# Integrated Shoreline Dynamics Assessment Using QSCAT and Random Forest Along the Phetchaburi Coastline, Thailand

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## ABSTRACT

**The Phetchaburi coastline faces significant erosion risks, exacerbated by human activities and climate change. This research evaluates shoreline shifts and mangrove cover modifications along the 88.5 km coastline, utilizing the QGIS Shoreline Change Assessment Tool (QSCAT) plugin and Random Forest (RF) classification on Landsat 8-9 OLI/TIRS images from 2017 to 2023. The integration of these methods provides a robust framework for monitoring coastal changes in a data-scarce, microtidal environment. Results indicate a highly dynamic coastline with a maximum erosion distance of -108.71 m and a maximum accretion of +122.95 m. Statistical analysis of 1,766 transects reveals a critical erosion trend, with a maximum erosion rate reaching -38.66 m/year. Overall, 50.74% of the transects experienced erosion, while 48.98% showed accretion. The RF model demonstrated high effectiveness in land use classification, achieving an overall accuracy of 96.50% and a Kappa coefficient of 0.92. Spatiotemporal analysis reveals a strong link between mangrove degradation and increased erosion zones, emphasizing the protective function of vegetation. These findings provide essential quantitative benchmarks for developing targeted coastal management and restoration strategies in the Gulf of Thailand.**

***Keywords-coastal erosion; geoinformatics; mangrove restoration; QSCAT; random forest***

## I. INTRODUCTION

Global coastal zones are increasingly threatened by the combined effects of climate-driven sea-level rise and human activities, jeopardizing both ecological health and vital infrastructure [1, 2]. In Southeast Asia, the Upper Gulf of Thailand shows a unique case of morphodynamic vulnerability, caused by complex monsoonal wave patterns, rising sea levels, and coastal hazards [3-6]. This crisis is particularly evident in Phetchaburi, where empirical assessments have consistently identified severe erosion zones along the littoral boundary [7-9]. Specifically, shoreline segments adjacent to Mrigadayavan Palace and Puek Tian Beach have experienced significant regression. These morphological changes are mainly caused by the disruption of longshore sediment transport due to the proliferation of rigid coastal protection structures, such as breakwaters and seawalls, which often worsen downdrift erosion [10, 11]. The negative impact of detached breakwaters in Thailand has been specifically identified as a major factor contributing to localized erosion [12]. To address this monitoring challenge, Remote Sensing (RS) and Geographic Information Systems (GIS) have become essential alternatives to labor-intensive field surveys [13], offering comprehensive reviews of mangrove ecosystems [14] and shoreline detection methods [15]. For the quantitative assessment of shoreline dynamics, the QSCAT has recently been developed as a robust, open-source alternative [16, 17] to the traditional Digital Shoreline Analysis System (DSAS) [18], offering comparable statistical rigor [19]. Concurrently, machine learning algorithms have revolutionized biological assessment. The RF algorithm [20] has demonstrated superior accuracy over parametric classifiers in mapping coastal wetlands [21, 22].

Despite the availability of these advanced methodologies, significant gaps remain in their application to the Western Gulf of Thailand. While the stabilizing role of mangroves in reducing coastal erosion is well-documented on the muddy coasts of the region, there remains a lack of integrated frameworks that simultaneously analyze high-resolution shoreline kinematics and mangrove evolution specifically in Phetchaburi. Furthermore, existing literature frequently relies on historical extrapolation, which usually lacks the process-based understanding needed to grasp the rapid morphodynamic responses to recent, large-scale infrastructural projects.

This study fills these gaps by combining QSCAT with RF classification to examine coastal dynamics in Phetchaburi during the period of 2017–2023. This specific period was chosen to observe the immediate shoreline response to recent increases in coastal development. The primary objectives are to: (1) quantify spatiotemporal shoreline changes using statistical indicators; (2) map mangrove evolution with high precision; and (3) investigate the relationship between vegetative cover and erosion mitigation. The findings aim to establish a validated foundation for sustainable coastal management strategies, including ecosystem restoration and hazard zone delineation. To the best of our knowledge, this study is among the first to combine the QSCAT tool with an RF machine learning model specifically for the micro-tidal environment of the Phetchaburi coastline. Unlike previous studies that often use these methods separately, this hybrid approach uniquely combines detailed shoreline change data with high-precision land use classification. This enables a more thorough evaluation of the complex relationships between mangrove dynamics and shoreline stability.

## II. MATERIAL AND METHODOLOGY

This study employs an integrated geospatial framework to thoroughly assess the coastal dynamics of Phetchaburi Province, as shown in Figure 1, which depicts the sequential workflow from data collection to final analysis. The process begins with the Geoinformatics Data Processing phase, in which multi-temporal GIS datasets and satellite imagery are collected and harmonized to ensure spatial consistency across the study area, as shown in Figure 2. Subsequently, the workflow splits into two parallel analytical streams: a) the Shoreline Dynamics Modeling, which uses the QSCAT to mathematically measure erosion and accretion rates through standard statistical indicators such as Net Shoreline Movement (NSM), Shoreline Change Envelope (SCE), Linear Regression Rate (LRR), and b) the Remote Sensing-Based Mangrove Analysis, which simultaneously employs the RF machine learning algorithm to classify and map changes in mangrove forests. Finally, as shown at the framework's convergence point (Figure 1), these physical and biological outputs are combined to clarify the relationship between vegetative buffers and shoreline stability, providing a comprehensive basis for the coastal resilience planning described here.

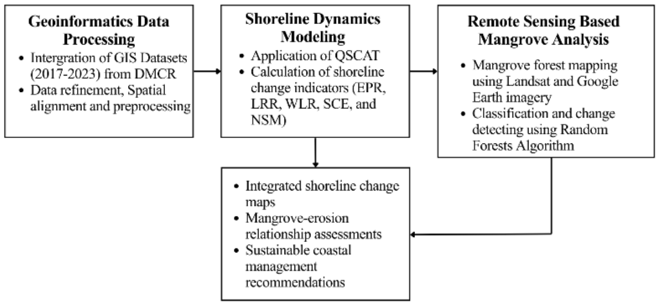


Fig. 1. The proposed framework for assessing shoreline dynamics and mangrove evolution.

### A. *Study Area*

The study area covers the entire littoral zone of Phetchaburi, extending approximately 90 kilometers along the western coast of the Upper Gulf of Thailand, as shown in Figure 2. Geographically, the coastline shows diverse morphological features: the northern districts (such as Ban Laem, Bang Khunsai, and Laem Phak Bia) are characterized by muddy tidal flats and extensive mangrove estuarine systems associated with the Phetchaburi River estuary, while the southern districts (including Chao Samran, Puek Tian, and Cha-am) mainly consist of sandy beaches that serve as key tourism destinations [9, 23]. Topographically, the coastal profile is characterized by low-lying terrains with a gentle gradient, making the region highly susceptible to hydrodynamic changes induced by seasonal monsoons, particularly the Northeast and Southwest monsoons, which influence sediment transport dynamics. This vulnerability is worsened by human-made modifications. As shown in the coastal classification map (Figure 2), the shoreline has been heavily modified by rigid protection structures. Notably, the construction of breakwaters and seawalls in areas such as Mrigadayavan Palace and Regent Cha-am Beach has disrupted the natural littoral drift, resulting in severe downdrift erosion [10, 28]. According to the Department of Marine and Coastal Resources (DMCR), the segment from Laem Phak Bia to Bang Khunsai is designated as a critical erosion hotspot, requiring urgent and precise monitoring [7, 24].

### B. *Data Acquisition and Pre-Processing*

Shoreline datasets spanning 2017 to 2023 were obtained from the Department of Marine and Coastal Resources (DMCR) [7, 24]. To ensure spatial consistency across multi-temporal datasets, all vector layers were standardized to the WGS 84 / UTM Zone 47N coordinate system. Additionally, geometric validation was performed by overlaying the shoreline vectors onto high-resolution Google Earth imagery to identify and correct any positional discrepancies, following the shoreline detection protocols outlined in [15]. For biological analysis, Landsat 8 OLI images were acquired for the study period. These datasets underwent rigorous pre-processing, including atmospheric and radiometric corrections, to reduce sensor errors and ensure spectral quality [14]. Furthermore, to minimize seasonal phenological variability, all images were selected from the dry season (December–April) and temporally normalized to maintain spectral consistency across the multi-temporal series, following protocols established for the Upper Gulf of Thailand [13].

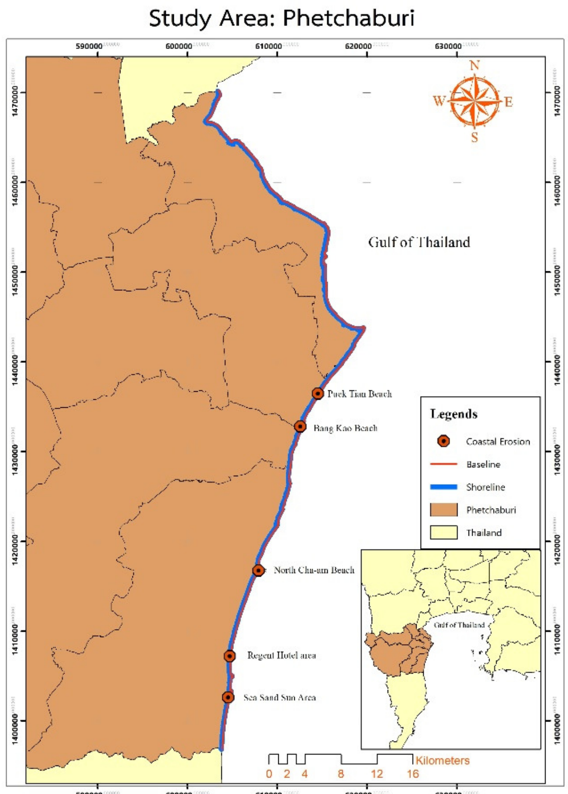


Fig. 2. Map of the study area along the Phetburi coastline.

## *C. QGIS Shoreline Change Analysis (QSCAT)*

Spatiotemporal shoreline changes were quantified using the QSCAT [16, 17]. This open-source algorithm operates on principles analogous to those of the traditional DSAS [18], generating transects perpendicular to the baseline to compute statistical metrics that describe coastal morphodynamics. The specific indicators calculated in this study are defined as follows:

Shoreline Change Envelope (SCE): SCE represents the maximum spatial variability of the shoreline at each transect, calculated as the distance between the most landward ($d_n$) and seaward ($d_f$) shoreline positions among all temporal samples [19]:

$$\text{SCE} = d_f - d_n \tag{1}$$

where $d_f$ = farthest year distance and $d_n$ = closet year distance.

Net Shoreline Movement (NSM): NSM quantifies the net distance between the earliest ($d_o$) and most recent ($d_i$) shoreline positions, indicating the total magnitude of accretion or erosion:

$$\text{NSM} = d_o - d_i \tag{2}$$

where $d_i$ = oldest year distance, $d_o$ = newest year distance.

End Point Rate (EPR): EPR calculates the annual rate of change (m/yr) based solely on the net movement over the elapsed time ($d_i - d_o$):

$$\text{EPR} = \frac{NSM}{d_i - d_o} \tag{3}$$

where: $d_i$ = newest year distance, $d_o$ = oldest year distance.

Linear Regression Rate (LRR): To capture long-term trends and minimize the influence of short-term outliers, LRR is determined by fitting a least-squares regression line to all shoreline intersection points:

$$\text{LRR} = \frac{\sum_{i=1}^{n}(\mathcal{X}_i - \bar{\mathcal{X}}) \times (\mathcal{Y}_i - \bar{\mathcal{Y}})}{\sum_{i=1}^{n}(\mathcal{X}_i - \bar{\mathcal{X}}) \times (\mathcal{X}_i - \bar{\mathcal{X}})} \tag{4}$$

where: $n$ = length of years and distances, $\bar{\mathcal{X}}$ = mean of the years, $\bar{\mathcal{Y}}$ = mean of distances, $\mathcal{X}_i$ = $i^{th}$ year, and $\mathcal{Y}_i$ = $i^{th}$ distance.

Weighted Linear Regression (WLR): To account for positional uncertainty in historical data, WLR assigns a weight to each data point based on its uncertainty error ($e$):

$$\text{weight} = \frac{1}{e^2} \tag{5}$$

where: $e$ = shoreline uncertainty value

$$\text{WLR} = \frac{\sum_{i=1}^{n}(\mathcal{X}_i - \bar{\mathcal{X}}_w) \times (\mathcal{Y}_i - \bar{\mathcal{Y}}_w) \times \text{weight}_i}{\sum_{i=1}^{n}(\mathcal{X}_i - \bar{\mathcal{X}}_w)^2 \times \text{weight}_i} \tag{6}$$

where: $n$ = length of years and distances, $\mathcal{X}_i$ = $i^{\text{th}}$ year, $\mathcal{Y}_i$ = $i^{\text{th}}$ distance, $\bar{\mathcal{X}}_w$ = weighted mean of years, $\bar{\mathcal{Y}}_w$ = weighted mean of distances, and weight = $i^{\text{th}}$ weight.

## *D. Machine Learning-Based Mangrove Classification*

Mangrove forest extent was mapped using the RF algorithm [20, 25]. RF was selected for its robustness in handling high-dimensional spectral data and its superior ability to model non-linear relationships compared to traditional maximum-likelihood classifiers [21, 22, 26]. The classifier was configured with 500 decision trees (ntree=500) to ensure convergence and stability, while the number of variables per split (mtry) was set to the square root of the total features, aligning with best practices in remote sensing [21, 27, 28]. The Gini impurity index was used as the splitting criterion [20]. To assess the model's performance, the reference dataset was randomly divided into a training set (70%) and a validation set (30%). This split allows for an independent evaluation of the classifier's accuracy using the held-out data. The classification process involved three separate stages:

- Feature Extraction: Spectral indices, specifically the Normalized Difference Vegetation Index (NDVI), were calculated to enhance the spectral separability of vegetation signals from water and urban features [29].

- Model Training: The classifier was trained using reference samples derived from Phetchaburi's specific mangrove species composition [30], ensuring local ecological relevance.
- Accuracy Assessment and Change Detection: To ensure the reliability of the biological maps, the classification accuracy was validated using a confusion matrix approach, a standard protocol for assessing remote sensing data quality [23, 31].

Finally, a post-classification comparison was conducted to measure the net change in mangrove area (m2) between the 2017 baseline and the 2023 monitoring period. The accuracy of the Random Forest classification was evaluated using a confusion matrix generated from stratified random sampling. We used high-resolution historical imagery from Google Earth as reference data to verify the land-use classification and confirm the reliability of the shoreline positions.

## III. RESULTS

This section presents a synthesized analysis of physical and biological monitoring campaigns. The findings are categorized into three thematic domains: (1) spatiotemporal shoreline kinematics quantified by QSCAT; (2) mangrove ecosystem evolution assessed via machine learning; and (3) the functional association between vegetative shielding and erosion mitigation.

### *A. Shoreline Change Analysis Verification*

To validate the reliability of QSCAT outputs, a linear regression analysis was performed between the SCE and the Weighted Standard Error (WSE). As illustrated in Figure 3, the analysis reveals a strong positive correlation with a coefficient of determination $R^2 = 0.95$.

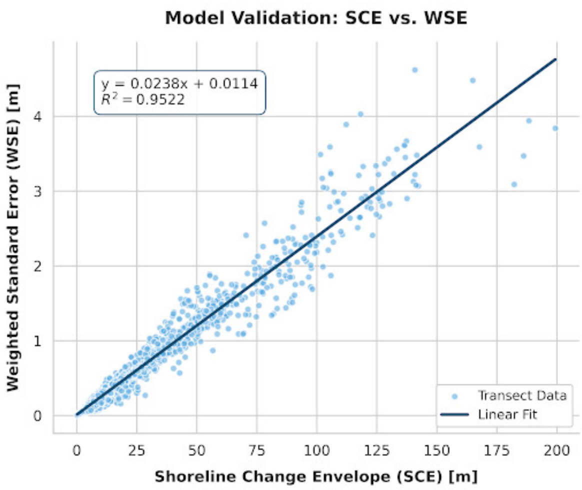


Fig. 3. Validation of shoreline change statistics: Linear regression analysis between the SCE and WSE. The strong positive correlation ($R^2 = 0.95$) indicates the high internal consistency and reliability of the calculated shoreline uncertainties derived from the QSCAT model.

This high value indicates that the calculated uncertainties are systematic and that the model has a high degree of internal consistency. Furthermore, validation against empirical datasets from the Department of Marine and Coastal Resources (DMCR) confirmed no statistically significant deviation from ground-truth surveys, reinforcing the robustness of the integrated findings [24].

### *B. Spatiotemporal Shoreline Dynamics*

The quantitative analysis using QSCAT reveals significant spatial variation in morphodynamic trends along the Phetchaburi coast. Table I summarizes the main statistical indicators for each district.

TABLE I. SUMMARY OF SHORELINE CHANGE STATISTICS DERIVED FROM QSCAT

| Location | NSM (m) | | EPR (m/yr) | | LRR (m/yr) | |
|---|---|---|---|---|---|---|
| | max | min | max | min | max | min |
| Puek Tian Beach | -108.71 | -34.57 | -18.12 | -5.76 | -13.64 | 0.01 |
| Cha-am Beach (Regent Hotel area) | -85.27 | -15.69 | -14.21 | -2.62 | -7.16 | -1.41 |
| Cha-am Beach (Sea Sand Sun Resort Area) | -25.51 | -15.32 | -4.25 | -2.55 | -5.76 | -0.34 |
| Bang Kao Beach | -40.65 | -5.83 | -6.78 | -0.97 | -5.92 | 0.22 |
| Northern Cha-am Beach | -57.15 | 4.88 | -9.52 | 0.81 | -3.74 | 2.06 |

As detailed in Table I, Puek Tian Beach emerged as the most critically degraded sector, exhibiting a maximum NSM of −108.71 m and an LRR of −13.64 m/yr. Similarly, the Cha-am Beach (Regent Hotel area) experienced significant erosion with an NSM of −85.27 m. In contrast, Northern Cha-am Beach displayed complex morphodynamics, with NSM values ranging from −57.15 m to +4.88 m, indicating a mix of erosional and accretional processes. To further characterize these changes, the shoreline was classified into erosion severity levels based on SCE and WLR. Table II presents the comparison of these metrics, highlighting that Puek Tian and Bang Kao Beaches fall under the "Severe Erosion" category.

TABLE II. COMPARISON OF SCE, WLR, AND EROSION SEVERITY CLASSIFICATION ALONG PHETBURI COASTLINE

| Location | SCE (m) | | WLR (m/yr) | | Erosion Severity |
|---|---|---|---|---|---|
| | max | min | max | min | |
| Puek Tian Beach | 125.95 | 55.91 | -13.64 | 0.01 | Severe erosion |
| Cha-am Beach (Regent Hotel area) | 107.16 | 17.59 | -7.16 | 1.41 | Moderate erosion |
| Cha-am Beach (Sea Sand Sun Area) | 42.45 | 24.11 | -5.76 | -0.34 | Moderate erosion |
| Bang Kao Beach | 59.86 | 18.95 | -5.92 | 0.22 | Severe erosion |
| Northern Cha-am Beach | 78.98 | 5.73 | -3.74 | 2.06 | Moderate erosion (with localized accretion) |

The spatial distribution of these changes is shown on the NSM map (Figure 4) and the EPR map (Figure 5), which identify specific erosion hotspots located near rigid coastal protection structures.

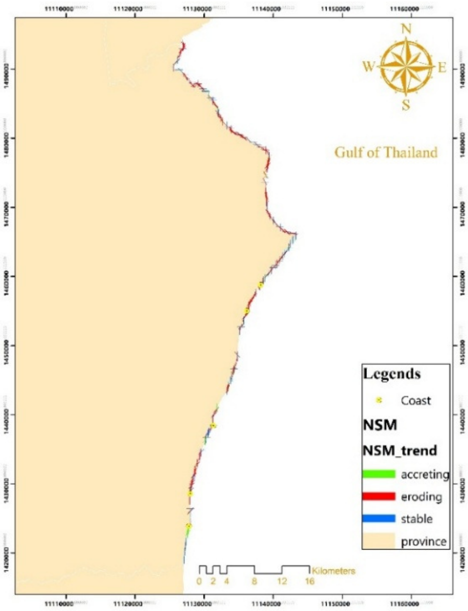


Fig. 4. Spatiotemporal visualization of NSM from 2017 to 2023.

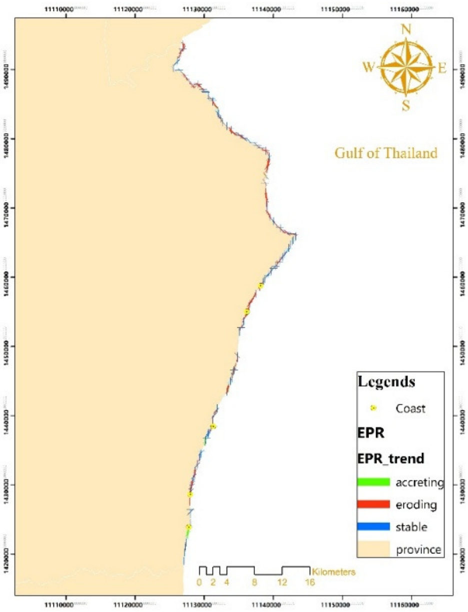


Fig. 5. Spatiotemporal.visualization of EPR from 2017 to 2023.

## C. *Mangrove Ecosystem Evolution*

The biological assessment employing the RF algorithm demonstrated high classification accuracy. The quantitative accuracy assessment yielded an Overall Accuracy (OA) of 96.50% with a Kappa coefficient of 0.92, as detailed in Table III. This high accuracy confirms the reliability of the machine learning classifier for coastal monitoring.

TABLE III. CONFUSION MATRIX AND ACCURACY ASSESSMENT.

| Class | Ground Truth: Mangrove | Ground Truth: Non-Mangrove | User's Accuracy |
|---|---|---|---|
| Mangrove | 58 | 3 | 95.08% |
| Non-Mangrove | 4 | 135 | 97.12% |
| Producer's Accuracy | 93.55% | 97.83% | Overall Accuracy = 96.50% |

Visual inspection of the classification results further confirms the model's performance. Figure 6 shows the spatial distribution of mangrove forests based on the RF classification for 2017, 2019, and 2023. The maps clearly mark the dense mangrove areas in the northern districts (e.g., Ban Laem) in contrast to the non-mangrove regions in the south. Based on this classification, the spatiotemporal development of mangrove coverage was examined. As summarized in Table IV, the total mangrove area grew from 4.98 km² in 2017 to 7.08 km² in 2023, showing a net increase of 42.11%. A significant acceleration in growth was observed between 2019 and 2023, with coverage increasing by 31.04%.

TABLE IV. MANGROVE FOREST AREA AND PERIODIC CHANGES (2017-2023).

| Year | Mangrove Area (m²) | Net Change (m².) | Percentage Change (%) |
|---|---|---|---|
| 2017 | 4,984,200 | - | - |
| 2019 | 5,405,400 | 421,200 | 8.45 |
| 2023 | 7,083,000 | 1,677,600 | 31.04 |

To quantify the impact of this mangrove expansion on coastal stability, a comparative analysis was conducted. Figure 7 illustrates the erosion rates (EPR) between mangrove-dominated zones (Transects 1–750) and non-mangrove zones (Transects >750). The analysis reveals that mangrove-covered areas exhibit significantly lower erosion rates than non-mangrove areas, empirically confirming the vegetation's protective capacity.

## D. *Spatiotemporal Dynamics and Drivers of Shoreline Change*

The results in Section 3.2 reveal distinct spatial differences in shoreline changes along the Phetchaburi coast. The severe erosion at Puek Tian Beach (NSM -108.71 m) and Regent Cha-am Beach (NSM -85.27 m) is consistent with the combined impacts of seasonal hydrodynamic forces and anthropogenic obstructions. During the Northeast Monsoon, high-energy waves generate strong southward longshore sediment transport. However, rigid coastal protection structures disrupt this balance. This finding aligns with [12], which noted that breakwater systems block littoral drift, causing sediment shortages in downdrift areas. Furthermore, the chronic erosion observed in these zones reflects the phenomenon of "coastal squeeze," where the shoreline is trapped between rising sea levels and fixed landward boundaries. This observation is consistent with [23], which described similar squeeze effects that limit the natural migration of coastal ecosystems in the Mekong Delta.

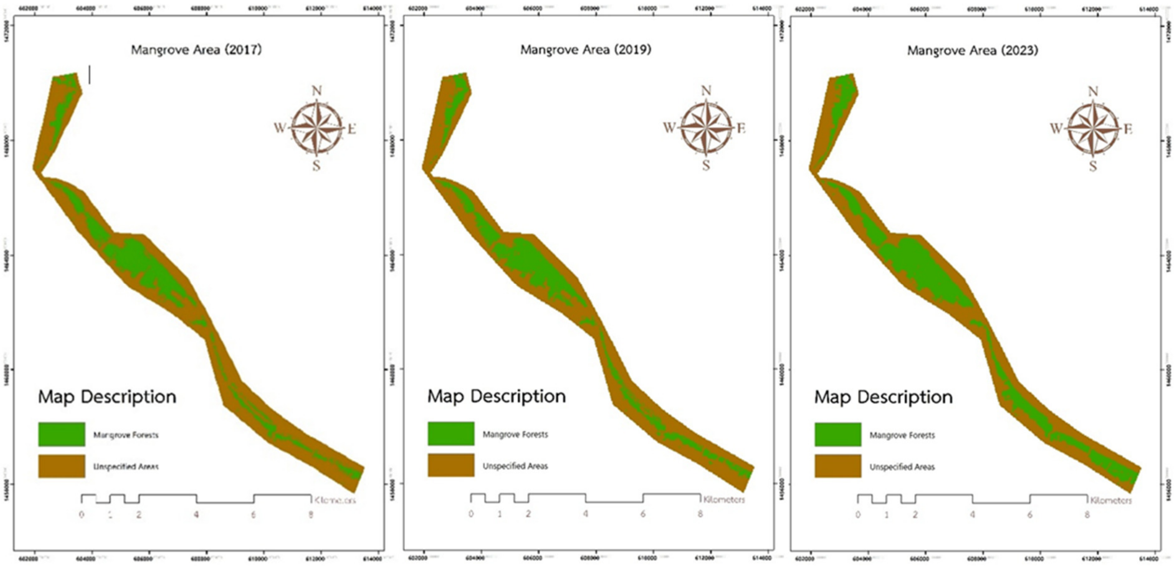


Fig. 6. Spatiotemporal evolution of the shoreline and land use along the Phetchaburi coastline observed in 2017, 2019, and 2023. The vertical comparison highlights the progressive changes in shoreline position and mangrove coverage over the study period.

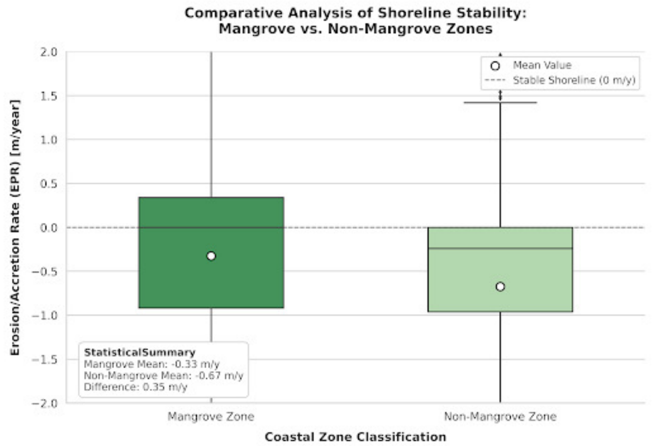


Fig. 7. Boxplot comparison of EPR between mangrove and non-mangrove zones, highlighting significantly lower erosion rates in mangrove-protected areas.

## IV. DISCUSSION

### *A. The Protective Role of Mangroves: Evidence from Integrated Analysis*

A key contribution of this study is the quantitative confirmation that mangrove ecosystems serve as effective bio-shields. The 42.11% increase in mangrove area (2017–2023) aligns with the stable shoreline segments in the northern districts. The comparative analysis presented in Figure 7 provides empirical evidence that mangrove-dominated zones experience significantly lower erosion rates than non-mangrove zones [32, 33]. These findings support the hypothesis that mangrove root systems effectively dissipate wave energy and increase bottom friction. This aligns with [34], which reported that healthy mangrove belts can reduce wave height by up to 20% over a distance of 100 meters. Additionally, the effective use of RF in this assessment reflects recent advancements in remote sensing, as demonstrated by [35], who successfully applied machine-learning indices for precise mangrove monitoring.

### *B. Efficacy of Nature-Based Solutions vs. Hard Structures*

The contrast between the stabilized mangrove zones and the eroding, structure-dominated coastline of Cha-am offers crucial insights for coastal management. While hard engineering structures provide immediate shoreline stability, they often shift erosion problems to nearby areas. In contrast, mangrove ecosystems demonstrate a sustainable capacity to reduce erosion without causing downstream impacts. This study, therefore, promotes an Ecosystem-based Adaptation (EbA) strategy that focuses on mangrove restoration rather than relying on rigid concrete structures in muddy tidal zones.

### *C. Model Reliability and Methodological Implications*

The reliability of these findings is underpinned by the rigorous validation of the analytical tools. The strong correlation ($R^2$= 0.95) between the SCE and WLR observed in Figure 3 confirms that the QSCAT-derived statistics are internally consistent. Furthermore, the high classification accuracy (96.50%) of the RF algorithm demonstrates the potential of machine learning to improve traditional coastal monitoring methods. While RF proved effective in this study, recent comparisons suggest that deep learning architectures, such as Convolutional Neural Networks (CNNs), also achieve strong performance in complex land-use classification [36]. Future research could investigate these advanced algorithms to compare with the RF approach used here.

## V. CONCLUSION

This study effectively combined the QGIS Shoreline Change Analysis Tool (QSCAT) with the Random Forest (RF) machine learning algorithm to evaluate the spatiotemporal changes of the Phetchaburi coastline from 2017 to 2023. The analysis uncovered a significant divide in coastal development stemming from interactions between human-made structures and natural biological barriers. The assessment identified severe erosion hotspots in the southern districts, especially at Puek Tian Beach and Bang Kao Beach [37]. Quantitative analysis showed critical shoreline erosion (NSM <−100 m) caused by the disruption of sediment transport due to rigid coastal engineering structures, such as vertical seawalls and breakwaters. This confirms the negative "downdrift erosion" effect of hard infrastructure, aligning with observations by [12]. In contrast, the northern sector (Ban Laem District) showed significant accretion, stabilized by mangrove ecosystems. The RF classifier proved highly effective for biological monitoring, achieving an Overall Accuracy (OA) of 96.50% and a Kappa coefficient of 0.92, demonstrating its superiority over traditional classification methods [36, 38]. The results indicate that mangrove coverage increased by 42.11% during the study period, mainly due to natural regeneration and conservation efforts. A pivotal finding of this research is the quantitative establishment of a clear pattern-based association between vegetative cover and erosion intensity. The comparative analysis confirmed that mangrove-dominated zones experienced significantly greater shoreline stability compared to non-mangrove zones. The reliability of this conclusion is supported by the statistical validation of the QSCAT model, which yielded a high coefficient of determination ($R^2$ = 0.95) between shoreline variability (Shoreline Change Envelope - SCE) and associated uncertainty, thereby validating the consistency of the outputs against empirical ground-truth data [24].

Based on these findings, this study recommends a paradigm shift from rigid structural interventions to ecosystem-based adaptation (EbA) strategies [39, 40, 41]. Specifically, it proposes a site-specific zoning approach: maintaining a mangrove buffer width of at least 100–150 meters in muddy tidal zones to enhance wave attenuation [42, 43]. Conversely, for severely eroded sandy beaches like Puek Tian, a hybrid engineering approach (such as permeable bamboo fencing) is recommended to promote sediment trapping and natural recolonization. Finally, the QSCAT-RF framework should be adopted as a standard protocol for ongoing coastal monitoring to identify early signs of 'coastal squeeze' [44].

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