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UNCERTAIN CLIMATE FUTURES - ON OPTIMALITY AND ROBUSTNESS OF CLIMATE ADAPTATION OPTIONS

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Abstract. Climate change poses significant risk to civil infrastructure systems, exacerbated by epistemic uncertainties (also known as deep uncertainty) arising from limited knowledge about climate change. Consistently accounting for these epistemic uncertainties in developing decision support for the planning, design, and assessment/adaptation of civil infrastructure systems presents a critical challenge for society. This study introduces a risk-informed decision support framework that incorporates a new approach to represent epistemic uncertainty in decision-making. In particular, the proposed approach assigns probabilities to relevant climate scenarios based on expert opinions (e.g., from climate scientists, engineers), reflecting the degree of belief they hold about the likelihood of different future projections. This probabilistic representation of epistemic uncertainty differs from conventional robust decision-making approaches, such as the minimax regret (MMR), which typically relies on non-probabilistic methods. A case study compares the proposed approach with MMR, showing that the proposed approach is more effective on selecting decisions that are both optimal and robust based on the associated risk, whereas MMR focuses solely on robustness while neglecting the optimality.

1 INTRODUCTION

Climate change presents growing challenges to the planning, operation, and adaptation of infrastructure systems due to the increasing intensity and variability of environmental hazards such as flooding, extreme precipitation, and storm surges. These hazards are subject to significant uncertainty, not only due to natural variability (aleatory uncertainty), but more critically due to epistemic uncertainty, i.e., uncertainty arising from limitations in knowledge, modeling assumptions, and future societal developments.

Classical decision-making methods under epistemic uncertainty has been extensively studied through various robustness metrics, including the maximin criterion (which selects alternatives based on their worst-case performance) (Wald 1950), the maximax rule (based on the best-case outcome) (Savage 1954), the Hurwicz optimism-pessimism compromise

(Hurwicz 1951), the minimax regret criterion (which minimizes the worst-case regret) (Savage 1951, Savage 1954), and the principle of insufficient reason (which assumes equal likelihood across all scenarios) (Laplace, 1951), etc. Among classical methods for decision-making under uncertainty, the minimax regret (MMR) criterion has been widely used for its simplicity and conservative orientation. It seeks to minimize the maximum possible regret (or surprise), defined as the loss incurred by not choosing the optimal action under the true state of nature. Applications in infrastructure planning and climate risk management have demonstrated the method's utility in contexts with deep uncertainty (Lempert & Collins, 2007; Kwakkel et al., 2016). However, the minimax regret approach has been criticized for its insensitivity to the probability distribution of scenarios and inability to incorporate expert knowledge regarding scenario likelihoods or structural dependencies (Hall et al., 2012). Beyond MMR, the Robust Decision Making (RDM) (Groves & Lempert, 2007) and Dynamic Adaptive Policy Pathways (DAPP) framework (Haasnoot et al., 2024) are developed in recent years. However, the MMR remains one of the most commonly used approaches in engineering systems due to its simplicity and conservation.

Different from these non-probabilistic approaches, Li et al., (2025) has proposed to incorporate probabilistic modeling of epistemic uncertainty and allow for adaptive, context-specific assessments. It involves assigning subjective probabilities to relevant climate scenarios based on expert judgment and integrating these into a risk-informed decision analysis framework. This enables consistent evaluation of adaptation strategies across multiple plausible futures, accounting not only for direct risks but also for the disbenefits of sub-optimal actions under alternative scenarios. By explicitly modeling epistemic uncertainty, such frameworks provide a more robust foundation for infrastructure adaptation planning, particularly when long-term decisions are irreversible or costly to revise.

On top of Li et al., (2025), this study further evaluates the impact of epistemic uncertainties on optimality and robustness of climate adaptation options by comparing with the widely used MMR. A simple case study addressing risk informed decision making for conceptual design of a civil infrastructure system is conducted to explore how different representations of epistemic uncertainty influence decision-making for climate adaptation. The findings have shown that the optimal decision selected by the proposed approach is both optimal and robust based on the associated risk, while the MMR method only considers robustness.

2 OPTIMAL AND ROBUST DECISION-MAKING IN THE FACE OF EPISTEMIC UNCERTAINTY

Decision-making under epistemic uncertainty poses unique challenges, particularly in climate adaptation contexts where future scenarios are difficult to predict and conventional probabilistic models may lack adequate support. In such settings, selecting an adaptation strategy that performs well across a range of possible but uncertain futures becomes essential. This section presents a comparison between existing non-probabilistic robust decision-making approaches and the proposed probabilistic approach in climate adaptation.

A wide range of decision criteria have been developed to support planning under epistemic uncertainty, where the probabilities of future states of the world are unknown or unknowable. Classical approaches for climate adaptation include five well-established robustness metrics: maximin, maximax, Hurwicz optimism-pessimism, minimax regret, and the principle of insufficient reason (Giuliani, 2016). The maximin rule focuses on security by selecting the alternative with the best worst-case outcome. The maximax rule, by contrast, chooses the alternative with the best possible payoff, assuming the most favorable outcome. The Hurwicz rule linearly combines the maximin and maximax metrics using a weighted parameter that reflects the decision-maker's degree of optimism. The principle of insufficient reason (Laplace, 1951) assumes that all scenarios are equally likely and selects the decision with the highest expected utility under a uniform distribution. Beyond these classical frameworks, Robust Decision Making (RDM) and Info-Gap theory offer modern alternatives for coping with epistemic uncertainty. RDM stresses robustness across a wide ensemble of futures by testing strategies against numerous plausible scenarios, seeking alternatives that satisfy performance thresholds rather than optimizing single-valued criteria (Groves & Lempert, 2007). The Info-Gap approach (Ben-Haim, 2006) introduces an uncertainty horizon α, representing the deviation from the best-estimate (Max Likelihood) model. It selects the decision that remains viable under the largest possible α, emphasizing tolerance to modeling error and ignorance.

Recently, the Dynamic Adaptive Policy Pathways (DAPP) framework (Haasnoot et al., 2024) incorporates a temporal dimension, where decisions are structured along a timeline. Through the introduction of "options" it allows for adaptive implementation: when a strategy reaches a tipping point or becomes ineffective due to emerging conditions, it can be revised or replaced by an alternative pathway. This makes DAPP particularly useful for long-term planning in contexts such as climate adaptation, where future developments unfold gradually and unpredictably. The adaptive capability over time, i.e., a strength of DAPP, has not been captured in most existing decision approaches, including the MMR approach and our current formulation. However, it is important to emphasize that our proposed approach is readily extensible to support adaptive decision-making. Furthermore, while DAPP is often applied in a qualitative or semi-quantitative manner, our framework supports probabilistic risk modeling and is explicitly designed to integrate differing expert judgments under epistemic uncertainty. This makes our method not only novel but also centrally important for engineering systems where quantitative, and expert-informed decision support is essential. As such, our work represents a significant advancement beyond existing adaptive planning methods by offering a flexible yet analytically robust framework for long-term, risk-informed decision-making.

Herein, the MMR is described in detail as it is one of the most commonly used approaches in engineering applications. The MMR criterion (Savage, 1951) is widely adopted for its simplicity and risk-averse orientation without requiring probability distributions. Regret is defined as the difference between the loss from a chosen decision and the best achievable loss under each scenario. The MMR decision rule selects the alternative that minimizes the maximum regret across all possible scenarios. Formally, let **d** be the set of possible decisions $\mathbf{d} = (d_1, d_2, \ldots, d_n)^T$ and **s** be the set of climate scenarios $\mathbf{s} = (s_1, s_2, \ldots, s_n)^T$. The objective value (e.g., the expected long term loss) of decision $d \in \mathbf{d}$ under scenario $s \in \mathbf{s}$ is denoted as $\mathbb{E}[LTL_{i,j}|s_i, d_j]$. The MMR rule can then be expressed as:

$$d^* = \arg\min_{d_j \in \mathbf{d}} \max_{s_i \in \mathbf{s}} \left[\mathbb{E}[LTL_{i,j}|s_i, d_j] - \min_{d_j \in \mathbf{d}} \mathbb{E}[LTL_{i,j}|s_i, d_j] \right] \tag{1}$$

where the optimal decision d^* minimizes the worst-case regret relative to the optimal outcome achievable in each scenario. MMR has been widely applied in domains where probabilities are not reliably specified (Manski et al., 2021; Anderson and Zachary, 2023). It is particularly suitable when avoiding catastrophic deviations from optimality is prioritized over expected value of utility performance.

Different from MMR, the proposed framework accounts for epistemic uncertainties of climate scenarios by assigning subjective probabilities and disbenefit-aware robustness metrics. Following the notations in Li et al. (2025), the optimal decision d^* under scenario s_i is based on the minimized expected loss:

$$d^*(s_i) = arg\,\min_{\mathbf{d}}\left(\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right]\right) \tag{2}$$

A key contribution of our approach lies in assigning subjective probabilities $p(s_i)$ to relevant climate scenarios s_i, where i=1, 2, ⋯, n, based on expert judgment. This feature allows for a more accurate representation of epistemic uncertainties, enabling decision-makers to incorporate varying degrees of belief in different climate outcomes, a significant improvement over traditional method. Then, the optimal decision d^* is determined by minimizing the expected long-term loss across all scenarios, weighted by their subjective probabilities:

$$d^* = arg\,\min_{\mathbf{d}}\left(\sum_{s=1}^{n} p(s_i)\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right]\right) \tag{3}$$

Beyond Li et al. (2025), in this study, we have quantified the robustness of the optimal decision $R_{\text{robust}}(d^*)$, which evaluates the sensitivity of the optimal decision to disbenefits in non-optimal scenarios:

$$R_{\text{robust}}(d^*) = 1 - \frac{p(s_i)\left[\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right] - \min_{\mathbf{d}}\left(\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right]\right)\right]}{p(s_i)\left[\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right] - \min_{\mathbf{d}}\left(\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right]\right)\right] + p(s_i)\mathbb{E}\left[LTL_{i,j}|s_i, d_j\right]} \tag{4}$$

where the robustness ranges from 0 to 1, with 1 indicating the most robust decision, while less robust decisions have values closer to 0. This robustness is based on the ratio of the expected value of indirect losses (losses associated with choosing a scenario for optimization that does not match the scenario which is realized) and divide this by the total losses (= the expected value of direct + indirect losses corresponding to the chosen optimal choice of scenario and risk management options) (Nielsen et al., 2019, JCSS, 2008). Different from the MMR approach, our proposed method ensures that the optimal decision is identified by considering both the expected value of losses and the robustness of the decision alternatives. Among possible decision alternatives with similar performances in terms of expected value of utility, this facilitates a selection of the more robust one.

3 CASE STUDY

This section provides a simple example by applying the MMR method and our proposed decision-making framework to a climate adaptation problem. In this study, the optimal decision is defined as the decision associated with the lowest long-term loss across all alternatives (Li et al. 2025).

3.1 Climate scenarios with equal probabilities

The first case study involves three climate scenarios (s_1, s_2, s_3) with equal probabilities ($p(s_1) = p(s_2) = p(s_3) = 1/3$) and four adaptation decisions (A, B, C, D). The long-term losses (LTL) in Million US dollars for each decision under each scenario are shown in Table 1.

Table 1: The long-term losses

Scenario	s_1	s_2	s_3
Decision A	20	38	60
Decision B	25	36	56
Decision C	30	38	52
Decision D	35	39	40

The MMR method identifies optimal decisions per scenario: o_1 = 20 (A), o_2 = 36 (B), o_3 = 40 (D). Regrets are calculated using Equation 1 and are shown in Table 2. The MMR ranks decisions as C, D, B, A (maximum regret = 12 for C).

Table 2: Regret of MMR method

Regret	s_1	s_2	s_3	Max Regret
Decision A	0	2	20	20
Decision B	5	0	16	16
Decision C	10	2	12	12
Decision D	15	3	0	15

For the proposed method, the expected utility and the robustness of each decision can be calculated as shown in Table 3. Our method ranks decisions as D, B, A, C (optimal D, expected loss = 38.00).

In addition to comparing expected losses and regrets, the robustness of each decision was evaluated under individual scenarios and collectively across all scenarios (as shown in Table 3), Decision D again ranks highest with a robustness score of 0.864, followed by Decision B (0.848), Decision A (0.843), and Decision C (0.833). These results reinforce the earlier finding that Decision D is not only optimal in terms of expected loss, but also the most robust option across varying scenario conditions. The robustness metric thus provides additional support for selecting Decision D, as it consistently delivers balanced performance and lower sensitivity to disbenefits in non-optimal scenarios.

Table 3: Expected utility and robustness of each decision under all scenarios of the proposed method

	Losses $E[LTL_{i,j}]$ under scenarios			$E[U(d_i)]$	$R(d_i)$
	s_1	s_2	s_3		
Decision A	20/3	38/3	60/3	39.33	0.843
Decision B	25/3	36/3	56/3	39.00	0.848
Decision C	30/3	38/3	52/3	40.00	0.833
Decision D	35/3	39/3	40/3	38.00	0.864

3.2 Climate scenarios assigned different probabilities

To further illustrate the behavior of our proposed decision framework under varying degrees of epistemic uncertainty, Figure 1 (a) presents a decision region map for the three-scenario case. This visualization plots the optimal decision regions across the full probability space spanned by scenarios s_1 and s_2, where the probability of s_3 is implicitly defined as $p(s_3) = 1 - p(s_1) - p(s_2)$. The feasible domain is thus constrained to the lower triangular area, bounded by the condition $p(s_1) + p(s_2) \leq 1$ and $p(s_i) \geq 0$ for all i. The upper triangle of the unit square is intentionally excluded, as it violates the fundamental axiom that total probabilities must sum to one. Each colored region in the triangle corresponds to the decision (A, B, or D) that yields the lowest expected value of the long-term loss under the associated probability distribution. Decision C is not shown because it is never optimal under any combination of scenario weights in this case, consistent with the earlier tabulated results. By scanning across the probability space, one can observe how changes in the subjective belief about scenario likelihoods lead to different preferred decisions. For instance, Decision A dominates when scenario s_1 is likely, while Decision D is preferable under high probability of s_3.

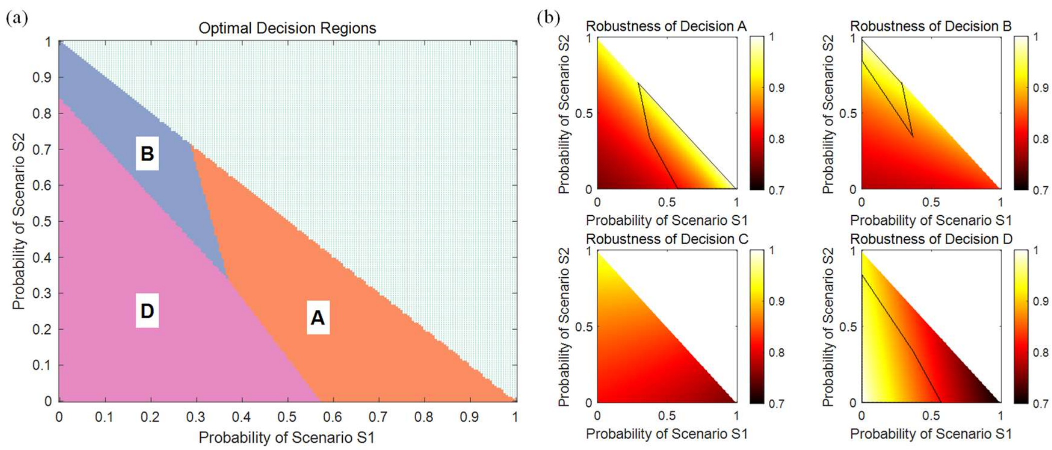

Figure 1: (a) Optimal decision regions under varying scenario probabilities; (b) Robustness surfaces of each decision alternative under varying scenario probabilities.

Figure 1 (b) presents heatmaps of the robustness index for each decision alternative (A, B, C, and D) across the scenario probability space. These robustness indexes quantify how well a given decision performs under the worst-case disbenefits relative to its expected loss. Each subplot highlights the performance sensitivity of one specific decision under changing beliefs about scenario likelihoods. As an illustrative example, consider Decision D in the fourth subplot of Figure 1(b). The black contour outlines the region where Decision D yields the lowest expected loss, i.e., the utility-optimal region. Within this area, the robustness of Decision D is noticeably higher compared to those of the other decisions at the same probability combinations. This alignment between high robustness and utility-optimality suggests that the proposed robustness measure strongly supports and reinforces the selection made based on expected utility. It highlights that Decision D is not only optimal in terms of average performance, but also reliable under adverse conditions in the corresponding probability region. The decision region map underscores a major advantage of our proposed method, that flexibility in adapting to available information. When precise subjective probabilities are known, a unique optimal decision can be identified. When probabilities are uncertain or disputed, the region map itself serves as a probability-conditional ranking tool, revealing how the preferred decision varies with beliefs. In contrast to fixed-rule methods such as minimax regret, this approach not only provides robust average-case performance, but also supports adaptation across diverse stakeholder perspectives.

3.3 Discussions

In the case study, MMR selects Decision C (maximum regret = 12) and gives ranking CDBA, while our method chooses D (expected loss = 38.00) and gives ranking DBAC. Additionally, if the minmax rule (similar to the maximin but focuses on the losses) is considered, i.e., ranked based on the worst-case scenario and neglecting regrets, the ranking is DCBA. These differences highlight that the MMR approach focuses solely on regret, while the minmax rule considers only the worst-case losses.

In contrast, our proposed method facilitates assigning equal probabilities to all scenarios - the Laplace approach, which is not accommodated by MMR or the minmax rule. More importantly, it is capable of integrating subjective probabilities. This flexibility provides greater adaptability and potential cost-effectiveness, especially when probability estimates can be reasonably elicited or constructed. Rather than viewing the reliance on probabilistic inputs as a limitation, we consider it a deliberate trade-off. When such information is available, our method facilitates more informed and balanced decisions by incorporating belief structures and scenario likelihoods. Furthermore, the proposed framework is readily extensible to adaptive decision-making, a direction we aim to explore in future research. Upcoming work will also investigate the use of more specific climate information for engineering applications, thereby demonstrating both the adaptive capacity and practical applicability of the proposed methodology.

4 CONCLUSIONS

This study evaluates the influence of epistemic uncertainties on the optimality and robustness of climate adaptation decisions by comparing the proposed decision support approach with the widely used MMR approach. This comparative analysis underscores the advantages of the proposed framework, which not only assesses decision alternatives within individual climate scenarios but also evaluates all relevant scenarios, accounting for both their associated benefits and disbenefits. A key strength of the proposed method lies in its ability to identify decisions that are simultaneously optimal and robust. In contrast, the MMR approach is primarily focused on selecting robust decisions, which may not always align with optimal outcomes. Thus, the proposed framework addresses a critical limitation of MMR by ensuring that decision-making balances both optimality and robustness under uncertainty. Additionally, the proposed framework introduces flexibility by allowing the assignment of subjective probabilities to various climate scenarios. This allows decision-makers to reflect expert judgment and context-specific beliefs into the analysis. However, MMR or other non-probabilistic approaches can be regarded as assigning equal weights to all relevant scenarios under epistemic uncertainty. In terms of robustness, both methods aim to avoid decisions that perform poorly under adverse scenarios, but they differ in scope. MMR focuses on minimizing the single worst-case regret, resulting in the selection of Decision C. However, the proposed method evaluates robustness across all scenarios using a disbenefit-based metric. Decision D demonstrates the highest overall robustness, indicating stable and balanced performance under varying future conditions. Overall, the proposed probabilistically enriched framework outperforms MMR by supporting flexible, robust, and effective decision-making under epistemic uncertainty.

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