Technical Report

Long-term policy to manage flood risk on the IJssel River.

EPA141A: Model-based Decision Making

Group 9 : Transport Company

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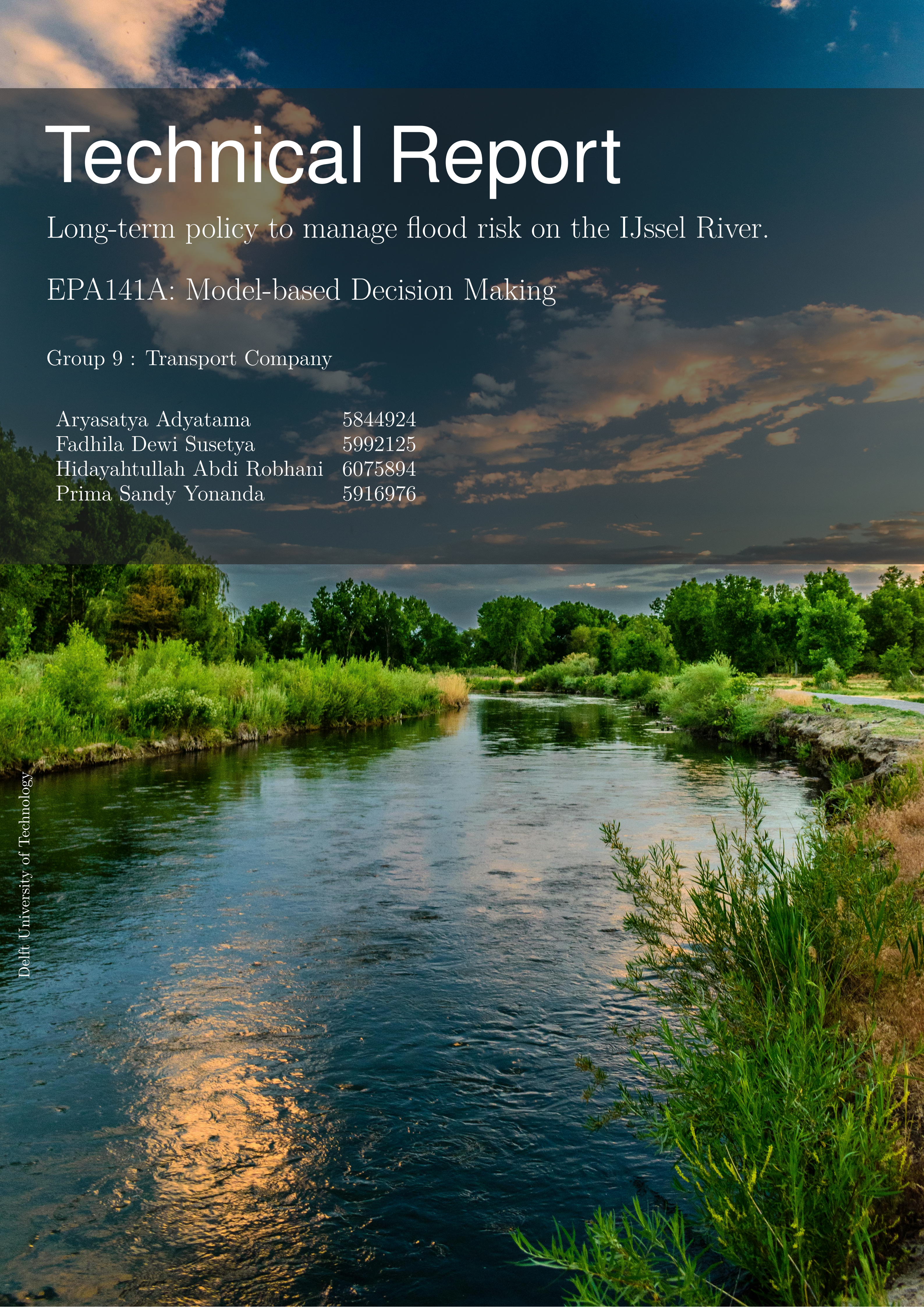

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Executive Summary

This report is developed by a transportation company to address the flood risk management strategies for the Ijssel River in the Netherlands. The Ijssel River, an essential waterway for our cargo transportation operations, presents significant flood risks due to its flat topography and the impact of high tides and elevated water levels from the Rhine. The Ministry of Infrastructure and Water Management has identified five critical locations: Doesburg, Cortenoever, Zutphen, Gorssel, and Deventer. We evaluated three primary flood mitigation strategies: dike heightening, creating more room for the river, and implementing early warning systems.

For our company, **minimizing flood risks along the Ijssel River is paramount**. We prefer **dike heightening** as it supports **operational security** by maintaining higher water levels, allowing larger ships to navigate, and thus **increasing profitability**. Additionally, dike heightening provides economic stability by preventing land use changes that could trigger public protests. Research supports dike heightening as a cost-effective and reliable flood protection method, especially in densely populated urban areas like Zutphen and Deventer.

Our analysis focuses on **dike ring 3 (Zutphen)** and **dike ring 5 (Deventer)** because we are particularly concerned with **urban areas**. These areas have higher population densities and greater economic activities, making them more vulnerable to flood impacts. Sensitivity analyses using methods like Sobol, feature scoring, and dimensional stacking highlight that these dike rings are particularly sensitive to uncertainties. This focus allows us to allocate resources more efficiently and implement targeted interventions that address the most critical areas. Evidence supporting this focus includes the high population density and economic significance of these urban areas, making flood protection crucial.

By applying scenario filtering and policy search techniques, which include robustness and vulnerability tests, we identified four robust policies that maintain zero expected annual damages and deaths in these areas in at least 75% of scenarios. The four final policies selected based on Signal-to-noise Ratio (SNR) and Maximum Regret metrics are **s248_p195, s982_p346, s632_p208**, and **s541_p149**. Further deep uncertainty analysis using these metrics refines these policies, ensuring they are resilient under a wide range of adverse conditions. Scenario discovery techniques are then employed to identify specific vulnerabilities, guiding targeted interventions to enhance policy resilience.

We conclude that a multi-faceted approach combining robust decision-making frameworks, detailed sensitivity and vulnerability analyses, and stakeholder engagement is essential for effective flood risk management along the Ijssel River. Future work should focus on refining models with more localized data, expanding stakeholder collaboration, and exploring innovative solutions like green infrastructure to further improve regional flood resilience. Our company is committed to implementing these strategies to safeguard our operations and enhance the safety and resilience of the Ijssel River region.

1. Problem Definition

1.1 Background

The Netherlands is traversed by four major European rivers: the Rhine, Maas, Schelde and Eems (De Bruijn et al., 2015). One of the branches of the Rhine is the **River Ijssel**, which crosses the Gelderland and OverIjssel provinces. Those regions are considered flood-risk areas due to potential high water levels in the Rhine and elevated water levels in the Ijssel, exacerbating the flood threat. Additionally, the flat topography of the surrounding regions and high tides further increase the vulnerability of these areas to flooding (Klijn, 2018). There are five locations which have been taken into consideration by the Ministry of Infrastructure and Water Management: Doesburg, Cortenoever, Zutphen, Gorssel, and Deventer (Figure 1).

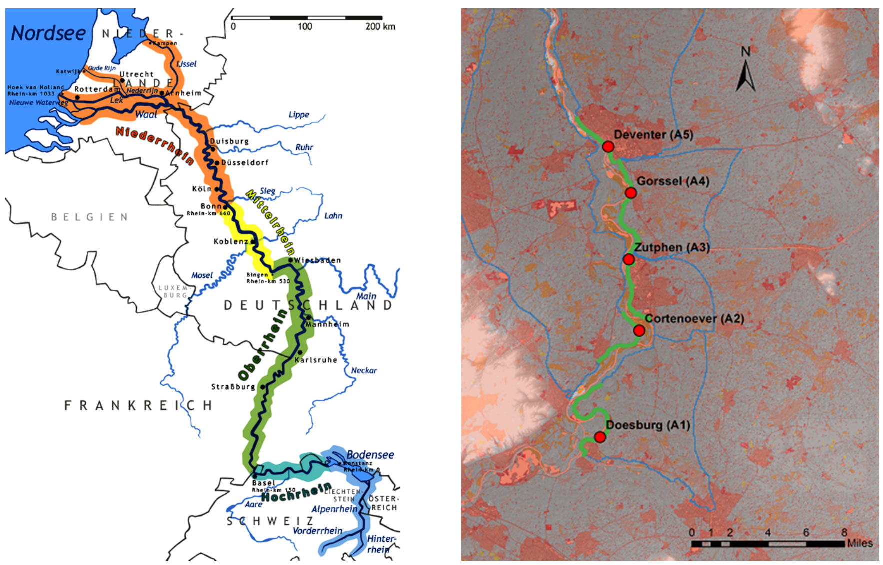


Figure 1. Ijssel River Map

In order to deal with the increasing flood risk in the Ijssel River, there are three alternative solutions that are currently considered:

- **Dike Heightening,** Increasing the resistance of the embankment system. Besides securing flood, these measures maintain water river and efficient usage of the river for transport
- **Room for River**, making more room for rivers to overflow safely during periods of high water. Broadening the area also can promote a natural river habitat ecosystem and biodiversity.
- **Early Warning System** allows a timely communication of the threat before the actual flood takes place. This would lead to lower the damage that is done to human life.

These solutions can be used complementary and can differ per location around the Ijssel. However, due to the river's geographical position, flood risk mitigation is not the decision of only one actor. The decision-making process can be understood from various perspectives of stakeholders who are interested in the economic, safety, and life quality concerns along the river. A map of stakeholders who hold an interest in the Ijssel River can be seen in Figure 2.

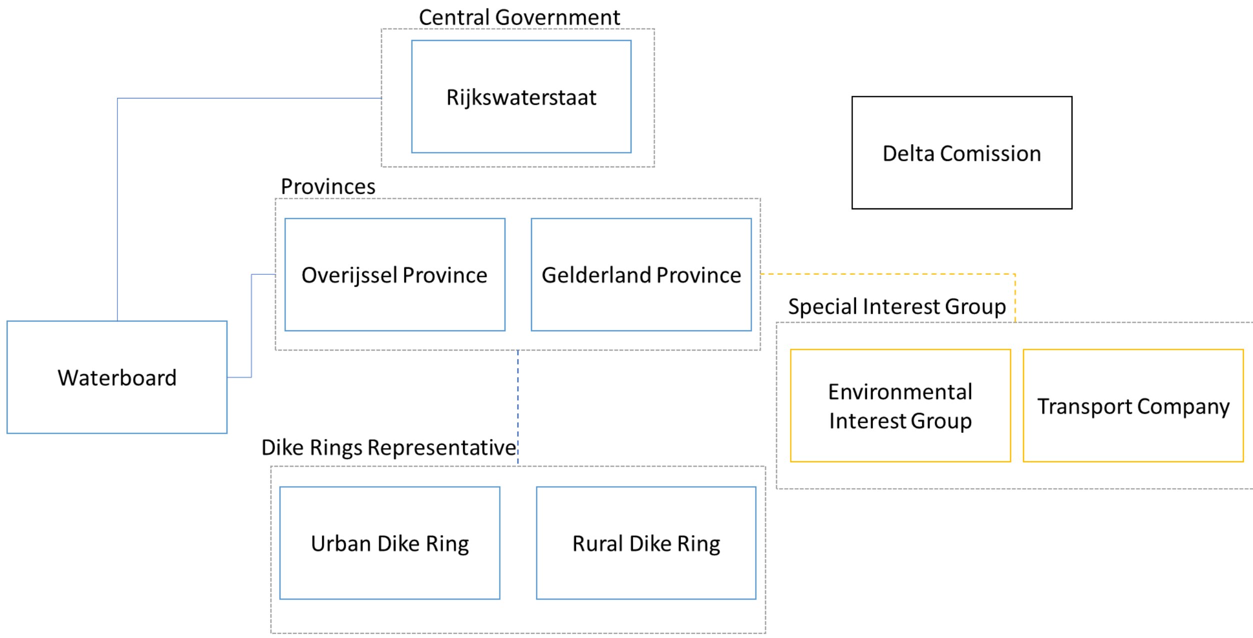


Figure 2. Relevant Stakeholders for Flood Risk Mitigation

1.2 Transportation Company Perspective

The diverse interests and objectives lead to different kinds of mitigation measures for the policy alternatives in the Ijssel River. This report is arranged from the perspective of the transport company to deal with the uncertainties regarding the flood risk.

Ijssel River is a significant waterway for cargo transportation in the Netherlands due to its strategic location, which links to the European inland waterway network. Based on the Bureau of Transportation Statistics, inland waterways offer a more energy-efficient and environmentally friendly alternative compared to road and rail transport. As a transportation company that uses the Ijssel River to transport goods, minimizing flood risk on the entire Ijssel river is necessary because it is impossible to transport goods if the river has broken down. Therefore, our main interest is to **minimize annual damage and the expected number of deaths** in the Ijssel River.

From available policy levers, transport companies favour promoting **dike heightening**. The rationale is we notice that the water level is also important for our operation security, and a higher water level means larger ships can sail, which translates into better profit. Contradictory, room for the river is considered less beneficial for the transportation companies because expanded floodplain areas allowed more space for water to spread out, which lowered the overall water levels during peak flows. Dike heightening also ensures economic stability in the region because it allows the land adjacent to the dike to remain in use without necessitating any relocation that may lead to public protest. From Gelderland and OverIjssel's perspective, Dike heightening is also cost-effective because it leverages existing infrastructure, minimizing the need for extensive land acquisition, evacuation, and maintenance costs. However, the comprehensive dynamics between key actors in the decision-making arena in the political reflection report.

Literature also shows several benefits from dike heightening as follows:

- Research by Klijn et al. (2018) shows that dike heightening provides a **direct and reliable** method for protecting areas from high water levels. Dike heightening has a proven track record in many countries, offering a straightforward way to increase flood protection without requiring significant changes to land use or river morphology
- Cost-benefit analysis by Kind (2014) indicates that dike heightening can be more **cost-effective** in the long term compared to creating additional space for rivers. This analysis takes into account the costs associated with land acquisition, relocation, and environmental mitigation necessary for the "Room for the River" projects.
- Dike heightening is more **practical** than the 'room for the river' approach because it allows simultaneous implementation with regular embankment reinforcement since embankment fragility is crucial in determining flood risk (Klijn, 2012).

The debate reveals that dike heightening is considered the more suitable flood risk measure in **urban areas** compared to the room for river due to several reasons, such as:

- Urban areas have high population densities, meaning that any flooding can affect a large number of people. Heightening dikes **directly protect these populations** by increasing the height of existing barriers.
- The "Room for the River" approach often requires converting land to floodplains, which can be **impractical in densely populated** urban areas where land is scarce and valuable.
- Implementing dike heightening in urban settings is often **less disruptive** than creating new floodplains.

Based on Figure 3, A3 (Zutphen) and A5 (Deventer) are located in a dark red region with a population of more than 35.881 (dense population). Therefore, this study grouped dike rings A3 and A5 as urban areas that have to be heightened and become the focus of further analysis to generate robust decision-making.

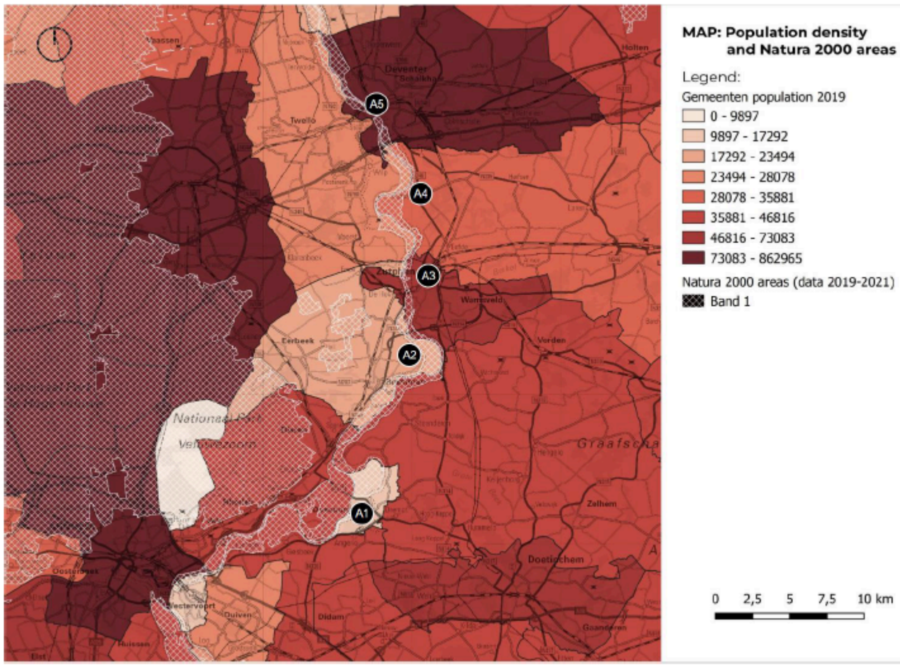


Figure 3. Map of population density in Ijssel River

1.3 Research Question

This report aims to identify the most desirable flood risk mitigation policies to minimize expected annual damage and expected number of deaths under deep uncertainty in Ijssel River, specifically in **A3 (Zutphen)** and **A5 (Deventer)** as urban areas.

In this study, we did not consider dike heightening, RfR, and evacuation costs as outcomes of interest because, as private companies, we are not allowed to participate in joint investments in public infrastructure. We select outcomes that **directly impact transportation company interests**.

2. Approach

We use **Many-Objective Robust Decision Making (MORDM)** to answer our research question. MORDM is the most suitable approach because it is a planning approach specifically designed for complex environmental systems like the Ijssel case. Theoretically, it combines the Multi-Objective Evolutionary Algorithm (MOEA) optimization technique, which approximates the optimal trade-off set of solutions to multi-objective optimization problems, with the Robust Decision-Making (RDM) framework that represents a decision-making approach under deep uncertainty, where decision options are evaluated over a large set of scenarios (Watson & Kasprzyk, 2017). By harnessing the power of MOEA, MORDM can effectively tackle problems with four or more conflicting objectives, producing a diverse set of alternative solutions for further evaluation within the RDM framework. However, a critical issue remains in selecting the most preferred solution among the trade-offs generated by MOEA. Therefore, solution robustness emerges as a promising approach to ensure satisfactory performance, even when the system conditions significantly deviate from those initially considered for evaluating the optimality of alternatives (Kasprzyk et al., 2013).

Our experiments were carried out using the EMA workbench in the Python library (Kwakkel, 2017). The library offers a flexible and user-friendly interface for connecting simulation models to the entire exploratory modelling and analysis process. The EMA Workbench is used for exploration rather than prediction purposes. The adapted framework can be seen in Figure 4.

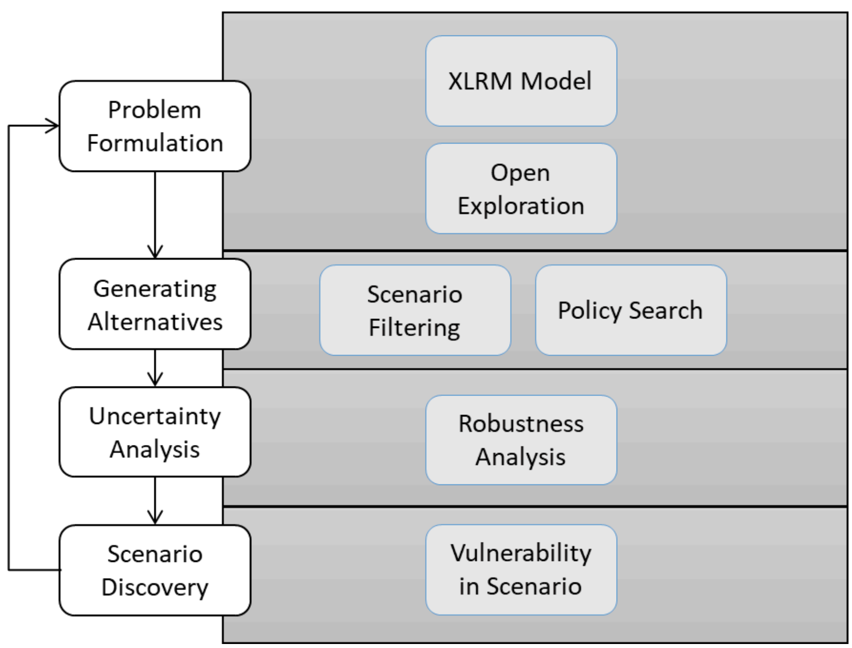


Figure 4. MORDM Framework for Ijssel River, originally developed by Kasprzyk et al. (2013)

The framework used in this analysis has four significant steps:

1. **Problem Formulation**

The MORDM framework's problem formulation component captures decision makers' evolving hypotheses about uncertainties, levers, relationships, and measures (XLRM) for their system. Decision levers are crucial for developing planning alternatives to improve system performance. Uncertainties must be considered when formulating a planning problem in the context of environmental change. In the case of Ijssel River, to create an appropriate problem formulation that is in line with the goals of the Transport Company, an initial open exploration analysis is done to see which variables are the most sensitive to uncertainties using **Sobol** as a global sensitivity assessment method, **Feature Scoring**, and **Dimensional Stacking**.

2. **Generating Alternatives**

   Decision makers use many objective problem formulations to understand necessary tradeoffs between their performance measures. Multi-objective evolutionary algorithms (MOEAs) help find these tradeoff solutions for complex environmental systems. For MOEAs to work well, they need to find a diverse group of solutions that cover all the tradeoffs in the application. Convergence is critical in measuring the proximity of the MOEA's solutions to the best possible ones. Diversity maintenance is also essential, ensuring the solutions are well-spread across the entire range of possibilities. In the case of the Ijssel River model, this step of MORDM is modified to prioritize a small number of scenarios to filter the scenario based on the goals (Eker & Kwakkel, 2018). The scenarios are filtered by using Patient Role Induction Methods (**PRIM**) to prioritize the scenarios where the threshold for death and damages on all dikes is more than 50% in order to show the worst-case scenarios. Then, we identify candidate solutions from filtered scenarios that represent diverse policy levers within our constraint using the **epsilon-NSGA II** algorithm.

3. **Uncertainty Analysis**

   Due to the uncertainty in factors, decision-makers are now considering various scenarios and using robustness metrics to evaluate how well different decision options perform under these uncertain conditions (McPhail et al., 2018). We explore the effects of uncertainties on the performance of the candidate solutions using two robustness metrics, which are the Signal-to-noise (**SNR**) ratio and **Maximum Regret.** To manage computational complexity and avoid excessive scenario runs, constraints that focus on **urban areas' damage** and **death** are applied to limit the solution space size. Employing these constraints effectively filters the number of scenarios required for evaluating each solution. This approach ensures a balance between exploring the effects of uncertainties and maintaining computational efficiency.

4. **Scenario Discovery and Tradeoff Analysis**

   Scenario discovery is conducted to identify vulnerabilities and assess the strengths of the decision levers based on specific interests or objectives. The relationship between uncertainties and outcomes is explored by systematically analyzing generated scenarios. This analysis helps understand the conditions under which the preferred policy may not perform as desired or achieve the desired objectives. Scenario discovery with **PRIM** provides valuable insights into the factors and conditions that influence the performance of different policy options, aiding in robust decision-making and policy evaluation.

3. Result

We conducted the MORDM framework in this study and generated results as follows:

3.1 Problem Formulation

There are two types of analysis in the problem formulation stage, as explained below:

3.1.1. XLRM Model

The study of analyzing the flood risk mitigation along the Ijssel River is done using the model made by A. Ciollo (Ciullo, de Bruijn, Kwakkel & Klijn, 2019). This model uses the XLRM framework to understand flood impact at five places along the Ijssel River. XLRM is a commonly used framework for structuring information in model-based decision support (Jafino et al., 2021). This model selects a set of policy levers against floods for each location by considering the uncertainties of external factors and generates outcomes of interest, as shown in Figure 5.

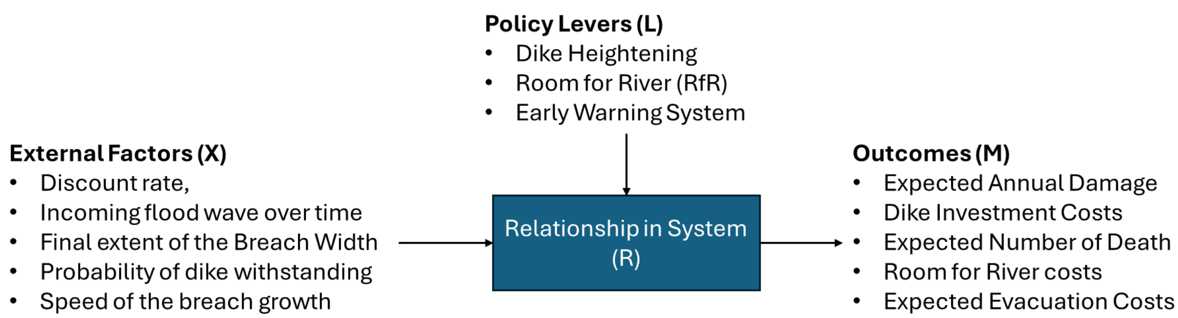


Figure 5. XLRM model of Ijssel River Case

3.1.2. Open Exploration

We developed an open exploration model to understand how regions in the uncertainty variables map to the whole outcome. This assessment is crucial to identify the significance of uncertainties to our outcome of interests. We incorporate three methods of sensitivity analysis such as **Sobol (GSA)**, **feature scoring,** and **dimension stacking** assessment as follows:

3.1.2.1. Sobol Sensitivity Analysis

Sobol is a form of Global Sensitivity Analysis (GSA) that evaluates the entire input space of a model to understand how variations in model inputs influence the outputs. Unlike local sensitivity analysis, which examines the effect of small changes around a specific point, GSA considers the effects of input variability across their entire possible ranges. This comprehensive approach provides a more robust understanding of model behaviour.

The results from our GSA using Sobol method are as follows:

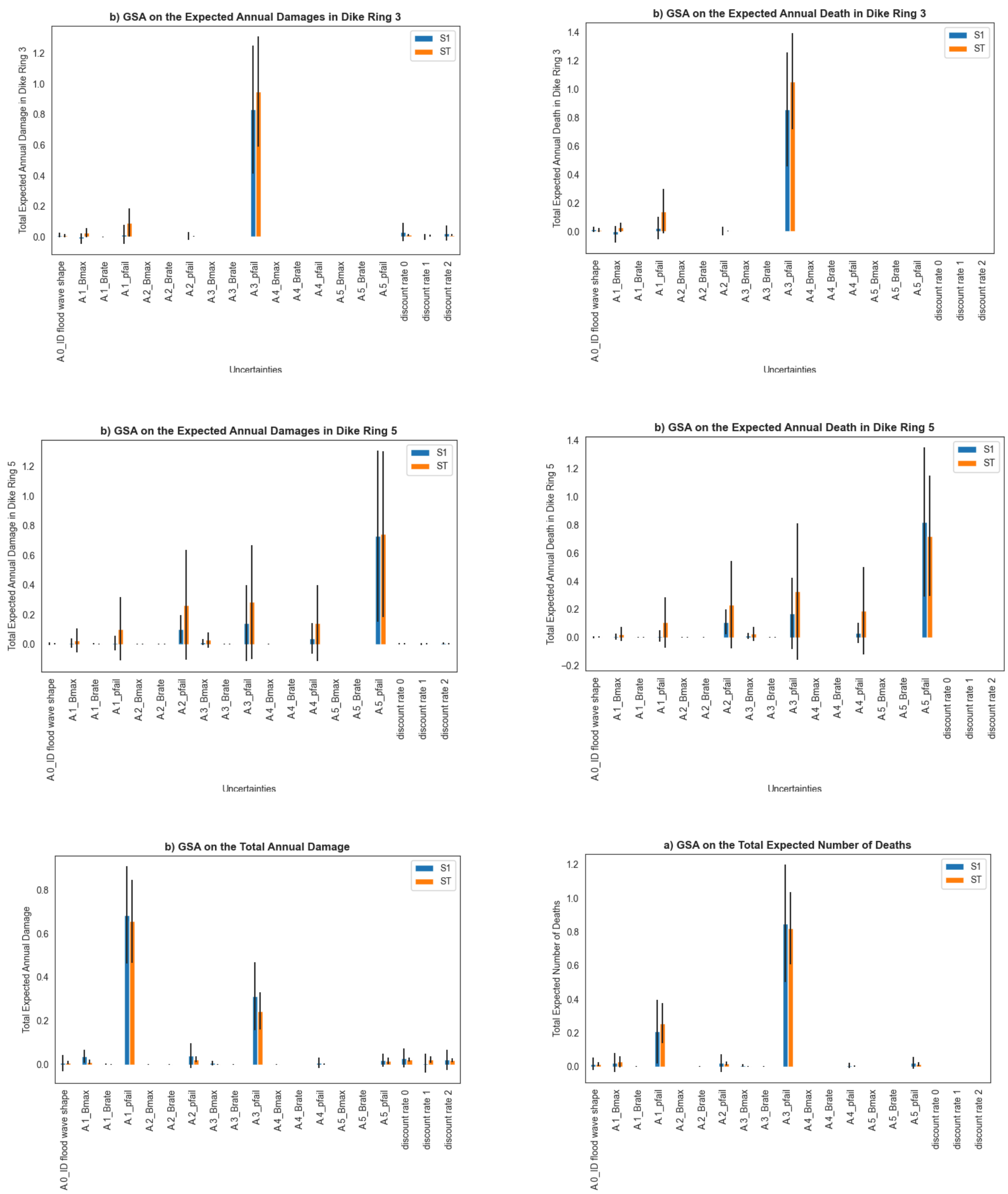


Figure 6. GSA on the Expected Annual Damages and Deaths in Dike Rings 3, 5, and all Dike Rings.

As seen in Figure 6, between the urban areas (A3 and A5), dike ring 3 is the most affected by both total annual damages and total expected annual deaths. By addressing their specific causes and impacts, we can ensure efficient use of resources and avoid unnecessary interventions in other dike rings.

Specifically, within Dike Ring 3, the expected annual damages and deaths are confined to this specific area, with no significant influence on or from the other dike rings. This finding highlights the importance of focusing efforts exclusively on Dike Ring 3. Whether the goal is to mitigate damages, enhance resilience, or centralize operations, attention should be concentrated solely on Dike Ring 3 to ensure the safety of all aspects.

In contrast, Dike Ring 5's annual damages and deaths are interconnected with those in Dike Rings 1, 2, 3, and 4, with a significant impact from Area 3. To centralize operations in Dike Ring 5, it is crucial to also mitigate the annual damages and deaths in the interconnected dike rings. This comprehensive approach ensures the overall stability and safety of the entire system, thereby supporting the centralization of operations in Dike Ring 5.

3.1.2.2. Feature Scoring and Dimensional Stacking

Feature scoring helps identify the most influential variables in a model. Quantitating the importance of each input allows analysts to determine which factors have the greatest impact on the model's output. This identification is crucial for understanding which variables drive the model's behaviour and should be prioritized in further analysis and decision-making. Our feature scoring is attached in Figure 7.

Dimensional stacking provides a holistic view of sensitivity analysis, capturing the full range of interactions between input variables. The detailed breakdown in the nested structure highlights both direct and indirect influences, offering a thorough understanding of the model's sensitivity. Our dimensional stacking is attached in Figure 8.

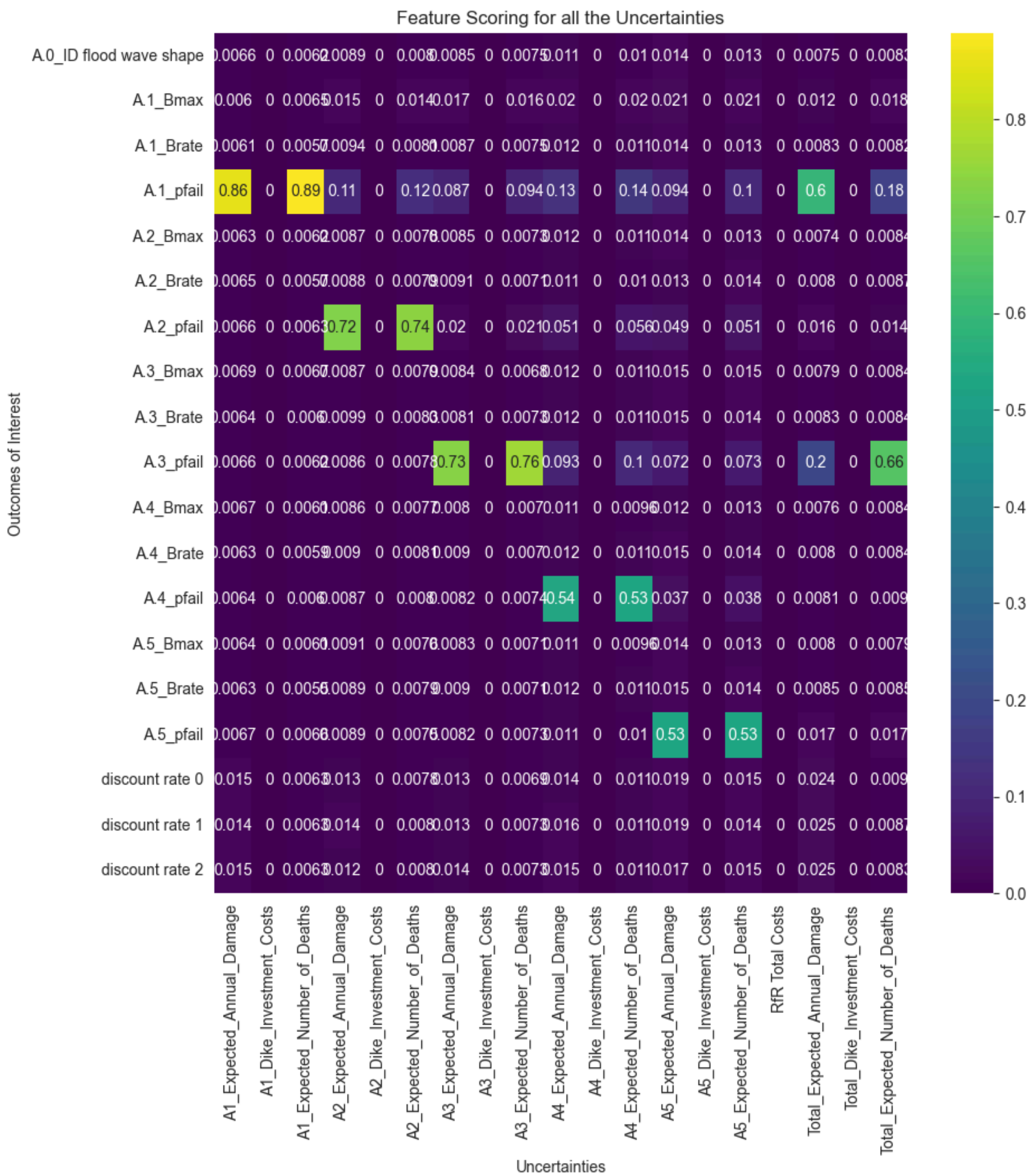


Figure 7. Feature scoring for all the uncertainties.

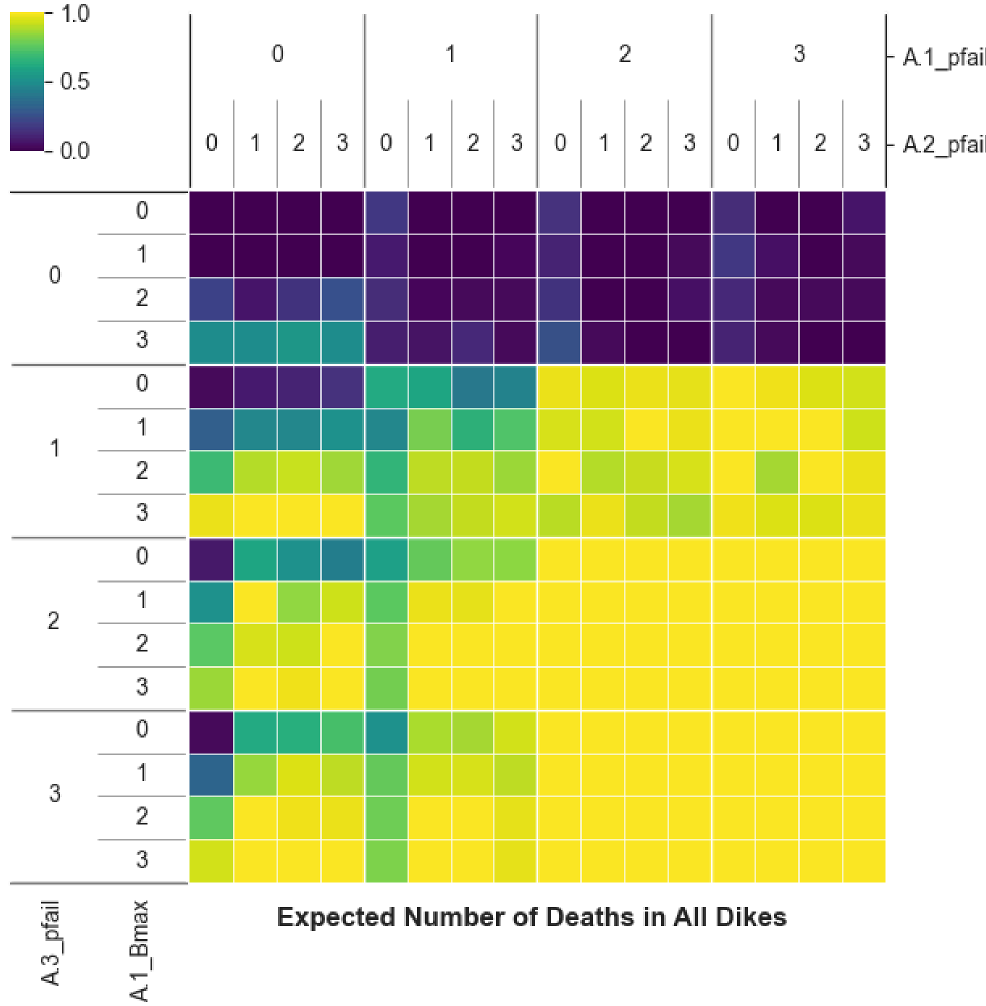


Figure 8. Dimensional stacking for all the uncertainties.

Figures 7 and 8 reveal that the expected annual damages and deaths within each dike ring are isolated, having no significant impact on other dike rings. Consequently, when applying feature scoring for sensitivity analysis, it is essential to evaluate each dike ring independently. This method allows for a more precise and effective understanding of the factors influencing each dike ring, ensuring that mitigation efforts are optimized for the best possible outcomes within each specific area.

To summarize, with the three sensitivity analyses that we use, it is known that 'A3_pfail' and 'A5_pfail' have **the highest influence** on the expected annual damages and deaths in the Dike Rings 3 and 5. Moreover, 'A3_pfail' is the most significant uncertainty towards total expected damages and deaths.

3.2 Generating Alternative

3.2.1. Scenario Filtering

From the 10,000 scenarios that we have, we subset the outcome of relevant scenarios. We choose 50% of the scenarios that produce the worst outcomes using PRIM. From those sets of scenarios, we select the most diverse ones for further steps.

Figure 9 shows the boxes found using PRIM's plot by their density (the proportion of scenarios within the subspace that are high-risk) and coverage (the proportion of high-risk scenarios captured). We consider both metrics as we want to be able to describe the coverage of these scenarios but at the same time focus on the scenarios that are aligned with our interests.

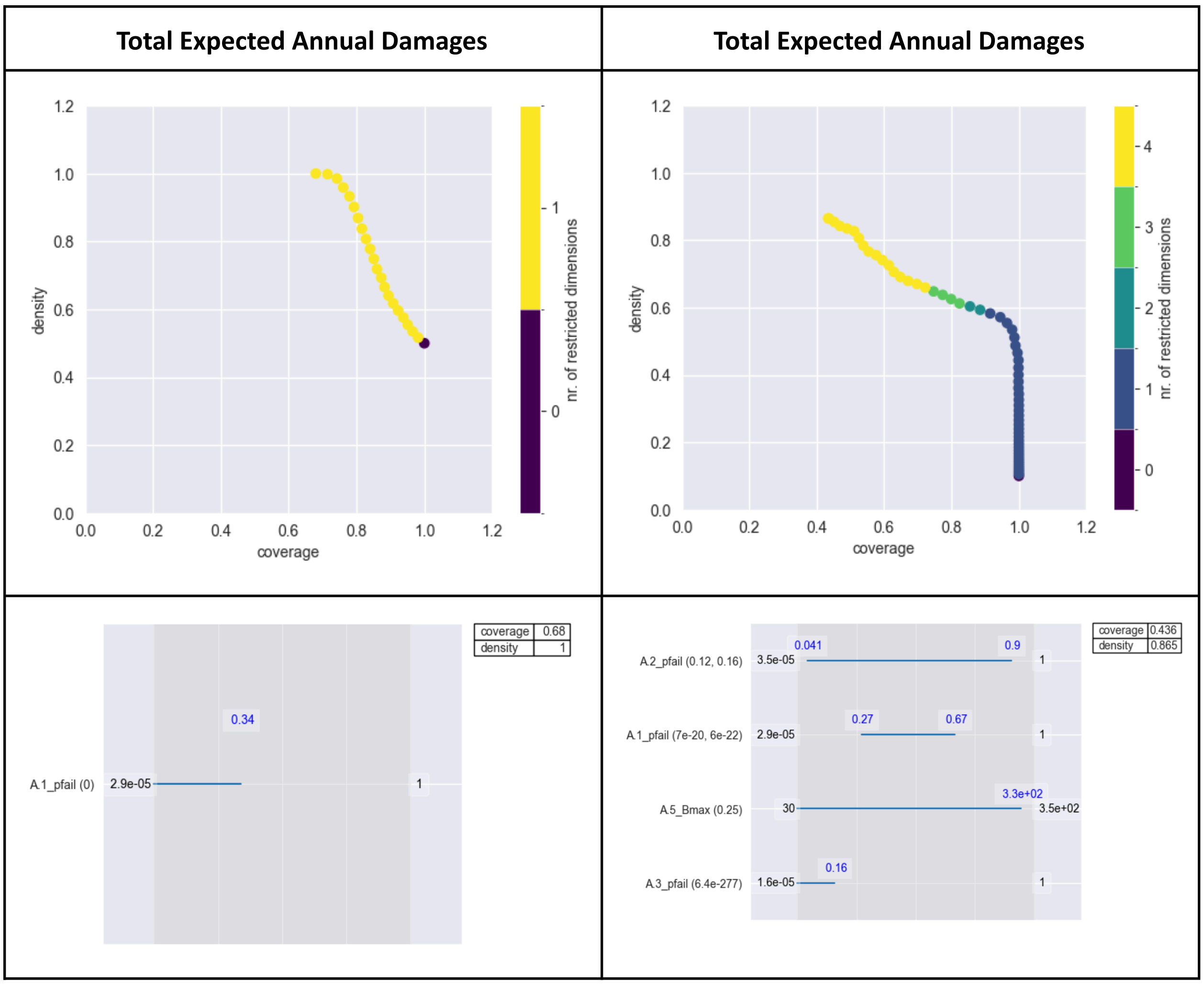


Figure 9. PRIM trade-off plot

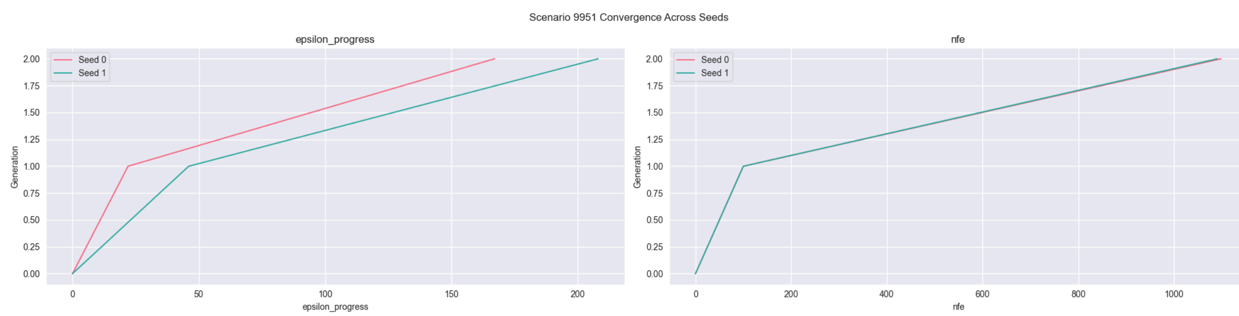
3.2.2. Policy Search

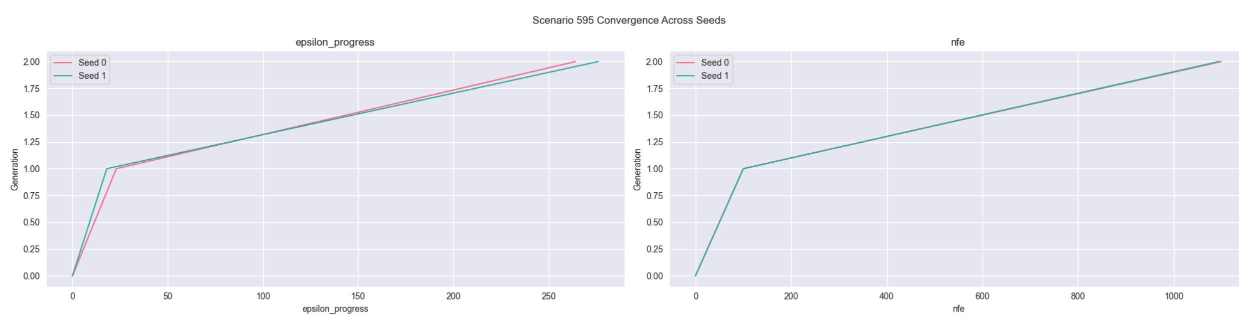
We apply policy search, which focuses on searching for desirable policies that answer our constraints as follows:

- Low expected annual damages in dike ring 3
- Low expected annual damages in dike ring 5
- Low expected annual number of deaths in dike ring 3
- Low expected annual number of deaths in dike ring 5

After the selected policies are generated, we do a first round of elimination for policies that are strictly inferior to others tested within the same scenario because they do not add value to further analysis. This eliminating process utilizes εNSGAII algorithms based on non-pareto filtering approaches. Essentially, we aim to filter 1000 scenarios across two seeds, considering the multitude of potential scenarios that could occur in our case.

To ensure that the generative algorithm allows enough generations to identify meaningful policies, we will plot various convergence metrics for each seed and scenario used in our search. This will help demonstrate that the algorithm had sufficient runtime to converge effectively.





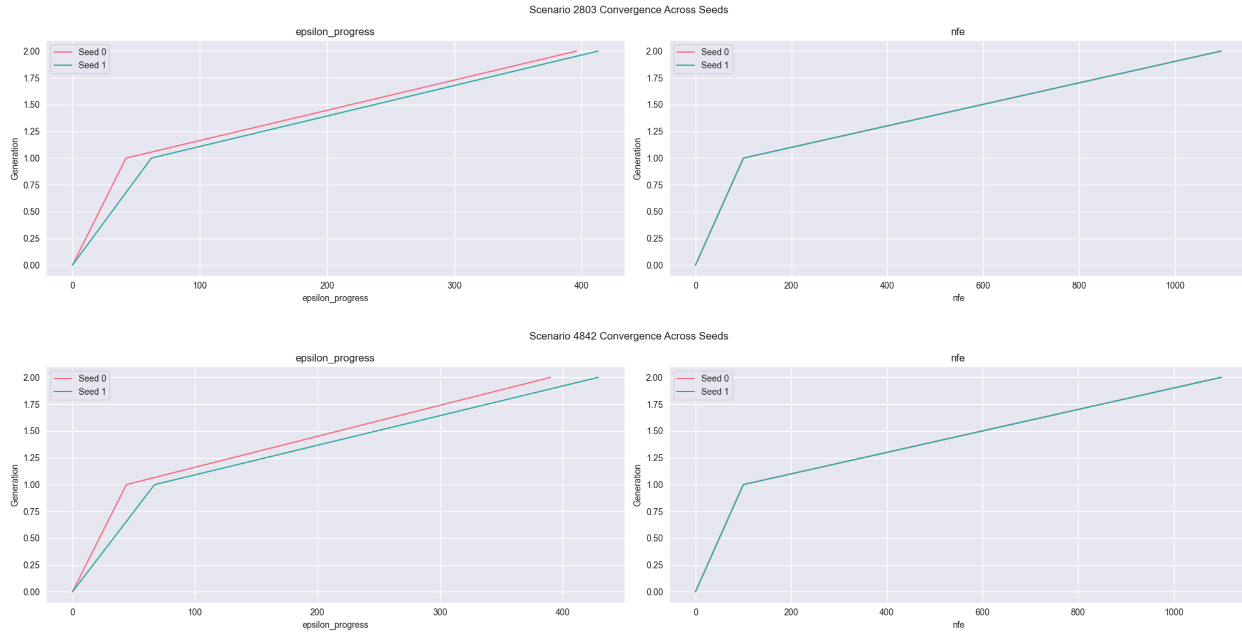


Figure 10. Policy Convergence Plot

The second round of policy filtering is conducted by selecting policies with a diverse set of levers, as shown in policies__constraints_filtered__diverse_set_50.csv.

3.3. Deep Uncertainty Analysis

In the deep uncertainty analysis, we try to further filter policies based on their **robustness**, using Signal-to-noise Ratio (SNR) and Maximum Regret as follows.

3.3.1. Signal-to-noise Ratio (SNR)

The Signal-to-noise Ratio (SNR) assesses expected performance across various scenarios, targeting low values to align with our goal of minimizing all outcomes, such as expected annual damages and deaths. It is calculated by multiplying the mean and standard deviation of the outcome values across all scenarios. After acquiring policy candidates, we test their robustness using the SNR. This measure is suitable for testing policy robustness because it ensures decisions are based on clear and reliable information. By focusing on policies with a low SNR, we can effectively distinguish between robust and weak policies. This clarity is crucial for making informed decisions, especially in complex and uncertain environments. A low SNR indicates that the policies are more robust, leading to better decision-making.

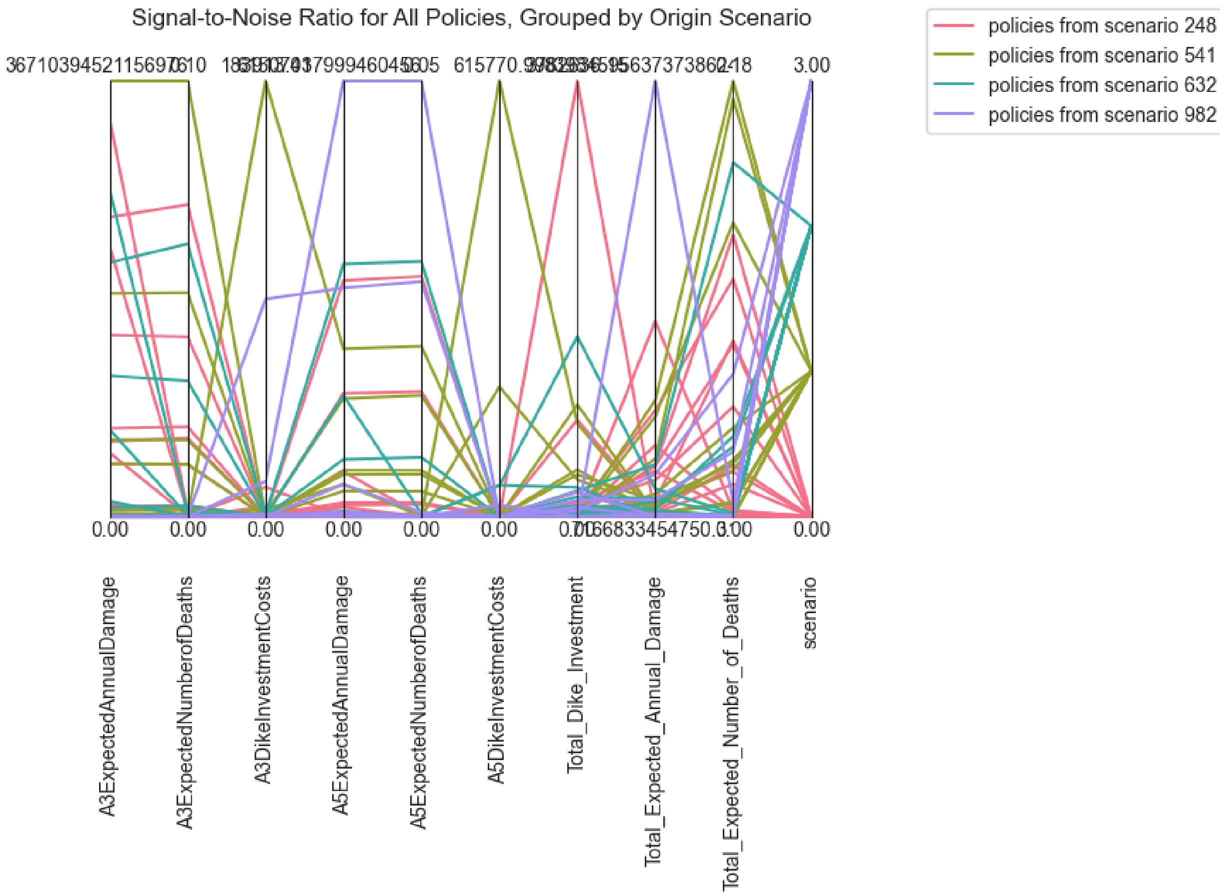


Figure 11. SNR of Diverse Policies

Based on SNR, we filter the below scenario for further analysis:

a) Levers based on Deaths
- in scenario 248, policies 195 and 693 are selected
- in scenario 541, policies 213 and 149 are selected
- in scenario 632, policies 22 and 208 are selected
- in scenario 982, policies 346 and 510 are selected

b) Levers based on Damage
- in scenario 248, policies 195 and 693 are selected
- in scenario 541, policies 149 and 301 are selected
- in scenario 632, policies 22 and 208 are selected
- in scenario 982, policies 346 and 510 are selected

3.3.2. Maximum Regret

Maximum Regret is a metric that evaluates the regret of a policy, defined as the difference between the policy's performance in a specific scenario and the best possible performance in that scenario. It is determined for each policy and outcome across all scenarios. Along with the Signal-to-noise Ratio (SNR), maximum regret is used to test the robustness of policies after narrowing down to the top 50 policy candidates. By focusing on policies with low maximum regret, we can distinguish between policies with potential losses and those without. Low maximum regret indicates more robust policies, leading to better decision-making.

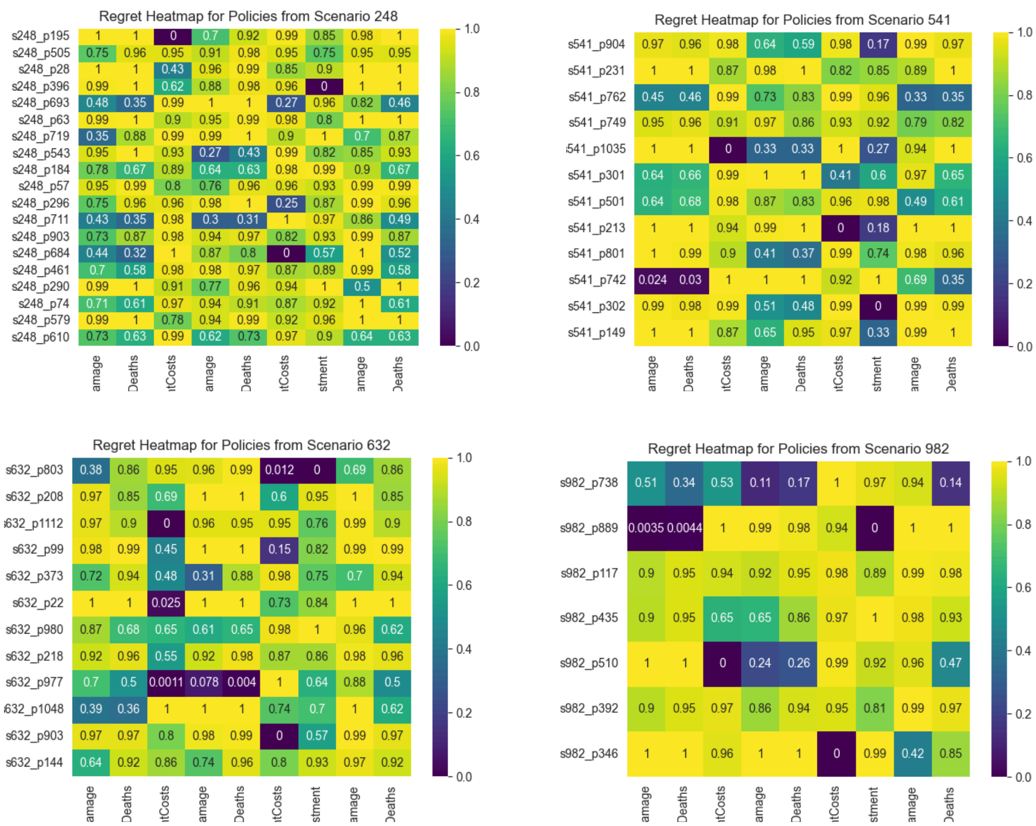


Figure 12. Maximum Regret

Based on maximum regret, we filter the below scenario for further analysis:

a) Levers based on Deaths
- in scenario 248, policies 684 and 711 are selected
- in scenario 541, policies 742 and 1035 are selected
- in scenario 632, policies 1048 and 977 are selected
- in scenario 982, policies 889 and 738 are selected

b) Levers based on Damage
- in scenario 248, policies 719 and 543 are selected

- in scenario 541, policies 742 and 1035 are selected
- in scenario 632, policies 803 and 977 are selected
- in scenario 982, policies 889 and 738 are selected

3.3.3. Policy Robustness

After analyzing both SNR and maximum regret, we select the final four policies based on the scenarios and policies that appear most frequently in both metrics. This approach ensures that the chosen policies are highly robust and effectively address our constraints. The four final policies are **‘s248_p195’**, **'s982_p346'**, **'s632_p208'**, and **'s541_p149',** as attached in Figure 13.

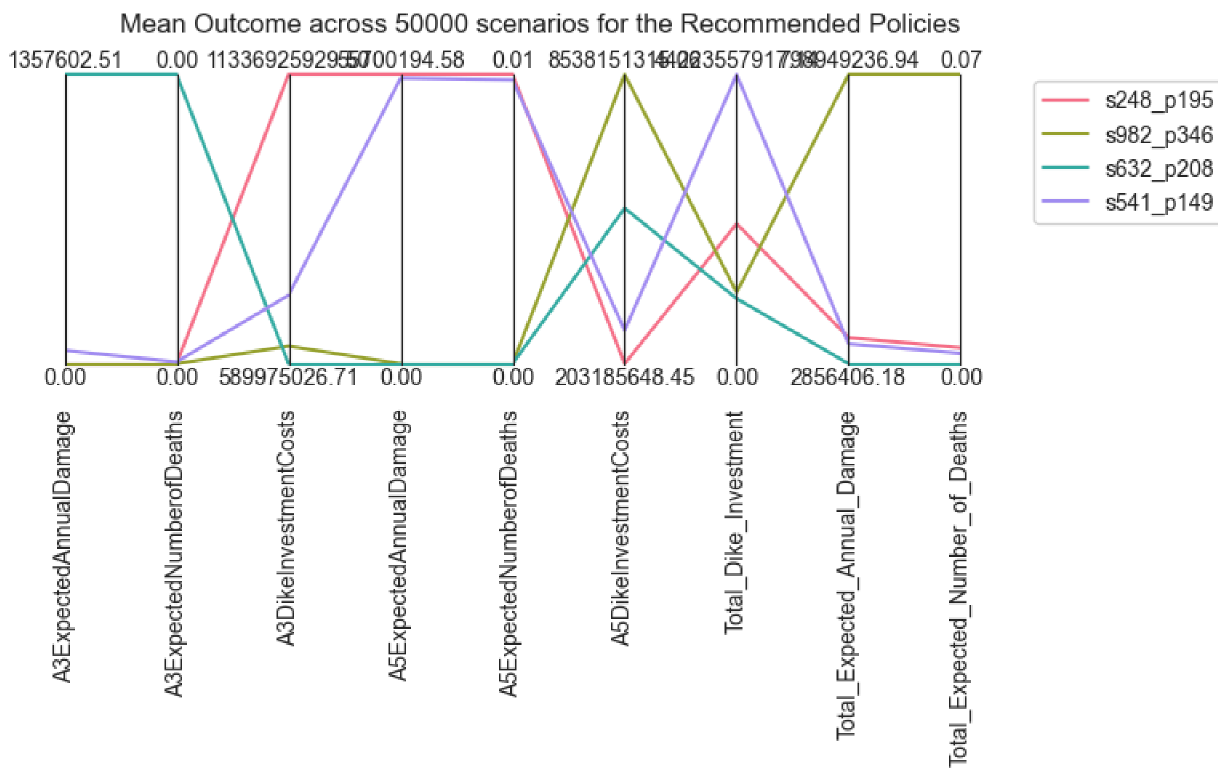


Figure 13. Final Policies

3.4. Scenario Discovery

After picking the four most robust policies, we still need to do a vulnerability test by using subspace discovery with PRIM because of its ability to target specific **vulnerabilities**, handle high-dimensional data, and provide robust, empirical insights. Its interpretability and flexibility across various domains further enhance its utility, making it an essential tool for us to design effective and resilient policies. By leveraging PRIM, we can gain a deeper understanding of the conditions that lead to policy failures and take informed actions to mitigate these vulnerabilities.

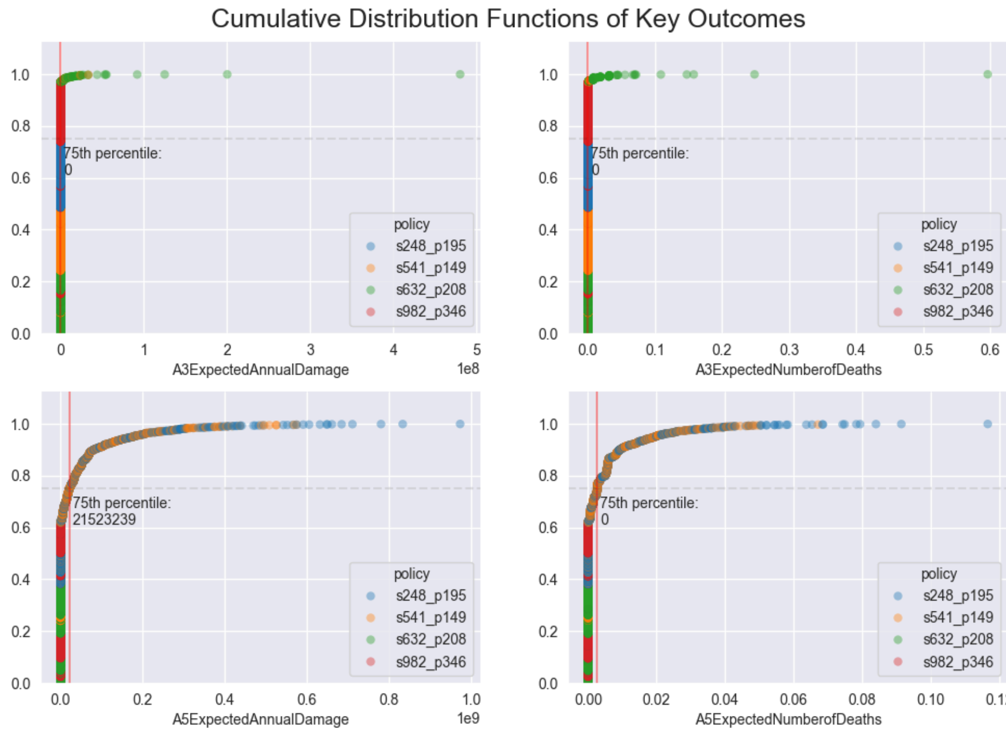


Figure 14. Top 4 Robust Policies

From Figure 14, we observe that under the already dangerous scenarios being studied, one policy (s248_p195) exhibits a much longer tail and results in higher damages and deaths compared to the other policies. This suggests that this policy is significantly **more vulnerable** to extreme conditions within the uncertainty space.

Additionally, we note that the 75th percentile value of Expected Annual Damage and Deaths in Dike Ring 3 is 0 for these policies. This indicates that these four policies maintain zero damage in at least 75% of scenarios. Given that one policy performs notably worse than the others, it is likely that the percentage of scenarios with zero damage is even higher for the other policies.

This sets the stage for an intriguing analysis: in the next step, when we apply our PRIM algorithm, we will be identifying a subspace that encompasses all scenarios where, despite the robust policies identified, damages are still expected in Dike Ring 3. This subspace is of particular concern to us as a Transport Company, as it highlights the scenarios where even our best policies fail to prevent damage.

4. Discussion

The analysis presented in this report underscores the complexities of managing flood risks along the Ijssel River, specifically targeting Dike Rings 3 and 5. Utilizing advanced decision-making frameworks such as Many-Objective Robust Decision Making (MORDM), combined with sensitivity analysis techniques, we have uncovered critical insights and robust strategies to mitigate flood-related damages and fatalities.

4.1. Limitation

This study limitation is divided into two categories as follows:

4.1.2. Methodology

Problem Framing Limitations

Given the transport company's interests, specific objectives and premature aggregation can influence the problem formulation (Ciullo et al., 2019). However, the effect of disaggregation can intensify the curse of dimensionality, a challenge that arises as the number of variables (dimension) increases (Bellman, 1959). Reflecting on the Ijssel River model, our model analyzes the **disaggregated** values of damages and deaths on all dike rings, resulting in an **information overload** and relying on the subjectivity of the problem owner in finding optimum policy trade-offs. This complexity is further compounded by the fact that the top-performing policy search can maintain a diverse search of up to 10 objectives (Kasprzyk et al., 2013).

Robustness Limitations

When it comes to robustness metrics, it's crucial to consider that the choice of the metric can have a significant effect, with metrics sometimes showing disagreement about which decision alternative is more robust (McPhail et al., 2019). The Ijssel River model produces a similar outcome in the expected value and regret-based robustness metrics. However, it's important to note that there are still metrics that are not used to measure robustness, which may give diverse outcomes. Thus, the robustness of the result is **not absolute**, highlighting the need for careful metric selection and interpretation.

Computational Limitations

Solving the environmental problem and the planning problem itself is a dynamic process that requires constant evolution and different iterations (Kasprzyk et al., 2013). The method chosen to tackle the uncertainties revolving around flood risk mitigation may create **computational constraints** (Carlsen et al., 2016). The iterative process of finding the suitable solution while maintaining the diverse scenario could be significantly resource-consuming, and while we have already incorporated the method of subsetting the scenario, this still poses a limitation on the overall scenario discovery.

4.1.3. Policy Arena

Policy arenas are non-authoritative locations where policy debates and conflicts emerge and play out (Hawkins, 2023). These places describe the setting for managing flood risks along the Ijssel River. By using decision-making frameworks like MORDM, these arenas show the complexities and challenges in the process. Critical issues such as the Arrow Paradox and the Curse of Dimensionality come up here, significantly influencing the development and implementation of effective policies.

Arrow Paradox

In our case, stakeholders' diverse and often conflicting objectives, ranging from our objectives as a transport company to Rijswaterstaat to Environmental activist groups to the provincial government such as OverIjssel and Gelderland, complicate the aggregation of preferences. Complications of this aggregation are explained in Arrow Paradox. This paradox illustrates the inherent difficulties in achieving a genuinely fair and democratic aggregation of individual preferences into a collective decision that accurately reflects the group's interests (Lagerspetz, 2016). This is especially relevant in a multi-stakeholder environment like the Ijssel River flood risk management, where stakeholders' diverging priorities and risk perceptions significantly challenge unified decision-making.

In the context of MORDM, the Arrow Paradox stresses the limitation of creating robust policies that simultaneously satisfy all stakeholder preferences. In other words, there is no single individual whose preferences determine the aggregate preferences. Despite utilizing sophisticated optimization techniques, developing a single flood risk management strategy that optimally meets all individual criteria set by various stakeholders is nearly impossible. This limitation necessitates a more iterative and inclusive approach to policy development, where ongoing **stakeholder engagement** and **compromise** are crucial to navigating conflicting interests and preferences effectively.

Curse of Dimensionality

The Curse of Dimensionality refers to the exponential increase in complexity that arises with each additional dimension (e.g., objectives, variables, or stakeholders) in a decision-making problem. In the realm of MORDM, where multiple objectives are analyzed simultaneously, this issue manifests as increased computational demands and decreased effectiveness in identifying optimal solutions.

This carries significant implications for the policy arena, particularly in the context of policy formulation and stakeholder engagement. As the number of dimensions—objectives, variables, or stakeholders—increases in decision-making frameworks like MORDM, not only does the computational burden intensify, but the political process of consensus-building becomes more cumbersome and fragmented. This complexity exacerbates the challenge of fully representing diverse stakeholder views in the decision-making process, which potentially leads to oversight or marginalization of less dominant perspectives.

In the policy arena, the expansive decision space resulting from multiple dimensions makes it difficult to achieve a comprehensive understanding and agreement among stakeholders. This can hinder the development of policies that are both inclusive and representative of all interests. Moreover, the sparsity of data across a high-dimensional space complicates the ability to discern clear patterns and trends, leading to higher uncertainties in policy outcomes. These factors can result in policies that are perceived as less legitimate or effective, diminishing trust in public institutions and their ability to manage complex issues like flood risk. Ultimately, the Curse of Dimensionality challenges the political arena to adopt more sophisticated and inclusive approaches to policy development, ensuring that solutions are not only technically sound but also democratically robust.

4.2. Implication

Four of our selected policies produced **zero** expected number of deaths and annual damage in urban areas (A3 and A5), which aligned with transportation company interests. At the aggregate level, these policies also generate **zero deaths** in all regions across the Ijssel River. Therefore, we expect these policies to help us minimize flood risk and ensure the continuity of our business operation.

In terms of promoting higher water levels that possibly transfer a better profit for us, these policies also strengthen the **importance of higher dike** in all Ijssel River's dike rings (A1 - A5) with varying heights of increase across time steps. Hence, we are not worried about the RfR initiatives that each policy set because they equipped RfR with sufficient dike heightening, as seen in Table 1.

Table 1. Selected policies result

Policies	RfR Location	Dike increase per time step (dm)				
		A1	A2	A3	A4	A5
s248_p195	0,1,2	5,5,3	4,10,1	10,3,10	1,1,3	1,4,0
s982_p346	2,3,4	0,1,0	2,1,2	9,1,3	7,6,0	10,9,1
s632_p208	0,1,2,3,4	1,7,5	6,1,2	5,4,2	6,1,6	10,4,5
s541_p149	0,1,2,4	1,6,4	9,6,9	8,5,6	3,7,10	1,7,4

S248_p195 and s982_p346 are considered policies that are more favourable for us because they have fewer RfR locations than the other 2 policies, which are 3 out of 5 available locations. They also set a relatively higher dike increase for each time step, reaching a maximum height increase of 10 decimeters. However, we notice that S248_p195 tends to be more vulnerable to extreme conditions in multiple scenarios based on PRIM analysis. Therefore, **s982_p346** represents a more desirable policy under deep uncertainty and meets all of our outcomes of interest, which are zero death and zero damage. We are fully aware that implementing **s982_p346** required a very high dike heightening investment cost at 21 billion euros. However, as a transportation company, we do not consider investment cost as an outcome of interest because it is not within our mandate, and private companies are not allowed to contribute to public infrastructure investment. This study focuses solely on searching for a policy that minimizes death and damage, especially in urban areas (A3 and A5).

As a reflection of this overall study, we realize that Ijssel River flood risk management needs a multi-faceted approach. Combining robust decision-making frameworks with detailed sensitivity and vulnerability analyses ensures that the selected policies are both effective and resilient. Rijkswaterstaat should prioritize areas with the highest risk and ensure that chosen policies can withstand a range of adverse conditions. Integrating SNR, Maximum Regret, and PRIM into the policy evaluation process provides a comprehensive toolkit for enhancing policy robustness and effectiveness.

4.3. Future Work

To address the methodological limitations, it's essential to do iterative optimization to frame the problem and find the middle ground between the premature aggregation of the problem and the overload of disaggregated objectives. While acknowledging that with multiple iterative problem framing, there could be more than one robustness definition, employing multiple robustness metrics could increase the confidence level of the model robustness. However, it's essential to consider that with multiple iterative problem framing, it could be both computationally constrained and expensive to do multiple scenario discovery. Notably, modelling cannot be substituted as a prediction method, but we can treat the result as an enlightening exploratory approach to finding the optimum solution for the future work reference.

Moreover, future work should prioritize stakeholder engagement and community involvement to ensure that proposed solutions are socially acceptable and economically viable. Collaboration with local governments, businesses, and residents will help develop and implement flood risk management plans that address their needs and concerns. Exploring the integration of green infrastructure and nature-based solutions with traditional engineering approaches could provide sustainable and cost-effective flood management options. Researching the benefits and feasibility of such hybrid approaches in the Ijssel River context would be valuable. Future efforts should build on this report's findings by refining models, expanding stakeholder collaboration, and exploring innovative solutions to enhance the region's resilience to flooding.

Lastly, future work should focus on enhancing flood risk management along the Ijssel River through more detailed and localized studies. Integrating granular data on land use, population density, and economic activities can help effectively tailor mitigation strategies. Advanced modelling techniques should be employed to simulate the impact of climate change on flood risks, aiding in the development of long-term adaptation plans. Additionally, expanding the Many-Objective Robust Decision Making (MORDM) framework to test additional scenarios and uncertainties will ensure the robustness of selected policies under a broader range of conditions. Incorporating real-time data and adaptive management approaches could further enhance the flexibility and responsiveness of flood risk strategies.

5. Conclusion

Based on our MORDM analysis, we have identified four **robust** policies: '**s248_p195', 's982_p346', 's632_p208'**, and **'s541_p149'.** These policies maintained zero expected annual damage and deaths in Dike Rings 3 and 5 (transportation company's concern) in at least 75% of scenarios, demonstrating their effectiveness. This rigorous selection process ensures that the chosen policies are resilient and capable of handling a wide range of scenarios, thereby reducing risks and enhancing safety. Our investigation into policy performance under various scenarios revealed that one policy (**s248_p195**) is particularly **vulnerable** to extreme conditions. From the selected policies, **s982_p346** is considered to represent the most desirable policy under deep uncertainty, which meets all of our outcomes of interest and has fewer RfR locations that may risk the river water level.

We are fully aware that our proposed policies are focused on minimizing the number of deaths and expected annual damage as our interest in the outcome and putting aside investment cost outcomes due to it not being our mandate as a private company to take part in public infrastructure investment. However, Rijkswaterstaat, as the decision maker, needs to explore deeper the investment outcome to come up with the most **win-win solution** that is still within the government's budget.

In conclusion, the proposed policy is specifically crafted to address the transport company's unique needs, placing their goals at the forefront. This ensures clarity and reaffirms the purpose of the policy. From the other perspectives, considering different objectives and framing the problems in various ways, alternative solutions may emerge from other stakeholders with diverse interests and goals for the Ijssel River. As a result, this model offers an exploratory approach to advocacy for a range of policies that maintain the transport company goals while allowing for a comprehensive examination and consideration of the complexities involved in deciding on the multi-actor arena.

6. Reference

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APPENDIX

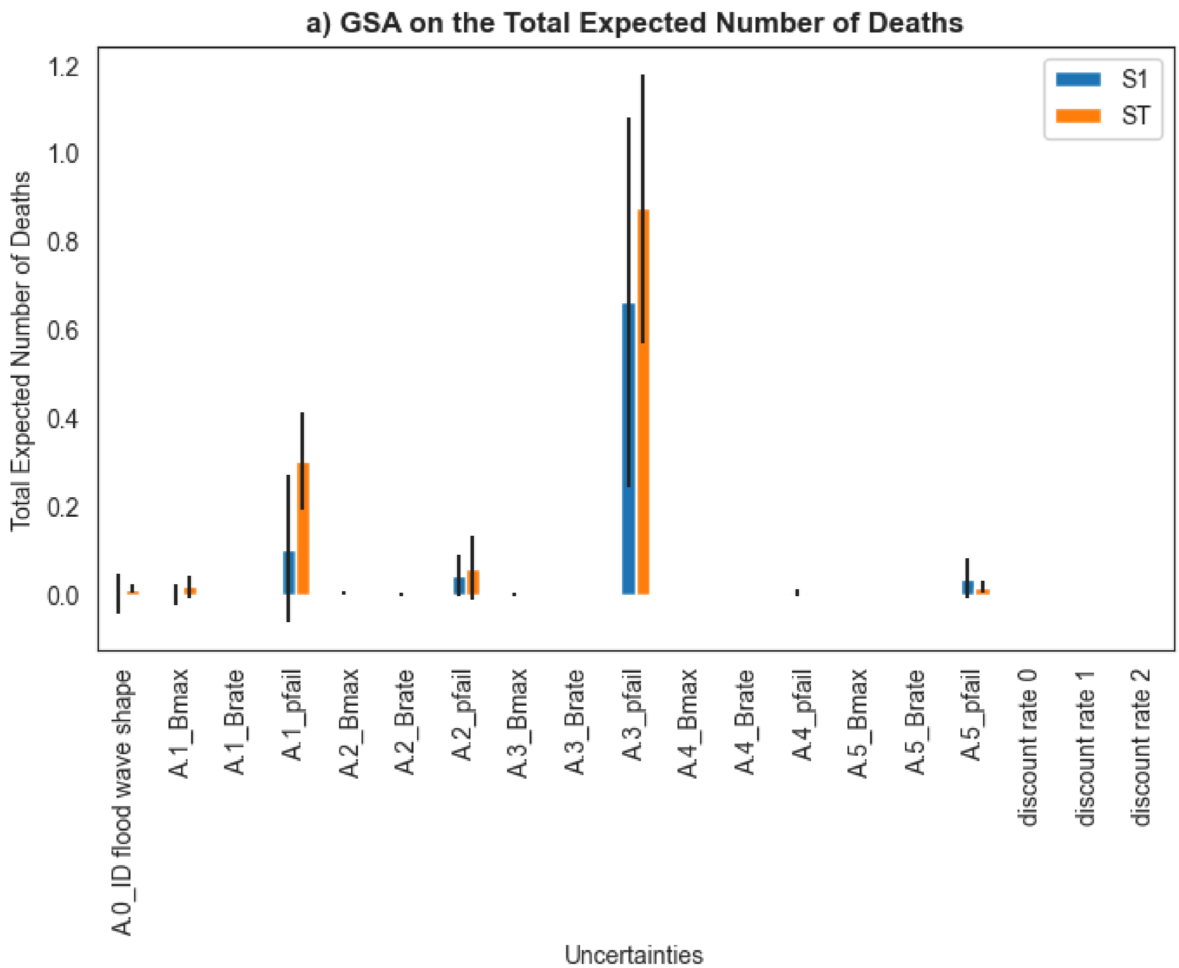
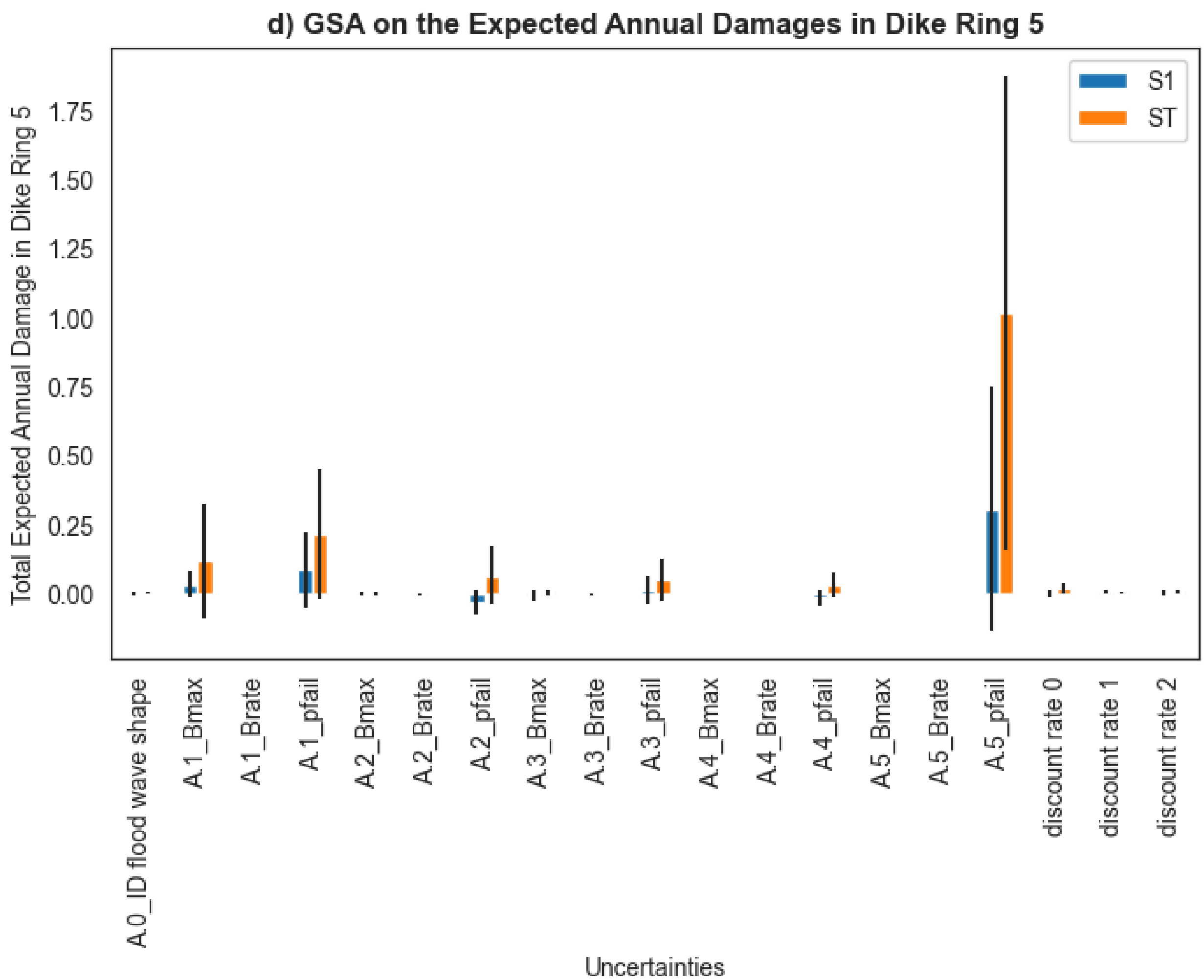
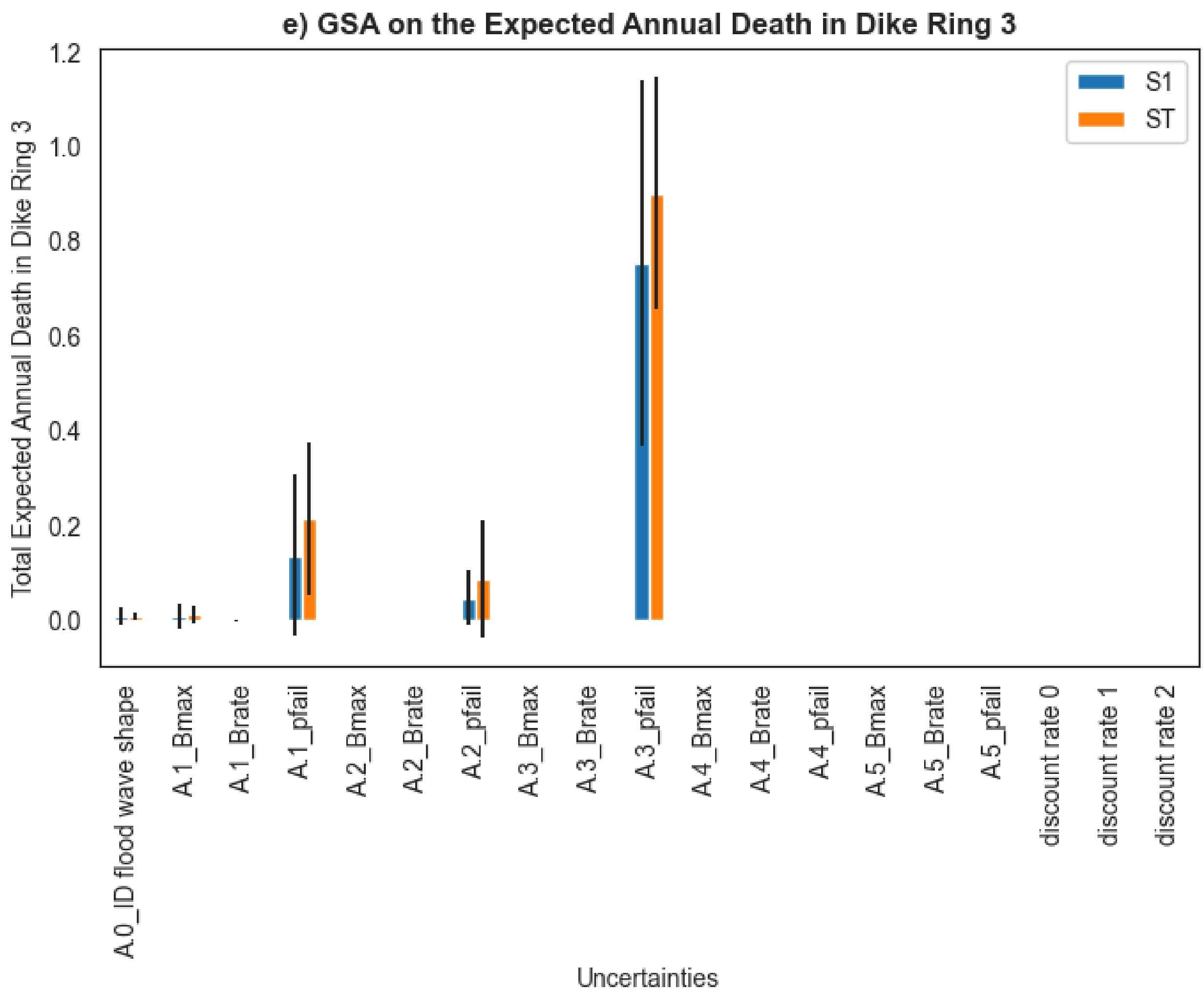
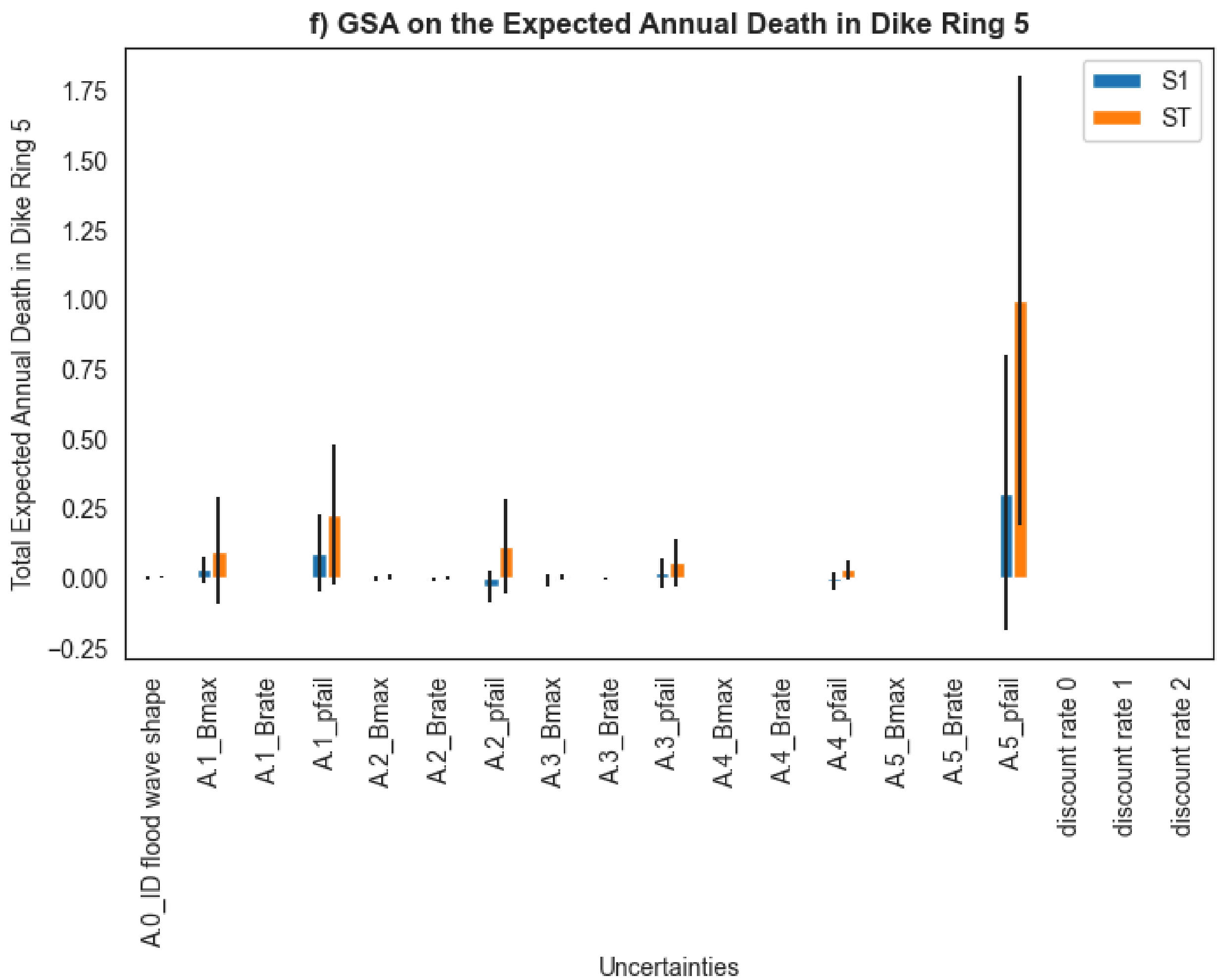


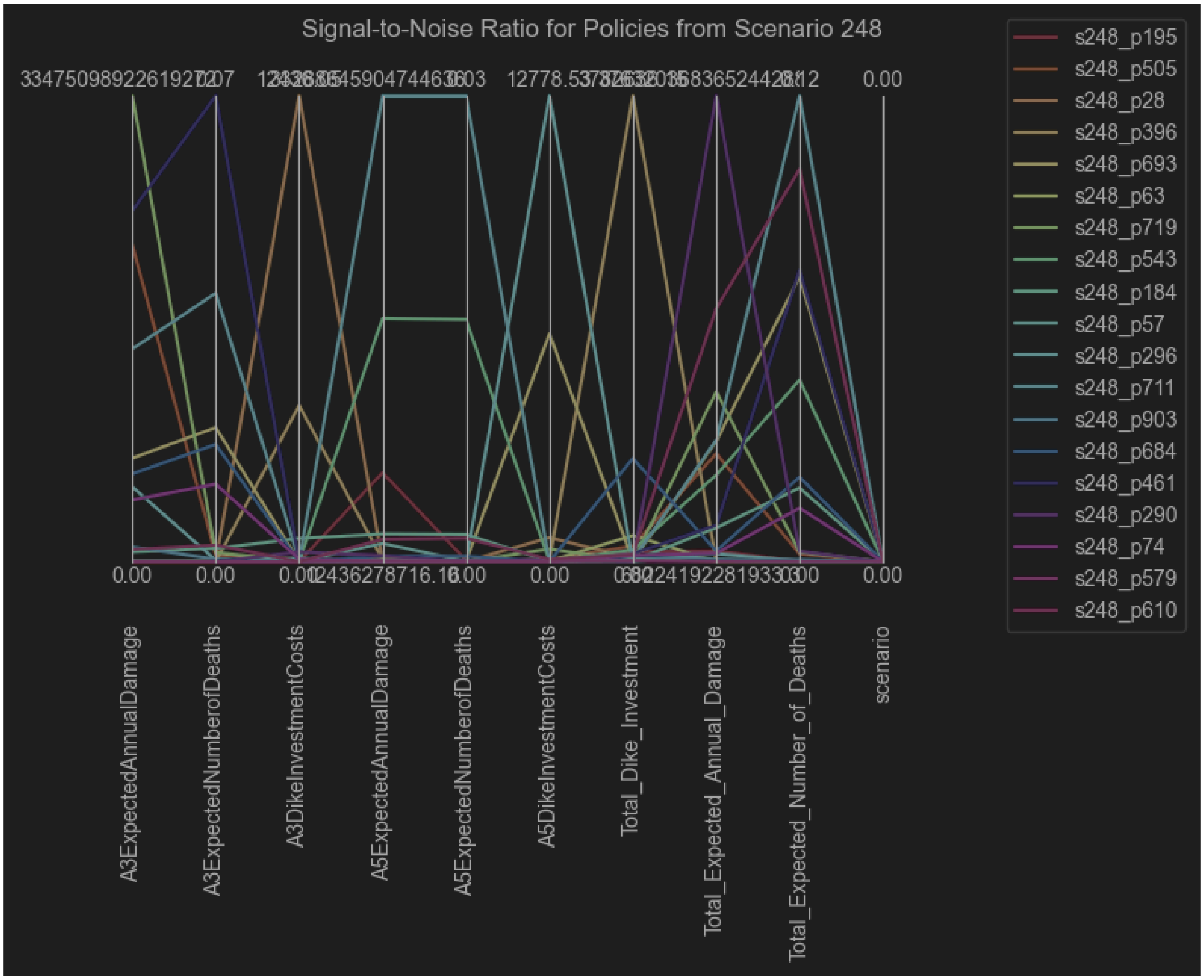
Figure A1. GSA on the Total Expected Number of Deaths


d) GSA on the Expected Annual Damages in Dike Ring 5
S1
ST
Total Expected Annual Damage in Dike Ring 5
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
A.0_ID flood wave shape
A.1_Bmax
A.1_Brate
A.1_pfail
A.2_Bmax
A.2_Brate
A.2_pfail
A.3_Bmax
A.3_Brate
A.3_pfail
A.4_Bmax
A.4_Brate
A.4_pfail
A.5_Bmax
A.5_Brate
A.5_pfail
discount rate 0
discount rate 1
discount rate 2
Uncertainties



e) GSA on the Expected Annual Death in Dike Ring 3
Total Expected Annual Death in Dike Ring 3
S1
ST
1.2
1.0
0.8
0.6
0.4
0.2
0.0
A.0_ID flood wave shape
A.1_Bmax
A.1_Brate
A.1_pfail
A.2_Bmax
A.2_Brate
A.2_pfail
A.3_Bmax
A.3_Brate
A.3_pfail
A.4_Bmax
A.4_Brate
A.4_pfail
A.5_Bmax
A.5_Brate
A.5_pfail
discount rate 0
discount rate 1
discount rate 2
Uncertainties


f) GSA on the Expected Annual Death in Dike Ring 5
Total Expected Annual Death in Dike Ring 5
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
S1
ST
A.0_ID flood wave shape
A.1_Bmax
A.1_Brate
A.1_pfail
A.2_Bmax
A.2_Brate
A.2_pfail
A.3_Bmax
A.3_Brate
A.3_pfail
A.4_Bmax
A.4_Brate
A.4_pfail
A.5_Bmax
A.5_Brate
A.5_pfail
discount rate 0
discount rate 1
discount rate 2
Uncertainties


Signal-to-Noise Ratio for Policies from Scenario 248
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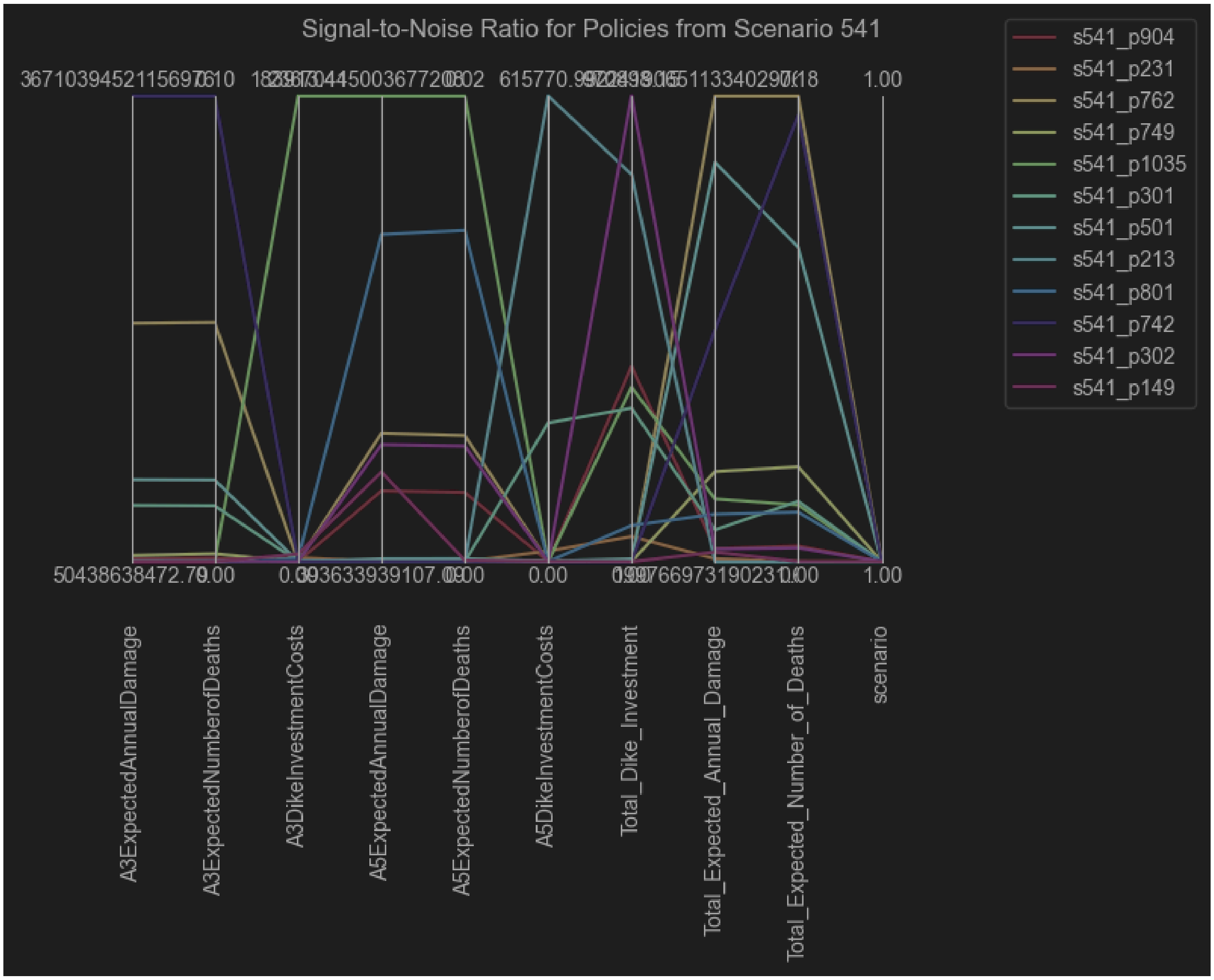
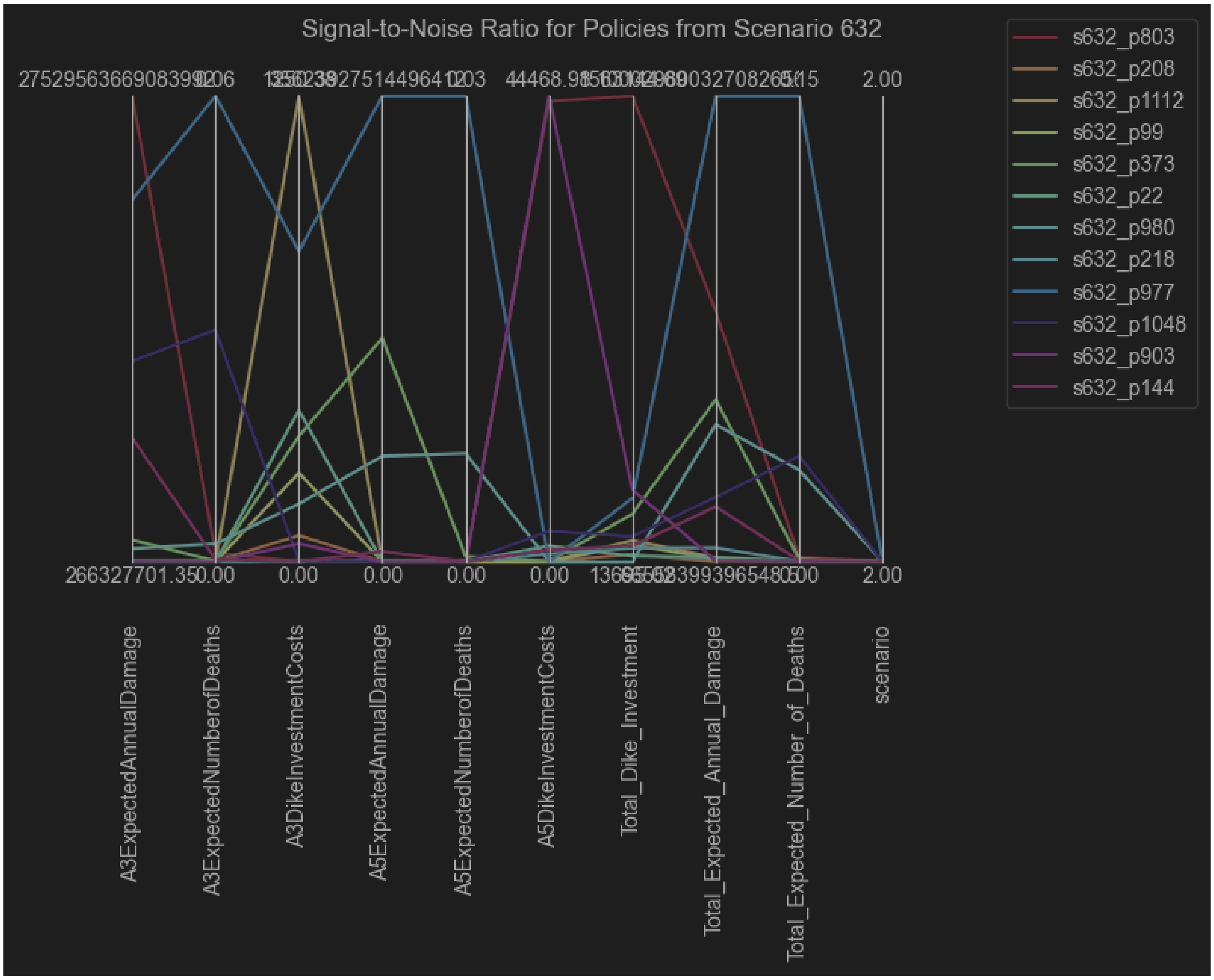
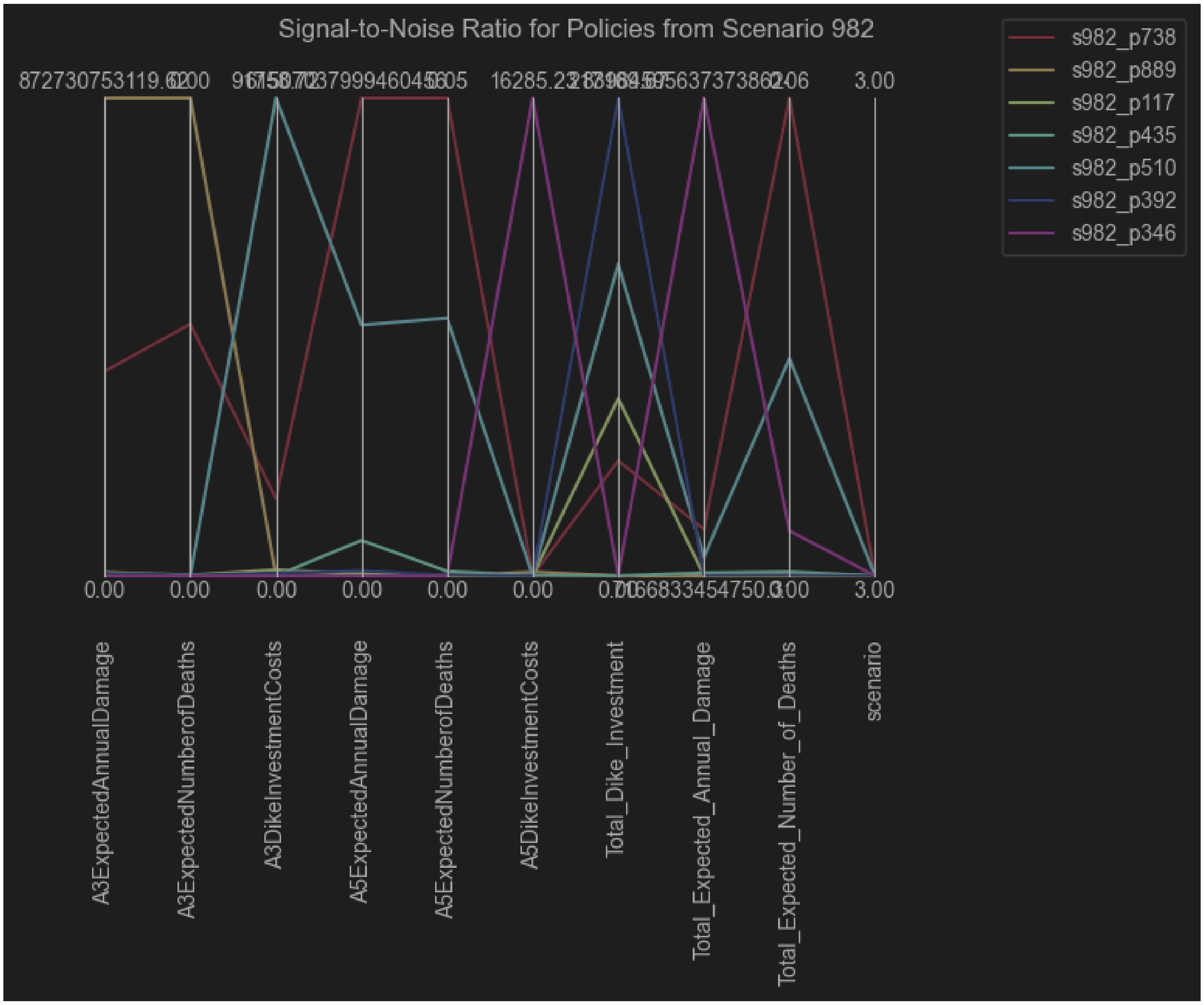
s248_p505
s248_p28
s248_p396
s248_p693
s248_p63
s248_p719
s248_p543
s248_p184
s248_p57
s248_p296
s248_p711
s248_p903
s248_p684
s248_p461
s248_p290
s248_p74
s248_p579
s248_p610
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
scenario


Signal-to-Noise Ratio for Policies from Scenario 541
s541_p904
s541_p231
s541_p762
s541_p749
s541_p1035
s541_p301
s541_p501
s541_p213
s541_p801
s541_p742
s541_p302
s541_p149
1.00
0.00
1.00
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
scenario

d



Signal-to-Noise Ratio for Policies from Scenario 632
s632_p803
s632_p208
s632_p1112
s632_p99
s632_p373
s632_p22
s632_p980
s632_p218
s632_p977
s632_p1048
s632_p903
s632_p144
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
scenario
0.00
2.00


Signal-to-Noise Ratio for Policies from Scenario 982
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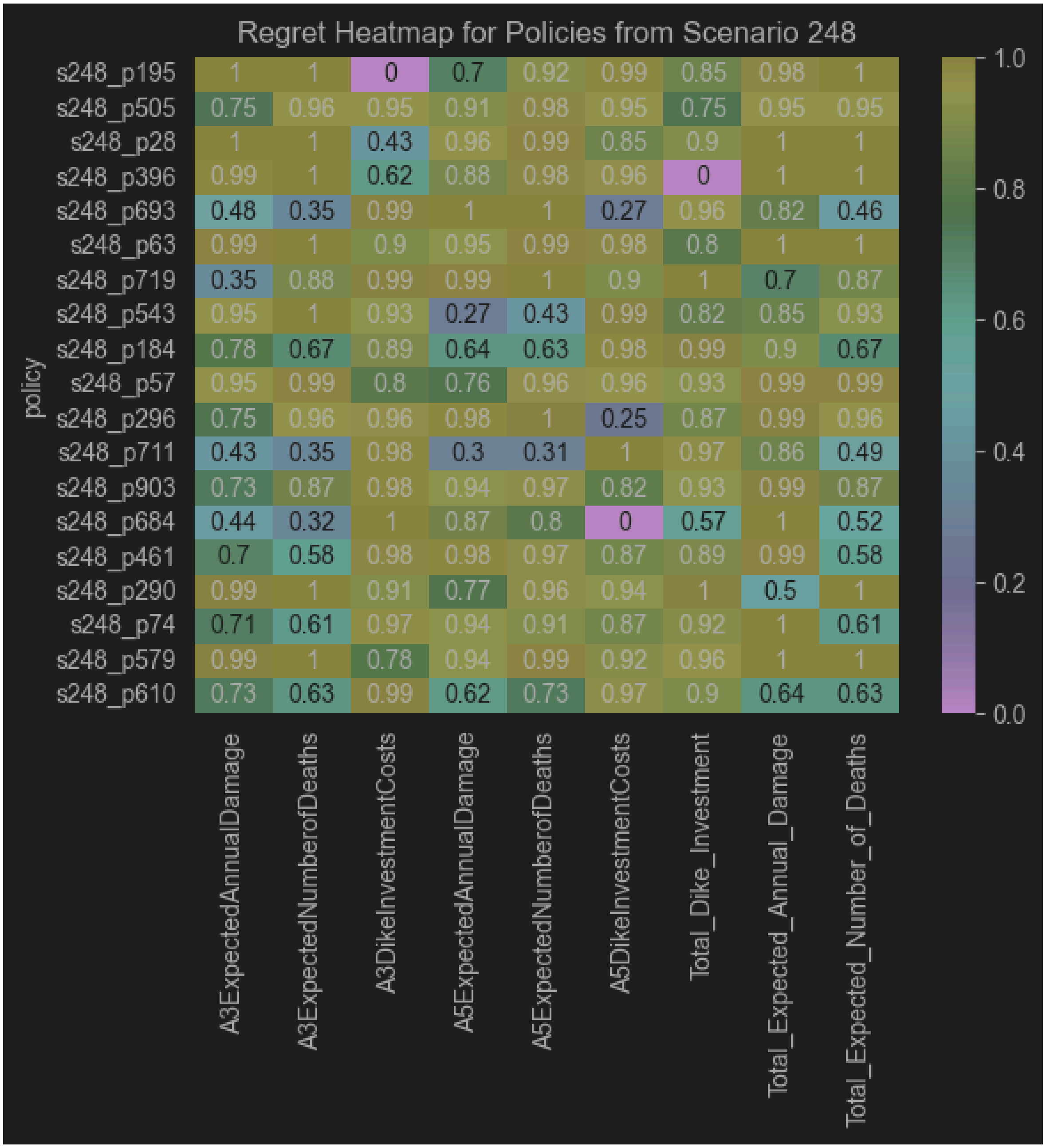
s982_p889
s982_p117
s982_p435
s982_p510
s982_p392
s982_p346
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
scenario


Regret Heatmap for Policies from Scenario 248
policy
s248_p195 1 1 0 0.7 0.92 0.99 0.85 0.98 1
s248_p505 0.75 0.96 0.95 0.91 0.98 0.95 0.75 0.95 0.95
s248_p28 1 1 0.43 0.96 0.99 0.85 0.9 1 1
s248_p396 0.99 1 0.62 0.88 0.98 0.96 0 1 1
s248_p693 0.48 0.35 0.99 1 1 0.27 0.96 0.82 0.46
s248_p63 0.99 1 0.9 0.95 0.99 0.98 0.8 1 1
s248_p719 0.35 0.88 0.99 0.99 1 0.9 1 0.7 0.87
s248_p543 0.95 1 0.93 0.27 0.43 0.99 0.82 0.85 0.93
s248_p184 0.78 0.67 0.89 0.64 0.63 0.98 0.99 0.9 0.67
s248_p57 0.95 0.99 0.8 0.76 0.96 0.96 0.93 0.99 0.99
s248_p296 0.75 0.96 0.96 0.98 1 0.25 0.87 0.99 0.96
s248_p711 0.43 0.35 0.98 0.3 0.31 1 0.97 0.86 0.49
s248_p903 0.73 0.87 0.98 0.94 0.97 0.82 0.93 0.99 0.87
s248_p684 0.44 0.32 1 0.87 0.8 0 0.57 1 0.52
s248_p461 0.7 0.58 0.98 0.98 0.97 0.87 0.89 0.99 0.58
s248_p290 0.99 1 0.91 0.77 0.96 0.94 1 0.5 1
s248_p74 0.71 0.61 0.97 0.94 0.91 0.87 0.92 1 0.61
s248_p579 0.99 1 0.78 0.94 0.99 0.92 0.96 1 1
s248_p610 0.73 0.63 0.99 0.62 0.73 0.97 0.9 0.64 0.63
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
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Total_Expected_Number_of_Deaths
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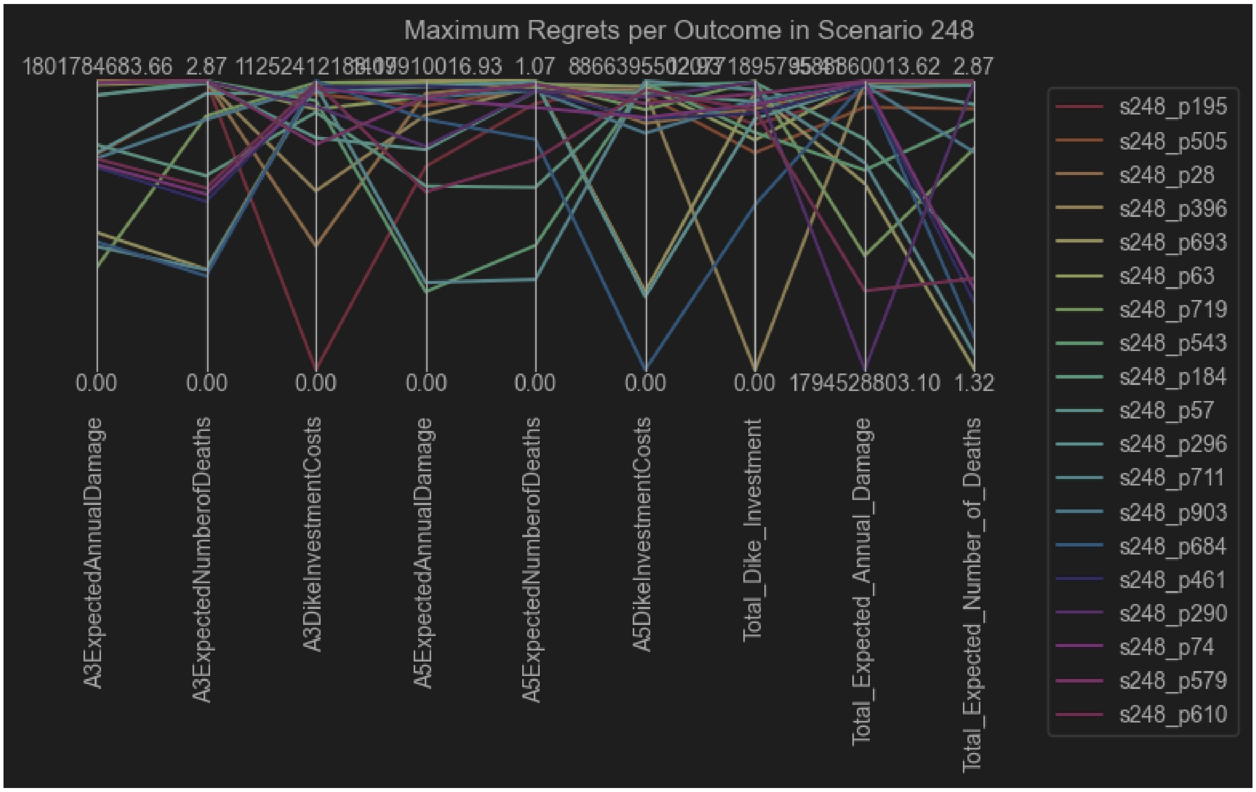
0.6
0.4
0.2
0.0


Maximum Regrets per Outcome in Scenario 248
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2.87
1125241218.07
1410910016.93
1.07
886639550.97
1207189579581
1860013.62
2.87
0.00
0.00
0.00
0.00
0.00
0.00
0.00
1794528803.10
1.32
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
s248_p195
s248_p505
s248_p28
s248_p396
s248_p693
s248_p63
s248_p719
s248_p543
s248_p184
s248_p57
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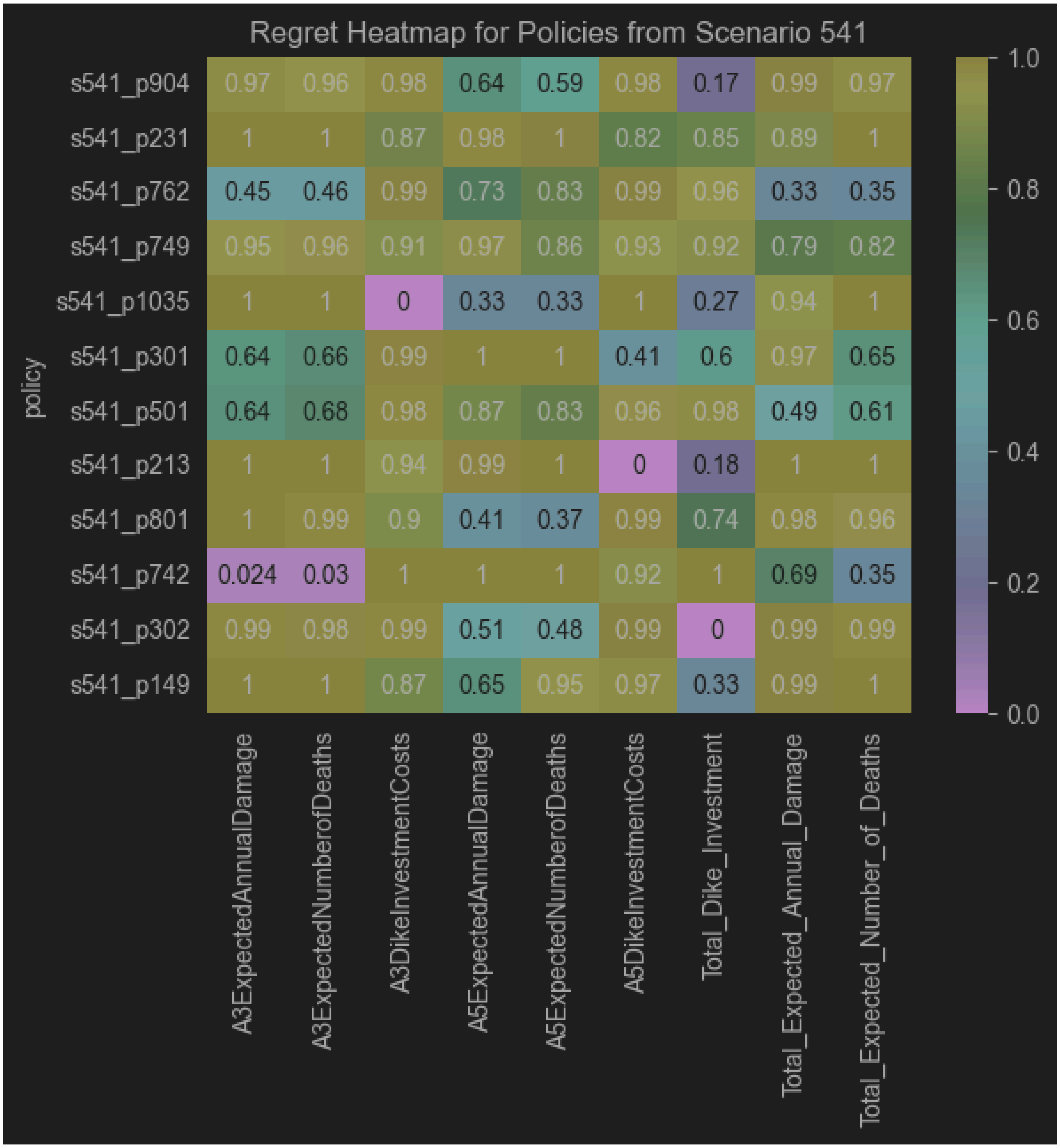
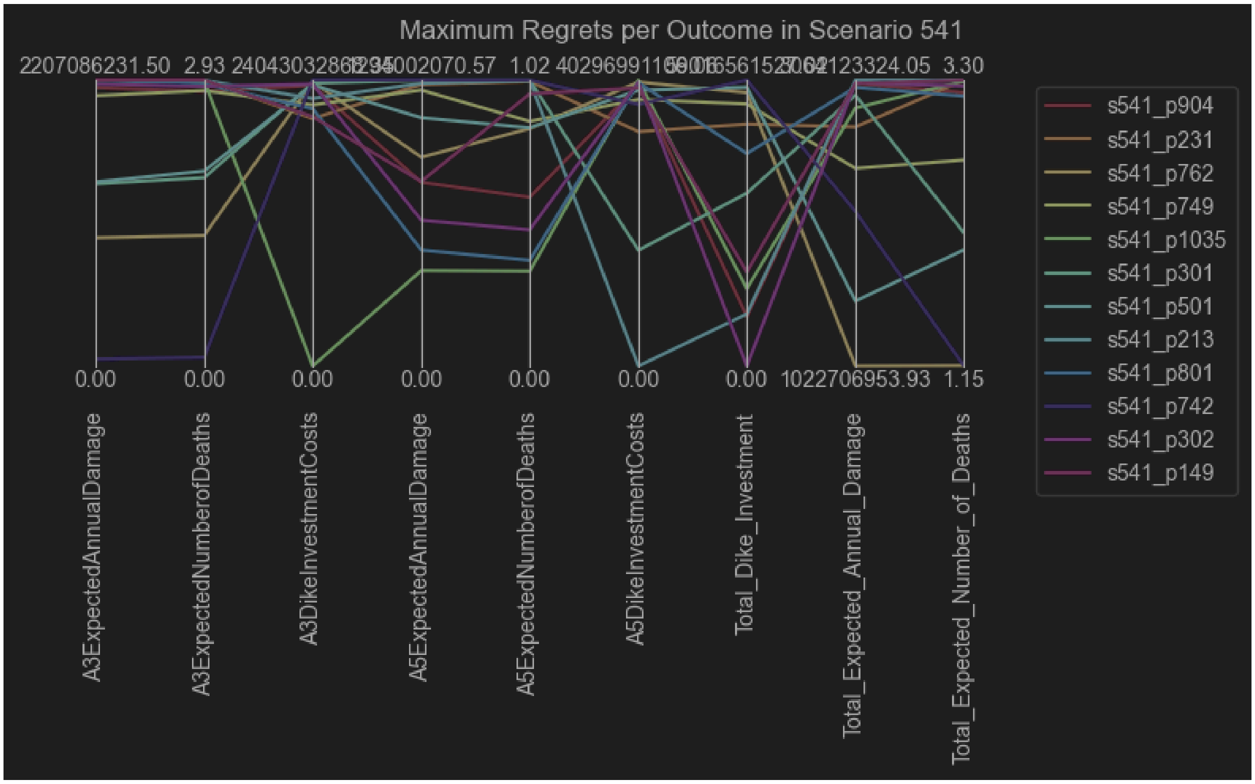
s248_p579
s248_p610



Regret Heatmap for Policies from Scenario 541
policy
s541_p904
s541_p231
s541_p762
s541_p749
s541_p1035
s541_p301
s541_p501
s541_p213
s541_p801
s541_p742
s541_p302
s541_p149
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths



Maximum Regrets per Outcome in Scenario 541
2207086231.50
2.93
0.00
0.00
0.00
0.00
0.00
0.00
0.00
1022706953.93
3.30
1.15
1.02
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
s541_p904
s541_p231
s541_p762
s541_p749
s541_p1035
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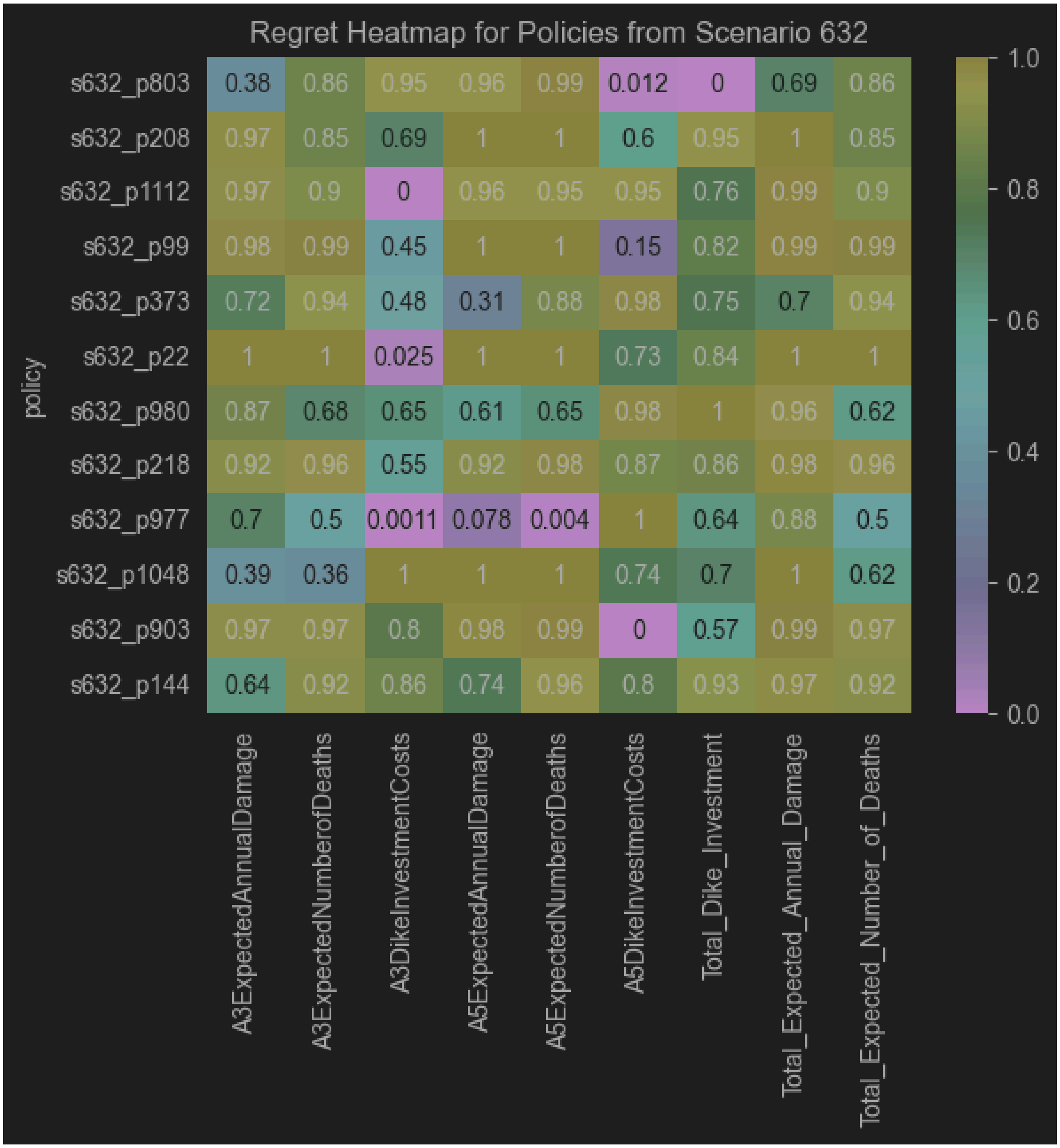
s541_p742
s541_p302
s541_p149


Regret Heatmap for Policies from Scenario 632
policy
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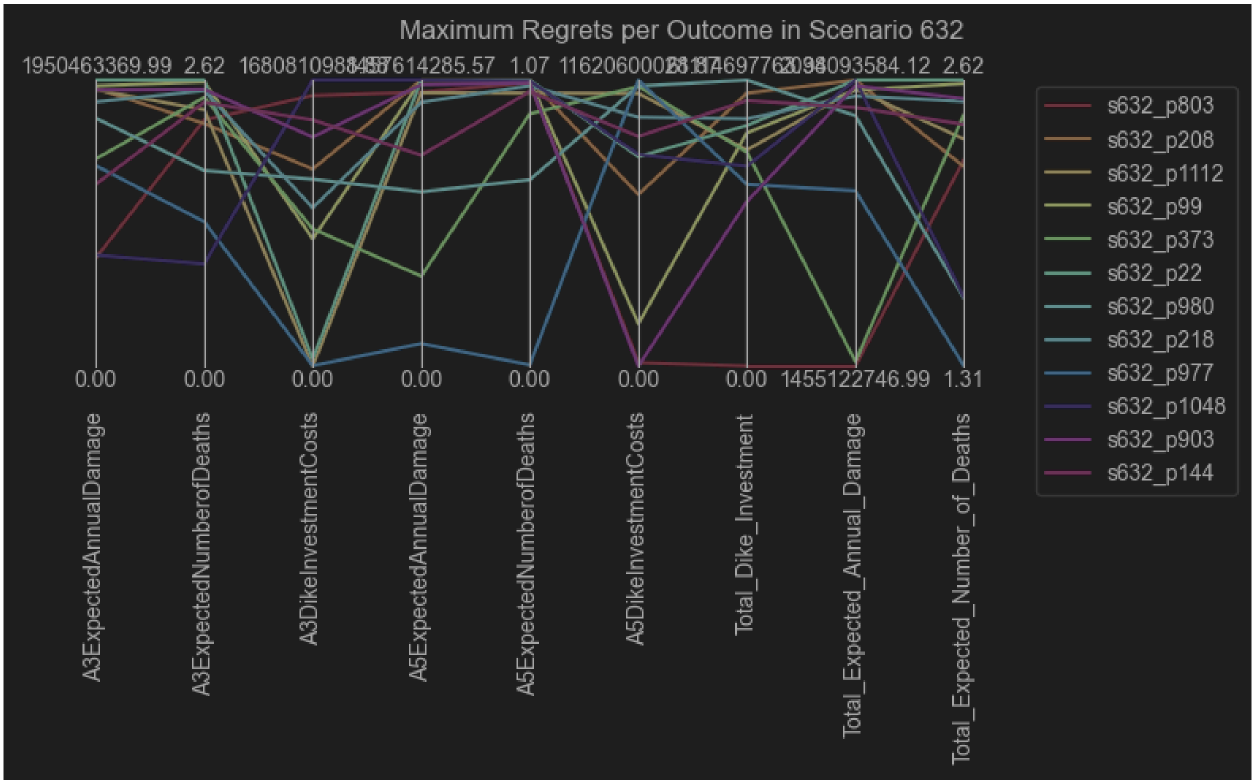
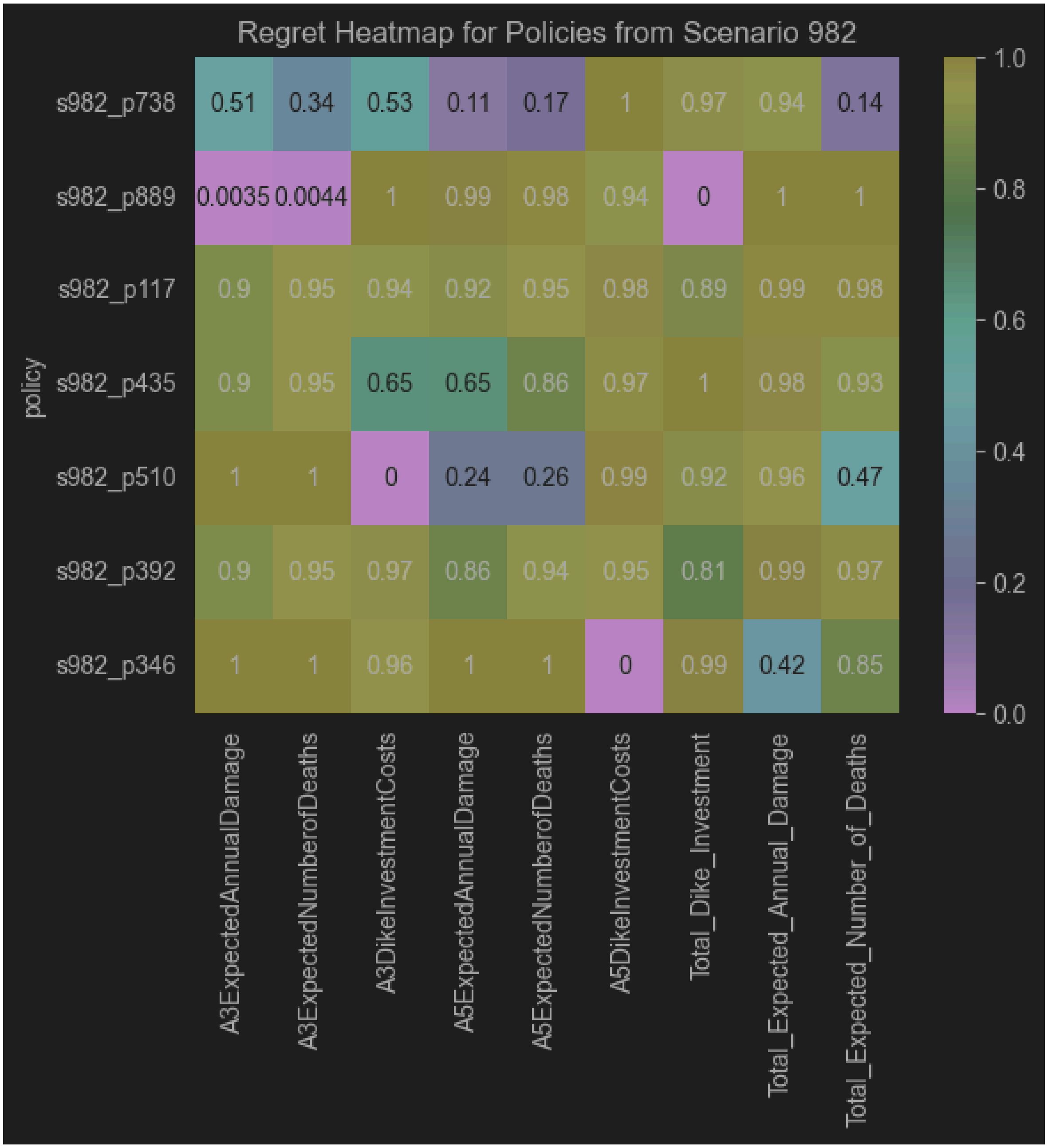
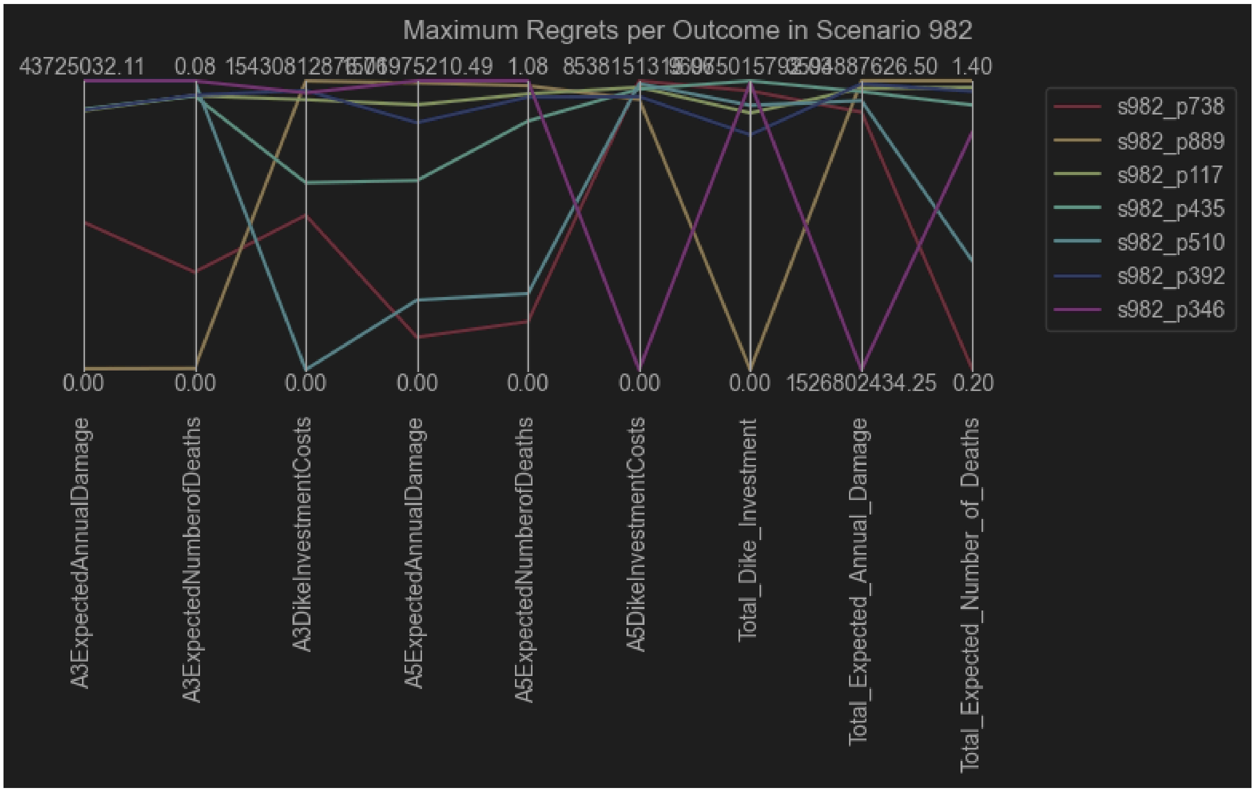
s632_p208
s632_p1112
s632_p99
s632_p373
s632_p22
s632_p980
s632_p218
s632_p977
s632_p1048
s632_p903
s632_p144
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
0.38 0.86 0.95 0.96 0.99 0.012 0 0.69 0.86
0.97 0.85 0.69 1 1 0.6 0.95 1 0.85
0.97 0.9 0 0.96 0.95 0.95 0.76 0.99 0.9
0.98 0.99 0.45 1 1 0.15 0.82 0.99 0.99
0.72 0.94 0.48 0.31 0.88 0.98 0.75 0.7 0.94
1 1 0.025 1 1 0.73 0.84 1 1
0.87 0.68 0.65 0.61 0.65 0.98 1 0.96 0.62
0.92 0.96 0.55 0.92 0.98 0.87 0.86 0.98 0.96
0.7 0.5 0.0011 0.078 0.004 1 0.64 0.88 0.5
0.39 0.36 1 1 1 0.74 0.7 1 0.62
0.97 0.97 0.8 0.98 0.99 0 0.57 0.99 0.97
0.64 0.92 0.86 0.74 0.96 0.8 0.93 0.97 0.92
1.0
0.8
0.6
0.4
0.2
0.0

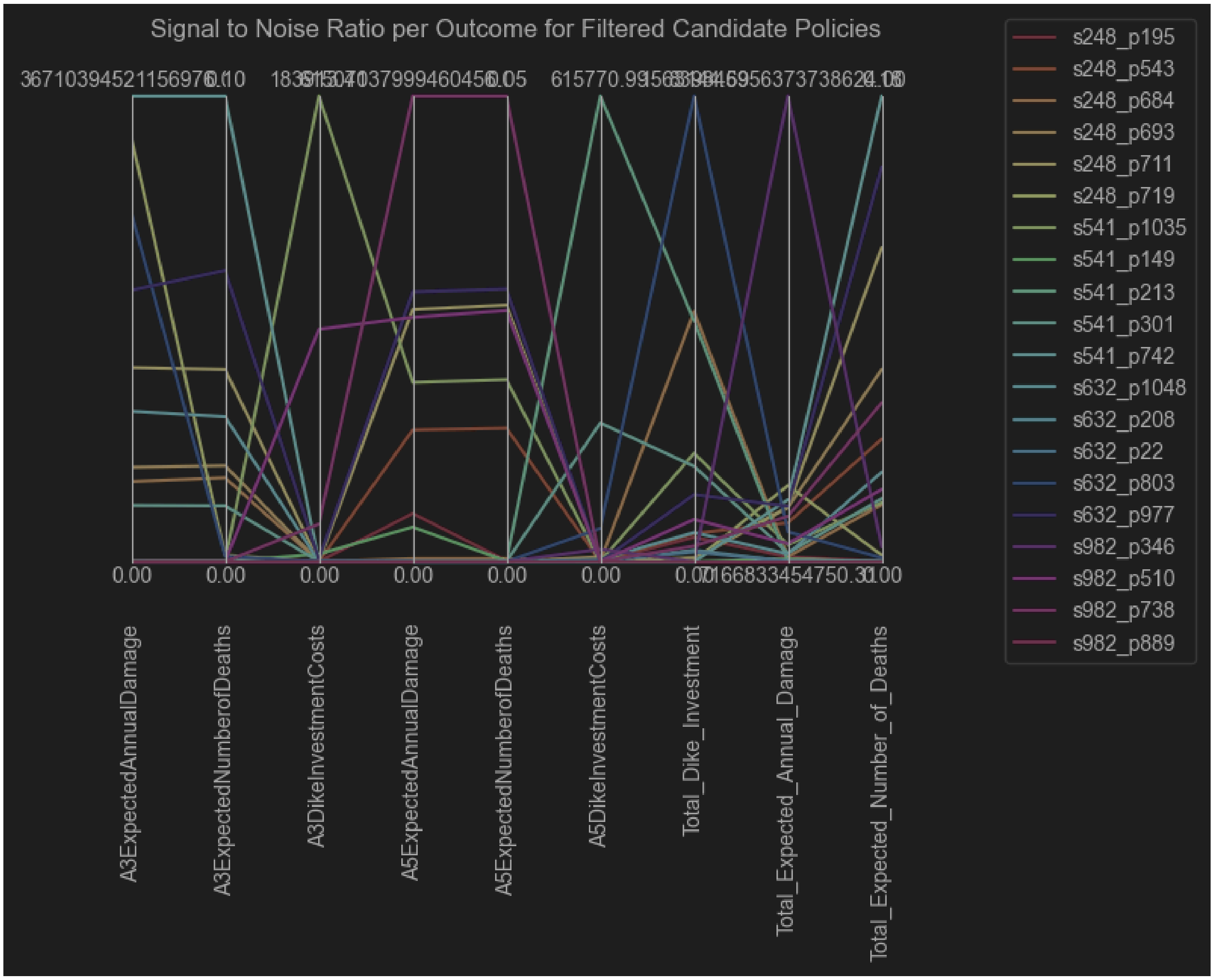


Maximum Regrets per Outcome in Scenario 632
1950463369.99
2.62
1680810988
457614285.57
1.07
1162060000
2817469776
20.98
4093584.12
2.62
0.00
0.00
0.00
0.00
0.00
0.00
0.00
1455122746.99
1.31
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
s632_p803
s632_p208
s632_p1112
s632_p99
s632_p373
s632_p22
s632_p980
s632_p218
s632_p977
s632_p1048
s632_p903
s632_p144


Regret Heatmap for Policies from Scenario 982
policy
s982_p738
s982_p889
s982_p117
s982_p435
s982_p510
s982_p392
s982_p346
0.51 0.34 0.53 0.11 0.17 1 0.97 0.94 0.14
0.0035 0.0044 1 0.99 0.98 0.94 0 1 1
0.9 0.95 0.94 0.92 0.95 0.98 0.89 0.99 0.98
0.9 0.95 0.65 0.65 0.86 0.97 1 0.98 0.93
1 1 0 0.24 0.26 0.99 0.92 0.96 0.47
0.9 0.95 0.97 0.86 0.94 0.95 0.81 0.99 0.97
1 1 0.96 1 1 0 0.99 0.42 0.85
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
1.0
0.8
0.6
0.4
0.2
0.0

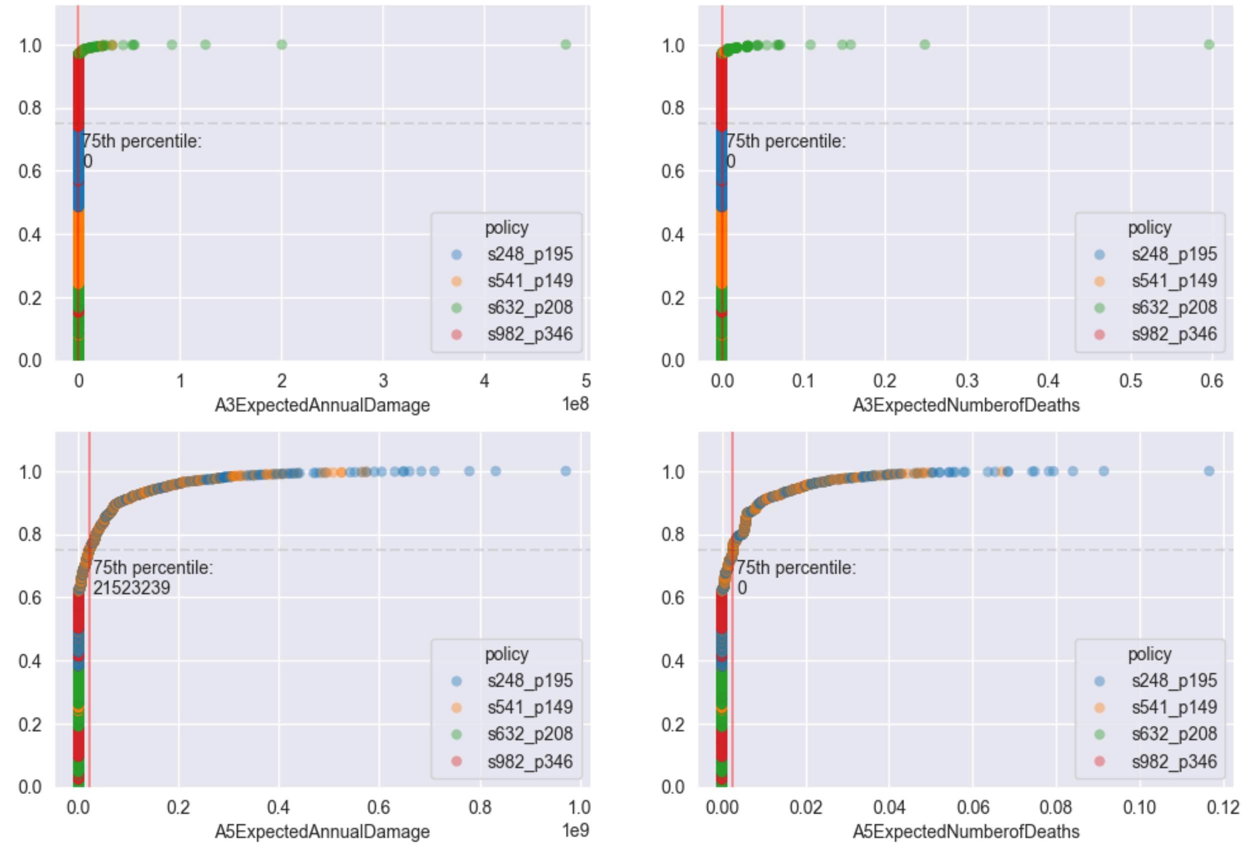


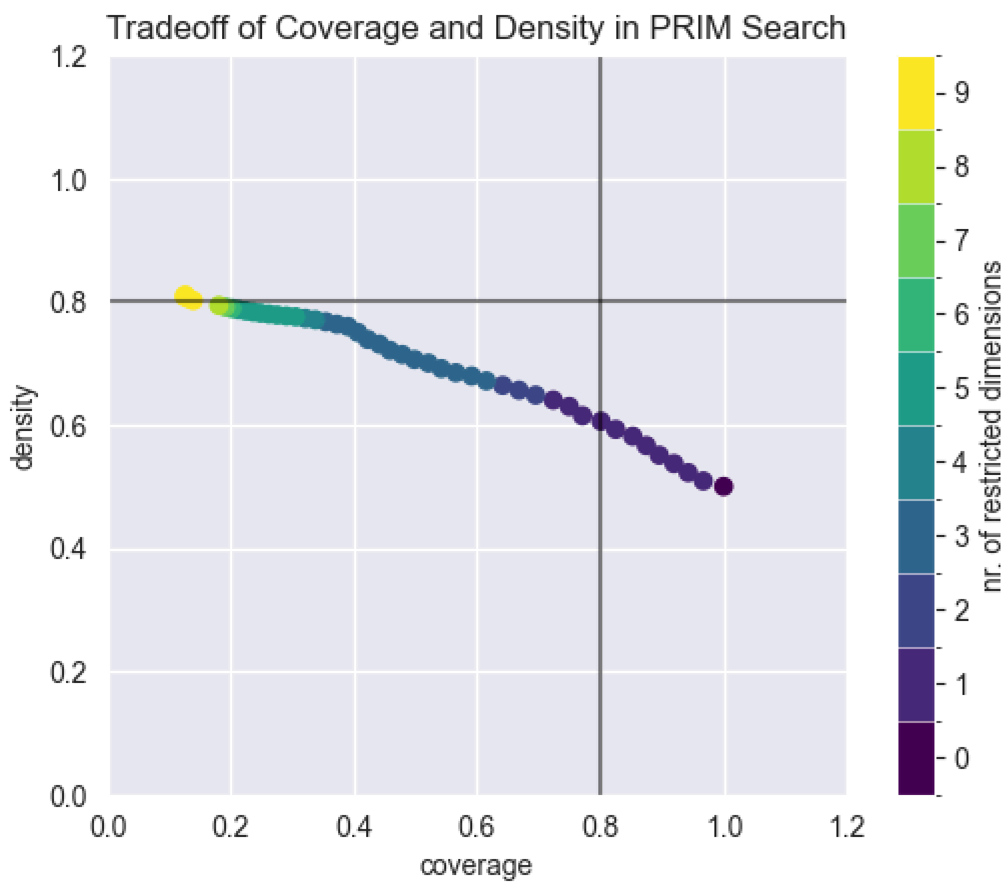
Maximum Regrets per Outcome in Scenario 982
43725032.11
0.08
1543081287
1576975210.49
1.08
8538151319
3697501579
3504887626.50
1.40
0.00
0.00
0.00
0.00
0.00
0.00
0.00
1526802434.25
0.20
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths
s982_p738
s982_p889
s982_p117
s982_p435
s982_p510
s982_p392
s982_p346



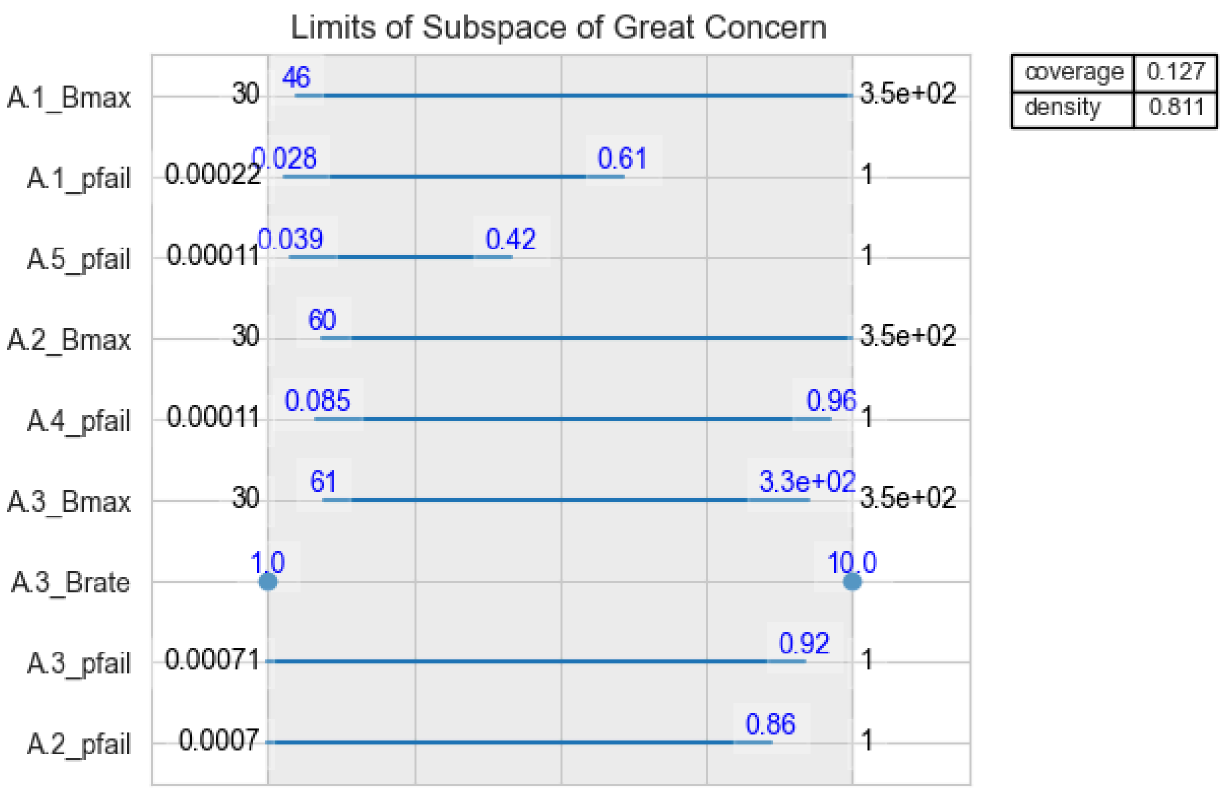
Signal to Noise Ratio per Outcome for Filtered Candidate Policies
s248_p195
s248_p543
s248_p684
s248_p693
s248_p711
s248_p719
s541_p1035
s541_p149
s541_p213
s541_p301
s541_p742
s632_p1048
s632_p208
s632_p22
s632_p803
s632_p977
s982_p346
s982_p510
s982_p738
s982_p889
A3ExpectedAnnualDamage
A3ExpectedNumberofDeaths
A3DikeInvestmentCosts
A5ExpectedAnnualDamage
A5ExpectedNumberofDeaths
A5DikeInvestmentCosts
Total_Dike_Investment
Total_Expected_Annual_Damage
Total_Expected_Number_of_Deaths

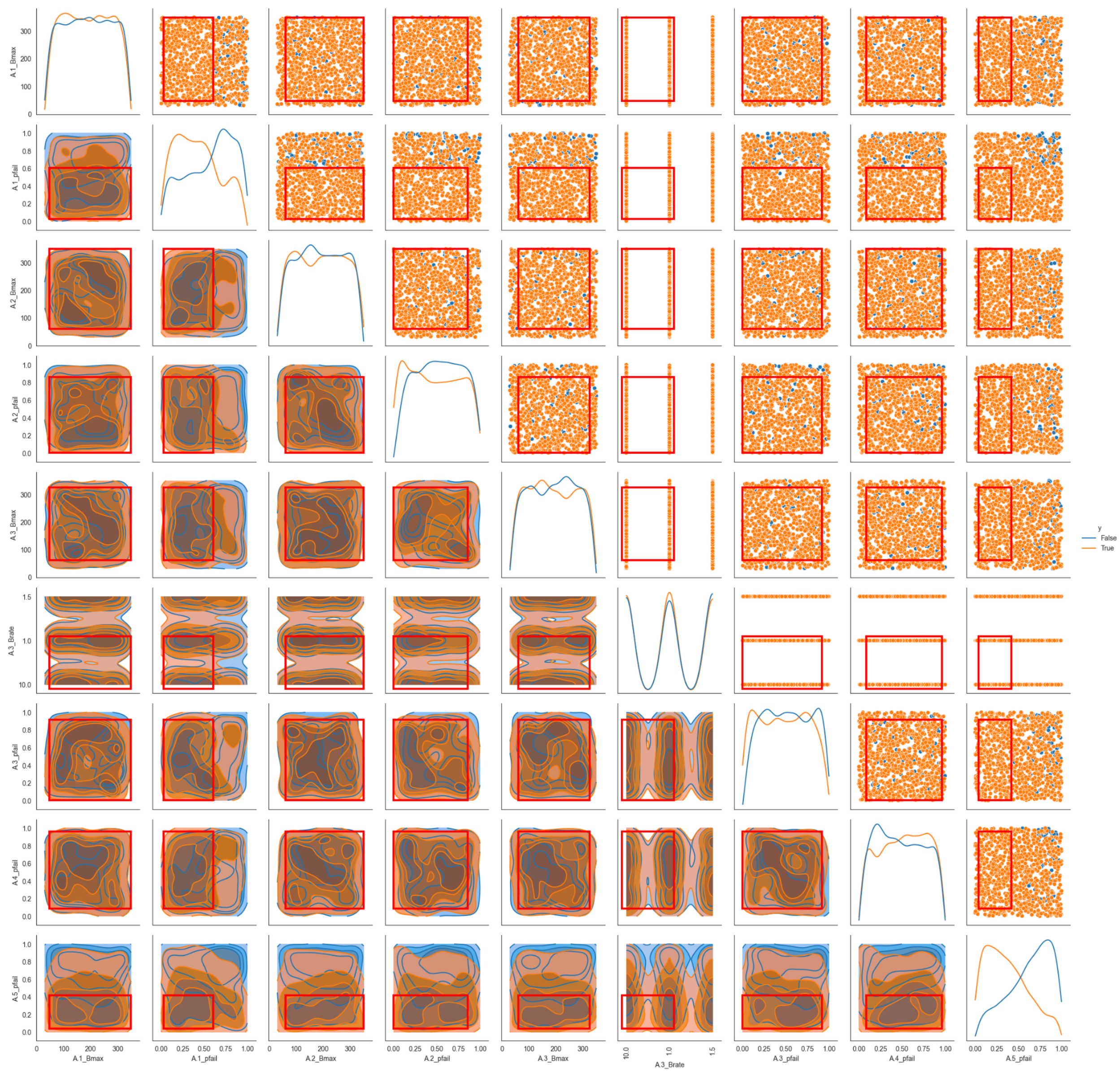
Cumulative Distribution Functions of Key Outcomes





Tradeoff of Coverage and Density in PRIM Search
density
coverage
nr. of restricted dimensions
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0
1
2
3
4
5
6
7
8
9


Limits of Subspace of Great Concern
A.1_Bmax
A.1_pfail
A.5_pfail
A.2_Bmax
A.4_pfail
A.3_Bmax
A.3_Brate
A.3_pfail
A.2_pfail
30
46
3.5e+02
0.00022
0.028
0.61
1
0.00011
0.039
0.42
1
30
60
3.5e+02
0.00011
0.085
0.96
1
30
61
3.3e+02
3.5e+02
1.0
10.0
0.00071
0.92
1
0.0007
0.86
1
coverage
0.127
density
0.811


A1_Bmax
A1_pfail
A2_Bmax
A2_pfail
A3_Bmax
A3_Brate
A3_pfail
A4_pfail
A5_pfail
y
False
True