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Decision analysis of shoreline protection under climate change uncertainty

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Abstract. If global warming occurs, it could significantly affect water resource distribution and availability. Yet it is unclear whether the prospect of such change is relevant to water resources management decisions being made today. We model a shoreline protection decision problem with a stochastic dynamic program (SDP) to determine whether consideration of the possibility of climate change would alter the decision. Three questions are addressed with the SDP: (1) How important is climate change compared to other uncertainties?, (2) What is the economic loss if climate change uncertainty is ignored?, and (3) How does belief in climate change affect the timing of the decision? In the case study, sensitivity analysis shows that uncertainty in real discount rates has a stronger effect upon the decision than belief in climate change. Nevertheless, a strong belief in climate change makes the shoreline protection project less attractive and often alters the decision to build it.

1. Introduction

The magnitude of climate change due to increasing concentrations of greenhouse gases could be large, but it is difficult to predict. General circulation models (GCMs) project temperature changes of +1°C to +4°C under a doubled CO_2 concentration scenario [*Intergovernmental Panel on Climate Change (IPCC)*, 1992]. Furthermore, regional temperature projections are more uncertain in that different GCMs show contradictory results for the same region. This is because GCMs differ in their methods of parameterizations of regional features and because "downscaling" GCM results to the regional level is difficult and arbitrary [*Paoli*, 1994].

The projected changes in temperature, and the more uncertain changes in precipitation, could significantly affect streamflows [*Leavesley*, 1994]. For the Laurentian Great Lakes, with their large surface areas, increased evapotranspiration is likely with higher temperatures. As a result, lower lake levels are projected under climate change, even though most GCM scenarios indicate an increase in precipitation in the region [*Croley*, 1990].

However, it is argued that (1) because climate change's hydrologic impacts would not be significant for decades and (2) because water resources decisions are often incremental (adjusted as system changes occur), the prospect of climate change is of little relevance to water resource decisions being made now [*Stakhiv*, 1991; *Rogers*, 1994]. Yet climate change is relevant to some water project decisions because they are long lived, irreversible, indivisible, and have benefits or costs that are affected by climate-influenced variables [*Hobbs et al.*, 1997].

Analyzing the impact of climate change uncertainty upon water resource planning requires an integrated set of models which include (1) climate change scenarios, (2) a hydrologic model, and (3) socioeconomic and environmental impact models. Several researchers have put together such studies for the Great Lakes [*Hartmann*, 1990; *Rogers and Harshadeep*, 1993; P. T. Chao et al., unpublished report, 1996]. While such integrated system models offer insight into the magnitude of impacts under particular scenarios, decisions concerning the system should be addressed by risk or decision analysis. Decision analysis can identify the sensitivity of decisions to different climate assumptions, the flexibility of policy options, the value of including climate change uncertainty in the decision process, and the relative importance of climate change uncertainty compared to other uncertainties [*Fiering and Rogers*, 1989; *Fiering and Matalas*, 1990]. We use this methodology to revisit the 1986 decision by the U.S. Army Corps of Engineers (Corps) to build breakwaters at Presque Isle, Pennsylvania, on the coast of Lake Erie.

Decision analysis has been applied to water resource decisions under climate change uncertainty. *Davis et al.* [1972] applied Bayesian decision theory to levee design given uncertainty in flood frequency parameters. *Fiering and Rogers* [1989] laid out a sequential decision tree framework for evaluating water resource projects with Bayesian updating of the probability of climate change. A. Patwardhan and M. J. Small (unpublished paper, 1993) looked at a one-time decision concerning the construction of bulkheads versus beach replenishment under sea level rise uncertainty. *Yohe* [1991], recognizing the importance of identifying the optimal timing of investment decisions, developed a sequential decision framework for an ocean shoreline protection problem. The decision in his study hinged upon when the state of the system crosses a threshold, past which the system can no longer operate properly. He suggested that contingency planning should recognize that there is no need to respond to sea level rise until a certain time, and at that time a specific discrete plan should be implemented. His framework is not applicable to the problem at Presque Isle, because no obvious threshold for making a decision exists.

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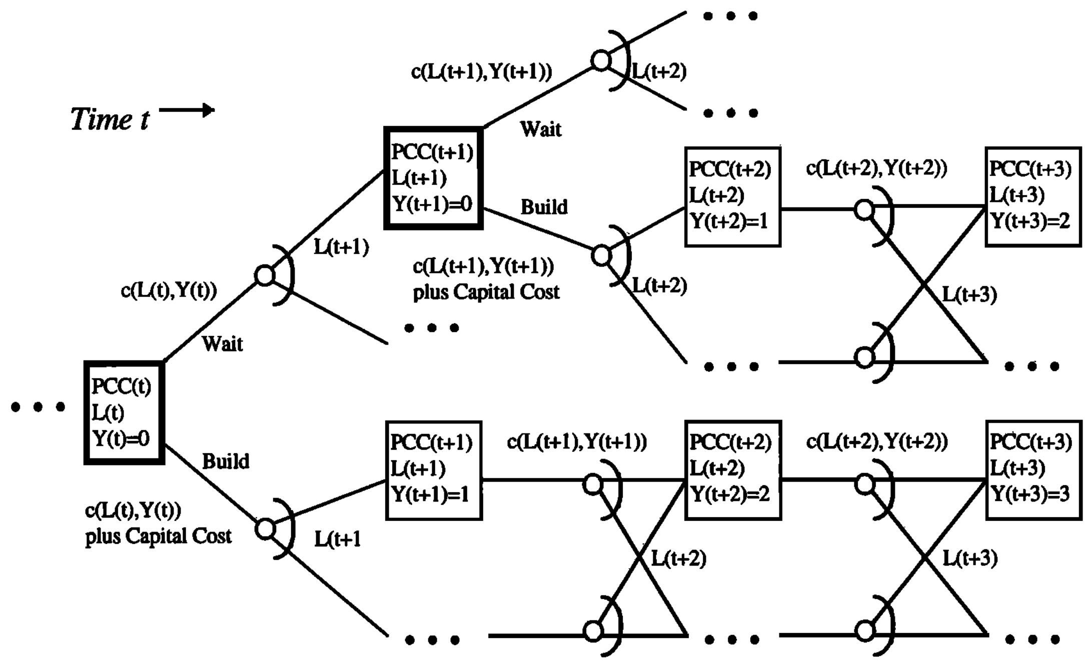

Figure 1. Stochastic dynamic program (SDP) structure.

A more general sequential decision framework is defined by *Krzysztofowicz* [1994] and is used in this paper. He outlines a stopping-control paradigm to determine when to invest ("stopping") as well as how to operate the system ("control"). He decomposes a planning problem under uncertainty into modeling (1) the uncertainty of the environment's future state using probability distributions that are updated over time as new information is gained, (2) social preferences through a multiattribute utility function, and (3) the sequential decision process through a decision tree or a stochastic dynamic program (SDP). This SDP can be viewed as a partially observable Markov decision process (POMDP) (see work by *Monahan* [1982] and *White* [1991] for surveys and *Ellis et al.* [1995] for an example). A POMDP assumes that the underlying state of nature (here, the magnitude of climate change) is not completely observable but that there is an observable Markovian variable (in our case, water levels) whose distribution is conditioned on the state of nature. In each period the posterior distribution of the state of nature can be updated according to Bayes' law given new observations. The distribution of the state of nature is then used to determine the probability transition matrix of the SDP.

The purpose of this paper is to investigate whether long-run climate change uncertainties could affect the decision to invest in a long-lived, irreversible project today. The decision for the erosion control project at Presque Isle was to build segmented breakwaters to protect recreational beaches [*U.S. Army Corps of Engineers* (*USACE*), 1986]. Erosion of the lakeside beaches of the sand spit caused the Corps to begin sand nourishment in the 1950s. By the 1980s, owing to the expense of sand nourishment plus the cost of dredging in the harbor channel because of littoral drift of the sand, the Corps investigated whether segmented breakwaters would be a cheaper, more effective alternative. A benefit-cost analysis conducted in 1986 by the Corps justified the construction of 52 segmented breakwaters, which were subsequently built by 1993. The benefit-cost analysis assumed a one-time decision and no climate change uncertainty. Climate warming would lower lake levels, leading to wider beaches and less need for sand nourishment and lowering the value of the breakwaters.

The decision to build breakwaters at Presque Isle is reevaluated with a SDP. The SDP redefines the decision by considering (1) whether to build or to delay construction of the breakwaters and (2) changes over time in the subjective likelihood of a decrease in average lake levels due to climate change as information is obtained in the form of observed lake levels. The trend in long-term mean water levels of Lake Erie is the state of nature. For simplicity, this variable is assumed to have two possible values: no change in mean levels (no climate change) and a linear decrease of 0.015 m/yr (climate warming). The observational variable is the annual mean water level of Lake Erie. Lake Erie water levels are modeled as a lag-1 Markov process conditioned upon the long-term mean scenario. The cost model is also a function of sand nourishment and dredging expenses, although uncertainties in shore processes (such as littoral drift) are not considered.

The SDP is analyzed to answer three questions: (1) Does climate change uncertainty have more influence upon the decision than other do parameter uncertainties? (2) What is the economic value of including climate change uncertainty in the decision process? (3) Does climate change uncertainty change the timing on the decision to build?

In the next section the SDP model is presented. In subsequent sections the numerical experiments (sensitivity analysis, quantification of the value of information, and timing analysis) are discussed.

2. SDP Model

Figure 1 shows the structure of the SDP. Given an initial state (specific discrete value for each of the three state variables defined below), there is a decision (shown by boxes with heavy outlines) to either (1) commence construction, "build", or (2) postpone the decision 1 year, "wait." After a decision is made, the system incurs the appropriate arc costs, consisting of sand nourishment costs, C, plus the capital cost of the breakwaters, if the decision to build is chosen. The system then transitions into a new state for the next year. If the decision is to wait, then another decision to wait or build is made in the following year. If, however, the decision is to build at time t, then the SDP enters a Markov chain, shown in the lower half of Figure 1, that simply calculates the expected sand nourishment cost over the project life. Note also that the decision to build breakwaters is irreversible and indivisible; thus there are no more decision nodes once a decision to build is made.

A SDP is essentially defined by four components, each of which will be described below: (1) state variables, (2) a probability transition matrix, (3) a cost function, and (4) a decision rule.

State Variables

The state variables, which must account for all factors that affect the cost function, are belief in climate change, PCC_t; annual average Lake Erie water level, L_t; and years since construction began, Y_t. PCC_t actually represents the belief in a specific climate change scenario in which the long-term mean water level decreases and is expressed as a subjective probability. The long-term mean water level change under climate change is assumed to be −0.015 m/yr. This value is based on the Intergovernmental Panel on Climate Change (IPCC) conclusion that temperatures in transient scenarios of climate change will lag temperatures in steady state scenarios [*IPCC*, 1990]. The reason for this lag is that the global climate system would take time to reach an equilibrium temperature. On the basis of IPCC guidelines we translated a 1.5-m drop under a steady state scenario [*Lee and Quinn*, 1992] into a transient scenario of −0.015 m/yr.

L_t is the annual mean level of Lake Erie (meters). L_t and Y_t determine the amount of sand nourishment necessary to maintain sufficient beach width for recreational purposes and dredge volumes from the harbor channel. The transition probabilities for L_t are conditioned on PCC_t.

Y_t is a state variable because it is assumed that during construction the breakwaters are only partially effective in reducing erosion. Y_t (years) is the number of years since construction began. Y' is the full construction period. Therefore Y_t/Y' represents the fraction of breakwater segments that have been constructed. The model assumes nourishment requirements will decrease linearly during construction from 100% of preconstruction requirements to 25%. After construction is completed, sand nourishment requirements are assumed to be 25% of preconstruction requirements.

Markov Transition Probabilities

Each element of the probability transition matrix, $P_{(ig)(jh)}$, is the product of the transition probabilities of the three state variables:

$$\begin{aligned} P_{(ig)(jh)} &= P(L^h_{t+1}, \mathrm{PCC}^j_{t+1}, Y_{t+1} | L^g_t, \mathrm{PCC}^i_t, Y_t) \\ &= P(L^h_{t+1}|\mathrm{PCC}^i_t, L^g_t) \times \mathrm{PCC}^j_{t+1}(L^g_t, L^h_{t+1}, \mathrm{PCC}^i_t) \\ &\quad \times P(Y_{t+1}|Y_t) \end{aligned} \tag{1}$$

The subscripts $(ig)(jh)$ denote that the system transitions from an initial state with discrete values of PCC^i_t and L^g_t to the next state of PCC^j_{t+1} and L^h_{t+1}.

$P(L^h_{t+1}|\mathrm{PCC}^i_t, L^g_t)$ is the transition probability of the mean annual water level, which is defined by applying the law of total probability:

$$\begin{aligned} P(L^h_{t+1}|\mathrm{PCC}^i_t, L^g_t) &= P(L^h_{t+1}|\mathrm{CC}, L^g_t) \times \mathrm{PCC}^i_t \\ &\quad + P(L^h_{t+1}|\mathrm{noCC}, L^g_t) \times (1 - \mathrm{PCC}^i_t) \end{aligned} \tag{2}$$

$P(L^h_{t+1}|\mathrm{CC}, L^g_t)$ and $P(L^h_{t+1}|\mathrm{noCC}, L^g_t)$ are the water level likelihoods given climate change and no climate change, respectively. The terms are derived from a lag-1 autoregressive Markov model [*Loucks et al.*, 1981]:

$$L^h_{t+1} = (1 - \phi)(\bar{L}_0 + \mathrm{Trend} \times t) + \phi L^g_t + \varepsilon \tag{3}$$

where $\bar{L}_0$ is the present long-term mean (equal to 174.13 m), ϕ is the lag-1 correlation coefficient, and ε is the error term (equal to $V_t\sigma(1 - \phi)^{1/2}$, where V_t is a standard normal random variable and σ is the standard deviation). Several researchers have shown that higher order autoregressive models of annual water levels for any of the Great Lakes are more appropriate [*Slivitzky and Mathier*, 1993; *Mathier et al.*, 1992]. But to maintain simplicity within the SDP, a lag-1 Markov model was fit. The model statistics were $\phi = 0.8784$, $\bar{L}_0 = 174.13$ m, $\sigma^2 = 0.1759$ m, and adjusted $R^2 = 0.77$. The effect of using this model rather than a higher order model is to lessen the range of water levels and also to alter the interannual pattern. A higher order regression model would make the SDP more complicated, because the state space would have to be expanded to include not just last year's level, but also those of previous years. Future work will address the use of more complex models.

If the error term of (3) is dropped, the equation gives the expected annual level for the subsequent year, or L^*_{t+1}. To calculate the Markov transition probabilities, $P(L^h_{t+1}|\mathrm{CC}, L^g_t)$ and $P(L^h_{t+1}|\mathrm{noCC}, L^g_t)$ between the predefined discrete lake levels, the following standard normal variates, Z^h_{lower} and Z^h_{upper}, are first calculated for the lower and upper bounds of state h (i.e., $L^h_{t+1} + 0.5\Delta L$ and $L^h_{t+1} - 0.5\Delta L$):

$$\begin{aligned} Z^h_{\mathrm{upper}} &= \frac{(L^h_{t+1} + 0.5\Delta L - L^*_{t+1})}{\varepsilon(1 - \phi^2)^{1/2}} \\ Z^h_{\mathrm{lower}} &= \frac{(L^h_{t+1} - 0.5\Delta L - L^*_{t+1})}{\varepsilon(1 - \phi^2)^{1/2}} \end{aligned} \tag{4}$$

ΔL is the water level increment (set at 0.2 m). Since the error term, ε, is assumed normal, the probability of attaining state h in $t + 1$ is then obtained as follows:

$$P(L^h_{t+1}|*, L^g_t) = \begin{cases} \Phi(Z^h_{\mathrm{upper}}) & h = 1 \\ \Phi(Z^h_{\mathrm{upper}}) - \Phi(Z^h_{\mathrm{lower}}) & 1 < h < n \\ 1 - \Phi(Z^h_{\mathrm{lower}}) & h = n \end{cases} \tag{5}$$

where Φ is the cumulative distribution for standardized normal variates and n is the number of discrete states of L_t. Equations (4) and (5) are calculated for both conditional water level likelihoods required by (2).

The transition probability for the belief state, $\mathrm{PCC}^j_{t+1}(L^g_t, L^h_{t+1}, \mathrm{PCC}^i_t)$, is derived by first applying Bayes' law to calculate the exact posterior probability, PCC^*_{t+1}:

$$\begin{aligned} P(\mathrm{CC}^*_{t+1}|\mathrm{PCC}^i_t, L^g_t, L^h_{t+1}) &= [P(L^h_{t+1}|\mathrm{CC}, L^g_t) \\ &\quad \times \mathrm{PCC}^i_t]/[P(L^h_{t+1}|\mathrm{CC}, L^g_t) \times \mathrm{PCC}^i_t + P(L^h_{t+1}|\mathrm{noCC}, L^g_t) \\ &\quad \times (1 - \mathrm{PCC}^i_t)] \end{aligned} \tag{6}$$

Table 1. Transition Probabilities for $P(Y_{t+1}|Y_t)$ for Two Decisions, a_t

Y_t	Y_{t+1}: 0	1	$Y_t + 1$	Y_t
	Sand Nourishment			
0	1	0	0	0
	Breakwater			
0	0	1	0	0
1 to $Y' - 2$	0	0	1	0
$Y' - 1$ and Y'	0	0	0	1

Since PCC_t has been discretized, the state PCC^*_{t+1} is unlikely to exist; because of this, we instead assume that the transition occurs to one or the other belief states adjacent to PCC^*_{t+1} according to the following interpolation rule:

$$PCC^j_{t+1}(L^g_t, L^h_{t+1}, PCC^i_t) = \begin{cases} 0 & j < k, j > k+1 \\ 1 - r & j = k \\ r & j = k+1 \end{cases} \tag{7}$$

k is the state in which $PCC^k_{t+1} \le PCC^*_{t+1} < PCC^{k+1}_{t+1}$. The ratio r is defined as

$$r = \frac{(PCC^*_{t+1} - PCC^k_{t+1})}{(PCC^{k+1}_{t+1} - PCC^k_{t+1})} \tag{8}$$

The last probability used in (1) is $P(Y_{t+1}|Y_t)$. $P(Y_{t+1}|Y_t)$ is defined in Table 1. The decision, a_t, is determined in Bellman's equation, (10a) and (10b). Essentially, Table 1 says that if breakwaters construction has begun, then Y_t increases by 1 up until project completion, Y'.

Cost Function

The cost function, which was obtained by statistical analysis of sand nourishment and dredge cost records, is [*USACE*, 1980; *Gorecki and Pope*, 1993]

$$C(L^h_t, Y_t) = \left[\frac{8.4 \times (1+\beta)^t}{(1+\alpha)^4} + \frac{5.18}{(1+\alpha)^8} \times 0.371\right] \cdot \max(0, -21{,}700{,}000 + 125{,}000 \times L^h_t) \cdot \left[\left(\frac{Y' - Y_t}{Y'}\right) \times 0.75 + 0.25\right] \tag{9}$$

where α (equal to 8.625%) is the real discount rate and adjusted $R^2 = 0.68$. The assumed costs per ton for sand nourishment and dredge volume removed (1986 dollars) are \$8.40 and \$5.18. The discount terms reflect that water levels affect sand nourishment and dredge volumes after lags of approximately 4 and 8 years, respectively. Since the littoral drift of nourished sand takes 2 or more years to travel around the peninsula to the channel entrance, dredge volume costs are lagged longer than sand nourishment costs. The factor 0.371 is the ratio of dredge volume to previous sand nourishment volume. The value β is the real escalation rate for the cost of sand nourishment, which is positive because sources of sand are limited. The effect of β is to make the breakwater alternative look more attractive in the future because sand nourishment costs increase exponentially. Last, the maximum operator reflects that below a certain water level, there is no need for sand nourishment because the beaches are wide enough.

Decision Rule

The available actions are to continue sand nourishment or to begin constructing breakwaters. The expected cost from time t onward, $V(L^g_t, PCC^i_t, Y_t)$, for a given state, (L^g_t, PCC^i_t, Y_t), is calculated using Bellman's equations:

$$V_t(L^g_t, PCC^i_t, Y_t) = \min \mathrm{FC} + \sum_j \sum_h P_{(ig)(jh)} \times [C(L^h_{t+1}, 1) + V_{t+1}(L^h_{t+1}, PCC^j_{t+1}, 1)]/[1+\alpha] \sum_j \sum_h P_{(ig)(jh)} \times [C(L^h_{t+1}, 0) + V_{t+1}(L^h_{t+1}, PCC^j_{t+1}, 0)]/[1+\alpha] \qquad Y_t = 0 \tag{10a}$$

$$V_t(L^g_t, PCC^i_t, Y_t) = \sum_j \sum_h P_{(ig)(jh)} \times [C(L^h_{t+1}, Y_{t+1}) + V_{t+1}(L^h_{t+1}, PCC^j_{t+1}, Y_{t+1})]/[1+\alpha] \qquad Y_t > 0 \tag{10b}$$

Bellman's equations include the cost of sand nourishment, C, and the fixed cost of building the breakwaters, FC, and reflects the irreversibility of the decision. The Corps found significant construction cost savings would occur if construction were to take place over a longer period and therefore examined three construction period alternatives: 2, 12, and 24. FC takes values of \$21.3 million, \$13 million, and \$8.8 million for $Y' = 2$, 12, and 24, respectively. The tradeoff of longer construction periods is that benefits are not accrued as quickly, which is reflected in the cost function (9). At $t = T$ (the last period of the SDP) we assume that $V(L^g_t, PCC^i_t, Y_t) = 0$. We assume the end effects are negligible given $T = 80$ and $\alpha > 0.05$.

By solving Bellman's equations for all states in each period t starting at the last period $t = T$ the optimal action in each state can be determined. The output of the SDP, a^{ig}_t, is then a matrix of binary decisions, 0 to continue sand nourishment and 1 to build breakwaters, one for each system state ($PCC^i_t, L^g_t, Y_t = 0$).

3. Experiment and Results

The three questions posed at the end of the introduction were addressed in numerical experiments with the SDP. The experimental methodology and results for the three questions are discussed in this section.

Does Climate Change Uncertainty Have More Influence Upon the Decision Than Other Parameter Uncertainties?

A factorial experiment of several uncertain model parameters was done to determine how each influenced the decision policy determined by the SDP. Table 2 shows the model parameters examined and the values they took.

The SDP was run for all the permutations of the values in the table, 108 times, and the decision policy for each run was examined to see if there was a difference in the pattern of decisions between $PCC^i_0 = 0$ and $PCC^i_0 = 1$. For example, assume the SDP was run with $m = 4$ discrete values of PCC^i_t and $n = 10$ discrete values of L^g_t (the actual run dimensions were $m = 9$ and $n = 19$); then the decision matrix for $t = 0$ of a run could be

$$\begin{array}{ll} \mathrm{PCC}\backslash L & [172 \quad \cdots \quad 175.6] \\ \begin{array}{c} 0.00 \\ 0.33 \\ 0.67 \\ 1.00 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \end{array}$$

Table 2. Parameters Varied in the Factorial Analysis and Their Values

Parameter	Low	Medium	High
Water level trend,* "Trend," m/yr	0.0075	0.015	0.030
Real discount rate,† α, %	5	8.625	···
FC, as percentage of nominal value‡	75	100	125
Real escalation of sand nourishment cost,‡ β, %	0	2	···
Construction period,† Y', years	2	12	24

*Equation (3).
†Equations (9), (10a), and (10b).
‡Equations (10a) and (10b).

The columns are for water levels from 172 to 175.6 m (0.4-m increments), and the rows are for belief in climate change from 0 to 1. In this case, for no belief in climate change (the first row), there are decisions to build for $L_t^i \geq L_t^6 = 173.6$ m. For a high belief in climate change ($\mathrm{PCC}_0 = 1.0$), there are decisions to build only at the very highest water levels ($L_t \geq 174.8$ m). Since high belief in climate change implies that construction is less attractive, one can conclude that belief in climate change makes a difference in this case.

On the other hand, if the results are, for example,

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

or

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

or

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

then belief in climate change has no effect on the decision policy.

To be consistent in examining the results of the 108 runs, a nonparametric method was developed in which we counted the number of changes in decision policies between the first row of the matrix, $\mathrm{PCC}_0 = 0$, and the last row, $\mathrm{PCC}_0 = 1$, for all the runs with a given value of one parameter while all the other parameter values varied. More specifically, we categorized the runs as likely to have the decision to act, if the run had at least one "1" within the 95% confidence interval of water levels, 173.4–174.8 m (which correspond to states between L_t^7 and L_t^{14}). Consider, for example, a run in which the parameter $\beta =$ 0%. If $a_0(\mathrm{PCC}_0^i = 0, L_0^g) = 1$ for at least one of $7 \leq g \leq 14$, then we would mark that run as a run in which building is likely given no belief in climate change. If, however, for the same run that there is never a decision to build given 100% belief in climate change (i.e., $a_0(\mathrm{PCC}_0^i = 1, L_0^g) = 0$ for all $7 \leq g \leq 14$), then the run was classified as a run in which climate change makes a difference in the decision. We continued to examine all 54 runs in which $\beta = 0\%$. Out of the 54 runs, only 6 showed changes in the likelihood to build.

Table 3 shows the results of this analysis, where "fraction" is the number of runs with differences in decision policy divided by the total runs for those values and "percent" is their respective percentages.

The primary insights from this analysis are the following:

1. At the lower discount rate, 5%, belief in climate change can matter, since 30% of the decision policies change from likely to build to unlikely to build. Essentially, the model shows that below approximately 5%, climate change belief is a factor in the decision. At 8.625%, the full decision matrix was all zeros; that is, building the breakwaters was not recommended regardless of belief in climate change and water level.

2. Similarly, belief in climate change affects scenarios in which FC ≤ 75%, $\beta \geq 2\%$, or $Y' \geq 24$. The number of runs with changes in decisions due to belief in climate change were, however, less than those for discount rates.

3. That the number of changes in decision policy was 4, 6, and 6, respectively, for the three levels of water level trend shows that belief in climate change is more important than the magnitude of climate change in the decision. In other words, for some cases it is not what one believes (the trend magnitude), but rather how much one believes (PCC_0). The lowest trend of 0.007 m/yr, which corresponds to a drop of 0.45 m in 60 years, is well within the natural variability of the system.

Last, since Table 3 shows that α and FC have a strong influence upon the decision policy, it is interesting to see how these two factors interact with each other. We used the same sensitivity analysis approach, but trend, escalation, and construction period were fixed at 0.015 m/yr, 0.02%, and 12 years, respectively. We varied first cost from \$6 million to \$17 million by \$1 million increments and discount rate from 2% to 11% by 1% increments. In total, there were 120 runs. The decision matrices from $t = 0$ to $t = 10$ were recorded. The decisions were classified as (1) build now ($a(\mathrm{PCC}_0^i, L_0^g = 174.2) = 1$, a decision to build at or above the mean water level), (2) wait and possibly build later within 10 years ($a(\mathrm{PCC}_0^i, L_0^g = 174.2) = 0$ and $a(\mathrm{PCC}_t^i, L_t^g) = 1$, for any g such that $173.4 \leq L_t^g \leq 174.8$ and $0 < t < 10$), or (3) wait at least 10 years ($a(\mathrm{PCC}_t^i, L_t^g) = 0$, for all g such that $173.4 \leq L_t^g \leq 174.8$ and $t \geq 10$).

Figure 2 shows two plots for this sensitivity test. The left-hand plot is for $\mathrm{PCC}_0^i = 0$, and the right-hand plot is for $\mathrm{PCC}_0^i = 1$. For extremely low discount rates, regardless of cost and climate belief, the decision was to always build, because the

Table 3. Nonparametric Measure of Influence of Climate Change

		Interest, %		Trend			Percent of First Cost			Escalation		Construction Period, years		
Value	All Runs	5	8.6	0.007	0.015	0.030	75	100	125	0	2	2	12	24
Fraction	16/108	16/54	0/54	4/36	6/36	6/36	8/36	5/36	3/36	6/54	10/54	3/36	5/36	8/36
Percent	15	30	0	11	17	17	22	14	8	11	19	8	14	22

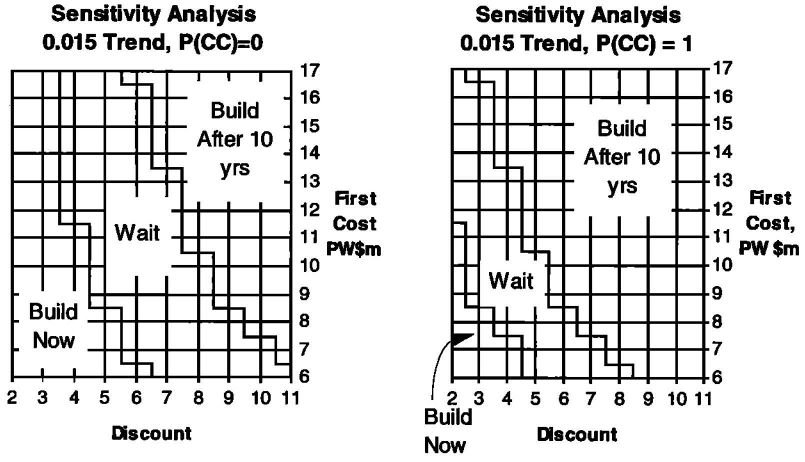

Figure 2. Sensitivity analysis of interest rate versus construction cost.

extra cost of paying for sand nourishment over time becomes too large. The effect of climate change belief was to make the decision to wait more favorable for all scenarios, which is seen by a leftward shifting of the "wait" band.

What is the Economic Value of Including Climate Change Uncertainty in the Decision Process?

Two measures were developed to assess the value of information concerning climate change: expected value of including uncertainty given perfect information about climate change (EVIUPI) and expected value of including uncertainty given imperfect information (EVIUII). These two measures differ from the traditional definition of EVPI and EVII in that prior analysis is based on ignoring climate change uncertainty rather than starting with an initial belief in climate change and not updating it. A general description is given of both, followed by more rigorous mathematical descriptions.

EVIUPI can be explained as follows. Suppose a planner makes a decision ignoring uncertainty about climate change (i.e., assuming $PCC_0 = 0.0$ for all t in the SDP). The resulting naive decision policy can then be evaluated using other beliefs by imposing that policy within an SDP with $PCC_0 > 0$. If instead someone provided the planner with perfect knowledge about the future climate, that planner could make a perfect decision using the SDP by setting $PCC_0 = 0$ (if no climate change will occur) or $PCC_0 = 1$ (if climate change is known to occur). We denote the difference in expected cost between the perfect knowledge and naive strategies as the expected value of perfect information. Of course, obtaining perfect information is not possible, but by taking the difference between the expected value of a naive decision and that of a perfect knowledge decision, one can find an upper bound of the value of information. A planner would not pay more than EVIUPI to a researcher to gather information about climate change.

Now consider EVIUII. EVIUII is the difference between the expected value of the naive decision, and the expected value of making a decision with imperfect information on climate. Imperfect information refers to taking the decision maker's initial belief in climate change, say $PCC_0 = 0.5$, and deriving a decision policy given information for updating PCC_t using (10). EVIUII is the expected improvement in the present worth of net benefits that results from making a decision using the planner's actual beliefs ($PCC_0 = 0.5$) rather than using the naive decision policy (from $PCC_0 = 0$ for all t). EVIUPI and EVIUII show the value of resolving or optimal consideration of the uncertainty in climate change and in the decision process.

Mathematically, we define EVIUPI as

$$\text{EVIUPI}^{ig} = \text{EV}^{ig}[\text{naive}] - \text{EV}^{ig}[\text{perfect}] \qquad (11)$$

The superscripts refer to the initial states of water level, L_0^g, and of belief in climate change, PCC_0^i. EVIUPI is solved for all initial ($t = 0$) states i and g. The two terms of (11) are defined in (12) and (14):

$$\text{EV}^{ig}[\text{naive}] = V_0^{\text{naive}}(L_0^g, PCC_0^i, Y_0 = 0) \qquad (12)$$

V_0^{naive}, calculated recursively from (13a) and (13b), is the value function when climate change is ignored.

$$V_t^{\text{naive}}(L_t^g, PCC_t^i, Y_t) = FC + \sum_{j=1}^{n} \sum_{h=1}^{m} P_{(ig)(jh)}$$

$$\cdot [c(L_{t+1}^h, Y_{t+1}) + V_{t+1}^{\text{naive}}(L_{t+1}^h, PCC_{t+1}^j, Y_{t+1})]/[1 + \alpha] \qquad (13a)$$

$$a_t^g(\text{naive}) = 1, \quad Y_t = 0$$

$$V_t^{\text{naive}}(L_t^g, PCC_t^i, Y_t) = \sum_{j=1}^{n} \sum_{h=1}^{m} P_{(ig)(jh)}$$

$$\cdot [c(L_{t+1}^h, Y_{t+1}) + V_{t+1}^{\text{naive}}(L_{t+1}^h, PCC_{t+1}^j, Y_{t+1})]/[1 + \alpha] \qquad (13b)$$

otherwise

Equations (13a) and (13b) are identical to (10a) and (10b) except $a_t^g(\text{naive})$, the naive decision array, determines the form of the value function; $a_t^g(\text{naive})$ is generated for all t by previously solving the SDP for only the states in which $i = 1$, that is, $PCC_0 = 0$. Equations (13a) and (13b) state that $a_t^g(\text{naive})$ is imposed on the SDP (10a) and (10b) for all the combinations of i and g. Therefore a naive decision based on no climate change is applied even when $PCC_0 \neq 0$.

We define the second term of (11), the value under perfect information, as

$$\text{EV}^{ig}[\text{perfect}] = PCC_0^i \times V_0^{\text{perfect}}(L_0^g, PCC_0 = 1, Y_0)$$

$$+ (1 - PCC_0^i) \times V_0^{\text{perfect}}(L_0^g, PCC_0 = 0, Y_0) \qquad (14)$$

$V_0^{\text{perfect}}(L_0^g, \text{PCC}_0, Y_0)$ is the value function given perfect information, which is solved recursively:

$$V_t^{\text{perfect}}(L_t^g, \text{PCC}_0, Y_t) = \min \text{FC} + \sum_{h=1}^{m} P_{(ig)(ih)}$$

$$\cdot [c(L_{t+1}^h, Y_{t+1}) + V_{t+1}^{\text{perfect}}(L_{t+1}^h, \text{PCC}_0, Y_{t+1})]/(1+\alpha) \sum_{h=1}^{m} P_{(ig)(ih)}$$

$$\cdot [c(L_{t+1}^h, Y_{t+1}) + V_{t+1}^{\text{perfect}}(L_{t+1}^h, \text{PCC}_0, Y_{t+1})]/(1+\alpha) \quad \text{(15a)}$$

$$Y_t = 0$$

$$V_t^{\text{perfect}}(L_t^g, \text{PCC}_0, Y_t) = \sum_{h=1}^{m} P_{(ig)(ih)}$$

$$\cdot [c(L_{t+1}^h, Y_{t+1}) + V_{t+1}^{\text{perfect}}(L_{t+1}^h, \text{PCC}_0, Y_{t+1})]/(1+\alpha) \quad \text{(15b)}$$

$$Y_t > 0$$

Equations (15a) and (15b) are similar to (10a) and (10b) except that the summation is taken only over h, not j and h, so that the transition probability matrix has the form $P_{(ig)(ih)}$, where $i = 1$ or m ($\text{PCC}_0 = 0$ or 1, respectively).

EV_t^{ig}[perfect] indicates the value if one knew immediately and perfectly what the future state of nature would be: either climate change, CC, or basis of comparison (present) climate, BOC. Information on water levels is not used to update the probability of CC or BOC.

EVIUII is a more representative measure of expected value of information than EVIUPI, because it measures the value of the actual information that will be gathered through Bayesian analysis. EVIUII is defined as

$$\text{EVIUII}^{ig} = \text{EV}^{ig}[\text{naive}] - \text{EV}^{ig}[\text{Bayes}] \quad (16)$$

Equation (16) represents the increase in expected value of the analysis, if the decision policy is based upon Bayesian updating of the belief in climate change (given information on water levels) over that of a decision policy based on zero belief in climate change. EV^{ig}[naive] is as defined in (12). The expected value of the Bayes analysis, EV^{ig}[Bayes], is

$$\text{EV}^{ig}[\text{Bayes}] = V_0(L_0^g, \text{PCC}_0^i, Y_0) \quad (17)$$

$V_t(L_t^g, \text{PCC}_t^i, Y_t)$ is solved recursively from (10a) and (10b).

Four of the 108 sensitivity scenarios were chosen for EVIUPI and EVIUII analysis. The scenarios differ in construction period and first cost, while trend (0.015), discount rate (5%), and sand cost escalation (2%) were constant. These runs were chosen because they exhibit significant differences in the decision arrays between $\text{PCC}_0 = 0$ and $\text{PCC}_0 = 1$, showing that belief in climate change influences the decision policy.

Figure 3 shows the EVIUPI results for the four scenarios. Since the decision array is identical for the naive analysis and for perfect information when $\text{PCC}_0 = 0$, EVIUPI equals zero at all water levels for that probability. But since a_t^g(naive) is being applied across all values of PCC_0, EVIUPI increases with PCC_0 at all water levels. This result shows that if the initial belief in climate change is high, but one ignores climate change uncertainty, there is a loss in the expected value of the decision. The peak for $\text{PCC}_0 = 1$ shown on all four graphs corresponds to the water level state where the decisions in $a_{t=0}^g$(naive) change from sand nourishment to breakwaters.

The right-hand-side graphs, which correspond to the 75% first cost scenarios, show zero EVIUPI for the highest water levels. The reason for this result is that regardless of the initial belief in climate change, the SDP model recommends building immediately at the highest water levels. Therefore the decision is the same under perfect information and under ignoring climate change. The 75% cost scenarios also lead to lower EVIUPI over the whole range of water levels and PCC_0. This result makes intuitive sense, because the lower cost means lower risk of regretting that the breakwaters were constructed. Likewise, the 24-year construction period scenarios result in lower EVIUPI than the 12-year scenarios. Again, the lower cost of the 24-year construction period alternative makes it a less risky proposition.

To put the magnitude of EVIUPI in perspective, the cost-benefit analysis of the Corps yielded a net present worth of $11.6 million (based on an annual benefit of $635,000 for 50 years at a 5% discount rate) for the 12-year construction alternative over continued sand nourishment. EVIUPI ranges from zero to approximately $5 million and is strongly dependent on PCC_0. Somebody with a strong initial belief in climate change will value information concerning climate change since its worth is as high as one third of the net project benefit.

Figure 4 shows the ratio of EVIUII to EVIUPI. This percentage represents the "efficiency" of the Bayesian inference process relative to perfect information. For example, although EVIUII matches EVIUPI when $\text{PCC}_0 = 0$, there is no efficiency in information value because EVIUPI equals zero when $\text{PCC}_0 = 0$. On the other hand, when $\text{PCC}_0 = 1$, EVIUII is 100% efficient, because EVIUII is identical to EVIUPI when $\text{PCC}_0 = 1$.

Does Climate Change Uncertainty Change the Timing on the Decision to Build?

Actually, two timing questions were examined: When will climate change be detected given information on water levels? and When will a decision to build breakwaters be made?

When will climate change be detected? The decision model was tested to see how fast PCC_t would update toward either 0 or 1 (weak or strong belief) given information on water levels. The test was a Monte Carlo simulation under three scenarios of water level trends, "Trend" = −0.0075, −0.015, and −0.030 m/yr. PCC_t was updated according to (6), (7), and (8), given water levels which were generated stochastically from (3). The rate at which climate change could be detected depended strongly on Trend. Figure 5 shows results in which $\text{PCC}_0 = 0.5$. For Trend = −0.015 m/yr, the model tended to $\text{PCC}_t = 1$ within 25 years. A limitation of the model is that the observed water levels were generated from the same lag-1 autoregressive model used in the updating equation. In reality, observed water levels do not fit a lag-1 autoregressive model, and therefore it might take longer to tend to $\text{PCC}_t = 1$. Furthermore, events outside the basin (e.g., a major climate study) could change PCC_t as well. External changes in knowledge could be modeled in a more general SDP as random events that could be included in Bayes' law. In that case, both lake levels and external events would affect PCC_t.

When will a decision to build breakwaters be made? We developed two measures for the timing of the decision: (1) the probability of making the decision to build at time t given initial water levels and initial climate change beliefs, P_t^{ig}(build), and (2) the expected time until a decision is made to build break-

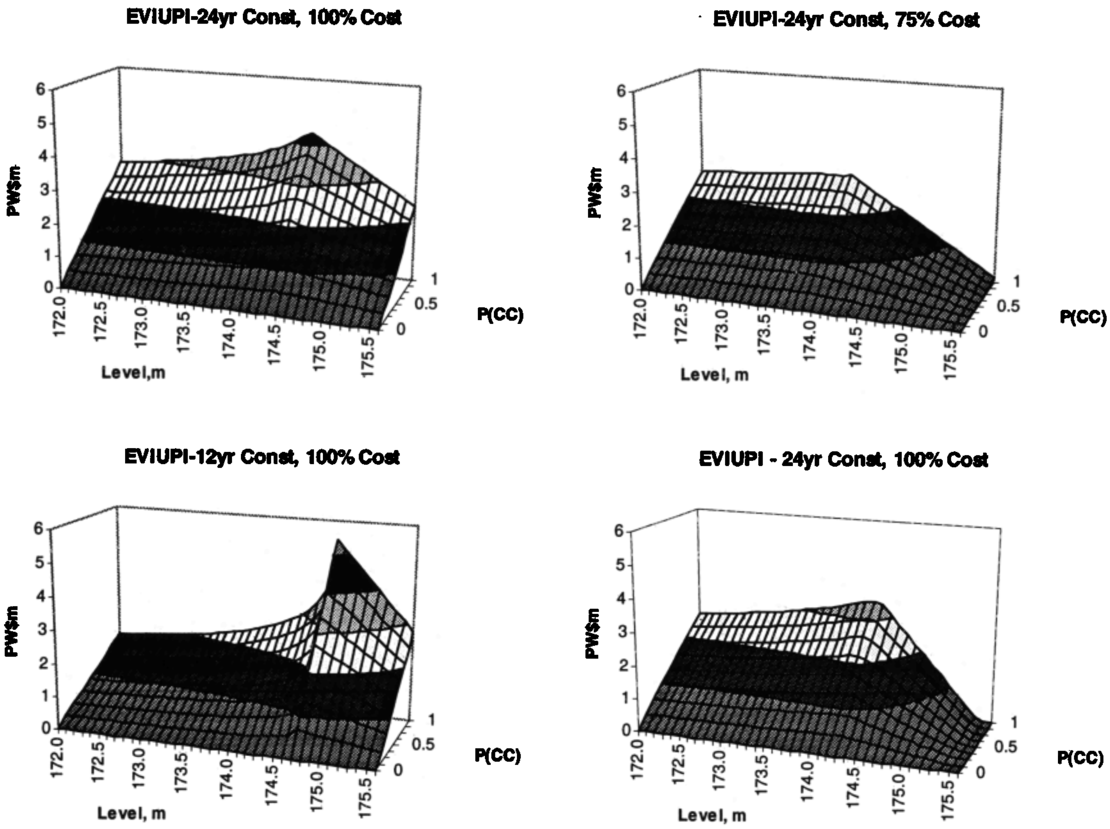

Figure 3. EVIUPI results.

waters, given initial water levels and initial climate change beliefs, $E^{ig}[T_{\text{build}}]$. Since the initial state (water levels and belief in climate change) affects the decision policy, these measures show whether initial states have a long-term influence on the subsequent decision policies. For example, if the SDP yields a decision to continue sand nourishment for stage 0 and water level 172.5 m, the planner may want to know whether the decision to build is likely to occur any time soon.

The probability of a breakwater decision is similar to a geometric probability distribution in which there are t straight years of sand nourishment decisions (success) until a decision to build (failure):

$$P_{0t}^{(ig)(jh)}(\text{build}) = \sum_{f=1}^{n} \sum_{k=1}^{m} P_{0(t-1)}^{(ig)(fk)}(\text{notbuilt}) \times P_{t-1}^{(fk)(jh)} \times a_{t-1}^{jh} \tag{18}$$

(fk) and (jh) denote the states at time $t-1$ and t, respectively. The double summation over f and k adds up the probabilities of entering state (jh) at time t given a previous state of (fk). $P_{t-1}^{(fk)(jh)}$ is the one-step transition probability matrix at time $t-1$; a_{t-1}^{jh} is the decision array at time $t-1$ which is based on the decisions defined by (10a) and (10b). $P_{0(t-1)}^{(ig)(fk)}(\text{notbuilt})$ denotes the $(t-1)$-step transition probability matrix in which the decision to build has yet to be made since $t=0$. This term is calculated recursively from

$$P_{0\tau}^{(ig)(jh)}(\text{notbuilt}) = \sum_{f=1}^{n} \sum_{k=1}^{m} P_{0(\tau-1)}^{(ig)(fk)}(\text{notbuilt}) \times P_{(\tau-1)}^{(fk)(jh)} \times (1 - a_{(\tau-1)}^{jh}) \qquad \tau = 2, 3, \cdots, t \tag{19}$$

Equation (19) actually denotes the probability of deciding to build given the initial state (ig) and the final state (jh). Summing over (jh) gives the marginal probability of having decided to build by time t given the initial state (ig), regardless of the final state:

$$P_{0t}^{(ig)}(\text{build}) = \sum_{h=1}^{n} \sum_{j=1}^{m} P_{0t}^{(ig)(jh)}(\text{build}) \tag{20}$$

We calculate (20) for the two scenarios used for EVIUPI and EVIUII which had a 24-year construction period (Figure 6). Figure 6 is arranged sequentially for values of $t = 1$, 5, and 20. For $t = 1$, there is a high probability of deciding to build for high water levels and low PCC_0. The two scenarios shown have different decision patterns at high values of PCC_0 which result in different probabilities of building at $t = 1$. The plots for subsequent time periods start shifting until, for $t = 20$, it is quite clear that the probability of having built varies primarily with PCC_0 and not with L_0. The reason for this behavior is that for low values of PCC_0 even if the initial water level is low, it is likely that the water levels will rise to the point where the decision to build will be made. At higher values of PCC_0 it becomes less likely high water levels will be reached. This result is useful for planning because it shows over the long run that given these two scenarios, regardless of the initial water level, belief in climate change will be a major determinant of whether the breakwaters should be built.

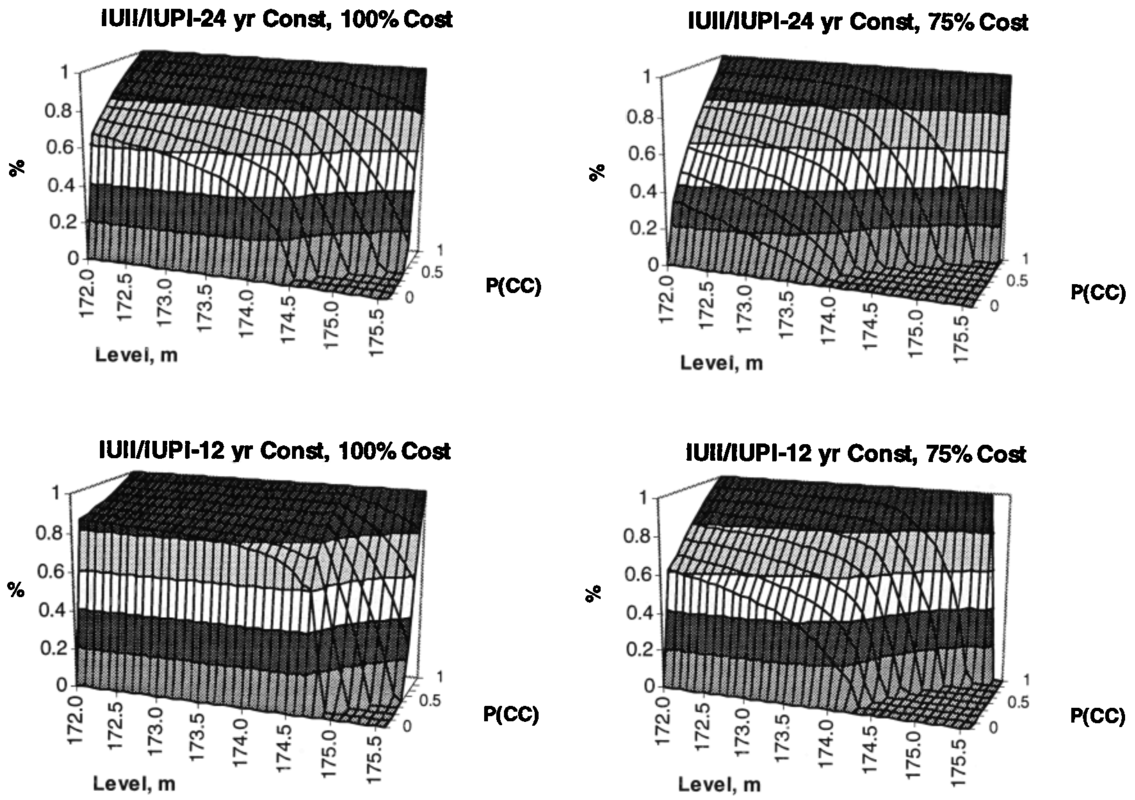

Figure 4. Ratio of EVIUII to EVIUPI.

Equation (21) is the expected time to build:

$$E^{ig}[T_{\text{build}}] = \sum_{t=1}^{\infty} tP_{0t}^{(ig)}(\text{build}) \qquad (21)$$

which is in a form similar to the expected value for the geometric distribution. For computing purposes, it is not possible to sum to infinity, so there is a truncation error in calculating $E^{ig}[T_{\text{build}}]$. We define a lower bound on $E^{ig}[T_{\text{build}}]$ as follows:

$$E^{ig}[T_{\text{build}}] \geq E^{ig}[T^{\text{LB}}_{\text{build}}] = \sum_{t=1}^{T-1} tP_{0t}^{(ig)}(\text{build}) + TP_{0T}^{(ig)}(\text{notbuilt}) \qquad (22)$$

$E^{ig}[T^{\text{LB}}_{\text{build}}]$ is calculated (in Figure 7) for the same two scenarios used in Figure 6. The plots show that if the decision is to build in year 1 (high initial water levels and low belief in climate change), then $E^{ig}[T^{\text{LB}}_{\text{build}}] = 1$. The lower plot shows $E^{ig}[T^{\text{LB}}_{\text{build}}] = 1$ at high water levels even for higher beliefs in climate change. This result shows that under these circumstances belief in climate change is not a factor in the decision. But for lower water levels, the plots show that $E^{ig}[T^{\text{LB}}_{\text{build}}]$ increases significantly with increasing PCC_0, indicating that climate change beliefs can matter.

4. Discussion and Conclusion

The objective of this research was to demonstrate how risk analysis, specifically SDPs, can be applied to understand the effect of climate change uncertainty upon water resource planning. The case study was the erosion control project at Presque Isle, Pennsylvania, in which segmented breakwaters were built in 1992. While the benefits of building breakwaters seemed clear in the short term when the decision was made, in 1986, the long-term stream of benefits from the breakwaters is more difficult to predict because of the natural fluctuation of lake levels. Greenhouse gas–induced climate change, which may lower mean water levels, might significantly decrease the stream of benefits and result in economic regret, since breakwaters are a long-term, irreversible investment. The uncertain nature of climate change makes it difficult to assess what the future stream of benefits may be.

We applied decision analysis to the erosion control project by modeling the problem as a sequential decision process with a stochastic dynamic program. A SDP allows the decision maker to determine the optimal action given the state of the system and to determine the value of information that is gathered to reduce the amount of uncertainty in climate change or for any uncertain factor.

The process of developing the SDP for the case study was to (1) identify state variables, (2) develop a state transition probability matrix, and (3) develop a cost function. The state variables for the SDP were mean annual Lake Erie water level, L_t; belief in climate change, PCC_t; and the year since construction began, Y_t. The transition probability matrix was the product of the distributions of these three variables. We estimated a cost function which linked water levels to the two primary annual costs: sand nourishment and dredging. The SDP model, solved according to Bellman's equations, provided sequential decision policies over time as a function of two of the state variables, L_t and PCC_t.

To assess the sensitivity of the sequential decision policy to various model parameters, we applied a factorial experiment

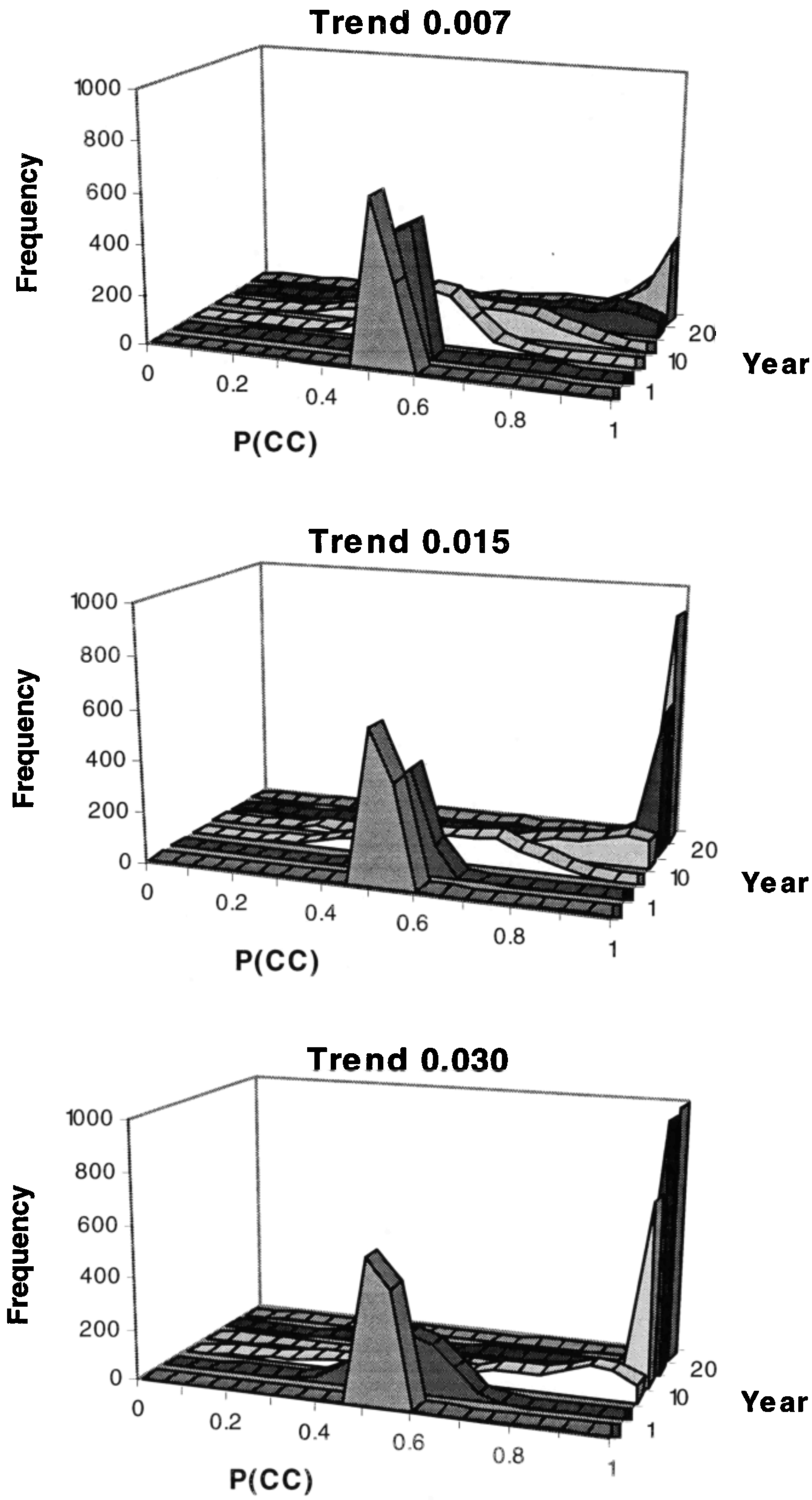

Figure 5. Monte Carlo simulation of Bayesian updating with trend in mean observed levels (i.e., with climate change) but starting at $PCC_0 = 0.5$.

on the parameters in Bellman's equations. To measure the value of waiting to gather more information on climate change, we developed two measures: expected value of including uncertainty given perfect information, EVIUPI, and expected value of including uncertainty given imperfect information, EVIUII. We also developed two other measures to examine the timing of the decision: probability of building by time t, P_t(build), and expected time until construction, $E[T_{\text{build}}]$.

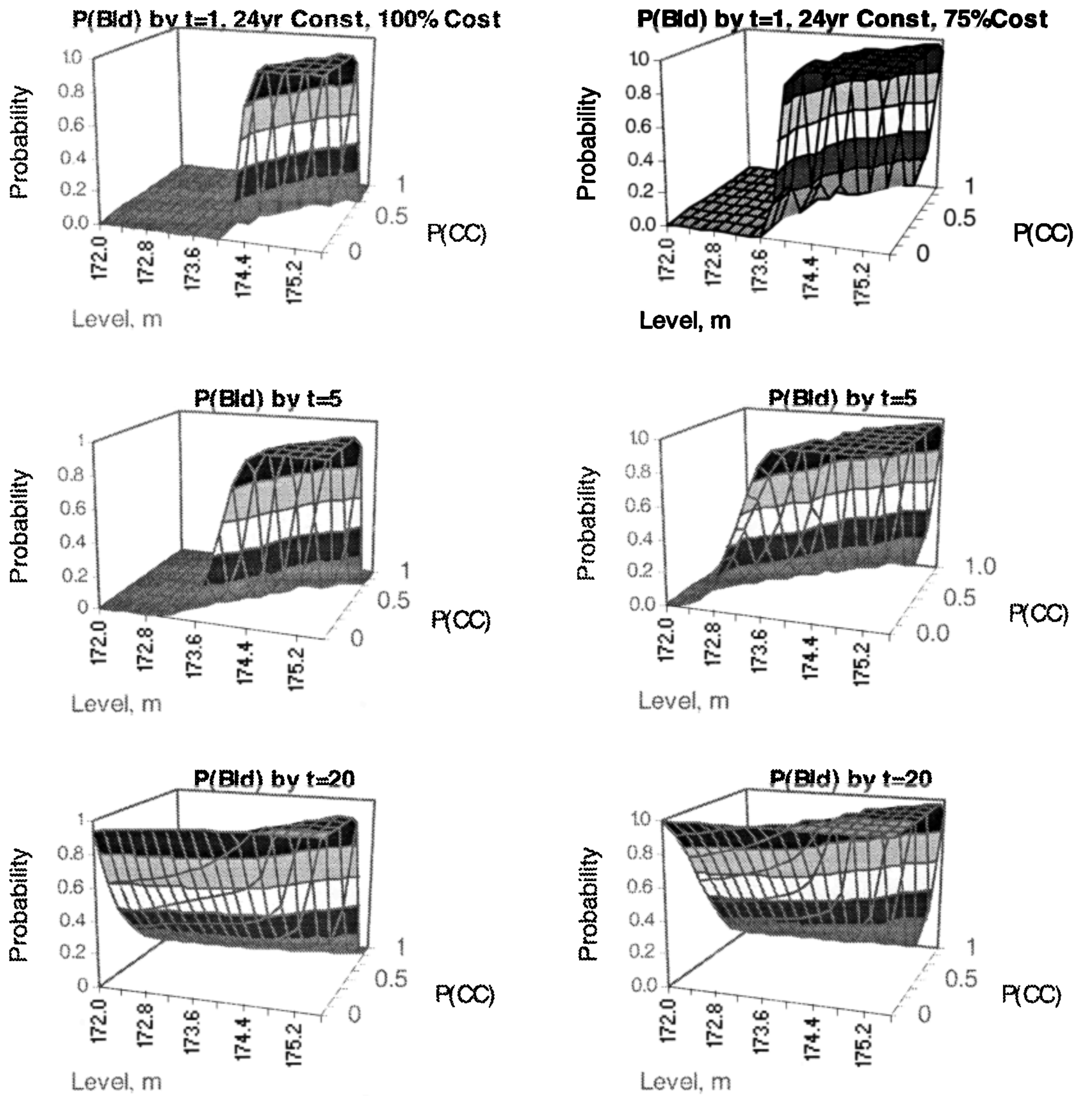

Figure 6. Probability of building at times 1, 5, and 20 years for a 24-year construction period scenarios and different construction costs.

The main conclusions derived from these numerical experiments are the following:

1. Changes in discount rates have the most effect on the decision. In general, discount rates above 6%–7% make the breakwaters less attractive than sand nourishment, regardless of climate change belief. Belief in climate change is less important but still makes a difference in 15% of the cases examined.

2. If a decline in water levels is certain, even with a shallow trend, then breakwaters should never be built. As a result, if there is a strong belief in climate change, there is value in waiting and gathering information. The value in waiting increases with the magnitude of the trend.

EVIUPI and EVIUII put a value upon resolving the uncertainty, which can then be compared to the overall value of the decision. These values thus give a measure for the decision maker to determine whether there is significant value in delaying a decision. These measures also provide a measure of regret, if the decision maker chooses to ignore climate change. For the scenarios examined, both EVIUPI and EVIUII increase with PCC,, growing to as much as $5 million. This value is significant since the first cost of construction is on the order of $10 million. However, it should be noted that while the results shown for EVIUPI and EVIUII are insightful, they are for only a select set of scenarios. EVIUPI and EVIUII are zero for the scenarios where belief in climate change does not alter the decision array. Therefore the results from the sensitivity analysis gives a better overall sense of the decision problem.

The model is limited by data availability and the curse of dimensionality in the SDP. In particular, the SDP cost function is a function of only three state variables and is based on a yearly time step. We ignored or treated as constant other factors which may affect costs. For example, we did not account for possible changes in the frequency of events, such as storms, that occur on a smaller time interval. It is quite possible under climate change that the direction, distribution, and magnitude of storms may change, thereby altering erosion rates and thus the value of breakwaters. Since GCMs do not yield credible predictions of severe storm frequencies, it is difficult to assess potential changes to erosion rates. Furthermore, the presence of ice cover, which retards erosion during the colder months, is not modeled. The loss of ice cover under climate warming

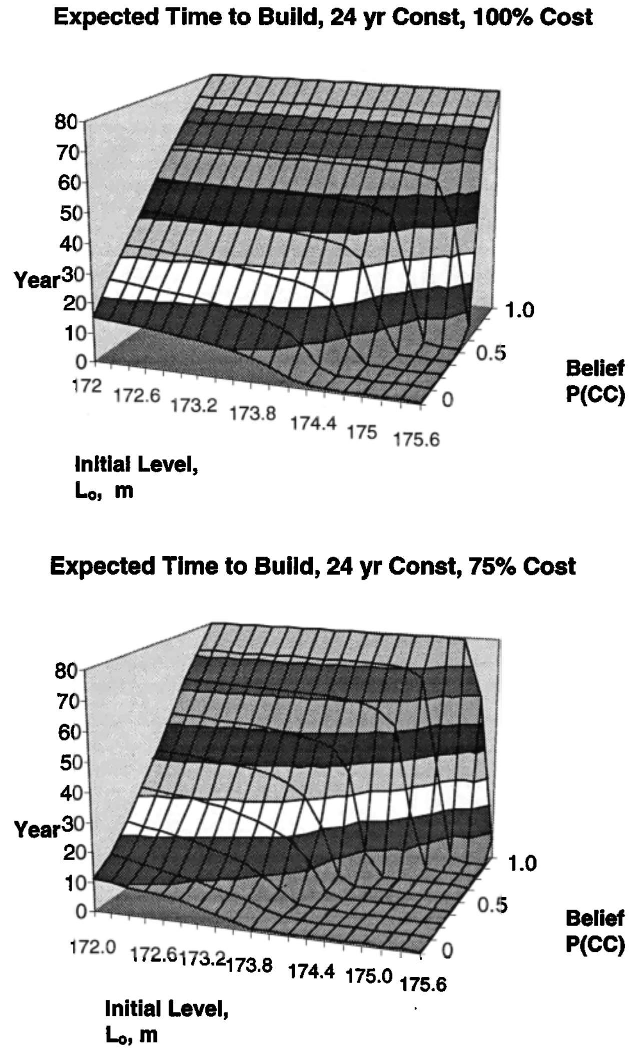

Figure 7. Expected time to build.

would result in greater erosion rates, perhaps making the breakwaters more attractive.

In deriving the cost functions, we assumed recreational beach and harbor demand would remain constant. Under climate change, it is possible that recreation demand will increase because of the longer season and warmer temperatures. If this is the case, then there is more value in maintaining beach width. If warmer temperatures are accompanied by a drop in lake levels, then breakwaters would not be advantageous. If, however, warmer temperatures are accompanied by an increase in precipitation that maintains lake levels, then breakwaters would be more favorable. It is also possible that future demand for the Port of Erie may decrease, either through market changes of goods shipped through the harbor or through increasingly high dredging costs due to lower water levels. If, for example, the harbor were to shut down, then the cost of dredging should be dropped from the cost function, with the result that breakwaters would become less favorable.

The transition probability matrix is a critical part of the SDP. The results showed that water levels can be used to detect climate change through Bayesian updating. The weakness of the Bayesian updating model is that the stochastically generated observed water levels come from the same lag-1 autoregressive model that is used in the likelihood function. In reality, however, the observed water levels would come from a much more complex nonstationary distribution. The nonstationarity of the distribution makes it difficult to assess the short-term benefits of breakwaters, which is critical with higher discount rates. The nonstationarity might also cause the Bayesian updating of PCC_t to proceed at a slower pace since there would be more noise in the signal or in the wrong direction. A more sophisticated likelihood function, possibly involving a higher order autoregressive integrated moving average (ARIMA) time series model and shifting mean levels [*Mathier et al.*, 1992], would provide better tracking of real observed levels. More sophisticated approaches could involve looking at more variables than just water levels to detect a climate change scenario such as global temperature changes.

The drawback of developing a more complex cost function or more sophisticated Bayesian updating model is that the number of states of the SDP would increase. Computer and memory speed limits the fineness of the discretization. Computational tests show that if the discretization of water level states is too coarse, then the water level trend may not be detected in the Bayesian updating [*Chao*, 1996].

One area that could be further investigated is different climate change scenarios. The SDP is limited to one scenario of decreasing linear trend in water levels. Other possible scenarios are shifting mean levels or increasing linear or nonlinear trends. The drawback of combining more than one scenario with the basis of comparison is that the number of states increases exponentially with the number of scenarios. For example, for a three-scenario SDP, rather than using just PCC_t to define the state of nature, $PCC1_t$ and $PCC2_t$ would have to be defined instead. Alternative approaches to solving large SDPs, such as partially observable Markov decision process algorithms or discrete differential dynamic programs, might be used as means of dealing with models with more state variables.

The decision framework developed here also could be applied to other Great Lakes management problems subject to climate change uncertainty, such as lake level regulation, water diversions, and wetland restoration. In addition, the SDP framework could be adopted for shoreline management under sea level rise uncertainty.

We have demonstrated that beliefs in climate change can be addressed in water resources management problems through risk analysis. More generally, to assess whether climate change affects water resources management problems, *Hobbs et al.* [1997] propose that the decision maker should first apply deterministic scenario analysis to assess whether climate change uncertainty affects system performance as much as other uncertainties. If climate change does matter, then risk analysis may be applied to analyze how belief in climate change affects decisions.

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