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Integration of Marine Spatial Planning, Remote Sensing and IoT Data for Adaptive Biodiversity Conservation in Shallow Water Ecosystems: A Case Study of the Tidung Islands, Indonesia

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Abstract

Coastal biodiversity conservation is challenged by fragmented datasets and the limited integration of environmental conditions into marine spatial planning (MSP). This study develops an operationalized adaptive Marine Spatial Planning (MSP) to support biodiversity conservation by linking remote sensing data, IoT-based water quality measurements, and spatial optimization within Spatial Decision Support System (SDSS). The Tidung Islands are used as a case study, where benthic habitats are mapped from 3 m PlanetScope imagery. Water quality observations are processed into the Nemerow Pollution Index (NPI) and subsequently interpolated through an ensemble approach that combines inverse distance weighting, random forest, and gradient boosting. A key innovation of this study is the incorporation of the Nemerow Pollution Index (NPI) as a dynamic environmental cost layer within Marxan-based conservation prioritization. These data were incorporated alongside anthropogenic pressures to evaluate multiple conservation scenarios The ensemble interpolation demonstrated strong predictive performance (R^2=0.76;MAE=0.0306), enabling reliable spatial representation of environmental conditions. The results show that integrating environmental quality into MSP significantly improves spatial efficiency, reduces fragmentation, and enhances ecological representation compared to conventional approaches based on static variables. Moderate conservation targets (≈30%) produced the most optimal solutions (~2,200 cost; ~11 km boundary), while more ambitious targets resulted in fragmented and inefficient spatial configurations. The proposed framework offers a transferable approach for data-limited coastal regions, contributing to the advancement of adaptive biodiversity conservation strategies.

Keywords: marine spatial planning; remote sensing; marxan; nemerow pollution index; benthic habitat; adaptive biodiversity conservation

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1. Introduction

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Biodiversity plays a critical role sustaining ecosystem services and supporting human well-being and promote environmental sustainability. However global biodiversity is in rapid decline, with significant losses observed across marine ecosystems by 73% in the last 50 years [1,2]. Coastal and shallow marine environments in South Asia, including Indonesia, is particularly vulnerable due to increasing anthropogenic pressures, including pollution, overexploitation, and climate change [3]. Indonesia is the world's largest archipelagic country, around 62% of Indonesia's territory is sea, faces similar challenges [4–7]. The Indonesian sea is part of the Coral Triangle, boasting a marine wealth of more than 76% of the world's coral reef species and habitat for 3000 fish species and 6 of the seven turtle species in the world [8,9]. In response to these challenges, marine spatial planning (MSP) has emerged as a key approach to balance conservation and sustainable resource use by organizing human activities within marine spaces in a systematic and adaptive manner.

One of the critical areas in Indonesia, characterized by a shallow marine ecosystem rich in biodiversity is the Seribu Islands, particularly Tidung Island [10,11]. This area comprises a cluster of small islands, mangroves, seagrass beds, and coral reefs that are vulnerable to degradation due to anthropogenic activities such as pollution, overfishing, and land conversion [12–14]. In addition, the waters of Tidung Island have an average overall seagrass coverage 30.4% [15]. Therefore, an adaptive conservation approach based on multisource data are important to conserve biodiversity and achieve a balance between human activities and coastal ecosystem.

Despite its growing adoption, the effectiveness of MSP is often constrained by limited data integration and the reliance on static environmental variables. Many existing MSP frameworks primarily utilize habitat distribution or species occurrence data, while overlooking dynamic environmental conditions such as water quality, which directly influence ecosystem health and conservation outcomes [16]. In addition, the lack of real-time monitoring and integration of multi-source data reduces the ability of MSP to respond adaptively environmental conditions change [17].

To support sustainable conservation and management, a data-driven scientific approach, such as remote sensing, is necessary to accurately monitor biodiversity conditions [18–21]. Remote sensing has proven effective in mapping marine ecosystems, such as coral reefs and seagrass beds, as shown by research by [22], which showed high accuracy (93.4%) using SPOT 6 and the Object-Based Image Analysis (OBIA) approach. [22] found that remote sensing can map plankton and environmental parameters such as sea temperature (accuracy>90%) and chlorophyll-a (accuracy 75-85%), as well as detect individual species (<50%).

Recent advances in remote sensing, Internet of Things (IoT) technologies, and spatial optimization tools provide new opportunities to enhance MSP processes. The utilization of 3-m PlanetScope imagery provides a significant advantage over 10-m Sentinel-2 data in detecting micro-scale habitat patches and benthic heterogeneity, which is critical for precise conservation planning in small island ecosystems [23], while IoT-based sensors allow continuous monitoring of water quality parameters. Furthermore, spatial optimization tools such as Marxan support scenario-based planning by balancing ecological targets, spatial efficiency, and socio-economic constraints. However, the integration of these technologies into a unified MSP framework remains limited.

Marine Protected Areas (MPAs) are the main conservation areas that usually have specific protection regulations [24–26]. However, not all areas with conservation value are officially designates as conservation areas. Therefore, the concept of Other Effective Area-Based Conservation Measures (OECM) emerged, which is recognized by the Convention on Biological Diversity (CBD) in Aichi Biodiversity Target 11 .[5,26–28]. Marxan analyzes various conservation scenarios and optimizes area selection based on conservation costs, biodiversity, and the impact of human activitie [29–31].

The integration of MSP and remote sensing data remains a significant area for development in the context of marine biodiversity monitoring. Decision support systems (DSS) can enhance the analysis and interpretation of remote sensing data by integrating multiple data sources, spatial modeling, and automated analytics to support the decision-making process. In addition, integrating the Internet of Things (IoT) in DSS enables analysis with real-time data, which can improve the

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accuracy of spatial analysis. The real-time data collected are seawater quality parameters, which are then processed into a seawater quality index using the Nemerow Pollution Index method, also adapted by the Indonesian Ministry of Environment [32–34].

This study advances marine spatial planning by developing an integrated framework that combines remote sensing, IoT-based environmental monitoring, and spatial optimization within a Spatial Decision Support System (SDSS). Using the Tidung Islands as a case study, it aims to: (1) develop a high-resolution remote sensing approach for monitoring shallow marine ecosystems; and (2) design an adaptive MSP framework that integrates environmental quality and anthropogenic pressures into biodiversity conservation prioritization using Marxan.

In terms of science, this study contributes to the MSP literature in three key novelties. First its integration of high-resolution remote sensing and IoT based real time water quality monitoring into spatial planning processes. Second it introduces the use of the Nemerow Pollution Index (NPI) as a dynamic environmental cost layer in conservation biodiversity prioritization. Third it operationalizes these frameworks within a SDSS to support evidence-based on adaptive decision making.

2. Materials and Methods

2.1. Study Area

The study area is located in Tidung Island, within Thousand Islands, Jakarta, Indonesia**.** The thousand islands are a group of 110 islands located north of Jakarta, Indonesia, with an area of 8.69 km² [35]. This study focuses on Tidung Island, one of the main islands in the Thousand Islands group, consisting of Tidung Besar (50.13 ha) and Tidung Kecil (14.45 ha) [36,37] (Figure 1). This island serves as the economic center based on tourism and fisheries, with Tidung Besar as a residential area and Tidung Kecil as a conservation area [38]. Tidung Besar Island is inhabited by approximately 4,000 residents, with the primary economic sectors based on tourism and fisheries. Since developing as a marine tourism destination in 2010, the number of tourists has increased to 65,258 people in 2024, which has encouraged the growth of various local businesses [35,39].

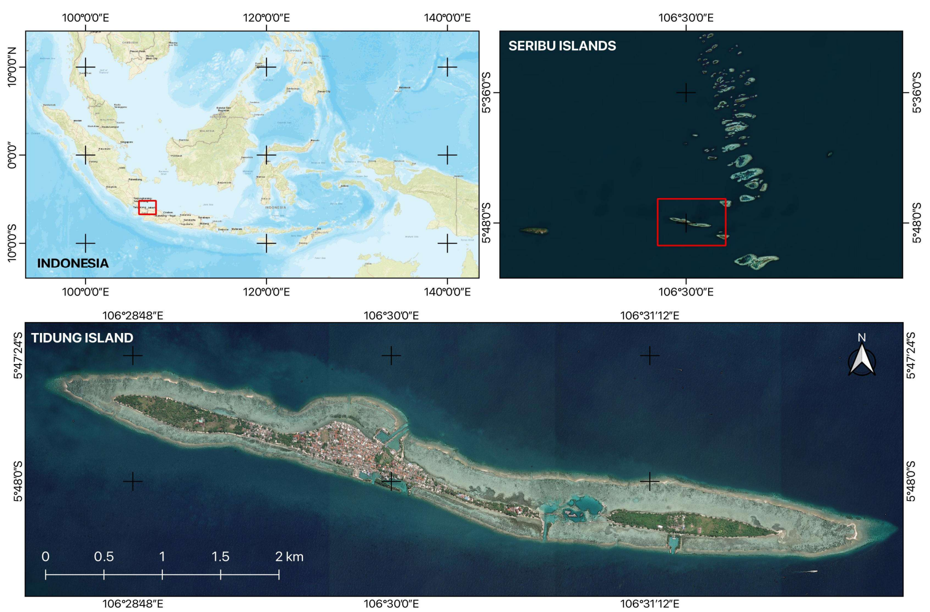

Figure 1. The study area is located in Tidung Island, within the Thousand Islands, Jakarta, Indonesia.

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Tidung Island is also recognized as a biodiversity hotspot, primarily due to its diverse coral reef ecosystem, seagrass beds, and surrounding mangroves. The coral reefs around Tidung Island are home to 16 genera from the Scleractinia family, which serves as habitats for reef fish such as Paracanthurus hepatus (botana fish) and Amphiprion ocellaris (clown fish) [40]. In addition, the crustacean biota associated with coral reefs is also very diverse, with more than 41 species of crabs from 13 families found in the waters of Tidung Island [37]. The seagrass surrounding the island sustains diverse types of fish and mollusks, serving as a crucial home for the increasingly endangered Dugong dugon (duyung) [36]. The mangrove ecosystem of Tidung Kecil Island serves as a habitat for diverse migrating shorebirds, including Tringa totanus (plover) and Egretta garzetta (little egret), along with juvenile fish species that utilize the mangrove roots for cover [36].

The growing tourism industry has increased individual incomes while simultaneously harming on coastal ecosystems [37]. Uncontrolled snorkeling activities harm coral reefs, resulting in coral mortality rates of 46.15% due to physical contact with tourists, ship anchors, and sedimentation from coastal operations. The rising influx of tourists contributes to the accumulation of plastic debris, with microplastic concentrations in coral reef sediments varying from 60 to 340 particles per kilogram of dry weight [38]. The growth of urbanization and the expansion of the tourism industry lead to unregulated alterations in land use [41]. This condition has led to a decline in green space and increased vulnerability to coastal abrasion, as the loss of natural vegetation reduces the coastline's capacity to buffer wave energy. Tidung Island is also exposed to climate change impacts, including rising sea surface temperatures that trigger coral bleaching and sea-level rise that elevates the risk of tidal flooding, posing a threat to coastal infrastructure and local communities

2.2. Methodology

This research is based on empirical data collected from multiple sources, including high-resolution satellite imagery and IoT-based sensors used to measure water quality. These datasets are brought together within a unified framework that integrates remote sensing, spatial analysis, and conservation modelling. This methodology consists of several stages, including identifying the study area, specifically Tidung Island, Jakarta, Indonesia (Figure 2); pre-processing of satellite imagery and benthic classification for marine biodiversity has been done from previous research [18] ; and monitoring water quality in real-time using IoT sensors. The Nemerow Pollution Index (NPI) calculates the seawater quality index. Potential sites for adaptive conservation zone by utilizing the Marxan algorithm for spatial modeling. Finally, the validation and testing process adopts a continual improvement approach.

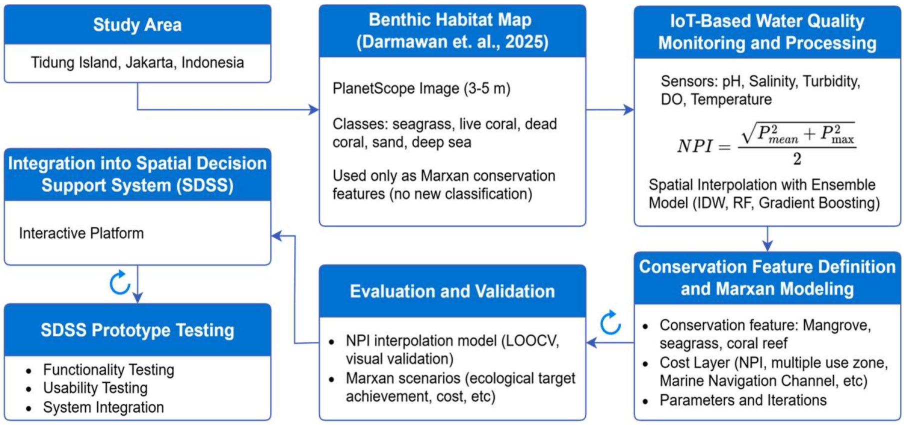


Figure 2. Research methodology.

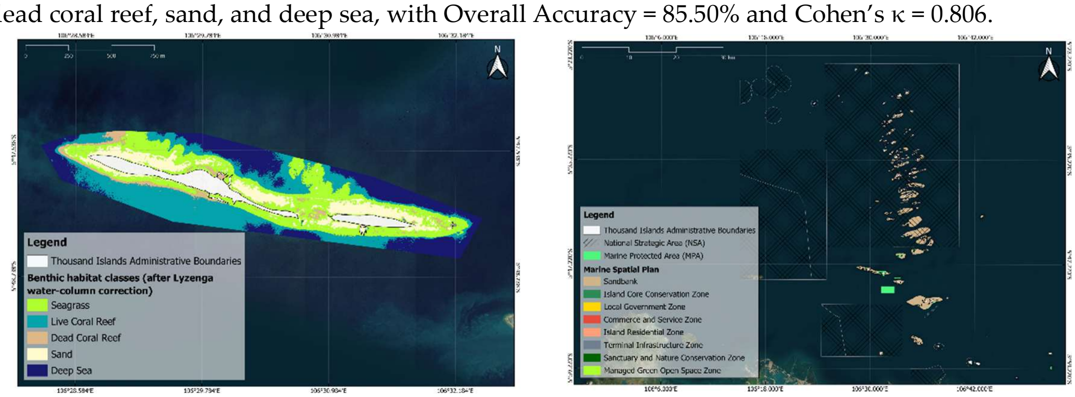
2.2.1. Data Sources

This study utilizes a combination of primary and secondary data. The utilized data sources comprise benthic habitat map data, marine thematic data, base maps, and environmental data obtained from in situ monitoring. Table 1 presents the primary and secondary data collected, including data formats, sources, and the years of acquisition.

Table 1. Geospatial and Environmental Data Sources.

No.	Data Type	Format	Data Provider	Year
1	Benthic habitat map around Tidung Island	GeoTIFF	BRIN – Research Center for Geoinformatics (Darmawan et al., 2025)	2024
2	Jakarta Marine Spatial Planning (including Marine Protected Area (MPA))	Shapefile (.shp)	Jakarta Regional Development Planning Agency	2023
3	1:1000-Scale Base Map of Jakarta (administrative boundaries, coastline, mangrove forest)	Shapefile (.shp)	Jakarta Provincial Office of Human Settlements, Spatial Planning, and Land Affairs	2022
4	Marine water quality parameters (pH, DO, salinity, temperature, turbidity)	CSV	Local IoT sensors installed by the research team	2024
5	Zoning and Conservation Area Data from SDSS Platform (Marxan output)	Shapefile	Internal modeling output using Marxan	2024

This research used the 3-m PlanetScope benthic habitat map of Tidung Island (Figure 3a). It was initially produced using a Lyzenga depth-invariant (water-column) correction, followed by supervised classification into five classes from previous research by [18]: seagrass, live coral reef, dead coral reef, sand, and deep sea, with Overall Accuracy = 85.50% and Cohen's $\kappa = 0.806$.



(a) (b)

Figure 3. Secondary data used in research: (a) Benthic habitat map around Tidung Island, (b) the Seribu Islands marine spatial planning.

This study incorporates marine spatial data from DKI Jakarta Province along with satellite data. The data encompasses the delineation of marine conservation areas, specifically Marine Protected Areas (MPAs), from the provincial government (Figure 3b). This data elucidates the context of marine zoning policies and plans that have been implemented, serving as the primary reference in the conservation-oriented spatial planning process. The study utilizes the base maps, which consist of coastlines, administrative boundaries, basic infrastructure, and mangrove vegetation, sourced from the Jakarta Provincial Office of Human Settlements, Spatial Planning, and Land Affairs. This data facilitates the identification of coastal transition zones to ascertain conservation features.

This study uses water quality parameters, pH, temperature, Total Dissolved Solids (TDS), dissolved oxygen (DO), turbidity, and salinity, collected via Internet of Things (IoT)-based monitoring tools. These parameters are used to compute the shallow sea water quality index based on the Nemerow Pollution Index (NPI).

2.2.2. Water Quality Assessment Using the Nemerow Pollution Index (NPI)

The Nemerow Pollution Index (NPI) method is used to assess water quality. The NPI approach is a comprehensive method to determine the level of pollution in coastal water environments, including coastal waters [33]. This method integrates the average and maximum values of the pollutant parameter ratio to the quality standard value, so that it can show the overall coastal water quality conditions and the potential for extreme pollution at a particular observation point with a more comprehensive representation [42]. This approach is similarly employed in the evaluation of water quality in Indonesia, as evidenced by the Minister of Environment and Forestry of the Republic of Indonesia's Regulation Number 27 of 2021 regarding the Environmental Quality Index.

The first step in calculating the NPI is to determine the pollution ratio for each water quality parameter (P_i) [43]. The calculation of each parameter is based on the comparison between the actual concentration (C_i) and the threshold value according to environmental quality standards (S_i). This study derived its parameters from sensors based on the Internet of Things (IoT), specifically pH, dissolved oxygen (DO), turbidity, salinity, and temperature. Each parameter was evaluated against the corresponding standard quality value as outlined in the national seawater quality standard, specifically the Decree of the Environment State Minister Number 51 of 2004 regarding Sea Water Quality Standards. Upon calculating all pollution ratios, two primary statistical values were determined: the mean value of P_i and the maximum value of P_{max} for all pollutant parameter ratios. Additionally, both values were incorporated into the final formula for calculating the Nemerow index (NPI) [33,34,43].

$$P_i = \frac{C_i}{S_i}, P_{mean} = \frac{1}{n}\sum_{i=1}^{n} P_i \text{ and } P_{max} = max(P_1, P_2, \dots, P_n) \quad (2.1)$$

$$NPI = \sqrt{\frac{{P_{mean}}^2 + {P_{max}}^2}{2}} \quad (2.2)$$

The index values are classified into four quality categories: good, slightly polluted, fairly polluted, and heavily polluted (Table 2). The water quality classification is based on national quality standards as outlined in the Regulation of the Minister of Environment and Forestry of the Republic of Indonesia Number 27 of 2021 [34].

Table 2. Classification of seawater quality standards according to the *NPI value.*

NPI Value	Water Quality Category
NPI ≤ 1.0	Meets water quality standards (Good)
1.0 < NPI ≤ 5.0	Slightly polluted
5.0 < NPI ≤ 10.0	Fairly polluted
NPI > 10.0	Heavily polluted

(Source: Regulation of the Minister of Environment and Forestry of the Republic of Indonesia Number 27 of 2021).

The NPI results for each observation point are subsequently interpolated utilizing inverse distance weighting (IDW), random forest, and gradient boosting ensemble methods. This ensemble method is a sophisticated spatial interpolation technique that integrates distance weighting from IDW with the non-linear regression capabilities of machine learning algorithms to enhance estimation accuracy. The IDW method is a deterministic interpolation technique that posits a diminishing influence of a data point on an unmeasured location as the distance increases [44–46]. The primary

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function of Random Forest is to identify non-linear relationships between spatial predictor variables and NPI values, while also minimizing model variance by aggregating numerous weak estimators [47,48]. Gradient boosting primarily aims to enhance prediction accuracy by concentrating training efforts on challenging data points. Gradient boosting effectively captures nuanced patterns and intricate interactions among spatial variables [48]. Gradient boosting is well suited to capturing subtle patterns and complex interactions among spatial variables [45]. When combined with random forest in an ensemble framework, it enhances the model's ability to represent non-linear relationships between pollutants and hydrodynamic factors. While, inverse distance weighting (IDW) preserves retain local spatial structure [49].

In this study, Leave-One-Out Cross-Validation (LOOCV) was used to validate the performance of the ensemble interpolation model, which integrates three approaches: inverse distance weighting (IDW), random forest regression, and gradient boosting regression. Predictions from each method were averaged to estimate NPI values at each validation point. Model performance was evaluated using five statistical metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), and Median Absolute Error (MedAE).

2.2.3. Adaptive Biodiversity Conservation Model Using Marxan Algorithm

Conservation area modeling in this study was carried out using the Marxan framework. This approach applies a heuristic optimization method to support systematic conservation planning by identifying priority areas efficiently [50,51]. Marxan allocates space to meet predefined conservation targets for specific ecosystems or species, while accounting for cost, feature representation, and spatial connectivity among selected areas. Calibration of the Boundary Length Modifier (BLM) plays an important role in reducing spatial fragmentation, helping to produce more compact conservation configurations with lower boundary-to-area ratios and minimizing potential conflicts with marine navigation routes [52].

The study area was divided into a set of planning units [52,53]. These units can be defined using different spatial geometries, such as rectangular grids, hexagons, or irregular polygons, depending on spatial resolution requirements, coastline complexity, and data availability. The size of each unit can be adjusted to reflect the ecological scale of the conservation features or the operational scale of management. Both the shape and size of planning units are important, as they influence model complexity, spatial outputs, and the interpretation of conservation priorities.

Each planning unit is associated with information on conservation costs and features that reflect its contribution to conservation targets[51,54].

Costs may represent various factors, including economic value of land, intensity of human activities, habitat condition, or other proxies of environmental pressure. Conservation features considered in the model include key habitats such as mangroves, coral reefs, and seagrasses, as well as biodiversity indicators, ecosystem service values, and other relevant biophysical variables. These data are typically organized in a planning unit–feature matrix (e.g., *puvspr.dat*), which defines the relationship between each unit and the conservation features it contains.

The four scenarios were established based on international policy references, national regulations, and scientific conservation literature. Each scenario is explained below:

Scenario 1 (global baseline) has a conservation objective of 30% for all attributes. This ratio pertains to Aichi Biodiversity Target 11 and is emphasized in the Kunming-Montreal Global Biodiversity Framework, which advocates for the conservation of 30% of terrestrial and marine regions by 2030 (CBD, 2018; Donald, Buchanan, Balmford, Bingham, Couturier, de la Rosa, et al., 2019; Pusparini et al., 2023).

Scenario 2 (ecological maximum) establishes a target of 100% for all features, embodying a maximal conservation strategy grounded in the ecological persistence principle articulated by [57], alongside the comprehensive protection concept advocated in the Marine Ecoregions of the World (MEOW) [58].

Scenario 3 (representative proportions) pertains to conservation values derived from ecosystem services and the capacity for local pressure absorption. The objectives of 35% for corals, 25% for seagrasses, and 40% for mangroves pertain to international agreements and blue carbon conservation strategies that advocate for enhanced safeguarding of tropical coastal flora [59–61].

Scenario 4 (adaptive ambitious) employs substantial proportions (coral 40%, seagrass 30%, mangrove 50%) as a long-term ecological risk-based strategy, using the concepts of adaptive conservation to address climate change and anthropogenic pressures [62,63].

Marxan enables planners to establish conservation targets in various formats [64]. The selection of target types is aligned with planning objectives, data availability, and the capacity to measure and monitor success. Proportional targets (prop) refer to a specified proportion of the overall distribution of features that must be addressed by the conservation solution. The numerical target refers to the quantity of planning units or the specific area that requires conservation. Targets based on existence refer to the minimum number of planning units that must be selected to encompass a specific feature.

Additional critical parameters to consider include the Species Penalty Factor (SPF) and the Boundary Length Modifier (BLM). The SPF parameter represents the penalty weight applied when the target is not met [64,65]. SPF regulates the priority assigned by Marxan to the achievement of each feature in relation to other considerations, including cost. The Boundary Length Modifier (BLM) parameter in Marxan serves to minimize spatial fragmentation in the resultant solution [64,66]. A high BLM value promotes the selection of adjacent units to create a compact and consolidated conservation zone. A low BLM value tends to produce more dispersed and fragmented solutions. Therefore, careful calibration of the BLM parameter is essential to balance the achievement of ecological targets with spatial efficiency [67].

Marxan employs a "Marxan score" to evaluate the effectiveness of selected planning unit configurations in achieving conservation objectives, while minimizing costs and spatial fragmentation [64,66]. This function operates by combining three key elements, which consist of the total cost of the selected planning unit, the total length of the selected area boundary, including fragmentation penalties, and the penalty incurred if the conservation target is not met. The Marxan score formula is expressed mathematically as an Equation **Error! Reference source not found.**.)

$$\overbrace{\textstyle\sum_{PUs} Cost}^{1} + \overbrace{BLM \textstyle\sum_{PUs} Boundary}^{2} + \overbrace{\textstyle\sum_{\substack{Con\\Value}} FPF \times Penalty}^{3} = \boldsymbol{Marxan\ Score} \quad \textbf{(2.3)}$$

The initial component computes the aggregate cost of the chosen planning units (PUs). The second component computes the penalty for area fragmentation by multiplying the total length of the chosen PU boundaries (boundary) by the Boundary Length Modifier (BLM) value. The third component computes the penalty for not achieving conservation targets for all features, based on the cumulative product of the Feature Penalty Factor (FPF) and the penalty associated with each feature. This formula is employed to examine different combinations of planning units and identify the solution with the lowest total score as the most spatially and ecologically efficient option.

3. Results

3.1. Shallow Marine Biophysics Mapping with Remote Sensing

We use the previously research on biodiversity index map, which indicates coverage of live coral reefs around Tidung Island [18]. PlanetScope satellite imagery, which has high spatial resolution (3 meters) and daily temporal resolution, apply for biophysics of shallow marine ecosystems such as coral reefs, seagrass, and mangroves. Applying the Lyzenga water column correction is essential to decouple the substrate reflectance from water depth attenuation, thereby minimizing spectral confusion between live coral and macroalgae in heterogeneous shallow-water environments [68].

Table 3 and Figure 4 displays classification result and percentage of each class obtained from the previous research. The coastal and marine regions of Tidung Island are primarily characterized by thriving coral reefs, which comprise around 29.97% of the area. The expanse of the shallow sea surrounding Tidung Island is considerable, resulting in a substantial region of sandy terrain. Seagrass

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beds are vital components of the coastal ecosystem surrounding Tidung Island, occupying a significant area of 150.98 hectares (17.87% of the total). The seagrass species examined in this study consist of Thalassia hemprichii (Pacific turtlegrass), Enhalus acoroides (Large seagrass), and Cymodocea rotundata (Ribbon seagrass).

Table 3. The area and percentage of classification results.

Class	Area (ha)	Percentage
Seagrass	150.97680	17.87%
Living coral reefs	253.14660	29.97%
Dead Coral Reefs	128.22480	15.18%
Deep sea	202.87260	24.02%
Sand	109.45440	12.96%

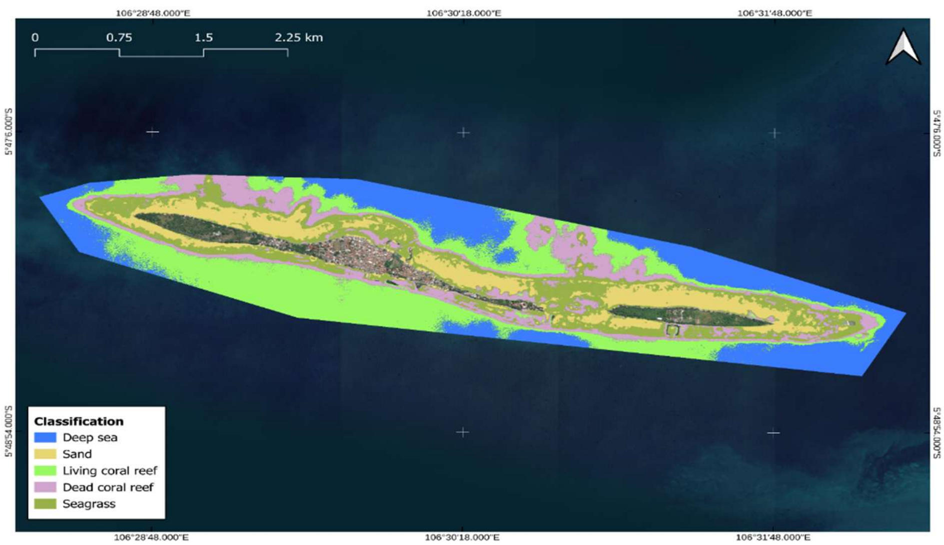


Figure 4. Benthic classification in Tidung island.

3.2. Evaluation of Shallow Marine Water Quality Mapping Based on IoT Sensor Data and the Nemerow Pollution Index

Table 4 summarizes the optimal value ranges established by the standards. The standards in Table serve as essential minimum thresholds for benthic habitat conservation, as the physical-chemical conditions of the waters significantly impact the health of the seabed ecosystem. Benthic organisms, including living coral reefs and seagrasses, rely significantly on stable water quality parameters, particularly dissolved oxygen and turbidity levels, for essential processes such as photosynthesis, respiration, and tissue growth.

Table 4. Standards for water quality concerning marine organisms.

Quality Standards	
Ph	**7-8.5**
Temperature (oC)	28-30
Turbidity (NTU)	< 5
DO (mg/l)	> 5
Salinity (%)	33-34

(Source: Decree of the Environment State Minister Number 51 of 2004).

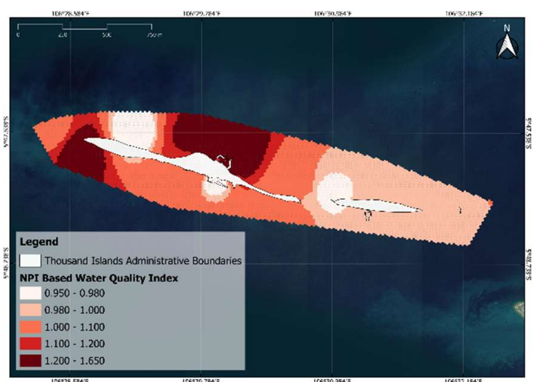
Table 5 summarizes water quality data from 13 observation points around Tidung Island, indicating NPI values ranging from 0.9696 to 1.6499. The maximum value was recorded at a location characterized by elevated turbidity and reduced dissolved oxygen levels, suggesting the likelihood of slightly polluted water.

Table 5. Water quality measurements and NPI from 13 observation in Tidung Island.

No.	Lat	Long	pH	Temp (°C)	Turbidity (NTU)	DO (mg/l)	Salinity (%)	NPI
1	-5.7967	106.4989	8.44	30.3	6.312	10.752	30.90	1.1213
2	-5.7930	106.4949	8.38	29.9	6.851	9.171	26.40	1.2119
3	-5.7921	106.4861	8.36	30.6	4.133	9.267	31.50	0.9690
4	-5.7918	106.4737	8.40	30.4	5.910	8.341	32.00	1.0780
5	-5.7948	106.4778	8.44	30.9	4.971	11.219	22.50	1.2496
6	-5.7989	106.4935	8.39	30.4	5.910	7.623	33.70	1.0783
7	-5.7997	106.4986	8.36	30.8	4.442	7.662	33.20	0.9696
8	-5.8042	106.5083	8.34	30.7	5.030	5.040	32.00	1.0191
9	-5.8024	106.5125	8.35	30.8	4.442	6.944	31.50	0.9920
10	-5.8017	106.5155	8.32	30.9	4.971	11.557	31.50	0.9751
11	-5.8018	106.5117	8.47	31.5	5.211	11.620	28.70	1.0474
12	-5.8051	106.5218	8.37	31.5	5.211	11.360	31.40	0.9847
13	-5.7967	106.4990	8.40	27.6	10.278	9.180	32.60	1.6499

The final estimate on each spatial grid is obtained by averaging the predicted values from the three models. Figure 5 presents the results of the interpolation across three panels: (a) the distribution of actual NPI values from sensor observation points, (b) the spatial interpolation map of the ensemble model results, and (c) the classification of water quality status based on NPI values into the categories of good, slightly polluted, fairly polluted,

(a)



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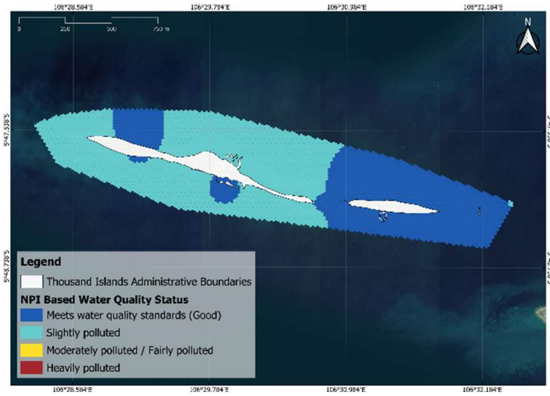

(c)

Figure 5. Spatial distribution of seawater quality around Tidung Island based on the Nemerow Pollution Index (NPI): (a) Point-based NPI values. (b) Ensemble Interpolation Model of NPI. (c) NPI-based water quality status.

Leave-One-Out Cross-Validation (LOOCV) was implemented to ensure model reliability and minimize overfitting, providing a robust accuracy assessment for the spatially constrained dataset typical of small island monitoring [69]. This method is suitable for small datasets because all data points can be utilized without needing to be divided into different subsets. In LOOCV, the model is trained on all data except one point, which is set aside for validation testing. This process is repeated continuously until every data point has its turn as test data. In this way, all data plays a role in both training and validation.

Performance metrics of ensemble models for predicting shallow seawater quality using NPI observation points are presented at Table 6. The MAE value of 0.0306 indicates that the average absolute difference between the actual NPI value and the model's predictions is approximately 0.03. This value indicates a small difference, so the model can be considered quite accurate in predicting water quality. The RMSE value of 0.0445 is slightly higher than the MAE; it indicates that some predictions deviate significantly, but this deviation is still within reasonable limits. The coefficient of determination (R^2) value (0.7605) indicates that the ensemble model is able to explain about 76% of the variation in the actual NPI values, indicating good predictive performance. Meanwhile, the MAPE of 2.89% indicates an average relative error below 3%, indicating a high level of predictive reliability. Finally, the MedAE of 0.0143 indicates that half of the absolute errors are below this value, confirming that most predictions are very close to the actual values.

Table 6. Performance metrics of ensemble models for predicting shallow seawater quality using NPI observation points.

LOOCV Metric	Value
MAE	0.0306
RMSE	0.0445
R^2	0.7605
MAPE	0.0289
MedAE	0.0143

Figure 6 shows the validation results, divided into two sections. The left diagram presents the histogram of the error distribution (actual minus predicted), revealing that most errors are concentrated within the range of 0 to 0.05. This indicates that the model predictions are typically very close to the observed values. The diagram on the right illustrates the scatter plot correlating the actual NPI values with the predictions from the ensemble model. Most data points align closely with the dashed red line, which signifies the ideal prediction (y = x), demonstrating a strong correlation between the predictions and the actual data, despite minor deviations at certain points.

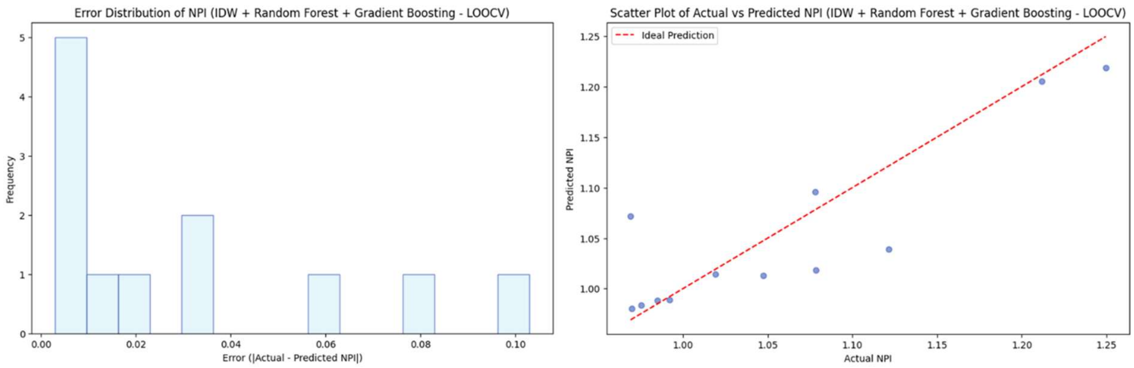

Figure 6. Error distribution (left) and actual versus predicted NPI scatter plot (right) from the ensemble model under LOOCV for shallow seawater quality prediction.

In addition to LOOCV, validation was also carried out through visual comparison. This approach evaluates the interpolation results of seawater quality by directly comparing them with field observations. It provides insight into how well the spatial distribution of the Nemerow Pollution Index (NPI) predicted by the model reflects actual conditions, while also helping to identify potential systematic biases or localized anomalies that may not be evident from statistical metrics alone.

Figure 7 presents a visual comparison between NPI values obtained from IoT-based observations and the spatial interpolation map produced by the ensemble model. Observation points are shown as colored circles representing measured NPI values, while the background surface illustrates the interpolated results, classified into five categories ranging from good (NPI ≤ 1) to slightly polluted (1.0 < NPI ≤ 5.0).

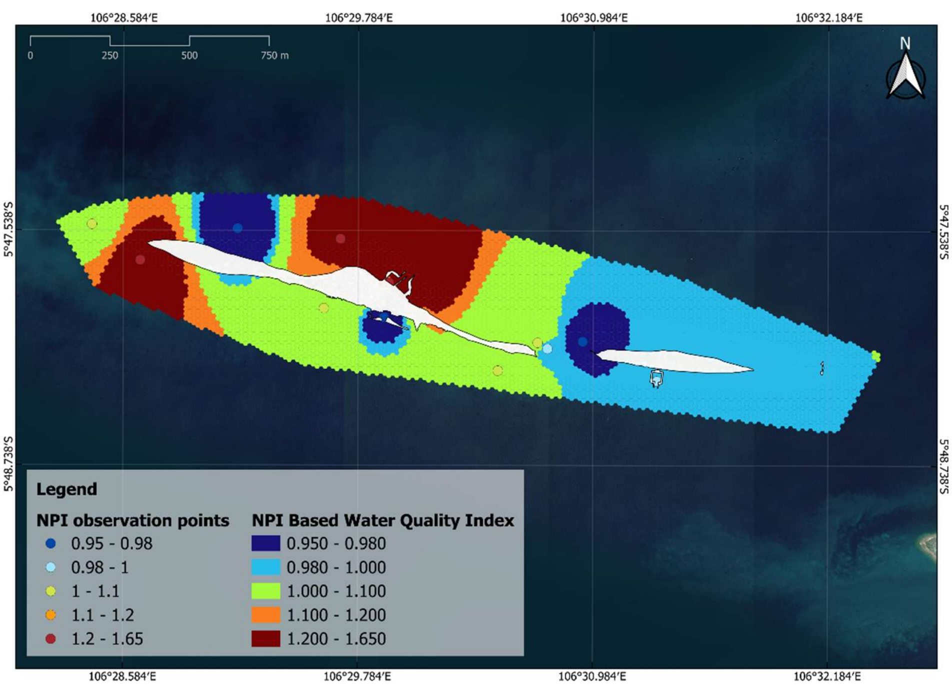

Figure 7. Visual comparison between observed NPI data points and spatially interpolated NPI values using an ensemble model.

Overall, the observed data and model outputs show a strong spatial correspondence. Areas with higher NPI values, particularly in the northwest and central parts of the island, are represented in

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red to orange zones, indicating reduced water quality. In contrast, lower NPI values, represented by blue to green areas, are mainly found in the northeast and southern regions, corresponding well with observation points that indicate better conditions. This pattern suggests that the ensemble model is able to capture the main spatial gradients with good visual consistency

Visual validation indicates the presence of distinct transition zones that require further observation. Furthermore, isolated extreme values may indicate potential spatial irregularities. The observed effect may result from the machine learning model's interaction with sparsely distributed data; thus, additional analysis is required to elucidate the emerging patterns. This visual approach complements the previously conducted quantitative validation. This method enhances the spatial comprehension of the model's reliability. The visual approach serves as a crucial tool for identifying areas needing further attention in monitoring shallow marine environments, thereby facilitating a more comprehensive evaluation process.

3.3. Spatial Prioritization for Adaptive Biodiversity Conservation Using the Marxan Algorithm

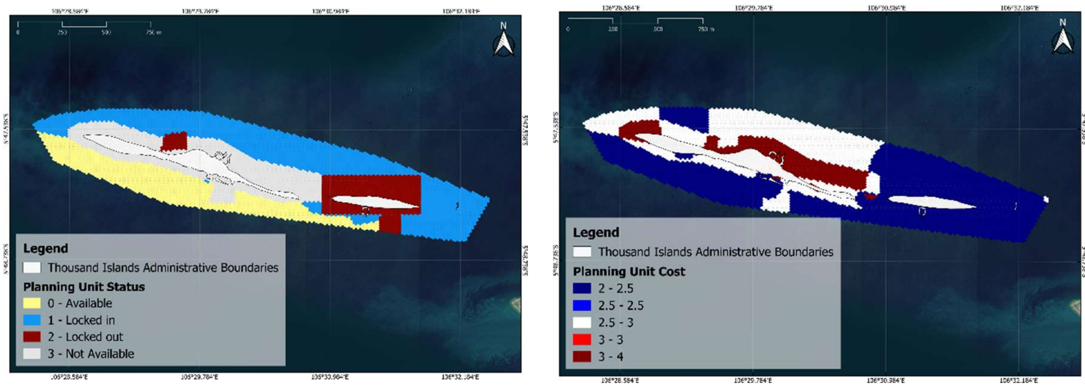
In this study, we used Marxan, a spatial planning tool based on simulated algorithms, to model conservation areas. Marxan can identify optimal conservation area designs by balancing cost efficiency, ecological representation, and spatial connectivity [70].

In spatial-based conservation area planning utilizing the Marxan algorithm, numerous geographical pressure factors significantly affect the planning units that may be selected or excluded. These factors are denoted as cost variables (pu_cost), indicating the degree of difficulty or ecological, social, and economic barriers to designating a unit as part of a conservation area. Table delineates the six types of spatial pressures used in the model, together with their conceptual impact on pu_cost values and corresponding contextual elucidations. All of these factors are designated with the attribute "potential to increase" regarding pu_cost, indicating that their presence will elevate the relative cost of the planning unit as a conservation area. Ports and marine aquaculture zones are linked to elevated human activity, shipping traffic, and competing economic interests. Hence, conservation in these areas necessitates additional restoration or security precautions.

Table 7. Spatial pressure factors and their conceptual influence on the cost of planning units (pu_cost) in marine spatial planning using Marxan.

No.	Spatial Pressure Factor	Impact on pu_cost	Explanation
1	*Port Area*	Potential to increase	High human activity and marine traffic make conservation challenging.
2	*Aquaculture Zone*	Potential to increase	Overlap with economic activities can cause land-use conflicts.
3	*Subsea Pipeline and Cable Corridor*	Potential to increase	Technical infrastructure limits access and increases complexity.
4	*General-Use Marine Area*	Potential to increase	Intensively used areas may need compensation or restoration.
5	*Pipeline and Cable Security Zone*	Potential to increase	Restricted access due to safety regulations.
6	*Nemerow Pollution Index (NPI)*	Potential to increase	Poor water quality adds ecological stress and restoration costs.

Figure 8 presents a spatial depiction of the configuration of the planning unit. Panel (a) illustrates the status of each planning unit, classified into four categories: available, locked in, locked out, and unavailable due to spatial constraints. Restricted zones generally include areas with high levels of protection or infrastructure, such as ports and submarine cable networks. In contrast, locked-in units are prioritized in the conservation design because they contain key ecological features, including seagrass beds and live coral reefs. Panel (b) presents the spatial distribution of cumulative *pu_cost* values, derived from the integration of six spatial pressure layers. Higher cost values, shown in darker red tones, indicate areas under greater anthropogenic pressure, while lighter blue areas represent lower-cost units that are more suitable for conservation.



(a) (b)

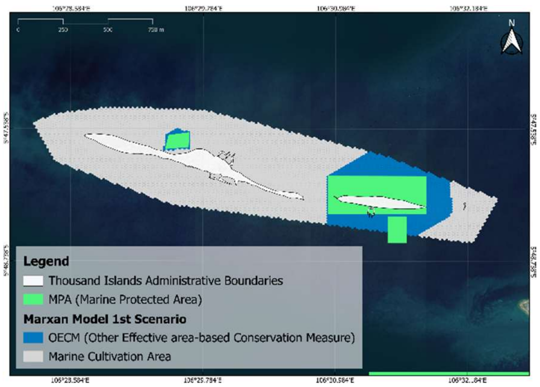
Figure 8. Spatial configuration of planning units in Tidung Island is shown as follows: (a) unit status based on constraints and model inputs, and (b) cost layer representing cumulative spatial pressures.

Table 8 summarizes the performance of the four conservation target scenarios. Scenario 1 (30% target for all features) achieves all conservation targets (MPM = 1.000). In contrast, Scenario 2 (100% target for all features) fails to meet any targets (MPM = 0.442), indicating that such an ambitious target is not feasible within existing spatial constraints. Scenarios 3 (35% coral reefs, 25% seagrass, 40% mangroves) and 4 (40% coral reefs, 30% seagrass, 50% mangroves) partially meet their targets: both achieve the coral reef and seagrass targets but fall short for mangroves (MPM = 0.952 and 0.895, respectively). The strong performance of Scenario 1 aligns with the Kunming–Montreal Global Biodiversity Framework's "30 by 30" target, supporting the development of compact and manageable conservation areas [71]. These findings suggest that balanced and achievable targets tend to produce more effective outcomes, whereas overly ambitious or spatially constrained targets reduce overall performance.

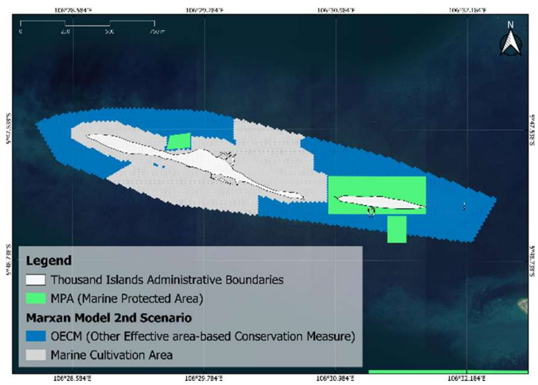
Table 8. The effectiveness comparison of four conservation scenarios.

Scenario	Target (m²)	Amount Held (m²)	Amount Met (m²)	Target Met	Mean Proportional Met (MPM)
1st	1463526.00	1641835.00	1463526.00	*yes*	1.000
2nd	4878419.00	2378013.00	2378013.00	*no*	0.442
3rd	1569996.00	1616981.00	1554266.00	*no*	0.952
4th	1827443.00	1856073.00	1784661.00	*no*	0.895

Figure 9 presents the Marxan outputs, showing the spatial allocation of Marine Protected Areas (MPAs) and Other Effective Area-Based Conservation Measures (OECMs) across scenarios. In Scenario 1 (Figure 9a), conservation areas are efficiently distributed around key ecological features and low-cost regions, resulting in a compact configuration. In Scenario 2 (Figure 9b), the more ambitious targets produce larger but fragmented conservation areas that frequently overlap with existing uses such as marine culture zone, indicating lower spatial efficiency. Scenario 3 (Figure 9c) demonstrates a more focused and balanced configuration, with conservation areas concentrated on priority features while maintaining a relatively compact spatial structure. The fourth scenario (9d) presents a more dispersed conservation design while still preserving relatively high coverage of target features.



(a)



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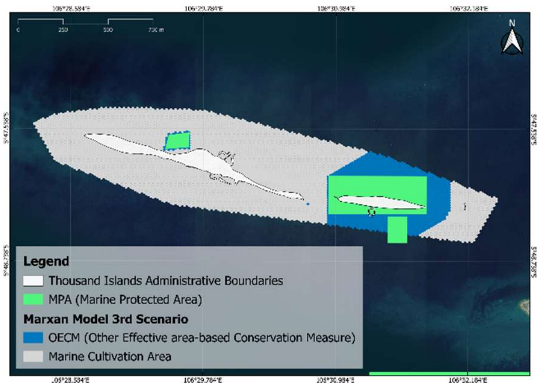
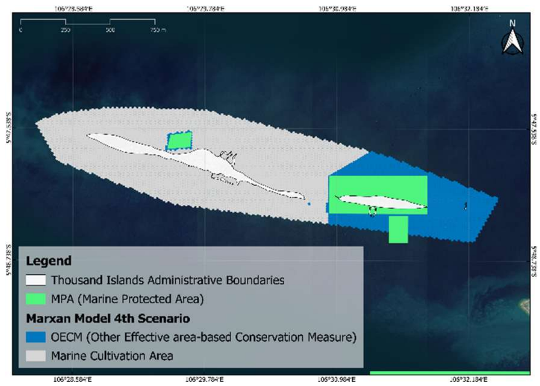


(c)



(d)

Figure 9. Spatial conservation prioritization in Tidung Island under four target scenarios: (a) 1st scenario: 30% for all features, (b) 2nd scenario: 100% for all features, (c) 3rd scenario: 35% coral reefs, 25% seagrass, 40% mangroves, and (d) 4th scenario: 40% coral reefs, 30% seagrass, 50% mangroves.

The assessment of spatial efficiency and fragmentation is shown in Table 9. The first scenario performed best with the shortest conservation boundary length (~10,750 m) and the lowest optimal cost (~2,200), and a spatial interpretation classified as compact and efficient.

Table 9. Assessment of compactness, fragmentation, and conservation efficiency for each target scenario.

Scenario	Optimal BLM	Boundary Length (m)	Optimal Cost	Spatial Interpretation
1st	0.1	~10.750	~2.200	Compact, efficient
2nd	1.23	~21.725	~6.000	High fragmentation, inefficient
3rd	0.1	~11.000	~2.200	Compact and consolidated
4th	0.21	~12.175	~2.500	Slightly more dispersed

The third scenario also showed a compact configuration, although slightly longer (~11,000 m). In contrast, the second scenario showed the most extended conservation boundary length (~21,725 m) with much higher costs (~6,000) and a fragmented and inefficient spatial interpretation due to conservation targets that were too large and disproportionate to the available area. The fourth scenario shows moderate results, with slightly longer conservation boundaries and more evenly distributed areas, but is still more efficient than the second scenario.

3.4. Spatial Analysis Between Conservation Priority Areas and Marxan Input Parameters

Overlay analysis evaluates the strengths and limitations of each Marxan conservation planning scenario. It compares priority conservation zones generated by Marxan, seawater quality status based on the Nemerow Pollution Index (NPI), and input parameters such as planning unit status and cost, which are affected by spatial pressure factors including harbors and cable pipe corridors. This approach provides important insights into the spatial effectiveness of conservation planning under actual environmental conditions and pressure factors.

Figure 10a illustrates the overlay results between the conservation zones of the first scenario Marxan model and the Marine Protected Area (MPA) layer regulated by the local authority. Most of the conservation zones derived from the modeling overlap with the MPA. Consequently, Identifying high-value conservation areas outside traditional Marine Protected Areas (MPAs) supports the implementation of Other Effective Area-based Conservation Measures (OECMs), which are vital for achieving the 30% protection threshold [72].

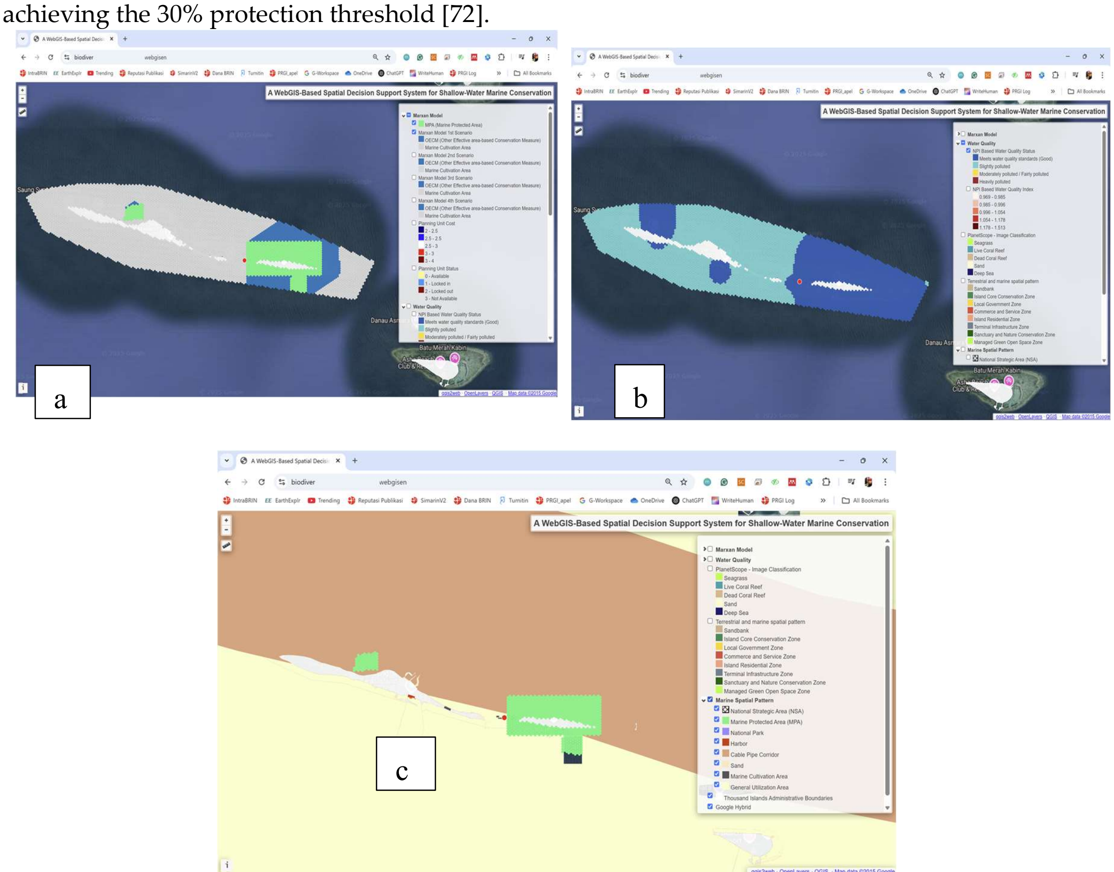


Figure 10. Spatial overlay analysis combines Marxan output with key conservation and the pressure variables: (a) prioritization result for Scenario 1, (b) spatial variation in NPI values, and (c) spatial pressure factors.

Figure 10b illustrates the water quality status derived from the NPI interpolation outcomes. The conservation area unit in the east coincides with an area of good water quality, whereas in the west, it is located in an area with slightly polluted water quality. The finding is significant as it underscores the necessity for further restoration or preservation measures in these areas to ensure the long-term effectiveness of the designated conservation zones.

Figure **Figure** 10c shows the input parameters for Marxan, including the harbor, cable pipe corridor, and marine cultivation area, which can influence conservation costs (planning unit cost). Numerous conservation units are located in areas of elevated pressure, increasing their pu_cost. This factor must be considered during policy implementation, as it may complicate conservation management in practice.

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Subsequent analysis of Figure 10a- 10c and the benthic habitat overlay results on the SDSS platform indicates that the conservation area in the northwest of Tidung Island is less favored by the Marxan model, despite encompassing seagrass beds, live coral reefs, and dead coral reefs. This pattern is likely driven by the presence of submarine cable corridors and general-use zones, which contribute to higher planning unit costs (*pu_cost*) in the Marxan framework. As a result, planning units near these corridors tend to be deprioritized in the conservation optimization process. This finding reinforces the earlier visual analysis and highlights the importance of incorporating anthropogenic spatial pressures into adaptive conservation planning supported by a SDSS. Overall, the integration of conservation outputs, environmental quality indicators, and spatial pressure layers strengthens the role of SDSS in identifying spatial overlaps, mismatches, and potential opportunities for optimizing conservation strategies.

4. Discussion

4.1. Integration of Remote Sensing, IoT, and Spatial Analysis for Adaptive Conservation

This study demonstrates that integrating remote sensing, IoT-based environmental monitoring, and spatial optimization modeling provides a more comprehensive and adaptive framework for marine biodiversity conservation. Unlike conventional approaches that rely primarily on static ecological variables, this framework incorporates dynamic environmental conditions, allowing conservation planning to better reflect real-world ecosystem variability.

The benthic habitat classification derived from PlanetScope imagery achieved high accuracy (Overall Accuracy = 85.50%; Kappa = 0.806), confirming the reliability of high-resolution satellite data for mapping shallow marine ecosystems. User Accuracy ranged from 77.78% to 90%, while Producer Accuracy ranged from 77.78% to 87.50%. These results are consistent with previous studies suggesting that classification accuracy above 85% is adequate for ecological applications [73,74]. For example, [75] indicate that a minimum accuracy threshold of ≥85% for remote sensing-based classification is generally considered acceptable within the field. However, beyond accuracy, the use of high spatial resolution imagery (3 m) allows for improved detection of fine-scale habitat heterogeneity, which is critical in small island ecosystems such as Tidung Island, where spatial patterns strongly influence biodiversity distribution and conservation effectiveness.

In vulnerable coastal ecosystems such as the Tidung Islands, the main challenge lies in the fragmentation of data and the static nature of conventional marine spatial planning. Through the use of 3 m PlanetScope imagery, Internet of Things (IoT)-based water quality sensors, and Marxan algorithms, the study seeks to fill a crucial gap between real-time environmental monitoring and conservation policy [76].

The transition from static biodiversity monitoring to Adaptive Biodiversity Conservation (ABC) requires data streams that have high spatial resolution and tight temporal frequencies. The use of PlanetScope in this study is particularly relevant because it offers a resolution of 3 meters that allows the identification of benthic habitat heterogeneity at the microscale, an advantage that intermediate sensors such as Sentinel-2 (10 m) or Landsat (30 m) do not have [23]. However, it should be emphasized that high spatial resolution often comes with a compromise on the number of spectral bands compared to Sentinel-2 [77]. Sentinel-2 provides 13 spectral bands, including the Red-Edge and Short-Wave Infrared (SWIR) channels that are absent from PlanetScope. [77] highlight that this wider spectral range enhances Sentinel-2's utility for a wide range of scientific missions that require the detection of fine bio-optical signals, while PlanetScope is superior in the precision aspect of objects.

4.2. Role of Dynamic Water Quality in Biodiversity Conservation Planning

This study utilizes seawater quality parameters, including pH, temperature, turbidity, dissolved oxygen (DO), and salinity, collected from IoT sensors deployed in the field as one of parameter for adaptive biodiversity conservation. The assessment of overall water quality conditions involves

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evaluating five parameters according to the marine environmental quality standards outlined in the Decree of the Minister of State for the Environment Number 51 of 2004, which establishes the ideal limits for marine waters that sustain marine organisms.

A key contribution of this study lies in the integration of water quality, represented by the NPI, as a dynamic cost layer in conservation prioritization. Traditional spatial conservation planning tools, including Marxan, typically rely on static inputs such as habitat distribution, species presence, or fixed anthropogenic pressures. This approach often overlooks temporal variability in environmental quality, which can significantly affect ecosystem health and resilience.

The results show that areas with higher NPI values (indicating poorer water quality) tend to be deprioritized in conservation scenarios due to increased ecological stress and restoration costs. This finding highlights that environmental degradation is not only an ecological issue but also a spatial planning constraint that directly influences conservation efficiency. By incorporating NPI into the cost function, the model produces solutions that are not only ecologically representative but also more realistic in terms of implementation feasibility.

Furthermore, the use of IoT-based sensors enables near real-time monitoring, which introduces the potential for adaptive conservation strategies. This is particularly relevant in coastal environments where water quality conditions can change rapidly due to tourism, land-based pollution, and climate-related factors. Therefore, this study advances the concept of dynamic marine spatial planning, where conservation priorities can be periodically updated based on environmental conditions.

The implementation of national seawater quality standards in the Nemerow Pollution Index (NPI) analysis extends beyond the mere assessment of pollution conditions. This index serves as a significant indicator for evaluating the appropriateness of an area for designation as a marine biodiversity conservation zone, particularly concerning benthic habitats. This method facilitates a comprehensive assessment of environmental quality, enabling conservation policies to be grounded in precise and quantifiable scientific metrics.

The main innovation in this manuscript is the transformation of water quality data into a cost layer variable in Marxan modeling using the Nemerow Pollution Index (NPI). Traditionally, Marxan used fixed costs such as distance from the coast or the economic value of land (https://marxansolutions.org/costs/).

Using NPI, this model is able to accommodate spatially and temporally variable ecological risks. The NPI is very effective because it highlights the parameters with the highest pollution ratio, which is often a limiting factor for the survival of sensitive marine life [79]. Integrating the Nemerow Pollution Index (NPI) as a dynamic cost layer allows the Marxan model to treat environmental degradation as 'ecological resistance,' steering the optimization process toward areas with higher resilience and lower restoration requirements (Marxan, 2022b).

This study used an ensemble interpolation model that combines Inverse Distance Weighting (IDW), Random Forest (RF), and Gradient Boosting (GB). This method is able to capture non-linear relationships between geographic coordinates and coastal environmental parameters [81]. The results of the evaluation showed an R2 of 0.76 and an MAE of 0.0306, which indicates a strong predictive performance. The use of Leave-One-Out Cross-Validation (LOOCV) provides a high level of confidence in the model despite the limited sample size (n=13) [81].

Compared to single-method interpolation, the ensemble approach provides more robust and stable predictions, especially in data-sparse environments such as small island systems. This is important because data limitation is a common challenge in developing countries, where monitoring infrastructure is often limited. The ability to generate reliable spatial estimates from limited observations significantly enhances the applicability of this framework in similar contexts.

The interpolation map of the water quality indicates that the central and northwest regions of Tidung Island reveal higher NPI values, suggesting comparatively poorer water quality than other regions. In contrast, the northeast and south exhibit lower NPI values and are nearer to optimal conditions. These findings give a notable spatial framework for escalating environmental monitoring

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and conservation efforts. Thus, the incorporation of quality-verified IoT sensor data, along with an ensemble modeling approach, facilitates improved accuracy and representation in the mapping of seawater quality. Through this approach, we emphasize the importance of systems that ensure data quality, leverage machine learning and spatial technologies to support evidence-based decision-making for coastal ecosystem management.

4.3. Adaptive Biodiversity Conservation Using the Marxan Algorithm

This study evaluates four conservation target scenarios to examine how the Marxan algorithm performs in generating spatially efficient conservation solutions in the Tidung Island region. The four scenarios were organized according to differing conservation area objectives, uniformly across all components, or concentrated on certain aspects. Marxan was applied to test four conservation scenarios, each varying the proportion of areas allocated to three key coastal ecosystem features of Tidung Island: coral reefs, seagrass, and mangroves. We found that the first and third scenarios are recommended as the most effective biodiversity conservation strategies. Both scenarios balance target achievement, spatial efficiency, and the financial burden of conservation costs. We highlight this finding in relation to the need to calibrate conservation targets against current spatial capacity and needs. Therefore, a spatial validation of the solutions generated by the Marxan algorithm confirms that the methodology used is evidence-based and adaptive, thus facilitating more effective conservation decisions.

The effectiveness of each scenario was evaluated using conservation target fulfilment metrics (Amount Met and Mean Proportional Met – MPM) [82], spatial configuration (border length and area distribution) (Ball et al., 2009), and total cost (the optimal cost) [83].

The results highlight clear trade-offs between conservation ambition, spatial efficiency, and implementation feasibility. The first scenario, which applies a 30% conservation target, yields the most balanced outcome. It achieves all conservation targets (MPM = 1.000), maintains relatively low cost (~2,200), and produces a compact spatial configuration. This outcome is consistent with global conservation priorities, particularly the “30 by 30” target under the Kunming–Montreal Global Biodiversity Framework [56]

By contrast, the second scenario, which applies a 100% target, results in a fragmented and spatially inefficient configuration with substantially higher costs. This suggests that overly ambitious targets can be counterproductive when spatial constraints and anthropogenic pressures are not adequately accounted for. Scenarios with differentiated targets (Scenarios 3 and 4) offer partial improvements, particularly in balancing efficiency and ecological representation. However, they still fall short of achieving all targets, especially for ecosystems under higher pressure, such as mangroves.

More broadly, these findings point to a persistent challenge in marine spatial planning: the limited integration of ecological conditions, environmental quality, and human pressures within a single analytical framework. In line with this research, [84] also found that many MSP implementations still fail to integrate human pressures, environmental quality, and cross-regional connectivity comprehensively and it is also mentioned that the ecosystem-based approach is still often partial.

Many existing approaches rely on fragmented datasets, which can lead to static or suboptimal conservation outcomes [85]. In response, this study demonstrates how integrating multi-source data within a Spatial Decision Support System (SDSS) can support more adaptive and evidence-based conservation planning. The proposed framework is particularly relevant for small island systems and developing regions, where data constraints and rapid environmental change often complicate decision-making.

Importantly, the incorporation of dynamic environmental indicators, such as NPI, represents a methodological advancement that can be applied globally. This approach enhances the ability of spatial planning tools to account for ecosystem health, not just habitat presence, thereby improving the ecological relevance and long-term effectiveness of conservation strategies.

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Globally, coastal ecosystems such as coral reefs and seagrass beds are biodiversity hotspots that are increasingly threatened by climate change, pollution, and overexploitation. Marine spatial planning (MSP) has been widely recognized as an essential approach to balance conservation and resource use; however, its effectiveness is often constrained by fragmented governance and data limitations, as well as the reliance on static datasets that fail to capture the dynamic nature of marine systems [16]. By integrating remote sensing, IoT-based water quality monitoring, and spatial optimization modelling, this study provides a comprehensive and data-driven framework that enhances the accuracy and relevance of conservation prioritization under real-world environmental conditions.

Furthermore, this research contributes to advancing adaptive and data-driven conservation approaches at the global scale. The incorporation of water quality, represented by the Nemerow Pollution Index (NPI), as a dynamic cost layer in spatial optimization is a significant innovation. Previous conservation planning studies have largely relied on static ecological variables, such as habitat distribution or species occurrence, often overlooking the influence of environmental degradation on ecosystem viability [86]. By explicitly integrating dynamic environmental conditions, this study demonstrates that conservation solutions can be more cost-efficient, spatially compact, and ecologically realistic. This approach improves the capacity of spatial planning tools, such as Marxan, to account for both ecological integrity and environmental stressors simultaneously.

At the global level, the proposed framework is highly relevant for supporting international conservation targets, particularly the Kunming–Montreal Global Biodiversity Framework, which aims to protect 30% of the world's land and ocean by 2030. One of the major challenges in achieving this target lies in identifying priority conservation areas that minimize socio-economic conflicts while maximizing ecological benefits. Spatial optimization approaches that integrate multi-source data have been shown to significantly improve conservation effectiveness and reduce trade-offs [30]. This integrated framework provides a scalable solution for 'data-limited MSP' in developing nations, bridging the gap between national mandates like Law No. 6/2023 and international biodiversity commitments [87].

Despite its contributions, this study has several limitations. First, the spatial interpolation of water quality is based on a limited number of observation points, which may affect the representation of fine-scale variability. Second, certain parameters, such as Total Dissolved Solids (TDS), were excluded due to sensor limitations, highlighting the need for improved monitoring technology in marine environments.

5. Conclusion and Recommendations

This study effectively addressed the main research question regarding the integration of remote sensing data, IoT-based water quality monitoring, and spatial conservation modeling using the Marxan algorithm within a Spatial Decision Support System (SDSS). IoT sensors enabled near real-time monitoring of seawater quality, which was subsequently evaluated using the Nemerow Pollution Index (NPI). The ensemble interpolation approach, combining IDW, random forest, and gradient boosting, showed reliable performance ($R^2 = 0.76$; MAE = 0.0306).

The resulting spatial information was incorporated into conservation planning using Marxan, considering ecological features, spatial pressures, and environmental quality. The findings indicate that scenarios integrating both environmental conditions and anthropogenic pressures tend to produce conservation configurations that are not only spatially efficient but also ecologically representative.

Certain regions with important ecosystems that exhibit inadequate water quality or overlap with infrastructure zones, such as submarine cables, tend to be excluded from conservation priorities. This underscores the necessity of incorporating spatial conflicts in the design of protected areas.

These results underscore the value of coupling dynamic environmental data with spatial optimization tools to support more adaptive conservation planning. By moving beyond static inputs, the proposed framework allows conservation priorities to better reflect ongoing environmental

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changes and localized pressures. In practice, this can improve the relevance and feasibility of conservation zoning, particularly in coastal systems where ecological conditions are highly variable.

This study is important because it addresses a key challenge in contemporary marine conservation: the limited integration of spatial data, environmental quality, and dynamic anthropogenic pressures in conservation planning. The future development of this system aims to incorporate a spatial prediction module utilizing machine learning, automate the calculation of spatial biodiversity indices, and integrate feedback mechanisms from stakeholders. Enhancing the analytical and visualization capabilities of the SDSS system is anticipated to facilitate more adaptive, evidence-based, and responsive governance of marine areas in response to future environmental changes.

Overall, the study demonstrates that an integrated SDSS approach can enhance decision-making by providing a more comprehensive basis for balancing conservation goals with existing uses. This is particularly important for small island environments such as Tidung Island, where space is limited and competing demands are intense.

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