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Exploratory analysis of marine reserve site selection by Monte Carlo mixed integer programming

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ABSTRACT

Marine reserve site selection is a complex process that requires balancing ecological conservation, socio-economic considerations, and management feasibility. Traditional multi-objective optimization methods often rely on the weighted sum approach, which introduces subjectivity and uncertainty in weight estimation. To enhance transparency and robustness, this study introduces an exploratory framework that integrates Mixed Integer Programming (MIP), Monte Carlo (MC) experiments, and Decision Tree (DT) analysis. Using Xiao Liuqiu Island in Taiwan as a case study, we ran an MIP site selection model 10,000 times to systematically explore different weighting scenarios for 21 ecological, socio-economic, and management features. The MC results revealed that 90 % of simulations consistently identified a single high-priority conservation zone, which exhibits high ecological, low socio-economic, and high management values. Two alternative zones emerged under specific weight conditions. The DT analysis pinpointed the threshold conditions that drive site selection shifts towards these zones, highlighting the most influential features shaping the decision-making process. By reducing reliance on predefined weights, this approach ensures globally optimal marine reserve configurations while providing decision-makers with clearer insights. The findings contribute to marine spatial planning, adaptive conservation strategies, and stakeholder-driven decision-making, fostering more effective and informed marine protection efforts.

1. Introduction

The establishment of Marine Protected Areas (MPAs) is a critical strategy for conserving marine biodiversity, mitigating anthropogenic impacts, and ensuring the long-term resilience of marine ecosystems (Day et al., 2019). No-take marine reserves are reported to be one of the most effective types of MPAs, by spatially restricting fishing activities (Relano and Pauly, 2023). Well-designed marine reserves may increase the number of species, density, and overall biodiversity within their boundaries (Molloy et al., 2009; Sala and Giakoumi, 2018; Rojo et al., 2019), promote fish population recovery outside the reserve through “spillover effects” (Abesamis and Russ, 2005; Stobart et al., 2009; Silva et al., 2015), serve as scientific baselines for studying marine ecosystems (Costello, 2014; White, 2021), and support local economies through ecotourism (White, 2021; Phillips et al., 2023).

However, the effectiveness of marine reserves depends significantly on site selection, which must balance ecological, socio-economic, and management considerations (Gong et al., 2023). Poorly selected sites may fail to achieve conservation goals, face resistance from local communities, or become difficult to enforce (Agardy et al., 2011). Nowadays, the selection process often balances ecological goals (habitat protection and biodiversity improvement) with spatial adequacy, costs and impacts to local communities, and long-term governance (van Kerkhoff et al., 2019; Précoma-de la Mora et al., 2021). Comprehensive

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representation of habitats and s pecies is crucial (Roberts et al., 2003), and the reserve's design, including number of parcels, size, and shape, heavily influences user acceptance (Halpern and Warner, 2003). Site selection models now also incorporate future challenges (i.e., climate change) projections to ensure the resilience of marine reserves under changing conditions (Harrison et al., 2008; Runting et al., 2018; Múnera-Roldán et al., 2023) and consider how marine reserves can function as refugia, providing long-term benefits for biodiversity (Graham et al., 2019) and local communities (van Kerkhoff et al., 2019). Lastly, day to day management is a critical factor for the success and sustainability of marine reserves (Gill et al., 2017).

The use of Multi-Objective Optimization (MOO) algorithms in marine reserves site selection has evolved from stochastic methods to exact optimization techniques. Early approaches, such as the BioSelect algorithm (Nicholls and Margules, 1993), the SITES reserve selection system (Fischer and Church, 2005), the dynamic reserve design model (Harrison et al., 2008) or Marxan (Ball et al., 2009), were employed to provide practical solutions for identifying quasi-optimal reserves sites. These methods, however, could not guarantee optimality. As computational power increased, the focus shifted to exact methods such as Mixed Integer Programming (MIP), which guarantees globally optimal solutions (van der Kam et al., 2007; Cheng et al., 2015) and faster execution (Beyer et al., 2016; Schuster et al., 2020).

A difficulty that remains for both multi-objective stochastic methods and MIP is the elicitation of individual weights for competing objectives (Marler and Arora, 2010). Although several elicitation methods exist (Eckenrode, 1965; Esmail and Geneletti, 2018), the representation of stakeholders priorities is dependent on the consultation process and stakeholders involvement (Estévez and Gelcich, 2015) and remains highly subjective.

To address this challenge, we propose a framework that integrates MIP and Monte Carlo (MC) experiment to explore the variability of

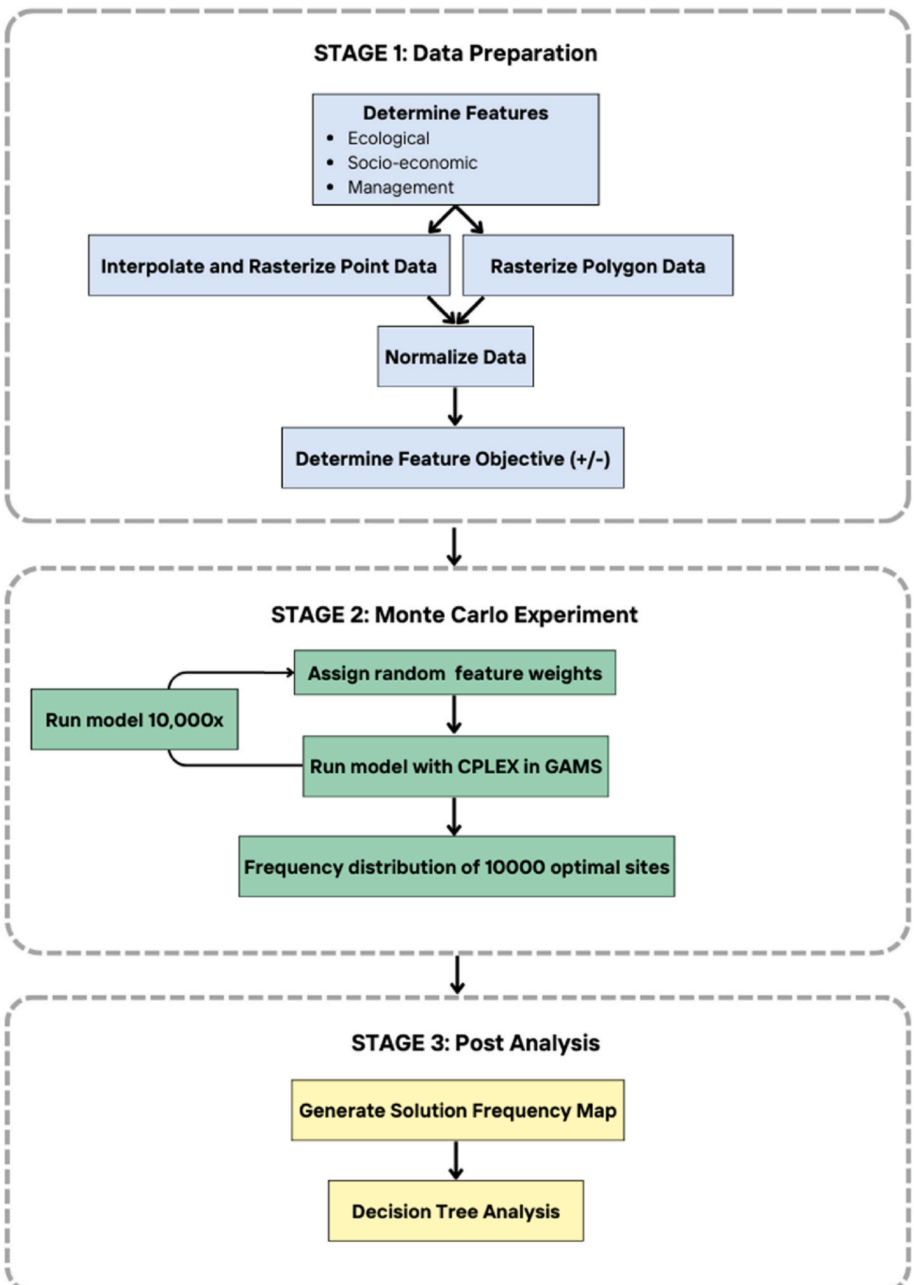

Fig. 1. Workflow of the exploratory modeling framework.

selected sites under varying stakeholder priorities. We use Decision Tree (DT) analysis to identify key threshold conditions under which optimal solutions shift. We illustrate the use of our method on the Northern part of Xiao Liuqiu Island, Taiwan.

2. Materials and methods

This study integrates MIP, MC, and DT analysis to explore patterns of optimality in reserve selection, under varying stakeholder priorities. The methodological approach consists of three major stages: 1) Data preparation in which we collected and preprocessed spatial data for 10 ecological features (benthic and fish diversity, fish population density, the coverage of crustose coralline algae, hard corals, soft corals, macroalgae, and turf algae, sea turtle nest count and population density), 7 socio-economic features (freediving, helmet diving, SCUBA diving, shore fishing, snorkeling, spearfishing, and standup paddleboarding areas), and 4 management features (coastal landscapes, community recommended areas, research hotspots, and strategic management areas); 2) MC experiment, where we executed the MIP model with randomized weights; and 3) Post analysis, where we visualized the MC findings with a frequency selection map and a DT (Fig. 1).

2.1. Data preparation

2.1.1. The planning region

Xiao Liuqiu exemplifies the complex challenges of balancing marine conservation and economic development in a small island setting. Traditionally, the island thrived on a vibrant fishing industry, which is a testament to its economic dependence on a healthy marine environment. However, the island's economy shifted in the 2000s when it became a part of the Dapeng Bay National Scenic Area. This newfound fame transformed Xiao Liuqiu into a major tourist destination, bringing economic benefits to the local community (Chen, 2015) and significant amounts of pollution (Lim et al., 2022).

The island's coastal area was designated as an MPA in 2000 to safeguard four specific aquatic resources: lobsters, sea urchins, sargassum, and coral reef fishes. In 2014, the MPA was restructured into three separate MPAs, each with varying levels of marine resource protection under the Liuqiu Aquatic Organisms Propagation and Conservation Zoning Plan (Fig. 2). The Round Island Protected Area (RIPA) focuses on the protection of marine organisms such as lobsters, sea urchins, and sargassum. The Northwest Protected Area (NWPA) safeguards lobsters, sea urchins, sargassum, coral reef fish, and other aquatic species, excluding migratory species. The Intertidal Zone Conservation Demonstration Area (IZCDA) is composed by three no-take zones that protect all marine animals and sargassum.

The increasing number of tourists (Fig. 3) has significantly pressured the island's marine resources. The demand for fresh seafood and the surge in recreational activities such as snorkeling and diving have heavily impacted fish populations and coral reefs, especially in the NWPA. Furthermore, inadequate enforcement of marine resource protection has exacerbated the situation.

A local tourism association has lobbied managers to establish a no-take marine reserve within the NWPA to enhance the management of marine resources in the region. However, the fishermen's association contends that if the management of the MPA is to be strengthened, it should not only restrict fisheries but also prohibit entry for all individuals, including tourists, creating a no-entry zone. The proposed marine reserve should be compact and seamlessly integrate with existing MPAs. Its regulations should facilitate stricter and more straightforward enforcement by offering full protection from fishing, tourism, and other anthropogenic activities.

The Northern part of Xiao Liuqiu was divided into a grid of 50 square meters of planning units (PUs) to create the planning region and account for the spatial distribution of 21 ecological, socio-economic, and management features. A total of 5978 PUs were generated and rasterized into a matrix with 98 rows and 61 columns.

2.1.2. Features

Ecological data, such as benthic and fish diversity, fish population

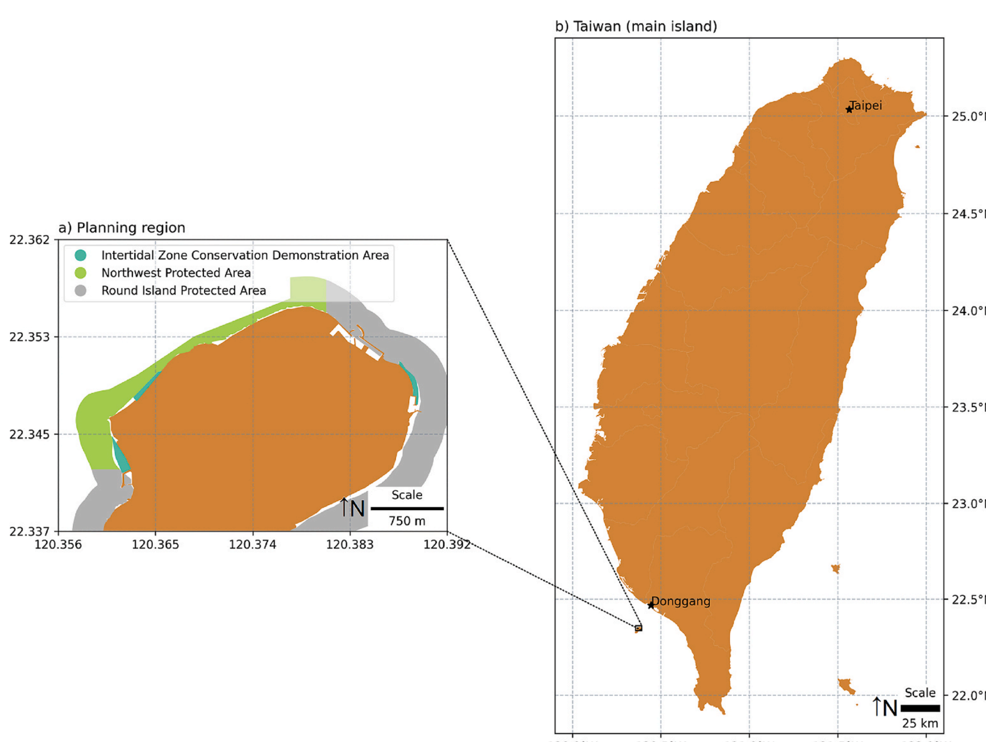

Fig. 2. Location of Xiao Liuqiu Island, Pingtung County, Taiwan. Inset shows the extent of the planning region with the three significant protected zones stated in the Liuqiu Aquatic Organisms Propagation and Conservation Zoning Plan (2014).

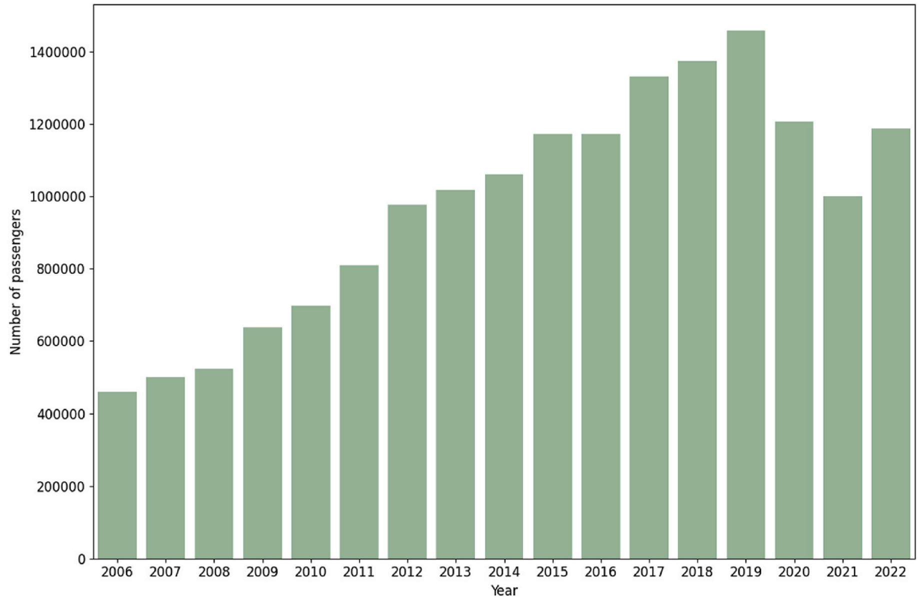

Fig. 3. Number of passengers coming from Donggang Port to Xiao Liuqiu (Ministry of Transportation and Communications ROC, 2023).

density, the coverage of crustose coralline algae, hard corals, soft corals, macroalgae, and turf algae, were collected through line transect methods for benthic features and underwater visual surveys for fishes, conducted by the authors in 2022. Additionally, sea turtle distribution data, encompassing nest counts from terrestrial observations and population density from aerial photography, were obtained from reports published by the Ocean Affairs Council (Ocean Affairs Council, 2021, 2022). The mapping of socio-economic features, which represent human activities within the planning region, was obtained through geographic information system-assisted semi-structured interviews with local stakeholders (Chang et al., 2022). These features include: freediving, helmet diving, SCUBA diving, shore fishing, snorkeling, spearfishing, and standup paddleboarding areas. Finally, management-related spatial data, reflecting the specific management needs of the planning region, were compiled through a collaborative mapping effort involving the authors and two local experts with in-depth knowledge of Xiao Liuqiu's management framework. These features include: coastal landscapes (vulnerable areas with ecological and visual significance), community recommended areas (zones suggested by local stakeholders for enhanced protection based on cultural or practical importance), research hotspots (sites already monitored and thus offering built-in support for enforcement), and strategic management areas (locations identified as feasible for regular patrols, surveillance, and practical enforcement due to their accessibility and proximity to existing surveillance structures). These features were selected to ensure that the reserve design reflects not only ecological or socio-economic priorities, but also day-to-day operational feasibility, governance realities, and existing institutional presence.

Data compilation, management, and preparation were performed using QGIS 3.22.16. All ecological data was interpolated using the ordinary Kriging method from the pykridge Python toolkit (Murphy and Muller, 2022), while the rest of the features were simply rasterized. The values assigned in each PU were normalized using Equation (1).

$$x_n = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Wherein x_n corresponds to the normalized value, x_i is the initial value, x_{min} is the minimum value in the matrix, and x_{max} is the maximum value in the matrix.

Features were selected for maximization or minimization based on their ecological, socio-economic, and management impacts. A majority of ecological features were prioritized for maximization to promote biodiversity and ecosystem health. Only turf algae cover was minimized due to its detrimental effects on corals. To reduce the opportunity cost to human activities, socio-economic features were minimized, except spearfishing which was maximized due to its illegal nature. Vulnerable habitats, including coastal landscapes and research hotspots were prioritized to strengthen management and conservation efforts. Strategic management areas, identified for effective foot patrol and surveillance, were also maximized, alongside sites preferred by local communities, thereby incorporating local knowledge and stakeholder input into the decision-making process.

2.2. Monte Carlo experiment

Each of the 21 selected features was assigned a random weight prior to optimization. These weights were sampled uniformly between 0 and 1 and scaled around unity, according to the following formula:

$$w_k = \frac{21 * r_k}{\sum_{k=1}^{21} r_k}, with\ r_k = uniform(0, 1) \tag{2}$$

With w_k, the randomized weight of feature k.

The MIP model was executed using the randomized combination of weights and the optimal solution was stored in a file. The procedure was repeated 10000 times to ensure a thorough exploration of the parameter space.

The marine reserve selection model maximizes the weighted sum of the features, given a specific total area and compactness (Cheng et al., 2015). Compactness is measured by calculating the external boundary length of the selected reserve (Wright et al., 1983). Low compactness values result in compact solutions, while high compactness values result in fragmented solutions. The CPLEX solver of the GAMS software was used to perform the maximization. Each of the 21 features (Fig. 4) was either added to or subtracted from the objective function based on the criteria set during the initial consultation. The objective function (Z) below (Eq. (3a)) describes a marine reserve design built upon PUs with maximal ecological (except for turf algae cover), minimal socio-economic (except for spearfishing areas) and maximal management values, under specific total area (Eq. (3b)) and compactness (Eq. (3c)) constraints:

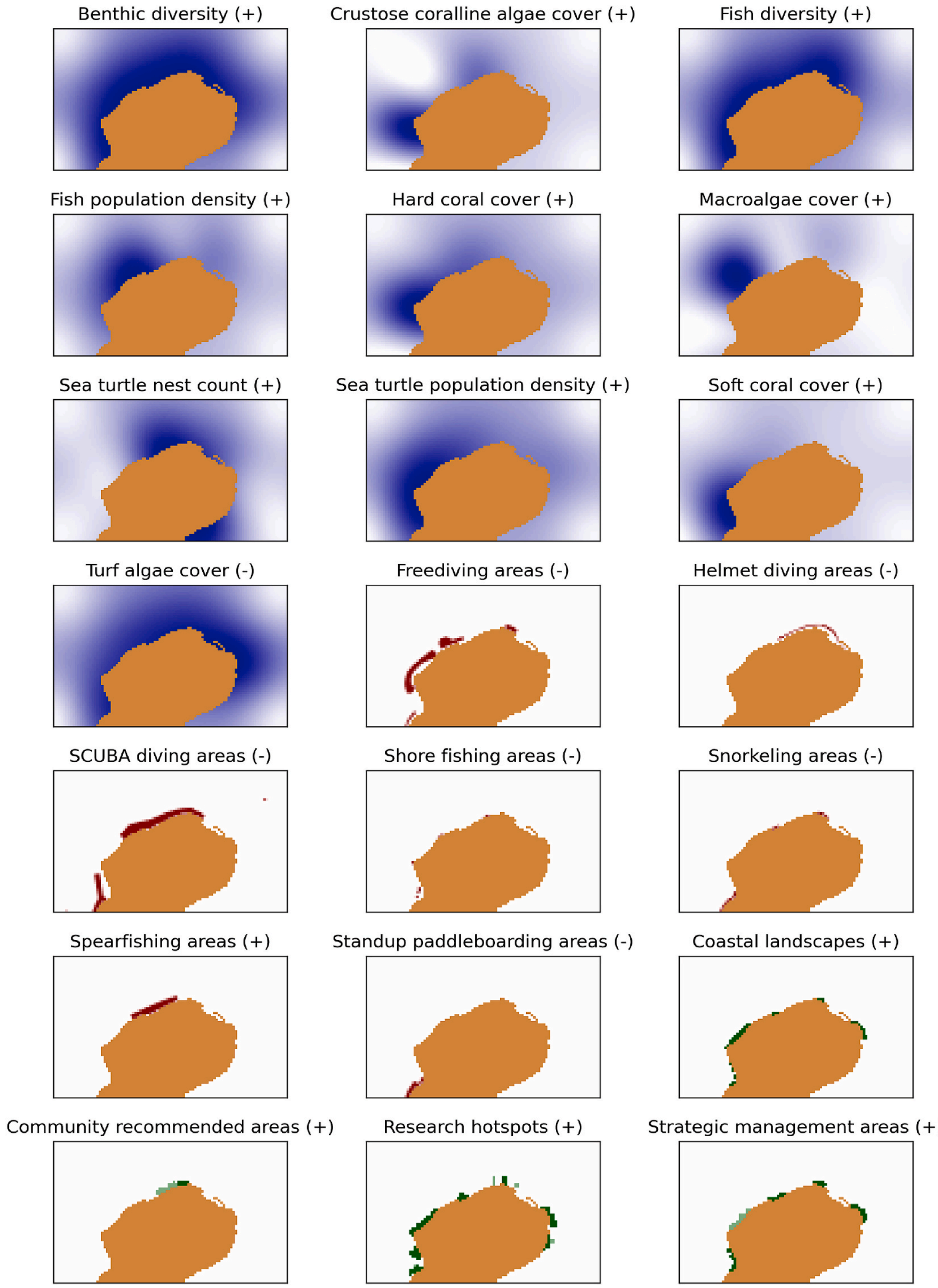

Fig. 4. Spatial distributions of all features in the planning region. Ecological features are colored in blue, socio-economic features are in red, and management features are in green. The signs in parenthesis indicate whether the feature should be included in the reserve selection (+) or not (−). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

$$Maximize\ Z = \sum_{k=1}^{21} \sum_{i=1}^{N} w_k l_k x_i \tag{3a}$$

Subject to:

$$\sum_{i=1}^{N} x_i = 50 \tag{3b}$$

$$\sum_{i=1} \sum_{j \in T_i} (P_{ij} + N_{ij}) = 34 \tag{3c}$$

$$x_i - x_j - P_{ij} + N_{ij} = 0, \forall i, j \in T_i \tag{3d}$$

$$P_{ij} + N_{ij} \leq 1x_i, P_{ij}, N_{ij} = 0, 1 \tag{3e}$$

Where w_k is the weight expressing the relative importance of a feature k;

l_k is the spatial layer of data for feature k, N is the total number of PUs; and x_i is a binary variable ($x_i = 1$ if the PU is included in the reserve set, otherwise 0), i and j denotes indices (when i is a selected cell, j is the adjacent cell); P_{ij} and N_{ij} are dummy variables used to calculate the external boundary length. $P_{ij} = 1$ if $x_i = 1$ and $x_j = 0$, otherwise 0 and $N_{ij} = 1$ if $x_i = 0$ and $x_j = 1$, otherwise 0; M is the total area of the reserve, L is the total number of external boundaries allowed in the reserve design, and T_i is the set of cells adjacent to i. The external boundary length of the reserve was determined using the formulas below (Wright et al., 1983):

$$B^M_{min} \le L \le B^M_{max} \tag{4a}$$

$$B^M_{max} = 4M \tag{4b}$$

$$B^M_{min} = 4\left(\lfloor\sqrt{M}\rfloor\right) + 2t \tag{4c}$$

$$t = 0 \text{ if } M - \left(\lfloor\sqrt{M}\rfloor\right)^2 = 0 \tag{4d}$$

$$t = 1 \text{ if } M < \left(\lfloor\sqrt{M}\rfloor\right)^2 + \left(\lfloor\sqrt{M}\rfloor\right) + 1 \tag{4e}$$

$$t = 2 \text{ if } M > \left(\lfloor\sqrt{M}\rfloor\right)^2 + \left(\lfloor\sqrt{M}\rfloor\right) + 1 \quad \text{with } \lfloor\sqrt{M}\rfloor = \textit{integer part of } \sqrt{M} \tag{4f}$$

The total area (Eq. (3b)) was set to 50 PUs or 2500 square meters. Following equations (4a) to (4f), when M = 50, the outer boundary length can be assigned to values between 32 and 200. In order to prevent reserve fragmentation, L was assigned a value of 34 external boundaries (Eq. (3c)).

2.3. Post analysis

We developed a DT to complement the findings of the MC experiment. A DT is a flowchart-like structure that utilizes a series of yes/no questions to classify a target value (Shorabeh et al., 2022). In our case, the DT was used to identify key features that influence PUs selection under specific weight combinations. The samples represent the simulations conducted by each MC run. The value at each node reflects how many samples fall into each class, ultimately predicting the zone where PUs were most likely to be located. The DT was setup with a predefined maximum depth of 3, a minimum sample leaf of 300, a minimum sample split of 600 and a balanced class weight to help represent all three classes. These constraints helped prevent the model from becoming excessively complex, striking a blance between accuracy and simplicity (Bohanec and Bratko, 1994). A 80/20 ratio was used for training/testing the model. The Gini score was used to quantify the impurity of each node (Aluja-Banet and Nafría, 1998). A Gini score of zero indicates a pure node, where all samples belong to the same class. Conversely, a Gini score greater than zero indicates that some samples within that node belong to different classes. The algorithm finds the split that results in the largest decrease in Gini impurity. An optimized CART (Classification And Regression Trees) implementation (Steinberg, 2009) from the Scikit-learn package in Python (Pedregosa et al., 2011) was used to derive the DT from the overall results of the MC experiment and the DT was drawn using the dtreeviz package (Parr and Grover, 2020).

3. Results

3.1. Selection frequency map

The selection frequency map illustrates the number of times each PU was selected across all MC runs (Fig. 5). This helps visualize the relative importance of each PU for creating an efficient marine reserve based on randomized prioritization weights.

Selected PUs were found to belong to three distinct zones. The PUs within Zone 2 were selected 88.9 % of the time (Fig. 5). The PUs located within Zone 1 and Zone 3 were selected 1.7 % and 9.4 % of the time respectively, under some particular sets of feature weighting. These results suggest that the PUs within Zone 2 are suitable for an efficient marine reserve under most combinations of prioritization criteria. Notably, Zone 2 overlaps with areas of high value in *coastal landscapes* and *research hotspots*, and moderate levels of *strategic management suitability*, suggesting that it not only meets ecological criteria but also holds promise for effective implementation. The PUs rarely selected, like those within Zone 1 and Zone 3, are suitable for more specific prioritization criteria combinations that were uncovered with the DT.

3.2. Decision Tree

The DT (Fig. 6) provides insights into which combination of weights leads to a marine reserve in each of the three identified zones. The DT's accuracy is 72 %, striking a reasonable compromise between model accuracy and simplicity. For each node of the DT, a histogram is shown that displays the distribution of weights in the classified MC runs. Since weights have been scaled, a weight higher than 1 indicates that the feature is given a relatively higher priority than other features. The pie charts represent the DT's leaves, i.e the selection frequencies of each zone under specific weight combinations.

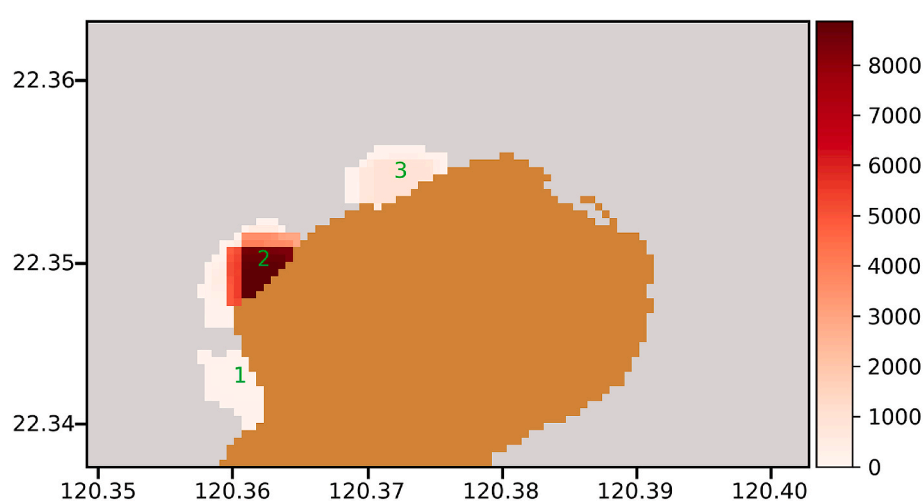

Fig. 5. Selection frequency map. Selected sites belong to three distinct zones, highlighted with green numbers. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

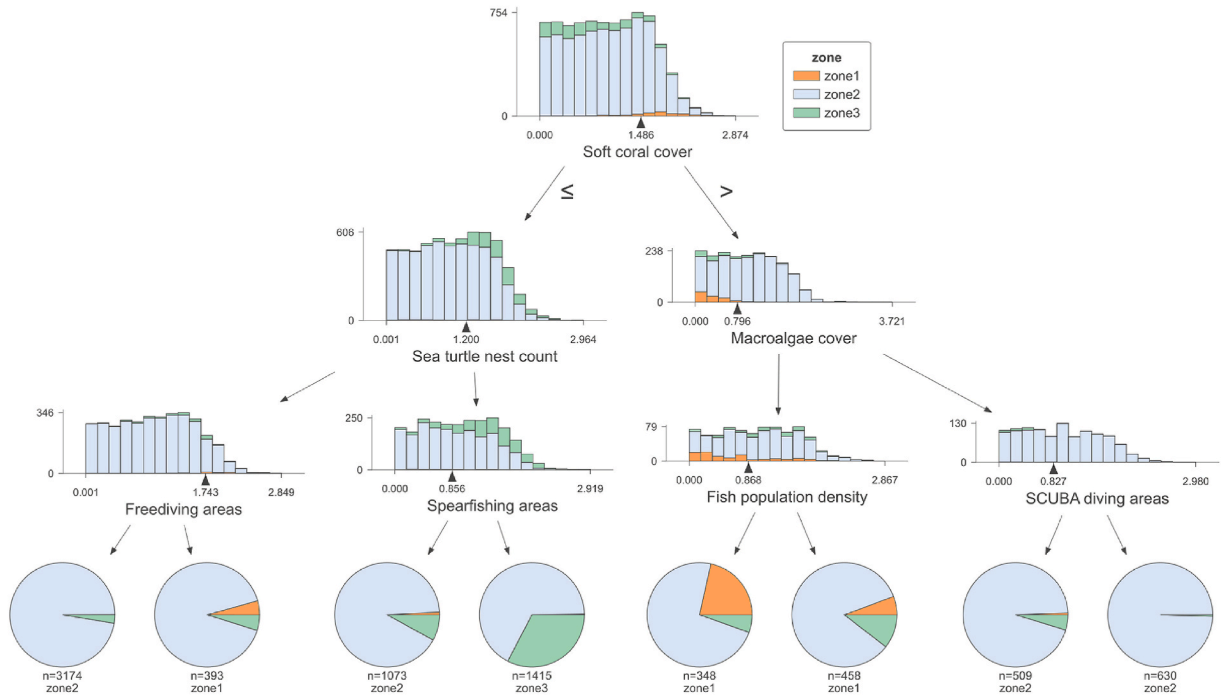

Fig. 6. Decision Tree of the Monte Carlo results.

Following the root node, the DT shows that the site selection has around 30 % chances to favor Zone 3 (green) if the weighting values for the following features are satisfied: less than or equal to 1.486 for Soft coral cover, more than 1.2 for Sea turtle nest count, and more than 0.856 for Spearfishing areas. Conversely, Zone 1 (orange) has around 20 % chances of being selected if the weighting values for the following features are satisfied: more than 1.486 for Soft coral cover, less than or equal to 0.796 for Macroalgae cover, and less or equal to than 0.868 for Fish population density. In any case, it should be noted that under any of the presented paths, the area that is most likely to be selected is always Zone 2 (blue).

These results show that Zone 2 is by far the strongest candidate for a potential marine reserve in Northern Xiao Liuqiu Island. Indeed, these marine waters contain high ecological, low socio-economic, and high management values (Fig. 4).

4. Discussion

4.1. Pertinence of the exploratory approach for marine reserve site selection

Traditional marine reserve site selection methods, such as Marxan, primarily rely on heuristic-based optimization, which lacks guaranteed global optimality. Additionally, fixed-weight MOO models require precise weight estimations, which are difficult to justify in complex conservation scenarios. Our study improves upon these approaches by integrating MIP optimization with MC, allowing for an exploratory assessment of multiple prioritization criteria. This approach reduces weight estimation bias while ensuring globally optimized solutions that account for diverse conservation objectives and stakeholder concerns. Our results show that the coastal waters of Zone 2 are the most suitable candidate for a marine reserve in Northern Xiao Liuqiu (Fig. 5), under any prioritization scenario (Fig. 6). This finding underscores the stability of Zone 2 under diverse weighting scenarios and demonstrates the advantage of using an exploratory approach instead of predefined weights. Its alignment with high-value areas for research and coastal landscape, as well as intermediate suitability for patrol, also highlights the zone's practical feasibility for real-world management and enforcement efforts. Moreover, our approach ultimately provides decision-makers with more options. Without the MC experiment, Zone 1 and Zone 3 may not have been identified. Lastly, each zone appears as a selection gradient, which can be used to identify potential sites for buffer zones or future areas of expansion.

While the MC method provides the decision-makers with more options, the DT (Fig. 6) provides a clear and visual explanation into how these options are generated. By pruning the DT, we achieved a balanced trade-off between accuracy (72 %) and simplicity (only 8 leaves), making the DT more practical and interpretable. Our analysis highlights how key features such as Soft coral cover, Sea turtle nest count, Spearfishing, Macroalgae cover, and Fish population density are important into shifting the selection from Zone 2 towards other zones. This narrows down the list of features decision-makers need to consider when planning for conservation in Northern Xiao Liuqiu, allowing them to focus on these critical features.

4.2. Potential limitations and challenges

There are a few key points to consider regarding the proposed framework. First, the MC experiment requires the use of MIP, as each run ensures a unique solution that directly corresponds to a specific set of weights. In contrast, a stochastic algorithm would yield only an approximate solution, introducing randomness into the association between the weights and their resulting solutions.

Second, the spatial budget (50 PUs) and the compactness level (34 external borders) in the MIP model, played a significant role in shaping our results. These strict constraints limited the model's ability to select alternative zones. If these constraints were relaxed, the optimization would likely have resulted in more fragmented reserves, which would, in turn, complicate the subsequent DT analysis.

Third, while our framework circumvents the challenge of eliciting weights, it is not intended to replace public consultation. Instead, it serves as a rapid exploratory tool for assessing potential solutions, enabling decision-makers to make informed choices and streamline the marine reserve site selection process. Eventually, it would be very good practice to elicit a realistic set of user-driven priorities and explore the sensitivity of optimal solutions around these values.

Finally, we encourage exploring open-source software solutions like the Gurobi or Coin-or Branch and Cut (CBC) solvers and tapping into university expertise for technical support. While financial constraints and limited local capacity may pose challenges, securing stakeholder buy-in remains the top priority. We believe our framework can enhance public consultation and foster greater transparency.

4.3. Implications for management

Integrating our framework into the conventional participatory process for marine reserve site selection offers clear advantages in efficiency, responsiveness, and stakeholder engagement. Traditional methods often involve lengthy post-processing steps that delay feedback and extend consultation timelines (Pınarbaşı et al., 2017). Our approach addresses this by providing fast computational feedback, allowing stakeholders to view outcomes dynamically as priorities and inputs are discussed. By removing the need for explicit feature weight elicitation, the MC experiment streamlines the process, reducing the need for repeated consultation rounds. This does not diminish stakeholder involvement; rather, it enables a more continuous, interactive and transparent consultation process, where feedback can be integrated as results are generated.

The framework also incorporates management feasibility directly into reserve design through the inclusion of operational constraints such as enforcement suitability, patrol logistics, and areas preferred by local communities. For instance, Zone 2's proximity to key access points and monitoring infrastructure makes it more feasible for cost-effective enforcement. This integration ensures that selected sites are not only ecologically valuable but also practical to manage, an aspect often under-emphasized in existing tools focused primarily on ecological or economic trade-offs. By grounding the design in real-world conditions and local governance structures, the framework supports more implementable and institutionally aligned outcomes.

From a different angle, the framework provides managers with a scientific foundation for engaging community stakeholders in selecting MPAs. Communities often face conflicts among stakeholders when promoting tourism development, primarily due to tensions between the economic benefits of tourism and traditional community values, which can lead to social unrest (Christie et al., 2003; Lei et al., 2023), and is particularly evident in Xiao Liuqiu. A local group has actively pursued the establishment of an MPA in Northern Xiao Liuqiu, but their proposed site has faced objections from other community factions questioning potential private interests. Additionally, community groups tend to focus on a limited number of factors, often influenced by self-interest or fragmented knowledge, resulting in a lack of a holistic view of ecosystem benefits. In this context, the framework, which incorporates various factors derived from prior stakeholder interviews and research, can provide the government with a solid and impartial scientific basis to persuade both the local group and the wider community about the suitability of the best choice (Zone 2).

In future applications, the framework could be extended to account for budgeting and capacity constraints by incorporating cost-related features such as patrol frequency, infrastructure requirements, and personnel availability into the MIP formulation. This would support more financially realistic reserve designs and allow planners to evaluate trade-offs between conservation benefits and operational costs.

Finally, the presented framework is well-suited to adaptive management. It can readily incorporate new data or respond to shifting priorities without requiring a complete redesign. This flexibility supports ongoing learning and adjustment, which are increasingly necessary for effective conservation under changing environmental and social conditions.

5. Conclusions

Our framework integrates 21 ecological, socio-economic, and management features to guide marine reserve site selection. To our knowledge, it is the first to explicitly incorporate day-to-day management considerations. This practical focus supports the implementation of enforceable, community-aligned marine reserves and complements ongoing efforts to strengthen MPA governance at the local level. The MC experiment described offers decision-makers a broader perspective on optimal marine reserves, while the DT translates the complex relationships between feature weights and selected zones into a clear visual summary. By providing rapid outputs, this framework has the potential to support timely and informed decision-making.

CRediT authorship contribution statement

Donna Ross Saycon: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shui-Kai Chang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation. **Tung-Yung Fan:** Writing – review & editing, Data curation. **Chen-Lu Lee:** Writing – review & editing, Data curation. **Yang-Chi Chang:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Pierre-Alexandre Château:** Writing – review & editing, Visualization, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests or personal relationships that could have influenced the work reported in this paper.

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Data availability

Data will be made available on request.

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