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Evaluating Bioeconomic Tradeoffs of Fishing Reserves Via Spatial Optimization

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Abstract

No-take marine reserves are common strategies used in spatial fisheries management. There are at least four general objectives for marine reserve design: (1) maximizing conservation, (2) minimizing total reserve area, (3) maximizing reserve compactness, and (4) minimizing socioeconomic opportunity cost (e.g., fisheries revenue). A spatial optimization model was developed to solve for reserve placements under those four objectives, while evaluating the bioeconomic tradeoffs and potential gaps of a subset of bottomfish restricted fishing areas (BRFAs) for the Hawaiian bottomfish fishery. Optimized reserve placements with minimal opportunity costs had little overlap (< 9%) with the placements of the BRFAs, opportunity cost values 50-83% less than that of the BRFAs with 40-54% higher potential conservation value. When reserve placements were optimized to provide a maximal opportunity cost, solutions had up to 49% overlap with the BRFAs, highlighting a potential drawback of the BRFA system with respect to socioeconomic impacts. When opportunity cost was instead calculated as total area, the optimized placements also had considerable overlap (up to 42%) with the BRFAs, highlighting the importance of socioeconomic data to the reserve design process. The solutions that provided maximal reserve compactness may be the most pragmatic for a reserve design team with specific area and/or conservation targets, as these solutions produced compact reserve placements that best matched those targets at a minimal opportunity cost. This analysis emphasized the use of spatial optimization models to not only guide the reserve design process, but to highlight tradeoffs of conflicting fisheries objectives in reserve design.

Keywords: Multiple-Criteria Decision Making (MCDM); Integer Linear Programming (ILP); Systematic Reserve Design; Marine Protected Areas; Fisheries

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1. Introduction

Marine reserves are spatial tools in marine conservation and fisheries management used globally to protect biodiversity, essential habitat features, and/or rebuild over-exploited populations (Lester et al. 2009; Edgar et al. 2014; Costello and Ballantine 2015). Networks of no-take marine protected areas (MPAs) can reflect a precautionary approach in fisheries management, hedging against the uncertainties of the statuses of exploited populations, management limitations, and long-term sustainability of fisheries (Lauck et al. 1998). Although MPAs are not the panacea for all fisheries management issues (Hilborn et al. 2004; Kaiser 2005; Hilborn et al. 2006), they have the potential to address key conservation goals in fisheries management related to fish biomass, average size, biomass of apex predators, and biodiversity (Halpern and Warner 2002; Friedlander et al. 2007; Lester et al. 2009; Molloy et al., 2009; Edgar et al. 2014) as well as resilience to climate change (Micheli et al. 2012).

The challenge of designing the placements of marine reserves in spatial fisheries management is addressing many diverse and often conflicting conservation, management, and socioeconomic objectives that define the fishery (Jennings et al. 2001; Gaines et al. 2010). For example, the conversion of fishing grounds to no-take restricted fishing areas may fulfill clear conservation goals, however at the expense of the social and economic value lost from those areas. Foregone fishing effort as a result can be either displaced to the open area, shifted to a different fishery, and/or dissipated completely (Horta e Costa et al. 2013; Stevenson et al. 2013). Accessibility and perceived sociocultural importance of fishing grounds are also opportunity costs that complement the economic opportunity costs of marine reserves (Hamel et al. 2018).

Systematic conservation planning is an approach that can guide the design and placement of fishery reserves and other area-based management strategies (Margules and Pressey 2000; Leslie 2005). Its purpose is to provide an objective framework that clearly states the objectives and goals of the reserve design, analyzes the tradeoffs of these objectives, and involves stakeholders in the design process (NRC 2001). For example, Marxan (Ball et al. 2009) is a widely used software in natural resource management that utilizes simulated annealing to heuristically place networks of minimum opportunity cost marine reserves according to user-defined levels of conservation feature targets and reserve configurations (Airame et al. 2003; Klein et al. 2008; Leathwick et al. 2008; Ball et al. 2009). The conceit of this modelling framework is that networks of marine reserves can be optimized to protect specified levels of various conservation features of interest (e.g., essential habitat, spawning aggregations, nursery areas) at a minimal opportunity cost. Systematic approaches to marine reserve design have been shown to provide higher representation of conservation targets (Hansen et al. 2011) and lower potential economic impact to commercial users (Stewart and Possingham 2005; Klein et al. 2008) than reserves designed *ad hoc*.

Multiple-Criteria Decision Making (MCDM) can be a useful approach to appropriately assist fisheries managers of the tradeoffs among conflicting objectives in reserve design (MCDM; see Romero and Rehman 2003 for technical details). There are a handful of MCDM applications in fisheries (see reviews by Mardle and Pascoe 1999 and Leung 2005). Modern applications of MCDM include, e.g., optimal fleet configurations (Pascoe and Mardle 2001), tradeoffs between profit maximization and turtle interactions in the Hawaiian longline fisheries (Pradhan and Leung 2006), and tradeoffs among rent, employment, and income in the Barents Sea cod fishery (Leung et al. 2001). Pan et al. (2001) used a multi-objective programming model to evaluate optimal considerations of fleet mix, harvest levels of multiple species, and spatiotemporal distribution of fishing effort in the Hawaiian deepwater and pelagic fisheries. Stigner et al. (2016) evaluated the tradeoffs of shorebird conservation and recreational activities within a coastal protected area in the Moreton Bay Marine Park in Queensland, Australia and found that shorebird conservation targets could be met while posing low recreational opportunity costs.

The Hawaiian Deep Seven Bottomfish species complex is a federally and state-managed group of six eteline snappers (*Etelis coruscans*, *E. carbunculus*, *Pristipomoides filamentosus*, *P. sieboldii*, *P. zonatus*, and *Aphareus rutilans*) and one endemic grouper (*Hyporthodus quernus*). The fishery is a primarily hook-and-line fishery with a fluid mixture of recreational, subsistence, and part- and full-time commercial fishers (Hospital and Beavers 2012). From 1986-2004, the statuses of bottomfish species were measured using spawning potential ratios (SPRs) calculated from commercial logbook data. The Sustainable Fisheries Act of 1996, an amendment to the Magnuson-Stevens Fishery Conservation and Management Act (MSFCMA), instituted a quantitative benchmark for characterizing for overfishing and overfished levels. This translated to a definition of SPR < 20% as the overfished definition for the bottomfish fishery. Spawning potential ratios calculated for the two *Etelis* spp. in the main Hawaiian Islands (MHI) were consistently below this threshold during the 1980s and 1990s and when the MSFCMA was amended, these two species were considered overfished. As part of the mandated rebuilding plan, nineteen areas across the main Hawaiian Islands were designated as bottomfish restricted fishing areas (BRFAs). In 2007, the number of BRFAs was reduced to 12 and the placements of the BRFAs were revised to include more relevant aspects of the habitat (e.g. high relief, hard-bottom areas) for all Hawaiian Deep Seven bottomfish species. Around this time, the stock assessment of the Deep 7 complex shifted to surplus production modelling and biological reference points based on maximum sustainable yield. The new configuration of the BRFAs had clear biological objectives relevant to reducing fishing mortality and rebuilding bottomfish biomass within the BRFAs, with the intention that the reserve-associated biomass and larval products can be exported into the open areas, however socioeconomic tradeoffs were not considered in the reserve design process. There has, since the implementation of the BRFAs, not been a careful consideration of the biological and socioeconomic tradeoffs of the current placement of the BRFAs.

A multi-objective binary linear programming model was developed to evaluate the tradeoffs of the conflicting biological, socioeconomic, and management objectives relevant to the current network of bottomfish restricted fishing areas (BRFAs) for the Hawaiian deepwater snapper-grouper fishery. The objectives included in the model were: (1) minimizing socioeconomic opportunity cost, (2) maximizing conservation value, (3) minimizing total reserve area, and (4) maximizing reserve aggregation. These solutions with respect to the four objectives were compared to the placements of the BRFAs to identify potential gaps and tradeoffs of the current regulations. To investigate the hypothesis that the BRFAs placed a maximal opportunity cost to commercial fishers, a separate model run was conducted with the opportunity cost function switched from minimization to maximization, and these solutions were also compared to the placements of the BRFAs. This tradeoff analysis emphasized the use of MCDM to not only guide the reserve design process, but to highlight tradeoffs of conflicting fisheries objectives in the reserve design problem.

2. Methods

2.1 Study Area

This analysis focused on the coast surrounding the most populated island in the MHI, Oahu, and its two BRFAs (Figure 1). A 500 x 500 m grid of planning units (PUs) was superimposed within the 50-400 m depth range of the coastline resulting in 4753 PUs. This depth range was chosen because it contained the depth ranges of the species distribution maps that were used as data inputs (see Section 2.2). A 500 m PU resolution was chosen a reasonable PU resolution, as computation time was inversely related to the PU resolution.

2.2 Data Sources

Conservation feature data were derived from habitat-based species distribution maps created for each of the Deep Seven Bottomfishes species (Oyafuso et al. 2017). The species distribution maps for each of the Deep Seven Bottomfishes can be accessed from the Data Dryad Depository (https://doi.org/10.5061/dryad.f78r6). Mean probability of occurrence for each of the species was calculated within each PU (Figure 1). Opportunity cost was defined as the per-PU gross revenue of total Deep Seven bottomfishes. Catch revenue data were collected by the State of Hawaii Division of Aquatic Resources by species and statistical fishery reporting area (see bottom-right panel in Fig. 1). Data from 1990-1996 were used to represent the spatial distribution of fishing activity before the implementation of the BRFAs. Trip cost data are very scarce for this fishery (Hospital and Beavers, 2012) and were not available for the time period of interest. Annual total gross revenue summed over the seven bottomfish species was tabulated for each statistical fishery reporting area, then divided equally amongst the PUs within the fishery reporting area. This calculation does not account for the spatial heterogeneity in fishing activity within a fishery reporting area, but rather reflects the resolution that the data were collected.

[approximate location of Figure 1]

2.3 Objective Functions

A multi-objective binary integer linear programming model was constructed to select a set of PUs under four objectives:

(1) Minimize opportunity cost:

$$\min \sum_{i=1}^{N} x_i c_i \tag{1}$$

Where x_i is a binary decision variable (x_i = 1 if the i^{th} PU is chosen, 0 otherwise), c_i is the opportunity cost of reserving the i^{th} PU, and N is the total number of PUs. Total reserve set opportunity cost is reported in the Results Section as a proportion of the total opportunity cost of the PUs within the spatial domain.

(2) Maximize conservation value

$$\max \sum_{i=1}^{N} x_i r_{is} \tag{2}$$

Where r_{is} is the attribute, i.e., predicted probability of occurrence, for the s^{th} species ($s: 1, 2, \ldots, S$) in the i^{th} PU, and S is the total number of species (i.e., S = 7). There are S objective functions representing each species feature. The conservation value of the reserve set is reported in the Results Section as a proportion of the summed species attributes of the PUs within the spatial domain, averaged across species.

(3) Maximize reserve aggregation

In most systematic reserve design exercises, it is advantageous for the decision maker to be able to control the spatial arrangement of the PUs to favor more aggregated or connected networks of reserves. The incorporation of interactions among PUs involves the addition of non-linear terms, and thus is problematic in a linear programming framework. Beyer et al. (2016, but also see Billionnet 2013) described methods to linearize these non-linear terms by the addition of decision variable b_{ij}, with the following objective function:

$$\max \sum_{(i,j) \in E} b_{ij} v_{ij} \tag{3}$$

Where b_{ij} is a binary decision variable that denotes the selection of adjacent PUs i and j. E is the set of adjacent cell interactions in the spatial domain of the PUs. v_{ij} is the length of the shared boundary between the i^{th} and j^{th} PUs. Note that in a lattice structure, v_{ij} is constant and thus can be removed. The addition of each decision variable is accompanied with three additional constraints to ensure that $x_i = x_j = 1$ if $b_{ij} = 1$.

$$b_{ij} - x_i \leq 0 \tag{4}$$

$$b_{ij} - x_j \leq 0 \tag{5}$$

$$b_{ij} - x_i - x_j \leq -1 \tag{6}$$

The aggregation value of a reserve set is reported in the Results Section as a proportion of the total number of potential adjacent PU interactions.

(4) Minimize total reserve area

$$\min \sum_{i=1}^{N} x_i a_i \tag{7}$$

Where a_i is the area of the i^{th} PU. Note that in a lattice structure, a_i is constant and thus can be removed. The total area of the reserve set is reported in the Results Section as a proportion of the total number of PUs in the spatial domain.

2.4 Structural Constraints

To directly compare the solutions with the placements of the BRFAs, additional structural constraints on the objectives were included such that the chosen reserve set:

(1) did not exceed the total opportunity cost of the PUs contained within the boundaries of the BRFAs (C)

$$\sum_{i=1}^{N} x_i c_i \leq C \qquad (8)$$

(2) did not exceed the total number of PUs contained within the boundaries of the BRFAs (A)

$$\sum_{i=1}^{N} x_i \leq A \qquad (9)$$

(3) had summed species attribute values greater than or equal to those of the PUs contained within the boundaries of the BRFAs (R_s)for each species.

$$\sum_{i=1}^{N} x_i r_{is} \geq R_s \qquad (10)$$

2.4 Multi-Objective Integer Linear Programming Model

The epsilon-constraint method is a classical technique in MCDM (Romero and Rehman 2003) used to solve multi-objective optimization problems. Briefly, one of the objectives is solved in a single-objective problem, transforming the other objectives as constraints. This process is iterated using an interval of constraints across a user-defined range for each objective to generate the Pareto set of efficient solutions. Compromise programming is a distance-based method to assist the decision maker in narrowing down the set of feasible solutions on the Pareto frontier. The best-compromise solution is defined as the solution that is closest to the ideal point, i.e., the theoretical solution where all objectives are at their optimal values. When objectives are in conflict, the ideal point is infeasible. The proximity of a solution to the ideal point is quantified in the form of a family of L_p distance measures (Romero and Rehman 2003). Distance of the p^{th} degree is calculated using a generalization of the Euclidean distance:

$$L_p = \left[\sum_{j=1}^{J}\left(W_j \frac{\left|Z_j^* - Z_j(\bar{x})\right|}{\left|Z_j^* - Z_{*j}\right|}\right)^p\right]^{\frac{1}{p}} \tag{11}$$

Where Z_j^* is the ideal value of the j^{th} objective, Z_{*j} is the anti-ideal (nadir) point of the j^{th} objective, $Z_j(\bar{x})$ is the value of the j^{th} objective of a reserve set $\bar{x}$, and W_j is the weight given to the j^{th} objective. J is the total number of objectives. The objectives are assumed to be equally weighted in the calculation of the distance metrics and were normalized by their respective distances between their ideal and nadir points. Both the L_1 and L_∞ distances (both referred to herein as "distance-based solutions") were reported following Leung et al. (2001) as an efficient range of solutions. The binary integer linear program was solved using a branch and bound algorithm with a 1% gap tolerance using the Gurobi Optimizer (v.7.0) operated within the "gurobi" package in the R software environment following Beyer et al. (2016).

2.5 Alternative Reserve Desgin Scenarios

To evaluate the potential impact of the BRFAs to fishers, three models of reserves placements under different reserve design perspectives regarding the opportunity cost objective were developed. For each scenario, the placements and objective attributes of the optimized reserves were compared to the placements of the BRFAs. First, total opportunity cost was calculated as total area, reflecting a management perspective that considers the opportunity cost across PUs to be uniform. This reduces the problem to a three-objective framework, as total area is equivalent to total opportunity cost.

Second, opportunity cost was defined as fisheries revenue as described in Section 2.2 and opportunity cost is minimized as described in Section 2.3. This scenario represented a management perspective similar to conventional systematic reserve design software (i.e., Marxan) that attempt to configure compact, minimal opportunity cost (i.e., foregone fisheries revenue) reserve placements that meet specific species/conservation feature targets.

Third, the hypothesis that the BRFAs presented a high impact to fishers in terms of potential forgone bottomfish revenue was investigated. This was achieved programmatically by reversing the opportunity cost optimization from minimization to maximization. This optimization represented a management perspective that opted to prioritize reserve placements in areas where opportunities of fishing activity were the highest.

3. Results

3.1 Scenario 1: Uniform Opportunity Cost, Opportunity Cost-Minimization Solutions

The opportunity cost for these solutions was uniform across PUs (i.e., related to area), reducing the model to a three-objective problem. The uniform-cost L_1 and L_∞ optimizations were sparse networks of reserves around the western, southern, and eastern parts of the island (Figs. 2D, E). The conservation values of the distance-based solutions were greater (L_1: 0.270, L_∞: 0.213) than the BRFAs (0.145), however were smaller and less aggregated (Table 1A). Between 8-16% of the PUs contained within the boundaries of the BRFAs were included in both distance-based solutions. The solution with the highest aggregation objective value suggested a reserve network of two large and compact areas, one on the western tip of the island overlapping almost entirely with the western BRFA and one on the northeastern portion of the island (Fig. 2C). The objective attribute values of the maximal aggregation solution were very similar to those of the BRFAs (radar plot, Fig. 2C). The solutions with the highest conservation value and the smallest total area were very sparse and distributed across the island except for the northern part of the island (Fig. 2A, B).

[approximate locations of Figure 2 and Table 1]

3.2 Scenario 2: Non-Uniform Opportunity Cost, Opportunity Cost-Minimization Solutions

The opportunity cost scenario for these solutions was proportional to foregone fisheries revenue and the opportunity cost objective was minimized. The distance-based solutions suggested reserve placements in the southern and northeastern parts of the island (Figs. 3E-F). These solutions had conservation values higher than those of the BRFAs and opportunity cost values 2-6X lower than the BRFAs, but were smaller and less aggregated than the BRFAs (Table 1B). These solutions had little overlap (0% and 8.67% for the L_1 and L_∞ solutions, respectively) with the PUs contained within the boundaries of the BRFAs. The reserve placement that maximized conservation value was spread out over most of the coast and included areas within the boundaries of the BRFAs (~15% overlap with the BRFAs Fig. 3A) but had the highest opportunity cost of the four solutions of the payoff matrix (Table 1B). The solution that maximized the aggregation objective had the lowest conservation value across the four solutions of the payoff matrix and no overlap with the PUs contained within the boundaries of the BRFAs.

[approximate location of Figure 3]

3.3 Scenario 3: Non-Uniform Opportunity Cost, Opportunity Cost-Maximization Solutions

Similar to Section 3.2, the opportunity cost for these solutions was proportional to fisheries revenue, except opportunity cost objective was maximized. The cost-maximizing L_1 and L_∞

solutions were sparsely placed on the western and eastern sides of the island, with some overlap (9-11%, Table 1C) with the PUs contained in the BRFAs (Figs. 4E, F). The reserve placement with the highest aggregation had similar objective function values to those of the BRFAs, had a 48.8% overlap with the PUs contained in the BRFAs (Table 1C), and was positioned on the eastern side of the island, including the eastern BRFA (Fig. 4C). The reserve placements with minimal area, maximal conservation value, and maximal opportunity cost (Figs. 4A, B, D) were sparsely placed more towards the western and eastern portions of the islands, with moderate overlap (9-18%) with the PUs contained in both BRFAs.

[approximate location of Figure 4]

4. Discussion

Optimizations were conducted under three opportunity cost scenarios to represent different reserve design perspectives. First, opportunity cost was considered uniform across PUs, reducing the exercise to a three-objective (i.e., area as opportunity cost, conservation value, and aggregation) problem. This is a common tactic used in systematic reserve design problems (e.g. Airame et al. 2003; Klein et al. 2008; Ban and Klein 2009). The major assumption under the first scenario was that opportunity cost was proportional to area (i.e., spatial accessibility), and all PUs posed the same opportunity cost. The first opportunity cost scenario may represent a situation where spatial socioeconomic use data does not exist for the fishery or socioeconomic opportunity costs are not considered in the reserve design criteria (e.g., Airame et al. 2003). Under this opportunity cost scenario, reserves placements were within and/or adjacent to BRFAs especially when maximizing for the aggregation objective, suggesting some agreement with this design scenario and the placements of the BRFAs.

In the second opportunity cost scenario, opportunity cost was related to fisheries revenue, and when minimized represented a compact reserve design that maximized species protection at a minimal socioeconomic impact to fishers. This represented conventional frameworks of systematic reserve design software like Marxan (Ball and Possingham 2009). The non-uniform cost-minimization distance-based solutions identified areas that offered potentially similar conservation value, were smaller in area and lower in opportunity cost, but were less compact than the BRFAs (Table 1B). These placements were in different areas than the placement of the BRFAs, suggesting that the design of the BRFAs did not fully incorporate or account for the potential socioeconomic impacts of the reserve design or perhaps placed more emphasis on reducing local fishing mortality by closing areas of high fisheries activity. Regardless of the reason, the advantage of the MCDM approach used here is that the tradeoffs in fisheries objectives that characterize the reserve design problem can be analyzed and the gaps in current reserve placements can be objectively evaluated. *Ad hoc* reserves have been shown to impose a high opportunity cost compared to reserves calculated under a systematic reserve design (Stewart et al. 2003; Stewart and Possingham 2005). In this study, calculated reserves under this scenario had up to one-half the opportunity cost than that of the current placement. Other gap analyses have revealed that a systematic reserve design can suggest new reserve networks or modifications of reserve networks that provide higher conservation feature coverage (Rondinini et al. 2005; Hansen et al. 2011; Moore et al. 2016).

The inclusion of spatially explicit socioeconomic opportunity cost data into the design process is generally thought to increase the robustness of the reserve design process (Stewart and Possingham 2005; Ban et al. 2009; Teixeira et al. in press), and substantially changed the placements of the reserve network when incorporated in this analysis (Scenario 1 vs Scenario 2).

Gross revenue was the only opportunity cost data available in this study. Net revenue would be a more favorable quantity to use as it incorporates the various sources of costs incurred by fishers. Stewart and Possingham (2005) also compared spatial optimizations of marine reserves using different opportunity cost data inputs and found that using socioeconomic opportunity cost was more effective in reducing socioeconomic impact as opposed to using total area as opportunity cost. In this analysis, when opportunity cost was uniform across PUs, more PUs in areas of high fishing activity were chosen than when opportunity cost was proportional to fisheries revenue. Thus, although collecting information on socioeconomic use/impact may be costly in some instances, its explicit use in systematic reserve design generally leads to more robust and less user-impactful solutions (Teixeira et al. in press).

The last reserve design scenario was similar to the second scenario, except the opportunity cost objective was maximized, representing a reserve design that prioritized closing popular fishing areas, i.e., closing areas with presumably favorable fish habitat with high socioeconomic impact to fishers. Opportunity cost maximization is intuitively not the goal of marine reserve design but may mimic a management scenario where the prioritization of reserve placement was informed by fisheries-dependent information on the spatial distribution of catches and trips, which is similar to the design of the original placements of the BRFAs. This approach may relieve local fishing pressure, but potentially ignores the socioeconomic impacts and implications of closure. The non-uniform cost-maximization placements had considerable overlap with the eastern BRFA, an area with historical and current high use in the fishery (Fig. 1; Parke 2007). Formulating the reserve design process within an MCDM framework is useful in addressing the socioeconomic impact of marine reserves by increasing the transparency of reserve tradeoffs during the design process. Transparency and stakeholder inclusion in the reserve design process supported by evidence-based systematic reserve design potentially reduces the potential "grab" of resources from fishers via opaque regulatory processes (Bennett et al. 2015; Bennett 2016).

Conservation feature coverage and representation are major conservation objectives of the marine reserve problem. The MCDM approached used here allowed for an exploration of the range of possible levels of conservation value, including the maximal level of conservation value under the constraints of the other objectives in the model. For example, across the three reserve design scenarios, the maximum level of the conservation feature achieved under the distance-based solutions was between 0.20-0.27, higher than the total conservation value of the BRFAs (0.145). The difference in conservation value between the optimized spatial configurations and the BRFAs describes the potential gap in the conservation objective. In other systematic reserve design problems, the reserve set is programmed to represent various conservation features, the targets of which are set *a priori* by either consensus of the reserve designers or through expert recommendation. In the Marxan software, minimum coverage targets for each conservation feature are defined *a priori*. For example, a reserve design exercise conducted by Moore et al. (2016) applied a 10% minimum target coverage across 765 conservation features as recommended by the Convention of Biological Diversity for a spatial planning design applied to the marine waters within the Exclusive Economic Zone in northwest Australia. The authors that used systematic reserve design for a network of marine reserves along the central California coast under the Marine Life Protection Act Initiative used a 30% target for each conservation feature as recommended by the IUCN (Klein et al. 2008).

Tradeoffs among objectives are difficult to visualize in higher dimensions, however can be partially visualized via the payoff matrix. First, in all scenarios, maximizing conservation value was generally associated with the highest total reserve area (Table 1). With a higher conservation value requirement, more cells need to be included in the reserve set. However, the solutions with the maximum levels of species protection were very sparse (Figs 2A, 3A, and 4A), reflecting the patchiness of the distributions of the species with different habitat requirements (Fig. 1; also see Oyafuso et al., 2017) . This highlights the second major tradeoff associated with aggregation and area. Highly compact reserves were generally associated with higher area compared to loosely aggregated reserves for a given level of conservation value. This was demonstrated clearly from the uniform-cost reserve design scenario, where the minimum area and maximum aggregation solutions offered similar levels of the conservation value objective (~0.16, Table 1A), but the maximum aggregation solution was approximately double the area of the minimum area solution. Given the patchy and restricted distributions of the species of interest (Figure 1), a highly compact reserve will invariably contain areas with higher conservation value along with adjacent areas with lower conservation value. Across reserve design scenarios, the solutions with the maximum aggregation and maximum conservation value were similar in total area (~0.14) but there was an inverse relationship between compactness and conservation value.

The solution that maximized aggregation was the only solution that matched the area, aggregation, and conservation objectives of the BRFAs (Figs. 2C, 3C, 4C). The reserve aggregation objective is certainly an important reserve design attribute in terms of management implementation and feasibility. When objectives were weighed equally, the compromise (*i.e.*, distance-based) solution among objectives was a solution that partially fulfilled each objective, thus solutions with intermediate levels of aggregation. If the design planning team of a marine reserve network set specific area and conservation feature coverage levels, the solution with the maximal aggregation objective under the method used here could be a potential recommendation, as this is the solution that was shown to meet the specified area and conservation targets, configure highly compact reserves, and produce the lowest opportunity cost. Further, formulating the reserve design problem within a linear programming framework (e.g., Cocks and Baird 1989; Williams and ReVelle 1998; Önal and Briers 2005) provides exact and computationally fast solutions relative to heuristic approaches (Rodrigues and Gaston 2002; Vanderkam et al. 2007; Beyer et al. 2016).

One drawback of this method is that these optimizations are static in their interpretation. Thus, its usefulness as a fisheries management tool should be tested within a simulation framework that incorporates uncertainties in fish populations, differences in fish life history (e.g., growth rates, longevity, movement rates, home range), environmental fluctuations, and fleet dynamics over time and in response to the implementation of the reserves (e.g., Williams et al. 2004; Metcalfe et al. 2015; Kruek et al. 2017). Another avenue of research is to test via simulation whether placements optimized within an MCDM framework can meet explicit biological (e.g., population size, spawning potential) and socioeconomic (e.g., profit, participation) objectives when implemented over time. For example, the solutions with the highest aggregation objective values for the cost-minimization and cost-maximization scenarios had similar aggregation, area, and conservation objective values. The differences between these solutions were the opportunity cost and the placements of these solutions. Thus, from a management perspective, these two reserve networks suggestions have the same conservation potential but are expected to have different socioeconomic effects. The cost-maximization solutions have potentially higher socioeconomic impacts to fishers because of the closure of popular fishing grounds and the displacement of effort either to finding other fishing grounds in the open area (Stevenson et al. 2013), other fisheries, or to other sources of income outside the fishery. A simulation approach is most appropriate to test hypotheses of reserve design and their effects on fish and fisher populations.

References

Airame, S., Dugan, J. E., Lafferty, K. D., Leslie, H., McArdle, D. A., & Warner, R. R. (2003). Applying ecological criteria to marine reserve design: A case study from the California Channel Islands. *Ecological Applications*, *13(1)*, 170-184, doi:https://doi.org/10.1890/1051-0761(2003)013[0170:AECTMR]2.0.CO;2

Ball, I. R., Possingham, H. P., & Watts, M. (2009). Marxan and relatives: software for spatial conservation prioritisation. In *Spatial conservation prioritisation: quantitative methods and computational tools*. (pp. 185-195). Oxford: Oxford Univeristy Press.

Ban, N. C., & Klien, C. J. (2009). Spatial socioeconomic data as a cost in systematic marine conservation planning. *Conservation Letters, 2,* 206-215, doi:http://doi.org/10.1111/j.1755-263X.2009.00071.x

Ban, N. C., Hansen, G. J. A., Jones, M., & Vincent, A. C. J. (2009). Systematic marine conservation planning in data-poor regions: socioeconoic data is essential. *Marine Policy, 33*, 794-800, doi:http://dx.doi.org/10.1016/j.marpol.2009.02.011

Bennett, N. J. (2016). Using perceptions as evidence to improve conservation and environmental management. *Conservation Biology, 30(3)*, 582-592, doi:https://doi.org/10.1111/cobi.12681

Bennett, N. J., Govan, H., & Satterfield, T. (2015). Ocean grabbing. *Marine Policy, 57*, 61-68, doi:https://doi.org/10.1016/j.marpol.2015.03.026

Beyer, H. L., Dujardin, Y., Watts, M. E., & Possingham, H. P. (2016). Solving conservation planning problems with integer linear programming. *Ecological modelling*, *328*, 14-22, doi:https://doi.org/10.1016/j.ecolmodel.2016.02.005

Billionnet, A. (2013). Mathematical optimization ideas for biodiversity conservation. *European Journal of Operational Research*, *231(3)*, 514-534, doi:http://dx.doi.org/10.1016/j.ejor.2013.03.025

Cocks, K. D., & Baird, I. A. (1989). Using mathematical programming to address the multiple reserve selection problem: an example from the Eyre Peninsula, South Australia. *Biological Conservation*, *49(2)*, 113-130, doi:https://doi.org/10.1016/0006-3207(89)90083-9

Hamel, M. A., Pressey, R. L., Evans, L. S., & Andréfouët, S. (2018). The Importance of Fishing Grounds as Perceived by Local Communities Can be Undervalued by Measures of Socioeconomic Cost Used in Conservation Planning. *Conservation Letters*, *11(1)*, e12352, doi:https://doi.org/10.1111/conl.12352

Horta e Costa, B., Batista, M. I., Gonçalves, L., Erzini, K., Caselle, J. E., Cabral, H. N., et al. (2013). Fishers' Behaviour in Response to the Implementation of a Marine Protected Area. *PLoS One*, *8(6)*, *e65057*, doi:https://doi.org/10.1371/journal.pone.0065057

Costello, M. J., & Ballantine, B. 2015. Biodiversity conservation should focus on no-take Marine Reserves: 94% of Marine Protected Areas allow fishing. *Trends in Ecology and Evolution*, *30(9)*, 507-509.

Edgar, G. J., Stuart-Smith, R. D., Willis, T. J., Kininmonth, S., Baker, S. C., Banks, S., Barrett, N. S., et al. (2014). Global conservation outcomes depend on marine protected areas with five key features. *Nature*, *506*, 216-220, doi:10.1038/nature13022

Friedlander, A. M., Brown, E. K., & Monaco, M. E. (2007). Coupling ecology and GIS to evaluate efficacy of marine protected areas in Hawaii. *Ecological Applications*, *17(3)*, 715-730, doi:https://doi.org/10.1890/06-0536

Gaines, S. D., White, C., Carr, M. H., & Palumbi, S. R. (2010). *Proceedings of the National Academy of Sciences*, *107(43)*, 18286-18293. doi:https://doi.org/10.1073/pnas.0906473107

Halpern, B. S., & Warner, R. R. (2002). Marine reserves have rapid and lasting effects. *Ecology Letters*, *5(3)*, 361-366, doi:https://doi.org/10.1046/j.1461-0248.2002.00326.x.

Hansen, G. J. A., Ban, N. C., Jones, M. L., Kaufman, L., Panes, H. M., Yasué, M., et al. (2011). Hindsight in marine protected area selection: A comparison of ecological representation arising from opportunistic and systematic approaches. *Biological Conservation*, *144*, 1866-1875, doi:https://doi.org/10.1016/j.biocon.2011.04.002

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., et al. (2004). When can marine reserves improve fisheries management? *Ocean & Coastal Management*, 47, 197-205, https://doi.org/10.1016/j.ocecoaman.2004.04.001

Hilborn, R., Micheli, F., and De Leo, G. A. (2006). Integrating marine protected areas with catch regulation. *Canadian Journal of Fisheries and Aquatic Sciences*, 63, 642-649, https://doi.org/10.1139/f05-243

Hospital, J., & Beavers, C. (2012). Economic and Social Characteristics of Bottomfish Fishing in the Main Hawaiian Islands. Pacific Islands Fisheries Science Center, National Marine Fisheries Service, NOAA, Administrative Report H-12-01.

Jennings, S., Kaiser, M., & Reynolds, J. D. (2001). Marine fisheries ecology. Hoboken, NJ: Wiley-Blackwell.

Kaiser, M. J. (2005). Are marine protected areas a red herring or fisheries panacea? *Canadian Journal of Fisheries and Aquatic Sciences*, 62, 1194-1199, doi:https://doi.org/10.1139/f05-056

Klein, C. J., Chan, A., Kircher, L., Cundiff, A. J., Gardner, N., Hrovat, Y., et al. (2008). Striking a balance between biodiversity conservation and socioeconomic viability in the design of marine protected areas. *Conservation Biology*, *22(3)*, 691-700, doi:http://dx.doi.org/10.1111/j.1523-1739.2008.00896.x

Krueck, N. C., Ahmadia, G. N., Possingham, H. P., Riginos, C., Treml, E. A., & Mumby, P. J. (2017). Marine Reserve Targets to Sustain and Rebuild Unregulated Fisheries. PLOS Biology, 15(1), e2000537, doi:http://dx.doi.org/10.1371/journal.pbio.2000537.

Lauck, T., Clark, C. W., Mangel, M., & Munro, G. R. (1998). Implementing the precautionary principle in fisheries management through marine reserves. *Ecological Applications*, *8(sp1)*, 72-78, doi:http://dx.doi.org/10.1890/1051-0761(1998)8[S72:ITPPIF]2.0.CO;2

Leathwick, J., Moilanen, A., Francis, M., Elith, J., Taylor, P., Julian, K., et al. (2008). Novel methods for the design and evaluation of marine protected areas in offshore waters. *Conservation Letters*, *1(2)*, 91-102, doi:http://dx.doi.org/10.1111/j.1755-263X.2008.00012.x

Leslie, H. M. (2005). A Synthesis of Marine Conservation Planning Approaches. *Conservation Biology*, *19(6)*, 1701-1713, doi:http://dx.doi.org/10.1111/j.1523-1739.2005.00268.x

Lester, S. E., Halpern, B. S., Grorud-Colvert, K., Lubchenco, J., Ruttenberg, B. I., Gaines, S. D., et al. (2009). Biological effects within no-take marine reserves: a global synthesis. *Marine Ecology Progress Series*, *384*, 33-46, doi:https://doi.org/10.3354/meps08029

Leung, P., Heen, K., & Bardarson, H. (2001). Regional economic impacts of fish resources utilization from the Barents Sea: Trade-offs between economic rent, employment and income. *European Journal of Operational Research*, 1*33(2)*, 432-446, doi:https://doi.org/10.1016/S0377-2217(00)00192-2

Leung, P. (2005). Multiple-criteria decision-making (MCDM) applications in fishery management. *International Journal of Environmental Technology and Management*, *6(1-2)*, doi:https://doi.org/10.1504/IJETM.2006.008255

Margules, C. R., and Pressey, R. L. (2000). Systematic conservation planning. *Nature*, *405*, *243-253*, doi:https://doi.org/10.1038/35012251

Mardle, S., & Pascoe, S. (1999). A review of applications of multiple-criteria decision-making techniques to fisheries. *Marine Resource Economics*, *14(1)*, 41-63, doi:https://doi.org/10.1086/mre.14.1.42629251

Metcalfe, K., Vaz, S., Engelhard, G. H., Villanueva, M. C., Smith, R. J., & Mackinson, S. (2015). Evaluating conservation and fisheries management strategies by linking spatial prioritization software and ecosystem and fisheries modelling tools. Journal of Applied Ecology, 52(3), 665-674, doi:https://doi.org/10.1111/1365-2664.12404.

Micheli, F., Saenz-Arroyo, A., Greenley, A., Vazquez, L., Espinoza Montes, J. A., Rossetto, M., et al. (2012). Evidence that marine reserves enhance resilience to climatic impacts. *PLoS One*, *7(7)*, e40832, doi:https://doi.org/10.1371/journal.pone.0040832

Molloy, P. P., McLean, I. B., & Côté, I. M. (2009). Effects of marine reserve age on fish populations: a global meta-analysis. *Journal of Applied Ecology*, *46(4)*, 743-751, doi:https://10.1111/j.1365-2664.2009.01662.x.

Moore, C. H., Radford, B. T., Possingham, H. P., Heyward, A. J., Stewart, R. R., Watts, M. E., et al. (2016). Improving spatial prioritisation for remote marine regions: optimising biodiversity conservation and sustainable development trade-offs. *Nature Scientific Reports*, *6*, srep32029, doi:https://doi.org/10.1038/srep32029

National Research Council (NRC). (2001). Marine Protected Areas: Tools for Sustaining Ocean Ecosystem. Washington, DC: The National Academies Press.

Önal, H., & Briers, R. A. (2005). Designing a conservation reserve network with minimal fragmentation: a linear integer programming approach. *Environmental Modeling and Assessment*, *10*, 193-202, doi:https://doi.org/10.1007/s10666-005-9009-3

Oyafuso, Z. S., Drazen, J. C., Moore, C. H., & Franklin, E. C. (2017). Habitat-based species distribution modelling of the Hawaiian deepwater snapper-grouper complex. *Fisheries Research*, *195*, 19-27, doi:https://doi.org/10.1016/j.fishres.2017.06.011

Pan, M., Leung, P., & Pooley, S. G. (2001). A decision support model for fisheries management in Hawaii: a multilevel and multiobjective programming approach. *North American Journal of Fisheries Management*, *21*, 293-309, doi:http://dx.doi.org/10.1577/1548-8675(2001)021<0293:ADSMFF>2.0.CO;2

Parke, M. (2007). Linking Hawaii fisherman reported commercial bottomfish catch data to potential bottomfish habitat and proposed restricted fishing areas using GIS and spatial analysis. Islands. Pacific Islands Fisheries Science Center, National Marine Fisheries Service, NOAA, Technical Memorandum NMFS-PIFSC-11.

Pascoe, S., & Mardle, S. (2001). Optimal fleet size in the English Channel: a multi-objective programming approach. *European Review of Agricultural Economics*, *28(2)*, 161-185.

Pradhan, N. C., & Leung, P. (2006). Incorporating sea turtle interactions in a multi-objective programming model for Hawaii's longline fishery. *Ecological Economics*, *60(1)*, 216-227, doi:https://doi.org/10.1016/j.ecolecon.2005.12.009

Rodrigues, A. S. L., & Gaston, K. J. (2002). Optimisation in reserve selection procedures—why not? *Biological Conservation*, *107*, 123-129, doi:https://doi.org/10.1016/S0006-3207(02)00042-3

Romero, C., & Rehman, T. (2003). Agricultural decision analysis with multiple criteria. Amsterdam: Elsevier.

Rondinini, C., Stuart, S., and Boitani, L. (2005). Habitat suitability models and the shortfall in conservation planning for African vertebrates. *Conservation Biology*, *19(5)*, 1488-1497, doi:https://doi.org/10.1111/j.1523-1739.2005.00204.x

Stevenson, T., Tissot, B., & Walsh, W. (2013). Socioeconomic consequences of fishing displacement from marine protected areas in Hawaii. *Biological Conservation*, *160*, 50-58, doi:https://doi.org/10.1016/j.biocon.2012.11.031

Stewart, R. R., Noyce, T., & Possingham, H.P. (2003). Opportunity cost of ad hoc marine reserve design decisions: an example from South Australia. *Marine Ecology Progress Series*, *253*, 25-38, doi:https://doi.org/10.3354/meps253025

Stewart, R. R., and Possingham, H. P. (2005). Efficiency, costs and trade-offs in marine reserve system design. *Environmental Modeling and Assessment*, *10*, 203-213, doi:https://doi.org/10.1007/s10666-005-9001-y

Stigner, M. G., Beyer, H. L., Klein, C. J., Fuller, R. A., & Carvalho, S. (2016). Reconciling recreational use and conservation values in a coastal protected area. Journal of Applied Ecology, 53(4), 1206-1214, doi:https://doi.org/10.1111/1365-2664.12662

Teixeira, J. B., Moura, R. L., Mills, M., Klein, C., Brown, C. J., Adams, V. M., et al. (in press). A novel habitat-based approach to predict impacts of marine protected areas on fishers. *Conservation Biology*, doi:https://doi.org/10.1111/cobi.12974

Vanderkam, R. P. D., Wiersma, Y. F., & King, D. J. (2007). Heuristic algorithms vs. linear programs for designing efficient conservation reserve networks: evaluation of solution optimality and processing time. *Biological Conservation*, *137*, 349-358, doi:https://doi.org/10.1016/j.biocon.2007.02.018

Williams, J. C., & ReVelle, C. S. (1998). Reserve assemblage of critical areas: a zero-one programming approach. *European Journal of Operational Research*, *104(3)*, 497-509, doi:https://doi.org/10.1016/S0377-2217(97)00017-9

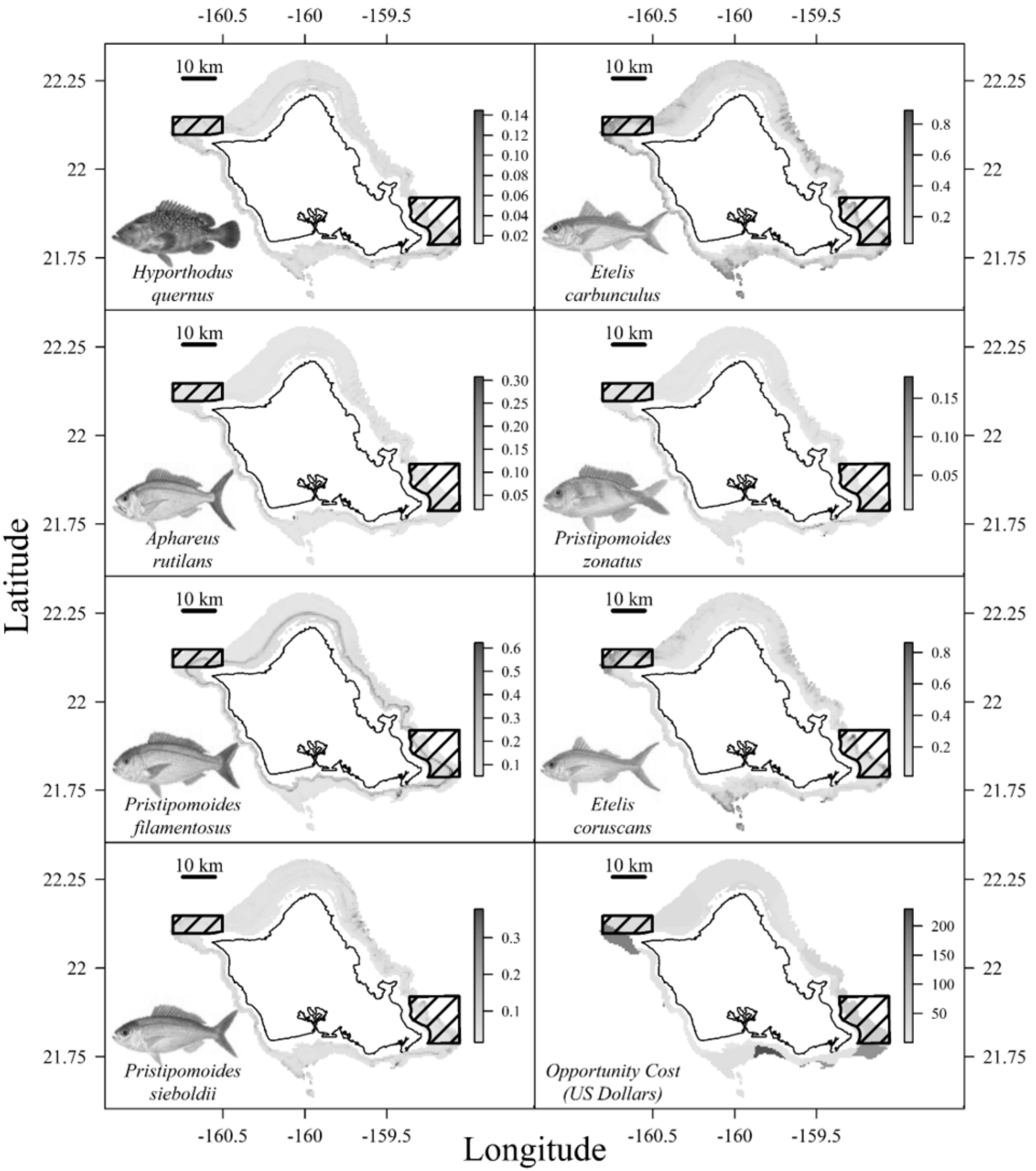
Williams, J. C., ReVelle, C. S., and Levin, S. A. (2004). Using mathematical optimization models to design nature reserves. *Frontiers in Ecology and the Environment*, *2(2)*, 98-105, doi:https://doi.org/

Fig. 1: Data input layers: probability of occurrence for each of the seven species in the complex and opportunity cost were aggregated to each 500 x 500 m planning unit for the island of Oahu (Hawaii, USA). The two textured polygons denote the placement of the bottomfish restricted fishing areas used for comparison in the study. Fish illustrations by Les Hata©, Hawaii Department of Land and Natural Resources.

Fig. 2: Reserve placements under uniform-cost minimization optimizations that represent A) maximum conservation value, B) minimum total reserve area, C) maximum aggregation, and solutions based on the minimum D) L_1 and E) L_∞ distance metrics. The two textured polygons denote the placement of the bottomfish restricted fishing areas (BRFAs) used for comparison in the study. A radar plot comparing the three objective values (Spp = conservation value, Area = area, Agg = aggregation) between the reserve solution (gray) and the current BRFAs (black) are provided in the upper-right corner of the plots. The distance between the center of the radar plot to the vertex of the radar polygon is proportional to the objective attribute value.

Fig. 3: Reserve placements under non-uniform cost minimization optimizations that represent A) maximum conservation value, B) minimum total reserve area, C) maximum aggregation, D) minimum opportunity cost, and solutions based on the minimum D) L_1 and E) L_∞ distance metrics. The two textured polygons denote the placement of the bottomfish restricted fishing areas (BRFAs) used for comparison in the study. A radar plot comparing the four objective values (Spp = conservation value, Area = area, Agg = aggregation, Cost = opportunity cost) between the reserve solution (gray) and the current BRFAs (black) are provided in the upper-right corner of the plots. The distance between the center of the radar plot to the vertex of the radar polygon is proportional to the objective attribute value.

Fig. 4: Reserve placements under non-uniform cost maximization optimizations that represent A) maximum conservation value, B) minimum total reserve area, C) maximum aggregation, D) minimum cost, and solutions based on the minimum D) L_1 and E) L_∞ distance metrics. The two textured polygons denote the placement of the bottomfish restricted fishing areas (BRFAs) used for comparison in the study. A radar plot comparing the four objective values (Spp = Conservation Value, Area = Area, Agg = Aggregation, Cost = Opportunity Cost) between the reserve solution (gray) and the current BRFAs (black) are provided in the upper-right corner of the plots. The distance between the center of the radar plot to the vertex of the radar polygon is proportional to the objective attribute value.


Latitude
Longitude
-160.5
-160
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22.25
22
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10 km
Hyporthodus quernus
0.14
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0.08
0.06
0.04
0.02
Etelis carbunculus
0.8
0.6
0.4
0.2
Aphareus rutilans
0.30
0.25
0.20
0.15
0.10
0.05
Pristipomoides zonatus
0.15
0.10
0.05
Pristipomoides filamentosus
0.6
0.5
0.4
0.3
0.2
0.1
Etelis coruscans
0.8
0.6
0.4
0.2
Pristipomoides sieboldii
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0.2
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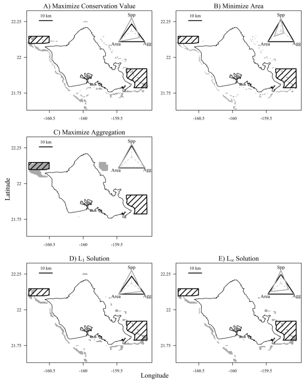
Opportunity Cost (US Dollars)
200
150
100
50



A) Maximize Conservation Value
B) Minimize Area
C) Maximize Aggregation
D) L_1 Solution
E) L_∞ Solution
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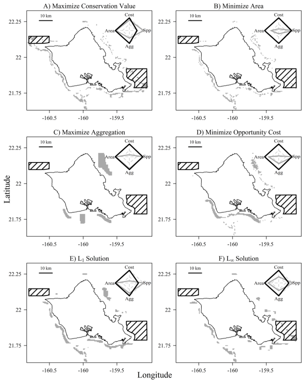

A) Maximize Conservation Value
B) Minimize Area
C) Maximize Aggregation
D) Minimize Opportunity Cost
E) L_1 Solution
F) L_∞ Solution
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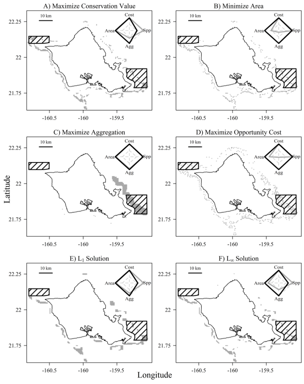

A) Maximize Conservation Value
B) Minimize Area
C) Maximize Aggregation
D) Maximize Opportunity Cost
E) L_1 Solution
F) L_∞ Solution
10 km
Cost
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-160
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Latitude
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Table 1: Payoff matrices of the three opportunity cost scenarios. Area, aggregation, opportunity cost, and conservation objective values are reported as proportion of their respective total values. The conservation objective attribute is reported as a mean across the seven species. The last column is the percentage of the planning units that were contained within the boundaries of the bottomfish restricted fishing areas (BRFAs). The diagonal elements (in bold) are the optimal values for each objective and comprise the ideal point solution. The last three rows are the objective values of the solutions with the lowest L_1 and L_∞ distance metrics and the current BRFAs.

1A) Uniform Cost, Cost Minimization

	Area	Aggregation	Conservation	% BRFA Overlap
Minimize Area	**0.075**	0.030	0.165	6.94
Maximize Aggregation	0.140	**0.140**	0.164	41.91
Maximize Conservation	0.143	0.091	**0.276**	17.20
L_1	0.145	0.110	0.270	16.04
L_∞	0.111	0.085	0.213	8.82
BRFAs	0.146	0.145	0.145	

1B) Non-Uniform Cost, Cost Minimization

	Area	Aggregation	Conservation	Cost	% BRFA Overlap

Minimize Area	**0.080**	0.036	0.162	0.026	2.31
Maximize Aggregation	0.140	**0.135**	0.155	0.030	0
Maximize Conservation	0.140	0.085	**0.270**	0.156	14.88
Minimize Cost	0.105	0.077	0.158	**0.014**	0
L_1	0.140	0.115	0.223	0.033	0
L_∞	0.110	0.085	0.204	0.093	8.67
BRFAs	0.146	0.145	0.145	0.190	

1C) Non-Uniform Cost, Cost Maximization

	Area	Aggregation	Conservation	Cost	% BRFA Overlap
Minimize Area	**0.08**	0.019	0.156	0.190	9.97
Maximize Aggregation	0.14	**0.136**	0.152	0.190	48.84
Maximize Conservation	0.14	0.085	**0.270**	0.190	18.21
Maximize Cost	0.10	0.005	0.156	**0.190**	14.88
L_1	0.140	0.115	0.246	0.190	9.68
L_∞	0.110	0.075	0.217	0.190	10.69
BRFAs	0.146	0.145	0.145	0.190	