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Reducing risk in reserve selection using Modern Portfolio Theory: Coastal planning under sea-level rise

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Abstract

1. Climate change is expected to impact many species and ecosystem services, although it is difficult to predict when and how these impacts may arise. Due to this uncertainty, it is difficult to plan management actions, such as designating protected areas, intended to adapt to climate change impacts. The danger of ignoring uncertainty is that resulting plans may fail to achieve conservation objectives, yet this is not usually incorporated in conservation planning.
2. Recent studies have accounted for uncertainty by applying Modern Portfolio Theory—an approach for risk-sensitive resource allocation used in the finance sector—to conservation planning. However, these approaches are not directly applicable to many conservation planning problems that typically include discrete site selection, multiple conservation objectives and a consideration of connectivity.
3. We extend previous applications of Modern Portfolio Theory by incorporating these additional conservation planning requirements in the context of designing a reserve system and apply it to conserving coastal wetlands and associated ecosystem services under uncertain rates of sea-level rise. This allows us to identify an optimal set of properties to preserve, while maintaining connectivity for landward migration of wetlands and accounting for risk. We compare spatial plans that resulted from our risk-sensitive approach to reserve selection that ignored risk to determine whether, and how, explicitly accounting for risk alters planning outcomes.
4. We demonstrate that incorporating sea-level rise, but ignoring uncertainty, is a high-risk strategy, even when planning for the worst-case sea-level rise scenario. In contrast, diversifying site selection through Modern Portfolio Theory can ensure the supply of ecosystem services by reducing the risk of failure across all sea-level rise scenarios.
5. *Synthesis and applications*. Climate change will continue to drive profound changes to socio-ecological systems that are difficult to predict. In this context, risk

reduction in spatial planning is a neglected but essential strategy for avoiding comprehensive failure and improving the long-term effectiveness of conservation efforts. Modern Portfolio Theory, as presented here to account for the characteristics of real-world conservation planning problems, provides a rigorous way forward in dealing explicitly with risk for many conservation planning exercises.

KEYWORDS
blue carbon, climate change, coastal wetlands, conservation planning, ecosystem services, Modern Portfolio Theory, sea-level rise, uncertainty

1 | INTRODUCTION

Conservation planning in the context of a changing climate is inherently uncertain (Lawler, 2009). Changes in climate can alter the distribution of species and ecosystem structure, but the extent and direction of these changes are difficult to predict because they arise from complex interactions among biotic and abiotic factors (Pearson & Dawson, 2003). These uncertain changes also have implications for the services that flow from species and ecosystems, with these ecosystem services facing similarly uncertain impacts (Runting, Bryan, et al., 2017). Consequently, planning long-term conservation actions are subject to substantial risks that need to be addressed in planning (Reside, Butt, & Adams, 2017).

Identifying spatial conservation priorities based on different deterministic scenarios of climate change is a common approach to understanding the potential implications of this uncertainty (e.g. Adams-Hosking, McAlpine, Rhodes, Moss, & Grantham, 2015). In this context, scenario analysis can play an important role in participatory planning by stimulating dialogue and revealing the possible consequences of alternative futures (Peterson, Cumming, & Carpenter, 2003). However, selecting a single climate change scenario on which to base decisions essentially assumes that the future emissions scenario (and impacts) is known with certainty. Implementing a conservation plan based on only one scenario (or expected outcome) could fail to account for potential losses from more extreme changes or, alternatively, potential windfalls from less severe impacts.

Previous approaches to incorporating the uncertainty surrounding climate change projections into spatial conservation plans include methods to reduce the risk in missing conservation targets due to the impacts of climate change (e.g. Carvalho, Brito, Crespo, Watts, & Possingham, 2011), or to improve the robustness of the solution by incorporating robust decision theory into spatial prioritisation (Kujala, Moilanen, Araújo, & Cabeza, 2013; Moilanen et al., 2006). Significantly, these approaches assess the risk posed by climate change for each planning unit (or site) *individually* within the optimisation or prioritisation. However, climate change often produces spatially variable impacts within and across different emissions scenarios (IPCC, 2014), so any pair of planning units could have a similar individual risk (or variance) but different responses to alternative climate change scenarios (covariance). Therefore, assessing risk independently for planning units misses the opportunity to further reduce the overall risk of the final solution by considering the covariances among planning units and adjusting their selection accordingly (Ando & Mallory, 2012).

Modern Portfolio Theory is a mathematical framework that allows these covariances to be incorporated explicitly in estimation of the overall risk of a set of decisions. It was originally developed to select a financial investment portfolio (a collection of *assets*) that maximises expected returns for a given level of risk (or minimises risk for a given level of expected returns) (Markowitz, 1952). The overall risk can be reduced by investing in complementary combinations of assets that have negative correlations in returns (or at least low positive correlations). However, there is usually a trade-off between returns and risk reduction such that the more risk-averse the decision maker, the lower the expected returns. Ultimately, this method reveals what fraction of the investor's budget to optimally invest in each financial asset to achieve the desired level of risk (or returns) (Markowitz, 1952).

Modern Portfolio Theory has previously been applied to non-spatial problems to inform investment of resources in the management of species, populations or ecosystem services (e.g. Halpern, White, Lester, Costello, & Gaines, 2011). However, recent advances have considered spatial planning units as assets, allowing overall risk to be reduced by allocating conservation investment across space (Ando & Mallory, 2012; Mallory & Ando, 2014; Shah, Mallory, Ando, & Guntenspergen, 2017). Several opportunities exist to improve upon these previous spatial applications of Modern Portfolio Theory. First, previous applications have been formulated as problems with continuous decision variables representing the proportion of resources to allocate to each planning unit. However, many conservation planning decisions are more appropriately formulated using a discrete decision variable representing, for example whether a planning unit is selected or not, or what action to apply to a decision variable (Ball, Possingham, & Watts, 2009). Second, rather than focusing on a single conservation objective, multiple conservation objectives are often required. This is important because conservation planning usually involves more than one objective, such as multiple species, ecosystems, or ecosystem services, and is moving towards the integration of multiple stakeholder values (Ban et al., 2013). Considering multiple objectives simultaneously facilitates identification of good-compromise solutions among objectives and hence more cost-effective solutions (Tzeng & Huang, 2011). Third, it is also necessary to consider how planning regions need to be biologically or functionally connected in space (Crouzeilles, Beyer, Mills, Grelle, & Possingham, 2015). This connectivity can take the form of a simple clustering of protected areas to minimise the impacts of habitat fragmentation and edge effects (Ball et al., 2009), asymmetric hydrological connectivity for freshwater systems or explicit spatial planning for species dispersal (Beger et al., 2010). Consequently, the current spatial formulations of Modern Portfolio Theory would benefit substantially from the incorporation of these additional conservation objectives and constraints.

We extend the approach developed by Ando and Mallory (2012) to include binary decision variables corresponding to the decision of whether to select a planning unit or not and multiple objectives, with preference weightings that the decision maker can adjust to balance the relative contribution of each objective. Our flexible formulation also includes a constraint that can be used to ensure connectivity requirements are met. Ultimately, this formulation selects a complementary set of connected planning units, for a given budget, that meet a set of conservation objectives while hedging the risk posed by different future scenarios. This formulation more closely resembles the types of problems conservation planners typically solve (i.e. with tools such as Marxan; Ball et al., 2009), while accounting for risk through the covariance structure among sites.

We apply this approach to planning for coastal wetlands and associated ecosystem services under sea-level rise. Coastal ecosystems can be lost with climate change due to continual inundation from sea-level rise, but they can also migrate landward if land at suitable elevations is available. These uncertain changes in coastal wetland distributions, along with imperfect elevation data and sea-level rise projections (IPCC, 2014), makes coastal climate adaptation planning particularly challenging. Coastal land also faces significant development pressure, which can result in a high opportunity cost in setting aside land to allow for wetland migration (Mills et al., 2014; Runting, Lovelock, Beyer, & Rhodes, 2017). In addition, any coastal climate adaptation strategies should also consider the important ecosystem services provided by these ecosystems to ensure benefits to humans from conservation (Ruckelshaus et al., 2013). Consequently, it is vital that coastal planning is not only cost-effective but is also robust to uncertainty and considers multiple ecosystem services. In our coastal wetlands application, we use our new method to: (i) determine the risk-return trade-offs; (ii) compare this to scenario-based planning strategies; and (iii) determine the trade-offs among different conservation objectives, and how these are altered by incorporating risk.

2 | MATERIALS AND METHODS

2.1 | Modern Portfolio Theory and reserve selection

We advanced the application of Modern Portfolio Theory to conservation problems by combining a portfolio approach (Ando & Mallory, 2012; Markowitz, 1952) with a parcel-level reserve selection problem (Beyer, Dujardin, Watts, & Possingham, 2016). This required several modifications to the original applications of Modern Portfolio Theory to financial markets. First, as in Ando and Mallory (2012), we replaced financial assets with spatially implicit planning units and included an additional constraint to exclude negative allocations (which would represent the short-selling of assets). Second, in finance (and in Ando and Mallory (2012)), the problem addressed is what proportion of total capital should be invested in each asset (a continuous decision variable). Although this is also applicable to some conservation planning problems, it is more common for reserve planning problems to determine what discrete set of planning units to select to best achieve the conservation objectives. For example, if assets represent land ownership parcels, it may be necessary to purchase the entire parcel rather than a fraction of it. Here we represented discrete site selection with a binary decision variable. Third, conservation problems often consider multiple objectives. Although in some cases a single, combined index, or indicator of multiple objectives is used, this may not be possible or desirable in many cases (Fleishman, Noss, & Noon, 2006), particularly as conservation planning is moving towards including a wider array of stakeholder preferences and policy objectives (Runting et al., 2015). Here we allow for multiple weighted conservation objectives. Finally, conservation problems differ from finance problems as there is usually some degree of spatial connectivity between planning units that needs to be accounted for in reserve selection problems to ensure ecological functionality (Beger et al., 2010), so we explicitly included connectivity.

Our risk-sensitive parcel-level reserve selection problem was formulated as an integer quadratic programming problem, which has the general form:

$$\text{maximise: } \sum_{k=i}^{K} w_k \sum_{i=1}^{N} (r_{ik} x_i) - \lambda \mathbf{x}' \Sigma \mathbf{x}$$

$$\text{subject to: } \sum_{i=1}^{N} c_i x_i \le B$$

$$\sum_{j \in M_i} x_j - m x_i \ge 0, \quad \forall\, i, i = 1 \ldots N,$$

$$x_i \in \{0,1\} \tag{1}$$

where w_k is the weight given to conservation objective k ($w \ge 0$; $\sum_k w_k = 1$), N is the number of planning units, r_{ik} is the expected (mean) conservation returns of planning unit i for objective k, $\mathbf{x}$ is a vector of binary decision variables representing whether each planning unit is selected or not, x_i are elements of $\mathbf{x}$, and λ is a term representing the risk tolerance of the decision maker, where larger values represent higher risk aversion and $\lambda \ge 0$. Σ is the combined covariance matrix for the weighted conservation returns. Calculating the covariance matrix for the weighted conservation returns rather than for each conservation objective separately ensures that potential interdependencies among conservation objectives are accounted for. The relative preference weightings for each conservation objective can be adjusted by the decision maker(s). We assume that returns (and risks) can only be realised if the planning unit is selected.

The first constraint ensures that the sum of the costs (c) among all selected planning units does not exceed the total budget (B). The second constraint ensures connectivity among planning units, and can be adjusted based on the strength and direction of connectivity required for a specific planning problem. Specifically, M_i defines a set of planning units that are connected to planning unit i. M_i can refer to all adjacent planning units, a subset of adjacent planning units (in the case of unidirectional connectivity requirements), or nonadjacent planning units that are functionally connected (Beger et al., 2010). The parameter m can take any value between 1 and $|M_i|$. If m is set to $|M_i|$, planning unit i can be selected only if the entire set of related planning units are also selected; if m is set to 1, planning unit i can be selected only if at least 1 of the related planning units are selected. An even more flexible approach to connectivity can be formulated as a penalty for disconnected planning units in an additional term in the objective function (as described in Beyer et al., 2016), but here we focus on the former formulation.

It has been argued that to avoid issues surrounding "complete markets" (where any payoff vector can be produced, given unlimited initial wealth; Flood, 1991), the number of scenarios which characterise the uncertainty must always exceed the number of planning units (assets) in spatial conservation problems (Mallory & Ando, 2014; Shah et al., 2017). While the concept of complete markets is important for modelling equilibrium in financial markets, where the short-selling of securities is permitted and there is a continuous decision variable (Arrow & Debreu, 1954), our extensive modification of the original formulation means that there will not be issues arising from the concept of complete markets in our problem formulation (see Section 4).

2.2 | Application to coastal wetlands

We applied our reserve selection approach to a 400 km^2 section of Moreton Bay and adjacent coastline in Queensland, Australia (Figure 1) to find the optimal reserve configuration for multiple conservation objectives under risks associated with the uncertain effects of sea-level rise on coastal wetlands. Moreton Bay contains internationally important coastal wetlands (Ramsar listed) which provide key ecosystem services and are likely to face distribution shifts with sea-level rise (Runting, Lovelock, et al., 2017). The area is also highly threatened by further urban development. Effective planning for sea-level rise that is robust to uncertainty and incorporates multiple objectives is therefore critical for this region.

To design our reserve system, we first simulated how the distribution of coastal wetlands and their ecosystem services could change under alternative scenarios of sea-level rise through to 2100. To simulate wetland change, we incorporated uncertainties in future sea-level rise, elevation data and other biophysical parameters within the Sea Level Affecting Marshes Model 6.2 (SLAMM) (Clough, Park, Polaczyk, & Fuller, 2012). SLAMM simulates the key processes driving coastal wetland conversions under sea-level rise, including uplift and subsidence, salt water intrusion, tidal ranges, erosion and sedimentation, wetland transition dynamics, and physical barriers to these dynamics (Clough et al., 2012). We sampled from a probability distribution of each SLAMM input parameter to produce 804 simulations of future wetland change in 2100. We then mapped the distribution of blue carbon sequestration (Table S2) and nursery habitat for fisheries for each of the SLAMM simulations (Supplementary Information).

To apply our problem formulation (Equation 1), property boundaries were used as the spatial unit for analysis (i.e. the units represented by the decision variable vector **x**), and each property parcel was either set aside for wetlands (i.e. protected, taking on an acquisition cost, c_i), or assumed to be lost to future development ($x_i \in \{0,1\}$) (Supplementary Information). The total budget, B, was set to AUD$50 million, which represents *c*. 3% of the total land value in the study area and was considered to be a modest budget for addressing this problem.

Specific connectivity requirements for coastal wetlands under sea-level rise were also incorporated. In reserving a parcel, the connectivity constraint ensured that neighbouring seaward parcels were also preserved, to allow for the process of wetland migration. Specifically, M_i was used to define the set of neighbours adjacent to property i that had wetlands present in a previous year (based on mean year of first occurrence from the SLAMM modelling). The parameter m was specified as $0.5^*|M_i|$ (half of the number of neighbours of planning unit i). This meant that planning unit i could be selected only if *at least half* of the neighbours are selected. $0.5^*|M_i|$ was chosen to strike a balance between ensuring connectivity while providing flexibility in reserve selection.

2.3 | Targeting strategies

We optimised for three conservation objectives in the year 2100: wetland area (ha), blue carbon sequestration (Mg CO_2/year), and nursery habitat (ha). Each of the 1,225 planning units had 804 estimates of each of these three objectives in 2100, arising from the SLAMM scenarios. The values for each objective were standardised (Supplementary Information) to facilitate calculation of a single covariance matrix and to ensure the selected weights were comparable. Four separate targeting strategies were developed. This included three single-objective problems where weights for the other two objectives were zero (wetlands only, blue carbon sequestration only and nursery habitat only) and a problem in which all three objectives were equally weighted. In order to quantify the trade-offs among pairs of objectives, we also solved the problem across a wide range of weights among objectives. λ was iteratively changed to evaluate different decision maker risk preferences.

For comparison, we also developed conservation plans for each of the four primary targeting strategies based on the means of each of the IPCC projections of sea-level rise (i.e. Representative Concertation Pathways [RCP] 2.6, 4.5, 6.0 and 8.5), rather than the

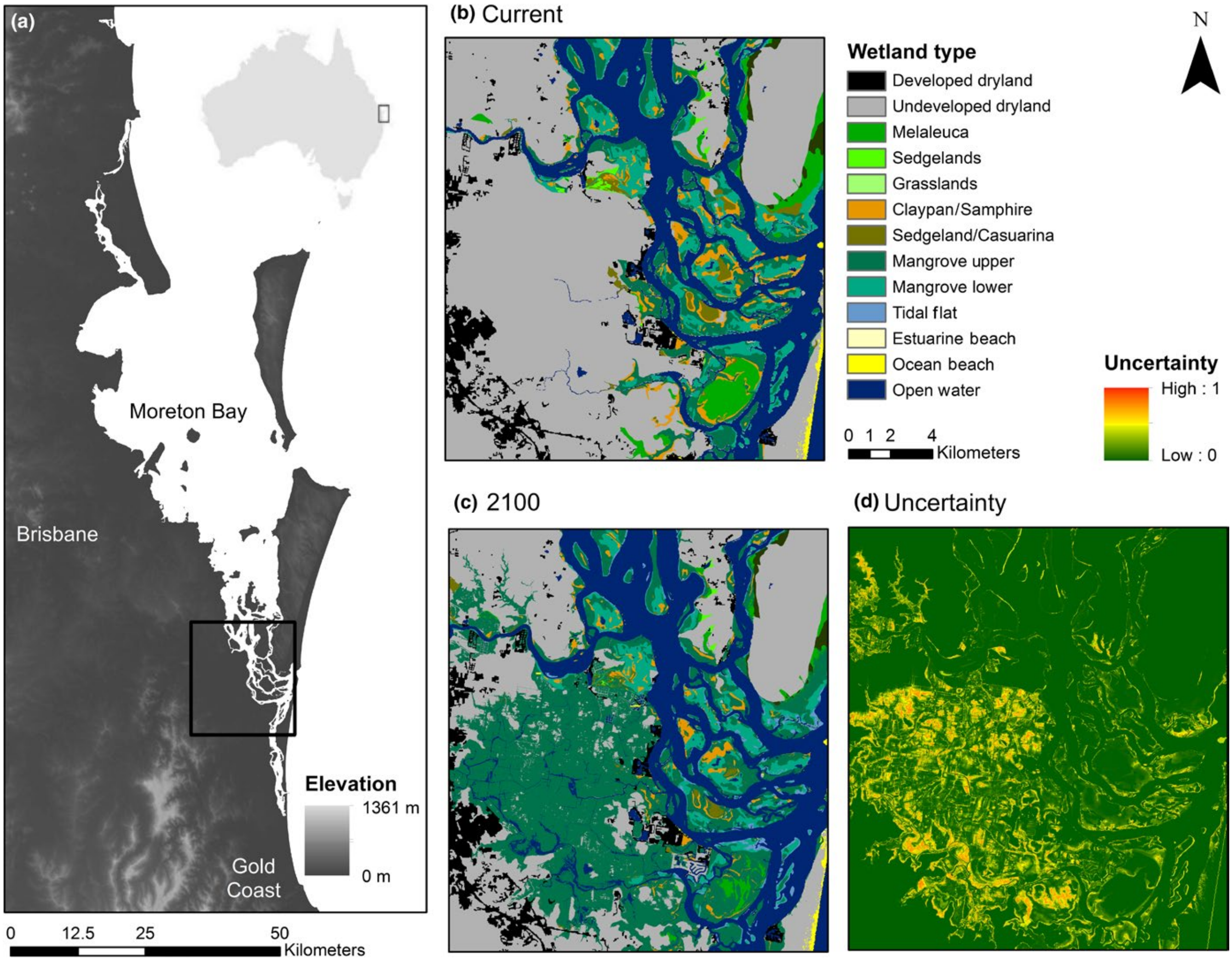

FIGURE 1 Coastal wetland change under sea-level rise for Moreton Bay, Queensland, Australia. Panel (a) shows the location of the study site from 153°14′49″E – 153°26′36″E to 27°38′59″S – 27°50′15″S. Panel (b) shows the current distribution of wetlands, and (c) shows the average (mode) wetland type projected to occur in 2100. The uncertainty in allocating each pixel to dryland, wetlands (any type) or water is shown in panel (d) and described in the Supplementary Information

distributions. These scenarios were also based on the means for all other parameters in SLAMM (from Table S1). Here we sought to maximise the conservation objectives without consideration of risk to characterise a more typical conservation planning approach (i.e. λ was set to 0, representing a risk-neutral decision maker).

3 | RESULTS

3.1 | Wetland and ecosystem service change

We found that there was a substantial change in the distribution of wetlands in 2100 under sea-level rise, with mangroves migrating landward, replacing saltmarsh, *Melaleuca*, and dryland areas (Figure 1b and c, Figure S1). However, there was also considerable uncertainty surrounding these future distributions (Figure S1). Spatially, the highest uncertainties occurred at the lowest and highest elevations of the future wetland distribution due to potential losses (continual inundation) and gains (landward movement) in the coastal wetland extent (Figure 1d). This variation in the future extent and type of coastal wetlands also affected the ecosystem services that flow from these wetlands, which exhibited even greater variation than the distribution of wetlands (Figure 2). The greater variation in ecosystem services is to be expected as the calculation of blue carbon sequestration and nursery habitat propagated additional uncertainty from the wetland distributions.

3.2 | Risk-return trade-offs

We found that reductions in the risk of the final solutions were possible, but this came at the expense of reduced ecosystem service returns (Figures 3 and 4). For example, relative to a risk-neutral solution ($\lambda = 0$; Figure 3), a 49.8% reduction in the variance of the solution can be achieved for a 25.3% reduction in expected returns ($\lambda = 3 \times 10^{-5}$; Figure 3). Reducing risk also changed the spatial configuration of the reserve network considerably (Figure 3). Selecting combinations of properties that were negatively correlated or uncorrelated with reduce risk drove these changes, and often resulted in more expensive properties being purchased at the expense of a larger area being protected. While targeting all objectives simultaneously may be ideal, in our study area targeting any of the objectives individually still achieved solutions that were relatively close to combined multiobjective solutions (Figure 3a). This is expected, given that the initial expected value of wetland

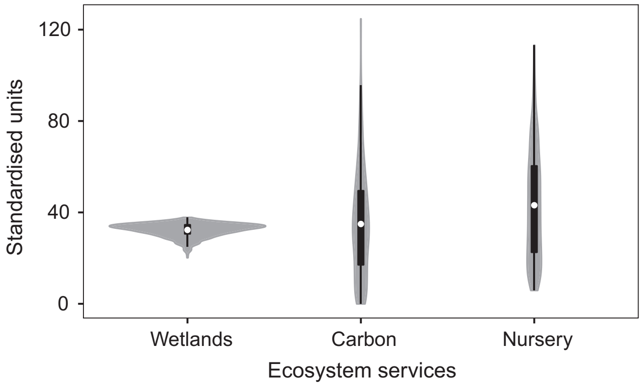

FIGURE 2 The variation in the total amount of ecosystem services provided by the study site in 2100. "Wetlands" refers to wetland area, "carbon" refers to blue carbon sequestration and "nursery" refers to the nursery habitat value. The units for each ecosystem service were standardised by the range of the expected (mean) returns over the 804 scenarios. White circles indicate the mean, the black rectangle indicates the interquartile range and the black line represents the range less outliers. The grey shading shows the distribution of values

area and blue carbon sequestration in 2100 were highly correlated ($R^2 = 0.95$). However, optimising only for nursery habitat identified solutions further from the combined multiobjective solutions, as the locations that provided nursery habitat were more constrained (i.e. along the land–ocean interface) than the other two objectives. Importantly, the variation in returns resulting from risk aversion far exceeds the differences in returns resulting from alternate weighting of objectives. The optimisations based on deterministic modelling of sea-level rise produced high expected returns, but were also the highest risk strategies irrespective of which RCP scenario informed the optimisation (as seen in the overlapping points in Figures 3 and 4).

3.3 | Relationships among services

We found that even though our three conservation objectives were largely synergistically provided in the landscape, there were still some trade-offs among objectives. Although blue carbon sequestration and wetland area exhibited negligible trade-offs at all levels of risk (Figure 5a), optimising for nursery habitat area somewhat competes with wetland area (Figure 5b) and shows a clear trade-off with blue carbon sequestration (Figure 5c). In all cases, the relationships among conservation objectives were relatively insensitive to different levels of risk; however, intermediate levels of risk produced wider Pareto frontiers, indicating a larger trade-off space (Figure 5). Lower levels of risk restricted the range of optimal planning unit combinations, narrowing the trade-off space, while higher levels risk forced solutions towards the cheapest planning units with the highest expected returns, resulting in more similar planning unit combinations in the solutions across the range of weights.

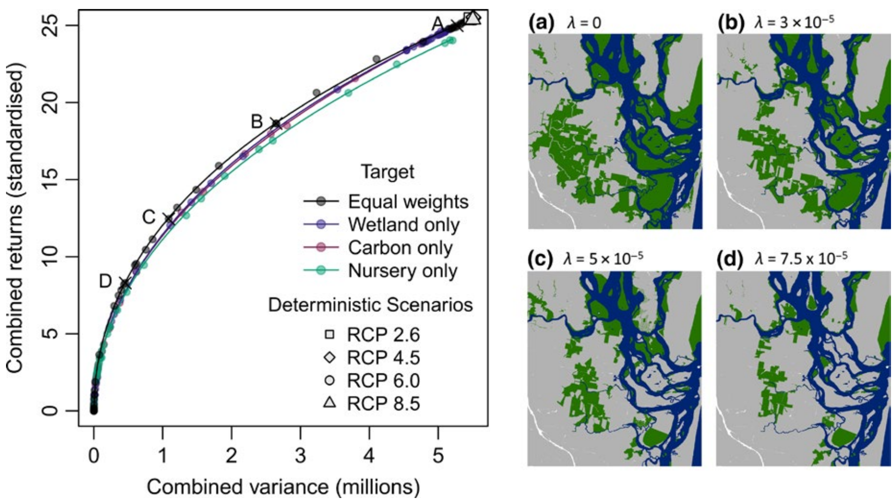

FIGURE 3 Risk-return trade-off curves (or Pareto frontiers) under different conservation targeting strategies. Each point represents a potential reserve network, and moving left along a curve indicates increasing risk aversion (λ). The curves approach, but do not reach, zero variance. The spatial distribution for four points along the curve are illustrated, with green representing selected properties, blue representing (current) water and grey showing unselected properties. The risk and expected return of the scenario-based approaches targeting wetlands are also shown

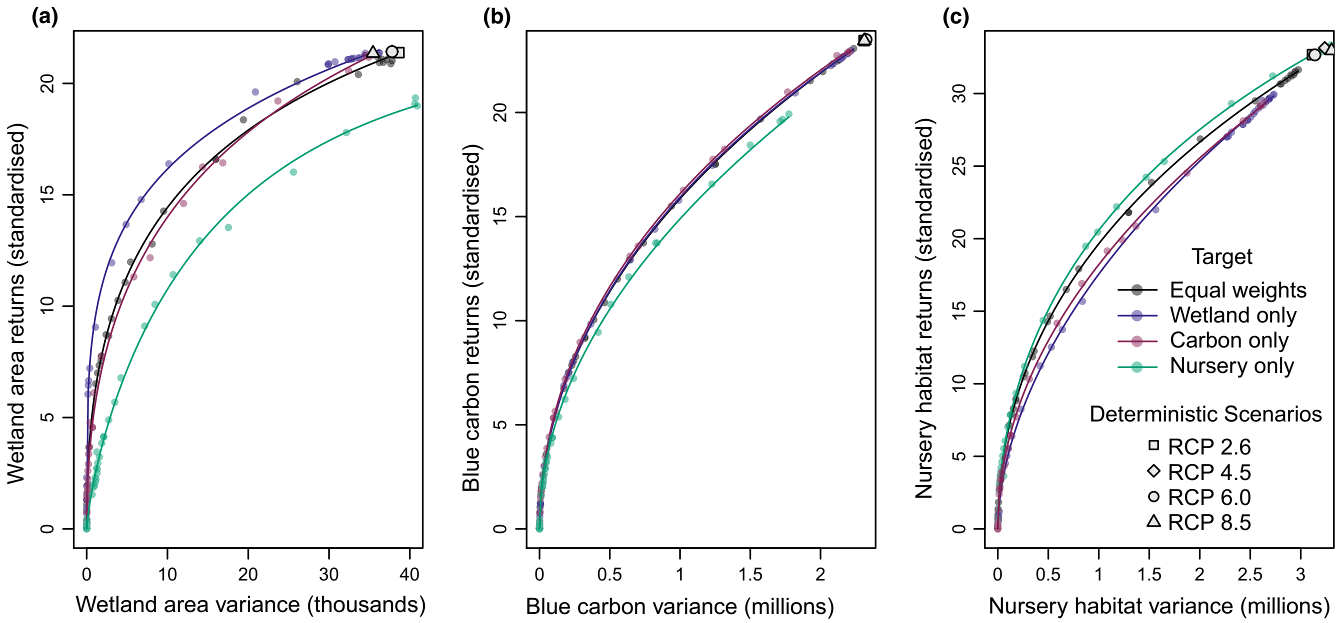

FIGURE 4 Risk-return trade-off curves (or Pareto frontiers) for different targeting strategies against each individual objective: (a) wetlands, (b) blue carbon and (c) nursery habitat. Each point represents a potential reserve network, and moving left along a curve indicates increasing risk aversion (λ). The curves approach, but do not reach, zero variance. The risk and expected return of the deterministic scenario-based approaches are also shown in each panel (falling in the upper right)

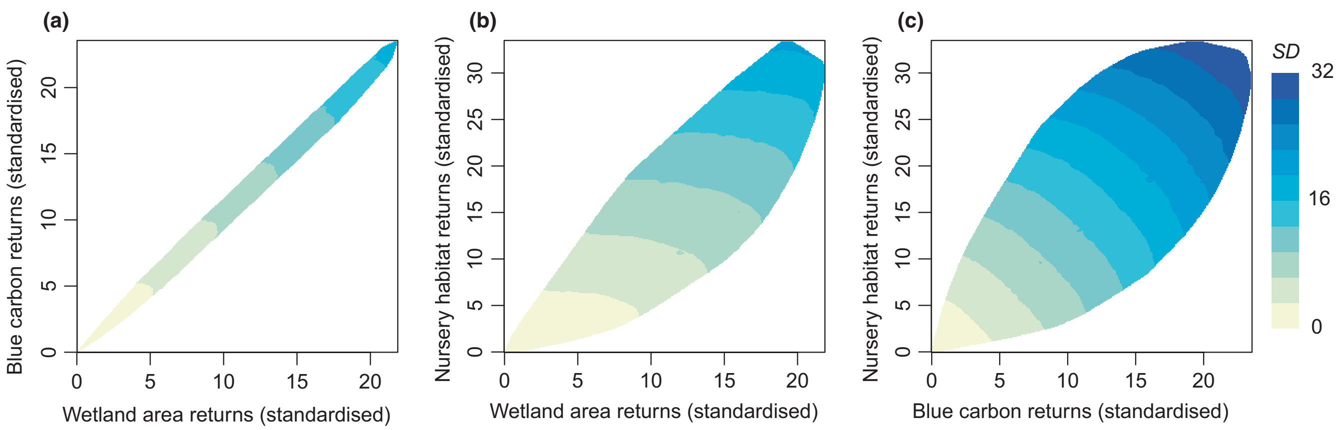

FIGURE 5 Risk and relationships among (a) blue carbon and wetland area, (b) nursery habitat and wetland area and (c) nursery habitat and blue carbon. Risk is represented by the standard deviation across all solutions, with contour lines showing different risk thresholds

4 | DISCUSSION

Developing conservation plans that are successful under uncertain patterns of ecosystem change and incorporate multiple objective require innovative planning approaches. Here, we advanced concepts from Modern Portfolio Theory (Markowitz, 1952) to a reserve selection problem (Beyer et al., 2016). Rather than allocating a fraction of the project budget to each planning unit (Ando & Mallory, 2012), we framed investment in each planning unit as a binary decision, a common formulation of conservation planning problems (Ball et al., 2009). We also incorporated connectivity requirements among planning units to ensure that important functional connectivity between current and future wetland areas was maintained, and included multiple conservation objectives. This novel problem formulation allows the selection of a complementary set of connected planning units that maximise a set of conservation objectives while hedging risk under climate change uncertainty.

Planning based on only the most severe climate change scenario (i.e. the highest rate of sea-level rise) resulted in a high-risk outcome compared to risk-averse optimisation (Figures 3 and 4). In fact, the risk was similarly high across all deterministic optimisations (Figures 3 and 4). This is because planning based on deterministic scenarios do not account for the covariance of benefits among planning units, and are therefore unable to select a complementary set of sites to minimise risk. As such, planning for only the worst-case climate change scenario is unlikely to reduce risk in conservation contexts where the impacts of climate change on species, ecosystems and their services vary spatially over different climate change scenarios. In these cases, risk-sensitive conservation planning is needed to reduce risk to the desired level and ensure the continued provision of biodiversity and ecosystem services (Reside et al., 2017).

We found that the variation in returns arising from increasing risk aversion far exceeded the differences in returns resulting from alternate weighting of objectives (Figures 3 and 4). In our study, all targeting strategies were a relatively good substitute for each other across the spectrum of risk aversion. However, targeting an individual conservation objective may not be a good surrogate for others where there is strong competition among species, ecosystem services or other objectives. For example, when incentivising terrestrial restoration actions for biodiversity and carbon sequestration objectives across Australia, targeting only carbon delivered poor outcomes for biodiversity (Bryan et al., 2016). In these cases, the level of risk aversion may also influence the extent of the trade-offs among objectives.

It has been argued that the issue of "complete markets" has limitations for the spatial application of Modern Portfolio Theory because any level of return can be guaranteed in a complete market, thus unrealistically removing all risk (Mallory & Ando, 2014; Shah et al., 2017). Specifically, Mallory and Ando (2014) reason that in order to avoid producing a complete market, the number of future scenarios modelled (N) must always exceed the number of planning units (assets), such that there can never be more than $N - 1$ planning units (Mallory & Ando, 2014). However, our problem formulation has several characteristics that ensure the "market" is incomplete, thus not requiring a consideration of this constraint. Complete markets do not only require that the number of assets are at least equal to the number of modelled future scenarios but also that the markets are frictionless (i.e. no transaction costs) and that assets are perfectly divisible (Cutland & Roux, 2013). In contrast, our problem formulation has a binary constraint on the selection of any planning unit, meaning that our "assets" are not divisible, precluding the existence of a complete market. In addition, complete markets typically require that the short-selling of securities is possible (Arrow & Debreu, 1954), yet our binary decision variable excludes negative allocations. The additional requirement of some degree of connectivity among planning units (assets) adds further constraints.

Furthermore, although Mallory and Ando (2014) argue that a key issue with the existence of a complete market for the application of Modern Portfolio Theory is that any level of return can be obtained with certainty, this is only true if initial wealth is unconstrained (Flood, 1991). Risk-return trade-offs for an individual investor still exist in complete markets when there is an investment budget (i.e. constrained wealth), which is the case for all practical conservation planning applications. While the mean expected returns can be obtained with certainty in a complete market, achieving returns between the mean and maximum expected returns is not risk-free, with a trade-off between risk and expected returns. Depending on the characteristics of the problem, risk-free returns could also be obtained in an incomplete market (although this is not guaranteed). Furthermore, portfolio theory is regularly used to hedge against risks in complete markets within the operations research and finance literature (e.g. Lim & Zhou, 2002). Consequently, complete markets are unlikely to be an issue for most conservation planning applications of Modern Portfolio Theory that aim to identify trade-offs between risk and returns.

Whether the "market" is complete or not, Modern Portfolio Theory is only able to hedge against the risks as they are modelled (Dunkel & Weber, 2012), which would rarely represent all possible risks. Consequently, in applications of our approach, it is important to check for risk-free solutions and consider whether this is realistic for the application. While diversification is still useful across a small number of scenarios, including more modelled future scenarios is likely to better characterise the risks, particularly if the scenarios include uncertainties from multiple sources.

The key uncertainties we incorporated into our models and optimisation were based on the best available information for our study region. Uncertainty was incorporated into a coastal impact model (SLAMM; Clough et al., 2012) via a Monte Carlo simulation approach that included probability distributions for all input parameters. The combination of this recent functionality in SLAMM and our novel problem formulation could be of major benefit to coastal conservation planning in the region of our case study and elsewhere. Yet the characterisation of these probability distributions was inexact and they may change as more information becomes available. Reductions in uncertainty for key parameters, such as future rates of sea-level rise, would be useful for projecting future wetland distributions and planning for them (Chu-Agor, Muñoz-Carpena, Kiker, Emanuelsson, & Linkov, 2011; Runting, Wilson, & Rhodes, 2013).

Nonetheless, the absence of perfect information does not justify delaying the formulation and implementation of climate adaptation plans (Grantham, Wilson, Moilanen, Rebelo, & Possingham, 2009), particularly when known uncertainties have been accounted for when formulating the plan. Importantly, we note that our approach does not include unknown unknowns, which may have catastrophic impacts (Makridakis & Taleb, 2009), such as the impacts of severe storms or droughts which can influence the distribution of coastal wetlands (Gilman, Ellison, Duke, & Field, 2008). Info-gap decision theory attempts to deal with this issue (Kujala et al., 2013; Moilanen et al., 2006); however, even this method has been criticised for starting from a best estimate and not considering all possibilities (Sniedovich, 2007). Methods are emerging to incorporate deep uncertainty in a spatially explicit manner (e.g. Gao et al., 2016), but further development is needed for combining probabilistic information (known unknowns) with methods for dealing with unknown unknowns.

We have assumed here that conservation returns (and risks) are realised if the planning unit is selected (i.e. protected) and lost otherwise. While this is a reasonable assumption for our application, which faces high urban development pressure (Department of

Infrastructure and Planning, 2009; Runting, Lovelock, et al., 2017), it is unlikely to always be appropriate. In many cases, unprotected areas still have conservation values, particularly when the alternative uses do not completely degrade habitat. Likewise, protected areas may not completely preserve conservation values, particularly if they are inadequately managed (Geldmann et al., 2013). Ideally, in these cases the counterfactual (i.e. the most likely alternate use) and the expected outcome under protection would be adjusted to reflect these realities. In addition, it may be relevant in some cases to plan for multiple zones for different conservation management actions or land/sea uses (Watts, Ball, & Stewart, 2009). Future work could extend our problem formulation to address these issues by incorporating more nuanced counterfactuals and multiple planning actions.

We employed a mean-variance approach to account for the uncertainty in sea-level rise projections and other model inputs. However, the mean-variance approach may be insensitive to highly skewed distributions, or may not closely match the manner in which the decision maker thinks about risk (Dunkel & Weber, 2012). In such cases, the objective function may need modification to reflect the decision maker's perception of risk. For example, Shah and Ando (2015) developed a problem formulation to optimise conservation investment among regions where the decision maker is particularly averse to returns below the amount given by the current climate in each region (i.e. downside risk aversion). This approach has similarities to some applications of info-gap decision theory (Moilanen et al., 2006), but differs in that it explicitly incorporates the probability distribution of risks and covariance among sites. Incorporating downside risk (and choosing a threshold for downside risk aversion) is dependent on the context of the analysis and preferences of the decision maker, so it is not appropriate for all cases. However, incorporating different risk functions into our approach would be highly beneficial for generalising its use across different applications.

5 | CONCLUSIONS

Guiding principles for conservation planning under climate change include expanding reserve networks to accommodate future impacts, increasing connectivity, and including a diversity of sites to ensure resilience and complementarity (Lawler, 2009). Here we have adapted Modern Portfolio Theory to a reserve selection problem that simultaneously incorporates these principles for multiple conservation objectives while accounting for uncertainty. Our application to coastal planning under sea-level rise showed that a diversification of site selection could ensure ecosystem service supply with relatively low risk of failure across all climate scenarios, and that that ignoring uncertainty was a high-risk strategy. This application addresses risks arising from sea-level rise and uncertainties in model parameters, but these are not necessarily the only potential applications. Other threats to ecosystems and their services, such as fire and land-use change, can have spatially variable and uncertain impacts across scenarios and could benefit from the explicit consideration of risk. Additionally, this approach is not restricted to designing reserve networks: it could similarly be used to design plans for multiple conservation actions, such as restoration or the control of invasive species. Although reducing the risk of any conservation plan will inevitably trade-off with its expected returns, accounting for risk can identify how to improve the resilience of the solution through diversification and help ensure the continued supply of ecosystem services into the future.

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AUTHORS' CONTRIBUTIONS

R.K.R. and J.R.R. conceptualised the ideas; R.K.R., Y.D., J.R.R. and H.L.B. developed the problem formulation; R.K.R. and C.E.L. parameterised SLAMM; R.K.R. conducted all analyses, with all authors interpreting the results; and R.K.R. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

DATA ACCESSIBILITY

Simulations of the distribution of wetlands under sea-level rise in 2100 (from SLAMM) are available in the University of Queensland eSpace repository https://doi.org/10.14264/uql.2018.354 (Runting et al., 2018).

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SUPPORTING INFORMATION

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