A subjective Bayesian framework for synthesizing deep uncertainties in climate risk management

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Key Points:

- Decisions about how to manage climate risks are often made under deep uncertainty
- We introduce a Bayesian framework to transparently synthesize and characterize deep uncertainties with the goal to support decision-making
- We demonstrate the framework using a simple case study of coastal flood risk management

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Abstract

Projections of future climate risks can vary considerably between sources without a consensus about their relative probability. This deep uncertainty poses considerable communication and decision-analytical challenges. One such challenge is how to present trade-offs under deep uncertainty in a salient and interpretable manner. Some common approaches include analyzing a small subset of projections or invoking Laplace's principle of insufficient reason to justify a simple average. These approaches (i) can underestimate risks, (ii) provide little insights into which assumptions drive decision-relevant outcomes, and (iii) can nudge how people choose their decisions-making frameworks. Here we introduce and demonstrate a transparent Bayesian framework for synthesizing deep uncertainties to inform decision support. The first step of this workflow is to create an ensemble of simulations representing possible futures and analyze them through standard exploratory modeling techniques. Next, a small set of probability distributions representing subjective beliefs over possible futures is used to weight the scenarios. Finally, these weights are used to compute and characterize trade-offs, conduct robustness checks, and reveal implicit assumptions. We demonstrate the framework through a didactic case study analyzing how high to elevate a house to manage coastal flood risks.

Plain Language Summary

What are sound strategies to manage risks driven by climatic changes? Addressing this question is complicated by the large uncertainties surrounding projections of the coupled natural-human systems. These uncertainties often arise from choices experts have to make, for example about technical detail on how to model future water levels. Different experts can disagree about these choices and provide different plausible projections. Analyzing decisions in such a situation of deep uncertainty poses nontrivial challenges. For one, just picking one of these projections or just an average can lead to poor decisions. On the other extreme, communicating results separately for all projections can overwhelm decision-makers. To make matters worse, typical approaches to this problem are mostly silent on what assumptions make a difference for the decisions at hand. We develop and demonstrate a framework to address these challenges. The framework provides a transparent approach (i) to combine a large number of deeply uncertain projections to a more understandable and smaller sample and (ii) to provide insights as to how assumptions and modeling choices made by experts influence decisions. We demonstrate the approach with a relatively simple example question of how high to elevate a house in the face of deeply uncertain projections about future water levels.

1 Introduction

Many critical infrastructure services around the world are aging and inadequate for a changing climate (*e.g.*, Doss-Gollin et al., 2021, 2020; Chester et al., 2020). Looking to the future, it is expected that changes to regulation, economics and finance, patterns of population and infrastructure use, as well as climate, will further stress infrastructure systems. This motivates the question: which possible futures should infrastructure systems and components be designed for? The answer to this question depends in part on values: intrinsic trade-offs between safety, performance, cost, and other objectives depend on context and stakeholder preferences (Keller et al., 2021) and are often regulated by statue or industry guidelines. For example, hospitals and critical infrastructure are generally designed to a higher standard of risk protection than ordinary buildings. At the same time, performance depends upon future conditions, and so decisions about which scenario to design for are necessarily subject to implicit or explicit assumptions about the likelihood or possibility of different future conditions.

1.1 Current practice

Current practice in engineering, infrastructure design, and local governance relies heavily upon standards that specify particular design events or conditions that buildings and infrastructure should safely withstand (American Society of Civil Engineers, 2013; Bruneau et al., 2017). These are often, though not always, informed by probabilistic analysis of relevant data. For example, the Federal Emergency Management Agency (FEMA), local governments, and engineering consultants produce local floodplain maps in many communities. These trigger specific floodplain regulations, such as a requirement for homes in the 100-year floodplain with federally backed mortgages to be covered by flood insurance (Kousky & Kunreuther, 2014). Additionally, local building codes (based on guidance such as American Society of Civil Engineers, 2006; The Federal Emergency Management Agency, 2011) may require new construction in flood zones to be elevated freeboard above a nominal base flood elevation (BFE). Design standards are also used to design large-scale infrastructure. For example, some levees in the Netherlands are required to be designed such that the annual probability of failure is less than 1 in 4000 (Eijgenraam et al., 2014), while a seawall proposed as part of a $29 billion coastal protection project for Galveston Bay was designed by setting the nominal annual probability of overtopping to 1% (United States Army Corps of Engineers, Galveston District & Texas General Land Office, 2021, Appendix D., p. 2-59).

There are many advantages to standards-based design. In particular, these heuristics are scalable and explainable, do not require complex analysis to apply, and are fair in at least a procedural sense. However, there are also limitations. In particular, this sort of one-size-fits-all guidance may not be an efficient or desirable way to balance trade-offs. This has motivated economically informed approaches, like risk-based design and cost benefit analysis (Eijgenraam et al., 2014; van Dantzig, 1956; Xian et al., 2017), that place "a strong emphasis upon a proportionate response to risk, so that the amount invested in risk reduction is in proportion to the magnitude of the risk and the cost-effectiveness with which that risk may be reduced" (Merz et al., 2010). These quantitative cost-benefit analyses also rely on probabilistic descriptions of relevant hazard, and may be particularly sensitive to representation of tail probabilities.

Currently used methods for estimating these probability density functions (PDFs) emphasize data-driven, nominally objective methods that can be applied consistently across locations. For example, United States Geological Survey (USGS) Bulletin 17C specifies procedures for estimating flood frequency and the National Oceanic and Atmospheric Administration (NOAA) Atlas 14 provides estimates of the intensity, duration, and frequency of extreme rainfall. Among several statistical assumptions these analyses make that have been recently called into question is stationarity (the assumption that past and future hazard come from the same PDF; see Merz et al., 2014, for a review). For example, clear trends in extreme rainfall are apparent across much of southeastern Texas (Fagnant et al., 2020; Nielsen-Gammon, 2020), and trends in many other hazards are consistent with observations (see International Panel on Climate Change, 2022, for a comprehensive summary). While some methods have been proposed for incorporating trends into these analyses (see Salas et al., 2018, for a review), these assume specific forms of non-stationarity which may not fully represent physical processes or true levels of uncertainty (Doss-Gollin et al., 2019; Montanari & Koutsoyiannis, 2014; Serinaldi & Kilsby, 2015). Ultimately, the difficulty of incorporating nonstationarity into existing frameworks has led to continued reliance on stationarity despite recognition of the associated limitations (see (England et al., 2019), p. 2, or (Perica et al., 2018) p. A.4-42).

1.2 Emerging paradigms

Projecting nonstationary hazard is difficult because many future hazards depend on intrinsically unpredictable human decisions (*e.g.*, the rate of future greenhouse gas emissions) or on physical processes that are poorly constrained by existing data (*e.g.*, collapse of the West Antarctic ice sheet; see DeConto & Pollard, 2016). In other words, they are deeply uncertain (Keller et al., 2021; Walker et al., 2013; Lempert, 2002). These deeply uncertain nonstationary hazards challenge not only the existing stationary estimates but, more fundamentally, the premise that objective estimates of future hazard exist and can be estimated empirically.

Recognizing the challenges of decision making under deep uncertainty (DMDU), many frameworks for identifying robust decisions have been proposed. Most emphasize the use of models in an exploratory ("what-if") framework to learn about interactions between decisions and system dynamics (Bankes, 1993). For example, robust decision making (Lempert et al., 2003) evaluates models over large ensembles of possible futures to assess the performance of different policies under each, then applies statistical analysis to identify the conditions under which particular policies perform well or poorly. When the decision space is complex, many analyses use policy search (often using multiobjective optimization tools) to identify promising actions (Kasprzyk et al., 2013, 2012; Hadka et al., 2015). In addition, many studies formally quantify robustness to deep uncertainties (Herman et al., 2015; McPhail et al., 2019) and use this as a criterion for policy comparison.

Although these methods for DMDU have proven valuable in a wide range of settings, they still require necessarily subjective assessments about the likelihood of future conditions. Even exploratory models require the analyst to choose which uncertainties are considered and how they are sampled. When analyses use metrics that integrate performance over many possible futures, whether to compute sensitivities, estimate expectations, or compute robustness metrics, they necessarily make assumptions about the likelihood of different futures. For example, uniform priors are often justified by deferring to Laplace's principle of insufficient reason (see Stigler, 1986, p. 135), but even this choice makes strong assumptions that are sensitive to factors such as parameterization (Gelman et al., 2014, p.54). While one interpretation of deep uncertainty is that that specifying a joint PDF over inputs is inappropriate, assumptions about the ranges and independence of parameters to sample are just as subjective as the choice of probability distribution (Schneider, 2002; Quinn et al., 2020) and, indeed, can be interpreted as a specific choice of probability distribution (we revisit this point in section 2.2). This motivates the development of decision analytic frameworks that draw from the strengths of DMDU methods such as exploratory modeling, vulnerability assessment, robustness checks, and iterative stakeholder critique, but that embrace the reality that assumptions about the future are inescapable.

1.3 Research gaps and objectives

We are motivated by parallels between decision making under deep uncertainty and the statistical problem of model selection. Oreskes et al. (1994) argues that because natural systems are never closed and model results are never unique, validation and verification of models representing these systems is necessarily qualitative and subjective. In the literature on decision making under deep uncertainty, this has led to recognition of the need to develop strategies that are robust to model imperfections. We find parallels to this challenge in the Bayesian literature on model selection, particularly in the "$\mathcal{M}$-open" case in which there is no "true" model to identify and all models are imperfect representations of reality. This is a theoretical contrast to the "$\mathcal{M}$"-closed case in which a true model can be identified and written down but is one amongst finitely many models from which an analyst has to choose as well as the "$\mathcal{M}$"-complete case in which a true model exists but is inaccessible in the sense that even though it can be conceptualized it cannot be written down (Bernardo, 1994). Whereas model selection in the $\mathcal{M}$-closed case seeks to asymptotically identify the true model from a set of candidate models, model selection in the $\mathcal{M}$-open case emphasizes a subjective view, both of probability itself and of the modeling process, for which probability offers a self-consistent language with which to reason about the unknown rather than a statement of objective truth (see (Gelman & Shalizi, 2013), (Ramsey, 2016), or (Jaynes, 2003) for a discussion of Bayesian philosophy and (Piironen & Vehtari, 2017) for a technical discussion of methods for model selection). From a practical perspective, model selection in the $\mathcal{M}$-open case emphasizes building models iteratively, simulating the consequences of these models, and subsequently using these simulations to critique and improve them (Gelman et al., 2020).

In this paper we offer a first conceptual step towards bridging the fields of DMDU and Bayesian model building. We consider a didactic case study of whether to elevate a hypothetical house, and if so how high, as a specific example of a decision problem subject to both shallow (storm surge) and deep (sea level rise (SLR)) uncertainties. Prior studies have found that floodproofing and building-scale vulnerability reduction measures, including house elevation, can effectively reduce local flood damages in many contexts (de Moel et al., 2014; de Ruig et al., 2020; Kreibich et al., 2005; Slotter et al., 2020; Rözer et al., 2016; Mobley et al., 2020; Aerts, 2018), and both local building codes (American Society of Civil Engineers, 2013; Bruneau et al., 2017; American Society of Civil Engineers, 2006) and federal policy (The Federal Emergency Management Agency, 2011) require elevation in some cases. Guidance for homeowners, notably from FEMA, recommends elevating to the BFE (typically the 100 year flood) plus a freeboard (The Federal Emergency Management Agency, 2014; ASCE, 2015; The Federal Emergency Management Agency, 2014) but recent research has demonstrated that neglecting uncertainty in the cost-benefit analysis can lead to poor decisions (Zarekarizi et al., 2020). Focusing on deep uncertainty in SLR over the 70 year design life of a hypothetical house, we seek to answer the research question "*how can deep uncertainties be transparently synthesized for decision analysis?*"

We proceed as follows. In section 2 we present three formal decision analytic frameworks for analyzing an ensemble of SLR simulations, building through existing approaches for exploratory modeling (section 2.1) and scenario analysis (section 2.2) towards a formal Bayesian method for transparently synthesizing deep uncertainty through subjective prior beliefs. In section 3 we describe the case study in detail. Next in section 4 we present results for each of the three decision lenses and discuss the advantages and limitations of each theoretical approach. Finally in section 5 we discuss key findings, future research needs, and implications for research, policy, and practice.

2 Decision analytic framework

In this section we outline our framework for decision analysis under deep uncertainty, maintaining a high level of generality. In the next we discuss application to the house elevation case study.

Following fig. 1, we consider using J states of the world (SOWs), $\mathbf{s} = \{s_1, s_2, \ldots, s_J\}$, to evaluate I candidate decisions, $\mathbf{x} = \{x_1, x_2, \ldots, x_I\}$. For each scenario $s_j \in \mathbf{s}$ and decision $x_i \in \mathbf{x}$ we use a system model f (comprised of multiple components) to calculate a set of metrics describing the performance of decision x_i on SOW s_j, which we denote $u_{ij} = f(x_i, s_j)$. While we assume for simplicity that the decision space is known and finite, this approach could be coupled to a policy search model that proposes candidate decisions.

2.1 Explore

A first analytical step is to use the model in an "exploratory" mode. Exploratory modeling is averse to making explicit assumptions about the likelihood of different SOWs and instead seek to generate new knowledge (Bankes, 1993) by systematically explor-

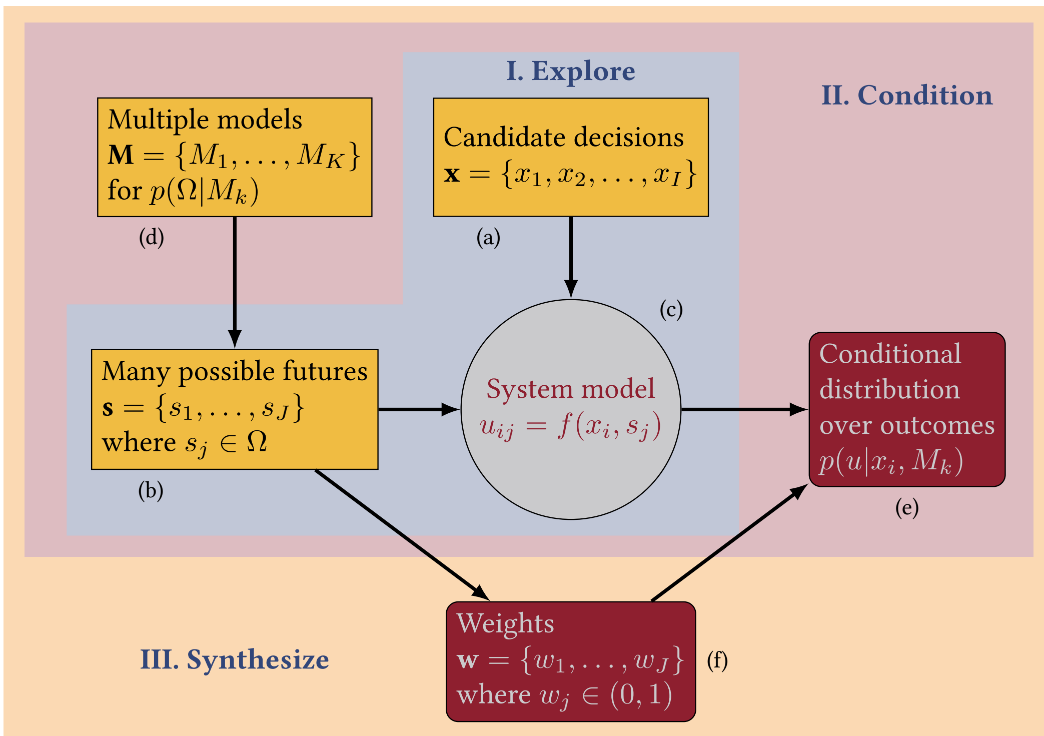

Figure 1: Outline of the proposed decision-analytic framework. In section 2.1 we use an exploratory framework to quantify the performance (c) of candidate decisions (a) under a large ensemble of possible futures (b). In section 2.2 we illustrate the "multiple PDF problem" by creating probability distributions over outcomes (e) that are conditional upon specific models describing the likelihood of different futures (d). In our case study, these are representative concentration pathway (RCP) scenarios and physical models of sea level rise. Finally in section 2.3 we propose a subjective Bayesian framework for synthesizing across deep uncertainties by re-weighting sampled futures (f).

ing a large number of possible futures, emphasizing interactions between different uncertainties (Reed et al., 2022). Exploratory modeling is often paired with analyses that identify relevant scenarios (Lamontagne et al., 2018; Groves & Lempert, 2007) or summarize a system's response to forcing (Poff et al., 2015; Steinschneider et al., 2015; Sriver et al., 2018). Despite the aversion to strong assumptions about the likelihood of different futures, subjective modeling decisions such as the choice of system model, the set of candidate decisions, the criteria used to assess outcomes, and the choice of how to sample SOWs strongly influence results (Quinn et al., 2020).

2.2 Condition

Although exploratory modeling is a useful framework for understanding systems, there are many questions that it cannot answer. For example, answering questions like "what is the 95th percentile of metric u under decision x" or "which decision minimizes expected damages" or "what is the probability of exceeding a critical threshold" requires constructing estimators for the probability distribution over outcomes (Schneider, 2002).

One way to interpret an ensemble of SOWs is as independent and identically distributed (IID) draws from some true data generating process. We call this scenario-conditional probabilistic analysis, which commonly arises when a probabilistically calibrated model for relevant outputs (*e.g.*, a physical model for mean relative sea level (MSL); see section 3.1) is forced by a deterministic scenario (*e.g.*, a RCP scenario). In this case, *the set of available SOWs is assumed to come from the true (often called population) distribution, and thus the sample statistics are assumed to reflect the true values.* We add this concept to our framework with boxes (d) and (e) of fig. 1, denoting the particular scenario (*i.e.*, the assumed input) M_k. If the SOWs are drawn IID from M_k, the set of outcomes $u_{i,j}$ can be interpreted as IID draws from the conditional distribution over outcomes, $p(u|x_i, M_k)$, allowing estimation of descriptive metrics. This approach allows for quantification of uncertainty *within models*, but can only qualitatively characterize uncertainty *between models* (Wong & Keller, 2017; Ruckert et al., 2019; Sharma et al., 2021).

We can also use this approach to understand DMDU methods that sample a set of parameters from fixed ranges. For example, Sriver et al. (2018) sample parameters describing the rate of SLR across a range of values to inform coastal adaptation. Similarly, Trindade et al. (2020) checks the performance of candidate decisions against an ensemble of synthetic time series of streamflow, water demand, and other parameters by sampling parameters that transform the available data over a plausible range (*i.e.*, robustness metrics; see McPhail et al., 2019; Herman et al., 2015, for details). Since sampling over a range is equivalent to sampling from a Uniform distribution, this assumption is equivalent to assuming the true inputs to come from independent Uniform distributions (one for each parameter) bounded by the plausible range.

Our primary concern is not that subjective assumptions about the likelihood of different futures are wrong – this is, almost surely, inevitable – but that when these assumptions are opaque and presented without critique or validation they may lead to inscrutable decision processes and suboptimal decisions.

2.3 Synthesize

If the SOW ensemble is not drawn IID from the true distribution (*e.g.*, if one deliberately over-samples low-probability but high-impact SOWs) or if one wishes to synthesize *across* multiple scenarios $M_1, M_2, \ldots, M_K$, then additional measures must be taken. One possibility is to discard the SOWs ($\mathbf{s}$) and resample from some "true" distribution, which we shall denote p_{belief}. In practice, this is impractical because simulating $\mathbf{s}$ may rely on complicated models that are computationally expensive to re-run.

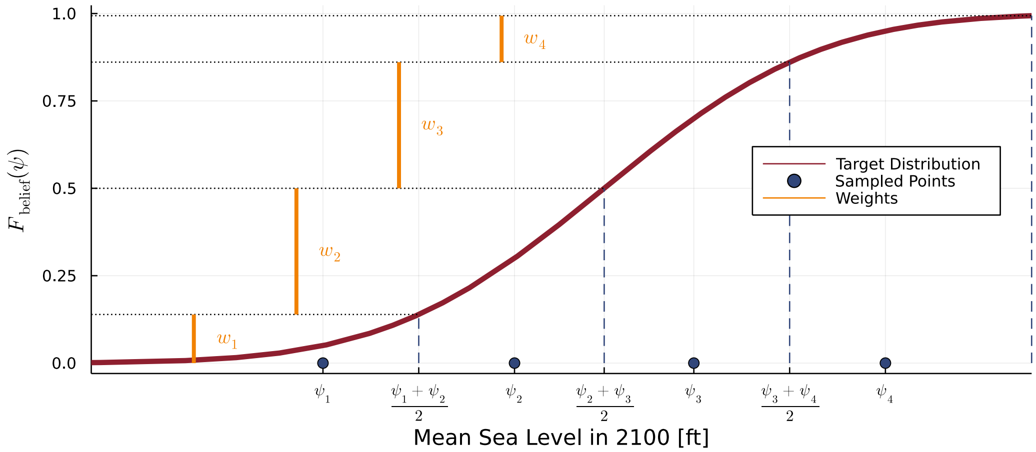

Figure 2: Schematic of SOW weighting scheme defined in eq. (1). This method is illustrated for a hypothetical target distribution (dark red line) and $J = 4$ samples $\psi_1, \psi_2, \psi_3, \psi_4$ (blue dots). As shown in eq. (1), the weights w_j (orange vertical lines) are calculated based on the cumulative distribution function of the target distribution at the halfway points $\frac{1}{2}[\psi_j + \psi_{j+1}]$ (vertical dashed lines).

Instead of attempting to re-sample $\mathbf{s}$, we instead consider re-weighting. A simple approach would be to assign each SOW s_j a weight w_j equivalent to the ratio of the desired (often called target distribution in survey analysis) distribution, p_{belief} and the sampling distribution, which could be approximated through methods such as kernel density estimation. Paralleling joint probability methods for statistical analysis of tropical cyclones, we use a grid-based approach (Johnson et al., 2013; Resio, 2007; Toro et al., 2010). First, we project the SOWs $\mathbf{s} \in \Omega$ onto a low-dimensional representation, which we denote $\{\psi_1, \psi_2, \ldots, \psi_J\} \in \Psi$. This allows us to specify a prior belief over this reduced space $p_{\text{belief}}(\Psi)$ instead of over the full space $p_{\text{belief}}(\Omega)$. We then calculate a probabilistic weight $w_j \in [0, 1]$ for each SOW s_j so that the weighted distribution of ψ_j closely approximates $p_{\text{belief}}(\Psi)$.

We present here the case where the ψ_j are one-dimensional. We first sort the ψ_j from least to greatest so that $\psi_{j-1} \leq \psi_j$, $(j \neq 1)$. Defining $F_{\text{belief}}(s)$ to be the cumulative distribution corresponding to p_{belief}, we calculate weights as

$$w_j = \begin{cases} F_{\text{belief}}\left(\frac{1}{2}[\psi_1 + \psi_2]\right) & j = 1 \\ F_{\text{belief}}\left(\frac{1}{2}[\psi_j + \psi_{j+1}]\right) - F_{\text{belief}}\left(\frac{1}{2}[\psi_{j-1} + \psi_j]\right) & 1 < j < J \\ 1 - F_{\text{belief}}\left(\frac{1}{2}[\psi_{J-1} + \psi_J]\right) & j = J. \end{cases} \tag{1}$$

This step is illustrated in fig. 2. For higher dimensional projections, this equation can be extended by partitioning the parameter space, then integrating the PDF p_{belief} over each region. From a practical perspective, many simulation models round outputs, meaning that there is a possibility of having ψ_j that are equal; in this case it may be helpful to add a small amount of noise to the ψ_j before computing the weights. Diagnostic checks, such as examining the histogram of weights (not shown), may be valuable protections against degeneracy.

The aim of this re-weighting framework is to integrate an ensemble of SOWs used for exploratory modeling into formal decision analysis, even when the SOWs deliberately over- or under-sample some regions of the parameter space. As in section 2.2, we must condition on a model: where the analysis of section 2.2 conditions upon deep uncertainties, the approach outlined in this subsection synthesizes across them. We reiterate that stakeholders and experts will not, in general, agree on p_{belief} because its there is no "true" value of p_{belief} that could be objectively ascertained (Oreskes et al., 1994; Walker et al., 2013). However, we posit that since we cannot be "right," it is valuable to maximize the transparency of our implicit probabilistic assumptions, and suggest that writing down an explicit model for p_{belief} supports this aim.

3 Demonstrating the concept with a case study

To illustrate the proposed decision analytic framework, we model a one-time decision of whether to elevate a house, and if so by how much (fig. 3). We focus on a case study of a *hypothetical* house in Norfolk, VA. For interpretability, we focus on deep uncertainty in MSL and approximate other model parameters as shallow uncertainties as shown in table 1. We use the notation developed in the previous section to describe the case study. Specifically,

1. The decision vector $\mathbf{x}$ is comprised of discrete possible house heightenings (Δh); we consider $\Delta h = \{0\,\text{ft}, 0.25\,\text{ft}, \ldots, 12\,\text{ft}\}$ f
2. The SOWs describe annual time series of MSL over the $T = 70$ year house lifetime so $\mathbf{s} \in \mathbb{R}^T$
3. The system model f quantifies up-front costs and lifetime expected damages, given a decision x_i and SOW s_j, by integrating economic and engineering damage models over a probability distribution for storm surge.

In the remainder of this section we describe data sources and treatment of SLR (section 3.1), storm surge (section 3.2), damages and metrics (section 3.3), and finally the subjective priors p_{belief} used to apply the re-weighting method described in section 2.3 to this case study (section 3.4).

3.1 Sea level rise

We analyze simulations of MSL at Sewells Point, VA from four probabilistic physical models using data published in Ruckert et al. (2019). The four models considered are (i) the BRICK model (version 0.2) with slow ("BRICK Slow") and (ii) fast ("BRICK Fast") ice sheet dynamics (Wong et al., 2017), (iii) the Kopp et al. (2014) model ("K14"), and (iv) the DeConto and Pollard (2016) model ("DP16"). The Kopp et al. (2014) and DeConto and Pollard (2016) models have a ten year time step, which we linearly interpolate onto a one year time step for consistency. These four models represent physical processes, particularly of ice sheet dynamics, in different ways, leading to diverging sensitivity of MSL to forcing. For a discussion of these model outputs we refer the reader to Ruckert et al. (2019).

Estimates of nonstationary MSL also depend on anthropogenic forcing, which is itself deeply uncertain (Ho et al., 2019; Srikrishnan et al., 2022). To sample this uncertainty, we use simulations from each physical model under four RCP scenarios, yielding sixteen time-varying distributions of MSL.

The choices of physical model and RCP scenario jointly determine future MSL $p(\overline{y}|t)$. Figure 4(a) shows the time-varying 90% credible intervals of MSL for three representative models. The divergence between the the best-case (blue) and worst-case (red) models is small in the early 21st century and increases rapidly thereafter. Figure 4(b) shows the PDFs of mean sea level in 2100 (dashed vertical line in panel (a)) under each of the sixteen models considered. We return in section 4.2 to the problem that these multiple models poses to decision makers.

Table 1: Summary of parameters, their notation, and how their uncertainty is represented. Symbols describing the decision-analytic framework are described in fig. 1.

Name	Symbol	Uncertainty
MSL	$\overline{y}(t)$	Deeply uncertain: four physical models × four RCP scenarios
Storm surge	$y'(t)$	Probabilistic: Bayesian inference on a stationary GEV model
Annual maximum flood	$y(t)$	Deterministic: $y(t) = \overline{y}(t) + y'(t)$
Discount rate	ρ	Determinitic: 2.5% per year
Depth-damage	$D(h - y)$	Deterministic: based on HAZUS model (see Zarekarizi et al., 2020)
Elevation cost	$C(\Delta h)$	Deterministic: a piecewise linear model following Zarekarizi et al. (2020)
Initial height	h_0	Deterministic: 1 ft below the BFE, unless otherwise noted
House floor area	–	Deterministic: 1500 ft^2
Structural value	–	Deterministic: $200 000
House lifespan	T	Deterministic: 70 years

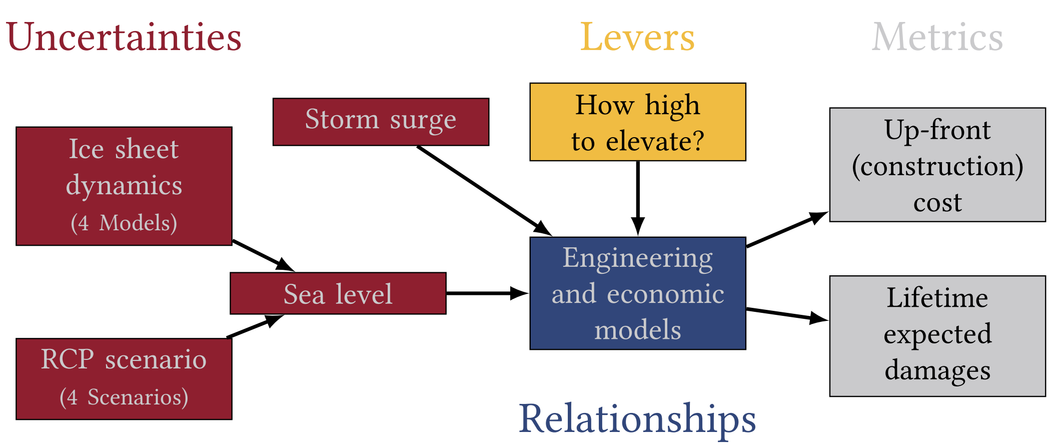

Figure 3: Conceptual diagram of the considered example. A state of the world (SOW) consists of a description of the uncertain factors (red). We model a problem with a single lever (yellow), which is how high to elevate a house (Δh). For each SOW (red) and each value of Δh, the system model (blue) is used to calculate performance metrics (gray).

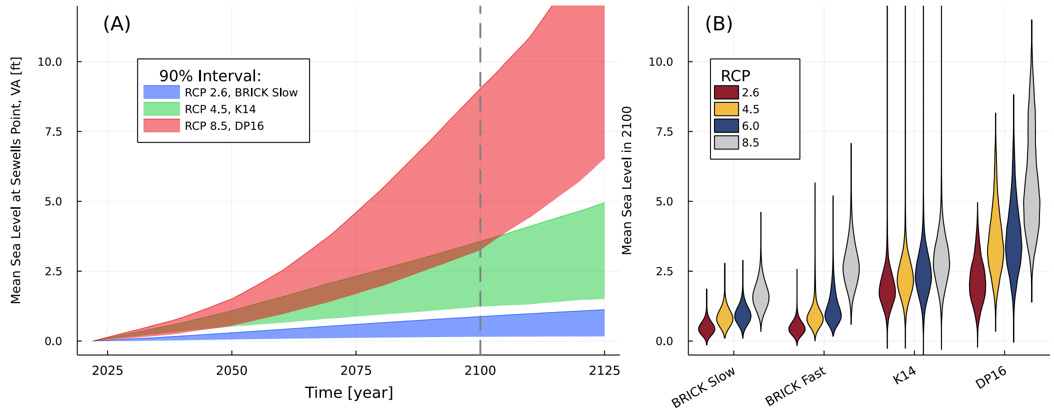

Figure 4: Projections of future mean sea level depend strongly on the choices of physical model and forcing. (A): 90% confidence intervals for mean sea level at Sewells Point, VA as a function of time for a representative subset of three probabilistic models (out of sixteen). (B): probability distribution of MSL at Sewells Point, VA in the year 2100 for each probabilistic model considered.

3.2 Storm surges

Following prior work (*e.g.*, Garner & Keller, 2018; Sriver et al., 2018), we model annual maximum floods $y(t)$ as the sum of sea level $\overline{y}(t)$, described in the previous subsection, and annual maximum storm surges $y'(t)$, neglecting hydrodynamic effects.

Data on storm surge comes from Sewells Point, VA (gauge 8638610) from the freely available NOAA tides and currents data archive (National Oceanographic and Atmospheric Administration, 2022). Hourly recordings of water level are available from 1928 to the present; we use data from the period January 1, 1928 to December 31, 2021. For each calendar year we first remove the annual mean, then calculate the maximum water level. We refer this time series of annual maximum storm surges as $y'(t)$. We display this time series of annual maxima storm surges in fig. 5(a). The largest recorded surge was the Chesapeake-Potomac hurricane of 1933, which caused a surge of over 7 ft at this gauge, but other hurricanes and Nor'easters have caused surges above 6 ft.

We model future storm surge using a stationary GEV model:

$$y'(t) \sim \mathrm{GEV}(\mu, \sigma, \xi), \tag{2}$$

where $y'(t)$ is the storm surge (above MSL) in year t and a GEV distribution with location, shape, and scale parameters μ, σ, and ξ, respectively, has the probability density function given in eq. (S1). This model assumes stationarity, neglecting any potential time dependence.

Our approach to model assessment is based on the concept of principled workflow design for model building and checking (see Gelman et al., 2020, for details). One model choice, analogous to the choice of statistical distribution or the assumption of stationarity, is the choice of how to represent prior information. We include two forms of prior information. First, we constrain the shape parameter to be positive, $\xi > 0$, to reflect knowledge about the support of y', which for a variable distributed according to eq. (S1) is:

$$\mathrm{supp}\ y' = \begin{cases} \xi < 0: & y' \in (-\infty,\ \mu - {}^{\sigma}/_{\xi}) \\ \xi > 0: & y' \in (\mu - {}^{\sigma}/_{\xi},\ \infty). \end{cases}$$

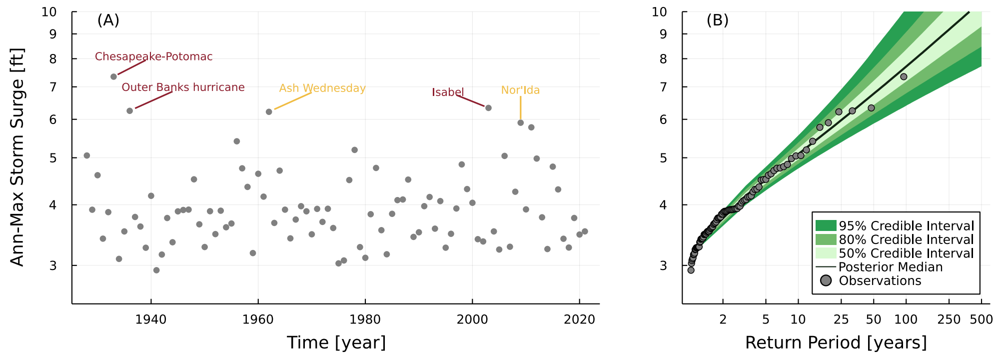

Figure 5: Annual maximum storm surges (after subtracting mean relative sea level) at Sewells Point, VA from the freely available NOAA tides and currents data archive (National Oceanographic and Atmospheric Administration, 2022). (A): time series of historic storms. Red (yellow) arrows denote notable tropical cyclones (Nor'easters). (B): return periods. Dots indicate observed values; their x-value is their plotting position using the Weibull formula (eq. S5). Gray lines show the 50, 80, and 95% posterior confidence intervals from the Bayesian generalized extreme value (GEV) fit (section 3.2).

Since storm surges cannot be negative, only the latter is physically defensible, justifying our choice to constrain the shape parameter to be positive. Second, we add weakly informative priors. Rather than applying prior information directly over the joint distribution of the parameters $\{\mu, \sigma, \xi\}$, we instead apply a prior over extreme quantiles of the distribution, as in Coles and Tawn (1996). Specifically, we apply Inverse Gamma priors over the 2, 10, 100, and 500 year return levels, with means of 4 ft, 6 ft, 10 ft and 15 ft and standard deviations of 1.5 ft, 1.75 ft, 2.25 ft and 2.75 ft, respectively. The parameters of the Inverse Gamma distribution can be calculated from these moments (see eq. S3). These means and standard deviations were chosen to represent plausible physical ranges (fig. S4).

For inference, we draw 10 000 samples from the posterior distribution $p(\mu, \sigma, \xi | y')$ using Hamiltonian Markov Chain Monte Carlo (Betancourt, 2017; Hoffman & Gelman, 2011) implemented in the Turing package of the Julia programming language (Perkel, 2019; Ge et al., 2018; Tarek et al., 2020; Besançon et al., 2021; Bezanson et al., 2012). Diagnostics suggest (though cannot guarantee) convergence (see table S1). We evaluate the model's fit using posterior predictive checks (see Gelman et al., 2020, section 2.4 and references therein). Using the lag 1 and 2 partial autocorrelations, sample maximum, sample minimum, sample median, and Mann-Kendall test value as Bayesian test statistics, we find that draws from the posterior predictive distribution match the observed test statistics credibly (fig. S9) although panels (a) and (b) suggest the possibility of temporal structure not captured by our stationary IID model. Future efforts could represent this structure by conditioning the parameters of the distribution on relevant climate indices (as in Wong, 2018; Farnham et al., 2018, 2017; Ossandón et al., 2021).

Other model validations lend confidence to the stationary GEV model selected. For example, fig. 5(b) shows the estimated return periods for these storm surges; the estimated return period of the (shading) matches the (dots) the empirical plotting position dots. Further, a positive control test (fig. S6) validates the model's ability to recover known parameter values.

3.3 Damages and metrics

The system model ("relationships" in fig. 3) is comprised of two key pieces. The first is a fragility model that estimates the expected flood damages for a particular year ("expected annual damages"), given the elevation of the house and the mean sea level for that year. The second model converts a time series of annual expected damages into lifetime expected damages.

We define expected annual damages in year t as the expectation of the damage function with respect to storm surge. This expectation depends on the house's height ($h = h_0 + \Delta h$) where h_0 is the initial height relative to the gauge and Δh is the amount by which the house is elevated. The expected annual damage is thus

$$\mathrm{EAD}(t) = \mathbb{E}[D(h - \overline{y}(t))] = \int_{y'} p(y') D(h - (\overline{y}(t) + y'))\, \mathrm{d}y' , \tag{3}$$

where $D(h-y)$ is a deterministic function specifying damage as a function of flood depth (relative to the house). Following Zarekarizi et al. (2020), we use the we use the Hazard U.S. (HAZUS) depth-damage curves provided by FEMA; this depth-damage relationship is shown in fig. S1. For comparison, fig. S1 also shows the "Europa" depth-damage relationship developed by the Joint Research Center of the European Commission's science and knowledge service (Huizinga & Szewczyk, 2016). Although Zarekarizi et al. (2020) demonstrate that the choice of fragility function is important for informing house elevation, we use only the HAZUS model for simplicity.

The expected annual damage is sometimes calculated by assuming analytically tractable functional forms for the depth-damage relationship and for the distribution of hazard (*e.g.*, van Dantzig, 1956). However, the convolution of the HAZUS depth-damage equation with the GEV posterior does not have a tractable analytic solution so we instead estimate it through a Monte Carlo method (see section S1.2 for details). Then, because the expectation in eq. (3) depends only on $h - \overline{y}(t)$, we calculate expected annual damages for a wide range of possible heights, then use this to train a computationally efficient surrogate model (using linear interpolation; see section S1.3).

The second component of the system model converts a time series of EAD into lifetime expected damages, which we define as the up-front discounted sum of expected annual damages:

$$\mathrm{LED} = \sum_{t=t_i}^{t_f} \gamma^{(t-t_i)} \mathrm{EAD}(t), \tag{4}$$

where $\gamma = 1 - \rho$ (ρ being the discount rate), the initial time $t_i = 2022$, and the end time $t_f = t_i + T - 1$. Although Zarekarizi et al. (2020) show that uncertainty in the discount rate is important for decision support, we use a fixed discount rate (see table 1) for the purposes of this didactic study. For a more theoretical discussion see Arrow et al. (2013).

To assess the performance of a given decision for a specific SOW ("Metrics" in fig. 3), we calculate the following metrics for each decision-SOW combination:

1. "Up-front cost" is the cost of elevating a house. Following Zarekarizi et al. (2020), we use estimates of construction cost from the Coastal Louisiana Risk Assessment (Fischbach et al., 2012). We normalize this cost by house value. This cost curve is shown in fig. S3.
2. "Lifetime expected damages" is calculated following eq. (4).
3. "Expected lifetime costs" is the sum of lifetime expected damages and up-front costs.

3.4 Prior over sea level rise

We construct three probabilistic models for $p_{\text{belief}}(\psi)$, which represents the amount of SLR from 2022 to 2100.

We use a Gamma distribution for all three priors, parameterized following eq. (S4). Table 2 specifies the parameters of these distributions, as well as some quantiles of the distributions. Their PDFs are also plotted in fig. 8(A).

Table 2: Subjective priors over SLR from 2022 to 2100, *i.e.* $p_{\text{belief}}(\psi)$. The name of the distribution, the parameters of the Gamma distribution with shape α and scale θ, and the 2.5, 25, 50, 75, and 97.5th percentiles (values in ft).

Name	Parameters		Percentiles (in ft)				
	α	θ	2.5	25.0	50.0	75.0	97.5
Slow SLR	1.75	0.50	0.08	0.39	0.72	1.19	2.57
Uncertain SLR	1.75	1.25	0.21	0.98	1.79	2.97	6.41
Rapid SLR	3.50	1.25	1.06	2.66	3.97	5.65	10.01

We developed these priors for didactic purposes, to illustrate a range of possible beliefs. We can compare them, for example, with analysis published by NOAA, which project 1.94 ft, 2.62 ft, 4.27 ft, 5.25 ft and 6.89 ft for the low, intermediate, low intermediate, intermediate high, and high scenarios, respectively (Sweet et al., 2022, table. 2.4). We can also compare to the analyses of Sriver et al. (2018) which use a rescaled Beta distribution with bounds of 255 mm to 2508 mm (0.83 ft to 8.2 ft) and a most plausible estimate of 950 mm (3.1 ft). Our samples bound all of these estimates.

4 Results and discussion

We illustrate our approach to synthesizing uncertainties by sequentially analyzing the house elevation problem through the lenses of exploratory modeling (section 4.1), scenario-conditional analysis (section 4.2), and finally the proposed synthesis method (section 4.3).

4.1 Exploratory modeling

We begin by using our model in an "exploratory" mode with an aim of learning about interactions between system dynamics and decisions.

One application of explotatory analysis is to reveal the range and variation in outcomes, conditional on taking a particular decision. Figure 6 shows the dependence of expected lifetime costs (damages plus up-front costs; y-axis) as a function of SLR over the house lifetime (x-axis), height increase (Δh; columns), and initial elevation (h_0; rows). The outcomes with lowest total lifetime costs arise when the house is not elevated ($\Delta h = 0$) and SLR is minimal (bottom left corners). The outcomes with highest total lifetime costs arise when the house is elevated only slightly and SLR is rapid. As Δh increases, the best-case scenario becomes more expensive because up-front costs increase, but worst-case scenarios become less expensive because even if SLR is substantial, damages will be negligible.

This analysis answers "what-if" questions like "given h_0 and Δh, what is the range of total costs a homeowner could face if SLR over the house lifetime is 1 ft or 10 ft." For some decision-makers, contextualizing this information against a few scenarios of SLR

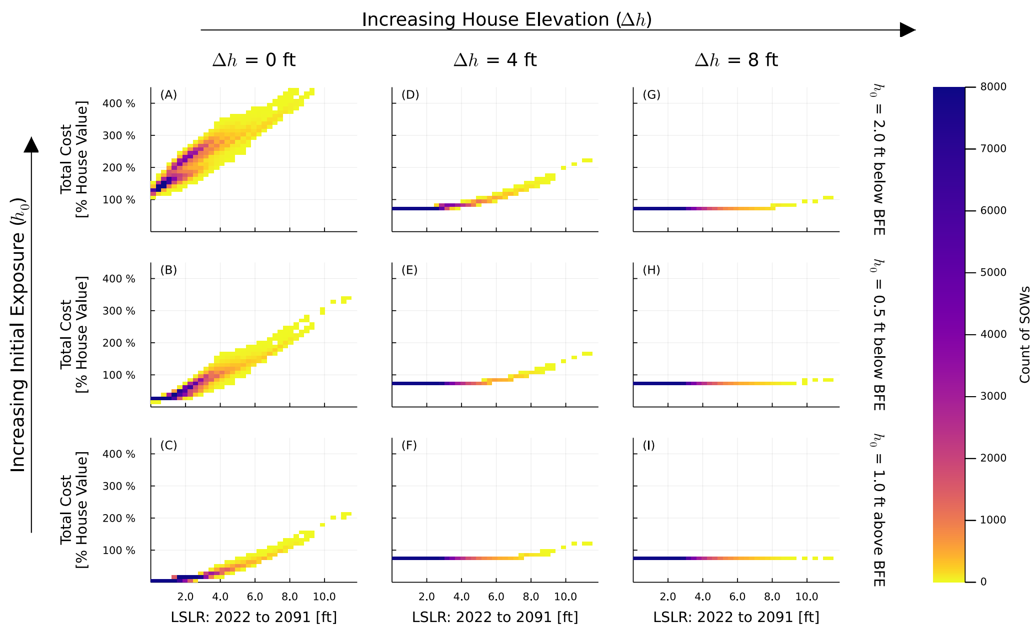

Figure 6: Scenario maps show the dependence of expected lifetime cost (damages plus up-front cost) as a function of MSL in 2100 for several values of initial height (h_0) and house elevation (Δh). Colors indicate the density of SOWs; the color of each grid box corresponds to the number of SOWs falling within that box. The lowest-cost outcomes occur when both exposure is low (h_0 is large and SLR is minimal) and the house is not elevated (no up-front cost). The highest-cost outcomes arise when exposure is high (h_0 is small and SLR is rapid) and investment is inadequate. In all cases, elevating the house reduces the variance in total lifetime cost. Values are sensitive to model constants; see table 1.

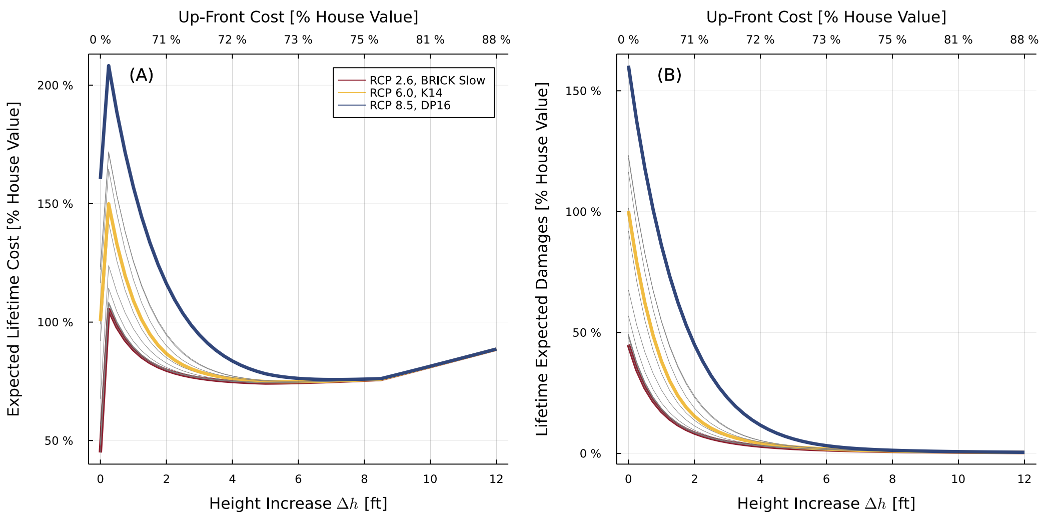

Figure 7: Each probabilistic model or scenario leads to a different estimate of the Pareto frontier. For emphasis, we highlight three representative models: the Brick Slow model (Wong et al., 2017) under RCP 2.6, the K14 (Kopp et al., 2014) model under RCP 6.0 and the DP16 model (DeConto & Pollard, 2016; Kopp et al., 2017) under RCP 8.5. (A): trade-off between up-front cost (which is a monotonic function of height increase) and expected lifetime costs. (B): trade-off between up-front cost and lifetime expected damages (eq. 4). Light gray lines show estimates for all 16 models (four RCP scenarios times four physical parameterizations) considered. Colored lines highlight three representative models for emphasis.

(*e.g.*, those of Sweet et al., 2022) may prove sufficient for decision making. This would be analogous to decision scaling methods that plot climate model projections on a scenario map of water system performance as a function of changes in key climate variables (Brown et al., 2012; Steinschneider et al., 2015). Scenario mapping is also commonly used in robust decision making (RDM) analyses (Lempert, 2019; Sriver et al., 2018). However, this analysis does not shed light on cost-benefit analyses or return periods, nor does it permit quantitative comparison against other possible decisions unless strong implicit assumptions are made.

4.2 Scenario-conditional optimization

We now turn to the scenario-conditional analysis described in section 2.2. Whereas the exploratory analysis of the previous subsection interpreted each time series of future sea level as a sample from the space of possible futures, we can also interpret each SOW as a draw from one of the sixteen models of SLR shown in fig. 4. As discussed in section 2.2, this allows a formal estimation of decision metrics.

This probabilistic interpretation allows us to compute, for example, expected values. For example, fig. 7(a) plots the expected total lifetime cost as a function of Δh for the sixteen models considered (we highlight three representative models). Similarly, fig. 7(b) plots the lifetime expected damages as a function of Δh. For small Δh, expected costs are low under optimistic models (*e.g.*, RCP 2.6 with slow ice sheet dynamics; red lines) and high under pessimistic models (*e.g.*, RCP8.5 with the DP16 model; blue lines). For example, under the most pessimistic model (blue line), the cost-minimizing height increase is 6 ft, which incurs an up-front cost of 73% of the house value but reduces lifetime expected damages by over 150% of house value. Converseley, under the most optimistic model (gray line), the cost-minimizing decision is to not elevate, as elevating 6 ft incurs the same up-front cost of 73% of house value yet reduces lifetime expected damages by less than 50% of house value.

This approach is, in a sense, another form of exploratory modeling: instead of considering a very large ensemble of SOWs, we consider a much smaller set of probabilistic models. This approach is attractive because it allows modelers to focus on their domain expertise (*e.g.*, the response of ice sheets and global sea levels to a particular climate future). However, conditioning simulations on a set of climate futures and physical models presents what we term "the multiple PDF problem" because it leaves decision makers with many PDFs to choose from. The multiple PDF problem has also been shown in other contexts. For example, Sharma et al. (2021) model the reliability of stormwater infrastructure under different climate models and downscaling methods, finding diverging estimates of future rainfall hazard, even under a single RCP scenario. Similarly, Wong and Keller (2017) construct 18 probability distribution functions for future flood risk in New Orleans, considering multiple models for ice sheet dynamics and storm surge and multiple RCP scenarios. And Lempert (2019) Although this scenario-conditional analysis is appropriate for understanding differences between models, its key limitation is that it **places the burden for deciding which model to design for onto the end user.**

4.3 Synthesizing deep uncertainties for decision analysis

The proposed approach can help overcome the limitations of scenario-conditional analysis. We illustrate how the re-weighting method described in section 2.3 can shed light on climate risk management under deep uncertainty. We present results using each of the models for p_{belief} outlined in section 3.4. These three distributions are shown in fig. 8(A).

One application of this method is to diagnose which assumptions different p_{belief} are consistent with. Figure 8(B-D) shows the average weight that each prior assigns to SOWs generated by each RCP scenario and physical model. For example, the rapid SLR scenario (green line in fig. 8) places most weight on the DP16 model, and particularly on RCP 8.5 which by some accounts is unlikely given current policy (Hausfather & Peters, 2020; Srikrishnan et al., 2022). Conversely, the slow SLR scenario (red line) places most weight on the BRICK models, particularly RCP 2.6 (also unlikely given current policy) and RCP 4.5. The uncertain SLR scenario (blue line) places approximately equal weight across models.

This method can also be used to calculate expectations, allowing us to revisit the trade-off diagrams of fig. 7. Figure 9 shows the total lifetime cost (panel A) and lifetime expected damages (panel B) under each model. Notably, they give different guidance. Under an assumption of rapid SLR, elevating the house by approximately 6 ft costs 73% of house value and reduces damages by over 100% of house value, yielding a benefit to cost ratio of approximately 1.25. Under an assumption of slow SLR, elevating the house by 6 ft reduces damages only by 50% of house value, yielding a benefit to cost ratio of approximately 0.7. Under the intermediate / uncertain SLR assumption, the expected lifetime costs are similar for elevating or not elevating the house, and thus the benefit to cost ratio is nearly 1. Under all assumptions, elevating by only a few feet is impractical because it involves paying the large fixed costs of elevation (fig. S3) but offers relatively little flood reduction.

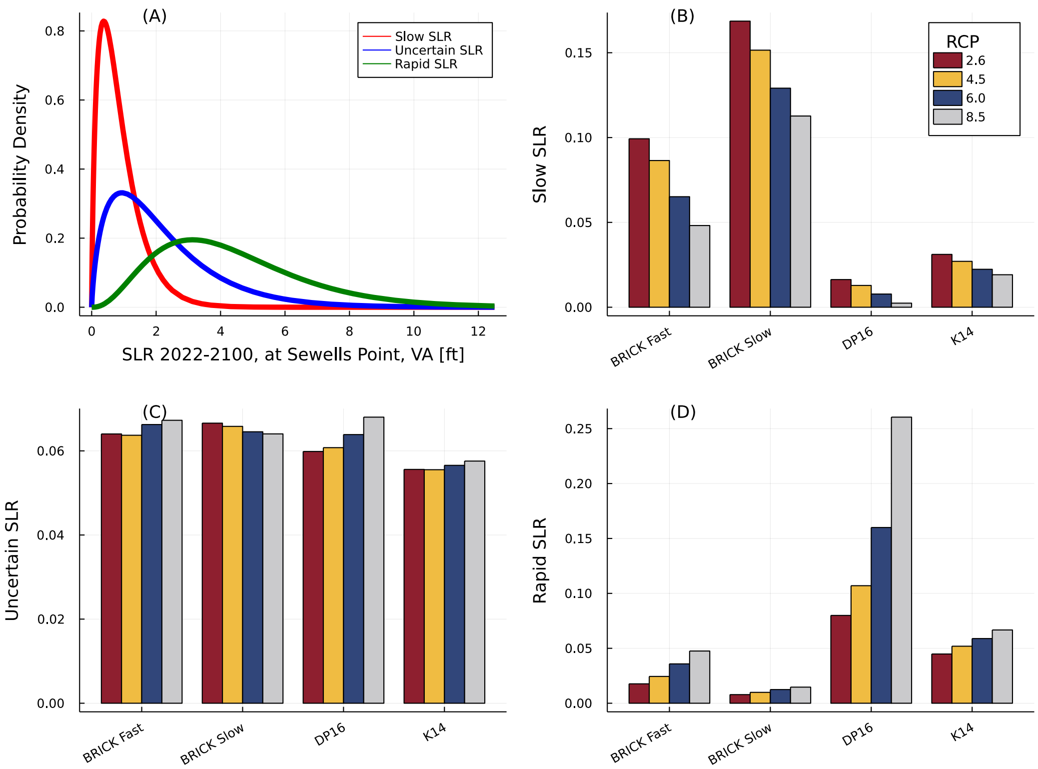

Figure 8: Impact of subjective priors for local sea level on implicit weight given to each RCP scenario and physical model. We develop three distributions ("subjective priors") representing plausible probabilistic beliefs about MSL at Sewells Point, VA in 2100, relative to the present. The PDFs of these subjective priors are shown in panel (A). In panels (B-C) we show the relationship between these subjective priors and the 16 probabilistic models (four RCP scenarios and four physical representations) available. Specifically, (B-C) show the average weight given to each model by each of the subjective priors.

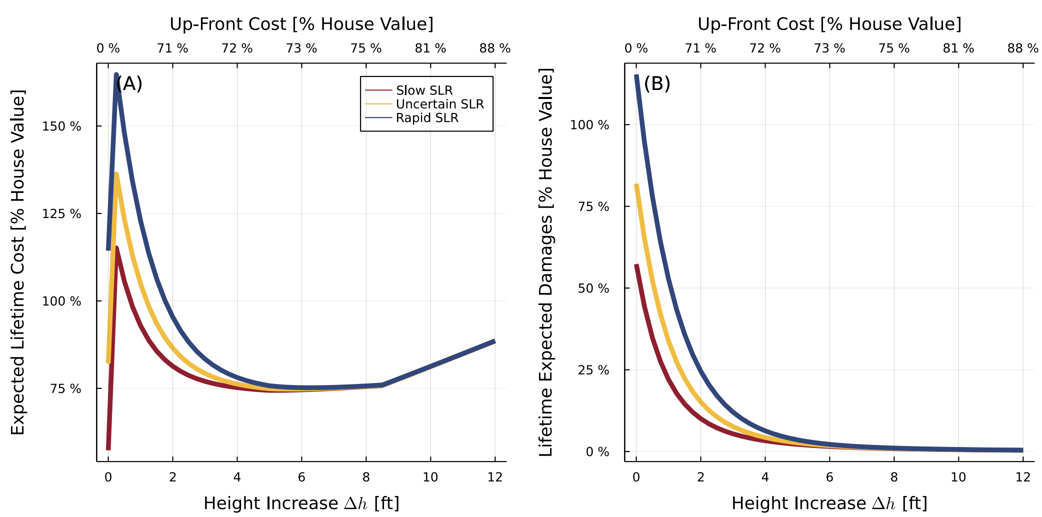

Figure 9: As fig. 7, but with Pareto frontiers for the full distribution of outcomes using the three models of p_{belief} (colors).

5 Conclusions

This study develops a framework to increase the transparency of assumptions about the likelihood of different SOWs. Additionally, we develop a framework capable of blending iterative, stakeholder-driven exploratory modeling with subjective probabilistic expert assessment. Such an approach is urgently needed given that deeply uncertain nonstationarity hazards pose a fundamental challenge to classical methods of hazard estimation. We use a didactic case study of house elevation in the coastal zone to illustrate a method for transparently synthesizing across deep uncertainties.

There are several limitations to our study that merit further discussion. The first category has to do with limitations of the underlying methodology proposed for reweighting state of the world. For example, we develop a subjective prior belief $p_{\text{belief}}(\Psi)$ over MSL in the year 2100. Although this is a low-dimensional representation of the full time series, it is not a sufficient statistic; prior studies have shown that using Approximate Bayesian Computation to calibrate models on low dimensional statistics using that are not sufficient statistics can lead to biased estimates of the posterior (Csilléry et al., 2010; Marjoram & Tavaré, 2006). Although we are not performing calibration here, and this is thus not a direct concern, time series with the same MSL in 2100 may differ in other ways, and experts may have prior information about the likelihood of these differences not represented in our model. A related concern is that we developed our three distributions for $p_{\text{belief}}(\Psi)$ in an *ad hoc* fashion that may not represent well-calibrated beliefs. Although this is appropriate for our didactic illustration, recent advances in Bayesian elicitation of expert opinion (see Mikkola et al., 2021, and references therein) can be applied to improve decision making in real world case studies. More fundamentally, our method assumes that there exists an expert capable of integrating over the many processes that drive SLR, from global greenhouse gas emissions to the global carbon cycle to climate sensitivity and ice sheet response (Morgan, 2014). An alternative approach would be to build a probabilistic model for each of these steps, and to use each as input to the next to develop a fully probabilistic model for SLR. Yet while some progress has been made developing probabilistic models for specific elements of this model chain (*e.g.*, Srikrishnan et al., 2022; Wong et al., 2017), this remains a computational and conceptual challenge. Finally, while our aim in this paper has been to demonstrate the value of integrating Bayesian workflow (Gelman et al., 2020) into DMDU, further work is needed to improve this integration.

The second category of limitations has to do with the case study and our interpretation of the house elevation decision problem. This problem intersects with decisions about where to live and how to manage household finances, both of which are highly complex. One extension of our analysis would be to consider additional decision objectives. In particular, we hypothesize that incorporating improved representations of risk aversion into decision support may substantially improve their usability. One could also extend the analysis to consider additional sources of uncertainty such as depth-damage relationships (Rözer et al., 2019; Nofal et al., 2020), the cost of elevating a house, the house lifespan, the effective discount rate, and value of the land on which the house is built (Zarekarizi et al., 2020, provides a framework for addressing some of these). Finally, while here we consider the decision to be a one-time decision, one could also frame this as problem a sequential decision. The aaalysis of sequential decision problems applies tools from control theory and reinforcement learning to identify policies that map "triggers" (*i.e.*, state variables) to decisions (Herman et al., 2020). Yet although framing the decision through a sequential lens can increase adaptability and improve outcomes (Fletcher et al., 2017; Garner & Keller, 2018), the optimized policy rules are necessarily sensitive to the characterization of uncertainty, and thus the problem of synthesizing across deep uncertainties remains (Herman et al., 2020).

These limitations motivate several directions for future research. From a methodological perspective, developing model chains that capture uncertainties in global energy and economic pathways, global climate sensitivity, and local hazard response (see fig. 1 of Moss & Schneider, 2000) offers a principled framework for fully probabilistic estimates of local hazard, subject to (still necessarily subjective) priors over key parameters. From a decision support perspective, improved understanding of the conditions under which household-scale strategies for flood risk management, like elevation, achieve relevant objectives could support improved resilience and adaptation. Additionally, since developing bespoke analyses for each house may be impractical, identifying decision rules that scale to different house characteristics may add value.

The proposed scenario weighting framework can be applied to inform critical challenges in climate risk management. An obvious area of application is to the design of infrastructure for climate risk management. For example, much of the stormwater infrastructure in the United States is inadequate for current climate (Lopez-Cantu & Samaras, 2018), let alone future changes. Yet upgrading this infrastructure is costly and subject to large uncertainties between rainfall models (Sharma et al., 2021) and RCP scenarios. Similarly, decisions like levee heightening (Garner & Keller, 2018; Oddo et al., 2017; van Dantzig, 1956) and sea wall design (as discussed in the Introduction) are subject to deep uncertainties in sea level rise. This framework can also be applied to uncertainties in non-physical variables. For example, investments in water resources planning and management depend on assumptions of future water demand, availability, and technologies (Trindade et al., 2019). Similarly, analyses of climate change mitigation options, such as estimates of the social cost of pollutants (Errickson et al., 2021) or cost-minimizing energy transition pathways, are conditional on probabilistic models for inputs like technology prices and population.

Of course, all models are ultimately wrong (Box & Jenkins, 1976). Thus seeking decisions that perform well across a range of assumptions, and improving the deccision space through robust design and flexibility, can improve outcomes. Yet whenever decisions are compared quantitatively, assumptions about the probability of different possible futures are necessarily made. We call for researchers studying climate risk management to make these implicit assumptions explicit, and we suggest that coordinated guidance can help practitioners determine better design criteria.

6 Open Research

All code, including source code, is available under the GNU Public License (version 3) at `https://github.com/jdossgollin/2021-elevation-robustness`. This code is written in the open source Julia programming language and detailed instructions for reproducing our results are provided. A permanent, citeable archive of the precise version of the codes used in this study is also available on Zenodo at TBD.

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