Delft University of Technology

Model-Based Decision Making
EPA1361

Flood Risk Management of the IJssel River

A Model-Based Advisory Report for Rijkswaterstaat

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Summary

This report provides a policy advice for Rijkswaterstaat on flood risk management policies for the IJssel river case. The IJssel river is of great importance, from both an ecological and economic perspective, for surrounding areas. The fact that current flood risk management is substandard leads to the need for research into possible interventions. As this case is subject to deep uncertainty, Rijkswaterstaat must choose a robust policy in this respect that performs well in the complex multi-actor arena and the uncertainties embedded in the system. This report uses model-based analysis of the complex problem to provide Rijkswaterstaat with an objectively best set of policies to implement.

The MORDM approach is applied to the IJssel river case to find and analyze suitable and robust policies. This is a framework for supporting decision-making under deep uncertainty. This method, applied to the flood risk model generates Pareto optimal solutions of the problem. These solutions are then filtered on hard constraints which were taken to include the perceptions and desires of stakeholders in the system. The main constraint that all actors agree on was safety. Therefore that was applied to the solutions. Moreover, a constraint was applied considering the investment costs of the project. After these constraints 11 viable policies were found. These policies thus minimize expected casualties and the investment costs.

These 11 policies are analyzed on robustness through uncertainty analysis and scenario discovery. As the system contains deep uncertainty, analyzing the performance of polices under different uncertainties and scenarios increase robustness of the policy advice. All 11 policies are run for 1.000 different scenarios. Afterwards, their robustness was calculated using the Signal-to-Noise and the Maximum Regret measurements. After calculating these metrics a scenario discovery was performed, to see how the policies perform under the uncertainties and which uncertainties significantly influence the outcomes of the policies.

As a result of this analysis the model-based advise for Rijkswaterstaat is that 2 policies are found that are most viable and robust to implement for making the IJssel river flood proof. Both of these policies focus on heightening the dikes in all the locations of interest. One policy applies Room for the River only in Doesburg, and both policies include a Room for the River project near Zutphen.

These two policy options should be considered by Rijkswaterstaat when making the decision on how to make the IJssel river flood proof. When opting for a policy implementation, Rijkswaterstaat must make a choice that fits well within the multi-actor perspective of this case. The two policies found have a trade-off when looking at actor preferences, thus implementing a policy could still lead to some tensions in the multi-actor playing field. As local actors oppose the implementation of RfR, the policy with just one room for the river project should count on more support.

Rijkswaterstaat should however, as all model-based decision-makers, realize that this advise is based on a model. Every model is a simplified representation of reality and has its limitations. This model is no exception. Therefore the proposed policy solutions should be used as a guideline for decision-making, as the used model is simply not able to account for all uncertainties and variables in the real-world. Therefore, it is advised to carefully read the conclusion (Chapter 4) and the Discussion (Chapter 5) next to this summary.

Contents

1 Policy Problem Formulation and Context

1.1 Introduction

In 2006, Al Gore, former Vice President of the United States, produced the shocking documentary *'An Inconvenient Truth'*, exposing the impact of humanity on the environment (Gore, 2006). This started a global trend where climate change and global warming became more and more present on the political agenda. Now, 15 years later, global politics revolve around the climate (The Economist, 2020). Due to global climate change, the sea level is rising at an accelerating pace every year. Since 1880, the global mean sea level has risen approximately 21 to 24 centimeters. About a third of this increase has happened over the last 25 years (Lindsey, 2021). Not only has the rise of water levels become a bigger problem over the last decades, the rate of sea level rise is also accelerating, as it has more than doubled throughout most of the twentieth century. These problems create a dire need for flood management (Hoozemans and Hulsbergen, 2021).

The Netherlands, located largely below sea level, are known for their never-ending battle with water (McVeigh, 2017). After the North Sea Flood of 1953, major projects were set up to protect the country against the water (De Haan and Haagsma, 1984). As expressed by Saeijs (1991): "God created man, but the Dutch created their own land". Where until recently the most important instrument was the strengthening and heightening of dikes, now increasingly extensive resilience strategies are applied (Vis et al., 2003). This has led to the development of a comprehensive flood protection strategy called 'Room for the River' (Rijke et al., 2012; De Bruijn et al., 2015). Room for the river is one of the largest projects the Dutch have created in their fight against water. Its purpose is to generate more space for the IJssel river while creating an alternative for the heightening or construction of dikes.

However, these kind of flood risk management implementations often also bring up negative side-effects. Due to the uncertain nature of resilience and the large number of actors involved, each with their own incentives to exploit these uncertainties, the problem has a win-lose character (De Bruijn et al., 2015). There is no one-size-fits-all approach to flood risk management.

These uncertainties, as well as natural uncertainties, have long been considered an important facet of environmental decision-making (McPhail et al., 2018); and there has been an increased focus on including deep uncertainty for robust decision-making (Maier et al., 2016). Deep uncertainty is defined as the situation in which parties to a decision do not know, or cannot agree on, how the system under consideration work, how important the various outcomes of interest are, and/or what the relevant exogenous inputs to the system are and how they might change in the future (Kwakkel et al., 2010; Walker et al., 2013). This system, with its uncertain external factors and win-lose actor characteristics, is excellently characterized by the points that describe deep uncertainty. Robustness is being used increasingly for incorporating deep uncertainty in decision analysis (McPhail et al., 2018; Maier et al., 2016).

In this paper, we will address this resilience management problem by applying these strategies on the IJssel river in the Netherlands, with the aim of drawing up a robust flood risk management plan for effective flood risk management, which can also count on consensus within the political agenda of the actors involved.

1.2 Room for the River Program: IJssel River Case

The Room for the River program is a national flood risk management program in the Netherlands. This program consists of multiple measures in order to increase the discharge capacity of the main rivers in the Netherlands while also enhancing environmental and spatial quality (Ministerie van Infrastructuur en Waterstaat, 2021b). Within this report the focus lies on the upper branch of the IJssel river. Due to climate change, the future Rhine discharge could raise from 16.000 to 18.000 m3/s (Mens and Klijn, 2015). As the Rhine partially flows into the IJssel river, measures are needed to ensure that the IJssel river and the hinterland is ready for the coming decades. The Room for the river project is set to be realized at 34 different location surrounding the IJssel river (Ministerie van Infrastructuur en Waterstaat, 2021c). The focus of this research lies on five, so called, dike rings (ring shaped dikes that protect flood prone area). The locations of interest are Doesburg, Cortenoever, Zuthpen, Gorssel and Deventer, as can be seen in Figure 1 .

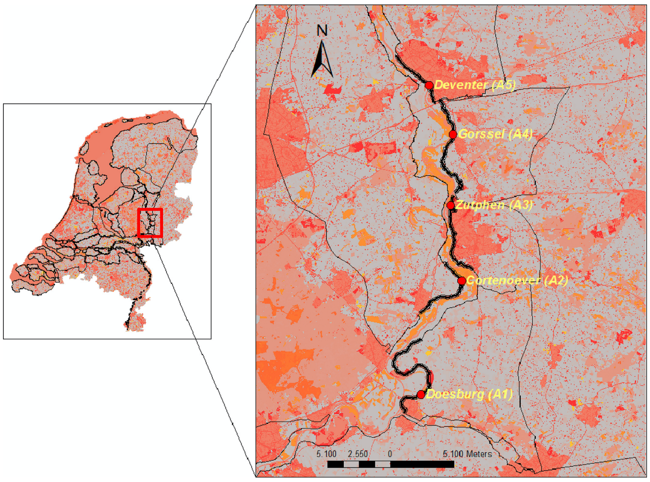

Figure 1: IJssel river case (Ciullo et al., 2019a)

1.3 Actor Analysis

In order to get a full understanding of the IJssel river case, it is crucial to look at the political arena and the actor system as a whole. As can be seen in Figure 2, the actors involved can be categorized into 4 different groups and all have some form of a relation with one another. These relations, either formal or out of special interest, bring interdependencies with them. In figure 1 the system is portrayed as a hierarchical structure, which formally is correct within the Dutch government (van Leerdam, 1995). However, this actor-system can also be seen as a network structure, due to aforementioned interdependencies (De Bruijn et al., 2015), which could cause a situation where actors obstruct the decision-making process in the case that their own desires are not fulfilled to their will (De Bruijn et al., 2015).

This has implications for reaching a potential policy outcome for the IJssel River case that Rijkswaterstaat can deem as feasible. The policy that will be implemented should entail outcomes within the bounds of acceptability for all actors' desires. This adds much complexity to the problem, because not all actors involved have aligned interests with each other. The vision of several proposed measurements were questioned by engineers, economists and politicians (Rijke et al., 2012). Arguments in favor or against a particular measurement are then used by one of the actors for their own interest.

A detailed description of these interests and positions can be found in appendix A. This overview results in rough guidelines for the policy direction that involved actors find acceptable, which is useful for further analysis but not enough to base policy on.

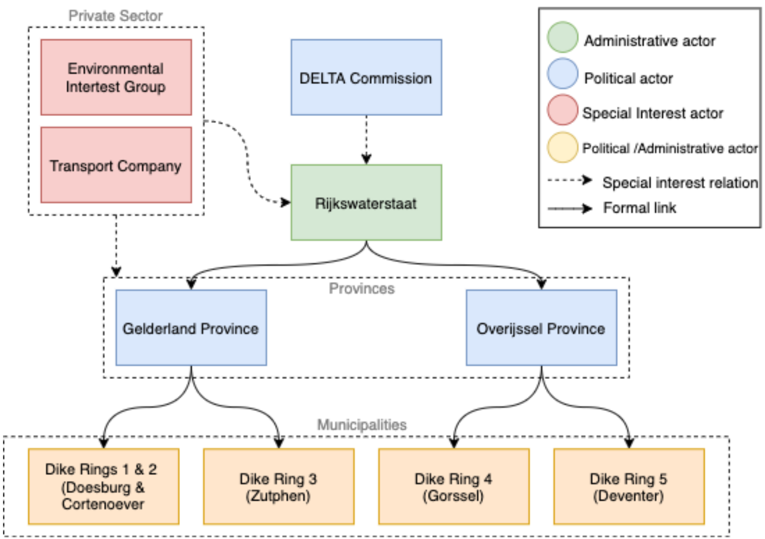

Figure 2: Multi Actor Arena

1.4 Deep Uncertainty

The multi actor characteristics make this project not only technical, but also brings a political aspect to it De Bruijn et al. (2015). As briefly mentioned in section 1.3 and more elaborate in appendix A, the actors and stakeholders do not know or cannot agree on the outcomes of interest, the system under study, or future developments. This leads to sets of plausible models, sets of outcomes of interest without an 'a priori' weighting and sets of scenarios (Kwakkel and Haasnoot, 2019). These uncertainties can have societal and economic impact. The uncertainty that arises from the political field is epistemic uncertainty: there is a lack of knowledge, which leads to different views on the system and its outcomes. This system however also contains ontic uncertainty: the probabilistic nature of the system are intrinsic reasons for uncertainty. Due to this epistemic and ontic uncertainty there are sets of plausible models. This forces the decision makers to shift from a *'predict and act'* approach towards a more *'explore and adapt'* approach.

1.5 Problem Formulation

The Room for the River project aims to prevent flooding in the Deventer, Gorssel, Zutphen, Cortenoever and Doesburg locations by means of flood management. The aim of the project is to distribute the benefits of the Room for the river project as fair as possible. This implies that the risks of flooding must be evenly distributed between the different areas. The same applies to the corresponding costs and nuisance. With regard to this policy problem, different stakeholders are involved with different objectives and preferences. The actors; Rijkswaterstaat, Delta commission, Environmental Interest Group, Transport Company, Gelderland province and Overijssel province have to come to a mutual agreement that is acceptable to all involved parties. Rijkswaterstaat, the initiator of the project, is looking for a robust and maximally effective solution that is analytically substantiated. This leads to the following problem statement:

'How can a safe flood risk management policy be implemented, which is robust under multiple deep uncertainties, in a way that is cost-efficient acceptable to all relevant actors involved?'

The fact that so many different actors are involved whose preferences will be heard means that different dilemmas will arise. It will never be possible to find an optimal solution for everyone. This implies that when a fair solution for several parties is sought, concessions have to be made. In a model it is possible to give preferences and boundaries to a problem formulation.

In this report, two ways of arriving at a final solution are distinguished: The political, multi-actor approach and the analytical approach. These methods show great differences, but are often used in combination to extract the best possible solution in a multi-actor case. The dilemma between political and analytical incentives manifests itself in the difference between forming a solution in debate and drawing conclusions from models and analysis. In this report, information of the multi-actor arena is gathered through two separate debates. Also, through discussion, Rijkswaterstaat aims to arrive at a policy proposal which will be accepted by a majority of stakeholders. The proposed policies will then be used as input for the analytical analysis.

1.6 Report Structure

This report consists of 5 chapters. The first chapter introduces the case, its actors, and the surrounding problems which will be analyzed and discussed in later chapters. The second chapter elaborates on the methodology used for the assessment of this case. An explanation of the used model and the modeling methods in this report is given. Chapter 3 analyzes policies for the Room for the River case and show the results. The findings in chapter 3 will then be concluded in chapter 4, resulting in a policy recommendation. Chapter 5 will discuss our findings, made assumptions, and the implications of our policy recommendation.

2 Methodology

In this chapter the methodology will be discussed. In section 2.1 the MORDM framework is presented which is used for the IJssel river case. In addition, each step of this framework is discussed more in-depth. Lastly, in section 2.2, the used modeling tool to perform the necessary calculations, is briefly addressed.

2.1 MORDM Framework

The project for the IJssel river case is approached within this report by the Many-Objective Robust Decision Making (MORDM) framework, as presented by Kasprzyk et al. (2013) and Watson and Kasprzyk (2017). This is a framework for supporting decision-making under deep uncertainty (DMDU) (Kwakkel and Haasnoot, 2019). Decision Making for the future depends on anticipating change and rare events in which uncertainty may be defined as limited knowledge about future, past, or current events (Walker et al., 2013). Hence, for long-term decision making, deep uncertainties are in most cases a given. Although reduction in uncertainty seems favorable to keep things clear, this is highly undesirable for this project. As for the case of flooding, excluding uncertainties could lead to an implemented policy which is not well-prepared for these rare events, leading to an undesired number of casualties (Bloemen et al., 2018).

MORDM tools use algorithms to identify the regions of a Pareto surface over many objectives that are most robust to uncertainty (Marchau et al., 2019). The MORDM framework combines the strengths of MOEA optimization and Robust decision-making (RDM). As this report tries to find the optimal set of flood risk management measures, under deep uncertainty, in relation with multiple (conflicting) objectives, this approach can be considered as suitable. Besides, the MORDM framework is used, and found useful, in several scientific literature for similar problems as the IJssel river case (Hall et al., 2012; Singh et al., 2015)

The steps of the MORDM framework, as used by Kasprzyk et al. (2013), are shown in Figure 3. Each of these four steps are described below.

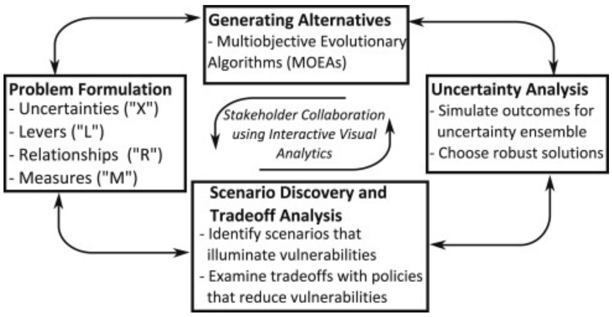

Figure 3: The four steps of the MORDM framework (Kasprzyk et al., 2013)

2.1.1 Step 1: Problem Formulation

The conceptual model is developed using the XLRM framework, where the elements of analysis are grouped into four categories (Lempert, 2003). In this framework, X stands for the *exogenous uncertainties*, factors outside the control of the decision-maker; L are the *policy levers*, the available strategies or interventions the decision-maker wants to explore; M (of measure) are the *performance metrics*, the outcomes of interest used to rank the desirability of the different policies (L) in the face of the exogenous uncertainties (X); and, finally, R refers to *relationships in the system*, a ways in which the exogenous uncertainties (X), policies (L) as well as outcomes (M) are tied together and relate to each other, namely the actual simulation model (Ciullo et al., 2019b). The parameter set-up for the IJssel river case within the XLRM framework can be found in Figure 4.

As this report is written for Rijkswaterstaat, the performance metrics is adapted to their outcomes of interest. Mentioned in section 1.5, Rijkswaterstaat has the ultimate objective to implement a safe and cost-efficient flood-risk management policy, which is acceptable to all relevant actors involved. The outcomes of interest includes all relevant costs, regarding both policy investments costs and expected annual costs. These costs are summed over all locations, as costs are easy to redistribute and settle and thus this research is most interested in policies that minimize the total costs for all locations.

In addition to the costs, the expected annual deaths are included in the performance metrics. Rijkswaterstaat has the legal and moral objective to ensure safety in general (Ministerie van Infrastructuur en Waterstaat,

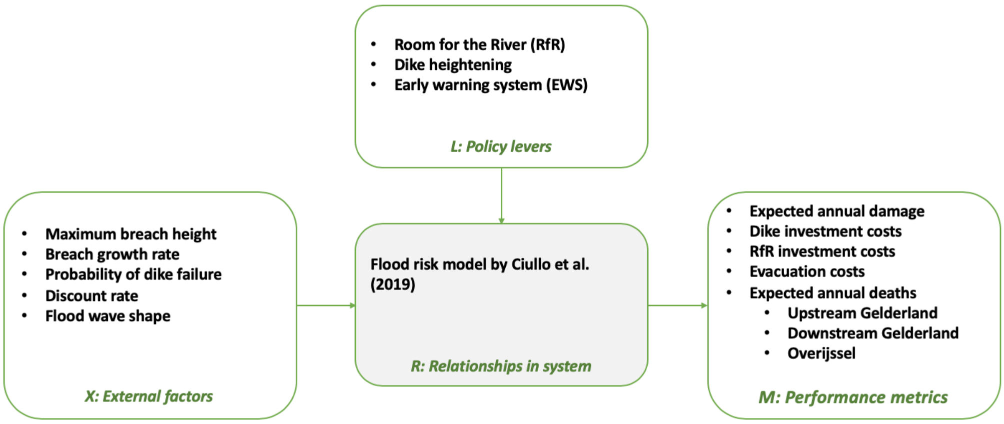

Figure 4: Conceptual model: XLRM Framework

2020). As the policy must be acceptable to all actors, the expected annual deaths are subdivided by three geographical locations: upstream Gelderland, downstream Gelderland and Overijssel. As casualties are not easy to re-allocate or compensate, the casualties across the locations should be minimized to ensure support from all regional actors. Lastly, the insights gained from subdividing the expected annual deaths per location, can be used for a fair distribution of potential cost in regard to their according risk.

Within this step, a base-case scenario will be explored; This is the scenario in which no policy will be implemented. These results give us insight into the costs and risks (spreading) if no policy is implemented. The base case can then serve as a reference for analyzing policies; which also makes it possible to better analyze for whom the policy implementation generates the most progress in safety (a decrease in expected annual deaths). These results will be presented in section 3.1.

2.1.2 Step 2: Generating Alternatives

In the second step alternatives are generated to search for Pareto optimal solutions. Multi Objective Evolutionary Algorithms (MOEAs) are used to find the optimal set of multi-objective solutions. MOEAs provide an effective way to discover trade offs between KPIs (Kasprzyk et al., 2013). By using a population based search algorithm, MOEAs are able to approach the Pareto optimal front and determine multi-objective solutions based on the full set of preferences given by the involved actors (Deb and Sundar, 2006). The iterative process of the MOEA evaluates all possible alternatives until it is able to deliver a set of the best policy options. Through the repetition of the evolution process over a certain number of runs while using different sets of settings, the entire trade off space can be achieved (Tang and Wang, 2013). Convergence and diversity are two important measures to determine the performance of a MOEA search (Kasprzyk et al., 2013). The convergence of a search stands for the closeness of the MOEA approximation to the actual Pareto optimal solution space. Diversity stands for the MOEAs ability to analyze the full set of possible alternatives, and by doing so covering the entire Pareto optimal front.

After the search for the solutions on the Pareto optimal front, the set of solutions will be reduced to a more limited set that satisfies some constraints. This will be the final output space to discover in more detail in steps 3 and 4. The constraints, that generate the boundaries of the final output space are introduced for two reasons. First, actor preferences impose constraints. Actors will never agree to a policy, which may be very cheap, but results in an unsafe future. Thus, it is meaningful to set a constraint on, for instance, the expected maximum number of deaths. Second, the Pareto optimal solutions, found by MOEA, contains policies that are insufficient or excessive, while the goal is to investigate efficient policies, also known as ALARP (as low as reasonably practicable) (Melchers, 2001). By setting boundaries to the Pareto optimal solutions, these insufficient or excessive policies are filtered and the final output space is narrowed down to policies with a realistic cost-risk trade-off.

These values of the constraints are presented in Table 1. The constraints for the total expected number of deaths is 0.01 as a constraint set by the Ministry of infrastructure and water management (Ministerie van Infrastructuur en Waterstaat, 2020). This constraint sets the boundary of limiting insufficient measures. The constraint on total investment costs is set on 500 million euros and this consists of both the RfR and and dike investment costs. This constraint sets the boundary for limiting excessive measures.

Table 1: Constraint values for the KPIs

Variable	Constraint
Total Expected Number of Deaths	0.01
Total Investment costs	500 Million Euros

2.1.3 Step 3: Uncertainty Analysis

MORDM has been performed to derive a more specific set of potential Pareto Optimal Solutions. After this, constraints have been set to narrow these solutions and make them comply with criteria. The 11 resulting policies will be compared in step 3 based on the extent to which these measurements perform on all different simulated scenarios. The ultimate goal of the uncertainty analysis is to conceive a formulation and set of solutions that exhibit Pareto-satisficing performance for a wide range of possible scenarios. This makes it possible to deliver analytical advice that meets the criteria set by Rijkswaterstaat, with the provision of a robust solution as one of the main criteria. The measures used to compare the policies based on robustness are the Signal to Noise Ratio and the Maximum Regret value.

In relation to problems related to deep uncertainty, the measurement robustness is increasingly used (McPhail et al., 2018). Decision-makers can use different metrics regarding robustness. The satisfying metric called the Signal-to-Noise ratio is used to calculate the degree of robustness per policy per variable. This is obtained by dividing the mean by the standard deviation of the performance of a particular policy across all simulated scenarios (Doumpos et al., 2016). When the aim is to act risk averse, the Maximum Regret value is an important robustness metric that is calculated per policy in comparison to other policies (Savage, 1951; Giuliani and Castelletti, 2016). Based on these metrics, the Uncertainty Analysis is performed to assess the robustness of the obtained policies.

2.1.4 Step 4: Scenario Discovery

The fourth step from the MORDM framework that will be executed is scenario discovery. This step aims to detect the vulnerability of the generated candidate solutions as well as improving these solutions. This is done by assessing uncertain conditions and policies under which poor performance arises. Poor performance, in this case, is based on outcomes that are highly undesirable for all actors involved. The metric used to asses this is the sum of the number of deaths over all the provinces. Scenario discovery can be applied using various different approaches. This report uses the Patience Rule Induction Method (PRIM), a lenient hill climbing optimization algorithm that narrows down uncertainty space in an iterative manner. This technique is very useful for scenario discovery because of its interactiveness, visualization capabilities and the fact that it is able to present multiple options for the choice of the scenarios (Bryant and Lempert, 2010). PRIM also makes it possible to select different trade-offs among the three main measures for scenario quality, coverage, density and interpretability (Rozenberg et al., 2014). PRIM identifies certain candidate boxes that lie on a Pareto optimal surface described by these measures (Kasprzyk et al., 2013). What these metrics describe and how the trade-offs between the measures can be interpreted is further explained in 3.4. Figure 5 portrays the three main steps for scenario discovery using the PRIM algorithm.

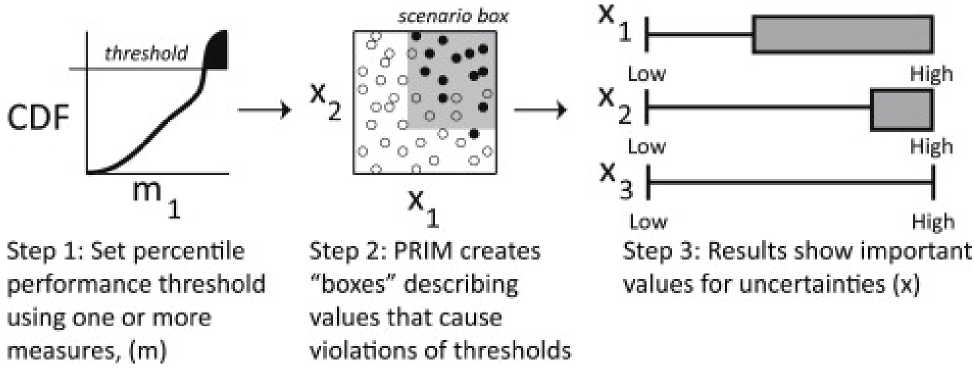

Figure 5: Three steps of the PRIM algorithm (Kasprzyk et al., 2013)

2.2 EMA Workbench

As mentioned in section 1.5 the decision makers have to adopt an exploratory approach towards this problem. Therefore, the analysis done on the IJssel river will be done using the Exploratory Modeling Workbench, created by Kwakkel (2017). This is a workbench that supports model-based decision making where computational experiments are used to assist decision makers in systems with deep uncertainty (Bankes, 1993).

3 Results

This section will elaborate on the results generated when using the framework explained in section 2 and implementing it in the EMA workbench. The results will be discussed while maintaining the structure applied in the previous section, namely the four steps of the MORDM framework by Kasprzyk et al. (2013).

3.1 Step 1: Problem Formulation

To understand the found policy solutions it is important to have a base case for comparison. Therefore a preliminary analysis has been performed on the outcome of the KPIs without any policy measures implemented. The descriptive statistics of the output variables of the model over 5000 scenario's is presented in the following appendix C.1.

The results of running the base case over 5000 scenario's shows that the number of casualties for three KPIs concerning expected deaths is way above the threshold set by the government. This implies that inspecting policy implementations is a viable thing to do.

As a more visual approach to analyzing the outcomes of interests, Figure 6 was generated. These plots clearly indicate the distribution of the scenarios, in which is directly visible that the base case scenario results have a good possibility of a highly undesirable future situation resulting many casualties.

To conclude, analyzing the base case scenario, in which no policy measures are implemented, provides clarity about the seriousness of the situation and the need for better flood risk management. It also provides insight into the current safety of the various areas and this, in combination with the improvements of the found policy implementations, can be useful at a later stage in a fair distribution of costs.

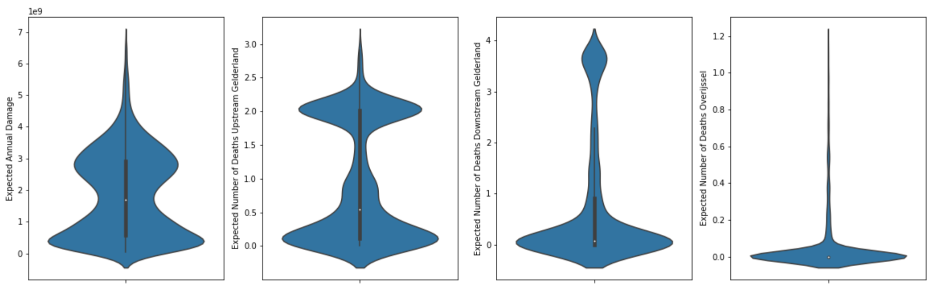

Figure 6: Basecase (no policy measures)

3.2 Step 2: Generating Alternatives

In the second step a directed search for candidate solutions was performed. These were identified through search with a multi-objective evolutionary algorithm. It was performed with seven outcomes considered. The epsilon that was chosen for these outcomes determines the grid size on which the solutions will be formed. The epsilon values depends on the domain of the objective. The chosen epsilon values for the optimization are presented in Table 2.

Table 2: Epsilon values for the outcomes

Model output	**Expected range**	**Epsilon**
Room for the River costs	0 - 1e7	1000
Evacuation costs	0 - 1e9	1000
Dike investment costs	0 - 1e9	1000
Expected annual damages	0 - 1e5	10
Expected annual deaths Overijssel	0 - 10	0.00001
Expected annual deaths downstream Gelderland	0 - 10	0.00001
Expected annual deaths upstream Gelderland	0 - 10	0.00001

A run of the MOEA is dependent on the number of function evaluations. Finding the right number of function evaluations is a process of trial on error. It is computationally intensive to run an optimization with a large number of function evaluations, but it is needed to reach convergence. In this step the optimization was first ran with 5.000 nfe. The convergence was measured using ϵ-progress. Another measure that can be used to inspect convergence is hypervolume, but since this is even more computationally heavy it has been left out of the scope of this process due to time constraints.

To inspect if 5.000 nfe's is sufficient to reach convergence the ϵ-progress was measured. This indicates how often the algorithm was able to find a substantially better solution. This will happen less frequently over the course of the optimization. When the ϵ-progress stabilizes, the algorithm has converged (Kwakkel et al., 2016a).

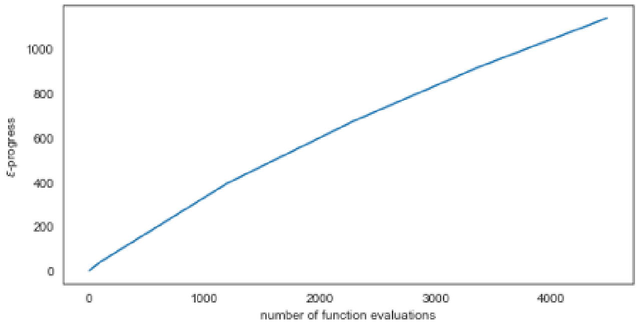

Figure 7: ϵ-Progress per nfe

Figure 7 shows how the convergence was assessed per number of function evaluations. The ϵ-progress shows that a nfe of 5.000 is not sufficient to reach convergence. Therefore, another run should be done with a much higher number of function evaluations, such as 50.000. Due to the heavy computational power that is needed for this and the time constraints of this project, this has not been done. The results of the run with 5.000 function evaluations will be used for further analysis. This optimization resulted in 554 pareto optimal solutions. These 554 solutions were filtered on two constraints. Firstly, the total investment costs should stay below 500 million Euros. Secondly, the total number of deaths in the three areas must be below 0.01. This filter resulted in 11 viable policies on which the uncertainty analysis will be performed. The outcomes of these policies are presented in Table 3.

Table 3: Outcomes of interest of the generated scenarios

Policy	**Expected Annual Damage**	**Dike Investment Costs**	**RfR Investment Costs**	**Evacuation Costs**	**Expected Number of Deaths Upstream Gelderland**	**Expected Number of Deaths Downstream Gelderland**	**Expected Number of Deaths Overijssel**
8	5.2297e+06	4.6334e+08	3.0700e+07	0.00	0.0013	0.0024	0.0000
9	1.9448e+07	4.1836e+08	3.0700e+07	1143.83	0.0025	0.0000	0.0000
67	5.9168e+06	4.6779e+08	3.0700e+07	154.82	0.0024	0.0000	0.0000
117	4.2582e+07	3.3249e+08	1.1530e+08	2767.78	0.0000	0.0001	0.0048
127	5.8276e+07	3.4333e+08	3.0700e+07	3278.25	0.0003	0.0065	0.0031
142	2.1431e+07	3.8940e+08	3.0700e+07	1177.97	0.0027	0.0000	0.0000
195	3.5941e+07	3.4534e+08	1.1530e+08	2179.66	0.0006	0.0005	0.0032
261	9.2969e+06	4.2395e+08	6.1400e+07	531.53	0.0000	0.0022	0.0000
314	4.3804e+07	3.1863e+08	3.0700e+07	2138.02	0.0024	0.0000	0.0041
359	0.0000	3.5519e+08	1.1530e+08	0.00	0.0000	0.0000	0.0000
398	2.3243e+07	3.8922e+08	3.0700e+07	578.66	0.0034	0.0000	0.0044

The run of 5.000 nfe's generated 554 solutions. The trade offs for these solutions are presented in Figure 8. The trade offs for the 11 viable policies between the outcomes are plotted in Figure 9. Figure 8 shows relatively high outcomes for the expected number of deaths in all three areas. As these are filtered out and only the policies with less than 0.01 expected number of deaths are taken into consideration, these values are lower in Figure 9. Furthermore, it can be concluded from a first look at the plots that low investment costs result in a higher expected number of deaths.

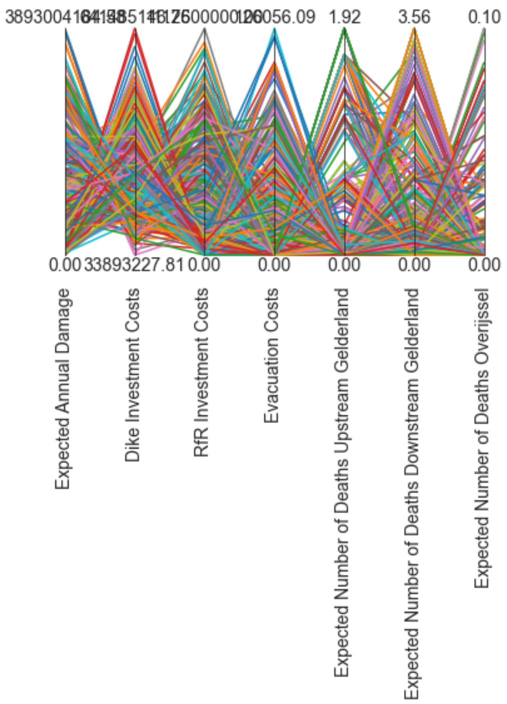

Figure 8: Trade offs for all solutions

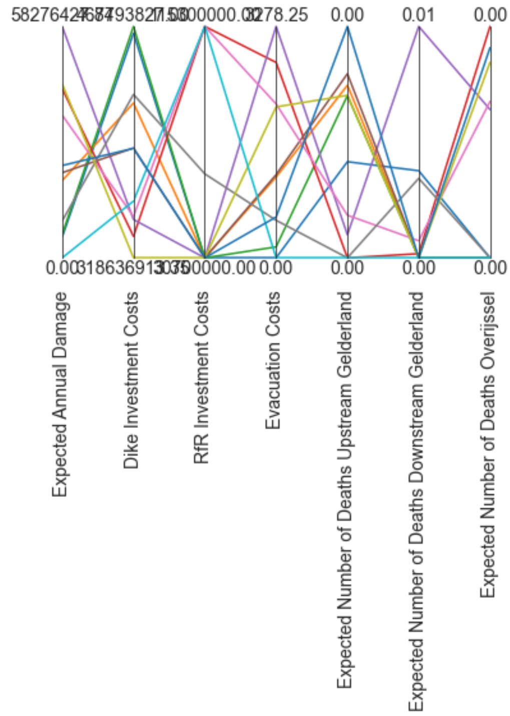

Figure 9: Trade offs for the 11 policies

A detailed description of the 11 policies that resulted from the directed search can be found in Appendix C.2 in Table 13. Each policy was ran for 1.000 scenarios, resulting in 11.000 experiments. On these experiments the uncertainty analysis in step 3 will be performed.

3.3 Step 3: Uncertainty Analysis

In the Uncertainty Analysis, the solutions resulting from the optimization run at section 3.2 are reassessed. This time they are tested against a wide range of scenarios. In this way, robustness can be tested for the solutions that are subject to uncertainties of input values in the model.

The signal-to-noise ratio provides a clear picture of average values in terms of robustness as it is based on the average value of performance of a policy over the different scenarios divided by their standard deviation. Due to this type of calculation, the SNR is highly valued as a substantiation for advice as it is based on all 1000 scenarios. The smaller the values of the Signal to Noise Ratio (SNR) and thus closer to zero, the more robust a policy is for that particular Key Performance Indicator (KPI). It is important to consider that for numbers with scientific notation due to the number of decimal places, policies with values of the highest negative power are the most robust. In the SNRs shown in Table 4, it can be clearly read for all 11 policies that the SNR of all RfR Investment Costs is 0. The reason for this is that the 'RfR Investment Costs' are independent of external uncertainties. The 'RfR Investment Costs' is a decision variable that can be shifted and that influences the other variables but cannot be influenced in itself. The four most robust policies in terms of 'Dike investment costs' with an SNR of 0 are the policies 117, 314, 398, and 359, respectively, are the purple, turquoise, green and blue lines. In this way it can be read in Table 4 and Figure 13 shown in Appendix C.3 which policy is the most robust per Key Performance Indicator (KPI).

Table 4: Signal to noise scores

	Expected Annual Damage	Dike Investment Costs	RfR Investment Costs	Evacuation Costs	Expected Number of Deaths Upstream Gelderland	Expected Number of Deaths Downstream Gelderland	Expected Number of Deaths Overijssel
8	5.1434E+15	55.234379	0	0.0000E+00	8.5000E-04	7.1843E-05	1.1280E-03
9	1.8719E+16	74.809203	0	5.8607E+07	1.6700E-04	5.2712E-07	1.0000E-05
398	3.6111E+16	0	0	2.3026E+07	7.8800E-04	8.8913E-06	1.4240E-03
67	1.6336E+16	27.882685	0	1.2478E+07	8.6200E-04	2.4200E-06	3.4300E-04
117	4.7421E+16	0	0	2.0106E+08	1.4000E-05	3.1179E-07	4.5300E-04
127	5.5123E+16	20.464209	0	2.0805E+08	2.5000E-05	4.6550E-05	4.1600E-04
142	3.5125E+16	23.210052	0	1.0941E+08	1.4500E-04	1.4948E-06	1.1400E-04
195	3.4038E+16	41.168152	0	1.4015E+08	8.5000E-05	3.8781E-06	2.0700E-04
261	1.6518E+15	25.269786	0	6.3534E+06	5.0000E-06	4.5789E-06	2.0000E-06
314	4.0100E+16	0	0	9.9187E+07	2.1300E-04	5.6295E-06	2.8800E-04
359	1.3720E+16	0	0	5.0120E+07	5.0000E-06	5.4817E-07	1.1700E-04

Table 5 ranks the top 3 most robust policies per KPI in order to get a clear picture of which solutions are most applicable per criteria. It can be clearly deduced that no policies emerge that are robust for all KPIs. This is logical given that a trade-off will always have to be made between different the different outcome variables. The SNRs can be used to determine for the solution series that fall within the constraints for which criteria they are an effective policy under most circumstances.

Table 5: Most robust policies per KPI

Rank	Expected Annual Damage	Dike Investment Costs	RfR Investment Costs	Evacuation Costs	Expected Number of Deaths Upstream Gelderland	Expected Number of Deaths Downstream Gelderland	Expected Number of Deaths Overijssel
1st	261	398, 117, 314, 359	All	8	261, 359	117	261
2nd	8	127	All	67	127	9	9
3rd	359	142	All	398	195	359	142

Policy 359 seems to be the most promising for this test of SNR values with regard to costs and expected annual damage. Policy 359 scores very robustly, i.e. a low SNR, in the area of 'Expected Annual Damage', 'Dike Investments Costs' and 'Expected Number of Deaths' for both upstream and downstream Gelderland. Policy 9 and 261 score well on the three 'Expected Number of Deaths' variables. It should also be noted that 261 also scores best in terms of robustness in 'Expected Annual Damage'. Policy 8 in turn scores well on 'Expected Annual Damage' and 'Evacuation Costs', but underperforms on 'Expected Number of Deaths'. It is interesting to see whether there are extreme outliers within this average that may need to be taken into account. For this, the Maximum Regret measurement has to be taken into account.

The second variable to look at is the measure of Maximum Regret. Regret consists of the difference between the outcome for every scenario for every policy and the best outcome of the scenario. This means that if the difference is large between these two values, the regret has a high value, implying that there are one or more scenarios where there is a lot of regret and a unfavorable performance of the corresponding KPI. However, it can't be deduced from the Maximum Regret Ratio itself how many negative scenarios are part of the 1000 scenarios that will have to be taken into account in the sense of a relatively unfavorable outcome. The closer the Maximum Regret value is to zero, the less regret there is and the more attractive a policy is in terms of this measure.

The policies 8 and 398 perform well on the Maximum Regret measure, with 8 showing extremely low values for 'Expected Number of Deaths'. Policy 9 and 359 score well in the SNR analysis, but come out worse in the area of Maximum Regret. An important thing to consider when choosing between policies is that the Regret values indicate the extent to which a value differs from the maximum favorable outcome. This also means that this value can give a distorted picture when only one extremely high maximum value occurs with one of the policies. The advice takes more account of the SNR compared to the Maximum Regret Ratio. However, the Maximum Regret Ratio with regard to the number of deaths is considered, since small chances of extreme scenarios are taken into account here.

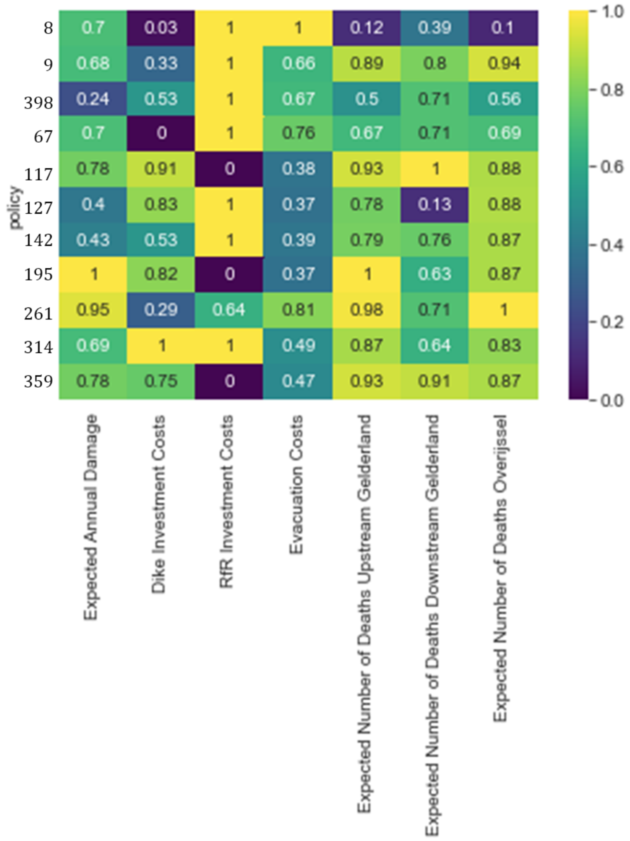

Figure 10: Maximum regret per policy and per outcome

3.4 Step 4: Scenario Discovery

The 11000 policy scenario obtained from step 3 in the MORDM process are used to detect the vulnerabilities of these generated candidate solutions. This is done by assessing the uncertain conditions under which poor performance arises. Poor performance, in this case, has been defined as the total number of deaths in each compartment being higher than the 3rd quartile (Ciullo, 2020), thus the worst 25% of the cases. The PRIM algorithm firstly, iteratively narrows down the uncertainty space to find boxes that lie on a Pareto optimal surface described by coverage, density and interpretability.

This results in the pealing trajectory plot (C.4), showing the trade-off curve between coverage (fraction of cases of interest within the box) and density (fraction of cases in the box which is of interest). Both measures need to be maximized to obtain a valuable insight, and the rule of thumb used here is a density of 0.8 (Kwakkel and Jaxa-Rozen, 2016). This has resulted in the selection of box 35. This candidate box has a density just below 0.8 (0.73), but in order to maintain a sufficient coverage (0.44) and not lose much interpretability, this was deemed as suitable for this analysis. However, the values for these measures implicate less accurate results than desirable for PRIM, which will be further explained in the discussion. Interpretability, defined as the number of uncertainties that are used to characterize the candidate box, gives 5 dimensions. The results are presented below in Figure 11:

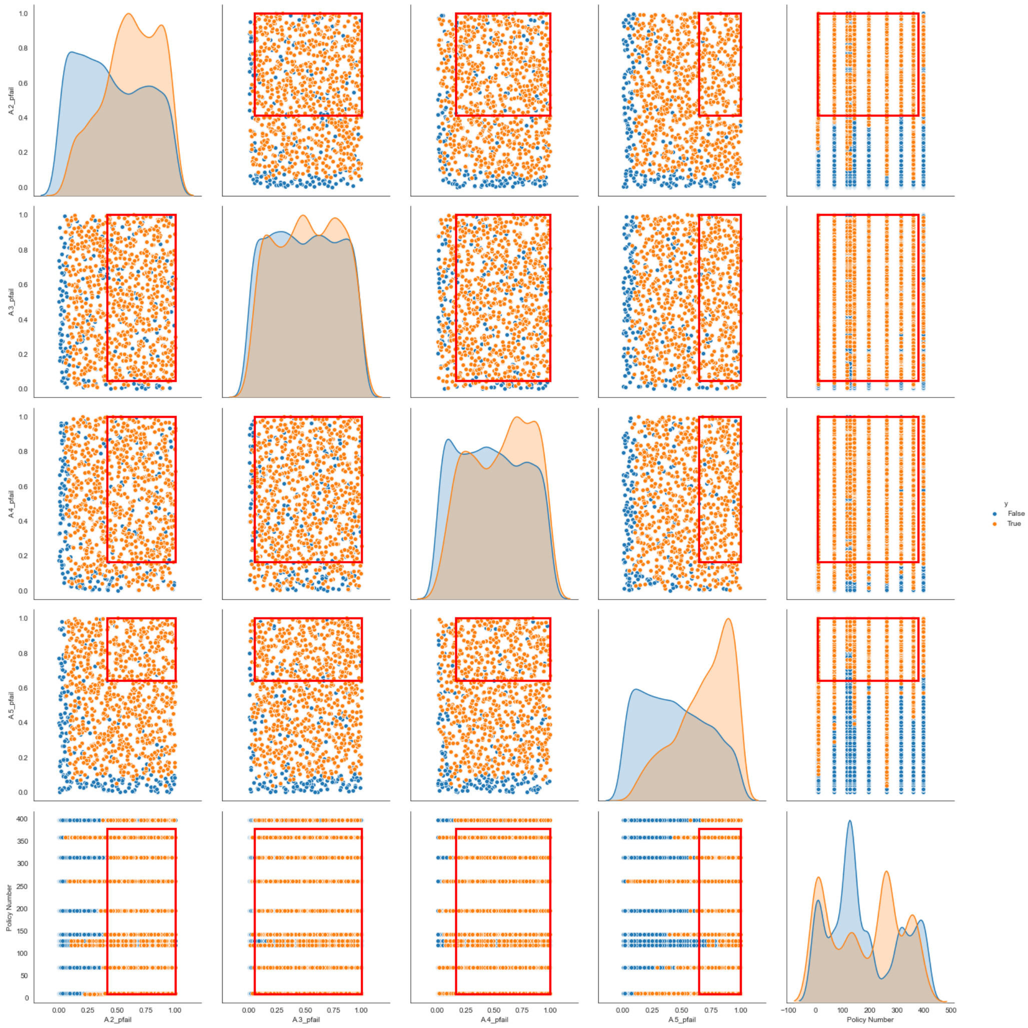

Figure 11: Probability distribution scatter plot matrix for uncertainties (Total expected deaths)

The results show that the total number of deaths is sensitive for *A2_pfail*, *A3_pfail*, *A4_pfail* and *A5_pfail*. The number of total deaths is the most sensitive for *A2_pfail* and *A5_pfail* (i.e. the chance of dike failure in Cortenover en Deventer). Besides, most of the candidate policy solutions can be considered reasonably vulnerable against uncertainties, but this can largely explained due to the constraints set in section 3.2. This does not count for policy 261, 8 and 9 as these policies are the least vulnerable for poor performance (for expected number of deaths) under the uncertainties.

In order to verify the influence of the uncertainties, the statistical significance of the imposed limits on the uncertain dimensions is observed, by looking at the Quasi p-values (a one sided binomial test, proxy for statistical significance of each restricted uncertainty in isolation). If p is larger than 0.05, then it is not significant and the uncertainty can be discarded. All values are well below 0.05, therefore it can be concluded that the results are statistically significant.

This PRIM analysis was also performed for the metric 'Expected Annual Damage'. However, since this metric shows very similar behavior as the total number of deaths, it has been left out of the main analysis and can be found in Appendix C.4.

4 Conclusion

This report provides a policy advice for Rijkswaterstaat through the use of a model to analyze flood risk management policies for the IJssel river case. Rijkswaterstaat must choose a robust policy in this respect that performs well in the complex multi-actor arena and the uncertainties embedded in the system.

More specifically, this report tried to answer the problem formulation, as stated in section 1.5:

'How can a safe flood risk management policy be implemented, which is robust under multiple deep uncertainties, in a way that is cost-efficient acceptable to all relevant actors involved?'

The report thus has aimed to find an optimal set of policies, that are both safe and cost-efficient under deep uncertainty, and are acceptable to all relevant actors. As the actors involved each have their own opinion on the best policy solution, the policy must fit within the complex multi-actor system.

11 different policies were identified, which minimize both the expected casualties due to flooding and the amount of (investment) costs needed for measurements. All the 11 found policies propose to implement Room for the River in Zutphen and increase dike heightening for all of the 5 locations of interest in order to successfully mitigate the associated risks with flooding.

Analyzing the 11 policies on robustness, the robustness metrics in section 3.3 indicate no clear winner for all KPIs (Performance Metrics). Policy 9, 261 and 359 score best on the overall robustness, but show poorer results in the extreme worst case; while policies 8 and 398 score poorly for signal-to-noise ratio and best on maximum regret analysis. Considerations are made between:

1) Good and robust overall performance (low scores on signal-to-noise ratio) and good performance in the extreme worst-case scenario (low scores on maximum regret). Since signal-to-noise metrics checks robustness for 1000 scenarios per policy, this is more important than the maximum regret, which only looks at 1 scenario that 'coincidentally' produced very bad scores.

2) Minimizing the scores for the number of expected deaths or minimizing the scores for the costs involved. The top priority, as derived from the problem formulation, is to minimize the number of expected deaths. The policies also do not differ much in costs, so choosing a more safe policy does not lead to excessive costs.

Based on these considerations, it follows that policies 261 and 359 score best on the uncertainty analysis.

The scenario discovery showed that the total number of deaths and annual damage is the most sensitive to the probability of dike failure Cortenoever, Zuthpen, Gorssel and Deventer. However, this analysis also shows that policies 8, 9 and 261 appear to decrease the vulnerability of the four probabilities on the total number of deaths. In other words, these three policies may be considered as more robust for these uncertainties compared to the other 9 found policy solutions.

Thus, it can be concluded that policies 261 and 359 are the most promising policies from an analytical perspective, of which the policy measures are shown in Table 6.

Table 6: Policy measures of the two advised policies

Policy	**Measure**	**Doesburg**	**Cortenoever**	**Zutphen**	**Gorssel**	**Deventer**	**Early Warning System**
261	**RfR (% of times steps)**	0	0	66%	0	0	3 days
	Dike Heightening (total dm)	9	6	15	6	11	
359	**RfR (% of times steps)**	33%	0	33%	0	0	3 days
	Dike Heightening (total dm)	9	7	11	12	3	

Note: The policy measures presented in table 6 are summed over the three times steps within the model. For the complete list of measures, per policy, per time step, see appendix C.2.

4.1 Policy Advice

The model-based generated policies 261 and 359 appear to be the best policies in this system. However, these policies should also fit into the political perspective. As Rijkswaterstaat is not the only actor involved, and not the only lender and decision maker, there must be a broader consensus for the policy alternative among actors involved.

As indicated in section 1.3 and appendix A, all actors have the highest priority on a policy that guarantees the safety of citizens near the IJssel river and avoids excessive costs. There is, however, disagreement in the implementation of measures. Regional actors, local municipalities and provincial authorities, prefer dike strengthening and heightening over the room for the river project. While the transport companies aspire to deep rivers and the environmentalists strives for room for the river.

Looking at the most promising policies from a political perspective, policy 359 implements RfR in both Doesburg and Zutphen, while policy 261 implements more RfR only in Zutphen. As both Zutphen, Cortenoever and the province of Gelderland are not keen on implementing room for the river, a trade-off becomes visible and this choice needs to be discussed within political debate. Besides, as concluded in section 4, policy 261 is more focused on minimizing the expected number of deaths; the main goal shared by all actors. This implies that policy 261 will have a broader consensus in political aspect.

Another advice is to invest in dike monitoring to guarantee that failures, or signals indicating near future dike failure, are detected in an early phase. By doing so dikes may possibly be repaired before they completely fail, what would result in casualties and damage. The scenario discovery shows that the number of deaths and annual damage is the most sensitive to the uncertainty of dike failure. Therefore it is desired to minimize the chance of dike failure or detected dike failure in an early phase to minimize possible negative effects on casualties and damages.

5 Discussion

The results in Chapter 3 and the conclusions in chapter 4 provides specific policy measures based on the model used for the analysis. Therefore is it important to understand the limitations and assumptions made within the model to validate these specific policies and to formulate possible recommendations.

5.1 Limitations

There are multiple limitations in the used model and approach to for this report. These limitations mostly concern the use of the MORDM approach, as well as the used model for this report.

First of all, the MORDM approach is heavy on computational power, which results in multiple limitations. Due to limited computational power, the optimization during step 2 in section 2.1.2 was run with a low amount of nfe which is insufficient to assess convergence. As a result, our set of Pareto optimal policies is incomplete and there may be more efficient policies that are not currently included in the analysis and therefore our policy advice. besides, during the scenario discovery a limited number of experiments were run on the 11 found policies. An improvement on the number of experiments, by increasing the number of scenarios, would enhance the accuracy of the analysis.

Besides, a good implementation of the MORDM approach requires iterations of the 4 steps (Kwakkel et al., 2016b). During this refinement of the analysis, more reliable results could have been achieved. Due to the lack of computational power and time to perform the analysis and construct this report, a limited number of iterations are performed within the analysis. Increasing the number of iterations, and incorporating the results found in these iterations, would improve the reliability of the research and the accuracy of the results.

Secondly, the simulation model has limitations. The number of variables included in the model is limited and some variables, which are interesting for some of the actors, were not taken into account. For instance, transport companies are interested in deepening the IJssel river as a solution to the flooding problem, but this measure is not incorporated in the model. Besides, as the model is an simplification of reality, the MORDM approach simulates a wide variety of future scenario's by only requiring an assumption of plausible ranges of exogenous factors (Kasprzyk et al., 2013). Therefore, this assumption should be taken into account when considering to implement the proposed policy measures.

It is also important to name that the model has a limited scope. As this model only considers the upper IJssel river, the model leads to really simplistic results, in which important uncertainties are not incorporated. the IJssel flows from the Rhine, so the IJssel River depends heavily on the Rhine and measures or uncertainties taken in that branch of the river. These uncertainties or measures are not modeled for this case. Because of the scope of the model, it is important for decision-makers to realize the abilities and intended use of the model. The model is not fit for finding one optimal policy solution that satisfies all actors. It is merely a tool to provide Rijkswaterstaat with a set of options they can consider when approaching the decision-making process. Also, the performed analyses is only able to consider the chosen model variables. Therefore, advice solely based on these variables should be drawn from the model. When using our model-based advice for policy, this should be carefully considered and communicated to all stakeholders affected by the policies.

5.2 Recommendations

These limitations emphasize the need for recommendations to limit the limitations and thus improve the project. It can be argued that providing more time and resources would greatly improve the reliability of the analyses. Giving time for iterating the MORDM steps would increase reliability of the results and increasing computational power resources allows for more runs to be performed, increasing the accuracy of the results.

However, one can also wonder whether the MORDM approach was the right tactic within this problem and given the limited time and resources. Applying multi-scenario MORDM better includes robustness considerations within the search phase (Watson and Kasprzyk, 2017). Traditional MORDM first optimizes a problem under a baseline scenario, then evaluates candidate solutions under an ensemble of uncertain conditions, and finally discovers scenarios under which solutions are vulnerable. Multi-scenario MORDM directly incorporates these discovered scenarios within the search. Including severe scenarios within the optimization yields more robust solutions and reduces the computer power needed.

Regarding the model, it can be extended to better respond to the complex environment. Incorporating the model with more variables would strengthen the model and enrich the policy advice. Extending the model to a larger scale ensures that many uncertainties which are currently outside the model, due to the limited scope, can be included in the analysis.

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A IJssel River Case: Multi-actor System

The stakeholders and their position in the multi-actor system are analyzed using two different approaches. Firstly a preliminary overview is constructed, entailing the actors' power and interest towards RfR, using broad labels as Low, Medium and High, as proposed by Varvasovszky and Brugha (2000). Secondly, the actors are more specifically discussed in terms of their general and case-specific objectives, attitude towards RfR, as well as their limitations and capabilities within the decision making process.

Table 7: Actor overview and positions

Actor	Power	Interest
Delta Commission	High	High
Dike Rings 1 an 2 (Doesburg & Cortenoever)	Low	High
Dike Ring 3 (Zutphen)	Low	High
Dike Ring 4 (Gorssel)	Low	High
Dike Ring 5 (Deventer)	Low	High
Environmental Interest Group	Low-Medium	Medium-High
Gelderland Province (Upstream/Downstream)	Medium-High	High
Overijssel Province	Medium-High	High
Rijkswaterstaat	High	High
Transport Company	Low-Medium	Medium-High

A.1 Rijkswaterstaat

Rijkswaterstaat is the executive branch of the Dutch Ministry of Infrastructure and Environment and is responsible for the construction, design, maintenance and general management of the most important infrastructural facilities in the Netherlands (Rijke et al., 2012). Generally speaking, Rijkswaterstaat aims to ensure safety, mobility and a high quality of life for all Dutch citizens (Ministerie van Infrastructuur en Waterstaat, 2021a). Rijkswaterstaat's objectives regarding the Room for the River case are quite clear and they also fall in line with the aforementioned general goals. Rijkswaterstaat is responsible for reaching the RfR objectives, while keeping all the relevant stakeholder content and maintaining their support in the process. Social, spatial, economic and safety/security factors play a role within the process, meaning that policy eventually will rely on certain trade-offs that have to be made. Rijkswaterstaat facilitates the communication between the involved stakeholders regarding the trade-offs and the specifics of the to be implemented policies.

A.2 Delta Commission

The Delta Commission is an independent advisory group that consults the Dutch cabinet on water security and the urgency of flood risk management (Delta Commissie, 2008). The commission was officially relieved of its duties and formally disbanded in 2008, but in the RfR case-study it acts as a decision making authority with veto-powers within the voting process. Their goal is to find a long term solution that protects the stakeholder interests.

A.3 Transport Companies

The transport sector relies very strongly on the accessibility of the Netherlands as whole and the IJssel specifically (CBS, 2009). Transport companies have interest that can be seen as conflicting with other stakeholders, because safety and security of the region is not formally an objective of the transport companies. Fast, reliable and efficient flow of ships and goods across the Dutch river network is the main objective of the transport companies. In order for this to be successful, the depth of the river is crucial. If the depths of the IJssel were to be decreased or if the IJssel were to be narrowed, this could have dire consequences for the amount of cargo that can be transported across the river (Jonkeren and Rietveld, 2009).

A.4 Environmental Interest Group

The environmental interest group focuses on preserving the environment in terms of nature and wildlife. The Room for the River project has many characteristics that environmental interest groups can deem as desirable. The 'working with nature' and the 'environmental restoration' objectives entailed in the project (STOWA, 2021) result in environmental groups to have a positive position towards the RfR project in general. However, there are stakeholders that would choose safety and security over environmental preservation, if necessary. Therefore, the environmental interest groups may need to accept that this trade-off is a realistic scenario.

A.5 Gelderland Province

The Gelderland Province is the largest province of the Netherlands. Dike rings 1 through 4 are within the provincial domain of Gelderland and the provincial government (Provinciale Staten and Gedeputeerde Staten) is therefore responsible for their well-being. The province can be divided into an upstream and downstream region. Scientific publications and news articles about the Province's position regarding RfR are very limited. However, the regional water planning program has been made available to the public for inspection, review and even suggestions (Provincie Gelderland, 2021). This portrays a transparent and open attitude of the province towards its municipalities and citizens. Further views towards RfR can be obtained from the EPA1361 political debate. The students imitating the Gelderland province have argued that the most important interest for the province are: economic freedom and entrepreneurship, prevent loss of farmlands and provide safety. The provinvial government has relatively high power within this political arena and has instruments to deny strategies that Rijkswaterstaat proposes, if this is in the best interest of the province's municipalities and citizens. In the debate, the students indicated that this is a strongly considered option if their 'demands' were not to be met properly.

A.5.1 Dike rings 1 & 2: Doesburg & Cortenoever

Doesburg and Cortenoever are both upstream municipalities. The debate pointed out that both municipalities care for safety in their region and do not accept deaths due to flooding over the coming 60 years. Besides this, economic prosperity of the region is important for both cities. What also became evident from the debate is that these municipalities strongly prefer dike strengthening/heightening over channel construction/RfR-type implementations and that the costs for this should not exceed EUR 100 million over 60 years for Doesburg and EUR 180 million for Cortenoever. On what basis these figures are grounded is unclear.

A.5.2 Dike Ring 3: Zutphen

Zutphen is in a relatively unsafe position in case of a flooding. The debate did not bring extensive details forward about Zutphen's position, except for the fact that they crave safety and security without having to undergo massive land reductions. This is a similar standpoint as Dike rings 1 and 2.

A.5.3 Dike Ring 4: Gorssel

Gorssel relies largely on its agricultural sector, which results in a high dependence on land availability for farming. This implicates that the municipality has a relatively negative attitude towards RfR initiatives and prefers dike heightening/strengthening. Just like Dike rings 1, 2 and 3, Zutphen cares deeply about the safety and security of the region. Gorssel has a positive attitude towards EWS.

A.6 Overijssel Province

The IJssel river separates Gelderland from the eastern province of Overijssel. This province has similar authoritative power as Gelderland and also represents multiple municipalities' interest on a national level. In the RfR however, the only relevant municipality Overijssel's provincial government represents is Deventer. Scientific publications and news articles about the Province's position regarding RfR are also very limited. Therefore, the standpoints obtained from the EPA 1361 student debate will be used to describe the province, thus Deventer's, attitude towards RfR further.

A.6.1 Dike Ring 5: Deventer

Deventer is localized in a relatively safe position regarding flood risks. The municipality obviously values safety and security of the region deeply, but dike strengthening is not a desirable method to facilitate this. Deepening the river is preferable for Deventer, for this will keep the region safe again potential flood risks and will encourage the local economy, specifically the transport sector.

B Model Specification

B.1 Model Structure and Values

The XLRM framework shown in figure 12 takes external factors and policy levers as input and produces, through the use of the flood risk model by Ciullo et al. (2019a), values for the performance metrics as output. These variables (based on the course guide on Brightspace (Kwakkel, 2021)) will be specified in this appendix.

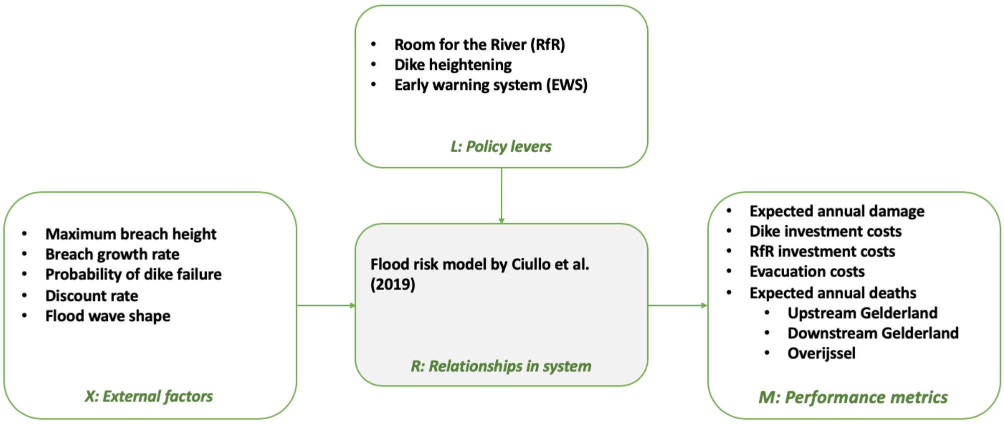

Figure 12: The XLRM Framework

The external factors that influence the model are described in more detail in Table 8.

Table 8: External factors

Factor	Description
Maximum breach height	The final extent of the breach width. The larger the width, the greater the volume of water flowing into the floodplain.
Breach growth rate	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.
Probability of dike failure	Probability that the dike will stand the hydraulic load. The higher this number, the 'stronger' the dike.
Discount rate	It determines the present value of the future expected damage. The lower the value, the more damage to future generations is valued
Flood wave shape	A normalized curve describing the way discharges at the most upstream location change over time. There are 140 possible wave shapes.

The model contains various decision variables in which choices can be made to what extent they are applied. These policy levers are explained in more detail in table 9.

Table 9: Policy levers

Policy lever	Description
Room for the River (RfR)	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.
Dike heightening	Amount of dike raising. The higher the dike, the higher the hydraulic loads it can stand.
Early warning system (EWS)	Early warning systems anticipate a threat and help limiting 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's trust into the authority. Waiting too long is also problematic as the efficacy of late alerts is poor. In the model you can choose how much time in advance to give the alert.

The various performance metrics that are used to assess the policies are provided with a further explanation in table 10.

Table 10: Performance metrics

Metric	Description
Expected annual damage	The expected annual value for flood damage for each location. The lower this value, the better. The costs are calculated over the planning period.
Dike investment costs	The investment costs of raising dikes.
RfR investment costs	The investment costs of the RfR project.
Evacuation costs	Evacuation costs expressed in the function of the number of people evacuated and the number of days they need to be away from their homes.
Expected annual deaths	The expected number of deaths over the planning period. This metric consists of three values for three different location; Gelderland downstream, Gelderland upstream, and Overijssel.

B.2 Expected Range for Directed Search

For the expected range of outcomes table 11 shows the order of the minima and maxima that the values can assume. For example, it can be seen that the number of annual deaths in Overijssel and up- and downstream Gelderland is between 0 and 10.

Table 11: Expected range for the outcomes

Variable	Expected range
Expected annual damages	0 - 1e5
Dike investment costs	0 - 1e9
Evacuation costs	0 - 1e9
Room for the River costs	0 - 1e7
Expected annual deaths upstream Gelderland	0 - 10
Expected annual deaths downstream Gelderland	0 - 10
Expected annual deaths Overijssel	0 - 10

C Results

C.1 Step 1: Problem Formulation

The descriptive statistics of the KPI's of the model over 5000 scenario's is presented in table 12:

Table 12: Descriptive statistics of the base case scenario

Variable	Expected annual damage	Dike investment costs	RfR investment costs	Evacuation costs	Expected Number of Deaths Upstream Gelderland	Expected Number of Deaths Downstream Gelderland	Expected Number of Deaths Overijssel
Mean	1.841441e+09	0	0	0	0.941094	0.752953	0.055539
Std	1.338518e+09	0	0	0	0.878972	1.234428	0.164409
Min	4.049679e+07	0	0	0	0	0	0
Max	6.612337e+09	0	0	0	2.906304	3.780421	1.180085

C.2 Step 2: Generating Alternatives

In table 13 the 11 found policy solutions are presented with their levers. For explanations of the values within this table see appendix B.

Table 13: Policies with their levers

	8	9	67	117	127	142	195	261	314	359	398
0_RfR 0	0	0	0	0	0	0	1	0	0	0	0
0_RfR 1	0	0	0	0	0	0	0	0	0	0	0
0_RfR 2	0	0	0	1	0	0	0	0	0	1	0
1_RfR 0	0	0	0	0	0	0	0	0	0	0	0
1_RfR 1	0	0	0	0	0	0	0	0	0	0	0
1_RfR 2	0	0	0	0	0	0	0	0	0	0	0
2_RfR 0	0	0	0	0	0	1	0	1	1	0	0
2_RfR 1	0	1	0	0	0	0	0	0	0	0	0
2_RfR 2	1	0	1	1	1	0	1	1	0	1	1
3_RfR 0	0	0	0	0	0	0	0	0	0	0	0
3_RfR 1	0	0	0	0	0	0	0	0	0	0	0
3_RfR 2	0	0	0	0	0	0	0	0	0	0	0
4_RfR 0	0	0	0	0	0	0	0	0	0	0	0
4_RfR 1	0	0	0	0	0	0	0	0	0	0	0
4_RfR 2	0	0	0	0	0	0	0	0	0	0	0
EWS_DaysToThreat	0	3	1	3	3	3	3	3	2	3	1
A.1_DikeIncrease 0	7	7	7	6	7	7	7	9	7	6	7
A.1_DikeIncrease 1	6	3	5	0	0	0	0	0	3	0	0
A.1_DikeIncrease 2	1	0	0	2	2	4	7	0	0	3	0
A.2_DikeIncrease 0	4	0	1	4	4	0	1	3	0	5	1
A.2_DikeIncrease 1	0	2	2	1	1	2	2	3	3	2	5
A.2_DikeIncrease 2	5	1	0	0	0	7	0	0	0	0	0
A.3_DikeIncrease 0	8	7	7	10	4	7	6	5	6	8	7
A.3_DikeIncrease 1	0	1	7	0	3	1	2	3	3	0	5
A.3_DikeIncrease 2	4	3	4	1	1	0	0	7	4	3	4
A.4_DikeIncrease 0	1	6	9	2	1	3	3	2	2	3	2
A.4_DikeIncrease 1	8	6	0	5	3	2	6	1	2	5	3
A.4_DikeIncrease 2	5	9	5	4	4	2	0	3	3	4	4
A.5_DikeIncrease 0	5	5	2	1	1	2	2	5	2	3	1
A.5_DikeIncrease 1	0	0	3	0	0	1	0	3	0	0	1
A.5_DikeIncrease 2	0	1	3	0	0	0	0	3	0	0	3

C.3 Step 3: Uncertainty Analysis

The Signal to Noise Ratio is calculated for 11 different policies that emerged in step 2; 'Generating Alternatives'. The scores calculated for this can be read in the graph. Each line represents a specific policy. The baseline concerns the value zero for which a policy is robust in terms of SNR. The graph shows that trad-offs will always have to be made in the choice between different solutions, since not one of the lines is on the baseline.

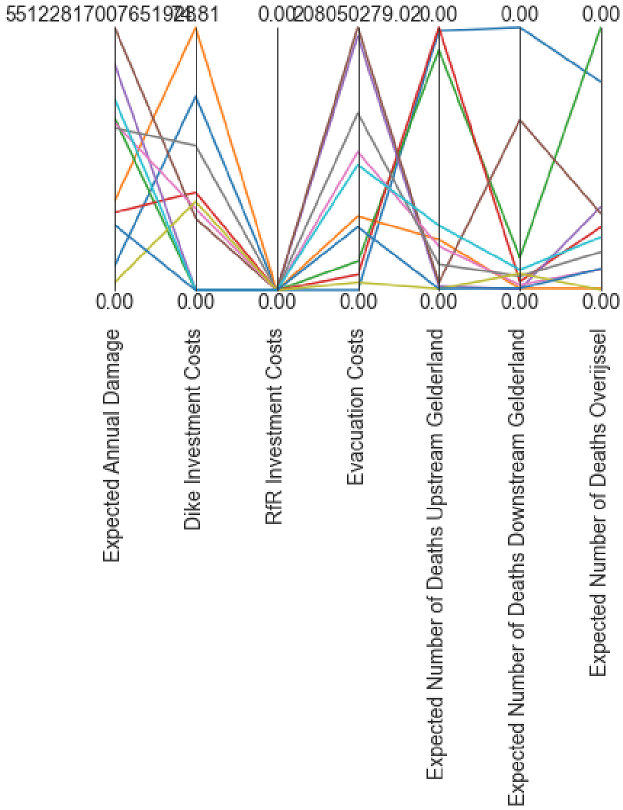

Figure 13: Signal to Noise scores

C.4 Step 4: Scenario Discovery

In this appendix the outcomes of the performed scenario discovery are presented in several graphs. The first graph 14 presents the pealing trajectory, the trade-off between the density and coverage when performing PRIM. Graph 15 show that the found uncertainties are significant.

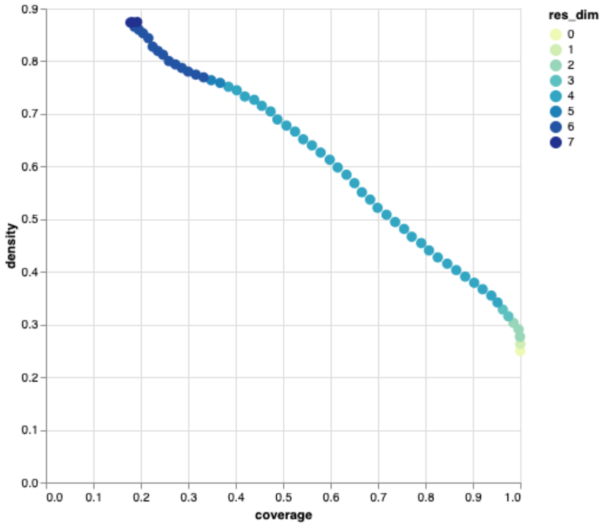

Figure 14: Trade-off density coverage (Total expected deaths)

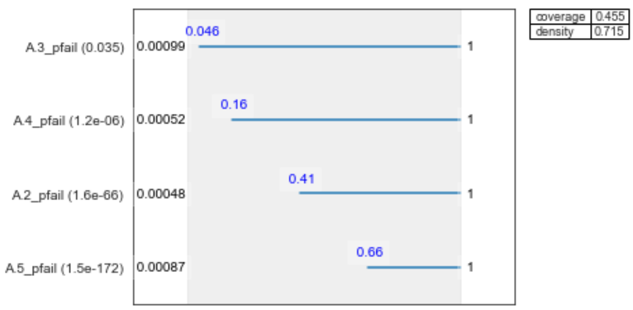

Figure 15: P-values (Total expected deaths)

C.4.1 PRIM: Annual damage

The figures below show the results from the PRIM analysis for the expected Annual damage. These results are similar to results for the PRIM analysis as described in chapter 3.4.

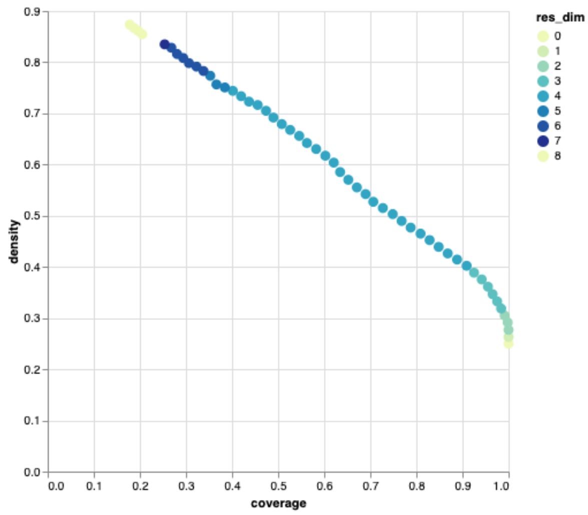

Figure 16: Trade-off density coverage (Annual damage)

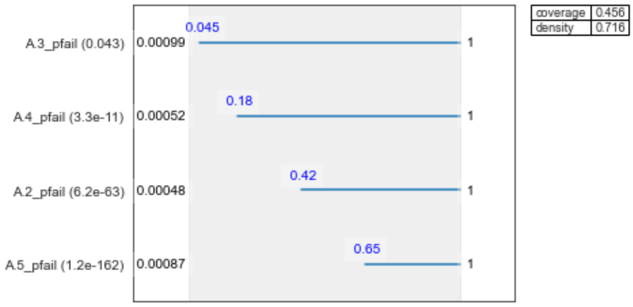

Figure 17: P-values (Annual damage)

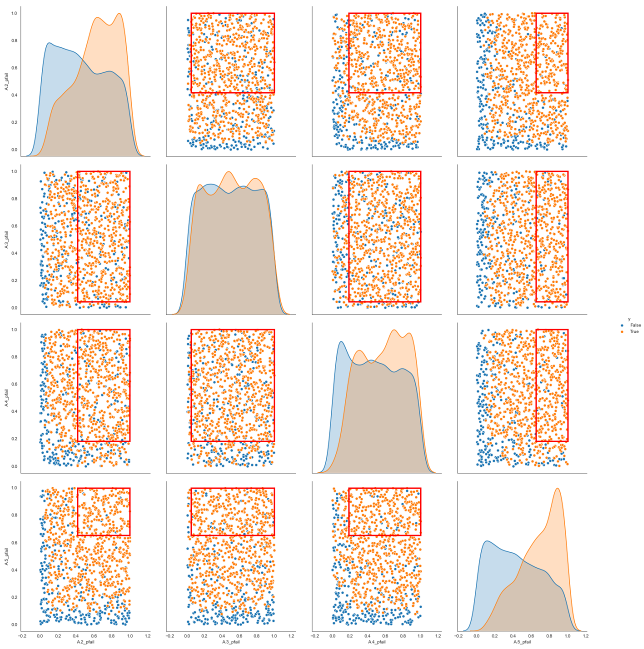

Figure 18: PRIM boxes (Annual damage)