Climatic Change (2011) 107:185–202
DOI 10.1007/s10584-011-0085-x

Structured decision making as a proactive approach to dealing with sea level rise in Florida

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Received: 25 May 2010 / Accepted: 31 March 2011 / Published online: 10 May 2011

Abstract Sea level rise (SLR) projections along the coast of Florida present an enormous challenge for management and conservation over the long term. Decision makers need to recognize and adopt strategies to adapt to the potentially detrimental effects of SLR. Structured decision making (SDM) provides a rigorous framework for the management of natural resources. The aim of SDM is to identify decisions that are optimal with respect to management objectives and knowledge of the system. Most applications of SDM have assumed that the managed systems are governed by stationary processes. However, in the context of SLR it may be necessary to acknowledge that the processes underlying managed systems may be non-stationary, such that systems will be continuously changing. Therefore, SLR brings some unique

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considerations to the application of decision theory for natural resource management. In particular, SLR is expected to affect each of the components of SDM. For instance, management objectives may have to be reconsidered more frequently than under more stable conditions. The set of potential actions may also have to be adapted over time as conditions change. Models have to account for the non-stationarity of the modeled system processes. Each of the important sources of uncertainty in decision processes is expected to be exacerbated by SLR. We illustrate our ideas about adaptation of natural resource management to SLR by modeling a non-stationary system using a numerical example. We provide additional examples of an SDM approach for managing species that may be affected by SLR, with a focus on the endangered Florida manatee.

Abbreviations

SDM structured decision making
SLR sea level rise

1 Introduction

The projected extent of sea level rise (SLR) along the coast of Florida represents an enormous challenge for management and conservation over the long term (IPCC 2007; Parkinson and Donoghue 2010). Although many consequences of SLR may be out of the control of decision makers, there may be great potential for managers and decision makers to adapt to potentially detrimental effects of SLR (IPCC 2007; Parkinson and Donoghue 2010). Structured decision making (SDM) provides a rigorous and transparent framework for the management of natural resources (Peterman and Anderson 1999). In the context of SLR, SDM provides a decision analytical framework that integrates scientific knowledge related to climate change and policy making. Structured decision making is a method for analyzing a decision by breaking it into its components: management objectives, potential actions, models, optimization, and monitoring (Clemen and Reilly 2001; Martin et al. 2009; Williams et al. 2002). Some of these components may also be affected by important sources of uncertainty, which need to be identified and incorporated into the SDM process (Halpern et al. 2006; Williams et al. 1996). The aim of SDM is to identify the decisions that are optimal with respect to management objectives and the current knowledge of the system (Williams et al. 2002; Martin et al. 2009). Although SDM is gaining some popularity in the conservation and management communities, few papers have discussed SDM in the context of SLR. Most applications of SDM have assumed that the managed systems are governed by stationary processes that will ultimately reach some steady state. However, in the context of SLR it may be more appropriate to account for the fact that the processes underlying managed systems may be non-stationary, such that systems will be continuously changing (Nichols et al. 2011). Although we believe that SDM is well suited to deal with non-stationary dynamics induced by SLR, it is important to be aware of some key features in order to appropriately account for continuous changes in the system state and the processes that govern system dynamics. The intent of this paper is to review some of these key characteristics and to discuss some approaches to deal with decision making in the face of SLR in Florida.

SLR brings some unique considerations to the application of decision theory to the management of natural resources. In particular, SLR is expected to affect each of the components of SDM (Nichols et al. 2011). For instance, management objectives may have to be reconsidered more frequently than under more stable conditions. The set of potential actions may also have to be adapted over time as conditions change. Models have to account for the transitory nature of the modeled system processes. Each of the important sources of uncertainty in decision processes (environmental stochasticity, partial observability, partial controllability, and structural uncertainty) is expected to be exacerbated by SLR. Finally, monitoring programs will have to be adapted in the face of SLR. Nichols et al. (2011) discuss some of these points in the context of climate change in general and then focus on the adaptive harvest management of waterfowl. Here, we focus on issues specifically related to SLR in Florida. We illustrate our ideas with specific examples of these issues considering an application of the approach to management of the endangered Florida manatee, a Florida icon that lives at the marine–freshwater interface in both natural and built waterways. The manatee is a useful example for our purposes as adaptation could proceed through direct management actions to maintain or improve survival and reproduction of individuals within the population or through actions to modify, improve, or maintain critical aquatic habitat that we expect to be affected by SLR. Critical habitat includes seagrass and freshwater aquatic vegetation for forage, freshwater for drinking, and warm-water refuges in winter to prevent mortality from cold stress (Hartman 1979). Increasing sea surface temperatures may affect manatee thermoregulation in summer, particularly in the shallow shoals where seagrass occurs. Water resources directly affect manatee habitat, and water management will play a key role in developing adaptive strategies for humans, manatees, and other species that use the same critical habitats. Water-resource risk assessment and planning, however, face large challenges due to non-stationarity in hydroclimatic processes for which changes are currently underway (Milly et al. 2008). We illustrate our ideas about adaptation of natural resource management to SLR by considering numerical examples to provide specific insights on how to implement the approaches that we describe.

2 Effect of SLR on the primary elements of SDM

2.1 Objectives in the face of SLR

Any formal decision making process requires that decision makers (with input from a larger group of stakeholders) offer a clear statement of objectives, specifying what they are trying to achieve through management actions. These objectives are based on the value judgments of decision makers, and should be expressed as quantitative measures in order to select among competing management actions and evaluate the success of the decision taken (Nichols and Williams 2006). Typically, decision makers have to identify intermediate (and measurable) *means objectives* in order to achieve some more *fundamental objectives*. For example, a fundamental objective may be to maintain the Florida manatee (*Trichechus manatus latirostris*) population above some specified size over an indefinite time horizon. Since Florida manatees need warm water habitat to survive cold winters, a means objective may be to maintain warm water capacity at some specified amount (FWRI management plan 2007). Once objectives have been identified they can then be converted into an objective function—a formal mathematical expression of values-based objectives used to quantify the benefit accrued over the time horizon of the decision problem by implementing specific actions at each time step (Lubow 1995; Williams et al. 2002; Fonnesbeck 2005).

Changes in environmental conditions may lead to changes in the means objectives, while the fundamental objectives may remain unchanged. Because of the large environmental changes that are predicted due to SLR, decision makers may have to revisit their means objectives more frequently than if the system was stationary (Nichols et al. 2011). For instance, in the manatee example, under current conditions a means management objective may be to maintain artificial warm water capacity (e.g., from power plants, see Edwards et al. 2007) above some level deemed necessary for the persistence of a desired number of manatees in a particular region. However, if SLR or other environmental changes linked to climate change result in a disruption to these artificial sources of warm water in ways that could not have been predicted, then managers may have to revisit their means objectives in order to adjust to these new unexpected conditions. For example, with SLR and saltwater intrusion, sources of freshwater for human consumption will diminish with greater demands for groundwater removal, affecting spring flow and thermal capacity at manatee winter aggregation sites (Rouhani et al. 2005; Leeper et al. 2010). Additionally, SLR could disrupt coastal power plant operations that provide artificial warm-water refuge (see Edwards et al. 2007). If some power plants have to be relocated because of SLR, the means objectives related to increasing the capacity of these particular plants become irrelevant to the fundamental objectives (e.g., meet a population target statewide). In this case new means objectives have to be identified in order to meet the fundamental objectives.

2.2 Potential actions and SLR

To achieve the fundamental objectives, a decision maker chooses from among a set of potential management actions, actions that might guide the managed system toward a desired state as defined by the means objectives. As with the management objectives, SLR can lead to the consideration of a very different set of potential management actions. For example, the habitats of several plant species in the Florida Keys are immediately threatened by SLR (Maschinski et al. 2011). Under current conditions, some of the efforts to protect some of these species are directed at controlling invasive species; however, before sea water completely floods these habitats, managers may have to consider the *assisted migration* of plants from the keys into mainland habitats (Maschinski et al. 2011). As new (unexpected) potential actions become available, it may be necessary to review and revise the complete decision process. The process of reframing the decision problem periodically has been referred to as double-loop learning (e.g., Williams et al. 2007).

2.3 Model(s) of system behavior

Model(s) of system behavior are used to predict the consequences to the system of interest of implementing any of the identified management actions. That is, models link the actions to the objectives. For example, a model is used to predict the future state of the system, x_{t+1}, based on the value of the system state at the current time step, x_t, and the action taken (decision) at that step, d_t. In the case of sequential and dynamic decisions, the decision maker may care about how value accrues over time as a series of decisions are implemented; in this case the models need to predict both the immediate return and the change in system state due to a decision at time t. Traditionally, models have been state-dependent, but not time-dependent; that is, the predicted responses depend on the current state of the system, but the dynamics are stationary across time (e.g., Johnson et al. 1997; Williams et al. 2002; Martin et al. 2009).

SLR is likely to induce changes in the dynamics of many natural systems in Florida (Noss 2011). One way to account for these changes is to include in the system model(s) one or more additional state variables that vary according to time. One of the largest winter aggregation sites for manatees in Ten Thousand Islands (TTI) area in southwest Florida is an inshore canal system that provides a halocline of warmer saltwater trapped below cooler freshwater that acts as a barrier to vertical mixing (Stith et al. 2010). Monitoring and hydrologic modeling indicate that a certain level of freshwater discharge is needed within the canal system to maintain water temperatures above a threshold that separates suitable, higher temperatures from those considered stressful for manatees. The Picayune Strand Restoration Project will redistribute freshwater discharge away from this canal system to restore sheet flow and maintain freshwater head across a portion of the TTI basin, thus helping mitigate the effects of SLR on the TTI marsh systems. In this case, the reduced freshwater discharge to the canal may affect the warm water characteristics of the manatee refugium (note that climate change may have direct effects on temperature that may also need to be considered). To reflect these temporal dynamics, either freshwater discharge or time itself can be included as a state variable in the model, and used to predict the manatee warm-water refuge temperature, as influenced by the rate of freshwater discharge. Below we provide a numerical example that illustrates how reduction in water delivery due to SLR can be incorporated into the SDM modeling framework.

2.4 Analytical method to identify optimal decisions in the face of SLR

The purpose of the optimization component of SDM is to identify decisions that are optimal with respect to the management objectives and the system model(s) (reflecting our current knowledge of the system, Williams et al. 2002). Many natural resource management problems involve sequential decisions that are linked to each other, and that also often involve large levels of uncertainty. When the management problem can be reasonably approximated with fairly simple system models and objectives, stochastic dynamic programming can provide globally optimal solutions (Bellman 1957; Clark and Mangel 2001). Interestingly, in most stochastic dynamic programming applications the managed system is treated as stationary (Anderson 1975; Johnson et al. 1997). This is because when managing natural systems one often seeks a sustainable strategy, and finding time-independent policies can be useful in this context. However, in the face of climate change, it may be unreasonable to assume stationarity, particularly when systems are changing rapidly and are expected to do so for some unknown or indefinite time horizon. Natural systems in Florida that will be affected by SLR provide a good case for considering alternative approaches to stationary solutions. For instance, one of the stated goals of the Comprehensive Everglades Restoration Project is to improve the quality of native habitats and increase diversity and abundance of native plants and animals by primarily acting on hydrology and water quality (RECOVER 2005). Because a large portion of the Everglades is predicted to be flooded by seawater within this century due to SLR, accounting for the non-stationarity of the system will be an important consideration when managing the Everglades ecosystem (Noss 2011).

2.5 Numerical example

Martin et al. (2009) described a hypothetical numerical example to demonstrate SDM in the context of sustainable resource management. Here, we modify this same example to illustrate the optimal management of a non-stationary system affected by SLR. In our example, a large wetland impoundment in coastal Florida serves dual purposes of storing water for surrounding agricultural needs and providing habitat for a species of concern. The management objectives for this wetland are to provide maximum outflow for agricultural benefit while maintaining a minimum volume of water in the wetland to ensure sufficient habitat for the species of concern. The volume of water, L, in the wetland directly affects habitat suitability and, therefore, the proportion of habitat occupied by the species (ψ_t). As described by Martin et al. (2009), managers of the wetland desire that a minimum of 30% of the wetland habitat be occupied (i.e., below a utility threshold of $\psi = 0.30$, the value of water for irrigation is greatly devalued; see *Utility function* below). At the start of year t, the wetland impoundment contains L_t units of water, which are augmented over the course of the year by p_t units of rainfall. The impoundment holds a maximum volume of $K = 2000$ units of water; any surplus water is lost. A decision is made at the start of the year to release I_t units of water for agricultural use. It may not be possible, however, to release this many units of water because the reservoir only holds K units and, in addition, there is an exogenously determined amount, O_t, of water used for non-agricultural human use. More specifically, the variable O_t reflects a new external demand on the impoundment, namely, water withdrawals for human consumption, because of salt-water intrusion into traditional aquifers due to SLR. Determining the optimal water release policy to maximize the agricultural benefits, while maintaining a minimum of 30% occupancy of our species of interest, can be accomplished by using dynamic programming for deterministic problems and stochastic dynamic programming for stochastic problems (Bellman 1957; Lubow 1995).

2.5.1 Objective function

The objective of our numerical example was to maximize irrigation while maintaining at least 30% of the sites occupied by the species of interest. We formalized our objective into a utility function, which describes the value (return) associated with the annual decision to release I_t units of water for agricultural purposes:

$$U_t = \begin{cases} 0, & \psi_{t+1} < 0.3 \\ R_t, & \psi_{t+1} \geq 0.3 \end{cases} \text{ with } \quad R_t = \min\left(\max\left(0, \min\left(K, L_t + p_t\right) - O_t\right), I_t\right) \tag{1}$$

This expression states the utility value at time t (U_t) of the decision depends on the state of the system at time t (water levels (L_t) and the expected proportion of sites occupied after the decision is taken (ψ_{t+1})) and on the decision that was taken at time t. The utility is equal to R_t (the amount of water made available for agriculture) if the decision is expected to maintain occupancy in the wetland at or above 30% in the following year, given the current year's available water, L_t. If occupancy is predicted to fall below the utility threshold of 0.30 (i.e., if the proportion of sites occupied is less than 30%), the value of the water released for irrigation is equal to zero. The objective is to maximize the sum of the utility function over a specified time horizon. Here, the number of water units to release, I_t, is restricted to increments of 20 units, up to the maximum capacity of the impoundment, K. The set of possible management decisions is, therefore: $I_t \in \{0, 20, 40, \ldots, K\}$.

2.5.2 Models of system behavior

Determining the optimal decision policy for water release requires that we monitor the state variable water level, L, over time. The dynamics of this state variable are expressed by:

$$L_{t+1} = \max\left(0, \min\left(K, L_t + p_t\right) - O_t - I_t\right)\right) \tag{2}$$

Annual rainfall, p_t, followed a normal distribution with a mean set at 550 water units and a standard deviation of 104. The variable O_t reflects a new external demand on the impoundment, namely, water withdrawals for human consumption, because of salt-water intrusion into traditional aquifers due to SLR. Hereafter we simply refer to this additional external demand as "water demand", whereas we view R_t as the amount of water used for agriculture. Because of this increasing demand, there is less water available for irrigation over time. Martin et al. (2009) did not include the water demand variable in their model. Here we consider O_t to increase in expectation linearly over time due to SLR (see Fig. 1):

$$O_t = \beta_1 t\, e_t \tag{3}$$

β_1 corresponds to the slope parameter between the new external demand on the impoundment (O_t) and time t; e_t corresponds to a random variable that follows a gamma distribution with mean 1 and a variance of 0.2, and represents random variation in the additional water demand.

Solving the optimal decision policy requires that we keep track of a second state variable, site occupancy (ψ_t, which can be viewed as the proportion of sites occupied at time t). Site occupancy dynamics can be described generally by:

$$\psi_{t+1} = \psi_t \times (1 - \varepsilon_t) + \left(1 - \psi_t\right) \times \gamma_t, \tag{4}$$

where ε and γ are probabilities of local site extinction and colonization, respectively (MacKenzie et al. 2006). In other words, ε is the probability that a site that was occupied at time t becomes unoccupied at time $t + 1$; γ is the probability that a site that was unoccupied at time t becomes occupied at time $t + 1$. As stated previously, water volume (L_t) in the impoundment is a strong determinant of habitat availability and, thus, affects the colonization and extinction probabilities of the species of

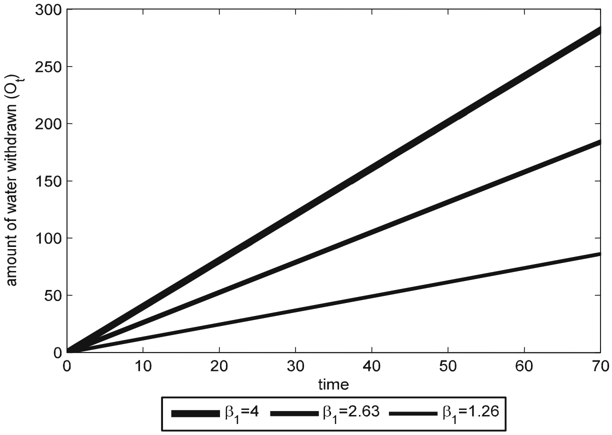


Fig. 1 Relationships between time (t) and amount of additional water lost from the wetland because of demand induced by SLR (O_t). There is a linear relationship between time and the amount of water lost: $O_t = \beta_1 t e_t$, where β_1 is the slope parameter for the relationship between time and water demand due to SLR, e_t corresponds to a random variable that represents uncertainty associated with additional water demand due to SLR (for simplicity in this figure we set $e_t = 1$). Each line corresponds to a different scenario ($\beta_1 = 4$: thick line; $\beta_1 = 2.63$: medium line; $\beta_1 = 1.26$: thin line). This is an hypothetical example and therefore the units are arbitrary

concern. We modeled the relationship between γ and L as an ecological threshold in which the proportion of empty sites that is colonized (γ) falls sharply when water volume falls below a threshold value, T (here, $T = 1500$ units of water):

$$\gamma_t = \frac{0.1}{1 + e^{(0.035 \times (T - L_t))}}. \tag{5}$$

The relationship between probability of local extinction (ε) and the water volume in the impoundment (L) was modeled as a linear-logistic response:

$$\varepsilon_t = \frac{1}{1 + e^{(-\alpha_1 - \alpha_2 \times L_t)}}. \tag{6}$$

In our case the probability of extinction decreases as the amount of water in the impoundment (L_t) increases (our example sets $\alpha_1 = 6.9$ and $\alpha_2 = -0.007$). We made a deliberate decision to keep the numerical example simple. For instance, we could have developed a model that assumed that rainfall was also affected by climate change. It is also probable that political pressure from agricultural interests as water levels change may change the manager's decision problem, i.e., with declines in the amount of water available for irrigation. We were concerned, however, that adding too much realism (i.e., adding complexity) to our example would distract the reader from the main purpose of this example, which is to illustrate an SDM approach for dealing with non-stationary systems.

2.5.3 Optimization

We used stochastic dynamic programming to identify sequences of optimal decisions. We solved the finite time horizon problem by using backwards recursion on the value function (Miranda and Fackler 2002) within the software MDPSOLVE (Fackler, software under development). This software package is in MATLAB programming language, and is used to solve general discrete-state and discrete-action dynamic programming problems. Unlike in Martin et al. (2009), we focused on time-specific solutions, because of changes in the non-stationary environmental variable O_t with time. We assume that the water demand increases for 70 years, after which it remains constant. The terminal value for the 70 year optimization is determined by solving the infinite horizon problem using the time-constant year 70 water demand level.

We summarized the optimal results in plots showing the optimal irrigation decisions as a function of water levels, proportion of sites occupied, and time. So, for example, as shown in Fig. 2a, at time 0 (i.e., during the first year), if the proportion of sites occupied is 0.6 and water level during that year is 1750, the optimal irrigation decision would be to release 600 units of water for irrigation. The decision plots (Fig. 2a and b) show the same general pattern found by Martin et al. (2009). Indeed,

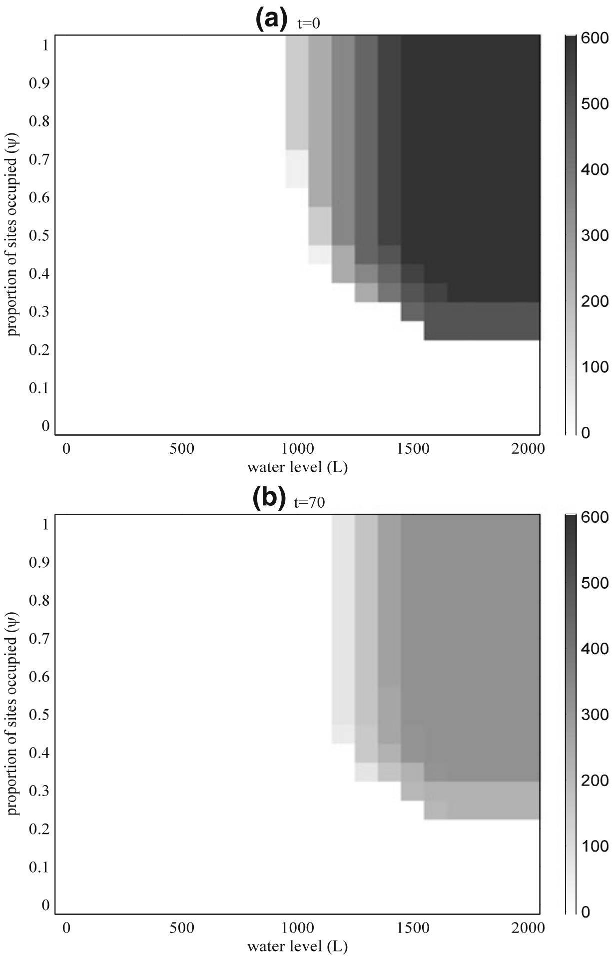


Fig. 2 Plots of optimal irrigation decisions as a function of water level (L), proportion of sites that are occupied (ψ) and time (t). The shades of gray correspond to the amount of water released for irrigation (from 0 water units [*lighter shade*] to 600 units [*darker shade*]). **a** corresponds to the optimal irrigation policy at time $t = 0$; whereas **b** corresponds to the optimal irrigation policy at time $t = 70$. At time $t = 0$, $O_t = 0$, and the irrigation policies are similar to the stationary policies presented by Martin et al. (2009). However, at $t = 70$, setting $O_t = \beta_1 t e_t$ (here e_t follows a gamma distribution with mean = 1, and variance = 0.2) leads to substantially reduced irrigation

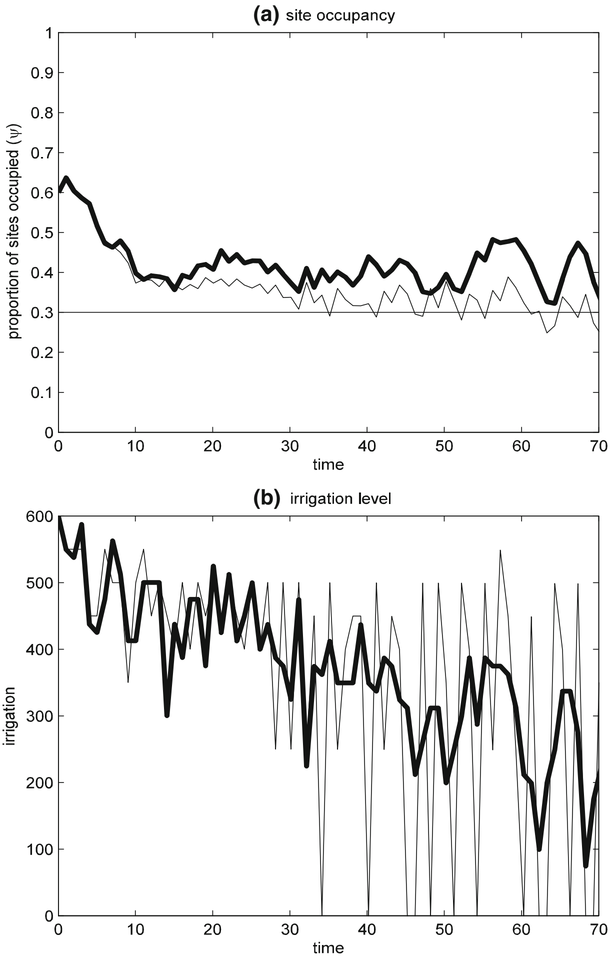
both figures demonstrate that as more water is available in the impoundment, or as more sites become occupied, a greater volume of water can be released for irrigation. The main difference between these results and those of Martin et al. (2009) is that now the optimal policies change over time. Figure 2a corresponds to the beginning of the decision time horizon ($t = 0$), whereas Fig. 2b corresponds to a later time ($t = 70$). The difference between optimal policies for the 2 different times (difference between Fig. 2a and b) shows that optimal irrigation potential decreases over time because water available for irrigation decreases over time (due to an increase in O_t). Specifically, for any two values of the state variables, occupancy and water level, at t (i.e., at any point in the state space of the figures), the optimal decision is to release less water for irrigation at the later time step.

When we considered a scenario that assumed no increase in water loss (i.e., $O_t = 0$) linked to SLR in the optimization, the optimal decisions were identical to the ones obtained by Martin et al. (2009), because a stationary solution could be found. However, if we assumed that sea level rise induced an increase in water loss ($O_t = \beta_1 te_t$), the decisions became time-dependent. Not surprisingly, if the "true" model followed $O_t = \beta_1 te_t$, but stationary solutions were implemented (i.e., assuming $O_t = 0$), the average amount of water released for irrigation was less than the average amount of water when the optimal, time-dependent policy was implemented (Fig. 3; note the larger variance in irrigation levels for the stationary policy). In addition, the occupancy of the species of interest fell below the utility threshold if the stationary policy was followed, whereas it stayed above the utility threshold if the optimal time dependent policy was implemented (Fig. 3). In the case that we described above, the difference may not seem very large, but this will depend on the value judgments of stakeholders, specifically on the value of every unit of water. The differences would have been greater if we had considered larger values of β_1 and/or longer time horizons. This example illustrates the use of simulation to evaluate the relative risk of ignoring non-stationary dynamics.

The terminal value of the objective function (how state variables are valued at the last step of the time horizon) is especially relevant to optimal solutions for time-dependent optimization problems. For example, if we had set the terminal value to 0 (i.e., if there is no benefit in maintaining water in the system after the last occasion of the time period that we wish to manage for) the optimal policy would have been to remove all of the water from the wetland on the last occasion. This is because, according to our objective function, there is no benefit in maintaining water in the system after the last occasion of the finite time horizon that we selected. Obviously, this is probably not how most managers would want to manage natural systems. Therefore, it is important to consider the incorporation of terminal values for problems with finite time horizons (e.g., Nichols et al. 2011). Our approach in the numerical example was to assume that the system is stationary after that point (i.e., after $t = 70$, O_t remained constant). One consideration when using this approach would be to try to leave the system in a "good place" by the time it reaches the end of the specified time horizon.

Up to this point we have assumed that the slope (β_1) of the relationship between time and water demand due to SLR, O_t, is known. However, as with many aspects of climate change, there will likely be uncertainty about the rate of change in variable O_t. It may be important to account for such model uncertainty (or structural uncertainty) via use of multiple models for change in O_t. We will explain how to account for model uncertainty below (*Structural uncertainty*).

Fig. 3 **a** Simulation of proportion of sites that are occupied (ψ) of the species of interest over 70 years under different management policies. **b** Simulation of corresponding irrigation levels. The *thick lines* indicate simulation results when optimal irrigation policies are followed [with $O_t = \beta_1 t e_t$; with $\beta_1 = 4$; where O_t is the amount of additional water lost from the wetland because of demand induced by SLR, and β_1 is the slope parameter for the relationship between time (t) and water demand due to SLR; here e_t follows a gamma distribution with mean = 1, and variance = 0.2]. The *thin lines* correspond to the results when stationary suboptimal policies are followed [decision rule is optimal if $O_t = 0$, so SLR does not induce an increase in additional water demand due to SLR]. For all simulations, the true underlying model assumes a positive relationship ($\beta_1 = 4$) between t and O_t



3 Sources of uncertainty affected by SLR

Uncertainty influences virtually all decision making processes (Williams et al. 1996; Burgman 2005; Halpern et al. 2006). Incorporating uncertainty in an explicit manner should affect optimal decision policies. Recognizing that there are multiple sources of uncertainty, and that SLR may affect each in different ways, can aid decision-makers in understanding the impacts of uncertainty on making optimal decisions (see Nichols et al. 2011 for a detailed discussion of the effect of climate change on some of the sources of uncertainty described below).

3.1 Environmental stochasticity and partial controllability

Variation in weather patterns and resulting changes in habitat structure are a form of environmental stochasticity (Williams et al. 1996, 2002). The IPCC projects that global climate change will lead to an increase in the frequency of droughts in the central and western U.S. and to more intense storms in Florida. This uncertainty can be incorporated in the same way that we accounted for O_t (incorporated into models as a state variable and estimated each year via monitoring). Experts from several research agencies have also predicted that SLR will affect availability of freshwater in Florida, and this in turn may affect the ability of managers to control the system, especially when coupled with an increase in frequency of drought and hurricanes (IPCC, Park et al. 2011). Uncertainty associated with the inability of decision makers to precisely control the system (i.e., remove precisely the desired amount of water [e.g., variance in I_t in our example]), is often referred to as partial controllability, and should be accounted for when appropriate (Williams et al. 2002).

3.2 Process uncertainty

Demographic stochasticity is due to the probabilistic nature of birth and death (Melbourne and Hastings 2008). The importance of this source of uncertainty in driving the population dynamics of natural populations increases as the abundance of these population decreases. SLR is projected to significantly reduce the amount of natural habitats in Florida by 2100 (Noss 2011). Therefore the abundance of many populations will be considerably reduced in the future due to SLR. An analogous source of uncertainty (hereafter referred as process uncertainty) in the context of occupancy dynamics can be linked to the fact that site extinction and colonization are stochastic processes applied to discrete units (see Eq. 4). For example, the colonization in period t of a site that is not occupied in period $t-1$ is viewed as a Bernoulli trial with probability γ (Eq. 4). If in the numerical example that we considered the number of sites occupied was large (e.g., 1000 sites), this process uncertainty would have very little influence on the population dynamics and optimal decisions. However, if the total number of sites was small (e.g., 20), then it may have been important to account for this source of stochasticity.

3.3 Structural uncertainty

Experts from the IPCC envisioned several scenarios of SLR based on different hypotheses about human responses to anthropogenic climate change (IPCC 2007). The uncertainty about which scenarios represent the best approximations of reality can be viewed as model uncertainty (or structural uncertainty). It is possible to account for this uncertainty in the optimization by including multiple models and implementing an adaptive optimization algorithm (Williams et al. 1996, 2002; Martin et al. 2011). Two approaches can be applied to account for and reduce this uncertainty: passive and active adaptive optimization. Passive adaptive optimization algorithms hold model weights (representing relative degrees of confidence in each model in the model set) constant over the time horizon of the optimization. Adaptive learning, in this sense, is a byproduct of management whereby model-specific predictions are compared to observations of the system state via a monitoring program (Williams et al. 2002). Active adaptive algorithms were developed to include model weights as information states in the optimization process, thus anticipating the long-term benefits of learning (updating confidence in one or more model as observations are compared with model predictions) while also optimizing the short-term benefits of optimal management decisions based on the objective function (Williams 1996;

Williams et al. 2002). With either approach, model or structural uncertainty can be reduced as model weights are updated using Bayes' theorem (Williams et al. 2002).

3.4 Numerical example: structural uncertainty about the effect of SLR

To illustrate the process of adaptive management we use the numerical example described earlier and follow a passive adaptive management approach to optimization. We considered three models that have the same structure, but have different β_1 coefficients (see Eq. 3; Fig. 1; remember that β_1 corresponds to the slope parameter between the new external demand on the impoundment due to SLR (O_t) and time). The β_1 coefficient was 4 for model 1, 2.63 for model 2, and 1.26 for model 3. In other words, model 1 assumed a large increase in O_t over time, model 2 assumed a moderate increase, and model 3 assumed a small increase. The models were assigned equal weights (0.33) initially. These model weights were updated via Bayes' Theorem based on direct observations of O_t. Time-specific demand was simulated as stochastic, with $\mathrm{var}(e_t) = 0.5$. The evolution of the expected water demand over time with these three parameter values is illustrated in Fig. 1. Figure 4a shows the evolution of the belief weights over a 40-year time horizon, assuming that model 1 was the true model (i.e., $\beta_1 = 4$). Figure 4b and c show the evolution of the weights assuming that models 2 and 3 are the true models, respectively. In all three cases the adaptive management process was able to discriminate among the three models, and identify the true model sometimes in less than 10 years (e.g., Fig. 4c). Identifying the true model rapidly would enable managers to get greater returns (i.e., higher utilities) quicker. Because in our example we assumed that the water demand (O_t) could be perfectly measured each year, our learning about the slope (β_1) of the relationship between O_t and time is independent of the irrigation decisions taken. Hence, in this case, there is no benefit in using an active adaptive optimization because the passive adaptive optimization leads to identical results.

For the first 10 years of the simulated management process, the irrigation policies are almost identical for the three different models representing truth (Fig. 5b). All policies result in decreased irrigation over time because of the increase in the additional water demand due to SLR, O_t (Fig. 1). Not surprisingly, for the time path under consideration, irrigation decreases more rapidly for the models that assumed a higher value for the coefficient β_1. In all cases, the optimal decisions allowed managers to maintain the species of interest above the desired utility threshold of 0.3 (Fig. 5a).

3.5 Partial observability and monitoring

In the numerical example we assumed that the values of ψ_t and L_t could be determined with certainty. This may be reasonable in the case of L_t, but will be less likely in the case of ψ_t. The uncertainty associated with the values of the state variables (e.g., ψ_t.) is generally due to the imperfection of the sampling approaches used to estimate the values of the state variables (Martin et al. 2009). This type of uncertainty is often referred to as partial observability. Partial observability may be affected by detection probabilities less than 1 and spatial variation (e.g., because of the inability to appropriately sample organisms everywhere). Nichols et al. (2011) discuss the possibility that climate change may influence monitoring by affecting

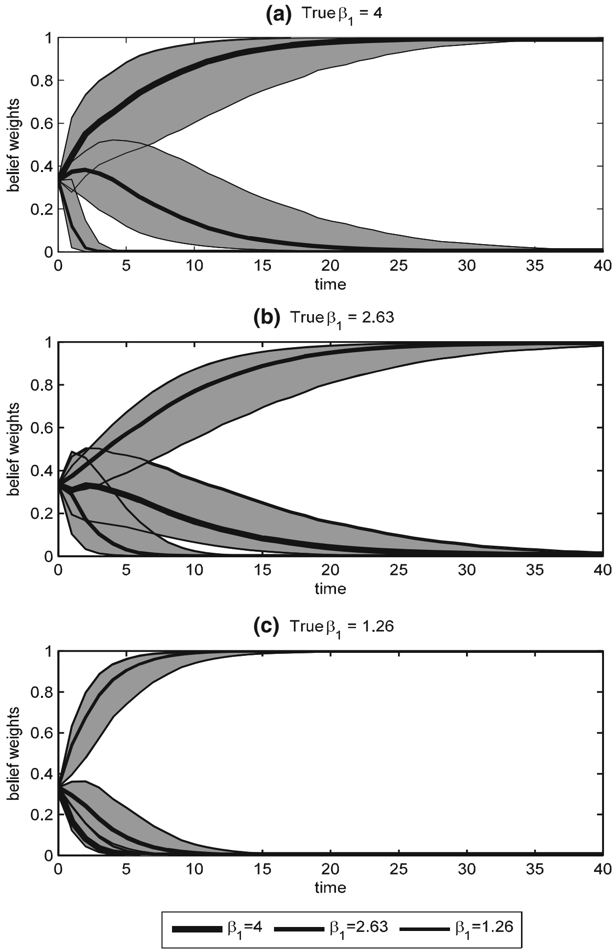


Fig. 4 Median time paths for the evolution of belief weights. *Center lines* show the median belief weights for the three alternative values of the slope parameter (β_1). *Shaded areas* display the interquartile range. Values are computed using 10,000 simulated paths beginning with equal weights. Here, the variance of the water demand noise (e_t) is set to 0.5. **a** The true model is based on $\beta_1 = 4$ (model 1). **b** The true model is based on $\beta_1 = 2.63$ (model 2). **c** The true model is based on $\beta_1 = 1.26$ (model 3)

both spatial variation and detection probabilities. In the case of SLR in Florida it is easy to envision such examples. For instance, the increase in sea level may lead manatees to shift their distribution, which could in turn affect detectability (e.g., because the water in the new habitats may have different levels of turbidity, see Edwards et al. 2007; Langtimm et al. 2011). Therefore, monitoring programs should be revised appropriately to account for these two primary sources of variations in the monitoring data (Yoccoz et al. 2001).

3.6 Discounting

When applying SDP to identify optimal solutions, it is possible to modify the value of a discount factor. The discount factor quantifies the value of a return obtained in the next period relative to the same return obtained in the current period. This number is between 0 and 1, when it is 1, returns in all periods are given equal values. If we go back to the numerical example, a discount factor of 1 would give equal weights

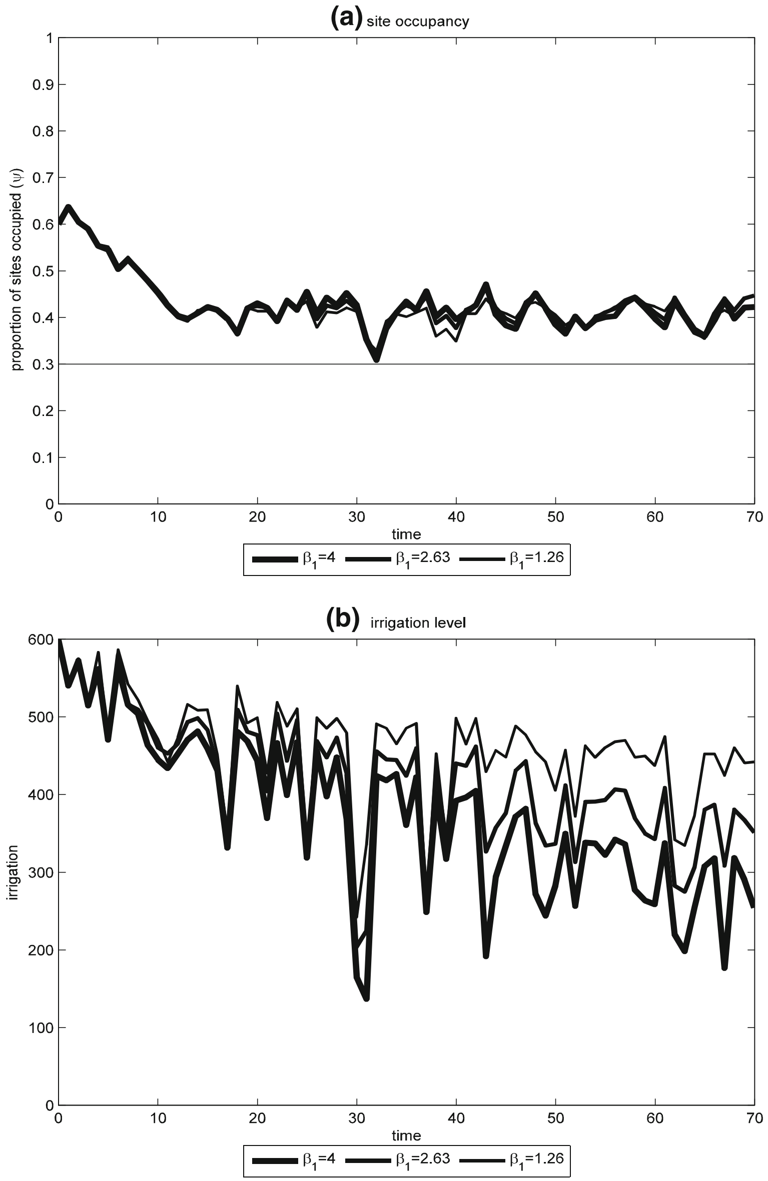


Fig. 5 Simulations of the adaptive optimization algorithm for the numerical example. Simulations over seventy years for 3 alternative models in which the slope parameter (β_1) between time and water loss ($O_t = \beta_1 t e_t$; here the variance of the water demand noise (e_t) is set to 0.2) varied; the true model was either based on $\beta_1 = 4$ (*thick line*, model 1), $\beta_1 = 2.63$ (*medium line*, model 2) or $\beta_1 = 1.26$ (*thin line*, model 3). **a** Simulation of proportion of sites that are occupied. **b** Simulation of the irrigation level

to the current return (i.e., the amount of water irrigated when the proportion of sites occupied by the species is at or above 30%) and future returns. If the discount factor is substantially less than 1, however, current returns will be weighted more than future returns. In the numerical example we used a discount factor that was set to 1 (i.e., non-discounted case). Moore et al. (2008) conducted an analysis to examine the consequences of selecting different types of discounting on decision making. The considerations discussed in their paper are relevant to problems dealing with SLR, because the discounting will affect the way we value our return in the short versus the long term. In other words it may capture our concerns for the benefits to future generations. Because discounting represents a component of the management objectives, policy makers and relevant stakeholders should be closely involved in deciding how to value future returns.

4 Conclusion

We believe that SDM provides a useful approach to integrate science and management in the face of rising sea level. We have discussed some of the challenges and benefits of applying SDM to help managers adapt to SLR in Florida. We have also provided examples of how to address problems in which system dynamics cannot be assumed to be stationary. We have seen that many of the existing tools generally used in SDM can be adapted to deal with non-stationary systems. From a technical point of view the optimization component of the SDM process is probably one of the most challenging, because it is currently difficult to obtain optimal solutions for problems with high dimensions; and the non-stationarity induced by SLR is likely to increase the dimensionality even further (e.g., because of incorporation of new environmental state variables related to changing climate). Computer scientists are actively working on improving optimization methods. Unfortunately, the newest breakthroughs from operations research can take some time to permeate other fields of research. Thus, there is a great opportunity for natural resource managers to collaborate with computer scientists.

SDM provides an effective framework for collaborative research, because the development and identification of each of the elements of the SDM process may require different kinds of expertise. For instance, social scientists, economists, and psychologists can help with the identification of objectives, ecologists can contribute to the development of ecological hypotheses and system models, and computer scientists can help identify or devise the most appropriate optimization methods. Assembling such teams of experts can be costly, but it may be an appropriate investment when dealing with multi-million dollar decisions. For simpler problems with less at stake, this high level of expertise may be less important. But even for high profile problems it may make sense to start with a simple SDM prototype that can be developed over a few days and add layers of complexity (and additional experts) as needed during the implementation phase. Simple prototypes can offer numerous and valuable insights at a relatively low cost and can help identify the most important impediments to the decision process (e.g., Martin et al. 2010).

Finally, we realize that managing natural resources in Florida will be contentious and difficult, especially during a time of rapidly rising sea level. However, because SDM brings transparency (by stating the objectives explicitly) and rigor (by developing models based on the best available science) to the decision process, this framework should be well suited to dealing with contentious issues (Martin et al. 2010). Several authors have noted that these characteristics make the SDM process compatible with existing laws and regulations such as the National Environmental Policy Act (NEPA) (Thrower 2006; see also Martin et al. 2010).

Acknowledgements The authors thank Leslie Ward-Geiger, Timothy E. O'Meara and Allan O'Connell, and two anonymous reviewers for their helpful comments. Langtimm and Stith were supported in part by the USGS FISCHS Project (Future Impacts of Sea Level Rise on Coastal Habitats and Species), which is funded by USGS Ecosystems Mapping and USGS Greater Everglades Priority Ecosystems Science.

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