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ORIGINAL ARTICLE

A decision analysis approach to climate adaptation: a structured method to consider multiple options

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Abstract Decision-making for climate adaptation operates in an uncertain environment. Formal processes to decision-making under uncertainty weigh the ability of a decision rule to achieve multiple and sometimes conflicting objectives in an evaluation procedure. Increasingly, computer simulation models are being applied for this reason, so that the effectiveness of decisions can be evaluated before actually implementing them in reality. In this paper, we develop a simple stochastic simulation model of beach recession under climate change in Australia and evaluate decision rules for beach replenishment in the context of three management objectives: (i) to reduce beach recession, (ii) reduce variation in beach recession, and (iii) do so cost-effectively. Results indicate that a decision to intervene and replenish the beach based on a trigger level would be effective at maintaining shoreline position, with relatively little variation, but did so at a relatively high cost of multiple interventions. A decision procedure to intervene at a fixed period resulted in greater shoreline position variation but constrained management efforts and costs. This structured approach offers an evidence-based process to decision-making that lays bare the assumptions upon which decisions are made. This, in turn, allows for a more complete analysis of all the uncertainties and better outcomes.

Keywords Simulations · Decision analysis · Adaptation pathway · Sea-level rise · Climate change · Beach recession

1 Introduction

Policy planners and decision-makers around the world are required to consider the implication of adapting to the impacts of human activity. The science required to support robust planning,

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policy, and decision-making in the context of multiple sectors of society is relatively nascent, but progress is being made in characterizing the performance of different options in relation to climate adaption under uncertainty (Groves and Lempert 2007). One of the big challenges is that climate change adaptation decisions are made with incomplete system understanding and incomplete knowledge about the consequences of implementing different adaptation options (Daron 2014). The need to combine quantitative data with qualitative understanding and competing environmental, socioeconomic, and political factors all pose significant obstacles to adaptation and require decision makers to make trade-offs (Daron 2014). Because of this complex decision space, it is often difficult to know how to make decisions that are rational and scientifically defensible.

Combining information about global and regional climate change with local environmental and socioeconomic factors creates a cascade of uncertainty that can overwhelm decision makers, leading to decision paralysis (New and Hulme 2000). Several approaches have been developed independently over the past two decades to assist decision-making in complex dynamic systems. These approaches, termed robust decision-making (RDM) (Lempert and Collins 2007) and management strategy evaluation (MSE) in natural resource management (Sainsbury et al. 2000; Bunnefeld et al. 2011), both attempt to provide a method in which decision makers can maintain flexibility in decision-making over time in order to consider new information as it becomes available. This ability to change decisions as needed is thought to assist in the decision paralysis which prevents decisions from being made. As a heuristic decision framework, these approaches are compliant with the International Standards Organization standard for environmental management (ISO 14000) plan-do-check-act and have been adopted by adaptation scientists in framing and managing climate risk by wrapping the decision-making process into a computer model (Dessai and Wilby 2011).

The decision-making process captured by RDM and MSE has three main requirements: (i) a set of goals or objectives for making a decision; (ii) a set of alternative choices, actions, or decisions taken to achieve the objectives, and (iii) some understanding of how each action is able to meet the specified goals or objectives, often summarized in a model (Hammond et al. 1999). In many cases, this model can be mental, mathematical, or computer generated. Computer simulation models are increasingly used where there is great uncertainty associated with the outcomes of decisions, which complicates mental and simple mathematical models. Stochastic simulation models are used widely in coastal management (Jongejan et al. 2011), natural resource (Punt and Hilborn 1997), conservation management (Harwood 2000), and health (Muenning 2008) and are used by decision analysis processes like RDM and MSE to show trade-offs in achieving management objectives under different management actions (Mapstone et al. 2008). The benefit of such an approach is that a formal mathematical and computer representation can explicitly address a broad range of uncertainty in the decision-making process and show the effect of uncertainty (Callaghan et al. 2013; Fulton et al. 2011). A further advantage is that these models facilitate an engagement process with multiple stakeholders by showing how actions or decisions are able to meet the objectives of other stakeholders and the necessity of accepting trade-offs in stakeholder objectives when deciding a course of action (Boschetti et al. 2010). Computer models are able to encapsulate the current understanding of processes and show how actions and decisions affect the processes and objectives of other stakeholders. Where uncertainty in the process exists, alternative models can be examined and the effect of decisions evaluated under different hypothetical conditions. Such an evaluative process may not only help to choose an action, but it may also help to choose a course or sequence of actions (Bunnefeld et al. 2011) as many decision processes occur continually, as information or data are gathered, and actions are taken based on decision rules. Plaganyi et al. (2013), for example, developed a computer simulation of béche-de-mer (sea cucumber) harvesting by the local islanders in the tropical Australian Torres Strait and evaluated different rules for managing the system including what types of monitoring and adaptive feedback are needed to manage the risk of climate change.

Here, we link the concept and methods associated with RDM and MSE into a coastal decision-making application using publicly available data provided on coastal climate risk. We show how a decision support framework like RDM or MSE can add value by modeling the effect of management control processes and weighing the trade-offs between cost and actions. While there are a number of complex tools in existence for decision-making, we aim to show how local decision makers can use increasingly available public on-line data for informing and managing climate risk.

Such an approach is capable of evaluating risk management strategies and pathways in a broader climate adaptation context because it provides an evidence-based practice to decision-making and determine defensible and transparent climate adaptation responses. Here, we apply this method to a commonly faced problem in many seaside communities: shoreline recession from sea-level rise. We outline a simple approach to assess a range of decision rules available to local councils dealing with issues of shoreline recession under present and future sea-level rise. We then apply it to show the utility of such models in defining the potential uncertainty of outcomes and their efficacy in decision-making scenarios.

2 Methods

2.1 Defining the problem

Global sea-level rise will likely initiate or accelerate coastal recession (Ranasinghe et al. 2012) through the physical removal of sediment by wave action, depositing the material further offshore. Highly urbanized coastal locations are widely perceived to be on the front line for climate change because increased frequency and magnitude of coastal storm events and sea-level rise pose direct, near-term threats to property, infrastructure, and economic activity (Beach 2002; Collins 2009; IPCC 2012). Increasing sea-level rise and extreme storm events will cause damage to important coastal infrastructure, and the loss of land for community-desired uses affects coastal planning decisions and quality of life (Adger et al. 2009; Milligan et al. 2009; Rosenzweig et al. 2011). Adaptation assessment approaches that clearly present the probability of climate effects, the utility of various adaptation options, and the timing and costs of implementation will allow managers to consider the range of options available to protect threatened coastlines.

Many beach areas are expected to recede in the coming decades. This poses a large socioeconomic risk to coastal communities and the economic revenue expected from beach tourism (Nicholls et al. 1995). Coastal land loss can be prevented through a range of options, but one of the most often considered ones is that of artificial beach nourishment, a well-known technique that has been extensively discussed in the context of sea-level rise (Nicholls et al. 1995; Smith et al. 2009). Here, we focus on the adaptation option of coastal nourishment, where coastal land loss is combatted by replacing lost sand on the beach by pumping new sand (usually from offshore).

2.2 Defining the management objectives

Operational objectives of coastal management for beach recession are not well defined at the scale of local councils, where climate adaptation decision-making is needed. This is because there is usually more than one objective with broad stakeholder interests, as well as a range of values to consider. Defining policy objectives, which embody societal and stakeholder values, operationally in terms of quantitative performance indicators, is critical to successful climate adaptation planning because performance indicators measure whether objectives are achieved. We provide three simple objectives and associated performance indicators. Such criteria speak to many of the needs of local councils.

Objective:

1. Low frequency of management interventions—each management intervention has a specific financial cost, and this cost compounds as the number of interventions increases. Reducing the number of interventions will help keep costs low. The performance indicator used to capture this objective is the number of interventions over a 90-year forecast period (between 2010 and 2100).
2. Maintain shoreline position over time—local councils, residents, and stakeholders generally desire to keep shoreline position as close to a reference level as possible in order to provide this amenity for local communities as well as to attract tourism and the economic benefits of tourism in the local area. This objective desires to keep shoreline position as close to 2010 levels as possible, with the performance indicator measuring the average beach recession between 2010 and 2100.
3. Minimize the variation in shoreline position over time—given that shoreline position will vary according to stochastic fluctuations, trends in recession, and management intervention, this objective requires as low variability in shoreline position as possible over the time period of 2010 to 2100 to ensure that local communities and tourists are able take advantage of this natural amenity continuously. The performance indicator for this objective measured the maximum amount of recession between 2010 and 2100.

2.3 Defining the possible actions

Courses of action in adapting to climate change require understanding realistic possibilities. For the problem of beach recession, we examined three alternative decision procedures for beach replenishment that could be used to achieve the specified objectives listed above. For comparison purposes, we also examined the possible outcome if no action was taken. The three types of decision rules for managing beach recession in the model were as follows:

Decision rule 1—beach replenishment to move shoreline position a fixed amount is made at fixed intervals. Three amounts of beach replenishment at two time intervals were considered:

1. 1 m of replenishment every 20 years
2. 5 m, every 20 years

3. 5 m, every 50 years
4. 10 m, every 50 years

Decision rule 2—beach replenishment is performed to the initial shoreline position based on a defined trigger level of recession. The modeled trigger levels of recession were as follows:

1. 5 m
2. 10 m
3. 20 m

This management decision rule considers that replenishment may occur fewer times initially, thereby cutting down costs of replenishment, but as sea-level increases and more extreme storms occur, it is expected that the frequency of exceeding the trigger level that initiates beach restoration would result.

Decision rule 3—fixed period of beach replenishment of a variable amount (restored to the initial shoreline position). Because the response to a specific trigger level may only work for a certain period of time before it becomes too frequent to be cost-effective, a more flexible option that replenishes the beach to its original state at fixed intervals was examined. The intervals for beach restoration were as follows:

1. 20 years
2. 30 years
3. 40 years
4. 50 years

As the amount of beach recession increases due to sea-level rise and more extreme events, the amount of replenishment will have to increase as well.

2.4 Determining the consequences

An evidence-based approach to climate adaptation decision-making ultimately requires some sort of evaluation of the possible actions: weighing one action against another. In order to determine the consequences and, thus, the effectiveness of the management actions, a model is required. We developed a simple stochastic simulation model of beach recession and the management response.

This model was constructed to project coastal beach recession based on data derived from the sea-level rise calculator Canute (http://canute2.sealevelrise.info/; Mariani et al. 2012) for rhythmic bar and beach in New South Wales, Australia, under moderate climate impact (IPCC scenario A1B). Rhythmic bar and beach type commonly occurs around the southern Australian coast, usually consisting of relatively fine-medium (0.3 mm) sand exposed to waves. These beaches are characterized by an outer sand bar which is separated from the beach by a deep trough with converging feeder currents flowing seaward through the sand bars as a rip current (Short 2012).

Canute provides estimates of the likelihood of future flooding from the sea and also provides shoreline recession calculators to address the likelihood of coastal recession due to sea-level rise based on IPCC AR5 projections. We used the shoreline recession calculator version 2.0, which calculates shoreline recession using the Bruun model with Bruun factors calculated using XBeach (Mariani et al. 2012). Projections from the sea-level rise calculator in Canute gave average beach recession with the 5 and 95 percentiles calculated from Hunter (2010) every 10 years starting in 2010 (Table 1). These parameters were linearly interpolated every year to obtain an annual average beach recession (with 5 and 95 percentiles). A stochastic simulation model of beach recession based on these data was then specified as follows:

$$X_y = N\left(\overline{X}_y, s^2_{X_y}\right) - \sum_{i=1}^{y-1} u_i - u_y$$

where

X_y is the beach recession in year y

u_y is a control measure at year y that changes beach recession

$\sum_{i=1}^{y-1} u_i$ is the effect of all previous management control measures

$\overline{X}_y$ is the mean beach recession in year y

$s^2_{X_y}$ is the variance of the beach recession expected in year y, calculated based on the assumption that the 95 percentile is two standard deviations from the mean.

As a first approximation, we represented annual beach recession as a normal deviation around the average annual recession, $\overline{X}_y$, obtained from Canute (Cowell

Table 1 Mean projected beach (5 and 95 percentiles: $X_{0.05,y}$, $X_{0.95,y}$) recession from the sea-level rise calculator Canute by decade

Year (y)	Recession (meters relative to level in 2000) $\overline{X}_y$	$X_{0.05,y}$	$X_{0.95,y}$
2010	1	0	2
2020	3	2	4
2030	5	3	7
2040	7	4	10
2050	10	6	14
2060	13	7	19
2070	16	8	23
2080	19	9	28
2090	22	11	33
2100	25	12	37

et al. 2006). Management intervention is captured by the variable u_y for a given year, y.

2.5 Model simulations

One thousand replicate simulations of each scenario were run, and the probability density of beach recession was determined through the 90-year period from 2010 to 2100. For each decision rule, the average and variance of each performance indicator was calculated each year, across the 1000 simulations.

For each decision rule, the amount of replenishment and frequency of intervention indicate cost (see Table 2). This cost is a combination of both a fixed cost for each management intervention to replenish the beach (F) and a variable cost per meter of replenishment (V). We calculated the relative cost in each replicate simulation for each decision rule based on the ratio between $F:V$ as cost$=\sum_y e^{-\delta y}(F+Vx)$, where δ is the discount rate (0.05) and x is the amount of replenishment per management action. This cost thus incorporates the frequency of management intervention (objective 1) as well as the total amount of replenishment that would result.

Table 2 Performance summary of three decision rules against the stated management objectives defined in Sect. 2.2 and relative cost

Decision rules		Objectives			Average relative cost		
		1. Frequency of management action (2010–2100)	2. Average beach recession (m) 2010–2100	3. Maximum beach recession 2010–2100	$F:V$ 1:1	10:1	100:1
No action		0	12.02	33.23	0	0	0
1. Fixed periodic, fixed replenishment	Replenishment level; intervention period						
	1 m; 20 years	4	10.22	29.43	3.1	17.3	158.7
	5 m; 20 years	4	2.99	15.02	9.4	23.6	165.0
	5 m; 50 years	1	9.77	28.10	6.5	16.2	113.6
	10 m; 50 years	1	7.51	23.25	11.9	21.6	119.0
2. Trigger-based, replenishment to 2010 baseline level	Trigger level (m)						
	5	16.13	1.83	11.46	4.8	25.3	230.1
	10	10.65	5.31	16.46	2.0	8.8	76.9
	20	4.93	9.85	26.12	0.5	1.7	14.2
3. Fixed periodic, replenishment to 2010 baseline level	Intervention period (years)						
	20	4	3.37	16.01	3.0	8.1	58.9
	30	3	5.00	18.80	2.1	4.7	30.4
	40	2	5.60	20.07	1.5	2.9	16.7
	50	1	6.75	22.02	1.0	1.8	9.2

The performance indicators were calculated for the 90-year period of 2010 to 2100 and then averaged across the 1000 simulations. Relative cost is a function of the fixed cost for each management intervention (F) and the variable cost per meter of replenishment (V) in each intervention and was based on the relative ratio between them as cost $=\sum_y e^{-\delta y}(F+Vx)$, where δ is the discount rate (0.05) and x is the amount of replenishment per management action

3 Results

3.1 Evaluating the consequences of the decision rules

Results are shown for management actions that could be considered by a local council in deciding on a course of action to meet the main objectives. In the baseline projections (green line), there is an inflection point which represents an accelerated recession in the data used that is expected after 2040, changing from 2 to 3 m/year. In two of the four scenarios associated with decision rule 1 (Fig. 1a, b), insufficient replenishment occurred to maintain beach width, with Fig. 1a showing an average shoreline position close to a scenario where no management actions occurred (baseline). The two scenarios in Fig. 1c, d showed a greater chance of keeping recession close to 0 by the end of the 90-year period.

Under decision rule 2, the lower the threshold that triggers replenishment, the closer the average shoreline position that stays to 2010 levels (Fig. 2). The average recession under all three scenarios of decision rule 2 was generally lower than in the no-action case with lower trigger levels resulting in more replenishment events (right-side panels, Fig. 2). Replenishment also started earlier within the 90-year simulation run when the trigger level is lower (right-side panels, Fig. 2). Under decision rule 3, higher frequency intervention that restores the beach to 2010 levels kept recession relatively low compared to scenarios with lower-frequency intervention (Fig. 3).

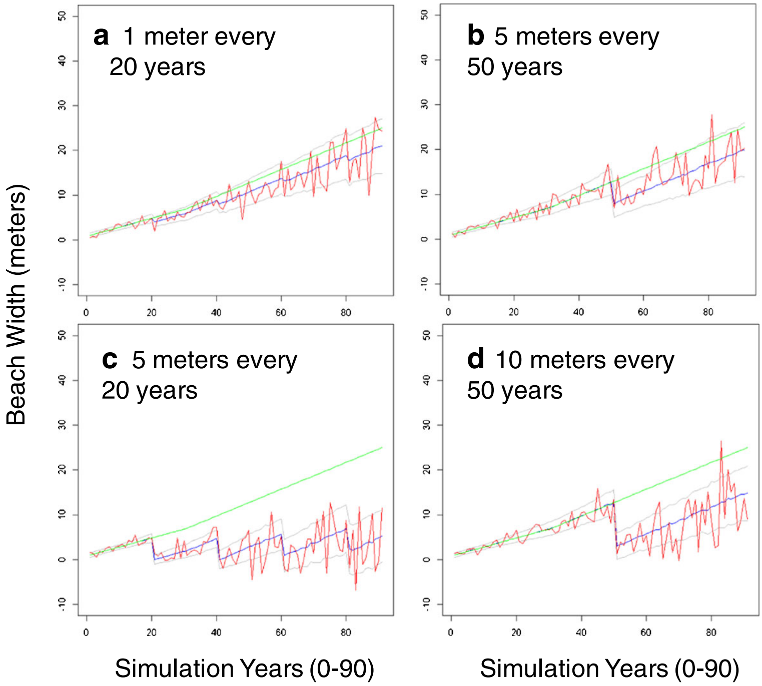

Fig. 1 Simulation figures for decision rule 1 with fixed periodic beach replenishment of a specific amount: **a** 1 m every 20 years, **b** 5 m every 50 years, **c** 5 m every 20 years, and **d** 10 m every 50 years. The amount and frequency of the replenishment may affect costs over time. *Green* is the baseline where no management actions were taken, *blue* is the average of the 1000 iterations, *grey lines* represent the standard deviation of the mean, and the *red line* represents one single example run of each of the decision rules

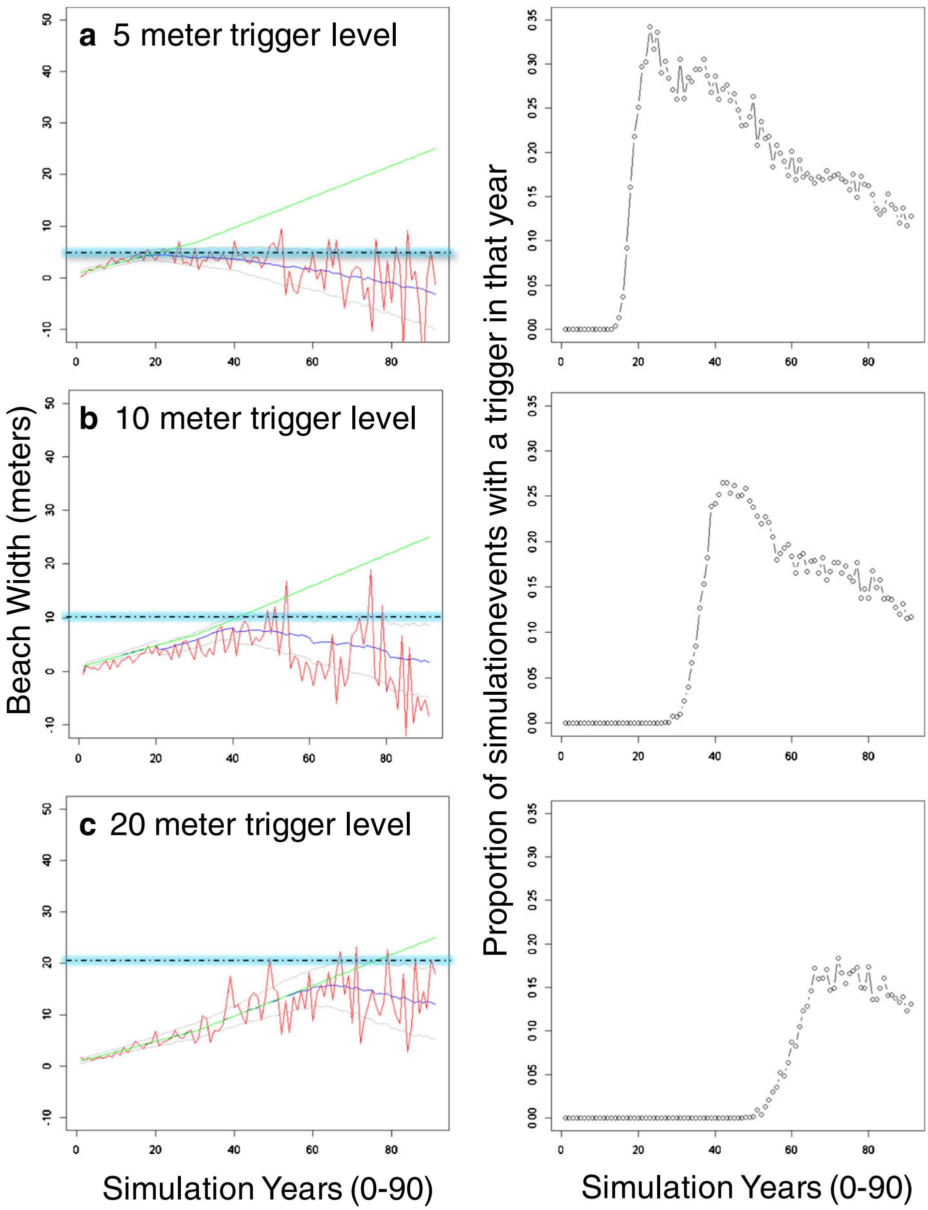

Fig. 2 Simulation figures for decision rule 2—beach replenishment based on a trigger level of **a** 5, **b** 10, and **c** 20 m. The *left column* represents the simulation data of the shoreline position with expected recession and the adaptive response. *Green* is the baseline where no action management actions were taken, *blue* is the average of the 1000 iterations, *grey lines* represent the standard deviation of the mean, and the *red line* represents one single run of each of the decision rules. The *dotted line* represents the trigger and indicates how many times the single run reached that level. The *right column* represents the proportion of trigger events that happen in each simulation year throughout the 1000 simulations. Lower triggers lead to a higher rate of trigger points in the earlier part of the 90 years but diminishes with time

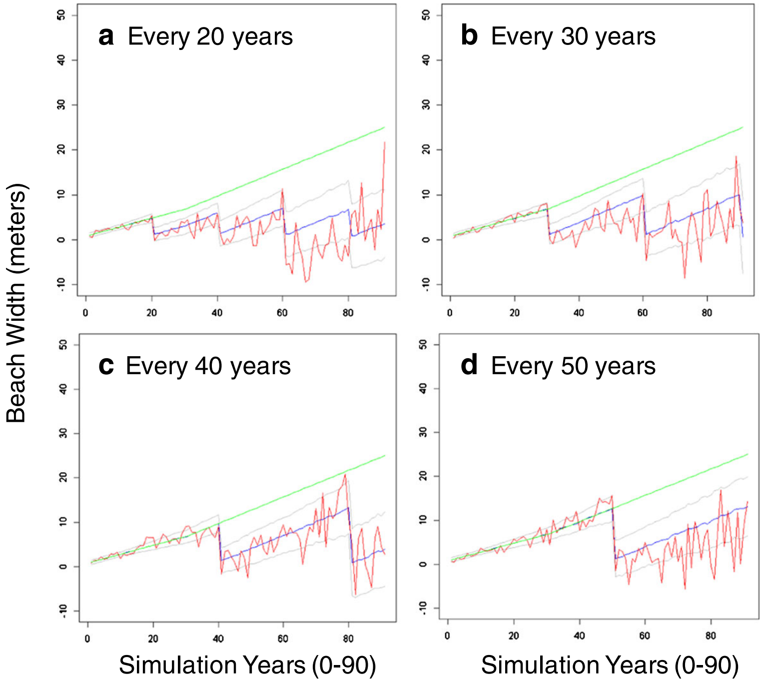

Fig. 3 Decision rule 3 based on fixed period beach replenishment to 2010 levels using **a** 20-, **b** 30-, **c** 40-, and **d** 50-year intervals. *Green* is the baseline where no action management actions were taken, *blue* is the average of the 1000 iterations, *grey lines* represent the standard deviation of the mean, and the *red line* represents one single example run of each of the decision rules

3.2 Evaluating the decision rules against the management objectives

A summary of performance (Table 2) shows how each decision rule and scenario performed according to the management objectives represented by a performance indicator. Where no action is taken, there would be an average beach recession of 12.02 m in the 90-year period of the simulation and an average maximum beach recession across the 1000 simulations of 33.23 m, but the cost of intervention would be 0.

The decision rules have varying levels of success in reaching the different management objectives. In general, there is a trade-off between management objective 1, which represents cost of intervention, and management objective 2, representing the average beach recession, and objective 3, the variability in shoreline position.

In general, with increased management intervention, the average beach recession declines, as does the variability in shoreline position. As frequency of replenishment increases, the ability to keep the shoreline position as close to 2010 levels becomes more successful. A 5-m replenishment in 20 years, for example, has lower average beach recession of 2.99 m and an average maximum recession of 15.02 m, compared to 5-m replenishment in 50 years (9.77 and 28.10 m, respectively). With low frequency and low levels of replenishment (1 m/20 years), the beach recession over time was not greatly different from the no action scenario (Table 2), potentially making such types of management interventions not very cost-effective considering the result.

Decision rules 1 and 3 perform better than decision rule 2 under the first objective mainly because they were both specified as fixed periods of intervention so that the management agency would be able to plan intervention points. Decision rule 2, however, is relatively inexpensive as long as the trigger level is not too low (Table 2).

The general relationship outlined in Table 2 is that as beach recession declines as a result of management intervention, cost increases. In general, the relationship between fixed costs F and variable costs V influences the cost of each decision rule relative to the others. For example, a small intervention (1 m) relatively frequently (every 20 years) was relatively inexpensive if the fixed costs were small relative to the variable cost (1:1) but would increase relative to the other scenarios if the fixed cost for each intervention was more expensive (e.g., 100:1).

4 Discussion

Many management problems, including those associated with climate adaptation, can be viewed as a process of continual decision-making. Decision-making, in general, has three elements: a goal or set of objectives, representing the reason that management decisions are required, a set of alternative actions or options, and some understanding of the nature of the system being managed, often summarized in a model. These characteristics are shared by a wide range of decision-making frameworks (Wise et al. 2014). In general, the mathematical theory for deriving optimal decision rules has been well developed for relatively simple problems (Bather 2000), but more complex problems have tended to replace an optimal solution with a sufficient one (Keeney and Raiffa 1976). Climate adaptation to beach recession is an example of such a problem because different stakeholders have multiple and often conflicting objectives and because the process of long-term beach recession is complex and uncertain. We show how such a complicated decision-making process can be structured and decision pathways evaluated by coupling management objectives with management actions whose effects are captured using a simple quantitative stochastic model and summarized in a decision table (Table 2).

Three adaptive management actions were simulated which monitor and act to address beach recession based on a specific decision rule, such as a trigger or fixed period and level of beach replenishment. Thus, we evaluated the ability of the management process to achieve specific climate adaptation outcomes. The weight that decision-makers attach to each of the objectives would dictate which management action should be taken. If the sole objective was to minimize beach recession with no concern for cost or frequency of intervention, then a trigger-based management with a low trigger value like 5 m and full restoration to 2010 beach levels would work best. Such a management arrangement would result in about 16 beach replenishment operations in the 90-year projection, with an average maximum recession of 11.46 m occurring in that period. Alternatively, if cost was more important and less-frequent beach replenishment was desired, say every 20 years, then the choice would be to replenish the beach at a fixed amount (1 or 5 m) or do a full restoration to 2010 levels. Each of these, in turn, has a cost trade-off in that the lower the replenishment amount and the more affordable the intervention, the greater the amount recession would be expected.

In general, there is a limited experience with beach nourishment in much of the world and, hence, few costs estimates for nourishment. A cost of US \$5/m^3 (circa 1990s) has been calculated based on locally available supplies of suitable sand or beach fill but is sensitive to availability and rises rapidly as transport distances increase (Nicholls et al. 1995). In the

Netherlands, average costs were about US \$6–7/m^3 (Hillen and de Haan 1993). The costs in Table 2 may change over time and space; thus, a more detailed comparison amongst the different options will have to be further calculated by the practitioner in a specific location.

Uncertainty complicates the ability of a decision to achieve an objective (Raiffa 1979; Peterman and Anderson 1999), and uncertainty is increasingly being considered (Stainforth et al. 2005; New et al. 2007) in climate projections and risk analyses. Several classes of uncertainty have been identified to affect decision-making (Dessai and Hulme 2004; Milner-Gulland and Rowcliffe 2007; Fulton et al. 2011). Process uncertainty is the natural variability in biophysical processes that operate at timescales too fine to capture in the mathematics or the computer. Process uncertainty was the only source of uncertainty captured in our decision analysis; it was done so as a normal deviate $N\left(\overline{X}_y, s^2_{X_y}\right)$ with parameter values inferred from simple model applications (http://canute2.sealevelrise.info/), and the results showed the effect of the random interannual variability in shoreline position.

Other sources of uncertainty that are potentially important are parametric uncertainty, which applies to the biophysical model parameters (Cowell et al. 2006), and model uncertainty, the extent to which the actual biophysical system is captured by the model (Francis and Shotton 1997). We relied on the model and parameter values based on Mariani et al. (2012) and did not include the effect of potentially realistic alternative parameter specifications or model structure representations. Such issues are increasingly addressed with Bayesian methods (Hilborn and Mangel 1997).

In circumstances where measurement and sampling are important to a management decision, observation uncertainty occurs as a result of inconsistent and incorrect measurements. Observation uncertainty was not considered to apply in this beach recession case, but it could if intra-annual shoreline position is highly variable. Lastly, decision analysis usually assumes that the decision or management action is successfully implemented. Implementation uncertainty relates to the ability of a management action to be successfully implemented (Rosenberg and Brault 1993). The decision to establish the Australian emission trading scheme (Jotzo and Betz 2009), for example, might have considered the uncertainty in its successful implementation and operation.

A structured decision analytical approach using simulation models offers an evidence-based decision-making process to climate adaptation and mitigation issues, particularly where uncertainties can influence the effectiveness of any decision. By capturing the uncertainty in the simulation model, decision analysis will indicate the conditions and the likelihood that a particular decision will work. Approaches such as RDM and MSE have had wide application because they can show associated costs and benefits of different policy options in achieving the stated objectives. Our applied example examining sea-level rise and rates of beach replenishment shows how such modeling can elucidate the trade-offs of the decision rules available to decision-makers based on range of potential outcomes from management decisions. Such insight into management outcomes will become increasingly important, as decisions are made around uncertain climate change effects. By taking into account the simple rules to guide adaptation decision-making such as having a long time horizon and taking into account the uncertainties of climate change, as well as the ability to enhance the flexibility and resilience of systems to react to and cope with climate shocks and extremes (Fankhauser et al. 1999), decision makers will be able to minimize the regret of earlier decision-making in the event of changes within the system (Weaver et al 2013).

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