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Using direct policy search to identify robust strategies in adapting to uncertain sea-level rise and storm surge

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ABSTRACT

Sea-level rise poses considerable risks to coastal communities, ecosystems, and infrastructure. Decision makers are faced with uncertain sea-level projections when designing a strategy for coastal adaptation. The traditional methods are often silent on tradeoffs as well as the effects of tail-area events and of potential future learning. Here we reformulate a simple sea-level rise adaptation model to address these concerns. We show that Direct Policy Search yields improved solution quality, with respect to Pareto-dominance in the objectives, over the traditional approach under uncertain sea-level rise projections and storm surge. Additionally, the new formulation produces high quality solutions with less computational demands than an intertemporal optimization approach. Our results illustrate the utility of multi-objective adaptive formulations for the example of coastal adaptation and point to wider-ranging application in climate change adaptation decision problems.

Software availability

Model source code and data are available at https://doi.org/10.18113/D3XD32. Model requires Gnu C++ compiler 5.3.1 (https://gcc.gnu.org/), OpenMPI 1.10.1 (https://www.open-mpi.org/), NetCDF 4.4.1 (https://www.unidata.ucar.edu/software/netcdf/), Boost 1.61.0 (http://www.boost.org/), and Borg 1.8 (http://borgmoea.org/) or later versions.

1. Introduction

Sea-level rise (SLR) drives considerable risks to coastal communities, ecosystems, and infrastructure around the world (Eijgenraam et al., 2014; Le Cozannet et al., 2015; Miller et al., 2015; Moftakhari et al., 2015; Nicholls and Cazenave, 2010). The Intergovernmental Panel on Climate Change reports that global mean sea-levels will likely rise by 0.52–0.98 m by the year 2100 (relative to the 1986–2005 period) under a high greenhouse gas concentration scenario (Church et al., 2013). A potential collapse of portions of the Antarctic ice sheet would irreversibly drive SLR well beyond this range (DeConto and Pollard, 2016; Pollard et al., 2015; Wong et al., 2017; Wong and Keller, 2017). Additionally, climate change is contributing to changes in the distribution of storm surge events, especially with regard to the extreme tail-area events (Arns et al., 2017; Grinsted et al., 2013, 2012; Neumann et al., 2015). Though SLR and storm surge have been, and continue to be, extensively studied, they remain deeply uncertain across decision-relevant time scales (Buchanan et al., 2016; Hinkel et al., 2014; Le Cozannet et al., 2015; Lempert et al., 2004; Sriver et al., 2018). Those in position to enable coastal adaptation strategies rely on decision support tools to process this deeply uncertain information to inform their decisions (Lempert et al., 2004; Liverman et al., 2010; Sriver et al., 2018).

Developing and applying these decision support tools poses conceptual and methodological challenges. One approach is to build an optimization tool that finds the time-series of dike heightenings that minimizes the total economic cost of building dikes or levees (Eijgenraam et al., 2014; Kind, 2014; Slijkhuis et al., 1997; Speijker et al., 2000; Van Dantzig, 1956; van der Pol et al., 2014). To incorporate uncertainty, this process can be repeated over various sets of model parameters and the expectation of the total costs can be minimized.

This approach, however, is silent on several key decision-making aspects. First, the single-objective formulation can hide important tradeoffs among stakeholder preferences of which the decision maker must be aware (Garner et al., 2016; Quinn et al., 2017; Singh et al., 2015). For example, a climate mitigation strategy derived by maximizing the expectation of an *a priori* defined utility function may be blind to

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important tradeoffs in environmental objectives and remove relevant stakeholders from the negotiations (Garner et al., 2016). Second, insufficient sampling of uncertainty can under-represent extreme events that may weigh heavily in the decision (Garner et al., 2016; Lempert et al., 2004). Lastly, this formulation does not make use of important state-related information, such as the level of the water with respect to the top of the dike, which can be used to inform the decision (Quinn et al., 2017; van der Pol et al., 2014). The Robust Decision Making (RDM) framework provides a means of approaching these concerns (Herman et al., 2015; Kwakkel et al., 2016; Lempert et al., 2006; Weaver et al., 2013). We expand on this framework with an additional component to include endogenous learning and adaptive decision making.

In this study, we reformulate the problem to begin addressing these concerns. Specifically, we split up the total cost metric into its investment cost and damage components to illustrate the direct tradeoffs between the two objectives. We use a states-of-the-world (SOWs) approach about SLR and storm surge to introduce uncertainty to the SLR adaptation model and provide coverage of tail-area events. Finally, we apply Direct Policy Search (DPS), an adaptive state-based method of endogenous learning, to incorporate new information and adapt the decision through the simulation period (Deisenroth et al., 2013; Giuliani et al., 2016). We hypothesize that these changes will provide an improvement in solution quality over the traditional approach.

2. Methods

The following sub-sections describe our approach to formulating the problem and designing the experiment. The sub-sections largely follow the taxonomy proposed in the XLRM framework where the decision problem is comprised of exogenous uncertainties (X), levers or actions at the disposal of the decision maker (L), the model or relationship (R) mapping the decision maker's actions to the performance metrics or objectives (M) (Lempert et al., 2006).

2.1. Base model (R)

The base model used in this analysis is an SLR adaptation model used in the Netherlands to help inform safety standards for the numerous dikes protecting the country. The model is described extensively in (Eijgenraam et al., 2014). The key components are briefly summarized below.

The objective is to find the time series of annual dike heightenings u_t that minimizes the total discounted social cost over the simulated time horizon of 300 years

$$\min\left\{\sum_t I(h_t^-, u_t)e^{-\delta t} + S_t e^{-\delta_1 t}\right\}, \tag{1}$$

where I is the investment cost to heighten the dike and S_t is the expectation of damages at year t. Both investment cost and the expectation of damages are discounted by a factor of δ and δ_1 respectively. The investment cost component is defined by an exponential function of the increase in dike height at a given time

$$I(h_t^-, u_t) = \begin{cases} 0 & if\ \ u_t = 0 \\ (\kappa + \upsilon u_t)e^{\lambda(h_t^- + u_t)} & if\ \ u_t > 0 \end{cases}, \tag{2}$$

where κ, υ, and λ are positive constants and u_t is the additional height added at time t to the dike at height h_t^-. The increase in dike height reduces the probability of a flood (P_t) and thus reduces the expectation of damages according to

$$S_t = P_t V_t \tag{3}$$

$$V_t = V_0^- e^{\gamma t} e^{\zeta(H_t - H_0^-)}, \tag{4}$$

where V_t is the damage incurred in the event of a flood at time t, V_0^- is the damage incurred by a flood before $t = 0$, H_t is the dike height at time t, H_0^- is the dike height just before $t = 0$, γ is the economic growth rate within the area protected by the dike, and ζ is the increase in loss per unit of dike heightening. Values for these parameters are listed in Table 1, which are consistent with the parameter values for dike ring 16 in (Eijgenraam et al., 2014). The probability of flooding (P_t) is handled differently in our formulations and is discussed in section 2.2.

Table 1
Parameter values of the economic component of the base model.

Parameter (symbol)	Value	Unit
Discount rate of investment cost (δ)	0.04	yr^{-1}
Discount rate of expected damages (δ_1)	0.04	yr^{-1}
Initial investment cost to heighten dike (κ)	324.6287	Euros
Linear parameter in investment cost (ν)	2.1304	Euros/yr
Exponential parameter in investment cost (λ)	0.01	cm^{-1}
Economic growth rate within dike (γ)	0.02	yr^{-1}
Increase in loss per unit of dike heightening (ζ)	0.002032	cm^{-1}
Initial height of dike prior to t = 0 (H_0^-)	118.6837	cm
Loss due to flood prior to t = 0 (V_0^-)	22656.5	Euros

2.2. Uncertainty in SLR and storm surge (X)

In the base model, the probability of flooding is represented by an exponential distribution of extreme flood events. A steady rate of increase in the effective water height is used to represent rising sea-levels, and in the case of the Netherlands, land subsidence. This rate parameter is used in the exponential distribution to determine the probability of a dike failure as a function of time. Sea-level rise, however, is a deeply uncertain consequence of a changing climate (Church et al., 2013) and a steady rate of sea-level rise represents only one possible future state. In the reformulated analysis, the probability of flooding is replaced with an explicit representation of states of the world (SOWs) (Garner et al., 2016; Singh et al., 2015; Sriver et al., 2018). In this approach, parameters that represent future states of the world do not have a single value, but rather a distribution of possible values. Drawing a sample from each parameters' distribution would represent a single state over which the model is evaluated. Repeating this process provides a series of outcomes from which expectations and reliability metrics can be calculated.

In order to use the SOW approach to represent uncertainty, we incorporate new structural representations of sea-level rise and storm surge events into the base model. Future mean annual sea-level rise is approximated by the approach used in Sriver et al. (2018)

$$z_t = \begin{cases} a + bt + ct^2 & if\ \ t \le t^* \\ a + bt + ct^2 + c^*(t - t^*) & if\ \ t > t^* \end{cases}, \tag{5}$$

where parameters a, b, and c are the initial sea-level rise anomaly, linear rate of change of sea level, and the acceleration of sea-level change respectively. The c^* and t^* parameters represent a potential abrupt change in sea-level rise such as the sudden collapse of an ice sheet (DeConto and Pollard, 2016; Diaz and Keller, 2016; Pollard et al., 2015). The linear rate would increase by c^* when t exceeds t^* in the simulation. The joint distribution of these parameters are estimated through the calibration process described in Oddo et al. (2017) and used in this analysis to derive SOWs.

Storm surge events occur on top of the mean annual sea level. These events are estimated through inverse-transform sampling of the stationary generalized extreme value (GEV) distribution calibrated in Oddo et al. (2017).

$$x_t = \begin{cases} \mu + \sigma ln\left(\frac{1}{\ln(1/p)}\right) & if\ \ \xi = 0 \\ \mu + \frac{\sigma((\ln(1/p))^{-\xi})}{\xi} & if\ \ \xi \ne 0 \end{cases}, \tag{6}$$