Model-Based Decision Making

Final Report

Developing a Flood Risk Management Plan for the Ijssel River

Student	Student Number
Agathe Mommeja	5726816
Aaron Paris	5890780
Carolina Niewöhner	5889073
Emma Lombardo	4464249
Justus Hinze	5898234
Mira Kopp	5892953

Research by

ECAMJA | Analytics

Table of Contents

Summary

Report content: This report presents key recommendations for flood management in the Ijssel River region. The analysis was conducted by a team of analysts advising Rijkswaterstaat, with the objective of formulating effective policies to address the complex challenges associated with flood management in the area. The report emphasises the diverse objectives of all actors, highlighting the wicked nature of the problem. To reach a consensus on one flood management policy, the interests of the Delta Commission, the different provinces, as well as dike rings, have to be considered. However, the concerns of the environmental groups about the environmental impacts of the plans, as well as the interest of the transport company in keeping their economic viability stable should not be ignored.

Importance of Action: The report highlights the criticality of taking action to address flood management concerns. It stresses the **significance of proactive measures over inaction**. The urgency to mitigate potential economic damage, loss of life, and evacuation costs associated with flood hazards is underscored.

Uncertainty Considerations: The report acknowledges the inherent uncertainties associated with flood hazards and the economy. Several outcomes, such as **economic damage, casualties, and evacuation costs, are identified as being sensitive to these uncertainties**. Therefore, any policy approach must account for these factors and their potential impact on decision-making.

Complex Combinations: The report suggests that **simple solutions are insufficient** for effectively managing floods in the Ijssel River region. Instead, the analysis highlights the need for complex combinations of measures. The report provides a set of robust optimised policies, illustrating their efficacy in addressing the multifaceted challenges of flood management.

Our policy recommendation: The adoption of a policy that combines **dike heightening in all rings downstream of dike ring 2** with the creation of **room for the river in Havikerwaard** is recommended. Furthermore, additional **dike heightening and the creation of additional room for the river from 2090 onwards** are advised.

→ This policy is identified as one of the most **robust** of a selected set, meaning that it will perform well within the range of considered scenarios.

→ This policy is identified as one of the most **optimal** in terms of economic and safety considerations among all policies tested.

→ However other optimal and robust policy options may exist, suggesting the need for ongoing exploration and analysis.

Recommended next steps: The report emphasises the importance of **engaging stakeholders** in discussions, especially regarding outcome thresholds in the future. This process enables policy plans to be adapted according to future situations. The report suggests adopting an **adaptive pathway approach** to account for changing circumstances and stakeholder perspectives, enabling the stakeholders to already have a plan to follow in case of different futures, avoiding having to restart such a political process.

In conclusion, this report provides valuable insights and recommendations for flood management in the Ijssel River region. The analysis highlights the necessity of proactive measures, the consideration of uncertainties, the implementation of complex combinations, and the engagement of stakeholders. By adopting these recommendations and incorporating diverse modelling approaches, considering different scopes, Rijkswaterstaat can navigate the complexities of flood management effectively and ensure the long-term resilience of the region.

Problem Framing

Introduction to the case study

Climate change has arrived and will accelerate in the coming decades (IPCC, 2022). Delta areas like The Netherlands are particularly threatened by both ocean submersion and river flooding (Severinatne et al., 2021). Dutch people have built their identity by resisting and living with the water and thus acquired expertise in water management. However, water management is not just about technical solutions, but also about the ability to agree on long-term decision-making about a common resource and issue full of uncertainties and complexity. In this report, we explore the contribution of a model-based approach to achieving this challenge.

The Ijssel River traverses multiple provinces, including Gelderland and Overijssel, which together have more than 3 million inhabitants. The river plays a crucial role in transportation, agriculture, and water management. Its connection to the Rhine, as well as its integration into the larger Delta Works project, highlights its importance in managing water levels and preventing flooding in the region.

Several stakeholders, different perspectives

The challenge of flood management along the Ijssel River involves different types of stakeholders. The most important ones are classified by their power and interest in flood management at the Ijssel River in Figure 1.

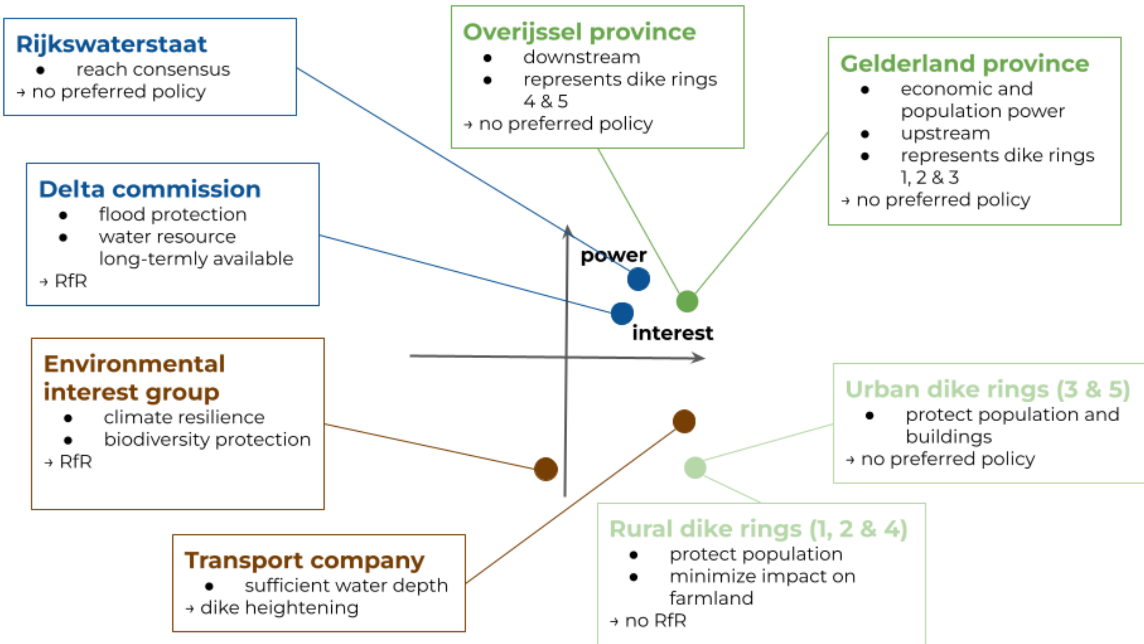

Figure 1: Power vs Interest matrix representing all stakeholders, with their core aims and preferred policy levers.

There is a shared **interest**: every stakeholder aims at minimising the intensity and recurrence of flooding: this is a threat to human lives, but also to crop yield and freight. However, some stakeholders have more specific interests related to the river:

- *The transport company* aims at keeping the level of water deep enough for freight transport,
- *The rural dike rings* would like to avoid losing farmland,
- *The environmental group* prefers to avoid human intervention along the river,
- *Dike rings and their representatives*, Overijssel and Gelderland provinces, are not only morally concerned by saving lives, but directly affected.
- The *Rijkswaterstaat* and the *Delta Commission* both have responsibilities involved in case of flooding and are financially highly involved to implement the policies as well.

The **power** of the stakeholders can be explained in different ways.

- The *environmental group and the inhabitants* (dike rings) do not have immediate levers to defend their interests,
- The *transport company* can argue that its services benefit the wider economy,
- The *provinces* have the strength of the number, given the size of the population they represent. They can also argue on their contributions to the wider economy,
- *Delta Commission* has financial power, and a veto right translating into executive power
- *Rijkswaterstaat* decides about and is responsible for implementing the chosen policy.

In order to tackle the problem, **three policy levers are to be discussed** and negotiated among the actors for designing the policy. According to the IPCC (2022, p. 8), in order to adapt to climate change consequences, "combinations of non-structural measures like early warning systems and structural measures have reduced loss of lives in case of inland flooding (medium confidence)", which answer to the core interest of the stakeholders. The policy levers can be implemented independently at each dike ring and at several timesteps. However, as their implementation has an impact on the rest of the river, the chosen policy will be the result of a combination, which is the subject of debate.

- *Room for the River* aims at increasing the capacity of rivers and reducing the risk of flooding by creating more space for water within the river system. It involves a combination of measures such as widening the riverbed, constructing floodplains, and lowering floodplain levels to safely accommodate high water levels during periods of heavy rainfall or river discharge (Rijke et al., 2012).

  → in various locations (cf. Appendix B), no turning back once implemented (representation in the model, not necessarily the case in reality).

- *Dike heightening* involves raising the height of existing dikes or embankments to increase their capacity to protect against rising water levels and prevent flooding. It aims to enhance the structural integrity of the dikes, ensuring they can withstand potential flood events and provide adequate protection to the surrounding areas.

  → range of heights available (1-10 dm).

- *Evacuation warning* is the issuance of alerts or notifications to residents in flood-prone areas, advising them to evacuate to safer locations due to an impending or ongoing flood threat. It serves as a crucial early warning system to ensure the safety of individuals and reduce the potential loss of life or property damage caused by flooding (Hoss et al., 2011).

  → no warning or from 1 to 4 days before a suspected threat.

Their advantages and drawbacks are summarised in Table 1.

Table 1. Impacts, framed by advantages and drawbacks, of the three available levers to be combined among the dike rings and over time, in order to build a policy.

Levers	Advantages	Drawbacks
Room for river	• positive for the biodiversity • long-termly more resilient • breaks the flow of the river downstream	• loss of farmland
Dike heightening	• no loss of farmland	• acceleration of river flow downstream
Evacuation warning	• if early enough, decreases the number of casualties	• if too early, reduced efficiency due to more frequent unfounded alarms

Building consensus around the best policy: our role as analysts for Rijkswaterstaat

Rijkswaterstaat, for whom we work as analysts, has an executive power that aims at providing the best policy possible, in line with the vision of the Delta Commission. Their aim is to reach a consensus among the actors and to deliver a concrete policy as an outcome.

In order to create the consensus, **our client must first take all the power, interests and a priori preferred solutions into account.** The goal is thus to find the constraints in the event of flooding, but also any side-effects of the policies that could be implemented. Above all, adopting the approach of adaptive planning, e.g. in the form of dynamic adaptive policy pathways (Haasnoot et al., 2013) is highly recommended due to the inherent uncertainty in the case.

Furthermore, creating consensus implies **taking a wide range of possible uncertainty scenarios into account**. The model proposes to consider 5 types of **uncertainties**, that will then be combined or stressed in different ways:

- Different *discount rate for calculating the present-day value of damages* is considered to account for unforeseeable developments of interest rates and opportunity costs,
- As the river's behaviour as a fluid and the severity of precipitation events upstream is intrinsically uncertain, *132 possible normalised curves describing the shape of the incoming flood wave over time* are considered,
- As the mechanical behaviour of the dike in response to river stresses is uncertain, the *final extent of the breach width*, the *probability that the dike will withstand the hydraulic load* and *how fast the breach grows over time* are considered uncertainties.

In order to build the consensus, our team of analysts considered a **wide range of outcomes to assess the policy from as many angles as possible**:

- The damages flooding would lead to, according to its strength, assessed as *expected annual damages*,
- The key for the stakeholders being to find a trade-off financially speaking, both the costs the implementation of the policy would lead to, thus the *dike heightening and room for river investment costs*, as well as the costs flooding would lead to - *evacuation costs* - are considered.
- Of course, the *expected number of deaths* in case of flooding is considered as well, being the most essential outcome.

These outcomes are linked to the uncertainties in such a complex way, that it is impossible to assess, to what extent, any scenario - i.e. any combination of a given value of uncertainties - will lead to the value of each outcome. The link between the categories of uncertainties and outcomes are shown in Figure 2. The model-based approach will precisely help to define the nature of these links.

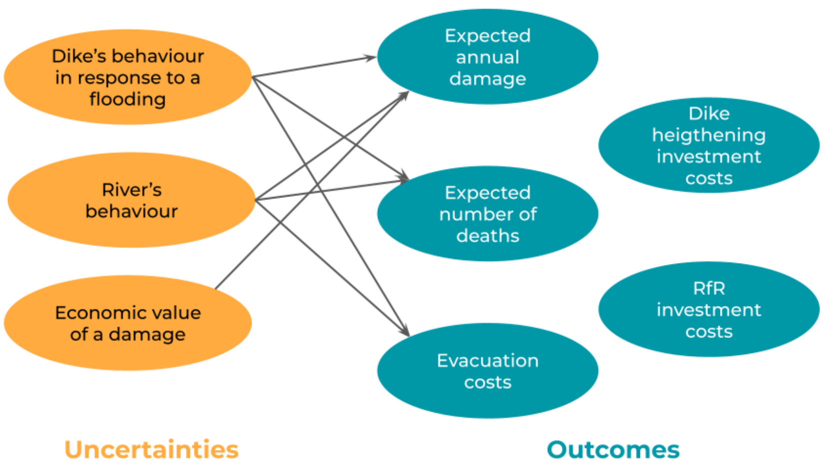

Figure 2: Uncertainties grouped by significance, and how they have an impact on the considered outcomes.

To put it in a nutshell, our role as analysts for the Rijkswaterstaat is to navigate among the rival problem framings and to get all players on board for the best possible policy. Thus, this report aims at answering the research question:

How can deep uncertainty methods be applied to find and build consensus around optimal and robust policies for the IJssel River flooding management case?

Method

Due to the high level of uncertainty within the above-described problem, exploratory modelling was used to analyse potential policies and their outcomes. Exploratory modelling was first introduced by Bankes (1993) as an analytic tool to generate more information in contrast to consolidative modelling aiming at providing predictions. More specifically the Exploratory Modeling Workbench was utilised, a tool to facilitate decision-making under deep uncertainty (Kwakkel, 2017). The model is based on the XLRM framework (see Appendix A) taking into account external factors (uncertainties), policy levers and relationships in the system, which all affect the performance metrics (outcomes) of the modelled problem.

The analysis consists of two subsequent steps. First, an open exploration was conducted to gain global insights into the system and its uncertainties as well as the policy lever space, as described by Kwakkel and Haasnoot (2019). In order to arrive at a rich set of policy alternatives performing well over multiple scenarios, which is especially relevant for the goals of Rijkswaterstaat, the next step was the use of multi-objective robust decision-making (MORDM) (Bartholomew and Kwakkel, 2020).

Open exploration

The open exploration involved six distinct policies to be implemented in the first time step:

- The first policy simulated a **Business-As-Usual** (BAU) scenario, where all levers were set to zero, indicating no interventions or changes in the system.
- The second policy focused **solely on dike heightening**, where the dikes were uniformly raised by 1 m to their maximum height at each location.
- The third policy implemented a **Room for the River** (RfR) strategy, utilising available river space at every possible location from the first time step.
- The fourth policy involved **early evacuation**, with evacuation measures implemented four days in advance.
- The fifth policy represented the **collaborative efforts of the actors involved in the preliminary debate**, combining dike heightening in dike ring 3 and 5 and RfR measures in dike ring 1 and 4.
- Lastly, the sixth policy **resulted from the discussion in the final debate** and received the agreement from the majority. Again a combination of measures was decided on including 2 RfR projects and dike heightening at all locations.

To obtain results for the entire IJssel area, the exploration utilised the ema-workbench, running 300 scenarios based on Problem Formulation 2 (PF2). This aggregated formulation was chosen to provide a comprehensive overview of the outcomes, while still distinguishing between different types of costs as these might be carried by different actors (Delta Commission vs. Rijkswaterstaat). An overview of the outcomes considered per problem formulation is given in Appendix C.

Optimisation

The open exploration was followed by the identification of optimal and robust policies using multi-scenario MORDM. Due to the multitude of involved actors and goals, **RDM was not chosen. Multi-scenario MORDM,** an extension of MORDM to multiple scenarios as introduced by Watson and Kasprzyk (2017), **was preferred over single-scenario MORDM and many-objective robust optimisation (MORO)** due to its superior balance between robustness over a large ensemble of scenarios and optimality in chosen reference scenarios (Bartholomew and Kwakkel, 2020). Furthermore, MORO requires much higher computational power, especially considering the wide range of lever combinations that can be implemented within the model (Bartholomew and Kwakkel, 2020). Taking into account the main objectives of Rijkswaterstaat, this method allows the actor to select a policy that is robust over various scenarios as well as performs well on the most relevant outcomes, decreasing total economic damages and investment costs as well as achieving a desired level for casualties.

Figure 3 shows the framework of multi-scenario MORDM. The first step, the model specification, includes the definition of the problem, including objectives, external factors and policy levers. It can be found in the chapter "Problem Framing".

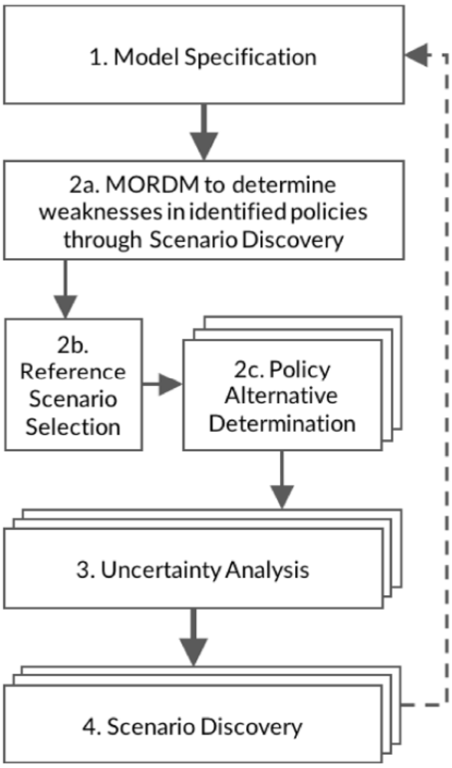

Figure 3: Multi-scenario MORDM framework (Bartholomew and Kwakkel, 2020)

Subsequently, a **multi-objective evolutionary algorithm (MOEA) was used to determine policies for a reference case**, which form a Pareto optimal front (Kwakkel, 2019). Because no specific reference scenario was available or negotiated in the political debates, the mean of each uncertainty parameter was used (see Table 2). To find an optimal 'function evaluations-epsilon' pair, two combinations were analysed. The first 50,000 function evaluations with an epsilon of 0.25 were run. Then, 10,000 functional evaluations were run with an epsilon of 0.5. However, in both cases, convergence was not reached. Due to the high runtime, 10,000 functional evaluations were chosen in the end. Long run times are a typical challenge associated with the use of evolutionary algorithms (Maier et al., 2019). Bartholomew and Kwakkel (2020), for example, used 500,000 function evaluations for their case example, which surpasses our computational capacity by far.

Table 2: Uncertainty parameter values for reference scenario

Uncertainty parameter	Value
Discount rate	2.5
Flood wave shape	66
Final breach width	160 m
Breach width growth rate	1.5 times/day
Dike failure probability	0.5

Afterwards, **the number of policies was reduced for subsequent evaluation** by selecting only those policies that result in the lower half of expected number of deaths in the reference scenario. This was done to reduce the computational cost and because of a strong (qualitative) agreement of all actors in the debates that deaths must be minimised. The remaining policies were tested by re-evaluating each over 1000 scenarios, aiming at a compromise between the robustness of the approach and computational cost.

Following the single-scenario MORDM analysis, **a new set of scenarios for the multi-scenario MORDM analysis was chosen**. This is a crucial moment for the quality of a multi-scenario MORDM (Bartholomew and Kwakkel, 2020). We applied the worst-case method, identifying the 5 scenarios in which the produced policy proposals from the first modelling round performed weakest. As Rijkswaterstaat was considered to be rather risk-averse, the worst-case method was preferred over the best-case method. Notably, only 3 of the 5 identified worst-case scenarios are unique. Table 3 shows the uncertainty parameters of the identified scenarios.

Table 3: Uncertainty parameter values for identified scenarios for multi-scenario analysis

Scenario	1	2	3	4	5
Initial flood wave shape	124	99	99	24	124
Breach Width Rate DR1	1.0	1.0	1.0	1.0	1.0
Breach Width Rate DR2	1.5	10.0	10.0	10.0	1.5
Breach Width Rate DR3	1.5	1.0	1.0	1.5	1.5
Breach Width Rate DR4	10.0	1.0	1.0	1.0	10.0
Breach Width Rate DR5	1.0	10.0	10.0	10.0	1.0
Dike Failure Probability DR1	0.2	0.5	0.5	0.4	0.2
Dike Failure Probability DR2	0.2	0.1	0.1	0.0	0.2
Dike Failure Probability DR3	0.0	0.1	0.1	0.0	0.0
Dike Failure Probability DR4	0.6	0.6	0.6	0.9	0.6
Dike Failure Probability DR5	0.1	0.3	0.3	0.7	0.1
Final Breach Width DR1	314.4	76.6	76.6	169.5	314.4
Final Breach Width DR2	315.9	311.0	311.0	249.6	315.9
Final Breach Width DR3	221.4	334.8	334.8	289.9	221.4
Final Breach Width DR4	154.5	173.0	173.0	144.9	154.5
Final Breach Width DR5	335.3	236.5	236.5	248.0	335.3
Discount rate 2023-2089	4.5	1.5	1.5	2.5	4.5
Discount rate 2090-2156	1.5	2.5	2.5	1.5	1.5
Discount rate 2157-2223	1.5	1.5	1.5	2.5	1.5

The optimisation resulted in 1,452 policies. However, one should note that, as visible in Table 3, Scenarios 2 and 3 and 1 and 5 are the same as the uncertainty values led to two worst-case outcomes for different lever combinations, resulting in only three distinct scenarios. Unfortunately, due to long computing time and a technical issue that could not be solved (see Appendix E), the analysis could not be performed over multiple seeds, which is generally good practice (Bartholomew and Kwakkel, 2020). Furthermore, the results were not checked for convergence because the same amount of functional evaluations as for single-scenario MORDM was used. Future research should repeat the analysis with more function evaluations and a second convergence analysis for this part of the modelling.

In the next step, **the computed policies were re-evaluated under deep uncertainty**. Before the re-evaluation was performed, the solution space was partitioned again by solely considering results where the expected number of deaths as well as the expected annual damage was below the median value from the preceding analysis. This choice was reasoned by the long computation time and common agreement to minimise expected deaths as well as economic costs from damages. The analysis was performed over 100 scenarios. The rather low number of scenarios was caused by the high computing time.

Finally, **two robustness metrics**, the minimum regret method as well as the signal-to-noise ratio were used to identify the most robust policies. The **minimum regret robustness metric** measures the disparity between a candidate policy's performance in a specific scenario and the best attainable performance for that same scenario (McPhail et al., 2018). The metric is assessed for each policy and each outcome indicator, by subtracting the individual outcomes from the outcome under the best scenario. To normalise the results, the regrets for each outcome are divided by the maximum outcome. As the best-performing outcome will always be smaller than the outcomes of the other policies for that scenario or equal, the results will be negative or zero. Therefore, the absolute values are taken for further analysis. Policy options with low minimum regret values are favoured. The top ten policies with the lowest minimum regret value were chosen for the second robustness check. Choosing the robustness metric as a final criterion for the policy selection seemed the most reasonable as the two rounds of subspace partitioning over the expected number of deaths and the expected annual damage already ensured an acceptable level for the two outcomes. Additionally, there was no convergence reached at the beginning of the analysis, indicating that the proposed policies are not optimal and therefore, robustness might seem more important. Lastly, Rijkwaterstaat is rather risk averse and thus the robustness of policies plays a significant role in the decision-making process.

The second robustness metrics used is the signal-to-noise ratio, which serves as a descriptive analysis tool aimed at achieving a balance between the average and variability of a decision alternative's performance across different scenarios (McPhail et al., 2018). It is calculated by dividing the mean of the dataset by its standard deviation. In this minimisation problem, a low mean is desired as well as a low standard deviation. As shown in the open exploration, the dike investment and RfR investment outcome parameters are not affected by changes in uncertainties. Following, the standard deviation, considering only one policy over different scenarios will always be zero. Hence, these two outcomes are excluded from the signal-to-noise ratio analysis.

Finally, a **global sensitivity analysis** (SOBOL) was performed for the final policy chosen to give political actors insights into what uncertainties the policy performance is prone to. Sensitivity analysis is a crucial tool to understand where uncertainty really matters and thus, for example, where to focus on improving a model (Razavi et al., 2021). Here the direct first-order effects are captured, as well as the interaction effects of the uncertainties and the total order sensitives aggregating the preceding two (Saltelli et al. (2019).

Results

Open Exploration

By applying the aforementioned methodology for the open exploration the following results were generated (Figure 4).

Figure 4: Open exploration with 6 diverse policies

The open exploration – conducted on the policies described in section XX – yields several important findings. Firstly, it becomes evident that not implementing any measures, such as in the Business-As-Usual (BAU) policy, results in a high number of expected deaths, emphasising the necessity of interventions. Conversely, **implementing early evacuation measures effectively limits the expected number of deaths**, highlighting the significance of proactive strategies in mitigating flood damage. While evacuation reduces immediate casualties, it still exhibits a wide range of expected annual damage. Notably, **dike heightening measures proved effective** in reducing the expected annual damage, demonstrating their efficacy in minimising infrastructure and asset losses. **Solely implementing RfR along all dike rings leads to high upfront investment costs and covers a wide range of values for the other outcomes**. In general, the outcomes 'expected number of deaths', 'evacuation costs', and 'expected annual damage' are sensitive to uncertainties. The first debate policy representing a compromise between the actors displays the tradeoff between the outcomes. The mixed measures exhibit rather low investment costs for Dikes and RfR and no investment costs for evacuation. The expected number of deaths is reduced compared to a BAU and RfR policy. The outcomes of the final debate policy mix are only slightly different from the preceding results. The dike investments are doubled, but the expected number of deaths is significantly reduced. Following the open exploration, one can see that a policy combining different levers seems to be most beneficial. This translates into the need for collaboration in the decision-making arena, including all actors in the discussion.

MORDM

As described in section XX, after multiple iterations, the epsilon-nfe pair 0.25 and 10,000 was chosen. In Figure 5 the convergence analysis is displayed. It is clearly visible that no convergence was found for function evaluations below 10,000. Indicating that in future research the analysis should be repeated with a higher number of function evaluations to find truly optimal policies and to exclude potential artefacts.

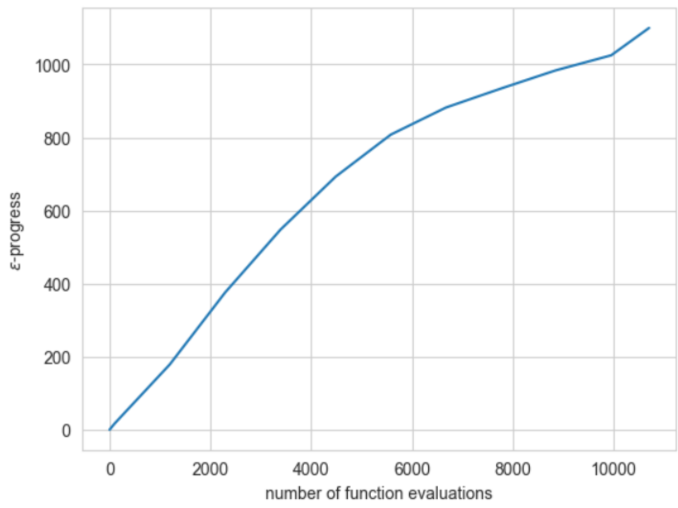

Figure 5: Convergence analysis

Despite missing convergence, the optimisation was continued. The single-scenario MORDM analysis, resulted in 187 optimal policies. The left parallel axes plot in Figure F1 (see Appendix F), shows the different policies mapped against their outcome performance. Due to the high number of policies, the graph is difficult to read and interpret. Thus, the following step was to apply a simple form of subspace partitioning to the expected number of deaths. The right plot in Figure F1 (see Appendix F) displays the reduced number of policies from 187 to 93. Although single policies are better identifiable, drawing a conclusion from this visual outcome is challenging.

Multi-scenario MORDM

To increase the robustness of the optimal policy set, the single-scenario MORDM was extended by a multi-scenario MORDM. The 93 optimal solutions were re-evaluated over 1000 scenarios based on the available computational power. As mentioned in section XX, the best-worst-case method was applied to then identify 5 worst-case scenarios for the further analysis (Figure 6). The blue highlighted lines display the results that perform either weakest or strongest for one of the outcome parameters.

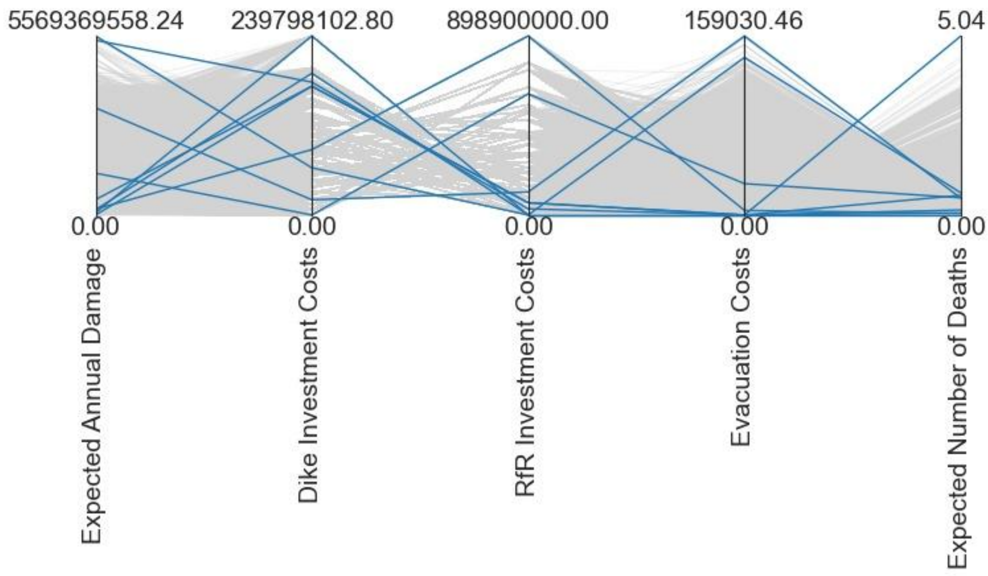

Figure 6: Best-worst-case scenarios

The policy results of the second round of optimisation over the multiple scenarios, were reduced by performing again subspace partitioning, this time for the expected number of deaths as well as the expected annual damage. This resulted in 363 optimal policies visualised in Appendix G. Again due to the high number of policies, the readability is limited and a further reduction of the solution space was required.

Robustness evaluation

Apart from the optimality of the policies in specific scenarios, their performance over multiple scenarios is crucial. The minimum regret analysis resulted in the selection of the top 10 cumulative-lowest-regret policies displayed in Figure 7. The values for the outcomes 'expected annual damage', 'evacuation costs' and 'expected number of deaths' are for all 10 zero, as the optimal results found in the preceding step applied to most policies, setting the difference between the minimum value of a scenario and the other values often equal to zero. "Scenario 1 option 6" and "Scenario 1 option 3" exhibited the lowest regret value over the 100 scenarios sampled for Dike Investment Costs and a rather low regret value for RfR investment costs and therefore are considered the most robust. The policy "Scenario 1 option 3" requires early investing in the RfR project Havikerwaard, later investment in RfR project Tichelbeekse Waard in the second and third time period, as well as dike increases in the Dike Rings 2, 3, 4, and 5 in the first time period by respective 3dm, 4dm, 6dm and 7dm. Furthermore, in time period 2 the dike in ring 4 has to be increased by another decimetre. The policy "Scenario 1 option 6" proposes very similar levers. The RfR project in dike ring 1 is moved to the second time period. The increases in the dikes differ only marginally. However, this policy foresees an evacuation warning 3 days before the threat is expected. The details for these policies can be found in Appendix F. Both policies represent a mix of different levers, emphasising the need for collaboration between the actors and a political discussion about who has to carry the burden of prevention and actual flood damage. Interesting to note is that besides the RfR project Tichelbeekse Waard, optimal and robust outcomes are achieved by investing early in levers, implying that preventive measures are in this case most effective.

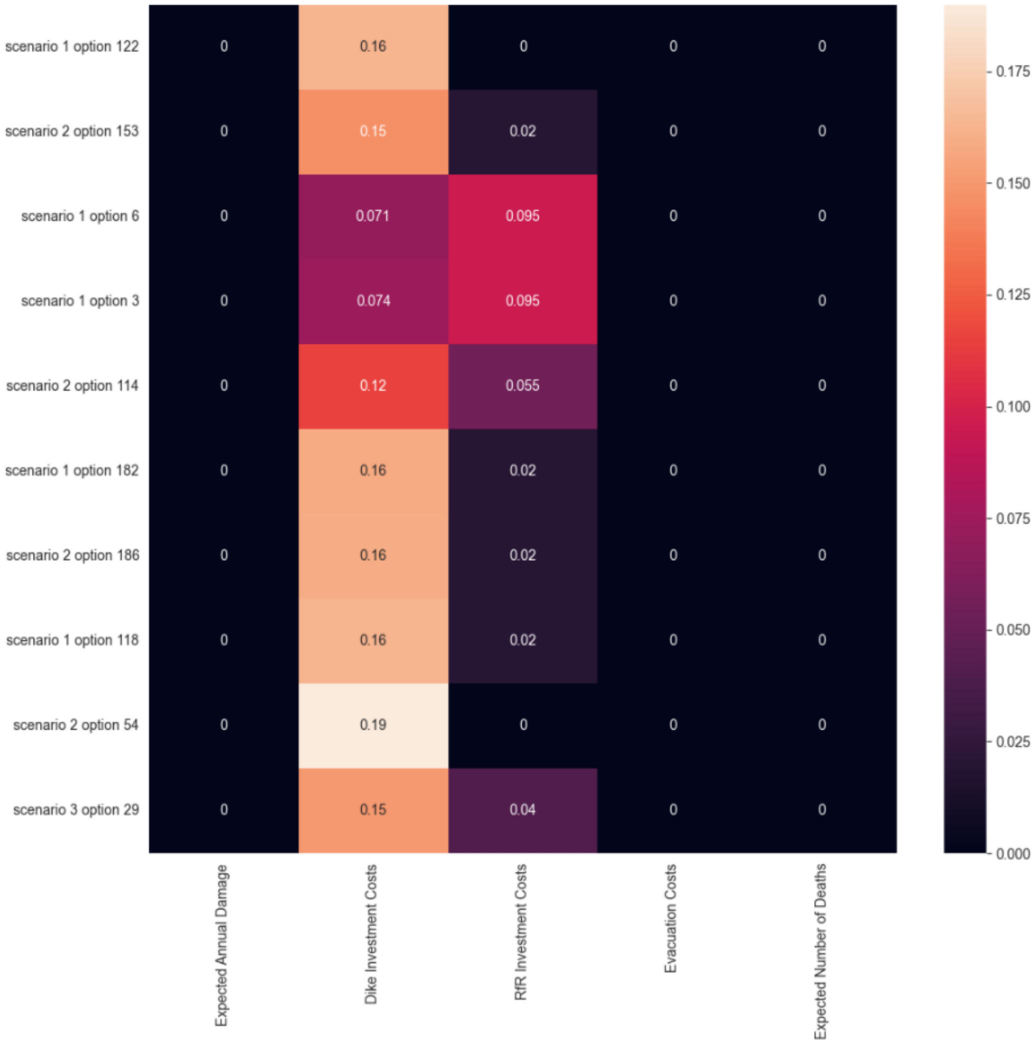

Figure 7: Heat map of minimum regret robustness check

Moreover, the signal-to-noise ratio of the top 10 policies was analysed to get insights into the robustness of each policy over the 100 scenarios. As the investments in dikes and RfR projects are independent of the uncertainties (as discovered in the open exploration), their standard deviation is constant zero and thus, the two outcome parameters are neglected for this part of the analysis. The policies with the lowest signal-to-noise ratio (lowest mean and lowest standard deviation of outcomes over the 100 sampled uncertainty scenarios, i.e. best and safest in terms of economic damage, evacuation cost and deaths) are “scenario 1 option 3”, “scenario 3 option 29” and “scenario 2 option 114” (Figure 8). Therefore, “scenario 1 option 3” seems to be robust in both dimensions, signal to noise ratio as well as minimum regret and is thus proposed as the policy to be implemented considering the goals of Rijkswaterstaat

In comparison to the final debate decision, it is interesting to note that nowhere the maximum dike increase was chosen by the optimisation, and RfR Tichelbeekse Waard was not even discussed in the debate; at the same time even without detailed modelling by the groups, the final debate outcome managed to be approximately comparable to this robust solution in that the first RfR project was selected in both processes as well as dike increases in most dike rings downstream were chosen. The policy “scenario 3 option 29” found during the last robustness check, was the only policy that was closer investigated that did not foresee an RfR at any point in time for dike ring 1. The variety of lever combinations proposed as robust optimal policies, stresses the importance of a multi-scenario MORDM analysis. The modelling of the levers over the uncertainties allows the actors to look past the policies studied in the open exploration and identify new sets of levers. One example is the time dimension that was only briefly touched upon in the final debate, and plays a crucial role in the optimal solutions found from the multi-scenario MORDM analysis as many levers are to be implemented in the second time period.

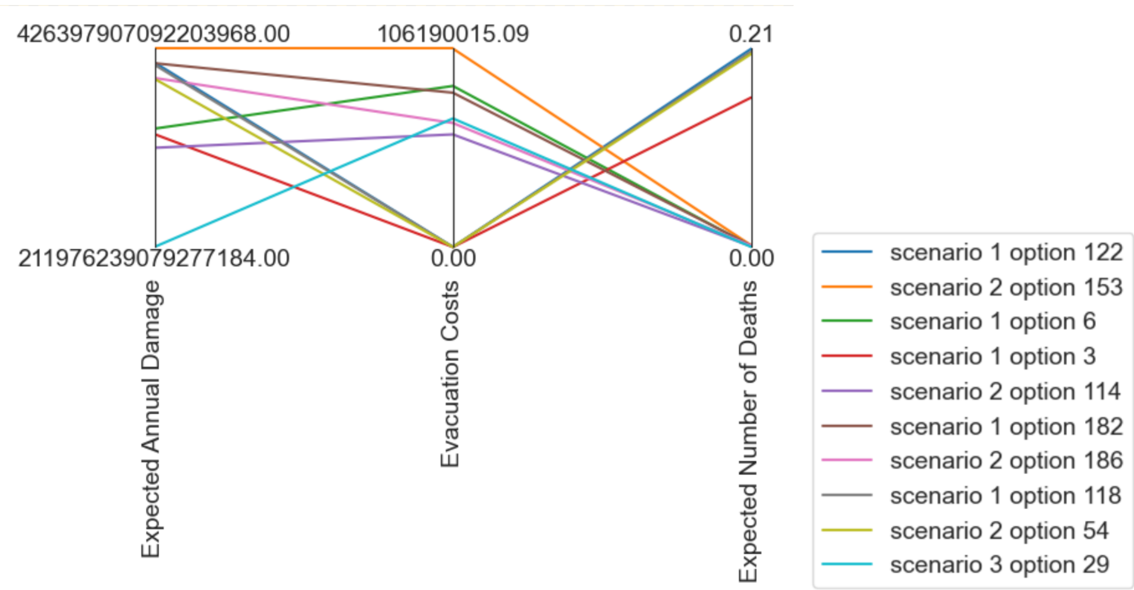

Figure 8: Parallel axes plot of signal-to-noise ratio for top 10 policies

Sensitivity Analysis

Lastly, Sobol indices were calculated for the 'robust policy' ("scenario 1 option 3") and the policy developed in the final debate (see Appendix I). Both policies are very sensitive to a failure of the dike in ring 1, both through direct effects of the uncertainty as well as interaction effects. Interestingly, for the combination "Final Debate Policy" and "Expected Number of Deaths", the direct effect (S1) is higher for some than the total index (ST), indicating that interaction effects reduce the influence of S1. Additionally, the policy from the final debate exhibits some sensitivity to the failure of the dike in ring 2. All other uncertainties seem to have almost no effect on the selected policies. Thus, decision-makers should consider the high risk of the dike in ring 1 notwithstanding the hydraulic load. Preventive measures that strengthen the dike in ring 1 might therefore be beneficial and should be included in the discussion. Furthermore, additional information should be gathered to improve the model in this aspect.

Discussion

The analysis was conducted in order to answer the research question: How *can deep uncertainty methods be applied to support building consensus around optimal and robust policies for the IJssel River flood management case?* is subject to two limitations, that are rooted in the proposed modelling tool, and in the use of this tool in the political arena.

Limits of the model and deep uncertainty methods conducted

The outcomes of the conducted analysis are subject to **limitations due to our limited computational power**. In particular, we had to lower the number of function evaluations (from 100,000 to 10,000) and the number of scenarios (first, 1000, then only 100) because of computing time. An important implication of this low number of function evaluations is the **lack of convergence**, implying that other 'optimal' solutions can be found when running the same code again (Maier et al. (2019). This late convergence is especially known for MOEAs in the field of water resource management (Reed et al., 2013). A different set of optimal solutions would also affect each policy's assigned minimal regret values in absolute terms, but not the signal-to-noise ratio and the ranking of policies by minimal regret. Hence, the robustness results of this analysis are more reliable than the optimality results. The optimality of the selected policies is further constrained by the fact that **no seed** was used for the multi-scenario MOEA which implies that the optimisation algorithm was based on only one random distribution per scenario. Eventually, **simple partitioning of outcomes** by performance threshold using the median on both axes (economic damage and casualties) had to be considered instead of Patient Rule Induction Algorithms which means no thresholds of uncertainties were identified that could guide adaptive planning.

Beyond this, the outcomes of this analysis also face limitations due to the way the case of the IJssel River has been modelled.

First, **for all time periods, the same uncertainty ranges** were assumed as given in the provided model. This has the benefit of yielding results that can easily be compared to the results of other actors. Still, uncertainty ranges, for instance in the case of possible flood wave shapes, may increase with time due to developments like climate change which can result in more extreme precipitation events and hence new flood wave shapes (Severinatne et al., 2021). This is particularly relevant as the time horizon of this model spans 200 years.

Second, **the levers considered do not cover the range of flood management techniques available** and actually used in the Netherlands, such as river deepening, dams, or indirect techniques like urban water management including measures to increase soil permeability. Increasing the number of levers analysed could achieve a more realistic policy outcome and raise the robustness of the strategy.

Third, the considered outcomes are also limited. In particular, the **model does not consider metrics that are essential for specific stakeholders** such as biodiversity metrics for the Environmental Interest Group. However, it is not necessarily recommended to increase the complexity of the model, but rather to use separate models combined and discuss trade-offs qualitatively (Saltelli et al., 2020).

Limits of the modelling approach as a decision-making tool

The modelling approach as a decision-making tool can be questioned due to the following reasons:

First, in the Ijssel River case, we could argue that **the availability of the modelling tool has prevented the stakeholders to focus on the essential** – to find common ground between diverging interests and come to a consensus-based policy. Ideally, the debate should have focussed on defining some thresholds and agreeing on them in order to build an adaptive pathway, i.e. a plan including possible developments, signposts and trigger responses as well as a monitoring system in order to be able to react immediately to changing factors in the environment (Walker, 2019). Instead, the stakeholders focussed on defending their by default preferred policies and interests, i.e. looking at the solution before looking at the range of possibilities. Our client, as debate organiser, should have focussed on this goal during the debates. As analysts, we could have assisted this with a focus on partitioning the subspace of uncertainties rather than calculating optimal and robust policies.

Furthermore, the modelling approach should primarily **be used for building a process and feeding the political discussion. The results should not be considered as the truth** or as a goal to necessarily reach. It can even be argued that several types of models, with different levers, uncertainties and outcomes, should be combined in the decision process, in order to broaden the view. This is especially true for the RfR measure (Schut et al., 2010). The scopes included by the models are indeed necessarily limited, as discussed in the previous section.

Finally, as addressed above, an **adaptive strategy would be favourable considering the large uncertainties** faced with (Haasnoot et al., 2013). Including adaptivity in models, however, is difficult due to the fact that thresholds and reactions to them heavily depend on negotiations between the actors. Models can supported by illustrating outcomes of specific pathways only if the actors come up with those in a joint decision-making process, in which potentially undesirable policy lock-ins are considered as well.

Conclusion & Advice

With our current knowledge, we would advise on using policy 'scenario 1 option 3' or one of the other four policies outlined in Appendix H Table H1. This is not to claim that these options would be stable Pareto-efficient optima for economic damage, costs and casualties under the three worst case scenarios. Rather, these policies are among the top 363 policies in terms of robustness. What all of the top 10 robust policies of this set have in common is dike heightening in Dike Rings 2, 3 and 5 in the first time step. Additionally, 8 out of these top 10 most robust worst-case policies implement some Room for River in Havikerwaard or Tichelbeekse Ward, mostly only towards the end of the century. Evacuation Warning Systems can be added at a rather low cost to further minimise casualties. To avoid failure and connected economic damages and casualties, regular checks and reinforcement of dikes in Dike Ring 1 is recommended when implementing 'scenario 1 option 3' as well as when sticking to the final debate outcome.

It is important not to take those top 10 policies as the definite solution to the multi-objective optimisation but rather to appreciate their position within the smaller set. There might be other, even more robust and cost-efficient policies which have not been identified using this non-converging optimisation. To be clear, 7.5×10^{50} number of different policy mixes would be possible, so even 363 is only a tiny subset of this. To have more confidence in the optimality of this solution, our script could be run on a supercomputing cluster for a number of function evaluations reaching convergence. This would also enable the use of more experiments in the re-evaluation under uncertainty and sensitivity analysis, improving the robustness of the analysis itself.

Still, even a supercomputed robust and Pareto-efficient optimum for the objective of minimising total damage, costs and casualties will not necessarily be accepted by the political actors. Under this 'optimal' policy, some dike rings might be disproportionally burdened by mitigation measures for downstream communities. Hence, compensation will play a key role in finding political consensus. Additionally, as mentioned before this model and problem formulation misses some of the key objectives of political actors which need to be given consideration outside of the pure modelling or, better, by using complementary models.

Most importantly, Rijkswaterstaat should acknowledge that the policy process does not end with this policy, even with the aim of long-term solutions. The process will continue, which is why we recommend facilitating an adaptive strategy designed with the stakeholders.

References

Bankes, S., 1993. Exploratory Modeling for Policy Analysis. Operations Research 41, 435–449.

Bartholomew, E., Kwakkel, J.H., 2020. On considering robustness in the search phase of Robust Decision Making: A comparison of Many-Objective Robust Decision Making, multi-scenario Many-Objective Robust Decision Making, and Many Objective Robust Optimization. Environmental Modelling & Software 127, 104699.

Bryant, B.P., Lempert, R.J., 2010. Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. Technological Forecasting and Social Change 77, 34–49.

Haasnoot, M., Kwakkel, J.H., Walker, W.E., Maat, J. ter, 2013. Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. Global Environmental Change 23, 485–498.

Hoss, F., Jonkman, S. N., & Maaskant, B. (2011, September). A comprehensive assessment of multilayered safety in flood risk management–the Dordrecht case study. In *Proceedings of the 5th International Conference on Flood Management (ICFMS),* Tokyo, Japan (pp. 57-65).

IPCC, 2022: Summary for Policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In: *Climate Change 2022: Impacts, Adaptation, and Vulnerability.* Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 3-33, doi:10.1017/9781009325844.001. (pp 8)

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. Environmental Modelling & Software, 96, 239-250.

Kwakkel, J.H., 2019. A generalized many-objective optimization approach for scenario discovery. Futures & Foresight Science 1, e8.

Kwakkel, J.H., Haasnoot, M., 2019. Supporting DMDU: A Taxonomy of Approaches and Tools, in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty. Springer International Publishing, Cham, pp. 355–374. https://doi.org/10.1007/978-3-030-05252-2_15.

Maier, H.R., Razavi, S., Kapelan, Z., Matott, L.S., Kasprzyk, J., Tolson, B.A., 2019. Introductory overview: Optimization using evolutionary algorithms and other metaheuristics. Environmental Modelling & Software 114, 195–213.

McPhail, C., Maier, H.R., Kwakkel, J.H., Giuliani, M., Castelletti, A., Westra, S., 2018. Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? Earth's future 6, 169–191.

Razavi, S., Jakeman, A., Saltelli, A., Prieur, C., Iooss, B., Borgonovo, E., Plischke, E., Lo Piano, S., Iwanaga, T., Becker, W., Tarantola, S., Guillaume, J.H., Jakeman, J., Gupta, H., Melillo, N., Rabitti, G., Chabridon, V., Duan, Q., Sun, X., Smith, S., Sheikholeslami, R., Hosseini, N., Asadzadeh, M., Puy, A., Kucherenko, S., Maier, H.R., 2021. The Future of Sensitivity Analysis: An essential discipline for systems modeling and policy support. Environmental Modelling & Software 137, 104954.

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: The past, present, and future. Advances in Water Resources 51, 438–456.

Rijke, J., van Herk, S., Zevenbergen, C., & Ashley, R. (2012). Room for the river: Delivering integrated river basin management in the netherlands. International Journal of River Basin Management, 10(4), 369–382.

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., Wu, Q., 2019. Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. Environmental Modelling & Software 114, 29–39.

Schut, M., Leeuwis, C., & van Paassen, A. (2010). Room for the river: Room for research? The case of depoldering De Noordwaard, the Netherlands. Science and Public Policy, 37(8), 611–627. https://doi.org/10.3152/030234210X12767691861173.

Seneviratne, S.I., X. Zhang, M. Adnan, W. Badi, C. Dereczynski, A. Di Luca, S. Ghosh, I. Iskandar, J. Kossin, S. Lewis, F. Otto, I. Pinto, M. Satoh, S.M. Vicente-Serrano, M. Wehner, and B. Zhou, 2021: Weather and Climate Extreme Events in a Changing Climate. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*[Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1513–1766, doi: 10.1017/9781009157896.013.

Walker, W.E., Marchau, V.A.W.J., Kwakkel, J.H. (2019). Dynamic Adaptive Planning (DAP), in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty. Springer International Publishing, Cham, pp. 53–69.

Watson, A.A., Kasprzyk, J.R., 2017. Incorporating deeply uncertain factors into the many objective search process. Environmental Modelling & Software 89, 159–171. https://doi.org/10.1016/j.envsoft.2016.12.001.

Appendix

Appendix A: XLRM framework

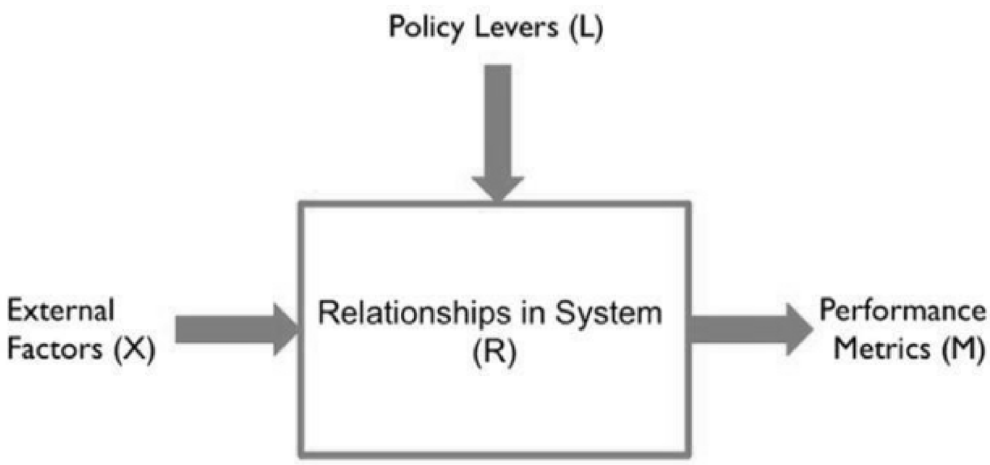

Figure A1: XLRM Framework. External factors (X) represent uncertainties; Levers (L) are the set of measures studied that combined translate into policies; Performance metrics (M) are indicators assessing how the levers perform; Relationships (R) are a set of rules or mathematical expressions linking X, L and M.

Appendix B: Map of the case study

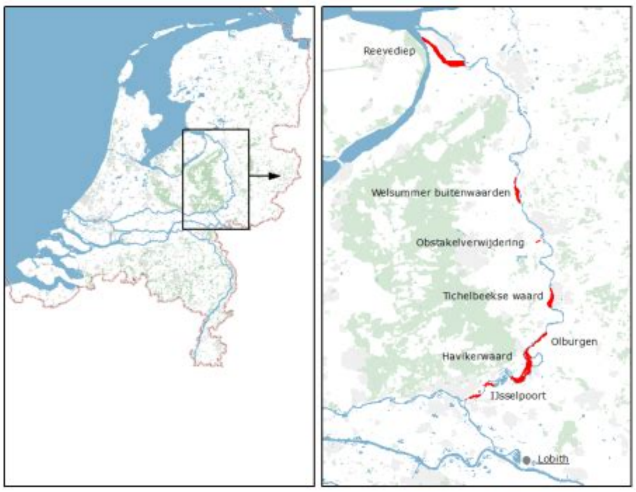

Figure B1: Map of the Ijssel region where the Room for River projects are located (in red). Ciullo, n.d., p.11.

Appendix C: Problem formulations

Table C1: Outcomes considered in each problem formulation

Outcome	PF0	PF1	PF2	PF3	PF4	PF5
Expected Annual Damage	X	X	X		X	
Total Investment Costs		X				
Dike Investment Costs			X		X	
RfR Investment Costs			X	X	X	
Evacuation Costs			X	X	X	X
Total Costs				X		X
Expected Number of Deaths	X	X	X	X		X

Appendix D: Python code and data

The used jupyter notebooks and data can be found in the following github repository:

AaronParis/epa1361_group25_2023
https://github.com/AaronParis/epa1361_group25_2023.git

Appendix E: Error message with random seeds calculation

Figure E1: Error message with random seeds calculation (potentially a bug?)

Appendix F: Results MORDM analysis

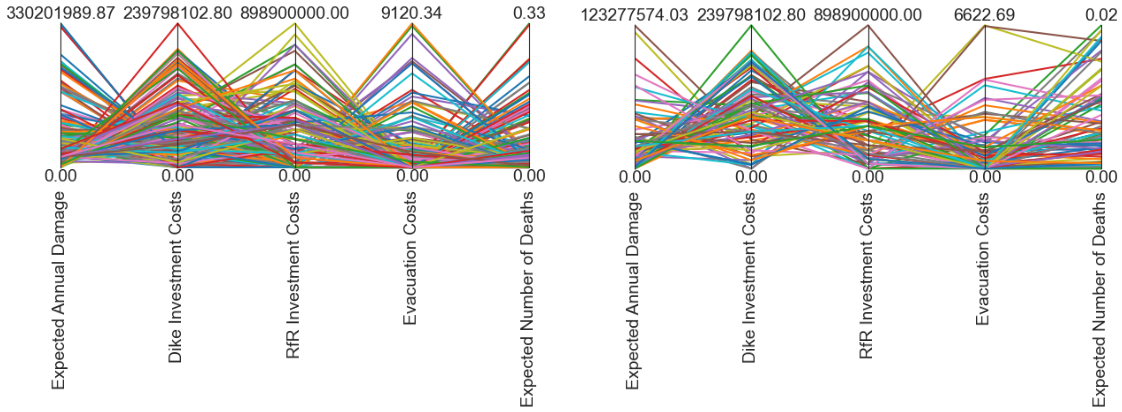

Figure F1: Single-scenario MORDM policy optimisation (left: without subspace partitioning, right: with subspace partitioning for expected number of deaths)

Appendix G: Results multi-scenario MORDM analysis

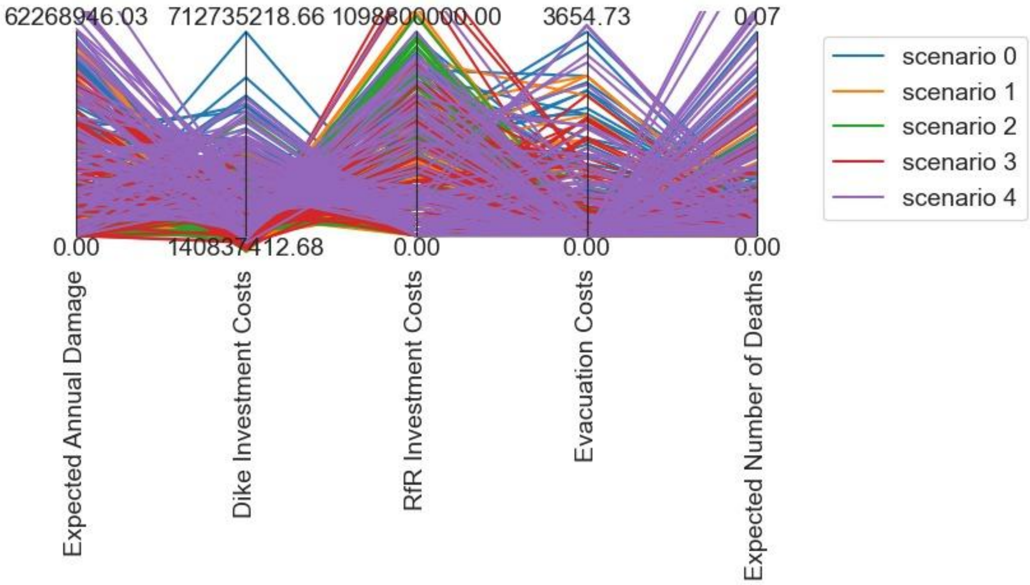

Figure G1: Multi-Scenario MORDM policies

Appendix H: Results top 10 robust multi-scenario MORDM policies

Table H1: Robust policies of multi-scenario MORDM (minimum regret and signal to noise ratio)

Policy	Scenario 1 option 3	Scenario 1 option 6	Scenario 3 option 29	Scenario 2 option 114
0_RfR 0	1	0	0	0
0_RfR 1	0	1	0	1
0_RfR 2	0	0	0	0
1_RfR 0	0	0	0	0
1_RfR 1	0	0	0	0
1_RfR 2	0	0	0	0
2_RfR 0	0	0	1	0
2_RfR 1	1	1	1	0
2_RfR 2	1	1	0	0
3_RfR 0	0	0	0	0
3_RfR 1	0	0	0	0
3_RfR 2	0	0	0	0
4_RfR 0	0	0	0	0
4_RfR 1	0	0	0	0
4_RfR 2	0	0	0	0
EWS_DaysToThreat	0	3	4	3
A.1_DikeIncrease 0	0	0	3	0
A.1_DikeIncrease 1	0	0	0	0
A.1_DikeIncrease 2	0	0	0	0
A.2_DikeIncrease 0	3	4	5	7
A.2_DikeIncrease 1	0	0	0	0
A.2_DikeIncrease 2	0	0	0	0
A.3_DikeIncrease 0	6	7	6	7
A.3_DikeIncrease 1	0	0	0	0
A.3_DikeIncrease 2	0	0	0	0
A.4_DikeIncrease 0	4	1	2	7
A.4_DikeIncrease 1	1	2	1	0
A.4_DikeIncrease 2	0	0	0	0
A.5_DikeIncrease 0	7	5	6	7
A.5_DikeIncrease 1	0	0	0	0
A.5_DikeIncrease 2	0	0	0	0

Table H2: Top 10 policies with minimum regret of multi-scenario MORDM

policy	scenario 1 option 122	scenario 2 option 153	scenario 1 option 6	scenario 1 option 3	scenario 2 option 114	scenario 1 option 182	scenario 2 option 186	scenario 1 option 118	scenario 2 option 54	scenario 3 option 29
0_RfR 0	0	0	0	1	0	0	0	0	0	0
0_RfR 1	0	0	1	0	1	0	0	0	0	0
0_RfR 2	0	0	0	0	0	0	0	0	0	0
1_RfR 0	0	0	0	0	0	0	0	0	0	0
1_RfR 1	0	0	0	0	0	0	0	0	0	0
1_RfR 2	0	0	0	0	0	0	0	0	0	0
2_RfR 0	0	0	0	0	0	0	0	0	0	1
2_RfR 1	0	0	1	1	0	1	0	1	0	1
2_RfR 2	0	1	1	1	0	0	1	0	0	0
3_RfR 0	0	0	0	0	0	0	0	0	0	0
3_RfR 1	0	0	0	0	0	0	0	0	0	0
3_RfR 2	0	0	0	0	0	0	0	0	0	0
4_RfR 0	0	0	0	0	0	0	0	0	0	0
4_RfR 1	0	0	0	0	0	0	0	0	0	0
4_RfR 2	0	0	0	0	0	0	0	0	0	0
EWS_DaysToThreat	0	3	3	0	3	3	3	0	0	4
A.1_DikeIncrease 0	2	2	0	0	0	2	2	2	2	3
A.1_DikeIncrease 1	0	0	0	0	0	0	0	0	0	0
A.1_DikeIncrease 2	0	0	0	0	0	0	0	0	0	0
A.2_DikeIncrease 0	7	7	4	3	7	7	6	7	7	5
A.2_DikeIncrease 1	0	0	0	0	0	0	0	0	0	0
A.2_DikeIncrease 2	0	0	0	0	0	0	0	0	0	0
A.3_DikeIncrease 0	7	7	7	6	7	6	7	7	7	6
A.3_DikeIncrease 1	0	0	0	0	0	0	0	0	0	0
A.3_DikeIncrease 2	0	0	0	0	0	0	0	0	0	0
A.4_DikeIncrease 0	1	1	1	4	7	1	5	1	6	2
A.4_DikeIncrease 1	0	0	2	1	0	0	0	0	0	1
A.4_DikeIncrease 2	0	0	0	0	0	0	0	0	3	0
A.5_DikeIncrease 0	7	4	5	7	7	7	7	7	7	6
A.5_DikeIncrease 1	0	0	0	0	0	0	0	0	0	0
A.5_DikeIncrease 2	0	0	0	0	0	0	0	0	0	0

Appendix I: Results sensitivity analysis

Table I1: Total and first order Sobol indices for the “Robust Policy” and “Final Debate Policy“ and the outcome of interest “Expected Number of Deaths” and “Expected Annual Damage”

	Robust Policy - Expected Number of Deaths		Robust Policy - Expected Annual Damage		Final Debate Policy - Expected Number of Deaths		Final Debate Policy - Expected Annual Damage	
	S1	ST	S1	ST	S1	ST	S1	ST
A0_ID flood wave shape	0.002	0.002	0.001	0.002	0.002	0.003	0.001	0.002
A1_Bmax	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000
A1_Brate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A1_pfail	0.931	0.935	0.945	0.981	0.797	0.783	0.875	0.885
A2_Bmax	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A2_Brate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A2_pfail	0.027	0.030	0.016	0.016	0.298	0.287	0.171	0.164
A3_Bmax	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A3_Brate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A3_pfail	0.023	0.024	0.003	0.004	0.001	0.002	0.000	0.000
A4_Bmax	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A4_Brate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A4_pfail	0.003	0.001	0.004	0.001	0.004	0.003	0.010	0.006
A5_Bmax	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A5_Brate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A5_pfail	0.006	0.008	0.004	0.005	0.000	0.000	0.000	0.000
discount rate 0	0.000	0.000	0.002	0.010	0.000	0.000	0.000	0.008
discount rate 1	0.000	0.000	0.016	0.010	0.000	0.000	0.003	0.009
discount rate 2	0.000	0.000	0.001	0.009	0.000	0.000	-0.002	0.007

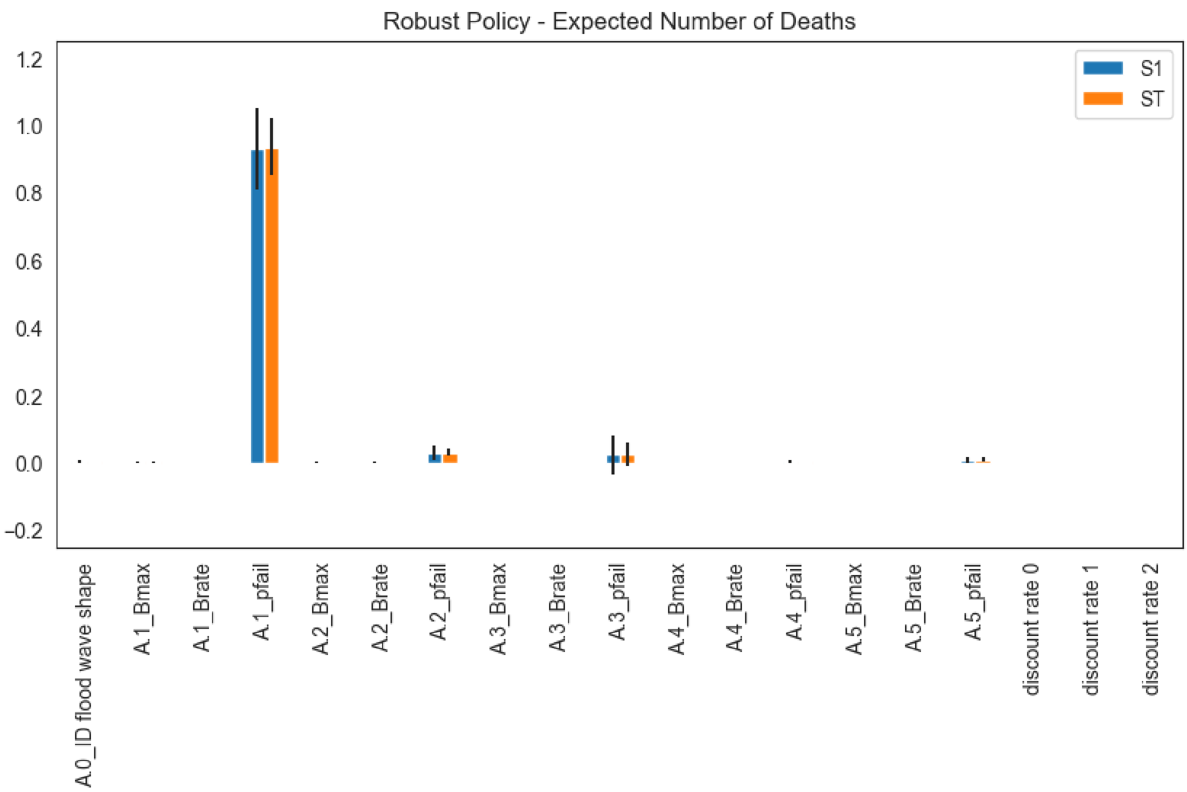

Figure I1: Total and first order Sobol indices for the “Robust Policy” and the outcome of interest “Expected Number of Deaths

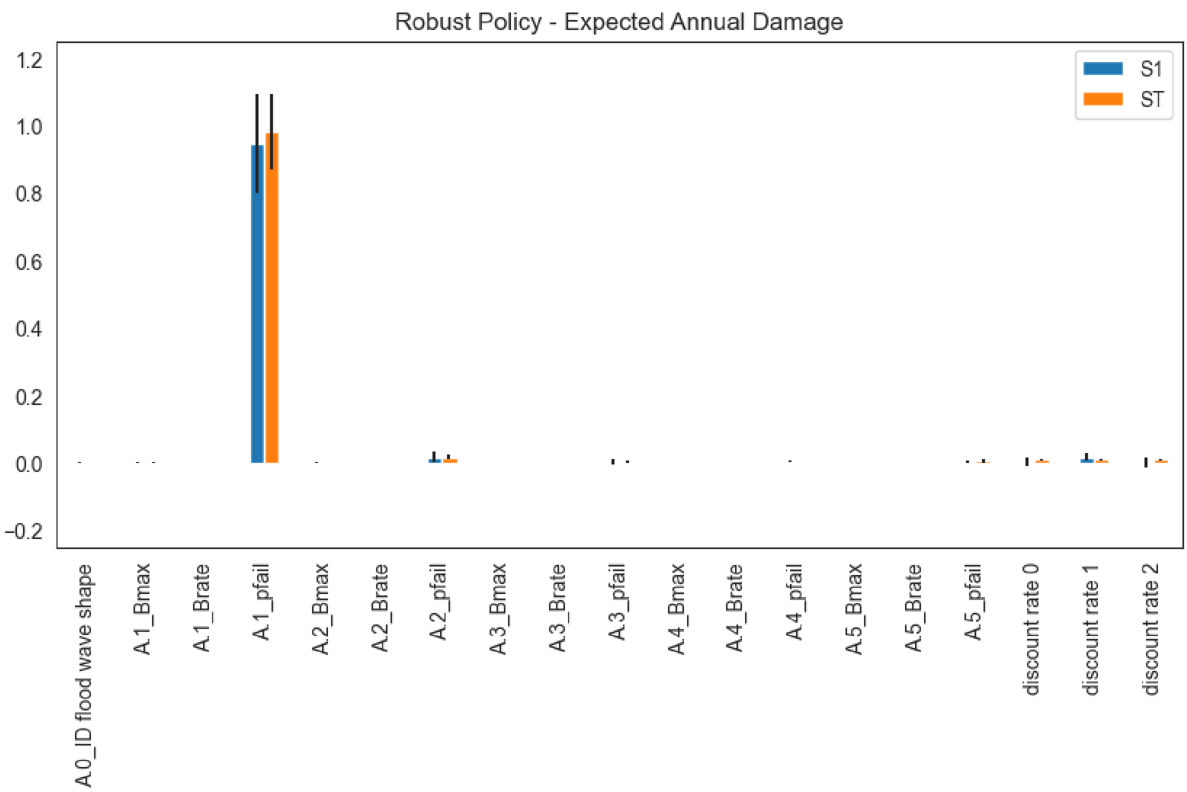

Figure I2: Total and first order Sobol indices for the “Robust Policy” and the outcome of interest “Expected Annual Damage”

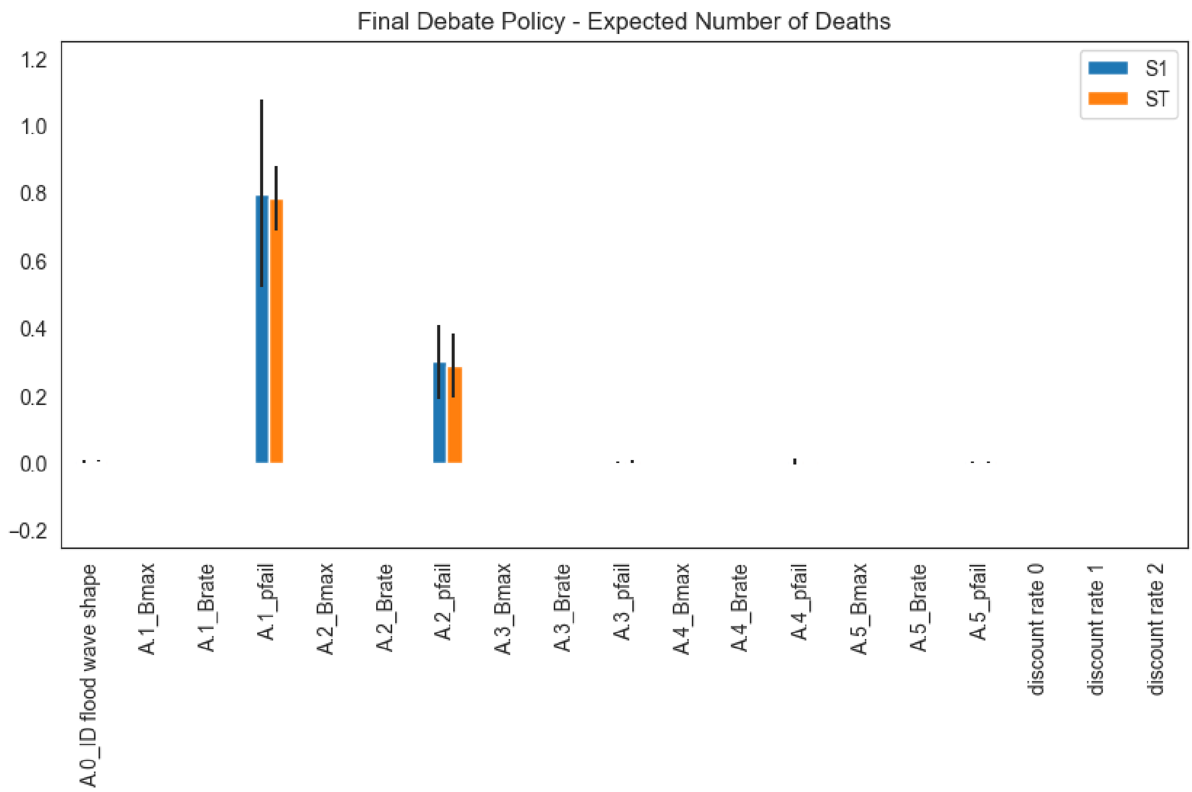

Figure I3: Total and first order Sobol indices for the “Robust Policy” and the outcome of interest “Expected Number of Deaths”

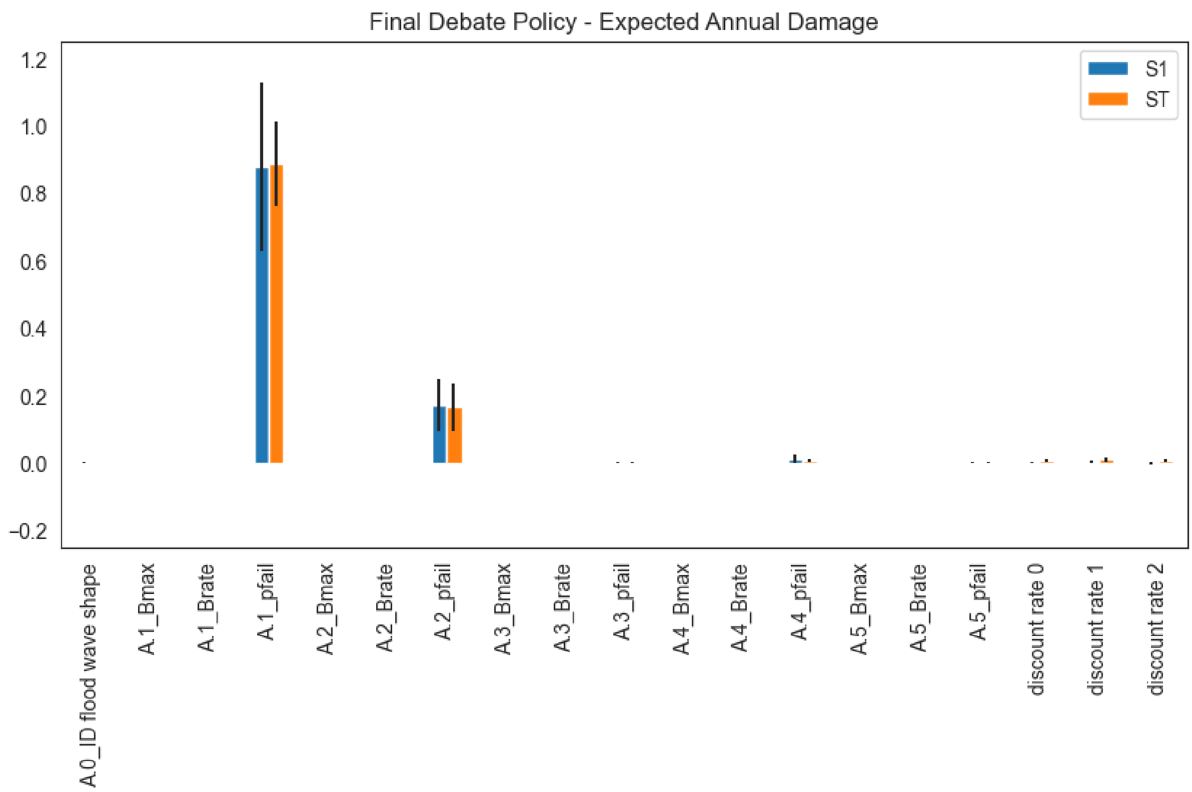

Figure I4: Total and first order Sobol indices for the “Robust Policy” and the outcome of interest “Expected Annual Damage”