

U-Net Based Mangrove Mapping and Carbon Stock Assessment in the Sundarban Using Optical and SAR Remote Sensing Data

ATANU BHATTACHARYYA

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ABSTRACT

Mangrove ecosystems are among the most productive coastal environments and play a significant role in carbon sequestration, shoreline protection, biodiversity conservation, and climate change mitigation. The Sundarbans, the world's largest mangrove forest, are ecologically sensitive and highly vulnerable to environmental degradation, sea-level rise, and anthropogenic disturbances. Accurate mangrove mapping and biomass assessment are therefore essential for sustainable coastal management and blue carbon estimation. This study developed an integrated geospatial and deep learning-based framework for mangrove mapping, Above Ground Biomass (AGB) estimation, carbon stock assessment, and carbon sequestration analysis within the Indian Sundarbans mangrove ecosystem.

The research utilized Sentinel-1 SAR imagery, Sentinel-2 multispectral imagery, vegetation and moisture indices including NDVI, NDWI, MNDWI, NDMI, SAVI, and Mangrove Vegetation Index (MVI), along with Random Forest supervised classification and U-Net deep learning segmentation techniques. The Random Forest classification generated an initial mangrove distribution map, while the U-Net model provided refined mangrove segmentation with improved

spatial continuity and boundary delineation. Field-based survey observations and regression modelling approaches were integrated for biomass estimation and model validation.

The Above Ground Biomass map revealed substantial spatial variability in biomass distribution across the study area, with dense mature mangrove forests concentrated mainly in the southern and southeastern tidal regions exhibiting very high biomass values. The estimated total biomass of the study area was approximately 2,416,438 Megagrams (Mg). Carbon stock estimation demonstrated that the Sundarbans function as a major blue carbon reservoir with an estimated total carbon storage of approximately 1,135,726 Mg Carbon, equivalent to nearly 1.14 million tonnes of stored carbon. The Random Forest regression model achieved strong predictive performance with an R^2 value of 0.890, indicating high agreement between observed and predicted biomass values.

The findings highlight the effectiveness of integrating remote sensing, machine learning, deep learning, and field survey data for mangrove ecosystem assessment within complex tidal environments. The study provides valuable insights for blue carbon monitoring, climate change mitigation, mangrove conservation, and sustainable coastal ecosystem management in the Sundarbans region.

Keywords: Sundarbans, Mangrove Mapping, U-Net, Random Forest, Biomass Estimation, Carbon Stock, Blue Carbon, Sentinel-1, Sentinel-2, Remote Sensing, Deep Learning, Carbon Sequestration.

1. INTRODUCTION

The Sundarban mangrove ecosystem is one of the largest and most ecologically significant coastal wetland systems in the world. Recognized as a UNESCO World Heritage Site, the Sundarbans are jointly shared between India and Bangladesh and represent a globally important deltaic landscape formed through the interaction of the Ganges, Brahmaputra, and Meghna river systems. This extensive deltaic environment has evolved through continuous fluvial deposition, tidal action, sediment transportation, and estuarine processes, resulting in a highly dynamic and environmentally sensitive coastal ecosystem. The unique geomorphological and hydrological characteristics of the Sundarbans create a complex environmental setting characterized by tidal influence, salinity gradients, periodic inundation, sediment deposition, and frequent cyclonic disturbances. These environmental conditions strongly influence mangrove species composition, vegetation structure, ecological productivity, biomass accumulation, and carbon storage patterns across the region.

The Sundarbans function as an important ecological transition zone between terrestrial and marine environments and support an exceptionally rich biodiversity. The ecosystem contains numerous mangrove species along with diverse aquatic organisms, reptiles, avifauna, and endangered wildlife species including the Royal Bengal Tiger. Apart from their ecological significance, mangrove forests play a crucial role in protecting coastal regions from natural hazards such as cyclones, tidal surges, shoreline erosion, and sea-level rise. The dense mangrove root systems stabilize coastal sediments, reduce wave energy, and minimize shoreline vulnerability, thereby contributing significantly to coastal resilience and environmental sustainability. Mangrove ecosystems also support local livelihoods through fisheries, forest resources, tourism, and other ecosystem services that are directly dependent on the health and stability of the coastal environment.

Mangrove ecosystems are widely recognized as one of the most productive and carbon-rich ecosystems on Earth and serve as highly efficient natural carbon sinks. The carbon stored within mangrove ecosystems is commonly referred to as “Blue Carbon,” which includes carbon accumulated within above-ground biomass, below-ground biomass, dead organic matter, and coastal sediments. Mangrove forests possess exceptionally high carbon sequestration potential due to their rapid biomass productivity, dense canopy structure, extensive root networks, and slow decomposition rates under waterlogged and anaerobic environmental conditions. Consequently, mangrove ecosystems play an essential role in regulating the global carbon cycle by absorbing and storing significant quantities of atmospheric carbon dioxide over long temporal scales.

Among global mangrove ecosystems, the Sundarbans are considered one of the most significant blue carbon reservoirs because of their extensive spatial coverage, dense vegetation canopy, high ecological productivity, and dynamic environmental processes. However, despite their ecological and climatic importance, the Sundarban mangrove forests are increasingly threatened by both anthropogenic and natural stressors. Human-induced pressures such as deforestation, overexploitation of forest resources, aquaculture expansion, agricultural encroachment, industrial development, and urbanization have significantly altered the natural landscape and ecosystem stability of the region. Simultaneously, natural hazards including cyclones, saline water intrusion, coastal erosion, sea-level rise, sediment instability, and extreme climatic events continue to degrade mangrove habitats and influence vegetation health, species composition, biomass distribution, and ecosystem productivity. These environmental changes directly affect the carbon storage capacity and long-term sustainability of the mangrove ecosystem.

Accurate estimation of biomass, carbon stock, and carbon sequestration potential within the Sundarbans has therefore become increasingly important for understanding ecosystem functioning, climate change mitigation potential, and sustainable coastal management. Reliable carbon stock assessment is essential not only for climate change adaptation and mitigation planning but also for blue carbon accounting, biodiversity conservation, ecosystem restoration, coastal zone management, and environmental policy formulation. Furthermore, spatial assessment of biomass and carbon distribution provides valuable information regarding vegetation productivity, ecosystem health, and ecological vulnerability within mangrove-dominated coastal regions.

Traditional field-based biomass estimation methods are often labor-intensive, time-consuming, expensive, and spatially limited, particularly within inaccessible mangrove environments such as the Sundarbans. Dense vegetation cover, muddy terrain, tidal inundation, saline water conditions, and difficult accessibility make extensive field surveys highly

challenging. Consequently, remote sensing and geospatial technologies provide efficient, cost-effective, and large-scale alternatives for mangrove biomass and carbon stock assessment. The integration of satellite remote sensing with Geographic Information Systems (GIS), machine learning, and deep learning techniques has significantly improved the capability for accurate mangrove mapping and environmental monitoring.

Recent advancements in satellite remote sensing technologies have enabled more reliable estimation of vegetation characteristics, biomass distribution, and ecosystem dynamics. Optical satellite datasets such as Sentinel-2 provide high-resolution multispectral information related to vegetation greenness, chlorophyll activity, canopy reflectance, and moisture conditions. Simultaneously, Sentinel-1 Synthetic Aperture Radar (SAR) imagery provides important structural information related to canopy density, vegetation texture, and biomass accumulation through microwave backscatter analysis. SAR imagery is particularly useful in coastal and tropical environments because it can penetrate cloud cover and operate under varying atmospheric conditions, thereby improving monitoring capability within highly humid and cloud-prone mangrove regions. The combined use of optical and SAR datasets significantly enhances mangrove discrimination and biomass estimation accuracy.

In addition to conventional remote sensing approaches, machine learning and deep learning techniques have become increasingly important in environmental and ecological studies. Random Forest supervised classification has demonstrated high efficiency in land cover classification and mangrove discrimination due to its ability to handle complex spectral variability and nonlinear relationships. Similarly, deep learning models such as U-Net have emerged as powerful tools for semantic image segmentation and high-accuracy mangrove extraction. The U-Net model analyses both spectral and spatial characteristics of imagery and improves the delineation of mangrove vegetation boundaries under heterogeneous environmental conditions. These advanced computational approaches significantly enhance classification accuracy and contribute toward more reliable biomass and carbon estimation workflows.

The present study aims to estimate Above Ground Biomass (AGB), carbon stock, and CO₂ sequestration potential within the Sundarban mangrove ecosystem using an integrated geospatial framework combining Sentinel-1 SAR imagery, Sentinel-2 optical imagery, field-based biomass sample data, Random Forest supervised classification, regression modelling, and U-Net deep learning techniques. Field-derived biomass measurements collected through GPS/GCP-based sampling were integrated with satellite-derived spectral and SAR variables to develop a regression-based biomass estimation model. Several spectral indices including NDVI, NDWI, MNDWI, NDMI, SAVI, and MVI were calculated to enhance mangrove discrimination, vegetation analysis, moisture assessment, and biomass estimation accuracy.

The integration of field observations, remote sensing datasets, SAR backscatter information, machine learning algorithms, and deep learning approaches provides a scientifically robust framework for biomass and carbon stock estimation within complex mangrove ecosystems. The outputs generated from this study, including mangrove distribution maps, biomass maps, carbon stock maps, and CO₂ sequestration maps, are expected to contribute toward improved understanding of blue carbon dynamics, ecosystem productivity, climate change mitigation potential, and sustainable mangrove management strategies within the Sundarbans region. Furthermore, the study highlights the importance of advanced geospatial technologies for monitoring and conserving one of the world's most ecologically sensitive and climatically significant coastal ecosystems.

Mangrove ecosystems are globally recognized for their exceptional ability to store and sequester carbon, making them a critical component of climate change mitigation strategies. Over the last two decades, advancements in remote sensing and geospatial technologies have significantly enhanced the capability to estimate mangrove biomass and carbon stocks across diverse spatial and temporal scales. Numerous studies have explored optical, radar, and LiDAR data to quantify above-ground and below-ground carbon pools, providing valuable insights into mangrove structure, health, and carbon dynamics.

Patil et.al.(2015) in this paper used a methodological approach for assessing mangrove carbon stocks using remote sensing and GIS techniques in the Thane Creek region of Mumbai. Their study integrated with field-based biomass measurements with satellite-derived indices, including the Normalized Difference Vegetation Index (NDVI), Light Use Efficiency (LUE), and Photosynthetically Active Radiation (PAR) to estimate carbon stocks in mangrove stands. Although the study is combined ground observations with satellite data, it was defined to a limited spatial extent and concentrated mainly on above-ground biomass estimation. Important components such as below-ground carbon pools

and temporal variability were not considered. Additionally, the applicability of the proposed methodology was not evaluated in extensive and hydrologically dynamic mangrove systems like the Sundarban, where tidal regimes, species diversity, and environmental gradients are considerably more complex.

Wicaksono, Danodero, Hartono, and Nehren (2016) conducted a spatial assessment of mangrove above-ground biomass and carbon stocks in the Karimunjawa Islands of Indonesia using multispectral imagery acquired from the ALOS AVNIR-2 sensor. This study analyze that passive optical remote sensing data could be effectively employed to estimate mangrove biomass in island-based coastal ecosystems through statistical relationships between spectral reflectance and field-derived biomass measurements. The research relied exclusively on single-date optical satellite data, which are often constrained by cloud cover and limited sensitivity to structural variations in dense mangrove canopies. The absence of time-series analysis restricted the ability to capture seasonal and interannual dynamics of mangrove biomass. Furthermore, the study did not utilize cloud-based geospatial platforms for large-scale processing, nor was the approach tested in highly heterogeneous and tidally influenced systems such as the Indian Sundarban. These limitations underline the need for scalable, cloud-based methodologies capable of addressing spatial complexity and temporal variability in mangrove blue carbon assessments.

Hastuti et al. (2017) demonstrated the use of medium-resolution satellite data, particularly Landsat imagery, for estimating mangrove carbon stocks in the Perancak Estuary of Bali. The study established a relationships between vegetation indices such as NDVI and field-derived biomass parameters. Above-ground and below-ground biomass were estimated and converted into carbon stock using standard carbon fraction coefficients. This findings confrom that remotely sensed vegetation metrics can serve as reliable process for biomass estimation in mangrove environments, especially in mangrove regions where extensive field sampling is difficult. However, the study also highlight the limitations associated with spatial resolution and species-specific variability in biomass estimation. through NDVI we just not Only Captured or Identify the Magrove trees, masking the using NDVI is difficult or Impossible .

Similarly, [Bindu et al. 2020](#) applied an integrated Remote Sensing and GIS framework to assess mangrove carbon stocks in Kannur, India. Using multi-sensor satellite data from Resourcesat LISS-3, LISS-4, and IRS-1D LISS-4, combined with ground-based plot measurements, the study estimated both above-ground and below-ground biomass. The research emphasized the importance of incorporating field inventory data to improve the accuracy of satellite-based carbon estimates. While effective at a regional scale, the approach relied heavily on generalized allometric equations, which may not fully capture local species composition and structural complexity. Long-term monitoring of mangrove cover change and its implications for carbon storage has been addressed by Upakankaao et al. (2018) in their study of Samuth Songkram Province, Thailand. By analyzing multi-temporal satellite data from 2001 to 2021, the authors documented an overall increase in mangrove area, attributed largely to conservation initiatives and restoration programs. The study linked land-cover change analysis with carbon stock estimation across multiple carbon pools, including above-ground biomass, below-ground biomass, dead wood, litter, and soil carbon. The integration of remote sensing data with forest inventory information enabled estimation of potential carbon emission reductions under REDD+ and carbon offset schemes. Despite its comprehensive scope, the study depended on projected estimate for future carbon sequestration, introducing uncertainties related to policy and land-use dynamics. A broader methodological perspective is provided by Pham et al. (2019), who reviewed remote sensing approaches for monitoring blue carbon ecosystems, including mangroves, sea grasses, and salt marshes. The review highlighted the dominance of Landsat time-series data in long-term carbon monitoring due to its extensive historical archive and consistent global coverage. The authors emphasized the growing role of multi-sensor integration and time-series analysis for understanding ecosystem changes and carbon fluxes. However, the review also identified critical challenges such as spectral confusion in coastal zones, limited penetration of optical sensors in dense canopies, and the need for improved calibration with field data. Recent studies have increasingly focused on high-resolution and advanced sensor technologies to overcome the limitations of conventional optical imagery. Sarkar et al. (2020) demonstrated the potential of UAV-based LiDAR data for capturing fine-scale variations in mangrove canopy height and structure. Their findings revealed that tall mangrove species such as *Heritiera fomes* store substantially higher carbon stocks than previously estimated using coarse-resolution satellite data and aslo using LiDAR we get more than 30% accuracy of the data. This study underscored the importance of three-dimensional structural information for accurate carbon assessment, while also noting the limited spatial coverage because of high suervey costs of UAV-LiDAR. In the Indian Sundarbans, Ghosh et al. (2021) employed Sentinel-2

imagery combined with field plot measurements to map above-ground biomass and carbon stocks. The study estimated a significant total carbon stock while simultaneously documenting a notable decline in dense mangrove cover between 2000 and 2020. Coastal erosion, sea-level rise, and aquaculture expansion were identified as major drivers of mangrove loss. The research highlighted the sensitivity of mangrove carbon stocks to both natural processes and anthropogenic pressures, reinforcing the need for continuous monitoring using satellite data. The integration of radar data has further improved biomass estimation in structurally complex mangrove forests. Kumar et al. (2022) combined Sentinel-1 SAR data with optical imagery to estimate above-ground biomass in the Bangladesh Sundarbans. Their hybrid modeling approach significantly reduced estimation errors compared to optical-only models, demonstrating the advantage of SAR data in penetrating dense canopies and capturing structural information. The study confirmed that multi-sensor data fusion enhances carbon stock estimation accuracy, particularly in cloud-prone tropical regions. More recently, Sudarna et al. (2023) focused on estimating and mapping above-ground mangrove carbon stocks in Benoa Bay, Bali, using Sentinel-2 derived vegetation indices and ground-truth data. By applying classification and regression algorithms, the study effectively distinguished mangrove and non-mangrove areas and quantified spatial variations in carbon stock. While the results validated the utility of Sentinel-2 data for local-scale carbon assessment, the study acknowledged uncertainties arising from algorithm selection and limited ground reference data.

2. MATERIALS AND METHODS

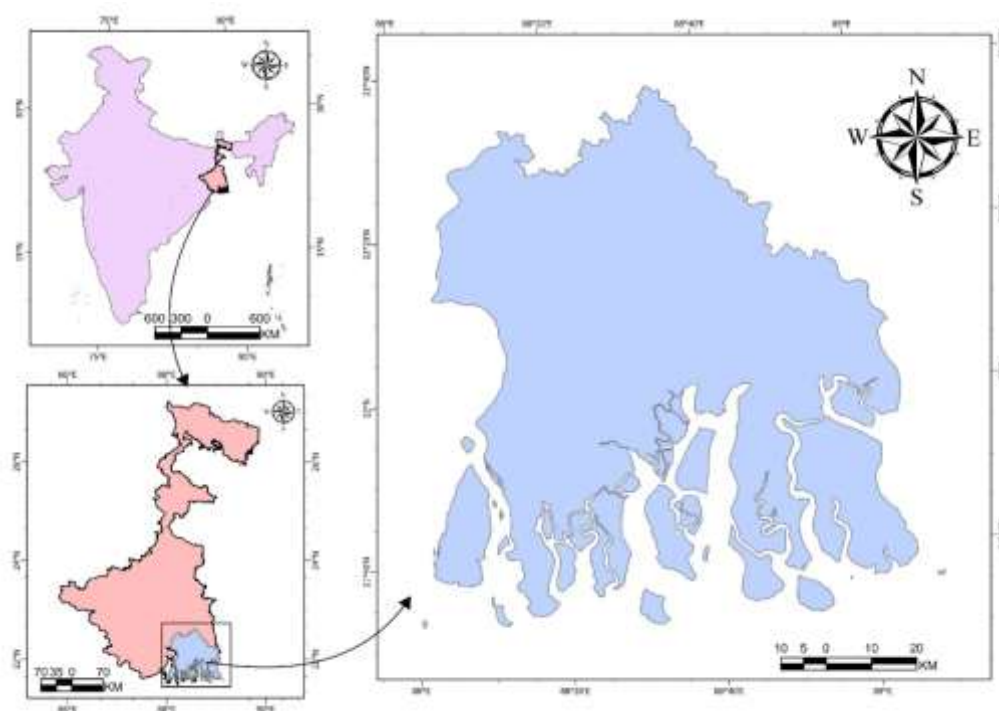
2.1. STUDY AREA

The present study focuses on the Indian part of the Sundarban mangrove ecosystem, situated within the lower Ganga–Brahmaputra–Meghna delta along the eastern coast of India, primarily in the southern part of West Bengal. The Sundarbans represent one of the largest contiguous mangrove forest ecosystems in the world and form a globally significant coastal wetland environment shared between India and Bangladesh. The Indian Sundarbans are geographically located approximately between 21°32'N to 22°40'N latitude and 88°05'E to 89°00'E longitude.

The study area is characterized by a highly dynamic deltaic landscape consisting of an intricate network of tidal rivers, estuaries, creeks, mudflats, islands, and intertidal wetlands. The region has been formed through continuous sediment deposition and fluvial processes associated with the Ganges, Brahmaputra, and Meghna river systems. Tidal influence plays a dominant role in shaping the geomorphology, hydrology, and ecological processes of the region. The continuous interaction between freshwater discharge and saline tidal water creates a complex estuarine environment that significantly influences mangrove vegetation distribution and ecosystem productivity.

The Sundarbans are internationally recognized for their ecological importance and were designated as a UNESCO World Heritage Site because of their exceptional biodiversity and environmental significance. The ecosystem supports diverse mangrove species including *Avicennia marina*, *Rhizophora mucronata*, *Sonneratia apetala*, *Bruguiera gymnorhiza*, and *Excoecaria agallocha*. The region also serves as an important habitat for numerous aquatic organisms, reptiles, birds, and endangered wildlife species, particularly the Royal Bengal Tiger (*Panthera tigris tigris*).

The climate of the study area is predominantly tropical monsoonal, characterized by high temperature, elevated humidity, and substantial seasonal rainfall associated with the southwest monsoon. Average annual rainfall in the region is generally high, with the majority of precipitation occurring during the monsoon season between June and September. The climatic conditions support dense mangrove growth and high biological productivity within the ecosystem.



2.2. Data Acquisition and Preprocessing

Multi-source remote sensing datasets were utilized in this study to map mangrove forests and estimate their above-ground biomass and carbon stock in the Indian Sundarban. Optical imagery acquired from the Sentinel-2 MultiSpectral Instrument (MSI) and Synthetic Aperture Radar (SAR) data obtained from the Sentinel-1 Ground Range Detected (GRD) mission were selected because of their complementary capabilities in characterizing vegetation spectral responses and structural properties. Sentinel-2 imagery provides high spatial resolution multispectral observations suitable for vegetation discrimination, while Sentinel-1 SAR data offer cloud-independent measurements that are sensitive to canopy structure and moisture conditions, making them particularly valuable in tropical coastal environments where persistent cloud cover frequently limits optical observations.

All satellite datasets were accessed and processed using the Google Earth Engine (GEE) cloud computing platform. Sentinel-2 Level-2A surface reflectance imagery was filtered based on the study area boundary and acquisition period, and scenes with excessive cloud cover were excluded from the analysis. Cloud and cirrus contamination were removed using the quality assurance (QA60) band and cloud-masking algorithms available within GEE. Subsequently, median image compositing was performed to generate a cloud-free optical dataset representing the study period.

Sentinel-1 GRD imagery acquired in the Interferometric Wide (IW) swath mode with dual-polarization (VV and VH) was also filtered according to the study area and temporal range. Standard preprocessing operations, including orbit file correction, thermal noise removal, radiometric calibration, terrain correction, and conversion of backscatter coefficients to decibel (dB) values, were applied using the preprocessing routines available in Google Earth Engine. The processed VV and VH polarization bands were retained for subsequent feature extraction and biomass modelling because they effectively capture vegetation structure and canopy characteristics.

Several spectral indices were derived from the Sentinel-2 imagery to enhance the discrimination of mangrove vegetation and characterize environmental conditions within the study area. These included the Normalized Difference Vegetation Index (NDVI) for vegetation vigor, the Normalized Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI) for water body

delineation, the Normalized Difference Moisture Index (NDMI) for vegetation moisture assessment, the Soil-Adjusted Vegetation Index (SAVI) for minimizing soil background effects, and the Mangrove Vegetation Index (MVI) for improved identification of mangrove ecosystems. These indices were computed using standard mathematical formulations and incorporated into the analysis as additional predictor variables.

Sl. No.	Dataset	Type	Purpose
1	Sentinel-2 MSI	Optical satellite imagery	Mangrove mapping, spectral index generation, and vegetation analysis
2	Sentinel-1 SAR	Radar satellite imagery	Vegetation structure analysis and SAR backscatter extraction
3	Field Biomass Data	Field survey	DBH measurement, species identification, and biomass estimation
4	GPS/GCP Coordinates	Field survey	Geolocation of sample plots and validation
5	Spectral Indices (NDVI, NDWI, MNDWI, NDMI, SAVI, MVI)	Derived datasets	Vegetation, water, moisture, and mangrove feature extraction

Following preprocessing, all optical bands, SAR backscatter layers, and derived spectral indices were resampled to a common spatial resolution and projected into a unified coordinate reference system to ensure spatial consistency. The processed datasets were subsequently stacked into a multilayer raster dataset that served as the primary input for machine learning classification, U-Net-based semantic segmentation, biomass estimation, and carbon stock assessment. This integrated preprocessing workflow ensured high-quality and spatially consistent datasets, thereby improving the reliability of subsequent modelling and analysis.

Sl. No.	Software/Method	Purpose
1	Google Earth Engine (GEE)	Satellite image preprocessing, spectral index calculation, and data export
2	ArcGIS Pro	Spatial analysis, raster processing, regression modelling, and map preparation
3	QGIS	Spatial visualization and GIS data handling
4	Python (Jupyter Notebook/Google Colab)	Data processing, regression analysis, and deep learning implementation
5	TensorFlow/Keras	Development and training of the U-Net model
6	Random Forest	Supervised mangrove/non-mangrove classification
7	U-Net	Semantic segmentation and mangrove mask generation
8	Raster Calculator	Biomass, carbon stock, and CO ₂ estimation
9	Regression Analysis	Biomass prediction from remote sensing variables
10	Microsoft Excel/CSV	Field data management and statistical analysis

2.3. Multi-band Image Stack Preparation

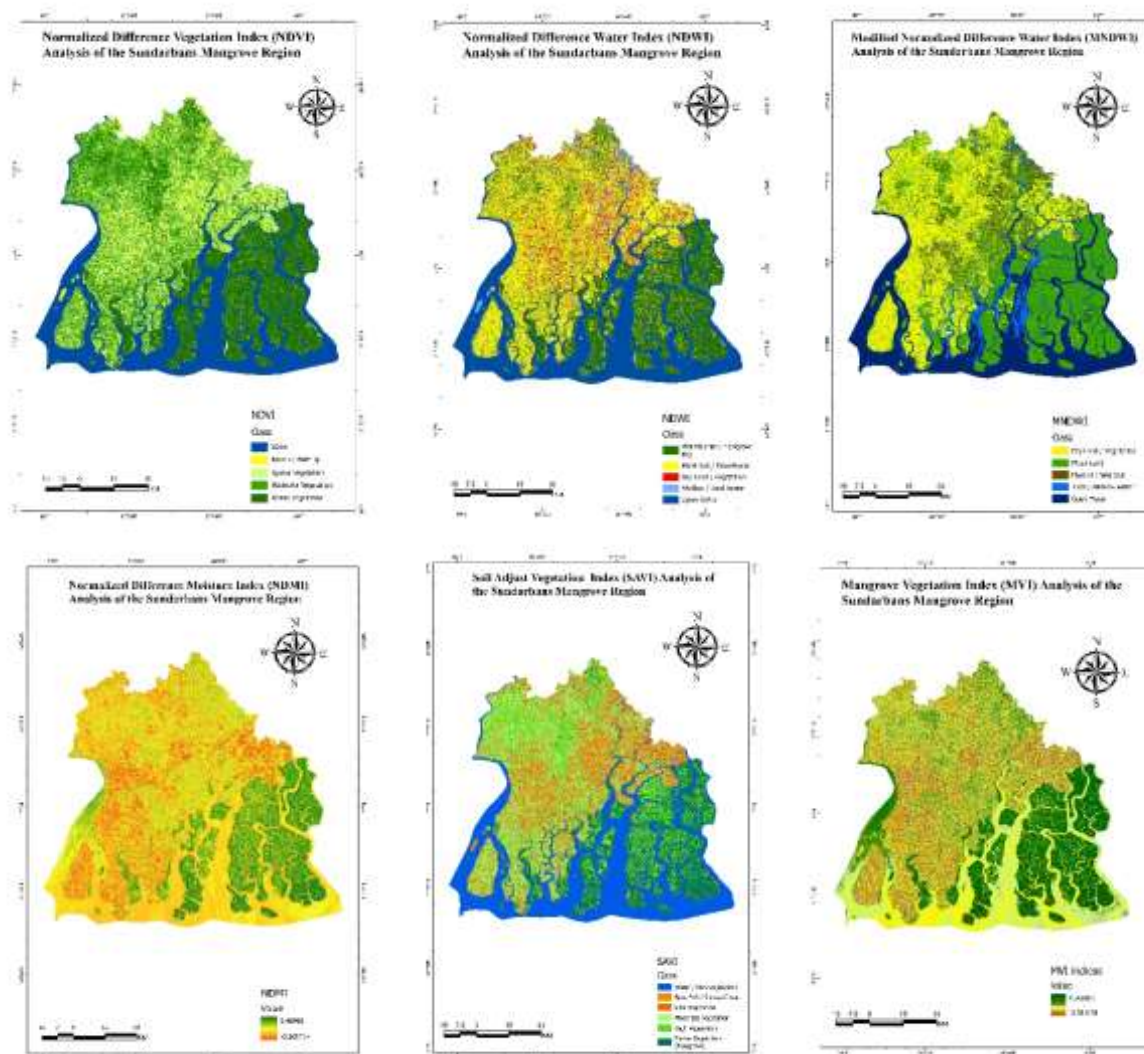
The preparation of a multi-band image stack was a critical step in developing the input dataset for machine learning classification and deep learning-based mangrove mapping. Following the preprocessing of Sentinel-2 optical imagery and Sentinel-1 Synthetic Aperture Radar (SAR) data, all relevant spectral bands, SAR backscatter layers, and derived spectral indices were integrated into a single multi-layer raster dataset. This approach enabled the simultaneous utilization of spectral, structural, and environmental information, thereby improving the representation of mangrove characteristics under complex coastal conditions.

The optical component of the image stack comprised the Sentinel-2 multispectral bands that are highly sensitive to vegetation properties, while the SAR component included the VV and VH polarization backscatter coefficients derived from Sentinel-1 imagery. In addition, six spectral indices, namely the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Normalized Difference Moisture Index (NDMI), Soil-Adjusted Vegetation Index (SAVI), and Mangrove Vegetation Index (MVI), were generated from the Sentinel-2 imagery to enhance vegetation discrimination, moisture characterization, and water-body extraction. These indices provided complementary information for distinguishing mangrove forests from adjacent land-cover classes and capturing variations in vegetation health, canopy moisture, and tidal influences.

To ensure spatial consistency, all raster layers were resampled to a common spatial resolution of 10 m and projected to the same coordinate reference system. The datasets were spatially aligned and stacked in a predefined band sequence to create a unified multi-band raster. This integrated dataset served as the primary input for both the Random Forest classifier and the U-Net deep learning model, allowing the algorithms to exploit complementary information from optical reflectance, radar backscatter, and spectral indices during feature learning and classification.

Sl. No.	Spatial Data Layer	Source	Purpose
1	Sentinel-2 MSI (Level-2A)	European Space Agency / Google Earth Engine	Optical imagery for vegetation analysis and mangrove mapping
2	Sentinel-1 SAR (GRD)	European Space Agency / Google Earth Engine	Vegetation structure analysis and SAR backscatter extraction
3	NDVI	Derived from Sentinel-2	Assessment of vegetation greenness and biomass potential
4	NDWI	Derived from Sentinel-2	Delineation of water bodies and wetlands
5	MNDWI	Derived from Sentinel-2	Enhanced extraction of water features and tidal channels
6	NDMI	Derived from Sentinel-2	Estimation of vegetation moisture content
7	SAVI	Derived from Sentinel-2	Vegetation analysis with reduced soil background effects
8	Mangrove Vegetation Index (MVI)	Derived from Sentinel-2	Improved discrimination of mangrove vegetation
9	VV Backscatter	Derived from Sentinel-1	Characterization of vegetation structure and canopy properties
10	VH Backscatter	Derived from Sentinel-1	Biomass estimation and mangrove structural analysis
11	Field Biomass Sample Plots	Field Survey	Model calibration and validation
12	GPS/GCP Locations	Field Survey	Georeferencing and accuracy assessment

The multi-band image stack significantly enhanced the predictive capability of the classification framework by reducing spectral ambiguity between mangrove and non-mangrove land-cover classes while improving the detection of vegetation structure and moisture conditions. The integration of optical and SAR datasets also minimized the limitations associated with cloud contamination in optical imagery and improved the robustness of mangrove mapping in the dynamic coastal environment of the Sundarban. A schematic representation of the multi-band image stack used in this study is presented in **Figure X**, illustrating the complete set of input layers employed for subsequent machine learning, deep learning, biomass estimation, and carbon stock assessment.



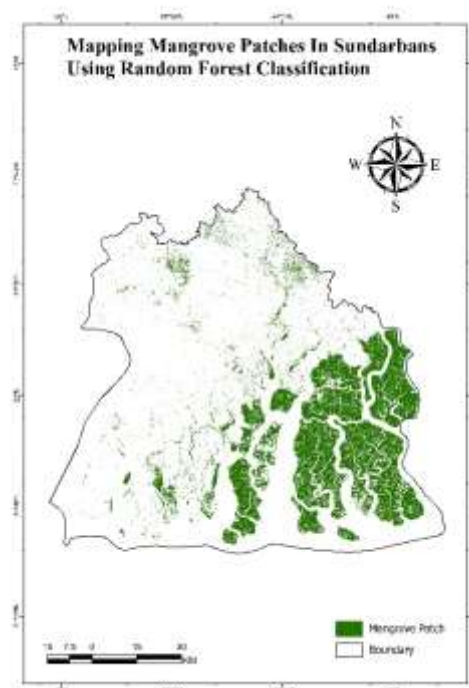
2.4. Random Forest Classification

A Random Forest (RF) supervised classification approach was employed to generate an initial mangrove distribution map and to provide reliable training labels for the subsequent deep learning framework. Random Forest is an ensemble machine learning algorithm that constructs multiple decision trees using randomly selected subsets of training samples and predictor variables. The final class assignment is determined through a majority voting strategy, which enhances classification accuracy while minimizing overfitting. Owing to its robustness, computational efficiency, and ability to handle high-dimensional remote sensing datasets, the Random Forest algorithm has been widely adopted for land use/land cover mapping and vegetation classification.

Representative training samples for mangrove and non-mangrove classes were prepared through visual interpretation of high-resolution satellite imagery, field observations, and ancillary reference data. The training dataset was designed to capture the spatial variability of different land-cover types across the study area, ensuring balanced representation of both vegetation and non-vegetation classes. The Random Forest classifier was then trained using these labelled samples to classify the entire study area into binary mangrove and non-mangrove classes.

Following classification, post-processing techniques were applied to reduce isolated pixels and improve the spatial consistency of the classified map. The resulting binary mangrove mask served as the reference dataset for training the U-Net deep learning model, providing accurate pixel-level labels for semantic segmentation. This hybrid workflow combined the robustness of machine learning with the feature-learning capability of deep learning, thereby improving the reliability of the final mangrove classification.

The classification accuracy was evaluated using an independent validation dataset and a confusion matrix. Performance metrics, including Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), Precision, Recall, F1-score, and the Kappa coefficient, were computed to quantify classification performance. These statistical measures provided a comprehensive assessment of the Random Forest model and established a reliable baseline for comparison with the subsequent U-Net deep learning results. The final Random Forest classification map is presented in **Figure X**, while the corresponding confusion matrix and accuracy statistics are reported in the Results section.



2.5. Deep Learning Framework and Biomass Estimation

A deep learning framework based on the U-Net architecture was developed to achieve accurate mangrove segmentation using integrated optical and Synthetic Aperture Radar (SAR) remote sensing data. The U-Net model was selected because of its ability to perform semantic image segmentation while preserving fine spatial details through encoder–decoder networks connected by skip connections. This architecture enables the extraction of both high-level semantic information and low-level spatial features, making it particularly suitable for mapping heterogeneous coastal ecosystems such as mangrove forests.

Prior to model development, Sentinel-2 multispectral bands, Sentinel-1 SAR backscatter layers (VV and VH), and the derived spectral indices, including NDVI, NDWI, MNDWI, NDMI, SAVI, and the Mangrove Vegetation Index (MVI), were integrated into a multi-band raster stack. The stacked dataset provided complementary spectral, structural, and moisture-related information that enhanced the discrimination of mangrove vegetation from surrounding land-cover classes. An initial binary mangrove mask generated using the Random Forest classifier served as the reference dataset for training the U-Net model. The image stack and corresponding binary masks were divided into image patches of equal dimensions and used as input and target datasets, respectively.

The U-Net model was implemented using the TensorFlow–Keras deep learning framework in Python. During training, data augmentation techniques, including rotation, flipping, and scaling, were applied to improve model generalization and reduce overfitting. The network parameters were optimized through iterative training using the training dataset, while model performance was continuously monitored on an independent validation dataset. After convergence, the trained model was applied to the complete image stack to generate a high-resolution mangrove segmentation map. The resulting classification exhibited improved boundary delineation and spatial consistency compared with conventional pixel-based classification approaches.

Biomass estimation was subsequently performed by integrating field-derived Above-Ground Biomass (AGB) measurements with remotely sensed variables. Field observations, including Diameter at Breast Height (DBH), species composition, and wood density, were used to estimate AGB using established allometric equations. Spectral indices and SAR backscatter values corresponding to the field sampling locations were extracted from the processed satellite datasets and statistically related to the measured biomass through regression analysis. The best-performing regression model was then applied to the entire mapped mangrove area to generate a continuous spatial distribution of above-ground biomass.

The estimated biomass values were converted to carbon stock using a biomass-to-carbon conversion factor of 0.47, while the equivalent carbon dioxide (CO₂) sequestration potential was calculated by multiplying the carbon stock values

by the molecular weight conversion factor of 44/12. The final outputs comprised spatially explicit maps of mangrove distribution, above-ground biomass, carbon stock, and CO₂ sequestration potential. This integrated framework combining multisource remote sensing, deep learning, and field observations provides an effective and scalable approach for blue carbon assessment and long-term monitoring of mangrove ecosystems.

