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Mangrove Forest loss and Future Risk Analysis for Southeast Asia using Satellite-derived data and Machine learning

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Abstract

Mangrove forests are a critical part of our ecosystem, which works continuously to fight the carbon footprint, coastal erosion and provides support for biodiversity. However, these forests are encountering notable loss across tropical areas. To save these diverse ecosystem it is important to identify the mangrove loss factors and future risk zones. In this study, I have worked on a multi-country data-driven framework to understand the mangrove loss in Southeast Asia and to forewarn future loss risks.

Global Mangrove Watch(GMW) data set was used to extract the mangrove data for 1996, 2007,2010,2015,2020 timeline. Lateron, Google Earth Engine was used to extract Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), elevation, and slope data for Bangladesh, Thailand, Myanmar, and Indonesia. After sampling and balancing the data, four ensemble machine learning models were applied to model mangrove loss.

Random Forest, Gradient Boosting, XGBoost, and LightGBM models were tested, and among them, Random Forest outperforms others with a ROC-AUC of 0.96 and an F1-score of 0.90. Elevation was identified as the primary cause of mangrove decline, followed by NDVI and NDWI, suggesting increased vulnerability in low-lying, water-stressed mangrove areas. While country-level comparisons revealed similar loss intensities throughout the research region, temporal analysis revealed comparatively steady loss rates between 1996 and 2020. About 36% of mangrove habitats were classified as high or very high risk in future risk projections for 2025–2030, with low-elevation coastal zones being specifically vulnerable.

The suggested methodology facilitates the evidence-based prioritizing of conservation and management measures and offers a scalable and adaptable method for regional mangrove monitoring.

Introduction

Mangrove forests are critically crucial for the environment of the coastal ecosystem. These forests are highly productive wetlands that provide shoreline stabilization and protection against coastal hazards. These forests are well-known carbon sinks protecting the coastal areas from erosion and storm surges. However, these ecosystems are encountering threats due to climate change and anthropogenic pressures. Mangroves around the world have been facing losses over recent decades. The drivers responsible for these losses and the areas which are at high risk should be identified to take necessary steps for the conservation of these ecosystems.

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Southeast Asia holds the highest proportion of the world's mangrove area. The area of this study (Bangladesh, Indonesia, Myanmar, and Thailand) contains around 35,872.3377 square kilometres of mangrove forest1.

Name	Area(Square Km)
Bangladesh	4320.4932
Indonesia	24094.5561
Myanmar	4947.4602
Thailand	2509.8282

Table 1. National level Mangrove forest area in 2020

These mangrove forests are not only important for the environment but also support the dense coastal population of this region economically. Due to the rapid change of nature and different development projects taking place in the coastal area of this region to improve the living standards of people are contributing to mangrove degradation in this region. Simultaneously, vulnerability to environmental change is increased by natural features, including low elevation, tidal inundation, and hydrological stress. One of the biggest research challenges is still figuring out how these drivers interact over time and geography.

A strong framework for simulating intricate, non-linear interactions between environmental causes and ecosystem outcomes is provided by machine learning approaches. Because of their resilience and capacity to manage varied predictor variables, ensemble-based models, such as Random Forest and boosting algorithms, have demonstrated promise in ecological applications. These techniques can assist data-driven evaluations of ecosystem risk when paired with satellite-derived indicators, including vegetation indices, topography variables, and hydrological proxies.

Previous research worked to understand mangrove loss for a single country or over a short period of time. As there were no large-scale datasets available, the future mangrove loss prediction remained unexplored. However, with the availability of satellite data, we can now get the long-term global mangrove datasets such as Global Mangrove Watch(GMW). This helped us to develop a multi-country machine learning framework to understand the mangrove loss in the Southeast Asia region between 1996 and 2020 and to project future risks for the time period of 2025-2030. I have uncovered the main causes of mangrove loss by methodically comparing several ensemble models. To assist with early warning and conservation priority, I have also produced spatially explicit risk estimations.

The objective of this study is to:

1. Understand the temporal and spatial patterns of mangrove loss in Bangladesh, Indonesia, Thailand, and Myanmar;

2. Identify the environmental factors responsible for mangrove loss;

3. Assess how well several ensemble machine learning models perform in terms of loss prediction;

4. Assess future risk of mangrove loss.

This study offers a scalable and reproducible method for assessing regional mangrove vulnerability and delivers evidence-based insights to help sustainable coastal management by combining long-term remote sensing data with machine learning.

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Related Work

Early research on mangrove forest have mainly focused on understanding environmental factors for understanding the reasons for mangrove loss and monitoring spatial-temporal dynamics. The earlier works on mangrove worked to find out the mangrove decline patterns using satellite data [1], [2]. Meanwhile, recent studies work to refine the earlier analysis using higher spatial resolution and temporal consistency [3], [4]. The studies often use remote sensing platforms like Sentinel and Landsat for getting the accurate mangrove change [5].

For improving the mangrove classification analysis techniques, such as NDVI and NDWI, are widely applied [6], [7]. These indices are important for differentiating the mangrove canopy from other types of canopies, and these indices are widely used across diverse geographic contexts [8]. Moreover, in regional studies in Kerala and Indonesia, it can be noticed that the researchers are using Google Earth Engine and machine learning together to get high-resolution mangrove change scenarios [9], [10].

Machine learning algorithms can handle high-dimensional datasets and capture nonlinear relationships, and because of this, their use in ecological studies for both classification and predictive modeling has increased dramatically [11], [12], [13]. These algorithms include Random Forest, Gradient Boosting, XGBoost, and LightGBM. For instance, recent work has demonstrated XGBoost's good performance in categorizing mangrove species using multisource remote sensing information [14] while other studies use deep convolutional models for semantic segmentation of mangrove extents [15].

Another area of active research is the understanding of environmental vulnerability. The authors are measuring Mangrove susceptibility in the Sundarbans through vegetation health evaluation utilizing indices and machine learning [16], while mangrove vulnerability to cyclone threats in Bangladesh has been examined through geospatial studies [17]. Utilizing machine learning models and remote sensing, studies also examine the potential for carbon sequestration in mangroves, emphasizing the ecosystem's contribution to climate mitigation [18].

Despite these developments, few studies have combined extensive ensemble machine learning frameworks for multi-country prediction and long-term risk assessment with long-term global mangrove datasets. In order to assess past loss trends and forecast future mangrove risk throughout South and Southeast Asia, this study fills that gap by integrating Global Mangrove Watch (GMW) data with satellite-derived environmental variables.

Methodology

Study Area

Our study focuses on Southeast Asia. I have selected Bangladesh, Thailand, Myanmar, and Indonesia, four countries that have a significant proportion of the world's total mangrove forest 1.

Fig 1. Choropleth map showing country-level mangrove extent for Bangladesh, Indonesia, Myanmar, and Thailand derived from Global Mangrove Watch v3 data

Data collection

I used Google Earth Engine(GEE) to obtain the mangrove extent data from the Global Mangrove Watch(GMW) dataset. The dataset provides high-resolution maps of

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mangrove distribution across Southeast Asia. As a reference condition, I used the mangrove extent data of 1996. The succeeding GMW layers were used to estimate mangrove loss for four temporal intervals:

- 1996-2007
- 2007-2010
- 2010-2015
- 2015-2020

To understand the mangrove loss, I highlighted the transition from mangrove presence to absence in these particular countries between the given timeline. I have executed all the experiments in the identified mangrove areas to avoid any false loss detection in non-mangrove regions.

Environmental Predictor Variables

A collection of biophysically significant environmental factors that are frequently linked to mangrove vulnerability and health was chosen:

- Normalized Difference Water Index(NDWI)
- Normalized Difference vegetation Index(NDVI)
- Elevation
- Slope

Google Earth Engine (GEE) was used to extract these characteristics from satellite-derived datasets and resample them to a uniform spatial resolution. In order to reduce multicollinearity and preserve ecological interpretability, variables were chosen.

Sampling

For creating the dataset, I have used stratified random sampling for each country. Sampling was strictly constrained to mangrove-covered pixels and Coastal zones. I labelled Mangrove loss areas as Label=1 and Mangrove persisted areas as Label=0 for each pixel. Moreover, I ensured balanced sampling to ensure an equal number of loss and no-loss samples across countries and time intervals. 180000 samples were collected across all countries and periods.

Data preprocessing

After creating the samples, I exported them as CSV files for each country, which were later merged into a unified dataset. From the unified dataset, I removed all the missing and invalid inputs. Moreover, I verified class imbalance and country-wise distribution of the data. I ensured that our final dataset contains no missing values, and there are four predictor variables and one binary target variable.

Model Development

Four tree-based machine learning models were implemented to model mangrove loss over this time frame:

1. Random Forest

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2. Gradient Boosting
3. XGBoost
4. LightGBM

These models were selected because of their expertise in handling non-linear relations and complex environmental interactions common in land-cover change studies. To ensure fair comparison, all the models were trained using identical train-testing splits and the same predictive variables. I have used 200 as the number of trees for all the models, maximum depth was set to 20 for the random forest, and 10 for the other three models, learning rate was 0.1 and class weighting was balanced. The dataset was split into a 70:30 portion, and to ensure the balance of mangrove loss and persistence classes, stratified sampling was executed. Precision, F1-score, Recall, and ROC-AUC values were calculated to evaluate the model's performance.

The Random Forest model outperformed the other models and achieved the highest ROC-AUC with a stable precision and recall value. Based on these outcomes, I have selected the Random Forest model as the primary model for feature importance analysis and future risk prediction(2025-2030).

Feature Importance Analysis

For identifying the dominant environmental drivers responsible for mangrove loss, I have used a Random Forest model instead of using Gradient Boosting, XGBoost, or LightGBM, as these models often offer reduced interpretability in comparative ecological analysis.

Future Risk Prediction

The Random Forest model was also used to understand future mangrove loss risk(2025-2030) and for projecting this loss most recent time period data were used as baseline input. Using class probability outputs, the trained Random Forest model produced pixel-level loss probabilities. These probabilities were catagorized as Low risk class($\leq$ 0.50), Moderate risk class(0.5-0.75), High risk class(0.75-0.90), and Very high risk class($>$0.90). To find spatial patterns of future mangrove vulnerability, risk maps and country-specific risk summaries were created.

Results

Random Forest, Gradient Boosting, XGBoost, and LightGBM model outcomes were assessed for mangrove loss prediction. All the models were assessed using an identical model configuration and train-test splits. All models performed strongly, but Random Forest outperforms all other models in terms of precision and recall values across all countries and time intervals. Random Forest performed an overall precision of 0.895, a recall of 0.905, an F1-score of 0.90 and an ROC-AUC of 0.965. The outcomes demonstrate exceptional discrimination between mangrove loss and endurance.

The other three machine learning models showed good accuracy; however, they delivered less stable feature importance estimates. Table 2 illustrates a comparison between all the models.

Feature Importance Analysis

The result of the feature importance analysis proves that mangrove loss is highly associated with low-lying coastal environments and degraded vegetation conditions. The

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Table 2. Performance comparison of ensemble-based machine learning models for mangrove loss prediction.

Model	Precision	Recall	F1-score	ROC–AUC
Random Forest	0.8948	0.9050	0.8998	0.9646
Gradient Boosting	0.8812	0.8924	0.8868	0.9581
XGBoost	0.8876	0.8989	0.8932	0.9614
LightGBM	0.8891	0.9013	0.8952	0.9627

Random Forest model indicated that elevation(37.5%) was the main reason for mangrove loss. Significant contributions were also made by indices linked to vegetation and water, with NDVI and NDWI contributing 29.9% and 20.7% of the total. The remaining 11.9% came from Slope. Figure 2 shows the bar graph highlighting the features associated with mangrove loss.

Fig 2. Top Features Associated with Mangrove Loss in Southeast Asia

Temporal patterns of mangrove loss

The outcome of the study shows some interesting insights about the loss rate of mangrove forests in recent years. I noticed a marginal decrease of 0.02 percentage in the mangrove loss rate compared to the base year of our research. During the period of 1996-2007, the loss rate was 49.90% which in the timeline of 2015-2020 became 49.88.

The decline in mangrove loss rate is obviously a positive sign, though the rate is very low. However, the overall mangrove loss rate is still alarming as it was before. Figure 3 illustrates the temporal loss trend.

Fig 3. Southeast Asia Mangrove loss rate comparison from 1996 to 2020

Mangrove Loss Patterns

A statistical chi-square test was conducted to understand the mangrove loss rate among the countries. The test results suggest similar loss magnitude across the region. The highest mangrove loss was observed across Myanmar(50.37%) and Indonesia(50.29%). Even the loss rate of Bangladesh(49.79%) and Thailand(49.72%) was pretty close to the highest mangrove loss rate. Figure 4 shows the country-wise mangrove loss comparison.

Fig 4. Country-wise mangrove loss comparison for South-east Asia countries

Environmental Factors Responsible for Mangrove Loss and Persistence

I compared the loss and no-loss areas by comparing different environmental drivers to understand the key factors responsible for mangrove loss. The results show that the mangrove loss area illustrated lower NDVI, elevation, slope and higher NDWI value in comparison to the no-loss area.

Strong environmental contrasts between stable and lost mangrove sections were shown by all changes being statistically significant ($p < 0.001$) and having substantial impact sizes.

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Fig 5. Environmental Factor Analysis for loss and no-loss mangrove locations

Future mangrove loss risk projection

Comparing all the models, the Random Forest model outperformed the other models. Based on this, I used the Random Forest model for future risk prediction for mangrove forests for the period 2025-2030. The outcome shows that 35.64% mangrove pixels are at very high risk, while 49.85% are categorized as low risk locations.

Country-wise future mangrove loss risk assessment6 showed the highest mean risk in Thailand, followed by Bangladesh, Myanmar, and Indonesia.

Fig 6. Overall Future Risk Prediction 2025-2030

Discussion

The study shows that mangrove loss depends highly on topographic and vegetation-related drivers, such as elevation and NDVI, which are the main factors behind mangrove instability in Southeast Asia. On the contrary, temporal loss rate analysis revealed that mangrove loss rates between 1996 and 2020 are not rapidly accelerating. This indicates that baseline pressures on mangrove ecosystems are still chronically high, even though it may also represent better conservation efforts in some areas. The need for ongoing monitoring rather than depending solely on short-term trend evaluations is highlighted by the weak temporal distinction.

However, the future of south-east asias mangrove area are at very high risk. Around one-third of the mangrove area is at high loss risk. High mean risk probabilities were found in countries like Bangladesh and Thailand, highlighting the necessity of focused conservation efforts. Rather than being deterministic forecasts, these projections should be understood as relative risk indicators that are meant to enable geographic prioritizing and early warning systems rather than precise loss quantification.

This study works to understand the future of mangrove forests in Southeast Asia, but from my perspective, I could not consider all the possible socio-economic drivers responsible for mangrove loss in this region. Factors like climate change, urbanization, and poor policy interventions were not modeled due to data limitations.

In the future, I would like to extend my work by addressing these limitations of our research. I would like to integrate climate change projections and other socio-economic indicators.

Conclusion

This study uses ensemble machine learning techniques to give a thorough, multi-country assessment of future risk and mangrove loss causes throughout Southeast Asia. The findings show that the main factors causing mangrove decline are low elevation, deteriorated vegetation, and hydrological vulnerability.

Though the temporal variation rate is low, the mangrove loss rate is very high throughout the time period of 1996 to 2020. Moreover, one-third of the total mangrove area is in a very high-risk zone in the future. The results of Random Forest modeling show that proactive conservation strategies must be taken to save this biodiversity from extinction.

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This work offers practical insights for conservation planning, policy creation, and early-warning systems targeted at protecting fragile mangrove ecosystems by identifying high-risk areas and important environmental variables.

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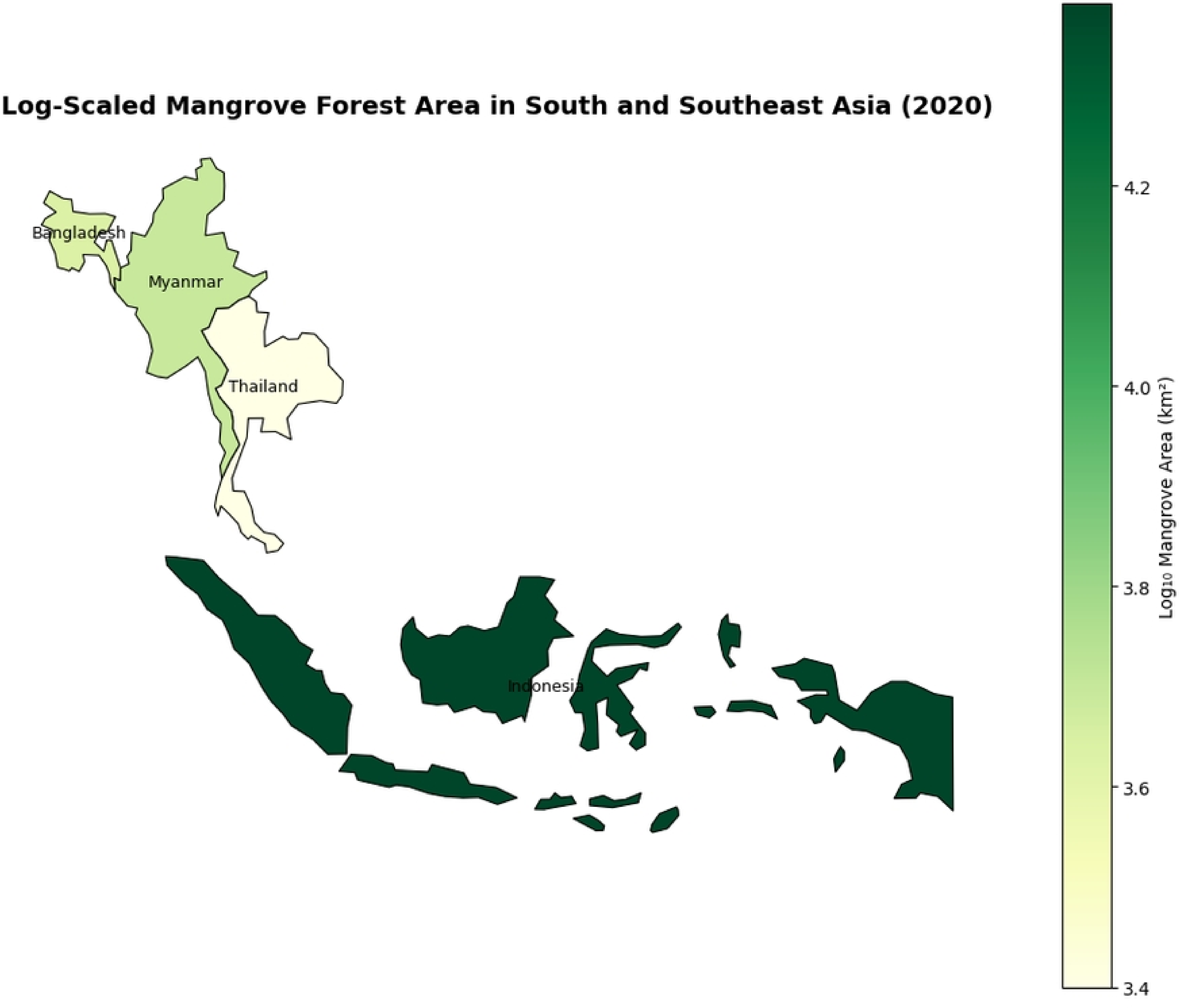
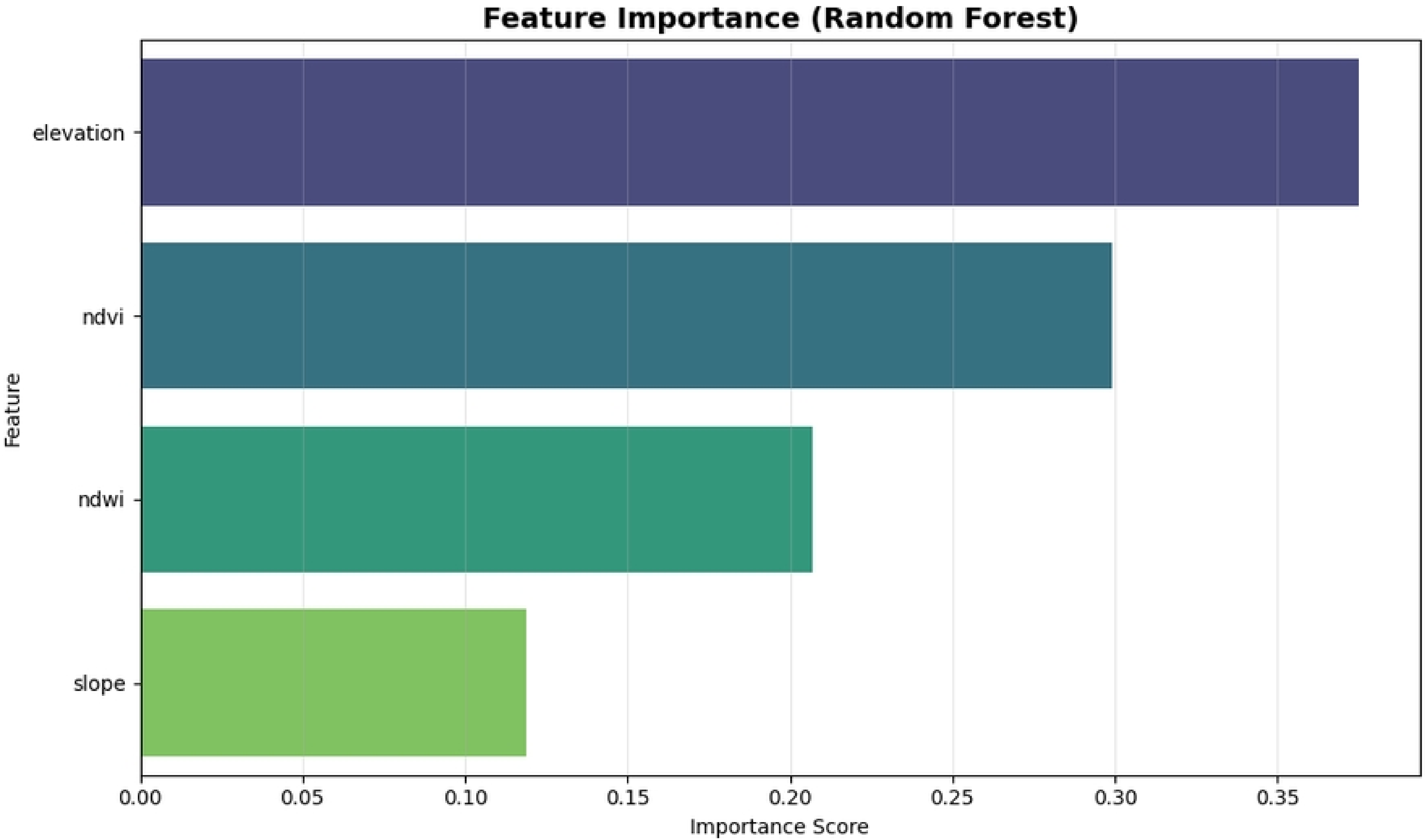
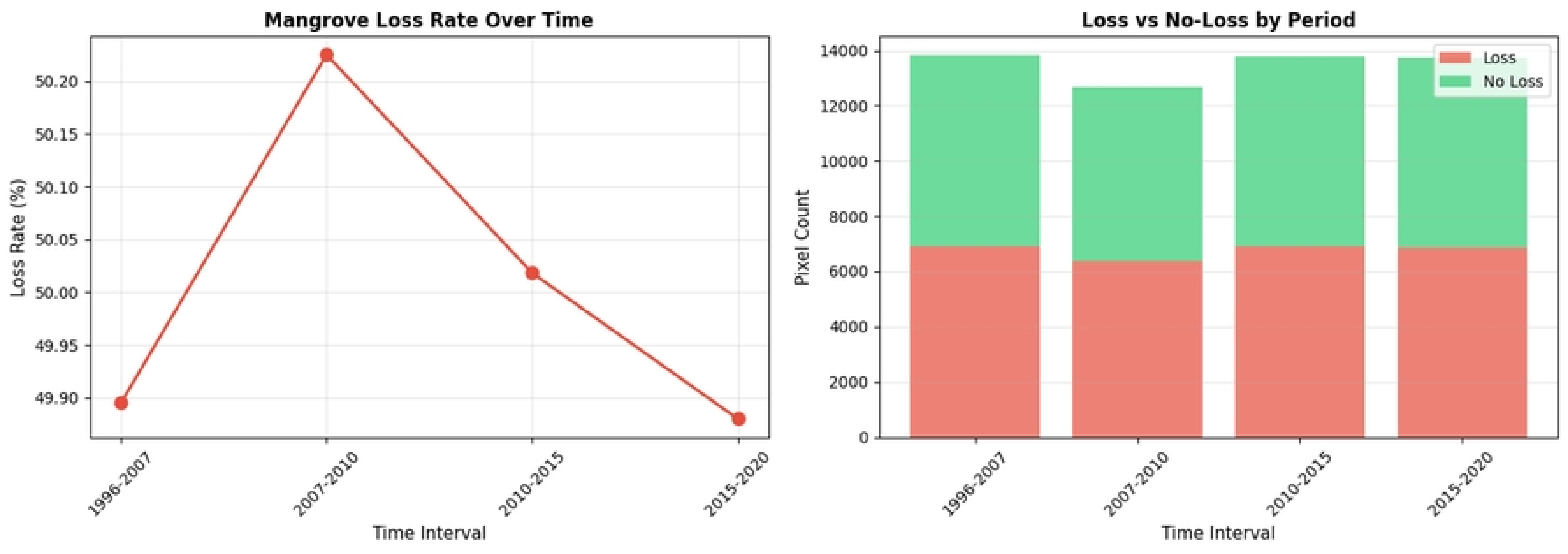
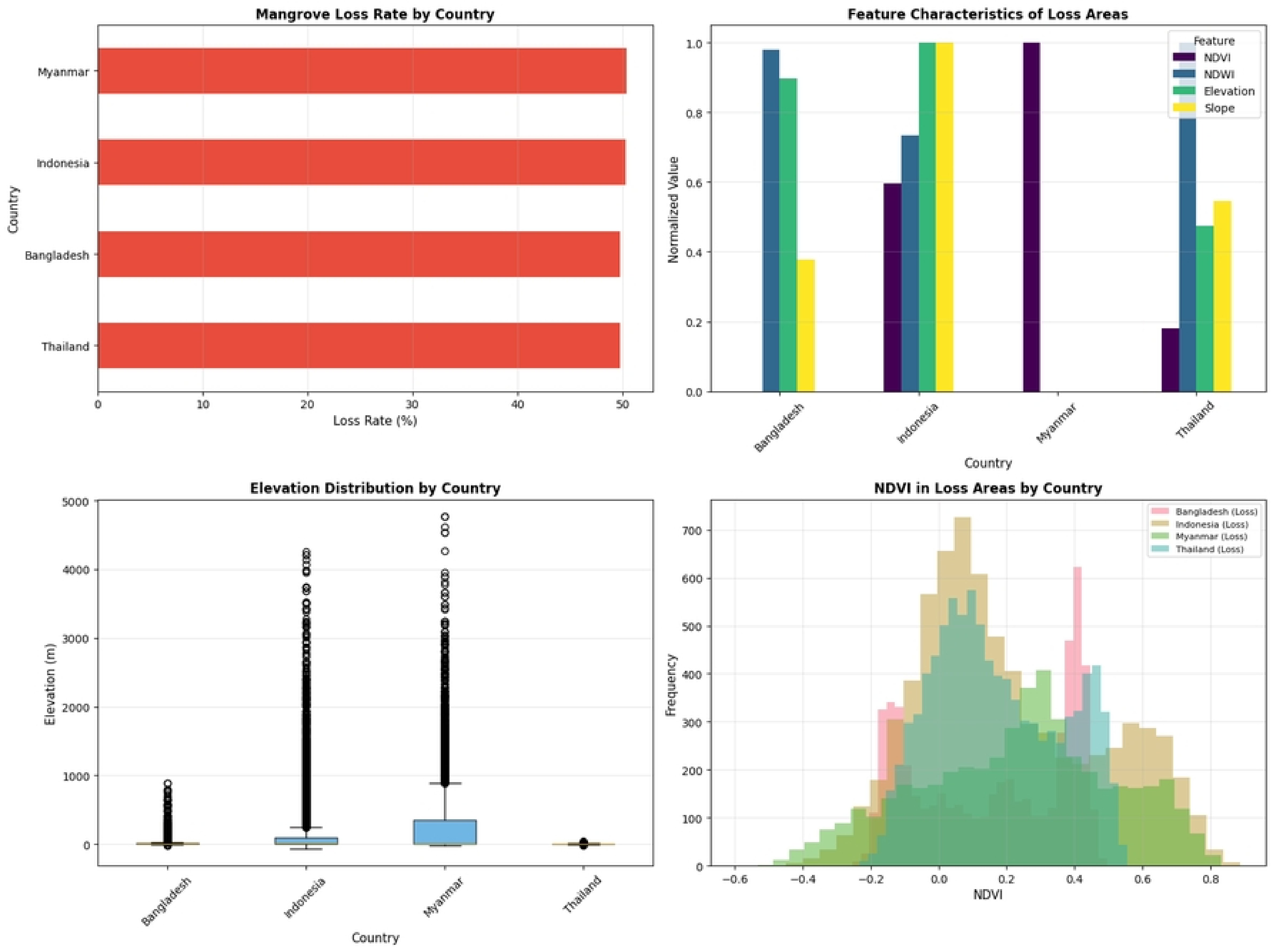

Log-Scaled Mangrove Forest Area in South and Southeast Asia (2020)
Bangladesh
Myanmar
Thailand
Indonesia
Log₁₀ Mangrove Area (km²)
4.2
4.0
3.8
3.6
3.4



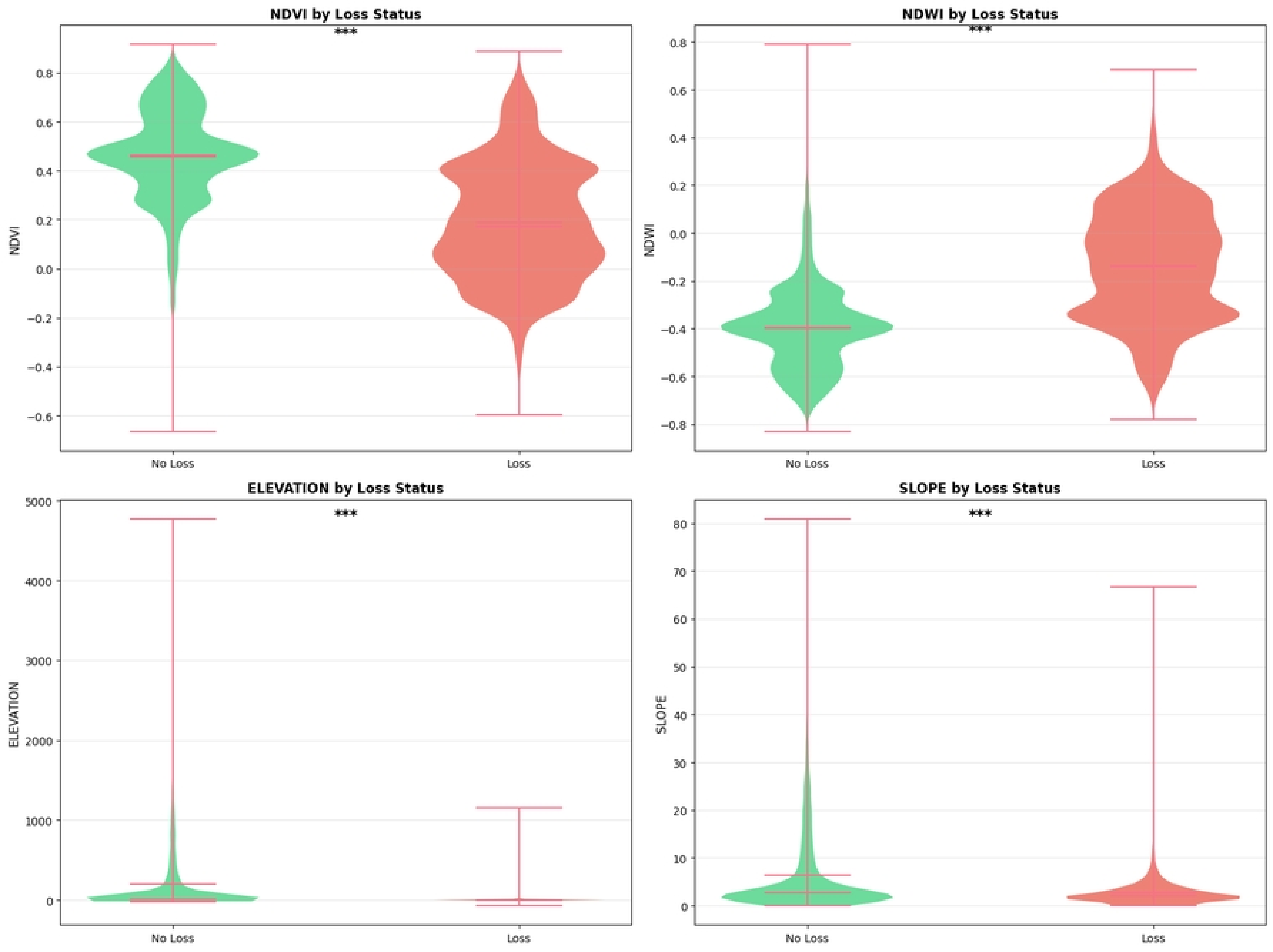
Feature Importance (Random Forest)
elevation
ndvi
ndwi
slope
Feature
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Importance Score



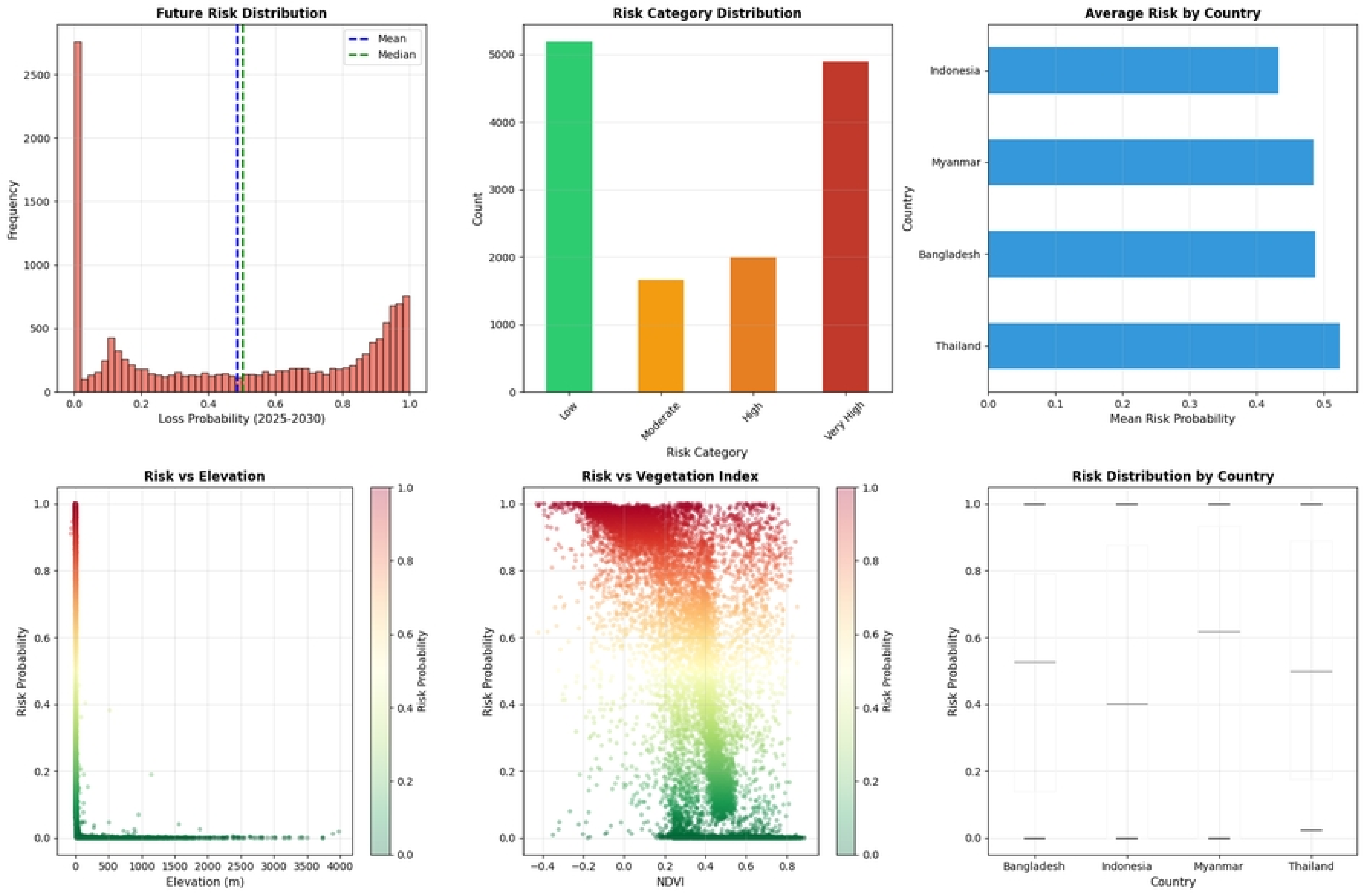
Mangrove Loss Rate Over Time
Loss Rate (%)
50.20
50.15
50.10
50.05
50.00
49.95
49.90
1996-2007
2007-2010
2010-2015
2015-2020
Time Interval
Loss vs No-Loss by Period
Loss
No Loss
Pixel Count
14000
12000
10000
8000
6000
4000
2000
0
1996-2007
2007-2010
2010-2015
2015-2020
Time Interval



Mangrove Loss Rate by Country
Myanmar
Indonesia
Bangladesh
Thailand
Country
0
10
20
30
40
50
Loss Rate (%)
Feature Characteristics of Loss Areas
Feature
NDVI
NDWI
Elevation
Slope
Normalized Value
0.0
0.2
0.4
0.6
0.8
1.0
Bangladesh
Indonesia
Myanmar
Thailand
Country
Elevation Distribution by Country
Elevation (m)
0
1000
2000
3000
4000
5000
Bangladesh
Indonesia
Myanmar
Thailand
Country
NDVI in Loss Areas by Country
Bangladesh (Loss)
Indonesia (Loss)
Myanmar (Loss)
Thailand (Loss)
Frequency
0
100
200
300
400
500
600
700
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
NDVI



NDVI by Loss Status
***
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
NDVI
No Loss
Loss
NDWI by Loss Status
***
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
NDWI
No Loss
Loss
ELEVATION by Loss Status
***
5000
4000
3000
2000
1000
0
ELEVATION
No Loss
Loss
SLOPE by Loss Status
***
80
70
60
50
40
30
20
10
0
SLOPE
No Loss
Loss


Future Risk Distribution
Mean
Median
Frequency
Loss Probability (2025-2030)
Risk Category Distribution
Count
Low
Moderate
High
Very High
Risk Category
Average Risk by Country
Indonesia
Myanmar
Bangladesh
Thailand
Country
Mean Risk Probability
Risk vs Elevation
Risk Probability
Elevation (m)
Risk vs Vegetation Index
NDVI
Risk Distribution by Country
Bangladesh
Indonesia
Myanmar
Thailand
Country