Delft University of Technology

Engineering and Policy Analysis MSc Thesis

Using Robust Decision Making to support the development of Dynamic Adaptive Policy Pathways and its associated monitoring system: A Helensville case-study

Author:
Xander Smits

Supervision:
Prof. Dr. Ir. Jan Kwakkel
Dr. Ir. Igor Nikolic

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Summary

Poor and coastal regions are increasingly at risk from the effects of climate change. These risks are accompanied by a high level of uncertainty, which is also called deep uncertainty. Current planning approaches lose efficacy under deep uncertainty, necessitating new approaches that function better under these conditions. Decision making under deep uncertainty (DMDU) is the name for the family of approaches that attempt to deal with this level of uncertainty. Bangladesh, the Netherlands, and New Zealand have all already adopted the use of DMDU techniques. Research into local implementation of these techniques is also being done.

Two DMDU techniques often deemed as complementary are robust decision making (RDM) and dynamic adaptive policy pathways (DAPP). RDM can be seen as a computational extension of scenario planning, where proposed plans are tested against every potential combination of uncertainties. DAPP is a flexible policy framework that allows decision-makers to keep long-term plans in mind while making short-term decisions. DAPP especially has seen increased adoption in national delta protection plans such as in the Netherlands, Bangladesh, and New Zealand.

To design DAPP, currently a combination of many-objective robust optimization (MORO) and participatory processes are used. These methods both have their own issues. MORO requires the upfront specification of rules and policies and is computationally expensive, while the participatory approach is qualitative and can be insufficient when dealing with complex systems. RDM is seen as a potential improvement in supporting the DAPP policy structure in two main ways. First, RDM can be used to iteratively develop and/or stress-test potential actions and pathways. Second, the vulnerabilities identified through RDM can be used to lay the base for a monitoring system by identifying promising signposts and signals.

While RDM is seen as a potentially helpful tool to support DAPP, there is a lack of studies that have established a systematic and analytical approach which uses the robust decision making process to support the development and monitoring of DAPP. This research proposes a novel approach based on literature to achieve this. The approach uses the vulnerabilities identified through RDM to iteratively inform and develop more robust actions and to lay the basis for the technical side of a monitoring system. This approach is then illustrated by way of the adaptation case of a wastewater treatment plant in Helensville, New Zealand. This wastewater treatment plant serves a small community and will have to retreat at some point in the future due to increasing risks from compound flooding, which are exacerbated by rising sea levels.

The results of the case illustration show the benefits of using RDM to better understand vulnerabilities in the system in two main ways. First, the vulnerability analysis (which included a sensitivity analysis) helped to identify factors most important to the outcomes to inform potentially effective actions. Second, RDM helped in the development of the monitoring system. Those factors making up the identified vulnerabilities formed the basis of the technical signposts selected. Using the coverage-density tradeoff from the scenario discovery results, promising signals could be selected, although timing was not taken into account. This could potentially partially solve a common problem for monitoring DAPP: the selection of trustworthy signals.

There were three main recommendations. The first is to further work through a case such as this, since due to time constraints only the first iteration of the process was followed in this research. This could help identify more potential benefits or issues. A main issue here is also how to identify when an action is fully developed, as the process could continue indefinitely. Second, it is recommended to do further research into determining adaptation tipping points using other scenario discovery methods, and to use the coverage-density tradeoff from the scenario discovery results to modify adaptation tipping points based on policy regret. Third, is to further the monitoring system by posing open questions to support the deliberation on signpost and signal selection, taking timing into account to identify triggers, and by adding a signpost map next to the signal map to visualize signpost interaction, hierarchy, and quality.

Contents

Abbreviations

- AEP: Annual Exceedance Probability
- ARI: Average Recurrence Interval
- DAPP: Dynamic Adaptive Policy Pathways
- DEM: Digital Elevation Model
- DMDU: Decision Making under Deep Uncertainty
- DSC: Deep South Challenge
- EMA: Exploratory Modeling and Analysis
- FLORES: Flood Risk Reduction Evaluation and Screening
- HAT: Highest Astronomical Tide
- IPCC: Intergovernmental Panel on Climate Change
- MHWPS: Mean High Water, Perigean Springs
- NZVD: New Zealand Vertical Datum
- OECD: Organisation for Economic Co-operation and Development
- PRIM: Patient Rule Induction Method
- RDM: Robust Decision Making
- RFSM: Rapid Flood Spreading Method
- SLR: Sea Level Rise
- WTP: Wastewater Treatment Plant

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Chapter 1

Introduction

1.1 Introduction

1.1.1 Climate risks to infrastructure

Infrastructure is often seen as the backbone of society. It connects people, provides them with various services, and helps to keep them safe. Current infrastructure is at risk from climate change and its associated effects, however. Droughts, heat, wildfire, sea level rise, extreme precipitation and the increased frequency of storms are just some of these risks. To manage these risks, infrastructure will have to become more resilient. The OECD (Organisation for Economic Co-operation and Development) has estimated that in order to adapt current infrastructure to these effects, over 6.3 trillion US dollars will have to be invested worldwide yearly between 2016 and 2030 (Mullan, 2018).

Since it is hard for infrastructure to adapt to changes within a system, the uncertainty related to climate change poses an extra risk for infrastructure. This is due to a combination of factors. First, infrastructure is often embedded in complex systems, where changes can come from a number of directions. Second, infrastructure often has long life-spans combined with rules and regulations. This leads to choice lock-in, where initial choices made cannot be changed halfway through. These risks are further exacerbated by the high up-front investments costs needed for infrastructure (Stanton & Roelich, 2021).

1.1.2 Planning approaches for different levels of uncertainty

Different levels of uncertainty warrant different planning approaches. Marchau et al. (2019) has divided the degree of uncertainty into four different levels, which can be seen in Figure 1.1, limited by complete determinism on one side to total ignorance on the other side. The level of uncertainty encountered is dependent on external factors, the complexity of the system, and system outcomes.

Probabilistic approaches and scenario planning

Probabilistic approaches are the most widely used planning method, and are often used for uncertainty levels 1 and 2 as seen in Figure 1.1. These approaches assume that external factors, the system model, and its outputs can be described in a probabilistic manner. Projections of the future are then made, which form the basis for further planning. These approaches work well on a shorter time scale, when the system is clear, or when external forces on the system are well-defined.

For cases where probabilities cannot be ascribed to the external factors, system model, or to the outcomes, which can be seen as level 3 uncertainty in Figure 1.1, scenario planning is used. Scenario planning examines a few mutually exclusive plausible scenarios in order to make "robust" decisions: those that lead to a satisfactory outcome in multiple different futures. By exploring various scenarios, decision-makers can better prepare for uncertainties and make strategic choices for policies that perform well across a range of possible futures. Compared to the probabilistic approaches, choices are not made based on a prediction of what will likely happen, but rather on what could potentially happen. This works well when there are only a few mutually exclusive plausible scenarios.

	Complete determinism	Level 1	Level 2	Level 3	Level 4 (deep uncertainty)		Total ignorance
					Level 4a	Level 4b	
Context (X)		A clear enough future	Alternate futures (with probabilities)	A few plausible futures	Many plausible futures	Unknown future	
System model (R)		A single (deterministic) system model	A single (stochastic) system model	A few alternative system models	Many alternative system models	Unknown system model; know we don't know	
System outcomes (O)		A point estimate for each outcome	A confidence interval for each outcome	A limited range of outcomes	A wide range of outcomes	Unknown outcomes; know we don't know	
Weights (W)		A single set of weights	Several sets of weights, with a probability attached to each set	A limited range weights	A wide range of weights	Unknown weights; know we don't know	

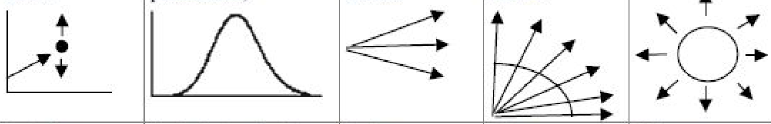


Figure 1.1: The progressive levels of uncertainty ranging from complete determinism on the left to total ignorance on the right. Context encompasses all external forces on the system, and weights denotes the preference of system outcomes by stakeholders. Probabilistic predictive approaches work well for levels 1 and 2, and scenario planning works well for level 3. Decision making under deep uncertainty techniques attempt to deal with level 4a and 4b uncertainty (Marchau et al., 2019).

Decision Making under Deep Uncertainty (DMDU)

In cases where uncertainty is even more profound, also called deep uncertainty seen as levels 4a and 4b in Figure 1.1, scenario planning can lose efficacy as well. Decision Making under Deep Uncertainty (DMDU) is the collection name of techniques that attempt to deal with this level of uncertainty. These techniques recognize that the future is inherently uncertain, and attempt to make decisions that are not only robust against uncertainty but also flexible enough to adapt to evolving circumstances. There are multiple DMDU techniques, each with their own strengths and weaknesses. Two popular DMDU methods that are deemed to be complementary are Robust Decision Making (RDM) and Dynamic Adaptive Policy Pathways (DAPP) (Haasnoot et al., 2019; Kwakkel & Haasnoot, 2019; Kwakkel et al., 2016a; Lempert, 2019).

Robust Decision Making (RDM) and Dynamic Adaptive Policy Pathways (DAPP)

Robust Decision Making (RDM) can be seen as an extension of scenario planning. Rather than making a selection of just a few mutually exclusive plausible scenarios as done for scenario planning, RDM samples through every combination of possible uncertainties. The two main benefits of this search are the ability to discover the conditions under which the system is vulnerable, as well as the ability to develop robust policies by iteratively adapting them to better deal with the discovered vulnerabilities.

Dynamic Adaptive Policy Pathways (DAPP) is a flexible policy framework. One of the key benefits of DAPP is the intuitive way the pathways show the different policy options or actions in a metro map. This metro map also aids in splitting up large actions into smaller, more actionable ones. This illustrates potential lock-ins, allowing decision makers to keep long-term strategy in mind while making choices with a shorter planning horizon (Haasnoot et al., 2019). For these reasons, the method has quickly gained in popularity, with DAPP being implemented for the Dutch Delta Programme, the Bangladesh Delta plan, and on a national as well as on a more regional scale in New Zealand (Lawrence et al., 2018, 2019).

1.1.3 Designing dynamic adaptive policy pathways

As mentioned before, the use of Dynamic Adaptive Policy Pathways (DAPP) is increasingly popular. Currently there are two main ways of building DAPP: by using MORO or participatorily.

Many-Objective Robust Optimization (MORO) uses an evolutionary algorithm to optimize the sequence of actions. MORO needs upfront specification of sequencing rules, policy options or actions, possible triggers or Adaptation Tipping Points (ATPs), and the definition of robustness. It then tests potential pathways for each possible future state of the world, and assesses their robustness based on multiple objectives (Haasnoot et al., 2019; Kwakkel et al., 2015a, 2016a). MORO searches the uncertainty space thoroughly and arrives at a pareto optimal set of pathways that show clear trade-offs. There are two main drawbacks, however. First, it is computationally expensive. Secondly, it requires the upfront specification of many rules, which can be difficult in practice.

On the other hand, the pathways can be designed using a participatory process. This is done by getting the main stakeholders together in workshops or serious games to facilitate discussion. Combined with expert judgment, policy options and adaptation triggers can be defined to form a DAPP map. This participatory process can also be used to decide upon the rules necessary to run MORO (Blackett et al., 2021; Haasnoot et al., 2019; Lawrence et al., 2019). This approach is quite qualitative however. It has been shown that human reasoning is insufficient when dealing with complex systems, where nonlinearities and other dynamics can be encountered (Kwakkel & Haasnoot, 2019; Sterman, 1994). With oftentimes tens of thousands of potential combinations of uncertainties this can lead to vulnerabilities being overlooked when it is not supported with computational techniques.

As mentioned earlier, Robust Decision Making (RDM) is seen as a potential method of supporting the development of DAPP (Groves et al., 2019; Haasnoot et al., 2019; Kwakkel & Haasnoot, 2019; Kwakkel et al., 2016a). RDM presents a model-based way of identifying vulnerabilities within the system and within the policy actions. This is done through the scenario discovery phase, where groups of scenarios where the action performs poorly are clustered together. These vulnerabilities can be used to inform adaptation tipping points, and to iteratively develop more robust actions and pathways. Additionally, RDM can be used to inform a monitoring system for DAPP (Groves et al., 2019; Kwakkel et al., 2016a). While the vulnerabilities identified through RDM have been used to inform pathways or other adaptive plans, no analytical approach for using RDM in this manner has been laid out yet (Ramm et al., 2018a, 2018b; Trindade et al., 2019).

1.1.4 Climate risks in New Zealand

Coastal areas are among the most susceptible to the effects of sea level rise and increases in storm frequency, and these risks will likely increase by at least one order of magnitude by 2100. These risks disproportionately affect low-income households, and this inequality grows over time (Arias et al., 2021; McDermott, 2022; WMO, 2019). DMDU approaches are being used to combat these risks.

New Zealand, being an island, currently has over 240,000 people living within 2 meters of the mean high tide line (level, 2021). Next to the risks climate change poses to its population, New Zealand's public infrastructure, divided into three waters, roading, and building/facilities, is also greatly at risk with rising sea levels. At 0.5 meters sea level rise, more than $2.7 billion is at risk, which balloons to $13.4 billion for a rise of 3.0 meters (LGNZ, 2019). The area that is the most at risk the quickest is the Auckland, where a total replacement value of $620 million worth of infrastructure is already at risk at a mean high water springs of 0.5 meters (LGNZ, 2019). This area, which is most exposed, has been deemed as having priority when adapting.

Deep South Challenge and Helensville case study

In order to help all New Zealanders mitigate the most important effects of climate change as equitably as possible, the Deep South Challenge initiative has been set up. Enabled by NIWA, a New Zealand research institute, the Deep South Challenge is one of New Zealand's 11 National Science Challenges. The DSC's mission is to "enable New Zealanders to adapt, manage risk and thrive in a changing climate" ("Our research: Deep south challenge", 2021). In order to facilitate this, research is being done at multiple adaptation case sites throughout New Zealand.

Figure 1.2: Location of the Deep South Challenge's case site in Helensville n.d.

One of the adaptation planning case studies part of the Deep South Challenge is located in Helensville (Stephens et al., 2018, 2021). Helensville is a small, low-lying town near Auckland which is expected to increase in population in the coming years. This community is currently being served by a wastewater treatment plant, the location of which can be seen in Figure 1.2. Wastewater treatment plants are especially exposed to the effects of climate change, since they are often placed in low-lying areas near open bodies of water, and are affected by the effects of droughts and storms (Friedrich & Kretzinger, 2011; Hummel et al., 2018; Woetzel et al., 2020). The treatment plant in Helensville will also have to adapt to these effects, and most likely retreat inland at some point in the future when risks from compound flooding become excessive.

1.2 Research Outline

1.2.1 Problem statement

Coastal regions are increasingly at risk from the effects of climate change, which are accompanied by a high degree of uncertainty also called deep uncertainty. Infrastructure is especially at risk to this uncertainty, due to a combination of long life spans, complexity of the systems it is embedded in, and the high upfront investment costs necessary. Current infrastructure planning approaches lose efficacy under deep uncertainty, necessitating new approaches that function better under these conditions. The family of approaches that attempt to deal with this are also called Decision Making under Deep Uncertainty (DMDU).

Bangladesh, the Netherlands, and New Zealand have all already adopted the use of DMDU techniques. Research into local implementation of these techniques is also being done. The Deep South Challenge (DSC), a local research institute in New Zealand, is looking at how to combine two DMDU techniques called robust decision making (RDM) and dynamic adaptive policy pathways (DAPP). RDM can be seen as a computational extension of scenario planning, where proposed plans are tested against potential combinations of uncertainties. DAPP is a flexible policy framework that allows decision-makers to keep long-term goals in mind while making short-term decisions.

To design DAPP, currently a combination of MORO and participatory processes are used. RDM is seen as a potential improvement in supporting the DAPP policy structure in two main ways. First, RDM can be used to develop and/or stress-test potential pathways. Second, the vulnerabilities identified through RDM can be used to lay the base for a monitoring system by identifying promising signposts and signals. While literature suggests RDM to be a potentially helpful tool in supporting the DAPP approach, there is a lack of studies that have established a systematic and analytical approach using the robust decision making process to support the development of DAPP. Additionally, there exists nearly no literature on the development of a monitoring system for DAPP, even though it is proposed RDM could be helpful in this regard as well.

1.2.2 Objective

The objective of this research is to present a novel systematic and analytical approach which uses the robust decision process to support the development of a DAPP map and its associated monitoring system. This approach should achieve two main goals. First, it should present a systematic way to iteratively develop actions and design pathways. Second, it should present a way to employ the vulnerabilities identified through RDM to identify signposts and signals for a monitoring system.

1.2.3 Research Questions

How can the robust decision making process be used to inform and design dynamic adaptive policy pathways and identify signposts and signals for a monitoring system?

- **How can promising actions and pathways be informed and designed analytically using the robust decision making process?**
  In the New Zealand context pathways have mostly been designed using a participatory approach. In this research, an approach which uses the RDM process to inform and design actions and pathways will be laid out. In order to illustrate this approach, the first iteration will be done for a case site in Helensville, New Zealand.

- **How can signposts and signals be identified using the multidimensional adaptation tipping points found through scenario discovery?**
  There exists nearly no literature on the development of a monitoring system for DAPP, and none on using RDM to achieve this. It has been suggested that the vulnerabilities identified through scenario discovery can be considered as multidimensional adaptation tipping points. Using this information, signposts and signals can be identified to lay the groundwork for a monitoring system.

1.2.4 Approach

Before introducing the novel approach, a description of the building blocks will be given based on literature. This forms the foundation for the further development of the approach. Describing the building blocks has two main goals: first, it helps to better understand the processes of RDM and DAPP, to understand when these are applicable, and their taxonomies. Second, clearly describing the building blocks helps to understand their working definitions. This is especially important when there is much disagreement about processes or definitions in literature, as is the case in a relatively new field such as this.

After the development of the approach, it is then illustrated by way of an adaptation case in Helensville, New Zealand. Here, a wastewater treatment plant serves a small community and will have to retreat at some point in the future due to increasing risks from compound flooding, which are exacerbated by rising sea levels. The main goal here is to illustrate how this approach would be implemented in an actual case, although due to time constraints in this case only the first iteration of the approach is included. After this first iteration, the main findings of this work will be discussed.

1.3 Reader's guide

The rest of this report is structured as follows.

Chapter 2 further explains some of the concepts introduced in this chapter, laying out the building blocks for the novel approach. This includes an introduction of the use cases and taxonomy of Decision Making under Deep Uncertainty (DMDU) in Section 2.1, the methodology of Dynamic Adaptive Policy Pathways (DAPP) in Section 2.2, the methodology of Robust Decision Making (RDM) in Section 2.3, and finally the taxonomy, development, and evaluation of a monitoring system in Section 2.4.

These building blocks will be used to introduce a novel method for using RDM to support the development of DAPP and its associated monitoring system in Chapter 3. This starts with the first part of the approach which focuses on informing and developing actions and pathways in Section 3.2. The second part of the approach focuses on developing a monitoring system in Section 3.3. Finally, the chapter concludes with a summary of the complete approach in Section 3.4.

Chapter 4 describes the case study in Helensville, which is used to illustrate the proposed approach. This chapter follows the different steps from the approach laid out in the previous chapter.

Chapter 5 discusses some of the caveats as well as interesting findings of the research expressed in this report, and their implications on the validity of the results.

Finally, Chapter 6 is split into the conclusions and the recommendations. The conclusions answer the research questions by focusing on some of the main aspects of the proposed approach. The recommendations lay out avenues for further research based on limitations and strengths of this research.

Chapter 2

Review of the building blocks

This chapter will give background on the family of decision making under deep uncertainty approaches in Section 2.1, as well as more detailed introductions of the dynamic adaptive policy pathways and robust decision making concepts respectively in Sections 2.2 and 2.3. The way a monitoring system is currently developed is laid out in Section 2.4. Finally, relevant literature on how robust decision making can be used to support the development and monitoring of dynamic adaptive policy pathways is explained in Section 2.5.

2.1 Decision Making under Deep Uncertainty (DMDU)

This section further introduces the DMDU family of approaches. First the subsection of policy cases where the DMDU approaches are applicable are laid out. This is in part reliant on the level of uncertainty encountered. Second, the family of approaches is broken down into its essentials.

2.1.1 Levels of uncertainty

Different levels of uncertainty warrant different planning approaches. Marchau et al. (2019) has divided the degree of uncertainty that can be encountered into four different levels, limited by complete determinism on one side to total ignorance on the other side. These levels can also be seen in Figures 1.1 and 2.1.

While these levels attempt to split up the degree of uncertainty into different levels to clarify which approach should be taken, in reality multiple degrees of uncertainty are present concurrently depending on the scale of the decision making, and approaches are complementary. An example is that for the same problem, when taking into account long-term goals care should be taken to stay flexible to be able to deal with potential unexpected events, whereas for short-term decisions probabilistic methods can be used.

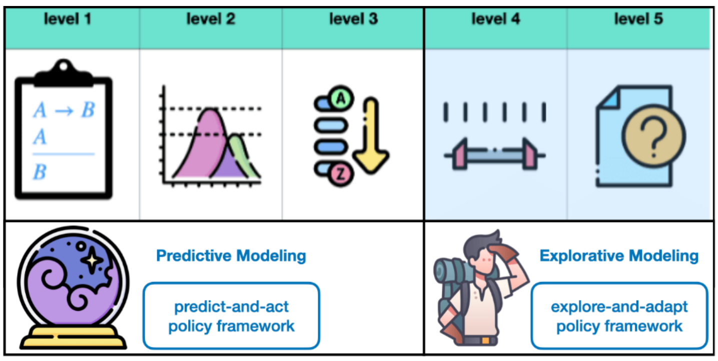


Figure 2.1: Different levels of uncertainty and their approaches. Based on illustrations by Reddel (2023)

Levels 1, 2, and 3: Predict and act

The first phase of accepted uncertainty is level 1. At this level the planner admits to not knowing the future exactly, but the system is clearly defined and the past assumed to be a good predictor for the future so the future is nearly deterministic. An example of where this occurs is with very short term decisions. When it is found necessary to deal with this type of uncertainty, most often a sensitivity analysis is done, where the effects of small changes in the inputs on the outputs are assessed.

Level 2 uncertainty occurs when the system or its inputs are not as clearly defined, but can be described in a probabilistic manner. In this case, probability and statistics are used to estimate the distributions of the outcomes, based on which a preferred option can be chosen. An example of dealing with level 2 uncertainty is the calculation of failure probabilities.

In the case of level 3 uncertainty, no probabilities can be assigned to the different system models, inputs, or outcomes. Instead, there is a clear and compact range of plausible futures which can be ranked in likelihood of their occurrence. An example of dealing with level 3 uncertainty is scenario planning.

For levels 1 through 3, actions are based on the expected unfolding of the future. This is also called the "predict and act" framework as seen in Figure 2.1. In these cases, it is assumed that the future can be predicted at least relatively well, and actions are based on these predictions.

Levels 4a and 4b (deep uncertainty): Explore and adapt

Level 4, which is described as deep uncertainty, is the focus of this research. Level 4 uncertainty can be split into two levels: 4a and 4b. For level 4a, the system can still be characterized, but the amount of plausible futures makes scenario planning unusable and no clear ranking in the probability of occurrence of these futures can be given. Level 4b encompasses the situations where we don't know what we don't know. This includes black swan events, which are events which cannot be predicted by anything that happened in the past. As will be shown in the coming sections, in these cases there is a need for DMDU techniques.

For level 4 or deep uncertainty, it is assumed that making predictions of the future are not possible. In these cases the focus shifts from prediction of the future to exploration of the system, and policy options can be employed once more is known. This is also called the "explore and adapt" framework.

2.1.2 When to use decision making under deep uncertainty approaches

The level of uncertainty encountered determines in part which planning approach to take, along with other factors such as the complexity of the system, or how well the system is understood, and the number of policy options available. A visual representation of this can be found in Figure 2.2, and the approaches denoted here will be explained further below.

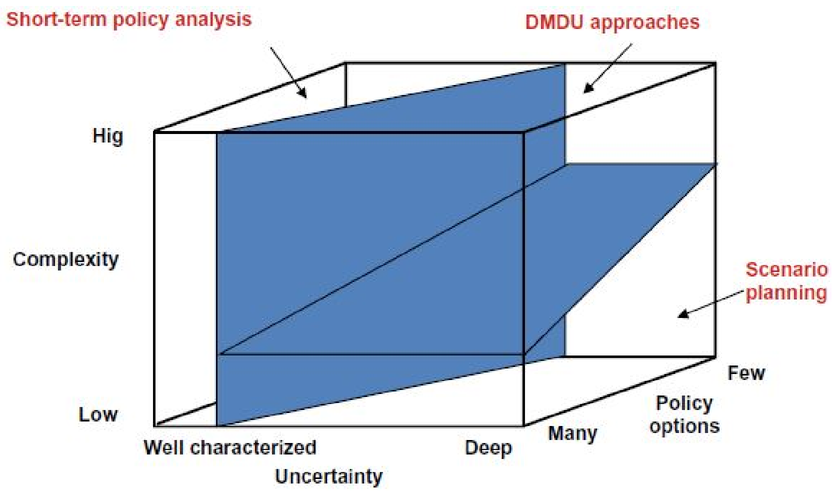


Figure 2.2: Efficacy of different planning approaches depending on levels of uncertainty, complexity of the system, and the number of policy options (Marchau et al., 2019).

Short-term policy analysis

When contextual uncertainty is well-characterized, short-term policy analysis is often used. This family of approaches even works relatively well for slightly deeper uncertainty if there are only a few clear policy options available. Examples are decision making on a shorter time scale, or decision making in slow changing systems. Problems arise, however, when the level of uncertainty increases.

Short-term policy analysis consists largely of probabilistic predictive approaches (Marchau et al., 2019). This group of approaches starts by building a model of the system, which is then used to calculate the outcomes of interest with confidence intervals around them. Outcomes are evaluated using methods like a cost benefit analysis or a multi-criteria analysis. Another approach is to use decision trees, which also use probabilistic assessments to assist decision making. In this case, each decision is represented as a node, which affects the failure probability of the system.

Scenario planning

When the level of uncertainty becomes deeper and the complexity of the system is relatively low, scenario planning is used as can be seen in Figure 2.2. Complexity of the system in this case is a measure of how well the system is understood (Marchau et al., 2019). In this case, the goal is not to optimize, but rather find those decisions that lead to a sufficient outcome in each different scenario. These decisions are also called "robust". Scenario planning works well when uncertainty is relatively high but the complexity of the system is low, so potential future scenarios can be predicted, and the effects of policies on the outcomes can be linked by expert knowledge. When the system becomes more complex, however, scenario planning loses efficacy since predictions of the future system, its behavior, and the effects of policies on outcomes become harder to make (Marchau et al., 2019).

In general, scenario planning uses the best current knowledge of the system to select a small number of mutually exclusive plausible future states. After this, each possible decision is applied to the different scenarios, in order to identify those that perform well in a number of them. Scenario planning facilitates "what if" thinking to explore possible changes in the system and to prepare for them (Marchau et al., 2019; Walker et al., 2013).

Decision Making under Deep Uncertainty (DMDU) approaches

When the level of uncertainty is deeper and the complexity of the system is higher, DMDU approaches are best used as can be seen in Figure 2.2. These approaches focus on dealing with situations where system complexity complicates predicting the future system, its behavior, and the effects of policies on outcomes (Marchau et al., 2019). Some also attempt to deal with so-called "black swans": situations where the future is not necessarily based on the past and thus cannot reasonably be predicted.

Various DMDU approaches have been developed over the years, some of which are Engineering Options Analysis (EOA), Info-Gap Decision Theory (IG), Dynamic Adaptive Planning (DAP), Robust Decisionmaking (RDM) and Dynamic Adaptive Policy Pathways (DAPP) (Marchau et al., 2019). These approaches each have differing focuses and application domains, which will be further explained in the next section.

2.1.3 Taxonomy of DMDU approaches

Key ideas underlying DMDU approaches

While each DMDU approach has a different focus, they all rely on a few key ideas. From Kwakkel and Haasnoot (2019), these ideas are exploratory modeling, adaptive planning, and decision support. The first, exploratory modeling, can be seen as an extension of scenario planning where a systematic search is done of the consequences of all plausible scenarios. This is often done using a model. The second key idea, adaptive planning, has to do with how a plan adapts to change. In the case of adaptive planning, adaptations are made based on observed changes rather than just at predetermined times. The last key idea, decision support, states that rather than trying to find the "correct" decision, the focus should be on showing all possible options, and facilitating discussion and deliberation between the main stakeholders. This can be done by illustrating the tradeoffs and robustness for different policy options.

In order to support exploratory modeling and decision support especially, computational tools such as the Exploratory Modeling and Analysis (EMA) workbench or sdtoolkit are often used (Bryant, 2012; Kwakkel, 2017). The EMA workbench is a Python package that provides a range of tools and algorithms for model exploration, sensitivity analysis, multi-objective optimization, and scenario discovery. These results can then also be easily visualized for decision suppport, through links with seaborn and matplotlib.

General taxonomy of DMDU approaches

A categorization of current DMDU approaches can serve as a starting point for further combination and development of new DMDU methods such as the one proposed in this work. An initial taxonomy proposed by Herman et al. (2015) and expanded upon by Kwakkel and Haasnoot (2019) will be laid out in this subsection. Although not all methods explicitly consider each of the categories used in the taxonomy, it can still serve as a starting point for comparison.

Policy architecture
There are two main policy architectures, protective adaptivity and dynamic adaptivity. Protective adaptivity focuses on protecting a basic plan against uncertainties using potential contingency actions when necessary. Dynamic adaptivity, on the other hand, does not differentiate between the basic plan and the contingency actions, but creates a framework of potential alternatives to choose between based on the way the future unfolds.

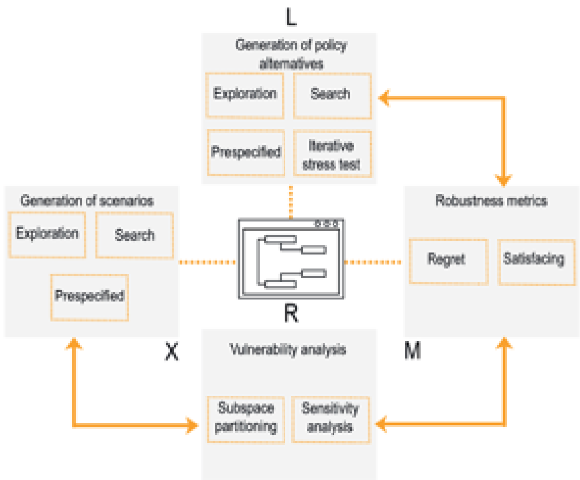


Figure 2.3: Taxonomy of DMDU approaches presented in an XLRM framework from Mannucci (2021)

Generation of scenarios
Scenarios are defined as the relevant combinations of input uncertainties taken into account, which can be seen in Figure 2.3. There are three main strategies to generate scenarios: exploration, search, and using pre-specified scenarios. In practice, these three ways of generating scenarios can be combined. For exploration, the uncertainty space is systematically sampled. This gives global insights into the characteristics of (combinations of) input uncertainties. This systematic sampling is often done using Monte Carlo, Latin Hypercube, or factorial sampling. With a search strategy, the uncertainty space is more narrowly sampled, looking for points with specific properties such as a worst or best case scenario. For this, optimization techniques are used. Lastly, a pre-specified scenario generation means scenarios are selected in advance, which is often done in conjunction with expert opinion.

Generation of policy alternatives
Policy alternatives to take into account can be selected with four main strategies, similarly to the generation of scenarios: exploration, search, pre-specified and iterative. Exploration systematically samples the policy lever space to identify under what scenarios policies perform well (or poorly). This gives global insights into their performance. Similarly to the generation of scenarios, a sampling scheme can be used for this. Search samples the policy lever space more narrowly, for example to identify which policy would work best or worst for a certain scenario. Pre-specified indicates the policies to be used are selected in advance. Additionally,

an iterative generation of policy alternatives combines the other strategies to stress-test an initial policy and adapt it based on the results in order to create more robust policy.

Vulnerability analysis
A vulnerability analysis is used to investigate the performance of policies across different scenarios. There are two main types of vulnerability analysis which can be combined: subspace partitioning and sensitivity analysis. Subspace partitioning tries to find subspaces within the experiments (combinations of scenarios and policies) that result in similar outcomes. This can be used to find combinations of policies and uncertainties that perform particularly well (or not). A sensitivity analysis is used to understand the relative influence of different input uncertainties or policies on the outcomes. This can help to identify the most important uncertainties to monitor or policies to implement.

Robustness metrics
To describe the performance of policies, robustness metrics are used. While there are many different metrics that can be used, there are two main categories for robustness metrics: regret and satificing. A regret metric compares the performance of a policy against the best performing policy or a pre-specified baseline for specific scenarios. A robust policy according to this metric is one that gets as close as possible to the baseline or best performing policy across all scenarios. On the other hand, a satisficing metric measures in how many scenarios a policy performs above a pre-specified threshold. According to this metric, a policy is said to be more robust if it performs above the threshold in more scenarios.

2.2 Introduction to Dynamic Adaptive Policy Pathways (DAPP)

2.2.1 Background of DAPP

Based on a combination of the concepts of dynamic adaptive planning, adaptation pathways and adaptation tipping points, Dynamic Adaptive Policy Pathways (DAPP) was proposed by Haasnoot et al. (2013). Initially, the goal was creating climate resilient pathways for water management by combining the best aspects of these concepts to design a dynamic adaptive strategy that strives to deal with black swan (level 4b) events by creating a network of potential actions, between which can be chosen based on the way the future unfolds (Haasnoot et al., 2019). This can be seen in Figure 2.4b.

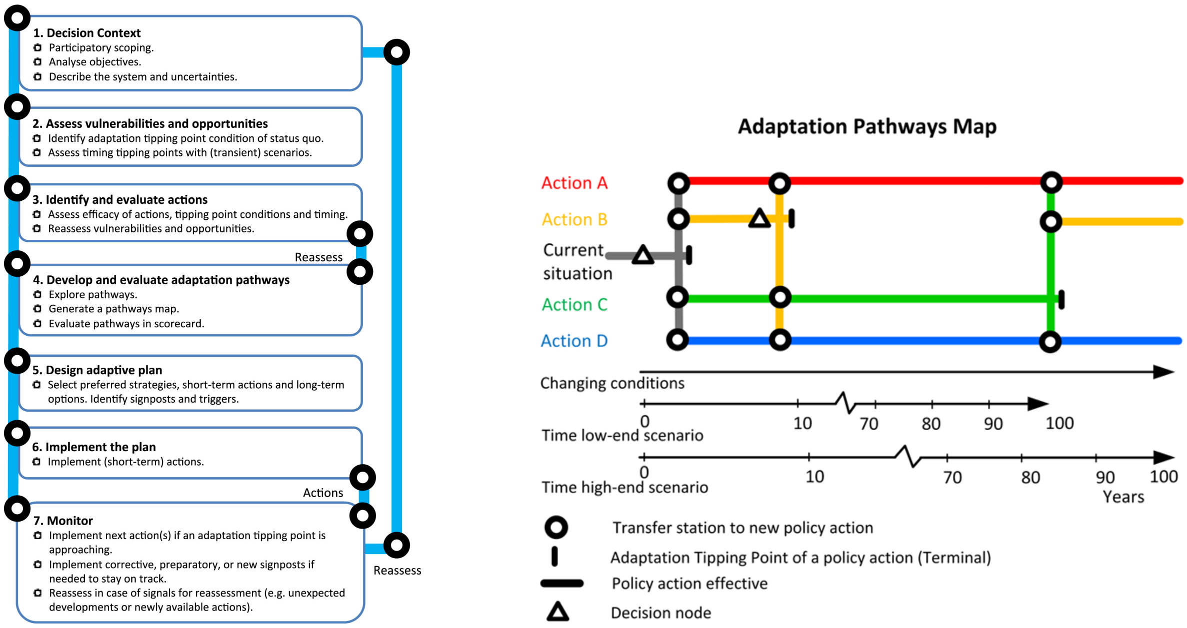
One of the key benefits of DAPP is the intuitive way the pathways show the different policy options or actions in a metro map. This metro map also aids in splitting up large actions into smaller and more actionable ones. Additionally, by using these pathways, potential lock-ins are made explicit allowing decision makers to keep long-term strategy in mind while making choices with a shorter planning horizon (Haasnoot et al., 2019). For these reasons, the method has quickly gained in popularity, with DAPP being implemented for the Dutch Delta Programme and the Bangladesh Delta plan, as well as on a more regional scale in New Zealand (Lawrence & Haasnoot, 2017; Lawrence et al., 2018, 2019).

Taxonomy of DAPP

The taxonomy of decision making under deep uncertainty approaches was introduced at the end of Section 2.1, as a way of comparing different approaches. There are 5 categories in the taxonomy, although not each approach explicitly considers each category. These categories are policy architecture, generation of scenarios, generation of policies or actions, vulnerability analysis, and robustness metrics. The taxonomy given is based on the work by Kwakkel and Haasnoot (2019), which is bolstered by examples from the methodology below.

DAPP explicitly takes into account dynamic adaptivity as the policy architecture, which can be seen in the map of potential alternative pathways in Figure 2.4b. DAPP does not explicitly consider the generation of scenarios, although transient scenarios are needed to time adaptation and performance of the different pathways. This can be seen as the x-axis in Figure 2.4b. The generation of policy alternatives is in general pre-specified for DAPP, since these form the basis of the different pathways. This can be seen as the y-axis in Figure 2.4b. The vulnerability analysis used for DAPP, adaptation tipping points, can be seen as subspace partitioning by defining in which cases failure is likely to occur. Lastly, the robustness metrics for DAPP is typically focused on satisficing measures by performing at least above a certain threshold (the adaptation tipping point), although when selecting a preferred pathway there can also be a focus on regret metrics as seen in Step 5 of the methodology below.

2.2.2 Methodology of DAPP



(a) DAPP process

(b) DAPP map

Figure 2.4: DAPP process and end result (Haasnoot et al., 2019)

Taken from the DAPP process in Figure 2.4 and Haasnoot et al. (2019), Kwakkel and Haasnoot (2019), and Kwakkel et al. (2015b, 2016a), the steps taken to design a DAPP map are laid out below.

Step 1: Decision context

The DAPP process starts by setting the decision context in an XLRM framework. Here, X stands for the exogenous uncertainties that can affect an action's influence on the objectives, L stands for the levers or possible actions that can be taken, R stands for the relationships within the system between the actions, the uncertainties and the objectives (XLM), and M stands for the measures of performance or the objectives of the decisionmaker (Lempert, 2019).

Step 2: Assess vulnerabilities and opportunities

In the second step, the thresholds and timing of Adaptation Tipping Points (ATPs) for the status quo are identified. To identify these ATPs, either a bottom-up or a top-down approach can be taken. A bottom-up approach first determines the thresholds for adaptation before it determines the timing of these thresholds using scenarios, while a top-down approach uses different scenarios to determine when a change would be necessary.

Step 3: Identify and evaluate actions

In the third step, different potential actions are identified that deal with the system's vulnerabilities and opportunities identified in the previous step. Additionally, the adaptation tipping points (including their thresholds and timing) for these potential policy actions are identified. Currently a multi-objective robust optimization (MORO) approach is used for this, although the available actions as well as ways to sequence them have to be pre-specified. This also reveals the main benefit of a combination with RDM, since for MORO no way is given to design or stress-test these actions (Kwakkel et al., 2016a).

Step 4: Develop and evaluate adaptation pathways

The fourth step of the DAPP process consists of the designing and evaluating of pathways. This is done by combining the actions from the previous step into different pathways. This creates a map, after which each individual pathway can be evaluated.

Step 5: Design adaptive plan

In the fifth step, preferred pathways are selected based on the evaluation of the pathways in the previous step. From this, an adaptive plan is created which consists of short-term actions to be followed to achieve long-term goals. This step also identifies signals and triggers for this adaptive plan to indicate when adaptation is necessary, which forms the basis of a monitoring system.

Steps 6&7: Implement the plan and monitor

These steps consist of the implementation and monitoring of the adaptive plan designed in the previous step. There is also an iterative component in DAPP, where the plan is reassessed from time to time when there are unexpected developments, newly available actions, or newly available data.

2.3 Introduction to Robust Decision Making (RDM)

2.3.1 Background of RDM

Developed by the RAND corporation, Robust Decision Making (RDM) combines different techniques to build on scenario planning by using exploratory modeling to sample the entire uncertainty space. This means that instead of just a selection of a few scenarios RDM samples the uncertainty space in order to explore behavior for many possible combinations of uncertainties. The two main benefits are the ability to discover the conditions under which the system is vulnerable, as well as the ability to iteratively develop robust strategies that deal well with these vulnerabilities.

While RDM is a good method for identifying the vulnerabilities that threaten a system and iteratively design plans to deal with these vulnerabilities, it does not offer a clear structure for implementing these plans in an adaptive fashion (Kwakkel et al., 2016a; Lempert, 2019).

Taxonomy of RDM

The taxonomy of decision making under deep uncertainty approaches was introduced at the end of Section 2.1, as a way of comparing different approaches. There are 5 categories in the taxonomy, although not each approach explicitly considers each category. These categories are policy architecture, generation of scenarios, generation of policy alternatives, vulnerability analysis, and robustness metrics. The taxonomy given is based on the work by Kwakkel and Haasnoot (2019), which is bolstered by examples from the methodology below.

RDM does not explicitly have a policy architecture, although it is often used to create a robust policy and thus fits more under the nomer of protective adaptivity. The way scenarios are generated for RDM are through exploration, where the uncertainty space is sampled as explained in step 2 below. The generation of policies for RDM is generally pre-specified and iteratively stress-tested, where existing policies are tested against the generated scenarios and improved upon. The vulnerability analysis RDM uses for this iterative stress-testing is scenario discovery, which falls under subspace partitioning as explained further in step 3 below. Lastly, the robustness metric used by RDM is a satisficing metric to calculate the vulnerabilities using scenario discovery, and regret metric for the trade-off analysis in step 4 below.

2.3.2 Methodology RDM

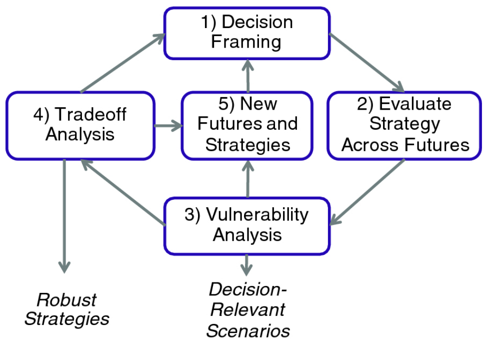


Figure 2.5: The robust decision making process (Lempert, 2019)

The RDM process can be found in figure 2.5. While the steps below seem linear, in reality RDM is an iterative process where the results influence the way the problem is seen and potential policies.

Step 1: Decision framing

To start, the problem at hand is usually organized in an XLRM framework. Here, X stands for the exogenous uncertainties that can affect an action's influence on the objectives, L stands for the levers or possible actions that can be taken, R stands for the relationships within the system between the actions, the uncertainties and the objectives (XLM), and M stands for the measures of performance or the objectives of the decisionmaker (Lempert, 2019).

Step 2: Evaluate strategy across futures

In the next step, samples are taken from the combined uncertainty and policy lever spaces, and simulation models are used to calculate the results for these samples. Often random sampling schemes such as Monte Carlo are used for this, although quasi-random schemes such as Latin Hypercube or SOBOL can be used to achieve a more uniform coverage of the uncertainty space at the cost of a higher computational load. Literature also suggests adaptive sampling could lead to increased efficiency (Groves et al., 2019; Lempert, 2019)

The result of this is a database with each entry being the performance of a policy in a scenario. This is often done using integrated exploratory modeling software such as the EMA workbench. Integrated software such as this makes it easier to organize the problem in an XLRM framework, to generate runs, to run the vulnerability analysis, and to visualize the results (Groves et al., 2019; Kwakkel, 2017).

Step 3: Vulnerability analysis

For the vulnerability analysis, a scenario discovery algorithm is usually used. This algorithm filters through the database of runs as described in the previous paragraph and finds clusters of runs where the objectives are not met. This is most often done using the Patient Rule Induction Method (PRIM) due to its ease of use and interpretability, although there are also other options such as a Classification and Regression Tree (CART), and logistic regression (Bryant & Lempert, 2010; Lempert et al., 2008). These clusters are then further analyzed to define relevant scenarios, which are one of the outputs of the RDM process (Kwakkel, 2017; Kwakkel et al., 2016a; Lempert, 2019).

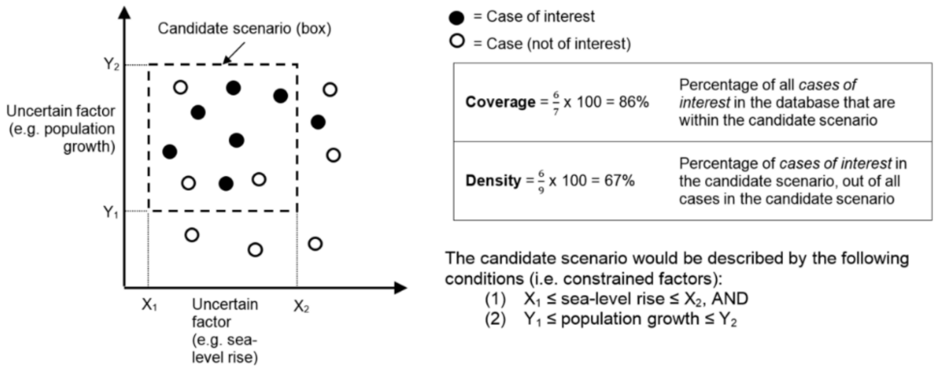


Figure 2.6: Visualization of the box found through scenario discovery (Ramm et al., 2018a)

Scenarios are combinations of relevant input uncertainties, which are visualized as boxes as seen in Figure 2.6. These boxes are usually described through the coverage and density of the box which can also be seen in Figure 2.6. Here, the coverage is the percentage of all cases of interest that fall within the selected box, and the density is the percentage of cases that fall within the box that are cases of interest. Additionally, a quasi-p value is calculated to estimate the probability that an input value is selected by chance, and whether it is statistically significant (Bryant & Lempert, 2010; Kwakkel et al., 2016a).

Step 4: Tradeoff analysis

In the fourth step, the vulnerable scenarios discovered in the previous step are used to visualize the tradeoffs between policies for one or more objectives. This helps facilitate discussion about policies between stakeholders, which allows decisionmakers to select their preferred robust actions.

Step 5: New futures and strategies

In step five, the vulnerabilities defined in scenarios in step 3 and the results of the tradeoff analysis from step 4 are used to reassess the decision framing, and to identify and assess new, potentially more robust, policies. This increase in robustness is sometimes achieved by combining short-term actions, signposts, triggers and contingent actions (Groves et al., 2019; Lempert, 2019). This is one potential way RDM can be used to set up adaptive strategies.

2.4 Monitoring system

2.4.1 Introduction and relevance

A monitoring system to know when to implement change is an important part of adaptive planning, which is one of the key ideas of decision making under deep uncertainty. For DAPP specifically, the timely and correct implementation of the necessary action depends on monitoring the performance of the plan as seen in step 7 in Figure 2.4. Setting up a monitoring system depends in part on the recognition of signals when adaptation is necessary. This is tough to do in practice, and is currently one of the main points of attention for DAPP (Haasnoot et al., 2018, 2019; Lawrence et al., 2019; Stephens et al., 2018).

The idea of this section is to give an idea of how a monitoring system would currently be set up. This will be done following Haasnoot et al. (2018) with additional literature when necessary. The paper by Haasnoot et al. (2018) is used due since it is one of the only papers available with a ready implementation for DAPP and systematic nature. In the next chapter relevant literature will be used to propose possible changes in this method using robust decision making to support the design of the monitoring system with DAPP. Explicitly for the discovery of signposts, indicators and signals. The focus here is on technical rather than political signposts, indicators, and triggers as the latter is outside the scope of this research.

In the next subsections first the general taxonomy of a monitoring system will be laid out, after which the current way of setting up a monitoring system will be explained. The last part of this section consists of the evaluation of a monitoring system.

2.4.2 Taxonomy of a monitoring system

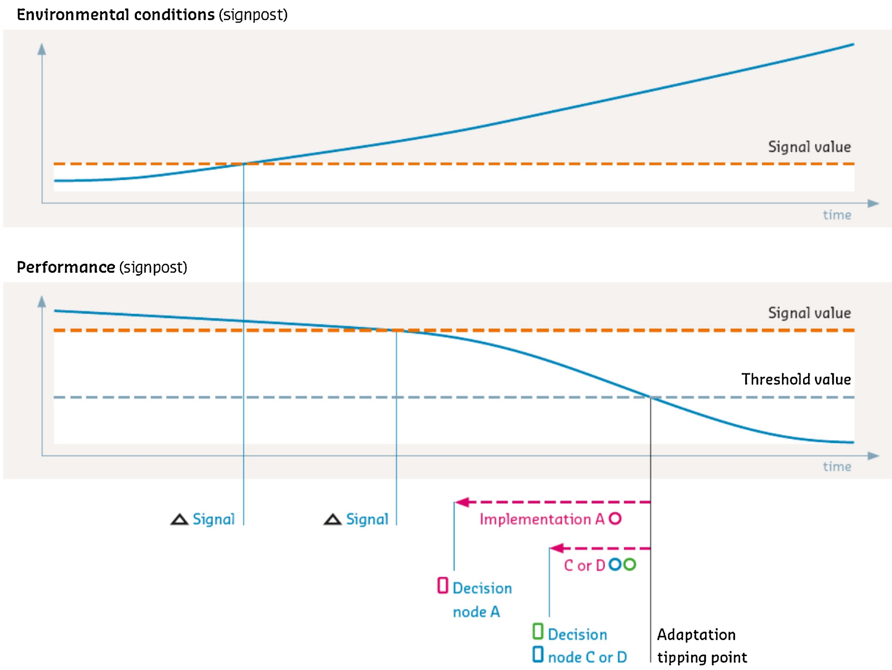


Figure 2.7: General set up of a monitoring system taken from Haasnoot et al. (2018)

In DMDU literature, the different aspects of a monitoring system are defined in various (sometimes conflicting) ways (Haasnoot et al., 2018; Hermans et al., 2017; Marchau et al., 2019). For this research the following definitions will be used for each part of the monitoring system based mostly on the work by Haasnoot et al. (2018) due to its ready implementation for the dynamic adaptive policy pathways approach, which is also the focus of this research.

- **Signposts:** These are the variables to be tracked in order to evaluate the performance of the current action. In practice multiple signposts are used to get a good idea of the current situation. There are three main categories: performance signposts which measure the performance of a system to see if the implemented action still performs sufficiently, environmental signposts which measure external conditions to see if potential risks to the implemented action are increasing, and implementation signposts which measure whether there are any unintended and unwanted consequences of the implemented action, or that monitor the status of potential future actions or plans by looking at things that could make their implementation easier and/or cheaper (Haasnoot et al., 2018; Swanson et al., 2010).
- **Indicators:** Oftentimes signposts are hard to measure, either due to noise in the system, or due to reliance on extreme events which are not directly observable. In these cases, a collection of derivative signposts (here called indicators) can be used as a proxy for the original signpost Haasnoot et al. (2018) and Hermans et al. (2017). Indicators can also be used to better understand the changing system, which helps to further validate when adaptation is needed.
- **Adaptation Tipping Point (ATP):** An adaptation tipping point is the point at which the performance of an action dips below the threshold for a certain signpost or indicator as set by decision makers. This can also be seen in Figure 2.7.
- **Triggers:** Since the implementation of a new action takes time, the decision for a follow-up action should be made well before an ATP occurs. Triggers are values of signposts or indicators that indicate

adaptation is necessary, while leaving enough time for the implementation of the new action. In the context of DAPP, triggers correspond to decision nodes as also seen in Figure 2.7, and indicate when a new path can and should be accessed.

- **Signals:** A signal is a value of a signpost or indicator that gives an early warning that a trigger or ATP is approaching. In reality, good signals are hard to find. This is partly due to the uncertainty in timing, which could either give a false warning, or overlap with triggers leading to late adaptation. Even weak signals, however, can still be helpful in spurring further research or action (Haasnoot et al., 2018; Lawrence et al., 2019; Stephens et al., 2018).

2.4.3 Development of a monitoring system

While a monitoring system is crucial in the implementation of any adaptive plan and a crucial tenet of DMDU approaches, there are not many systematic approaches in literature on how they can be developed (Haasnoot et al., 2018; Raso, Kwakkel, Timmermans, & Panthou, 2019). Haasnoot et al. (2018) developed a framework for creating a signpost monitoring system which can be seen in Figure 2.8. This consists of five steps applicable to most adaptive plans, even though they were designed with DAPP in mind. The first step is to identify key decisions, actions, and adaptation tipping points. Second, developments are identified that could trigger those key decisions or impact the effectiveness of a potential future action. The third step consists of identifying signposts and indicators that follow these developments and are able to give signals in order to monitor them. Fourth, if these signals are measurable they are evaluated based on timeliness and reliability. Last of all, an optimal combination of signposts with differing measures of measurability, timeliness, and reliability are selected. These signposts need to be corrected for correlation, to avoid overconfidence. The goal here is to give decision makers multiple signposts with different signals in order for them to better understand the changing system (Haasnoot et al., 2018; Hall & Borgomeo, 2013).

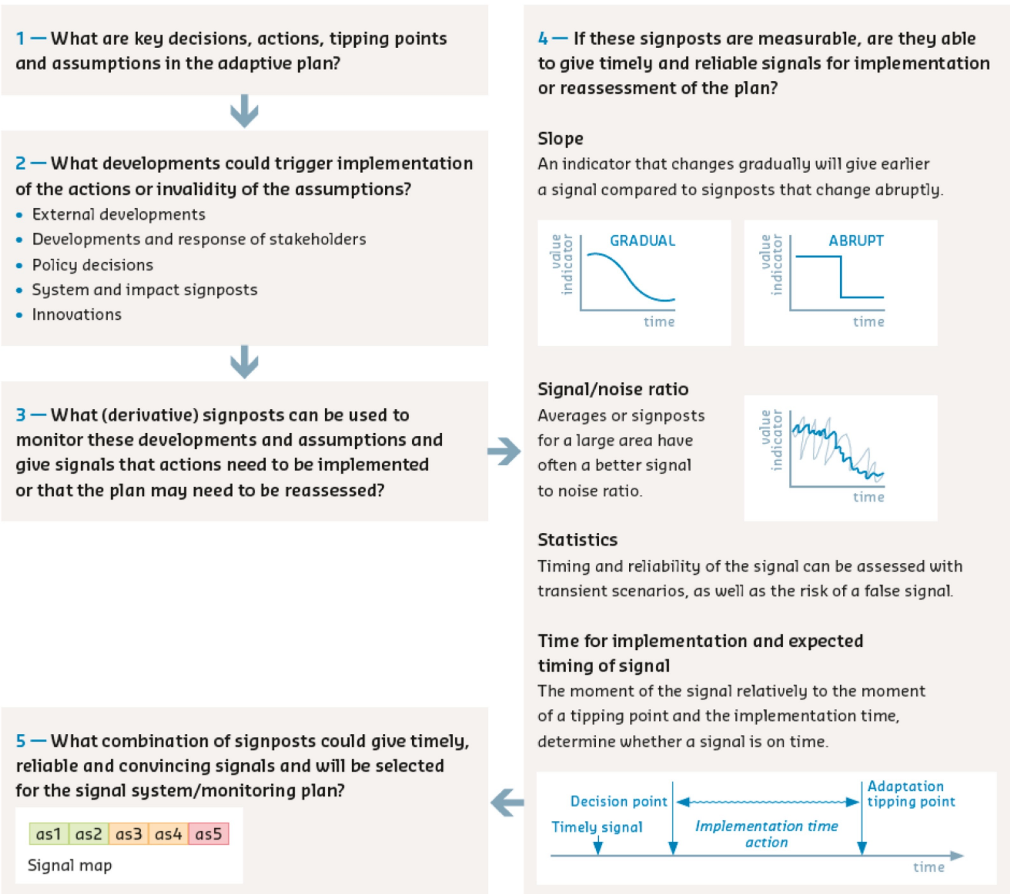


Figure 2.8: The steps to create a monitoring system according to Haasnoot et al. (2018)

The selection of signposts, signals, and triggers

Literature does suggest some ways signposts, signals and triggers can be selected, which are often combined with each other (Haasnoot et al., 2018; Raso, Kwakkel, Timmermans, & Panthou, 2019). Signposts and trigger values can be selected based on expert opinion (Haasnoot et al., 2013, 2015; Lempert & Groves, 2010). Optimization techniques such as MORO can be used to calculate triggers based on predefined rules (Herman et al., 2014; Kwakkel et al., 2015b; Zeff et al., 2016). Lastly, signposts and corresponding adaptation tipping points can also be discovered through the results of scenario discovery, which will be further explained in the next chapter (Groves et al., 2013, 2015; Hamarat et al., 2013).

2.4.4 Evaluation criteria for a monitoring system

The evaluation and the design of a signpost monitoring system go hand in hand. Evaluating leads to the iterative selection of better signposts and signals, and thus a better monitoring system. For this research specifically, political or social evaluation criteria are outside the scope since the focus is on the technical, model-based side. There is no consensus on which evaluation criteria to use for a monitoring system or its signals and signposts. There are two main papers describing the evaluation of a monitoring system by Haasnoot et al. (2018) and Raso, Kwakkel, Timmermans, and Panthou (2019) respectively. More in-depth discussions of these two papers can be found in Appendix A.

Between these two papers, there are slightly differing criteria which can be explained by their differing focuses. While Haasnoot et al. (2013) is more high-level, focusing on general criteria and political aspects, Raso, Kwakkel, Timmermans, and Panthou (2019) does not take the social and political context into account, and instead focuses the evaluation on the technical analysis of the signposts and monitoring system. This is something implicitly done in Step 4 in Figure 2.8 by Haasnoot et al. (2018).

Another interesting point, which most likely also has to do with these differing focuses is the disagreement on the number of signposts to be taken. Raso, Kwakkel, Timmermans, and Panthou (2019) works with the parsimony concept, where as little signposts as possible should be chosen to prevent redundancy in the case of high dependency. Haasnoot et al. (2018) instead focuses on using multiple signposts, while correcting for any correlation between them. The reasoning here, is that using multiple signposts and signals gives a decision maker a better view of the changing system, and to act as validation.

2.5 Using Robust Decision Making (RDM) to inform the development and monitoring of Dynamic Adaptive Policy Pathways (DAPP)

Since DAPP presents a clear dynamic adaptive policy framework, and RDM presents a way to iteratively develop robust policies and identify thresholds using scenario discovery, combining the two approaches has been suggested (Haasnoot et al., 2019; Kwakkel et al., 2016a; Lempert, 2019; Ramm et al., 2018a). There are disagreements on how this can best be achieved, and no clear method for combining the two approaches.

There are three main points where the literature differs, which are all discussed in this section. These sources are discussed more in depth in Appendix B. These are how to use RDM to help develop an adaptive plan, how to visualize the vulnerabilities identified through scenario discovery, and on how to build a monitoring system using these identified vulnerabilities.

2.5.1 Protecting or adapting a plan

Kwakkel and Haasnoot (2019) and Kwakkel et al. (2016a) suggest there are two ways to use RDM to support the development of pathways for DAPP. The first is to already start with a pathways map created through some other method, and to stress-test these pathways. The second is to use RDM to develop the pathways by iteratively designing policies or actions that deal well with the vulnerabilities identified through scenario discovery. This second approach is also the focus of this research.

Some examples of this second approach can also be seen in literature. In the Colorado basin study and in the research triangle Bloom (2015) and Trindade et al. (2019) the results of RDM are used to monitor important external uncertainties. These uncertainties are then used to decide when to move to a different action. The initial plans are not adapted to deal with the identified vulnerabilities, however. Meanwhile, Mannucci (2021) and Ramm et al. (2018a, 2018b) use the vulnerabilities identified through RDM to iteratively develop more robust actions which make up the pathways.

2.5.2 Visualizing the vulnerabilities identified through scenario discovery

There is also disagreement on how to deal with the vulnerabilities identified through scenario discovery, which can be seen as multi-dimensional adaptation tipping points. DAPP was designed for one dominant driver, using transient scenarios to indicate when this driver crosses a threshold or adaptation tipping point, as also explained in Sections 2.2 and 2.4. When dealing with vulnerabilities which consist of multiple drivers with their own thresholds, the question becomes how to define these adaptation tipping points and how to incorporate them within the DAPP map.

Bloom (2015) and Groves et al. (2015) use a single dominant driver for the DAPP map, while incorporating the other drivers part of the vulnerabilities as signposts for a monitoring system as explained in Figure B.3.

In the research triangle, Palmer and Characklis (2009), Trindade et al. (2019), and Zeff et al. (2016) also use a single driver. This 'rate-of-failure' driver combines all identified vulnerabilities using a probabilistic assessment with historical and current data. In this manner, the multi-dimensionality of the vulnerabilities is taken into account while still keeping a singular map. This can be seen in Figure B.7.

Molina-Perez (2016) also keeps one map, but incorporate the vulnerabilities by attaching the conditions under which it is successful to each pathway. Adaptation tipping points are then labeled to indicate the conditions under which a common pathway split into multiple individual ones, or when a pathway is no longer feasible. This makes it visually easy to see the multiple thresholds seen in Figure B.4. Ramm et al. (2018a, 2018b) also put all drivers directly under each adaptation tipping point as seen in Figure B.5.

2.5.3 Designing a monitoring system using scenario discovery

Most literature stops at the suggestion of some signposts and indicators based on the results of the vulnerability analysis of RDM to use as a monitoring system for DAPP (Groves et al., 2015; Mannucci, 2021; Molina-Perez, 2016; Ramm et al., 2018a). There are two small exceptions.

First, the research triangle combines all identified vulnerabilities into a single rate-of-failure signpost. This signpost is based on a probabilistic assessment using historical and current data, combined with the results of scenario discovery. When the probability of failure becomes too high based on either a pre-defined threshold or on the opinion of a decision maker, adaptation is triggered (Palmer & Characklis, 2009; Trindade et al., 2019; Zeff et al., 2016).

Second, Bloom (2015) take the results of the scenario discovery and design a monitoring system using a participatory process. In this case, water planners together determine triggers based on their assessments of prior convictions, projections, and current data.

2.5.4 Conclusion

The sections above highlight some of the ways RDM and DAPP could potentially be combined. However, there exists no analytical and systematic approach to use the RDM process to both develop pathways and build a monitoring system for DAPP. There is some literature on the subject of iteratively developing more robust actions using scenario discovery, but a lot less on the use of this for the development of DAPP. Moreover, no literature uses RDM to develop a monitoring system for DAPP. There is little literature on the subject of how to build such a monitoring system in general, as well as considerable issues in the identification of timely signals (Haasnoot et al., 2019). As a first suggestion for the development of a monitoring system, literature does connect DAPP to RDM through the adaptation tipping points, labeling the vulnerabilities identified through scenario discovery as "multi-dimensional adaptation tipping points" (Ramm et al., 2018a). Combined with other studies which use scenario discovery to inform signposts and thresholds to monitor developments, this forms a potential basis for the use of RDM to build a monitoring system.

Chapter 3

A novel robust decision making-based approach to develop dynamic adaptive policy pathways and its associated monitoring system

This chapter introduces the novel approach proposed by this research. This will start with the relevance and contribution of this research in Section 3.1. After the relevance and proposed contribution of this research are clear, the novel approach is introduced. This is split up into two parts. Section 3.2 discusses the first part of the approach, which uses the robust decision making process to develop actions and pathways. Section 3.3 focuses on the second approach, which uses robust decision making to identify promising signposts and signals for a monitoring system. Finally, Section3.4 shows how these two parts combine to form the proposed novel approach and concludes the chapter.

3.1 Relevance and contribution

3.1.1 Relevance of the research

The last chapter explained two important canonical approaches within the decision making under deep uncertainty family of approaches: dynamic adaptive policy pathways and robust decision making. It was also suggested that robust decision making is potentially supportive to the development of dynamic adaptive policy pathways and its associated monitoring system. The vulnerabilities identified through the robust decision making process could potentially offer benefits compared to the approaches currently used.

Kwakkel (2018) says about combining approaches approaches: "Canonical approaches ... are recipes. Recipes are great if you are learning to cook, but once mastered you can creatively recombine them as well as adapt them to your taste, skill, and what is available." To stick with this metaphor, while the literature suggests some ways ingredients can be recombined, as also shown in Section 2.5, no true recipes exist which use robust decision making support the development of dynamic adaptive policy pathways. Additionally, there exists nearly no literature on the development of a monitoring system for DAPP, even though it is proposed RDM could be helpful in this regard as well.

3.1.2 Contribution

This chapter presents a novel systematic and analytical approach which uses the robust decision process for the development of a DAPP map and its associated monitoring system. This approach should achieve two main goals. First, it should present a systematic way to iteratively develop actions and design pathways.

Second, it should present a way to employ the vulnerabilities identified through RDM to identify signposts and signals for a monitoring system.

This chapter will introduce this novel systematic and analytical approach, split up into two parts and then combined in Section 3.4. The first part uses the RDM process to inform actions and design pathways. The second part adds onto the first by using the vulnerabilities identified through RDM to develop a monitoring system for DAPP.

After the introduction of the approach in this chapter, the next chapter will illustrate the approach using the case of a wastewater treatment plant in Helensville, New Zealand. More information on the specifics of the case and some of the caveats can be found in Section 4.1.

3.2 Part 1: Using RDM to iteratively develop actions and design pathways

The first part of the novel approach focuses on the development of actions and pathways. This is based mostly on the RDM and DAPP approaches as laid out in the last chapter. For each proposed step, sources and reasoning will be given.

To explain the proposed combination in terms of the taxonomy provided in the last chapter, DAPP provides the policy architecture. RDM provides a method for generating scenarios, which form the basis for a more comprehensive vulnerability analysis compared to the one currently used for DAPP to iteratively stress-test and develop (pre-specified) actions.

In plain language, this research proposes to use RDM to better understand the vulnerabilities within the system and develop actions for DAPP based on that.

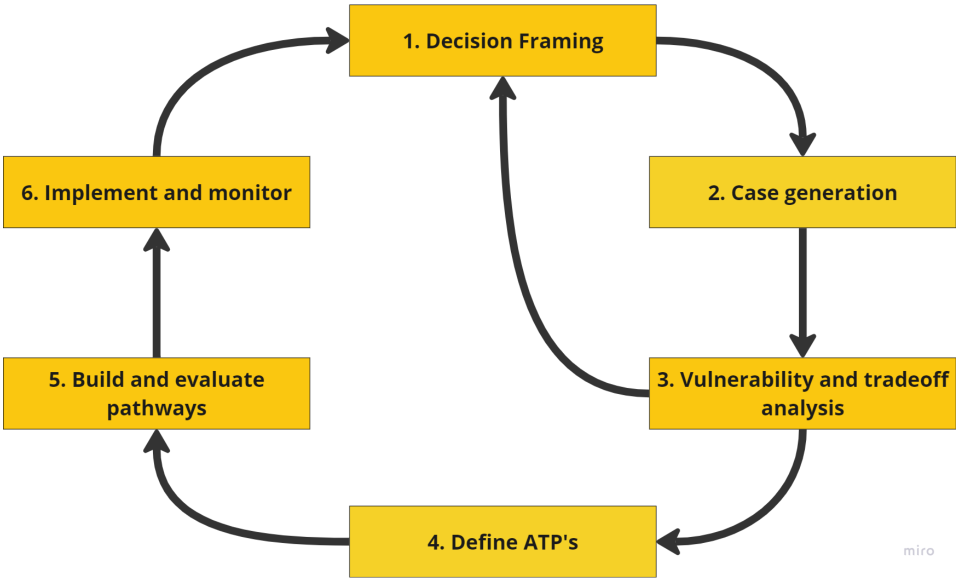


Figure 3.1: First part of the proposed novel approach which uses RDM to develop actions and DAPP

Step 1: Decision framing

The first step consists of the decision framing following Lempert (2019). This step identifies the key uncertainties, policy options, relationships, and goals for the system of interest. This is done in deliberation with key stakeholders and experts. Once there is a general consensus on these, the system is summarized in an XLRM framework and this step is finished. An XLRM framework stands for uncertainties (x), policies (L), relations within the system (R), and the performance metrics (M).

Step 2: Case generation

After the decision framing, cases are generated using a model which represents the key relationships. This model is simulated many times to calculate the performance of each potential action for each potential scenario or combination of input uncertainties. This is identical to the RDM process Lempert (2019). This step ends with a database of the performance of the potential actions for different combinations of input uncertainties.

Step 3: Vulnerability and tradeoff analysis

This step consists of the vulnerability and tradeoff analysis. Here the vulnerabilities of each action is assessed. Scenario discovery is used to identify vulnerabilities for the system similarly to the RDM process. A sensitivity analysis is also conducted to understand the relative contributions of the different input uncertainties on the identified vulnerabilities.

This research proposes that the inclusion of a sensitivity analysis could be a helpful addition to the vulnerability analysis. A sensitivity analysis calculates the relative contributions of input uncertainties, helping to prioritize them. By identifying the most influential input uncertainties, a sensitivity analysis helps to emphasize those factors that that are most important to take into account when developing new potential actions. In a similar way, the use of a sensitivity analysis can also help to better the understanding of system relations by identifying which factors are most or least important. This is based partly on work by (Herman et al., 2014; Kwakkel & Haasnoot, 2019; Trindade et al., 2019).

Based on the results of the vulnerability analysis, which consists of the scenario discovery and sensitivity analysis, the decision framing can change. This is done in deliberation with experts and stakeholders. This can be due to a number of reasons, notably to include new actions or due to changes in problem understanding. In these cases, a loop returns back to Step 1. This is similar to the standard RDM process.

After a few iterations, once a clear understanding of the system is established and each action is considered fully developed, the vulnerabilities for each action are quantified. If necessary, tradeoffs between actions are also explored in this step. Once fully developed actions with tradeoffs have been defined, which are based on a clear understanding of the system, this step is considered finished. This is an amalgamation of Steps 3 and 4 of the RDM process as seen in Figure 2.5, with the addition of a sensitivity analysis.

Step 4: Define adaptation tipping points

This step forms the basis of the merging between the RDM and DAPP approaches. The vulnerabilities identified through RDM are translated to adaptation tipping points for the developed actions. Using the vulnerabilities quantified in the last step, the conditions under which a given action performs poorly are described. This can be used to define adaptation tipping points for these actions, which consist of multiple thresholds for the different input uncertainties. This is similar to Step 2 of the current DAPP process found in Figure 2.4.

Step 5: Build and evaluate pathways

This step is similar to Step 4 in the DAPP process. Using either transient scenarios or a single driver, actions can be combined to form pathways using the adaptation tipping points, while keeping sequencing rules in mind. It has also been proposed to form pathways by taking one action, running the vulnerability analysis again and then developing consequent actions to deal with the identified vulnerabilities (Bloom, 2015; Lempert, 2019). This can continue until a pathway is developed.

Having built the pathways, they can then be evaluated based on the results from the tradeoff analysis and the preferred sequencing. This evaluation requires some deliberation on what is preferred. Once the evaluation is done and there is a general consensus on the preferred pathway, this step is finished.

As mentioned before, the vulnerabilities identified through RDM can be seen as multi-dimensional adaptation tipping points. In order to incorporate this for DAPP, which was developed for one dominant driver, the different thresholds are placed underneath the adaptation tipping point. This is described as the quantitative point where the performance of the current action crosses this combined failure threshold. This adds the visualization concept as demonstrated by Molina-Perez (2016) and Ramm et al. (2018a) to Step 4 of the DAPP process to incorporate the adaptation tipping points in a multi-dimensional manner. An example of how this would look can be found in Figure 4.7.

Step 6: Implement and monitor

The last step consists of the implementation of the preferred pathway from the DAPP map. The proposed monitoring system explained in the following section is used to monitor changes in the system. In the case of any significant changes in the system or for other aspects relevant to the decision framing, the approach loops back to Step 1 similarly to the DAPP process (Haasnoot et al., 2018, 2019). This step also requires deliberation to discuss when these changes are deemed significant.

3.3 Part 2: Using RDM to lay the groundwork for a DAPP monitoring system

The second part of the novel approach focuses on laying the groundwork for a DAPP monitoring system. This is based on the vulnerabilities quantified in Step 4 of Section 3.2. These vulnerabilities are used to identify signposts and signals. Due to the model-based nature of this research, the approach focuses mostly on those signposts part of the model. However, by including additional deliberation, other signposts can be identified as well.

There is scarce and conflicting literature on designing a monitoring system. This second part of the approach is reliant on concepts from Haasnoot et al. (2018), Raso, Kwakkel, and Timmermans (2019), and Raso, Kwakkel, Timmermans, and Panthou (2019), but recombines and extends them when necessary.

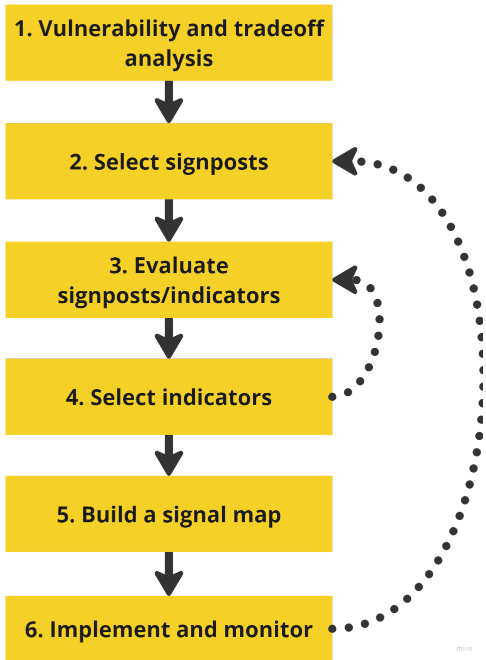


Figure 3.2: Second part of the proposed approach which uses RDM to lay the groundwork for a DAPP monitoring system

Step 1: Vulnerability and tradeoff analysis

Step 4 of the first part of the approach described in Section 3.2 is the first step in the building of a monitoring system. The outputs are the results of the vulnerability analysis as described in that section.

Step 2: Select signposts

To start the selection of signposts, environmental signposts are selected based on the identified vulnerabilities from the previous step. In this case each input uncertainty that leads to vulnerability is selected as a signpost. Additional signposts are also selected in this step based on deliberation with experts and stakeholders. These can consist of performance signposts which measure the performance of an action, or implementation signposts which monitor potential unintended consequences of implemented actions or the status of potential future actions. Both these types of signposts are explained further in Section 2.4. Once there is a general consensus on the selected signposts, this step is finished

Step 3: Evaluate signposts/indicators

After the selection of signposts, they are evaluated based on the criteria of accuracy, precision, and timeliness from Raso, Kwakkel, Timmermans, and Panthou (2019) and Haasnoot et al. (2018) as discussed in Section 2.4. The main goal is to see whether a signpost would allow for the identification of timely and accurate signals and triggers. This step also requires the deliberation with key stakeholders and experts to evaluate the signposts (and indicators in later iterations). This helps to achieve a sense of legitimacy and credibility as defined by Cash et al. (2002) and Haasnoot et al. (2018). Once each signpost (or indicator in later iterations) is evaluated, this step is finished.

Step 4: Select indicators

The signposts selected and evaluated in the previous step are important. If a signpost does not meet the evaluation criteria outlined in this previous step, for example due to noise in the system or reliance on extreme events which are not directly observable, it cannot be used to define signals and triggers in later steps. In such cases, a collection of derivative signposts called indicators are selected to act as a proxy for the signpost. Indicators can function separately or be combined, and can be found in a variety of ways. A starting point could be to think about which factors could cause changes in these signposts (Haasnoot et al., 2018; Ramm et al., 2018a). This step can also require deliberation with experts and key stakeholders to ensure the correct selection of indicators.

After defining the indicators, this step loops back to the previous one to evaluate them. This is done until either each signpost or its indicators are deemed to be sufficient.

Step 4: Build a signal map

Once signposts and indicators are selected and evaluated, they can be used to find various signals. Signals are values of a signpost or indicator that give an early warning that a trigger or adaptation tipping point is approaching. These signals can then be organized into a signal map. To help policy makers, a variety of signals can be used to give an indication one of the thresholds is coming closer as explained in Section 2.4.

The building of a signal map is based in part on the concept by Haasnoot et al. (2018). This is extended to include the results of RDM. For the signposts identified through scenario discovery, this research proposes signals can be developed by using the scenario discovery results. This new method requires selecting scenario discovery results with a higher coverage (which describe more of the cases of interest) as signals, since the adaptation tipping point will usually have a higher density and lower coverage. For the other signposts, signals can potentially be found using using transient scenarios or deliberation as suggested by Haasnoot et al. (2018).

Step 5: Implement and monitor

Step 5 consists of the implementation of the monitoring system. The monitoring system will be used to monitor the preferred pathway implemented in the last step of part 1 (Section 3.2). Additionally, if changes occur within the system which could potentially alter the performance of the existing signposts and indicators, the approach loops back to the selection of signposts.

3.4 Full approach

In this chapter two parts of a novel sytematic and analytical approach were laid out that use RDM to support the development of DAPP and its associated monitoring system. The first part focused on using the vulnerabilities identified through RDM to develop actions and build a DAPP map. The second approach focused on using these same vulnerabilities to lay the groundwork for a monitoring system by identifying signposts, indicators, and signals. The overlapping steps in both parts are integrated in order to arrive at the full novel approach found in Figure 3.3.

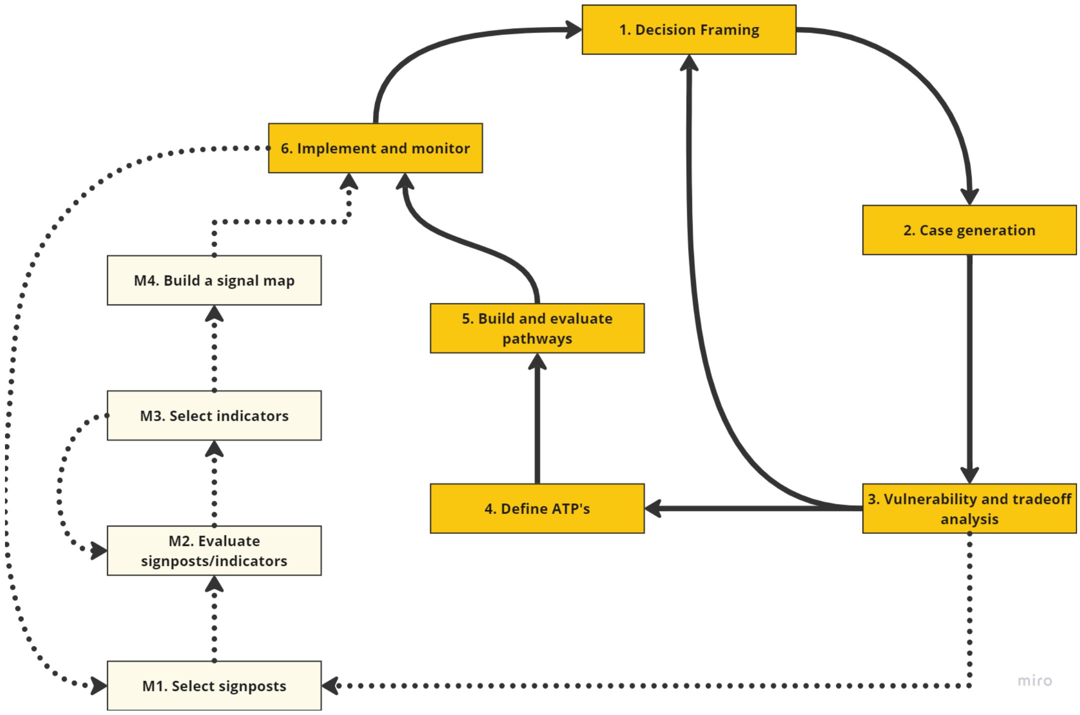


Figure 3.3: Full approach as a combination from Figures 3.1 and 3.2. Light yellow are the main steps in building the monitoring system, and darker yellow are the steps in building the dynamic adaptive policy pathways.

Taxonomy

In order to further facilitate future recombinations of the ingredients or methods employed for this approach, it is decomposed in the same DMDU taxonomy as RDM and DAPP. An explanation of the different categories of this taxonomy can be found in Section 2.1.

Policy architecture: ***Dynamic adaptivity***
The overarching policy architecture is taken from the DAPP, although individual actions or policy options are iteratively changed to protect them against uncertainties which can be considered as protective adaptivity.

Generation of scenarios: ***Exploration***
Scenarios are generated similarly to the RDM process, where the uncertainty space is explored by way of sampling.

Generation of policy alternatives: ***Pre-specified, iteratively refined***
The way policy alternatives are generated for this approach is similar to the RDM process. Initial actions, as well as the do-nothing approach, are pre-specified and iteratively refined to identify and develop more robust actions.

Vulnerability analysis: ***Subspace partitioning, sensitivity analysis***
Additionally to the normal scenario discovery used for RDM and the adaptation tipping points concept which use subspace partitioning, a sensitivity analysis is also undertaken to better understand the identified vulnerabilities.

Robustness metrics: *Satisficing, Regret*
This is taken from the RDM robustness metrics. The scenario discovery phase uses a satisficing robustness metric to identify the vulnerabilities. Meanwhile, both the trade-off phase in Step 4 and the selection of the preferred pathway in Step 6 rely on a regret metric.

3.4.1 Main additions

Besides incorporating multiple independent pieces of literature into one cohesive approach to design DAPP, there are two main additions done in this chapter. First is the addition of a sensitivity analysis. The sensitivity analysis helps prioritize the most important input uncertainties. It is proposed that this helps in knowing which factors are most important when developing new actions. It can also help to better the understanding of the system by identifying the relative influence of different factors are most important (Herman et al., 2014; Kwakkel & Haasnoot, 2019; Trindade et al., 2019).

The second main addition is the development of a monitoring system. There is currently scarce information on how this can be achieved, and it is mainly done in a participatory manner. Finding good signals is also hard to achieve in practice (Haasnoot et al., 2018; Lawrence et al., 2019; Stephens et al., 2021). This approach provides a new systematic way to use the results of RDM to find both signposts and signals. Additionally, the research expands upon the concept of Haasnoot et al. (2018) to build a signal map.

3.4.2 Deliberation with analysis

The proposed approach uses deliberation with analysis, also called decision support. This is a key tenet of DMDU techniques and relies on using model-based analysis in conjunction with expert opinion and discussion with key stakeholders. Knowing where in the approach this is necessary helps to know when stakeholders and experts should be brought in. While the steps in Sections 3.2 and 3.3 mention when deliberation with experts and stakeholders is necessary, this section gives a small overview of which sections are reliant on deliberation, analysis, or both.

In the first part of the approach, the decision framing is completely based on discussions with stakeholders and experts, while the case generation is completely based on analysis. The results of the vulnerability analysis are achieved through analysis, but deliberation is needed using those results to define when the results constitute a change in problem understanding or to identify which actions to develop. Defining the adaptation tipping points is mainly analysis, as is the building of the pathways keeping sequencing rules in mind. The evaluation part of Step 5, however, is reliant on deliberation to come to a preferred pathway. Lastly, while the implementation and monitoring is mostly just following the plan set up at the start, it requires deliberation to discuss when changes in the system are deemed significant enough to loop back to the decision framing.

In the second part of the approach, deliberation is used to select signposts other than the environmental signposts found through the vulnerability analysis. Deliberation is also necessary for the evaluation of signposts and selection of indicators, although some criteria for this exist already. The building of a signal map from the signposts found through the vulnerability analysis is relatively straightforward, while signals for other signposts require more deliberation. Lastly, for the implementation deliberation is necessary to decide if system changes significantly affect signpost quality, and a new selection is necessary.

3.4.3 Strengths and limitations of the approach

Strengths

Compared to the current way DAPP are developed, this approach provides a model-based way to develop new actions. The addition of the sensitivity analysis further helps to point towards the most important input uncertainties that need mitigating.

Another strength is the straightforward way to build a monitoring system. For DAPP the selection of signposts is a purely participatory process, and the selection of signals is often an issue. For this approach, the results of the vulnerability analysis can be used to quickly define signposts and signals to form a monitoring system.

Limitations

The Many-Objective Robust Optimization (MORO) approach to build DAPP explores the uncertainty space extremely in depth to come to an optimized set of pathways, if the actions are known in advance. This approach does not lead to such an optimized set of pathways. Rather it focuses on the iterative development of these actions and pathways. Although this is not necessarily an issue for the eventual robustness of individual pathways, MORO is slightly better at balancing robustness across objectives and arriving at a set of pareto-optimal pathways (Bartholomew & Kwakkel, 2020).

This approach is still a model-based approach. While it includes deliberation with stakeholders, it can be easy to overlook more qualitative aspects of actions, and does not explicitly take politics between stakeholders into account.

Chapter 4

Case illustration of the novel approach

This chapter takes the novel systematic and analytical approach introduced in the last chapter (pictured in Figure 3.3), and illustrates it using a real world case in Helensville, New Zealand. This chapter is built up in the same way as the approach.

First Section 4.1 gives some background on the case. This includes why it is considered a relevant case to illustrate the novel approach, and the link with other research done in the area. After this background, 4.2 introduces the case and executes the decision framing. The following steps follow the rest of the first part of the approach, ending in Section 4.7. The part of the approach outlining the building of the monitoring system starts in Section 4.8 and ends in Section 4.13.

4.1 Background case

4.1.1 Deep South Challenge

The case of the wastewater treatment plant in Helensville is one of the adaptation case sites used by the Deep South Challenge (DSC). Enabled by the National Institute of Water and Atmospheric Research (NIWA), a New Zealand research institute, the DSC is one of New Zealand's 11 National Science Challenges. The DSC's mission is to "enable New Zealanders to adapt, manage risk and thrive in a changing climate" ("Our research: Deep south challenge", 2021).

For the Helensville case, RDM was used previously to stress-test existing actions which were already placed in a DAPP map (Stephens et al., 2021). This was the extent of the use of RDM, which was not used in a systematic way, not used to further develop either new or existing actions, and not used to develop a monitoring system. This illustrates the current gap in knowledge explained in Section 2.5 and 3.1 well.

4.1.2 Linked thesis

The research done in this report is also linked to another thesis on the same Helensville case done at the Hydraulic Engineering (HE) faculty at the TU Delft, which can be found at http://resolver.tudelft.nl/uuid:bca15e29-75e1-4cc1-9cca-653f61a32686. In this research, it is cited as Smits (2024).

The HE thesis built two models of differing complexity based on an assessment of compound flooding risks affecting the case site. At several points in the next steps links will be made to this, especially for matters regarding model domain, boundary conditions, and the set up of the hydraulic model.

4.1.3 Fit for purpose

The goal of this case is to illustrate the approach. For this purpose, it should be sufficient. While it is not possible to follow the entire policy process using the approach, it is not a hypothetical case and enough is known to understand the decision arena as well as motivations of key stakeholders. This is in part due to the earlier research done at the case site. For this, stakeholders were already present in earlier stages, allowing the author of this thesis to listen in on workshops where they shared questions and concerns.

4.2 Step 1: Decision framing

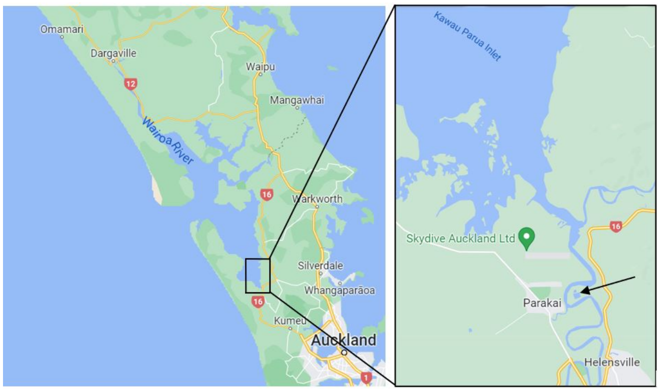
The first step of the approach focuses on better understanding the problem at hand. It starts with the background of the Helensville wastewater treatment plant and its surroundings in 4.2.1. Next some of the current and future risks affecting the wastewater treatment plant are discussed in 4.2.2, which will show the most relevant aspect to look at are the effects of compound flooding. Using this, a schematization of the system as will be used is given in 4.2.3. Finally, a summary of the decision framing is given in 4.2.4.

4.2.1 Context of the Helensville Wastewater Treatment Plant (WTP)

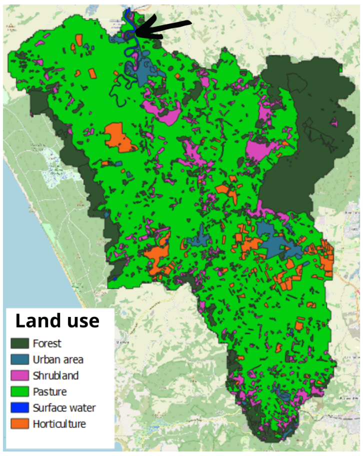
Background Helensville and Parakai

The Helensville wastewater treatment plant can be seen in Figure 4.1a. The small plant functions through a two-stage oxidation pond, and discharges its effluent into the small Kaipara river based on gravity (Beca et al., 2020; Ho et al., 2009). A more detailed analysis of the plant and its surroundings can be found in Smits (2024).

This plant services a small and rural community of around 5000 people (Watercare, 2024). The population of the community seem to be growing. The current increase is a bit over 1% yearly by the latest census (Statistics New Zealand, 2018). The area surrounding the communities and upstream is mostly rural as can be seen in Figure 4.1b. While there are some townships and roads, urban use only accounts for about a total of 2.5 percent of the catchment. Almost 64% of the catchment exists of pastures used for grazing cattle and sheep (Landcare Research, 2021).



(a) Location of the case site in relation to the Kaipara harbor and Auckland metropolitan area. The wastewater treatment plant is demarcated with a black arrow. Helensville and Parakai are also labeled in the picture on the right. The river that flows past these towns and the wastewater treatment plant is the Kaipara river. From google maps.



(b) Land use in the Kaipara river basin. The wastewater treatment plant is demarcated with a black arrow. Derived from Landcare Research (2021) using QGIS.

Figure 4.1: Location and land use in the area of the wastewater treatment plant.

Land use in the Helensville area is a sensitive subject. Originally inhabited by local 'iwi' or tribes, their relationship with the land and sea is based on a cultural and spiritual connection. This includes the careful consideration of which natural resources to take.

After European settlers laid claim to the area, much of the land was adapted first for logging, and then for agricultural use as can be seen in Figure 4.1b. This greatly affected water use, river and water body characteristics, depleted natural resources, and lead to a decline in local flora and fauna (Auckland Regional Council, 2001). The effects of this can still be seen in a higher level of erosion in the catchment, and the mono-culture encountered compared to other parts of the Kaipara harbor (Green & Daigneault, 2018; Reeve et al., 2009).

The Resource Management Act (RMA), introduced in New Zealand in 1991, specifically takes both these links into account when crafting policy. This means both practical concerns as well as cultural and spiritual associations with the water have to be taken into account (NIWA, 1991).

Kaipara water quality: importance and ramifications

The Kaipara river itself has a lower water quality compared to other outlets of the Kaipara harbor. This is mostly due to the combination of water runoff from the agricultural use and the tidal discharge from the wastewatet treatment plant (Auckland Regional Council, 2001; Watercare, 2024). Both of the local 'iwi' or tribes in the area agreed that both direct pollution from sewage as well as its indirect effect on water quality for the Kaipara river and harbor were an issue (Watercare, 2024). Additionally, the low water quality in the Kaipara river has lead to the decline of local trout and salmon populations (Auckland Regional Council, 2001).

In practical terms, this means strong effluent limits have been introduced to keep water quality sufficient, and large scale pollution of the river due to storm events is seen as unacceptable. It also means that the wastewater controller has the goal of reducing discharge from the wastewater treatment plant into the Kaipara river for the coming years (Watercare, 2024).

4.2.2 Climate risks affecting the wastewater treatment plant

Functioning of the plant

The Helensville plant has previously been conceptualized by the Deep South Challenge, which can be seen in Figure 4.2 (Stephens et al., 2021). The main hazards affecting the plant can be split up into two main categories: internal stresses leading to the treatment ponds overflowing, or external stresses affecting pond functionality.

The first category of hazards is caused by an excess influent due to a combination of pluvial flooding, infiltration, and planned inflow. This has been studied in the past (DSC, personal communication, January 8, 2023). The second involves external stresses due to a combination of sea level rise, increased river flow, storm surge, rainfall, and tidal amplitude. These stresses can lead to slumping or overtopping of the plant's pond embankments, the erosion of the access road, or an increase in the groundwater table.

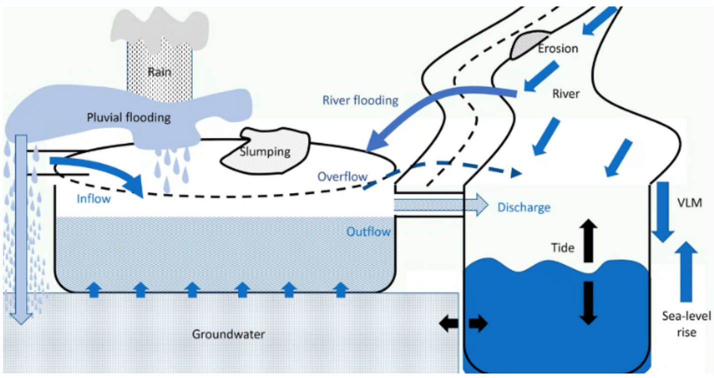


Figure 4.2: Conceptual model of the wastewater treatment plant. The plant is on the left, and the Kaipara river is schematized on the right. The figure also shows various failure mechanisms such as slumping, overflow, and erosion. The hazards facing plant functioning can be placed into two main categories: internal stresses leading to treatment ponds overflowing, or external stresses affecting pond functionality (Stephens et al., 2021)

Climate risks

Like many other wastewater treatment plants, the plant in Helensville faces risks from rising sea levels, increased intensity and frequency of storms, and changing system behavior (Beca et al., 2020; Cao et al., 2020). A managed retreat will most likely be necessary at some point in the future, although the goal is to keep the plant at the same location for as long as possible to save money (Stephens et al., 2021; Watercare Services Limited, 2015).

It is clear the wastewater treatment plant is already facing some of the expected effects of climate change (Watercare Services Limited, 2015). This can be seen in high groundwater levels, increasingly high tides and storm surge, and the increased frequency and intensity of precipitation events. Pictures of some of these events can be found in Appendix C.

Compound flooding

Climate risks most directly make up the second category of hazards, placing external stresses on the functioning of the ponds. This is echoed in emails from the Deep South Challenge which mention the lack of knowledge of, and interest in, the effects of compound flooding on the wastewater treatment plant. Additionally, Watercare (2024) mentions the risks of tidal amplitudes, storm surge, and sea level rise due to the low-lying placement of the plant. Consequently, the focus of this illustration will be researching the effects of compound flooding on water levels around the wastewater treatment plant.

4.2.3 System schematization

As mentioned before, the main focus of this illustration will be on the effects from compound flooding. A diagram of the compound flooding affecting the wastewater treatment plant can be found in Figure 4.3a. The storm-tide boundary found in this diagram is also provided in more detail in Figure 4.3b.

Model domain

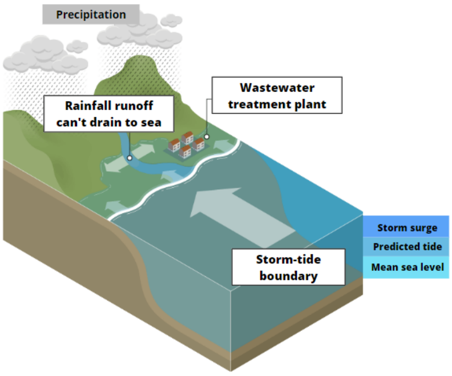
Compound flooding will be calculated for the entire Kaipara river watershed, bound by the intertidal flats at the downstream end, and the mountain ranges upstream. More information on the surroundings of the wastewater treatment plant can be found in Appendix C. Taking the entire watershed within the model domain ensures the inclusion of all rainfall within the system. The Kaipara river watershed is quite steep, meaning rainfall runoff will be quick. This is why the storm event is schematized to have a duration of 24 hours. This has also been used in previous work in the region (Council, 1999).

Forcing: Compound flooding

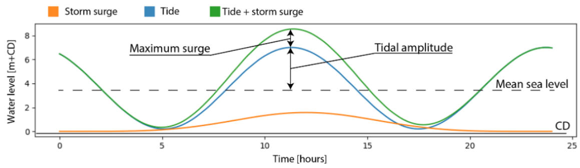
The compound flooding is due to a combination of precipitation and storm-tide. From the flow data of the Kaipara river, it is concluded that nearly all the flow in this river is due to drainage of rainfall from the basin. This is why it was chosen not to include a river flow in the system. More information on this can also be found in Smits (2024).

Precipitation
The rainfall is assumed to be both spatially and temporally uniform for the duration of the storm. Spatially and temporally varying the rainfall would introduce additional uncertainties and complexity with regards to their proposed distribution, significantly increasing computational time needed. Using a uniformly distributed rainfall most likely underestimates the runoff as the drainage is constant, although this is also dependent on various additional factors including catchment size, timescale, catchment slope, infiltration, and the height of the peak (Zhou et al., 2021).

Storm-tide
The storm-tide is made up of a mean sea level, storm surge, and tidal amplitude as seen in Figure 4.3b. These are combined as a water level boundary where the maximum tide reaches a peak at the same time as the storm surge, which can be seen in Figure 4.3b. This is similar to previous modeling cases (Stephens et al., 2016; van Berchum, 2019), and should give a good insight into the effects of peak storm-tides.



(a) Conceptual diagram of compound flooding affecting the wastewater treatment plant. Diagram is based on a picture by McGrath (2019).



(b) Breakdown of the storm-tide boundary used in Figure 4.3a (van Berchum et al., 2020)

Figure 4.3: Schematization of the system and the forcing.

Failure mechanism: Overtopping of pond embankments

The high water levels around the wastewater treatment plant due to compound flooding place external stress on the functioning of the wastewater treatment plant. While there are multiple potential failure methods of the treatment plant, in this case the focus will be on the overtopping of the pond embankments. This failure mechanism is on the same timescale as the compound flooding event, gives good insight into which factors lead to high water levels, and doesn't require additional geotechnical information. Overtopping also most directly affects pollution of the Kaipara river.

The lowest point of the embankment is 3.38 meters NZVD2016, while the highest is 3.8 meters. This can all be seen in Figure C.6 in Appendix C. Overtopping is assumed to happen when the average maximum water level around the wastewater treatment plant reaches 3.60 meters. 33 of the 70 spot heights around the embankment are below this threshold. The duration of the water level exceeding this threshold is not considered in this research. The key focus is on understanding the main processes and vulnerabilities, and the specific number chosen for the water level serves as a practical threshold for this illustration.

4.2.4 Conclusion in XLRM framework

Summary

In this first step it was found that the wastewater treatment plant is increasingly facing risks from climate change. At some point in the future the plant will most likely have to face a managed retreat, but this is not yet preferable due to costs. One of the main hazards is compound flooding. Compound flooding places external pressures on the wastewater treatment plant, and potentially leads to overtopping of the pond embankments.

This overtopping is especially problematic since a key requirement for the wastewater controller is to reduce the discharge of effluent from the plant into the Kaipara river and harbor. This effluent is problematic because it upsets local 'iwi' or tribes who have a strong cultural and spiritual connection to the water bodies, and because it reduces water quality which has lead to a decline in local fish populations and recreation. Water quality in the Kaipara river and harbor is already an issue due to runoff from agriculture further upstream.

The Resource Management Act (RMA) protects these natural resources, meaning large scale pollution of the river due to compound flooding events is unacceptable. With climate change, these events are likely to happen more and more often. Balancing the cost of moving the wastewater treatment plant with the likelihood of polluting the Kaipara river and harbor means the main goal is to find under which conditions the plant can stay in the same spot, and when adaptation is necessary.

XLRM

To end the first step, the problem and its schematization is brought back into an XLRM framework, which forms the basis for the rest of the steps.

The **uncertainties (X)** consist of the different variables that make up the compound flooding: rainfall intensity, storm surge, tidal amplitude, and mean sea level. For the first iteration of the approach, no **Policies (L)** or actions are included yet. Instead, the focus is on quantifying the vulnerabilities for the current situation at the wastewater treatment plant, and identifying potential actions to deal with these vulnerabilities. In future iterations, these actions can be developed to be more robust if necessary. The **relationships (R)** as mentioned earlier are the compound flooding of the input uncertainties on the water level at the case site. The **performance metric (M)** taken into account is the water level at the case site. If this reaches above 3.60 meters, it is assumed the pond embankments are overtopped and failure occurs.

4.3 Step 2: Case generation

The second step consists of the case generation, where a data base comprised of combinations of input uncertainties and their outcomes will be generated. This database will be used in the vulnerability analysis. This section provides the model selection, configuration, and linking with the EMA workbench. Additionally, the ranges for the input uncertainties and the sampling method are chosen.

4.3.1 Model selection

Use of a technical model

In this case, the failure mechanism of overtopping of the wastewater treatment plant's embankments directly leads to a polluting discharge in the Kaipara river. The overtopping of the wastewater treatment plant's embankments is also directly reliant on the water level around them. This means that for this failure mechanism a purely technical model is most likely sufficient, especially since the focus of the illustration is under which conditions overtopping becomes more likely.

If the level of pollution becomes more important, which is outside the scope, a translation should take place to link the type and degree of overtopping to total pollution. This could include the water level at the point of overtopping (higher being more polluting), as well as a variety of other factors including which ponds are overtopped, how quickly the storm surge wanes (quickly disposing of pollution), and whether other parts of the storm create pollution (such as extra runoff from farms upstream).

Selection and background model

In order to calculate the water levels around the wastewater treatment plant for compound flooding using a storm-tide and rainfall, the FLORES model was selected. In Smits (2024), I compared the FLORES model to a more complex model, showing that it was significantly quicker, while gaining very similar results, only losing slightly on accuracy.

FLORES was originally developed by van Berchum et al. (2020), and adapted/reconfigured for this research. More information on how the model is built up can be found in the github linked in the next section. FLORES is based on the rapid flood spreading model family of hydraulic modeling approaches. It is, in part, a continuation of previous work by Shen et al. (2016). Additionally, it includes rainfall run-off and the effects of flow over intertidal flats, something usually not seen in conceptual hydraulic models. This method is computationally cheap and relatively straight forward to implement, even in data-scarce environments (van Berchum et al., 2020).

4.3.2 Model configuration

More information on the configuration of FLORES can be found in the adjacent thesis by Smits (2024), which includes a link to the github page with the model code as built for this research at https://github.com/

xan-source/FLORES_Helensville.git. The adjacent thesis gives further background on this model, including information on how the model was built, which data was used, and the hydraulic concepts that form the basis for its water level calculations. Additionally, it includes both the calibration and validation of FLORES, which was for a 100 year average return period storm-tide event.

4.3.3 Vulnerability analysis configuration

Computational configuration

The vulnerability analysis was run using the Exploratory Modeling and Analysis (EMA) workbench developed by Kwakkel (2017). This python-based workbench supports conducting both the sensitivity analysis and the scenario discovery, as well as various other options for further exploration and visualization of the results. Since both the scenario discovery and sensitivity analysis are supported by the EMA workbench, if the same sampling scheme is used only one run-through is necessary which can save a significant amount of time.

The vulnerability analysis was run from a home laptop, which is an Acer Swift 5 Pro SF514-55T-77BX. This laptop has an Intel Core i7 processor with 4 cores and 16 GB of RAM.

Input uncertainty ranges

When conducting a sensitivity analysis it is important that the ranges of the chosen uncertainties are relatively representative, as otherwise the results can be skewed. This is less of a factor for the scenario discovery, since the emphasis is on exploring the uncertainty space rather than quantifying the overall sensitivity to uncertainties. The ranges chosen for each uncertainty can be found in Table 4.1 with an explanation as to why these values were chosen. A timescale of 100 years was chosen.

There were also various model uncertainties tested, although these were shown not to have an effect. More detail on this can be found in the adjacent thesis. Notably for FLORES, this includes the infiltration rate (rate at which rainfall can infiltrate the ground).

Input uncertainty	Range	Explanation
Storm surge	0 - 1.3 m	The model is calibrated for a 1.3 meters storm surge in the case of a 100 year ARI storm-tide event
Tidal amplitude	1.5 - 2.3 m	The Kaipara harbour is a dynamic place, with lots of tidal flats and deep channels. This means the tidal amplitude could potentially change in the future. The amplitude at Pouto point, at the mouth of the Kaipara harbour, for the highest astronomical tide is around 1.5 meters, and for the Helensville tidal gauge this is 2.3 meters.
Mean sea level	-0.13 - 1.05 m	The current mean sea level is at -0.13 meters NZVD2016. Taking into account current sea level projections for New Zealand, this could rise to 1.05 by 2100 (Tonkin+Taylor, 2021).
Rain intensity	0 - 8.6 mm/hour	A 100 year ARI rainfall intensity is 8.6 mm/hour for a 24 hour event in the Auckland region (Bell et al., 2018).

Table 4.1: Inputs for the global sensitivity analysis and the scenario discovery.

4.4 Step 3: Vulnerability and tradeoff analysis

This section explains and visualizes the vulnerability analysis conducted. Normally a tradeoff analysis would also be a part of this. This was not included in this illustration, as for this first iteration there is only one action: do nothing, as well as only one objective due to only looking at overtopping: no failure

The section starts with a recount on how the cases were generated, after which the results of the sensitivity analysis and scenario discovery are presented. Last, the section ends with a discussion of the results and its consequences.

4.4.1 Cases generated

The outcomes were defined as the highest water level in the model's runtime. Cases included this outcome, along with the combination of input uncertainties that lead to it in a database.

The used SOBOL scheme is a quasi-random sampling scheme which better discretizes the uncertainty space compared to fully random sampling (Saltelli et al., 2010). This sampling scheme was used for both the sensitivity analysis and scenario discovery, allowing for only one run-through to be done which saves a significant amount of time.

In total 512 scenarios were run. Using the SOBOL sampling with second order effects on and 5 uncertainties taken into account (rainfall intensity, mean sea level, tidal amplitude, storm surge, and infiltration rate) this lead to $512 * (2 * n + 2) = 6144$ cases generated (Saltelli et al., 2010; Sobol, 2001). As mentioned before, the infiltration rate was found not to be statistically significant which is why it was filtered out. More detail on this and other model uncertainties taken into account can be found in the adjacent thesis by Smits (2024).

4.4.2 Vulnerability analysis

Sensitivity analysis

The results of the sensitivity analysis show that the the rainfall intensity has no influence on the water level at the wastewater treatment plant at all. This could be due to a difference in the order of magnitude between the water level due to the storm-tide boundary, which can be up to several meters compared to the rainfall, which is a couple of centimeters.

The results of the sensitivity analysis show the water level at the wastewater treatment plant was most sensitive to the storm surge and mean sea level, and then to the tidal amplitude which can be seen in Figure 4.4. This lower sensitivity to the tidal amplitude is in part due to the smaller chosen range for tidal amplitude, and in part due to tidal amplitude being divided into flood and ebb. This second part means it has less influence on the high water levels.

Lastly, it is interesting to note that there are no second order effects visible in the sensitivity analysis. This is most likely due to the negligible effect rainfall had on the water levels, while the storm surge, mean sea level, and tidal amplitude are calculated by a simple addition as seen in Figure 4.3b.

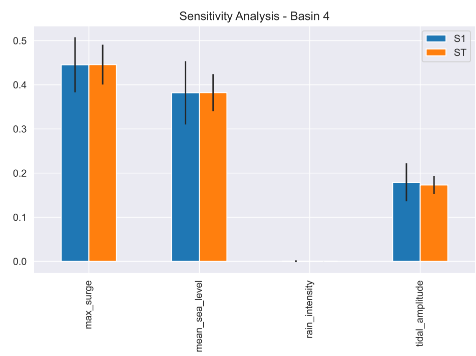


Figure 4.4: Sensitivity analysis for FLORES. The y-axis gives the percentage of sensitivity explained by the variable. All sensitivities for all variables should add up to 1 if the results have fully converged. S1 gives the first order sensitivity, while ST gives the total sensitivity. The white black gives the 95% confidence bounds. No second order effects can be seen, as the S1 and ST values are the same.

Scenario discovery

Scenario discovery was done using the PRIM algorithm. This algorithm provides interpretable and robust results which is why it was used for this first iteration (Bryant & Lempert, 2010; Kwakkel & Jaxa-Rozen, 2016). Once more is known about the distribution of the outcomes, other algorithms and methods can also be used.

PRIM works using a box which consists of thresholds for the input uncertainties to bound relevant outcomes. This is based on coverage and density. These concepts are explained in Section 2.5. As mentioned earlier, coverage is a measure of the percentage of all cases of interest (failure) that fall within a box's thresholds. Density is the percentage of all cases located within a box's thresholds that are of interest. Ideally, both coverage and density are as high as possible. There is always a tradeoff, however. A high coverage often leads to a low density, since the box includes a lot more cases. A high density could lead to a low coverage, where the box misses a lot of the cases of interest. This tradeoff curve can be found in Figure 4.5. Based on this figure, the box chosen for this first iteration of the scenario discovery balances a coverage of 73.7% with a density of 73.3%.

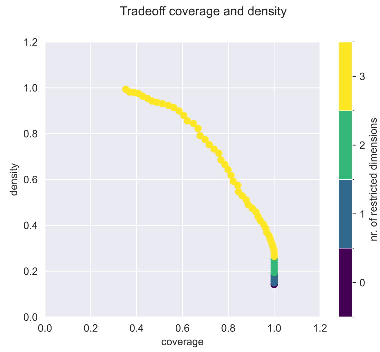
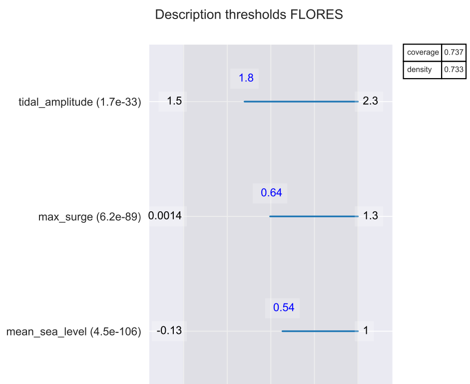
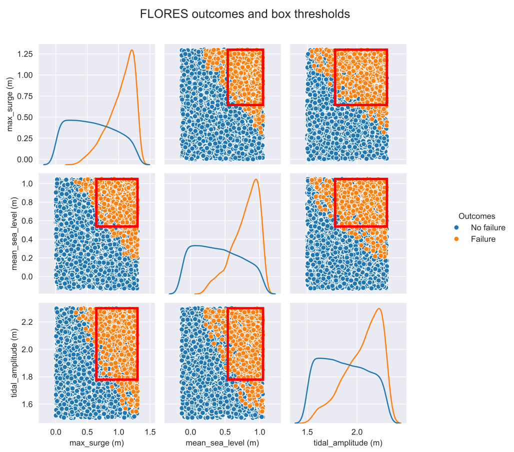


Figure 4.5: PRIM results for the FLORES model. The graph shows the tradeoffs between coverage and density for a maximum water level greater than 3.60 meters. Each point on the graph represents a potential box. The legend shows the number of restrictions, this is the number of input uncertainties are necessary to take into account to arrive at the points of interest.

The selected box restricts three input uncertainties to describe failure. These three factors also followed from the sensitivity analysis as the most influential factors: mean sea level, storm surge, and tidal amplitude. The quasi-p score, which is the number behind the uncertainties in Figure 4.6a, indicates these found values are statistically significant.



(a) Description of the chosen box for FLORES. The coverage and density of the box can be seen in the top right, and the quasi-p score is behind the variables on the left. These terms are explained further in Section 2.3.2 in Step 3. The numbers in blue are the thresholds of the box.



(b) Scatter plot showing all calculated outcomes. Each outcome is a combination of the uncertainties for the maximum water level in basin 4. The points are binary: orange points are where failure occurs, while for blue points no failure occurs. A probability distribution function for both these types of points can also be seen. Lastly, the box described in detail in Figure 4.6a can be seen in red.

Figure 4.6: Description of box thresholds and their visualization.

The box thresholds, also shows in Figure 4.6a, indicate the following: any outcome where the mean sea level is above 0.54 meters combined with a storm surge of at least 0.64 meters and tidal amplitude of at least 1.8 meters has approximately a 73.3% chance of leading to failure. Additionally, this combination of factors describe 73.7% of all outcomes where failure occurs.

The scatter plot in Figure 4.6b is a visual representation of the box thresholds from Figure 4.6a. It shows that the relationship between storm surge, mean sea level, and tidal amplitude is extremely linear. Similarly to the sensitivity analysis, this shows the lack of existence of second order effects due to the insignificance of rainfall intensity and the simplicity in the way the storm-tide is calculated. Even though this linear relationship clearly hampers the effectivity of the PRIM algorithm, the found box still represents 73.7% of all cases of failure, meaning it is still relevant.

4.4.3 Results vulnerability analysis

The results of the sensitivity analysis and scenario discovery normally loop back to the decision framing and lead to the definition of adaptation tipping points.

Problem understanding

The results of the sensitivity analysis show that rainfall has no influence on the outcomes. This is echoed by the results of the scenario discovery. While this can be explained due to a difference in magnitude, it could also be due to the spatially and temporally uniform way the rainfall was schematized, or due to a latent river flow not taken into account. More research on whether a change in schematization makes a difference is necessary, by potentially including a river flow, or using rainfall peaks as opposed to a uniform distribution.

It was also seen that there was a linear relationship between storm surge, tidal amplitude, and mean sea level. While the PRIM was still able to clearly define a box that represented 73.7% of the cases where failure occurs, another scenario discovery method such as logistic regression or a principal components analysis to achieve better coverage and density and thus better describe the outcomes where failure occurs.

The linear relationship within the storm-tide boundary and lack of influence by rainfall intensity most likely lead to a lack of interaction effects. This means the choice for this conceptual model were valid. A more complex model might be necessary once stronger interaction effects occur which influence water levels.

Potential actions

Looking at the linear relationship in Figure 4.6b, the FLORES model potentially starts flooding for a mean sea level of 0.25 meters, which is likely to occur around 2050 (Tonkin+Taylor, 2021). For this mean sea level, the upper range of storm surge and tidal amplitude would also be necessary for flooding to occur. This is unlikely, especially since the current definition of the storm-tide boundary is already an overestimation, with both tidal amplitude and storm surge reaching their maximum at the same time.

The wastewater treatment plant only starting to flood around 2050 for a RCP4.5 scenario means there is still time for adaptation. The primary goal would be to try to mitigate the storm surge in order to keep the plant operable at the same location as long as possible. This has two reasons. First, the sensitivity analysis found the storm surge to have the most influence on water levels. Second, storm surge is much less predictable compared to mean sea level and tidal amplitude, which change slower. Actions to mitigate storm surge would have to have a timeline of around 20-30 years, depending on sea level rise. After this, most actions would likely focus on relocating the wastewater treatment plant.

Some key considerations to take into account when deciding on an action to mitigate storm surge are the importance of the natural resources to stakeholders, and the costs of the actions. First, as mentioned in Section 4.1 the Kaipara river and harbor have a special significance to local tribes, which is protected by law. This means 'hard' measures such as dams, inflatable storm surge shields, or other barriers are most likely out of the question. Instead the focus should be on more nature-based solutions, such as the reshaping of the Kaipara river to prevent amplification of storm surge and tidal motions, or the increase of heavy vegetation on the intertidal flats downstream which could help absorb the water.

The second point are the costs. As mentioned before, actions to mitigate storm surge have a timeline of around 20-30 years. Additionally, water infrastructure often has a lifespan of around 50-75 years, which is also the case in Helensville (Watercare, 2024). This means that once the water infrastructure reaches the end of its lifespan, the wastewater treatment plant will most likely be moved regardless of whether it could remain in the same place slightly longer, since investments would be useless. Combined with the fact that the plant only services a small community, costs of an action would most likely have to be low.

4.5 Step 4: Define adaptation tipping points

The adaptation tipping points are based on the results of the scenario discovery. The vulnerability found in the previous step which describes 73.7% of the cases where failure occurs has a mean sea level of at least 0.54 meters, combined with a storm surge of 0.64 meters and tidal amplitude of 1.8 meters. A mean sea level of 0.54 meters could be reached before 2070 for a high emissions trajectory, and around 2120 for a low emissions trajectory (Tonkin+Taylor, 2021). A storm surge of 0.64 meters under current conditions has a return period of around 2 years (Stephens et al., 2016). A tidal amplitude of 1.8 meters under current conditions is around equal to the mean high water spring tide that is exceeded around 10% of the time (Stephens et al., 2016).

Since these three thresholds have a strong relationship with each other, the use of a logistic regression would greatly influence the ability to describe the tipping point. This is especially the case since the current thresholds for storm surge and tidal amplitude can currently already be reached. Still, the PRIM results describe the conditions where failure occurs fairly well.

4.6 Step 5: Build and evaluate pathways

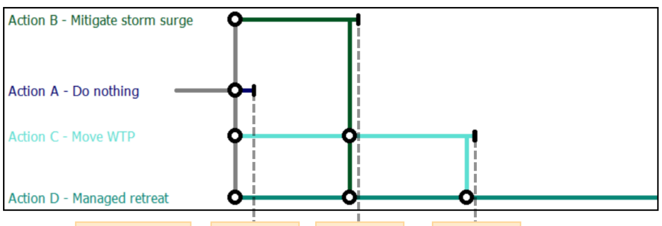
4.6.1 Define actions

While only one iteration is done for this illustration, policy advice was already given based on the results of 4.4. In the short-term it was advised to mitigate storm surge with a cheap, nature-based approach (Action B in Figure 4.7). In the long term a managed retreat of the wastewater treatment plant would be necessary (Action C in Figure 4.7). Additionally, if risks from compound flooding increase beyond that point, parts of the community will most likely have to move since their locations are not that different from the wastewater treatment plant (Action D in Figure 4.7).

Actions are defined as those the Auckland region and wastewater manager have control over. There are of course also actions more sizable than a managed retreat of the plant and its surrounding population if the New Zealand government saw fit. For example, the mouth of the Kaipara harbor (which is only around 7 km wide) could be closed off with a tidal barrier (Bellvé et al., 2007), protecting its inhabitants from the effects of sea level rise and storm surge. This would allow the ecosystems within the harbor to stay relatively similar, although it is debatable whether this adheres to the Resource Management Act as explained in Section 4.2.

4.6.2 Build pathways

Using the actions as defined and labeled in the previous subsection, pathways are built in a similar manner to the DAPP process. Some aspects to take into account are their sequencing and transfers between actions. An example visualization of the the pathways built out of examples of potential policy actions can be found in Figure 4.7. Each adaptation tipping point is visualized in a way similar to Ramm et al. (2018a).



Adaptation tipping point	ATP 1	ATP 2	ATP 3
Mean sea level	≥ 0.54 meters	...	...
Storm surge	≥ 0.64 meters	...	...
Tidal amplitude	≥ 1.8 meters	...	...
...	—	...	...

Figure 4.7: Visualization of potential pathways. Actions C, B, and D are explained in 4.6.1, and serve as illustration.

4.6.3 Evaluate pathways

Next to the evaluation done below, normally the results of the tradeoff analysis in Step 3 would also be used to help evaluate the pathways and select a preferred one.

Based on what is known about the case, it is preferred to keep the wastewater treatment plant in the same position for as long as possible. In order to achieve this, mitigating storm surge (Action B) will be helpful in the short term. When either the risks become too high or the lifespan of the water infrastructure in Helensville reaches its end the transfer from Action B to Action C will most likely occur to facilitate a managed retreat. Once the treatment plant moves, it is likely that (parts of) the community it services will also have to move since they will also experience increased risks of flooding. This retreat will likely garner resistance, however, due to the inhabitants' connection to the area. While it is not preferred, there seems to be no other options that lie within the control of the wastewater controller and Auckland regional authorities.

4.7 Step 6: Implement and monitor

Step 6 consists of the implementation of the preferred pathway of Action B to C to D, and the monitoring of the system. When the monitoring system below deems necessary, a step back to the decision framing is made to allow for changes in problem understanding.

4.8 Monitoring Step 1: Vulnerability and tradeoff analysis

The first step of the building of a monitoring system starts with the quantification of the vulnerabilities, analogous with Step 4 described above. The vulnerability, also shown in Figure 4.6a and 4.6b, indicate the following: any outcome where the mean sea level is above 0.54 meters combined with a storm surge of at least 0.64 meters and tidal amplitude of at least 1.8 meters has approximately a 73.3% chance of leading to failure. Additionally, this combination of factors describe 73.7% of all outcomes where failure occurs.

4.9 Monitoring Step 2: Select signposts

Step 2 of the approach for designing a monitoring system defines the signposts. As outlined before in Section 2.4, signposts can be based on external environmental factors, the performance of an implemented action, or implementation signposts which monitor conditions required for a potential future implementation of an action.

4.9.1 Signposts derived from the vulnerabilities

The signposts derived from the vulnerabilities are all environmental: tidal amplitude, storm surge, and mean sea level. These signposts are only for the current 'do nothing' approach. For other actions, other signposts could potentially also be relevant. While these signposts are measured separately, in reality they are related, as can also be seen through the linear relationship discovered in Section 4.4. This means that a higher storm surge with a lower mean sea level and tidal amplitude can still lead to failure.

4.9.2 Signposts from deliberation

As mentioned before, a strong consideration for the implementation of the managed retreat of the treatment plant is the lifespan of the water infrastructure in the area. This is why this lifespan is incorporated as an implementation signpost.

While not necessarily measurable as signposts, some assumptions made in earlier steps to keep track of are the willingness of the local population to move, and the sentiment or rules towards nature conservation. The first could introduce the first steps towards a population move such as Action D. The second could mean that even stronger measures against sea level rise and storm surge could be taken, potentially even damming up the Kaipara harbor as mentioned in 4.4.3.

4.10 Monitoring Step 3: Evaluate signposts/indicators

Step 3 evaluates the selected signposts (and indicators in later iterations). This is based on the criteria outlined in Sections 3.3 and 2.4.

4.10.1 First iteration

The first iteration consists of the signposts selected in the previous step. There were two categories of signposts selected in that step: the environmental signposts based on the identified vulnerability, and the implementation signposts found through deliberation.

Environmental signposts

The environmental signposts for the 'do nothing' approach are storm surge, tidal amplitude, and mean sea level. Of these, tidal amplitude and mean sea level can be measured relatively easily and accurately, and their increases have a gradual slope allowing for the potential identification of timely signals and triggers.

Measurements for the storm surge signpost are a lot noisier. The storm surges of interest have long return periods, and events can be extreme. This means this signpost is hard to measure accurately, and developments in increases have an abrupt or noisy slope. this means indicators will have to be chosen as a proxy way to track them.

Implementation signposts

The implementation signpost was the lifespan remaining for the water infrastructure surrounding the wastewater treatment plant. This lifespan is something measured and taken into account by the wastewater treatment facilities regardless of its use here. This means that this signpost is relatively accurate and measurable, with the potential identification of timely signals and triggers.

There was also the issue of potentially changing sentiment in the community as described in Section 4.9. Such sentiment could lead to a different choice in pathways, or different proposed actions altogether. While signals and triggers would be harder to define for something like sentiment, keeping track of community opinions in yearly or multiyearly meetings could provide insight into these changing beliefs and attitudes.

4.10.2 Second iteration

The second iteration retains the signposts evaluated positively from the first iteration, along with the indicators selected in the next step in Section 4.11.

The indicators selected were the height and frequency of storm surges which is further explained in the following step. These two factors can be used to determine extreme storm surges using a Pareto distribution. Storm surge height and storm surge frequency can both be measured relatively simply using the tidal signal, and the predicted storm surge can be calculated from this relatively easily.

The predicted storm surge has some issues. It is not very accurate, with very wide 95% confidence bounds in most cases, and is reliant on past data, while changes might occur rapidly. Still, there seem to be few alternatives, and it does allow for an indication of the probability of an extreme storm surge.

4.11 Monitoring Step 4: Select indicators

The results of the first iteration in Section 4.10 showed that most of the signposts were evaluated positively, with the exception of storm surge. Increases in storm surge with high return periods is hard to measure due to noise and occurrence probability, and has an abrupt slope, making the definition of signals and triggers difficult.

Indicators will be used as a proxy for storm surge. In this case, the indicators could be storm surge height and frequency. These two factors can be used in conjunction with each other to indicate that storm surge heights for higher return periods are increasing. Using a generalized Pareto distribution, extreme storm surges can be determined (Stephens et al., 2016).

4.12 Monitoring Step 5: Build a signal map

Step 5 of the monitoring system builds a signal map. This section starts with a reminder of the chosen signposts and indicators. After this, signals for these signposts and indicators are identified, and a signal map is built.

4.12.1 Signposts and indicators

The signposts and indicators selected and evaluated are as follows: storm surge (with the indicator predicted storm surge based on surge frequency and surge height), mean sea level, tidal amplitude, lifespan of water infrastructure, and community sentiment.

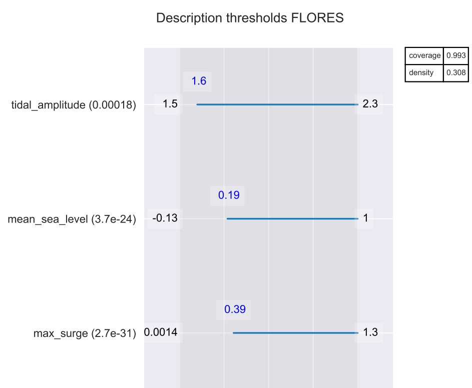
4.12.2 Finding signals

From identified vulnerability

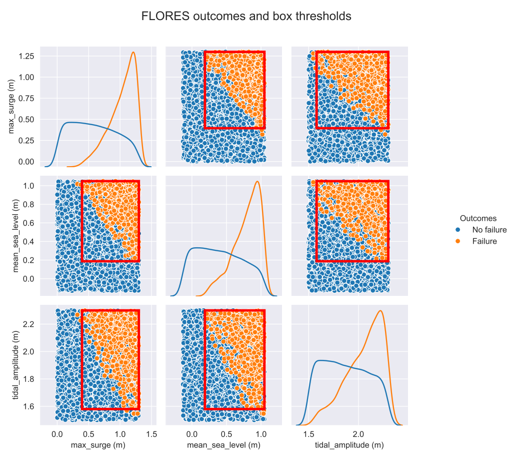
As shown in the tradeoff plot in Figure 4.5, there are many more potential boxes describing the outcomes where failure occurs. A logical step seems to be to select signals based on boxes with a higher coverage and a lower density. These boxes describe a larger portion of the outcomes where failure occurs, while having a lower chance of failure when the thresholds are reached. In this way, a sort of gradient can be described of thresholds with increasing failure probability.

To visualize this, in this case signals with a difference in coverage of around 10 percent were chosen. In reality, as many of these boxes as possible could be chosen. Also important to note is that the thresholds of the signposts are linked together. More information on how to interpret this can be found in Section 4.13.

The two signals can be seen in Figures 4.8 and 4.9. As can be seen, signal one uses thresholds that describe the conditions where failure first starts to occur. This is the first signal. Signal two has more stringent thresholds where failure becomes more likely once the thresholds are reached. By layering signals like this to the point where the adaptation tipping points are reached, a signal map is created.

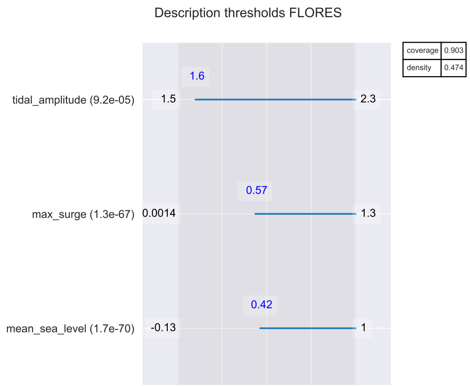


(a) Description of signal 1. The coverage and density of the box can be seen in the top right, and the quasi-p score is behind the variables on the left. These terms are explained further in Section 2.3.2. The numbers in blue are the thresholds of the signal.

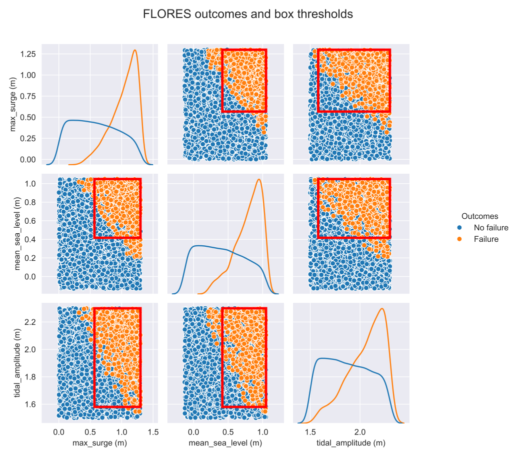


(b) Scatter plot showing all calculated outcomes at the wastewater treatment plant. The points are binary: orange points are where failure occurs, while for blue points no failure occurs. A probability distribution function for both these types of points can also be seen. Lastly, the signal described in detail in Figure 4.6a can be seen in red.

Figure 4.8: Description and visualization of signal 1.



(a) Description of signal 2. The coverage and density of the box can be seen in the top right, and the quasi-p score is behind the variables on the left. These terms are explained further in Section 2.3.2. The numbers in blue are the thresholds of the signal.



(b) Scatter plot showing all calculated outcomes at the wastewater treatment plant. The points are binary: orange points are where failure occurs, while for blue points no failure occurs. A probability distribution function for both these types of points can also be seen. Lastly, the signal described in detail in Figure 4.6a can be seen in red.

Figure 4.9: Description and visualization of signal 2.

From deliberation

The signposts identified through deliberation were the lifespan of water infrastructure and community sentiment. For the first, signals and triggers can easily be obtained. Signals would be the approaching end of the life cycle, and the trigger would be the lead-off time needed for the implementation of the relocation of the wastewater treatment plant.

Finding signals and triggers for community sentiment is a bit more difficult since it requires a look into the minds of local citizens, which can be volatile. This requires the best judgment of decision makers, and a continuous testing of the assumptions made about the sentiment of the community. A trigger would present itself as key stakeholders such as locals (or the New Zealand government) changing their views on nature preservation or housing as described in Section 4.9.

4.12.3 Signal map

Building the signal map requires the placing of the signals in a table ranging from current conditions to the adaptation tipping point. As mentioned before, the two signals developed in the previous section had a large difference in coverage. In reality, there are 4 boxes between these two signals identified through the density-coverage tradeoff curve (Figure 4.5), which can be used to create a further gradient if needed.

The signals for the other two signposts are also filled in, although these are more qualitative in nature. In the case of the signal map for the water infrastructure lifespan shown in Figure 4.10b, the current status quo and triggers are purely illustrative. The main point is to show which signals will most likely arrive before a trigger, and to illustrate that when the trigger hits, enough time is left for either the (partial) rebuilding of water infrastructure if the environmental signposts indicate this is possible, or the retreat of the wastewater treatment plant if they indicate this is not. It is assumed bot these actions would take around 5 years, which is of course a simplification.

For the case of the community sentiment, signals are even more qualitative. They have currently been filled in with potential ways signals could be implemented that indicate a change in sentiment. This is only for illustratory purposes, however, and in reality someone close to the source would most likely have a much better understanding of which signals would be relevant.

Indicators	Surge frequency, Surge height		
Signposts	Storm surge	Mean sea level	Tidal amplitude
Status quo	1.21	-0.13 m	1.8
Signal 1 Coverage: 0.993 Density: 0.308	≥ 0.53 m	≥ 0.27 m	≥ 1.6 m
Signal 2 Coverage: 0.903 Density: 0.474	≥ 0.57 m	≥ 0.42 m	≥ 1.6 m
Signal ... Coverage: ... Density: ...	...	...	...
ATP Coverage: 0.737 Density: 0.733	≥ 0.64 m	≥ 0.54 m	≥ 1.8 m

(a) Signal map to monitor for the 'do nothing' approach. Only two signals are filled in. In reality, many more could be added dependent on the boxes found through scenario discovery.

Indicators	
Signposts	Water infrastructure lifespan
Status quo	~ 30 years (guess)
Signal 1	20 years
Signal 2	15 years
Signal ...	...
Trigger	5 years (guess)

(b) Signal map for water infrastructure lifespan. The numbers for status quo and the trigger are purely for illustration.

Indicators	
Signposts	Community sentiment
Status quo	No change in sentiment
Signal 1	Small changes in sentiment for minor stakeholders
Signal 2	Small changes in sentiment for some key stakeholders
Signal ...	...
Trigger	Complete change in sentiment for key stakeholders

(c) Signal map for community sentiment. Signals and triggers in this map are qualitative and require deliberation with key and minor stakeholders.

Figure 4.10: Visualization of a signal map for each of the different signposts.

Relationships between signposts and signals

Important to note for a decision maker is that while the signal map makes it look like once a trigger is reached, an action should be implemented. In reality, the signposts also interact. The most obvious example of this are the three environmental signposts, the relationship between which was explained before. Additionally, for the signal map of an implementation signpost such as the water infrastructure lifespan or community sentiment only speaks to the ease of implementation of a new action, which is also dependent on the environmental signals.

4.13 Monitoring Step 6: Implement and monitor

Step 6 of the development of the monitoring system applies the monitoring system to the preferred pathway from Step 6 in 4.7. In the case of significant changes in the system, or at pre-determined times, the signposts and indicators can be re-assessed.

4.13.1 Example using signal map and signposts

As an example of how the signal map and signposts can be implemented, the status quo condition as visualized in Figure 4.10 can be imagined, which is also the 'do nothing' approach (Action A in Figure 4.7). In this situation, the accepted risk is the combination of 1.8 meters Mean High Water Perennial Spring (which is the tidal amplitude reached around 10% of the time) and a 100 year storm surge of 1.21 meters, along with a mean sea level of -0.13 meters. The water infrastructure is expected to be around 30 years removed from the end of its life span, and there is no change in community sentiment.

For these conditions, if we compare the environmental status quo conditions to the first signal as shown in Figure 4.8, we can see this signal has not been reached yet since the point is not in the box defined by this signal in Figure 4.11. This means the conditions are still safe from the accepted risk factors.

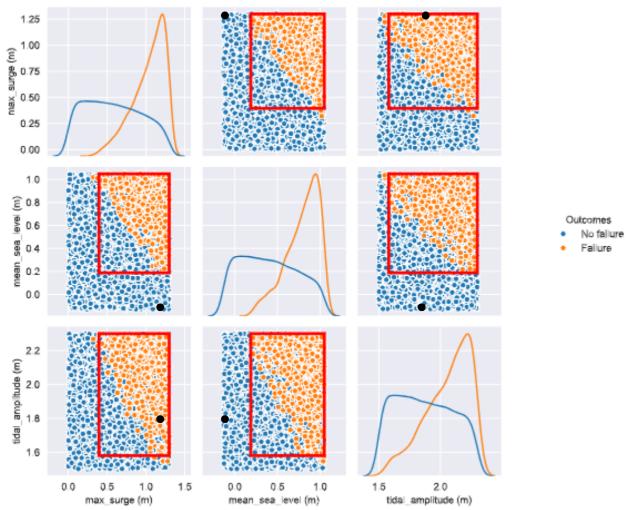


Figure 4.11: Example of the status quo as identified in Figure 4.10, compared to Signal 1 as shown in Figure 4.8. The status quo is represented by a black dot.

Chapter 5

Discussion

The discussion is split up into three main points. Section 5.1 discusses the use of robust decision making to design dynamic adaptive policy pathways, or the first part of the approach discussed in Chapter 2. Section 5.2 discusses the second part of the proposed approach from that same chapter, which is the design of a monitoring system using robust decision making. Lastly, Section 5.3 dives deeper into the case illustration done in Chapter 4, and discusses the choices made here as well as potential improvements.

5.1 Development of dynamic adaptive policy pathways (Part 1 of the approach)

5.1.1 General

The first part of the approach consisted of informing the design of actions and pathways. To do this, multiple partial methods found in literature were combined into one cohesive approach. The main goals were to inform actions and develop pathways. In general, this was achieved. The focus of this section will mostly be on some of the caveats, and interesting findings which could lead to future research.

The structure of the section will broadly follow the steps of part 1 of the approach, starting with the informing of actions, identifying tipping points, visualizing adaptation tipping points and pathways, and finally the evaluation of pathways.

5.1.2 Informing actions

Sensitivity analysis and sampling methods

The addition of a global sensitivity analysis was a big help in identifying potential actions. The inclusion of the sensitivity analysis was made easier by the fact that it could be run at the same time as scenario discovery using the EMA workbench. This did mean, however, that both the scenario discovery and the sensitivity analysis used the same quasi-random SOBOL sampling scheme. The effects of sampling schemes such as adaptive or truly random sampling on convergence for this approach could be the focus of future research, leading to potentially more efficient sampling.

Defining action finality

Due to time constraints, only the first iteration of the approach was done to inform actions. While this was sufficient for the point of illustrating the approach, it would be interesting to develop these actions further over multiple iterations to see if any unexpected challenges arise. This is especially relevant since one issue that arises when using robust decision making to design pathways is how to decide which actions are fully developed or final. In the proposed approach, and for this research, deciding this was based on deliberation. In theory, the development or improvement of actions is not limited which raises a question on how to determine this.

5.1.3 Identifying adaptation tipping points

Successive scenario discovery methods

For this research, PRIM was used for the scenario discovery due to its robust nature. It was found after the first iteration that a linear relationship exists between the three main input uncertainties. While PRIM simplified the shape of the vulnerability as square, it still described it with sufficient coverage and density for the purposes of this research. Other scenario discovery methods such as logistic regression and principal components analysis could be used to more accurately describe the vulnerability. Incorporating these methods explicitly in future versions of the approach could help better describe the conditions of failure, independent of the relationship between the input uncertainties.

Selecting adaptation tipping points

Adaptation tipping points were determined based on the results of the scenario discovery, which has a tradeoff between coverage and density as explained earlier. The adaptation tipping points shown in the case illustration contained a balance between coverage and density. It could be interesting to play with this dial in order to define adaptation tipping points that better take into account the opportunities/drawbacks of individual actions. For example, the adaptation tipping points selected for high-regret actions could be defined by boxes with higher density since unnecessary implementation could prove costly, while those for low-regret actions could be defined by boxes with a higher coverage. Work on further understanding and implementation of this mechanism in future versions of the approach could prove to be useful.

5.1.4 Visualizing adaptation tipping points and pathways

The DAPP approach is meant to be used for one dominant driver. However, the results of the vulnerability analysis reveal multiple drivers for failure that interact with each other, which can be seen as a multi-dimensional adaptation tipping point. There are a number of potential ways of visualizing these multi-dimensional adaptation tipping points, as also explained in Section 2.5. The main question seems to be whether to stick with one driver such as sea level rise and move other factors to the monitoring system, or not to distinguish between drivers as done in this research. In this case, adaptation tipping points are visualized in a multi-dimensional manner, and transient scenarios are used as drivers as described in Section 4.6. Further exploration of both these visualization methods could help to develop a clearer understanding of their benefits and drawbacks. In turn, this can help to identify when and how each could best be used.

5.1.5 Evaluation of pathways

Explicit incorporation tradeoff analysis

The pathways were evaluated using deliberation to pick a preferred pathway. While this worked well, a potential enhancement would be the further integration of a tradeoff analysis. In this case, this was not used since the vulnerability analysis only included one objective. More explicitly incorporating this in future versions of the approach could help facilitate the deliberative evaluation in order to come to a preferred pathway.

Using MORO to optimize pathways

Another possible enhancement in the evaluation and development could be the use of MORO in a later phase. MORO uses pre-specified rules and actions to develop a pareto-optimal set of pathways as explained in Section 2.2. The approach described in this research helps in development of those rules that should be pre-specified, which solves one of the main issues for MORO (Kwakkel et al., 2016a). MORO searches the decision space much more thoroughly and could lead to even more robust pathways, albeit at a potentially high computational cost. It is suggested that this is most worth it when achieving robustness across objectives is more important (Bartholomew & Kwakkel, 2020). Under which conditions including MORO in the approach is worth the added computational demand would be an interesting subject for further research.

5.2 Design of monitoring system (Part 2 of the approach)

5.2.1 General

In general, the design of the monitoring system using the proposed approach is promising. While there was sparse literature regarding the subject, the approach incorporated these sources and built upon them using the results of the vulnerability analysis. Finding signals based on the results of scenario discovery specifically is a novel approach, and seems to be a promising way to partly solve a long-standing issue within the building of a monitoring system for DAPP.

This section broadly follows the steps of Part 2 of the approach, based on where interesting findings or caveats are found. This starts with the selection and evaluation of signposts and indicators, and the identification of signals and other factors regarding the signal map.

5.2.2 Signpost selection and evaluation

Supporting the deliberative selection of signposts

There were two ways the signposts were selected, based on the vulnerability analysis and through deliberation. The signpost selection based on the vulnerability analysis was relatively straightforward. This selection was based on the results of the scenario discovery. There were also two signposts identified through deliberation: the lifespan of the water infrastructure, and community sentiment. These were selected based on an understanding of the case, although the process was quite unstructured. While it is never possible to completely remove the risks of missing an important signpost in the face of uncertainty, it would be helpful to pose some open questions regarding implementation and performance of actions to facilitate discussion and deliberation. This could help to give analysts in the future a more structured way to arrive at signposts.

Incorporation of sensitivity analysis in signpost evaluation

The results of the sensitivity analysis were currently not used in the signpost selection or evaluation. This could be a missed opportunity, since it gives extra information about the importance of the signposts identified through the vulnerability analysis. For example, in the case illustration it was found that storm surge had the largest influence on water levels. This means potential changes and errors for this signpost have a much larger effect on decision making. Care should be taken not to use the results too literally, however, since they are also sensitive to arbitrary factors like the chosen ranges for each input uncertainty, which could be seen in the results for tidal amplitude. The incorporation of sensitivity analysis results could further help in understanding and evaluating the selected signposts.

Additional evaluation for indicators

When signposts were evaluated poorly, indicators were selected with the goal of acting as a proxy for signposts. In the current version of the approach, the measurability of the indicators individually was the main focus. What was found in the case illustration was that while both indicators were evaluated well on measurability, their prediction of storm surge was lacking, especially for higher return periods. Taking the quality of proxy into account in defining extra evaluation criteria for indicators could help improve evaluation criteria.

5.2.3 Building a signal map

Identification of signals

Signals for the environmental signposts were identified through scenario discovery, using boxes with a higher coverage compared to the adaptation tipping points. This is a new method that seems promising. By choosing boxes with a higher coverage and lower density a gradient of potential signals could be identified, ranging from the status quo to the determined adaptation tipping points. In this case PRIM was used to identify the boxes, but the manner in which signals were identified would be similar when using other scenario discovery methods such as logistic regression or principal components analysis.

Other signals were based on deliberation. Similarly to the selection of signposts, having some open questions to facilitate this process would help more structurally define signals for those signposts.

Identifying triggers by including timing

One issue with the current way the signal map is designed is that timing is not explicitly taken into account. While this is not an issue for signals and adaptation tipping points, which are based on conditions, identifying triggers requires knowledge about how much time is needed to implement a new action, as well as on how quickly a signpost will change. Determining how quickly a signpost changes requires the use of transient scenarios in conjunction with expert opinion.

Further structuring of the process of identifying triggers would be helpful. The way the signal map is set up using a gradient could help with this in the case of the environmental signposts and signals. By looking at the size of changes between thresholds for signposts of consecutive signals, an analyst can get a view of how quickly risks will increase. In the case of many consecutive signals with near identical thresholds change can happen quickly, while in the case of large differences in thresholds between consecutive signals change is slower.

Visualizing signpost quality

After the signposts were selected, they were evaluated. Evaluation of signposts was mostly based on their measurability, including accuracy, precision, and timeliness. A noisy signpost such as storm surge in the case illustration is less trustworthy when making decisions regarding adaptation. While the quality of signposts was known to the analyst, it was not clearly visualized in the signal map or in their further use. Being able to see the quality of each proposed signpost could further help decision makers by allowing them to include this in the assessment of the situation before making adaptations. Raso, Kwakkel, and Timmermans (2019) and Raso, Kwakkel, Timmermans, and Panthou (2019) could start as a starting point to further incorporate trustworthiness of a signpost regarding potential adaptations.

Visualizing interactions between signposts

One thing to note which was also mentioned within the text was the interaction between the different signposts. In the case of the environmental signposts this was solved by using the scatter plot of a signal to visualize when it was reached. This works well and allows for the interaction between these different signposts.

The implementation signposts also interacted with the environmental signposts. In the case an implementation trigger was reached, a decision had to be made which was reliant on the development of the environmental signposts. While certain conditions lead to a decision trigger, since these signposts were reliant on the environmental signposts in this case no adaptation tipping points could be reached. As an example, reaching the trigger for the water infrastructure lifespan would not force the retreat of the wastewater treatment plant, but merely suggest this to be a good time for doing so. Further clarification and visualization of the hierarchy and interactions between different signposts could help support deliberation, especially if multiple categories of signposts are present.

5.3 Case illustration

5.3.1 General

Overall, the case was a good fit to illustrate the approach. There was sufficient knowledge of the case to be able to reflect on potential policy implications, and there was a detailed understanding of the technological aspects of the wastewater treatment plant. Due to time constraints, only the first iteration of the approach was followed. More iterations will help to further investigate the case and sharpen the understanding of the case. Discussion of some of these aspects can be found below.

This section follows the case illustration chapter. It starts with discussion points regarding decision framing and model choice, moves to the vulnerability analysis and results for the case, discusses the developed actions and pathways, and finally discusses the monitoring system.

5.3.2 Decision framing

Failure methods

The chosen failure method of overtopping was relatively simple, but directly affected pollution and was affected by compound flooding making it a good choice to illustrate the case. There are a number of ways this could be improved upon, if deemed necessary.

First, overtopping was assumed to happen once a certain threshold was reached, which was defined as the height higher than 50% of the spot heights surrounding the embankments (as seen in Figure C.6. Time above this threshold was not taken into account, and this definition of the threshold was somewhat arbitrary.

Second, only overtopping was taken into account, while compound flooding also affects other hydraulic failure mechanisms such as slumping of embankments, geotechnical failures. More research into different potential failure mechanisms, which is likely to occur first, and their effects on pollution could give a better insight into the actual performance of the wastewater treatment plant.

Third, compound flooding was only assumed to affect the wastewater treatment plant, while in reality it would also lead to flooding of the surrounding communities. Taking this flooding and its effects into account for the modeling would help to understand the broader system. In turn, this could help understand when thinking about a managed retreat for the community would be reasonable and how the wastewater treatment plant plays into this.

Rainfall intensity

The results of the sensitivity analysis showed rainfall intensity to have no effect on the water levels at the case location. This can be explained in multiple ways. However, one of the assumptions was a spatially and temporally uniform rainfall for the model domain, which is an underestimation. In reality, there are spikes in rainfall which leads to peak discharges in the Kaipara river. While for the case illustration this made little difference, for future iterations of the decision framing more research into these effects should be done to accurately represent the effects of rainfall.

Model choice

The main issue affecting the case site was the pollution of the Kaipara river and harbor due to compound flooding. It was chosen to have a technical model to calculate the overtopping of the wastewater treatment plant's pond embankments. It is important to realize that a translation should take place from overtopping to pollution. This could also potentially affect model choice in later iterations, when other failure methods are taken into account or actions are identified that affect this translation.

The FLORES model was chosen to represent the compound flooding due to its ready implementation for scenario discovery and quick runtime. The thesis by Smits (2024) showed that this model is sufficient for this case, although it slightly overestimates water levels compared to a more complex model. This could potentially influence the timing of adaptation. For future iterations where this timing becomes more important, this is something to take into account.

Model complexity is most likely also influenced by the interactions between input uncertainties. In this case, the only factor influencing water levels was the storm-tide, which interacted by simple addition. If more complex dynamics become important at the case site, due to increasing rainfall or the inclusion of a river flow, it might be prudent to choose a more complex model.

5.3.3 Vulnerability analysis

Sensitivity analysis

While it was not explicitly mentioned, input uncertainties other than forcing could also be taken into account to test for potential actions. Smits (2024) tested several model uncertainties including roughness and infiltration rate and found these had no influence on the water level outcomes at the wastewater treatment plant. Based on the choice of input uncertainties taken into account, the model choice might also differ.

The sensitivity analysis showed no interaction between the three major input uncertainties. This is most likely due to the simple way they are combined, using addition of their values as explained in Figure 4.3b.

The sensitivity analysis is partly reliant on the ranges chosen. In order to accomplish this, the return periods of the various input uncertainties were for around 100 year return periods. This was not possible for the tidal amplitude, however, since this does not use the same concepts of return periods. To see whether this had a significant influence, sensitivity to the choice of range should also be tested.

Scenario discovery

The first iteration of the scenario discovery found that there was a linear relationship between storm surge, mean sea level, and tidal amplitude. Still, PRIM is a robust method that was able to explain failure at the treatment plant with a relatively high coverage and density. Knowing that the relationships between input uncertainties is linear, other scenario discovery methods such as logistic regression and a principal components analysis could potentially lead to an even better description in future iterations.

5.3.4 Developed actions and pathways

Developed actions

The main short-term action developed was the mitigation of storm surge, which was not resolved further. There are many ways storm surge could be mitigated, which can even combined with each other. Future iterations could focus on the development of both nature-based as well as more 'hard' approaches to see how they compare and how well they can be combined.

Developed pathways

The combinations of the short-term actions combined with the long-term actions lead to pathways. Unlike short-term actions, long-term actions can be resolved further in a later stage. Care should be taken to ensure there are enough long-term actions to cover each potential family of approaches. This is why it is also recommended to include more outlandish actions such as the proposed damming of the Kaipara harbor, even though there is currently no support or need for this action. These long-term actions can be developed through deliberation with key stakeholders. If many similar long-term actions are developed in this way, such as many different similar ways to use engineering to dam Kaipara harbor or otherwise significantly alter the natural environment to keep conditions at the case site similar, they can be merged into more general actions until there is a need for them to be developed further.

5.3.5 Monitoring system

The monitoring system showed the status quo had not even reached the first environmental signal yet. It did show, however, that some of the current risks were already near the top of the ranges for input uncertainties. In the case one of the input uncertainties exceeds one of the identified ranges, a new scenario discovery should be conducted with higher thresholds.

Chapter 6

Conclusion and recommendations

6.1 Conclusion

As a reminder, the main research question as well as its two subquestions which were outlined in Chapter 1 were:

How can the robust decision making process be used to inform and design dynamic adaptive policy pathways and identify signposts and signals for a monitoring system?

- ***How can promising actions and pathways be informed and designed analytically using the robust decision making process?***
- ***How can signposts and signals be identified using the multidimensional adaptation tipping points found through scenario discovery?***

6.1.1 How can promising actions and pathways be informed and designed analytically using the robust decision making process?

The first question focused on the way actions and pathways are designed. Currently, actions and pathways for the dynamic adaptive policy pathways approach are designed in two main ways: through many-objective robust optimization (MORO) or in a participatory manner. These methods both have their own issues. MORO requires the upfront specification of rules and actions and is computationally expensive, while the participatory approach relies exclusively on expert opinion.

In order to solve some of these issues, literature has suggested that using the robust decision making approach can be used to identify vulnerabilities within the system, and to use these vulnerabilities to iteratively develop robust actions and pathways (Haasnoot et al., 2019; Kwakkel et al., 2016a). While this is suggested in literature, no analytical approach to achieving this exists yet.

This research proposed a novel approach based on literature which uses robust decision making to inform actions and identify adaptation tipping points to develop dynamic adaptive policy pathways. Main additions are the inclusion of the sensitivity analysis in the vulnerability analysis to inform actions and identify adaptation tipping points, and integrating these adaptation tipping points within the DAPP map.

Informing potential actions using the vulnerability analysis results

Potential actions were informed based on deliberation using the results of the vulnerability analysis, which included the scenario discovery and sensitivity analysis. The scenario discovery described the vulnerability for the current "do nothing" approach, which is made up of several input uncertainties. The inclusion of the sensitivity analysis, which was suggested by Kwakkel and Haasnoot (2019) to help in factor prioritization, was helpful in identifying those input uncertainties which had the largest influence on the outcomes at the wastewater treatment plant. This helped to identify those factors with the most influence on the identified vulnerability. Consequently, this helped to identify potentially effective actions, proving the inclusion of the sensitivity analysis to be a valuable addition.

Identification of adaptation tipping points

The adaptation tipping points were selected using the results of PRIM scenario discovery. Selection of the adaptation tipping points using other scenario discover techniques should also be possible. In the case illustration, the choice was made for a box with a balanced density and coverage. This also showed that using the results of the scenario discovery to select adaptation tipping points provides a promising way of further integration with actions. For this, adaptation tipping points can be selected based on whether actions are high-regret or low-regret as discussed in Section 5.1.3.

Integration of adaptation tipping points

The adaptation tipping points were also integrated within the DAPP map slightly differently compared to the standard DAPP approach due to the identified vulnerability being similar to multi-dimensional adaptation tipping points. This means that rather than using only one driver, which is what the DAPP approach was developed for, the vulnerabilities identified through scenario discovery constitute multiple drivers. These were visualized by identifying those adaptation tipping points on the map, and using transient scenarios to find timing. This is similar to the approaches used by Molina-Perez (2016) and Ramm et al. (2018a).

6.1.2 How can signposts and signals be identified using the multi-dimensional adaptation tipping points found through scenario discovery?

The second question was focused on designing a monitoring system. There is no consensus in literature on how to set up an effective monitoring system, with only a few relevant papers on the subject. For the monitoring system for dynamic adaptive policy pathways as described by Haasnoot et al. (2018), signposts are selected based on deliberation or expert opinion, as are most signals. There exists also a difficulty in identifying effective signals for the pathways approach (Haasnoot et al., 2019).

This research proposed a novel approach which uses the identified vulnerabilities from the robust decision making approach to identify signposts and signals, forming the basis for the monitoring system. Key concepts of the monitoring system were taken from (Haasnoot et al., 2018). Main additions done in this research were the use of the identified vulnerabilities to select signposts and indicators, and identify signals. It also extended the signal map concept proposed by Haasnoot et al. (2018).

Signpost and indicator selection and evaluation

Signposts were selected both based on the results of the scenario discovery, as well as through deliberation. The signpost selection based on scenario discovery results was straightforward, and determined relevant signposts. The signpost selection based on deliberation were selected based on an understanding of the case and signpost categories: implementation and performance signposts. While using these categories already helped to support deliberation, the process was still a bit unstructured.

The different selected signposts were evaluated, using mainly the criterium of measurability. Based on this, potential indicators were selected when needed. This system of identifying indicators to act as proxy went well, although no explicit regard was given to the quality of proxy. In the case illustration, while both the indicators for storm surge were evaluated well, their combined prediction of storm surge was still poor. This was especially the case for longer return periods.

Signal identification

Signals for the scenario discovery signposts were also found through scenario discovery, while for the signposts found through deliberation the signals were also based on deliberation.

The results of the PRIM scenario discovery also helped to identify potential signals, which was done using the tradeoffs between coverage and density. This manner of identifying signals for a monitoring system is new. Boxes with a higher coverage were used as signals, since these boxes explain more of the total number of outcomes where failure occurs. By identifying multiple signals in this manner, a gradient was created from the status quo to the adaptation tipping point. While timing was not explicitly considered in this work, which would be necessary to identify triggers, finding signals in this manner seems promising and the multiple signals visualized in a gradient gives an indication of timing.

Signals based on deliberation also showed promise, by identifying potential situations that would lead to a decision trigger in the case of the implementation signposts. These signals in this case required more expert opinion, since timing was not taken into account. These signals also potentially suffered from a lack of structured deliberation, similarly to the signpost selection.

Signal map

Once signals were identified they were placed in maps. These maps extended the signal map concept as identified by Haasnoot et al. (2018), and seem very promising. There are also some suggestions on its further development to further assist decision makers explained in Section 6.2.2: the addition of a signpost map to show the relationships between signposts, and including a visual way to show the quality of the different signposts.

In the case of the implementation signposts, no adaptation tipping points were included but only triggers, since reaching this threshold would only mean a decision on implementation had to be made, but would not force it.

Seeing if a signal based on the scenario discovery results had been reached was easily achieved and visualized by placing the conditions as a point onto the scatter plot with the PRIM box of the signal. This incorporates the multi-dimensional nature of the signal and makes their monitoring a lot easier.

6.2 Recommendations

From the work done in this report, three categories of recommendations can be identified. The first in Section 6.2.1 describes further work developing the first part of the novel approach, which informed and designed promising actions and pathways. The second in Section 6.2.2 describes further work developing the second part of the approach, which identified signposts and signals. The last part in Section 6.2.3 recommends further case-specific actions which can be used for further work regarding the Helensville wastewater treatment plant.

6.2.1 Further work developing part 1 of the novel approach

Informing actions and determining finality

Actions were informed in part by the use of the sensitivity analysis, as well as the results of the scenario discovery. In order to save time for running both these analyses, the same quasi-random SOBOL sampling scheme was used for both. Literature has suggested the use of adaptive sampling could save time for the scenario discovery (Lempert, 2019). Whether this is possible when running a concurrent sensitivity analysis, and how much time this saves should be the subject of future research.

Only one iteration of the approach approach was followed for the case illustration. In theory, the development of new actions through looping back from the vulnerability analysis can continue indefinitely. In the proposed approach, the finality of actions is based on deliberation. Further exploration of how to support this deliberation and what constitutes a fully developed action should be further investigated.

Identifying adaptation tipping points

The adaptation tipping points were identified using the results of the scenario discovery. For this, PRIM was used due to its robust nature and easy interpretability. The case illustration showed that the relationship between the three main factors was linear, however. While PRIM still describes the vulnerability well and is recommended for use in the first iteration, it is also recommended to investigate the benefits of the implementation of other scenario discovery methods such as logistic regression or a principal components analysis in later stages of the approach. Examples of their use can be found in the 'read the docs' of the EMA workbench.

The density and coverage tradeoffs for the identified vulnerability can be used in a variety of ways. In the research this tradeoff was used to identify signals that indicate an increasing probability of failure. It could also be used to align better with different actions. High regret actions warrant a higher density since unnecessary implementation could prove costly, while low regret actions could be implemented in an earlier stage (higher coverage). Additionally, by looking at how the thresholds change between different boxes it could also be used to better understand the shape of the vulnerability. It is recommended to further investigate the use of this dial, which could give insight on the identified vulnerability which in turn potentially can improve identified actions and the monitoring system.

Integration of adaptation tipping points

As also mentioned in Section 5.1 the identified vulnerabilities constituted multi-dimensional adaptation tipping points, which made their integration in the DAPP map difficult. There are several ways to achieve this integration. The main difference seemed to be whether to choose one dominant driver such as sea level rise and move the other factors of the identified vulnerability to the monitoring system, or not to distinguish between drivers using adaptation tipping points and transient scenarios as described in Section 4.6. Both methods have their benefits and drawbacks: having one driver increases interpretability, but places undue focus on one of the drivers while in reality all factors of the identified vulnerability influence failure. Further exploration of different visualization methods could help create a clearer understanding of their benefits and drawbacks.

Supporting the evaluation of pathways

In the current version of the approach, the pathways were evaluated based on deliberation. For future versions, it is recommended to explore two promising ways to further support this.

First, it is recommended to more explicitly incorporate the tradeoff analysis and its results in the evaluation (and design) of actions. This was not done for the case illustration since only one objective was selected, and one action ('do nothing') was tested. Incorporating this analysis could help support evaluation of pathways by identifying tradeoffs between the actions that make up the pathways.

The second recommendation is to explore the use of Many-Objective Robust Optimization (MORO) in conjunction with the novel approach. At the cost of additional computational demand, MORO can search the decision space extremely thoroughly and develop a pareto-optimal set of pathways (Bartholomew & Kwakkel, 2020). Achieving such a set where no single pathway is strictly better than another for all objectives could help decision makers to better understand tradeoffs and support the evaluation of pathways. Under which conditions the inclusion of MORO is worth the added computational demand, or at all, would be an interesting subject for further research. Combining RDM and MORO in a similar fashion was also eluded to by Kwakkel et al. (2016a).

6.2.2 Further work developing part 2 of the novel approach

Assisting the deliberative selection of signposts and signals

While the selection of signposts and signals based on the results of the vulnerability analysis was relatively straightforward, this was less so the case for those found through deliberation. It is recommended to put further work into the posing of open questions to facilitate deliberation in order to improve the select of signposts and signals.

Additional evaluation of signposts and indicators

The evaluation of signposts was currently done mostly on the criteria of measurability. Some additional points of evaluation are recommended which would help to further the understanding of the monitoring system and quality of signposts. First, the inclusion of the sensitivity analysis results would help to better understand the relative importance of the signposts identified through scenario discovery. Second, and related to this first topic, the effects of noise for a signpost was not taken into account. Raso, Kwakkel, and Timmermans (2019) and Raso, Kwakkel, Timmermans, and Panthou (2019) already did some work on including the effects of signpost noise on Type I and II errors, and their consequences.

Regarding indicators, the case illustration showed that while the measurability for both indicators of storm surge was good the indicator itself still was not very accurate, although it did mark an improvement over the storm surge signpost itself. Taking this extra factor into account it is recommended to define and test extra evaluation criteria to evaluate indicator quality such as quality of proxy.

Addition of a signpost map

Much of the information known about the signposts was known but unorganized. This includes information on the quality of the different signposts and the way they interacted with each other. While it was fine in this case where only a few signposts were present, when dealing with more complex relations or a larger number of signposts it could be easy for an analyst or decision maker to lose track. It is recommended to find a way to develop a signpost map alongside the signal map. This signpost map can show the interactions and hierarchies, as well as the quality or trustworthiness of the different signposts to assist decision makers.

Including timing to identify triggers

One issue with the signal map for the signals identified through the scenario discovery was that timing was not taken into account, making the identification of triggers difficult. Identifying triggers can be done using transient scenarios and expert knowledge, but the gradient of the signal map can also help. By looking at the size of changes between thresholds for signposts of consecutive signals, an analyst can gauge how quickly risks will increase. In the case of many consecutive signals with near identical thresholds change can happen quickly, while in the case of large differences in thresholds between consecutive signals change is slower. It is recommended to define a systematic approach to identify triggers using a combination of the options outlined above.

6.2.3 Recommendations case illustration

Decision framing

Only overtopping was taken into account as a failure method. While this was a good choice to represent the case due to its direct link between pollution and compound flooding. First, taking a more arduous look at the value taken for overtopping and taking time of flooding into account could represent the failure method more accurately. Additionally, there are also other potential failure methods. It is recommended to further investigate these to see which is likely to occur first and what their effects on pollution of the Kaipara river would be in order to gain better insight into the actual performance of the wastewater treatment plant.

From the vulnerability analysis, it was found rainfall intensity did not influence water levels at the wastewater treatment plant at all. While this is likely true, more investigation on why this is would be prudent. Factors like a latent river flow or peak in rainfall intensity (compared to the spatially and temporally uniform intensity used for this research) could significantly affect results, so it is recommended to investigate this further.

Vulnerability analysis

The sensitivity analysis showed storm surge was most influential to the water levels at the case site, followed by mean sea level and tidal amplitude. The range chosen for the tidal amplitude was much smaller than that of the mean sea level and storm surge. It is recommended to also take into account the sensitivity of the input uncertainties to their chosen ranges to see whether this had a significant influence.

The case illustration used the PRIM method for scenario discovery. The results showed a linear relationship between the storm surge, mean sea level, and tidal amplitude. While the choice for PRIM was justifiable, it is recommended to use scenario discovery methods that better take into account this linear relationship. This would allow for a better description of where failure occurences are likely, with a higher coverage and density. Potential methods are a principal components analysis or logistic regression.

Further development of actions

In the short-term it was recommended to focus on actions that mitigate storm surge. While regulations and the objectives of key stakeholders mean the focus for this should be on nature-based approaches, it is recommended to also look at other more artificial options to see whether there is a significant difference between the two, and/or if they can be combined to some degree.

It is also recommended to define additional long-term actions based on deliberation. These should be categorized based on general aspects and resolved further when applicable. Including these actions, even there is currently no support for it, helps to further mitigate choice lock-in, and provides both stakeholders and decision makers with a good idea of which options are available.

Monitoring system

The signposts and signals were partly based on the identified vulnerabilitiy, and partly on deliberation. Those based on deliberation were defined by the analyst based on knowledge of the case. While this is sufficient for the case illustration, further deliberation on these signposts and signals with key stakeholders is recommended to better define them.

The signal map showed that the status quo did not reach the first signal yet. However, in the case of the environmental signposts the boundaries of the chosen ranges were almost reached already. This is why it is recommended to choose larger ranges for the next iteration. These ranges should still be relatively similar between input uncertainties to gather accurate results for the sensitivity analysis.

Bibliography

(n.d.). https://traveltrade.newzealand.com/

Arias, P., Bellouin, N., Coppola, E., Jones, R., Krinner, G., Marotzke, J., Naik, V., Palmer, M., Plattner, G.-K., Rogelj, J., Rojas, M., Sillmann, J., Storelvmo, T., Thorne, P., Trewin, B., Rao, K. A., Adhikary, B., Allan, R., Armour, K., … Zickfeld, K. (2021). Technical summary [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 33–144). Cambridge University Press. https://doi.org/10.1017/9781009157896.002

Auckland Council & (LINZ), T. T. W. L. I. N. Z. (2020). Auckland north, new zealand 2016-2018 [https://doi.org/10.5069/G92R3PVR].

Auckland Regional Council. (2001). Kaipara river catchment water allocation strategy 2001.

Bartholomew, E., & Kwakkel, J. (2020). On considering robustness in the search phase of robust decision making: A comparison of many-objective robust decision making, multi-scenario many-objective robust decision making, and many objective robust optimization. Environmental Modelling & Software, 127, 104699.

Batstone, C., Lawless, M., Tawn, J., Horsburgh, K., Blackman, D., McMillan, A., Worth, D., Laeger, S., & Hunt, T. (2013). A uk best-practice approach for extreme sea-level analysis along complex topographic coastlines. Ocean Engineering, 71, 28–39.

Beca, GHD, & Miskell, B. (2020, October). The new zealand wastewater sector. https://environment.govt.nz/assets/Publications/Files/wastewater-sector-report.pdf

Bell, R. G., Bostock, H., Carey-Smith, T., Collins, D. B., Fedaeff, N., Kachhara, A., Macara, G. R., Mullan, B., Paulik, R., Somervell, E., et al. (2018). Auckland region climate change projections and impacts: Prepared for auckland council, council controlled organisations, and district health boards/prepared by petra pearce (climate scientist), rob bell (principal scientist-coastal and estuarine processes), helen bostock (marine geologist), trevor carey-smith (climate scientist), daniel collins (hydrologist), nava fedaeff (climate scientist), ayushi kachhara (air quality technician), gregor macara (climate scientist), brett mullan (principal scientist-climate variability), ryan paulik (hazards analyst), elizabeth somervell (air quality scientist), abha sood (climate scientist), andrew tait (principal scientist-climate), sanjay wadhwa (gis analyst), john-mark woolley (climate research scientist).

Bellvé, A. R., Austin, G., Woods, B., & Power, T. (2007). Pathway to energy generation from marine tidal currents in new zealand's kaipara harbour.

Bibby, R. L., & Webster-Brown, J. G. (2005). Characterisation of urban catchment suspended particulate matter (auckland region, new zealand); a comparison with non-urban spm. Science of The Total Environment, 343(1), 177–197. https://doi.org/https://doi.org/10.1016/j.scitotenv.2004.09.041

Blackett, P., FitzHerbert, S., Luttrell, J., Hopmans, T., Lawrence, H., & Colliar, J. (2021). Marae-opoly: Supporting localised māori climate adaptation decisions with serious games in aotearoa new zealand. Sustainability Science, 1–17.

Bloom, E. (2015). Changing midstream: Providing decision support for adaptive strategies using robust decision making. Pardee RAND graduate school.

Bosboom, J., & Stive, M. J. (2021). Coastal dynamics. TU Delft Open.

Bryant, B. P. (2012). Sdtoolkit: Scenario discovery tools to support robust decision making. http://cran.r-project.org/web/packages/sdtoolkit/index.html

Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. Technological Forecasting and Social Change, 77(1), 34–49.

Cao, A., Esteban, M., & Mino, T. (2020). Adapting wastewater treatment plants to sea level rise: Learning from land subsidence in tohoku, japan. Natural Hazards, 103(1), 885–902.

Cash, D., Clark, W., Alcock, F., Dickson, N., Selin, N., & Jager, J. (2002, December). Salience, credibility, legitimacy and boundaries: Linking research, assessment and decision making. https://doi.org/10.2139/ssrn.372280

Chow, V. T. (2009, January 1). Open-channel hydraulics (Paperback). The Blackburn Press.

Council, A. R. (1999). Guidelines for stormwater runoff modelling in the auckland region. Auckland Regional Council Technical Publication No, 108.

Dejeans, B. S., Mullarney, J. C., & MacDonald, I. T. (2022). Lagrangian observations and modelling of turbulence along a tidally influenced river. Water Resources Research, e2020WR027894.

Eckley, N., Clark, W., Farrell, A., Jaeger, J., & Stanners, D. (2001). Designing effective assessments: The role of participation, science and governance, and focus, vol. 26. European Environment Agency.

Friedrich, E., & Kretzinger, D. (2011). Vulnerability of wastewater infrastructure of coastal cities to sea level rise: A south african case study. Water SA, 38, 755–764. https://doi.org/10.4314/wsa.v38i5.15

Green, M., & Daigneault, A. (2018). Kaipara harbour sediment mitigation study: Summary. Prepared for Northland Regional Council and Auckland Council by Streamlined Environmental, Report NRC170-1 (minor revision), Hamilton.

Groves, D., Bloom, E., Lempert, R. J., Fischbach, J. R., Nevills, J., & Goshi, B. (2015). Developing key indicators for adaptive water planning. Journal of Water Resources Planning and Management, 141(7), 05014008.

Groves, D., Fischbach, J., Bloom, E., Knopman, D., & Keefe, R. (2013). Adapting to a changing colorado river: Making future water deliveries more reliable through robust management strategies.

Groves, D., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust decision making (rdm): Application to water planning and climate policy. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 135–164). Springer.

Haasnoot, M., Kwakkel, J., Walker, W. E., & Ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. Global environmental change, 23(2), 485–498.

Haasnoot, M., Schellekens, J., Beersma, J., Middelkoop, H., & Kwadijk, J. C. J. (2015). Transient scenarios for robust climate change adaptation illustrated for water management in the netherlands. Environmental Research Letters, 10(10), 105008.

Haasnoot, M., van 't Klooster, S., & Van Alphen, J. (2018). Designing a monitoring system to detect signals to adapt to uncertain climate change. Global Environmental Change, 52, 273–285.

Haasnoot, M., Warren, A., & Kwakkel, J. (2019). Dynamic adaptive policy pathways (dapp). In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 71–92). Springer.

Haggitt, T., Mead, S. T., & Bellingham, M. (2008). Review of environmental information on the kaipara harbour marine environment. Auckland Regional Council.

Hall, J., & Borgomeo, E. (2013). Risk-based principles for defining and managing water security. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 371(2002), 20120407. https://doi.org/10.1098/rsta.2012.0407

Hamarat, C., Kwakkel, J., & Pruyt, E. (2013). Adaptive robust design under deep uncertainty. Technological Forecasting and Social Change, 80(3), 408–418.

Heath, R. (1975). Stability of some new zealand coastal inlets. New Zealand journal of marine and freshwater research, 9(4), 449–457.

Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? Journal of Water Resources Planning and Management, 141(10), 04015012.

Herman, J. D., Zeff, H. B., Lamontagne, J. R., Reed, P. M., & Characklis, G. W. (2016). Synthetic drought scenario generation to support bottom-up water supply vulnerability assessments. Journal of Water Resources Planning and Management, 142(11), 04016050.

Herman, J. D., Zeff, H. B., Reed, P. M., & Characklis, G. W. (2014). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. Water Resources Research, 50(10), 7692–7713.

Hermans, L., Haasnoot, M., ter Maat, J., & Kwakkel, J. (2017). Designing monitoring arrangements for collaborative learning about adaptation pathways. Environmental Science & Policy, 69, 29–38.

Ho, I., Deshpande, A., & Floyd, J. (2009). Wastewater reclaimation for high quality reuse - a case study in helensville [(Accessed on 17/02/2022)].

Hume, T., Nichol, S., Smith, K., & Liefting, R. (2003). Kaipara sand study: Component 1b: Geomorphic evidence of sand movement and storage in historical times. NIWA Client Report: HAM2003-028.

Hummel, M. A., Berry, M. S., & Stacey, M. T. (2018). Sea level rise impacts on wastewater treatment systems along the us coasts. Earth's Future, 6(4), 622–633.

Ingley, R. (2021). River water quality state and trends in tāmaki makaurau: Auckland 2010-2019: State of the environment reporting. Auckland Council, Te Kaunihera o Tāmaki Makaurau.

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

Kwakkel, J. (2018, November). https://www.deepuncertainty.org/wp-content/uploads/2018/01/13Nov-1600-Kwakkel-DMDU-taxonomies.pdf

Kwakkel, J., & Haasnoot, M. (2019). Supporting dmdu: A taxonomy of approaches and tools. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 355–374). Springer.

Kwakkel, J., Haasnoot, M., & Walker, W. (2016a). Comparing robust decision-making and dynamic adaptive policy pathways for model-based decision support under deep uncertainty. Environmental Modelling & Software, 86, 168–183.

Kwakkel, J., Haasnoot, M., & Walker, W. E. (2015a). Developing dynamic adaptive policy pathways: A computer-assisted approach for developing adaptive strategies for a deeply uncertain world. Climatic Change, 132(3), 373–386.

Kwakkel, J., Haasnoot, M., & Walker, W. E. (2015b). Developing dynamic adaptive policy pathways: A computer-assisted approach for developing adaptive strategies for a deeply uncertain world. Climatic Change, 132(3), 373–386.

Kwakkel, J., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. Environmental Modelling & Software, 79, 311–321.

Landcare Research, M. W. (2021). Lcdb v5.0 - land cover database version 5.0, mainland, new zealand [data retrieved from LRIS Portal, https://lris.scinfo.org.nz/layer/104400-lcdb-v50-land-cover-database-version-50-mainland-new-zealand/]. https://doi.org/doi:10.26060/W5B4-WK93

Lawrence, J., Bell, R., Blackett, P., Stephens, S., & Allan, S. (2018). National guidance for adapting to coastal hazards and sea-level rise: Anticipating change, when and how to change pathway. Environmental science & policy, 82, 100–107.

Lawrence, J., & Haasnoot, M. (2017). What it took to catalyse uptake of dynamic adaptive pathways planning to address climate change uncertainty. Environmental Science & Policy, 68, 47–57.

Lawrence, J., Haasnoot, M., McKim, L., Atapattu, D., Campbell, G., & Stroombergen, A. (2019). Dynamic adaptive policy pathways (dapp): From theory to practice. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 187–199). Springer.

Lempert, R. J. (2019). Robust decision making (rdm). In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 23–51). Springer.

Lempert, R. J., Bryant, B. P., & Bankes, S. C. (2008). Comparing algorithms for scenario discovery. RAND, Santa Monica, CA.

Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the american west. Technological Forecasting and Social Change, 77(6), 960–974.

level. (2021). Site analysis. http://www.level.org.nz/site-analysis/hazards/rising-sea-levels/

LGNZ. (2019, January). Vulnerable: The quantum of local government infrastructure exposed to sea level rise. https://www.lgnz.co.nz/assets/Uploads/0bb3c3d32a/Planning-for-Sea-Level-Rise-v7-FINAL.pdf

Mannucci, S. (2021). Embracing uncertainty in urban design: An adaptive planning approach to increase urban resilience in mediterranean compact cities. an application at district level in the city of rome [Doctoral dissertation, Sapienza Universitá di Roma].

Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T. M., & Popper, S. W. (2019). Introduction. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision making under deep uncertainty (pp. 1–20). Springer.

Marchau, V. A., Walker, W. E., & van der Pas, J.-W. G. (2019). Dynamic adaptive planning (dap): The case of intelligent speed adaptation. Decision Making under Deep Uncertainty: From Theory to Practice, 165–186.

McDermott, T. K. (2022). Global exposure to flood risk and poverty. Nature Communications, 13(1), 3529.

McGrath, M. (2019). Climate change: Warming to drive 'robust increase' in UK flooding — bbc.com [[Accessed 9-03-2024]].

Mitchell, S. B., Green, M. O., MacDonald, I. T., & Pritchard, M. (2017). Field studies of estuarine turbidity under different freshwater flow conditions, kaipara river, new zealand. Estuarine, Coastal and Shelf Science, 198, 542–554.

Molina-Perez, E. (2016). Directed international technological change and climate policy: New methods for identifying robust policies under conditions of deep uncertainty [PhD Dissertation]. Pardee RAND Graduate School. https://doi.org/10.7249/RGSD369

Mullan, M. (2018). Climate-resilient infrastructure: Policy perspectives [(Accessed on 04/13/2022)]. OECD.

NIWA. (1991). Resource Management Act | NIWA — niwa.co.nz [[Accessed 24-06-2024]].

Our research: Deep south challenge. (2021, March). https://deepsouthchallenge.co.nz/our-research/

Palmer, R. N., & Characklis, G. W. (2009). Reducing the costs of meeting regional water demand through risk-based transfer agreements. Journal of environmental management, 90(5), 1703–1714.

Ramm, T. D., Watson, C. S., & White, C. J. (2018a). Describing adaptation tipping points in coastal flood risk management. Computers, Environment and Urban Systems, 69, 74–86.

Ramm, T. D., Watson, C. S., & White, C. J. (2018b). Strategic adaptation pathway planning to manage sea-level rise and changing coastal flood risk. Environmental Science & Policy, 87, 92–101.

Raso, L., Kwakkel, J., & Timmermans, J. (2019). Assessing the capacity of adaptive policy pathways to adapt on time by mapping trigger values to their outcomes. Sustainability, 11, 1716. https://doi.org/10.3390/su11061716

Raso, L., Kwakkel, J., Timmermans, J., & Panthou, G. (2019). How to evaluate a monitoring system for adaptive policies: Criteria for signposts selection and their model-based evaluation. Climatic Change, 153(1-2), 267–283. https://doi.org/10.1007/s10584-018-2355-3

Reddel, M. (2023, March). Model-based policy analysis under deep uncertainty - ea forum. https://forum.effectivealtruism.org/posts/kCBQHWqbk4Nrns8P7/model-based-policy-analysis-under-deep-uncertainty

Reeve, G., Swales, A., & Reed, J. (2009). Kaipara harbour sediments: Information review. Auckland Regional Council.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output. design and estimator for the total sensitivity index. Computer physics communications, 181(2), 259–270.

Schneider, V., Arcement Jr, G., et al. (1984). Guide for selecting manning's roughness coefficients for natural channels and flood plains (tech. rep.). United States. Federal Highway Administration.

Shen, J., Tong, Z., Zhu, J., Liu, X., & Yan, F. (2016). A new rapid simplified model for urban rainstorm inundation with low data requirements. Water, 8(11). https://doi.org/10.3390/w8110512

Smits, X. (2024). Supporting decision making under deep uncertainty techniques with hydraulic modeling [Master's thesis, TU Delft].

Sobol, I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their monte carlo estimates. Mathematics and computers in simulation, 55(1-3), 271–280.

Stanton, M. C. B., & Roelich, K. (2021). Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171, 120939.

Statistics New Zealand. (2018). 2018 Census place summaries | Stats NZ [[Accessed 24-06-2024]].

Stephens, S. A., Bell, R. G., & Lawrence, J. (2018). Developing signals to trigger adaptation to sea-level rise. Environmental Research Letters, 13(10), 104004. https://doi.org/10.1088/1748-9326/aadf96

Stephens, S. A., Lwarence, J., Allison, A., & Boyle-Gotta, A. (2021). Adaptive tools for decisions on compounding climate change impacts on water infrastructure.

Stephens, S. A., Wadhwa, S., & Tuckey, B. (2016). Coastal inundation by storm-tides and waves in the auckland region. Auckland Council, Te Kaunihera o Tāmaki Makaurau.

Sterman, J. D. (1994). Learning in and about complex systems. System dynamics review, 10(2-3), 291–330.

Swanson, D., Barg, S., Tyler, S., Venema, H., Tomar, S., Bhadwal, S., Nair, S., Roy, D., & Drexhage, J. (2010). Seven tools for creating adaptive policies. Technological Forecasting and Social Change, 77(6), 924–939.

Tonkin+Taylor. (2021). Coastal flood hazard assessment for northland region 2019-2020. (1012360.1000.v4). https://www.nrc.govt.nz/media/nfbhwhgs/t-t-cfhz-report-2021.pdf

Trindade, B., Reed, P., & Characklis, G. (2019). Deeply uncertain pathways: Integrated multi-city regional water supply infrastructure investment and portfolio management. Advances in Water Resources, 134, 103442.

Trindade, B., Reed, P., Herman, J., Zeff, H., & Characklis, G. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. Advances in Water Resources, 104, 195–209.

van Berchum, E. (2019). Rapid screening and evaluation of flood risk reduction strategies.

van Berchum, E., van Ledden, M., Timmermans, J., Kwakkel, J., & Jonkman, S. (2020). Rapid flood risk screening model for compound flood events in beira, mozambique. Natural Hazards and Earth System Sciences, 20(10), 2633–2646.

Walker, W. E., Haasnoot, M., & Kwakkel, J. (2013). Adapt or perish: A review of planning approaches for adaptation under deep uncertainty. Sustainability, 5(3), 955–979.

Watercare. (2024). Helensville and Parakai Servicing Strategy [[Accessed 24-06-2024]].

Watercare Services Limited. (2015). Wastewater treatment performance. https://www.watercare.co.nz/CMSPages/GetAzureFile.aspx?path=~%5Cwatercarepublicweb%5Cmedia%5Cwatercare-media-library%5Cwastewater-collection-treatment%5C2015_wastewater_treatment_performance_watercare.pdf&hash=aaa332c69c252b093aca40752be05827cd0497adaa91e27b5fa8dc7412d19085

WMO. (2019, September). United in science 2021. https://public.wmo.int/en/resources/united_in_science

Woetzel, J., Pinner, D., Samandari, H., Engel, H., Krishnan, M., Boland, B., Cooper, P., & Ruby, B. (2020, June). Will infrastructure bend or break under climate stress? (Tech. rep.). https://www.mckinsey.com/business-functions/sustainability/our-insights/will-infrastructure-bend-or-break-under-climate-stress

Zeff, H. B., Herman, J. D., Reed, P. M., & Characklis, G. W. (2016). Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways. Water Resources Research, 52(9), 7327–7346.

Zeff, H. B., Kasprzyk, J. R., Herman, J. D., Reed, P. M., & Characklis, G. W. (2014). Navigating financial and supply reliability tradeoffs in regional drought management portfolios. Water Resources Research, 50(6), 4906–4923.

Zhou, W., Zhu, Z., Xie, Y., & Cai, Y. (2021). Impacts of rainfall spatial and temporal variabilities on runoff quality and quantity at the watershed scale. Journal of Hydrology, 603, 127057.

Appendix A

Evaluation of a monitoring system

In this appendix two methods to evaluate signposts and monitoring systems will be described, from Haasnoot et al. (2018) and Raso, Kwakkel, Timmermans, and Panthou (2019). This underlies the last part of Section 2.4 which discusses the building blocks of a monitoring system.

Haasnoot et al. (2018)

Haasnoot et al. (2018) proposed a way of evaluating signposts based on Eckley et al. (2001) using the criteria found in Figure A.1. The three main criteria are salience or relevance, credibility, and legitimacy.

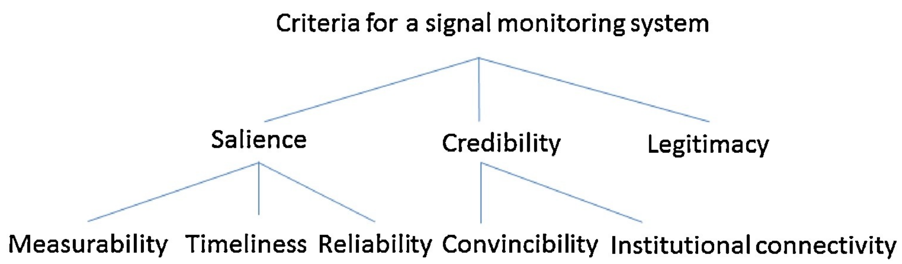


Figure A.1: Evaluation criteria for a monitoring system following Haasnoot et al. (2018) based on Eckley et al. (2001).

Salience is the relevance of a selected signpost. This means whether the selected signpost is relevant to the policy problem by describing important parts of the system or the plan. This criteria is divided into three subcriteria. ***Measurability*** indicates if a signpost or signal is observable. If it is less measurable, it is less relevant. ***Timeliness*** indicates if a signpost or signal is able to show changes with enough time to implement a new action. If a signpost can only show change at the last second or after the fact, that signpost is less timely and less relevant. Lastly, ***reliability*** is a measure of the probability that a signposts gives a correct signal. More probability of false or missed alarms means a signpost is less reliable and thus less relevant.

Credibility implies that a signpost should be scientifically and technically believable. This is to make the implementation of the monitoring system and follow-up actions acceptable. Credibility has two subcriteria: convincibility and institutional connectivity. ***Convincibility*** means a signpost is convincing to the monitoring system's users. This can be achieved through a scientific approach, or when there is consistency between the signposts and perceived developments. ***Institutional connectivity*** has to do with making sure signposts are politically believable. This means that the signposts take into account political, social, and decision contexts (Haasnoot et al., 2018).

Legitimacy has to do with general stakeholder engagement. If their interests and concerns have been taken into account in the creation of the monitoring system and selection of the signposts and signals, there is a broader support base for its implementation.

Raso, Kwakkel, and Timmermans (2019) and Raso, Kwakkel, Timmermans, and Panthou (2019)

Raso, Kwakkel, Timmermans, and Panthou (2019) use the criteria of relevance, observability, completeness, and parsimony to evaluate signposts for a monitoring system. These evaluation criteria form a base to take into account when building a monitoring system.

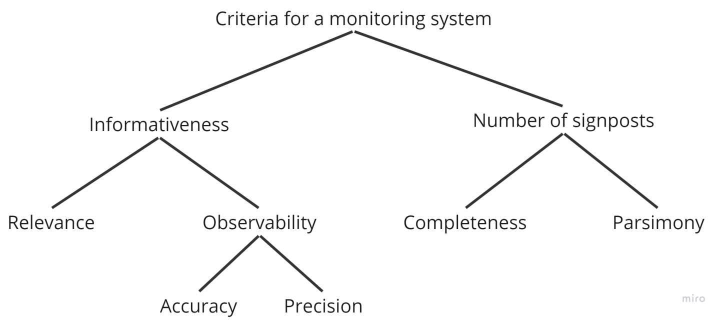


Figure A.2: Evaluation criteria for signposts based on the paper by Raso, Kwakkel, Timmermans, and Panthou (2019)

Relevance is similar to the salience criteria defined by Haasnoot and has to do with whether a signpost actually tracks the relevant critical uncertainties. Raso defines informativeness as relevance x observability. **Observability** goes further than the measurability concept from Haasnoot et al. (2018), also dealing with the quality of an indicator. Raso, Kwakkel, Timmermans, and Panthou (2019) decomposes it into two parts: accuracy and precision. ***Accuracy*** is a measure of the systematic error of the signpost. This shows how close to the actual parameter the estimate is. ***Precision*** is a measure of the noise present in the observations or the statistical variability of the signpost.

Completeness means all relevant uncertainties (those that affect the success of potential policy) are tracked. **Parsimony** means that as few signposts are used as possible while maintaining completeness. If two signposts have a high mutual dependency, one is most likely redundant according to (Raso, Kwakkel, Timmermans, & Panthou, 2019). Next to this, they state only signposts that actively affect a choice of policy should be used, as other signposts are unnecessary. In this way one signpost can potentially track multiple uncertainties, as long as changes in those uncertainties all lead to the same choice of policy.

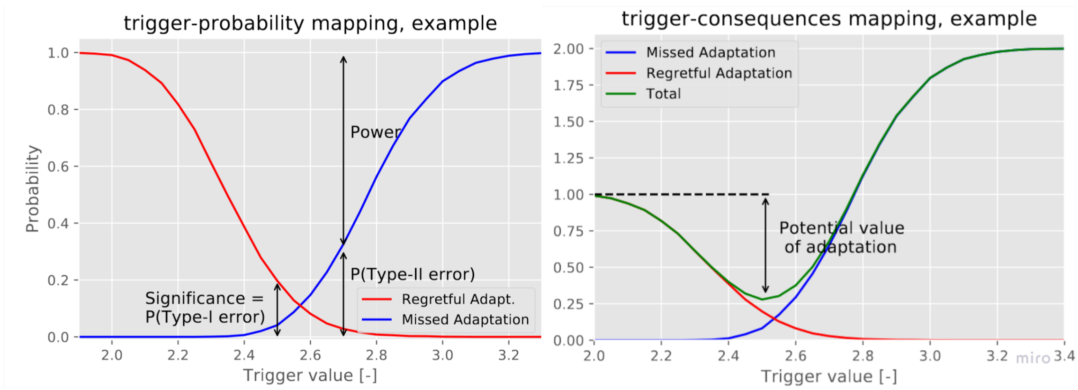


Figure A.3: Trigger-probability and trigger-consequences mapping from Raso, Kwakkel, and Timmermans (2019)

Next to the evaluation of signposts, Raso, Kwakkel, and Timmermans (2019) also evaluates the quality of specific triggers based on trigger-probability and trigger-consequences mapping which can be seen in figure A.3. Trigger-probability mapping uses the probability of a regretful action or missed adaptation (type I and type II errors respectively). For this, exploratory modelling and stochastic modeling are combined. The interplay between these errors, as well as their consequences (given in the trigger-consequences mapping), determines whether a trigger is effective. In the case a trigger is not effective, either the signpost, the policy action, or the trigger should be changed. In this way, they present a way to iteratively design triggers.

Appendix B

Different combinations of RDM and DAPP from literature

This appendix explains various different ways Robust Decision Making (RDM) and Dynamic Adaptive Policy Pathways (DAPP) can or have been combined from literature.

B.1 Kwakkel et al. (2016a) and Groves et al. (2019)

Kwakkel et al. (2016a) proposed two ways to combine existing RDM and DAPP methodologies. The first is to start with a pathways map created through either MORO or in a participatory manner, and to stress-test these plans in order to iteratively strengthen them. The second is to use the RDM cycle to iteratively develop adaptation pathways by using the vulnerabilities identified through scenario discovery. They also suggest that this second way could identify potential signposts and signals, laying the basis for a monitoring system.

Groves et al. (2019) suggests using RDM to identify vulnerabilities for low-regret policy options across a wide range of futures. The identified vulnerabilities can then be used to define and evaluate signposts, signals, and triggers for the low-regret options, and pathways are used to visualize which policy adjustments are needed once triggers for vulnerabilities are reached. In this case, the identified vulnerabilities are used as the adaptation tipping points for DAPP. In this case as well, there is a logical extension from the identified vulnerability to the development of a monitoring system through signposts, signals and triggers.

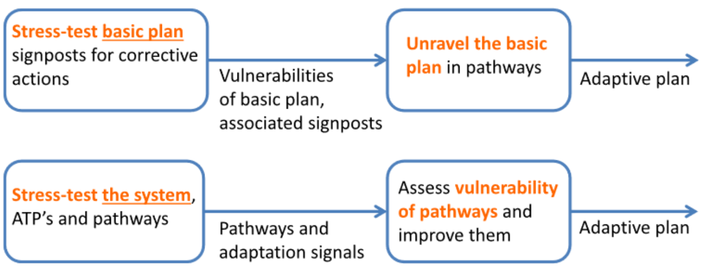


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Figure B.1: Two proposed ways of combining RDM and DAPP by Kwakkel et al. (2016a)

B.2 Colorado basin study

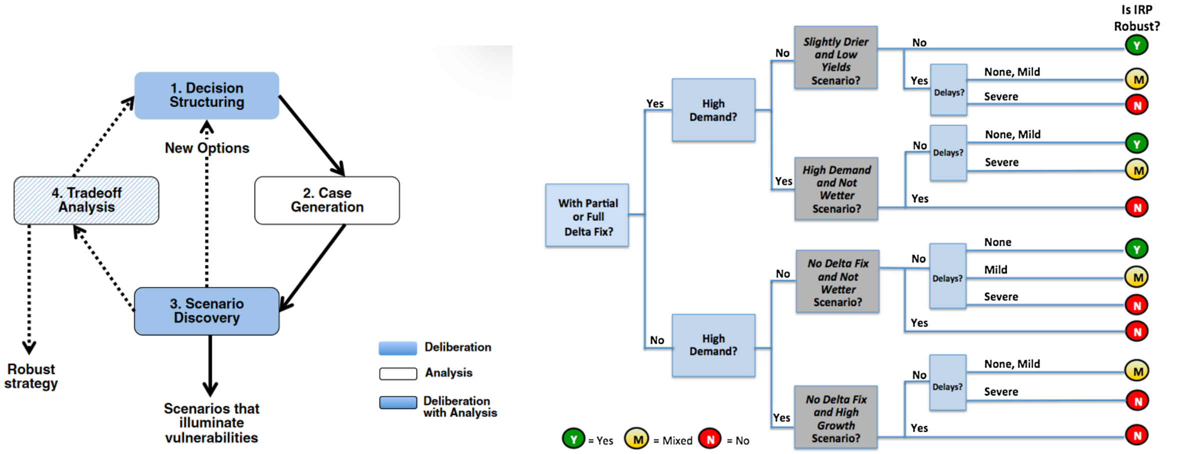


Figure B.2: Methodology to develop indicators for a monitoring system from Groves et al. (2015). On the left is the methodology which looks a lot like the RDM process. The focus for their research was on the solid black lines. On the right is the monitoring system they developed, which shows when the proposed plan is still robust. This monitoring system is based on various signposts from the identified vulnerabilities.

In the Colorado basin, Groves et al. (2013, 2015) used the RDM process to help build a monitoring system, laying the groundwork for an adaptive plan. First, a pre-specified policy was stress-tested to identify vulnerabilities. The identified vulnerabilities were split up into multiple signposts with rudimentary triggers such as "high demand", which forms the monitoring system as seen on the right in Figure B.2.

Research in the same area was also done by Bloom (2015). They went further, developing pathways based on the vulnerabilities identified through scenario discovery as can be seen on the left in Figure B.3. The vulnerabilities were used to find signposts and triggers, which in turn lead to the development of three basic pathways. These pathways were not further specified than simply being able to deal with the identified vulnerabilities, as can be seen on the right in Figure B.3. It is suggested to fill the pathways with robust policies as identified by the results of the tradeoff assessment in Step 4 in Figure B.3, however.

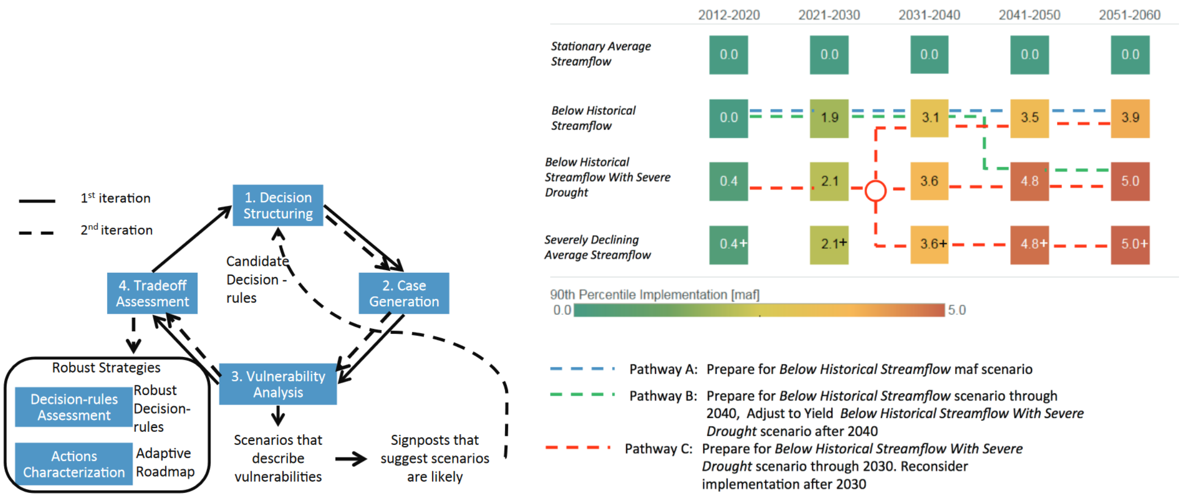


Figure B.3: Methodology to develop signposts and triggers for a monitoring system taken from from Bloom (2015). On the left is the methodology, which shows the development of an adaptive plan. On the right is the developed roadmap for the adaptive plan, where three different pathways are proposed based on the development of possible vulnerabilities. The precise policies making up these pathways have not been detailed further, although it is suggested to use the results of the tradeoff assessment in Step 4 on the left.

B.3 Molina-Perez (2016)

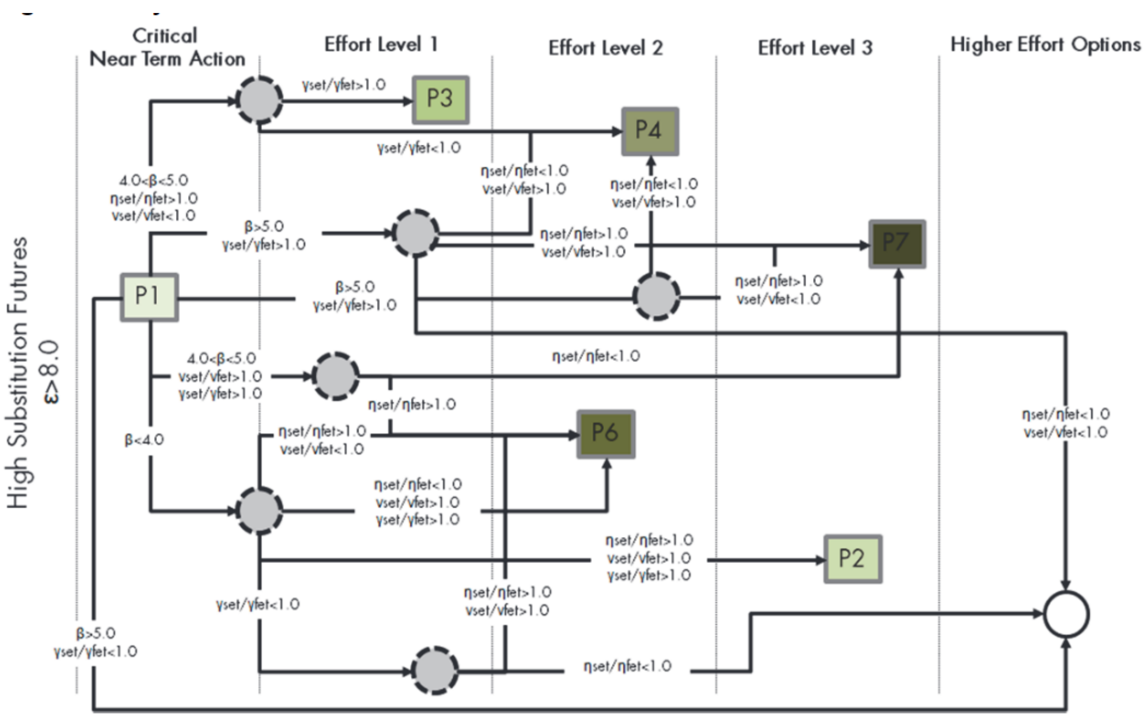


Figure B.4: Molina-Perez's way of visualizing the vulnerabilities identified through RDM. Pathways sharing common characteristics are labeled with their conditions. Nodes describe when a pathway sharing common conditions splits up into multiple different pathways. Each pathway eventually leads to a policy regime labeled from P1 to P7 and distinguished in effort level from necessary near-term actions on the left to high-effort long-term actions on the right (Molina-Perez, 2016).

Molina-Perez (2016) also used RDM to develop policy pathways. First scenario discovery was used to identify vulnerabilities for different policy regimes. Based on these identified vulnerabilities and sequencing rules, pathways were developed as seen in Figure B.4.

Labels were used to describe the conditions under which a pathway performed well, which can also be seen as the converse of the identified vulnerabilities. When performance between policies diverged, nodes were used to indicate the change in conditions under which this happened. The labels describing the performance of the pathways can also be seen as a monitoring system, with the variables chosen as signposts and their thresholds as adaptation tipping points.

B.4 Ramm et al.

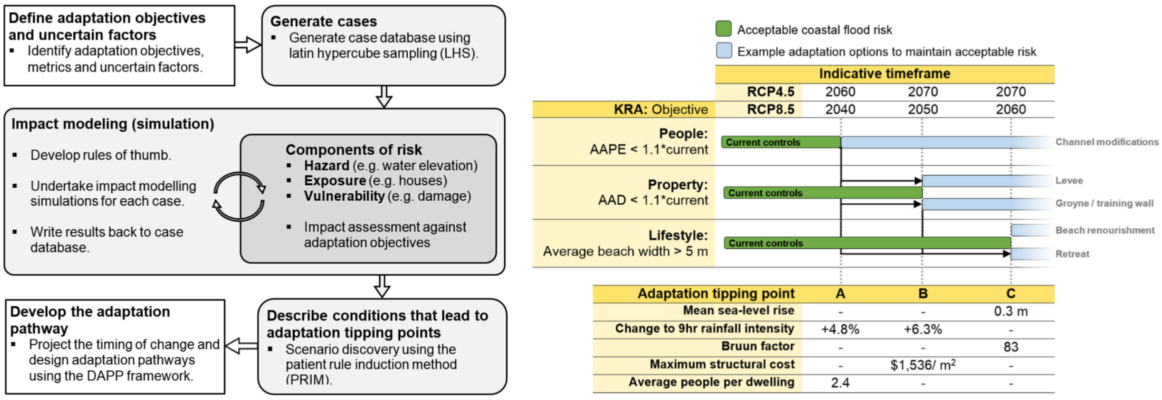


Figure B.5: Method to develop DAPP from RDM from Ramm et al. (2018a) on the left. The different thresholds from the vulnerabilities identified through RDM are placed under each adaptation tipping point in the figure on the right. Transient scenarios are included above the DAPP map to give an estimate of the use-by year of different policies.

Ramm et al. (2018a, 2018b) used RDM to develop DAPP for a case study in Australia. First scenario discovery was used to identify vulnerabilities, which were described as multi-dimensional adaptation tipping points. Next, transient scenarios were generated based on the rates of change of key uncertainties and the lead-time of policy options. These scenarios were used to estimate the use-by year of chosen policies in order to map adaptation pathways.

It is noted in this research that the use of RDM to find adaptation tipping points constitutes an improvement over current techniques because it allows for seeing interactions between different uncertain factors. Possible future improvements are also mentioned: research stopped at the mapping of pathways, and the identified vulnerabilities were not used to identify signposts, signals, and triggers.

B.5 Mannucci (2021)

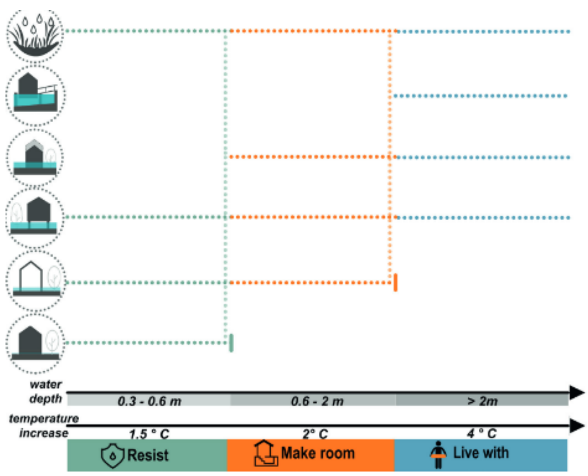


Figure B.6: Mannucci's DAPP map. Each pathway (Resist, Make room, Live with) is made up of multiple different policies which can be seen on the y-axis. the x-axis shows the different signposts with corresponding thresholds, as well as the pathways those thresholds correspond with (Mannucci, 2021).

Mannucci (2021) used the vulnerabilities identified through RDM to inform the design of DAPP for urban adaptation to flooding in the Rome region. Multiple combinations of different policies were stress-tested, and the identified vulnerabilities were used to define their adaptation tipping points to develop robust pathways.

No explicit effort was put into the development of a monitoring system using the identified vulnerabilities, although the x-axis in Figure B.6 shows two signposts: water depth and temperature increase, with thresholds which can be seen as tipping points.

B.6 Research triangle

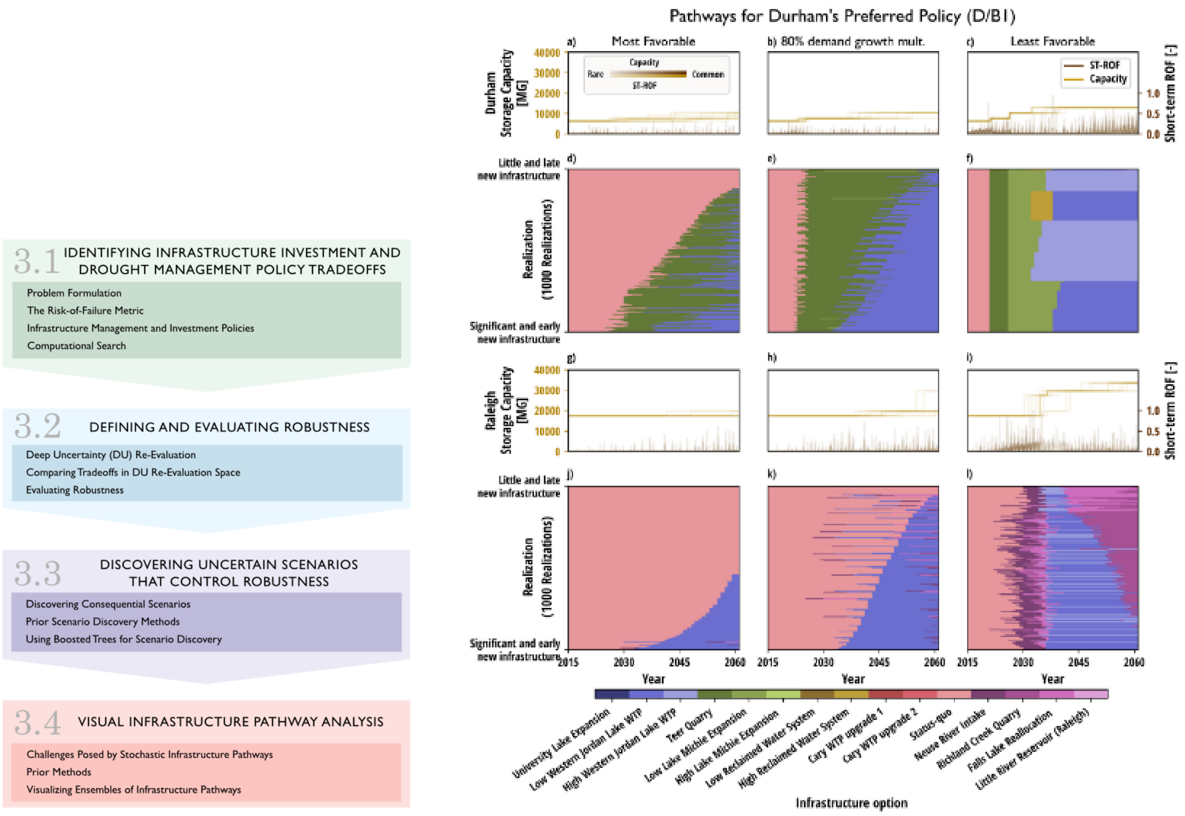


Figure B.7: Methodology and pathways for the research triangle's DU pathways (Trindade et al., 2019). The pathways are meant to protect Durham's preferred policy. From left to right the pathways are set for the most to least favorable potential future scenario. On the bottom are the effects of Durham's preferred policy in Raleigh, a neighboring city.

In the "Research Triangle" area in South Carolina, Herman et al. (2014, 2016), Trindade et al. (2017, 2019), and Zeff et al. (2014, 2016) have worked on developing Deeply Uncertain (DU) Pathways. Trindade et al. (2019) summarizes this process. Scenario discovery is used in conjunction with a sensitivity analysis to help protect or adapt pre-specified policy options from the most important external uncertainties. The created pathways then use dynamic "Risk-of-Failure" (ROF) triggers rather than adaptation tipping points to prompt adaptation. ROF triggers can be either short- or long-term, and can change based on new data. In this way, they act both as a monitoring system and as an adaptation tipping point. One issue with the ROF trigger is that due to the inclusion of multiple signposts with different weights, the process behind its calculation can be quite complex and the trigger itself can be difficult to interpret.

Appendix C

Helensville wastewater treatment plant

In this appendix additional data on the Helensville wastewater treatment plant will be given. This includes the surroundings of the treatment plant in Section C.1, the current hydraulic forcing in Section C.2, and different photos of the case site as provided by Watercare New Zealand in Section C.3. This includes pictures of the location of the treatment plant, pictures of high water events, pictures of high pond levels, and finally a topographic survey of the plant's embankments.

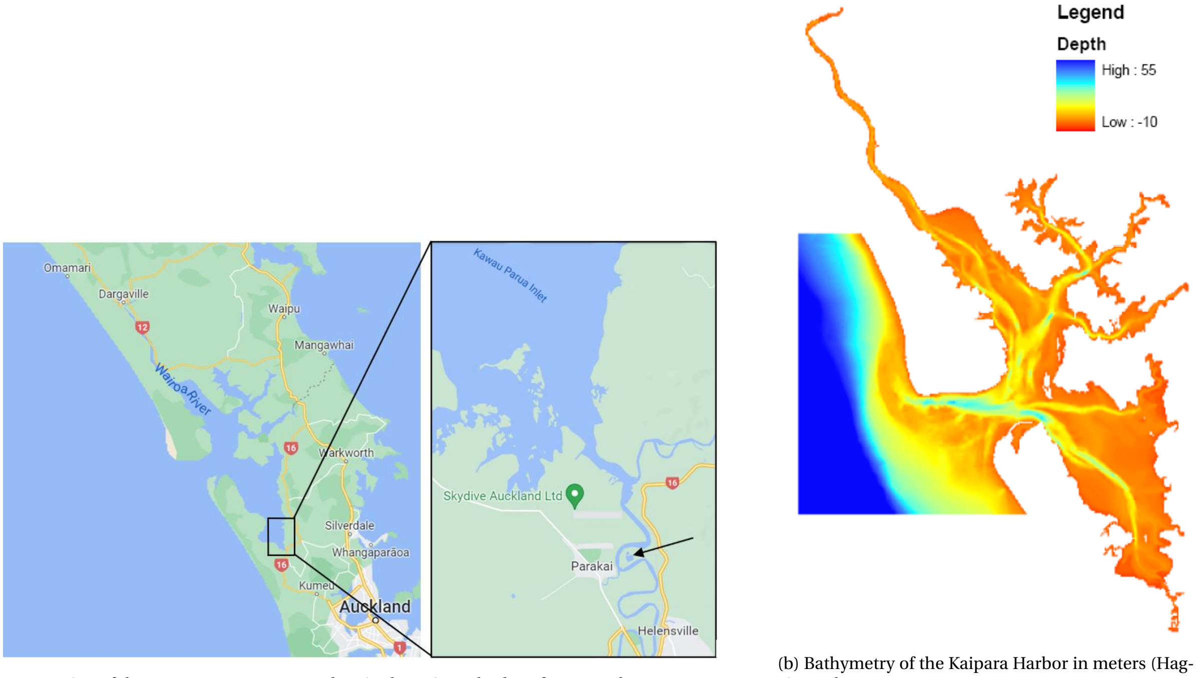
C.1 Wastewater treatment plant's surroundings

This subsection dives deeper into the surroundings of the wastewater treatment plant to better understand system behavior and the risks affecting the plant. It discusses, in order, the Kaipara harbor, Kaipara river catchment and the Kaipara river which flows past the plant.

C.1.1 Kaipara harbor

The Kaipara harbor, visible in Figure C.1, is located on New Zealand's North Island, just north of Auckland. The harbor is quite broad and shallow with clearly defined drainage channels, which can be seen in Figure C.1b. Almost 43% of the estuary is intertidal, with a surface area of around 947 km^2 at high spring tide and 538 km^2 at low spring tide (Haggitt et al., 2008; Heath, 1975). A large reason for this is the high sedimentation in the harbor, which is also the reason the harbor has become increasingly ebb-dominated (Bosboom & Stive, 2021; Haggitt et al., 2008; Reeve et al., 2009). The high sedimentation rate also leads to the locations of the channels and sandbanks constantly shifting, although there is a general lack of knowledge on the exact speed of these movements (Haggitt et al., 2008; Hume et al., 2003; Reeve et al., 2009).

The important takeaway is that the harbor is a dynamic place, where due to sedimentation intertidal flats and channels are constantly shifting. Over a few decades, this can affect the propagation of storm surge and the tidal amplitude, both of which are important factors for the water level at the wastewater treatment plant.



(a) Location of the wastewater treatment plant in the Kaipara harbor (from google maps)

(b) Bathymetry of the Kaipara Harbor in meters (Haggitt et al., 2008)

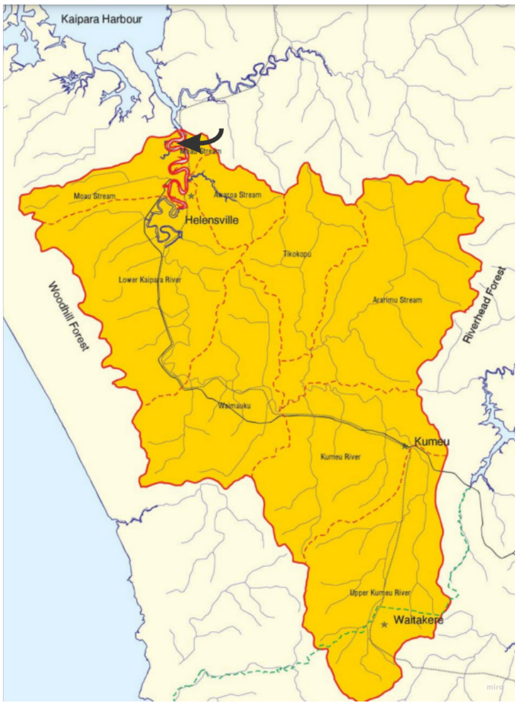
Figure C.1: Topography and bathymetry of the Kaipara harbor. The estuary is around 60 kilometers long from North to South (Reeve et al., 2009).

C.1.2 Kaipara river catchment

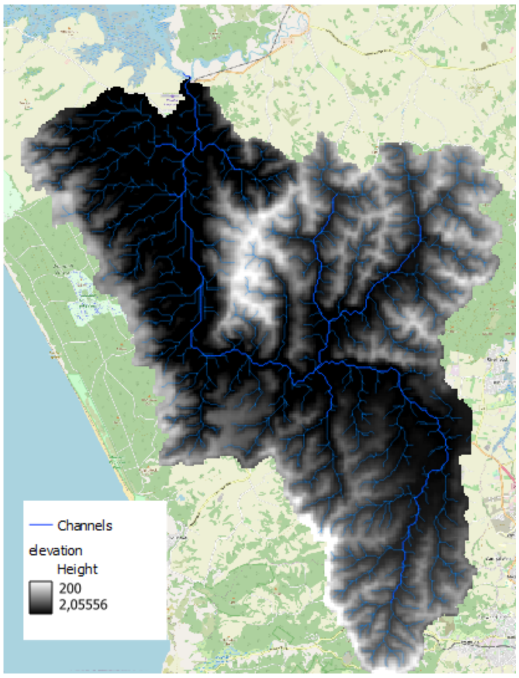
The Kaipara river catchment, where the wastewater treatment plant is located can be seen in Figure C.2. The topography of the catchment varies significantly. At the downstream end mangrove forests and intertidal flats separate the catchment from the Kaipara harbor, whereas in the upstream areas of the catchment large mountain ranges separate the catchment from both the Auckland harbor and the open coast. This difference in topography leads to slopes up to 17 degrees, with an average around 3.5 (Auckland Council & (LINZ), 2020).

Land use in the catchment is mostly rural. Almost 64% of the catchment is used as pasture for cattle and sheep, while urban use only accounts for about 2.5%. Surface water takes up less than 0.5 percent. (Bibby & Webster-Brown, 2005; Green & Daigneault, 2018; Landcare Research, 2021; Reeve et al., 2009). This has several effects on potential compound flooding of the wastewater treatment plant. First, the main use of the catchment is pasture or small crops, which in general have a low hydraulic roughness compared to cases where more vegetation is present (Chow, 2009; Schneider, Arcement Jr, et al., 1984). This could mean potential storm surge spreads further. Second, the low surface water percentage indicates any rainfall, in general, is not retained upstream but runs off. This quick runoff could be exacerbated by the large slopes in the catchment.

Soil characteristics also vary throughout the catchment, and with depth. In general the shallow soil layers consist mostly of silt and clay in the lower reaches of the catchment, and sand elsewhere (Haggitt et al., 2008; Reeve et al., 2009). Deeper soil layers in the catchment consist mostly of coarser, permeable sands. The small particle size in the lower reaches leads to significant sediment transport, 13.7 tons per year in 2014 (Green & Daigneault, 2018). At those current transport rates, the downstream intertidal flats are growing by 7 mm/year. This growth rate is almost double any of the other intertidal flats found throughout the Kaipara estuary (Green & Daigneault, 2018). The changing bathymetry introduces uncertainty about the propagation of storm surge and tidal amplitude, similarly to the behavior of Kaipara harbor mentioned earlier.



(a) The Kaipara river catchment including the different rivers and streams. The black arrow demarcates the location of the wastewater treatment plant. The Kaipara river flows past the treatment plant. The catchment is 26km long and 6km wide (Auckland Regional Council, 2001).



(b) Elevation map for the Kaipara river catchment. The height goes up to 256.8 meters, but is maxed at 200 meters for better visibility (Auckland Council & (LINZ), 2020)

Figure C.2: Location and elevation of the Kaipara river catchment

C.1.3 Kaipara river

The Kaipara river is the main river that functions as drainage for the entire catchment, and where the wastewater treatment plant discharges its effluent. It also has a strong tidal influence (Dejeans et al., 2022; Mitchell et al., 2017; Stephens et al., 2016). At the upstream part it is filled by various small streams, after which it flows past Helensville and the wastewater treatment plant as can be seen in Figure C.2a. River flows are mostly due to drainage, as the streams in the upper part of the catchment are intermittent. These flow can differ greatly. A 50 year ARI event has a peak flow of around 305 m^3/s, while low flows can be down to 0.1653 m^3/s for a 7-day Mean Annual Low Flow (MALF) (Auckland Regional Council, 2001; Ingley, 2021; Stephens et al., 2016). This indicates that flows in the river are most likely only due to either tides or precipitation events.

C.2 Hydraulic forcing of the Kaipara river catchment

In this section three main aspects of the current forcing of the Kaipara river catchment will be discussed: precipitation, wave climate and storm surge, and the tides.

C.2.1 Precipitation

The Kaipara river catchment is quite wet. From the Helensville raingauge dataset, which holds records between 2014 and 2019, the rainfall frequency is found to be around 55%. The catchment is also quite warm. Many surrounding measuring stations have not even recorded any temperatures under 0°C. This means that precipitation consists almost exclusively of rainfall (Bell et al., 2018). The amount of rainfall varies somewhat throughout the catchment. In the mountainous areas it is higher, with annual median rainfall levels of 1600 mm, while at the intertidal flats this drops to 1300 mm (Bell et al., 2018).

The current day extreme rainfall for the area can be seen in Figure C.3. Increases in temperature have been shown to further increase the frequency and intensity of extreme rainfall events. The increase in rainfall depth can be anywhere between 7% and 9% per extra degree of warming for a 24 hour storm, which is an additional source of uncertainty (Bell et al., 2018).

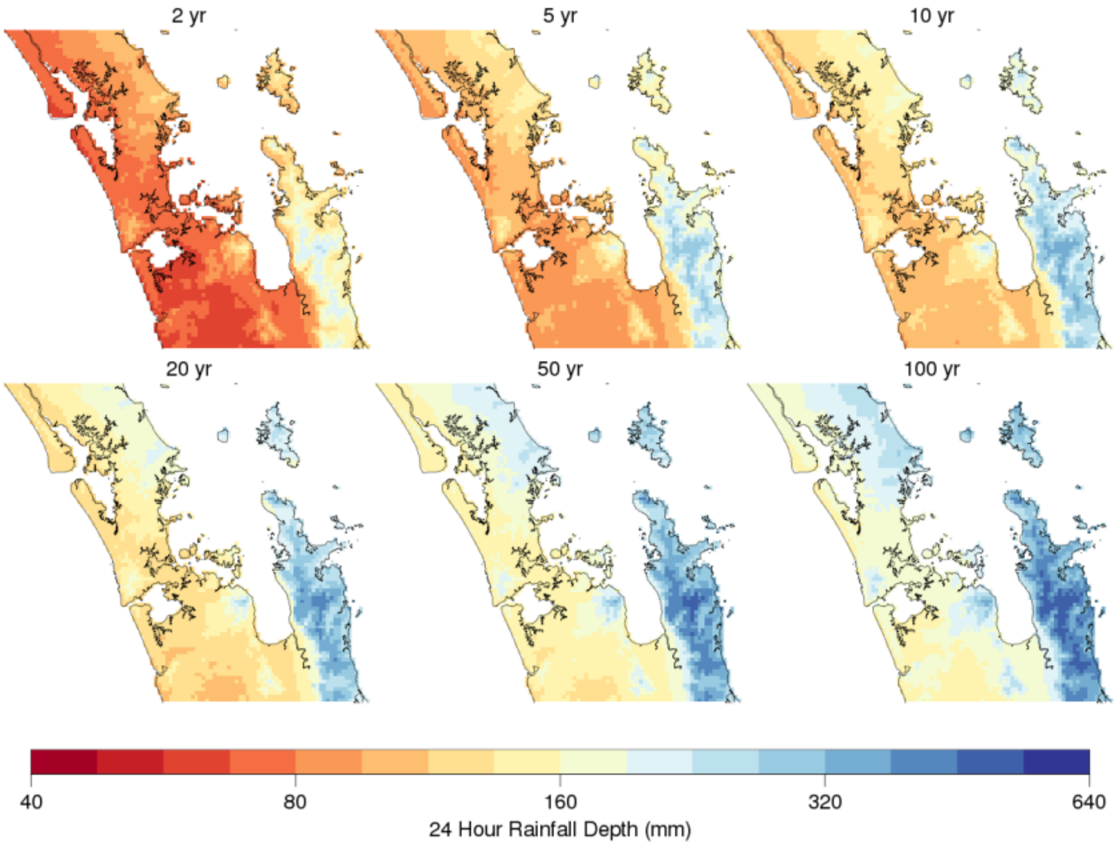


Figure C.3: Total rainfall for 24 hour storms of differing return periods in the Auckland region. The scale of the rainfall depth is logarithmic (Bell et al., 2018).

C.2.2 Waves and storm surge

Waves are most likely not relevant at the wastewater treatment plant. The waves that are present are wind-driven and created within the estuary. As mentioned before, the Kaipara harbour is around 60 kilometers long (North to South). The wind only comes from this direction less than 5% of the time (Stephens et al., 2016). Looking at a sustained 11 km/hr wind, which happens less than 0.5% from this direction, the significant wave height would be around 20 cm when it reaches the first intertidal flats at the downstream end of the Kaipara river catchment. This wave height most likely damps out on these flats and vegetation before it reaches the wastewater treatment plant, which is 3.5 km upstream.

Using the tidal gauge at Helensville a skew surge analysis was conducted by Stephens et al. (2016) to calculate the difference between the maximum recorded sea-level during a tidal cycle, and the predicted maximum astronomical tidal level (Batstone et al., 2013). Based on this dataset, a generalized pareto distribution was used to calculate extreme values. The 95% confidence range which indicates the interval of values wherein the real value is likely to fall is quite broad as can be seen in Figure C.4, indicating predictions of the storm surge are not very precise.

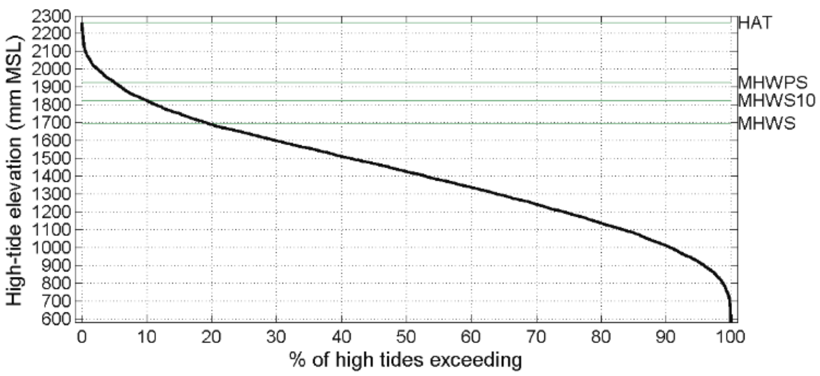
AEP = annual exceedance probability; ARI = average recurrence interval; GPD = generalised Pareto distribution fit to independent peaks over 230 mm threshold. All elevations calculated relative to MSL.

AEP	ARI	GPD max. likelihood (mm)	GPD lower 95% confidence interval (mm)	GPD upper 95% confidence interval (mm)
0.63	1	570	445	778
0.39	2	657	486	962
0.18	5	776	535	1252
0.10	10	870	569	1511
0.05	20	967	601	1812
0.02	50	1100	638	2281
0.01	100	1204	664	2700
0.005	200	1311	688	3184
0.002	500	1457	716	3939
0.001	1000	1571	735	4613

Figure C.4: Storm surges for differing return periods. Note that the 95% confidence intervals are very broad, especially for more extreme events (Stephens et al., 2016)

C.2.3 Tides

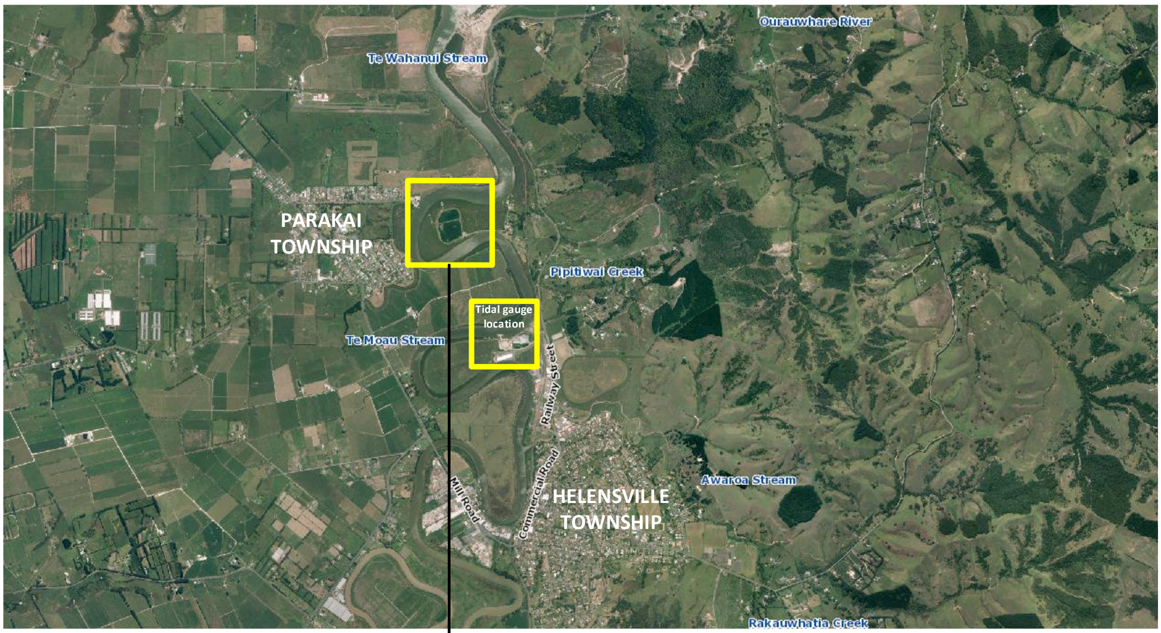
Tides have a large influence on the water level in the Kaipara harbor. Due to the large number of intertidal flats throughout the estuary, tides are amplified (Stephens et al., 2016). The wastewater treatment plant uses this high tidal range to discharge its effluent. Data from the tidal gauge at Helensville can be seen in Figure C.5.

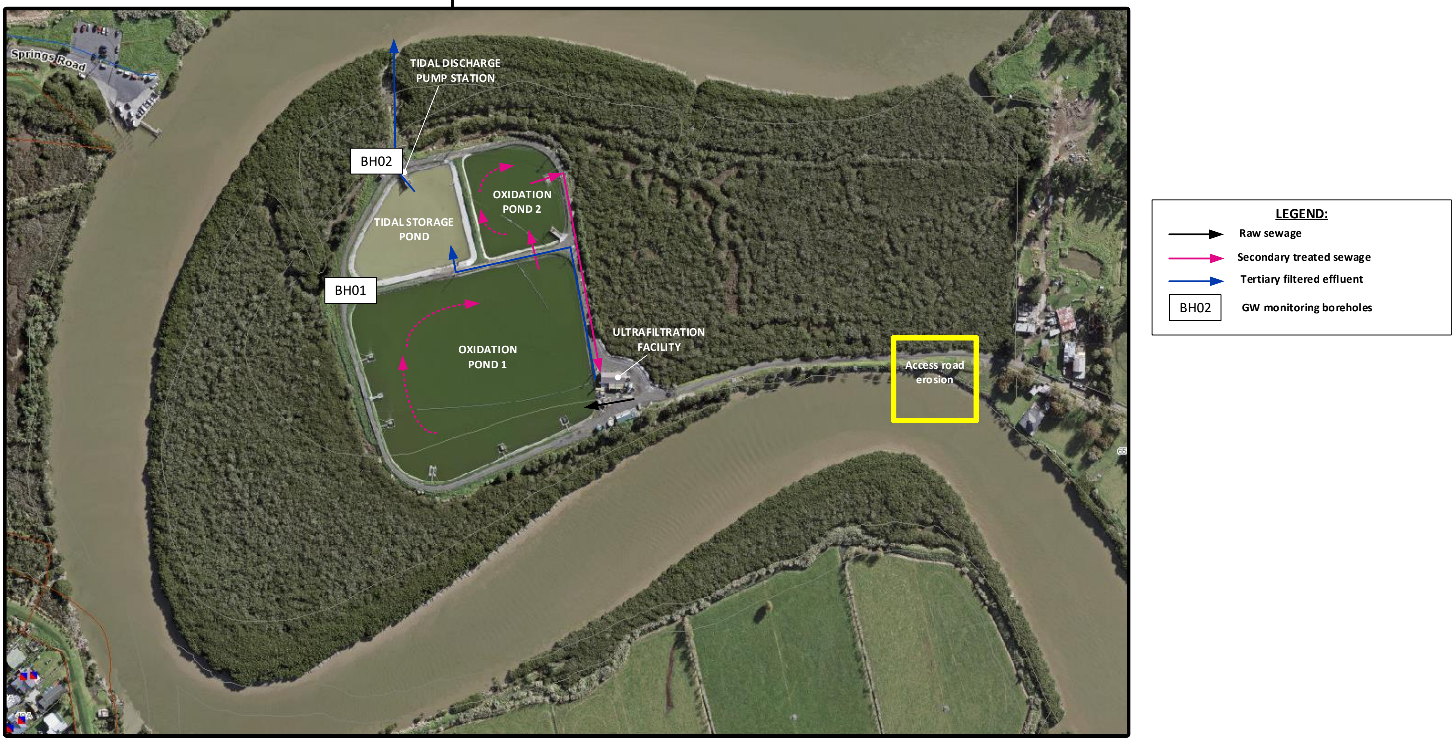


Tide	elevation (mm MSL)
M2	1371
S2	325
N2	231
MHWPS	1926
MHWS	1696
HAT	2264

Figure C.5: High tide exceedance curve and tidal components for the Helensville tidal gauge (Stephens et al., 2016)

C.3 Case site photos


Ourauwhare River
Te Wahanui Stream
PARAKAI TOWNSHIP
Pipitiwai Creek
Tidal gauge location
Te Moau Stream
Railway Street
Commercial Road
Mill Road
HELENSVILLE TOWNSHIP
Awaroa Stream
Rakauwhatia Creek


Springs Road
TIDAL DISCHARGE PUMP STATION
BH02
OXIDATION POND 2
TIDAL STORAGE POND
BH01
OXIDATION POND 1
ULTRAFILTRATION FACILITY
Access road erosion
LEGEND:
Raw sewage
Secondary treated sewage
Tertiary filtered effluent
BH02
GW monitoring boreholes

HIGH TIDE AND TIDAL EROSION PHOTOGRAPHS

Figure 1: 21st March 2019 Super full moon spring tide (3.8m above MLLW). Access road erosion also observed. This has accelerated (see next figure)

Figure 2: Access road erosion on the 9th September and 3rd October 2019. Approximately 0.5m erosion since the previous picture taken on 21st March 2019.

Figure 3: High tide at the boat ramp opposite the Helensville WWTP during the March 2019 super full moon. Photos taken just after peak levels as tide was receding.

WET WEATHER IMPACTS AT WWTP

Figure 1: 7th July 2017 wet weather event (60mm over 2 days). Pond levels at 1815mm. The pond will overtop the dam embankment into the harbour at 1.85m.

Figure 2: 9th September 2017 wet weather event (125mm between 3rd and 11th Sep). Pond levels at 1660mm. The pond will overtop the dam embankment into the harbour at 1.85m.

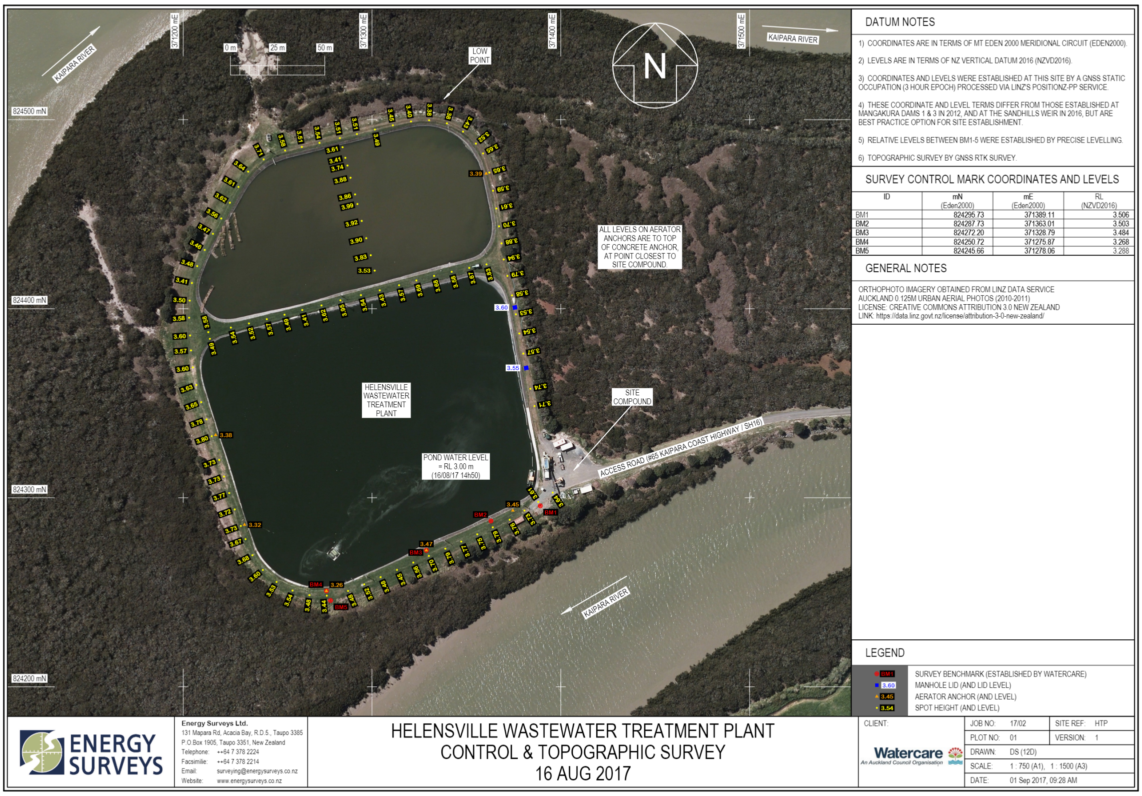


Figure C.6: Crest elevation of the pond embankments surrounding the wastewater treatment plant (Stephens et al., 2021)