Quantifying Multi-Objective Tradeoffs under Deep Uncertainty in the Design of Sea-Level Rise Adaptation Strategies

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NH13B-1934

Introduction

The effects of climate change are expected to raise global mean sea levels up to 1.8 meters by 2100. Sea level changes as small as 0.25 meters can increase flood risks by several orders of magnitude. Risk-prone areas commonly employ probabilistic risk assessments to inform flood management strategies.

The van Dantzig (1956) model was first developed as a response to the 1953 North Sea to determine optimal dike heights by minimizing the net present value (NPV) of total protection costs. However, the model has several deficiencies that limit its efficacy for modern decision-makers:

- It is silent on many structural and parametric uncertainties (Table 1)
- Considers only a single management objective

Table 1. Parameter values for van Dantzig (1956) and this study.

	Van Dantzig (1956)				*This Study*			
	Parameter (symbol)		Prior	Unit	Parameter (symbol)	Distribution	Prior mean (std. dev.)	Unit
Economic	Value of goods	(V)	2 x 10^{10}	Guilders	Value of goods (V)	Normal	2 x 10^{10} (1 x 10^9)	Guilders
Economic	Effective discount rate	(δ')	0.02	Percent/yr	Effective discount rate (δ')	Lognormal	0.02 (0.1)	Percent/yr
Economic	Cost rate of heightening	(k)	4.2 x 10^7	Guilders/m	Cost rate of heightening (k)	Normal	4.2 x 10^7 (4 x 10^6)	Guilders/m
Sea level rise	Subsidence rate	(η)	0.002	m/yr	Subsidence rate (η)	Lognormal	0.002 (0.1)	m/yr
Sea level rise	Sea level rise rate	(Φ)	0.008	m/yr	Sea level rise in 2015 (a)	Well-characterized joint probability distribution	-17.0–76.0	mm
					Sea level rise rate (b)		-0.70–3.9	mm/yr
					Sea level rise acceleration (c)		-0.0075–0.013	mm/yr^2
					Year of abrupt sea level rise (t*)	Deeply uncertain	2015–2090	Year
					Rate of abrupt sea level rise (c*)	Deeply uncertain	0–0.035	m/yr
Storm surge	Initial flood frequency	(p_0)	0.0038	Unitless	Anomaly location parameter (ξ)	Well-characterized Generalized Extreme Value distribution	-0.14–0.094	Unitless
Storm surge	Exponential flood frequency rate	(α)	2.6	Unitless	Anomaly scale parameter (μ)		278–291	Unitless
					Anomaly shape parameter (σ)		3.68–3.92	Unitless

Objectives

Here we implement and improve on a classic dike height model to represent multiple stakeholder objectives and parametric and structural model uncertainties. We use global sensitivity analyses to determine:

1. **the effects of structural and parametric uncertainties in a classic economic model of sea-level rise adaptation**
2. **the multi-objective tradeoffs between key management objectives**
3. **the parametric uncertainties that matter most for a given objective**

Methods

Model development

- Code baseline model into R and evaluate against van Dantzig (1956) to ensure it replicates results.
- Use Latin hypercube sampling to establish parametric uncertainty.
- Determine additional management objectives that can be evaluated in addition to Discounted total costs:
  - Discounted damages [minimize]
  - Reliability [maximize]
  - Investment costs [minimize]
- Evaluate model for each dike height from 0 – 10 meters.

Sea-level rise model

- Analyze tide gauge measurements from Delfzijl, the Netherlands.
- Use rejection sampling to calibrate 2nd order polynomial function to project sea-level rise up to year 2100.

Storm surge model

- Determine annual block maxima tide gauge observations and determine maximum likelihood estimation (MLE) for three generalized extreme value (GEV) parameters.
- Use Markov-Chain Monte Carlo to produce parameter chains for each GEV parameter.

Sensitivity Analysis

- Perform local sensitivity study using One-at-a-time analysis.
- Evaluate parameter interactions using Sobol sensitivity analysis (SALib framework).

Results

What are the effects of deep uncertainties in sea-level rise projections?

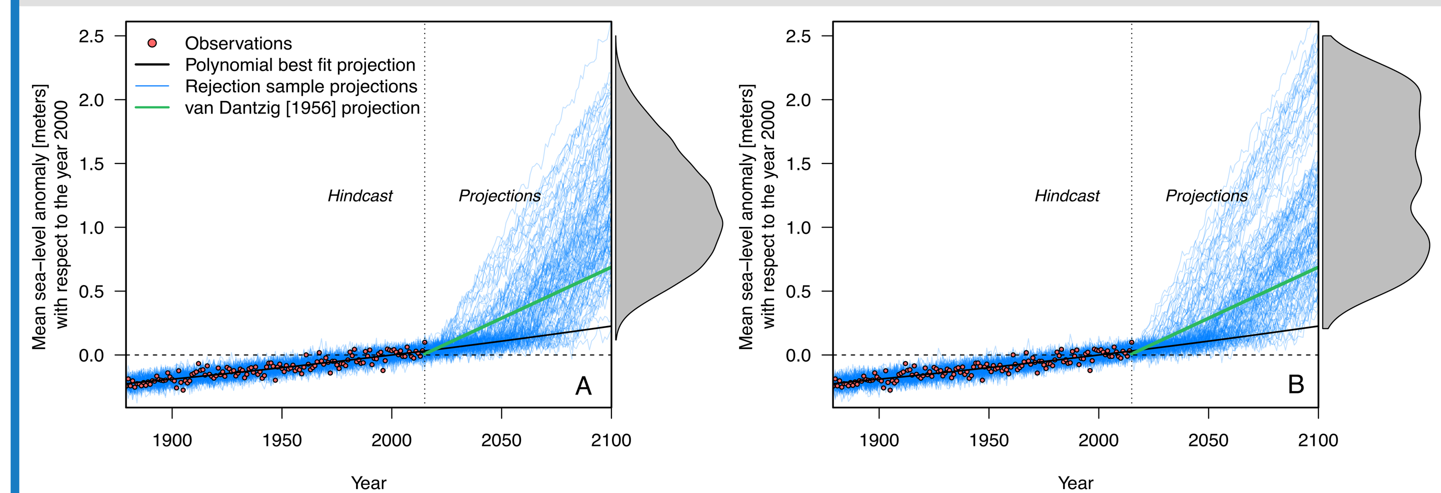


Figure 1. Sea-level rise hindcasts and projections to year 2100 . Shown are the polynomial model with uncertainty and the potential contribution of abrupt sea-level rise. Green line represents original van Dantzig (1956) linear approximation. The marginal PDF in gray approximates the expert assessment of sea-level-rise at year 2100 using an expert assessment beta distribution (A) and a uniform distribution (B).

How do improved statistical methods affect storm surge determinations?

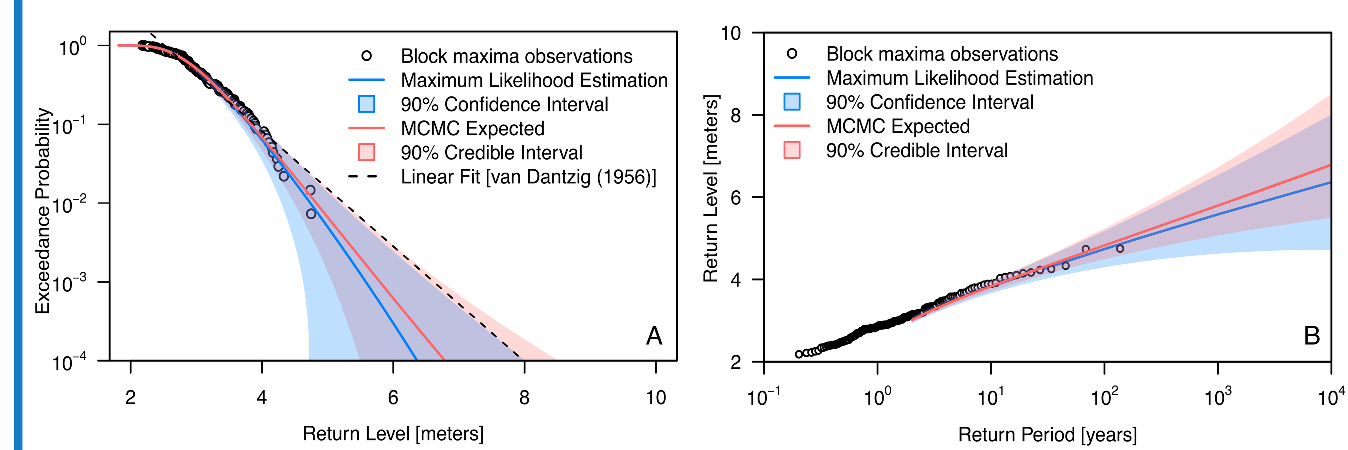


Figure 2. Observed and projected return levels (A) and return periods (B) for Delfzijl, the Netherlands. Shaded envelopes represent the 90% confidence interval and the 90% credible interval for the MLE and Markov Chain Monte Carlo methods, respectively. Solid lines show expected outcome for each method. Dashed line represents the van Dantzig (1956) linear extrapolation.

What are the uncertain tradeoffs between diverse management objectives?

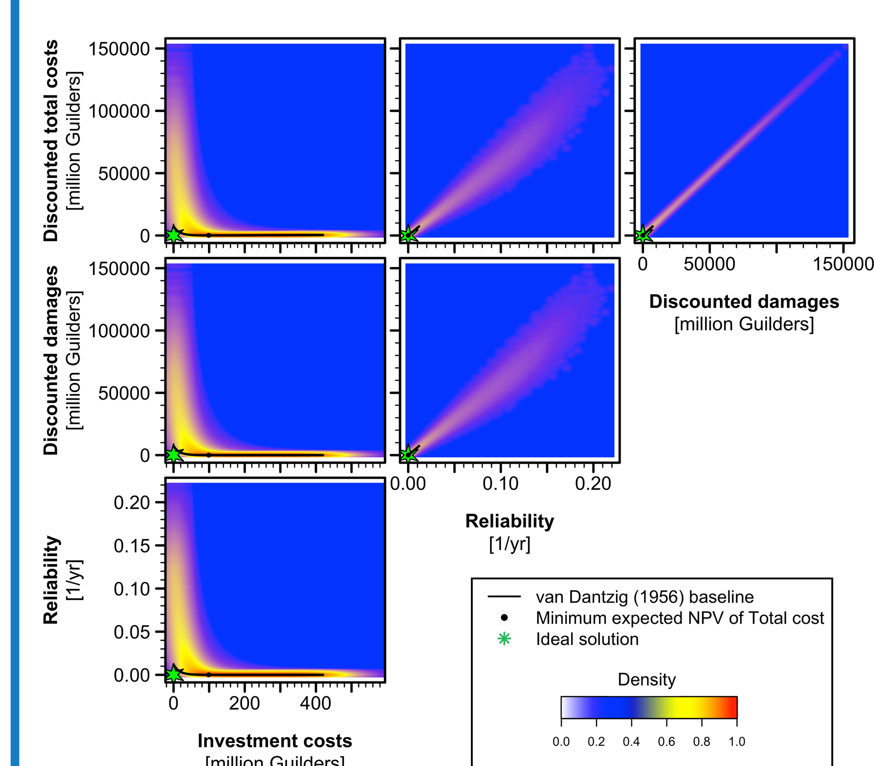


Figure 3. Multi-objective tradeoffs under uncertainty. Solid lines represent extent of baseline tradeoffs, and points indicate the index of the minimum expected net present value for total costs in the baseline model. Color shading represents the density of different outcomes. The green star represents the ideal solution according to each objective criteria.

How do structural and parametric uncertainties change the van Dantzig (1956) optimal dike height?

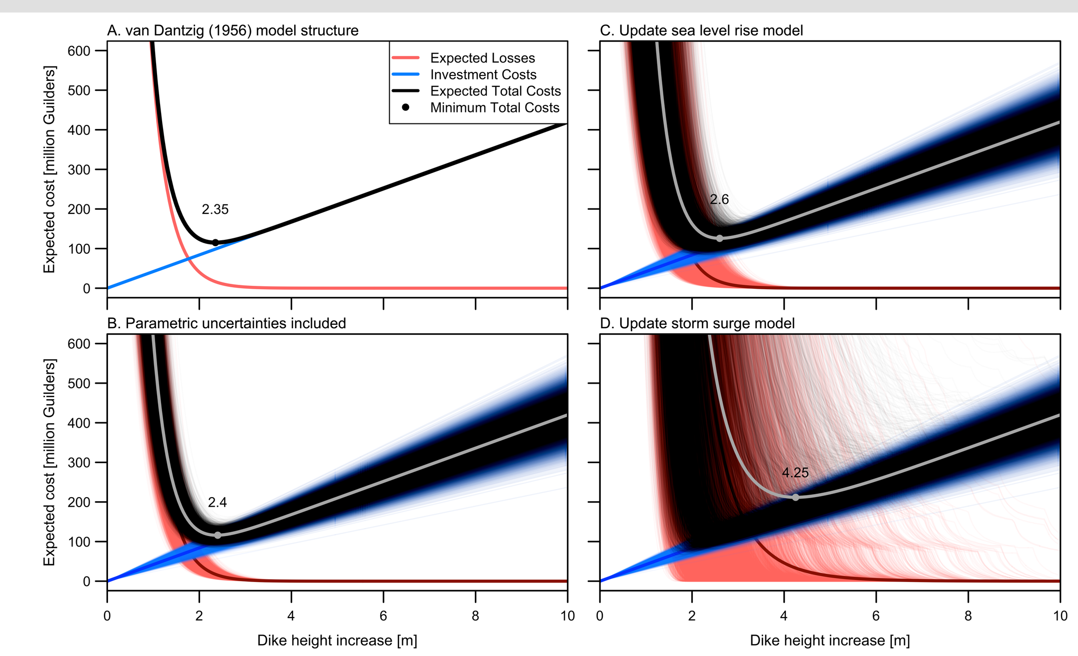
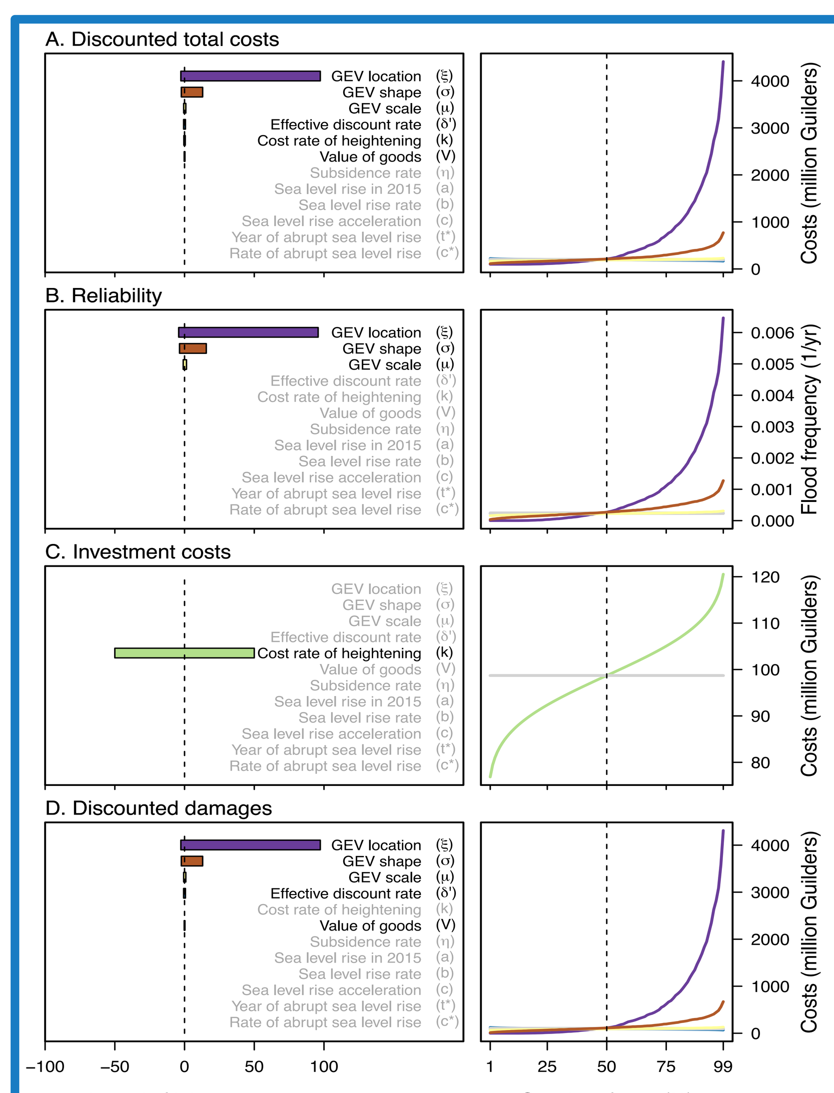


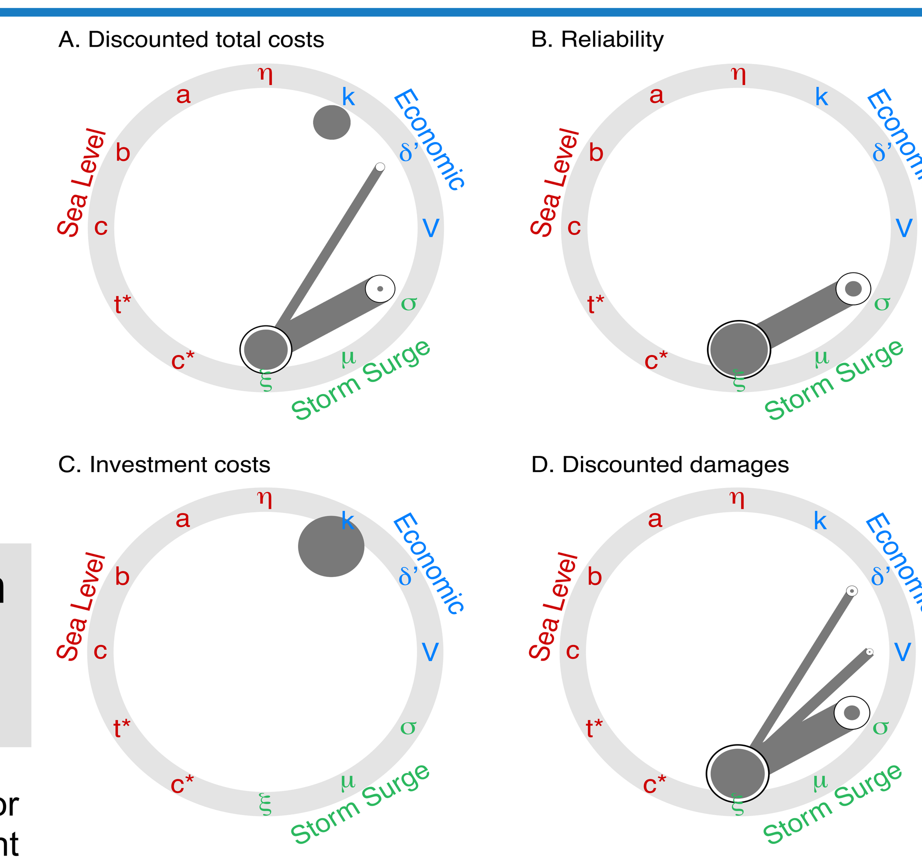
Figure 4. Results of van Dantzig optimization for 4 model versions, with increasing complexity. In panels B–D, gray line represents expected total cost curve, with the point representing the index of the minimum expected NPV for total costs (van Dantzig (1956) objective).



Which parameter sensitivities are most important?

Figure 5. One-at-a-time (OAT) sensitivity analysis for four management objectives with updated sea-level rise and storm surge models. Model parameters were held constant while varying a single one from the 1st – 99th quantile of the prior distribution

What parameter interactions can be identified using a global sensitivity analysis?



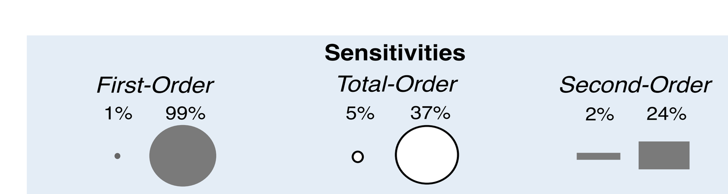


Figure 6. Results of Sobol sensitivity analysis for four management objectives. Solid circles represent the model sensitivity that can be directly attributed to a given parameter, connecting lines represent interactions between parameters, and white circles indicate total order sensitivities.

Discussion

- Parametric uncertainty alone has a small effect on the optimal dike height (5 cm) but may result in nontrivial costs.
- Increasing model complexity raises the optimal dike height by 1.9 meters as compared to the baseline model.
- Deep uncertainties in sea-level rise projections result in a 30 cm difference in optimal dike height when using a uniform vs. beta prior distribution.
- GEV storm surge projections have both larger upper limits and expected return levels than MLE estimates for all return periods.
- Storm surge parameters dominate sensitivity analysis for 3 out of 4 objectives.
- The Investment Cost objective dictates the nonlinear tradeoffs between objectives.
- Sobol sensitivity analysis captures significant interactions terms not identified by local methods.

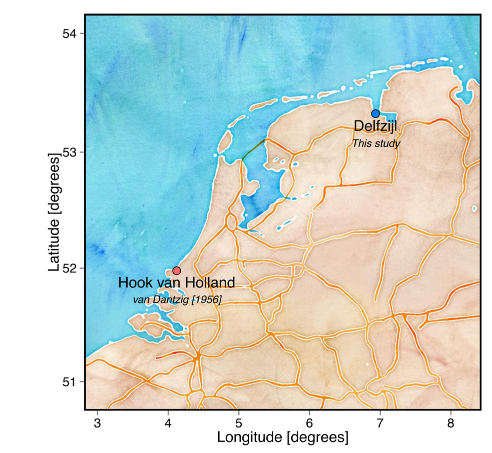


Figure 7. Site locations of van Dantzig (1956) study and the Delfzijl tide gauge used in this study. Annual block maxima records were used to calculate the storm surge GEV distributions.

Conclusions

- The van Dantzig (1956) model is a widely used but incomplete flood risk management framework.
- It can nonetheless be used as a didactic tool to investigate alternative model formulations and sensitivities.
- Improving the model scientifically by upgrading the sea-level rise and storm surge determinations results in significant changes to the considered management solution.
- Local OAT analysis can describe sensitivities to model parameters but excludes potentially important interactions.
- Global Sobol sensitivity analysis identifies interactions and nonlinearities between model parameters.

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Acknowledgments: This work was partially supported by the National Science Foundation through the Network for Sustainable Climate Risk Management (SCRiM) under NSF cooperative agreement GEO-1240507 as well as the Penn State Center for Climate Risk Management. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. We thank Alexander Bakker, Jonathan Lamontagne, and Julianne Quinn for their help and guidance.