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Improving social acceptability of marine protected area networks: A method for estimating opportunity costs to multiple gear types in both fished and currently unfished areas

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ABSTRACT

We present a novel method for calculating the opportunity costs to fishers from their displacement by the establishment of marine protected areas (MPAs). We used a fishing community in Kubulau District, Fiji to demonstrate this method. We modelled opportunity costs as a function of food fish abundance and probability of catch, based on gear type and market value of species. Count models (including Poisson, negative binomial and two zero-inflated models) were used to predict spatial abundance of preferred target fish species and were validated against field surveys. A profit model was used to investigate the effect of restricted access to transport on costs to fishers. Spatial distributions of fish within the three most frequently sighted food fish families (Acanthuridae, Lutjanidae, Scaridae) varied, with greatest densities of Lutjanidae and Acanthuridae on barrier forereefs and greatest densities of Scaridae on submerged reefs. Modelled opportunity cost indicated that highest costs to fishers arise from restricting access to the barrier forereefs. We included our opportunity cost model in Marxan, a decision support tool used for MPA design, to examine potential MPA configurations for Kubulau District, Fiji Islands. We identified optimum areas for protection in Kubulau with: (a) the current MPA network locked in place; and (b) a clean-slate approach. Our method of modelling opportunity cost gives an unbiased estimate for multiple gear types in a marine environment and can be applied to other regions using existing species data.

1. Introduction

The rapid degradation of marine resources resulting from human activity has motivated a global movement to increase the protection of the oceans (IUCN, 2009). The establishment of marine protected areas (MPAs) is a widespread and acknowledged tool for conserving biodiversity and providing ecosystem services, with widely reported increases in biomass of fisheries resources, size of target species, and species richness within protected areas (Lester et al., 2009). However, these benefits will only be realized through effective protected area design as well as compliance and enforcement.

Systematic conservation planning can account for trade-offs between benefits and social costs during the selection of areas by explicitly defining biodiversity, fisheries and socio-economic goals (e.g. Ban and Klein, 2009; Gaines et al., 2010). Systematic methods are currently preferred for designing MPA networks in developed countries (Sala et al., 2002). Despite progress in the technical aspects of designing effective networks, recent research highlights the need to more effectively include socio-economic data in conservation planning with the aim of increasing the potential to implement plans (Naidoo et al., 2006; Polasky, 2008).

Use of socio-economic information is especially important in the context of developing countries where these data are generally limited and social acceptance is a critical factor in determining MPA success (Johannes, 1998; Ban et al., 2009). While inclusion of socio-economic data in the design of MPAs has increased in the last decade (Ban and Klein, 2009), spatial variation in costs to stakeholder groups needs to be better understood (Klein et al., 2008; Adams et al., 2010). This is especially important in Pacific island countries where: communities are highly dependent on marine resources for subsistence (Adams et al., 1997); many fishers have limited spatial and occupational mobility (e.g. Cinner et al., 2009); and customary marine tenure places social and governance constraints on MPA network design (Aswani and Hamilton, 2004).

The most prevalent type of socio-economic data in conservation planning relate to fisheries catch (Ban and Klein, 2009). Catch per unit effort (CPUE) data are typically derived from log books in regulated fisheries or, more commonly in developing countries,

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from socio-economic survey questions about fishing location, gear used, and the type and amount of fish caught. These data reflect the spatial distribution of fishing effort and can be combined with ecological surveys to examine the effects of fishing on fish community composition (Jennings and Polunin, 1996). The collection of CPUE data is becoming standard practice, particularly for commercial fisheries within developed countries (Ban and Klein, 2009), while national-scale collection of artisanal and subsistence CPUE data is possible at relatively low-cost in developing countries (IAS, 2009). Recent studies have examined how to use CPUE data to plan for multiple fisheries so that MPAs do not displace opportunity costs disproportionately onto single stakeholder groups (Klein et al., 2008).

One limitation of CPUE data is that, by definition, they only capture the current fishing effort. This implies, often wrongly, that existing MPAs have no opportunity cost. It also ignores areas without current effort that might be suitable for harvest if currently fished areas became unavailable through the establishment of MPAs. A response to these limitations in conservation planning has been to define cost as a function of both effort and extent of areas being considered for conservation to ensure that no potential MPAs are seen as having zero opportunity cost (e.g. Game et al., 2008). However, for areas with no current fishing effort, assuming homogeneous per-unit-area cost does not capture the potential heterogeneity of effort. Areas outside MPAs can lack current fishing effort for several reasons, including the common inability of survey data to capture the seasonality of fishing distributions, and the lack of access to motor boats, particularly in developing countries (Salas and Gaertner, 2004). As access to motor boats increases, it is reasonable to expect that fishing effort will change and move further offshore to areas currently not fished.

Because of the limitations of CPUE data as a basis for conservation planning, a method is needed to estimate the opportunity costs of areas that are currently not fished. Decisions about MPA size and configuration can then account for the heterogeneous opportunity costs to fishers in both fished and currently unfished areas. A method has been developed to estimate the opportunity costs to agriculture of forested parts of landscapes (Naidoo and Adamowicz, 2006), but an analogous method has not been published for marine environments. In response to this need, we present a novel method for estimating the opportunity costs of establishing MPAs to groups of rural fishers using multiple gear types. We describe the model and then demonstrate its application with a case study from Kubulau District, Fiji, to show how the resulting map of opportunity costs can be used with conservation planning software to recommend a new, more socially acceptable, configuration of community-managed MPAs. We address four main questions that are relevant not only in Kubulau but also for fisheries management globally:

(1) Where are the preferred target fish species located?
(2) Where is current fishing effort focused and how does it vary by gear type?
(3) What are the differences between current and potential opportunity costs?
(4) How can the current MPA network be modified to reduce conflict with users?

2. Methods

2.1. Study area

Kubulau District is an administrative unit of Bua Province, in south west Vanua Levu, Republic of Fiji Islands (Fig. 1). Traditional fishing grounds (*qoliqoli*) in Fiji have been legally demarcated by the Fiji Native Lands and Fisheries Commission. The 261.6 km^2 of inshore waters within the Kubulau qoliqoli contain a diverse array of habitats, including reef flats, seagrass beds, coastal fringing reefs, soft bottom lagoons, patch reefs, offshore barrier reefs and deep channels. Estimates of biomass of targeted food fish from underwater visual census (UVC) surveys along Kubulau forereefs between 2007 and 2009 range from 0.04 to 15.8 tonnes ha^{-1} (WCS, unpublished data).

In 2005, the communities of Kubulau formally established a network of village-managed (*tabu*) areas and MPAs covering nearly 80 km^2 of the qoliqoli, including 17 tabu areas and three MPAs (Namena, Nasue and Namuri; Clarke and Jupiter, 2010). Tabu areas may be periodically harvested by owners of traditional fishing rights at the discretion of the village chief, while the MPAs are permanently closed. The initial design of the tabu areas and MPAs was informed by both socio-economic and biological research undertaken by local managers and their conservation partners – the Wildlife Conservation Society, WWF, Wetlands International-Oceania and the Coral Reef Alliance. A ridge-to-reef management plan was completed for Kubulau District in July 2009 and has been endorsed by the council of chiefs (WCS, 2009). However, lack of consideration for the traditional fishing rights of certain clans has created conflict over access to some closed areas, with violent altercations in at least one case between community fish wardens and locals wanting to fish in an MPA (Clarke and Jupiter, 2010).

The total population of Kubulau District is approximately 1000 people distributed across 10 villages and one settlement. Presently only five of the coastal villages (Navatu, Namalata, Kiobo, Natokalau, Nakorovou) have motorized vessels for fishing. In addition, one motor boat has been donated to the entire district by a local NGO for enforcement and is occasionally used for fishing. Six fishing gear types were identified, with preferred gear types including gill nets, spearguns and hand line (Supplementary material Table S1).

2.2. Opportunity cost and profit models

Fig. 2 shows a flow diagram of the data inputs, intermediate models and steps for the full models of opportunity cost and profit. The following sections describe the parts of the flow diagram.

2.2.1. UVC data for food fish species

In April–May and September 2009, underwater visual census (UVC) surveys were carried out at 63 locations within the Kubulau qoliqoli. Observers measured fish abundance and size within the following families that are targeted for consumption and sale: Acanthuridae, Balistidae, Carangidae, Haemulidae, Lethirinidae, Lutjanidae, Scaridae, Serranidae (groupers only) and Siganidae. Sites were chosen to maximize spatial representation across reef habitats with a minimum of three replicate transects per site, typically distributed across depth categories. Measurements of fish size (total length) and abundance were scored along replicate ($n = 3–5$) 5 m × 50 m belt transects. Transects were deep (12–15 m) and shallow (5–8 m) at most forereef sites, and shallow and reef-top (1–3 m) at backreef sites. Each sighted fish >2 cm was classified to species level within size categories (2–5, 6–10, 11–15, 16–20, 21–25, 26–30, 31–35, 36–40 cm). The length of fish >40 cm was estimated to the nearest cm to improve estimates of biomass. Biomass was calculated from size class estimates of length (L_T) and existing published values from Fishbase (Froese and Pauly, 2009) used in the standard weight-length expression $M = aL_T^b$, with a and b values preferentially selected from sites closest to Fiji (e.g. New Caledonia). If no length–weight (L–W) conversion factor was present for the species, the factor for a species of similar morphology in the same genus was used (Jennings and Polunin, 1996). If a suitable similar species could not be determined, the average for the genus was used. Because most of the New Caledonia fishes

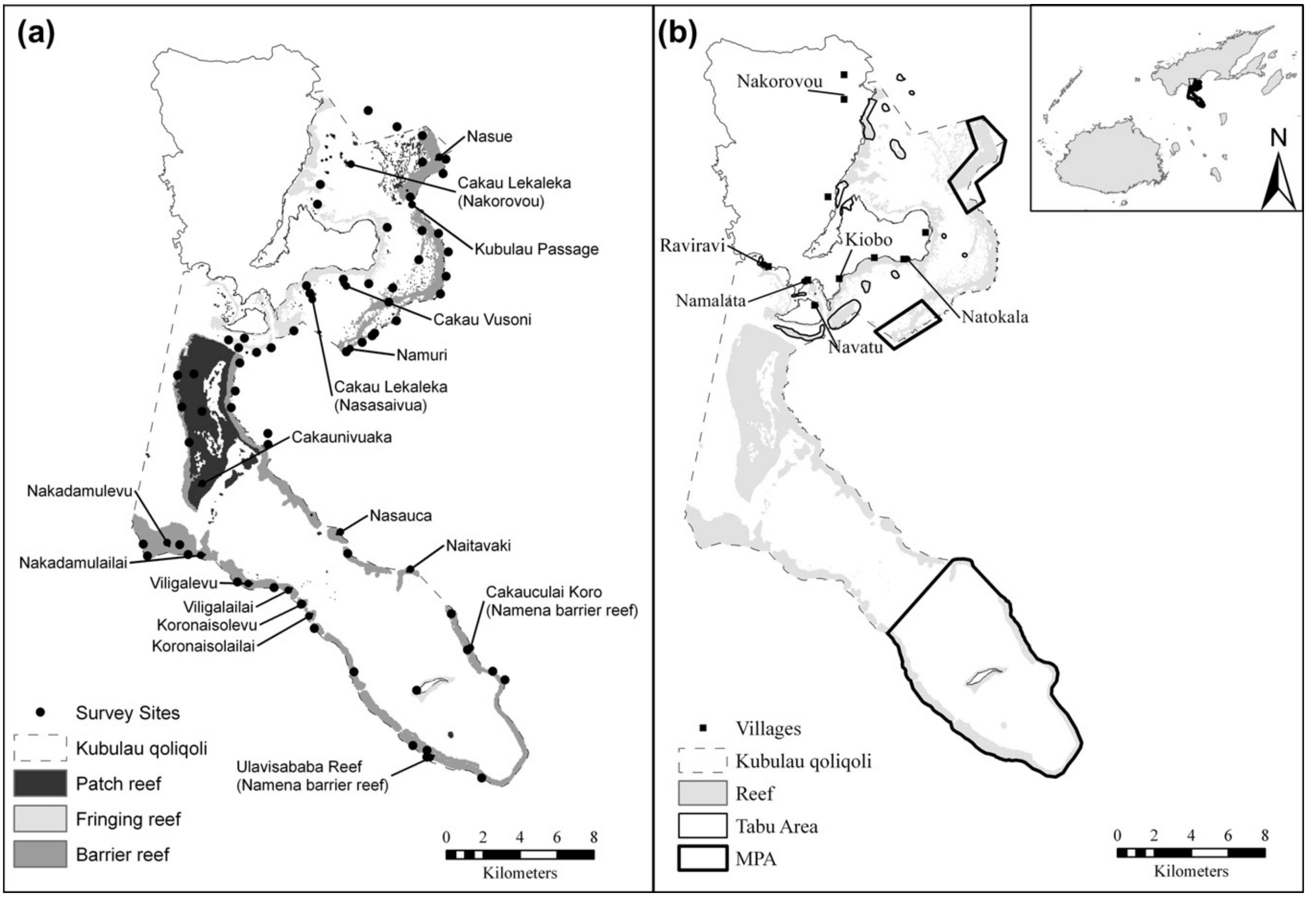

Fig. 1. The study area, Kubulau District, Vanua Levu, Fiji. Inset shows map of Fiji with Kubulau District and traditional fishing ground (qoliqoli) demarcated for reference. (a) Reef habitats (patch, fringing and barrier) in the Kubulau qoliqoli and names of reefs. Sites of biological surveys are also shown. (b) Villages in Kubulau District with labels indicating villages surveyed for CPUE data (Navatu, Kiobo, Nakorovou and Raviravi) and villages with motorized vessels (Navatu, Namalata, Kiobo, Natokalau, Nakorovou). Current tabu areas and MPAs are delineated.

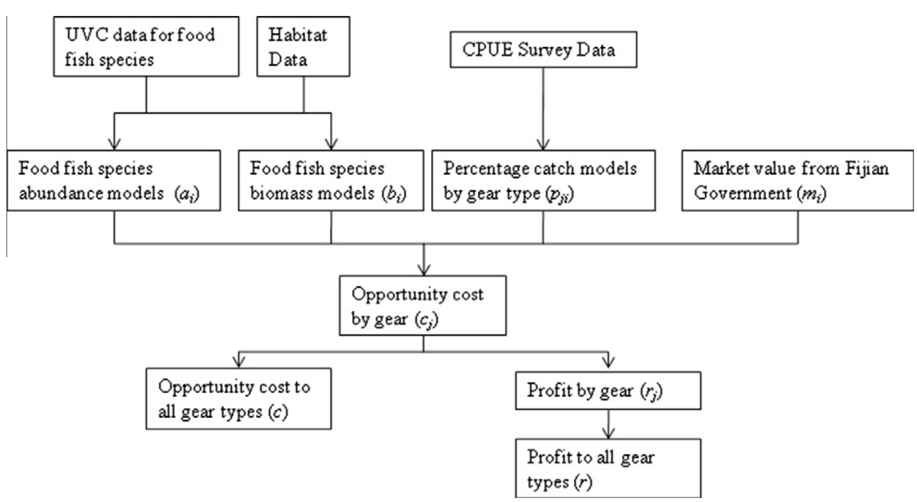

Fig. 2. Flow diagram of data inputs and model steps for opportunity cost and profit models for all gear types.

were measured to fork length (FL), a length–length (L–L) conversion factor was obtained from Fishbase where possible to convert from total length (TL) to FL before biomass estimation. Food fish species ($n = 148$) were selected from the recorded families for spatial modelling of abundance throughout the qoliqoli (see Section 2.2.3).

2.2.2. Habitat data and other predictor variables

We focused on coral reef habitats for our modelling because: (1) the majority of targeted fish biomass within the qoliqoli was found to be associated with coral reefs and (2) relatively comprehensive spatial layers were available for exposed and submerged coral reefs but not for other habitats. Exposed and submerged coral reefs were

Table 1
Reef habitat type, percentage of total reef cover in study region, area in study region, percentage of survey sites allocated, and conservation targets.

Habitat	Percentage of total reef cover in study region (%)	Area of habitat in study region (km^2)	Percentage of survey sites (%)	Conservation target (%)	Conservation target (km^2)
Barrier	54	36.9	63.5	30	11.1
Fringing	17	20.1	19.0	30	6.0
Patch	29	11.7	17.5	30	3.5

digitized by the Fiji Department of Lands from aerial photographs taken in 1994 and 1996. Where data were missing, we digitized exposed reefs from Fiji topographic map sheets at 1:50,000 scale but were unable to digitize additional submerged reefs. We classified reefs primarily as barrier, patch or fringing based on previous surveys and reference to Landsat data (Table 1). To derive biophysical predictor variables for species abundance models, we further classified the reef types by: exposure to tides; exposure to waves; and depth (Supplementary material Table S2). Depth was classified as shallow (depth $\leqslant$ 10 m) or deep (depth > 10 m) based on contour lines from digitized nautical charts. Other predictor variables were protection status and linear distance from shore (Supplementary material Table S2). Distance from shore for each survey location was calculated using ArcInfo 9.2 (ESRI) software.

2.2.3. Food fish species abundance models

Food fish species count and biomass were taken from the UVC survey data and pooled by site and standardized for number of transects. Because species abundance data are often characterized by a large number of zeros, zero-inflated models have recently been developed which allow for the concurrent estimation of occurrence and abundance (e.g. Joseph et al., 2009). For each species we considered four different models: Poisson (P), negative binomial (NB), zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) (see Supplementary material for mathematical details). The Poisson and negative binomial models are standard count models used to estimate abundance. The zero-inflated models simultaneously model probability of detection and abundance. Because Poisson models can be sensitive to low numbers we selected species for modelling that occurred in at least 15% of survey sites. This allowed us to use data on 54 species from 22 genera (Supplementary material Table S3).

We fitted the models using the general linear model (glm) and zero-inflated model (zeroninfl) functions in *R* (R Development Core Team, 2005). These packages use maximum likelihood to estimate coefficients for the generalized linear models (Poisson and negative binomial) and zero-inflated models. We used forward and backward removal to select the best subset of predictors for each model (see Supplementary material Table S3 for predictors selected for each species). For each species we selected the best model by comparing proportion of zeros (predicted zeros/observed zeros) and Akaike's information criterion (AIC, Akaike, 1974). The best-fitting model has the lowest AIC (see Supplementary material for discussion of goodness of fit). Abundance was predicted for each species across the qoliqoli on a 50 m grid to reflect abundance data pooled by site and standardized to abundance per 2500 m^2 (50 m $\times$ 50 m). To determine abundance by family and fish price class we predicted abundance by species and summed abundances for these groupings.

2.2.4. Food fish species biomass models

Because many of the food fish species exhibit ontogenetic movements from inshore to offshore, we modelled biomass for each species to capture heterogeneous distribution of biomass across habitats (e.g. *Lutjanus fulviflamma* juveniles are found in mangrove estuaries while adults commonly school in deep lagoons; Froese and Pauly, 2009). Based on UVC data, we estimated biomass for each species with multiple regression, using both forward and backward stepwise removal to select the best fit model (Supplementary material Table S4). All predictors considered for abundance were included in the biomass models.

2.2.5. CPUE survey data

Between May 2008 and June 2009, area specific catch per unit effort (CPUE) information (in catch person^{-1} h^{-1} m^{-2}) was collected from fishers from four villages (Raviravi, Navatu, Kiobo, Nakorovou) within Kubulau District. Trained community volunteers recorded information once per week from all fish landings in the village during a 24 h period. Fishers were asked for information on the total number of fish caught, the number of people fishing, the time spent fishing, the gear used for fishing, and the transport used for fishing. All participants (n = 191 total) were asked to indicate where they fished on a map. Of the 191 fishers, 72 drew polygons for fishing areas and the others identified their fishing spots with points. In cases where one of the polygons was associated with more than one gear type or method of transport, only the most efficient gear type and method of transport was chosen to represent the polygon to avoid underestimating opportunity costs.

To create a single layer to represent fishing effort, all fishing spots identified as points were translated into polygons with an area equivalent to that of the largest drawn polygon with the same combination of transport and gear, to ensure that the extent of fishing grounds was not spatially underestimated (Supplementary material Table S1). A final uniform CPUE was calculated for each polygon by dividing the catch by the number of people fishing, time spent and fishing area.

2.2.6. Percentage catch models by gear type

For each gear type we compared the predicted abundance of food fish species to the number of fish caught as reported in CPUE surveys and expressed this as percentage catch (catch/abundance). Percentage catch was modelled spatially by gear type across the entire qoliqoli using multiple regression analysis, where AIC was used to determine the best subset of predictors (Supplementary material Tables S5 and S6).

2.2.7. Market value from Fijian Government

Market value, or sale price, of species from 2009 was obtained from the closest Fiji Department of Fisheries district office in Savusavu (Table 2).

2.2.8. Opportunity cost by gear

To estimate the opportunity costs to fishing, we considered the gear types in the region and the food fish species for each as identified by catch records in the CPUE data. Based on the food fish species identified for each gear type, we defined the opportunity cost to gear type j to be c_j

Table 2
Fish price as set by the Fiji Department of Fisheries branch office in Savusavu, Vanua Levu, Fiji.

Class	Price (FJD/kg)	Family
A	$3.00	Lethrinidae, Serranidae, Siganidae
B	$2.50	Carangidae, Haemulidae, Lutjanidae
C	$2.00	Acanthuridae, Scaridae, Balistidae

$$c_j = \sum_{i=1}^{n} p_{ji} a_i b_i m_i$$

where n was the number of species for gear type j, p_{ji} was the percentage catch for gear type j of species i (Section 2.2.6), a_i was the expected abundance of species i (Section 2.2.3), b_i was the expected biomass of species i (Section 2.2.4), and m_i was the market value of species i (Section 2.2.7). Opportunity cost by gear type was estimated for all reefs on a 50 m grid to match the outputs of models of abundance and biomass.

2.2.9. Opportunity cost to all gear types

We defined the opportunity cost, c, of each 50 m reef grid cell as the sum of opportunity costs to all gear types weighted by the current proportion, w_j, of the total number of fishers represented by each gear type in the fishery:

$$c = \sum_{j=1}^{J} w_j c_j$$

where w_j was calculated as the number of fishers using gear type j divided by the total number of fishers. This approach captured the current distribution of gear types in the fleet, recognising that a fishing site is not exclusively available for fishing by any one gear type.

2.2.10. Profit by gear

In developing countries, such as Fiji, many of the fishers are subsistence and therefore are unlikely to be market-driven (e.g. Cakacaka et al., 2010). Also, not all opportunity costs are presently realized because most transport types restrict access to many reefs and fuel costs limit the attractiveness of using boats to fish on distant reefs. Therefore, we wanted to ensure that our model was capturing both current fishing effort as well as potential effort indicated by modelled opportunity cost. We incorporated input costs and differential access by considering expected profit, r_{jm}, from catches at each 50 m reef grid cell by gear type, j, with transport type, m. We excluded time costs, such as forgone revenue from other activities, in our profit model because occupational mobility in this region is limited. We restricted our consideration of input costs to supplies for motorized transport, in this case only fuel. For transport by boats, we considered profit by gear type, j, to be

$$r_{jm} = \max(c_{jm} - f, 0)$$

where c_{jm} is the opportunity cost and f is the fuel cost. Fuel costs were estimated at FJD\$0.78 per km using a 25 hp engine (based on expected average price of \$1.45 per litre, Fijian Government February 2009). For each gear type, j, with transport type, m, we set profit equal to zero for distances beyond the maximum possible distance travelled with transport type m and, in the case of boats, where profit becomes negative. For each 50 m reef grid cell the expected profit, r, for a gear type j is the weighted sum of transport types, m:

$$r_j = \sum_{m=1}^{M} t_{jm} r_{jm}$$

where t_{jm} is determined by the current distribution of transport types, m, for gear type j and calculated within each group of fishers using a particular gear type, j, as the number of fishers with transport type m divided by the total number of fishers.

2.2.11. Profit to all gear types

We defined the profit, r, of each 50 m reef grid cell as the sum of profits to all gear types weighted by the current proportion, w_j, of the total number of fishers represented by each gear type in the fishery:

$$r = \sum_{j=1}^{J} w_j r_j$$

where w_j was calculated as the number of fishers using gear type j divided by the total number of fishers.

2.2.12. Spatial correlations for costs and profit

To compare the opportunity cost and profit models with the CPUE data, Spearman's rank correlation was calculated by gear type and for total catch across 250 m grid cells in which CPUE data were present ($n = 952$). For these correlations, we aggregated our modelled data to 250 m grids because this was the size of the smallest reported fishing ground.

2.3. Design of cost-effective MPAs

We used Marxan software (Ball et al., 2009) to explore options for design and reconfiguration of a cost-effective MPA network for Kubulau that met the conservation targets for all reef types (Table 1). The conservation target of 30% was based on the Fijian Government's declaration at the Barbados Plan of Action in Mauritius in 2005 to protect 30% of its inshore waters. We used a 50 m grid for our planning units to match the resolution of our modelled opportunity costs. For each 50 m grid, we recorded the type of reef habitat and costs based on CPUE and estimated opportunity cost. We selected CPUE as a cost measure to reflect current fishing effort. We selected opportunity cost to capture the expected fishing distribution as access to motorized transport increases and fishing behaviour becomes more market-driven. We considered four scenarios:

- *Scenario* 1 – We used CPUE as the cost layer and did not include current tabu areas and MPAs (*clean slate CPUE*).
- *Scenario* 2 – We used CPUE as the cost layer and required that current tabu areas and MPAs were included in the reconfigured MPA network (*locked in CPUE*).
- *Scenario* 3 – We used opportunity cost as the cost layer and did not include current tabu areas and MPAs (*clean slate Opp*).
- *Scenario* 4 – We used opportunity cost as the cost layer and required that current tabu areas and MPAs were included in the reconfigured MPA network (*locked in Opp*).

Marxan uses a simulated annealing algorithm to find good solutions to the mathematical problem:

$$\text{minimize} \sum_{i=1}^{Ns} x_i c_i + b \sum_{i}^{Ns} \sum_{h}^{Ns} x_i * (1 - x_h) c v_{ih}$$

subject to the constraint that all the representation targets are met

$$\sum_{i}^{Ns} x_i r_{ij} \geqslant T_j \quad \forall\, j$$

and x is either zero or 1

$$x_i \in \{0, 1\} \quad \forall\, i$$

where r_{ij} is the occurrence level of feature j in site i, c_i is the cost of site i, N_s is the number of sites, N_f is the number of features, and T_j is the target level for feature j. The control variable x_i has value 1 for sites selected for the reserve network and value 0 for sites not selected.

The first equation minimizes the penalties associated with the cost of the network and its configuration or shape. The parameter cv_{ih} reflects the cost of the connection, in this case simply the shared boundary, of planning units i and h. The parameter b, is the boundary length modifier (BLM), a user-defined variable that controls the importance of minimizing the total boundary length

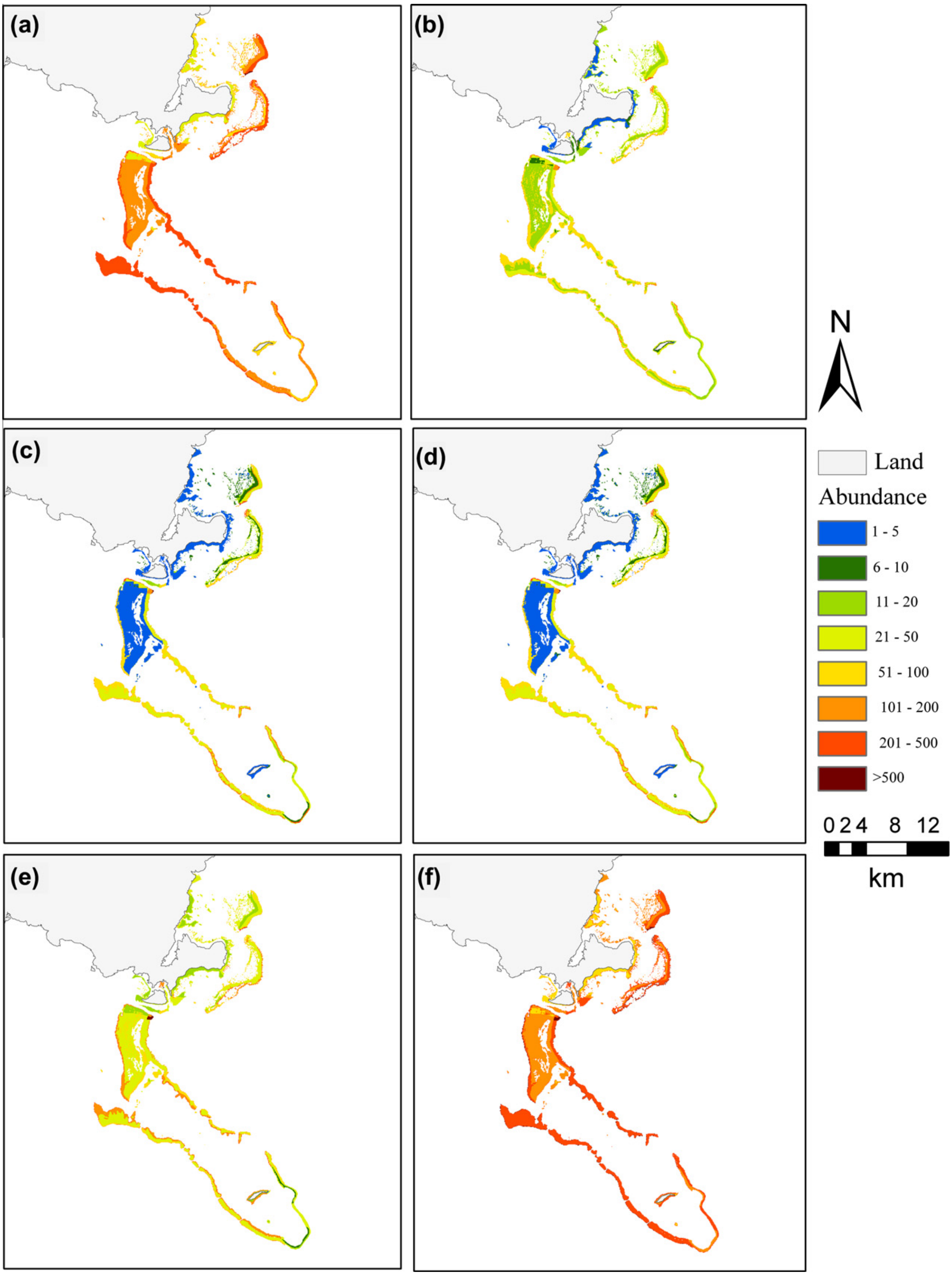

Fig. 3. Modelled abundance per 2500 m^2 (50 m × 50 m grid cell) for the three most abundant families and by market class in Kubulau District. (a) Acanthuridae. (b) Lutjanidae. (c) Scaridae. (d) Market class A; families included are Lethrinidae, Serranidae and Siganidae. (e) Market class B; families included are Carangidae, Haemulidae and Lutjanidae. (f) Market class C; families included are Acanthuridae, Balistidae and Scaridae.

of the selected areas. For each scenario, we selected the BLM with the method described by Stewart and Possingham (2005), intended to achieve a level of connectivity between selected areas that does not unduly increase the overall cost of the solution. For each

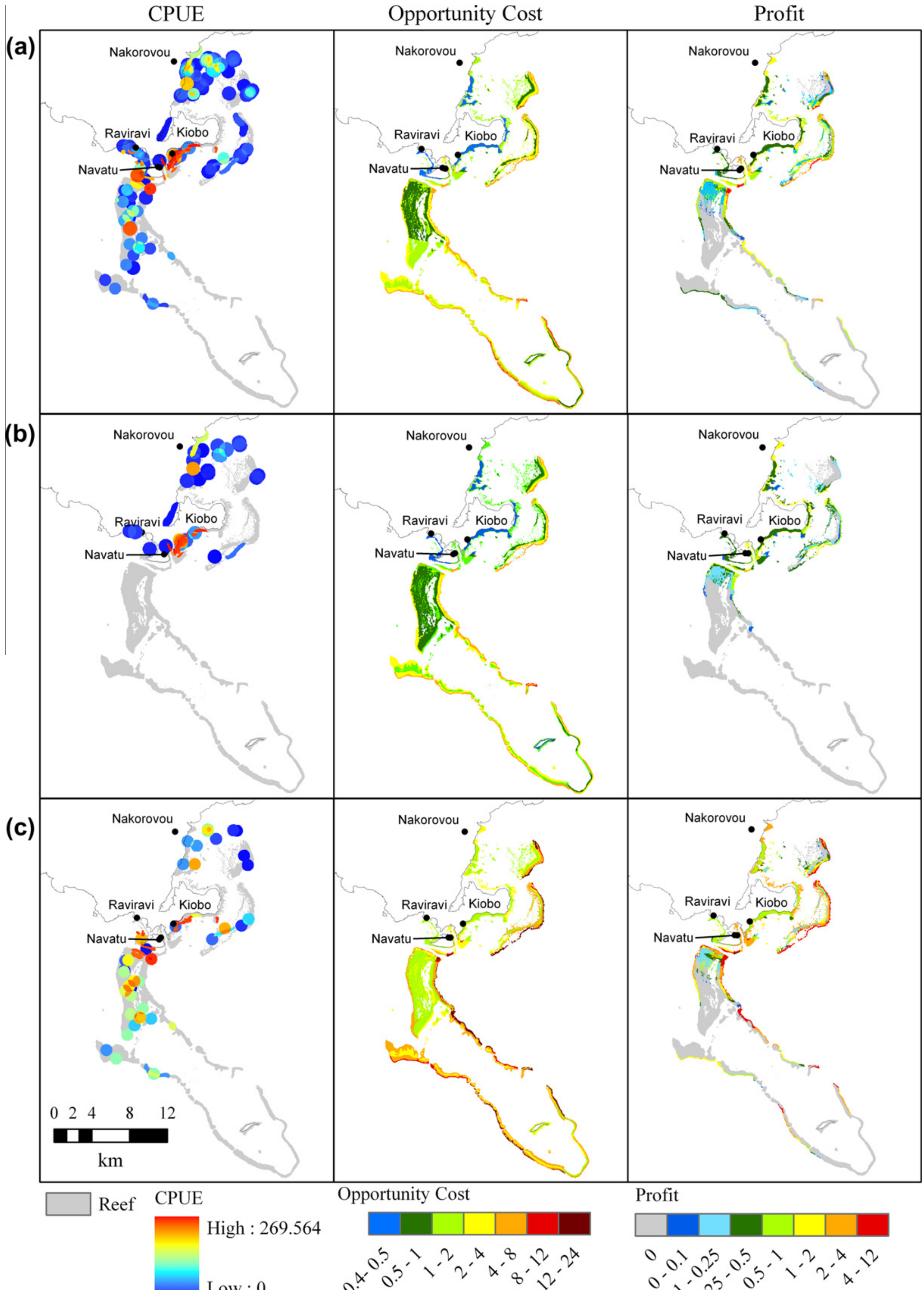

Fig. 4. Catch per unit effort (CPUE), opportunity cost and profit in Kubulau District. First column shows total CPUE, calculated as catch person^{-1} h^{-1} m^{-2}. Second column shows modelled opportunity cost in Fiji Dollars (FJD) per 2500 m^2 (50 m × 50 m grid cell). Third column shows modelled profit in Fiji Dollars (FJD) per 2500 m^2 (50 m × 50 m grid cell). (a) Total across all gear types. (b) Gill net. (c) Speargun.

scenario we then ran Marxan with the simulated annealing schedule and 1000 repeat runs. We measured the similarity of solutions from the four scenarios by spatial correlation (Spearman's) of selection frequency.

3. Results

Abundance models indicated that the greatest numbers of targeted fish were within the families Acanthuridae, Lutjanidae and Scaridae, which vary spatially in abundance across the qoliqoli (Fig. 3). Acanthurids were the most abundant family for all reef types (Fig. 3a). Acanthurids were most abundant on barrier forereefs and submerged patch reefs and occurred in medium densities on inshore fringing reefs (Fig. 3a). Lutjanids were most abundant on barrier forereefs (Fig. 3b). Scarids had high abundance on all types of submerged reefs, with highest abundance on forereefs and the fringing reef around Namenalala (Fig. 3c). Abundance by market class also varied spatially (Fig. 3). Species in class C were most abundant and widely distributed across all habitats in the qoliqoli, particularly on seaward facing slopes of patch reefs and forereef slopes of barrier reefs (Fig. 3f). Class B fish were most abundant on outer barrier forereefs (Fig. 3e), while class A fish were least abundant in these areas and most abundant on submerged inshore barrier and patch reefs (Fig. 3d).

For all gear types combined, CPUE, as indicated by fisher survey records, was relatively uniform across all inshore reefs with the highest effort occurring on fringing reefs near villages (Fig. 4a).

Table 3
Spearman's rank correlations (ρ) across currently fished reefs of catch per unit effort (CPUE) with modelled opportunity cost (opp) and profit (prof) for different gear types. Values correlated are for 250 m × 250 m grid cells (total area of 60 km^2, $n = 952$).

	$\rho_{\text{opp,CPUE}}$	$\rho_{\text{prof,CPUE}}$
Gill net	−0.311***	0.481***
Hand line	−0.024	0.197***
Hand spear	−0.115***	0.090**
Hawaiian sling	−0.007	0.065*
Speargun	0.285***	−0.102***
Trolling	0.049	−0.045
Total	0.158***	0.160***

* $p < 0.05$.
** $p < 0.005$.
*** $p < 0.001$.

Modelled total opportunity cost was highest for offshore barrier forereefs that are currently largely inaccessible to fishers without boats. Modelled total profit was highest for barrier forereefs that can be accessed with a communal raft known as a bilibili (within 3 km of the shore). Exposed fringing reefs had the lowest total values for opportunity cost and profit (Fig. 4a). Opportunity cost and profit had similar magnitudes, with maximum values of $12 FJD per 2500 m^2. Across areas with CPUE data, total modelled opportunity cost and profit were positively correlated with total CPUE (Table 3).

CPUE values were spatially dissimilar between gear types, with negative correlations or non-significant relationships between most gear types (Table 4a). CPUE from gill nets and spearguns were the least similar ($\rho = -0.256$). Total CPUE was positively correlated with all gear types except for Hawaiian sling and trolling. Total CPUE had the largest positive correlation with catch by speargun ($\rho = 0.601$). Opportunity cost and profit were spatially very similar between gear types, with much larger coefficients than for CPUE (Table 4b,c). The relative strengths of correlations between gear types for opportunity cost and profit were, however, similar to those for CPUE (Table 4b and c). For both opportunity cost and profit, speargun and gillnet had the largest positive correlations with total values.

Modelled opportunity cost and profit had similar distributions, but varied in magnitude and distribution by gear type (Fig. 4). Speargun users had the highest opportunity costs and profit of all fishers with a maximum value of $24 FJD/2500 m^2 (Fig. 4c) followed by gill net users (Fig. 4b). Speargun users had positive profit across more offshore reefs than other gear types, which predominantly had zero profit for offshore reefs (Fig. 4). Modelled opportunity cost had mixed spatial correlations with CPUE by gear type while profit by gear type was predominantly positively correlated with CPUE (Table 3). Modelled opportunity cost was negatively correlated with CPUE for gear types that are used primarily for nearshore fisheries (e.g. gill net, $\rho = -0.311$). Opportunity cost was positively correlated with CPUE for gear types that use offshore reefs (e.g. speargun, $\rho = 0.285$). The largest positive

Table 4
Spearman's rank correlations (ρ) between gear types of catch per unit effort (CPUE), opportunity cost and profit (total and by gear type) across the 60 km^2 of currently fished reefs. Values correlated are for 250 m × 250 m grid cells (total area of 60 km^2, $n = 952$). (a) CPUE from interviews; italics indicates non-significant relationship. (b) Modelled opportunity costs (all $p < 0.001$). (c) Modelled profit (all $p < 0.001$).

	Gill net	Hand line	Hand spear	Hawaiian sling	Speargun	Trolling
(a)						
Hand line	*0.007*					
Hand spear	0.266***	0.198***				
Hawaiian sling	−0.086**	−0.136***	*0.019*			
Speargun	−0.256***	−0.186***	*−0.046*	*−0.024*		
Trolling	*0.024*	0.056*	*0.048*	−0.069*	−0.172***	
Total	0.192***	0.184***	0.216***	*−0.019*	0.601***	−0.212***
(b)						
Hand line	0.957					
Hand spear	0.993	0.950				
Hawaiian	0.975	0.934	0.987			
Speargun	0.993	0.954	0.990	0.981		
Trolling	0.983	0.930	0.981	0.985	0.985	
Total	0.997	0.961	0.993	0.980	0.998	0.985
(c)						
Hand line	0.917					
Hand spear	0.938	0.840				
Hawaiian sling	0.901	0.865	0.975			
Speargun	0.843	0.838	0.723	0.718		
Trolling	0.905	0.868	0.975	0.997	0.772	
Total	0.889	0.867	0.776	0.762	0.994	0.766

* $p < 0.05$.
** $p < 0.005$.
*** $p < 0.001$.

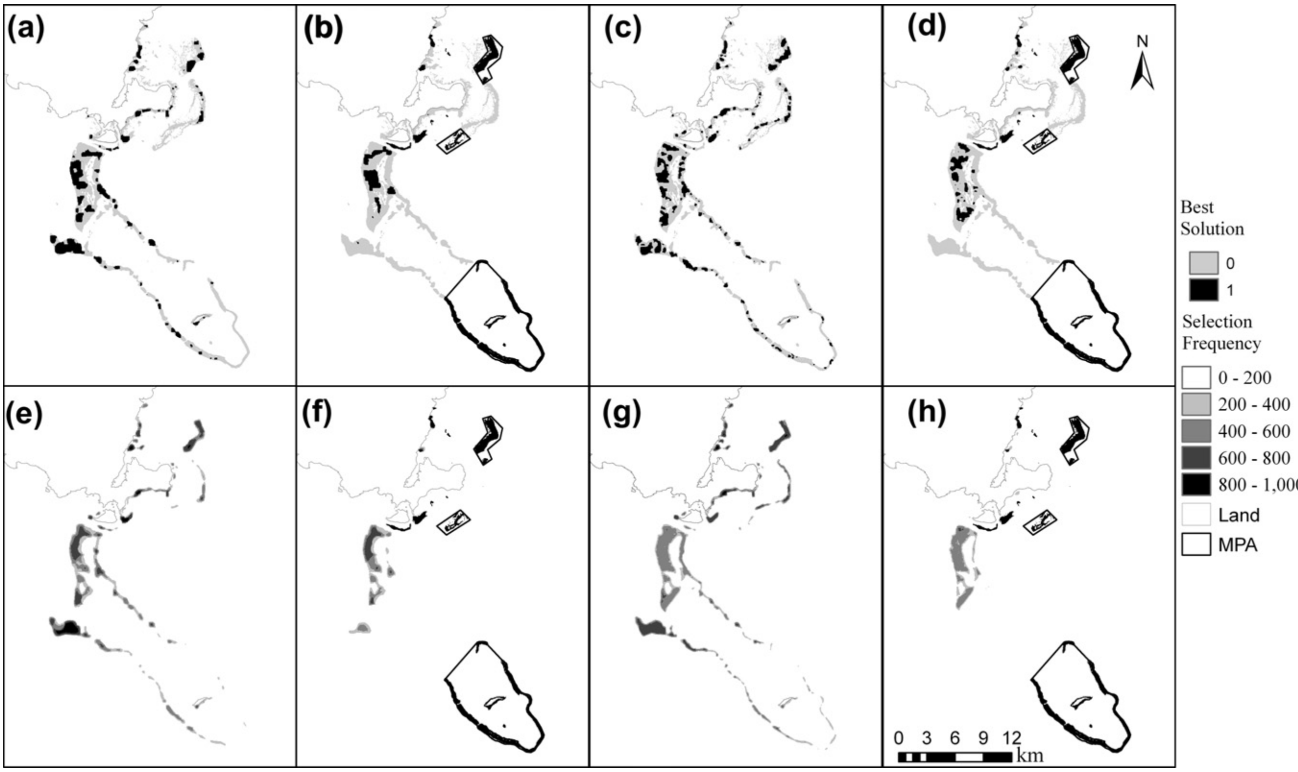

Fig. 5. Marxan best solutions (top row) and selection frequencies (bottom row) for the four scenarios for Kubulau District. (a) Best solution for scenario 1, clean slate catch per unit effort (CPUE). (b) Best solution for scenario 2, locked in CPUE. (c) Best solution for scenario 3, clean slate opportunity cost (Opp). (d) Best solution for scenario 4, locked in Opp. (e) Selection frequency for scenario 1, clean slate CPUE. (f) Selection frequency for scenario 2, locked in CPUE. (g) Selection frequency for scenario 3, clean slate Opp. (h) Selection frequency for scenario 4, locked in Opp.

correlation between profit and CPUE was for gill nets ($\rho = 0.481$). The largest negative correlation between profit and CPUE was for speargun ($\rho = -0.102$; Table 3).

The current network of tabu and MPAs in Kubulau qoliqoli cover 40% of all barrier reefs, 36% of fringing reefs, and 2% of patch reefs. Selection frequencies for the clean-slate scenarios with CPUE and opportunity costs were strongly and positively correlated ($\rho_{1,3} = 0.880$, $p < 0.001$). Selection frequencies for the locked-in scenarios with CPUE and opportunity costs were also strongly and positively correlated (Spearman's rank correlation coefficient $\rho_{2,4} = 0.867$, $p < 0.001$). Correlations were weaker but still significant between selection frequencies for the clean-slate and locked-in scenarios for CPUE ($\rho_{1,2} = 0.320$, $p < 0.001$) and opportunity cost ($\rho_{3,4} = 0.082$, $p < 0.001$). All scenarios selected portions of Cakaunivauaka reefs to meet the patch reef target of 30% (Fig. 5). For the locked-in scenarios, the barrier reef and fringing reef targets were predominantly met by the current tabu areas and MPAs, so nearly all additional areas selected were patch reefs within Cakaunivuaka Reef (Fig. 5b and d). Best solutions from the clean-slate analyses also selected areas of Cakaunivuaka Reefs while indicating that Namuri MPA plus some of the inshore community tabu areas could be replaced by adding protection to Nakadamulevu Reef (Fig 5a and c). Despite the strong overall correlation, there were some notable spatial differences in selection frequencies for the clean-slate scenarios using CPUE versus opportunity cost. Selection frequencies were higher in the southern portion of Namena barrier reef for the opportunity cost scenario but higher on the fringing reef near Navatu for the CPUE scenario (Fig. 5e and g).

There were two expected general results from analysis of total costs of scenarios (Fig. 6). First, CPUE and opportunity cost were each minimized when directly used in the Marxan analyses. Second, for both CPUE and opportunity cost, clean-slate solutions were less costly than locked-in solutions. Specifically, the opportunity cost scenarios resulted in best solutions that reduced opportunity costs and profit by approximately 12% compared to CPUE scenarios (Fig. 6). However, using opportunity cost resulted in selecting MPAs with substantially higher CPUE (5–20% of total CPUE, Fig. 6). CPUE and opportunity cost produced comparable results in terms of total area selected.

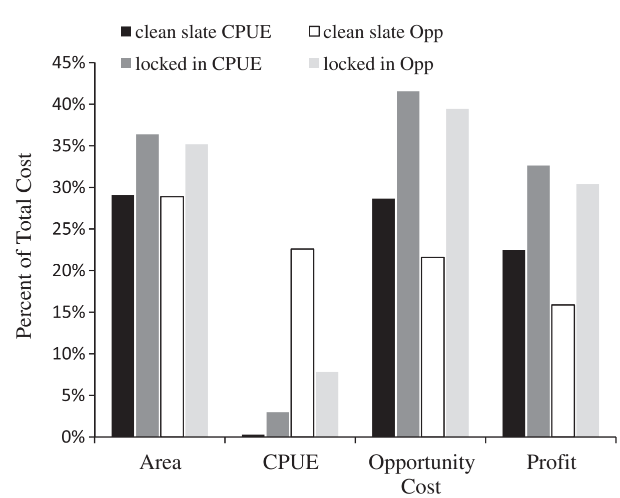

Fig. 6. Total cost to fishers in Kubulau District calculated for Marxan best solutions for the four scenarios, displayed as percentage of total cost for four cost metrics: area, catch per unit effort (CPUE), opportunity cost (Opp), and profit. We determined % total cost for all metrics by dividing the summed cost of the areas selected for protection by the total cost across the study area. We included area as a cost metric to demonstrate that summed areas selected in Marxan runs were comparable between cost scenarios, even though other metrics differed strongly.

4. Discussion

We first discuss the model components and outcomes with specific reference to the case study from Kubulau District and then discuss the broader application of our model, particularly in data-poor regions across the South Pacific.

4.1. Spatial distribution of catch and effort in Kubulau qoliqoli

Our models are based on the underlying assumption that reefs with high abundance will have higher catch and therefore be of higher value to fishers (e.g. Edwards et al., 2010). As observed in other studies in Fiji and the tropical Western Pacific, the greatest proportion of targeted fish available for catch are from the families Acanthuridae (market class C), Lutjanidae (class B) and Scaridae (class C) (Jennings and Polunin, 1995; Kuster et al., 2005). The highest predicted abundance for acanthurids and scarids was on the outer reef slopes and patch lagoon reefs, which is comparable with previous reports of high CPUE for reef fish on lagoon reefs and outer reef slopes in Fiji (Jennings and Polunin, 1995). Given that Kubulau fishers on the whole are largely targeting inshore fringing reefs for fish in classes B and C with lower value per kg, most do not appear to be influenced by market value of catch. If price variation were greater there might be more incentive for fishers with motorized boats to pursue Class A species in offshore reefs (Poos et al., 2010).

The spatial location of effort across Kubulau qoliqoli is primarily driven by access to transport. The majority of fishers from Kubulau do not have access to motorized boats and fish largely for subsistence (Cakacaka et al., 2010). Therefore, current effort across all gear types is highest on reefs closest to villages (inshore fringing and patch reefs). The same trend of heavy effort on nearshore reefs has been observed in other regions where access to motorized transport is limited (Aswani, 1998; Bene and Tewfik, 2001). Therefore, our profit model best reflected current fishing effort because, unlike the opportunity cost model, it considered accessibility and travel costs.

By contrast, the quantity of catch is largely driven by access to markets and more efficient gear, such as spearguns and gill nets, owned by several fishers mostly from Navatu and Kiobo operating on an artisanal scale. Highest profit values for gill nets are on the fringing reefs where they are typically used to target schooling fish, particularly mullets (Rawlinson et al., 1995). Meanwhile, high profits for spearguns are on the offshore barrier reefs, where they are a preferred gear type due to their ability to efficiently target larger, more valuable fish (Dalzell, 1996; McClanahan and Mangi, 2000; Kuster et al., 2005). Because spearguns and gill nets require considerable initial investment (approximately $300FJD for a speargun and $200FJD for a gill net), it is unlikely that fishers are willing to make the financial outlay unless they can guarantee revenue from catch (Veitayaki, 1990; Teh et al., 2009).

Fishers from Navatu, Namalata and Kiobo have reliable access to a middle man who lives in Navatu village and regularly sells fish to the markets in Savusavu (Clarke and Jupiter, 2010). Therefore, they have the financial incentive to invest in motorboats which enables them to access distant, high-density fishing grounds with highly efficient gear to maximize catch. Increased access to markets could drive purchases of spearguns and motorized transport, causing higher fishing effort on the offshore reefs causing the profit model to converge on the opportunity cost model. This type of market-driven fishing displacement has been observed in other multispecies fisheries, where the high value of catch has strongly influenced the location of fishing effort, particularly in situations with rising fuel prices and depletion of commercial stocks (Arrelano and Swartzman, 2010).

In fact, it is likely that the number of catch locations from artisanal fishers on outer barrier reefs is under-represented in CPUE surveys. Two likely reasons are a fear of releasing information on choice productive fishing grounds and awareness that some of these fishing locations violate community management rules (e.g. are within MPA boundaries). For example, within the past year, fishers from Navatu have been repeatedly caught fishing within the Namena Marine Reserve (Clarke and Jupiter, 2010), although these catch locations were never recorded on CPUE forms. In such cases where recorded fishing effort might not accurately match actual or future effort, the opportunity cost model provides an unbiased alternative. It allows conservation planners to value reefs that are currently reported as unfished and, when designing MPAs, to minimize displacement of fishers not included in surveys or who misreported their fishing grounds.

4.2. Marxan results and implications for reconfiguration of MPAs

There were notable similarities between the Marxan scenarios that used CPUE and opportunity cost. Both locked-in approaches indicated that high-priority additions to the MPA network were areas within Cakaunivuaka Reef. Both clean-slate approaches were spatially similar and indicated other potential areas that could be added to the network, such as those within Nakadamulevu Reef. However, the CPUE clean-slate approach identified the fringing reef near Navatu for protection because there is currently a tabu area on this reef and therefore no effort (Fig. 5a). In contrast, the clean-slate approach using opportunity cost left this reef open to fishing because of its high cost (Fig. 5c). The opportunity cost scenarios had lower total costs when considering opportunity cost and profit, but considerably higher costs when considering CPUE (Fig. 6). This indicates that using opportunity cost in Marxan reduces the impacts to both current and future fishing effort. However the communities should be consulted regarding the Marxan scenarios to determine whether the opportunity cost models produced amenable MPA selections. Consultation with the communities will allow the stakeholders to determine the relative importance of maintaining current fishing grounds over future fishing grounds.

Given that recent monitoring from the Namuri MPA suggests that it is being substantially affected by poaching (Jupiter et al., 2010), and outputs from both clean-slate scenarios do not select sites within Namuri, it would be worthwhile to suggest a trade-off to the Kubulau community. This would open portions of Namuri to fishing in exchange for protection of areas within Nakadamulevu and the adjacent Nakadamulailai Reefs. Closure of these areas could potentially also offset opening a portion of Namena Marine Reserve, which has been heavily contested by one of the Navatu clans, members of which have been repeatedly caught fishing in Namena.

Because the clan perceives inequity in the distribution of costs and benefits of the present tabu areas and MPAs, the Marxan solutions could reduce conflict by producing more socially acceptable configurations (Lal, 2005). Some of this conflict might have arisen because the environmental and social goals of MPA establishment and management were ill-defined from the outset. Having a clear understanding of these goals is critical to ensure that MPA design does not adversely affect current fishing industries and community identity (Klein et al., 2008; Ban et al., 2009).

4.3. Model applications and conclusions

The opportunity cost model provides data for use in decision support tools for conservation planning such as Marxan and Marxan with Zones (Ball et al., 2009; Watts et al., 2009).

Our modelling approach incorporates socio-economic considerations and can be applied in regions with poor data on human uses and those where people are highly dependent on natural resources to ensure that conservation actions minimize impacts on local communities (Ban et al., 2009; Ban and Klein, 2009). Standard socio-economic survey methods often have limitations. In marine applications, these include lack of participation by users of all gear types, partial disclosure of fishing areas, and lack of standardized methods for integrating spatial data (for methods on standardizing data collection with GIS see De Freitas and Tagliani, 2009). Our model differs from standard survey approaches by accounting for variation in the spatial distribution of natural resources rather than focusing on current extractive effort.

For marine regions, our model is appropriate for considering socio-economic goals in fisheries where gear preferences or access to transport are expected to change dramatically (Salas and Gaertner, 2004). In these regions, there may be little to no existing biological and socio-economic data. While our model requires multiple modelling steps, it can be adapted for data-poor regions. The main data restriction for our model is existing fish count surveys which may not exist in some regions. However, most regions in which NGOs are active will have fish abundance or presence/absence data would be suitable for the approach described here. The remaining data for predicting fish abundance could be acquired strictly from remote sensing and basic navigational charts (such as depth and reef classification). The socio-economic inputs such as percentage catch can be estimated based on several survey days in villages. Due to data quality issues and multiple model inputs, error in the model can be tested using standard techniques such as info-gap and sensitivity analysis (Halpern et al., 2006). Sensitivity analysis might be particularly useful if particular inputs in the model have higher associated error. For example, in our model the percentage catch models have high uncertainty associated with them due to small sample size. Therefore, a sensitivity analysis could demonstrate how modelled opportunity cost and profit vary with increments of error in estimates of percentage catch by gear type. This analysis could be incorporated into Marxan scenarios to investigate how sensitive area selections are to variability in the opportunity cost model.

Although Marxan is a static planning tool, recent applications have implemented Marxan in dynamic multi-year simulations (Visconti et al., 2010). Fishing effort and fish abundance are likely to interact dynamically through time and a multi-year dynamic approach to MPA design may be more realistic (e.g. see Christensen et al., 2009). Our models can be adapted to incorporate fisheries dynamics for multi-year simulations. For example, our profit and opportunity cost models can be used to examine how costs will change as market access drives changes in access to gear type and transport. Changes in gear type can be modelled with opportunity cost by exploring a range of weightings to reflect a larger proportion of fishers using efficient gear types such as spearguns. The effects of changes in transport on spatial effort can be explored in the profit model by altering weightings to reflect a larger proportion of fishers using motor boats, as has been observed across Fiji (Kuster et al., 2005).

Despite the acknowledged importance of socio-economic data in resource management, previous studies have suggested that artisanal fishers in developing countries are not always market-driven (Pet-Soede et al., 2001; Daw, 2008), with fishing behaviour being determined more by factors such as values on time, risk aversion, and cultural identity (Bene and Tewfik, 2001; Salas and Gaertner, 2004). These factors can be considered explicitly by treating them as additional input costs in the profit model. The expected costs from such scenarios can then be used in conservation planning software to provide a more thorough exploration of configuration options for MPAs and the range of impacts on local communities. The profit model therefore allows for a comprehensive analysis of trade-offs between conservation actions and local economic development that is not possible with CPUE data.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.biocon.2010.09.012.

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