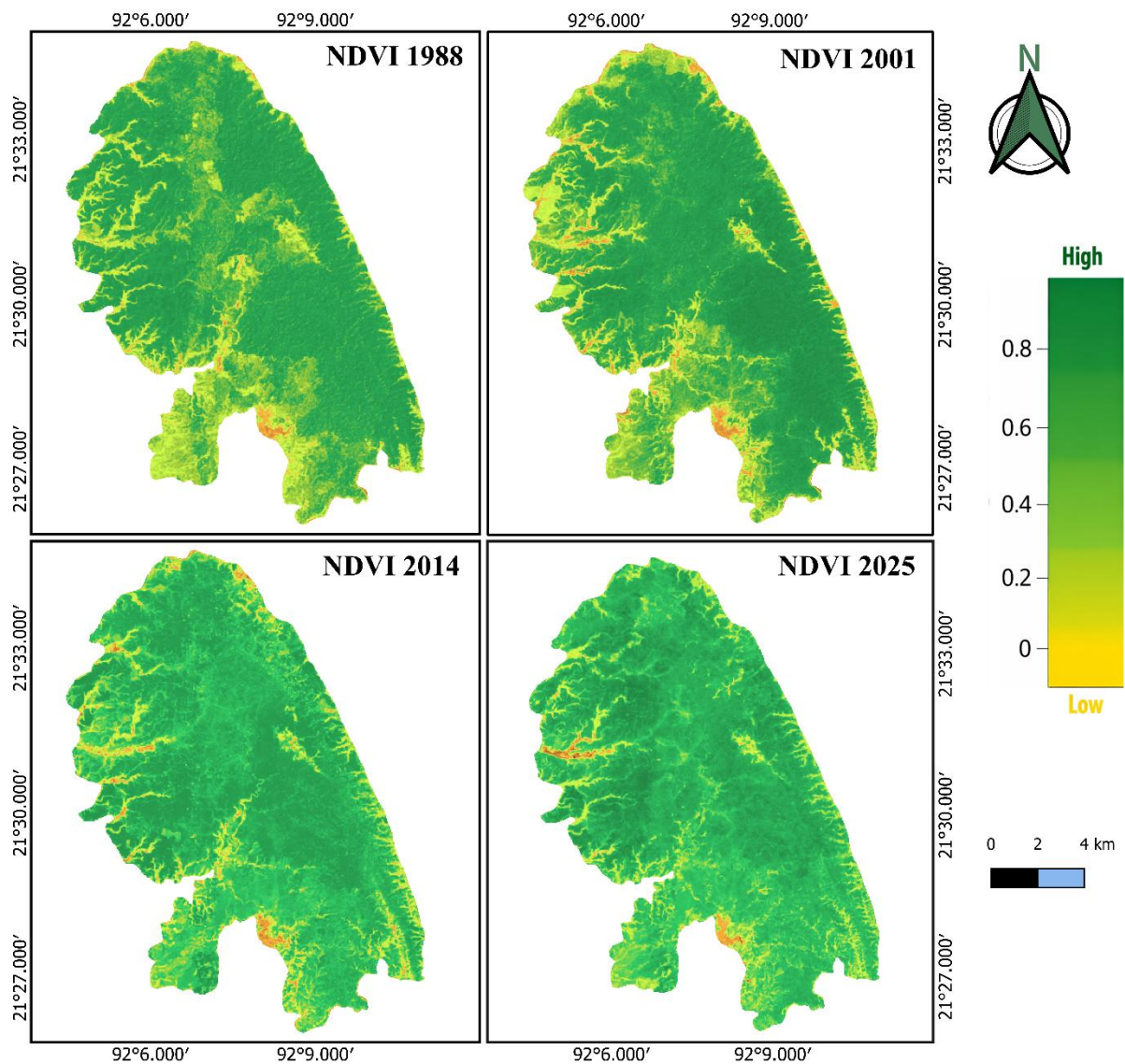


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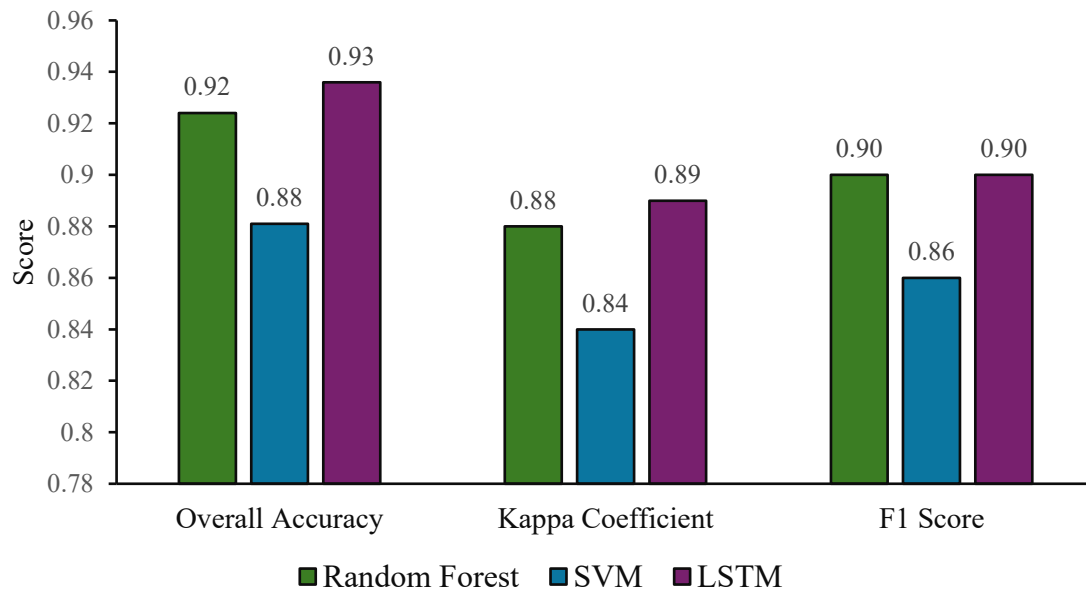


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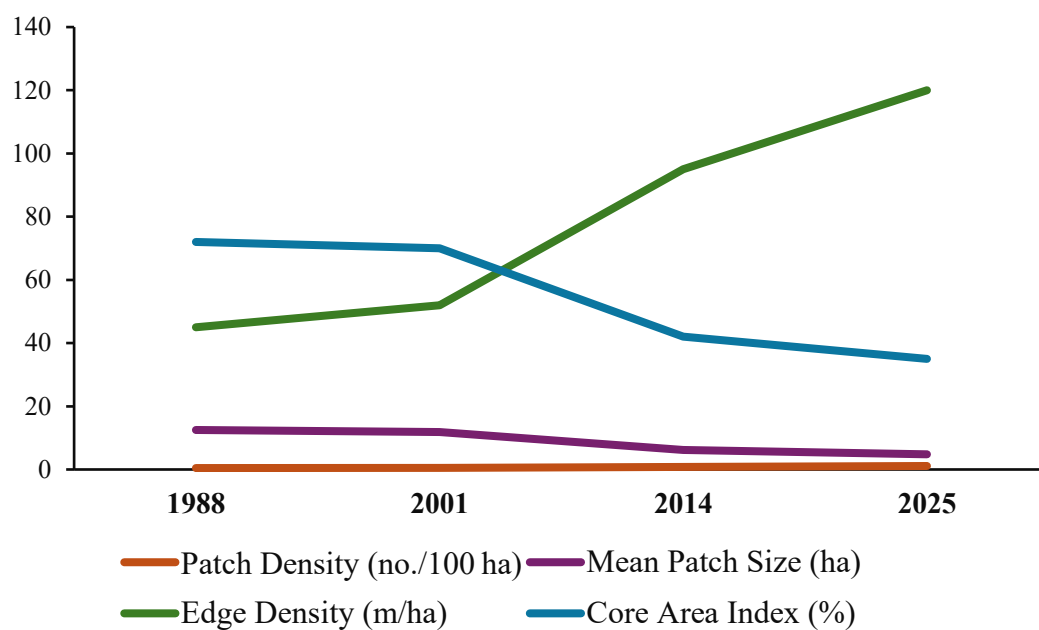


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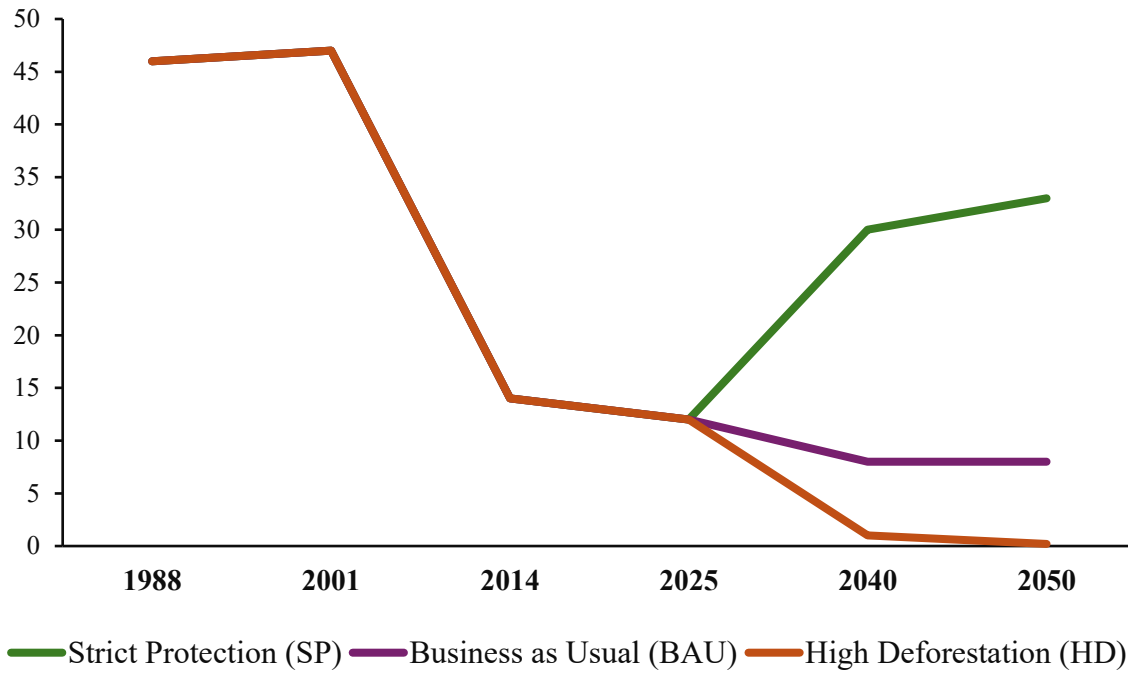


Fig. 9. Projection scenarios to 2050: Business-as-Usual, Strict Protection, and High deforestation scenarios.

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