Trade-offs between data resolution, accuracy, and cost when choosing information to plan reserves for coral reef ecosystems

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Abstract

Conservation planners must reconcile trade-offs associated with using biodiversity data of differing qualities to make decisions. Coarse habitat classifications are commonly used as surrogates to design marine reserve networks when fine-scale biodiversity data are incomplete or unavailable. Although finely-classified habitat maps provide more detail, they may have more misclassification errors, a common problem when remotely-sensed imagery is used. Despite these issues, planners rarely consider the effects of errors when choosing data for spatially explicit conservation prioritizations. Here we evaluate trade-offs between accuracy and resolution of hierarchical coral reef habitat data (geomorphology and benthic substrate) derived from remote sensing, in spatial planning for Kubulau District, Fiji. For both, we use accuracy information describing the probability that a mapped habitat classification is correct to design marine reserve networks that achieve habitat conservation targets, and demonstrate inadequacies of using habitat maps without accuracy data. We show that using more detailed habitat information ensures better representation of biogenic habitats (i.e. coral and seagrass), but leads to larger and more costly reserves, because these data have more misclassification errors, and are also more expensive to obtain. Reduced impacts on fishers are possible using coarsely-classified data, which are also more cost-effective for planning reserves if we account for data collection costs, but using these data may under-represent reef habitats that are important for fisheries and biodiversity, due to the maps low thematic resolution. Finally, we show that explicitly accounting for accuracy information in decisions maximizes the chance of successful conservation outcomes by reducing the risk of missing conservation representation targets, particularly when using finely classified data.

Key words: Marine Protected Area; conservation; spatial planning; cost-effectiveness; surrogate; habitat classification

1. Introduction

Through a systematic conservation-planning framework, planners can maximize the chance that reserves are located in areas that will protect desired proportions of biodiversity (Margules & Pressey 2000). However, trade-offs are inevitable in any planning situation. Although the location of marine reserves should be informed by high quality information on the distribution of biodiversity (Cabeza & Moilanen 2001), often such data are incomplete or inaccurate, with scarce financial resources and time limiting additional data collection (Grantham et al. 2008). Habitat maps can be cost-effective data options for informing spatial management decisions, but all maps have errors (Wilson 2010). Furthermore, their ability to represent biodiversity varies considerably depending on the features mapped (Mumby et al. 2008). A prevalent problem in marine spatial planning is using maps without understanding their classification accuracy (Tulloch et al. 2013). Knowing and accounting for differences in the accuracy of feature data used to plan reserves is crucial to ensure planning goals are achieved.

Remote sensing is rapidly becoming the most common method used to map marine habitats cost-effectively at a broad scale (Mumby et al. 1999; Hamel & Andréfouët 2010). However remotely-sensed habitat maps differ substantially in quality, depending on the types and pixel grain of satellite images used, the classification method and desired resolution of the final data, as well as the nature of features to be identified (e.g. geomorphology versus benthic habitat), and their spatial heterogeneity (Mumby et al. 2004, Goodman et al. 2013). Challenges exist in obtaining up-to-date accurate data for coral reefs due to their dynamic nature, as well as spectral similarities of certain reef cover types (Phinn et al. 2012). Because of this, errors and uncertainty in coral reef habitat map classification can be high (Phinn et al. 2008, Roelfsema & Phinn 2013). This uncertainty invariably propagates through the decision-making process (Grand et al. 2007, Moilanen et al. 2006). In the past, many conservation plans using habitat maps have not accounted for their classification accuracy, often because it was not available, or hard to obtain. One recent example is the Great Barrier Reef Marine Park Rezoning (Fernandes et al. 2005), which used bioregional maps and assumed these were representative of a range of coral reef habitats without any accuracy information. Management decisions can be prone to errors of omission (when a feature is mistakenly thought to be absent) or commission (when a feature is mistakenly thought to be present) if inaccurate spatial data are used (Rondinini et al. 2006, Beech et al. 2008).

The decision to represent certain conservation features in a reserve is constrained by budget limitations and data availability (Possingham et al. 2001). Remotely-sensed maps of abiotic coral reef features at coarse thematic resolutions (e.g. geomorphic zones) are useful surrogates in spatial planning, as they enable identification of priority areas when more detailed information about species distributions is lacking or too costly to obtain (Heyman & Wright 2011; Sutcliffe et al. 2015). Geomorphic maps can be very accurate due to the ease of delineating geomorphology at relatively large spatial scales (tens to hundreds of meters) directly from remote-sensing imagery (Andréfouët et al. 2006), but structural complexity and heterogeneity can be lost if the thematic scale of the classification is too coarse (Boyce 2006). Finer habitat classifications are more difficult to delineate using remotely sensed images alone, but integration of field calibration data can help identify small-scale biotic habitats (e.g. coral, algae). Although some researchers advocate the use of geomorphic features as surrogates for ecological processes and biota (Heyman & Wright 2011), others recommend using finer-resolution information describing coral reef habitats, as the higher thematic complexity provides a better proxy for associated species, ecological functions, and ecosystem services (Mumby et al. 2008; Dalleau et al. 2010). However, increasing the thematic resolution in a habitat map typically also increases classification error (Andréfouët 2008; Roelfsema & Phinn 2010). The sensitivity of conservation plans to increasingly complex habitat data, and the value of these data in representing true biodiversity, is of growing concern (e.g., Van Wynsberge et al. 2012; Deas et al. 2014). Despite this, error associated with increasingly complex features is rarely accounted for in spatial planning.

There are important trade-offs to consider when accounting for error and uncertainties in conservation planning. Approaches incorporating uncertainty typically result in larger (and therefore more costly) reserve systems to have a reasonable certainty of meeting targets (Allison et al. 2003, Tulloch et al. 2013). This is not always practical when management goals aim to balance economic (e.g., impact to fishers) and conservation objectives. Although accounting for socio-economic costs of implementing management is common practice in marine reserve design (Mills et al. 2010), there are other costs to consider for efficient conservation decisions. Collecting fine-resolution field and image data is expensive (Roelfsema & Phinn 2010). Given a limited budget for marine conservation and the urgency of conservation problems, evaluating the benefits of collecting more detailed feature data against the costs of collection is crucial but rare (see Hermoso et al. 2013; Tulloch et al. 2014).

Here we examine the sensitivity of marine reserve network design to habitat maps of increasing spatial and thematic resolution, and their associated classification accuracies, using a case study of the Kubulau District fisheries management area in Fiji. We explore how conservation prioritization outcomes change given finer classifications, addressing three questions relevant to reserve planning globally:

1. How do priority conservation areas change when habitat data of increasingly fine resolution, and different accuracies, are used to plan reserves?
2. How well do reserves designed using mapped habitat data of differing resolution and accuracy represent biotic habitats, and does this differ when using standard approaches compared to those that consider classification accuracy?
3. What are the trade-offs between habitat representation, accuracy and cost when we move from using maps describing coarse reef data to more detailed benthic habitat data, and consider mapping accuracy during the decision-making process?

We use our results to explore the surrogacy value of different input data in conserving coral reef habitats. We then evaluate the effect of incorporating socio-economic cost data on the prioritization outcomes, and perform a cost-effectiveness analysis to compare the value of developing and using coarse or fine coral reef data in reserve design. We use this information to investigate an applied conservation management question for the Kubulau District fisheries management area in Fiji, where the reserve network was recently reconfigured using habitat maps without accuracy data (Weeks & Jupiter 2013). We evaluate the adequacy of existing marine reserve networks at protecting targeted biodiversity, and identify how the existing marine network might differ if accuracy information had been used to minimize the risk that habitats were not adequately represented. We identify trade-offs associated with the use of more readily available data versus more risky and expensive options derived from further data collection. In doing so, we demonstrate ways to make more informed decisions about choosing data for reserve design to address issues of scale and find priority areas that are robust to uncertainty.

2. Material and methods

2.1 Study Area

Our study area is the Kubulau District fisheries management area (*qoliqoli)* situated in southwest Vanua Levu, Fiji, covering 261.6 km^2 (Fig. 1, inset) (WCS 2009). This area was chosen because hierarchical habitat data at increasingly spatial and thematic resolution are available. The area includes a diverse array of relatively pristine coral reef, seagrass beds, soft bottom lagoons, and deep channels (Knudby et al. 2011).

2.2 Data

We divided the region into 22,815 planning units (each 5000 m^2). Hierarchical habitat maps of the Kubulau *qoliqoli* have previously been developed using object-based image analysis (Blaschke et al. 2010) from high resolution satellite data (IKONOS, 2006 and QuickBird, 2007), at four scales of increasing thematic and spatial resolution: reef, reef type, geomorphic zone, and benthic community (Fig. 1a, see Knudby et al. 2011 for the full hierarchical classification scheme). The nine geomorphic zone classes describing reef structure and morphology (low spatial and thematic complexity, hereafter "coarse-classification", Table 1) were each further subdivided into smaller segments representing thirty-three finer scale benthic community classes with higher spatial resolution with more thematic complexity describing coral, algal, seagrass, and reef substrates (described by dominant habitat first, hereafter "fine-classification", Table 1). For example, Coral Algae Reef Matrix contained over 70% coral, with approximately 10% macroalgae and 10% reef matrix, whereas Algae Coral Reef Matrix was macroalgae dominant (over 70% coverage), and only 10% coral cover (see Knudby et al. 2011 for the full hierarchical classification scheme). Field survey data was obtained from the snorkel and scuba surveys and was divided in calibration data to create the map and validation data for accuracy assessment (Fig. 1a).

We converted overall user classification accuracy for each habitat in each map, derived from an error matrix comparing reference field data with classification of the same location in the habitat maps, to calculate a probability value quantifying the chance a classification was correct, used as input data uncertainty in our spatial prioritization (Knudby et al. 2011; Table 1). Accuracy values for the coarse-classifications ranged from 0.2 to 0.9 (the range reflects different values for different habitats, mean accuracy = 0.82, Fig. 1b), with a wider range of accuracy values for the fine-classification of 0.1 – 1.0 (mean accuracy = 0.66, Fig. 1c).

2.3 Prioritization approach, scenarios and analyses

We used two approaches to compare between the outcomes of prioritizations for reserves that firstly, use or, secondly, ignore accuracy information. First, to account for accuracy, we used a modified version of Marxan software v.2.43 (Ball et al. 2009) called Marxan with Probability (MarProb), which has the ability to include uncertainty measures such as information on the probability that habitats or species distribution is accurate (hereafter “accuracy” approach). MarProb identifies near-optimal reserve networks that minimize cost subject to meeting representation targets, and maximize the chance of protecting targeted habitats given uncertainty in the conservation feature distribution (here, the classification accuracy). A 90% certainty target was set for each run to ensure habitat targets achieved high reliability (for more detail see Tulloch et al. 2013, and Supplementary Material). We note, the probabilistic representation target for feature capture in MarProb increases as feature accuracy decreases (Tulloch et al. 2013). For our second approach, we used standard Marxan (hereafter “standard” approach), which cannot include data inaccuracies, and assumes all data are 100% correct.

For each approach, to compare marine priorities from using habitat data of differing resolution, we used first the coarsely-classified data (geomorphic zones) as input conservation features, then the finely-classified data (benthic habitats). We set equal representation targets of 30% for every conservation feature (Table 2). We recognize that recent conservation strategies had differing representation targets for reef and non-reef habitats (Mills et al. 2011), and acknowledge concerns regarding the setting of arbitrary representation targets (Carwardine et al. 2009), however for the purposes of a comparative analysis we chose equal representation targets. We performed 100 runs for every Marxan scenario.

2.3.1 Baseline prioritization scenario

In our baseline prioritization, all planning units were assigned an equal cost. We ran spatial prioritizations using the standard and accuracy approach for each conservation feature dataset and compared outcomes. Although there is a network of 24 marine protected areas (MPAs) spanning 130 km^2 in the region managed to protect coral reef habitats and maintain small-scale fisheries (Weeks & Jupiter 2013), we chose to ignore existing Kubulau reserves initially for the purposes of method testing the sensitivity of solutions to different data, thus every planning unit was available for selection.

2.3.2 Planning prioritization scenario

We then developed a more realistic conservation-planning scenario (hereafter “planning” scenario), which accounted for annual local fishing resource requirements in the region by using data on socio-economic costs, derived in Adams et al. (2011). This was based on previous surveys in the Kubulau District that describe catch per unit effort (CPUE) based on records from four Kubulau villages collected between May 2008 and June 2009, which was used to model fishing opportunity cost for the Kubulau qoliqoli (Adams et al. 2011).

2.3.3 Analysis

Reserve solutions were analyzed using the “selection frequency”, where frequently selected planning units (selection frequency > 75%) represent areas of high priority for protection, versus low priority planning units (those selected <25% out of the 100 runs), and the "best solution", which is the solution with the lowest objective function score. We used difference maps to highlight spatial prioritization differences between approaches and datasets. For the planning prioritization we evaluate socio-economic impact of reserves by calculating the total opportunity cost to fishermen for each approach, and compared these between datasets. Similarity matrices were then computed using the Bray-Curtis (BC) similarity index (Magurran 1988), and we evaluate how well reserves designed using standard approaches met representation targets that considered misclassifications.

2.3.4 Surrogacy evaluation

To test trade-offs between habitat data resolution, accuracy, and costs, we calculated the fraction of fine-classification habitats that were adequately conserved in the top 10 best reserve solutions resulting from the coarse data analysis, for both the standard and accuracy approaches. This allowed us to evaluate the "surrogacy value" of the coarse-classification in representing coral reef biodiversity, or in this case, in meeting standard and accuracy representation targets. Here we assumed that the fine-classifications were a truer surrogate for desired conservation features in the region, since (1) national conservation strategies in the region target fish species, invertebrates, and biogenic (e.g. coral) habitats (Mills et al. 2011), and (2) previous research suggests maps with higher habitat thematic complexity provide better biodiversity surrogates than simpler maps (Dalleau et al. 2010).

2.3.5 Current reserve evaluation

We evaluated habitat representation within the existing Kubulau reserve network, initially designed to represent coarse-scale habitats (Andréfouët et al. 2006) without accounting for their accuracy, to identify how well it represents the classified habitats used in this study once accuracy information is considered. By calculating the amount of each habitat in the existing reserve network, and comparing this with their probability targets in MarProb, we could evaluate the fraction of habitats in each dataset that are adequately protected in the existing reserve network.

2.4 Calculating cost-effectiveness of data

To find the cost-effectiveness of investing in and using different quality data in reserve planning we calculated the total benefit of reserving the *n* selected planning units in the best reserve network solution using the accuracy approach. For fine-classification scenarios, the reserve biodiversity benefit (*B*) was the summed area of habitat selected for reservation divided by the area of habitat, as follows:

$$B = \frac{\sum_{i=1}^{n} x_i \cdot (\sum_{h=1}^{H} a_{ih} \cdot)}{\sum_{i=1}^{n} \sum_{h=1}^{H} a_{ih} \cdot} \qquad (1)$$

where x_i is a control variable for planning unit *i* (*i* = 1…n) that takes the values 0 (not selected) or 1 (selected for reservation), and a_{ih} is the amount of each habitat (*h* = 1…H) that falls inside planning unit *i*. For accuracy scenarios, a_{ih} was multiplied by p_h, the probability of that habitat being classified correctly. For the coarse-classification, the reserve biodiversity benefit (*B*) was the surrogate value of the data, or the total area of fine-classification habitat selected in the "locked-in" solutions (again assuming fine-classifications are truer surrogates for biodiversity).

To calculate the total cost of using each dataset, we added the cost for each reserve network *(C)* to the cost of data collection (*D*), which included imagery purchase, field data collection costs, and paying a consultant at standard industry rates to produce each habitat dataset using object-based remotely-sensed image analysis integrated with expert knowledge for geomorphic maps and field calibration data for benthic maps. We assumed that the costs of data collection and compensation for reserve establishment (both in Fijian dollars, FJD) were born by the same organization, a not uncommon scenario (e.g., Gunn et al. 2010), and calculated the weighted sum relative to total cost for each metric and dataset to provide a measure of relative "investment". Although ideally a completely independent survey would be conducted to gather validation data for accuracy assessment, due to the expense and logistical challenges of organizing fieldwork, data can be divided in a "training" or "reference" set used to create the maps and a validation set to assess the accuracy of the maps, keeping costs lower (Roelfsema 2013). We estimated that the costs of not collecting map validation information would be 20% less than developing maps with accuracy information. The total scenario cost-effectiveness (*CE*) was the overall benefit divided by the total summed costs (Tulloch et al. 2014):

$$CE = \frac{B}{(C+D)} \tag{2}$$

3. Results

3.1 Accounting for accuracy

Accounting for accuracy changed the location of reserves (Fig. 2a & b) compared to outcomes from a standard approach, and increased the size of reserves regardless of the dataset used (Fig. 6). There were more spatial differences between standard and accuracy approaches using the fine-classification data, which resulted in 75% of the region (17074 planning units) having higher selection frequencies (higher priority for inclusion in reserves) once accuracies were considered. There were fewer spatial differences between approaches using the coarse classification regardless of the cost scenario (Table 3). Larger reserve networks resulted once accuracy was accounted for both the baseline and planning scenarios regardless of the dataset used (Fig. 6), though greater size differences were observed when using finely classified data, with reserve networks almost 1.5 times bigger than those of the standard approach (Fig. 6). The coarse-classification accuracy reserves were only on average 10% larger overall than those from the standard approach.

The planning scenario highlighted more overlapping priorities between standard and accuracy approaches for each dataset compared to the baseline scenario (Table 3). Including socio-economic data in the planning scenario also led to planning units having higher selection frequencies overall compared with the baseline scenario. Regardless of the approach, 15% of the region was always a high priority for meeting targets (selection frequency >50%), with 4% of these identified as irreplaceable (selected 100% of the time). High-priority areas were generally either very low cost or contained large amounts of habitats with low classification error, such as deep slope (99.9% accuracy) or lagoon reef (90.0% accuracy). Over 45% of the entire study region was excluded from all reserves, either because of high opportunity cost, or they contained common habitats whose targets had already been met while conserving other habitats.

When we evaluated how well reserves designed using standard approaches met representation targets that considered misclassifications, two-thirds of the finely classified features were under-represented, in some cases by up to 58% of their probabilistic representation target in MarProb (see Tulloch et al. 2013). All of the coral and reef-dominant habitats failed to meet their representation targets, while seagrass-dominant habitats were over-represented by approximately 20% of their target. In contrast, only one-third of the coarse classifications missed their representation targets by less than 20%, with the remainder of habitats only moderately over-represented (<10% of target).

3.2 Comparing priorities for fine versus coarse data

Regardless of the scenario, comparing priorities from using coarse versus fine habitat classifications identified some similarities in the location of priority areas using the standard approach (Table 3). There was significant spatial incongruence between reserves designed using different datasets once accuracy was accounted for (Table 3), with 18% of the highest priority planning units (selected 100% of the time) in the fine-classification reserves rarely or never selected in the coarse-classification reserves in the baseline scenario (Fig. 2c). The spatial congruence between coarse and fine classification prioritizations was substantially lower for the planning scenario when accounting for rather than ignoring accuracies (BC index 64.9% and 72.8% respectively, Table 3). Overall, the fine-classification accuracy reserve network was bigger than reserves designed using any other data or approach, though one fine classification consistently failed to meet its representation target using the accuracy approach, regardless of the cost data used, due to high classification error (coral/algae reef matrix, 27.5% accuracy, Table 1).

3.3 Surrogacy evaluation

When reserves designed using coarse-classification data were evaluated to see how well they represented fine-classifications, we found only four fine-classification habitats failed to meet their targets in the standard baseline scenario, requiring on average 1- 17% more area to reach their target. Once accuracies were considered, the number of fine-classification habitats failing to meet their targets increased, with three-quarters of the coral-dominant habitats under-represented by up to 50%, while one seagrass-dominant habitat met only less than one-third of its target (seagrass sediment, Fig. 4). The inclusion of socio-economic data in the accuracy planning scenario resulted in a higher number of fine-classification targets being met, though three of the four coral-dominant habitats still failed to meet their targets, while four of the six sediment-dominant habitats over shot their target by 100% or more regardless of whether accuracy was accounted for (Fig. 4).

3.4 Current reserve evaluation

The current reserve network, which covers 37% of the planning region, met almost all our coarse conservation feature targets of 30% when mapping accuracy was considered, with the one exception being reef crest (<1% of total habitat protected, Fig. 5a). The current reserve network also performs well at meeting most conservation targets for biogenic habitats, however four habitats failed to meet their targets (Fig. 5b). Notably, a key coral habitat and one seagrass-dominant habitat (seagrass sediment) met only 40% and 20% of their conservation targets respectively, whilst several sand, algae and rubble dominant habitats were significantly over-represented, in one case up to 9 times the targeted amount (sediment rubble patch features, Fig. 5b).

3.4 Cost-effectiveness of using different data

We found trade-offs between the accuracy of data and costs, with smaller reserve networks and lower opportunity costs for fishermen when accuracy values were not included, regardless of which data were used (Fig. 6). For the planning scenario, fish catch opportunity costs for the accuracy reserve network using coarse-classifications were on average ~30% more than those from the standard approach. Using fine classifications and accounting for mapping accuracy almost tripled potential fishing catch losses compared with when mapping accuracy was ignored (Fig. 6), with total costs to fishers reaching up to 17% of their total income. Reserves designed using coarsely classified habitats and accounting for classification accuracies cost on average half that of the reserves designed using the finely classified habitats (Fig. 6). Some areas with high opportunity cost were prioritized in reserve networks, not only because they contained highly accurate habitats, but also because they contained low accuracy habitats needing more of their area conserved to ensure targets were met.

Although the reserve networks designed using coarse-classifications had lower biodiversity benefits and met fewer representation targets for small-scale coral reef benthos when accounting for accuracy, the cost of deriving coarsely classified data was approximately one-tenth of the finely classified map (Fig. 6). Furthermore, total costs (data acquisition/processing and opportunity cost combined) for fine-classification accuracy reserves were almost six times that of the coarse-classification reserve network (Fig. 6b). Regardless of whether accuracy information was included, when the cost of data acquisition and processing was added to the opportunity costs, using coarsely classified data was most cost-effective (Fig. 6).

4. Discussion

Planners often have to use remotely sensed habitat maps to design reserve systems because species distribution data are scarce (Mumby & Edwards 2002), but these maps can be highly inaccurate. Despite this, only limited work has been done to explore issues of habitat mapping errors in marine conservation planning (Beech et al. 2008, Tulloch et al. 2013). Our findings demonstrate possible inadequacies in, and risks of, spatial prioritization analyses that do not consider habitat map accuracy, particularly when using remotely-sensed habitat maps with high thematic complexity, where detection and misclassification errors are more likely than with coarse-classifications (Roelfsema & Phinn 2013). We highlight trade-offs between cost-effectiveness and biodiversity representation that emerge from choosing coarse or fine habitat classifications to plan reserves. Using coarsely classified but highly accurate information to plan reserves is cheaper overall, as fine-classifications are more expensive to develop and have more error. However, use of these coarse-classifications as surrogates for broader coral reef biodiversity in planning processes can result in under-representation of high value reef habitats such as coral and seagrass. Planners can improve their chances of adequately representing more complex fine-classification habitats by obtaining classification accuracies for these data, and including them in the decision-making process.

We observed greater differences in the location of priority areas between standard and accuracy approaches using fine-classification data, resulting in larger errors of omission and commission in habitat representation (Fig. 3). This was driven largely by the proportion of highly inaccurate (less than 50% accuracy) classifications resulting in more area required to meet habitat targets with reasonable certainty (see Tulloch et al. 2013), which in turn drives greater differences in reserve size. Given the high misclassification errors, planners that use these data without considering accuracy risk protecting too much of some features, thereby misallocating resources and wasting funding, and not enough of others, thereby failing to achieve 'safe' levels of protection (Possingham et al. 2007). However this creates an added challenge for planners –

although validation methods are improving, accuracy information is rarely provided with habitat maps (Roelfsema & Phinn 2013). The onus is thus on map producers as well as map users to ensure that classification error information is calculated, made available, and then considered in conservation decisions.

By comparing reserve networks built using different habitat data we found important trade-offs between costs of developing and using a habitat map, and its accuracy. It was possible to reduce fishing opportunity costs using coarser geomorphic data, which supports the findings of previous studies (Deas et al. 2014). We took this research one step further by including data accuracy in our planning approach, which reduced the risk of missing habitat targets, though this was at an additional cost to the fishing community, particularly when we use finely classified habitat data that includes more detail and complexity (Fig. 5). Importantly, not only were the finer detail classifications more inaccurate, once we considered data acquisition costs, we found important savings could be achieved using the coarsely-classified data due to high costs of obtaining and ground-truthing more detailed habitat data (Fig. 6).

Limited resources mean these sorts of trade-offs are an important part of efficient decision-making (Stewart & Possingham 2005). One alternative is to defer reserve selection until we can better map low accuracy habitats, however inaction might increase the risk of further biodiversity loss (Grantham et al. 2008). If budgets were very limited, our results show cost savings might be found by obtaining freely available geomorphic data (e.g. Millenium Coral Reef Mapping Project (MCRMP), Andréfouët et al. 2006), which require no fieldwork, typically do not change over short time scales, can be highly accurate, and some argue are the most practical foundation for marine planning (Heyman & Wright 2011). However information on the accuracy of these freely available maps is typically unavailable, or hard to come by. Our analysis of the current reserve network that was designed using MCRMP data and no classification accuracies identified a number of over-represented sand, rubble and algal dominant habitats, which might be considered an unacceptable opportunity cost, as this habitat type supports fewer species and less fisheries production compared with mangroves and reefs

(Mills et al. 2010). Local communities could help verify the accuracy of maps at small scales, though this would be challenging for large regions. Moreover, research suggests that local-knowledge derived maps achieve a lower overall accuracy than remotely-sensed maps (Selgrath et al. 2016), and thus should be relied on with caution in particular for fine-scale habitat classification.

Maps of geomorphology cannot discriminate between differing biogenic communities across time or space, and thus may not be useful in informing short-term impacts of reserve establishment, even if they are highly accurate (Stevens and Connolly 2004). Instead, the hierarchical classification for the finely classified data used here could be used as a proxy for condition (with coral-dominance indicating better condition than algal-dominance), which is a more useful monitoring metric, given that these types of habitats can change and improve in condition substantially if protected (Mumby and Harborne 2010). This would however require the finely-classified data to be re-collected on a regular basis, requiring further funds and reducing even more the cost-effectiveness of this data over longer timeframes. Importantly, any conservation plan should be adaptive, and data used to create reserves should also be used to monitor the success of the reserves in the future. Building adaptive management into the process of creating, maintaining, and evaluating MPAs could help when the data available has a lot of accuracy problems.

A crucial issue for planners is how to decide on a scale for decisions and biological data that represents biota adequately and is relevant to management objectives and actions, whilst working within limited budgets. This can be achieved in three ways: firstly, by understanding the ecological surrogacy value of the data such as through pairing with field data (Mumby et al. 2008; Sutcliffe et al. 2015); secondly, by accounting for errors associated with mapped data during prioritization (Rondinini et al. 2006, Guisan et al. 2013, Tulloch et al. 2013); and thirdly, by accounting for data acquisition costs (Tulloch et al. 2014). The relevant spatial and thematic resolution of data will differ depending on the planning objective and values (e.g.

coastal protection, or increase biomass of fish), and target species (e.g. microhabitat of a table coral, or lagoon reef complex). Spatial resolution strongly influences surrogate effectiveness in complex systems such as coral reefs (Mellin et al. 2011). High thematic complexity is important for coral reef maps to be effective proxies for fish and invertebrate species richness (Chabanet et al. 1997, Jenkins and Wheatley 1998, McArthur et al. 2010). Our findings from the surrogacy evaluation of coarse-classification reserves highlight important concerns for plans that use a standard approach only. Initially, one might believe key coral habitats have exceeded representation targets when using a cheaper geomorphic map. However once mapping accuracies were considered, coral-dominant habitats are all significantly under-represented when a more coarsely classified geomorphic map was used to plan reserves, regardless of whether cost data were included. Similarly, the current MPA network in Kubulau (Weeks & Jupiter 2013) significantly under-represents two of the dominant coral and seagrass habitats in our finely-classified habitat map. Under-representing key coral habitats could have consequences for biodiversity and fisheries production (Jenkins and Wheatley 1998, McArthur et al. 2010). Coral-dominant substrates play an important role in structuring associated reef fish communities (Messmer et al. 2011), while seagrass supports fish nursery grounds as well as providing important ecosystem services through improving water quality (Beck et al. 2001). Inadequately conserving these key biogenic habitats makes the coarsely classified dataset risky to use. Although more detailed habitat maps provide more informative class structure (Banks & Skilleter 2007), they are typically less accurate and more costly to obtain (Fig. 4). Given these trade-offs, planners must decide on a tolerable level of error in their data, and weigh this against the amount of time and money it would take to reduce this uncertainty.

A number of other uncertainties are worthy of consideration here, though were beyond the scope of this research. We assumed opportunity cost data were accurate, however errors in socio-economic data are common, such as misreporting of catches (Adams et al. 2011). Expected value-of-information analyses (Runge et al. 2011) could be used in this case to evaluate which are the most important uncertainties, and identify where investment in improving accuracies through data collection would improve conservation outcomes. Further ground-truthing could be conducted to minimize the risk of errors in data classifications misleading site prioritization (Roelfsema & Phinn 2010), however this would come at an additional cost and possibly delay reserve establishment. To systematically deal with detection errors, the full range of classification errors could be included in the planning process, including the probabilities that habitats were misclassified, which can be calculated from the error matrix user/producer errors (Table S.1).

The cost-effectiveness approach used here has some limitations. We assumed all habitat features to have equal conservation value, irrespective of their species composition (for which no data were available), overall coverage in the study area (habitats covering smaller areas might be more important from a conservation perspective than habitats covering large areas), or sensitivity to human activities (habitats that are little affected by human activities might require a lower level of protection or no protection at all than habitats that are sensitive to activities). But this is not necessarily the case, and depending on the conservation objective, there may be costs associated with not adequately protecting critical habitats (such as nursery grounds for species of conservation concern), particularly if this results in reduced fish catches or loss of fish biodiversity. The static nature of our cost-effectiveness approach means that costs at the moment of reserve planning are accounted for, but future costs arising from insufficiently grounded reserve planning (such as from using coarsely-classified data that does not adequately represent biodiversity) are not. Similarly, our biodiversity benefit calculation might change dramatically depending on the subjective value placed on biodiversity versus socio-economic costs, which would affect final calculations and likely increase the overall cost-effectiveness of the fine classifications. In the end, gaining more knowledge through gathering more accurate data might actually be more cost efficient by creating more efficient reserves. Because of this, rather than advocate the use of cheaper coarsely-classified data to plan conservation, we instead highlight the risks associated with using finely-classified data without considering its accuracy, and its cost.

The issue of the quality and quantity of data required to adequately protect biodiversity is increasingly important to conservation planning. We show that trade-offs between the choice of habitat data, their accuracy, costs, and surrogacy value are important considerations during decision-making, affecting the location, size, and cost-effectiveness of priority conservation areas. We highlight here the need for error information to be provided with any habitat map, and then included in the decision-making process, to avoid risks of under-representing features, particularly when maps of high thematic complexity and error are used. This study not only provides valuable information for decision-makers deciding on data for conservation planning, but also has far-reaching implications for protecting global biodiversity, including prospects for redesigning existing reserves selected without considering data uncertainties.

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Tables

Table 1. Habitats, area and accuracies for the input conservation feature data used in the reserve design analyses. Coarse classifications describe geomorphology, while fine benthic classifications are composed of a combination of coral, algal, seagrass, sand, rubble and reef matrix substrata, described by the dominant habitat first, followed by sub-dominant, and so on.

Habitat type	**Percent total study area (%)**	**Accuracy *(p)***
GEOMORPHIC – COARSE CLASSIFICATION		
Inner Reef Flat	17.41	0.70
Inner Reef Flat Deep	6.84	0.90
Inner Reef Flat Terrace	9.71	0.90
Lagoon Reef	23.93	0.90
Lagoon Slope	15.86	0.85
Outer Reef Flat	13.23	0.85
Reef Crest	4.90	0.80
Reef Slope	8.11	0.80
BENTHIC – FINE CLASSIFICATION		
Algae Coral Reef Matrix	0.55	0.467
Algae Reef Matrix	0.46	0.61
Algae Rubble Sand	2.00	0.644
Coral	1.85	0.515
Coral Reef Matrix	5.55	0.769
Coral Rubble	6.04	0.697
Coral Rubble Sand	5.81	0.679
Coral/Algae Reef Matrix	0.43	0.275
Deep Lagoon	11.54	0.793
Deep Slope	4.63	0.999
Reef Matrix Coral	2.35	0.741
Reef Matrix Coral Algae	2.27	0.465
Reef Matrix Top	0.38	0.955
Rubble Coral	0.29	0.999
Rubble Reef Matrix Coral	1.92	0.88
Seagrass Sand	0.35	0.999
Seagrass/Algae Rubble Sand	10.19	0.429
Sand	28.67	0.637
Sand Seagrass/Algae	2.90	0.999
Sand Rubble	1.20	0.375
Sand Rubble Algae	0.66	0.9
Sand Rubble Coral	7.89	0.689
Sand Rubble patch features	0.37	0.6

Table 2. Details of the prioritization scenarios employed, detailing which approach was used (either standard Marxan, or MarProb to account for mapping error), dataset used, and cost information.

		Approach		Dataset used		Cost data	
Scenario	**Prioritization name**	**MarProb (accuracy values included)**	**Marxan (no accuracy values**	**Geomorphic zones**	**Benthic habitats and substrata**	**Equal costs for all planning units**	**Fishing opportunity costs**
Baseline	Coarse-classification standard		x	x		x	
	Coarse-classification accuracy	x		x		x	
	Fine-classification standard		x		x	x	
	Fine-classification accuracy	x			x	x	
Planning	Coarse-classification standard		x	x			x
	Coarse-classification accuracy	x		x			x
	Fine-classification standard		x		x		x
	Fine-classification accuracy	x			x		x

Table 3. Comparison of spatial dissimilarity for the eight prioritization scenarios using the Bray–Curtis similarity index (0 = completely dissimilar, 100 % = identical). Grey boxes indicate scenarios that were compared in the analysis.

		Baseline			Planning			
		Coarse-classification accuracy	Fine-classification standard	Fine-classification accuracy	Coarse-classification standard	Coarse-classification accuracy	Fine-classification standard	Fine-classification accuracy
Baseline	Coarse-classification standard	79.1%	81.1%	74.0%	40.2%	42.8%	39.8%	49.0%
	Coarse-classification accuracy	-	86.3%	74.0%	48.3%	51.8%	46.1%	55.7%
	Fine-classification standard	-	-	63.9%	45.1%	46.7%	44.5%	51.7%
	Fine-classification accuracy	-	-	-	46.6%	51.3%	47.2%	61.4%
Planning	Coarse-classification standard	-	-	-	-	89.3%	72.8%	64.7%
	Coarse-classification accuracy	-	-	-	-	-	68.2%	64.9%
	Fine-classification standard	-	-	-	-	-	-	78.7%

Figures

Figure 1. (a) Flowchart of classification process for habitat maps, identifying a snapshot of the full hierarchical classification process, (b) map of accuracy values for the geomorphic map (coarse-classification) and (c) benthic habitats (fine-classification), identifying areas of low classification accuracy and high error (10% accuracy value) to high classification accuracy and minimal error (100% accuracy value), derived from the error matrix for each habitat. Inset shows location of Kubulau in Fiji.

Figure 2. Differences in priority conservation areas between the standard (red, orange, yellow colors) and accuracy (blue shades) approaches using (a) the coarse-scale dataset, and (b) the fine-scale dataset. Highest priority areas are those selected as a priority 100% of the time for one approach, and never for the other. The final difference map (c) highlights priority areas identified using either the coarse-scale data (blue) or fine-scale data (red), using the accuracy approach. Highest priority areas in (c) are those selected as a priority 100% of the time using one dataset but never using the other dataset.

Figure 3. Maps showing the differences in spatial location of priority planning units using different habitat data, when opportunity costs were included, using a standard approach (a) and an accuracy approach (c). The scatterplots display the selection frequency of planning units when coarsely classified geomorphic zones are used compared to fine-classifications, using a standard (b) and accuracy (d) approach. Yellow units were important to meeting targets for both datasets, blue units were considered more important to meeting targets for the coarsely classified habitats, and red units were considered more important to meeting targets for the finely classified habitats. Grey planning units were considered relatively unimportant using either dataset.

Figure 4. Errors of omission (amount of under-represented habitats) and commission (over-represented benthic habitats) from the surrogacy scenario incorporating accuracy information, identifying which fine-scale benthic habitats failed to achieve representation targets in the reserves designed using coarse-scale geomorphic data. Negative values mean habitat targets were not met, positive values mean habitat targets were exceeded.

Figure 5. Errors of omission (amount of under-represented habitats) and commission (over-represented benthic habitats) from assessing which habitats failed to achieve representation targets once mapping accuracy was considered in existing reserves designed using habitat data (Andrefouet et al. 2006) that did not have accuracy information, for (a) geomorphic zones, and (b) benthic habitats. Features are ordered by highest mapped error at the top (inner reef flat, and coral/algae reef matrix), to lowest error at the bottom of each data set. Negative values mean habitat targets were not met, positive values mean habitat targets were exceeded.

Figure 6. Costs (opportunity and data acquisition in FJD), size, relative biodiversity benefit and final cost-effectiveness for the best reserve network (defined by Marxan as the solution with the lowest objective function score) designed using coarse or fine-classifications. We highlight differences between using the standard and accuracy approaches for the planning scenario where fishing opportunity costs were included.