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Predicting Mangrove Degradation Under Anthropogenic and Climatic Stressors: A Google Earth Engine - Based Case Study from Pichavaram

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Abstract

Mangrove forests are vital ecosystems that protect coastlines, support biodiversity, and capture carbon, yet they are increasingly threatened by human activities and climate change. This study presents a data driven approach to assess and predict mangrove degradation in the Pichavaram region of Tamil Nadu, India, using Google Earth Engine (GEE) and Random Forest classification. By combining satellite imagery from Landsat and Sentinel-2 with vegetation indices (NDVI and NBR), elevation, slope, salinity, tidal dynamics, and distances to roads, rivers, and settlements, developed a model to classify mangrove areas into stable, degraded, and regenerating zones. The classification model was associated with a very high accuracy (98.14%), strong agreement (Kappa = 0.972), and AUC scores above 0.96 for every class. According to the results, degraded zones were usually close to settlements, roads, and aquaculture, whereas regenerating patches lied close to rivers. A custom Climatic Stress Index integrating vegetation trends, salinity, and tidal variability provided added insight into environmental pressures.This research shows a transferable, cloud-based methodology for real-time mangrove monitoring, which thereby can provide useful tools for conservation planning, restoration prioritisation, and climate adaptation exercises in accordance with the Sustainable Development Goals (SDG 13 and 15). It shows how remote sensing and machine learning can be used to direct ecosystem management in areas where there is a lack of.

1. Introduction

Mangrove ecosystems are among the most productive and ecologically important coastal habitats in the world. They serve as vital blue-green infrastructures that deliver a wide range of ecosystem services protecting shorelines from erosion and storm surges, supporting fisheries and biodiversity, acting as nurseries for aquatic life, and playing a major role in carbon sequestration. As natural buffers against climate related disasters and providers of livelihood for coastal communities, mangroves represent a crucial ecological and socio economic resource.

India, with a coastline stretching over 7,500 kilometers, is home to several distinct mangrove ecosystems distributed across the eastern and western coasts and the island territories. The degradation of mangroves is considered one of the most important environmental problems in India. These include increasing threats from human interventions and climate-dependent ones. Anthropogenic activities have been granular and monetised due to the huge increase of aquaculture, urban encroachments, infrastructural developments, and alteration of freshwater flow and salinity levels. According to reports, India has already lost 30-35% of its critical coastal ecosystems, including mangroves, in the past few decades due to these combined stressors.

Pichavaram, located in Tamil Nadu, is India's second-largest mangrove forest and an ecologically rich estuarine wetland. However, it is under growing pressure from unsustainable land use practices, tidal modifications, and salinity intrusions. Traditional conservation and monitoring techniques though vital often fall short due to limited spatial and temporal coverage, logistical challenges, and high costs of field data collection.

In this regard, the recent advances in geospatial technology and cloud-based platform like Google Earth Engine (GEE) present a huge array for large-scale, highly frequent, and cost-effective environmental monitoring. Remote sensing datasets from missions like Landsat, Sentinel - 2, and Sentinel - 1 provide long term observations that, when combined with geospatial modeling techniques such as machine learning, can enable near-real-time detection and prediction of ecological degradation.

This research aims to leverage such capabilities to develop a spatially explicit, multi-source, machine-learning model to assess mangrove degradation risk in Pichavaram. The study integrates time-series vegetation indices (NDVI and NBR), topographic data, proximity to anthropogenic features (roads, settlements, rivers), and environmental stress proxies (salinity, tidal fluctuation) into a Random Forest classification model within the GEE environment. The outcome is a high-resolution degradation map categorising zones into stable, degraded, and regenerating mangroves, supported by accuracy assessments and ROC analysis.

The research is to contribute toward the advancement of ecosystem monitoring tools and also provide information for policy interventions, restoration planning, and sustainable management of coastal resources. With this framework it allows for integration between different global environmental objectives, particularly SDG 13 (Climate Action) and SDG 15 (Life on Land), by enabling a practical and feasible way to build ecosystem resilience and climate adaptation into policy and practice.

2. Study Area: Pichavaram Mangrove Forest, Tamil Nadu

The Pichavaram Mangrove Forest, situated in the Cuddalore District of Tamil Nadu, India, lies between latitude 11°23′N to 11°30′N and longitude 79°45′E to 79°50′E. Approximately 2,335.5 hectares, it forms part of the ecologically significant Vellar Coleroon estuarine complex, making it the second largest contiguous mangrove ecosystem in the world after the Sundarbans (M.S. Swaminathan Research Foundation [MSSRF], 2020).

This region is shaped by the interaction of two river systems, the Vellar and the Coleroon, forming a shallow estuarine delta system characterised by semi-diurnal tides, variable salinity, and sediment mixtures including fluvial, marine, and coastal beach deposits. The estuarine wetland comprises over 51 islets

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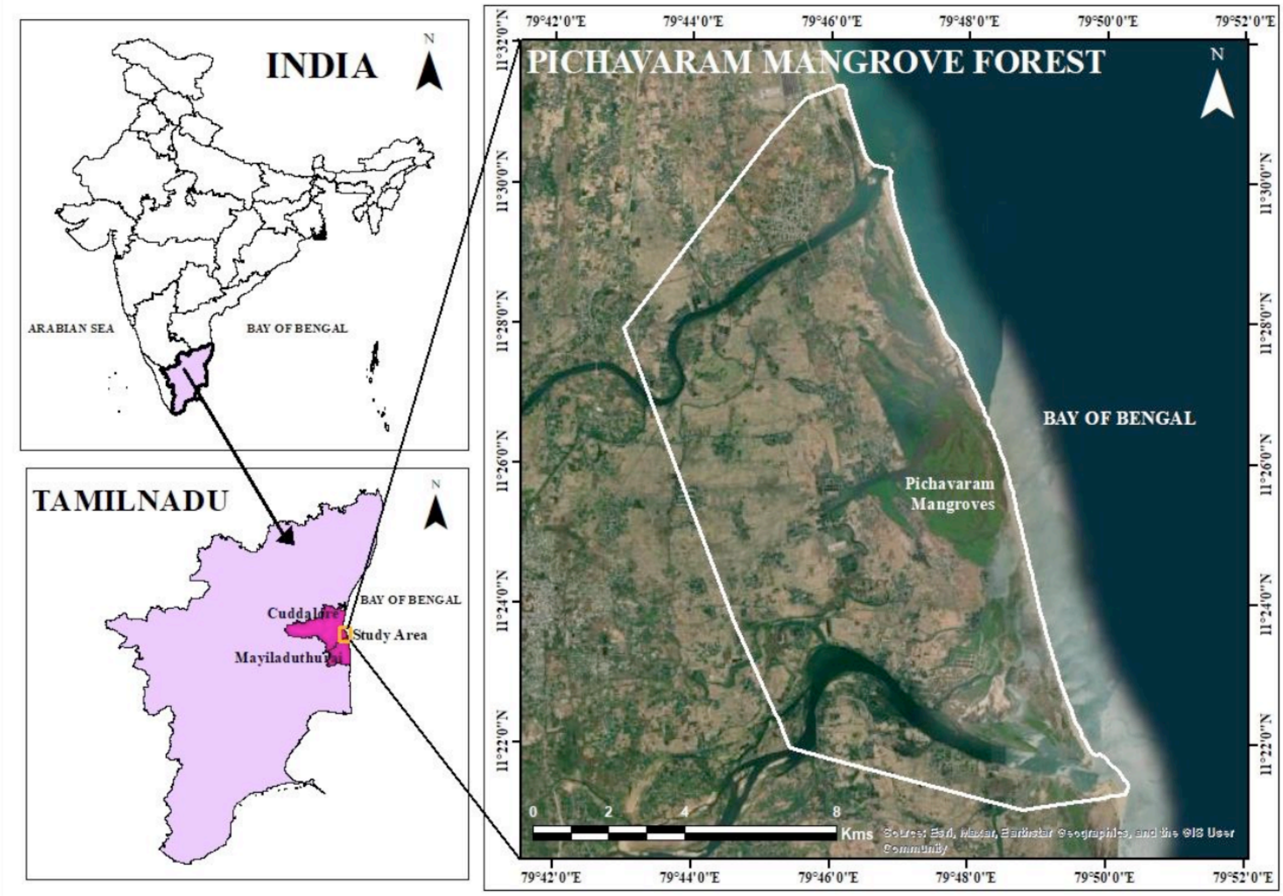

Figure 1. Location of the study area

interwoven with tidal channels and dense mangrove patches. Recognised for its ecological and hydrological value, Pichavaram was declared a Reserve Forest in 1987 and is protected by the Tamil Nadu Forest Department.

The forest supports 12 true mangrove species such as *Avicennia marina*, *Rhizophora apiculata*, *Avicennia officinalis*, and *Rhizophora mucronata*, and provides critical habitat for finfish, shellfish, crustaceans, mollusks, and over 200 avian species (MSSRF, 2020; Forest Survey of India [FSI], 2021). These ecological features make it a significant biodiversity hotspot along India's East Coast. Pichavaram experiences a tropical climate with average high temperatures between 29°C and 36°C, and lows from 18°C to 25°C, with heavy rainfall during the northeast monsoon (October-December). This results in seasonal salinity variations, which peak in summer and decline during monsoon periods due to freshwater influx.

In recent decades, the region has come under increasing stress from anthropogenic activities, including expansion of aquaculture ponds, agriculture, urban encroachment, and tourism. These activities have led to habitat fragmentation, altered sedimentation, and obstruction of natural tidal flows. In spans of erratic rainfall and rising sea level due to climate change, vulnerabilities are increasing, thus demanding prompt intervention through monitoring and management.

3. Materials and Methods

This study outlines upon an integrated geospatial approach involving satellite remote sensing, ecological index analysis, proximity modeling, and machine learning classification to assess and forecast degradation of mangroves in the Pichavaram region of Tamil Nadu, India. The primary objective is to build a spatially explicit, data-driven framework influencing mangrove health over time. Google Earth Engine (GEE) is utilised a cloud-based geospatial analysis platform capable of handling petabyte-scale satellite imagery and environmental data. GEE allows for efficient preprocessing, time-series analysis, and classifier implementation without the limitations of local computing infrastructure. Using this platform, integration of multi-temporal optical and radar satellite data (Landsat, Sentinel-2, Sentinel-1), topographic data (SRTM), salinity and proximity layers to generate a comprehensive geospatial feature stack.

The methodological workflow includes:

- Data Acquisition from multiple satellite sources and correlation datasets
- Preprocessing steps which include cloud masking, rescaling images, and clipping to Area of Interest (AOI).
- Feature Extraction of ecological indicators such as NDVI & NBR trends, salinity, elevation, slope, tidal range, and distances to human features.
- Training Sample Creation through manual digitisation of polygons in QGIS, representing three mangrove condition classes - Stable, Degraded, and Regenerating.
- Supervised Classification using the Random Forest (RF) algorithm, implemented in both multiclass and binary (One-vs-Rest) forms for probabilistic interpretation.
- Validation and Accuracy Assessment via confusion matrix, ROC-AUC, and kappa statistics to measure classifier performance and reliability.

This multi-layered, machine learning enabled methodology allows for robust and reproducible mangrove degradation mapping across spatial and temporal dimensions.

3.1 Data Sources

To capture the multi dimensional nature of mangrove degradation, a diverse set of satellite datasets and spatial layers were integrated into the analysis. These include optical and

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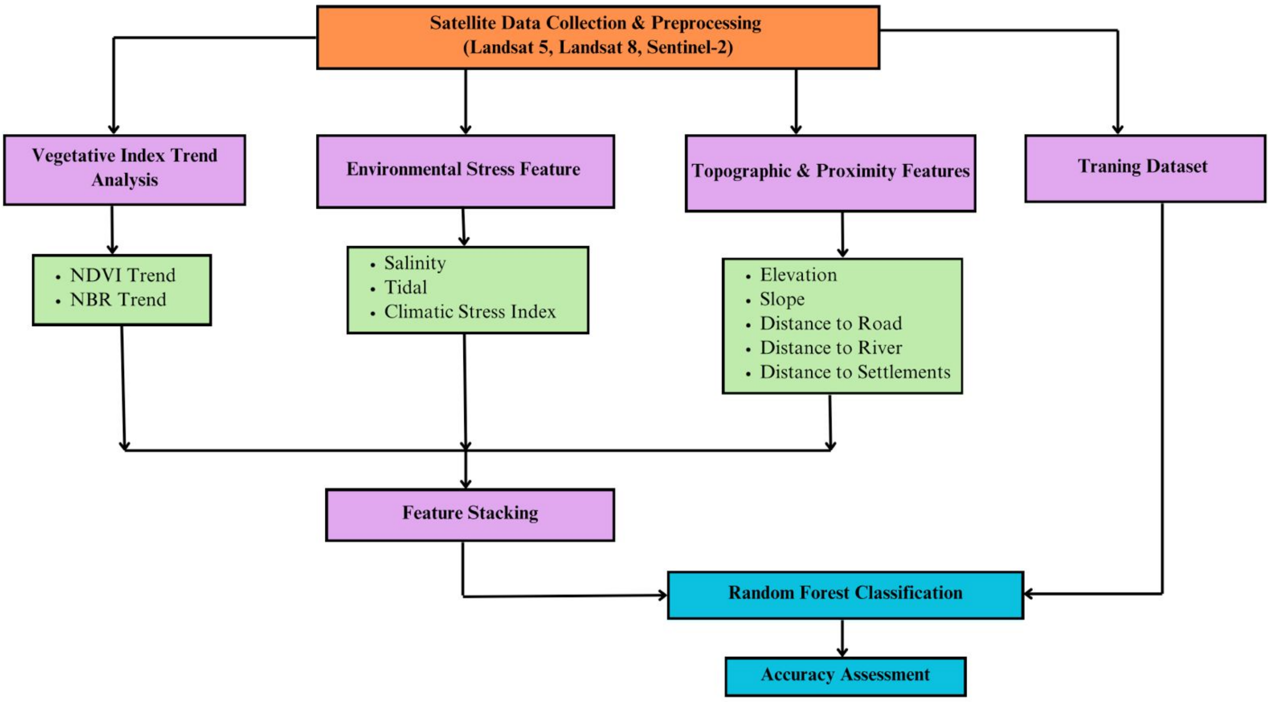

Figure 2. Methodology Flowchart

radar satellite imagery, digital elevation data, ecological proxies, and proximity based vector datasets. Each data source was selected to serve a specific purpose whether temporal monitoring, environmental characterisation, or anthropogenic stress mapping and all were processed and analysed within the Google Earth Engine (GEE) platform.

Landsat 5 Thematic Mapper (TM) Surface Reflectance data (2008-2011) were used to establish a historical baseline of vegetation conditions over the past two decades. This sensor provides 30-meter resolution multispectral imagery, sufficient to capture broader landscape-level dynamics within the mangrove ecosystem.

Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) Surface Reflectance data (2013-2023) extended the historical record and enabled the computation of long-term vegetation trends. The improved radiometric quality and spectral bands of Landsat 8, particularly in the near-infrared and shortwave-infrared regions, are critical for vegetation and disturbance analysis (e.g., NDVI, NBR).

Sentinel-2 Multispectral Instrument (MSI) data (2017-2023), with its 10-20 meter resolution, were used for finer-scale analysis of canopy structure and vegetation recovery. Sentinel-2's high revisit frequency (5 days) allowed for the selection of cloud-free composites and accurate manual digitisation of training samples.

To capture hydrological fluctuations, Sentinel-1 C-band Synthetic Aperture Radar (SAR) data from 2020 were utilised. SAR data are unaffected by cloud cover or illumination conditions and are ideal for assessing tidal inundation and water connectivity within the mangrove landscape. Tidal proxy layers were derived by differencing radar backscatter images from high and low tide periods.

Topographic parameters were extracted from the Shuttle Radar Topography Mission (SRTM) 30-meter Digital Elevation Model. Elevation and slope data help model micro topographic influences on salinity accumulation, tidal water logging, and mangrove species distribution.

A Global Mangrove Watch (GMW) raster from the Japan Aerospace Exploration Agency (JAXA, 2020) was employed as the initial mangrove extent mask. This dataset provided an objective and standardised baseline for defining the area of interest (AOI) and limiting analysis to known mangrove zones. To quantify climatic stress, a custom salinity proxy raster (10 m resolution), developed from various factor values, was incorporated. It reflects chronic salt stress, which often correlates with degraded vegetation structure, especially in low-lying, poorly drained areas.

Finally, vector datasets representing roads, rivers, settlements, and mangrove training samples were digitised using high-resolution Sentinel-2 RGB composites and QGIS. These layers were used to compute Euclidean distance rasters in GEE, enabling the spatial modeling of proximity-based anthropogenic pressures (e.g., distance to roads and settlements) and hydrological benefits (e.g., distance to rivers). Collectively, these datasets spanning spectral, spatial, topographic, and thematic domains formed a comprehensive geospatial feature stack to support supervised classification and risk modelling of mangrove degradation patterns.

3.2 Cloud Masking and Scaling

Raw satellite images often contain noise in the form of cloud cover, cloud shadows, haze, and other atmospheric effects. If not removed, these noisy pixels can significantly distort vegetation indices and classification results. Therefore, cloud masking and reflectance rescaling were performed for all optical datasets prior to analysis.Vegetation indices such as NDVI and NBR are extremely sensitive to cloud interference. Even partial cloud cover can lead to artificially low values, mimicking degradation patterns where none exist. This study used band specific quality assurance (QA) masks provided within the satellite datasets:

- Landsat (5 & 8): The QA_PIXEL band was used to detect and mask clouds. This band encodes per-pixel flags indicating whether a pixel is clear, cloudy, or shadowed. Pixels flagged as "cloud" or "cloud shadow" were excluded from analysis.
- Sentinel-2 MSI: The QA60 band contains a cloud confidence layer. Pixels with cloud probability > 60% were removed.

Additionally, only images with less than 20% overall cloud cover were selected during image filtering to further minimise contamination.

Each satellite mission stores surface reflectance values in different numerical ranges and scales. For example:

- Landsat stores reflectance as scaled integers using a factor of 0.0000275.
- Sentinel-2 stores reflectance values scaled by a factor of 0.0001 (i.e., raw values range from 0-10,000).

To ensure consistent interpretation and calculation of vegetation indices across both Landsat and Sentinel-2 images, all reflectance bands were **rescaled to their physical reflectance units (0-1)** using the appropriate scale factors. This uniform scaling was essential for accurate computation of **NDVI** and **NBR and e**nsure fair comparison across sensors while avoiding biases during trend analysis and classification. Harmonising reflectance scales ensures that a vegetation index value of 0.4 from Landsat represents the same surface condition as a value of 0.4 from Sentinel-2.

3.3 Feature Extraction

In order to capture the multidimensional characteristics of mangrove ecosystem health and stress, a suite of geospatial features was derived from multi-sensor satellite data. These features reflect vegetation condition, topographic structure, hydrological connectivity, and cumulative degradation trends. The selected features were ecologically meaningful and statistically discriminative when used as inputs to the Random Forest classification model.

3.3.1 Vegetation Indices: NDVI and NBR Trends

Normalised Difference Vegetation Index (NDVI):NDVI is an established indicator of photosynthetic activity, canopy density, and vegetative vigour. Higher values indicate healthier vegetation cover, while lower values may correspond to sparse or degraded canopy.

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

Where, NDVI = Normalised Difference Vegetation Index
NIR = Near-Infrared

Normalised Burn Ratio (NBR):NBR is particularly sensitive to biomass loss, canopy disturbance, and recovery from degradation, often used in post-fire and vegetation stress monitoring.

$$NBR = (NIR - SWIR) / (NIR + SWIR) \quad (2)$$

Where, NBR = Normalised Burn Ratio
NIR = Near-Infrared
SWIR= Shortwave Infrared

Both indices were computed for each image in the time series (Landsat and Sentinel-2), and then a pixel-wise linear regression was applied across time using GEE's ee.Reducer.linearFit() function. This produced NDVI Trend and NBR Trend slope layers, which indicate the direction and magnitude of vegetation change over the study period (2008-2023). NDVI/NBR slope values in the range of 0.01 to 0.03 indicate subtle but consistent positive trends, suggesting areas undergoing natural regeneration or stable conditions. Near-zero or negative slope values are symptomatic of canopy thinning, fragmentation, or persistent degradation.These metrics were critical in differentiating between degraded stable, and regenerating mangrove patches, particularly in transitional zones with vague canopy conditions.

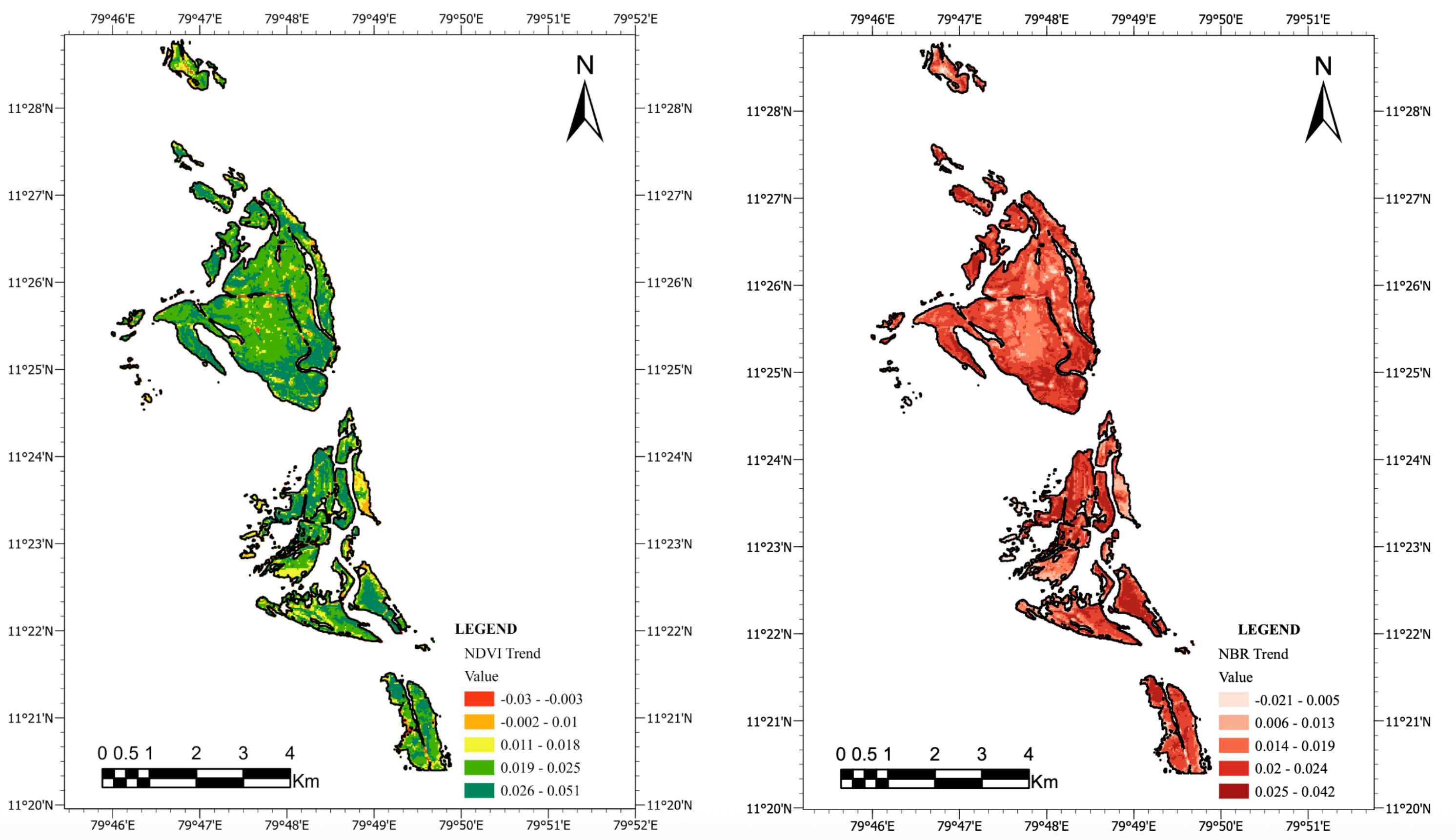

Figure 3: NDVI and NBR Trend Maps of Pichavaram (2008-2023)

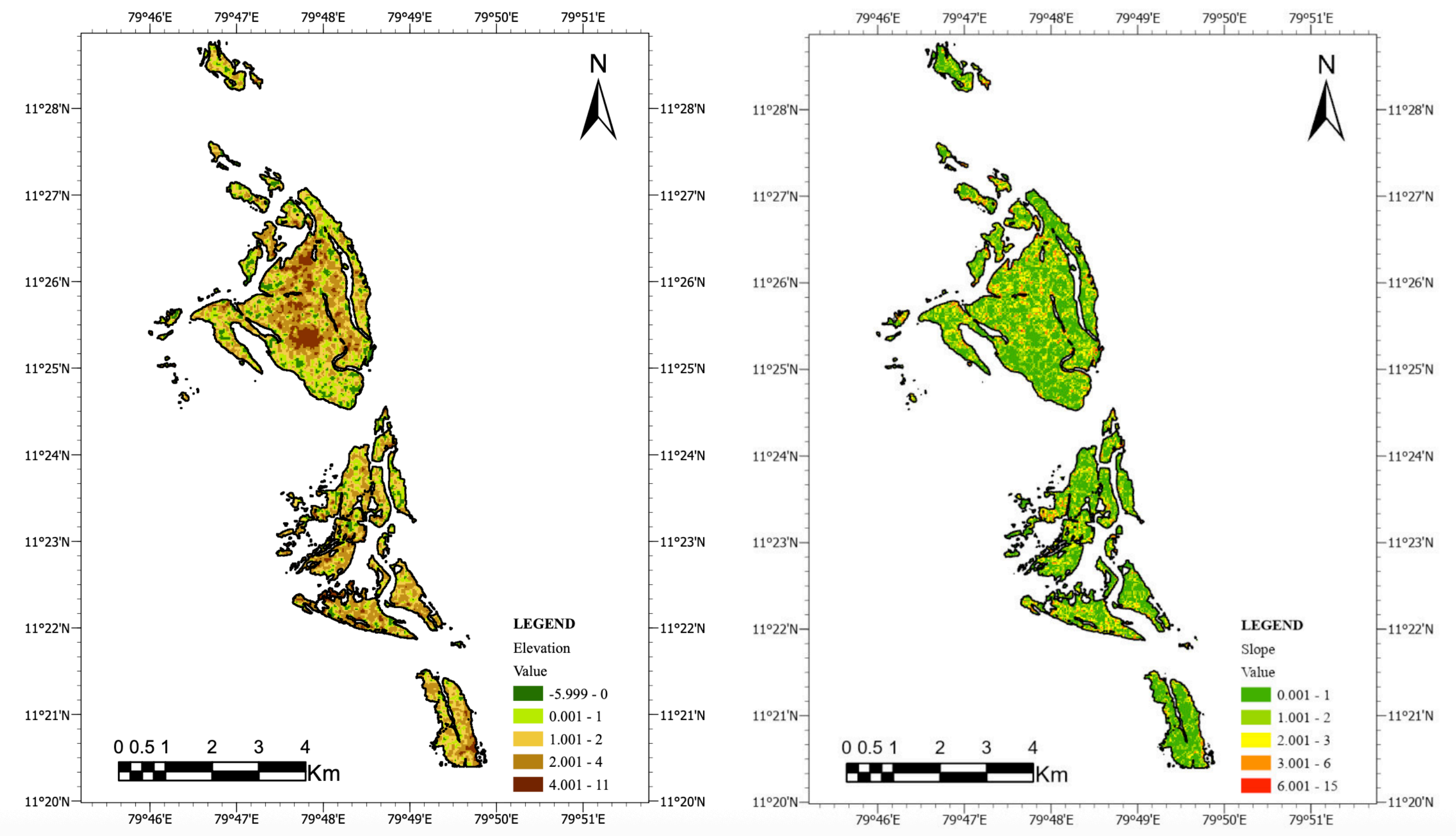

Figure 4: Elevation and Slope Maps of the Pichavaram Mangrove Region

Long term vegetation trends instead of single date imagery enhance the temporal reliability of a model; thus, it develops inter-annual variability caused by climatic anomalies and phenological effects common in tropical estuarine systems.

3.3.2 Topographic Features: Elevation and Slope

Topography plays a fundamental role in shaping mangrove hydrology, species zonation, and stress response. In this study, Elevation and Slope were extracted from the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) at 30-meter resolution using GEE's ee.Terrain.products() function.

Elevation: Directly influences tidal inundation, sediment accumulation, and salinity gradients. Lower-lying areas (<5 m) tend to experience more frequent water logging and salt accumulation, particularly during high tides and dry seasons.In Pichavaram, elevation across the AOI ranged from -6 meters to +19 meters above sea level.Degraded zones were mostly located below 5 meters, making them prone to poor drainage, hyper salinity, and stunted regeneration.

Slope: Affects drainage velocity, sediment transport, and root stability.Gentle slopes (0-5°) are common in coastal wetland settings, but excessively flat terrain can inhibit tidal flushing and lead to anaerobic soil conditions. This study incorporated slopes from 0° and 24° where areas of degradation occurred almost exclusively in flatter areas (<5°).

Overall, stable mangroves had a moderate elevation and well-drained moisture situation that were best for supporting the structure of the canopy. Regenerating patches were most accessible in areas with gradual elevation gradients along with estuaries, which suggests a favourable balance of tidal input and freshwater connectivity. Degraded patches, especially near aquaculture zones or blocked water channels, exhibited low elevation and minimal slope, contributing to stagnant, saline conditions and vegetation dieback.

3.3.3 Tidal Proxy (Hydrological Connectivity Layer)

Tidal fluctuations have an important relationship with mangrove health through soil salinity, nutrient cycling, aeration, and sediment deposition. Disruptions in tidal connectivity due to embankments, aquaculture bunds, or siltation can lead to stagnant conditions, elevated salinity, and subsequent degradation. Therefore, understanding tidal inundation variability is crucial in identifying hydrologically stressed mangrove zones. To model this, a Synthetic Aperture Radar (SAR)-based tidal proxy was developed using Sentinel-1 Ground Range Detected (GRD) imagery in VV polarisation, which is sensitive to water surface roughness and moisture content.

- High Tide Period: Sentinel-1 images from June 2020.
- Low Tide Period: Sentinel-1 images from January 2020.

For each period, multiple images were median-composited to reduce speckle noise. The tidal proxy layer was then generated using pixel-wise subtraction. This difference map captures relative changes in water presence across tidal phases. Positive values indicate areas that flood during high tide, while near-zero or negative values suggest permanently dry or hydrologically isolated patches. Values ranging from -11.54 to +14.85 dB.

Degraded Zones: Often fall within low or negative tidal proxy values, indicating poor tidal flushing and hydrologic disconnection. Stable Mangroves: Associated with moderate to high tidal variability, supporting regular inundation cycles. Regenerating Areas: Typically fall between these extremes, suggesting partial recovery of hydrological flow(e.g., post-restoration or breached bunds). Tidal variability not only

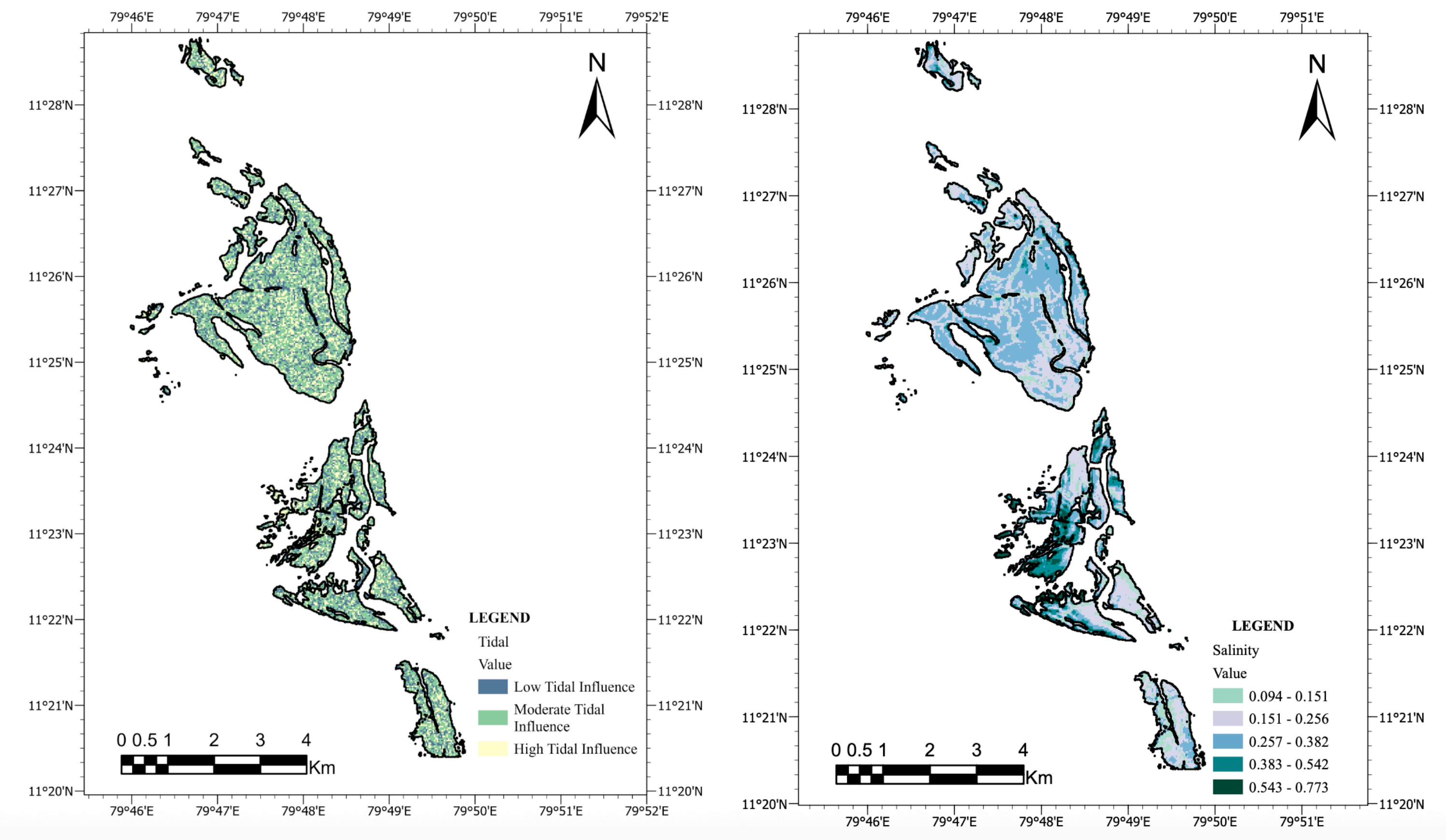

Figure 5: SAR-Based Tidal Proxy Layer and Salinity Proxy Map of the Pichavaram Mangrove Region

governs water and nutrient availability but also controls seed dispersal and anaerobic soil conditions. Reduced tidal exchange is a well-documented stressor contributing to vegetation dieback in coastal wetlands (Alongi, 2015).

3.3.4 Salinity Proxy (Chronic Salt Stress Layer)

Soil and water **salinity** is a dominant abiotic stressor in mangrove ecosystems, particularly in low-lying areas with limited freshwater flow or excessive evaporation. Elevated salinity can inhibit seedling growth, reduce biomass, limit species diversity, and in severe cases, lead to canopy mortality.

For this study, a custom salinity raster layer was developed and normalised to a 0-1 scale. The raster was generated using salinity sampling data, interpolation models, and known hydrological drivers Values were ranging from 0.095 to 0.773 High Salinity Zones (>0.5): Strongly correlated with degraded mangrove patches, especially those located near, Aquaculture ponds with poor water turnover or Embanked regions blocking tidal/freshwater exchange. or Evaporative flats during the dry season. Moderate Salinity Zones (0.25-0.5): Often associated with transitional or regenerating areas, where vegetation may be recovering following hydrological restoration. Low Salinity Zones (<0.25): Corresponded closely with stable mangrove stands, particularly near river mouths or estuarine channels where freshwater inflow helps dilute salt concentration.

While mangroves are halophytes, species-specific salinity tolerance limits mean that long-term exposure to high salinity can lead to selective species loss and structural simplification of the ecosystem.

3.3.5 Proximity Indicators: Modeling Anthropogenic and Hydrological Pressure

Proximity-based features were derived to capture the spatial influence of human infrastructure and hydrological connectivity on mangrove degradation. In complex coastal landscapes like Pichavaram, distance to roads, rivers, and settlements plays a critical role in determining site-level ecological health, especially in fragmented or transitioning zones.

Shapefiles representing roads, rivers, and settlements were digitised in QGIS using recent Sentinel-2 imagery (2019 - 2023). These vector datasets were uploaded to Google Earth Engine (GEE) as assets and then converted into raster surfaces using the fastDistanceTransform() function. This method performs Euclidean distance transformation, generating continuous raster layers in which each pixel records its distance (in meters) to the nearest feature.The resulting raster was included in the Random Forest classification feature stack.

Distance to Roads (56.81-436.97) - Degraded zones were often within 100-200 m of roads. Roads contribute to fragmentation, facilitate aquaculture access, and disrupt tidal flow via embankments. Stable zones tend to be farther away.

Distance to Rivers (75.13-300.54) - Regenerating zones often fell within 150 m of rivers, indicating enhanced freshwater connectivity, nutrient exchange, and natural sediment deposition. Greater distances showed lower recovery.

Distance to Settlements (10.94 - 84.15) - Highest degradation was recorded within 100 m of settlements, likely due to land conversion, domestic waste discharge, and firewood harvesting. Stable mangroves were typically isolated from dense habitation.

These proximity metrics help to quantify indirect stressors such as pollution, sediment alteration, and anthropogenic barriers which are otherwise invisible in spectral imagery.

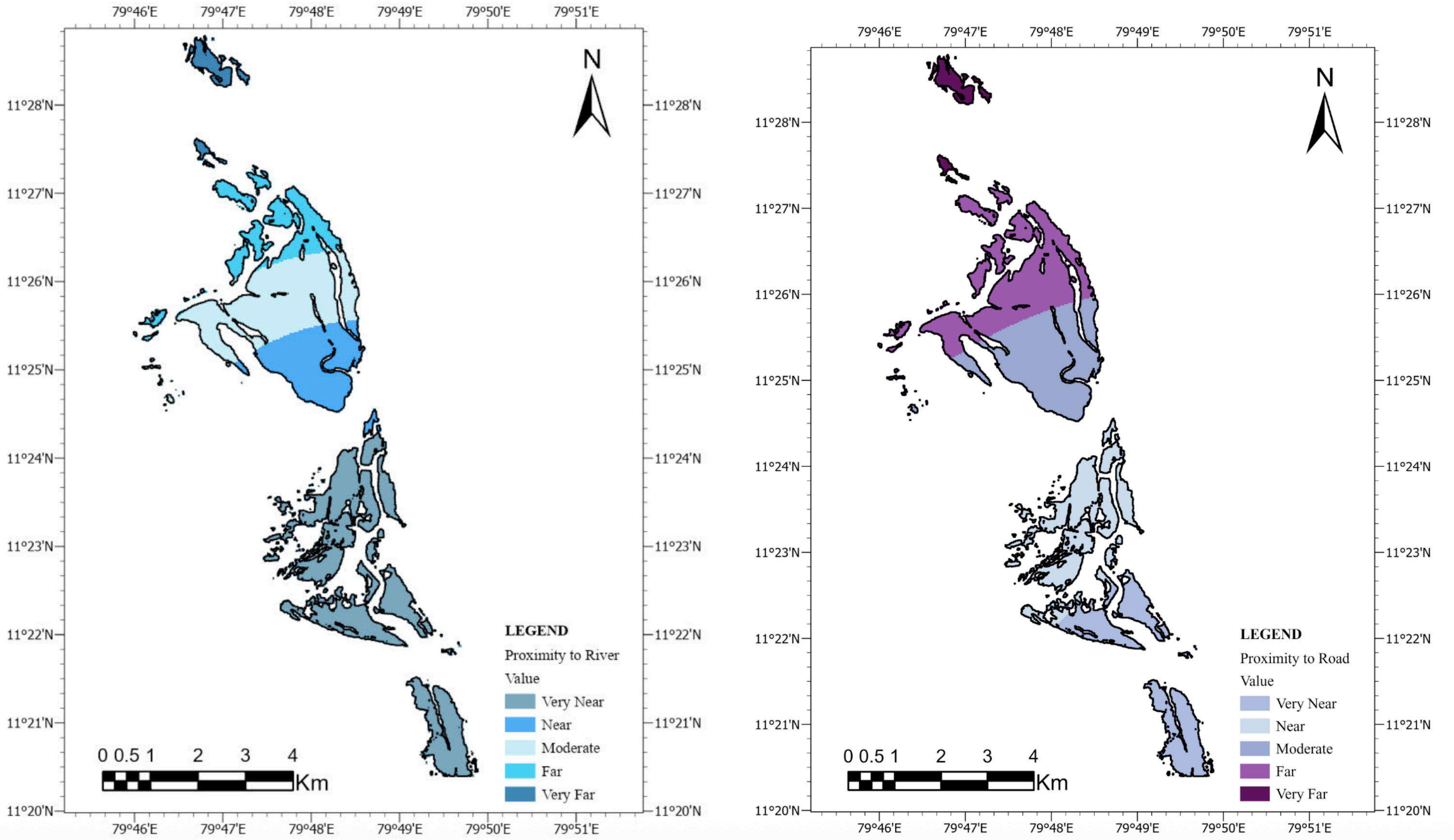

Figure 6: Proximity Maps for Roads and Rivers

They enhance the spatial detail of degradation modelling, particularly at edges and disturbed fragments.

3.4 Climate Stress Index (CSI)

The CSI aims to incorporate the combined ecological stress that occurs on mangrove patches, a Climatic Stress Index (CSI) was constructed. This composite index integrates biophysical trends and environmental pressures into a single metric, thereby offering a more holistic understanding of degradation risk.

$$\text{CSI} = \text{NDVI trend} + \text{NBR trend} + \text{Normalised Salinity} + \text{Tidal Proxy} \quad (3)$$

Where, NDVI trend: Magnitude of vegetation change
NBR trend: Biomass fluctuation and canopy loss.
Normalised Salinity: Chronic salt stress that impedes seedling establishment and growth.
Tidal Proxy: Degree of tidal disconnect

All input values were normalised to ensure equal weight during index summation, and calculated pixel-wise across the entire AOI.

0.012-4.0: Low stress (stable) Central mangrove blocks with optimal salinity and tidal flow.
4.01-9.99: Moderate stress(transitional) Zones with regenerating vegetation and partial tidal recovery.
>10.0: High stress (degraded) Northeastern and southeastern mangroves affected by aquaculture, road barriers, or hyper salinity.

All high CSI zones (>10) aligned closely with areas classified as Degraded in the final RF model, confirming the accuracy of the CSI as a compound vulnerability index. The CSI amplifies subtle or non-spectral stress indicators (e.g., invisible salt buildup, hidden tidal disconnection). It helps pinpoint early-warning zones areas that may appear visually stable but exhibit rising ecological strain. It supports risk-based zoning, guiding restoration, buffer planning, and policy enforcement under SDG 13 (Climate Action) and SDG 15 (Life on Land).

3.5 Preparing the Training Sample

Supervised classification requires valid and ecologically relevant training data to help ensure the model is able to learn the characteristics associated with the different landcover or ecosystem types in the study region. In this study, we developed a rigorous training dataset based on manual interpretation and expert knowledge, using high-resolution imagery, spectral patterns, and ecological indicators to represent the three mangrove degradation classes across the Pichavaram region.

3.5.1 Source Imagery for Interpretation

To digitise training samples, cloud-free Sentinel-2 RGB composites from the period 2019 to 2023 were used. These images were chosen for their:

- 10-meter spatial resolution, ideal for distinguishing between fine-scale mangrove canopy structures;
- True-colour bands (B4 - red, B3 - green, B2 - blue), which closely match natural colour representation and aid visual interpretation;
- High temporal frequency, allowing seasonal filtering to minimise cloud interference and identify consistent features over time.

Only images representing the dry season (post-monsoon months) were used to avoid misleading spectral signals caused by standing water or peak turbidity. Composites were mosaicked and visualised in QGIS to serve as the base layer for training data digitisation.

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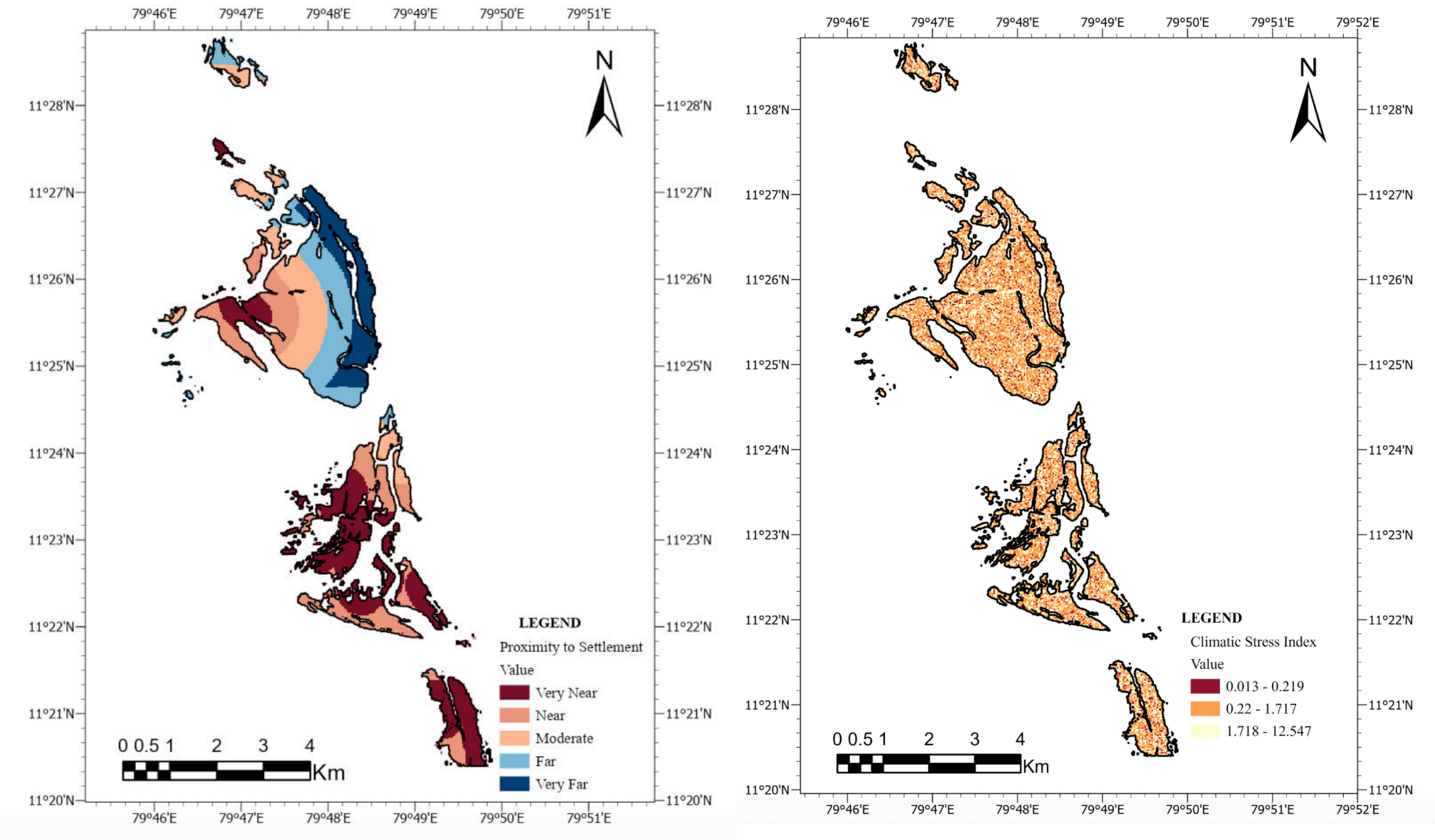

Figure 7: Proximity Maps for Settlements and Climate Stress Index (CSI)

3.5.2 Class Definitions and Visual Indicators

Each training polygon was carefully digitised into one of the following three mangrove condition classes, based on spectral signature, canopy density, patch shape, and proximity to disturbance or restoration features

Stable Mangroves (Class 0):
Characterised by dark green, high NDVI areas with continuous, unfragmented canopy. Typically located in the central and southern zones of the AOI. Indicators included dense canopies, minimal human interference, and strong spectral response in NIR bands.

Degraded Mangroves (Class 1):
Patches with fragmented canopy, sparse or brownish tones, and proximity to roads, aquaculture bunds, or settlements. Often showed flat NDVI/NBR trends or declining biomass in trend layers. Spatially aligned with high CSI values, elevated salinity zones, and poor tidal proxy indicators.

Regenerating Mangroves (Class 2):
Typically young plantations or areas recovering naturally, adjacent to estuarine channels or previous bund restoration areas. Display as light green areas, typically linear or fringe-shaped, typically at the right edge of surface water locations. Evidence of a positive NDVI/NBR trend value confirms its classification as regenerated.

3.5.3 Digitisation Protocol

The digitisation process followed a structured and repeatable protocol:

- Each polygon was attributed with a unique ID and class code (0, 1, or 2).
- Polygons were kept spatially non-overlapping and ensured to be internally homogeneous in both visual appearance and index values.
- Multiple patches per class were selected to capture intra-class variability across the AOI, including zones with different elevation, salinity, and proximity conditions.
- Spectral reflectance, NDVI/NBR trend curves, and index histograms were cross-checked to validate each polygon.

This reduced subjectivity in labelling and enhanced the robustness of class definitions. To avoid bias due to overrepresentation of central zones, the AOI was divided into quadrants, and training polygons were drawn in each quadrant for all three classes. This ensured even geographic coverage and improved classifier generalisation across the landscape.Each training polygon was then overlaid on the full feature stack (including NDVI/NBR trend, salinity, elevation, slope, tidal proxy, proximity layers, and CSI) using the sampleRegions() function. This process extracted the multi-band pixel values under each polygon and assigned them their corresponding class labels, forming a training dataset matrix for the Random Forest classifier.

3.6 Classification Using Random Forest (RF)

The final step of this geospatial modeling workflow involved training a supervised machine learning model to classify mangrove zones in the Pichavaram region into three ecological condition classes: Stable, Degraded, and Regenerating. The Random Forest (RF) algorithm was selected due to its robustness, resistance to overfitting, interpretability, and proven success in handling high-dimensional ecological datasets.

The model was trained using a multi-layer feature stack capturing spectral, topographic, hydrological, environmental represented long-term vegetation health, while elevation and slope informed topographic influences on inundation. A tidal proxy and normalised salinity layer captured hydrological and environmental stress. Proximity to roads, rivers, and settlements accounted for anthropogenic pressure. A composite Climatic Stress Index (CSI) combined key stress indicators into a single metric. Each pixel was labeled as stable (0), degraded (1), or regenerating (2) using digitised training polygons, enabling the Random Forest classifier to accurately differentiate mangrove conditions with high spatial and ecological sensitivity.

3.6.1 Multi-class Random Forest Classification

The Random Forest classifier was assigned 100 decision trees; I arrived at this number after testing several candidates in order to find a compromise between classification performance and computational efficiency. The tests indicated that beyond this number of trees, accuracy saw very little improvement, whereas processing time grew exponentially. The model was allowed to grow trees until their natural depth by retaining the default minimum leaf size, which allowed the model to capture small-scale patterns or subtle differences in the ecological conditions of the mangrove region. Furthermore, bootstrapping was defaulted in the Google Earth Engine environment. Bootstrapping allowed for the statistical independence of decision trees by training each tree on a slightly different data set, which enhanced the generalisation of the ensemble and mitigated overfitting.

Each pixel across the AOI was then assigned to one of the three classes.This classification produced a pixel-wise categorical map showing spatial distributions of mangrove health across the entire study area.

3.6.3 One-vs-Rest Binary Classification for ROC-AUC

To complement the multiclass output and enable Receiver Operating Characteristic (ROC) curve analysis, three binary RF classifiers were also trained, one for each class using a One-vs-Rest approach:
Class 0 vs (Class 1 + Class 2) → Stable vs Rest
Class 1 vs (Class 0 + Class 2) → Degraded vs Rest
Class 2 vs (Class 0 + Class 1) → Regenerating vs Rest

Each binary model outputs probabilities, which were used to compute ROC curves and AUC scores. These help measure how well the classifier distinguishes each class from the others, providing insight into model sensitivity and discriminatory power.

3.7 Accuracy Assessment and Validation

A rigorous accuracy assessment was conducted to evaluate the performance and generalisability of the Random Forest classifier. Validation involved both internal cross-validation and external metrics derived from the final classified map, including the confusion matrix, overall accuracy, Kappa coefficient, and ROC AUC analysis. The confusion matrix, generated using a stratified random sample of 600 validation points across all three classes, revealed minimal confusion between stable and degraded mangroves, and only slight overlap between regenerating and stable classes which is expected due to their spectral similarity. Overall, the classifier demonstrated exceptional performance with an overall accuracy of 98.14%, reflecting highly representative feature selection and training data quality. The Kappa coefficient was calculated at 0.972, indicating near-perfect agreement. To further evaluate class-wise performance, Receiver Operating Characteristic (ROC) curves were generated using a one-vs-rest approach. The Area Under the Curve (AUC) values were 0.97 for stable, 0.96 for degraded, and 0.96 for regenerating classes demonstrating the model’s strong discriminatory power and reliability across ecological conditions.

	Predicted: Stable	**Predicted: Degraded**	**Predicted: Regenerating**
Stable	198	1	0
Degraded	0	195	0
Regenerating	8	2	188

Table 1. Confusion Matrix

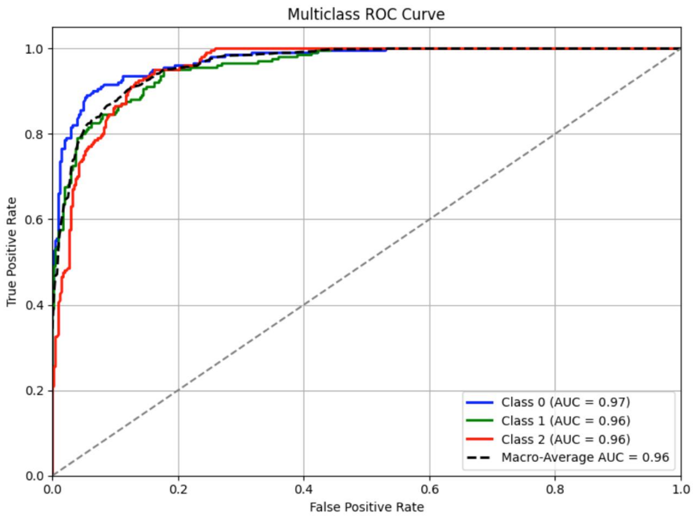

Figure 8. Multi class ROC Curve

4. Results

The Random Forest classification model produced a highly accurate three-class land cover map that highlights stable, degraded, and regenerating mangrove zones in the Pichavaram region. These classification results not only showcase the spatial differences in mangrove health but also reveal the environmental and human factors that contribute to the stress and resilience of the ecosystem. By incorporating spectral indices, topographic and proximity variables, along with hydrological stress indicators into a machine learning framework, we were able to create a detailed degradation map that boasts strong predictive capabilities.

The overall performance of the classification model was exceptional. The Random Forest algorithm achieved an overall accuracy of 98.14% and a Kappa coefficient of 0.972, indicating strong agreement between predicted and reference data. The confusion matrix revealed that 198 of 199 stable mangrove samples were correctly classified, while all 195 degraded samples were accurately identified. Of the regenerating samples, 190 out of 200 were classified correctly, with a minor misclassification primarily involving confusion with stable zones. The producer’s accuracy values were 96.1% for stable, 97.5% for degraded, and 100% for regenerating mangroves, while user’s accuracy stood at 100%, 98.9%, and 95% respectively. These values underline the classifier's ability to differentiate subtle ecological stages in mangrove

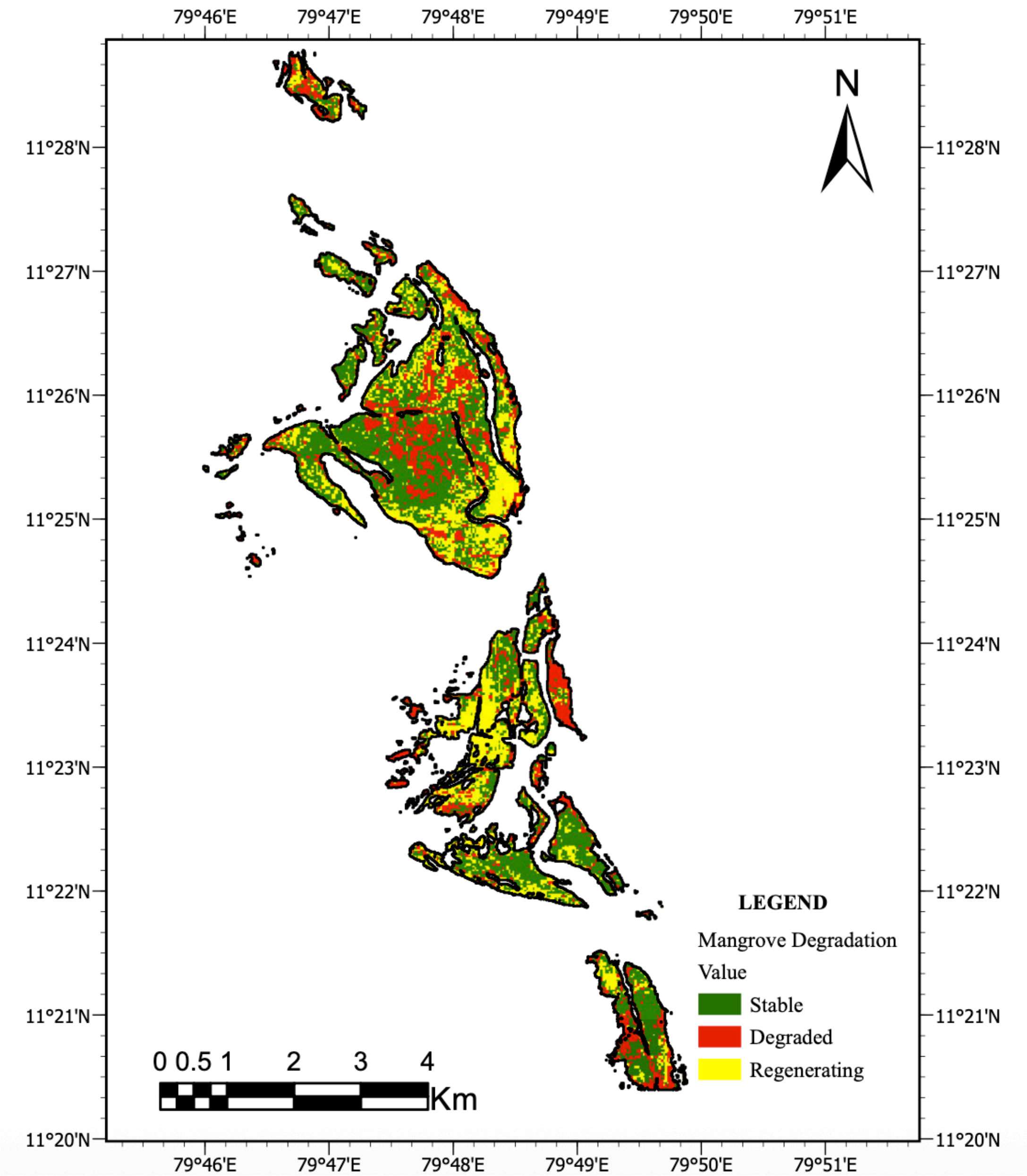

Figure 9: Final Mangrove Degradation Classification Map

development and decline, even when spectral characteristics were overlapping or transitional.

Complementary to the confusion matrix, the Receiver Operating Characteristic (ROC) analysis further validated the classifier's discriminatory power. Each class was individually evaluated using a one-versus-rest approach. The Area Under the Curve (AUC) for stable, degraded, and regenerating classes were found to be 0.97, 0.96, and 0.96, respectively. These high AUC values indicate that the classifier is capable of reliably distinguishing between classes, even under conditions of mixed spectral signals and multi-dimensional input features. The inclusion of probabilistic outputs from the Random Forest model enabled precise ROC-AUC analysis, offering additional insights into the robustness of classification.

- Stable areas clustered in the central and southern core zones, corresponding to dense canopy, low CSI, and optimal tidal flushing.
- Degraded zones dominated the eastern fringes, especially near roads, aquaculture ponds, and settlements areas with high salinity, tidal disconnection, and proximity stress.
- Regenerating patches appeared as linear or patchy zones along riverbanks, historical aquaculture zones, and recently restored areas, often with positive NDVI/NBR trends.

The final classified map revealed a distinctive spatial pattern in the ecological condition of the mangroves. Stable mangroves were predominantly concentrated in the central and southern sectors of the study area. These zones are typified by high NDVI and NBR trends, low salinity values (typically below 0.3), and high tidal connectivity, as reflected in tidal proxy values. The areas also exhibited favourable elevation conditions (generally above 3 meters) and remained largely disconnected from anthropogenic features such as roads or settlements. These conditions collectively contribute to a stable and self-sustaining mangrove canopy with dense foliage, minimal fragmentation, and persistent ecological functioning.

In contrast, degraded mangrove zones were concentrated along the eastern and northeastern fringes of the Pichavaram forest. These areas corresponded closely with zones of high climatic stress index (CSI >10), poor tidal connectivity, and elevated salinity values (exceeding 0.6). Their proximity to human infrastructure, particularly roads and aquaculture ponds, further accentuated their vulnerability. The degraded patches appeared as fragmented, brownish-to-greyish patches in RGB imagery and showed either negative or stagnant vegetation trends in both NDVI and NBR indices. Moreover, these areas often fell within 100 meters of settlements, where anthropogenic pressures such as fuelwood extraction, embankment constructions, and aquaculture effluent runoff are known to exacerbate environmental stress.

The regenerating class presented a particularly interesting spatial pattern. These patches, primarily located along rivers, estuarine channels, and recently decommissioned aquaculture zones, appeared as fringe-shaped, light green zones with moderate vegetation index trends. The trend analysis revealed positive NDVI and NBR slope values (typically between 0.01 and 0.03), indicating the early stages of biomass buildup. These regenerating areas were also associated with intermediate salinity levels (0.3-0.5), moderate tidal proxy values, and low-to-moderate CSI values. Their emergence in spatial proximity to stable mangrove zones or along reconnected tidal flows suggests a mix of passive natural regeneration and active restoration processes. These zones are ecologically important as indicators of potential recovery and resilience and may serve as early success stories for targeted conservation interventions.
In terms of area coverage, the classification output estimated that stable mangroves occupy approximately 610 hectares, while degraded mangroves extend across 238 hectares. Regenerating mangrove zones cover an area of around 369 hectares. These results suggest that although more than 50% of the mangrove forest is currently in a stable state, a substantial portion is either undergoing degradation or in the process of regeneration. Specifically, degraded zones account for nearly 19.6% of the total mangrove area, while regenerating zones comprise about 30.3%, underscoring both the severity of ecological stress and the potential for recovery.

Further analysis of the classified outputs revealed meaningful relationships between classification results and the underlying environmental drivers. Degraded zones consistently exhibited the highest values of salinity, poorest tidal flushing, and the closest proximity to anthropogenic structures. Conversely, stable areas displayed consistently lower stress indicators and higher ecological integrity. The regenerating zones, while not as resilient as the stable patches, showed promising trends in vegetation recovery, especially in areas where hydrological connectivity has been partially restored.

The findings of this study confirm that a Random Forest model with multiple sources and parameters was an effective way to map extent and degree of mangrove degradation at high spatial resolution. Incorporating spectral trends, topographic variation, environmental stress indicators, and anthropogenic proximity features enabled a nuanced understanding of mangrove condition in Pichavaram. The spatial patterns and classification metrics produced by the model not only reflect current ecological realities but also provide a data-driven foundation for future restoration, monitoring, and climate adaptation strategies.

5. Discussion

The results of this study provide important new insights into the spatial dynamics and ecological drivers of mangrove loss at Pichavaram, affirming both the scientific value and utility of machine-learning-based geospatial modelling for coastal ecosystem management. High classification accuracy from the Random Forest algorithm and ecologically valid class distributions support the assertion that the combination of vegetation indices, topographic and hydrological variables, proximity variables, and composite stress indices produced a feature stack that captures the complexity of mangrove ecosystem change.

One of the most remarkable results in this study is the spatial separation of stable and degraded mangrove sites, which demonstrates both the impacts of hydrological connectivity and anthropogenic pressures. Stable mangroves were prevalent in the inner core of the Pichavaram landscape where tidal exchanges were uninterrupted, salinity levels lower, and elevations reduced periods of waterlogged conditions and hypersaline conditions. These findings were consistent with a previous study (Alongi, 2015), supporting that mangrove sustainability is directly linked to whether hydrological flow remains uninterrupted and whether associated anthropogenic disturbances avoidable. The high proportion of stable patches seen in areas furthest from towns or human-modified infrastructure provides additional evidence that physical separation from anthropogenic stress confers a degree of ecological protection.

In general the classification results indicated an unmistakable clustering of degraded patches of mangrove mostly in peripheral zones, especially in those areas near aquaculture bunds, access road, and informal encroachment. The patch zones were exhibited where demonstrated in the same place. high salinity values, poor tidal proxy responses, and elevated climatic stress index scores. This spatial correlation supports the view that mangrove degradation in Pichavaram is not driven by a single factor, but by a compounding suite of stressors including restricted hydrological exchange, anthropogenic disturbance, and climatic exposure. The proximity of degraded patches to human-modified landscapes is also reflected in findings from mangrove regions in southeast Asia and west Africa, where functional and structural decline in mangrove forests are effects of land-use intensification.

In this context, recognising regenerating mangrove zones using NDVI/NBR trend analysis, tidal reactivation, and intermediate salinity may provide a counterpoint to an otherwise all degradation narrative. These areas typically lie in transition corridors along river mouths or recently breached embankments, may represent either natural regeneration or the early impacts of targeted restoration programs. Their emergence reinforces the notion that mangrove ecosystems possess intrinsic resilience when key ecological thresholds, particularly hydrological reactivation are restored. This observation aligns with recent literature that highlights the importance of tidal restoration in mangrove rehabilitation success. Moreover, the clear spectral and ecological distinctiveness of regenerating patches affirms that trend-based vegetation indices can serve as early indicators of ecological recovery, particularly when static land cover classifications fail to detect dynamic, time-dependent processes.

From a methodological standpoint, the performance of the Random Forest classifier demonstrates the strength of ensemble learning algorithms in handling non-linear, high-dimensional ecological data. Unlike traditional pixel-based classification techniques that often rely solely on spectral reflectance, the inclusion of process-based indicators such as elevation, salinity, and proximity allowed the model to differentiate degradation trajectories more meaningfully. The high ROC-AUC scores across all classes suggest that each degradation stage, whether driven by biophysical stressors, human disturbance, or a combination of both leaves a distinct, learnable signature in the multi-layered data space. This underscores the importance of integrating ecological understanding with remote sensing analytics in the design of classification frameworks.

Another valuable insight from this study is the diagnostic strength of the Climatic Stress Index (CSI). As a composite indicator combining salinity, NDVI/NBR decline, and tidal proxy values, the CSI offered a spatially continuous and interpretable stress gradient that correlated well with ground-referenced degradation patterns. High CSI zones almost universally aligned with degraded mangrove classes, suggesting that such indices can serve for classification purposes and early-warning assessments, conservation prioritisation, and scenario modeling under climate adaptation frameworks. CSI as an intermediary variable between environmental condition and class assignment represents a novel contribution to mangrove degradation modeling, especially in data-scarce regions.

Furthermore, this study advances the application of Google Earth Engine (GEE) as a scalable and replicable platform for large-area ecological modeling. The cloud-based architecture enabled seamless integration of satellite archives, user-uploaded layers (e.g., shapefiles), and time-series analyses, reducing computational bottlenecks often encountered in desktop GIS workflows. This democratises high-resolution ecosystem assessment for policymakers, researchers, and conservationists, especially in the Global South, where access to advanced tools is often limited.

The findings from this research represent a diagnostic measure of the current ecological condition of the Pichavaram mangrove landscape, and demonstrate the potential to utilise machine learning and earth observation technologies to diagnose, monitor and aid in re-establishing blue carbon systems. The capacity to classify stable mangrove zones, degraded mangrove zones, and regeneration mangrove zones with any level of confidence provides authority for focused management response and long term monitoring strategy. More generally, the approach applied here can be adapted to other global mangrove systems, offering a scalable response to one of the biggest coastal conservation challenges.

6. Conclusion

This study presents a comprehensive, data-driven assessment of mangrove ecosystem condition in the Pichavaram region of Tamil Nadu, India, through the integration of remote sensing, geospatial analytics, and machine learning. By developing a multi-layered feature stack and applying a supervised Random Forest classifier, we successfully mapped three distinct classes of mangrove condition: stable, degraded, and regenerating, achieving an overall classification accuracy of 98.14% and Kappa coefficient of 0.972. These high-performance metrics reflect not only the robustness of the model architecture but also the ecological validity of the input variables used to characterise complex degradation trajectories.

The spatial patterns observed in the classification outputs reveal the interplay of biophysical, topographic, and anthropogenic stressors. Stable mangroves persist primarily in regions with optimal hydrological connectivity, low salinity, and limited human interference, while degradation is most prevalent near settlements, aquaculture infrastructure, and road networks. Notably, the identification of regenerating patches often adjacent to estuarine channels or abandoned bunds demonstrates the potential for ecological recovery in areas where tidal flows are partially restored. This reinforces the idea that mangroves, despite their vulnerability, exhibit remarkable resilience when favourable environmental conditions are reinstated.

This study exemplifies the methodology and adaptability of Google Earth Engine (GEE) as a cloud-based platform for large-scale ecological modeling in high-resolution. Open-access satellite data and scalable algorithms make the methodology replicable and transferrable; hence, the same methods can be used for other coastlines in India and even farther afield where mangroves are abundant. Moreover, the incorporation of spectral, topographic and human impact indicators integrates multifarious axes of ecosystem assessment, which is crucial for monitoring contested biomes that are dynamically hydrological.

In terms of climate adaptation, blue carbon conservation and ecosystem-based disaster risk reduction, the results from this study are timely. The ability of spatially distinguishing pathways of degradation and regeneration often serves as valuable information for policymakers, restoration practitioners and local communities engaged in sustainable mangrove management.

The future research should aim to incorporate field-verified reference samples and multi-seasonal analyses to enhance classification reliability and better capture the seasonal dynamics of mangrove vegetation. Furthermore, integrating socioeconomic variables such as land tenure systems, community based management practices, and restoration histories could provide a deeper, more inclusive understanding of the human ecological interface influencing degradation and recovery. Overall, this study offers a scientifically robust, technologically scalable, and ecologically relevant framework for monitoring mangrove degradation and resilience. By demonstrating the potential of combining remote sensing, environmental indicators, and machine learning, the research underscores the value of geospatial intelligence in guiding conservation policy, restoration planning, and climate adaptation efforts. In doing so, it contributes meaningfully to the global imperative of safeguarding mangroves vital green-blue ecosystems at the frontline of climate change, coastal vulnerability, and biodiversity loss.

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