A Resilient IJssel River

An exploratory decision-support report providing water management policy alternatives under deep uncertainty for the upper branch of the IJssel River

EPA1361: Model-Based Decision-Making

Group 10

Delft University of Technology

TU Delft

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by

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Student Name	Student Number
Irene van den Bent	4603249
Hidde Bijlard	5418631
Mels van Gameren	4490282
Guillermo Prieto Viertel	5366909
Kerem Tunca	4601386

Instructor:	Dr.ir. J.H. (Jan) Kwakkel
Institution:	Delft University of Technology
Place:	Faculty of Technology, Policy, and Management, Den Haag
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Cover Image: River in The Netherlands. Image taken from Beeldbank Rijkswaterstaat.

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Summary

In this report, robust policies for water management on the IJssel River are identified. The specific focus is on mitigating flood risks by implementing Room for the River (RfR) projects relative to using alternative measures of protection such as dike heightening. Using a simulation model, it is analyzed how the client - the environmental interest group - can design a water management policy for the IJssel river that maximizes the environmental potential of RfR while being robust and effective under different uncertain future scenarios. The robust policy optimization process focuses on the computation of policies which are maximally effective against the worst manifestation of possible futures. Policies were evaluated based on five key performance indicators: 'Expected annual damage', 'Expected number of deaths', 'RfR costs', 'Dike heightening costs', and 'Evacuation costs'.

Throughout the analysis, the multi-actor arena of the decision-making process is central as it influences viable policy options for the client. In the light of this central point in the analysis, not one, but multiple possible policy options are recommended in this report. This gives the client more freedom and possibilities in the (political part of the) decision-making process. In general, the identified policies steer in the direction of implementing RfR projects to mitigate flood risks. The recommendations are as follows:

- The first policy option limits expected annual damage and RfR costs, but does include a relatively high amount of dike heightening. When looked at in the multi-actor aspect of the problem, this policy option would be the fittest one in case of cooperation with actors that represent farmlands or densely populated areas. Because of the relatively low amount of RfR measures in this policy option, these actors will not have to sacrifice a lot of land and thus are likely to accept it. Partnering with local stakeholders would be recommended, as they prioritize outcomes similarly.
- The second policy option largely consists of RfR measures and thus can be seen as an environmentally friendly option. It therefore aligns most with the interests of the client. The large number of RfR measures minimizes the amount of expected deaths most effectively, but also exceeds budget constraints set by Rijkswaterstaat. The minimization of deaths aligns with the interests if the Delta Commission, so possibilities for cooperation do emerge here. This policy option would be beneficial in case budget constrains are not strict and cooperation with actors representing farmlands and densely populated areas are not needed.
- A third policy option would be most fitting when the focus does not lay on minimizing investment costs and when sub-optimal robustness against some of the worst possible scenarios is acceptable. In light of the multi-actor perspective, this option represents the middle-mode when it comes to finding suitable alliance partners.
- The fourth policy option minimizes the investment costs. In effect, lower investments compromise on robustness and can result in higher annual damage and a higher number of deaths. This policy option would be most suitable in case of the budget constraint being strictly enforced by RWS. At the same time it does result in a relatively high amount of expected deaths, which is not favoured by the Delta Commissioner. Partnering with the Transport company might be possible, as they do not prioritize annual damage or number of deaths when negotiating policies.

Moreover, given the relatively high power of the stakeholders from Doesburg and Zutphen due to their potential to be big 'losers', it is in the favor of the client that the found policies entail RfR for both these locations. It is therefore recommended that the client reaches out to these stakeholder and seeks alliances in order to increase the likelihood of RfR being implemented.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
EMA	Exploratory Modeling and Analysis
KPI	Key Performance Indicator
LHS	Latin Hypercube Sampling
MOEA	Many-Objective Evolutionary Algorithm
MORDM	Many-Objective Robust Decision Making
MORO	Many-Objective Robust Optimization
NSGA	Nondominated Sorting Genetic Algorithm
PRIM	Patient Rule Induction Method
RfR	Room for River
RWS	Rijkswaterstaat

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1 Introduction

With a third of the country situated below sea level, the Netherlands is famous for their water management which prevents against major flooding (Infrastructure and Management, 2014; Pim, 2021). Here, flooding is defined as the (temporary) submergence of land by water outside its normal confines (Networks, 2021). Continuous innovation in water management techniques and fruitful cooperation between actors on multiple governmental levels ensure the art of flood protection in a challenging and vulnerable environment (Brouwer and Biermann, 2011; Disco, 2002). The most recent addition to the Dutch water management portfolio is Room for the River (RfR) (Rijke et al., 2012). This strategy literally aims to provide ”room for the river” instead of building and heightening dikes (H. De Bruijn et al., 2015).

The concept of resilience, i.e. the ability to endure a rise in water levels and return to the original water levels, is key within the RfR strategy (Desouza and Flanery, 2013; Alphen, 2020). Specifically, RfR accepts that flooding may occur and consequently seeks to exploit the advantages of flooding while mitigating the disadvantages (Warner et al., 2012; STOWA, 2021). In so doing, RfR utilizes natural dynamics such as water, wind, sediment, and vegetation to mitigate the disadvantages of flooding according to the wider strategy of ’working with nature’ (Zevenbergen, 2013). Advantageously, this strategy may lead to a positive effect on nature by allowing it to flourish (Ministry of Agriculture and Quality, 2021).

Besides introducing a new paradigm in flood protection, RfR also introduces more egalitarian forms of multi-actor network governance by including state-, provincial-, and municipality-level actors (Warner et al., 2012). This could make the decision-making process more complex as a new policy can only be implemented when the actions and interests of all stakeholders are aligned (STOWA, 2021). Nevertheless, it prevents policy designs in which there are clear ’winners’ and ’losers’, thereby advantageously preventing ’losers’ that sabotage or block the decision-making process (H. De Bruijn et al., 2015).

With RfR thus being a strategy with both technical and governance innovation, designing and implementing new RfR projects requires extensive *a priori* analysis. In this report, the case of the IJssel River is analyzed for which a new water management policy is needed due to the increasing pressure of global warming on flood risk in the Netherlands. With the purpose of doing so, the IJssel river flood risk management is approached as a system in which components and stakeholders such as resources, processes, people, and institutions interact (Desouza and Flanery, 2013). The complexity that arises from the interaction of the system elements requires an exploratory approach to aid in the decision-making process.

1.1. Room for the River: A case study of the IJssel River

This study will focus on the locations of Doesburg, Cortenoever, Zutphen, Gorssel, and Deventer (Figure 1.1). Each of these five locations of interest represent a separate dike ring that is prone to flooding (Huizinga, 2012). Dike rings are areas in The Netherlands which will be flooded in case of extreme hydraulic load from the sea, the lake IJsselmeer, or one of the other big rivers (Jak and Kok, 2000). For each of these locations, a tailored water management policy advice will be defined.

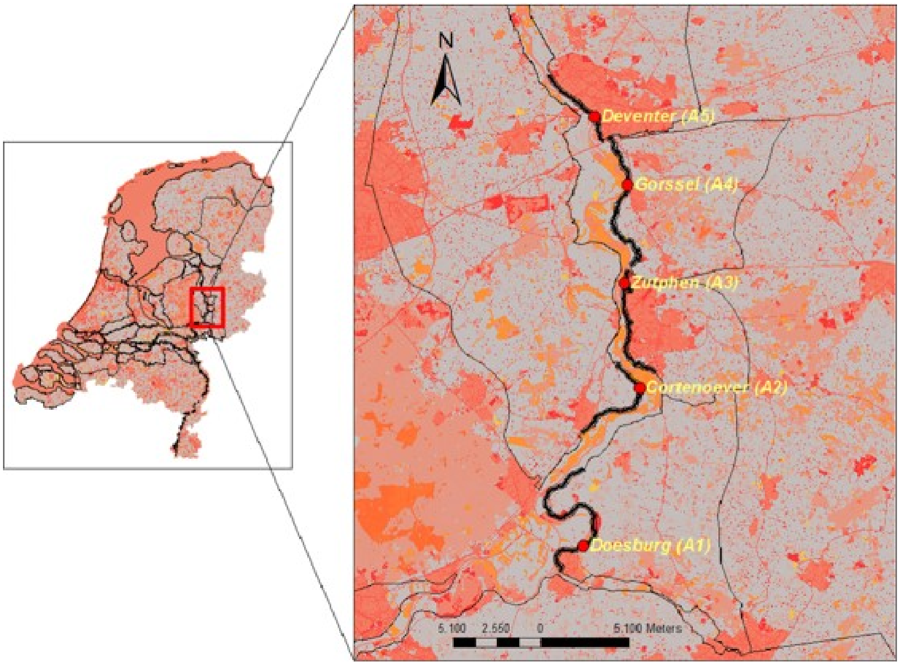


Figure 1.1: The area of interest with the IJssel River flowing from south to north. Red dots indicate cities or towns representing distinct locations of interest along the river (thick black lines). Image retrieved from (Ciullo, K. M. d. Bruijn, et al., 2019)

1.2. Water management policy design: A multi-actor case

Stakeholders for each of the locations of interest along the IJssel River are all (inter)connected in an actor arena (Figure 1.2). This results in a multi-actor decision-making process for the design of a final water management policy in which different interests need to be weighted (H. De Bruijn et al., 2015). A detailed description of all the stakeholders can be found in Appendix A. In general, it was found that most stakeholder agree on minimizing deaths and damage costs due to flooding while keeping costs to do so as low as possible. The central stakeholder is Rijkswaterstaat (RWS) that is responsible of maintaining and building flood management infrastructures (Infrastructure and Management, 2015). In the case of the IJssel River, they need to propose a policy that resonates with all involved actors to ensure its implementation (Van Doren et al., 2013; Lemke and Harris-Wai, 2015). This is especially important due to the formal power held by the Delta Commission which grants them veto power against project proposals they deem unfit, including a lack of addressing the interests of key involved stakeholders (Geest et al., 2008).

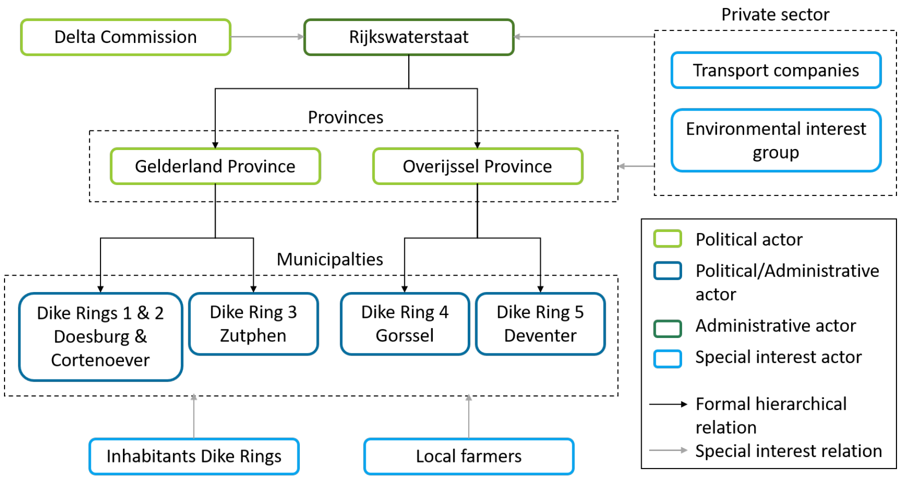


Figure 1.2: Actor arena for the decision-making process on a water management policy for the IJssel river. Administrative actors are vested with public authority and are concerned by the collective problem under consideration (Knoepfel et al., 2011).

1.3. Characterizing water management systems: Managing uncertainty

Floods are stochastic events governed by external triggers and complex internal dynamics causing the entire IJssel river flood risk management system to be highly complex and uncertain (Belayneh et al., 2009). Mental models are therefore not sufficient to analyze the system because these models can only contain a limited amount of information of the real system (Forrester, 1961).

Modeling and simulation is used to explore complex systems for which our mental models are not sufficient. Uncertainty is, however, still present in simulation models due to the modeler's imperfect knowledge of the real world (Forrester, 1961). Another source of uncertainty originates in the limited capacity to predict complex systems (J. H. Kwakkel and Haasnoot, 2019). A third and final source of uncertainty comes from the multiple possible interpretations that involved stakeholders can have of the system, problem formulation, and solution proposal as a consequence of their different values (J. H. Kwakkel and Haasnoot, 2019; Moallemi, J. Kwakkel, et al., 2020). The combination of this range of uncertainties that are not reducible to mere probabilities has been labeled as deep uncertainty (Lempert, 2003).

Flood risk management is characterised by its deep uncertainty and should be analysed accordingly. Besides the political aspect of uncertainty that arises from its multi-actor network governance, the system is inherently uncertain. First, there are multiple uncertain factors such as discount rates of dikes that affect the performance of the system and under which there is almost no control on. Second, a complex system like the environment is very difficult to predict. As Kasprzyk et al. (2013) points out, land use change and climate change are examples of human-induced activities that introduce deep uncertainty into the model. All in all, as the manifestation of the uncertainties in the system could result in multiple possible futures, there is a need for a policy that performs effectively in as many of these futures as possible.

1.4. Problem framing from the client perspective: Environmental Interest Group

This study is executed on behalf of the Environmental Interest Group (referred to as 'the client' from this point onwards) (Figure 1.2). This stakeholder aims to protect and/or improve the environmental status quo surrounding the IJssel river as much as possible. Due to the overarching character of the client, they operate beyond province borders and supports collective participation to preserve the ecology. In this regard, the client serves as an intermediary between the individual municipalities to impose a coercive order of distributive justice that takes into account the individual interests, but pursues a cosmopolitan protection of the environment (Pogge, 2005). This political stance clashes with the contractual position of the several municipalities and national institutions that have moral and political obligations to their citizens at different aggregation levels (Nagel, 2005). In an effort to work towards consensus between the client and the other stakeholders, the analysis considers general interests such as a fair distribution of costs and benefits of the policy recommendation.

To achieve their goal, the client relies on a number of strategies out of which we highlight the following (Pagé, 2004). First, the actor can take direct action in the form of environmental activism as public non-violent mobilization influences public opinion against the unsustainable practices of governments or corporations. Second, by means of public meetings, magazine articles or campaigning, the group can increase public awareness and education on sustainable practices. Third, the client could frame their opponents as villains that willingly refuse to acknowledge the importance of ecological restoration (H. d. Bruijn, 2019). Framing their opponents as villains influences the perception of the public on their opponents, which potentially benefits the position of the client. Finally, and the strategy in practice in the present case, is political lobbying. Representatives of the client persuade politicians to vote on legislation that favors the environmental interests. Likewise, they can lobby private groups such as the Transport company to collectively pressure the government or media gatekeepers to reach a global audience.

The client's preferred water management strategy is RfR because it (i) transforms polluting agricultural land into natural reserve areas (Sustainia, 2018), (ii) enhances the scenic beauty of countryside and urban environments (Klijn et al., 2013), (iii) is geo-ecologically robust as it is self-sustained and acquires a high degree of natural stability (Klijn et al., 2013), and (iv) enhances biodiversity (Straatsma et al., 2017; Conservation, 2012).

1.4.1. Problem formulation

The general aim of the new water management policy is to protect the entire region of the IJssel river from flooding. The client wants this policy to be as environmentally friendly as possible, and hence prefers the implementation of RfR over alternative flood protection measures. The diversity in the preferences and interests of other stakeholders, however, leads to different preferred policies among stakeholders. These include alternative flood protection measures. It is therefore of strategic importance for the client to identify which stakeholders push for less environmental friendly policies, which can be labelled as opponents. The principal opponent of the client is the Transport company, who is interested in maximizing profit by promoting the navigation of large vessels through the IJssel river. To meet this objective, the Transport company prioritizes having sufficiently high water levels so that goods can be transported on large vessels. Because of that, dike heightening is the preferred water management policy for the Transport company, in contrary to the RfR policies that are preferred by the client.

RWS will weigh all the interests of the stakeholders in the final policy proposal. The client understands that for some locations RfR is not economically feasible, nevertheless, their objective is to convince other stakeholders to vote for RfR.

Based on the perspective of the client, the following goals can be identified:

- Ensure environmental impact is taken into account in water management policy design.
- Maximize the potential of ecological restoration.
- Minimize dike heightening as this is working against nature.
- Reduce the impacts of flooding across the entire IJssel river region.

Based on these goals, the following research question has been formulated:

Which IJssel river water management policy best serves the interest of the Environmental interest group by maximizing the environmental potential of RfR, while being robust and effective under deep uncertainty as well as being acceptable in the multi-actor decision making process?

In this formulation, 'maximizing' relates to acknowledging that implementing RfR projects may not be feasible, although it could arguably be the best environmental option.

In order to answer the posed question, this report presents a roadmap towards recommendations for the client. Chapter 2 operationalizes the problem formulation and details the methodology used during the analysis. Chapter 3 presents the findings from the analysis. Chapter 4 discusses any shortcomings of the analysis and their implications on the presented results. Finally, chapter 5 will present policy recommendations for the client.

2 Methods

Given the deep uncertainty of the system, the model-based decision support provided in this report is of exploratory nature (J. H. Kwakkel and Haasnoot, 2019). Exploratory modelling provides a wide overview of the implications on decision-making under the various uncertainties. More specifically, it captures known uncertainties by systematically exploring the impact of a range of defined assumptions by means of intensive computational experiments (Moallemi, J. Kwakkel, et al., 2020). To this end, the analysis in this report was executed using the Exploratory Modeling Workbench by J. H. Kwakkel (2017). This Python library advantageously supports exploratory modeling, scenario discovery, and (multi-objective) robust decision-making.

2.1. Problem operationalization: Water management simulation model

In order to execute an insightful analysis, the problem formulation has to be effectively transformed into the model terms. On this account, the XLRM framework was used, which ensures that an exploratory simulation model is created (Figure 2.1) (J. H. Kwakkel, 2017; Moallemi, Elsawah, et al., 2020). Specifically, the XLRM framework ensures that exogenous uncertainties (X), i.e. factors outside the control of decision-makers that could influence the success of their strategies, are incorporated into a simulation model. Given some pre-defined policy levers (L), various combinations of policy measures can be explored to design multiple alternative strategies for decision-makers to explore. By means of the modeled relationships (R) in the water management system, it is possible to evaluate how system attributes evolve over time based on the decision-maker's choices of levers and the manifestation of the uncertainties. The consequent performance of the system is measured according to several metrics (M) that decision-makers use to rank the desirability of various scenarios.

The XLRM-based simulation model used in this study has been developed and extensively documented by Ciullo, K. M. d. Bruijn, et al. (2019) and extended by J. Kwakkel (2021). In short, the model is capable of calculating the consequences of water (mis)management both in terms of costs and deaths. Three policy levers are available: RfR, dike heightening, and an early warning system to evacuate local residents. The calculations can be made at different aggregation levels concerning locations, i.e. the five locations of interest, and time. The latter provides the possibility to alter policy decisions three times during the 200-year simulation time of the model, i.e. every 66 years new policy levers can be considered. Location disaggregation allows for the evaluation of the distribution of eventual damages over the various considered areas in the model. This allows the observer to be considerate towards the various municipalities and evaluate possible policy solutions accordingly. Advantageously, this allows

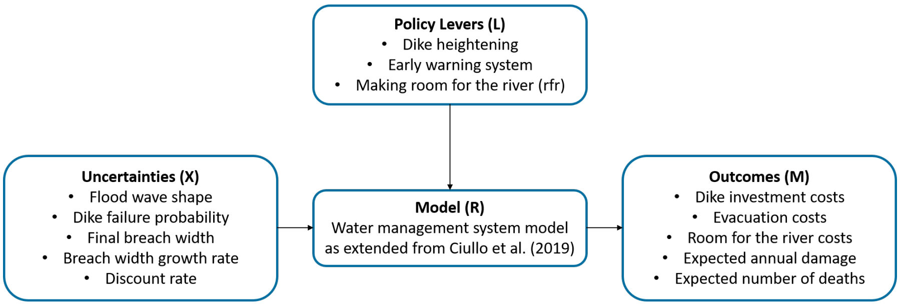


Figure 2.1: The XLRM framework applied to the water management simulation model. The factor R is the model itself. Figure adapted from (Ciullo, K. M. De Bruijn, et al., 2019).

to evaluate specific interests of local stakeholders and whether their policy lever preference is in accordance with the client or not. Secondly, time disaggregation allows the policy analyst to set up dynamic adaptive policy pathways, in line with the paradigm described by Haasnoot et al. (2013) and Marchau et al. (2019). This prevents the proposed policy from becoming rigid and/or outdated in the future and allows decision-makers to adapt to changing circumstances. An elaborate explanation of all the XLRM aspects of the used simulation model can be found in Appendix B.

2.1.1. Key Performance Indicators (KPIs) of the water management policy

To evaluate the performance of the water management policy, multiple Key Performance Indicators (KPIs) were used. The model as provided by J. Kwakkel (2021) returns five simulation outcomes (Figure 2.1). The expected annual damage, expected number of deaths, and dike investment costs are calculated per location and per timestep, thus resulting in 3 outcomes * 5 locations * 3 time stages = 45 KPIs. RfR costs and expected evacuation costs are only returned per time stage (so by default aggregated over all locations), thus resulting in 2 outcomes * 3 time stages = 6 KPIs. The simulation model therefore returns a total of 51 KPIs.

Besides these default KPIs, additional KPIs are been occasionally used to support the analysis. These include the total policy costs (dike heightening costs + RfR costs + evacuation costs) and the normalized variance of costs/deaths between locations. The variance is normalized by scaling to a unit interval to remove the influences of differences in ranges of KPIs between different locations. For instance, this makes it possible to directly compare if an outcome is among the worst 10% of outcomes for all locations. An overview of all used KPIs can be found in Table 2.1.

KPI	Disaggregation levels	Description	Unit
Expected annual damage	Locations and Time	Expected annual value of flood damage over the planning period	€
Expected number of deaths	Locations and Time	Expected number of casualties due to flooding	#
Dike investment costs	Locations and Time	Investment costs of raising dikes.	€
Evacuation costs	Time	Costs of preventive evacuation.	€
Room for the river costs	Time	Investment costs for the implemented Room for the river project.	€
Total policy costs		Dike heightening costs + RfR costs + Evacuation costs.	€
Normalized variance among locations		Variance in Expected number of deaths or Expected Annual Damage costs among the locations.	# or €

Table 2.1: Key Performance Indicators (KPIs) used to evaluate the performance of water management policies.

2.2. Modeling approach

The presence of a range of uncertainty values in exploring policy options allows for the creation of scenarios. Each scenario is a combination of specific uncertainty values that represent a possible future under which the water management system operates. As which scenario will represent the future most accurately is uncertain, it is important to find policies that perform effectively over a wide range of possible scenarios. This principle is more commonly known as *robustness* (Cameron McPhail et al., 2018).

In order to identify robust policies, multiple sequential and parallel analysis steps were followed (Figure 2.2). These steps were based on the given that water management is characterized by deep-uncertainty and thus a specific uncertainty-proof approach to find a robust policy is required. All steps are further elaborated on in the subsections below. Note that problem formulation using the XLRM framework was already discussed previously.

In short, the analysis was executed according to the Robust Decision Making (RDM) approach (Lempert, Groves, et al., 2006). Using tools from the EMA Workbench, pre-specified policies are selected and iteratively analysed across a range of possible scenarios. This allows for the evaluation of their robustness as well as their effectiveness. The pre-specified policies comprise a set of standardized or expert advised policies and are key to effective RDM needs that yields relevant results (J. H. Kwakkel, Walker, et al., 2016; Bartholomew and J. H. Kwakkel, 2020). In light of this, the Multi-Scenario Multi-objective Robust Decision Making (MORDM) framework can search for promising strategies using a Many-Objective Evolutionary Algorithm (MOEA) over multiple reference scenarios (Kasprzyk et al., 2013; Watson and Kasprzyk, 2017; Bartholomew and J. H. Kwakkel, 2020).

Similar to the specification of policy levers in RDM, the reference scenarios should be standardized or expert advised (J. H. Kwakkel, Walker, et al., 2016; Bartholomew and J. H. Kwakkel, 2020). To perform relevant experiment, worst-case reference scenarios were selected according to the Wald's maximin paradigm (Wald, 1945). It entails approaching the system in a pessimistic way by ranking policy options on the basis of their worst-case outcomes to minimize the maximum risk. Specifically, over a small set of worst-case scenarios, the policy with the least worst-case outcomes is the best policy option. In this analysis, the worst-case scenarios are therefore identified and consequently policies are optimized for these scenarios using multi-scenario MORDM.

Although optimizing policies only on the worst-case scenarios likely results in a policy that is also

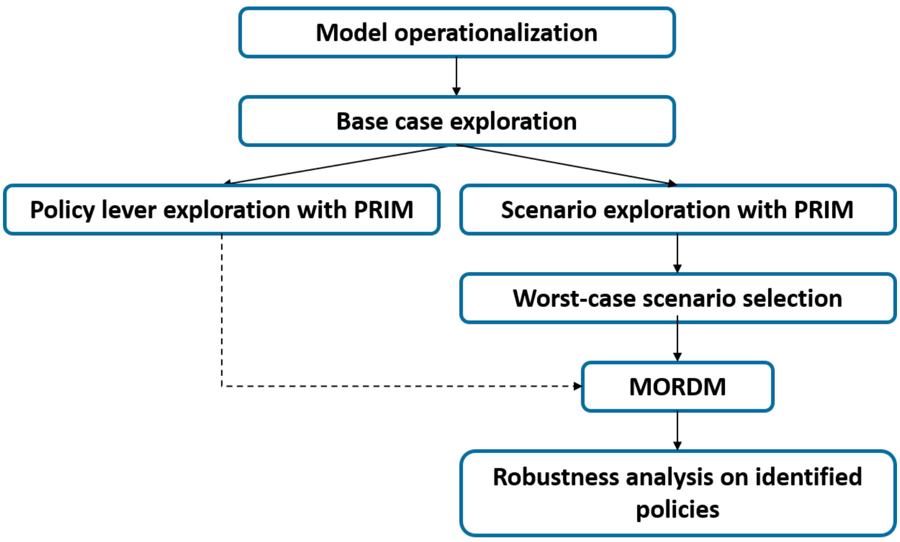


Figure 2.2: Analysis steps taken in this report. Continuous lines indicate steps that build upon each other. Dotted lines indicated some insights from one steps are used to execute another step.

effective under average and good scenarios, this cannot be ensured by optimization only. Given the limitations on computational power and time, however, evaluating which policy performs best on a few worst-case scenarios is the most viable option. To mitigate these effects of scenario dependence on the optimal policies, these were subsequently re-evaluated on a broader range of scenarios to validate their effectiveness and robustness.

2.2.1. Base case exploration

To be able to evaluate how well policies perform, we first need an understanding of how the water management system will perform if no policy is implemented. This is known as the base case. As such, the performance of policies will be evaluated relative to the base case throughout this report. Exploring the base case also helps to explore the uncertainty space and its effects on the range of model outcomes. In the analysis of the base case, 5000 random scenarios without any policies were generated using Latin Hypercube Sampling (LHS).

2.2.2. Scenario discovery

The water management simulation model gets input from the uncertain external factors as well as the policy levers. Combinations of these inputs result in outcomes that are desirable or not. Identifying the scenarios that result in these undesirable outcomes is useful to figure out which policies perform best in these scenarios. If this is satisfied, it can be assumed that the policy is robust according to the maximin paradigm.

To identify them, scenario discovery was conducted using the Patient Rule Induction Method (PRIM) algorithm as incorporated in the EMA workbench. PRIM is a technique developed by Friedman and Fisher (1999) that iteratively narrows down the uncertainty space until ”boxes” are found, each of which represents uncertainty intervals that can be statistically correlated to result in undesirable outcomes. A PRIM box encompasses a good trade-off between coverage (what fraction of the total outcomes of interest are in the box) and density (what fraction of all cases in the box are actually of interest). In PRIM’s attempt to increase the density-coverage measure by restricting uncertainty ranges, however, it could wrongly identify uncertainties that do not actually play a role in defining the outcomes of interest. Even so, PRIM is more easily interpretable than its alternative Classification and Regression Tree (CART) (Lempert, Bryant, et al., 2008).

The outcomes of interest for scenario discovery represent the base case outcomes with high damage costs, many deaths, and have a high variance among different locations in effects. As such, the outcomes that were simultaneously among the 25% of the worst outcomes for death and damage costs as well as among the 50% of the worst outcomes with high disadvantaged locations were selected. Making the scenario search more restrictive for the KPI of variance among location could result in scenarios with only high damage costs and deaths and low variance being disregarded, while these are also of key interest.

2.2.3. Policy lever exploration

Before optimizing policies on a small subset of worst-case scenarios, the policy levers were first explored using random policies. Doing so helps with exploring effective policies and their associated costs. To this end, 100 random policies were generated and each evaluated on 400 random scenarios.

To discover which policies are desirable in terms of costs and effectiveness, PRIM was used to find specific policy levers that contribute to a desired outcome. From the 40.000 executed runs (100 policies * 400 experiments), all policies were selected that resulted in the 35% of the lowest damage costs and number of deaths, the lowest 40% of total policy costs, the 50% of the lowest dike investment and RfR costs, and 80% of the lowest evacuation costs. Minimizing the deaths, damage costs, and total policy costs is generally desired for all actors. Given that evacuation costs present only a fraction of the total policy costs, they were not restricted much. Having the dike investment costs and RfR costs restricted ensures that policies that combine both levers are considered. PRIM was executed for both the aggregated time of the model, i.e. over 200 years, and for the timestep individually.

2.2.4. Worst-case (reference) scenario selection

In line with the maximin criterion, a small set of worst-case outcomes was selected under which policies will be optimized. Starting from the undesirable scenarios as identified during scenario discovery, the outcomes that accompany these scenarios were ranked from highest to lowest value with integers. Using integer ranking on all KPIs ensured that all locations were weighted equally as well as damage costs and deaths being equally important objectives. Specifically, 10 KPIs were ranked, being the time-aggregated expected number of deaths and expected damage costs. The other KPIs were not considered as the scenario discovery was performed on the base case and hence all policy costs will be zero. Subsequently, the rank numbers of the 10 KPIs were summed and the five scenarios which have the highest total rank, i.e. the ones that perform the worst, were selected.

2.2.5. Multi-scenario MORDM

Now that a set of scenarios has been constructed, a MOEA was applied to find a set of policies that minimize the KPI's values under the reference worst-case scenarios, in accordance with Kasprzyk et al. (2013), Watson and Kasprzyk (2017), and Bartholomew and J. H. Kwakkel (2020).

As discussed in section 1.4.1, the objective outcomes to be optimized by the MOEA aim to minimize the aggregated Expected Annual Damage, Dike Investment Costs, and Expected Number of Deaths. A disaggregated minimization of the variables would have yielded a more detailed result, however, the MOEA is computationally limited to a maximum of around 7 variables to optimize (J. Kwakkel, 2020). The other outcomes RfR Investment Costs and Evacuation Costs were not minimized because it is in the interest of the Environmental Interest group to consider policies in which RfR and Evacuation are implemented.

Besides looking for a policy that protects the interests of the client, it is also important to search for the most favourable and acceptable policy for other involved actors, especially Rijkswaterstaat and Delta Commission given they have veto power. Therefore, a constraint has been set on the Expected Number of Deaths by which the experiment outcomes cannot be above 0.01% * 3 time stages * 5 locations = 0.15%. This constraints look to meet the requirement set by the Delta Commission by which there cannot be more than 0.01% deaths per location and time stage. As a consequence of requiring to aggregate the outcomes, it is possible that this constraint is not met in the specific locations and outcomes, but at least ensures that this condition is met overall. More details on the specific implementation and configuration of MORDM can be found Appendix D.

As a final remark, Multi-Scenario MORDM was preferred to the alternative Many-Objective Robust Optimization (MORO) especially because of the high computational costs of MORO. As discussed by Bartholomew and J. H. Kwakkel (2020), Multi-scenario MORDM is generally the preferred method for a balance between optimality in the different scenarios, robustness and computational expense. Furthermore, the consideration of adaptive policies deems MORO as less appropriate for the present case.

2.2.6. Robustness analysis on identified policies

To counter scenario dependency that might result from optimizing policies only on the five previously selected worst-case scenarios, the identified policies were re-evaluated over a wider range of scenarios and determine their robustness. The results improve with an increase of the number of tested scenarios, however, due to time constraints it was kept to 500.

The robustness of the polices was assessed using the *domain criterion* robustness metric. This was the selected metric as it allows to evaluate which policies meet the thresholds specified by RWS and the Delta Commission during the debate.

- Rijkswaterstaat:

  Maximum RfR Investment Costs $\leq 1.1e9$ €

  Maximum Dike Investment Costs $\leq 3.04e8$ €

- Delta Commission:

  Maximum Expected Number of Deaths $\leq 0.0001 * 3 * 5$

The objective is to find a policy that satisfies this requirements at the same time that looks for the interest of the client, i.e. maximise RfR investment.

To this end, the domain criterion quantifies the volume of the uncertainty space in which the outcomes meet the thresholds established by the decision-makers (Herman et al., 2015). Following Culley et al., 2016, consider n external factors $x_1, ..., x_n$ that belong to the uncertainty space. Let p be the operating policy, such that $M(x_1, ..., x_n, p)$ is the model that maps each point of the uncertainty space into the outcomes space for a given policy p. The success subsystem S is represented by the set of scenarios that meet the threshold **f** of acceptable values such that:

$$S = \{(x_1, ..., x_n) \in R^n / M(x_1, ..., x_n, p) < \mathbf{f}\}$$

That being so, we define the robustness metric R for the domain criterion as:

$$R = \frac{S}{T}$$

where T is the total number of scenarios.

3

Results

Below, the modeling results and their implications on decision-making are discussed. It is recommended to read the sections in the order as presented in this report, due to some experiments building on previous experiments.

3.1. Open exploration: The Base Case situation

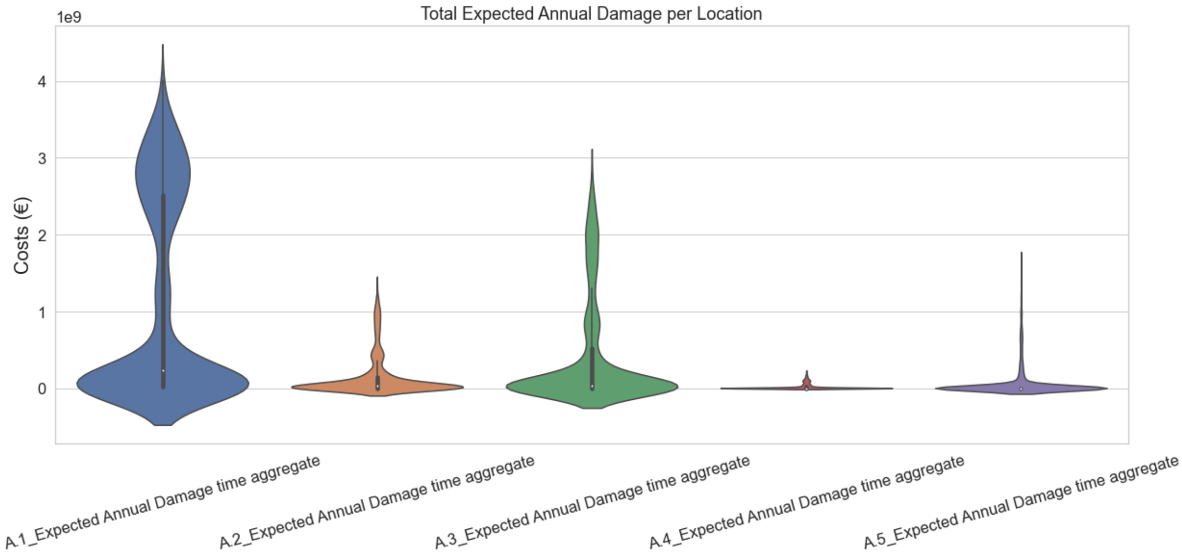
The base case was analyzed first and represents the performance of the current water management system if no additional policy is implemented. Using open exploration, the performance of the KPIs is assessed under a large range of scenarios.

3.1.1. Disadvantaged locations in terms of expected damage costs and deaths under certain scenarios

Evaluating the system under 5000 scenarios demonstrates that under the bulk of the scenarios both the expected number of deaths and the costs due to damage from water mismanagement remain low (Figure 3.1a, 3.1b). Location A.1 (Doesburg) and A.3 (Zutphen), however, experience considerable more damage costs and deaths relative to the other locations under some scenarios. Interestingly, damage costs and deaths are not necessarily proportional as for Doesburg the damage costs are higher than for Zutphen whereas the deaths are lower.

The observed differences in impact between locations could be the result of two underlying phenomena: (i) under certain scenarios the KPIs are performing relatively bad for all locations, but due to differences in magnitude this underlying trend is hard to observe, or (ii) under certain scenarios there are one or more locations at which the KPIs are performing relatively bad, but performing relatively good for other locations. 'Relatively' in this context means with respect to the other outcomes per location, so for instance being among the worst 10% of outcomes for a certain location. To investigate this, all KPIs were scaled to a unit interval to remove the influences of differences in magnitude, and consequently the variance in normalized KPI performance was calculated among the different locations.

For the damage costs, there are a few scenarios under which there is a large normalized variance between locations (Figure C.1a). This indicates that the costs are generally evenly distributed, so in case of high costs, most locations will have high costs. For the amount of deaths, however, there is a substantial amount of scenarios under which the normalized variance is quite high (Figure C.1b). While these insights hint that under certain scenarios the locations are indeed unevenly impacted (hypothesis (ii)), it is also of importance whether the variance is caused by an outlier above or below the average. Specifically, a certain location may be more disadvantaged if multiple locations have, for example, few deaths



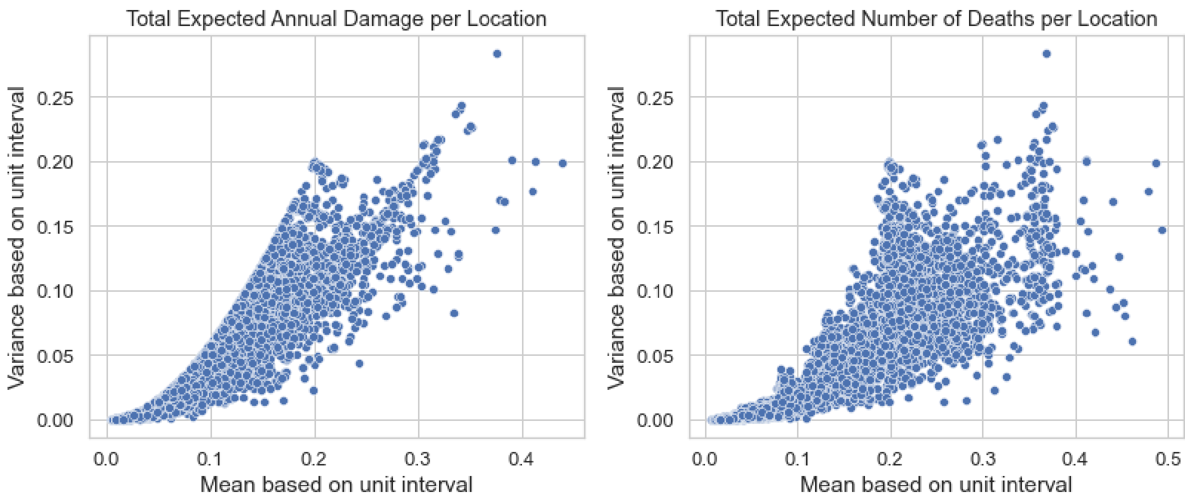
(a) Annual damage costs per location of interest.

(b) Deaths per location of interest.

Figure 3.1: Base case situation model outcomes under 5000 different scenarios per location of interest. Presented outcomes are time aggregated, i.e. summed over all three stages of the project. The violin plot shows on the x-axis the smoothed probability density, i.e. the wider, the higher the probability. The observable negative costs and deaths are an artifact of the smoothing. The vertical thick black line shows the interquartile range (IQR), the white marker shows the median value, and the vertical thin black line denotes the range equal to 1.5 times the IQR. Note that distributions are normalized over the x-axis as to present the highest count as the full width. This means that the same width can indicate a different number of cases at a particular KPI value between different locations.

and one location a high number of deaths than multiple locations having relatively high deaths and one location few deaths. A relatively low mean with high variance would thus indicate a disadvantaged location.

When observing this mean vs. variance relation, there is a roughly exponential trend for both the damage costs and the amount of deaths (Figure 3.2a, 3.2b). This could reflect hypothesis (i) as a higher mean likely indicates that all locations have a higher value for a certain KPI, but that the variance becomes larger due to the observed differences in magnitude. Still, there indeed can be scenarios under which there are disadvantaged locations, indicated by a relatively low mean and high variance (normalized mean around 0.2).



(a) Total annual damage costs.

(b) Total deaths.

Figure 3.2: Normalized variance and mean of base case situation model outcomes under 5000 different scenarios. The amount of costs and deaths per location were scaled to a unit interval and consequently the variance and mean between different locations was calculated. Presented outcomes are summed over all three stages of the project.

Overall, the differences between the locations of interest under the base case indicate that during the policy design it is important to consider that some stakeholders have more to lose than others, i.e. they suffer larger impacts. In turn, this could hinder the policy options that "the losers" consider acceptable and thus it can be anticipated that RWS safeguards the interests of these stakeholders by weighting them more heavily. One of the next steps is therefore to gain insights if any of these stakeholders prefers dike heightening over RfR, as the client will have to pay special attention to these stakeholders as opponents in the policy debate.

3.1.2. Discovery of undesirable scenarios

As there are scenarios under which either there are undesirable outcomes (high damage costs and deaths) or disadvantages locations, or both, it is important to identify these scenarios. In so doing, valuable insights concerning the system's environmental conditions and technical characteristics are provided. Monitoring for these in the real-world could help to anticipate if the future heads towards a worst-case scenario that results in undesirable outcomes.

Model outcomes were classified as undesirable if they encompassed high damage costs, many deaths, and had a high variance among different locations in effects. This resulted in the selection of 579 outcomes of interest. For the specifics, see Methods section 2.2.2. To find the scenarios under which the model produced these undesirable outcomes, the Patient Rule Induction Method (PRIM) scenario discovery algorithm was used. PRIM made a selection of scenarios with 44% coverage and 79% density.

Uncertain variable	Description	P-value	range
A.1 Bmax	Width of a potential dike breach at location A1 (Doesburg) in decimeters	0.016	[30, 299]
A.1 pfail	Probability of dike failure at location A1 (Doesburg)	2e-39	[0.00012, 0.41]
A.3 pfail	Probability of dike failure at location A3 (Zutphen)	2e-85	[0.000010, 0.18]

Table 3.1: PRIM scenario discovery results. The range indicates the values of uncertain variables that result in the undesirable outcomes. A p-value < 0.05 indicates that the variable significantly contributes to result in undesirable outcomes. Only significant identified variables are included in this table.

Table 3.1 shows the results of PRIM. Three uncertain variables (the external variables X from the XLRM model) were identified that significantly contribute to result in undesirable outcomes. In these scenarios, there is a relatively low probability that the dike will stand the hydraulic load at locations A.1 (Doesburg, $p<0.41$) and A.3 (Zutphen, $p<0.18$) as well as a relatively small width of a potential dike breach at location A1 (Doesburg, between 30-299 decimeter). Especially if during a scenario the probability for dike failure at both location A.1 and A.3 is low, there is a high likelihood of undesirable outcomes (Figure C.2). A low probability to withstand the hydraulic load implies a higher discharge and therefore a higher probability of damage, thus logically contributing to undesirable outcomes.

This in line with the previous results, given that the scenarios that translate into in undesirable outcomes are linked to locations A.1 and A.3 and these locations were previously shown to affect the desirability of the outcomes with the biggest magnitudes. This can be explained by a flood in these locations impacting many people at the same time as Zutphen and Deventer are both cities with many citizens close to the river.

3.2. Open exploration: The policy space

Given the multi-actor decision-making arena, it is important to explore what policy is most likely to be accepted by all stakeholders. Assuming they all agree on minimizing deaths and damage costs, the policy space was explored to identify which general policies perform best over a wide range of scenarios. They are general in the sense that no specific objective is centered in the search for a policy, and hence no specific stakeholder interest is reflected by it. To explore the policy space, the EMA workbench was used to generate 100 random policies based on the available policy levers.

3.2.1. Policy costs largely covered by savings in damage costs due to water management policies

When policies are implemented, both deaths and damage costs are effectively reduced (Table 3.2, Figure C.4). Implementing policies results in non-zero policy costs, however, most of this investment money is already 'won back' by having less annual damage (on average, 1.75 billion euros is won back, although this has quite a large variance). It also becomes clear that RfR policy levers contribute the most to the total policy costs.

Interestingly, comparing the total policy costs to the KPIs expected damage costs and deaths demonstrates that some effective policies have been generated while having a relatively low total costs (Figure C.3). These kinds of policies are of specific interest as they result in desirable outcomes while keeping low costs.

	Maximum		Mean		Standard deviation	
KPI	Basecase	Random	Basecase	Random	Basecase	Random
Expected annual damage	6.79e+09	2.73e+09	1.81e+09	5.01e+07	1.27e+09	1.56e+08
Expected deaths	5.85	2.39	1.72	0.022	1.25	0.10
Total Policy Costs	0	2.69e+09	0	1.75e+09	0	3.35e+08
Dike Investment Costs	0	9.33e+08	0	8.82e+08	0	1.08e+08
RfR Total Costs	0	1.88e+09	0	1.01e+09	0	3.17e+08
Evacuation Costs	0	1.25e+05	0	1.81e+03	0	6.50e+03

Table 3.2: Effect on KPIs from random policies relative to the base case. Performance measured are either from the Base case situation (basecase) or from randomly generated policies (random). Annual damage and costs are all expressed in Euros (€). Deaths are expressed in persons (#). Note that for the basecase 5000 model runs were conducted and for the random policies 40000 which makes one-to-one comparison of the stand deviation not trustworthy.

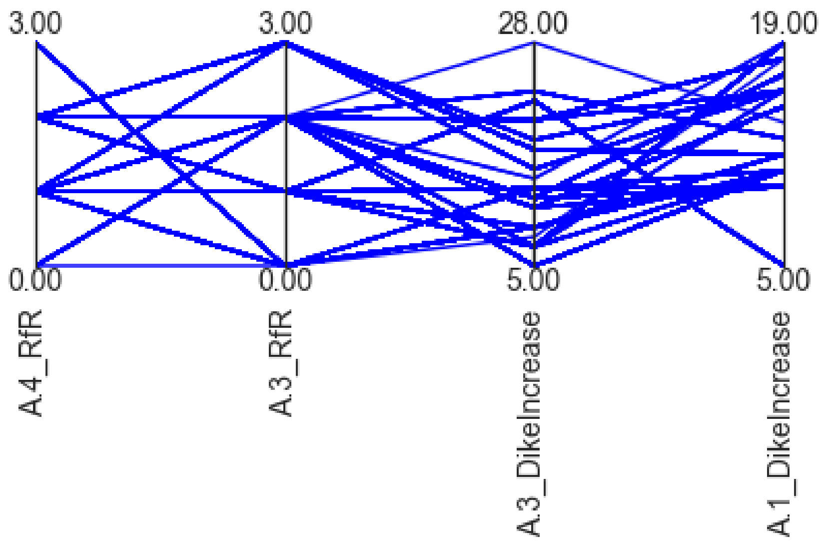


Figure 3.3: Trade-off between time-aggregated policy levers that significantly contribute to cost-effective policies under random scenarios. A value of 0-3 for RfR projects indicates in how many of the model timesteps RfR was implemented. The dike increase is given in dm, with a maximum of 10 dm increase possible per timestep.

3.2.2. Discovery of cost-effective Policy Levers

To discover which policies are likely the desirable policies in terms of policy costs and effectiveness for other stakeholders, PRIM was used to find specific policy levers that contribute to a desired outcome. Here, desired outcomes were defined as having low damage costs, low deaths, low total policy costs, low dike heightening costs, and low RfR costs. This resulted in the selection of 2520 outcomes of interest out of the 40.000 executed runs (100 policies * 400 experiments). For the specifics, see Methods section 2.2.3. Note that this selection may include only mild scenarios under which the outcomes are consequently desirable, and hence the following results do not reflect the performance of policies under worst-case scenarios. PRIM was executed for both the aggregated time of the model, i.e. over 200 years, and for the timestep individually.

Considering the total simulation model timespan of 200 years, implementing RfR at location A.3

Policy lever	Timestep	P-value	range
A.3 RfR	Aggregated	6.8e-52	[1.5, 3]
A.4 RfR	Aggregated	6.3e-19	[1.5, 2.5]
A.3 DikeIncrease	Aggregated	6.3e-19	[4, 22]
A.1 DikeIncrease	Aggregated	6.3e-19	[5, 20]
A.3 RfR	0	4.1e-119	[0, 0.5]
A.2 RfR	2	9.6e-221	[0, 0.5]
A.1 DikeIncrease	0	1.4e-18	[0, 9.5]
A.4 DikeIncrease	0	1.4e-18	[0.5, 10]
A.2 DikeIncrease	1	1.4e-18	[0.5, 7.5]
A.2 DikeIncrease	2	3.2e-88	[0, 6.5]
A.3 DikeIncrease	2	1.4e-18	[0, 9.5]

Table 3.3: PRIM policy levers discovery. Timestep indicates whether the policy lever is implemented at a specific moment in time or that the displayed result is the aggregate result over 200 years. The range indicates the values of policy levers that result in the desirable outcomes. Note that only the policy levers that significantly (p-value < 0.05) contribute to result in desirable outcomes are included in the table.

and A.4 as well as increasing the dike height at location A.1 and A.3 has been found to contribute to effective policies (Table 3.3, Figure C.5). For the RfR projects, it is most effective to implement RfR once to twice during the coming 200 years (indicated by their optimal implementation ranges not being 3, the number that indicates that RfR is implemented in every available timestep). For dike heightening it can also be observed that while minimum dike heightening is necessary, the maximum dike heightening (i.e. 30 dm) is not required to get the most effective policies. The above findings indicate that in order to get effective policies while having low total costs, it is not necessary to implement policy levers to their maximum.

It must be noted, however, that the effective policy levers as presented here often do not all need to be implemented simultaneously and with the same abundance (Figure 3.3). For instance, if RfR is implemented at location A.3, often the required amount of dike heightening is relatively low. Also, if RfR is fully implemented on location A.4, it can be noted that implementing RfR at location A.3 becomes unnecessary.

Interestingly, when exploring the policy levers for each timestep specifically, it can be observed that some policy levers should specifically not be implemented (Table 3.3, Figure C.6). For instance, for location A.2 it is not cost-effective to increase dike heightening much in the second or third timestep. On the other hand, it is cost-effective to heighten dikes at locations A.1 and A.4 in the first timestep. Interestingly, whereas it was previously observed that partially implementing RfR at location A.3 is cost-effective over all timesteps, it can be observed that implementing it in the first timestep is not cost-effective.

Overall, these results indicate that decisions on policy levers for one location impact the cost-effective policy levers on another location. Advantageously for the client, this demonstrates that there is room to negotiate for RfR projects on most locations. In addition, these results also demonstrate that adaptivity of the policies is viable as implementing or not implementing certain policy levers at a later timepoint does significantly impact the cost-effectiveness of the policies.

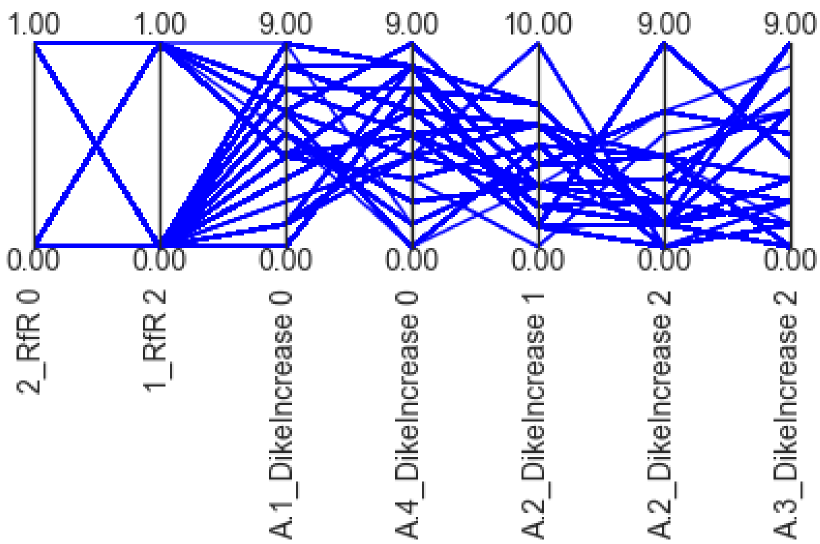


Figure 3.4: Trade-off between policy levers that significantly contribute to cost-effective policies under random scenarios. A value of 1 for RfR projects indicates an implemented RfR. The dike increase is given in dm. Note that a '2' in RfR indicates location A.3 and a '1' incidates location A.2.

3.3. Policy optimization: identifying optimal policies candidates for the client

The following sections aim to identify policies that are in line with the clients' interests while also being cost-effective as desired by the other stakeholders. Using multi-scenario MORDM under five worst-case scenarios, policy options that minimize deaths, damage costs, and dike heightening costs are searched for. RfR investment and early warning system policy levers are preferred over dike heightening and are therefore not constrained. The policy options that perform best under the five worst case scenarios are compared in terms of how they score on the various defined KPIs.

We analyse the epsilon-progress and hypervolume convergence metrics to track whether the Multi-Scenario MORDM has converged - i.e. no better solutions can be found within the demarcated policy space - to the possible optimum solutions. We can see that the epsilon-progress has not fully converged while the hypervolume metric has converged (Figure C.7). This suggests that the ranges established for the hypervolume metric were adequate. The epsilon-progress has started to stabilise for some of the scenarios, however, to ensure that no better solutions can be found, the algorithm should be executed with a larger number of function evaluations. Given that this is an exercise of trial and error and due to time constraints, we assume the algorithm found the found policies form a consistent Pareto front. In total, 42 policy options were identified. These are too many for suitable follow-up analysis, and hence in the following section a smaller selection of policies is made.

3.4. Robustness analysis of candidate policies

To prevent scenario dependence on the worst-case scenarios and observe how the candidate policies perform across all uncertain futures, the policies were re-evaluated over the same 500 random scenarios.

In order to roughly compare policies, the KPI values were scaled to a unit interval and the mean over all scenarios was taken. Based on this relative ranking of policies per KPI, it can be observed that policies often have clear trade-offs (Figure C.8). For instance, policies that minimize deaths and damage often have high investment costs. Looking only at the mean performance over all scenarios and KPI trade-offs to select favorable policies, however, does not give any information on how often a policy is robust.

3.4.1. Selection of optimal policies

From the 42 identified candidate policies, a smaller selection was chosen based on their domain criterion robustness. To do so, we systematically analysed which policies meet the requirements set by RWS

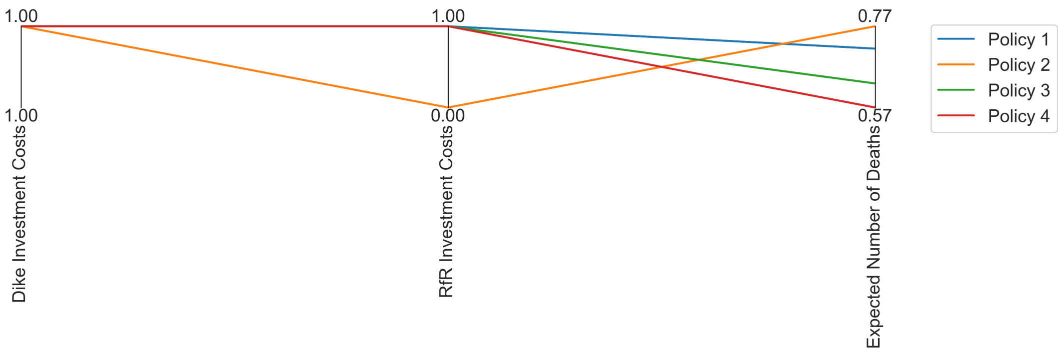


Figure 3.5: Trade-offs between the KPIs for the identified policies in therms of their domain criterion. Each policy was evaluated over 500 scenarios and a value between 0-1 indicated the fraction of times an outcome made the criterion threshold given the range of input scenarios.

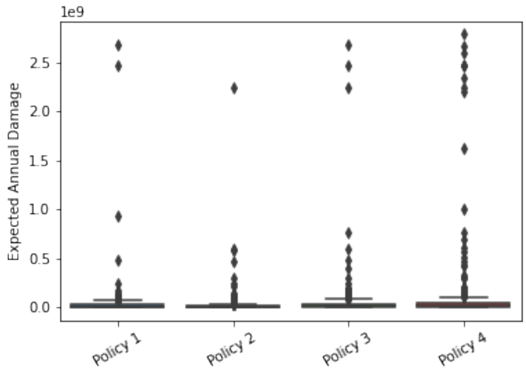
and the Delta Commission. First, we can observe that all of the optimized policies meet the constraint set by RWS on the dike costs under all scenarios. Second, we can see that only three policies meet the threshold set by RWS on the maximum RfR investment costs. Finally, there is no policy which is able to satisfy the requirement set by the Delta Commission on the maximum number of deaths under all scenarios.

From the previous outcomes we selected the policies that would potentially be supported by either RWS or the Delta Commission. Given that there are three policies which meet both RWS criteria, we assume that RWS will not settle down for less and include those three as candidate policies. Additionally, as there is no policy that satisfies the requirements for the Delta Commission, we decided to also consider as a candidate policy the most robust policy for the expected number of deaths in case the Delta Commission decides to be more lenient in their requirements. Note that this last policy only satisfied the criterion for 77% of the scenarios under which it was evaluated (Figure 3.5).

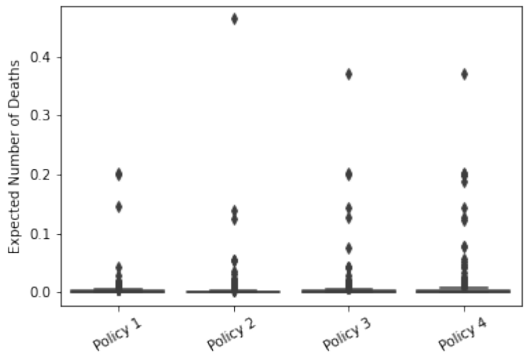
This led to the selection of four candidate policies (their specifics can be found in table 3.4). Concerning RfR, the identified policies are closely in agreement (Table 3.4. All policies entail implementing RfR at location A.2, A.3, and A.4. For location A.1 and A.5, there are differences between the policies.

Policy lever	Location	timestep	Policy 1	Policy 2	Policy 3	Policy 4
RfR	A.1	0	1	1	1	1
RfR	A.1	1	0	1	0	0
RfR	A.1	2	1	1	1	0
RfR	A.2	0	0	0	0	0
RfR	A.2	1	1	1	1	1
RfR	A.2	2	1	1	1	1
RfR	A.3	0	1	1	1	1
RfR	A.3	1	1	1	1	1
RfR	A.3	2	1	1	1	1
RfR	A.4	0	1	1	1	1
RfR	A.4	1	1	1	1	1
RfR	A.4	2	1	1	1	1
RfR	A.5	0	0	1	0	0
RfR	A.5	1	0	1	0	0
RfR	A.5	2	0	1	0	0
Early warning system	-	-	3	2	3	3
Dike increase	A.1	0	0	0	0	0
Dike increase	A.1	1	0	0	0	0
Dike increase	A.1	2	0	0	0	0
Dike increase	A.2	0	5	5	5	4
Dike increase	A.2	1	0	0	0	0
Dike increase	A.2	2	0	0	0	0
Dike increase	A.3	0	4	2	2	2
Dike increase	A.3	1	0	0	0	0
Dike increase	A.3	2	0	0	0	0
Dike increase	A.4	0	0	0	0	0
Dike increase	A.4	1	0	0	0	0
Dike increase	A.4	2	0	0	0	0
Dike increase	A.5	0	7	9	7	7
Dike increase	A.5	1	0	0	0	0
Dike increase	A.5	2	0	0	0	0

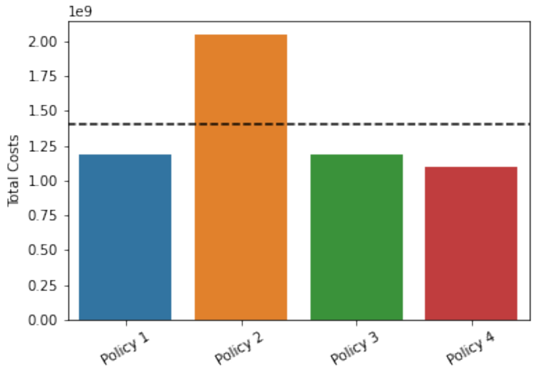
Table 3.4: Composition of policies found by multi-scenario MORDM. RfR implementation is binary indicated, with a 1 indicating implementation. Dike increase is expressed in dm. The early warning system is expressed in days. A '0' indicates the first timestep, a '1' the second, etc.



(a) Expected annual damage.



(b) Expected number of deaths.



(c) Total policy costs. The total costs are the sum of the costs for RfR measures, dike heightening costs and evacuation costs per location. Horizontal line indicates budget threshold set by RWS or Delta Commission.

Figure 3.6: Performance of selected policies on the KPIs. The box-whiskers plots show the interquartile range (IQR) with a box and the median as a bar across the box. Whiskers denote the range equal to 1.5 times the IQR. Outliers are presented by diamond shapes.

Interestingly, RfR is generally implemented at location A.1 in the first timestep and at location A.2 in the later timesteps. This reflects the shift of the flood burden to a downstream location if a new flood protection mechanism is implemented more upstream. The number of days before a flood that the early warning system is used differs only slightly between the policies. Dike heightening is in general not implemented and if it is implemented, it is only in timestep one. The large implementation of RfR and low implementation of dikes highlights the consideration of these policies on the interest of the client. Interestingly, only for location A.3 (Zutphen) a combination of both RfR and dike heightening is needed to effectively mitigate the flood risks. This observation is in line with the results from effective policy discovery based on random policies (Table 3.3, Figure C.6). This indicates that the optimization process was able to find policies that can be generalized beyond the worst-case scenarios under which they were generated.

Even though the policies are similar in design, their performance over all scenarios does differ a bit. For all policies, it can be observed that there are undesirable outcomes under certain scenarios in terms of damage costs and deaths as represented by the outliers (Figure 3.6a, 3.6b). Policy 2 shows the least spread outcomes when evaluated over various scenarios. The relative high amount of RfR measures implemented in this policy relative to the other policies could explain this observation (Table 3.4). More RfR projects would mitigate the flood risks more, however, it also makes policy 2 significantly more expensive than the other policies (Figure 3.6c). In fact, policy 2 is the only policy that does not satisfy the budget threshold for RfR measures as set by RWS or the Delta Commission (Figure C.9a). The costs

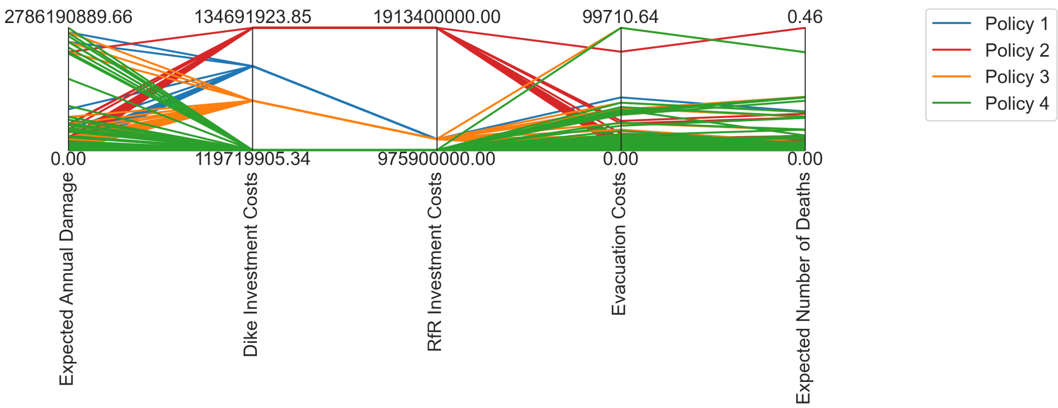


Figure 3.7: Trade-offs between the KPIs for the identified policies. Each line represents one scenario under which the policy was evaluated. Note that the same 500 scenarios were used for the evaluation of each policy.

for dike heightening are relatively similar for all policy options and, as already mentioned, none of the policies exceed the threshold for dike heightening costs as set by RWS C.9b.

Putting all KPIs side-by-side, it can be observed that the policies do present certain trends in trade-offs between the performance on KPIs even though there are influences of the different scenarios (Figure 3.7). For instance, policy 2 has high investment costs but performs best on reducing the amount of flood damage and deaths. Policy 3 and 4 seem to make the same trade-offs in which lower policy costs result in slightly more deaths and particularly more damage costs. Trade-offs can also be observed in robustness (Figure 3.5). Policy 3 is more expensive, but its performance is more robust over the different scenarios than the cheaper policy options.

3.4.2. Adaptive policy options

Even though the four identified policies are often the same, there are a couple key differences that stand out and offer room for flexibility:

- At location A.1, RfR is implemented in the first timestep for every policy option. It is thereafter possible to implement RfR in timestep two and three, only in timestep three, or not implement any additional RfR at all. Given that the policies are quite similar on the policy levers used at other locations, this implies that in 66 years it is possible to re-evaluate which next step for location A.1 is the best option.
- The number of days used in the early warning system can easily be altered by administrative means, and therefore offer flexibility.

All in all, the identified policy options provide opportunity for the client to weight their interests based on the different trade-offs that the policies make. Specific policy recommendations in light of the multi-actor arena will be made at the end of the report.

4 Discussion

Before policy recommendations are presented, it is important for the client to be aware of some key limitations of this analysis and their implications on the drawn conclusions. Additionally, ideas for future work are presented.

4.1. Critical analysis assumptions

As part of the analyses performed in this report, a number of assumptions were made. These assumptions, however, have always been explicitly mentioned throughout the report and substantiated with literature. Some of these assumptions were made on which policies would be most likely to be implemented.

First, policies that did not contain a (certain number of/enough) RfR measures were not recommended to the client as they were not considered environment-friendly options. Second, as RWS designs the eventual policy and had provided a threshold on the costs of RfR, identifying policies that obeyed this criterion was central due to the belief that too expensive policies would be disregarded by definition. This has implications for the recommendations given to the client as policies that suit their goals better might have been discarded based on the made assumptions.

Furthermore, it was assumed that using a domain criterion as robustness metric was the best option given its easy interpretability and time constrains. The used thresholds in the domain criterion were based on thresholds mentioned by RWS and the Delta Commission during a debate, however, these values have not been validated. Given the likely incomplete analysis from both stakeholders at the time of the debate, it is possible that the thresholds changed afterwards. Given the sensitivity of robustness to the thresholds, and hence policy recommendations, one of the thresholds changing could have a big influence on the policy recommendations that were given (Cameron McPhail et al., 2018).

Alternative robustness metrics such as maximum regret could be used in the future to complement the policy recommendations and make it less sensitive to the specified thresholds. Regret is defined as the difference in performance under a certain scenario and the best possible performance over all scenarios (Savage, 1951). Maximum regret thus identifies which policies could possibly perform the worst over a range of scenarios.

4.2. Simulation model limitations

The simulation model used in this study was provided by J. Kwakkel (2021). Advantageously, all stakeholders used the same simulation model in the design of policies, thereby creating common ground for their argumentation. There are multiple model characteristics, however, that limit the validity of the conclusions. Most profoundly, the model only provided outcome data on the KPIs of expected number of deaths, damage costs, and policy costs. For some actors, there were additional relevant outcomes missing. For instance, environmental impacts are of key interest for the client. Currently, it is assumed that RfR by definition is better for the environment than dike heightening. It could be the case, however, that a small or local increase in dike heightening does not weigh heavily on the environment while being highly effective. These sorts of environmental considerations have not been taken into account while finding 'optimal' solutions for the client. Alternatively, the biggest opposition for RfR projects comes from the transport company that fears too low water levels for doing business. The effects of RfR on these water levels is, however, also not included in the model and hence these claims cannot be validated. If it would be possible to demonstrate that RfR has for instance only a negligible impact on water levels, this would give the client strong leverage to argue in favor or environmentally friendly RfR projects. Finally, the simulation model as provided spans a time horizon of 200 years. Given the deep uncertainty of the water management system, it is questionable if valid predictions can be made for the far-future. Unknown environmental phenomena due to climate change, innovation in flood protection measures, and evolution of communities near the IJssel as well as future technological developments are completely disregarded. The three model timesteps, each representing 66 years, is also somewhat unrealistic as decision revision can already take place after less time. This leads the model to underestimate the potential of adaptive policies.

4.3. Implications of the usage of Walds maximin paradigm

The application of Wald's paradigm in selecting the scenarios over which Multi-scenario MORDM was performed creates an inherent bias towards policies that mitigate worst-case scenarios. Specifically, the identified policies are optimized to be effective on scenarios that are the result of 'doomthinking'. Although it may be arguably better to be safe than sorry, it is important that the decision-maker is wary of the process which was used to construct the proposed policy as this can have implications for the policies that were presented as most suitable. For example, if MORDM was performed over the best case scenarios, a different set of policies would have been selected as best performing policies. It also has consequences for the robustness of the presented policies as explained in the next section.

4.3.1. Alternative scenario selection paradigms

Given the current scenario dependency on worst-case scenarios, the addition of an alternative scenario selection paradigm could be useful to get a wider range of scenarios for which policies are optimized. For instance, Giudici et al. (2020) suggest creating the smallest possible subset of scenarios that is representative of the entire scenario space. Including these scenarios may result in more viable policy alternatives given the criterion of the Delta Commission. Ideally, this subset of representative scenarios would be validated by field experts. Indeed, a study by McPhail et al. (2020) found that the selection of scenarios strongly impacted the calculated robustness values for selected policies. They also noted, however, that scenario subsetting has relatively little impact on the eventual ranking of policies. This indicates that the act of scenario selection in Multi-scenario MORDM may be of little influence to the eventual policy recommendations, and thereby the policy recommendations that are made in this report can be considered sufficiently representative for the entire scenario space.

4.4. Insufficient robustness on number of deaths threshold

During optimization with multi-scenario MORDM, the constraint from the Delta Commission of the maximum deaths due to flooding being 0.0001 * 3 * 5 was used. This means that the identified policies meet this criterion for the worst-case scenarios as used during optimization. During robustness analysis of these policies, however, it became clear that this criterion is not fulfilled by the policies when evaluated under a wider range of scenarios. The scenario dependence that is induced by using the maximin paradigm in combination with multi-scenario MORDM complicates finding policies that perform effectively over a wide range of scenarios. Concretely, this means that the chosen optimization method in combination with the chosen paradigm might have caused the fact that none of the recommended policies fit the requirements of the Delta Commissioner. Alternatively, it is also possible that the worst-case scenarios were only the worst out of the 5000 base-case sampled scenarios, but a larger sampling would show that there are multiple worse scenarios.

Fortunately, the usage of adaptive policy planning can aid in mitigating the risk of overemphasizing risk (Haasnoot et al., 2013). In this paradigm, policies can be adapted without many consequences or lost investments at a later point in time when there is more certainty about the future state of the system. Based on future knowledge, some policy changes can therefore help to reach the deaths threshold.

4.4.1. Threshold on deaths by Delta Commission

It must also be noted, however, that the constraint on the amount of deaths was not formulated very clearly by the Delta Commissioner. The constraint was formulated as 0.0001 deaths. What remained unclear was whether this was a constraint on the maximum allowed amount of deaths per year or over the total amount of time that was modeled. Also, it was not specified if the given constraint entailed the accumulated deaths over the different locations along the IJssel river that were incorporated in the model or that the given constraint had to be applied per location. Given the fact that the model was ran to generate results for a period of 200 years and over five different locations, the exact specifications of the constraint could have made a big difference for how it was supposed to be interpreted. For this reason, it could also have a big impact on which policy satisfies the requirements for this constraint. Furthermore, the provided constrain also lacked a clear foundation. A possible way to address this challenge would be to find a more clear and better substantiated constraint which the Delta Commissioner could perhaps agree with. An example of such a clearly and well grounded constraint is given by Vrijling et al. (2005). In their work the maximum acceptable amount of deaths is defined as 0.00001/year per newly created situation. If the analysis performed were to be repeated, it could be beneficial for the results to verify how exactly the constraint by the Delta Commissioner has to be handled.

4.5. Ethical implications

As can be seen in Table 2.1, there are two units for the various KPIs, €and # of deaths. This implies the need for a consequentialist view to the decision-making process similar to the ethical considerations often encountered in social cost-benefit analysis (Hansson, 2007). Specifically, as advocated by Hansson (2007), the loss of human lives and monetary costs of a project may be incommensurable. During worst-case scenario selection in this analysis, deaths and costs were weighted equally. Additionally, all locations were weighted equally, which given the presence of disadvantaged locations is also debatable (Koopmans and Mouter, 2020). Apart from these ethical dilemmas of placing monetary value on human life, one could also wonder about the differences between damages and investments costs (Hansson, 2007). The analysis in its current state minimized the policy costs and damages. One could also minimize the sum of these components. This train of thought is only valid if you assume that the monetary value of damages is equal to the monetary value of flood protection costs. This substantiates an ethical question in which the input of the client is paramount. The option was, however, not discussed with the client during the analysis process and follow-up analysis on this report may want to investigate the client stances on the matter. Furthermore, the foundation of implementing new flood protection measures is based on interpersonal aggregation which comes down to accepting that a disadvantage for one can be fully compensated by advantage for another (Koopmans and Mouter, 2020). This is also ethically questionable as people can cognitively weigh the risks of living near water and another individual that suffers from the new water management policy may not deserve this. This is particularly visible for the farmers that generally have to be relocated in order to implement RfR projects.

4.6. Notes on execution of Multi-scenario MORDM

As discussed in the 2 section, Multi-scenario MORDM was chosen as method to find policies. Although recognized as generally preferred method by Bartholomew and J. H. Kwakkel (2020), it is interesting to investigate the results of the other available robust optimization methods. However, applying MORO on the dike model comes at extensive computational costs.

4.6.1. Seed Analysis

In this analysis $\epsilon - NSGAII$ is used as MOEA in order to find a set of optimal policies. This algorithm initially randomly generates a parent population P_0 (Deb, Pratap, et al., 2002; Deb, Mohan, et al., 2005). Due to the stochastic nature of this algorithm, a seed analysis needs to be carried out in order to ensure the stability of the found policy solutions and prevent misinterpretation of results (Madhyastha and Jain, 2019). This has currently not been done yet due to time constraints, but is of vital importance for valid results.

4.6.2. MOEA Selection

Due to the ease of use in the EMA workbench, $\epsilon - NSGAII$ was used in order to find the Pareto-optimal set of solutions. However, multiple MOEA algorithms exist that are able to find this Pareto-Optimal set. Examples are BORG, NSGA-III and MOEA/D, amongst others (Hadka and Reed, 2013; Cui et al., 2019; Zhang and Li, 2007). The usage of these algorithms instead may lead to more optimal, better distributed or computationally less expensive results. Therefore, it is worth investigating what the effect of the MOEA choice is on the set of optimal policies.

Overall, the points of attention discussed in this chapter do not make the upcoming policy recommendations invalid. They do, however, push for further analysis of the policy options to mainly identify is a particular useful policy option for the client was overseen.

5 Conclusion

The analysis presented in this report aimed to identify a set of policy options for improved water management of the IJssel river. These policies were designed with the interests of the client - the Environmental Interest group - in mind. The environmental interest group prefers RfR projects over alternative solutions such as dike heightening due to their positive environmental impact. Based on conversations with the client, the following problem statement was designed to capture the objectives of the client and guide this analysis:

Which IJssel river water management policy best serves the interest of the Environmental interest group by maximizing the environmental potential of RfR, while being robust and effective under deep uncertainty as well as being acceptable in the multi-actor decision making process?

In order to provide well-informed advice to this question, the multi-actor arena of the IJssel river was integrated into the analysis. All stakeholders agree that the policy should be effective, robust, and economically viable. Yet, a discrepancy is observed in the goals of the present stakeholders, as they have conflicting interests with the client. The Transport company benefits from higher water levels while disregarding ecological restoration, and some municipalities refuse to abandon valuable farmland, both conflicting with the client's interest.

From analysis of the current water management system without the implementation of a new policy, it becomes clear the consequences of floods are unacceptable to all stakeholders. The upstream regions are particularly vulnerable with possible damage costs as high as four billion €and four casualties. Particularly the locations of Doesburg and Zutphen are vulnerable to flood damage and deaths, and therefore RWS is likely to weight their interests more heavily during the policy design.

By means of a policy exploration, it was explored what objectively (i.e. no political interventions) the best policy options would be. From this exploration, it resulted that although some policies are expensive at first, due to their large investment costs, the return on investment takes place by preventing annual damage. Specifically, less flooding damage saves 1.75 billion euro's on average. Advantageously for the client, this makes advocating for RfR projects easier as their relatively high costs are no longer a limitation while they do contribute to the environment, something that local citizens can benefit from. The exploration also demonstrated that it is not necessary for policy levers to be implemented to their maximum. This allows room for negotiation, given that decisions on policy levers on one location impact the cost-effective policy levers on another location.

With the interests of the client at heart, this study also identified policy options for the client to use during the negotiation process. By performing multi-scenario MORDM, four possible policies were identified that perform reasonably robust given the range of possible futures of the water management system, and especially in the worst-case scenarios. In general, the identified policies steer in the direction of implementing RfR projects to mitigate flood risks, although for locations A.2 (Cortenoever) and A.3 (Zutphen) a combination of both RfR and dike heightening is needed. For these locations, dike increase should be performed in the first time step. In addition, all four policies should include an early warning system, varying from warning 2-3 days ahead of high water levels. Even though there are small differences between the policies, it can be concluded that solely implementing RfR projects would not reach the desired threshold. Instead, a combination of RfR, Early warning system and sometimes Dike height increase is regarded as optimal.

5.1. Recommendations

While all identified policies mitigate flood risks, they contain different trade-offs between KPIs. It is in the hands of the client to determine which of the KPIs is of most value to them. Nevertheless, different policies are recommended below for different objectives that the client could value most.

- **Policy 1.** If the policy should focus on low expected annual damage and relatively low RfR costs, while accepting dike height increase measures in order to increase robustness. Based on this focus, the client could partner with local stakeholders, who most likely prioritize the outcomes similarly.
- **Policy 2.** If the policy should focus on minimizing deaths as well as implementing as much environmentally beneficial RfR projects as possible, while the RfR costs are not a hurdle. As such, the client could partner with the Delta Commission, who prioritizes the outcomes similarly.
- **Policy 3.** If the policy should not necessarily focus on minimizing investment costs, while having relatively high robustness against worst case scenarios compared to other policies. Based on this focus, the client could partner with Rijkswaterstaat, who prioritizes the robustness and safety.
- **Policy 4.** If the policy should focus on minimizing investment costs, thus accepting a decrease in robustness, resulting in higher values for expected annual damage and expected number of deaths. Based on this focus, the client could partner with the Transport company, who prioritizes business continuation instead of expected annual damage.

Given the relatively high power of the stakeholders from Doesburg and Zutphen due to their potential to be big 'losers'. It is thus in the favor of the client that the found policies entail RfR for both these locations. It is therefore recommended that the client reaches out to these stakeholder and seeks alliances in order to increase the likelihood of RfR being implemented. Here, the client should exploit their power in changing public opinion on the environmental interest of other stakeholders. Nevertheless, it should be kept in mind that the trade-offs between KPIs might not be accepted by all stakeholders. Some stakeholders that represent farmlands or densely populated area's might not be willing (or even able) to give up land in order to create more room for the IJssel river. Convincing stakeholders that have little room for negotiation will be difficult due to the fact that their interests are not aligned with environmental interests. In short, the multi-actor perspective should be noted when negotiating with all stakeholders, as they might value the KPIs differently than the client would.

Finally, the observed possible adaptivity of the identified policies makes it possible to create more room for negotiation by arguing for more (joint-effort) research. The adaptivity of the proposed policies also strengthens the power of the client's policy proposals at the negotiation table.

Overall, given the recommendations made here, the client now should be in the position to make the trade-offs they find appealing. With the environment at heart, this allows them to contribute to a resilient IJssel river.

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A

Multi-actor decision-arena

In this section, a deeper look is provided into how actors are involved, what interest they have in the problem and to what extend actors are able to influence the potential outcomes. As the actor characteristics determine their behavior, having an in-depth understanding of their perspectives and their objectives is crucial when implementing policy. In order to get an overview of the objectives of involved actors, they are first elaborated on separately. Next, a Power-Interest Grid is displayed in order to graphically present the position each actor is in.

A.1. Delta Commission

The Delta Commissioner has an advisory role towards governmental decision-makers. Every year, the Delta Commissioner does a proposal with recommendations for the Delta Programme and hands it over to the coordinating minister and the other minister (Deltaprogramma, 2021). The Delta Programme contains plans from the government to prevent the Netherlands from flooding. Its main goals are: protect the Netherlands from flooding now and in the future, provide enough sweet water and make the design of the country climate-proof (Rijksoverheid, 2021).

A.2. Rijkswaterstaat

Rijkswaterstaat is the executive agency of the Ministry of Infrastructure and Water Management, primarily focused on maintaining safety, mobility and quality of life in The Netherlands (Rijkswaterstaat, 2021). Their main objective is to provide protection against flooding, while assuring plenty of green space, clean drinking water and travel possibilities are available. The trade-off Rijkswaterstat is facing mainly concerns the interests of economy, environment and quality of life.

A.3. Provinces

There are two provinces which are situated alongside the IJssel river: Gelderland (upstream) and Overijssel (downstream), displayed in figure A.1. The main task of the provinces, concerning water management, are to translate national policy into regional policy (government, 2021), making the policy suitable for their province. Naturally, if a policy is executed in Gelderland, not only does it affect the province itself, it also affects the water levels in parts of the IJssel in the downstream province Overijssel. The objectives of the provinces are mainly concerning safety and not having to trade an increased safety at the expense of valuable farmland. Climate change demands the provinces to incorporate safety more and more in the decision-making process around water management (IPO, 2021).

Figure A.1: Geographic presentation of the two provinces that are involved. The IJssel river clearly crosses through both Gelderland and Overijssel.

A.3.1. Gelderland Province

Dike ring 1, 2 & 3.

A.3.2. Overijssel Province

Dike ring 4 & 5.

A.4. Dike Rings

Dike rings are geographical areas that are protected by a given system of water barriers. These areas are separated by primary water barriers, such as dikes, dunes and other constructions for water management, like locks and pumping system. The dike rings that will be considered in the scope of this report are the Dike Rings of Doesburg, Cortenoever, Zutphen, Gorssel and Deventer.

A.5. Transport company

Inland waterways, such as the IJssel, are frequently used by barges to transport goods. Transport companies thus are highly dependent on the water levels of the river, making it possible for them to continue to operate. If the water level of the IJssel were to drop below a certain level, the heavy cargo ships become unusable, costing the transport companies significant amounts of investments. The transport companies will do everything in their power to ensure that they can move goods on the IJssel. By maximizing the amount of goods transported on the IJssel, their objective is satisfied. As long as the water level of the IJssel above their threshold, the transport companies are content. Therefore, dike heightening has their preference, as this will not decrease the water level of the IJssel river.

A.6. Environmental interest group

The environmental interest group is striving for minimum ecological damage, maximum amount of green land and reducing the carbon footprint as much as possible. In contrary to transport companies, environmentalists prefer the Room for River option, so that the nature surrounding the IJssel river has room to grow.

A.7. Power-Interest Grid

Figure A.2 depicts the position of the involved stakeholders in a Power-Interest grid. In this grid, the right side represents high interest, while the top side represents high power. It can be noted that all stakeholders have high interest in what kind of policies will be implemented in the IJssel river. Although all stakeholders have an interest in the problem, it does not imply that they have any influential power to adapt the design process of policies that will mitigate the problem. There are only two stakeholders with high power identified: Rijkswaterstaat and the Delta Commission. The other stakeholders are incapable of influencing the problem, even though they are heavily interested in the outcomes of the water management policies.

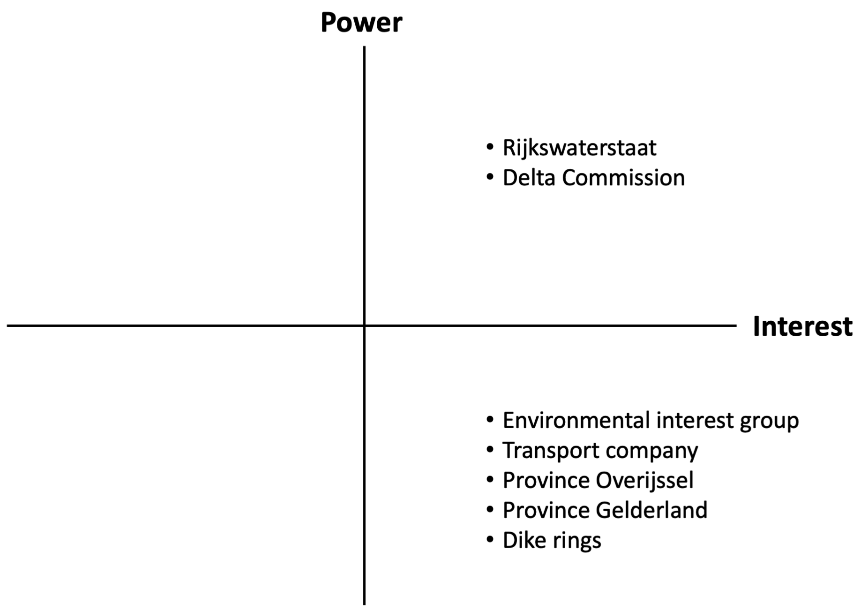


Figure A.2: Power-Interest grid displaying the position of all involved actors. 'Power' indicates the amount of influence a stakeholder has in the process of the policy design, 'interest' indicates how much they care about the upcoming policy decision.

B

Simulation model

B.1. Model specifications

The simulation model runs for 200 years and during its runtime, there are three distinct moment which allow for policy decisions to be implemented.

B.1.1. Water management system uncertainties

The simulation model aims to represent the IJssel river and its water management. The status of this system is, however, under continuous change due to changes in environmental conditions such as the weather and technical depreciation of current water infrastructures. In order to capture these deep uncertainties into the model, variables related to these types of factors are modeled with a range of values instead of a fixed value (Table B.1). In so doing, different combinations of values for the uncertain variables combine into different so-called scenarios. These scenarios can consequently be studied to find for instance the most likely scenario but also the worst-case scenario, resulting in most deaths and costs. The latter sets the benchmark for which one want to be prepared when designing a water

Uncertain variable	Description	Range/set	unit
Flood wave shape	A normalized curve describing the way discharges at the most upstream location change over time. There are 140 possible wave shapes.	0 - 140	
Dike failure probability	Probability that the dike will stand the hydraulic load, The higher this number, the 'stronger' the dike.	0 - 1	
Final breach width[1]	The final extent of the breach width. The larger the width, the greater the volume of water flowing into the floodplain.	30 - 350	m
Breach width model[1]	The way the breach width develops over time, with the uncertainty being the growth rate. The final breach width can be reached within 1, 3, or 5 days.	(1, 1.5, 10) for 5, 3, 1 day, respectively	1/day
Discount rate[2]	It determines the present value of the future expected damage. The lower the value, the more damage to future generations is valued.	(1.5, 2.5, 3.5, 4.5)	

Table B.1: Uncertain (external) factors of the simulation model.

management policy.

B.1.2. Possible policy levers

The model is equipped with three different types of policy interventions (Table B.2). Both the Room for the River and the heightening of dikes can be implemented on specific locations as well as in different timesteps. The model is capable of combining different policy levers and simulating their combined effect.

Policy lever	Description	Range/set	unit
Dike heightening[1,2]	Amount of dike raising. The higher the dike, the higher the hydraulic loads it can stand.	0 - 10	dm
Early warning	Early warning systems anticipate a threat and help limit damage and/or avoiding deaths. The earlier the alert, the more effective the response, but also the more uncertain it is that the event will actually happen. False alerts can be costly and undermine people' trust into the authority. Waiting too long is also problematic as the efficacy of late alerts is poor. In the model one can choose how much time in advance to give the alert.	0 - 4	days
Room for the River[2]	RfR projects widen the river bed thus lowering the water levels associated to a given water volume. There are five RfR projects which can be either implemented or not (1 or 0). Each project corresponds to a profile of water level reductions across locations.	0, 1	

Table B.2: Available policy levers in the simulation model.

B.1.3. Model KPIs

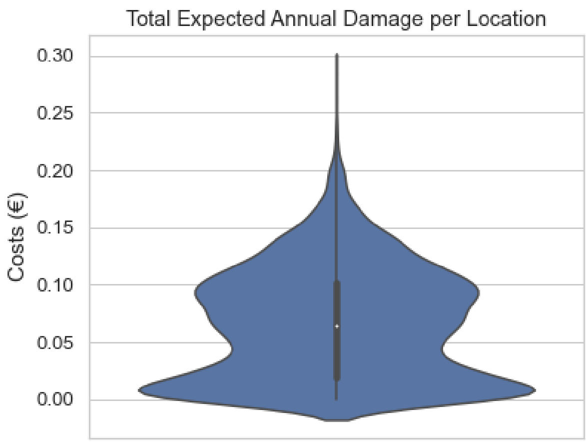
The output of the simulation model comes in the form of five KPIs (Table B.3). They can be grouped into two categories: (i) the costs of implementing protecting and mitigating measures, and (ii) the consequences of water mismanagement. The first category is proxied in the model by costs for RfR, dike heightening, and the early warning system. The second category is represented by the damage in case of a flood; the number of deaths and the costs of damage done to the properties.

KPI	Description	unit
Expected annual damage[1,2]	Expected annual value of flood damage over the planning period. Clearly, for each location, the lower this value, the better.	€
Expected number of deaths[1,2]	Same as above but related to the amount of casualties.	#
Dike investment costs[1,2]	Investment costs of raising dikes.	€
Evacuation costs	Function of the number of people evacuated and the number of days they need to be out from home. The estimation is based on the 1995 evacuations in the Netherlands.	€
Room for the river costs	Investment costs for the implemented Room for the river project.	€

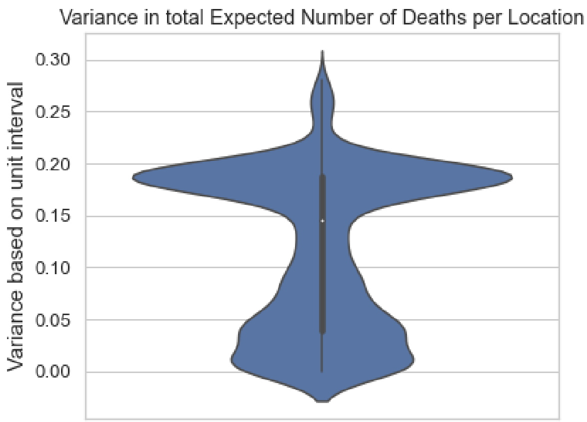
Table B.3: Available policy levers in the simulation model.

[1] This factor applies to each location, i.e. there are five factors, with potentially different values.
[2] This factor applies to each of the planning steps, i.e. there are as many as factors as the considered planning steps, with potentially different values.

C
Supplementary figures



(a) Total annual damage costs.



(b) Total deaths.

Figure C.1: Normalized variance of base case situation model outcomes under 5000 different scenarios. The amount of costs and deaths per location were scaled to a unit interval and consequently the variance between different locations was calculated. Presented outcomes are summed over all three stages of the project. The violin plot shows on the x-axis the smoothed probability density, i.e. the wider, the higher the probability. The vertical thick black line shows the interquartile range (IQR), the white marker shows the median value, and the vertical thin black line denotes the range equal to 1.5 times the IQR.

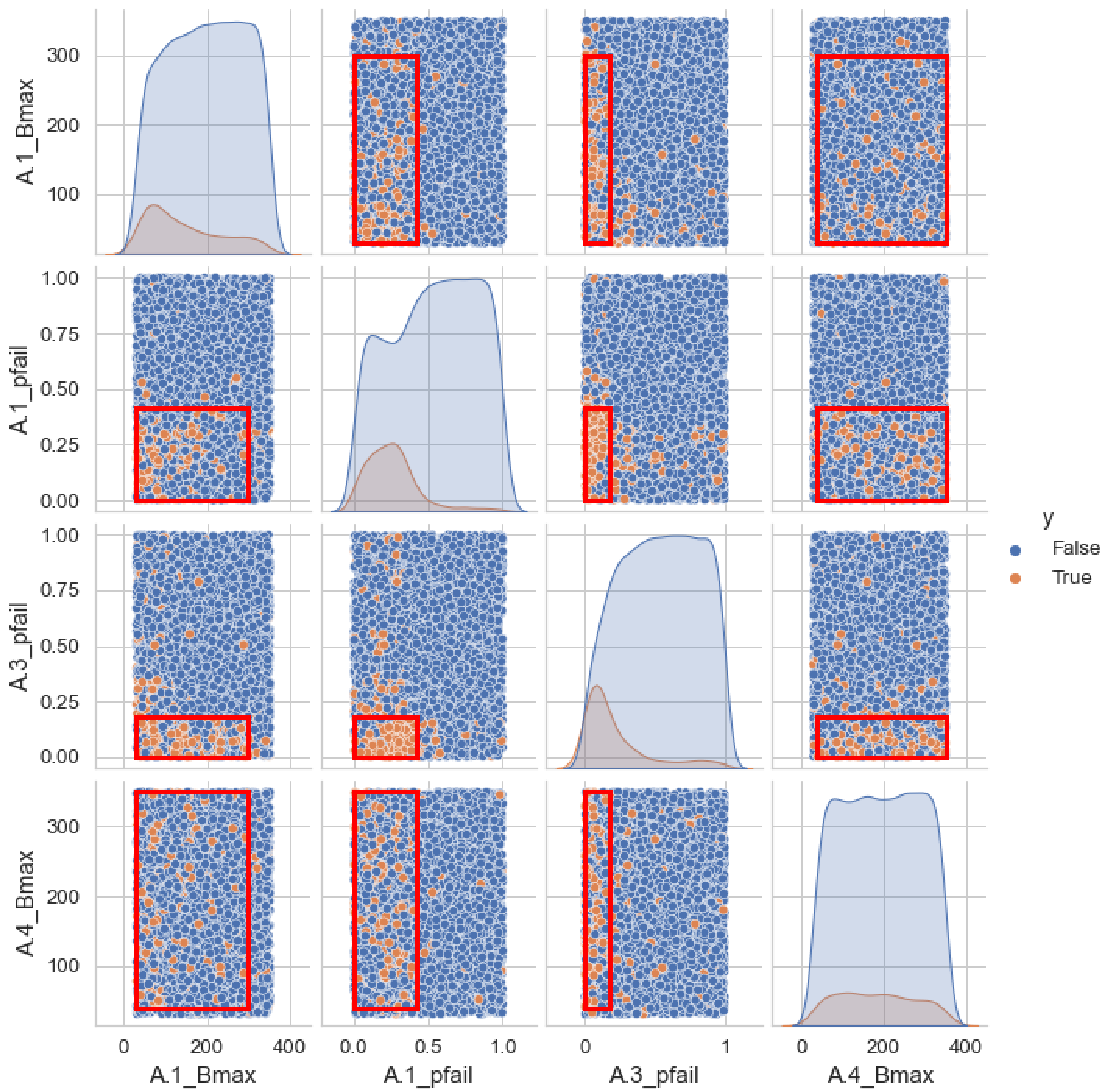


Figure C.2: Scenario discovery by PRIM. Uncertain variables are indicated on the axis. Orange dots represent outcomes of interest, i.e. desirable outcomes. Red boxes represent the range of values for which a variable contributes to undesirable outcomes.

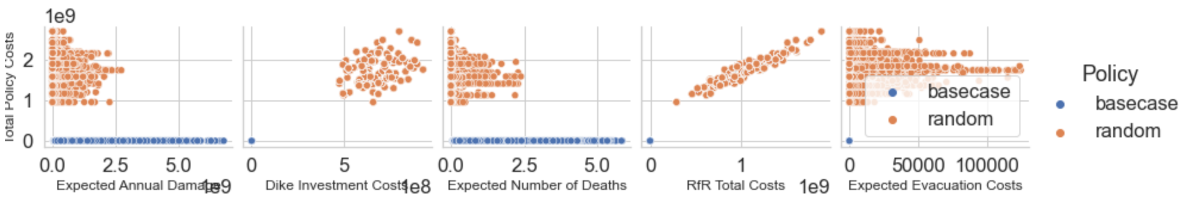


Figure C.3: Performance of random policies against basecase

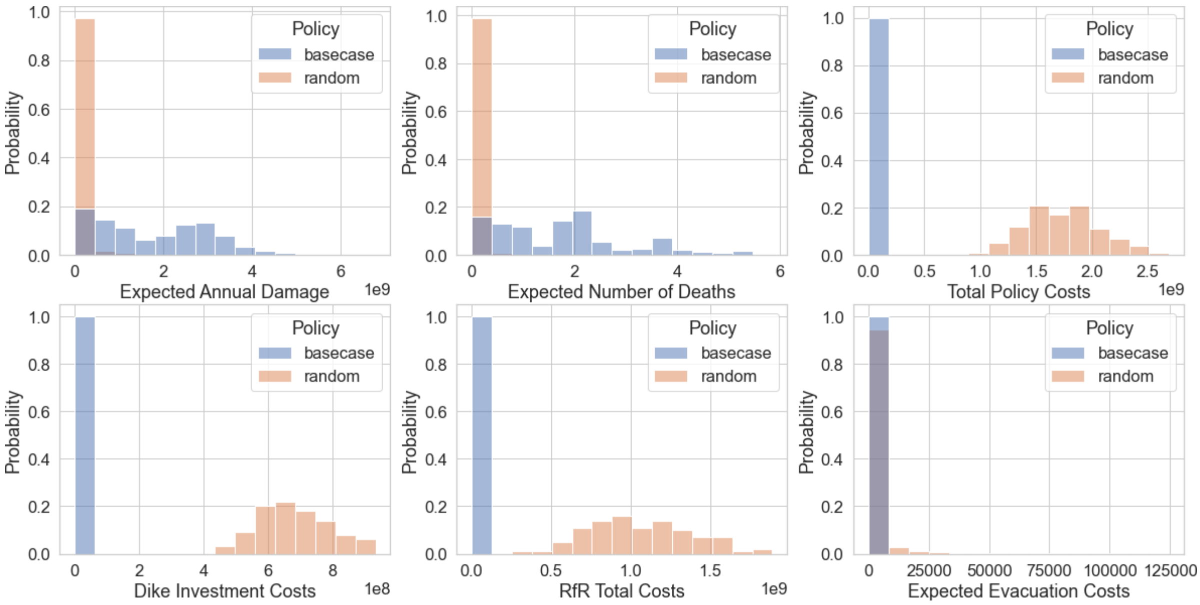


Figure C.4: KPI performance under random policies. Basecase (i.e. all policy levers unused) was run for 5000 scenarions. 100 random policies were created and evaluated on 400 scenarios each. Per policy type (indicated by colors), the histogram is normalized to sum to a value of one.

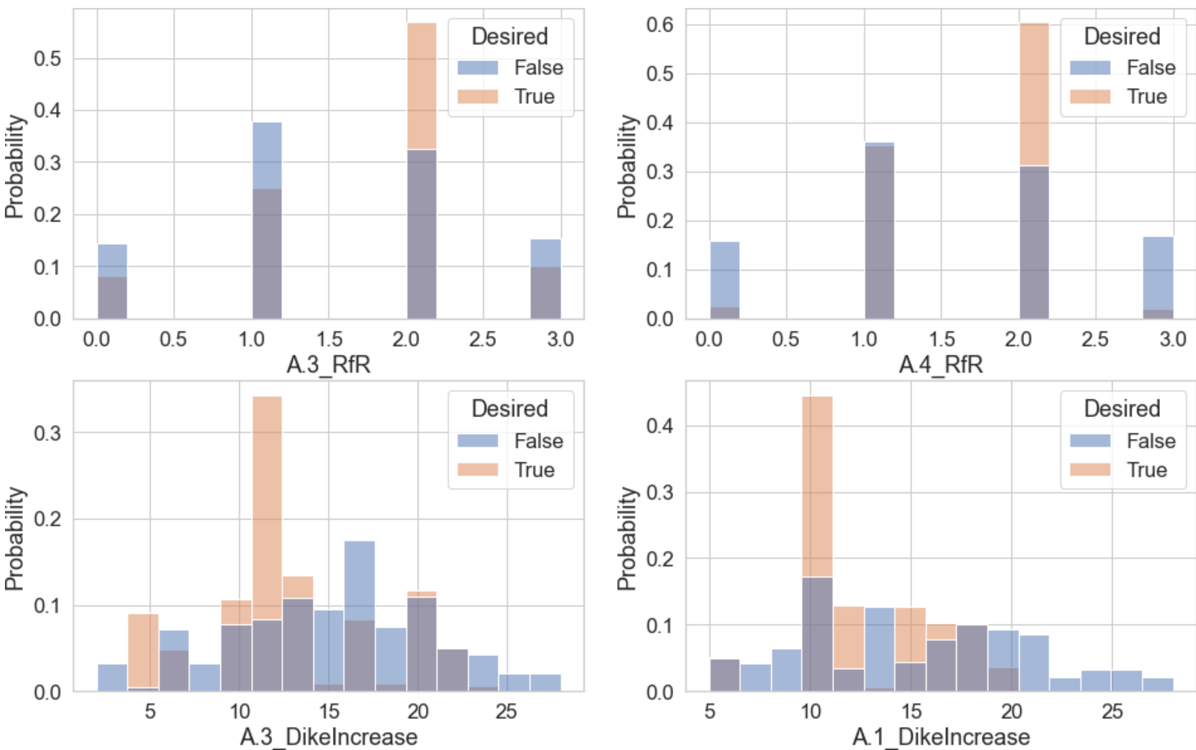


Figure C.5: Effective policy levers. Histogram of policy levers and their respective outcomes. Color indicates whether the outcome of the policy is desired or not.

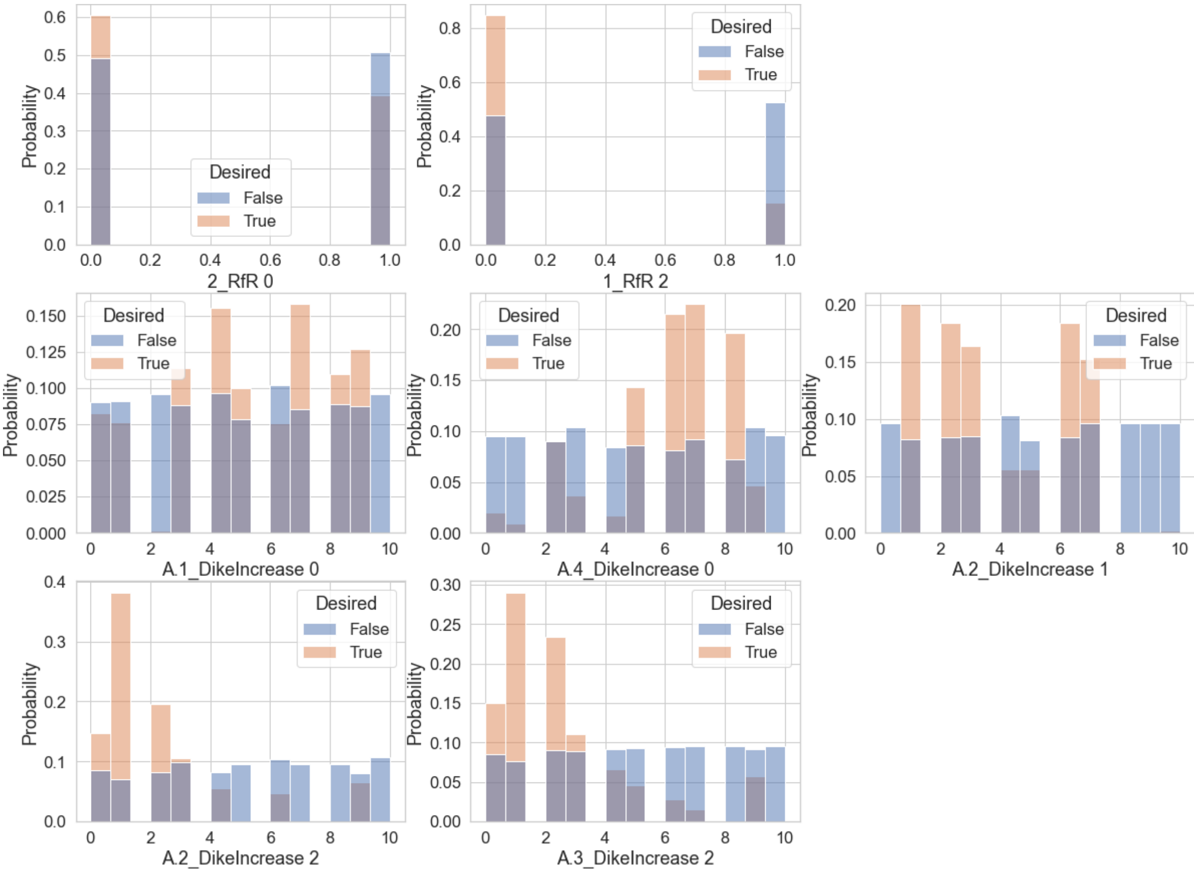


Figure C.6: Effective policy levers per timestep. Histogram of policy levers disaggregated in time and their respective outcomes. Color indicates whether the outcome of the policy is desired or not.

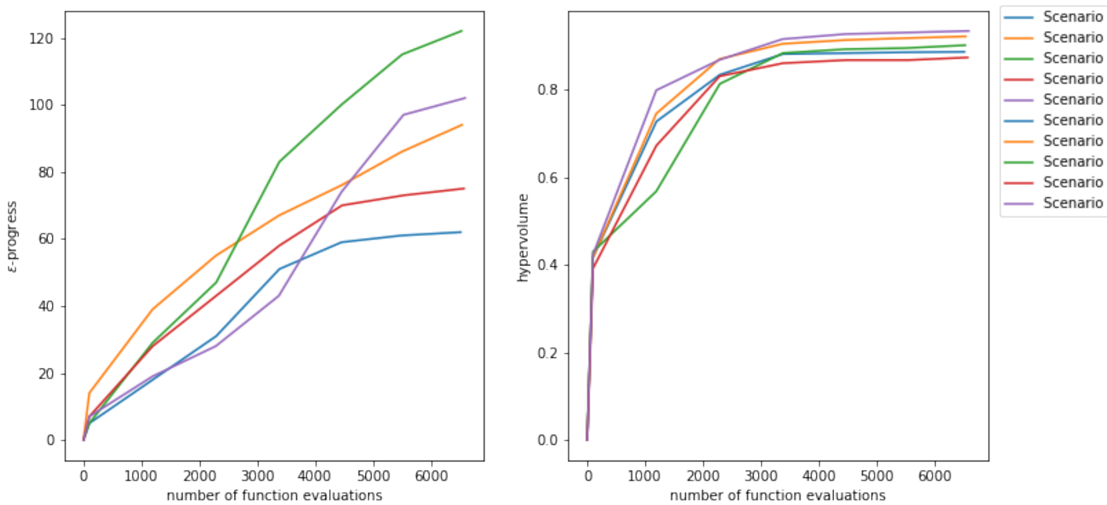


Figure C.7: Multi-scenario MORDM convergence metrics. Each color indicates a distinct worst-case scenario under which optimal policies were identified. A gradient approaching zero indicates convergence.

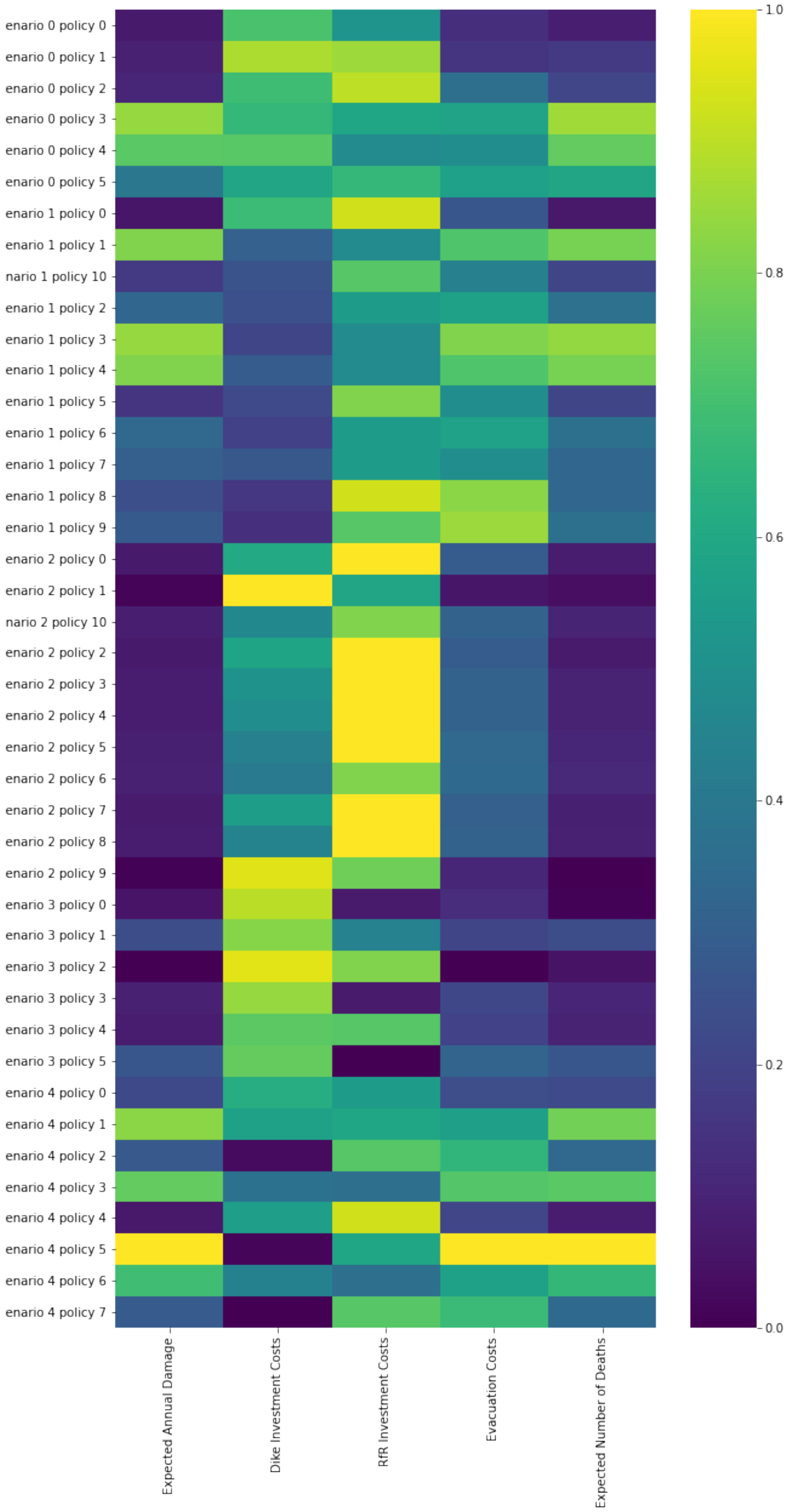
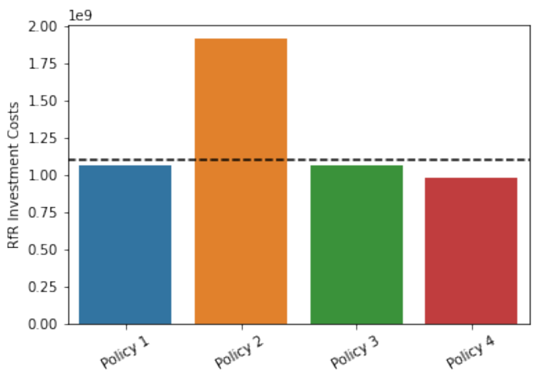
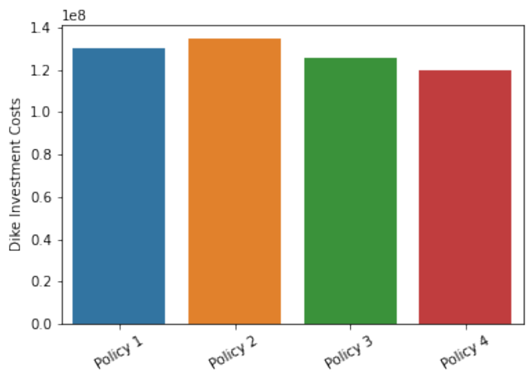


Figure C.8: Performance policies identified by multi-scenario MORDM. 'Scenario' indicates the worst-case scenario under which the policy was optimized.



(a) RfR costs.



(b) Dike heightening costs.

Figure C.9: Costs of the identified policies. Horizontal line indicates threshold set by RWS or Delta Commission.

D

MORDM details

$\epsilon - NSGAII$ is the chosen MOEA for the analysis. It imposes a grid on the objective space and looks for one solution in each grid. The granularity of the grid is specified through the ϵ values (J. Kwakkel, 2020). The values have been iteratively determined by performing several short runs and studying the amount of solutions obtained by decreasing the maximum values for each outcome in 2 orders of magnitude. These maximum values were obtained by searching for the maximum across the obtained outcomes from the policy lever exploration and the base case. In such manner, we get a rough estimation of the maximum values we can expect. Closer attention was payed to the ϵ value for Expected Number of Deaths as we were interested in finding multiple optimal policies that obeyed the threshold. For that reason, the chosen ϵ is one order of magnitude lower than the constraint value. The chosen final values are $1e7$ for Expected Annual Damage, $1e6$ for Dike Investment Costs, and $1e-5$ for Expected Number of Deaths.

In order to find optimal policies with sufficient certainty, the MOEA used by MORDM needs to converge. An indicator for this is Hypervolume, a metric that needs a value for the minimum and maximum expected value for each KPI (J. Kwakkel, 2020). As in the determination of the ϵ values, we searched for the minimum and maximum across the obtained outcomes from the policy lever exploration and the base case. In such manner, we get a rough estimation of the minimum and maximum values we can expect from the MORDM outcomes and to look for in the Hypervolume space. A second metric used to evaluate convergence is ϵ progress. It measures how often a solution in a new grid cell of the epsilon gridded output space is found. When progress becomes more difficult the algorithm starts to converge (J. Kwakkel, 2020). The number of function evaluations have to be sufficient to ensure that the algorithm has converged. Due to time constraints this has been set to 7500 function evaluations.