LETTER

Tradeoffs in marine reserve design: habitat condition, representation, and socioeconomic costs

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Abstract

We present a novel method for designing marine reserves that trades off three important attributes of a conservation plan: habitat condition, habitat representation, and socioeconomic costs. We calculated habitat condition in four ways, using different human impacts as a proxy for condition: all impacts; impacts that cannot be managed with a reserve; land-based impacts; and climate change impacts. We demonstrate our approach in California, where three important tradeoffs emerged. First, reserve systems that have a high chance of protecting good condition habitats cost fishers less than 3.1% of their income. Second, cost to fishers can be reduced by 1/2–2/3 by triaging less than 1/3 of habitats. Finally, increasing the probability of protecting good condition habitats from 50% to 99% costs fishers an additional 1.7% of their income, with roughly 0.3% added costs for each additional 10% confidence. Knowing exactly what the cost of these tradeoffs are informs discussion and potential compromise among stakeholders involved in protected area planning worldwide.

Introduction

Globally, protected areas are the cornerstone of most marine conservation strategies. Effectively managed marine protected areas (MPAs) consistently deliver ecological (Murray *et al.* 1999; Lester & Halpern 2008; McCook *et al.* 2010), economic (Roberts *et al.* 2001; Russ *et al.* 2004), and social benefits (Cinner *et al.* 2005). Yet there remains concern that MPAs, especially no-take reserves, deliver conservation outcomes at the expense of fishing interests. To reduce both real and perceived conflict, the location of new reserves should be driven by both ecological and socioeconomic factors (Fernandes *et al.* 2005; Klein *et al.* 2008; Green *et al.* 2009; Weeks *et al.* 2010).

A common approach to MPA design is to ensure that habitats and species are comprehensively represented in places of low value to fishers, where possible (Sala *et al.* 2002; Ban *et al.* 2009). Although this approach considers two prominent factors of MPA design, it ignores the impacts of other human activities on marine habitats. Habitats in MPAs may be in poor condition if they are negatively impacted by stressors that cannot be mitigated through protection (e.g., climate change). Planners are in need of prioritization approach that can incorporate information about stressors not abatable through MPAs. With such information, planners can choose to avoid the stressors or address the stressors through other conservation actions.

Recent research has developed novel approaches for mapping human impacts to marine ecosystems (Halpern *et al*. 2008; Halpern *et al*. 2009; Ban *et al*. 2010). This new information can be used as a proxy to estimate habitat condition, under the assumption that higher cumulative impact from human activities leads to lower habitat quality. This assumption is supported by the strong positive relationship between estimates of cumulative impact and empirical data on habitat condition (Halpern *et al*. 2008). We can incorporate this proxy for condition into MPA design to allow for more informed decisions, keeping in mind that different management goals exist and may not aim to protect the best quality habitat. In addition, planners may be interested in distinguishing between activities that can and cannot be managed with MPAs. For example, it may be desirable to avoid sites heavily impacted by land-based stressors as their management requires additional effort (Roberts *et al*. 2003).

The importance of considering a range of human impacts on marine habitats is often acknowledged (Kochin & Levin 2003; Lotze *et al*. 2006; Game *et al*. 2008b; Halpern *et al*. 2008; Claudet & Fraschetti 2010), but is rarely an explicit consideration in the systematic MPA design. Studies that have incorporated nonfishing impacts were not able to avoid placing MPAs in important fishing areas (Banks *et al*. 2005; Tallis *et al*. 2008; Ban *et al*. 2009; Green *et al*. 2009). Game *et al*. (2008b) is the only example of an approach that accommodates information about habitat condition and economic cost; however, they treated condition as a binary variable where habitat is either healthy or degraded due to one impact.

We demonstrate a novel approach to designing reserves that can incorporate information about both habitat condition and socioeconomic costs. We illustrate our approach in California and use cumulative human impact data as a proxy for habitat condition. Our objective is to minimize the chance that protected habitats are in poor condition and avoid places valuable to commercial fisheries. We considered habitat condition as determined by four different subsets of human activities to reflect the types of information that planners may consider when designing marine reserves (Table 1): (1) all quantifiable activities; (2) activities that cannot be managed with a marine reserve; (3) land-based activities; and (4) activities associated with climate change. We aim to determine how reserve design outputs change, if at all, when various types of human impacts are accounted for, highlighting tradeoffs between habitat condition, representation, and socioeconomic costs. Incorporating these important factors into marine reserve design will help support systematic and transparent conservation decisions and improve ocean health.

Methods

Planning region

Our analysis was conducted in one of the planning regions of the California Marine Life Protection Act Initiative (the "Initiative"), defined by the 5,556-m legal limits (i.e., state waters) from Pigeon Point to Alder Creek and around the Farallon Islands—exclusive of San Francisco Bay—a total area of 1,977.5 km^2 (Figure 1). MPAs have already been implemented in this region, thus our analysis aims to influence decisions in other places and not modify current protected area decisions in California. Consistent with the scale of the data, we divided the region into 3,337 square planning units (0.5′ square), each of which could be protected.

Data

We used the same spatial data representing habitats, depth zones, and fishing value as used in the Initiative. Habitats included coastal marshes, eelgrass, estuaries, hard bottom, kelp forests, soft bottom, surfgrass, and tidal flats (California Resources Agency 2007). We subdivided the habitats into three biogeographic regions (North, South, and the Farallon Islands) and three depth zones (intertidal, intertidal–30 m, and 30–100 m). Since not all habitats exist in each region/depth zone, we had 32 features, each of which was targeted for inclusion in a reserve.

Spatial fishing data were derived from 174 interviews with fishermen, conducted in 2007 (Scholz *et al*. 2011). These data include the monetary value of an area to individual fishermen across eight commercial fisheries: California halibut, chinook salmon, coastal pelagic finfish, Dungeness crab, deep nearshore rockfish, market squid, nearshore rockfish, and sea urchin.

Our prioritization approach uses probability theory to identify planning units containing good condition habitat. To implement our approach, we require information about the probability that each planning unit is in poor condition. We assume that the higher the cumulative impact from human activities the less likely the habitat is in good condition. We calculated the maximum human impact per planning unit across all habitats within that planning unit to account for the most impacted habitat. We then normalized this value to that of the maximum impact in the entire California Current as we wanted to represent the impact of a site relative to that of the

Table 1 Stressors considered in determining marine habitat condition for Scenarios 1–4

	Anthropogenic driver	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Land-based	Nutrient input	√	√	√	
	Organic pollution	√	√	√	
	Inorganic pollution	√	√	√	
	Coastal engineering	√	√	√	
	Human trampling	√	√	√	
	Coastal power plants	√	√	√	
	Sediment decrease	√	√	√	
	Noise/light pollution	√	√	√	
	Atmospheric deposition of pollutants	√	√	√	
	Commercial shipping	√	√		
	Invasive species	√	√		
	Ocean-based pollution	√	√		
Fishing	Recreational fishing	√			
	Pelagic low bycatch	√			
	Pelagic high bycatch	√			
	Demersal destructive	√			
	Demersal nondestructive low bycatch	√			
	Demersal nondestructive high bycatch	√			
Climate	Sea surface temperature	√	√		√
	Ocean acidification	√	√		√
	UV	√	√		√

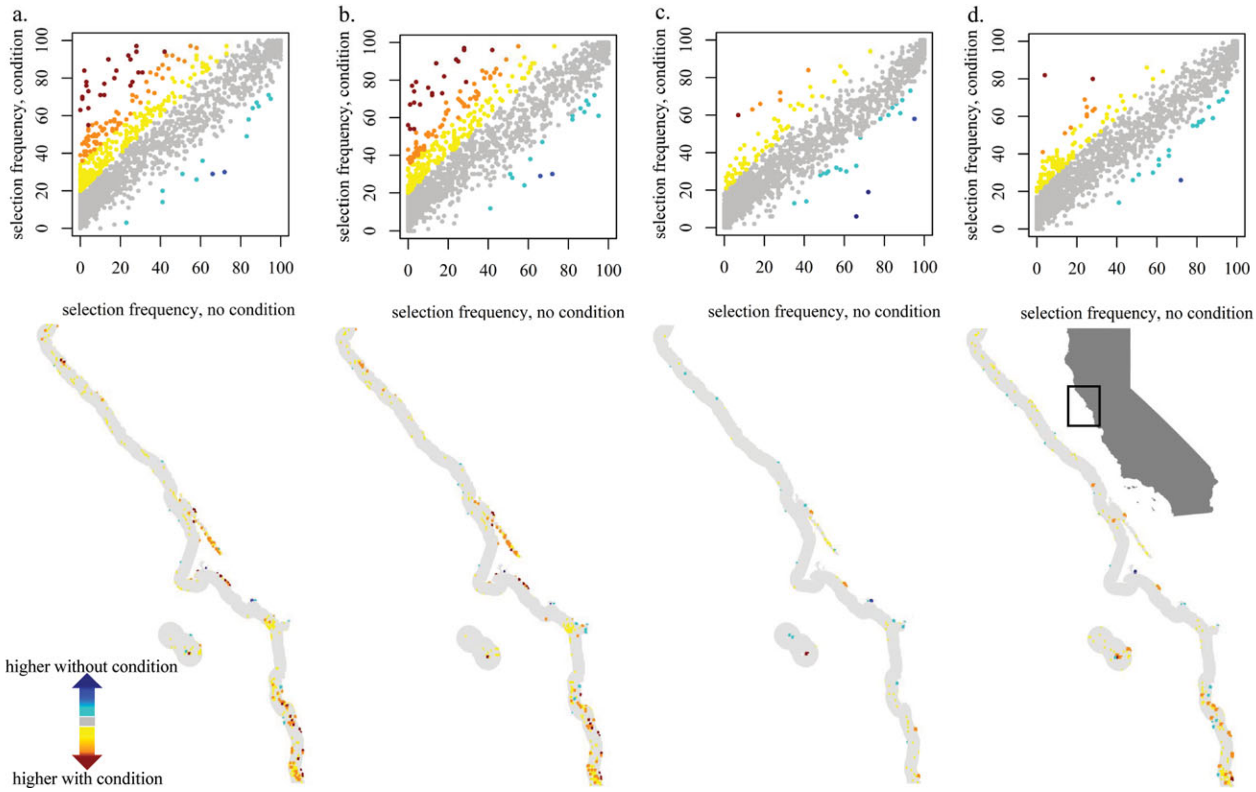

Figure 1 Difference in planning unit selection frequency when condition was not considered and when condition was considered under each of the four scenarios 1(a), 2(b), 3(c), and 4(d). Scatter plots showing the selection frequency for the planning units under the scenario without condition data (x-axis) compared to the selection frequency under each of the four scenarios using condition data (y-axis). Planning units are grey if they had a similar selection frequency (difference <20) between scenarios.

entire large marine ecoregion (Sherman 1991; Halpern *et al.* 2009). Although human impact data exist for the entire globe, we did not use it because it is less comprehensive and of lower quality than that used in the California Current impact study (Halpern *et al.* 2009). The higher the value, the higher the probability that that planning unit is in worse condition relative to all other places in the California Current, for the given impacts considered. We only considered the cumulative impacts on habitats targeted for protection; thus, two pelagic habitats considered in the cumulative impact study were excluded from our analysis.

We conducted our analysis with and without cumulative impact data, where the latter is the more traditional approach (Klein *et al.* 2008; Klein *et al.* 2010) and can be used for comparison to the scenarios with cumulative impact data. We considered four different subsets of cumulative impact data to reflect the types of condition information that planners in different places may consider when designing marine reserves (Table 1): (1) all drivers of human impact (Scenario 1); (2) all drivers of human impact that can not be mitigated by a marine reserve (e.g., nonfishing related drivers) (Scenario 2); (3) only land-based drivers (Scenario 3); and (4) only climate drivers (Scenario 4). In Scenario 1, different commercial fishing data were used to represent impact and fishing value as the data depict different aspects of commercial fishing (Halpern *et al.* 2009).

Prioritization approach

We used a modified version of the conservation planning software, Marxan, to prioritize areas for reservation (Ball *et al.* 2009). Marxan solves the minimum set reserve design problem (Cocks & Baird 1989) and aims to minimize the cost of selected planning units subject to the constraint that the conservation targets are achieved (Ball *et al.* 2009; Watts *et al.* 2009):

$$\text{minimize} \sum_{i}^{N} c_i x_i \tag{1}$$

$$\text{subject to} \sum_{i=1}^{N} r_{ij} x_i \geq T_j \quad \forall\, j. \tag{2}$$

where x_i is a control variable indicating if the planning unit ($i = 1 \ldots N$) was selected for reservation ($x_i = 1$) or not ($x_i = 0$) and c_i is the planning unit cost. Equation (2) is the constraint imposed to ensure that the target T_j for all habitats ($j = 1 \ldots M$) are achieved, where r_{ij} is the amount of feature j in planning unit i. The representation constraint (Equation (2)) is implemented through a penalty function in the objective function, as described in Watts *et al.* (2009).

Our objective is to minimize the chance that the reserved features are in poor condition, in addition to minimizing the cost of the reserves. To solve this problem, we impose an additional constraint, such that the chance that the habitat meets its target, T_j, is

$$p_j \geq P_j \quad \forall_j, \text{ where } 0 \leq p_j \leq 1. \tag{3}$$

The parameter p_j is computed using statistical approximations, described in Game *et al.* (2008b) (the higher the value, the higher the probability that habitats in the reserve system are in good condition). The parameter P_j is the target probability for representing each feature in good condition in the reserve system. Similar to the representation target constraint, the probability constraint is implemented through a penalty function in the objective function:

$$w \sum_{j=1}^{M} y_j H(P_j - p_j), \tag{4}$$

where w is a weighting value that controls the relative importance of the different terms in the objective function. A penalty, y_j, is imposed when the probability target, P_j, is not achieved and is proportional to the shortfall in achievement of the probability target for feature j. The Heaviside function, $H(P_j{-}p_j)$, takes a value of zero when the target ($P_j{-}p_j < 0$) is met and 1 otherwise.

For each scenario, we generated 100 solutions, each with a different spatial configuration. We evaluate the results using both the "best" solution (lowest objective function score) and selection frequency (Ball *et al.* 2009). Planning units that are selected frequently represent areas that are a high priority for protection.

Results

The value representing the probability that a planning unit was in poor condition ranged from 0 to 0.56 as the most impacted places in the California Current does not occur in our study region.

We found that when considering any type of condition data (Scenarios 1–4) the selection frequency of many planning units changed compared to when condition data were not considered (Figure 1), and the greatest differences were found when comparing Scenarios 1 and 2 and were predominantly in the northern and southern parts of the region. Increasing the chance that reserve networks (hereafter, solutions) were in good condition came at a minimal cost to the fishing industry; solutions that incorporate condition data cost the fishing industry 1% (Scenario 3) to 3.1% (Scenario 1) more than when condition data were not considered. Regardless of whether or not condition data were incorporated, 8% of the planning units were always identified as a high priority (selection

Figure 2 Planning units consistently selected frequently and infrequently across all scenarios, regardless if condition data were considered.

frequency >80%) and 57% of the planning units were always identified as a low priority (selection frequency <20%) (Figure 2).

We examined the differences between "condition" scenarios. In comparing any two scenarios, the selection frequency for the majority of planning units did not change and the average change was never greater than 5 (Table 2). The selection frequency of planning units in Scenarios 1 and 2 were the most similar, and the maximum change for any planning unit was 25 (out of a possible 100). In contrast, the maximum selection frequency changes were between 57 and 60 for all other "condition" scenario comparisons (Table 2). The loss to the commercial fishing industry ranged from 8.0% (Scenario 3) to 10.1% of their total income (Scenario 1).

We illustrate the tradeoffs between protecting good condition habitat and minimizing socioeconomic costs using one of many possible targets: ensure a 90% chance (i.e., $P_j = 0.9$) that 20% (i.e., $T_j = 0.2$) of each biodiversity feature is protected in good condition (Figure 3). To examine this tradeoff, we vary the relative importance (w) of achieving the target and minimizing cost to the fishers (Figure 3) (see Equation (4)). The biggest tradeoff occurs when we ensure >70% (Scenarios 1 and 2) and >

Table 2 Differences between the selection frequency of solutions from Scenarios 1–4 reported as the average and maximum change in selection frequency between any two scenarios. The mode is zero for all comparisons

	1		2		3	
Scenarios	Avg	Max	Avg	Max	Avg	Max
1						
2	2.7	25				
3	5.0	57	4.5	60		
4	4.3	57	4.0	50	3.1	58

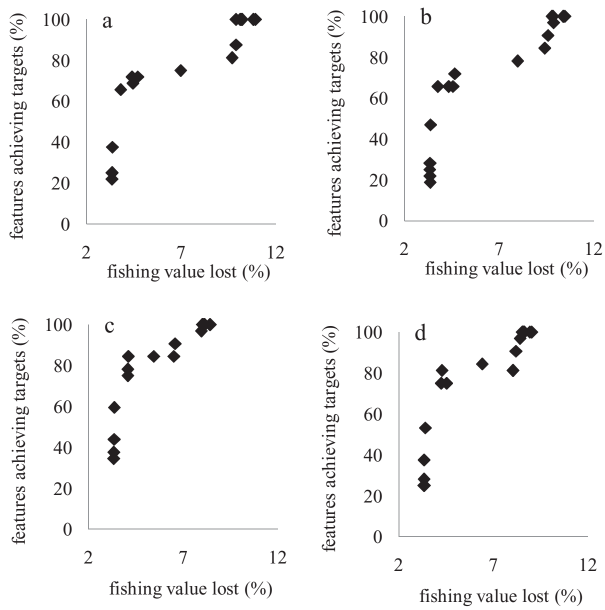

Figure 3 Tradeoffs between achieving targets (90% chance of representing 20% of each biodiversity feature) and fishing cost for scenarios 1(a), 2(b), 3(c), and 4(d).

80% (Scenarios 3 and 4) of features achieve the target. For example, for all scenarios, losses to the fishing industry are halved by triaging less than 29% of the features. In many solutions, some of the features fall short of the target only slightly (<1%), a result that would need further examination in an actual planning exercise. In addition, the targets for four (out of 32) features are consistently not achieved because they are in places costly to protect.

In addition to setting a target of ensuring a 90% chance that each feature is protected in good condition, we varied the probability target between 50% and 99% and found a tradeoff between probability targets and cost (Figure 4). We show the results of Scenario 2 as an example because the tradeoff curves from Scenarios 1 to 4 were similar. For a cost of 1.7% of the total income of the

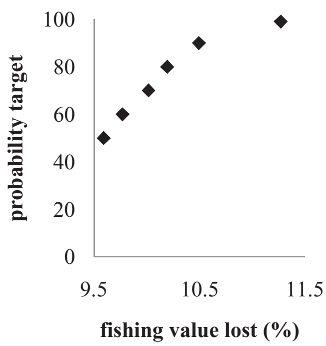

Figure 4 Tradeoffs between probability target and fishing cost for Scenario 2.

fishing industry, the confidence of protecting habitats in good condition doubles.

Discussion

Habitats and species are exposed to a range of stressors and can be threatened differently by each stressor, across space, and through time (Diamond 1984; Brook *et al.* 2008; Halpern *et al.* 2008). Recent advances in conservation planning tools allow for the consideration of information about threat probabilities, opening up substantial new avenues of research and relevance for conservation planning (Game *et al.* 2008b; Carvalho *et al.* 2011; Lourival *et al.* 2011). We apply one of these tools to address a common conservation goal of cost-effectively protecting habitats in good condition, where the probability that a site is in good condition is estimated using spatial data on the impacts of multiple human activities. This novel application provides several key results informative to reserve design that aims to protect either good condition habitats or places that are impacted by stressors that cannot be mitigated through reservation.

The results reporting costs to fishers do not encompass all socioeconomic tradeoffs as we only considered data for commercial fisheries. Thus, these findings are likely to change if other import economic factors were considered, such as recreational fishing, mining, and shipping. The economic tradeoffs found may differ if other types of fishing data were considered, such as dynamic data that consider the distribution of fishing over time and space. The commercial fishing data that we used represent a snapshot of fishing from one time period and our approach assumes that lost fishing effort is not redistributed to surrounding areas (Scholz *et al.* 2011).

Priority locations identified when condition data were considered (Figure 1) may be overlooked through traditional planning approaches, decreasing the chance of achieving conservation goals. Some sites consistently emerge as high priorities and a vast majority of sites are low priority, regardless of whether or not condition information was incorporated (Figure 2). The priority of these areas is driven by other goals, such as minimizing cost or representing the rare conservation features in our region. Our approach is useful for fine tuning reserve designs as it does not produce radically different outputs to when habitat condition is not considered.

The context of marine reserve design initiatives differ, and may warrant the consideration of different types of human impacts. We compare four plausible scenarios, varying only the number of impacts considered. For example, we avoid reserving places that are in poor condition due to human activities that cannot be managed with reservation (e.g., terrestrial runoff) as these activities may go on unmanaged, despite conservation efforts (Alvarez-Romera *et al.* 2011). On the contrary, implementation of a marine reserve may motivate management of activities that compromise its conservation, e.g., terrestrial runoff; in this case, planners may instead avoid protecting places in poor condition as a result of impacts associated with climate change, for example, that cannot be managed locally (Scenario 4). In addition, some threats, like the impacts of climate change can be incorporated into spatial prioritization in other ways, such as following size, spacing, and replication guidelines (McLeod *et al.* 2009), criteria that cannot be incorporated into Marxan. The similarities of results between these scenarios are due to the correlation of human impact data used. For example, the human impact data for the two most similar scenarios (1 and 2) are very correlated ($R^2 = 0.9822$) and for two scenarios that show more spatial differences (1 and 3) are less correlated ($R^2 = 0.4423$). It is important to think carefully about the planning context when determining which human activities to incorporate as it impacts priorities and costs.

In Scenario 1, commercial fishing information was used to assess cumulative impact and value. However, different datasets representing different aspects of commercial fishing were used to estimate cumulative impact and value. As the differences between Scenarios 1 and 2 were minimal (where the only difference is the inclusion of commercial fishing data), we conclude that using two different types of commercial fishing data to define cost and cumulative human impacts would not influence the location of MPAs in this case.

Some initiatives focus on representing good condition habitats and others on avoiding socioeconomic loses (Agardy *et al.* 2003). In our case study, the economic consequences of these different goals were profound (Figure 3). The drastic differences in costs when comparing scenarios that achieved 70% versus 80% of targets are due to a few planning units containing good condition habitat that are costly to protect. This suggests it is important to analyze multiple scenarios where the relative importance of achieving each goal is varied. Such tradeoffs are common in conservation planning; understanding them can help ensure strategic decision-making and avoid contentious outcomes.

Our approach allowed us to assess another tradeoff, how much it costs to increase the probability that good condition habitats are reserved. We found that the costs of increasing the probability were minimal (Figure 4); this result is because the maximum chance that a habitat was in poor condition in our region was 56%. Regions containing places that have a higher chance of being in poor condition (i.e., values nearer to 100%), are expected to have a more nonlinear tradeoff, where it is costly to increase the probability that good condition habitat is reserved. This is an example of why our results are not necessarily transferable to another planning region. Knowing exactly what the cost of these tradeoffs are informs discussion and potential compromise among stakeholders. This type of information would have been informative to decision makers involved in the Marine Life Protection Act Initiative as socioeconomic factors, although not formally part of the law, were considered when deciding on the location of MPAs (CDFG 2008).

Cumulative impact maps are a proxy measure for habitat condition, and they represent a current snapshot rather than a future prediction of how things will change (Halpern *et al*. 2008; Halpern *et al*. 2009). A comprehensive ground-truthing of how cumulative impact scores relate to habitat condition and a dynamic model that predicted habitat condition in the future would be ideal, but neither currently exists. Furthermore, our analysis narrowly plans for no-take reserves, even though other types of protected area are common (Klein *et al*. 2010), and does not consider spatial clumping of reserves. Further research is required to develop a tool that can accommodate different zones and threat probabilities. Although Marxan with Zones can identify priorities for multiple zones, it is unable to consider probabilistic targets and how activities impact marine ecosystems. Such a tool would allow for the inclusion of more comprehensive socioeconomic information (e.g., recreational fishing, shipping lanes) as well as more control over the extent of economic impact on different fisheries and industries.

We demonstrate one of many possible ways of incorporating habitat condition and human impact data into reserve design. Another approach would be to consider habitat condition through a stakeholder consultation process, an approach that would be especially useful as a smaller scale, where stakeholders can confidently estimate habitat condition across the entire region, or in places where community based planning drives conservation decisions. Our approach could be expanded to consider habitat- or species-specific probabilities (e.g., the probability that a species is threatened by a specific threat (Wenger *et al*. 2011)). Our goal was to avoid protecting habitats in heavily impacted places. Other planning goals may be contrary, aiming to place protected areas in heavily impacted places (Roberts *et al*. 2003; Game *et al*. 2008a). For example, by protecting an area in poor condition due to the impacts of fishing, its protection could help restore the area (Bevilacqua *et al*. 2006). This reinforces the importance of setting clear objectives prior to identifying conservation priorities.

The paucity of work on incorporating condition into reserve design is probably due to two factors: (1) Lack of comprehensive spatial data (which are typically limited to areas smaller than a planning region and focused on selected habitats, especially coral reefs (Pandolfi *et al*. 2005); (2) Until recently, there was not a planning tool that could incorporate such information into the standard approach of cost-effectively representing habitats. Prior to these developments, planners were forced to design reserves that either minimised costs or avoided threatened places (Tallis *et al*. 2008). The approach presented here offers an exciting tool for incorporating habitat condition or human impact information, and helps make tradeoffs between three important aspects of planning transparent. The generality of our results are unknown and we expect that the type and extent of tradeoffs are likely to vary from region to region as they are dependent upon the number and impact of human activities, socioeconomic costs, and the distribution of conservation features. We encourage planners to use our approach to determine the exact tradeoffs in their planning region to support informed and rational decisions about protecting biodiversity.

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