Biological Conservation 241 (2020) 108319

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Understanding biological and socioeconomic tradeoffs of marine reserve planning via a flexible integer linear programming approach

Zack S. Oyafuso[a,*], PingSun Leung[b], Erik C. Franklin[a]

[a] Hawaii Institute of Marine Biology, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, Kaneohe, HI, 96744, USA
[b] University of Hawaii at Manoa, Department of Natural Resources and Environmental Management, 1910 East-West Road, Sherman 101, Honolulu, HI, 96822, USA

ARTICLE INFO

Keywords:
Multiple-Criteria Decision Making (MCDM)
Integer Linear Programming (ILP)
Reserve selection models
Marine protected areas
Fisheries

ABSTRACT

Analyzing tradeoffs among ecological, economic, and management goals with respect to marine reserve network design is an important facet of systematic conservation planning. We designed an integer linear programming model to quantify tradeoffs among five marine reserve network aspects: ecological conservation value, economic opportunity cost, geographic domain size, total reserve area, and reserve spatial compactness. Using ecological and economic data from the Hawaiian deepwater bottomfish fishery as a case study, an integer linear programming model was designed to choose areas that 1) maximize conservation value and 2) minimize opportunity cost, defined as foregone fisheries revenue. Compromise solutions that equally weighted conservation value and opportunity cost resulted in solutions with dramatically lower foregone fisheries revenue and a relatively small loss in conservation value compared to solutions with the maximum conservation value. When opportunity cost was assumed uniform across the spatial domain, solutions had considerably higher foregone revenue for a given level of conservation value, highlighting the drawback of not including a spatially explicit metric of opportunity cost in reserve selection models. Inclusion of only indicator species, rather than the entire species complex, in the optimization led to considerable representation gaps in conservation value for non-included species. We found that optimizations performed at the archipelago scale provided geographically disproportionate reserve allocations and thus disproportionate conservation benefits and socioeconomic impacts across geopolitically distinct island regions. We showed how reserve selection models can be used to support systematic conservation planning exercises characterized by many diverse and conflicting objectives and parties.

1. Introduction

Spatial fishery closures, or marine reserves, are common instruments in fisheries management and have increased in number and total area in U.S. waters in the past 50 years (National Marine Protected Areas Center (NMPAC, 2015). Marine reserves are concurrent with a precautionary approach to fisheries management, hedging against the uncertainties of the status of exploited populations, management limitations, and long-term sustainability of fisheries (Lauck et al., 1998; Hilborn et al., 2004; Grafton and Kompas, 2005). Although not a "panacea" in fisheries management (Hilborn et al., 2004; Almany et al., 2013), reserves can be an effective component of a successful fisheries management strategy. A common biological goal of marine reserves is to provide spillover, the density-dependent net export of individuals and reserve-sourced larvae from the reserve to fished areas (Gell and Roberts, 2003; Gaines et al., 2010). Theoretical modelling and simulation testing have both shown positive biological and fishery effects of marine reserves conditional on the biological and socioeconomic characteristics of the system (e.g., Botsford et al., 2003; Hilborn et al., 2004; Lester et al., 2009; Edgar et al., 2014). Empirical examples have additionally shown positive biological effects of spatial protection (Roberts and Hawkins, 2000; Lester et al., 2009; Edgar et al., 2014; Emslie et al., 2015).

Socioeconomic factors are similarly important and complex as environmental and biological factors with respect to marine reserve design (Mascia, 2004). In the short term, marine reserves can have considerable negative economic impacts, especially if the most accessible fishing grounds are closed or opportunities in other fisheries are less valuable (Smith et al., 2010; Chen and Lopez-Carr, 2015). The fishing opportunities in closed areas are either displaced to the open fished areas (e.g., Mason et al., 2012; Murawski et al., 2005), a different fishery, other non-fishing opportunities, or dissipates completely

* Corresponding author at: Hawaii Institute of Marine Biology, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, PO Box 1346 (delivery: 46-007 Lilipuna Road), Kaneohe, HI, 96744, USA.
E-mail address: oyafusoz@hawaii.edu (Z.S. Oyafuso).

https://doi.org/10.1016/j.biocon.2019.108319
Received 2 March 2019; Received in revised form 30 July 2019; Accepted 28 October 2019
Available online 18 November 2019

(Stevenson, 2013). The displacement of fishing effort undermines the biological objective of reducing fishing mortality by potentially concentrating fishing pressure elsewhere (Halpern et al., 2004) or near the boundaries of the reserves (Kellner et al., 2007). However, fishers who cannot adjust to the reserve by either travelling farther to fishing grounds (Hattam et al., 2014) or expending time to find new fishing grounds may leave the fishery entirely. High discounting of future expectations of reserve impacts also undermines fishers' perceptions of potential reserve benefits (Smith et al., 2010; Hattam et al., 2014), emphasizing the need to account for socioeconomic impacts during the planning and design of reserve networks.

To balance many conflicting ecological, socioeconomic, and management goals, the design of marine reserves should involve the analysis of tradeoffs among these objectives as part of a systematic conservation planning process (Margules and Pressey, 2000). Explicit analyses of tradeoffs can improve transparency in the marine reserve design process by focusing on the most efficient solutions that maximize sector values (e.g., via a Pareto frontier), reveal "inferior" management options, and avoid unnecessary conflicts due to steep tradeoffs (White et al., 2012). Methods in multi-criteria decision making (MCDM) aim to quantify these tradeoffs to aid management decisions, with many examples in aquatic resource management (Villa et al., 2002; Leung, 2005; Lu et al., 2014; Farashi et al., 2016; Marre et al., 2016; Esmail and Geneletti, 2018). Reserve selection models mathematically calculate optimal reserves placements based on explicitly defined reserve objectives (e.g., Ball et al., 2009; Oyafuso et al., 2019) and are the means in which these tradeoffs can be analyzed. Understanding the "hidden" impacts stemming from assumptions in the model affects the interpretations of the model outputs and has clear implications to informing decision making (Adams et al., 2010).

Opportunity cost in reserve selection models is generally defined as the foregone activities, economic or otherwise, resulting from the conversion of an area to a reserve. Opportunity cost can simply be defined as total area, as marine reserves restrict spatial access, with fishing being one of many potential foregone activities (e.g., Airame et al., 2003; Klein et al., 2008a, 2008b; Ban and Klein, 2009). Many other types of metrics can be used to explicitly define opportunity cost across the spatial domain and are usually characterized by considerable spatial variation (Balmford et al., 2003). In fisheries examples, opportunity cost is defined as catch or effort per unit area (Adams et al., 2011; Klein et al., 2008a, 2008b), ex-vessel fishery revenue (Oyafuso et al., 2019), or some proxy for fishing activity (Ban et al., 2009). In a data-limited system, total area may be the best information available by default, however assuming uniform opportunity cost across the spatial domain in the reserve selection model leads to reserve solutions that have higher impacts on other metrics of opportunity cost (Stewart and Possingham, 2005). Less studied is the extent to which these opportunity cost deficits are present when other objectives within the reserve design process are considered.

Marine reserves restrict spatial access to a common fishery resource, thus there are considerable social ramifications to the placement of marine reserves. An important reserve design consideration is the allocation of reserve area across geopolitical units (Sanchirico et al., 2002; Jones, 2009; Klein et al., 2015). As important it is to spread the ecological benefits of marine reserves across geopolitical units, it is also important to spread the opportunity cost of marine reserves to achieve equitable management strategies. In an archipelago setting, the non-equal allocation of reserve area across islands can lead to an inequity of opportunity costs and reserve benefits across users. Across broad contiguous areas like a continental shelf, reserve placements can involve state, federal, and possibly international jurisdictions. A key aspect to incorporate equity into the reserve selection model is whether reserve optimizations should be conducted at whole domain scales or at geopolitically distinct scales and the resulting socioecological tradeoffs of that decision.

It is advantageous to include as many conservation features, species, and habitat types in the reserve model in order to maximize the ecological potential of the marine reserve. However in data-limited systems, information on all possible conservation features of interest may not be available to the reserve design team. In data-limited fisheries, often certain "indicator" species are chosen to represent a species complex to reduce the capacity needed to assess all species and because these indicator species represent major life history traits of many co-occurring species (Mouillot et al., 2002; Newman et al., 2016; Hill et al., 2016). The same challenge exists in reserve selection model exercises and it is uncertain to what extent indicator species provide an umbrella effect (Lambeck, 1997; Roberge and Angelstam, 2004) to the species complex where spatial data for all species of interest are not available.

We conducted a thorough analysis of the interactions and tradeoffs of key objectives within the reserve design process: reserve area, opportunity cost, conservation value, and reserve shape compactness. A binary integer linear programming model was constructed to select areas that maximize conservation value and minimize opportunity cost. We used the multispecies Hawaiian bottomfish fishery as a case study, but the model is applicable to other systems. We considered nine factorial scenarios consisting of combinations of three levels of total area and three levels of spatial compactness to allow for different "spatial budgets" to be visualized. Solving the reserve selection model resulted in a Pareto frontier of optimal solutions which described the tradeoffs between conservation value and opportunity cost for a given spatial budget. Using this general model, we first examined the effects of assuming opportunity costs proportional to total area ("uniform opportunity cost") versus opportunity costs related to fishing activity ("non-uniform opportunity cost"). Second, we investigated the consequences of only using a subset of indicator species representative of the majority of the bottomfish fishery in the reserve selection model versus using all species of interest with respect to species representation. The Hawaiian bottomfish fishery is managed on an archipelago scale, but there are de facto geopolitical island regions that dislocate the fishing fleet within the main Hawaiian Islands. Thus, we lastly examined the equity of reserve allocations (i.e., the allocation of reserve benefits and impacts) across island regions when reserve optimizations were conducted on an archipelago versus island region scale.

2. Methods

2.1. Spatial domain

The commercial fishery for Hawaiian bottomfishes was used as a case example and is a species complex of six deepwater snappers and one deepwater grouper (known collectively as the Deep Seven bottomfishes): hapuupuu (*Hyporthodus quernus*), ehu (*Etelis carbunculus*), lehi (*Aphareus rutilans*), gindai (*Pristipomoides zonatus*), opakapaka (*P. filamentosus*), onaga (*E. coruscans*), and kalekale (*P. sieboldii*). The domain of planning units (PUs) defined for the reserve selection model was created by superimposing a 500 m × 500 m grid within 50–400 m depth across the main Hawaiian Islands (dark grey shading in Fig. 1). This depth range approximates the depth range of the species distribution maps that were used as data inputs (Oyafuso et al., 2017). Regional optimizations were conducted separately within geographically convenient island regions, designated from northwest to southeast as follows: (1) Kaula Rock, Niihau, and Kauai (KNK), (2) Oahu, (3) Maui, Molokai, Kahoolawe, and Lanai islands (Maui Nui, MN), and (4) Hawaii Island (HI) (Fig. 1). This resulted in 3733, 4753, 19629, and 8363 PUs for the KNK, OA, MN, and HI regions, respectively.

2.2. Data sources

Conservation feature and opportunity cost data were similar to those used by Oyafuso et al. (2019) extended to all four island regions. Mean probability of occurrence predicted by habitat-based species

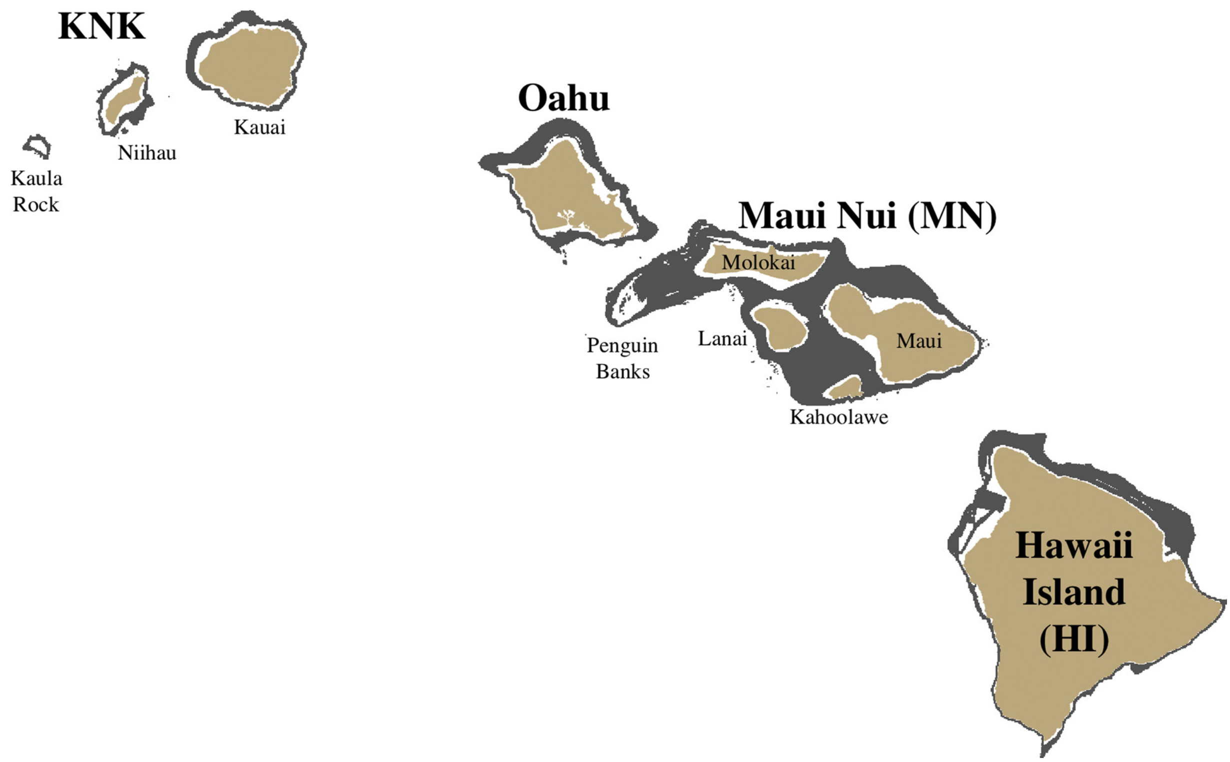

Fig. 1. The spatial domain (dark grey) of the reserve selection model was defined as those waters surrounding the main Hawaiian Islands and Kaula Rock between 50–400 m at 500 m cell resolution (oriented north). The bold labels (KNK, Oahu, MN, and HI) denote the spatial domains of the island region-scale optimizations. The non-bold labels are place names referenced in the text.

distribution models created by Oyafuso et al. (2017) were calculated for each PU in the spatial domain for each of the seven species. Opportunity cost was defined as the mean annual Deep Seven bottomfish ex-vessel fishery revenue collected from trip-level data provided by the State of Hawaii from 1990 to 1996 (see Oyafuso et al. (2019) for more detail). For the uniform opportunity cost scenarios, opportunity cost was proportional to area. Thus on a lattice, the opportunity cost is equal across PUs. Probability of occurrence for each species and revenue across PUs for each island region are provided in the Supplementary Material (Figs. S1–S4).

2.3. Binary integer linear programming model

A binary integer linear programming (ILP) model similar to Beyer et al. (2016) and Oyafuso et al. (2019) was constructed for the selection of reserve area from a domain of PUs subject to explicitly defined structural constraints. First the objective functions of the model were described followed by a description of the structural constraints.

2.3.1. Objective functions

Two objective functions were defined to describe the reserve selection model: minimize opportunity cost and maximize conservation value:

$$\min\sum_{i=1}^{N} x_i c_i \ (Opportunity\ Cost)$$

$$\max\sum_{i=1}^{N} x_i r_{is} \ (Conservation\ Value)$$

Where x_i is a binary decision variable ($x_i = 1$ if the i^{th} PU is included in the reserve set, 0 otherwise), c_i is the opportunity cost of reserving the i^{th} PU, r_{is} is the predicted probability of occurrence value of the s^{th} species for the i^{th} PU. N is the number of PUs.

2.3.2. Structural constraints (spatial budgets)

Two reserve objectives, total area and spatial compactness, were treated as hard constraints rather than optimizable objective functions. The decision to treat an objective as a constraint was for pragmatic reasons. Total area of the reserve network is often treated as a tangible target (e.g., 10%, 20%) of the spatial domain. Programmatically, the total area of the reserve set was to be no more than one of three proportions (A = 0.10, 0.20, or 0.30) of N:

$$\sum_{i=1}^{N} x_i \le AN$$

The second structural constraint controlled the level of spatial compactness, defined as the relative number of adjacent cell-to-cell interactions of the PUs contained in the reserve set. The incorporation of interactions among PUs involve the addition of quadratic expressions, i.e., non-linear components, and thus is problematic in an ILP framework. Beyer et al. (2016, but also see Billionnet, 2013) described methods to linearize these non-linear terms by first adding a new decision variable b_{ij}, and the total number of interactions is constrained to be greater than one of three proportions ($B = 0.01,\ 0.50\ and\ 1.0$) of the total number of adjacent cell-to-cell interactions in the domain (M):

$$\sum_{(i,j)\in E} b_{ij} \ge BM$$

Where b_{ij} is an added 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. The addition of each decision variable comes with three additional constraints to ensure that $x_i = x_j = 1$ if $b_{ij} = 1$:

$$b_{ij} - x_i \le 0$$

$$b_{ij} - x_j \le 0$$

$$b_{ij} - x_i - x_j \le -1$$

The nine combinations of area and compactness constraints

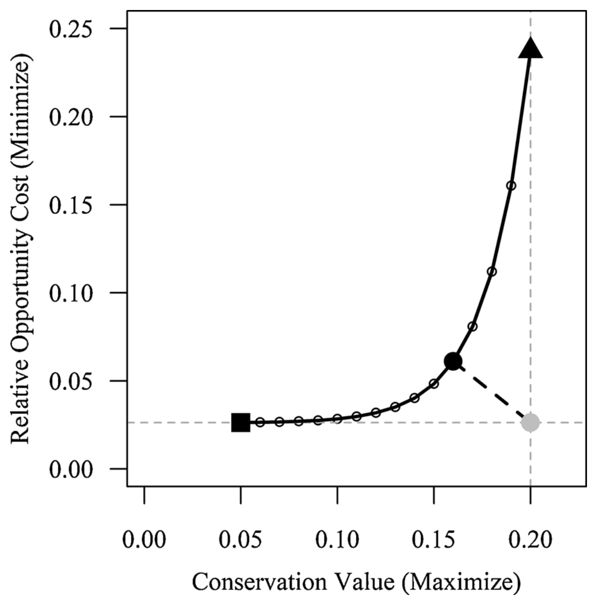

Fig. 2. Example diagram of the compromise solution along the Pareto frontier with two objectives: opportunity cost (y-axis) and conservation value (x-axis). The filled square and triangle points are the solutions with the lowest opportunity cost and highest conservation value, respectively, and the combination of those optimal values (gray filled circle) is the ideal point. The solution with the shortest distance to the ideal point (filled black point) is the compromise solution that is referred to in the text.

represent different scenarios of "spatial budget," i.e., the set of constraints that define the spatial extent of the reserve solutions.

2.3.3. Solving the linear programming model

The bi-objective ILP model was solved via the constraint method (see Romero and Rehman (1989) for background). Briefly, one of the objectives was optimized (i.e., opportunity cost) while the other objective (conservation value) was constrained to be greater than some *a priori* proportion (C) of the total conservation value summed across each of the PUs for each species:

$$\sum_{i=1}^{N} x_i r_{is} \geq C \sum_{i=1}^{N} r_{is}$$

The value of C was initially set at an arbitrarily low value (0.01), then incremented by a set interval until the solution was infeasible, tracing the entire range of conservation values for a given spatial budget. Note that the value of C was constant across the species included in the optimization model and different values of C among species were not considered. The range of feasible solutions calculated comprise the Pareto frontier (e.g., Fig. 2). Solutions on the Pareto frontier are non-inferior to each other: increasing conservation value is only possible by increasing opportunity cost; similarly decreasing opportunity cost is only possible by decreasing conservation value.

Optimizations were conducted using custom code modified from Oyafuso et al. (2019) and Beyer et al. (2016) using the Gurobi Optimizer (v.7.0) and the "gurobi" package in the R software environment. A branch and bound algorithm was used to solve the ILP models with a 1% tolerance gap. Refer to Z. Oyafuso's GitHub repository (github.com/oyafusoz) for reserve selection ILP vignettes written in R using both commercial software Gurobi and the open source GNU Linear Programming Kit R package.

2.4. Compromise solution

Compromise programming is a distance-based method used 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, the theoretical (i.e., non-existent) solution where all objectives are at their optimal values (Gray point, Fig. 2). When objectives are in conflict, the ideal point is an infeasible solution. Solutions that are closer to the ideal point are considered more favorable with respect to the objectives, and the distance (D) between a solution to the ideal point is quantified in the form of a family of weighted distance measures (Romero and Rehman, 1989):

$$D = \left[\sum_{j=1}^{J=2} \left(W_j \frac{|Z_j^* - Z_j(\bar{x})|}{|Z_j^* - Z_{*j}|} \right)^2 \right]^{\frac{1}{2}}$$

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 ($J = 2$). The objectives are naively 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. The solution along the Pareto frontier with the shortest distance to the ideal point is considered the compromise solution hereafter (black filled point, Fig. 2). As the weight of the conservation objective increases, the compromise solution converges to the solution with the maximum conservation value (triangle point, Fig. 2) and similarly with the opportunity cost objective (square point, Fig. 2).

3. Results

3.1. Opportunity cost scenarios

Across all scenarios, solutions with higher conservation values were associated with higher foregone fisheries revenue (Fig. 3). For the non-uniform opportunity cost solutions (solid lines, Fig. 3), foregone revenue increased with conservation value across all nine spatial budgets. The tradeoff between conservation value and foregone revenue varied across different parts of the Pareto frontier, with very steep increases in foregone revenue at higher levels of conservation value. For lower levels of conservation value, large gains in conservation value were associated with relatively small increases in foregone revenue. The general shape of this relationship was similar whether the optimization was conducted on the archipelago versus the island region scale. Increasing the level of compactness reduced the range of feasible conservation values, with the maximum feasible conservation value decreasing with higher levels of compactness.

Foregone fisheries revenue was not incorporated in the uniform opportunity cost solutions, therefore the points plotted in Fig. 3 highlighted the consequences of not incorporating impacts to fisheries revenue in the reserve selection model. All uniform opportunity cost solutions were expectedly inferior to the Pareto frontier with respect to foregone fisheries revenue. Similar to the non-uniform opportunity cost solutions, higher conservation value solutions were associated with higher foregone revenue. The relationship between conservation value and foregone revenue was approximately linear.

3.2. Effects of only including indicator species in reserve optimizations

Conservation value was treated as a hard constraint, guaranteeing the representation of each included species to at least the value of the constraint. Some species had conservation values greater than the conservation value constraint, i.e., were overrepresented relative to the constraint value (above identity line, Fig. 4). Overrepresentation was nearly consistent across conservation constraint values. When only indicator species (onaga and opakapaka) were included in the reserve selection model, the conservation value constraint only applied to those two species, so it was possible for the non-included species to be underrepresented (below identity line, Fig. 4). Overrepresentation for the

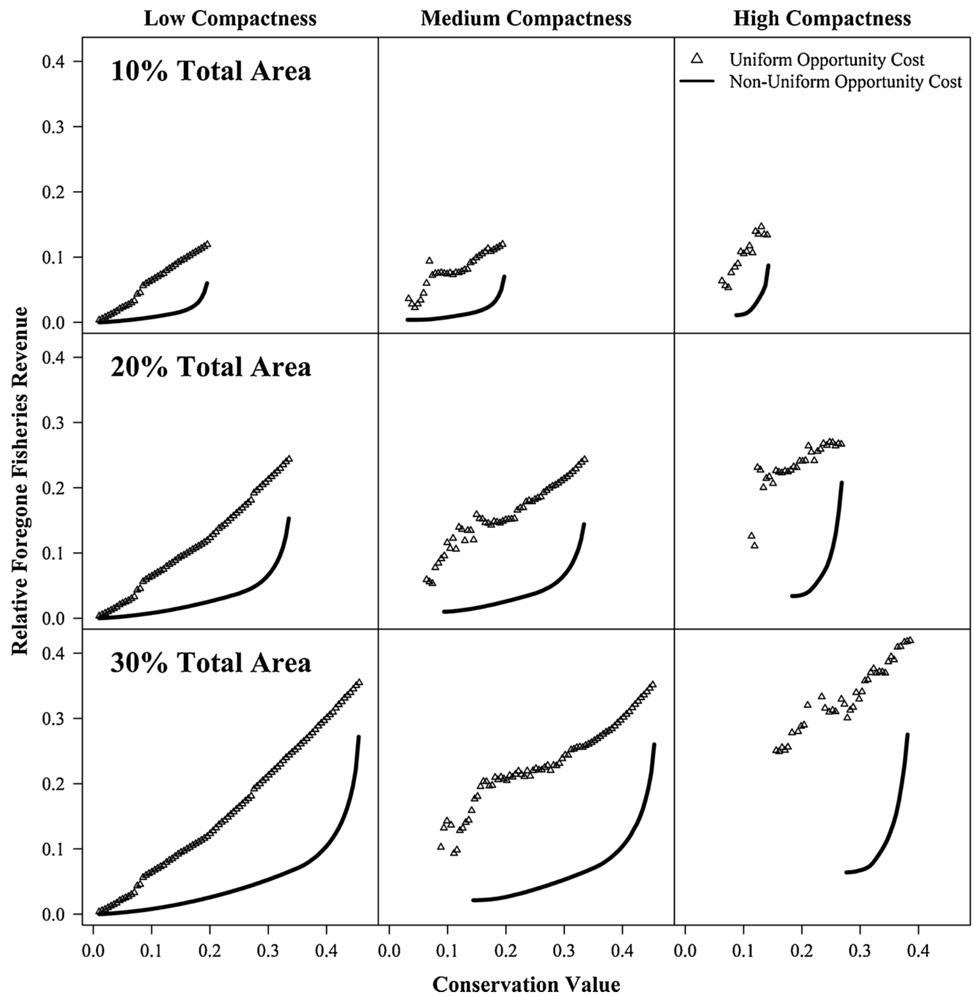

Fig. 3. Opportunity cost (relative foregone fisheries revenue) across varying levels of conservation values outputted from reserve selection models under three different levels of total area (rows) and compactness (columns) for the archipelago-scale optimizations. Solid lines denote solutions with fisheries revenue as the opportunity cost and open points denote solutions with area as the opportunity cost.

onaga-opakapaka only scenarios was apparent for lower conservation value constraints.

3.3. Effects of domain scale on the equity of solutions

Regionally-optimized placements offered similar quantities of area, foregone revenue, and species-specific conservation value across island regions (Fig. 5, left). Using the 30% total area, high compactness solution as an example, regionally optimized solutions represented roughly 30% of the total conservation value across species and 5–10% of the total fisheries revenue. When conducted at the archipelago scale, higher proportions of the spatial domain were allocated to the Hawaii

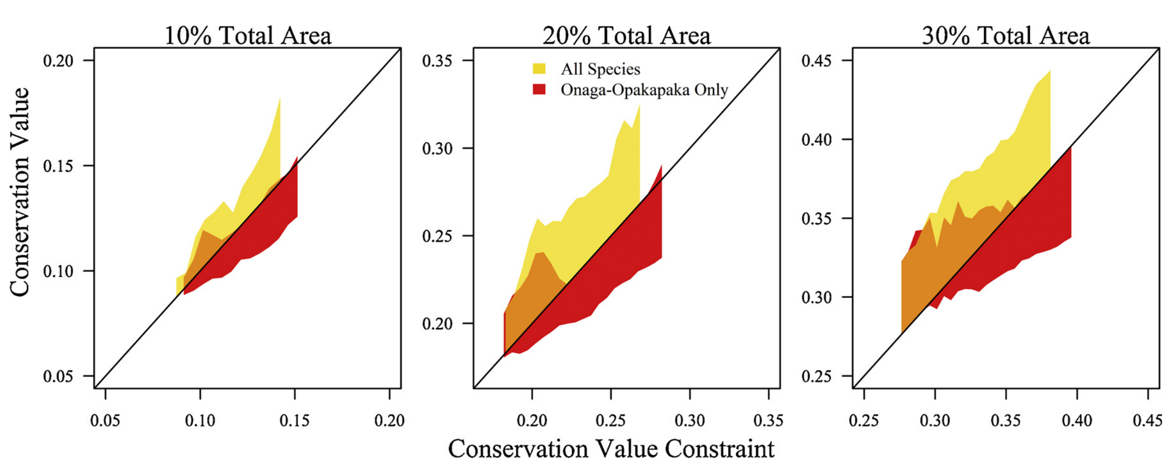

Fig. 4. Range of conservation values across species for a given level of the conservation value constraint for the two species representation scenarios. The vertical spaces above and below the identity line represents the levels of over- and under-representation, respectively, relative to the conservation value constraint. Only solutions within the high compactness scenario across the three total area scenarios were considered.

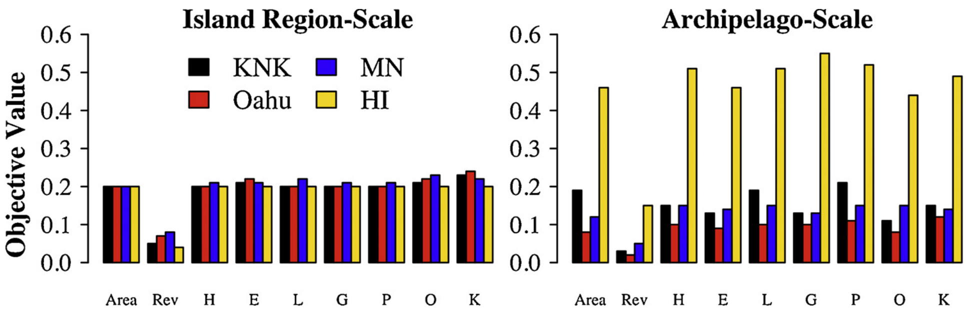

Fig. 5. Total area, opportunity cost and species-specific conservation values across island (bar colors) for the most compact solutions at 20% total area conducted at the island region-scale (left column) versus the archipelago-scale (right column). Objective values are presented as proportions of their respective total values. Legend for the x-axis is as follows: Area: total area; Rev: foregone fisheries revenue; conservation values for H: Hapuupuu (*Hyporthodus quernus*); E: Ehu (*Etelis carbunculus*); L: Lehi (*Aphareus rutilans*); G: Gindai (*Pristipomoides zonatus*); P: Opakapaka (*P. filamentosus*); O: Onaga (*E. coruscans*); and Kalekale (*P. sieboldii*).

Table 1
Opportunity cost (foregone revenue) and conservation value for the maximum conservation value (Max. Cons) and compromise solutions. Solution attributes are shown for the most spatially compact solutions at 10, 20, and 30% total area for each island region (KNK: Kaula Rock-Niihau-Kauai; MN: Maui Nui; HI: Hawaii Island). The slope defines the reduction of foregone value ($\$10^6$) per unit reduction in conservation value when shifting from the Max. Cons. to compromise solutions.

		10% Area		20% Area		30% Area	
Region	Solution Type	Foregone Revenue ($)	Conservation Value	Foregone Revenue ($)	Conservation Value	Foregone Revenue ($)	Conservation Value
KNK	Max. Cons.	12,670	0.112	12,408	0.222	28,404	0.332
	Compromise	3,213	0.100	6,360	0.199	11,230	0.301
	Slope	0.788		0.263		0.554	
Oahu	Max. Cons.	34,756	0.105	42,359	0.215	51,457	0.325
	Compromise	4,903	0.098	9,880	0.202	16,648	0.302
	Slope	4.26		2.50		1.51	
MN	Max. Cons.	88,960	0.128	174,192	0.254	221,662	0.363
	Compromise	20,532	0.102	53,233	0.214	82,157	0.311
	Slope	2.63		3.02		2.68	
HI	Max. Cons.	25,115	0.116	41,739	0.229	42,270	0.339
	Compromise	4,746	0.100	9,456	0.198	16,118	0.299
	Slope	1.27		1.04		0.654	
Archipelago	Max. Cons.	101,021	0.142	240,297	0.268	318,313	0.381
	Compromise	35,576	0.122	74,403	0.233	112,594	0.336
	Slope	3.27		4.74		4.57	

Island region relative to the Oahu and Maui Nui regions. Nearly 50% of the PUs in the Hawaii Island region were chosen whereas less than 10% of the PUs in the Oahu region were allocated. The imbalance of PUs allocated across island regions translated to similar imbalances of foregone revenue and representation of the seven species (Fig. 5, right).

3.4. Compromise between opportunity cost and conservation value

The compromise solution we chose to highlight equally weighted foregone revenue and conservation value update. The percent-decrease in foregone revenue from the maximum conservation value to the compromise solutions varied across island region but ranged from 49-85% (Table 1). The steepest drops in foregone revenue were in the magnitude of 10^5 for the Hawaii Island optimizations, which is substantial given the economic scale of this fishery. The concomitant decrease in conservation value ranged from 6–25%. When optimized at the archipelago scale, optimizations were lower in foregone revenue than the sum of the foregone revenue of the island region optimizations, while providing higher overall species representation. For example, for the 10% total area, high compactness solutions, archipelagic placements had a foregone revenue value of \$101021 and a conservation value of 0.142, but when calculated by island region, the total foregone revenue across regions was \$161501 and conservation values ranging 0.105-0.128. The total archipelagic foregone revenue of the compromise solution was similar regardless of the geographic scale of the optimization, however the conservation value of the archipelagic-scale optimization was slightly higher than the range of the regional-scale optimizations.

The linear slope between compromise and maximum conservation value solutions ($\$10^6$ per unit conservation value) is one way to quantify the tradeoff between lost fisheries revenue and conservation value. Using the KNK 30% total area scenario as an example, shifting from the maximum conservation value solution to the compromise solution resulted in a $< \$10^6$ reduction of the foregone revenue per unit decrease in conservation value, or an absolute reduction in foregone revenue of $\sim \$17 \times 10^5$ and a 0.03 reduction in conservation value. Tradeoffs were lower in the KNK and HI regions (0.263–1.27) and were highest in the Oahu and MN regions (1.51–4.26). Archipelago-scale optimizations had the highest slopes values between 3.27–4.74.

3.5. Reserve placements

Kaula Rock-Niihau-Kauai: The northern coast of Kauai was included in the compromise solutions at both island region and archipelago-scale optimizations. For the maximum conservation value solutions, PUs around the island of Niihau (eastern portion) and Kaula Rock were almost exclusively chosen in the archipelago-scale optimizations.

Oahu: At the island region level, the maximum conservation value solutions initially chose PUs at the northwestern tip of the island for the 10% area scenario, then shifted to the eastern, southern, and northwestern portions of the island for the 20 and 30% area scenarios. Compromise solutions selected areas in the northwestern and southern parts of the island. When solved at the archipelago level, PUs around Oahu were included at a lower proportion, however similar areas were generally selected.

Maui Nui: Island region and archipelago-scale optimizations resulted in similar placements in the Maui Nui region. Maximum conservation value solutions selected areas in Penguin Banks, North and East

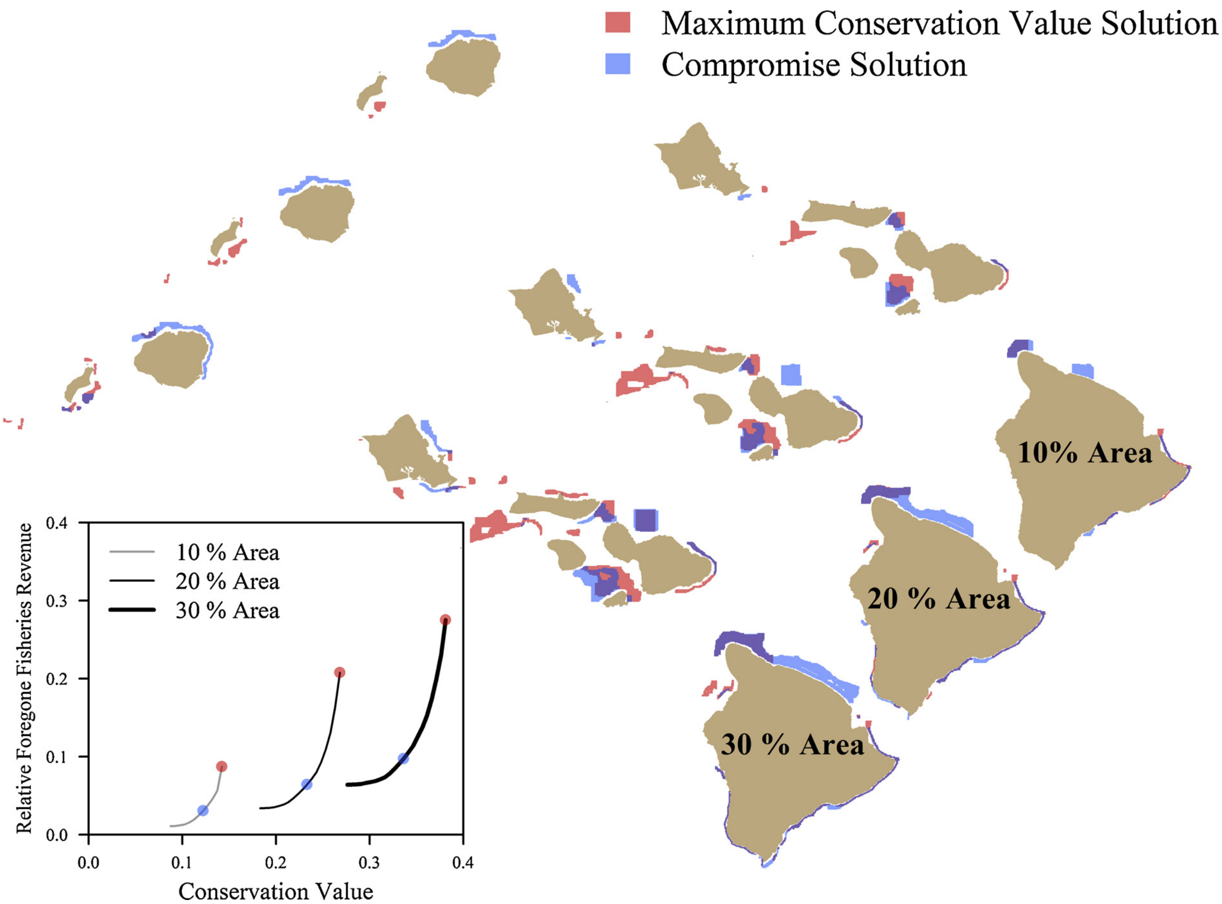

Fig. 6. Placements of reserve solutions conducted at the archipelago-scale corresponding to the maximum conservation value (red) and compromise (blue) solutions (oriented north). Only the most compact solutions are shown for each total area scenario. Purple areas denote the spatial overlap of the two solutions. The bottom-left inset shows the Pareto frontiers for each spatial budget, highlighting the tradeoff between conservation value and opportunity cost (foregone revenue) under non-uniform opportunity cost. The red and blue points on the frontiers correspond to the placements of the maximum conservation value and compromise solutions, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Molokai, and the PUs enclosed among the island of Kahoolawe, Lanai, and Maui. Compromise solutions chosen PUs enclosed among the island of Kahoolawe, Lanai, and Maui and areas north and northeast of Maui. Maximum conservation solutions tended to choose PUs closer to Maui while compromise solutions chose PUs more offshore of Maui.

Hawaii Island: PUs in Hawaii Island were disproportionately chosen when the optimization was conducted at the archipelago level (> 50% of Hawaii Island for the 30% area scenario, Fig. 5). Compromise solutions at the archipelago-scale selected most of the PUs surrounding Hawaii Island except for the northwestern portion of the island. Maximum conservation value solutions selected areas on the northern tip and southern parts of the island. There was considerable overlap between these two solutions, with the exception of the broad areas on the northeastern part of the island. When solved at the island region level, compromise solutions selected areas on the eastern portions of the island. Maximum conservation value solutions selected areas on the northwestern portion of the island and extended in overlapping areas with the compromise solutions on the eastern side of the island.

4. Discussion

A major strength of this analysis stems from the ability to evaluate major assumptions and data sensitivities via the reserve selection model. For example, ignoring the spatial variability in opportunity cost by assuming area as the opportunity cost led to inferior solutions when compared to the Pareto frontier estimated from assuming fisheries revenue as opportunity cost. While this pattern was also observed in previous analyses (Stewart and Possingham, 2005; Klein et al., 2008b), we observed this pattern for the entire range of feasible conservation values. This study is concurrent with conclusions from previous work on the importance of high-resolution socioeconomic data in reserve selection models to reduce the potential socioeconomic impacts of reserves (Richardson et al., 2006; Ban et al., 2009). That said, we only accounted for two types of opportunity costs: spatial access (total area) and foregone revenue. Other forms of opportunity cost, e.g., recreational fishing opportunities, recreational use areas, distance cost (Zhang et al., 2011), as well as conservation costs, e.g., management, acquisition, damage, and start-up costs of MPA establishment (McCrea-Strub et al., 2011; Naidoo et al., 2006) could also be integrated into the analysis by explicitly defining them as objectives. Then, an analysis could be designed to investigate the tradeoffs among the different sources of opportunity cost.

Understanding the effect of using surrogate species in reserve selection models due to data limitations or practical management needs of using indicator species to represent a larger subset of species is important when designing the conservation objectives. When only a subset of the species was included to represent the species complex, there were considerable representation gaps for the excluded species. Fig. 4 showed the ranges of underrepresentation across non-included species, especially when high conservation value constraints were placed on the indicator species. Even for a small set of species, using indicator species led to some species with less protection due to the differences in utilized habitat among the species in the complex (Oyafuso et al., 2017). As a result, the realized conservation value of the

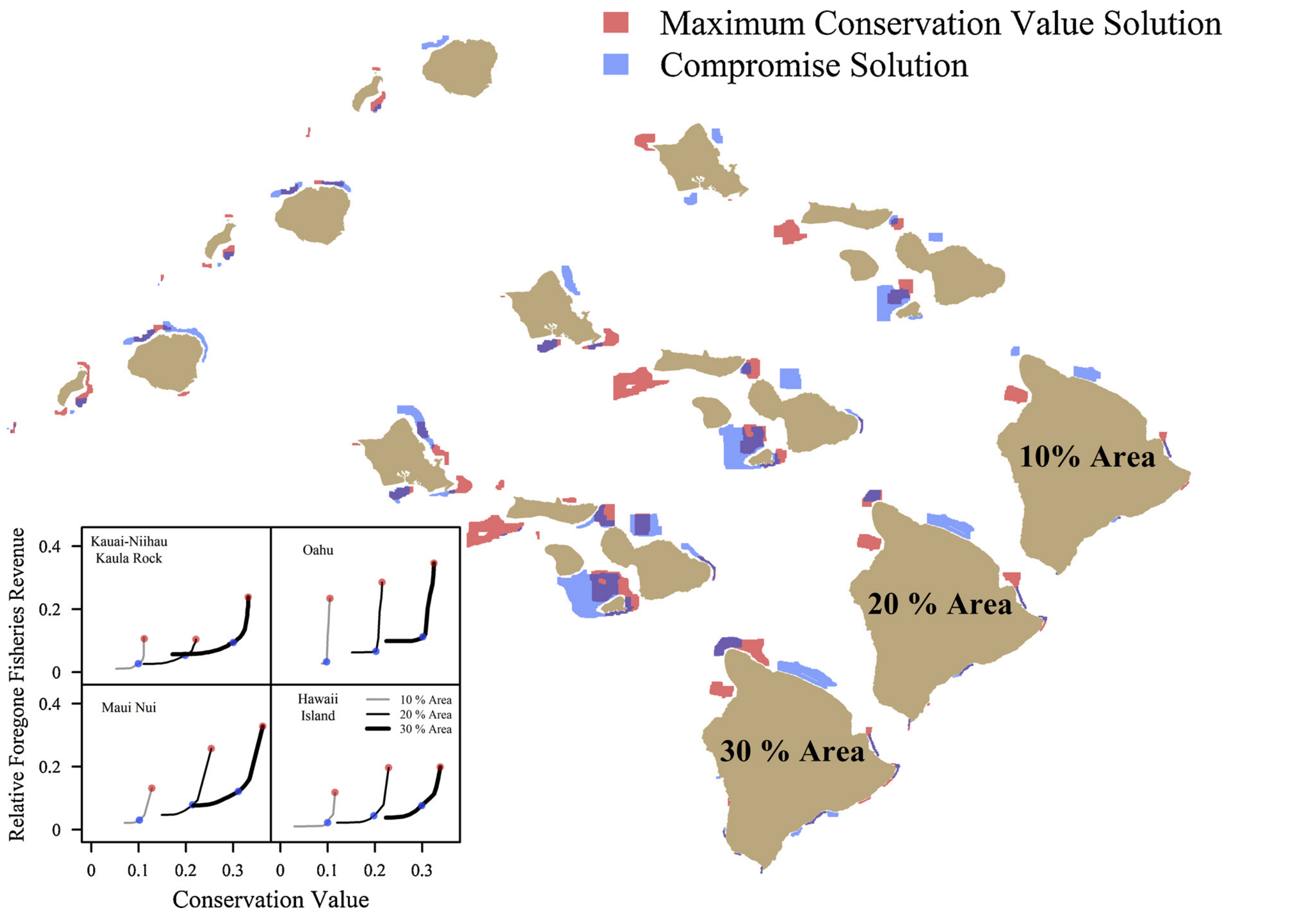

Fig. 7. Placements of reserve solutions conducted at the island region-scale corresponding to the maximum conservation value (red) and compromise (blue) solutions (oriented north). Only the most compact solutions are shown for each total area scenario. Purple areas denote the spatial overlap of the two solutions. The bottom-left inset shows the pareto frontiers for each spatial budget, highlighting the tradeoff between conservation value and opportunity cost (foregone revenue) under non-uniform opportunity cost. The red and blue points on the frontiers correspond to the placements of the maximum conservation value and compromise solutions, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reserve when only including indicator species was lower than the all-species scenario for a given conservation value constraint. The under-represented species were those that negatively co-varied with the included species, so it is important that choice of indicator species best represents the various types of biological features of interest (Caro and O'Doherty, 1999). Without information on species distributions, another tactic is to use surrogates for species distributions (e.g., habitat features, environmental diversity; Faith and Walker, 1996; Araújo et al., 2008).

The most widely known and used reserve selection software is Marxan (Ball et al., 2009) which heuristically calculates the lowest opportunity cost reserve solution given specified conservation representation targets. In this analysis, the minimum set problem was iteratively solved similar to Marxan, but across the entire feasible range of conservation values instead of choosing a priori conservation targets. This served two purposes: 1) the range of possible conservation values can be evaluated and 2) possible socioeconomic ramifications can be visualized on the Pareto frontier. Thus, this type of analysis can provide more informed and realistic conservation representation goals. What is uncertain from our analysis is the interpretation of the conservation value objective (Williams et al., 2005). Framing all the objectives of the reserve selection model to tangible quantities used in fisheries management, e.g., biomass, abundance, fleet size, profit, closely connects calculated reserve solutions to management objectives. Work is in progress to understand how the level of conservation value of a reserve network translates biologically to populations when implemented over time (Oyafuso et al., unpublished).

The conflict of reserve objectives leads to no one solution being perfectly satisfactory, but rather a set of optimal solutions as outlined by the Pareto frontier. Compromise programming can provide decision support by subsetting the range of relevant Pareto-optimal solutions based on the preferences of the design team. Our compromise solution assumed equal weight preference between relative levels of conservation value and socioeconomic opportunity cost. We felt this solution was the most intuitive, as this solution provided the highest level of conservation value just before steep tradeoff in opportunity cost, as visualized by the Pareto frontier (FigsFig. 2 6, 7 Fig. 6 Fig. 7). This resulted in a steep tradeoff of roughly $\$10^6$ more impact to the fishery per unit gain in conservation value. While useful to informing management, the preferences of the reserve design team (e.g. via indifference curves) should be incorporated to determine the appropriate weights for considering other optimal solutions on the Pareto frontier.

When optimizing reserve solutions, the scale at which optimizations were conducted affected the equity of conservation benefits and socioeconomic impacts across island regions. Fair allocation of accessible fishing grounds among spatially or geopolitically distinct fisher groups is an important social consideration of reserve planning (Sanchirico et al., 2002; Blaustein, 2007; Jones, 2009). Although the Hawaiian bottomfish fishery is managed at the state (archipelagic) level, there are de facto political and geographic island region distinctions that dislocate the spatial distribution of the fishing fleet. This concept can be extended to broader, contiguous areas where the spatial domain contains nearshore versus offshore fleets, or domestic or international jurisdictions. Accounting for outcome equity among island regions in our study led to solutions with conservation values and socioeconomic impacts that were slightly less optimal (when aggregated at the archipelago scale) than scenarios where spatial equity was ignored. The relationship between equity and reserve success is an important feature to address in the marine reserve design process (Halpern et al., 2013; Klein et al., 2015), with reserve selection models being the tools in which these tradeoffs can be explored. Other types of input and output equity measures, along with measures of absolute and relative equity (Klein et al., 2015) not addressed here can also be the focus of future work.

The aggregation objective was related to how chosen planning units were arranged, but indirectly addressed the issue of minimum patch size. The high-compactness sceanrios provided large and spatially clumped solutions, but the extent to which patch sizes will be biologically meaningful was not addressed. Some workers have included the size of clusters, groups of adjacent PUs, into spatial optimization models (Rebain and McDill, 2003; Constantino et al., 2008). The MinPatch algorithm is a software that reshapes reserve networks outputted from Marxan to meet a user-defined minimum patch area (Smith et al., 2010). Patch size, shape, and distribution are independent qualities, so although the addition of minimum patch area constraints would be an attractive feature of linear reserve selection models, it will not address other important spatial reserve attributes. Although there have been extensive reviews on reserve shape in reserve design and selected models (Williams et al., 2004, 2005), future work should directly compare different formulations of reserve shape in reserve selection models. Regardless of the function that is used to control reserve shape, it is the task of fisheries managers, along with scientists, fishers, and enforcement bodies to agree on reserve shapes and boundaries that are clear and culturally appropriate. The goal of reserve selection models is to provide guidance and not direct management recommendations for reserve design. The advantage of this approach is that although any spatial alterations of solutions for logistical purposes would technically be less optimal than the reserve solution, the gap between the reserve solution and the post hoc altered reserves can be quantified and documented.

We have presented an example of a type of tradeoff analysis that can used to guide the decision-making process for the creation of marine reserves. The types of data inputs used required synthesizing spatially explicit information about the activities that occurred within the spatial domain of the marine reserves, i.e., bottomfishing, as well as information of the conservation features of interest. Formulating the problem into an ILP model resulted in relatively fast and exact solutions (or rather, near-exact solutions with calculated levels of suboptimality). The relatively quick computation times of linear problems was integral to tracing the various tradeoffs within a multi-objective exercise (Beyer et al., 2016). The calculation of the Pareto frontier of solutions can guide discussions of different reserve placements under different preferences for each objective as well as highlight relevant tradeoffs of particular aspects, sensitivities, and assumptions of the reserve design problem.

Declaration of Competing Interest

This statement is to confirm that all authors do not have any conflicts of interest.

Acknowledgements

The authors thank J. Drazen and two anonymous reviewers for improving this manuscript. Funding provided by the NMFS-Sea Grant Population and Ecosystem Dynamics Fellowship award #NA16OAR4170184 (to ZSO) and NOAA award #NA10NMF4520163 (to ECF). This is University of Hawaii School of Ocean and Earth Science and Technology (SOEST) Publication 10838 and Hawaii Institute of Marine Biology (HIMB) Contribution 1775.

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