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OPINION

On the safe side: Uncertainty awareness for hydroclimatic risk and loss aversion

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Introduction

Hydroclimatic risk arises from the possibility of too much or too little water, where the amount is primarily dictated by weather and climate. Associated risk quantifications can be human-centric or related to environmental sustainability. Towards this end, scientists working within this broad domain study the distribution and dynamics of water in built and natural environments. However, not all sub-processes contributing to system dynamics are resolved at the studied scales [1,2]; therefore, any quantitative analysis is fraught with a cascading chain of uncertainties. For example, in relation to fluvial hazards, there might be inadequate information to characterize the infiltration capacity of a watershed, uncertainties related to the exceedance probability of regional rainfall under climate change, stochastic variability in flood-related erosion along an inhabited river bank, or uncertainty in observed inundations during past events.

The effort to study and quantify such uncertainties has been ongoing for several decades [1,3,4]. Beyond the forecast skill-related benefits of probabilistic predictions over their deterministic counterparts, one compelling reason to make uncertainties explicit is their crucial role in supporting risk-based decision-making[5,6]. Here, we discuss the necessity of uncertainty quantification and communication for allowing individuals to utilize risk and loss aversion. Risk-averse agents have a preference for certain outcomes over uncertain ones [7] and loss-averse agents prioritize avoiding losses over profiting from equivalent gains [8]. Using this line of reasoning, we support the research thrust towards more uncertainty-aware models.

Considering all possibilities

Without a quantitative or semi-quantitative conception of uncertainty, we are bound to the realm of ambiguity and ambiguity aversion [9]. When probabilities are assigned to event spaces, all potential outcomes are assigned a value, ensuring that even low-probability but potentially catastrophic events are accounted for. This is especially important in addressing hydroclimatic risks, such as those related to flash floods, debris flows, erosion along coastal waterfront, outburst floods and landslides due to glacial melting, riverine inundation extents, droughts, etc. Additionally, behavioral sciences have shown that people can have tendencies of loss aversion and/or risk aversion in a variety of decision-making contexts. For example, in prospect theory [10], the value function is s-shaped but asymmetrical, with more sensitivity to losses. Similarly, behavioral game theory incorporates psychological and behavioral insights into traditional game theory, studying how humans deviate from purely rational agents [11]. To allow for individuals to use these preferences and risk attitudes during hydroclimatic warning or design decisions, people would need to be aware of the uncertainties in quantitative analysis and forecasts.

Formally speaking, the posterior predictive distribution (Eq. 1), in particular, provides the conditional probability of a hazard occurring, given available data $[p(\mathbf{z}_{\text{predict}} \mid \mathbf{z}_{\text{obs}})]$. The right-hand side of the equation represents marginalization - i.e. the probability-weighted sum of conditional predictions - over model assumptions, multiple model structures $[\mathcal{M}]$, parameters $[\theta]$ and input forcings $[\mathbf{x}]$ - which are beset with deep uncertainties due to climate change. This enables a detailed uncertainty analysis. Furthermore, Bayesian updating refines predictions, narrowing the range of plausible options as new data becomes available. When there are no observations to condition the model structures and parameters, we can use prior distributions $[p(\theta), p(M)]$ based on expert opinion or transfer learning, which will provide a wider range of possibilities than an observations-constrained prediction.

$$p(\mathbf{z}_{\text{predict}} \mid \mathbf{z}_{\text{obs}}) = \sum_{M \in \mathcal{M}} \int \int \overbrace{p(\mathbf{z}_{\text{predict}} \mid \theta, M, \mathbf{x})}^{\text{Predictive likelihood}} \overbrace{p(\theta \mid \mathbf{z}_{\text{obs}}, M)}^{\text{Posterior over } \theta} \overbrace{p(\mathbf{x})}^{\text{Input}} \, d\mathbf{x} \, d\theta \quad \overbrace{p(M \mid \mathbf{z}_{\text{obs}})}^{\text{Posterior over } \mathcal{M}} \tag{1}$$

Uncertainty analysis - capturing system variability (aleatoric uncertainty) and knowledge deficits (epistemic uncertainty) - also relies on many assumptions, and, therefore, it can miss many components (some may focus on parameter uncertainty and not consider model structure uncertainty). However, such an analysis can be consequential as the spread of the predictive distribution can already trigger different preferences to accommodate loss and risk aversion of end users. Take, for example, evacuating a flood-risk zone or seeking more locally-sourced data to reduce uncertainty about building damage.

To be clear, not all individuals show such risk attitudes within the context of hydroclimatic hazards. For those who do utilize such preferences, there are arguments that these aversions can lead to suboptimal decision-making [12]. However, in many other contexts, the decision which avoids catastrophic risk is preferable, even if, based on inaccurate assumptions, it appears to have lower expected utility [13]. Ultimately, a loss- or risk-averse decision will only be possible when there is a sense of some nontrivial chance of unaffordable loss. In this way, while we do not claim that loss- or risk-averse decision-making is preferable in all contexts, what we want to stress is that an awareness of the uncertainty is necessary to allow individuals to utilize these preferences in their decision-making. However, deterministic model-based assessments are unable to provide such crucial information to the decision-makers.

Uncertainty-aware models

As we transition from parsimonious to highly parameterized models to characterize hydroclimatic risk [14], it is crucial to understand associated modeling uncertainties. Parsimonious models often make their assumptions explicit, whereas highly parameterized models may obscure them. At a regional level, high-impact hydroclimatic events tend to occur infrequently; therefore, before deploying such models for planning and design decisions, it is recommended to test that they are reliable in extrapolatory scenarios. This consideration transcends the debate between model parsimony, complexity, and explainability—it represents an orthogonal axis of progress (Fig 1). Any model architecture can be enhanced by attempts to address parametric, input, model-structure, and/or observational uncertainties. Therefore,

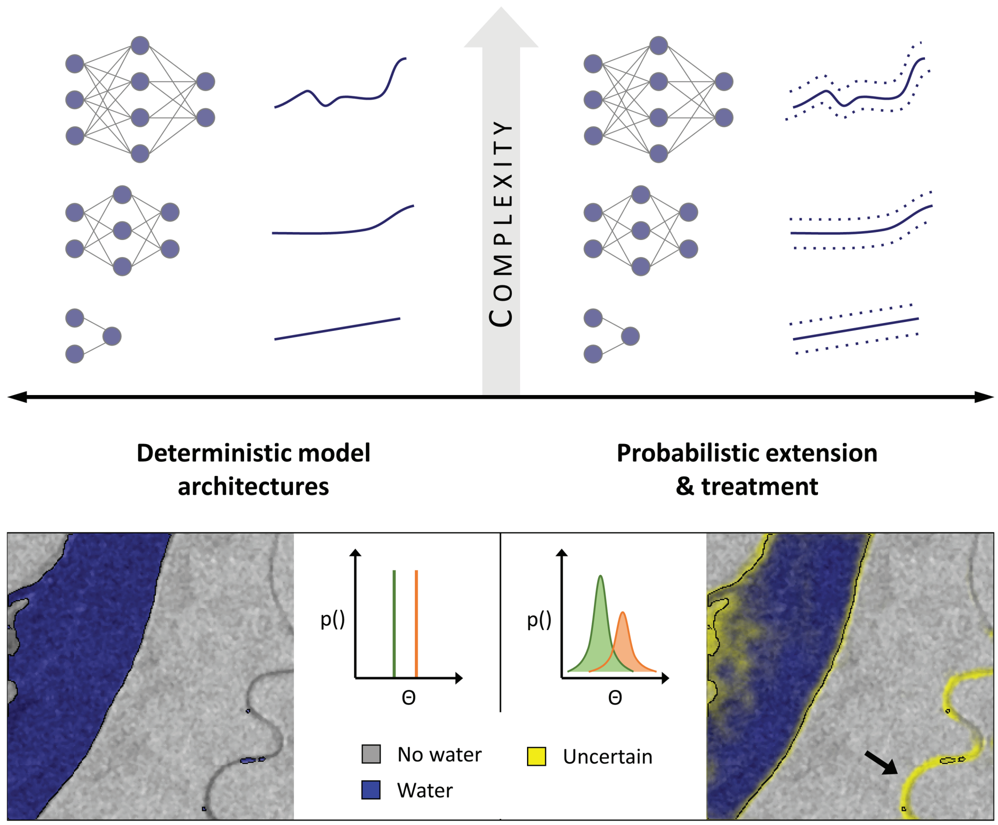

Fig 1. A schematic comparison of deterministic and probabilistic models. The complexity of the model is orthogonal to uncertainty awareness. You can have parsimonious or highly parameterized models, and they can be extended into probabilistic counterparts. In the didactic example (bottom panel), the difference in the output of two floodwater segmentation algorithms [15] captures the need for uncertainty quantification - the deterministic output misses a whole flooded channel.

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Monte Carlo simulations (in the most generic sense), which explore the effect of all probable model inputs to identify all probable outcomes, are foundational to reliable risk estimation and communication.

Beyond improving risk quantification and forecast reliability, methods that help make uncertainties explicit can meaningfully inform decisions in the face of systemic risks, allowing individuals or communities to err on the side of caution. Although there are diverse risk attitudes towards various hydroclimatic hazards, we echo the opinion that requisite uncertainty awareness is required to employ those preferences in making decisions.

Author contributions

Conceptualization: Omar Wani, Mason Majszak.

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Writing – original draft: Omar Wani, Mason Majszak.

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