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Increasing Area of Banlaem Mangrove Forest at Nakhon Si Thammarat in Southern Thailand: Land Cover Changes and Predictive Models

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ABSTRACT

Land cover changes significantly affect mangrove forests, driven by both anthropogenic activities and natural processes. The Banlaem mangrove in Nakhon Si Thammarat, Thailand, supports numerous mangrove plantation projects but lacks comprehensive assessments and monitoring related to land cover changes. This study aimed to (1) investigate land cover changes in the Banlaem mangrove from 1995 to 2023, and (2) generate a predictive model for future land cover changes. For land cover assessment, satellite imagery from multiple sources, including Sentinel-2 (Level 2A) and Landsat (Collection 2 Level 2), was utilized to examine and classify changes in mangrove cover within the Banlaem mangrove forest from 1995 to 2023, using supervised classification with the maximum likelihood algorithm. Various regression models were analysed to develop a predictive model based on area size and time. The mangrove area in the Banlaem mangrove forest steadily grew throughout the study period, with the total area increasing from 56.16 ha in 1995 to 527.55 ha in 2023. This study represents the first analysis of changes in the Banlaem mangrove cover. Throughout the tested models, they reveal an unclear pattern of mangrove expansion, yet they indicate a high rate of expansion in the Banlaem mangrove forest. In addition, these results are expected to encourage greater community involvement in the monitoring and management of the Banlaem mangrove. We recommend establishing a community monitoring network to engage local residents in tracking changes in mangrove cover, supported by training and resources.

Keywords: Land Cover; Landsat; Mangrove; Sentinel; Thailand

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1. Introduction

The study of mangrove ecosystems is essential because of their diverse range of services. Mangrove ecosystems are vital coastal environments that provide a broad range of ecological and socio-economic services [1]. Mangrove forests offer habitat for local wildlife, supplying food and other resources, and offering protection against natural disasters [2]. On a larger scale, mangrove forests also regulate carbon and nutrient cycles while providing cultural ecosystem services [3]. Mangrove forests are among the highest carbon density within tropical ecosystems [4]. Anthropogenic activities, including agricultural expansion, aquaculture, tourism, urban development, and overexploitation, are driving mangrove destruction, and if current loss rates persist, 30–40% of coastal wetlands and the full functionality of mangrove forests could be lost within the next century [5]. In Thailand, the mangrove area has exhibited considerable fluctuations from 2016 to 2022, beginning at 245,500 ha in 2016. The country experienced an almost 10% increase in mangrove coverage within the first year, followed by a subsequent decline of approximately 7% over the following three years. However, between 2020 and 2022, there was a resurgence, with a 9% expansion in mangrove area, ultimately reaching 271,600 ha [6]. The study of mangrove area changes, across scales ranging from local to global, would provide critical data that can assist land managers and communities in the effective management of coastal resources, especially within blue ecosystems, which mangroves serve as significant carbon sinks and provide various ecosystem services.

Currently, Geographic Information Systems (GIS) and remote sensing technologies are crucial for the assessment of mangrove cover changes. Recent advancements in the availability of remote sensing data, image-processing techniques, computing and information technology, and the development of human resources have facilitated the regular observation and monitoring of mangroves across local to global scales [5]. Advances in remote sensing have greatly enhanced Land Use and Land Cover (LULC) mapping for mangrove ecosystems [7]. A variety of tools were employed to map the LULC changes in mangrove forests, including the use of Sentinel-2 satellite imagery [6, 8–11], which provides open access and high spatial resolution (10 m). The generated map offers critical insights into the spatial distribution of land cover types within the mangrove ecosystem, thereby supporting evidence-based decision-making for conservation and sustainable management initiatives [8].

To classify land cover changes in a forest ecosystem, classification algorithms play a crucial role in the classification process. Various algorithms have been applied in forest ecosystem classification, including Maximum Likelihood, K-Means, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) [12, 13]. For mangrove ecosystem classification, Maximum Likelihood has been one of the most commonly used methods in previous studies [13–15]. To integrate with supervised classification, Maximum Likelihood classification is widely recognized as a well-known algorithm used in supervised classification as a parametric classifier [16]. Supervised classification enhances classification performance by incorporating additional knowledge from training data, improving the reliability of the final classifier [17]. Therefore, utilizing supervised classification with an appropriate algorithm is crucial for ensuring high-quality classification in a mangrove ecosystem. The selected algorithm directly impacts on the accuracy and reliability of the classification results, highlighting its importance in analyzing and understanding each ecological environment.

This study focuses on the mangrove forest within the Banlaem community, located in Tha Sala, Nakhon Si Thammarat, Southern Thailand. Between 1984 and 1994, the area underwent significant transformation, changing from a sandy beach into a muddy soil wetland [18]. This shift in the landscape laid the foundation for the introduction of various mangrove planting initiatives. Since then, multiple planting efforts, particularly those related to ecotourism, have been implemented in the area. These initiatives involved the introduction of loop-root mangroves (*Rhizophora mucronata*), which played a key role in stimulating the rapid development of the mangrove ecosystem [18]. In the community, most of the villagers are Muslims, and their main occupation is local fisheries [19]. The community participates in several economic activities, such as the mud spa, curry paste production, creating naturally dyed fabric from mangrove leaves, mangrove planting, and other related products [19]. However, there has been a lack of comprehensive monitoring and impact assessments since the initial planting of mangroves in the area [18], making it difficult to fully understand the ecological and environmental changes over time.

Comprehensive assessments play a crucial role in understanding ecological changes at both local and broader scales. A study conducted in Thailand examined the historical changes in Thai mangrove forest cover, along with the biodiversity of plant and animal species [20]. It also analyzed long-term study data, mangrove biomass and carbon storage, as well as various aspects of mangrove conservation and management [20]. Additionally, in Tong Tasae and Laem Makham Villages, located in Trang, Southern Thailand, it showed that the success of community-managed mangrove forests relies on multiple factors, with effective monitoring being one of the key elements [21]. This study focused on mangrove cover. One of the challenges in the monitoring activities, in the Banlaem community, is the lack of specific records on planting data. The monitoring of the Banlaem land cover change would provide valuable insights into ecosystem dynamics, supporting sustainable management and conservation efforts.

To address existing knowledge gaps in this mangrove area, this study aimed to (1) examine land cover changes in the Banlaem mangrove forest from 1995 to 2023 and (2) develop a predictive model to forecast future land cover changes. The Maximum Likelihood algorithm was utilized for supervised classification to analyze mangrove changes in the Banlaem community, while regression analysis was employed for predictive model generation. Understanding these changes is essential for effective environmental management and conservation planning in coastal ecosystems. This study provided a comprehensive approach to monitoring and managing mangrove ecosystems. The findings of this research offer valuable insights into the ongoing changes in the Banlaem mangrove forest. The results highlight critical patterns of mangrove expansion and loss, which are essential for informing conservation efforts. This study contributes significant information that can support the sustainable management of the Banlaem mangrove forest, helping policymakers, researchers, and local communities implement effective conservation strategies. Furthermore, the new data on mangrove cover changes, combined with predictive modeling, serve as essential resources for community-based environmental initiatives.

2. Materials and Methods

2.1. Workflow

This study employed multiple satellite images, including Sentinel-2 (Level 2A) and Landsat (Collection 2 Level 2), to analyze and classify changes in mangrove coverage within the Banlaem mangrove forest over the long term (1995–2023). To ensure the reliability of the classification, the accuracy of the generated thematic map was evaluated using accuracy assessment metrics, which are widely used methods for assessing classification performance. This approach ensured that the thematic map accurately represented the distribution and extent of mangrove forests during the study period. A quantitative analysis was performed using Geographic Information System (GIS) software to measure the extent of mangrove cover, track changes in size, and calculate the percentage of area lost or gained over time. To predict future trends in mangrove coverage, regression-based predictive models were developed to estimate annual changes in mangrove area. These models were developed using historical data on annual mangrove coverage and statistical analysis to identify patterns and relationships across different years that influence mangrove growth or degradation in the Banlaem mangrove forest. Both the coefficient of determination (R^2) and Root Mean Square Error ($RMSE$) were calculated and applied using k-Fold cross-validation to assess model performance and ensure robustness. Additionally, a one-way ANOVA was conducted to analyze potential differences in average values of both metrics among the tested regression models. **Figure 1** provides an overview of the workflow employed in this study, illustrating the sequential steps undertaken from data acquisition and classification to accuracy assessment, quantitative analysis, model development, and validation.

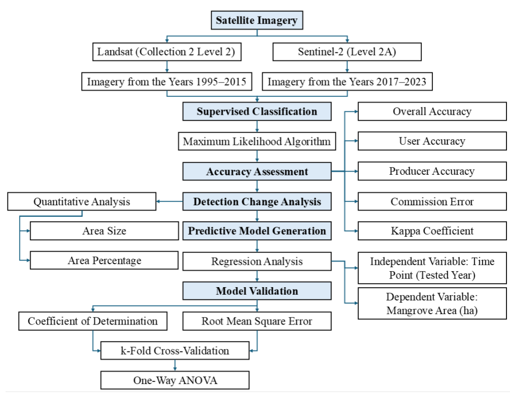

Figure 1. Workflow in this study.

2.2. Study Area

The study area was located in the Banlaem mangrove forest (8°36′32.7″ N, 99°57′59.0″ E), within the Banlaem community in Tha Sala, Nakhon Si Thammarat, Thailand (**Figure 2**). According to the Climate Center, Meteorological Department of Thailand [22], Nakhon Si Thammarat is a province located on the eastern coast of southern Thailand. Due to its geographical location adjacent to the sea, Nakhon Si Thammarat Province experiences minimal temperature variation between seasons and between day and night. The average temperature remains moderate, and extreme heat is uncommon. During the winter season, occasionally cool weather may occur. The mean annual temperature is approximately 27.3 °C, with an average maximum temperature of 32.5 °C and an average minimum temperature of 23.2 °C. In the eastern coastal lowland region, which includes the Ban Laem mangrove forest, heavy rainfall is prevalent throughout the northeasterly winds, with an average annual precipitation of approximately 2,701.1 mm. A mask highlighting the study area, covering 895.73 ha, was created through manual digitization and included mangrove areas, the seashore, and nearby sea bodies. Mangroves in this region have been planted through various ecotourism-related initiatives led by the community. The dominant mangrove species in this area are from the *Rhizophora* and *Avicennia* genera. In some sections of the forest, channels have been created by humans to allow boats to navigate to the open sea.

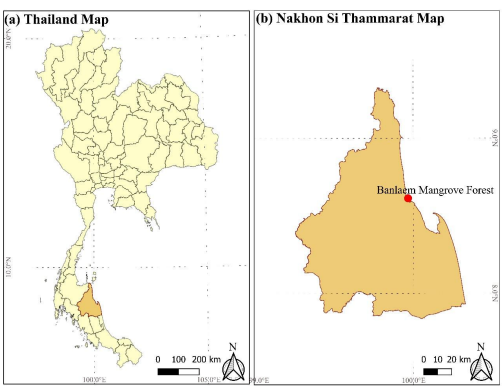

Figure 2. Study area (the map produced using QGIS): (**a**) Thailand map; (**b**) the Banlaem mangrove forest, Nakhon Si Thammarat, Southern Thailand.

2.3. Data Set

This study employed satellite imagery from the open-access Sentinel-2 and Landsat programs, which provide multi-spectral data suitable for environmental monitoring and long-term analysis of changes in the Banlaem mangrove forests (**Table 1**). The Sentinel-2 imagery used in this study features the Multi-Spectral Imager (MSI) at Level 2A, whereas Landsat imagery includes Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI), all parts of Collection 2 at Level 2 (atmospherically corrected surface reflectance). These imagery levels offer atmospherically corrected surface reflectance values, making them ideal for analyzing the surface characteristics of the mangrove forest. Sentinel-2 imagery was sourced from the European Space Agency's (ESA) Sentinel Scientific Data Hub [23], whereas Landsat imagery was obtained from the United States Geological Survey (USGS) [24]. Imagery from the years 1995, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019, 2021, and 2023 was selected for analysis, with a primary focus on minimizing cloud cover over the study area—the Banlaem mangrove forest. For Sentinel-2 imagery, the selection of either Sentinel-2A or Sentinel-2B in each year was determined based on image availability and minimal cloud cover over the study area during the specified period. This decision was crucial for ensuring the acquisition of high-quality, cloud-free images, which are essential for accurate classification and analysis of mangrove area dynamics. The selected years provide a range of temporal conditions, allowing for a meaningful analysis of long-term trends. While this study aimed to primarily use high-resolution, open-access Sentinel-2 imagery, it could not cover all changes in the Banlaem mangrove forest. Therefore, Landsat satellite imagery from 1995 to 2015 was used to fill these gaps, ensuring the robustness of the land cover change analysis. To accurately delineate the extent of the mangrove forest, a mask was created by manually digitizing the 2023 Sentinel-2 imagery, ensuring a precise boundary for the mangrove area. This mask was then applied to the pre-processed Sentinel-2 images across the selected years, allowing for consistent identification of mangrove zones in each dataset. Furthermore, the images were clipped to retain only the areas likely to contain mangroves, ensuring that the classification process would focus solely on the relevant regions for further analysis [25].

2.4. Image Classification

This study utilized supervised classification to identify the primary land cover types within the Banlaem mangrove forest, Nakhon Si Thammarat, Thailand. Supervised classifi-

Table 1. Satellite data utilized in this study.

No.	Image Codes	Date	Resolution (m)	Remarks
1	LT05_L2SP_129054_19950622_20200913_02_T1_SR	22/06/1995	30	Landsat-5
2	LT05_L2SP_129054_19971001_20200909_02_T1_SR	01/10/1997	30	Landsat-5
3	LT05_L2SP_129054_19990209_20200908_02_T1_SR	09/02/1999	30	Landsat-5
4	LE07_L2SP_129054_20010222_20200917_02_T1_SR	22/02/2001	30	Landsat-7
5	LE07_L2SP_129054_20030401_20200915_02_T1_SR	01/04/2003	30	Landsat-7
6	LT05_L2SP_129054_20050225_20200902_02_T1_SR	25/02/2005	30	Landsat-5
7	LT05_L2SP_129054_20070522_20200830_02_T1_SR	22/05/2007	30	Landsat-5
8	LT05_L2SP_129054_20090308_20200828_02_T1_SR	08/03/2009	30	Landsat-5
9	LT05_L2SP_129054_20111109_20200820_02_T1_SR	09/11/2011	30	Landsat-5
10	LC08_L2SP_129054_20130420_20200912_02_T1_SR	20/04/2013	30	Landsat-8
11	LC08_L2SP_129054_20150528_20200909_02_T1_SR	28/05/2015	30	Landsat-8
12	S2B_MSIL2A_20171118T034019_N0500_R061_T47PNK	18/11/2017	10	Sentinel-2B
13	S2B_MSIL2A_20190323T033719_N0500_R061_T47PPK	23/03/2019	10	Sentinel-2B
14	S2B_MSIL2A_20211227T034139_N0301_R061_T47PPK	27/12/2021	10	Sentinel-2B
15	S2B_MSIL2A_20230312T033539_N0509_R061_T47PPK	12/03/2023	10	Sentinel-2B

cation is a widely used remote sensing technique in which pixels with known classes serve as training data to classify unknown pixels based on spectral similarity [26]. This approach ensures accurate land cover classification by relying on well-defined reference samples. The Maximum Likelihood algorithm, a probabilistic method for supervised classification, was applied to satellite imagery from 1995 to 2023. This algorithm assigns each pixel to the class it most likely belongs to, considering the mean and variance of spectral signatures for different land cover types [26]. The classification process distinguished three primary land cover types from 1995 to 2021: mangrove forest, mudflat, and water body. For 2023, four primary land cover types were identified to analyse different mangrove types: vegetation type 1 (*Avicennia marina*), vegetation type 2 (a coexistence of *A. marina* and *Rhizophora* spp.), mudflat, and water body. For 2023, ground truth data was available, allowing the distinction of mangroves into two classes and facilitating comprehensive monitoring of mangrove changes in the area. To implement this classification, the Semi-Automatic Classification Plugin (SCP) version 8.3.0-infinity [27] was used within QGIS (version 3.34.1-Prizren). SCP facilitated the creation of thematic maps, training samples, and signature lists for the mangrove area. Training samples were selected as polygons representing distinct land cover types to derive accurate spectral signatures. A colour composite (near-infrared, red, and green bands) was used to facilitate the selection of training samples in all the selected satellite imagery. Mangroves stood out clearly (turning red) from other land cover types, making them easier to differentiate. Mudflats appeared brown, while water bodies ranged from blue to dark blue. For the 2023 colour composite, each mangrove type was distinguished by: vegetation type 1 appeared dark red, while vegetation type 2 appeared bright red. The resulting thematic maps provided a clear visualization of land cover changes over time, offering valuable insights into the dynamics of the Banlaem mangrove forest.

2.5. Accuracy Assessment

During post-classification, spectral classes were visually compared with reference data from multiple sources, including historical images, ground-truth inventory data, and unmanned aerial vehicle (UAV) imagery. For the years 1995–2021, reference points were verified using Google Earth historical images [13]. The assessment included 50 random points per class [28], totaling 150 points per image year. In 2023, the reference data included ground-truth inventory data and UAV imagery. The inventory data were used to verify mangrove types, whereas, UAV imagery (DJI Mavic 2 Enterprise Advanced), covering the sea front (water bodies and mudflats), was used to verify water bodies and mudflats (50 random points per class). Besides, the inventory data, collected between April 2023 and July 2024, included 48 sampling plots—12 plots on mudflats; thus, 36 plots were used for mangrove type assessment. Each plot covered approximately 153.4 m², corresponding to a circular plot with a 7 m radius. The accuracy assessment evaluated overall accuracy (OA), user accuracy (UA), producer accuracy (PA), and commission error (CE), providing a comprehensive measure of classification reliability. Additionally, Kappa analysis was conducted to quantify the agreement between classified and reference data, ensuring robust validation of the classification results. An error matrix was generated to present the accuracy assessment outcomes, offering valuable insights into the classification performance and highlighting potential misclassifications in the study area.

The mentioned metrics were calculated using the following formulas[28–30]:

$$PA_i = \text{True positives for class i/Total actual instances of class i} \quad (1)$$

Where PA (sensitivity) reflects the likelihood that a specific category in the reference data is accurately recognized in the classification output.

$$UA_i = \text{True positives for class i/Total predicted instances of class i} \quad (2)$$

Where UA reflects the likelihood that a predicted class label belongs to that class in reality.

$$CE_i = \text{False positives for class i/(False positives for class i + True positives for class i)} \quad (3)$$

Where CE or False Discovery Rate (FDR) reflects the unreliability of predicted positive classifications.

$$OA = \text{True positives for class i/Total number of predictions} \quad (4)$$

Where OA reflects the proportion of correctly classified instances across all classes relative to the total number of predictions.

$$\text{Kappa coefficient} = (n_{11} + n_{22} + \ldots + n_{kk}) - [(n_1 + n_{+1}) + (n_2 + n_{+2}) + \ldots + (n_k + n_{+k})]/N2 - [(n_1 + n_{+1}) + (n_2 + n_{+2}) + \ldots + (n_k + n_{+k})] \quad (5)$$

Where Kappa coefficient reflects agreement between classified data and reference data.

$i = 1,2,3, \ldots$

N is the total number of observations.

n_{ii} is the number of correctly classified observations for class i.

n_{i+} is the total number of observations in the reference data for class i.

n_{+i} is the total number of observations classified as class i.

k is the number of classes.

2.6. Detection Change Analysis

A quantitative analysis was performed to detect changes in mangrove cover from 1995 to 2023. The objective was to evaluate spatial variations in mangrove extent over time by conducting pixel-by-pixel comparisons, a straightforward yet effective method for detecting land cover changes[26, 31]. This approach enabled the identification of specific areas where mangrove forests had either expanded or shrunk, providing a clear understanding of the temporal dynamics of the mangrove ecosystem. The analysis was conducted using the Classification Report function within the Semi-Automatic Classification Plugin (SCP) in QGIS software, a tool that is beneficial in remote sensing for classifying land cover and generating detailed reports on classification. In addition to detecting spatial changes, the study also quantified the size of the mangrove area and calculated the percentage changes in mangrove extent over the tested years. These metrics provided a more comprehensive understanding of the magnitude of change in mangrove coverage, allowing for an assessment of the changes of the mangrove forest that had grown or diminished during the study period. By analyzing both area size and percentage changes, this analysis offered valuable insights into the long-term trends of mangrove dynamics, helping to inform conservation strategies and environmental management decisions in the Banlaem community.

2.7. Model Generation and Validation

This study employed various regression models to evaluate the predictive capability of forecasting future land cover changes in the Banlaem mangrove forest. This study applied multiple regression techniques, including linear, exponential, logarithmic, polynomial (order = 2, parabolic curve), and power models, to identify the best-fitting trend for mangrove area changes over time. These models were selected based on their common usage and ability to capture different patterns of change in ecological and environmental studies. The independent variable in the analysis was time, represented by the years 1995, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019, 2021, and 2023, while the dependent variable was the corresponding mangrove area for each year. By analysing historical data, the models aimed to estimate future trends in mangrove cover, supporting sustainable forest management efforts. Data processing and model fitting were conducted using Python in Google Colab, utilizing the NumPy, SciPy, Pandas, and Matplotlib libraries for statistical analysis and visualization [32–35].

In addition, cross-validation was performed to evaluate and compare the models. To validate the accuracy and reliability of these predictive models, the R^2 was used as a statistical measure of goodness-of-fit. Higher R^2 values indicated a stronger correlation between observed and predicted mangrove area, ensuring robust forecasting results. The R^2 value ranges from 0 to 1, with higher values indicating a better model fit [36]. In addition, the *RMSE* was applied to quantify the discrepancy between the model's predicted values and the actual observed values. The lower *RMSE,* the better the model's performance. Subsequently, the k-Fold cross-validation technique (with K = 5) was utilized to evaluate the model's effectiveness by randomly dividing the dataset into different subsets. These analyses were conducted using Python in Google Colab, utilizing scikit-learn, an open-source machine learning library [37]. The average R^2 and *RMSE*, along with their standard deviation, were performed. These performance metrics were analyzed using one-way ANOVA (Fisher's test) with the SciPy library [33] to evaluate potential differences among the tested regression models. Due to the limited availability of environmental data in the Banlaem mangrove forests, these analyses help enhance the model's effectiveness evaluation with a restricted set of environmental variables.

3. Results and Discussion

3.1. Mangrove Cover Analysis

This study evaluates the accuracy of land cover classification in the Banlaem mangrove forest using multi-temporal satellite imagery. The supervised classification of Landsat-5, Landsat-7, Landsat-8, and Sentinel-2 imagery identified three land cover types in the Banlaem mangrove forest over the study period (1995–2021): (1) mangrove forest, (2) mudflat, and (3) water body. In 2023, four land cover types were identified: (1) vegetation type 1 (*Avicennia marina*), (2) vegetation type 2 (coexistence of *Rhizophora* spp. and *A. marina*), (3) mudflat, and (4) water body. For the period 1995–2021, the classification of mangrove forest achieved PA, UA, and CE of 88–100%, 83.02–100%, and 0.00–18.33%, respectively. For mudflat, the PA, UA, and CE ranged from 58.00–96.00%, 66.67–97.62%, and 2.38–33.33%, respectively. For water body, the PA, UA, and CE ranged from 56.00–98.00%, 71.01–100%, and 0.00–28.99%, respectively. Overall, the classification achieved an overall accuracy of 82.67–94.59%, with a Kappa coefficient ranging from 0.82–0.95 (**Table 2**). In general, the Kappa coefficient value indicates a strong agreement (ranging from 0.80 to 0.90) to an almost perfect agreement (above 0.90) in the accuracy of the thematic maps [38]. For the year 2023, the classification of vegetation type 1 achieved a PA, UA, and CE of 64.71%, 64.71%, and 35.29%, respectively. Vegetation type 2 achieved a PA, UA, and CE of 68.42%, 68.42%, and 31.58%, respectively. The mudflat achieved a PA, UA, and CE of 100%, 98.94%, and 1.96%, respectively. The water body achieved a PA, UA, and CE of 98.00%, 100.00%, and 0.00%, respectively. Overall, for the year 2023, the classification achieved an overall accuracy of 90.44%, with a Kappa coefficient of 0.90 (**Table 3**). Its Kappa coefficient indicates a strong agreement in the accuracy of the thematic map. Overall, these Kappa coefficients (1995–2023) indicate that the classification accuracy was sufficient for analysing long-term changes at the study site.

The high accuracy in mangrove area classification enhances the reliability of the mangrove area expansion assessment in this study (**Table 2**). For the classification of the mangrove forest area, the PA or sensitivity, which measures a classification model's ability to correctly identify actual positive cases, ranged from 88% to 100% between 1995 and 2021, except for 2023. In 2023, the mangroves were classified into two vegetation types: vegetation type 1 had a PA of 64.71%, while vegetation type 2 had a PA of 68.42% (**Table 3**). Additionally, this study examined the CE, which indicates the proportion of predicted positive cases that were incorrect. The CE for the mangrove forest class ranged from 0.00% to 18.33% between 1995 and 2021. In 2023, the CE was 35.29% for vegetation type 1 and 31.58% for vegetation type 2. Overall, the high PA and low CE from 1995 to 2021 contributed to the high accuracy of the mangrove area expansion rate. However, the classification of mangrove forests in 2023 showed a lower PA and higher CE, which led to lower accuracy in distinguishing mangrove types. Nevertheless, this may not affect the calculation of the mangrove area expansion rate, as the total mangrove area in 2023 is based on the combined area of vegetation types 1 and 2. Additionally, the vegetation classification demonstrated high accuracy when distinguishing mangroves from mudflats or water bodies, as observed in the 1995–2021 maps. In addition, for both mudflat and water body classes, some imagery years, such as 2005 and 2015, exhibited a low PA. This may be due to the influence of sea tides, which affect classification accuracy. Differences in tidal conditions, such as variations in low and high tide timings between the tested satellite imagery and the reference map data, could contribute to these discrepancies.

The mangrove extent in the Banlaem mangrove forest consistently increased over the study period. The total area expanded from 56.16 ha in 1995 to 527.55 ha in 2023 (**Table 4**; **Figure 3**). Within the defined mask layer, mangrove vegetation increased from 6.28% to 58.92% (**Table 4**). Besides, the 2023 classification revealed the areas of two mangrove types (**Figure 4**): (1) 272.20 ha of vegetation type 1 (*A. marina*) and (2) 255.35 ha of vegetation type 2 (a coexistence of *Rhizophora* spp. and *A. marina*). On a broader scale, Thailand's mangrove forest area increased from 245,500 ha in 2016 to 271,600 ha in 2022, reflecting a 10.63% rise over this period [6]. In particular, the mangrove forest in Talumphuk Cape, Nakhon Si Thammarat Province, showed a noticeable increase, as observed in Sentinel-2 satellite imagery [6]. Given that the Banlaem mangrove forest is located approximately 30 km from Talumphuk Cape, the study found a 21.64% increase in mangrove cover from 2015 to 2023. This suggests that the Banlaem mangrove forest follows a similar trend to the overall mangrove expansion in Thailand but at a faster rate. In contrast, global mangrove forests experienced a 3.4% loss (524,500 ha) between 1996 and 2020 [39]. Overall, this growth reflects the successful mangrove plantation efforts by the Banlaem community through ecotourism, and the government's restoration initiatives, which include mangrove planting and encouraging public participation in ecosystem conservation and management [40]. These efforts are in line with the Ministry of Natural Resources and Environment's 20-year master plan for 2018–2037 [40].

Table 2. Accuracy assessment of classification in this study (1995–2021).

Year (Satellite Imagery)	Land Cover Classes										
	Mangrove Forest			Mudflat			Water Body			OA (%)	Kappa Coefficient
	PA (%)	UA (%)	CE (%)	PA (%)	UA (%)	CE (%)	PA (%)	UA (%)	CE (%)		
1995	88.00	83.02	16.98	82.00	89.13	10.87	92.00	90.20	9.80	87.33	0.87
1997	98.00	96.08	3.92	84.00	89.36	10.64	90.00	86.54	13.46	90.67	0.91
1999	92.00	97.87	2.13	94.00	94.00	6.00	96.00	90.57	9.43	94.00	0.94
2001	96.00	97.96	5.88	88.00	95.65	4.35	96.00	90.57	9.43	94.59	0.95
2003	92.00	95.83	4.17	74.00	84.09	15.91	94.00	81.03	18.97	86.67	0.86
2005	96.00	97.96	2.04	58.00	90.63	9.38	98.00	71.01	28.99	84.00	0.84
2007	92.00	93.88	6.12	90.00	80.36	19.64	86.00	95.56	4.44	89.33	0.89
2009	90.00	100.00	0.00	96.00	84.21	15.79	90.00	93.75	6.25	92.00	0.92
2011	92.00	100.00	0.00	94.00	78.33	21.67	82.00	93.18	6.82	89.33	0.89
2013	98.00	87.50	18.33	86.00	78.18	21.82	75.00	100.00	0.00	87.82	0.88
2015	96.00	96.00	4.00	96.00	66.67	33.33	56.00	100.00	0.00	82.67	0.82
2017	98.00	98.00	2.00	86.00	91.49	8.51	94.00	88.68	11.32	92.67	0.93
2019	100.00	98.04	1.96	78.00	97.50	2.50	98.00	83.05	16.95	92.00	0.92
2021	100.00	98.04	1.96	82.00	97.62	2.38	98.00	85.96	14.04	93.33	0.93

Table 3. Error matrix for classification in this study (2023).

Classified Data	Ground Reference Data				
	Rhizophora* spp. + *Avicennia marina	***Avicennia marina***	**Water**	**Mudflat**	**Row Total**
Rhizophora spp. + *Avicennia marina*	13	6	0	0	19
Avicennia marina	6	11	0	0	17
Water	0	0	49	0	49
Mudflat	0	0	1	50	51
Column total	19	17	50	50	136
PA (%)	68.42	64.71	98.00	100	
UA (%)	68.42	64.71	100.00	98.04	
CE (%)	31.58	35.29	0.00	1.96	
OA (%)	90.44				
Kappa coefficient	0.90				

Table 4. Changes in mangrove cover in the Banlaem mangrove forest from 1995 to 2023.

Year	Mangrove Percentage % (From the Mask Layer)	Mangrove Area (ha)
1995	6.28	56.16
1997	9.38	83.88
1999	6.68	59.76
2001	12.85	114.84
2003	12.83	114.66
2005	19.54	174.69
2007	24.12	215.64
2009	25.65	229.32
2011	31.72	283.59
2013	39.62	354.15
2015	48.52	433.71
2017	46.82	419.12
2019	49.51	443.3
2021	55.94	500.82
2023	58.92	527.55

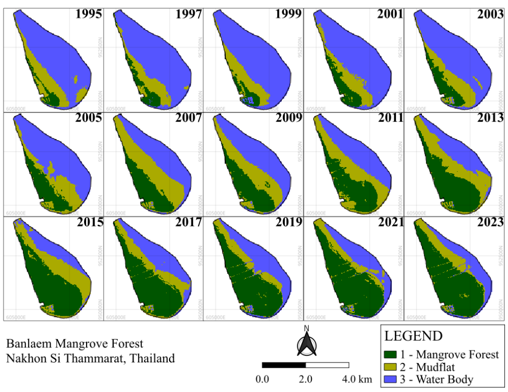

Figure 3. Land cover changes of the Banlaem mangrove forest from 1995 to 2023.

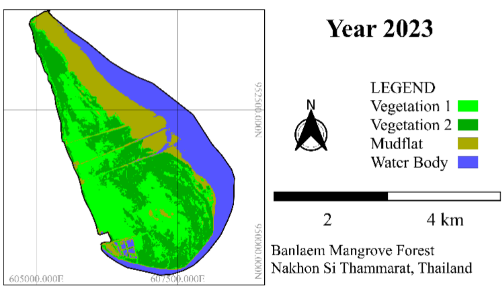

Figure 4. Land cover of the Banlaem mangrove forest in 2023, where vegetation type 1 represents *Avicennia marina*, and vegetation type 2 represents a coexistence of *A. marina* and *Rhizophora* spp.

In 2023, the significant expansion of vegetation type 1 (*A. marina*) in the Banlaem mangrove forest suggests that the area is influenced by natural secondary succession. While *Rhizophora* spp. was the only species actively planted as part of the plantation efforts in the study site, more than half of the vegetation was found to be *A. marina*. *A. marina* is known for its remarkable ability to maintain leaf structure, preserve the ultrastructural stability of palisade mesophyll and chloroplasts, and sustain photosynthesis under high salinity conditions, which contributes to its high salt tolerance [41]. *A. marina* has exceptional adaptability to a wide range of salinity levels, with its optimal growth occurring in salinities ranging from 10% to 90% seawater (salinity 35 ppt), depending on the source population and environmental factors [42, 43]. Furthermore, unlike *Rhizophora* spp., which has a stick-like propagule, *A. marina* produces an ellipsoidal to flattened ovoid propagule, characterized by its small size, lightweight structure, and buoyancy, allowing it to float in water [44]. In Thailand, *Rhizophora* typically dominates the seaward fringe of mangrove zones, often coexisting with *Avicennia* and *Sonneratia* spp. [45]. This study found that the planted *Rhizophora* spp. grows alongside naturally occurring *A. marina*, primarily at the mangrove patch edges. As a result, the expansion of the Banlaem mangrove area is influenced by both secondary succession and plantation efforts. These processes jointly contribute to mangrove growth and regeneration, with their relative influence varying according to environmental conditions. Future research should focus on exploring the environmental factors that affect mangrove growth in this area.

Mangrove forest expansion plays a critical role in tropical ecosystems by enhancing both carbon storage and biodiversity. They are among the most carbon-rich ecosystems in tropical regions, with an average carbon density of 1,023

Mg C ha^{-1}; this value is remarkably high compared to other major forest biomes worldwide [4]. In a mangrove ecosystem, most of the carbon is stored in the soil [4]. Carbon stocks are potentially linked to the success rates of planted mangroves, indicating that enhancing plantation success leads to increased greenhouse gas removal [46]. Additionally, increased mangrove coverage and diversity boost the diversity of microbenthic fauna and promote the presence of various birds, fish, and crustacean species, especially those with high commercial value [47]. In the case of the Banlaem mangrove forest, the expansion of mangrove area significantly enhances carbon storage capacity, contributing to the reduction of greenhouse gas emissions within the community. This expansion is also expected to enhance the diversity of local microbenthic fauna and increase the abundance of commercially valuable species. These ecological improvements have the potential to provide significant benefits to the local economy by promoting biodiversity-related services, such as enhanced fisheries, tourism, and other ecosystem functions associated with the high species diversity in the region.

This study has certain limitations related to the availability of satellite imagery and reference data for accuracy assessment, which may have affected the accuracy of the results. The uncertainty introduced by varying imagery resolutions could affect the temporal analysis of the Banlaem mangrove forest. This study first aimed to utilize high-spatial resolution (10m) imagery from the Sentinel-2 satellite [23]. However, since the Sentinel-2 satellite was launched in 2015 [48], it only began providing imagery of the Banlaem mangrove forest in 2016. Consequently, no satellite data were available for years prior to 2016, limiting the study's ability to assess long-term trends or conditions before that period. Therefore, this study utilized Landsat imagery for the classification of the Banlaem mangrove forest from 1995 to 2015 to increase the dataset available for temporal analysis. The Landsat imagery used in this study has a spatial resolution of 30 m [24]. The difference in spatial resolution may affect the calculation of the mangrove area, which in turn influences the temporal analysis of this study. This discrepancy not only impacts the mangrove area calculation but also affects the predictive model analysis, as higher classification accuracy leads to higher accuracy in the predictive models. For the reference data, ground truth data identifying the two types of mangroves were only available for 2023. As a result, only the 2023 data were classified into two types of mangroves, providing baseline information for the Banlaem mangrove forest. However, this did not affect the independent variable of predictive models, as the total mangrove area was used as the independent variable, allowing data from previous years to be utilized in the predictive models. Despite these limitations, the study provides valuable insights into mangrove dynamics. Future research would focus on the changes in mangrove types to better understand the dynamics of the mangrove ecosystem over time.

Another challenge is the classification of the two types of mangroves in the Banlaem mangrove forest, as observed in 2023. The PA was only 64.71% for vegetation type 1 and 68.42% for vegetation type 2, with a high CE of 35.39% for vegetation type 1 and 31.58% for vegetation type 2 (**Table 3**). Overall, this indicates the difficulty in distinguishing between these two vegetation types, even with the high-resolution Sentinel-2 imagery. In the 2023 color composite (near-infrared, red, and green bands), each mangrove type was distinguished for classification as follows: vegetation type 1 appeared dark red, while vegetation type 2 appeared bright red. However, according to the ground truth inventory data, the density of each species in vegetation type 2 varies. For example, some plots contained only a small percentage of *A. marina*, with *Rhizophora* spp. being the dominant species; other plots had 50% *A. marina* and 50% *Rhizophora* spp.; and some plots had a higher percentage of *A. marina*. This information describes the low accuracy in distinguishing between vegetation types. Thus, reference plots with a low density of *Rhizophora* spp. may be classified as vegetation type 2 (appearing bright red instead of dark red), affecting the accuracy in distinguishing mangrove types on the classification map. Additionally, 36 plots were used for the mangrove type assessment in this study due to limitations in data availability. As the reference size increases, the overall accuracy becomes higher and gradually stabilizes [49]. The assessment with a higher number of reference samples may enhance the reliability of the results.

3.2. Predictive Model Analysis

This study analyzed predictive models for the total mangrove extent over time (1995–2023) using regression analysis. The k-Fold cross-validation was applied to ensure the robustness of the tested model. Both R^2 and $RMSE$ were presented to provide complementary perspectives on model performance. Five different models were developed in this study (**Figure 5**). Overall, the tested models demonstrated a strong relationship between the independent and dependent variables[50]. Results of the k-Fold cross-validation (**Table 5**; **Table 6**) illustrate that the polynomial model (average R^2 = 0.964, *RMSE* = 24.0 ha) may be the most effective model in this study. However, to ensure their performance, a one-way ANOVA was applied to assess the metrics of these models. It was found that there is no significant difference in the R^2 between these models ($F_{(4,20)} = 2.57$, $p > 0.05$), and there is also no significant difference in the *RMSE* between these models ($F_{(4,20)} = 2.42$, $p > 0.05$). Therefore, there is no single model that can explain the pattern of increasing extent of the Banlaem mangrove. The increase in the Banlaem mangrove area may not follow a distinct pattern.

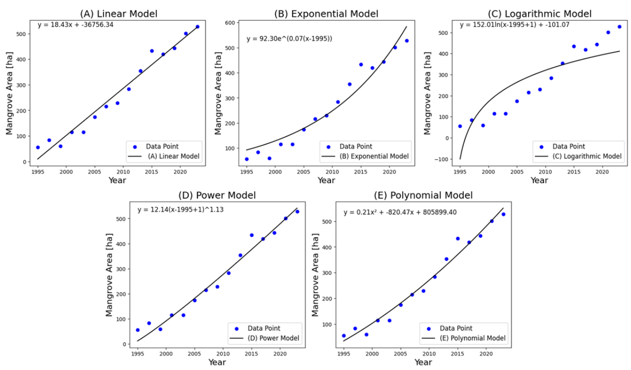

Figure 5. Predictive models developed in this study, including (**A**) linear, (**B**) exponential, (**C**) logarithmic, (**D**) power, and (**E**) polynomial regression models.

This study faces certain limitations related to environmental variables and the satellites used for model generation. Firstly, the available environmental variables were limited, with only annual mangrove extent data accessible. Secondly, differences in the resolutions of Landsat and Sentinel-2 satellites may impact the scatter plot patterns, potentially leading to misinterpretations. Additionally, the Banlaem mangrove forest consists of both planted mangroves and those that have naturally regenerated. The inconsistency of planting activities each year, combined with the influence of natural factors, may contribute to mangrove expansion without a clear pattern. Overall, the models can be sensitive to these factors, affecting their applicability over time.

The pattern of mangrove expansion in the Banlaem mangrove forest can be sensitive to a combination of human activities and natural factors, which may impact the long-term reliability of the models. Each month, an estimated 400 to 700 participants, including students, government officials, and travelers, take part in mangrove plantation activities in the Banlaem mangrove forest[18]. However, these figures are only projections, as there is no systematic record-keeping in place. Therefore, the number of participants may vary each year, leading to differences in the rate of mangrove expansion over time. In addition, because of the 2023 map (**Figure 4**), it showed a large area of vegetation type 1 (*A. marina*), which is the result of secondary natural succession. The fluctuation in participant numbers each year, combined with natural succession, results in an unpredictable pattern of mangrove expansion. Moreover, climate change can influence mangrove growth, further contributing to variability in expansion patterns. Mangrove responses to higher atmospheric CO_2 are complex, with certain species thriving, while others decline or show little to no change[51]. Whereas rising temperatures are expected to accelerate nutrient cycling, including the rates of soil nitrogen and phosphorus transformation processes[52]. Various factors influence mangrove patterns, and human activities in the Banlaem mangroves can vary annually. These factors contribute to the unpredictable long-term expansion of the Banlaem mangrove forest.

However, the tested models still indicate a high rate of mangrove expansion in the Banlaem mangrove forest. We recommend that the community continue plantation projects while systematically recording the number of participants, the number of propagules planted, and their survival rate. This data will help identify patterns of mangrove expansion, supporting sustainable management efforts in the community.

3.3. Impacts on the Banlaem Community

This study enhances comprehension of the mangrove forest dynamics in the Banlaem community, thereby informing the development of effective management strategies for the area. The novel data on mangrove cover changes present valuable tools for community-based applications. We recommend the establishment of a community network, primarily involving local residents, to systematically monitor mangrove forest changes and collaboratively formulate a plan for sustainable management and conservation within the community. Moreover, this study supports blue carbon

Table 5. Results of the k-Fold cross-validation (R^2).

Fold Number	R^2 of Linear Model	R^2 of Exponential Model	R^2 of Logarithmic Model	R^2 of Power Model	R^2 of Polynomial Model
1	0.945	0.925	0.944	0.938	0.974
2	0.980	0.990	0.979	0.830	0.997
3	0.984	0.913	0.984	0.722	0.979
4	0.864	0.796	0.863	0.817	0.877
5	0.992	0.988	0.991	0.927	0.995
Average Value	0.953	0.922	0.952	0.847	0.964
SD	0.0530	0.0788	0.0532	0.0887	0.0500

Table 6. Results of the k-Fold cross-validation (RMSE in ha).

Fold Number	*RMSE* of Linear Model	*RMSE* of Exponential Model	*RMSE* of Logarithmic Model	*RMSE* of Power Model	*RMSE* of Polynomial Model
1	36.905	43.417	37.269	39.255	25.674
2	19.401	13.783	19.722	55.899	7.157
3	26.957	63.408	27.093	113.399	31.368
4	48.749	59.586	48.854	56.376	46.319
5	12.539	15.268	12.684	37.177	9.671
Average Value	28.9	39.1	29.1	60.4	24.0
SD	14.3	23.7	14.3	31.0	16.2

management in the community. Blue carbon ecosystems are vital in the regulation of climate changes [53]. In response to global warming, nations and regions are actively pursuing carbon-neutral policies centered on carbon reduction and carbon sequestration [54]. The biogeochemical processes in coastal zones are heavily influenced by mangroves, which are among the planet's most carbon-dense ecosystems [54]. The increase in mangrove area observed in this study suggests a corresponding rise in carbon sequestration within the Banlaem mangrove forest. Community collaboration should prioritize carbon assessment in the mangrove forest, as this data is crucial in supporting the country's objectives of achieving carbon neutrality and net-zero emissions.

In addition, this study also focused on analyzing predictive models to assess changes and variations in the mangrove area. The findings suggest that these models indicate a rapid rate of mangrove expansion in the Banlaem mangrove forest. Based on these results, this study strongly recommends that relevant organizations, such as governmental agencies, the Department of Marine and Coastal Resources, and educational institutions, consider incorporating this model into their planning processes for conservation, sustainable management, and development in the Banlaem community. In this way, they would have access to an effective tool that can guide decision-making related to the protection and restoration of the mangrove forest, as well as broader environmental management strategies. Moreover, this study suggests that the model can be used as a tool to inform residents about the potential success of their mangrove planting efforts. Providing local communities with insights into the projected outcomes of their restoration work can serve to reinforce the importance of their contributions, boosting community engagement and pride in their efforts. The Banlaem community's approach to mangrove restoration can serve as a role model for other regions in Thailand, demonstrating the effectiveness of community-driven reforestation projects.

There are case studies that can serve as a baseline for mangrove forest management in the Banlaem community. A study evaluated the effectiveness of a community-based mangrove management (CBMM) program in coastal villages of Central Java, Indonesia [47]. It was found that a village successfully implemented the program, supporting a higher diversity of macrobenthic fauna and net reforestation coverage. The success of the program depends on several factors, including sustained long-term funding, strong acceptance of protective legislation, public support, and a broad spatial scale of mangrove restoration [47]. Furthermore, a study highlights the successful efforts of coastal villages in Trang Province, southern Thailand, in managing mangrove forests [21]. The communities' success was attributed to several factors, including the resources' importance to local livelihoods, support from an external non-governmental organization, and strong leadership [21]. These findings offer a valuable framework for the Banlaem community's mangrove management efforts. By implementing these strategies, the Banlaem community can enhance its mangrove forest management and foster the long-term growth and conservation of the mangrove ecosystem.

The study on mangrove cover and the Banlaem community's conservation initiatives significantly supports global efforts to address the climate crisis. Mangrove land cover change data can be utilized to evaluate variations in soil organic carbon, as well as aboveground and below-ground living biomass carbon stocks [55]. The 29th Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC COP29) highlighted that in 2024, the Earth's surface temperature hit a record high of 17.16 °C, raising concerns about the feasibility of maintaining the 1.5 °C target outlined in the Paris Agreement [56]. Thailand is a nation that has presented its Nationally Determined Contribution (NDC) to the UNFCCC. The Thailand Voluntary Emission Reduction (T-VER) Program is a mechanism established by the Thailand Greenhouse Gas Management Organization (Public Organization) (TGO) to voluntarily reduce greenhouse gas (GHG) emissions. The protocol states that remote sensing or alternative techniques can be employed to estimate carbon stocks if considered appropriate by the TGO [57]. Overall, the data on mangrove cover in the Banlaem mangrove forest can be used to assess its carbon storage and subsequently applied to the T-VER program to support Thailand's NDC under the Paris Agreement. Other countries with abundant mangrove ecosystems may adopt this approach for mangrove conservation as part of their efforts to combat the climate crisis.

4. Conclusions

This study provides valuable insights into the mangrove cover dynamics of the Banlaem mangrove forest, Nakhon Si Thammarat, Southern Thailand, emphasizing its significant growth in mangrove coverage from 1995 to 2023. The analysis of multiple satellite imagery revealed an increase in mangrove vegetation, which could be attributed to two key factors: (1) natural secondary succession and (2) active mangrove plantation efforts undertaken by local communities and conservation groups. These combined forces have contributed significantly to the restoration and expansion of the forest area, highlighting the resilience of mangrove ecosystems in response to both natural recovery and human intervention. Furthermore, predictive models show a rapid rate of mangrove expansion in the Banlaem mangrove forest. These findings support the broader understanding that mangrove forests are dynamic ecosystems that are influenced by a complex interplay of natural and human factors.

The increase in the Banlaem mangrove area aligns with Thailand's national goals of achieving carbon neutrality and mitigating climate change. The increase in mangrove coverage is particularly significant as it enhances the potential for carbon sequestration, an important factor in offsetting greenhouse gas emissions to combat climate change. Additionally, the Banlaem mangrove forest serves as an important role model for the broader efforts to protect biodiversity, preserve coastal ecosystems, and promote sustainable livelihoods.

Effective collaboration between local communities, government agencies, and scientific institutions is essential for maintaining the long-term health and resilience of this vital coastal ecosystem. Local communities provide invaluable knowledge and are key to implementing conservation efforts. Government agencies can offer policy support, funding, and coordination, while scientific institutions contribute data, research, and monitoring. Through cooperation, these groups can develop sustainable management strategies, strengthen the ecosystem's ability to adapt to challenges, and ensure the continued provision of important services of the mangrove ecosystem, such as carbon sequestration and ecotourism.

Author Contributions

Conceptualization, S.P. and S.C.; methodology, S.P. and S.C.; software, S.P.; validation, S.P.; formal analysis, S.P.; investigation, S.P.; resources, S.P.; data curation, S.P.; writing—original draft preparation, S.P.; writing—review and editing, S.C.; visualization, S.P.; supervision, S.C.; project administration, S.C.; funding acquisition, S.C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors confirm that there are no conflicts of interest associated with the publication of this paper. This research was performed independently, without any external funding or personal affiliations influencing the study's findings or interpretation.

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