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Incorporating uncertainty associated with habitat data in marine reserve design

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ABSTRACT

One of the most pervasive forms of uncertainty in data used to make conservation decisions is error associated with mapping of conservation features. Whilst conservation planners should consider uncertainty associated with ecological data to make informed decisions, mapping error is rarely, if ever, accommodated in the planning process. Here, we develop a spatial conservation prioritization approach that accounts for the uncertainty inherent in coral reef habitat maps and apply it in the Kubulau District fisheries management area, Fiji. We use accuracy information describing the probability of occurrence of each habitat type, derived from remote sensing data validated by field surveys, to design a marine reserve network that has a high probability of protecting a fixed percentage (10–90%) of every habitat type. We compare the outcomes of our approach to those of standard reserve design approaches, where habitat-mapping errors are not known or ignored. We show that the locations of priority areas change between the standard and probabilistic approaches, with errors of omission and commission likely to occur if reserve design does not accommodate mapping accuracy. Although consideration of habitat mapping accuracy leads to bigger reserve networks, they are unlikely to miss habitat conservation targets. We explore the trade-off between conservation feature representation and reserve network area, with smaller reserve networks possible if we give up on trying to meet targets for habitats mapped with a low accuracy. The approach can be used with any habitat type at any scale to inform more robust and defensible conservation decisions in marine or terrestrial environments.

1. Introduction

In the face of current global failure to stem the rate of biodiversity loss (Butchart et al., 2010), there is an imperative to enhance protection of the world's terrestrial and marine biodiversity. However, numerous uncertainties make conservation decisions difficult. For example, less than half of the world's species have been described (Barnes, 1989; May, 1992) and the distribution of most described species is poorly known (Bini et al., 2006). Limitations also exist in our knowledge of ecological processes because they are dynamic and complex (Davis et al., 1998; Pearson et al., 2006). Despite these knowledge gaps and uncertainties, planners are required to make decisions about what, where, and when to invest in biodiversity conservation, due to limited conservation funds and competing needs for resources.

Protected areas (or reserves) can be one of the most successful management tools for protecting biodiversity (Margules and Pressey, 2000). However uninformed decisions on the location and design of reserves could have serious repercussions for the effectiveness and efficiency of conservation strategies (Possingham et al., 2006). There is a need, therefore, to improve upon current conservation planning practices, such as reserve design, and increase the reliability of conservation decisions. This can be achieved by including measures of uncertainty in the planning process.

A tacit assumption of most conservation planning is that ecological data are certain (Possingham et al., 2009; Wilson et al., 2005). In reality, there is uncertainty inherent in all ecological data. In addition to gaps in our knowledge of biotic systems and processes, we know that there are many facets of risk, error and/or uncertainty in any prediction of species distribution (Regan et al., 2005; Rondinini et al., 2006). These include presence–absence data errors, incomplete species distribution data, measurement or processing errors, erroneous taxonomic attribution, partial system observability, scarce or outdated observational data, and

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population model uncertainties (Drechsler, 2004; McCarthy et al., 2003; Moilanen et al., 2006; Soberon and Peterson, 2004; Wilson et al., 2011). With doubt surrounding our understanding of ecological systems, species distributions, and data integrity, methods used to study them cannot be considered robust unless they account for uncertainty. Despite this, significant gaps still remain in the conservation planning literature, with many aspects of uncertainty not yet accounted for (Halpern et al., 2006; Langford et al., 2009; Stine and Hunsaker, 2001).

When planning for reserves, conservation planners would ideally have access to distribution information for all aspects of biodiversity. However, such information does not exist for even the most data rich areas in the world as it is difficult and costly to collect (Pressey et al., 1993). To compensate for this lack of data, planners often use habitat maps as surrogates for biodiversity (Cowling and Heijnis, 2001; Margules and Pressey, 2000). While many studies have found that habitat surrogates are far from perfect (Beger et al., 2007; Lindsay et al., 2008; Mumby et al., 2008; Sutcliffe et al., 2012), they are essential if we wish to conserve biodiversity now.

The increasing availability of spatial data obtained through remote sensing has led to the growth of its use in applied marine research worldwide, with innovative new techniques producing habitat maps of high spatial resolution depicting geomorphic and biological structures that could be essential in reserve planning decisions (Andrefouet, 2008; Mumby and Edwards, 2002; Roelfsema and Phinn, 2010). In coral reef environments, remotely sensed satellite imagery is particularly suitable for habitat mapping, however accurate representation of coral reef features are beset by numerous challenges, including: dynamic changes in benthic cover; spatial and temporal variation in water clarity; and interpretation errors often due to spectral similarity of important reef features (Mumby et al., 2004; Phinn et al., 2012). Errors in coral reef maps derived from remote sensing are common, leading to "acceptable" levels of overall map accuracy as low as 50–60% (Phinn et al., 2008). Yet during the planning process there is generally little recognition of the underlying errors created when habitat maps are produced or how the choice of a particular processing technique affects the classification accuracy of each habitat. Furthermore, many of the habitat layers to be used in conservation planning do not contain accuracy assessments or error information. Failure to consider these mapping inaccuracies in conservation planning can lead to poorly informed management decisions as features that support critical species or processes of interest may not be adequately protected (Brooks et al., 2006; Pimm et al., 1995).

To address these problems, Steele (2006) suggests setting high conservation targets – a risk-averse precautionary approach. This is not dissimilar to the approach adopted by Allison et al. (2003), where an insurance factor was created to buffer against the possibility of not achieving conservation targets under a given catastrophe scenario. However, such an approach would lead to errors of commission (where extra habitat other than features of interest are included), wasting valuable conservation resources on large reserve networks that are in many places inefficient or infeasible, especially in areas where fisheries management areas or tenure units are smaller and therefore larger reserves result in substantial opportunity costs (Grand et al., 2007). Conversely, errors of omission (where a reserve does not actually contain the desired conservation features) can occur if one assumes that the maps are accurate, when in fact the mapping process has erroneously under-represented conservation features. Assuming a habitat is present when it is actually absent is the most dangerous error in conservation planning because it increases the risk of under-protecting features in the reserve design (Rondinini et al., 2006). Conservation planning methods that include uncertainty associated with habitat-mapping accuracy can therefore increase reliability and robustness of final conservation solutions by helping us achieve conservation goals efficiently (Moilanen et al., 2006). Despite this, a paucity of research exists that accounts for uncertainty in habitat distributions in reserve design (but see Beech et al., 2008). This may be because habitat mapping accuracy information is often not readily available or accessible to conservation planners. A key issue is not merely to assess whether uncertainty affects the results of a spatial prioritization, but to highlight the value of producing and providing accuracy assessments with any habitat map, so that uncertainty information can be explicitly included in these decision-making processes (Wintle et al., 2011).

Here, we develop an approach to spatial conservation prioritization that can account for inaccuracies in coral reef maps derived from remote sensing image data, using a readily available systematic conservation decision-support tool, and apply it to the Kubulau District fisheries management area in Fiji. Our objective in this study is to demonstrate the value of knowing how accurate our habitat maps are, and show how to explicitly account for these inaccuracies in conservation planning. We design a network of marine reserves using mapped habitat distribution data that aims to maximize the probability of protecting every habitat type by accounting for habitat mapping inaccuracies. We compare the output (i.e. priority areas, costs) of our probabilistic method with that of a more standard approach to reserve design, where mapping accuracy is not considered. Finally we highlight the trade-offs between habitat representation and area of reserve network that occur when habitat mapping accuracy information is or is not available.

2. Methods

2.1. Study region

The study area comprises the Kubulau traditional fishing grounds (*qoliqoli*), centered at 16°51′S and 179°0′E, located in south-west Vanua Levu, Fiji (Fig. 1). The *qoliqoli* extends from the coastline of the district to the outer barrier reefs, including several small islands, covering a total area of 261.6 km^2 (WCS, 2009). With assistance from non-government organizations, Kubulau communities have already initiated marine management projects (Jupiter and Egli, 2011), for which habitat maps were developed (Knudby et al., 2011).

2.2. Habitat data

Coral reef habitat maps were derived for the Kubulau *qoliqoli* by Knudby et al. (2011) using high spatial resolution multi-spectral satellite imagery (QuickBird 2006 and Ikonos 2007). A fine-scale benthic community substrate map with 33 individual classes was derived for the entire study region using object-based image analysis (Roelfsema et al., 2010), which involved image segmentation and classification and integration with field data for training and accuracy assessment (Knudby et al., 2011) (Fig. 1a). Each benthic community class (hereafter "habitat") describes a combination of coral, algal, seagrass, sediment, rubble and reef matrix substrata at a scale between 1 and 10 m. Each benthic habitat was described by the dominant habitat first, followed by sub-dominant, and so on. For example, "sediment rubble" means sediment-dominated substrate with some rubble.

Individual mapped habitat accuracies were obtained from the error matrix produced during the object-based image classification. The error matrix compares reference samples (field data) with image classes to calculate classification accuracy statistics for overall accuracy and the individual map category user and producer accuracies (Congalton and Green, 1999) (Appendix A). The user

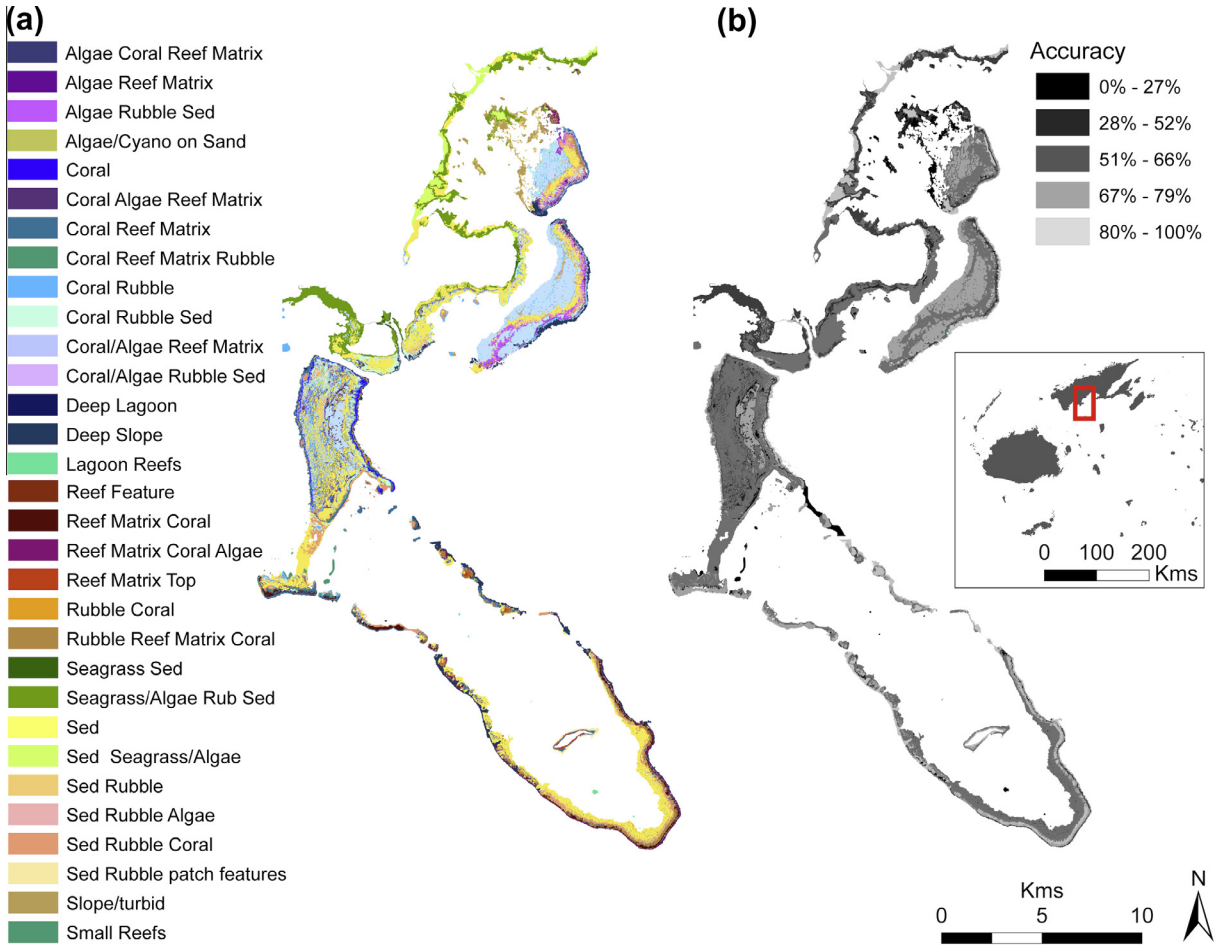

Fig. 1. Maps of (a) benthic communities and habitat substrata derived from remote-sensing imagery and (b) associated accuracy values for the Kubulau Fiji fisheries management area (*qoliqoli*). Inset shows the location of Kubulau in Fiji.

accuracy is the probability that the mapped habitat (e.g. coral) correctly represents its ground distribution and is calculated by dividing the number of correctly classified pixels in a habitat by the total number of pixels assigned to that habitat. This value is directly affected by commission errors and represents the conditional probability that a habitat is correctly classified. We used this value as individual habitat probability input data for this study. The accuracy values for the mapped benthic habitats varied from 0.275 to 1.0, with a mean accuracy of 0.666 (Fig. 1b and Table 1).

We divided the region into 22 815 hexagonal planning units (5000 m^2), and calculated the amount of each benthic habitat in every planning unit. We only considered habitats with an accuracy of greater than 25%, as it is unlikely that planners would consider protecting habitats with such known inaccuracies, and assigned to each habitat the probability value derived from the user accuracy in the error matrix.

2.3. Prioritization approach

Two conservation planning approaches were used for this study. In the standard approach we assume habitat distribution is certain (no mapping accuracy information included), and in the probabilistic approach we include uncertainty in the form of habitat-mapping accuracies.

For the standard approach we used the conservation planning software Marxan v.2.43 (Ball et al., 2009) to design a number of near-optimal reserve design solutions that conserved a set amount of every type of habitat in the Kubulau coral reef system. Marxan

Table 1
Habitats, accuracies derived from the error matrix, and proportion of study area covered by each habitat.

Habitat type	Accuracy p_{hi}	Amount of total study area (%)
Algae coral reef matrix	0.47	0.55
Algae reef matrix	0.61	0.46
Algae rubble sed	0.64	2.00
Breaking waves	0.63	0.54
Coral	0.52	1.85
Coral reef matrix	0.77	5.55
Coral rubble	0.70	6.04
Coral rubble Sed	0.68	5.81
Coral/algae reef matrix	0.28	0.43
Deep lagoon	0.79	11.54
Deep slope	1.00	4.63
Reef matrix coral	0.74	2.35
Reef matrix coral algae	0.47	2.27
Reef matrix top	0.96	0.38
Rubble coral	1.00	0.29
Rubble reef matrix coral	0.88	1.92
Seagrass sed	1.00	0.35
Seagrass/algae rubble sed	0.43	10.19
Sed	0.64	28.67
Sed seagrass/algae	1.00	2.90
Sed rubble	0.38	1.20
Sed rubble algae	0.90	0.66
Sed rubble coral	0.69	7.89
Sed rubble patch features	0.60	0.37

solves the minimum-set problem (Cocks and Baird, 1989; Moilanen et al., 2009) using a heuristic approach called simulating annealing (Ball et al., 2009; Kirkpatrick, 1983). Marxan aims to minimize the objective function which is a combination of the cost of selected planning units and boundary length of the entire system, subject to the constraint that the conservation targets are achieved (as described in Watts et al., 2009).

In the traditional version of Marxan, it is assumed that (1) there is no uncertainty, thus the amount of habitat in an area is known, and (2) conservation targets are met once the target amount of each habitat is represented in the reserve system. Once we include uncertainty in species or habitat distribution these assumptions are no longer valid. Our probabilistic approach deals with this uncertainty by using a modified version of Marxan called Marxan with Probability (hereafter "MarProb") that has the ability to include probability matrices describing the uncertainty of whether a habitat (or species) exists in a planning unit. MarProb combines information about the probability of a feature h occurring in planning unit i (p_{hi}), which in this study is the mapping accuracy of each habitat, and a "certainty target" (C_h), which is how sure we want to be to meet a representation target for feature h. In order to minimize the objective function, MarProb calculates the probability of failing to meet a given target for every conservation feature, in this case habitats, at each iteration using an approximate probability density function of the amount of habitat conserved in any reserve system. An additional constraint is imposed such that the probability of meeting the target for each habitat feature in the reserve network (P_h) must be greater than feature dependent parameter C_h, our certainty target, for every habitat feature in the reserve network. For example, setting a 90% certainty target within MarProb gives you a 90% chance of meeting a 10% conservation target for a defined habitat in the reserve system. Reserve systems designed using traditional Marxan will only meet targets 50% of the time assuming errors in mapping are equally likely to over and underestimate the extent of features in a planning unit (Game et al., 2008) (Appendix B and Fig. B.1).

The key difference in the MarProb algorithm is the addition of a new term in the objective function, $w\sum_{h=1}^{N_h} F_h H(S_h)(S_h/C_h)$, where a penalty, F_h, is applied to reserve solutions that do not meet the target amount of every feature with sufficient likelihood ($h = 1 \ldots N_h$). The shortfall, S_h, is the difference between the estimated probability of achieving habitat targets and the certainty target, given by $S_h = C_h - P_h$, where P_h is approximated by calculating a probability distribution for the amount of each habitat that is in the current reserve system. The Heaviside step function, H, is zero when $S \geqslant 0$ and 1 otherwise. A probability weighting (w) can be applied to emphasize the importance of this term in the objective function relative to the other terms (e.g. minimizing cost or boundary) (see Appendix B for details on the modified version of Marxan).

2.4. Scenarios and analysis

We designed a series of planning scenarios comparing reserve outputs that both ignore and consider mapped habitat accuracy, ensuring representation targets were the same for each comparative scenario, with equal cost of reserving each planning unit across all scenarios (see Table 2). We first ran a standard scenario to identify reserve networks using Marxan, where no accuracy information was included, and set the conservation targets to $t_h = 30\%$ for all habitat classes based on the desire of the Fiji Government to protect 30% of inshore waters (hereafter "national target scenario") (Jupiter et al., 2011). A comparative probabilistic national target scenario was then run with mapped habitat accuracy, p_{hi}, as the probability term for each habitat feature in each planning unit. As our aim was to be reasonably sure that the selected reserve network contained each habitat feature, given mapping accuracy, we set a certainty target $C_h = 90\%$ for all habitat classes, which means that each solution has a 90% probability that the representation targets, t_h, are met, and ensures final reserve outcomes have high reliability. We then varied the habitat representation targets from 10% to 90% for both scenarios. We did not set a target of 100% as this is equivalent to protecting the entire study region.

We then varied the probability weighting (w) for the national target probabilistic scenario (where the representation target equals 30%) to compare trade-offs between reserve area and representation of habitats. We also varied the certainty target, C_h, from 50% to 99% for this probabilistic scenario to evaluate trade-offs between reserve network area and confidence (i.e. how confident we are that the reserve solution achieves representation targets). Our maximum certainty target was 99% as it is impossible to meet a target with 100% certainty when all the data for a habitat feature is uncertain. Certainty targets lower than 50% were not considered, because it is unlikely a policy-maker would accept less than a 50% chance of achieving a conservation outcome.

For each scenario, we produced 100 solutions to the reserve design problem, each with a different spatial configuration. We compared how the best solution (i.e. the one with the minimum objective function score) and selection frequency (i.e. number of times a planning unit was selected across the 100 solutions) from each scenario differed between methods. Planning units selected frequently across solutions indicate those areas are a high priority for meeting representation targets. Difference maps were used to compare how the location of priority areas would change if we considered uncertainty, by subtracting the planning unit selection frequency of the standard scenarios from the probabilistic scenarios. We evaluated how well each habitat met the range of representation targets (10–90%) within the best solution for each scenario, as well as the overall performance of each solution in achieving all habitat targets. In order to quantify the probability of targets being missed when uncertainties are not considered, we took the 100 solutions from the standard scenario, ran 100 scenarios in MarProb "locking-in" each selected planning unit solution, and assessed which habitats failed to achieve their targets. To test trade-offs between representation, certainty and area of reserve between scenarios, we evaluated how many planning units were required to meet all habitat targets in the probabilistic scenarios when the certainty target was increased from 50% to 99%.

We then calculated the sensitivity of the spatial prioritization to differing habitat probability values using the planning unit selection frequencies for the national target scenario. We calculated the minimum and maximum probability within each planning unit based on the most inaccurate and accurate habitats that the planning unit contained. To account for the dataset having more than one habitat per planning unit, we calculated the sum of the accuracy of features within each unit ("summed probabilities"). We calculated the number of habitats, minimum, maximum and summed amount of habitat in each planning unit, and calculated a measure of the mapping uncertainty (or variance) for every planning unit (i), $\sigma^2 = \sum_{i=1}^{N_i} a_{hi}^2 p_{hi}(1 - p_{hi})$.

Preliminary analysis of a correlation matrix was conducted in order to establish potential variables that would be significantly correlated. The variables "summed amount of habitat" and "maximum amount of habitat" were excluded because they were highly correlated ($r^2 > 0.95$) with "number of habitats" and "summed probabilities", respectively. Stepwise multiple regression analyses were performed separately for the dependent variables (a) selection frequency using the probabilistic approach, and (b) difference between selection frequencies for probabilistic and standard approaches. We compared scatterplots with spatial selection frequency maps to highlight which areas were being selected as higher priority, and identify the drivers of these differences.

Table 2
List of scenarios identifying which methods and certainty targets were used, and any additional changes.

Scenarios	Benthic targets t_h (% of habitat area for each habitat)	Certainty target C_h	Other parameters
No accuracy (standard)	30 (national target)	N/A	N/A
Accuracy (probabilistic)	30 (national target)	0.9	Probability weighting sensitivity analysis
Trade-offs (standard)	10, 20, 30, 40, 50, 60, 70, 80, 90, 99	N/A	N/A
Trade-offs (probabilistic) –representation and accuracy	10, 20, 30, 40, 50, 60, 70, 80, 90, 99	0.9	N/A
Trade-offs (probabilistic) – certainty and area	30 (national target)	0.5, 0.6, 0.7, 0.8, 0.9, 0.95	N/A

3. Results

We found that spatial priorities changed when comparing scenarios that considered and ignored mapping accuracy (Fig. 2). The biggest differences between the two scenarios occurred when conservation targets were between 10% and 30%, with higher selection frequencies for the probabilistic scenarios that accounted for mapping errors (Fig. 3, Appendix C and Fig. C.1). For the national target scenarios (with a 30% conservation target), mean planning unit selection frequencies for standard solutions that ignored mapping accuracy (25.2) were below mean values for the probabilistic solutions that did account for mapping accuracy (mean of 38.4). Higher conservation targets (40–100% of total habitat) resulted in proportionally higher planning unit priorities for both methods, with solutions converging at high conservation targets (>70%) for both approaches (Appendix C and Fig. C.1).

When comparing results of standard and probabilistic scenarios, we also found that many areas that were a high priority in one scenario could be a low priority in another scenario, and vice versa (Fig. 2c). For example, 1% (169) of the planning units in the probabilistic national target scenario were selected in all 100 solutions, indicating their high priority to meeting conservation targets. However, in the standard national target scenario that ignored mapping accuracy, all of these planning units had a selection frequency of less than 75, a third of which were had a selection frequency of 20, indicating their relatively low priority for meeting habitat representation targets.

In the probabilistic national target scenario (i.e. ensure 90% chance of representing 30% of each habitat), we found that frequently selected planning units (>75) contained low accuracy habitats (e.g., coral/algae reef matrix: $p_{hi} = 0.275$; sediment rubble: $p_{hi} = 0.375$; reef matrix coral algae: $p_{hi} = 0.465$; algae coral reef

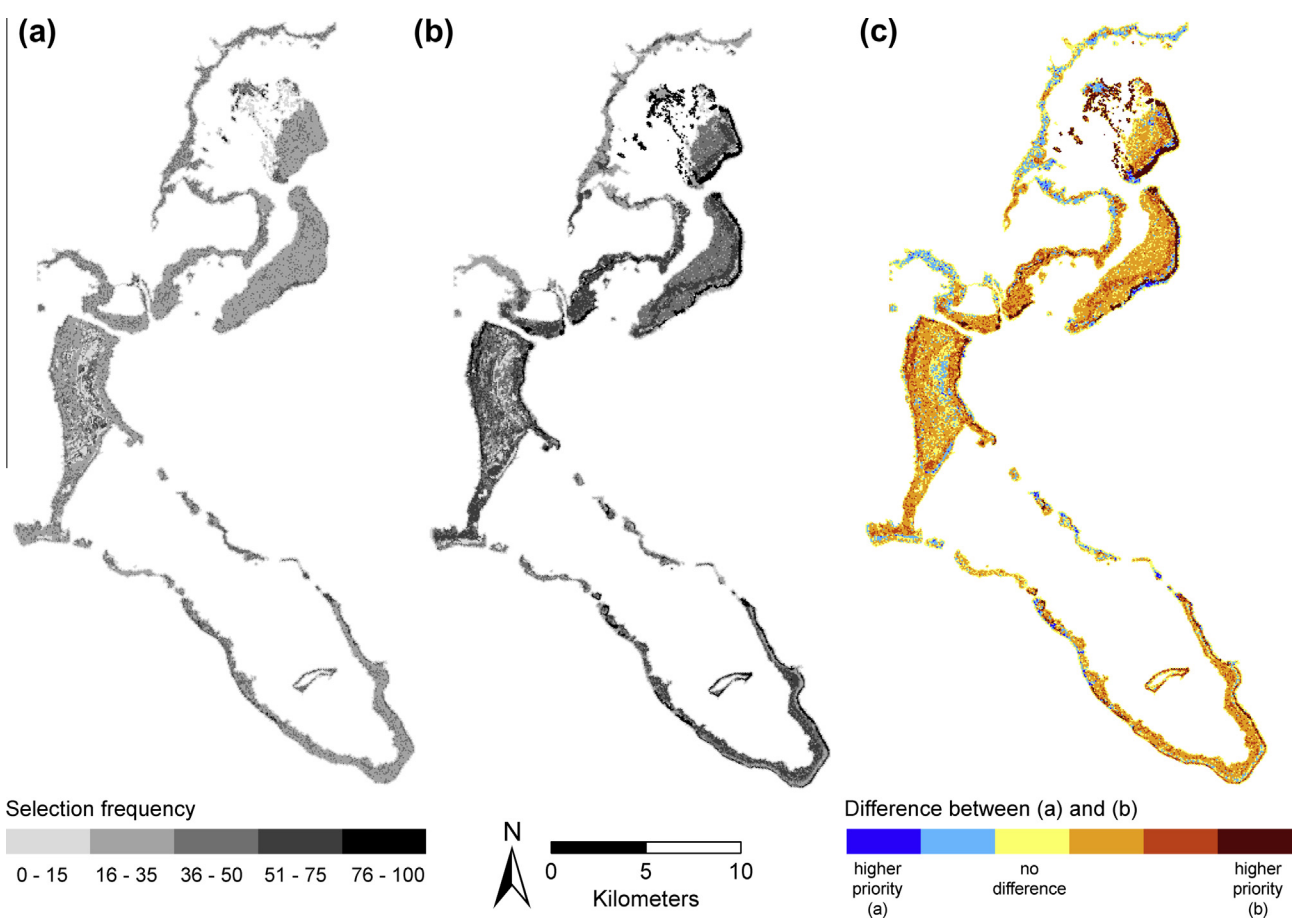

Fig. 2. Planning unit selection frequency from (a) standard scenarios that do not include habitat-mapping accuracy, and (b) probabilistic scenarios that include mapped habitat accuracy with a goal of being 90% confident that habitats are represented. For both scenarios, we targeted 30% of each habitat for inclusion in the reserve network. Panel (c) shows the differences in planning unit selection frequency between the two scenarios.

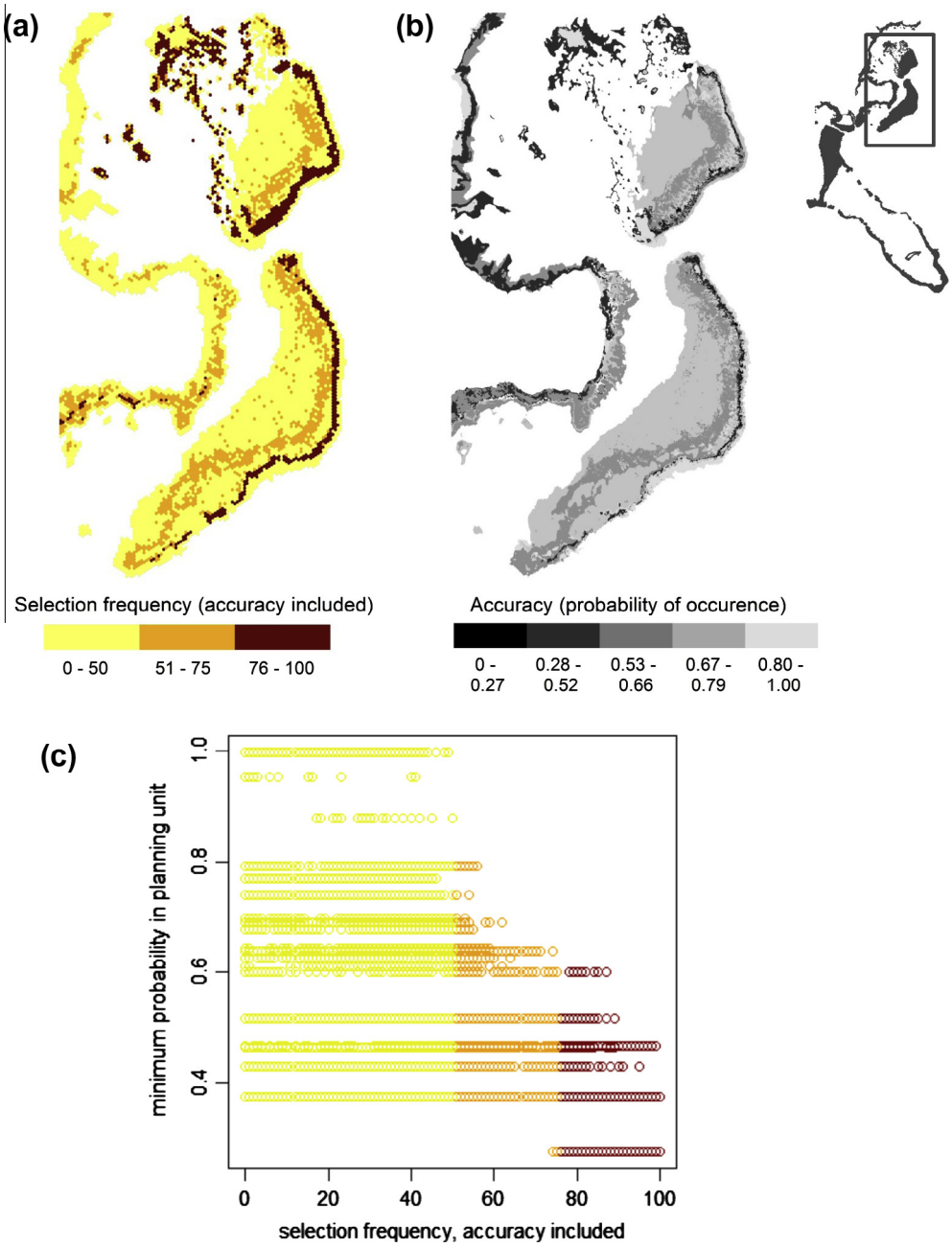

Fig. 3. Planning unit (a) selection frequencies, and (b) associated accuracy input values for the probabilistic scenario that aims to be 90% certain that 30% of each benthic habitat is represented in a reserve network. Linear regression of minimum probability in planning unit and selection frequency using the probabilistic approach (c) shows planning units of high selection frequency corresponded to planning units containing low accuracy habitats.

matrix: $p_{hi} = 0.467$; and coral-dominant: $p_{hi} = 0.515$) (Fig. 3). These planning units were selected more frequently than those containing high accuracy habitats. Larger amounts of habitats with low mapping accuracy were represented in reserve networks created through the probabilistic approach compared with networks creating using the standard approach (Fig. 4). Multiple regression identified that all variables except for "minimum habitat amount" and "summed variance" were effective combined predictors of the change between selection frequencies from excluding to including mapping accuracy ($r^2 = 0.590$, $P < 0.001$) (Appendix C.1). The residuals were normally distributed, all fell within the 95% confidence interval, and showed no patterning against the predicted outcomes. Considered independently, the minimum probability (lowest accuracy habitat) in the planning unit explained 53% of the variation in selection frequency differences between methods, while maximum probability (highest accuracy habitat) explained 13% (Appendix C and Fig. C.2).

When we locked-in the priority planning units from the standard approach into a probabilistic approach, we found most habitats failed to achieve their representation targets. Habitats with accuracy values less than 0.900 would never achieve their targets, whilst only five habitats (all with accuracy values greater than 0.900) had a chance of achieving conservation targets (>0.1 probability). Only three habitats (rubble coral, seagrass sediment, and sediment seagrass/algae) would have more than a 50% probability of achieving conservation targets, and all of these habitats had an accuracy of 0.999. The exception to this was deep slope, which had a mapped accuracy of 0.999 but a 66% chance of missing its target.

When representation targets were <40%, we found that the reserve networks from probabilistic scenarios that accounted for

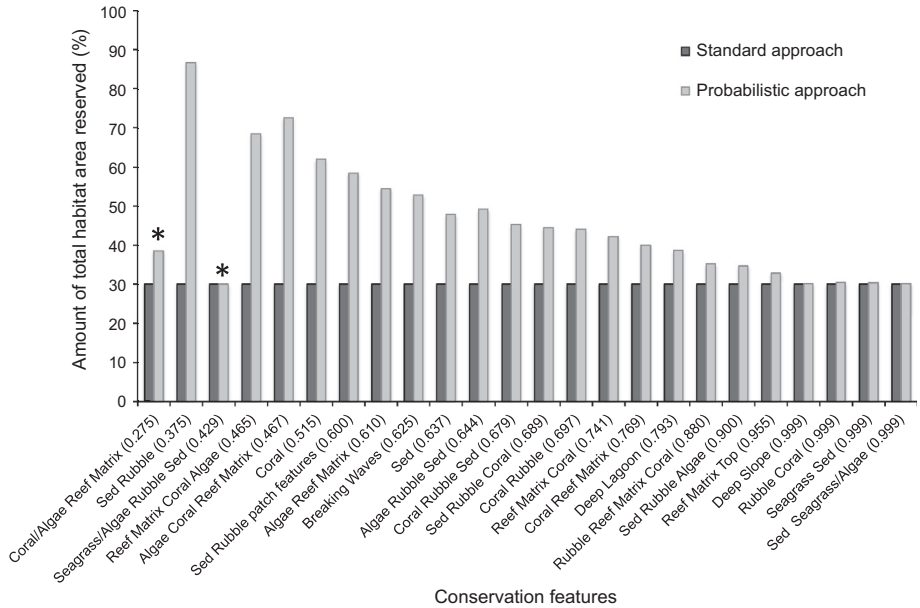

Fig. 4. Area of total habitat represented in the best solution (i.e. that with the lowest objective function score) for reserve network design using the standard approach (dark gray) and the probabilistic approach (light gray), both run using the 30% national target. Asterisks above the probabilistic result identify those habitats that missed meeting the target with 90% certainty once mapping accuracy was accounted for.

mapping accuracy were up to 50% larger than those designed using standard approaches (Fig. 5). As habitat representation targets increased greater than 50%, reserve networks that accounted for mapping accuracy became progressively smaller than those that did not include uncertainty. Furthermore, solutions using the probabilistic approach met fewer and fewer habitat targets as those targets increased beyond 20% (Fig. 5). Conservation targets became progressively unachievable as they increased using the probabilistic approach because it was impossible to select enough planning units to meet the certainty target (90%) for low accuracy habitats, and the reserve design algorithm effectively gave up on trying to meet representation targets. This resulted in smaller reserve networks using the probabilistic approach compared to those created with the standard approach for targets greater than 50% (Fig. 5).

When the certainty target was increased from 50% to 99% (and representation target equaled 30%), 2.1% more area was required to ensure targets were achieved for a 99% certainty target than a 50% target (Fig. 6a). Trade-offs in reserve network area and habitat representation were found when the probability weighting (w) was varied for the 30% representation target and 90% certainty target. By varying this probability weighting, we found we were able to reduce the total area of our reserve solutions by 7% if we were willing to give up on meeting representation targets for four low accuracy habitat categories (Fig. 6b).

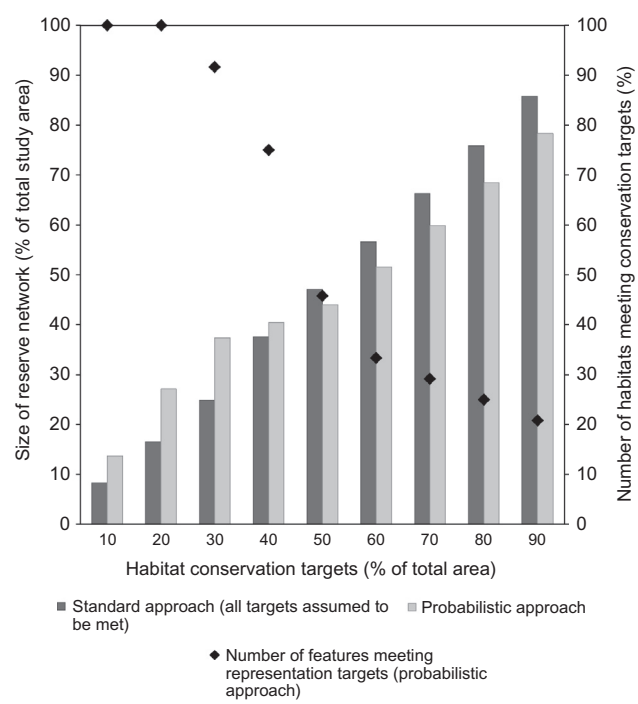

Fig. 5. The effects of increasing conservation targets on the expected adequacy (percentage of habitats that met their target) and size of reserve network from the best probabilistic (dark gray) and standard (light gray) solutions. Solutions using the standard approach met all conservation targets, however a point was identified on the trade-off curve after 20% target where probabilistic solutions were unable to meet all targets.

4. Discussion

Limited conservation funds mean that planners and managers must make decisions without perfect information (Possingham et al., 2007). Such decisions, whilst necessary, can reduce our confidence in conservation actions and outcomes. In this study, we illustrate a method for increasing confidence in reserve network solutions, minimizing the probability of missing conservation targets by including certainty data of habitat features. Although it has been well-documented that habitat maps contain multiple sources of error (Mumby and Edwards, 2002; Mumby et al., 1997), they are commonly used in reserve design without consideration of their accuracy as simple methods for incorporating mapping errors into reserve design have previously not existed, or accuracy information is not available. Recent advances in systematic conservation planning tools now allow for the inclusion of probabilities of species or habitat distributions (Carvalho et al., 2011; Game et al., 2008; Lourival et al., 2011), with this study the first to use these new tools to investigate how uncertainties associated with habitat-mapping change spatial priorities for reservation. The results presented here show that spatial conservation

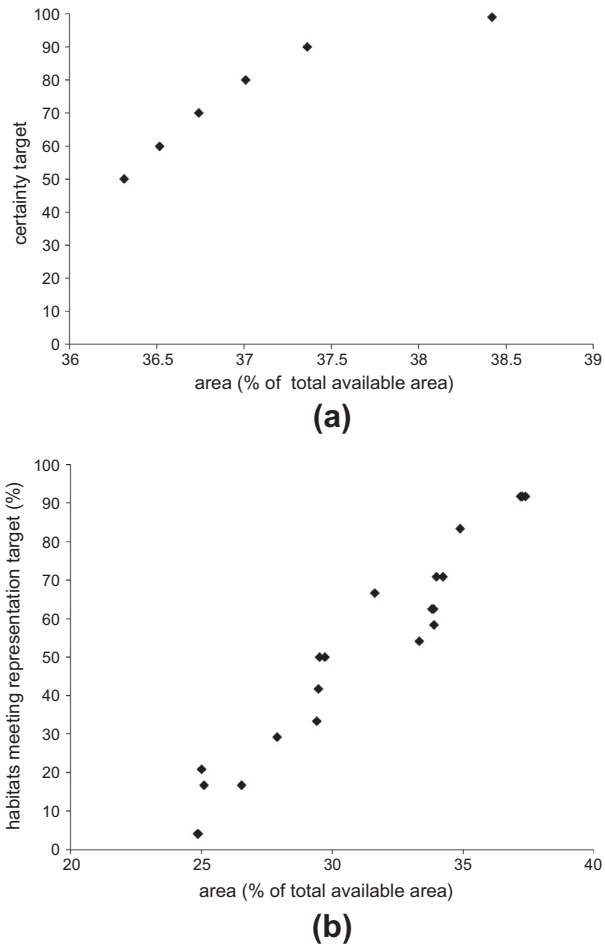

Fig. 6. Trade-offs between (a) total area conserved and certainty target, and (b) total area conserved and probability of habitats meeting representation targets (when probability weighting is varied to emphasize the importance of representing every habitat in each reserve network), in the best solution to reserve network design for the national target probabilistic scenario.

decisions can be significantly affected when habitat-mapping inaccuracies are considered, with consequences for conservation investment efficiency and representation of target features.

Conservation decision-makers often rely on planning unit priority values to identify priority areas for reservation (Carwardine et al., 2007). Our results show that the selection frequency of a planning unit once mapping accuracy is considered depends on the amount of the feature that it contains, and the certainty or confidence you have that it contains this feature. High planning unit selection frequencies using the probabilistic planning approach meant there was very little flexibility in the ability of individual reserve solutions to meet representation targets, as more areas became essential for meeting representation targets (Fig. 2), compared to high flexibility (and low selection frequencies) shown in solutions derived from standard approaches that ignored mapping accuracy. The addition of mapping accuracy into systematic planning methods makes it easier for planners to choose high priority sites that will protect habitats adequately and achieve efficient reserve networks, produces more decisive advice, and ensures conservation investments are more robust (Margules and Pressey, 2000; Nicholson and Possingham, 2007).

Our results show that consequences can occur by not accounting for mapping error in terms of the benefits for conservation and cost of management, with areas important to achieving representation targets for habitats in probabilistic scenarios largely excluded or considered unimportant (low selection frequency) from the standard scenarios (Fig. 2). Furthermore if only priority areas selected using a standard approach were protected, it would not be possible to meet representation targets for most habitats given uncertainty in the mapped features. These results indicate that conservation schemes based solely on the distribution of habitats that do not have information on mapping accuracy may fail to achieve adequate conservation outcomes, as they risk either (1) under-representing conservation features by missing out on protecting high priority areas, or (2) over-representing conservation features by including areas in the reserve network that are of low importance to meeting conservation goals, subsequently reducing efficiency of conservation investments.

Previous research demonstrates that spatial conservation prioritization generally avoids planning units with high uncertainty (Carvalho et al., 2011; Game et al., 2008). High uncertainty both reduces what we expect to get from a planning unit and increases the variance in what we get, and both effects reduce the chance of meeting a target (Langford et al., 2009; Wilson et al., 2005). This is contrary to our finding that configurations of the reserve networks that account for mapping accuracy were driven by low accuracy habitats. We note, however, that one probability value for each feature was used in this study, rather than a variable probabilistic distribution as in previous studies (e.g. Carvalho et al., 2011; Game et al., 2008; Lourival et al., 2011). In order to be sure of achieving habitat targets where the features were mapped with low probability, more sites with low accuracy features were required proportional to features of high accuracy, resulting in larger reserve networks using the probabilistic approach for low representation targets. In the previous studies, data inaccuracy created solutions that avoided uncertainty sites because they could be replaced with sites that had higher chances of conserving those same features – which is impossible for our problem.

The selection of high amounts of low accuracy habitats to meet conservation goals could be considered wasteful if the habitat itself is of low ecological value (Carwardine et al., 2009; Pressey et al., 2007). On the other hand, giving up on meeting targets for low accuracy habitats, as occurred in this study at higher representation targets using the probabilistic approach, could be considered an 'ethically pernicious' approach to conservation (Bottrill et al., 2008; Noss, 1996). Some disadvantages to using this probabilistic approach are thus highlighted, as in addition to giving up on some habitats, it resulted in less flexibility of reserve solutions (higher selection frequency values), perhaps making it harder to achieve targets if the location of reserves were being negotiated with stakeholders. Future research should consider including a range of probabilities for each feature, as planning units with a high probability of containing a feature would be more likely to be selected as high priority for meeting targets, and may increase flexibility of reserve solutions.

Trade-offs are necessary in any conservation planning process due to limited funds and resources and limitations in knowledge (Stewart and Possingham, 2005). In this study, adding consideration of mapping accuracy resulted in important trade-offs between area of reserve network, representation, and accuracy, with larger reserves required using the probabilistic approach to be more confident that habitats were adequately protected (Figs. 5 and 6a and b). This study quantitatively shows that standard approaches do not offer this confidence, with no low accuracy habitats adequately protected and at most only an 82% chance that high accuracy habitats would be adequately protected when there is uncertainty in our data but we use methods that do not include probability parameters. Whilst larger reserve networks that account for mapping accuracy could be more costly to manage, they are more robust to uncertainty than those that do not consider mapping accuracy, which are likely to contain many errors of

omission for planning units containing low accuracy habitats. Although larger, the key advantage of the probabilistic solutions with high certainty targets is that they increase confidence in achievement of conservation outcomes, making decisions more robust and less risky – a more precautionary approach to conservation (Regan et al., 2005). This new probabilistic approach allows us to quantify how often targets might be missed when uncertainties are not considered, enabling planners to evaluate necessary trade-offs, and understand the implications of not including uncertainty information in the planning process.

One reason for the lack of planning approaches that include certainty information may be that accuracy assessments are often not provided with data such as habitat maps. If uncertainty data are not readily available, planners have several options to ensure they are not ignoring the error inherent in their habitat maps. Firstly, planners could try to source more information about the habitat information that is often just assumed to be correct. For instance, how were the maps produced? Was there any validation? Which habitats may have been problematic and/or under-sampled? Secondly, planners could set different targets for each habitat, with higher targets set for habitats suspected to be uncertain. For example, some habitats are known to be commonly confused when mapped (e.g. because their spectral signatures or textural characteristics are very close or because they tend to occur in the same geomorphic zone in patchy habitats) (Mumby et al., 2004; Phinn et al., 2012), so planners could set higher representation targets and/or higher certainty targets for these habitats.

Decision-support tools used for conservation planning should allow planners to explicitly incorporate uncertainty associated with the data (Halpern et al., 2006; Regan et al., 2002). Spatially explicit conservation applications that incorporate uncertainty have been explored previously using fuzzy set theory (Wood and Dragicevic, 2007), info-gap analysis (Ben-Haim, 2001; Nicholson and Possingham, 2007; Regan et al., 2005), and bootstrapping methods (Beech et al., 2008). However, all of these approaches can be computationally challenging and difficult to interpret (Knight et al., 2006). Although others have used uncertainty measures in spatial planning (Carvalho et al., 2011; Game et al., 2008), this study is the first to use a readily-available decision-support tool to account for mapping error in reserve design. For the purposes of demonstrating the new approach, we did not attempt to account for any other aspects of uncertainty, such as spatial heterogeneity in habitat quality and distribution (Murdoch and Aronson, 1999). For example, the spatial distribution and associated mapping accuracy of each habitat was assumed to be homogenous, however in reality spatial heterogeneity exists within any mapped landscape. Furthermore, coral reefs are dynamic and constantly changing across temporal gradients (Connell et al., 1997; Done et al., 2010). One important form of uncertainty that was not considered concerns present and future habitat availability and species distributions, such as might occur with climate change (Araujo et al., 2005; Hodgson et al., 2009). Some recent studies have attempted address temporal uncertainty associated with loss and availability of habitat over time (Drechsler et al., 2009; Meir et al., 2004; Sarkar, 2006), as well as variability in population locations due to climate change (Araújo et al., 2004; Rodrigues et al., 2000). A recent study by Carvalho et al. (2011) was the first to quantify the inclusion of uncertainty in predicted species distribution changes over time to increase confidence in conservation investments. Whilst new methods of incorporating dynamic temporal uncertainty in reserve network planning are emerging (Game et al., 2008), this field is still in its infancy (Possingham et al., 2009). Given that there is so much uncertainty in all aspects of planning, decision-makers should attempt to include measures of uncertainty in planning approaches to ensure robust results. To do so, information on the errors in data, such as accuracy assessments, or confidence intervals surrounding biodiversity predictions, must become more readily available.

One of the greatest challenges in conservation planning is the research–implementation gap, and the oftentimes inability to translate research into cost-effective action (Knight et al., 2008). We were unable to evaluate trade-offs between total investment or effort required for each reserve network in this study and accuracy, as we used equal costs to isolate the effects of accounting for mapping accuracy and thus did not account for the actual costs of conservation. This resulted in reserve costs that were not representative of true socio-economic value. We also ignored boundary weightings resulting in highly fragmented reserve networks. Previous research has shown the need for appropriate and representative costs in conservation planning, as well as the efficiency benefits of compact reserves (Ban and Klein, 2009; Bode, 2008; Naidoo et al., 2006). This problem could be re-analyzed using the existing data to ensure reserve networks are well-connected and economically cheap (e.g. Adams et al., 2011).

5. Conclusion

Uncertainty is prevalent in ecological data and must be considered so that risks are managed or at the very least understood. Embracing uncertainty in conservation planning and reserve design is important in our search for more robust and defensible conservation decisions. Throughout this study we highlight the importance of accounting for mapping error, without which planners risk spending limited conservation budgets inefficiently by failing to adequately represent target features. As we try to balance the growing resource requirements of humans with the need to protect biodiversity, we need to reduce uncertainties stemming from trade-offs to ensure conservation investments are made wisely. Given the high uncertainty in both our understanding of current coral reef habitat distributions, as well as future spatial and temporal change, our challenge is to ensure data accuracy assessments or uncertainty information is more readily available, and find new methods of dealing with these uncertainties to allow the design of reserve networks that adequately and efficiently represent biodiversity.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biocon.2013.03.003.

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