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Case Study

Sentinel-2 satellite image application for establishing a coral reef distribution map in Bai Tu Long National Park, Quang Ninh Province, Vietnam

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Abstract

Coral reef ecosystems are crucial in coastal areas, providing valuable ecosystem services to humans. They are highly biodiverse and act as significant carbon sinks. Coral reef ecosystem conservation is a pressing issue for the world's most vulnerable ecosystems. Mapping coral reef ecosystems using satellite imagery enables informed decision-making for their restoration and protection, facilitating effective management strategies. With the help of machine-learning models and object-based image analysis (OBIA), this study constructed a map showing where coral reef ecosystems are found in Bai Tu Long National Park, Vietnam. The map was created using Sentinel-2 satellite images. The classification results revealed an overall accuracy (OA) of 91.70%, corresponding to a kappa coefficient of 0.89. The highest spectral reflection characteristic for coral reef ecosystems is in the blue spectral band and the lowest is in the SWIR2 spectral band. To understand the composition of these reefs, field surveys were conducted. The results of field surveys revealed that the coral reef ecosystem in Bai Tu Long National Park included nine families, 20 varieties and 32 species. Finally, this study has shown that a map of the distribution of coral reef ecosystems via satellite images and an object-based image analysis method combined with a machine-learning model is a valuable tool for the management and conservation of coral reef ecosystems. The

findings of this study play an important role in providing data for the restoration and conservation of coral reef ecosystems in coastal areas.

Keywords

coral reef, mapping, object-based image analysis method, Sentinel-2, wetlands ecosystem

Introduction

Coral reefs and wetland ecosystems are amongst the most valuable and biodiverse environments on Earth (Yap 2012, Sobha et al. 2023). They provide critical ecosystem services, including coastal protection, support for fisheries and carbon sequestration (Pascal et al. 2016, Barbier 2019, Hagger et al. 2022). However, these ecosystems are currently facing unprecedented threats from climate change, pollution and unsustainable human activities, resulting in widespread degradation and loss of biodiversity (Harvey et al. 2018, Livinus et al. 2025). To safeguard these vital resources and ensure their long-term sustainability, effective conservation and management strategies are urgently needed. Accurate mapping and monitoring of these ecosystems are essential first steps in developing and implementing such strategies (Levine and Feinholz 2015, Roelfsema et al. 2018).

Bai Tu Long National Park is located in Van Don District, Quang Ninh Province, northeast Vietnam, next to Ha Long Bay and has been a World Heritage Site since 1994 (Gawor et al. 2016). Bai Tu Long National Park is not only characterised by evergreen forests and mangrove ecosystems, typical of tropical islands, but also harbours diverse coral reefs, seagrass and tidal flat ecosystems (Sterling and Hurley 2008). These ecosystems support a variety of animal species that are valuable food sources, highlighting the Park's ecological significance (Gawor et al. 2016). The reef ecosystem here provides habitat for 68 species of reef fish, representing a typical subtropical fish fauna (Quan 2006). However, studies on wetland ecosystems, especially coral reef ecosystems in the Bai Tu Long Bay area, are still very limited in both the number and scale of related studies.

Coral reef ecosystems, often celebrated as 'tropical rainforests of the ocean' due to their exceptional biodiversity and economic importance (Shi et al. 2022), are vital coastal wetland habitats, predominantly located in tropical and subtropical marine environments. These ecosystems, found within China, primarily in the South China Sea as fringing reefs, barrier reefs and atolls (Shi et al. 2022), provide critical carbon sequestration services by accumulating carbon in the form of calcium carbonate skeletons and organic matter within their sediments (Keller 2011) and are culturally significant to indigenous populations (van Beukering et al. 2007, Gregg et al. 2015, Meng et al. 2024). Housing approximately 25% of global marine biodiversity, with an estimated 1–9 million species inhabiting (Reaka et al. 1997, Knowlton 2001) and supporting approximately one-third of all marine fish species (Shi et al. 2022), coral reefs function as key hotspots of marine life.

Nevertheless, coral reef ecosystems are facing escalating anthropogenic disturbances, including destructive fishing techniques, overexploitation, pollution from coastal development and climate change (Kleypas et al. 2011, Ateweberhan et al. 2013, Woodhead et al. 2019). This confluence of stressors has resulted in marked declines in coral cover and overall ecosystem health (Burt et al. 2020), underscoring the urgency of assessing the distribution and biodiversity of these vulnerable and ecologically significant environments for effective conservation management (Glynn et al. 2016).

Remote sensing and geographic information systems (GIS) have been used to study the current status and structure of wetland ecosystems for many years in many regions around the world, such as in the Mississippi River delta and Florida, United States of America (Butera 1983), the Ñeembucú Wetlands Complex in Paraguay (O'Leary 2022) and Europe (Schleupner 2010). Compared with measurement and field survey methods, remote sensing and GIS are modern tools that reduce time, effort and cost savings and detect changes in large wetlands (Ghosh et al. 2016). However, the application of remote sensing to study wetlands still faces significant challenges. The distribution of some wetland ecosystems varies, forming areas which may be smaller than the resolution of remote sensing images (Mishra et al. 2015). Flood areas affect spectral reflectivity, reduce the near-infrared (NIR) spectrum and shift the position of the red-edge spectral band, altering the effectiveness of some plant indices when these spectral channels are used (Kearney et al. 2009, Turpie 2013). Appropriate methods for classifying satellite images are necessary to address these difficulties.

Object-based image analysis (OBIA) is often used in coastal ecosystems, including coral reef ecosystems, to address the challenges of object classification during their classification and mapping (Wahidin et al. 2015). OBIA is a promising method for distinguishing wetland features (Moffett and Gorelick 2012). OBIA allows for the identification of object clusters that represent different surface overlays and object zones (Benz et al. 2004, Arbiol et al. 2006). The greatest advantage of the OBIA method is its ability to identify the characteristics of object types and adjacencies for analysis (Yu et al. 2008). While other methods, such as sorting by pixels, often suffer from spectral noise problems due to spatial heterogeneity and soil moisture, the OBIA method can solve these problems (Wright and Gallant 2007). In 2010, Costa and colleagues mapped Amazon floodplain communities via the OBIA Radarsat and JERS-1 radar spectral value segments (Costa et al. 2010). Gilmore and colleagues provided the first study of LiDAR data combined with optical imagery for wetland mapping via OBIA (Gilmore et al. 2008). In Honghu, China, Zhou and colleagues (2021) used the OBIA method combined with five machine-learning algorithms to classify wetland vegetation from drone images, achieving an overall accuracy of 89.76% (Zhou et al. 2021). In the wetland ecosystem of Dong Rui Commune, Vietnam, OBIA combined with the random forest algorithm has been used to establish wetland ecosystem maps from 1975 to 2022 (Ngo et al. 2023). In general, OBIA is an effective method for mapping wetland ecosystems, including coral reef ecosystems.

Combining OBIA with machine-learning techniques enhances mapping accuracy by leveraging the strengths of both approaches (Cechim Junior et al. 2023). OBIA utilises spatial information to delineate meaningful objects, while machine-learning algorithms automatically learn complex patterns from the data (Zhou et al. 2017, Abdi 2019). This synergistic approach has been shown to outperform traditional pixel-based methods in complex environments (Huang et al. 2020). While various machine-learning methods have been applied to support the establishment of mapping systems, including support vector machines and artificial neural networks (Liu et al. 2018, Jozdani et al. 2019), the Random Forest (RF) algorithm was chosen for other studies due to its high accuracy, ability to handle multidimensional data and ease of application (Zhang et al. 2017, Wu et al. 2022). The RF model has been evaluated for its ability to increase accuracy in the classification of objects from satellite imagery (Noroozi et al. 2024). RF is known for providing superior prediction accuracy and minimising the risk of model overfitting compared to other machine-learning algorithms, such as Support Vector Machines and Neural Networks (Rodriguez-Galiano et al. 2015, Sheykhmousa et al. 2020). Furthermore, the inherent ability of RF is to provide valuable insights into the spectral and spatial features that are most influential in distinguishing different wetland ecosystem types (Wang et al. 2019, Martínez-Santos et al. 2021). While other models can also provide feature importance measures, RF offers a relatively straightforward and readily interpretable approach (Aria et al. 2021).

Bai Tu Long National Park's valuable coral reef ecosystems are particularly vulnerable to climate change, pollution and overexploitation, underscoring the urgent need for effective conservation strategies. Mapping and assessing the distribution of these coral reef ecosystems is crucial for providing information for effective conservation efforts. This study addresses this challenge by combining OBIA and RF to enhance the accuracy of classifying wetland objects in satellite imagery. This novel approach, applied for the first time in Bai Tu Long National Park, allows for a more precise determination of the distribution and area of coral reef ecosystems, providing essential information for their effective management and protection. The objectives of this study are to: (1) develop an accurate and cost-effective method for mapping coral reef distribution in Bai Tu Long National Park using Sentinel-2 satellite images, OBIA and machine learning; and (2) assess the diversity of coral reef ecosystems in the Park based on the resulting map, providing a baseline for future monitoring and conservation efforts. The results help the people in charge of Bai Tu Long National Park determine how large and spread out the wetland ecosystems are in the Park's management area. The data on the size, distribution and diversity of wetland ecosystems help them devise plans to protect these ecosystems, which are both vulnerable and have great growth potential. Assessing the diversity of coral reef ecosystems is crucial because different coral species respond differently to environmental stressors. Understanding the distribution of these species is essential for developing targeted conservation strategies that protect the most vulnerable and promote overall ecosystem resilience.

Materials and methods

Study area

Bai Tu Long National Park is located in Bai Tu Long Bay, which is northwest of the Gulf of Tonkin, Vietnam (Fig. 1). Administratively, Bai Tu Long is located in the area of the Minh Chau and Van Yen Communes of Van Don District, Quang Ninh Province. Bai Tu Long Bay includes hundreds of large and small islands, the largest of which is Ba Mun Island and several other islands with large areas, such as Tau Nam and Tau Bac, which are part of Minh Chau Island (Hieu et al. 2018).

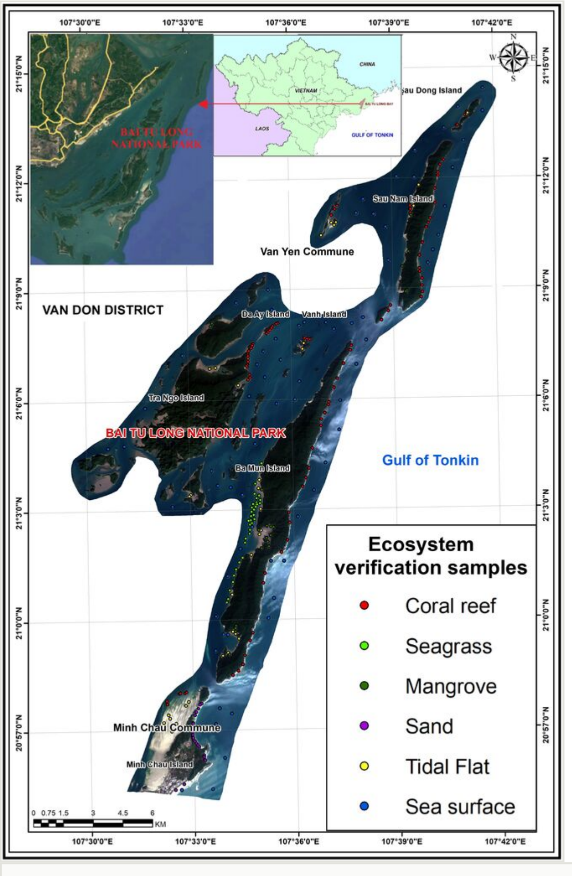

Figure 1.

Sentinel-2 satellite images (5 March 2024) and verification samples from the Bai Tu Long National Park area.

The climate of Bai Tu Long National Park is significantly shaped by several local factors, including ocean currents, tides and winds. The Bay experiences a subtropical monsoon climate, characterised by distinct seasonal variations. The average annual temperature is 22.8°C, with extremes ranging from 4.6°C (min) to 37.3°C (max). Rainfall is abundant, averaging 2400 mm annually, with the majority concentrated during the rainy season from May to October. Outside of this period, average rainfall decreased to approximately 200 mm. Humidity is also high, reaching 84% during the rainy season and decreasing to 70% in the drier winter months. In addition, heavy rainfall accompanied by storms from July to September can significantly affect the salinity of shallow waters. These climatic and hydrological factors combine to create a unique environment that influences local vegetation patterns, favouring the development of salt-tolerant species in coastal areas and shaping the distribution of various plant communities throughout the study area (Frontier Vietnam 2004a).

Bai Tu Long Bay supports a diverse array of ecosystems, contributing to its rich biodiversity. These include mangrove forests, which provide critical habitat for numerous species and protect the coastline from erosion; coral reefs, concentrated primarily along the coasts of Tra Ngo and Ba Mun Islands, particularly to the north of Tra Ngo Island (Frontier Vietnam 2004b); and pockets of rainforest ecosystems on some of the larger islands. While the coral reef ecosystems in this area exhibit relatively lower species diversity compared to other coral reef regions in Vietnam (Nguyen et al. 2022), they are characterised by a dominance of reef-building corals (primarily *Acropora* and *Porites* species) and a notable presence of soft-bodied corals.

Materials and methods

Research process

The research process is outlined in Fig. 2. A Sentinel-2 L2A image, with a spatial resolution of 10 m × 10 m, was selected to create a distribution map of wetland ecosystems within Bai Tu Long National Park. Following download, the satellite imagery underwent a series of processing steps, from image preprocessing to reflectance spectrum correction, before classification. A representative sample set of image interpretation keys was subsequently compiled to facilitate the classification of satellite images. The classification was then performed via an object-based image analysis (OBIA) approach, coupled with the random forest algorithm. For initial classification, 75% of the sample data were used, with the remaining 25% allocated for accuracy verification. The classification accuracy was assessed via an error matrix to determine both the overall accuracy and the kappa coefficient. If the overall accuracy exceeded 75%, the classification met the specified requirements and the map of wetland ecosystem distribution was then finalised. If the overall accuracy falls below 75%, reclassification is needed and an augmented classification sample is incorporated.

Selection and processing of satellite images

In this study, four Sentinel-2 images, taken on 5 March 2024, covering the Bai Tu Long Bay area, were used and the image parameters are shown in Table 1. Additionally, the images from 5 March 2024, were acquired during a period of relatively stable tidal conditions, which minimised potential variations in water levels that could affect the spectral signatures of intertidal habitats. The Sentinel-2 satellite images are stitched and spectrally normalised to serve the next image interpretation process.

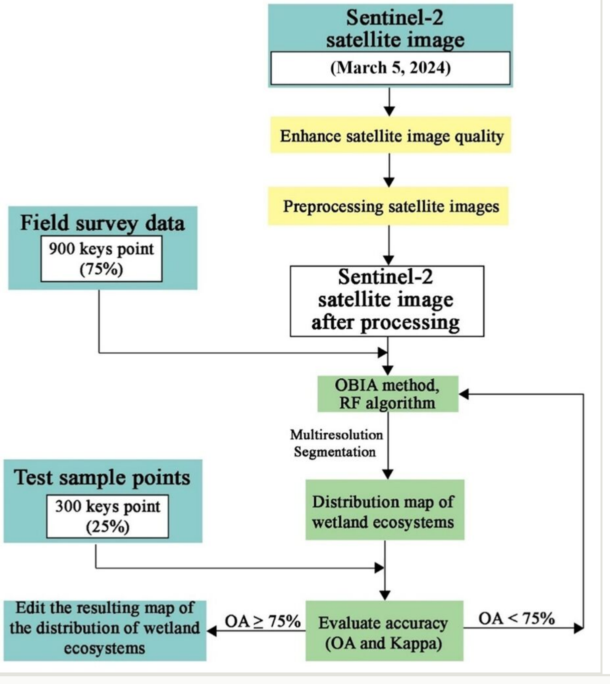

Figure 2.

Research process.

Table 1.

Sentinel-2 satellite image parameters.

№	Satellite image code	Resolution	Centre Wavelength (nm)
1	S2A_MSIL2A_20240305T031621_N0510_R118_T48QYH_20240305T073051	10 m x 10 m	Blue: 492.4 nm Green: 559.8 nm Red: 664.6 nm Near-Infrared: 832.8 nm SWIR1: 1373.5 nm SWIR2: 1613.7 nm
2	S2A_MSIL2A_20240305T031621_N0510_R118_T48QYJ_20240305T073051		
3	S2A_MSIL2A_20240305T031621_N0510_R118_T48QZH_20240305T073051		
4	S2A_MSIL2A_20240305T031621_N0510_R118_T48QZJ_20240305T073051		

Collect image classification keys

Classification keys were collected during scuba and snorkelling dives in April 2024. A stratified random sampling approach was used to select sample locations, ensuring representation of different habitat types and depth zones. At each location, a GPS unit was used to record the coordinates and underwater photographs were taken to document the substrate and benthic community composition. When a transect approach was used, sample points were collected every 50 metres along the transect line. Distances between transects varied from 50 to 100 metres, depending on the size and complexity of the habitat.

Before conducting the field survey, we utilised a combination of existing bathymetric charts, high-resolution satellite imagery from Google Earth and consultations with local fishermen and managers. This approach helped us to identify potential locations of coral reefs and seagrass beds. The information gathered was instrumental in guiding the selection of sampling sites, ensuring that we covered a representative range of habitat types.

The set of lock samples for classification and verification includes 1,200 sample points with the following objects:

1. coral reef (252 classification samples and 84 test samples);
2. seagrass (147 classification samples and 49 test samples);
3. tidal flat (99 classification samples and 33 test samples);
4. sand (114 classification samples and 38 test samples);
5. mangrove (78 classification samples and 26 test samples);
6. sea surface (210 classification samples and 70 test samples).

In April 2024, diving surveys were conducted at six locations within Bai Tu Long National Park to assess coral reef biodiversity. The sites were chosen, based on information from the Park's management board staff, who identified them as areas with known coral reef distribution. This selection process ensured that the surveys focused on locations that accurately represent the coral reef ecosystem within the Park, while also benefitting from the favourable weather conditions and water clarity typically found in April. Determining the diversity of coral reefs serves to determine the area providing coral seed sources for micro-fragment culture, according to the main objective of our project.

Coral reef species identification

To assess reef diversity, we identified coral species at each of the six dive sites. Coral identification was primarily performed in situ using the Reef Check method (English et al. 1997), which involves surveying coral populations along transects parallel to the shoreline. To maximise the assessment of species diversity, transects were established in both flat and slope reef areas. In situ identification was based on easily recognisable morphological features, live colouration and skeletal structure, guided by the taxonomic keys of Veron and Pichon (Veron and Pichon 1976). For species that could not be positively identified in the field, samples were collected for further analysis and preliminary identification. All coral species detected along the transects were recorded using digital photographs and video.

These data were then used to support laboratory analysis of species composition, based on skeletal morphology, following the taxonomic guidelines established by Veron and Pichon (Veron and Pichon 1976).

Classification of satellite images

We established a map of the distribution of wetland ecosystems in the Bai Tu Long National Park area by combining medium-resolution Sentinel-2 satellite images with field survey results. The sample test (300 samples) was used to verify the scene and evaluate the accuracy of the map after interpretation (Thinh and Hoa 2017). We prioritised the creation of a spatially representative validation set to ensure that our accuracy estimates reflected the real-world performance of the map across the entire Bai Tu Long National Park. To achieve this, validation samples were selected to cover the full range of environmental conditions and habitat types present in the study area. Furthermore, to minimise the potential for spatial autocorrelation to inflate our accuracy estimates, we maintained a minimum distance of 50 metres between any training and validation sample.

eCognition Developer v. 9.1 was used to make the map above. It splits an image into parts that are meaningful and closely related to the objects or real-world areas in it via the multi-resolution segmentation algorithm (Kavzoglu and Yildiz 2014). This algorithm combines areas in a bottom-up manner, beginning with single-pixel objects. Next, smaller image objects are merged into larger ones. When image objects are made, the basic optimisation process aims to keep the nh-weighted heterogeneity as low as possible. Here, n is the size of a segment and h quantifies the heterogeneity between image objects, guiding the merging process. The heterogeneity measure 'h' is utilised during the merging step of the multi-resolution segmentation algorithm. It is specifically calculated for each pair of adjacent image objects that are being considered for merging. The pair with the lowest 'h' value, which indicates the highest similarity, is merged, as long as the size of the resulting object does not exceed the specified scale parameter. Each step involves merging a pair of adjacent image objects. If the smallest growth exceeds the threshold determined by the scale parameter, the process stops (eCognition 2004).

In this study, the multi-resolution segmentation algorithm was configured with the following parameters: a scale parameter of 10, a shape parameter of 0.1 and a compactness parameter of 0.5. These values were chosen, based on a sensitivity analysis that tested scale parameters ranging from 5 to 20. The optimal combination was identified by visually assessing how accurately the algorithm represented the components of the wetland ecosystem, including coral reefs, seagrass beds and tidal flats. Additionally, overall classification accuracy was evaluated using a subset of field data. The shape and compactness parameters were further refined through visual inspection to ensure accurate boundary delineation, while minimising over-segmentation.

The heterogeneity *h* due to the deviation is described by the ratio between the actual border length *l* and the 2nd root of the number of pixels *n* that form this image, according to the formula (Karakış et al. 2006):

$$h = \frac{1}{\sqrt{n}}$$
(1)

To enhance segmentation and classification outcomes, we calculated the Vegetation Index before conducting object-based image analysis. In this process, we created and overlaid a layer of vegetation index information on to the satellite image. This approach aimed to improve the spectral differentiation of various components within wetland ecosystems. Studies in remote sensing image classification have demonstrated that the blue and green bands are especially sensitive to features in the marine environment (Nguyen et al. 2022).

To enhance the discrimination of different wetland ecosystem components, we calculated several spectral indices using the Sentinel-2 imagery. These indices are widely used in remote sensing studies to characterise vegetation and water properties (Gao 1996, Roy et al. 2006, Chen et al. 2020). The specific indices used in this study are described below:

Normalised Difference Vegetation Index (NDVI): Higher NDVI values indicate greater vegetation density and biomass. A measure of vegetation greenness, calculated as (Rouse et al. 1973):

$$NDVI = \frac{NIR - Red}{NIR + Red}$$
(2)

where NIR and Red are the reflectance values in the near-infrared and red spectral bands, respectively; higher NDVI values indicate greater vegetation density and biomass.

Soil-Adjusted Vegetation Index (SAVI): An improvement over NDVI that minimises the effects of soil background (Huete 1988):

$$SAVI = \frac{NIR - Red}{(NIR + Red + L) \times (1 + L)}$$
(3)

where L is a soil adjustment factor, typically set to 0.5.

Enhanced Vegetation Index (EVI): Another vegetation index that reduces atmospheric influences and is sensitive to canopy structural variations (Huete 1997):

$$EVI = G \times \frac{NIR - Red}{(NIR + C1 \times Red - C2 \times Blue + L)}$$
(4)

where L is a canopy background adjustment factor, C1 and C2 are coefficients that correct for atmospheric aerosol scattering and G is a gain factor.

Normalised Difference Built-up Index (NDBI): An index used to identify built-up areas (Zha et al. 2010):

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$
(5)

where SWIR1 is the reflectance value in the shortwave infrared spectral band.

Index-Based Built-Up Index (IBI): Further refines built-up area identification (Xu 2008), often in conjunction with NDBI:

$$IBI = \frac{SWIR1 \times Red}{NIR}$$
(6)

Normalised Difference Water Index (NDWI): An index used to delineate open water features and enhance their presence (McFeeters 2007):

$$NDWI = \frac{Green - NIR}{Green + NIR}$$
(7)

where Green is the reflectance value in the green spectral band.

Normalised Burn Ratio (NBR): An index used to identify burnt areas, but can also be useful in differentiating vegetation types and moisture (Roy et al. 2006):

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2}$$
(8)

In this study, we utilised NDBI and IBI to identify and mask any artificial structures, such as docks and seawalls, that might be present near the coral reef and wetland areas. This ensured that our analysis concentrated solely on natural features. Additionally, we employed NBR to differentiate between various types of vegetation, specifically distinguishing healthy seagrass beds from algae-dominated areas. This approach also helped to identify regions affected by coastal erosion or human disturbances that impact vegetation cover.

Random forest algorithm

There is a machine-learning technique called random forest (RF) that can be used for many tasks, such as regression and classification (Breiman 2001). It builds many decision trees during training and assigns each object to a category or predicts its mean (regression) (Genuer and Poggi 2020). The flexibility of RF algorithms provides excellent performance for classification problems (Kaya and Dengiz 2023). In this study, the RF algorithm was applied to improve the classification accuracy of wetland ecosystems in the Bai Tu Long National Park area.

In our implementation, spectral reflectance values were scaled (0-1) using min-max normalisation and missing values were imputed to the feature mean, a method chosen for its balance of computational efficiency and effectiveness given the dataset's characteristics. The hyperparameters were then optimised through a 5-fold cross-validation grid search to yield the following: 500 trees, a maximum tree depth of 10, sqrt(n_features) for the number of features considered at each node, a minimum sample split of 2 and a minimum sample leaf of 1. This configuration was found to provide a balance between accuracy and computational efficiency for our dataset.

Verification of accuracy

To assess the accuracy of the generated map, we calculated the Kappa coefficient (K) and constructed an error matrix (Congalton et al. 2019). The Kappa coefficient quantifies the agreement between the classification results and the verification data, accounting for the possibility of agreement occurring by chance (McGrath 2010). The error matrix provides a detailed breakdown of classification errors, with rows representing the actual classes and columns representing the predicted classes:

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} - x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} - x_{+i})}$$

(9)

In this context, the terms used in the Kappa coefficient calculation are defined as follows: 'r' is the number of rows (and columns) in the error matrix; 'Xii' represents the number of correctly classified pixels (i.e. pixels on the main diagonal); 'Xi+' is the total number of pixels in row i (representing the reference data for class i); 'X+i' is the total number of pixels in column i (representing the classified data for class i); and 'N' is the total number of pixels in the error matrix.

The K typically ranges from 0 to 1, with higher values indicating better agreement between the classification and the reference data. For interpretation, K values can be generally categorised as: high accuracy (K ≥ 0.8), moderate accuracy (0.4 ≤ K < 0.8) and low accuracy (K < 0.4) (Cohen 1960).

Results

Establishment of a map of the distribution of coral reef ecosystems in Bai Tu Long National Park

Accuracy assessment results

Table 2 presents the error matrix, which was generated using 25% of the image classification keys (300 samples) and provides a detailed assessment of the accuracy of the satellite image classification.

Table 2.

The matrix used to evaluate the accuracy of the satellite image classification results.

		Ground Reference						Total
		Seagrass	Coral reef	Tidal flat	Sand	Mangrove	Surface sea	
Classification	Seagrass	42	5				2	49
	Coral reef	3	78				3	84
	Tidal flat	3	1	26	2	1		33
	Sand	2			36			38
	Mangrove			1		25		26
	Surface sea		2				68	70
Total		50	86	27	38	26	73	300
User Accuracy (%)		84.00	90.70	96.30	94.74	96.15	93.15	92.51
Producer Accuracy (%)		85.71	92.86	78.79	94.74	96.15	97.14	90.90
Overall Accuracy (%)		91.70						
Kappa		0.89						

Accordingly, the overall accuracy of image classification (OA) reached 91.70%, corresponding to a kappa coefficient of 0.89 (high accuracy).

According to Table 2, the highest user accuracy belongs to the tidal flat subject, with a value of 96.30%, followed by the mangrove subject, with a value of 96.15%. The lowest user accuracy value was associated with seagrass (84%) when classified into coral reef (3/50 samples), tidal flat (3/50 samples) and sand (2/50 samples). To find coral reef objects, the user was correct 90.70% of the time. Amongst the 86 coral reef samples, five were seagrass objects, two were sea surface types and one was a tidal flat type.

For the producer accuracy value, the highest value belongs to the sand object, followed by the mangrove and sand types, with values of 97.14%, 96.15% and 94.74%, respectively. The lowest producer accuracy value was in the tidal flat area, with a value of only 78.79%.

Spectral reflex characteristics of objects

Overall, as shown in Fig. 3, the coral reef and seagrass objects with the greatest reflection spectral values are located in the blue band, whereas the tidal flat and sand objects are located in the NIR band. The common point amongst all four subjects is that the lowest reflection spectral values are located in the SWIR2 and SWIR1 spectral channels.

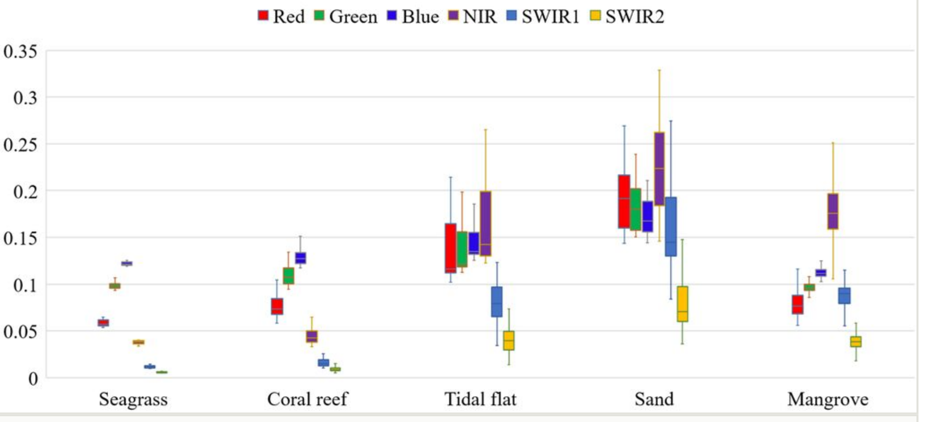

Figure 3.

Spectral reflectance characteristics of different wetland ecosystem components in Bai Tu Long National Park, derived from Sentinel-2 imagery. The box plots show the median, interquartile range and outliers for each component across six spectral bands.

Fig. 3 illustrates the spectral reflectance characteristics of four wetland ecosystem components across six spectral bands. While seagrass and coral reefs exhibit generally lower reflectance values compared to tidal flats and sand, distinct differences can be observed between these classes. Seagrass shows relatively higher reflectance in the green band compared to other bands, likely due to the presence of chlorophyll. Coral reef reflectance is highest in the blue spectral band, which is consistent with the spectral properties of clear water and the presence of photosynthetic pigments in zooxanthellae. In contrast, tidal flats and sand exhibit higher reflectance values in the red and NIR bands, which is characteristic of exposed sediments and vegetation. Notably, all four components show relatively low reflectance in the SWIR1 and SWIR2 bands, likely due to water absorption in these regions of the spectrum. These spectral signatures provide a basis for differentiating and mapping these wetland ecosystem components using remote sensing data.

Fig. 4 presents the distribution of various spectral indices for different wetland ecosystem components. As shown in Fig. 4, the average NDVI, SAVI and EVI indices of the tidal flat and sand objects are all greater than 0, ranging from 0-0.2. The mean values of the NDBI and IBI indices of the two tidal flat and sand objects are both less than 0, whereas the average values of the NDWI and NBR indices are both greater than 0, with the value points ranging from 0.1-0.7. Seagrass and coral reefs exhibit generally lower values for NDVI, SAVI and EVI compared to tidal flats and sand, indicating lower vegetation density and biomass. Notably, seagrass shows relatively higher values for NDWI and NBR, suggesting a greater water content and moisture levels. In contrast, coral reefs exhibit lower values for NDBI and IBI, which are associated with built-up areas, reflecting the absence of artificial structures. Tidal flats and sand generally show higher values for NDVI, SAVI and EVI, indicating a greater presence of vegetation or exposed sediments. However, the wide range of values observed for these classes suggests significant variability in their composition and environmental conditions. The NDWI and NBR indices show contrasting patterns, with tidal flat exhibiting lower values compared to sand, possibly due to differences in water content and sediment type.

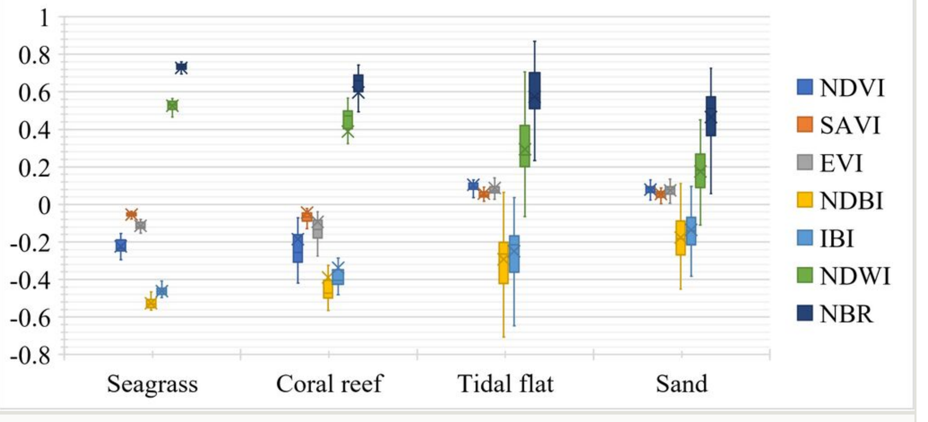

Figure 4.

Distribution of spectral indices for different wetland ecosystem components in Bai Tu Long National Park. The box plots show the median, interquartile range and outliers for each index.

Map of the distribution of wetland ecosystems

Fig. 5 shows the classification map of wetland ecosystems for the Bai Tu Long National Park area. It was created from the results of the classification of Sentinel-2 satellite images. The total area of coral reef ecosystems identified in this study is 81.53 hectares. While this area may not be large compared to other coral reefs in the region, it remains crucial for maintaining biodiversity and providing essential ecosystem services to Bai Tu Long National Park. As a result, at depths ranging from 1 to 5 m, coral reefs are concentrated at the islands' edges. The concentration of reefs on the island margins, between 1 and 5 m in depth, is primarily influenced by the availability of hard substrate, adequate light penetration and wave action. On the eastern side, which experiences strong and persistent wave energy, reefs tend to be elongated and narrow, with coral growth limited to more sheltered areas running parallel to the shoreline. This pattern reflects the sensitivity of many coral species to high wave energy, which can dislodge colonies and inhibit recruitment. The central and north-western areas of Bai Tu Long National Park, where the terrain is relatively flat and the seabed slope is low, feature highly diverse coral reefs. In particular, according to the survey results, the northern area of Tra Ngo Island has a relatively large coral reef area, with a high level of biodiversity and favourable conditions for the development of coral reefs.

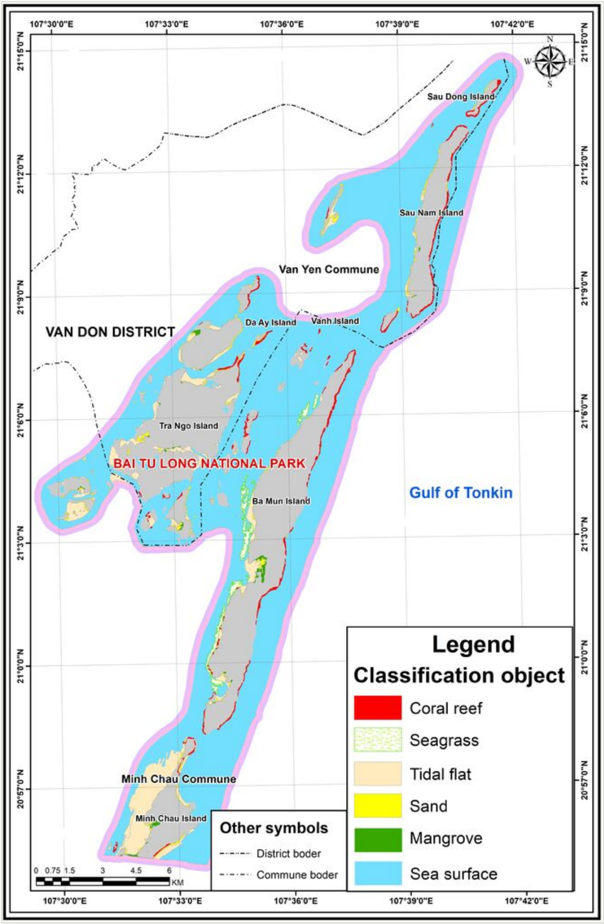

Figure 5.

Map of the distribution of wetland ecosystems in Bai Tu Long National Park.

In the Bai Tu Long National Park area, the seagrass ecosystem is concentrated west of Ba Mun Island. According to our survey results, the only species in the seagrass bed in this area is *Halophila ovalis*; however, the cover density is low, ranging from 3-5%. One of the outstanding ecosystems in the Bai Tu Long National Park area is the tidal and sandy beaches, which are distributed mostly on the Minh Chau, Ba Mun and Tra Ngo Islands. These ecosystems play important roles, as they constitute the habitat of many bivalve species with their abdominal legs. Management board reports from Bai Tu Long National Park have identified Minh Chau Island's intertidal zone as a key breeding ground for sea turtles (Chelonioidea).

Diversity of coral reef ecosystems in Bai Tu Long National Park

The results of this study indicate that the coral reef ecosystem is very diverse, with nine families, 20 varieties and 32 species (Table 3, Fig. 6). In particular, the Da Ay Island area recorded remarkable diversity in the region, with 21/32 coral species recorded here. The second most common coral reef diversity in the Bai Tu Long National Park area is the Vanh Island area, with 14/38 coral species recorded here. The northern area of Tra Ngo Island, which has the largest coral reef area amongst the survey diving areas, has recorded 11 out of 38 species. The south-eastern area of Ba Mun Island has the lowest level of coral diversity amongst the six study sites, with only eight out of 38 coral species recorded here. Waves strongly impact this area and the slope of the bottom surface is significant.

Table 3.

Composition of coral species recorded in the Bai Tu Long National Park area.

(Source: Research results of our team of authors 2024)

Coral name	North of Tra Ngo Island	Da Ay Island	Southwest of Ba Mun Island	Southeast of Ba Mun Island	Vanh Island	East of Ba Mun Island
Acroporidae						
Acropora aspera (Dana, 1846)						
Acropora microphthalma (Verrill, 1869)						1
Acropora sp		1				
Alveopora catalai (Wells, 1967)		1				
Alveopora fenestrata (Lamarck, 1816)	1	1				
Montipora sp.						
Lobophylliidae						
Echinophyllia echinoporoides (Veron and Pichon, 1980)	1	1	1	1	1	
Merulinidae						
Astraeosmilia maxima (Veron, Pichon & Wijsman-Best, 1977)	1					1
Dipsastraea maritima (Nemenzo, 1971)		1				

Coral name	North of Tra Ngo Island	Da Ay Island	Southwest of Ba Mun Island	Southeast of Ba Mun Island	Vanh Island	East of Ba Mun Island
Dipsastraea favus (Forskål, 1775)	1	1	1			1
Dipsastraea lizardensis (Veron, Pichon & Wijsman-Best, 1977)	1	1			1	
Goniastrea columella (Crossland, 1948)		1		1	1	
Goniastrea columella (Crossland, 1948)		1		1	1	
Merulina ampliate (Ellis và Solander, 1786)		1				
Orbicella annularis (Ellis and Solander, 1786)		1	1		1	1
Platygyra carnosus (Veron, 2000)	1		1		1	
Favites abdita (Ellis and Solander, 1786)		1			1	
Favites acuticollis (Ortmann, 1889)					1	1
Favites flexuosa (Dana, 1846)	1		1			1
Favites halicora (Ehrenberg, 1834)	1	1				
Favia sp.				1	1	1
Euphylliidae						
Euphyllia sp.		1				
Galaxea fascicularis (Linnaeus, 1767)	1	1	1		1	
Poritidae						
Goniopora djiboutiensis (Vaughan, 1907)		1	1			
Goniopora eclipsensis (Veron & Pichon, 1982)		1				1
Goniopora sp.	1		1	1		
Porites sp.		1		1	1	1
Leptastreidae						
Leptastrea bottae (Milne Edwards & Haime, 1849)				1	1	
Fungiidae						
Lithophyllon undulatum (Rehberg, 1892)	1					
Agariciidae						

Coral name	North of Tra Ngo Island	Da Ay Island	Southwest of Ba Mun Island	Southeast of Ba Mun Island	Vanh Island	East of Ba Mun Island
Pavona decussata (Dana, 1846)		1		1	1	1
Dendrophylliidae						
Turbinaria mesenterina (Lamarck, 1816)		1				
Turbinaria peltata (Esper, 1792)		1		1	1	
Total (9 families, 20 genera, 32 species)	**11**	**21**	**8**	**9**	**14**	**10**

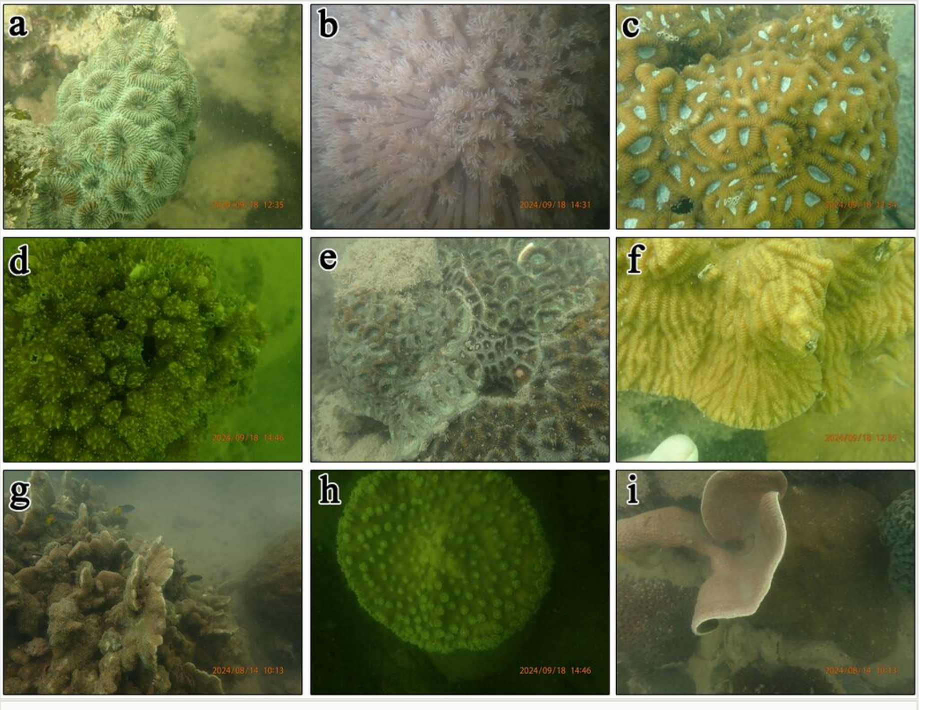

Figure 6.

Some coral species in the Bai Tu Long National Park area. **a** *Favita maritima* (Nemenzo1971); **b** *Alveopora catalai* (Wells, 1968); **c** *Favites abdita* (Ellis and Solander, 1786); **d** *Galaxea fascicularis* (Linnaeus, 1758); **e** *Goniastrea columella* (Crossland, 1948); **f** *Merulina ampliate* (Ellis và Solander, 1786); **g** *Pavona decussata* (Dana, 1846); **h** *Turbinaria patula* (Dana, 1846); **i** *Turbinaria mesenterina* (Lamarck, 1816).

Bai Tu Long National Park has less favourable natural conditions for coral development; this area also has a shallow seabed and a large amount of mud running close to the foot of the Island, so it has limited the growth of corals to depth. In the areas of Da Ay Island, Ba Mun Island, Sau Nam Island and Minh Chau Island, the coral distribution is both short and narrow and it is distributed only to depths of 7–9 m. In particular, Ba Mun Island and Sau Nam have high clarity in the east of the water, which is favourable for coral development, but much of the seafloor is quite steep and below the reef base is bedding; this factor may have limited the depth distribution of the corals. The coral coverage in the Bai Tu Long National Park area ranges from 25% to 70%; of this, on Da Ay Island, it is approximately 60–70%, the highest amongst the research sites.

Discussion

Global coral reefs face serious threats from climate change and human activities, including heat waves at sea and overfishing associated with coral reefs (Wang 2024, Wang et al. 2024). The severe decline of coral reef ecosystems around the globe has led to international commitments towards the conservation and restoration of some of the most important ecosystems (Tuwo and Tresnati 2021, Camp et al. 2024, Komala et al. 2024). This study demonstrates the effective use of Sentinel-2 imagery, OBIA and the RF machine-learning algorithm for mapping wetland ecosystems, including coral reefs, in Bai Tu Long National Park, Vietnam. Our findings align with those of previous research (Nguyen et al. 2022). The map we created serves as a valuable baseline for monitoring changes in these ecosystems and providing information for conservation efforts, particularly in identifying priority areas for protection. While we acknowledge limitations, such as the use of single-date imagery and spatial resolution constraints, future research should emphasise time-series analysis, the incorporation of higher-resolution data and field validation. These steps will help refine mapping accuracy and enhance the evaluation of conservation strategies.

Satellite image classification is an effective approach for mapping and monitoring coral reefs and wetland ecosystems, as demonstrated in this study. This technique provides comprehensive and cost-effective data over large areas, enabling efficient assessment of these valuable resources (Ampou et al. 2024, Zhong et al. 2024). The high overall accuracy achieved in our classification — 91.70% — confirms the suitability of the OBIA method combined with machine learning for this task. This finding is consistent with research conducted on Lemukutan Island in the Smart Island project (Zibar et al. 2025). We observed a 15-20% improvement in accuracy compared to pixel-based methods, which aligns with observations from previous studies (Zhou et al. 2018, Akhlaq and Winarso 2020, Butler et al. 2020). This improvement can be attributed to OBIA's ability to consider spatial context and reduce spectral variability within objects.

The careful selection of spectral bands was crucial for optimising image quality and classification accuracy. Specifically, the blue band was important for depth penetration (Kovacs et al. 2018), while the SWIR band was vital for cloud removal (Ipia et al. 2020, Segal Rozenhaimer et al. 2020). The significance of the blue band in the spectral signatures of coral reefs and seagrass further underscores its importance for mapping these habitats in our study area. Additionally, the successful integration of OBIA with RF algorithms contributed to the enhanced accuracy, as RF is known for its ability to handle complex datasets and minimise overfitting (Belgiu and Drăguț 2016). These results demonstrate the potential of remote sensing and machine learning for delivering valuable information that can aid in the management and conservation of coastal ecosystems.

Bai Tu Long National Park is home to nine families, twenty genera and thirty-two species of coral. However, this diversity is lower compared to equatorial regions like Bawean Island in Indonesia (Luthfi et al. 2024), Kota Kinabalu and the west coast of Sabah (Akmal et al. 2024). This difference may be attributed to Bai Tu Long's higher latitude, which leads to lower average water temperatures and greater seasonal temperature fluctuations, potentially limiting the number of coral species that can thrive. Additionally, the area experiences significant damage to its coral reef structure due to frequent storms and tropical depressions. Despite this, coral diversity in Bai Tu Long is notably higher than in other Vietnamese islands at a similar latitude, such as Co To Island and Bach Long Vi Island. This can likely be explained by the fact that Bai Tu Long is better protected from human impacts compared to these other islands.

This study successfully demonstrated a method for mapping and assessing coral reef ecosystems in Bai Tu Long National Park using Sentinel-2 imagery, the OBIA method and machine learning. The resulting maps provide a valuable database for future monitoring and conservation efforts related to coral reefs and other wetland ecosystems. However, the use of a single day of photography limits the ability to assess temporal changes in coral reef distribution. In addition, the relatively coarse spatial resolution of Sentinel-2 data may limit the accuracy of mapping in areas with complex reef structures compared to high-resolution satellite imagery, such as SPOT-6 (Siregar et al. 2020) or RapidEye (Coffer et al. 2020).

Our study highlights the importance of combining satellite mapping with field biodiversity assessments to provide information for effective coral reef conservation and restoration strategies. The resulting maps provide spatial information to understand the distribution of coral communities, while field surveys provide critical information on species composition, abundance and health. This integrated approach allows us to identify priority areas for protection and select appropriate species for restoration efforts. For instance, we discovered that Da Ay Island has both high coral cover and species diversity, making it a key priority for protection. The high coral cover and species diversity observed at Da Ay Island likely result from a combination of interacting factors. The Island's sheltered location, with its relatively flat seabed, optimal light penetration and low wave energy, creates favourable conditions for coral growth and survival. Especially, the area benefits from relatively low levels of human impact compared to other locations in Bai Tu Long National Park. These combined factors create an environment conducive to coral growth, survival and regeneration, ultimately contributing to the high biodiversity observed. This information can be utilised to develop targeted conservation strategies aimed at safeguarding the most vulnerable species and habitats in the Bai Tu Long National Park region.

To address these limitations, future research should focus on incorporating time series data, using higher resolution imagery (such as satellite imagery from drones or

WorldView) (Kabiri et al. 2018, Kabiri et al. 2020) and validating the results with field surveys. Furthermore, further research is needed to assess the impacts of factors affecting coral reef ecosystems, such as climate change and pollution, in Bai Tu Long National Park. At the same time, effective management strategies need to be developed to mitigate these threats. By addressing these knowledge gaps, we can improve our understanding of these valuable ecosystems and improve their long-term conservation.

Conclusion

We mapped the locations of coral reef ecosystems and other wetland ecosystems in Bai Tu Long National Park. This map uses both satellite image object classification methods and machine learning. This approach can be applied to northern coastal areas and other shallow waters. The results clarify the distribution, composition and diversity of coral reef ecosystems in the study area. With an overall accuracy of 91.70% and a Kappa coefficient = 0.89, this approach can achieve superior results in remote sensing when assessing the distribution of coral reefs. The identification of nine families, 20 varieties and 32 coral species revealed a high level of diversity in the coral reef ecosystem in Bai Tu Long National Park. The Da Ay Island area presented the highest level of diversity, with 18 out of 32 coral species recorded here.

The results point to the possibility of remote sensing image applications and object classification methods combined with machine learning to establish map distributions of coral reefs in shallow marine areas. In the future, with the development of remote sensing technology, higher satellite image resolution will yield more accurate results in the establishment of distribution maps of coral reef ecosystems as well as other wetland ecosystems.

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Author contributions

Conceptualisation: D.T.N.; Methodology: D.T.N.; Formal analysis and investigation: G.V.P., H.D.N and D.T.T.H.; Writing - original draft preparation: D.T.N. and G.V.P.; Writing - review and editing: D.T.N. and D.T.T.H.; Supervision: D.T.N. and H.D.N.

Conflicts of interest

The authors have declared that no competing interests exist.

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