

Article

Exploring Variation in α -Biodiversity in Mangrove Forests Following Long-Term Restoration Activities: A Remote Sensing Perspective

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Highlights

What are the main findings?

- Integration of LiDAR and Worldview-2 data with Gaussian process regression effectively predicts mangrove Shannon's diversity index.
- Mangrove α -diversity increased with the age of forest restoration; mangrove areas with long-established plantations exhibit richer biodiversity.

What are the implications of the main findings?

- This study provides a reliable remote sensing approach for long-term monitoring and assessment of mangrove biodiversity.
- Future mangrove restoration should emphasize multispecies planting to enhance ecosystem stability.

Abstract

Monitoring the α -biodiversity indicators of mangrove forests and understanding their spatiotemporal trends can guide mangrove restoration strategies. Taking Qinglan Port in Hainan Province, China, as our study area, we compared multiple machine learning methods to predict the spatial distribution of α -biodiversity indicator Shannon's diversity index (SHDI) by integrating LiDAR points and Worldview-2 images. In addition, the relationship between mangrove forests' SHDI values and growth years was analyzed. The study extracted 28 spectral features and 99 LiDAR features from Worldview-2 and LiDAR data, respectively. The RReliefF method was adopted to select informative features. Four machine learning methods, including support vector machines (SVMs), extreme gradient boosting (XGBoost), deep neural networks (DNNs), and Gaussian process regression (GPR), were used to establish SHDI prediction models. The leave-one-out cross-validation (LOOCV) method was used to evaluate prediction accuracy, and the optimal model was adopted to generate a spatial map of SHDI. Based on Google Earth and Worldview-2



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images, the spatial regions of mangrove forests in 2008, 2013, 2018, and 2023 were identified. The SHDI values within different restoration periods were statistically analyzed by using the mangroves' spatiotemporal distributions. The results showed that RReliefF selected a total of 30 features, including 13 spectral features and 17 LiDAR features. Using preferred features, GPR had the highest prediction accuracy, with an LOOCV R^2 of 0.51, followed by SVM ($R^2 = 0.44$) and DNN ($R^2 = 0.32$); the accuracy of XGBoost ($R^2 = 0.29$) was relatively poor. The increased areas of rehabilitated mangrove forests in the periods of 2008–2013, 2013–2018, and 2018–2023 were 0.31 km², 0.13 km², and 1.35 km², respectively. Mangroves growing before 2008 owned the highest mean SHDI value of 0.74, followed by mangroves in 2008–2013 and 2013–2018; mangrove forests restored in 2018–2023 had the lowest mean SHDI value of 0.63. The results indicated that mangrove SHDI can be predicted by integrating LiDAR and Worldview-2. The mangrove population exhibited more diverse α -biodiversity characteristics as growth time increased. In subsequent mangrove restoration processes, planting mangroves of diverse species is beneficial to ensure the stability of the mangrove community.

Keywords: Shannon's diversity index; LiDAR; Worldview-2; Gaussian process regression

1. Introduction

Mangrove forests are predominantly distributed in the intertidal zones of tropical and subtropical coastal mudflat shoals. They form a complex ecological network mainly composed of evergreen trees or shrubs, constituting a unique wetland woody plant community. Mangrove ecosystems are crucial for sustaining aquatic biodiversity [1], acting as natural buffers against coastal climate change [2,3], and providing protection from wind and waves while stabilizing shorelines [4], also playing a significant role in purifying water pollution [5]. The successful restoration of mangroves in the Guanabara Bay in Brazil and the Dongzhai Port in China has demonstrated their effectiveness in reducing the impact of pollutants and improving water quality, and highlights the importance of mangroves in coastal protection and climate resilience [6,7]. Moreover, mangroves are ideal for protecting and stabilizing tropical and subtropical muddy coastlines with their well-developed stilt roots [8]. Mangroves are also considered one of the most carbon-rich forest types in tropical regions, serving as important blue carbon sinks and storages [9,10], with significant importance in carbon cycling [11,12].

Explorations of the spatiotemporal variation in the restoration mangrove communities' biodiversity remain inadequate [13]. The rich biodiversity of mangrove ecosystems plays a crucial role in enhancing their stability and resilience [14,15]. This abundant biodiversity allows mangroves to better withstand natural disasters, resist disease, and adapt to climate change [16]. Correspondingly, a lack of biodiversity in mangrove ecosystems leads to weak resistance to environmental changes, making them particularly vulnerable to destruction [17]. Restoration efforts in Shenzhen Bay have highlighted the importance of promoting biodiversity in mangrove ecosystems [18]. Recently, some coastal regions have carried out restoration projects by artificially planting mangroves. Differing from native low shrubs, most of these artificially planted mangrove species are non-native to China. Studies have shown that the planting of non-native mangrove forests can, to some extent, affect the biodiversity and balance of mangrove communities, compressing the growth space of native mangrove species [19]. Therefore, surveying the mangrove biodiversity of artificially rehabilitated areas is of great significance for the protection and management of local mangroves.

Due to the low accessibility of mangroves thriving in costal shallows, traditional manual field surveys face difficulties in investigating them over large areas. Moreover, the lack of historical survey data hinders long-term dynamic monitoring [20]. Remote sensing has provided a technique for extensively monitoring the distribution and species of mangrove forests over the long term and large scales [21,22]. α -biodiversity indices, including Simpson's and Shannon's diversity indices, are important measures of mangrove species diversity [23]. Research mapping mangrove diversity indicators by using remote sensing techniques has been comparatively limited; therefore, it is necessary to expand the knowledge in this field. The SHDI is a classic indicator used in ecology to measure species diversity within a community. It simultaneously considers both the richness and evenness of species in a community, that is, the total number of species in the community and the evenness of individual distributions among species. Due to its importance, it is meaningful to explore the feasibility of predicting SHDI using remote sensing.

Current studies investigating mangroves by remote sensing techniques mainly focus on extracting their spatiotemporal changes. Meanwhile, studies on monitoring vegetation diversity primarily focus on terrestrial vegetation, such as crops [24], forests [25,26], and grasses [27]. Previous studies have demonstrated that multi-spectral [28,29] and LiDAR data [30,31] can effectively capture the physical and chemical characteristics of mangrove forests. Multi-spectral imagery is widely used for mangrove species identification due to its rich spectral information and textural features [32]. However, different tree species may exhibit similar spectral signatures, while the spectral characteristics of the same species can vary across different areas due to environmental influences [33]. Moreover, multispectral imagery is unable to obtain the three-dimensional vertical structure of mangrove canopies. LiDAR can accurately capture the three-dimensional canopy structure of trees, which serves as a direct indicator of mangrove growth and species composition [34]. Additionally, LiDAR-derived digital elevation models can precisely quantify terrain features, which influence the migration and accumulation of water, organic matter, and inorganic sediments, ultimately shaping the species distribution patterns of mangroves [35]. Currently, there are few studies integrating spectral and LiDAR data to monitor mangrove diversity using SHDI.

Recently, machine learning algorithms have gained widespread application in monitoring coastal mangrove forest ecosystems. For instance, in the domain of mangrove mapping, Jia et al. [11] applied object-based image analysis and a random forest classifier to produce a global mangrove map, namely, High-resolution Global Mangrove Forests (HGFMF_2020). Similarly, Hu et al. [19] utilized object-oriented algorithms and SVM to track temporal changes in mangrove forests in Shenzhen Bay. In the field of estimating biochemical components of mangrove forests, Zhao et al. [36] employed the XGBoost method to estimate the mangrove leaf area index (LAI), while Fu et al. [37] utilized DNN to construct a mangrove LAI inversion model. Zhen et al. [38] predicted the leaf chlorophyll content of mangrove forests using kernel ridge regression. Machine learning methods have been widely applied in mangrove species classification and estimation of growth biochemical indicators [39–41]. However, due to a lack of exploration of inversion methods for mangrove diversity indicators, this study aimed to compare multivariate machine learning methods for predicting the diversity indicator SHDI.

Because of the expansion of aquaculture and urbanization, mangrove forests have experienced significant losses globally. According to the Global Mangrove Watch Version 3.0's report, the net loss of mangroves from 1996 to 2020 was estimated to be 5245 km² [42]. In China, the area of original mangrove forests has decreased by 66% since the 1950s based on the investigation results of the State Forestry Administration (SFA) [43]. Fortunately, this decreasing trend has been reversed, and there has been a stable increase in mangrove

area since 2000 [44]. In September 2017, the Hainan Provincial Government Office outlined the wetland protection and restoration strategy, proposing the formulation of a provincial mangrove wetland restoration plan. Due to the implementation of this policy, the area of mangrove forests in Hainan has grown rapidly. The majority of planted mangrove species are exotic, including the rapidly growing, highly adaptable, and quickly spreading *Sonneratia apetala* Buch.-Ham. [45]. The rapid expansion of exotic species may eliminate native mangrove species, posing a potential invasive threat [45,46]. Studying the spatiotemporal trends of mangrove diversity in Hainan's mangrove restoration has practical significance and can provide guidance for other mangrove ecological restoration areas.

This study identifies the spatial distributions of mangrove forests in Qinglan Port Mangrove Nature Reserve for the years 2008, 2013, 2018, and 2023. Based on time-series maps, the restoration time and growth process of mangrove forests are extracted. The SHDIs of mangrove diversity were then predicted by using machine learning models. Based on the spatiotemporal distribution maps of 2008, 2013, 2018, and 2023, the distribution of SHDIs within different growth periods was extracted and analyzed. Through these processes, this study aimed to (1) explore the feasibility of integrating LiDAR and Worldview-2 to predict the mangrove α -biodiversity indicator SHDI; (2) compare multivariate machine learning methods to find the optimal approach for modeling SHDI; and (3) analyze the spatial changes in the SHDI within different restoration periods. This study provides a technical solution for integrating multi-spectral and LiDAR data for spatial mapping of mangrove diversity indicators, and spatiotemporal changes in mangrove diversity can provide a scientific basis for subsequent mangrove restoration.

2. Materials and Methods

2.1. Study Area

The Mangrove Nature Reserve in Qinglan Port, Wenchang City, Hainan Province, was selected as the research area, which is a famous mangrove ecological landscape (Figure 1). The soil of the reserve is a sandy soil with pH values ranging from 3.5 to 7.5. The reserve is characterized by a tropical marine monsoon climate, featuring an average temperature of 22.5–25.6 °C and an average annual rainfall of 1740.5 mm [47,48]. The northern part of Qinglan Port is Bamen Bay, with the Wenjiao River and Wenchang River flowing into the bay from both sides [49]. Mangrove forests thrive around the expansive mudflats within the harbor; the dominant species of mangrove trees in the area include *Bruguiera sexangula* (Lour.) Poir., *Sonneratia alba* Sm., and *Rhizophora mangle* L., etc. [50]. The Qinglan Port Provincial Nature Reserve is of great significance in biodiversity conservation, ecosystem maintenance, and environmental regulation. The aquaculture ponds near Qinglan Bay expanded from the period of 1987 (594 hm²) to 2010 (2192 hm²) [37,50]. Since 2018, the local municipal government has implemented compensatory recycling measures for these ponds, reconstructing and restoring them into mangrove wetlands [49]. By 2023, all aquaculture pond areas within the protected area were rebuilt as mangrove wetlands.

2.2. Field Surveys

A total of 61 sampling plots (10 m × 10 m) were randomly selected in January 2023, ensuring a minimum distance of 30 m between any two plots. The sampling plots included four categories of mangrove forest communities: C1, *Bruguiera sexangula* (19 samples); C2, *Bruguiera sexangula*–*Excoecaria agallocha* (18 samples); C3, *Sonneratia alba*–*Rhizophora mangle*–*Ceriops tagal* (14 samples); and C4, *Bruguiera sexangula*–*Rhizophora mangle* (10 samples). For each plot, the central and four corner locations were obtained using a GPS, and the species of each tree was recorded. Species diversity is an important indicator for measuring community stability, and the higher the index, the more stable the community. This article

used SHDI to investigate and indicate the diversity within mangrove communities, and its calculation formula is as follows [51]:

$$SHDI = - \sum_{i=1}^S P_i \ln P_i \quad (1)$$

$$P_i = \frac{n_i}{N} \quad (2)$$

where S represents the number of species in each plot; N is the sum of the individuals of all species; and n_i represents the number of individuals of the i th species. The larger the SHDI value, the higher the species diversity; that is, the more mangrove species there are in the landscape.

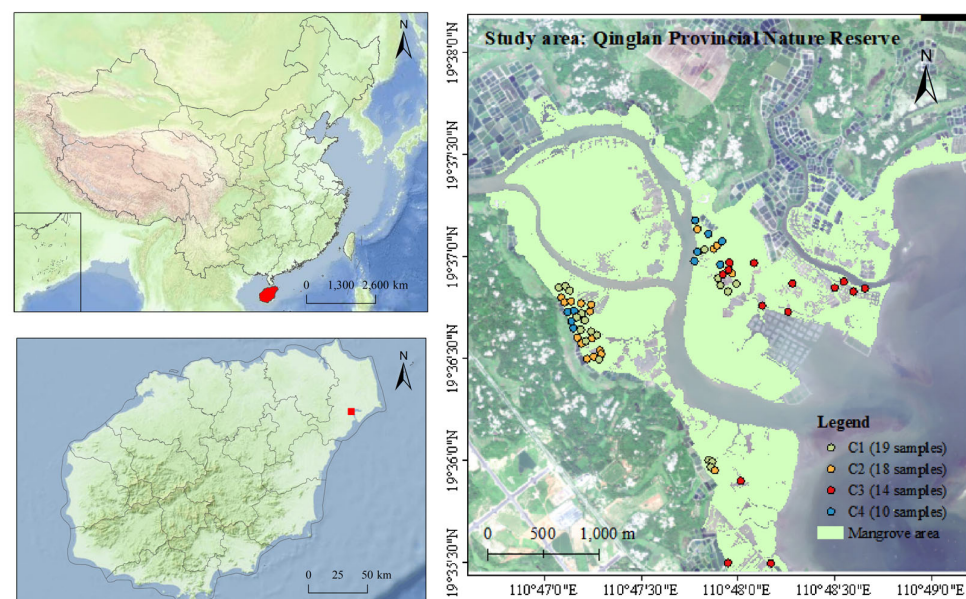


Figure 1. Location of the study area and the spatial distribution of 61 mangrove sampling plots. C1: community of *Bruguiera sexangula*; C2: community of *Bruguiera sexangula*–*Excoecaria agallocha* L.; C3: community of *Sonneratia alba*–*Rhizophora mangle*–*Ceriops tagal* (Perr.) C. B. Rob.; C4: community of *Bruguiera sexangula*–*Rhizophora mangle*.

2.3. Remote Sensing Image Data and Features

2.3.1. Worldview-2 Image and Vegetation Indices

The orthorectified and geometrically corrected Worldview-2 remote sensing images of the study area were purchased from DigitalGlobe and acquired on 16 September 2022. The data contained the 0.5 m panchromatic image and 2 m multispectral image, which included 8 bands: coastal (400–450 nm), blue (450–510 nm), green (510–581 nm), yellow (585–625 nm), red (630–690 nm), red edge (705–745 nm), near infrared-1 (770–895 nm), and near infrared-2 (860–1040 nm) [52]. The multi-spectral image was radiatively calibrated and atmospherically corrected to obtain the surface reflectance using the Flaash (fast line-of-sight atmospheric analysis of spectral hypercubes) algorithm. The multispectral and panchromatic images were then fused to produce a remote sensing image with 0.5 m resolution by using the Gram–Schmidt spectral sharpening method [53].

The vegetation indices calculated from two or more bands can highlight the informative features of vegetation characteristics and overcome the influences of the soil background, atmosphere and saturation limitations [54]. Therefore, in this study, we calculated 20 vegetation indices (Table 1) from the reflectance of the Worldview-2 image. These vege-

tation indices and 8 spectral bands were adopted as the input variables for the following modeling processes.

Table 1. The vegetation indices used for predicting SHDI in this study and the formulas.

Vegetation Indices	Formulas
Green-band normalized vegetation index (GNDVI)	$(R_{\text{nir}} - R_{\text{green}})/(R_{\text{nir}} + R_{\text{green}})$
Green-band optimized soil-adjusted vegetation index (GOSAVI)	$1.16 \times [(R_{\text{nir}} - R_{\text{green}})/(R_{\text{nir}} + R_{\text{green}} + 0.16)]$
Normalized difference vegetation index (NDVI)	$(R_{\text{nir}} - R_{\text{red}})/(R_{\text{nir}} + R_{\text{red}})$
Modified simple ratio index (MSRI)	$[(R_{\text{nir}}/R_{\text{red}}) - 1]/[(R_{\text{nir}}/R_{\text{red}}) + 1]^{0.5}$
Renormalized difference vegetation index (RDVI)	$(R_{\text{nir}} - R_{\text{red}})/(R_{\text{nir}} + R_{\text{red}})^{0.5}$
Difference vegetation index (DVI)	$R_{\text{nir}} - R_{\text{red}}$
Rededge-band renormalized difference vegetation index (RERDVI)	$(R_{\text{nir}} - R_{\text{rededge}})/(R_{\text{nir}} + R_{\text{rededge}})^{0.5}$
Chlorophyll absorption ratio index (CARI)	$(R_{\text{rededge}} - R_{\text{red}}) - 0.2 \times (R_{\text{rededge}} + R_{\text{red}})$
Optimized soil-adjusted vegetation index (OSAVI)	$(R_{\text{nir}} - R_{\text{red}})/(R_{\text{nir}} + R_{\text{red}} + 0.16)$
Normalized blue-green difference index (NBGDI)	$(R_{\text{green}} - R_{\text{blue}})/(R_{\text{green}} + R_{\text{blue}})$
Enhanced vegetation index (EVI)	$2.5 \times [(R_{\text{nir}} - R_{\text{red}})/(R_{\text{nir}} + 6 \times R_{\text{red}} - 7.5 \times R_{\text{blue}} + 1)]$
Triangle vegetation index (TVI)	$0.5 \times [120 \times (R_{\text{nir}} - R_{\text{green}}) - 200 \times (R_{\text{red}} - R_{\text{green}})]$
Atmospherically resistant vegetation index (VARI)	$(R_{\text{red edge}} - 1.7 \times R_{\text{red}} + 0.7 \times R_{\text{blue}})/(R_{\text{red edge}} + 2.3 \times R_{\text{red}} - 1.3 \times R_{\text{blue}})$
Excessive green index (EXG)	$2 \times R_{\text{green}} - R_{\text{red}} - R_{\text{blue}}$
Ratio vegetation index (RVI)	$R_{\text{nir}}/R_{\text{red}}$
Soil-adjusted vegetation index (SAVI)	$1.5 \times (R_{\text{nir}} - R_{\text{red}})/(R_{\text{nir}} + R_{\text{red}} + 0.5)$
Optimized vegetation index (OVI)	$1.45 \times [(R_{\text{nir}})^2 + 1]/(R_{\text{red}} + 0.45)$
Perpendicular vegetation index (PVI)	$R_{\text{nir}}/(R_{\text{nir}} + R_{\text{red}})$
Transformed difference vegetation index (TDVI)	$[0.5 + (R_{\text{nir}} + R_{\text{red}})/(R_{\text{nir}} + R_{\text{red}})]^{0.5}$
Modified non-linear index (MNLi)	$[(R_{\text{nir}}^2 - R_{\text{red}}) \times 1.5]/(R_{\text{nir}}^2 + R_{\text{red}} + 0.5)$

Note: In these formulas, R_{blue} , R_{green} , R_{red} , R_{rededge} , and R_{nir} are the reflectance of the blue (band 2), green (band 3), red (band 5), red-edge (band 6), near-infrared (band 7) bands, respectively.

2.3.2. LiDAR Data and Features

The LiDAR data was acquired from 9:00 to 11:00 on 24 January 2023, using a DJI Matrice 600 Pro UAV platform equipped with an ARS-100 LiDAR sensor. During data collection, the weather was clear with light winds, and the drone flight altitude was 200 m. Flight missions were designed with >50% sidelap between adjacent swaths to maintain a minimum point density of 8 pts/m² throughout the study area. The LiDAR points were processed by employing advanced denoising algorithms and adaptive smoothing filters to remove outliers and enhance signal quality. The ground points were classified using an improved progressive Triangulated Irregular Network (TIN) densification algorithm [55]. Subsequently, 0.5 m resolution digital elevation models (DEMs) and digital surface models (DSMs) were generated. Finally, canopy height model (CHM) was obtained by calculating the difference between the DEM and DSM. Then, the height, density, and canopy volume metrics [56] were derived. In total, 99 LiDAR-based features with a resolution of 2 m were calculated for the following modeling processes; for the features, formulas, and details, refer to the reference of [57].

2.4. Modeling Methods

For each 10 m × 10 m plot, the mean values of all pixel-based Worldview-2 and LiDAR features were calculated to generate plot-level remote sensing feature variables. These variables, combined with the corresponding field-measured SHDI, ultimately resulted in a dataset comprising 61 samples. The dataset is used for subsequent analyses, including feature selection, prediction model development, and SHDI mapping.

2.4.1. Feature Selection Methods

RReliefF, developed by Kira and Rendell, is a feature selection method originating from the Relief technique [58]. As a simple and non-parametric algorithm, RReliefF can efficiently search informative features from high-dimensional spaces [59]. The algorithm can improve the accuracy and generalization ability of the model, and is suitable for complex network models [60]. The main procedures of this algorithm are as follows:

- (1) Initialization: For each feature j , the initialization weight is set as 0.
- (2) Iterating through samples: For each sample x_i in the dataset, find the nearest neighbors $x_{i, nh}$ among similar samples, and find the nearest neighbor $x_{i, nm}$ in all samples, then calculate the difference in feature j between $x_{i, nh}$ and $x_{i, nm}$.
- (3) Weight update: Update the weight of the feature based on the difference and category distribution.
- (4) Normalization: Normalize the weights of all features to obtain the final scores.

2.4.2. Support Vector Machine

SVM regression is a regression algorithm that transforms features into a higher-dimensional space to fit nonlinear relationships [61]. This method uses a kernel function and determines the most ideal hyperplane to minimize the deviation of all data points. Commonly used kernel functions include linear kernel, polynomial kernel, and radial basis function. In this study, a radial basis function was adopted. The key parameters of SVM include the C parameter, which is the regularization parameter, and gamma, which represents the scale of the influence of the kernel function. C is the penalty coefficient of SVM; the larger the C value, the heavier the model's punishment for errors, which may lead to overfitting, while the smaller the C value, the lighter the model's penalty for errors, which may lead to underfitting. Usually, cross-validation is required to select the appropriate C value. The gamma parameter affects the width of the kernel function, thereby affecting the complexity and generalization ability of the model [62].

2.4.3. Extreme Gradient Boosting

The XGBoost algorithm is an optimized ensemble learning algorithm based on a Gradient Boosting Tree (GBDT) [63]. XGBoost enhances its model by incorporating regularization terms that penalize the weights of leaf nodes, thereby simplifying the model and preventing overfitting. Simultaneously, for each node of each tree, the second-order Taylor expansion is utilized to more accurately compute the reduction in the loss function at each split point, identifying the optimal split point and minimizing the value of the loss function. The key parameters include `learning_rate`, `max_depth`, and `n_estimators`. In addition, `subsample` is the proportion of data sampling, and `colsample_bytree` controls the proportion of feature sampling for each tree during training to avoid overfitting.

2.4.4. Deep Neural Networks

DNN usually consists of three parts, including an input layer, multiple hidden layers, and an output layer [64]. The number of neurons in the hidden layer has an impact on the performance of the regression model. In this study, a fully connected DNN prediction model with three hidden layers was built, and the number of neurons in each hidden layer was set to 10, 10, and 10, respectively. In the DNN model, an activation function was necessary to establish the nonlinear relationship between input and output neurons. The ReLU activation function was chosen for this model due to its effectiveness in enhancing training efficiency and avoiding the gradient vanishing problem. To mitigate overfitting, we incorporated a dropout function with a dropout rate of 0.5 [65].

2.4.5. Gaussian Process Regression

Gaussian process regression (GPR) was proposed by Rasmussen and Williams [66]. It is a Gaussian prior probabilistic method that involves training regression models to fit the mean and covariance. Compared with other machine learning methods, its most important advantage is its suitability for training small-sample models. Meanwhile, GPR fits nonlinear data to provide a posterior distribution of predicted samples and provide confidence intervals for the model's predictions with good model interpretability [67]. The kernel

function is used to measure the similarity between two data points. The kernel functions are the core part of the GPR, allowing it to achieve good model performance. Commonly used kernel functions include linear kernel, square exponential kernel, and quadratic rational kernel. To find the best kernel function, we evaluated all of the kernels and selected the quadratic rational kernel, which had the best performance. Furthermore, Bayesian optimization is usually used as an optimizer, and choosing appropriate optimization methods can improve the convergence speed and accuracy of models.

2.4.6. Accuracy Evaluation

The LOOCV method was employed to evaluate the models' performance, as it offers an effective method to assess the constructed model's accuracy [65,68]. The specific steps involve selecting one observed sample from the whole dataset as a validation set, utilizing the remaining data to build a regression model, and subsequently validating the model's accuracy with the excluded observed sample. And this process was repeated until each sample was used for validation. The predictive ability of the model was evaluated by root mean square error of prediction (RMSEP) and the coefficient of determination R^2 between the observed and predicted values of samples. The ratio of performance deviation (RPD) was utilized as a key indicator to assess the performance and accuracy of the model [62].

2.5. Extracting Spatial–Temporal Distribution of Mangrove Forests

We employed Google Earth images from 2008, 2013, and 2018 and Worldview-2 image from 2023 to extract the spatial distributions of mangrove forests. Registration and geographic correction were conducted to match the remote sensing images across different years. An object-oriented SVM classifier [69] was used to identify the spatial distributions of mangrove forests in 2008, 2013, 2018, and 2023. By conducting overlay analysis on the maps of mangrove forests from 2023 and 2018, the newly restored mangrove area from the period of 2018 to 2023 could be generated. Similarly, the restored mangrove forest areas from the periods of 2013–2018 and 2008–2013 were produced by using the same approach. Finally, restoration maps of mangroves could be obtained for the different time periods of 2008–2013, 2013–2018, 2018–2023, and before 2008.

2.6. Mapping and Analyzing the Spatial Distributions of SHDI

The regression model with the highest prediction accuracy was used to generate the SHDI map of the study area. The SHDI map was then cropped by using the spatial distribution of mangrove forests within different restoration periods obtained in Section 2.5. Spatial distribution maps of SHDI with different restoration periods were then produced. Statistical analysis was conducted to explore the spatiotemporal changes in mangrove biodiversity.

3. Results

3.1. Statistics of α -Biodiversity Index of SHDI

Table 2 displayed the statistics of the SHDI values of the 61 samples and the four mangrove communities. For the whole sample, the range of SHDI was 0 to 1.63, with a mean value of 0.56, and the standard deviation was 0.38 with a variance of 0.15. The C1 community (*Bruguiera sexangula*) had the smallest indicators in mean (0.25) and variance (0.06), indicating low diversity in this mangrove community. The C4 community of *Bruguiera sexangula*–*Rhizophora mangle* showed relatively high diversity out of the four communities in this study, with a mean SHDI of 0.84 and standard deviation of 0.26. Welch's analysis of variance (ANOVA) results showed an F-value of 9.42 and a significance level of $p < 0.05$, indicating significant differences among the four communities.

Table 2. Statistical descriptions of SHDI for four mangrove communities.

	Number of Samples	Mean	Std.	Variance	Coefficient of Variation	Min.	Max.
Whole sample	61	0.56	0.38	0.15	0.69	0	1.63
C1	19	0.25	0.24	0.06	0.95	0	0.72
C2	18	0.56	0.15	0.02	0.27	0.26	0.84
C3	14	0.78	0.52	0.27	0.67	0	1.63
C4	10	0.84	0.26	0.07	0.31	0.52	1.31

Note: Std., Min., and Max. are standard deviation, minimum, maximum, respectively. C1 to C4 are the mangrove communities of *Bruguiera sexangula*, *Bruguiera sexangula*–*Excoecaria agallocha*, *Sonneratia alba*–*Rhizophora mangle*–*Ceriops tagal*, and *Bruguiera sexangula*–*Rhizophora mangle*, respectively.

3.2. The Important Features

RReliefF selected 30 important features from the 127 optical features (spectral bands, vegetation indices) and LiDAR-based features. The important features included 13 optical features, which were RERDVI, EVI, SAVI, OSAVI, RDVI, TVI, MNLI, DVI, B7, GOSAVI, GNDIV, OVI, and B8, according to their importance weighting (Figure 2a). In addition, 17 LiDAR-based features, including Int_p5, Int_a70, Int_std, Int_a99, Int_a60, Int_p95, Int_aad, Int_variance, Int_max, Int_p99, Int_p90, Int_a95, Int_p60, Int_p75, Int_p70, Int_a80, and Gap Fraction, were selected, and the details of these LiDAR features are listed in Table 3. The RReliefF method eliminated uninformative variables and reduced the number of features from 127 to 30, which could effectively improve the time efficiency of the subsequent modeling process.

Table 3. The calculation formulas for the important LiDAR-based features selected by the RReliefF method.

Abbreviation	Variable Name	Formula
Int_aad	mean absolute deviation of intensity	$\text{int_aad} = \frac{\sum_{i=1}^n (I_i - \bar{I})}{n}$
Int_max	maximum intensity value	$\text{int_max} = \max(I)$
Int_std	intensity standard deviation	$\text{int_stddev} = \sqrt{\frac{\sum_{i=1}^n (I_i - \mu)^2}{n}}$
Int_variance	intensity variance	$\text{int_variance} = \frac{\sum_{i=1}^n (I_i - \bar{I})^2}{n}$
Gap Fraction	gap ratio variable	$\text{GapFraction} = \frac{n_{\text{ground}}}{n}$
Int_p5, p60, p70, p75, p90, p95, p99	ith intensity percentiles, i = 5, 60, 70, 75, 90, 95, 99	$\text{int_percentile_i} = \text{percentile}(I, i)$ In a specific statistical unit, the internally normalized LiDAR point cloud is sorted by intensity, and then the intensity of i% of points within each statistical unit is calculated. This represents the intensity percentile of that unit. $\text{int_All_i} = \frac{1}{n} \sum_{m=1}^{i\%n} I_m$
Int_a60, a70, a80, a95, a99	ith percentile cumulative intensity, i = 60, 70, 80, 95, 99	In a specific statistical unit, the internally normalized LiDAR point cloud is sorted by intensity, and the cumulative intensity of all points is calculated. The cumulative intensity at which i% of points within each statistical unit are located represents the cumulative intensity percentile of that unit.

Note: I: point cloud intensity; n: the number of points in a statistical unit.

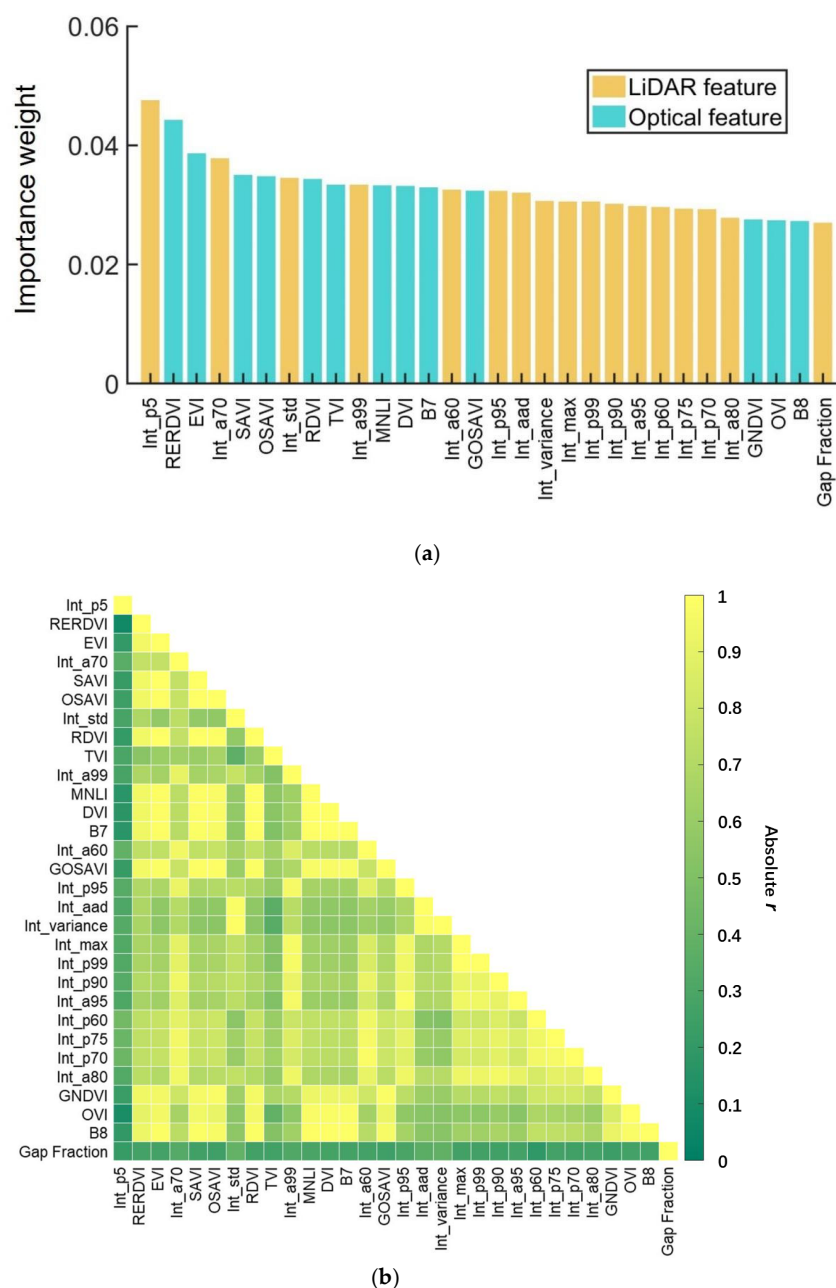


Figure 2. The important LiDAR-based and optical features selected by the RReliefF method (a), and the correlation coefficients among these features (b).

Figure 2b illustrates the multicollinearity among the top 30 most significant variables. It reveals that most variables exhibit relatively low levels of multicollinearity, particularly LiDAR feature variables (such as Int_p5, int_a70, int_std, etc.). In contrast, relatively high multicollinearity was observed among certain optical variables, including OVI, DVI, MNLI, and others. Given that these vegetation indices were predominantly calculated based on the same spectral bands, they consequently demonstrated a high degree of correlation with one another.

3.3. Regression Models and Mapping SHDI

The models' parameter settings and the LOOCV results of the four models are shown in Table 4. Among them, the GPR model had the highest accuracy for predicting SHDI, with an LOOCV R^2 of 0.51 and RMSEP of 0.20, and the RPD was 1.47 (Figure 3a). The SVM model ranked second in terms of accuracy, with $R^2 = 0.44$, RMSEP = 0.22, and RPD = 1.34

(Figure 3b). The prediction abilities of XGBoost (Figure 3c) and DNN (Figure 3d) were not ideal, with R^2 values of 0.32 and 0.29, and RMSEP values of 0.25 and 0.26, respectively. The distributions of scatter plots of GPR had a relatively concentrated scatter distribution, except for some high-value points that were underestimated, and most plots were concentrated near the 1:1 line. For all four models, there were cases of biased prediction, with underestimation of high measured values and overestimation low measured values.

Table 4. The parameter settings and the leave-one-out cross-validation results for multiple machine learning algorithms for predicting SHDI.

Algorithm	Parameters	Value	R^2	RMSEP	RPD
SVM	Kernel function	Radial basis function	0.44	0.22	1.34
	C	10^{-3} – 10^3			
	gamma	10^{-6} – 10			
	Epsilon	10^{-2} – 1			
GPR	Kernel function	Isotropic quadratic rational function	0.51	0.20	1.47
	Acquisition function	Expected improvement per second plus			
	Optimization algorithm	Bayesian optimization			
	Learning rate	10^{-3} – 1			
XGBoost	Tree depth	1–27	0.32	0.25	1.18
	Number of estimators	1–40			
	Number of learners	10–500			
	Number of neurons in each hidden layer	10, 10, and 10			
DNN	Activation function	ReLU	0.29	0.26	1.13
	Regularization intensity	0.1			
	Iterations	1000			

Note: SVM: support vector machine, GPR: Gaussian process regression, XGBoost: extreme gradient boosting, DNN: deep neural networks.

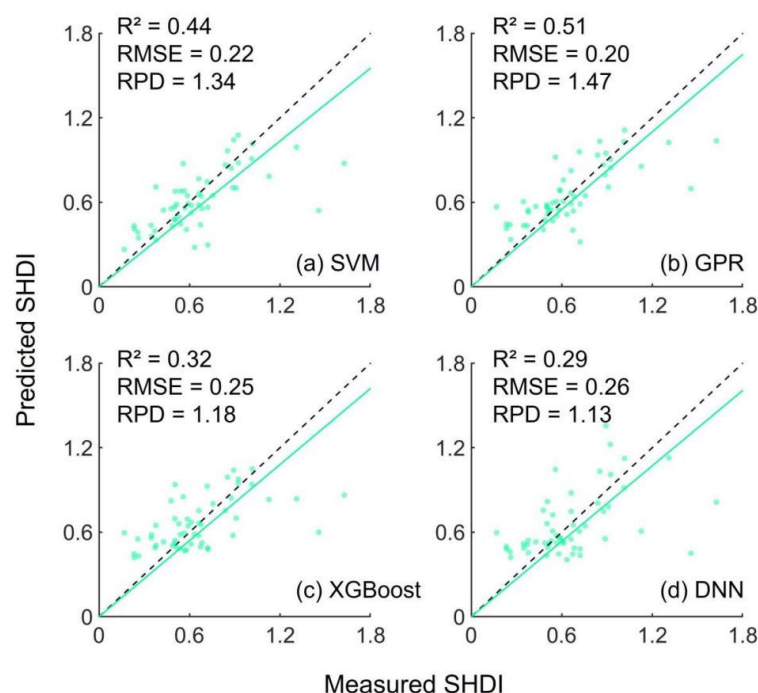


Figure 3. Scatter plots of the measured SHDI values against predicted values by using the regression models of (a) support vector machine (SVM); (b) Gaussian process regression (GPR); (c) extreme gradient boosting (XGBoost); (d) deep neural networks (DNN).

The mapping results of the four models (Figure 4) showed a consistent spatial distribution; the SHDI on the east side of the research area was relatively high, while low SHDIs were distributed on the northwest side. SVM (Figure 4a) and GPR (Figure 4b) could better express detailed changes in spatial patterns compared with XGBoost (Figure 4c) and DNNs (Figure 4d). The SHDI map predicted by the GPR model presented lower SHDI values compared to other regression models. Considering that the GPR model had the highest accuracy, we used the SHDI map produced by GPR in the subsequent analysis.

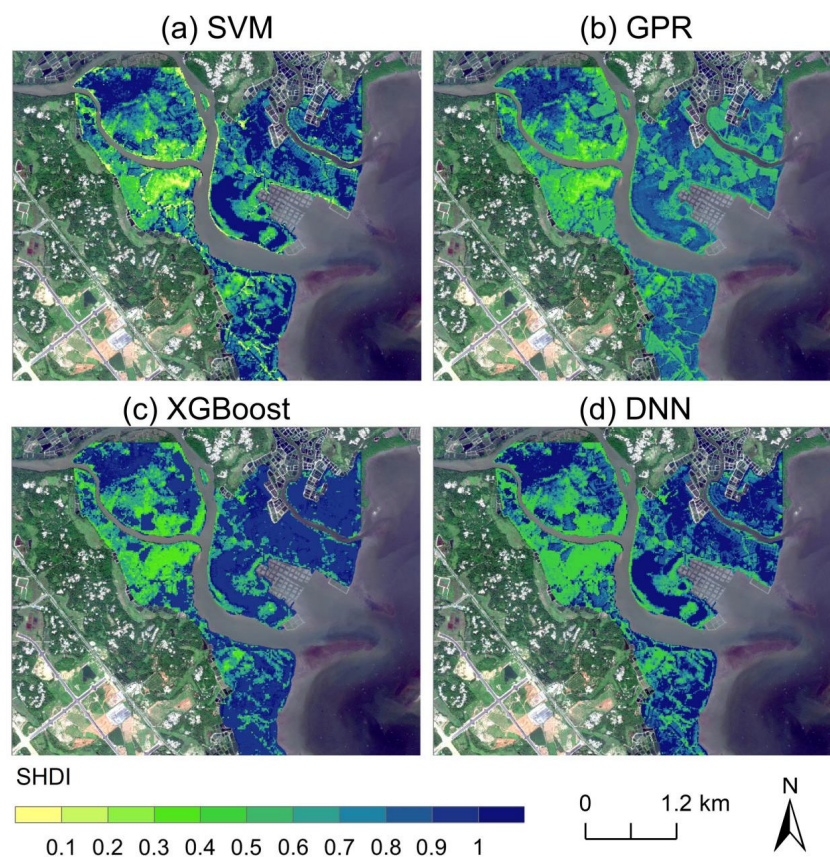


Figure 4. Maps of SHDI predicted by the models of (a) support vector regression; (b) Gaussian process regression (GPR); (c) extreme gradient boosting (XGBoost); (d) deep neural networks (DNN).

3.4. Spatial Distributions of Mangrove SHDI with Different Restoration Periods

As shown in Figure 5a, the area of mangrove forests that had already existed in 2008 was 3.61 km². The increased areas of mangrove forest restoration in the periods of 2008–2013, 2013–2018, and 2018–2023 were 0.31 km² (Figure 5b), 0.13 km² (Figure 5c), and 1.35 km² (Figure 5d), respectively. Mangrove forest area increased slowly by 0.44 km² in the period from 2008 to 2018, but rapidly increased by 1.35 km² in the period from 2018 to 2023. The increased mangrove area mainly came from aquaculture ponds, indicating that the policy of returning aquaculture to mangrove forests since 2018 played a positive role in mangrove restoration.

Figure 5 also demonstrated SHDI maps of mangrove forests within different growth times by using SHDIs derived from the GPR model (Figure 4b). And we statistically analyzed the SHDI values of mangroves within different restoration periods (Figure 6). Mangroves growing before 2008 had the highest SHDI, with a mean value of 0.74 and standard deviation of 0.20. The areas restored in the periods of 2008–2013 and 2013–2018 presented relatively low SHDI values, with mean values of 0.66 and 0.70, and standard deviations of 0.18 and 0.18, respectively. The mangrove forests restored in 2018–2023 had

the lowest SHDI value, with a mean value of 0.63 and standard deviation of 0.13. The statistical results indicate that the α -biodiversity of the mangrove forests in the restoration zone gradually became richer as time went on.

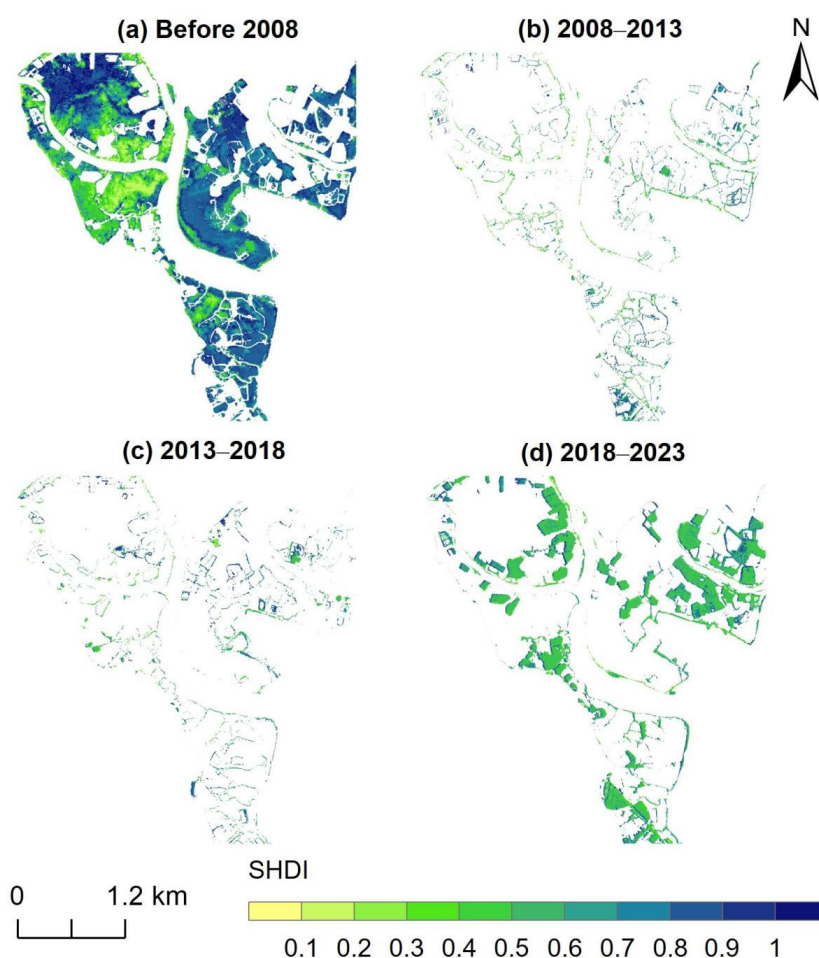


Figure 5. The mangrove forest areas that existed before 2008 (a), restored in the periods from 2008–2013 (b), 2013–2018 (c), and 2018–2023 (d). Shannon's diversity index values of mangroves are displayed.

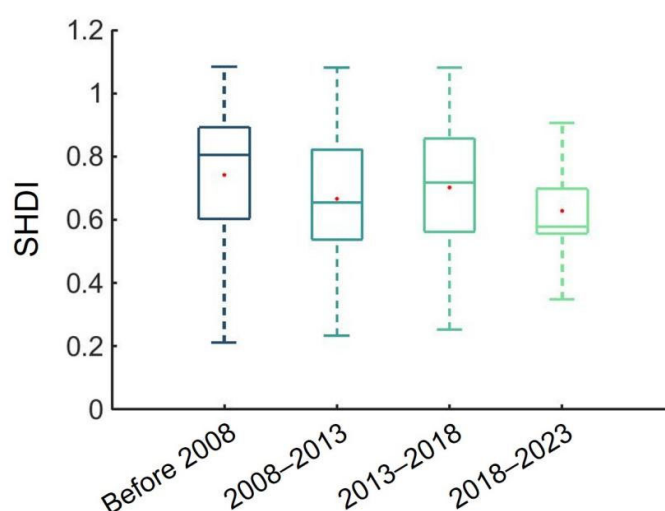


Figure 6. The statistics of the SHDI maps, in Figure 5, of mangrove areas restored in different periods: before 2008, 2008–2013, 2013–2018, and 2018–2023, respectively.

4. Discussion

Extensive studies have proven that remote sensing techniques accurately identify plant communities and species types [70]. Gholizadeh et al. [71] and Xu et al. [72] successfully mapped grassland diversity indices by using airborne spectral data, and the plant species diversity resulted in spectral diversity in endmembers, which guided the prediction. Additionally, Tian et al. [73] thought that canopy heterogeneity could also reflect the species diversity of plants, so they combined unmanned aerial vehicle LiDAR and hyperspectral data to evaluate a mangrove diversity indicator, the Simpson diversity index, in China's Pinglu Canal Estuary. Our study integrated LiDAR data and Worldview-2 multispectral data to predict the spatial distribution of the mangrove α -biodiversity indicator SHDI. Compared with a study by Wang et al. [74], who only used Worldview-2 multispectral image data to map mangrove α -diversity indicators in the same area, this study obtained a much better prediction accuracy. These results further demonstrate that mapping mangrove diversity by integrating LiDAR and remote sensing imagery is reliable.

This study was constrained by the limited amount of training data because of the significant difficulties and costs associated with field sampling. Although the sample size was limited, we employed LOOCV to tune model parameters and select the optimal regression model to avoid overfitting. Studies have demonstrated that LOOCV can effectively evaluate model predictive performance with small samples, producing validation results with robust statistical significance [75]. Moreover, during the feature selection process, maintaining a reasonable ratio between the sample size and the number of variables is crucial to avoid overfitting and ensure the model's generalization capability. In our research, the ratio of sample size to feature number stands at 2:1, an empirical proportion that has demonstrated optimal performance in numerous studies [76–78]. The decision to select the top 30 variables was made after considering factors such as sample size and computational efficiency. This number of variables was sufficient to capture the primary sources of variation in the data while avoiding excessive model complexity caused by an overabundance of variables. Furthermore, in our study, LiDAR and optical features represented two distinct types of data sources, each carrying unique information about the research subject. Maintaining a balance in the number of these two types of variables facilitates the full exploitation of their complementary nature, thereby enhancing the model's predictive accuracy and robustness. When selecting the top 30 variables, we indeed took note of this aspect and endeavored to ensure an approximate equality in the number of LiDAR and optical variables. However, it is important to emphasize that this decision was not solely based on the balance of variable types but instead placed greater emphasis on the weights and predictive capabilities of the features themselves.

Compared with the study by Wang et al. [74], who found a moderately positive correlation, with R^2 values ranging from 0.20 to 0.24, between the α -diversity indices derived from Worldview-2 images, our research obtained relatively higher inversion accuracy for the α -biodiversity index of SHDI, with R^2 ranging from 0.29 to 0.51, by using Worldview-2 remote sensing images and LiDAR. The improvement in accuracy may be attributed to two reasons: compared with only using spectral data in the previous study, our research simultaneously employed spectral and canopy structural information to predict SHDI; we used machine learning models to fit the nonlinear relationship between remote sensing data and α -biodiversity. The accuracy achieved by the optimal model (LOOCV R^2 of 0.51) remains moderate. Theoretically, the uncertainty in predicting SHDI could be the sum of uncertainties from the input features and regression model. The spatial resolution of remote sensing data may be the main uncertainty because SHDI is a landscape index, and its values will statistically fluctuate at different spatial scales. The remote sensing

signals being contaminated by surface soil and water could be another uncertainty limiting accuracy [74].

Numerous studies on predicting biodiversity have shown that, as plant species increase, the corresponding diversity of remote sensing spectra also increases, which is known as the “spectral variation hypothesis” [73,79]. Therefore, multispectral and hyperspectral remote sensing data are crucial approaches for monitoring biodiversity. Wang et al. [74] found that the green, red-edge, and NIR bands (Bands 3, 6, 7, and 8) of Worldview-2 were important bands for predicting the α -biodiversity indices of mangrove forests. Our study confirmed once again that these bands are crucial for α -biodiversity prediction. On the other hand, Torresani et al. [80] proposed the concept of the “height variation hypothesis”, which suggests that height heterogeneity is closely related to plant species diversity, and LiDAR CHM features are key features for predicting tree species diversity. In this study, we primarily utilized the LiDAR intensity metric for α -biodiversity prediction. This metric represents the energy intensity of laser pulses that returned to the sensor after interacting with surface objects, with its values influenced by multiple factors, including leaf inclination angle, laser travel distance, and atmospheric attenuation effects. Essentially, this metric reflects the three-dimensional structural characteristics of mangrove canopies, particularly their close relationship with key canopy geometric parameters such as tree height and leaf inclination angle. Due to their ability to reflect the vertical distribution of canopy geometry, studies have shown that intensity-related LiDAR metrics play a significant role in distinguishing forest tree species [81,82]. These reasons explain why intensity metrics were an important variable in predicting mangrove SHDI in this study. In summary, the fusion of optical images and LiDAR data can better reflect mangrove biodiversity compared to using single data.

The results of this study indicate that the GPR model had a higher accuracy than other models for predicting SHDI of mangrove forests. Similarly, Verrelst et al. [83] also found that, when using remote sensing data to invert vegetation biophysical parameters, such as leaf chlorophyll content, leaf area index, and fractional vegetation cover, GPR models performed better than other machine learning models, including ANN, SVM, and kernel ridge regression. In addition, in the field of predicting soil properties using multivariate features, GPR also showed better results compared to ANN and regression trees [84]. Possible causes include that GPR establishes the regression relationships by fitting a flexible Bayesian model in function space and ranks features and samples with stronger predictive abilities in modeling [85]. Thus, GPR is not very susceptible to data noise and highly adaptable to small samples [86]. In addition, GPR is more robust than other regression methods due to its advantage of offering the uncertainty of the predicted values [84]. Moreover, our study discovered other advantages of GPR. GPR is a very flexible non-parametric model, has a strict theoretical foundation in statistical learning, and is well-suited for handling complex problems such as high-dimensional, small-sample, and nonlinear problems. Unlike ‘black box’ models such as ANN, GPR has strong interpretability because of its statistical basis. GPR does not need to assume the distribution form of the data in advance, as the model is built based on the characteristics of the data itself [66].

The results showed that the area of mangrove forest in Qinglan Port has grown rapidly since 2018, indicating that the “Implementation Plan for Returning Ponds, Forests, and Wetlands in Hainan Qinglan Mangrove Provincial Nature Reserve” issued in 2018 played an effective role in mangrove protection and restoration. In addition, our research found that mangroves that grew before 2008 had a higher diversity, while mangroves that were newly restored later in 2008–2018 had relatively low species diversity. The results indicate that restored mangrove species are relatively homogenous, while the local native mangrove

diversity was more abundant. Meanwhile, as the growth time of mangroves increased, self-restoration of mangroves enriched species diversity.

According to research by Zhen et al. [87], the mangrove area in Qinglan Port declined continuously starting from 1987, but showed a recovery trend beginning in 2007. Mangroves before 2008 were mainly composed of native species with relatively high species diversity. Due to the introduction of relatively homogeneous non-native mangrove species for restoration, species diversity in the areas restored after 2008 decreased. However, as the restored mangrove areas aged, species diversity gradually increased. A possible explanation is that with the cessation of aquaculture activities in the protected areas, native mangroves were able to recover and expand naturally. The main factors affecting their growth shifted from human impacts to natural stressors such as diseases and typhoons. Non-native monocultures were generally less adapted to these natural disturbances compared to native species. As a result, native species gradually expanded into the restored areas, colonizing former aquaculture zones and thereby enhancing species diversity in the recovery regions. Previous studies have shown that a richer population diversity promotes more stable development and growth of mangroves [88]. As mangroves grow steadily, species diversity also becomes more abundant. In the future, regarding processes of mangrove restoration, more attention should be paid to the combination of mangrove species to improve species diversity and population stability in mangroves.

5. Conclusions

This study combined spectral features of Worldview-2 and LiDAR to spatially predict the mangrove α -biodiversity, using SHDI, in Qinglan Port, Hainan Province, and compared the predictive performance of various machine learning models. Finally, based on the SHDI mapping results, distribution patterns of mangrove α -biodiversity at different restoration times were analyzed. The main conclusions are as follows:

- (1) The fusion of LiDAR and Worldview-2 satellite imagery can be used to predict mangrove α -biodiversity with SHDI;
- (2) Compared to other machine learning algorithms, GPR is better able to handle high-dimensional and small-sample datasets, achieving higher accuracy in SHDI prediction;
- (3) The mangrove area in the research area increased by 33.3% after 2018, indicating the effectiveness of local mangrove conservation and restoration policies;
- (4) Mangrove forests that have grown for a longer period of time have higher α -biodiversity based on SHDI, indicating that during the growth process of mangroves, the mangrove population exhibits more diverse characteristics as the growth time increases. In future restoration efforts, planting a wider variety of mangrove species will enhance the stability of the entire community.

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