Joint Research Programme
BTO 2024.102| December 2024

Decision Making under Deep Uncertainty

Methods and application for the drinking water sector

Joint Research Programme

KWR

Bridging Science to Practice

Colophon

Decision Making under Deep Uncertainty

Methods and application for the drinking water sector

BTO 2024.102 | December 2024

This research is part of the Joint Research Programme of KWR, the water utilities and Vewin.

Project number

404300/033

Project manager

I. (Ina) Vertommen, MSc

Client

BTO - Verkennend onderzoek

Author(s)

dr.ir. J. (Joeri) Willet, F. (Federico) Andelsman Alvarez, P. (Peter) van Thienen, PhD

Quality Assurance

Prof. D.A. (Dragan) Savic, FREng

Sent to

This report is distributed to BTO-participants.

Report becomes public one year after publication.

Keywords

Deep uncertainty, decision making

Year of publishing

2024

More information

dr.ir. J. (Joeri) Willet

T 06-25460557

E joeri.willet@kwrwater.nl

PO Box 1072

3430 BB Nieuwegein

The Netherlands

T +31 (0)30 60 69 511

E info@kwrwater.nl

I www.kwrwater.nl

Management summary

Authors Joeri Willet, Federico Andelsman-Alvarez, Peter van Thienen.

Traditional planning methods are ill-suited to handle developments subject to deep uncertainty. Sources of deep uncertainty can be global, such as climate change, or local, such as stakeholder preferences. Methods for Decision Making Under Deep Uncertainty (DMDU) exist and are mature enough to be implemented in the context of the Dutch drinking water sector. In this research we elaborate on uncertainty as a concept, the key ideas of DMDU, the availability of DMDU methods, and provide a demonstration of their use based on a simplified synthetics case study. The synthetic case study represents a situation where the water level in an aquifer is connected to extractions for human use. In the case study the Engineering Options Analysis method is used to evaluate how adaptation measures perform over a wide range of possible futures, which helps decision makers choose between alternative strategies. Based on lessons from this case study we also suggest that the use of DMDU methods benefits from a clear distinction between adaptation and mitigation measures.

Interest: Deep Uncertainty, Decision Making
The presence and impact of deep uncertainty on the water sector is explored, methodological approaches are elaborated, and a synthetic case study is presented.

Method: Literature review, questionnaires, EOA, and DAPP
A literature review is used together with a questionnaire to explore deep uncertainty in the water sector from a scientific and from a practical perspective. Engineering Options Analysis and Dynamic Adaptive Policy Pathways are used to explore a synthetic case study.

Results: Gap in science and practice, method availability and applicability
The literature and questionnaire results show that there seems to be a gap between science and practice concerning the perception of the sources of deep uncertainty that affect the Dutch drinking water sector. DMDU methods are available and applicable to drinking water challenges, but require careful selection to ensure that the method is suitable for the specific case at hand. Moving towards an adaptive approach, a key idea in DMDU, requires a clear distinction between adaptation and mitigation measures.

Implementation: Multi risk and learning process
Adaptive, rather than static, approaches are needed when dealing with deep uncertainty. DMDU methods explicitly provide decision makers with an iterative process to help multiple stakeholders reach a joint decision.

The Report
This research is reported in report *Decision Making under Deep Uncertainty:* Methods and application for the drinking water sector (BTO-2024.102).

The complexity and interconnectedness of human systems has grown to the point where traditional (deterministic, stochastic, or scenario based) approaches to planning and design of systems are no longer sufficient to place confidence in their long-term success. To move beyond traditional planning approaches requires thinking about local and global developments from a different perspective, a perspective which acknowledges the presence of deep uncertainty. Over the last decades the field of Decision Making Under Deep Uncertainty (DMDU) has: 1) demonstrated the need to act on sources of deep uncertainty to ensure continued functioning of human systems, 2) developed methods to make decisions in the face of deep uncertainty. This research explores the awareness and adoption of these methods within the (Dutch) drinking water sector, provides and overview of promising DMDU methods, and applies DMDU methods to a synthetic case-study.

Drinking water professionals in the Netherlands are aware of many source of uncertainty that can influence the functioning of the drinking water supply system. A comparison with recent scientific literature shows that there is a disconnect between research and practice. Research tends to focus on sources of (deep) uncertainty resulting from global scale processes (such a climate change). Responses from experts in the field recognise these processes as sources of uncertainty, but do not necessarily characterize them as 'deeply uncertain'. This disconnect between science and practice was identified based on a limited questionnaire and requires further investigation.

Method development in the field of DMDU has produced many methods. The most common methods, discussed in this report, are: Robust Decision Making, Dynamic Adaptive Planning, Dynamic Adaptive Policy Pathways, Info-Gap Theory, and Engineering Options Analysis. Due to the strengths and weaknesses of each method it is important to evaluate their applicability on a case by case basis. A preliminary framework/taxonomy for method selections is presented.

A synthetics case study was developed to explore the potential measures to deal with declining aquifer levels as a result of extractions to cover drinking water demand. In this synthetic case study we demonstrates Engineering Options Analysis as a DMDU method and its potential application in the Dutch drinking water context. Exploratory modelling, with the EMA Workbench, was used to investigate the resulting water levels in an aquifer when applying several combinations of measures under many different scenarios.

Through the case study it became apparent that for effective use of DMDU methods a clear distinction between adaptation and mitigation measures relating to the source of deep uncertainty must be made. We stipulate that such a distinction is needed to account for the influence the decision maker has on the source of deep uncertainty. The more influence, the likelier mitigation measures are applicable. Less influence requires adaptive planning, in line with the key ideas of DMDU.

More information
dr.ir. J. (Joeri) Willet
T 06-25460557
E Joeri.willet@kwrwater.nl

PO Box 1072
3430 BB Nieuwegein
The Netherlands

Contents

1 Introduction

1.1 Motivation and goal

The complexity and interconnectedness of human systems has grown to the point where traditional (deterministic, stochastic, or scenario based) approaches to planning and design of systems are no longer sufficient to place confidence in their long-term success. They key reason for this is that there is too much uncertainty surrounding planetary and societal developments to remain in these traditional approaches. Some sources of uncertainty can be denoted as 'deeply uncertain' and are an integral part of complex systems involving feedback mechanisms, nonlinear interactions, and time delays (J. H. Kwakkel & Haasnoot, 2019a). An often cited source of deep uncertainty is climate change. Current climate modelling cannot accurately include all the complexity of the climate system, uncertainty of future emissions, tipping points, climate sensitivity, social impacts and human behaviour. An understanding of these individual aspects is not sufficient, the interactions between them is also needed. For the drinking water sector water demand and water availability are often cited as sources of deep uncertainty. Water demand depends on highly uncertain factors such as population size, which in turn is influenced by migration, and behaviour. Water availability is closely linked to changes in climatic conditions, which are also subject to deep uncertainty.

Despite more than a decade of research, awareness and appropriate actions to deal with deep uncertainty in the drinking water sector are still in their infancy. Due to the long lifetime of drinking water infrastructure, which makes it susceptible to deep uncertainty over a long period, it is important for the sector to become familiar with, and to start employing methods to deal with deep uncertainty. The objectives of this research are twofold: to make an inventory of the potential sources of deep uncertainty in the drinking water sector, and to give recommendations concerning the most suitable methods for Decision Making under Deep Uncertainty (DMDU) in relation to these sources of uncertainty. Both of these objectives focus on the context of the drinking water sector.

1.2 Approach and contents

The general approach of this research is to demonstrate academic knowledge/methods on DMDU through a case study which is representative for the drinking water sector. This approach is reflected in the structure of this report; Section 2 elaborates on the concept of 'uncertainty', in Section 3 elaborates on deep uncertainty in the drinking water sector, in Section 4 a case study representative for the drinking water sector is presented, Section 0 is a discussion on theoretical challenges within DMDU, and Section 0 provides conclusions and a set of recommendations,

2 Uncertainty in system planning and design

This section elaborates on uncertainty as a concept, methods for its quantification, and the potential consequences of ignoring it.

2.1 Recognizing the presence of uncertainty

Forecasts serve a very clear purpose in describing what is considered the most likely development of a system over time. In most cases, we cannot know the true likelihoods of such forecasts. Knowledge about the aleatory uncertainty (the random and unpredictable nature of a physical system) can help to set uncertainty bounds on forecasts; for epistemic uncertainty (lack of knowledge or understanding of the system's quantities and processes), this may become more difficult or even impossible (in case of "unknown unknowns" that may occur in incompletely understood processes). We illustrate the inherent presence of uncertainty with examples from different areas.

Climate change: the IPCC climate scenarios (IPCC, 2021)provide forecasts for the mean global surface temperature for the rest of this century. For each of the SSP scenarios (see Figure 1), a probability distribution of temperature trajectories is presented. This distribution represents the aleatory uncertainty of the underlying models and the part of the epistemic uncertainty that represents the differences in the inclusion, parameterization and discretization of relevant physical processes between the underlying models. The presented uncertainty distribution does not contain, however, the epistemic uncertainty associated with incompletely understood and/or inadequately represented physical processes which results from model resolution (e.g. Hewitt et al., 2022, McCarthy and Caesar, 2023). Moreover, the presence of deep uncertainty is reflected by the very fact that there are 5 SSP scenarios, each with different mean global surface temperature curves and associated probability distributions.

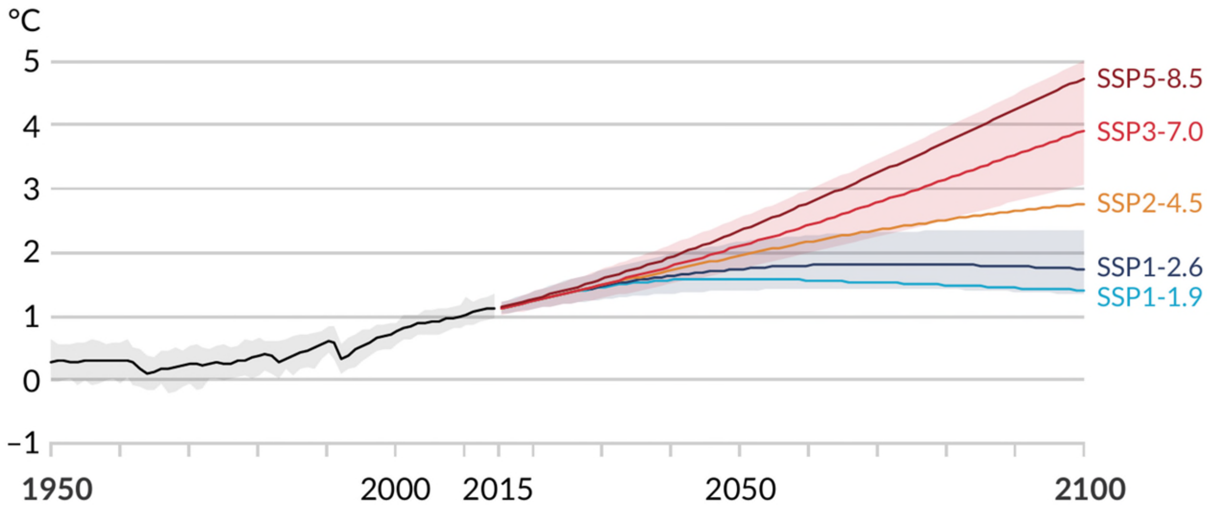


Figure 1: Temperature projections for five SSP scenarios. For SSP1-2.6 and SSP3-7.0, the uncertainty ranges have also been indicated. From IPCC (2021).

A subsequent step, relevant for the water sector is the translation of these global temperature projections to a shift regional temperature changes and shifts in precipitation patterns. These shifts in precipitation patterns are already causing major shifts in water utility planning processes (Kaatz et al., 2015). The temperature change projections for Europe from the IPCC report show a high degree of variability across the scenario's, which is in turn linked to a high variability in precipitation patterns (Figure 2). This uncertainty range is influenced by different choices of emission scenarios and different climate sensitivities, which results in a total of 134 models from 53 modelling centres. To make matters more complex, it has been reported that CMIP6 models have biases in the joint behaviour of mean and variability and that they have suboptimal performances in regions around the Arctic and Tropics (Abdelmoaty et al., 2021; Guarino et al., 2020; Jansen et al., 2020).

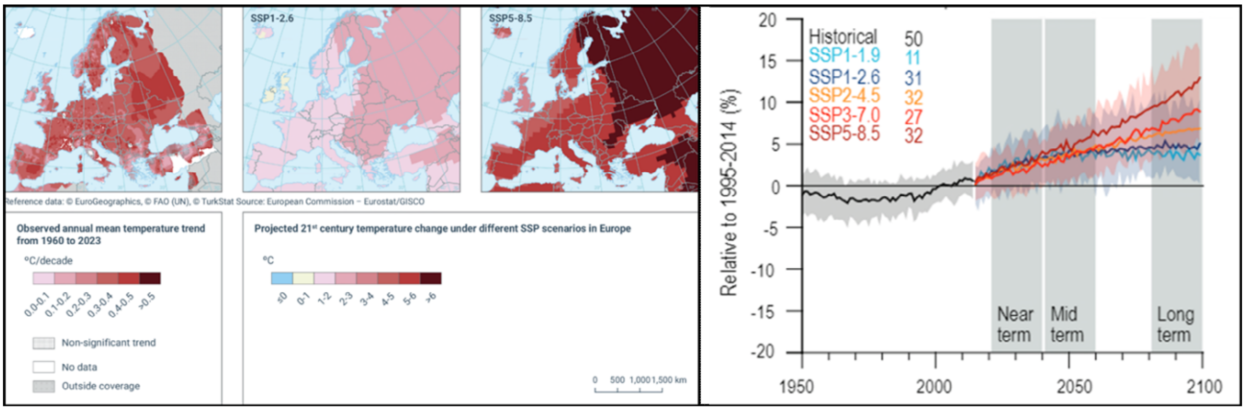


Figure 2: Mean temperature changes and projections in Europe (left, image reprinted from European Environment Agency, 2024), and Extratropical precipitation change in the northern hemisphere (right, image reprinted from Intergovernmental Panel on Climate Change (IPCC), 2023)

The recent and recurrent occurrences of extreme weather, leading to significant disasters in cities and agricultural systems and causing countless human casualties, demonstrate that society and water infrastructure systems are unprepared for the climate risks we currently face (C. Brown et al., 2020). In 2020, after 3 consecutive years of droughts, the National Institute for Public Health and the Environment (RIVM) declared a lack of immediate water reserves for the provinces of Gelderland, Overijssel, Groningen and the western part of South Holland. The Royal Dutch Netherlands Meteorological Institute (KNMI) has reported that 2023 was the hottest and wettest year on record, and heat records are arriving decades earlier than expected.

These changes in the climatic conditions have the potential to produce cascading effects through a multiplicity of interconnections, expanding the space of uncertainties even further. As an example, the heat wave in 2019 resulted in 400 deaths in the Netherlands and there was more than 430 million euros in damage due to the flooding in Limburg in 2021 (van Gaalen et al., 2024). At the same time, a quarter of the dikes in the Netherlands are primarily composed of peat, which has been shown to weaken significantly during extended periods of drought and could lead to an increase in flood risk (Lendering et al., 2015). Sea level rise will not only amplify the flood risk in certain regions but also aggravate saltwater intrusion in river estuaries. This can lead to the salinization of ground and surface waters , resulting in the loss of productive land and water supply (Béen & Beernink, 2020).

Water demand: Forecasts can easily go wrong when trends change due to changes in the underlying processes. A relatively simple example can be found in the history of water demand in the Netherlands. This is shown in Figure 3. This example is quite illustrative, because it shows two periods of more or less linear change in yearly water demand for 1-2 decades. This makes linear extrapolation very tempting and suggests a low uncertainty in these linear extrapolations, but two breaks of trendlines cause that the true water demand may diverge very rapidly from these linear extrapolations indeed. It must be noted that the population growth has been almost linear over the shown period, from 14 million individuals in 1980 to almost 18 million in 2023. The observed breaks in trendlines are discussed by Moerman et al. (2017). The strong increase in the period prior to 1990 can be ascribed changes in building legislation for hot tap water provision associated with the exploitation of newly found natural gas reserves from the 1960s as well as a strong increase in washing machine ownership, though most of this increase was already realized before 1980. The decreasing trend from the 1990s is related to an increase in efficiency of water using equipment. This has been reported for households (Moerman et al., 2017), for example through the increase in popularity of dual flush toilets. A saturation of households with water-using equipment has also been invoked (Baggelaar and Kuin, 2017), even though the household penetration of dishwashers only started in the 1990s and was far from saturation by 2015 (Moerman et al., 2017). An increase in water efficiency in industry from the 1990s has been reported as well (Baggelaar and Kuin, 2022). We observe yet another break of trendline in 2015 in Figure 3. The increase in demand from this year on can potentially be ascribed to increased water demand in hotter summers and growing popularity of rainshowers (Baggelaar and Kuin, 2022).

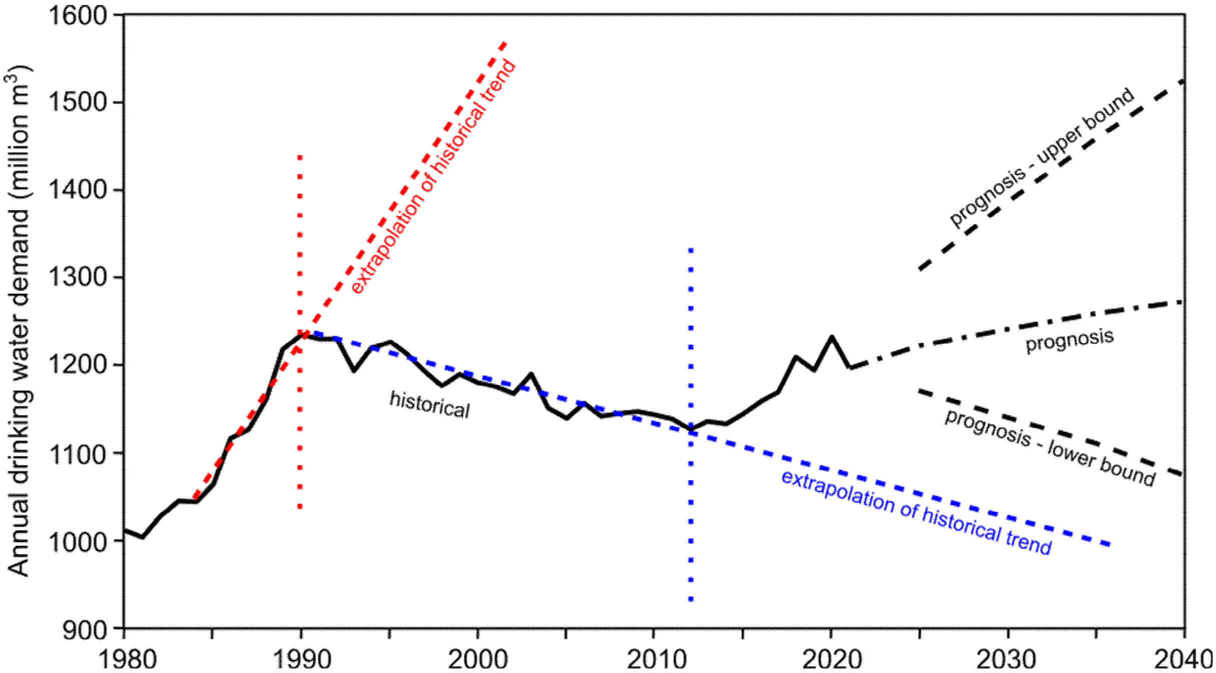


Figure 3: Drinking water demand in the Netherlands from 1980 through 2021 with prognoses up to 2040. Two very clear breaks in multi-year trends are observed. Data and prognoses from Baggelaar and Kuin (2022).

A shown in Figure 3, forecasts have a limited capacity to predict future water demands in the long term. Trends in one area (either industrial, technological, or socio-economic) can have knock on effects in other areas. The continued extraction of groundwater for industry or citizen consumption can worsen land subsidence (see Figure 4), which can lead to the sinking of roads, bridges, dykes, or houses, increase the risk of flooding in low-lying areas and compromise water system functions (Erkens, 2021). The combination of these factors creates a planning horizon with a high degree of uncertainty, especially in a country with an imperative need to expand its housing capacity by millions in the coming decades (CBS, 2024).

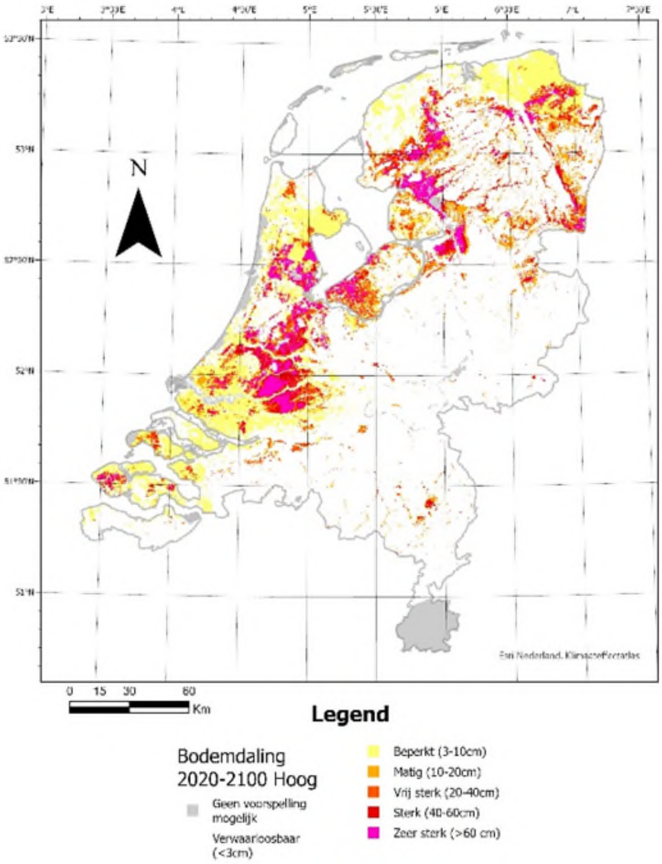


Figure 4: Projection of high land subsidence in the Netherlands. Both the extent and the possible impact on water system functions remain uncertain. Image derived from data obtained by Erkens (2021)

Black swans: there is a class of events that is described as black swans (Taleb, 2007). These are events that have a very low perceived likelihood of occurrence, but if they do occur, their impact is not only enormous but also capable to dominate the long term balance of the system. For example, in the world of finance a single day in 1987 represents such a black swan. On that day in 1987 the U.S. stock market crashed, which would have an impact until 2008 (Taleb, 2022)(Pickering et al., 2022). Due to the rareness of such events and possible rise from an infinite set of conditions, the prediction of this class of events remains an extremely difficult and unsolved problem (Pickering et al., 2022), but its study and consideration represent an opportunity for decision makers from different disciplines.

2.2 Types of uncertainty

It is worthwhile to be aware of the different possible types of uncertainty. Commonly used is the distinction between aleatory and epistemic uncertainty. The former is used to represent those aspects of uncertainty that relate to (presumed) intrinsic randomness of a process. The latter is used to refer to uncertainty resulting from a lack of knowledge or data. However, it is not always clear in which of these two categories a particular source of uncertainty should be placed (Der Kiureghian and Ditlevsen, 2009).

Tannert et al. (2007) expand on these two types of uncertainty and introduce a taxonomy of uncertainty (see Figure 5). They subdivide uncertainty into objective uncertainty and subjective uncertainty. Objective uncertainty is technical in nature, and can be further subdivided in epistemological/epistemic uncertainty, relating to gaps in our knowledge that can be addressed by research, and ontological/aleatory uncertainty, which involves stochastic elements that make deterministic predictions impossible. For example: not knowing whether a compound is toxic or not (epistemic) or what is the measured level of toxicity is (aleatory) due to measuring equipment. They also introduce a different branch of uncertainty, subjective uncertainty. Subjective uncertainty relates to morality, and also has two subclasses. The first, moral uncertainty, is caused by a lack of applicable moral rules, which requires one to fall back to more general moral rules; the second, rule uncertainty, relates to uncertainty in the moral rules themselves. Objective uncertainty is evidently quite important in decision making on technical systems such as water supply systems, for example relating to future demands and requirements. However, subjective uncertainty may be equally important, as this relates to questions such as how much risk to accept. This report mainly focuses on objective uncertainty.

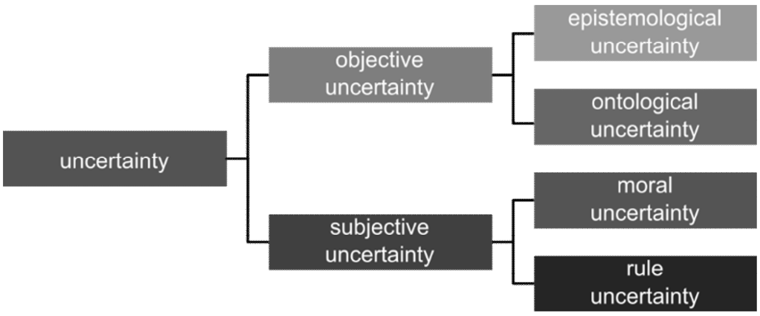


Figure 5: Taxonomy of uncertainty, according to Tannert et al. (2007)

An alternative subdivision of objective uncertainty into three types of uncertainty of a technical nature is offered by IPCC (2007); unpredictability, structural uncertainty (especially in models) and value uncertainty (especially in data). All three occur in modelling of water systems and decision making. They are associated with the state of objects and the completion of processes, and include stochastic (i.e., randomly occurring) and unknown (i.e., not determined or registered) parameters.

2.3 Levels of uncertainty and deep uncertainty

Irrespective of the position in the taxonomy (Figure 5), uncertainty can be classified according to different levels, which the last two levels pertaining to deep uncertainty. The Decision Making under Deep Uncertainty Society uses the following definition of deep uncertainty (DMDU Society, 2024), which is a refinement of the original definition that was proposed by Lempert et al. (2003):

“Deep uncertainty exists when parties to a decision do not know, or cannot agree on, the system model that relates action to consequences, the probability distributions to place over the inputs to these models, which consequences to consider and their relative importance. Deep uncertainty often involves decisions that are made over time in dynamic interaction with the system.”

As such, deep uncertainty is at the end of the uncertainty spectrum. This spectrum is often described by four (or five) practical levels of uncertainty that exist between the endmembers complete certainty and complete ignorance, both of which can be considered rather academic and of little practical use. This is illustrated in Table 1. For level 1 uncertainty, it is relatively easy to predict what is going to happen with a simple (deterministic) model. An example is the trajectory of an apple that is dropped from 1 m height from the floor. Level 2 uncertainty describes those situations in which we see a continuum of possible future states with probabilities that can be described by a single stochastic model. As an example, we can think of the sugar concentration in a cup of coffee, which is a direct function of the loading of the spoon that has put the sugar in the cup, which itself will be a stochastic and as such uncertain variable. The third level involves situations which have a limited number of plausible futures, such as the throw of a die, with equal or unequal (if the die is loaded) probabilities for the different possible outcomes. And finally, level 4 refers to deep uncertainty, as defined above, with a distinction between situations with many plausible futures and alternative system models (a 120-sided die with an irregularly shaped internal cavity that contains a mobile weight, thrown on an uneven table in a windy environment that is prone to earthquakes), which is designated by level 4a, and situations with completely unknown futures and unknown system models, indicated by level 4b. Sometimes, levels 4a and 4b are presented as levels 4 and 5, respectively (e.g., Warren et al, 2013).

Table 1: Overview of different levels of uncertainty. Reprinted from Marchau et al. (2019)

	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	

2.4 Continuity bias and the flaw of averages

One of the reasons for which it is difficult to appraise and recognize the presence of deep uncertainty is a phenomenon termed 'continuity bias'. Continuity bias shapes our vision and scenarios of the future: people have trouble envisioning a future which is not a variant of the past. Because of this people cannot easily consider the possibilities of discontinuities when shaping transitions. This phenomena was described in 1995 for the case of assessing future global scenarios, and an a posteriori evaluation confirms it (Figure 6). The a posteriori evaluation showed that elements of all the originally considered separate scenarios were to some extent present more than twenty years later.

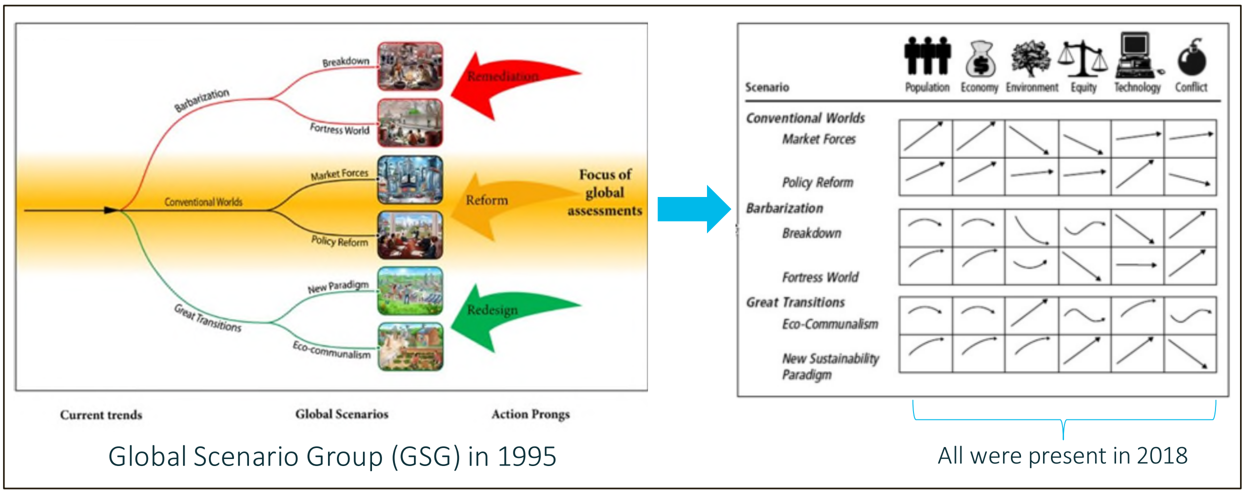


Figure 6: The continuity bias can cause plausible future scenarios to be left unconsidered (left, adopted from [https://greattransition.org/explore/scenarios/excludedfutures)](https://greattransition.org/explore/scenarios/excludedfutures) , evaluation of actual realization in 2018 (right, adopted from Gallopín (2018))

On top of, or maybe due to, the continuity bias traditional management techniques often emphasize measures of central tendency and tend to overlook variability. This approach can lead to the creation of plans based on average assumptions, which will be wrong on average (Savage, 2012). The previous case of water demand forecasts in the Netherlands illustrates the risks of using past averages. Even if managers are able to identify the trend changes, focusing on the calculation of a single expected value of water demand is likely to result in system underperformance. If the demand was overestimated this results in an inefficient use of resources (overinvestment), if it were underestimated there could be an inadequate supply.

Both climatology and hydrology have been some of the areas of most intense debate in terms of the importance of variability to understand future developments. Until the end of the 20th century, there was a generalized belief that any changes in the mean climate would lie within or not far outside those experienced in the past, and that society would be capable to adapt to any slow changes. Nevertheless, by the 1940s and 1950s, the statistician Emil Gumbel had already identified the importance of extreme values in the context of floods (Gumbel, 1958) and the problem of the statistical estimation of the "return period" of floods (Katz et al., 2002):

In order to apply any theory we have to suppose that the data are homogeneous, i.e. that no systematical change of climate and no important change in the basin have occurred within the observation period and that no such changes will takeplace in the period for which extrapolations are made (Gumbel, 1958).

By the 1980s, several researchers had already confirmed that in a future greenhouse-influenced world, impacts to human systems would originate not so much from slow fluctuations in the mean, but from extreme events where a climatic variable exceeds some absolute threshold (Wigley, 2009). Episodes such as the hot summer of 2003 in Europe (Figure 7) provided empirical support for these warnings and underscored the urgency of addressing two additional predictions made by Wigley in 1988:

1. The future will lead to much longer periods of protracted change in one direction, with final conditions well into the no-analogue region.

2. The main impacts will accrue through changes in the frequency of extremes.

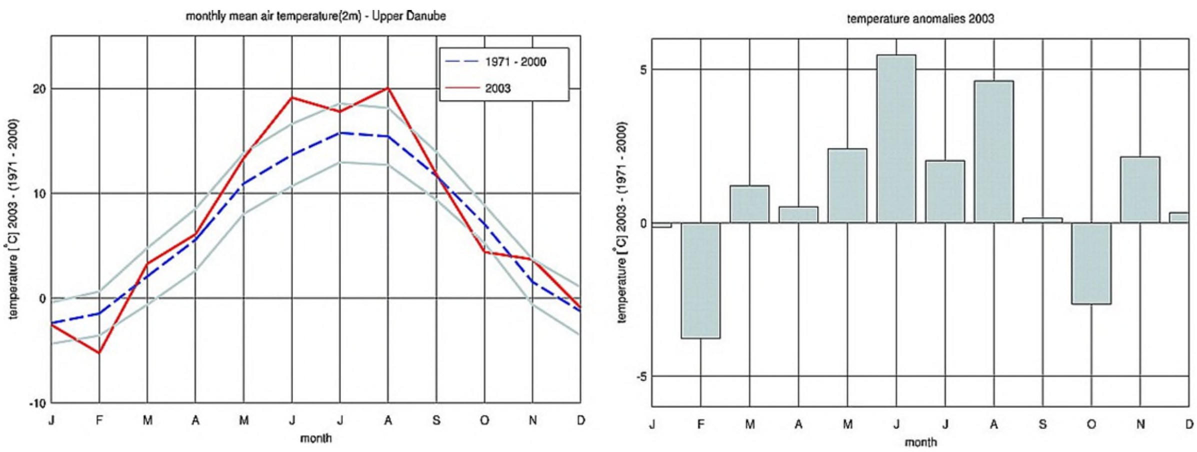


Figure 7 Air temperature (2 m height) of the year 2003 against the long-term average, where the grey lines indicate 1σ (left) and temperature anomalies for the individual months in the Upper Danube (right). Image reprinted from (Loew et al., 2009).

The statistics of extremes, which had previously been left aside in the context of climate change studies, slowly gained importance due to the confirmation of Wigley's predictions and the recent computational advances for extreme value analysis (Katz, 2010) and other deep uncertainty techniques. As researchers continue to expand the understanding of complex systems and extremes, we improve our capacity to plan for a diverse ensemble of plausible long-term futures.

2.5 Consequences of ignoring (deep) uncertainties

Humans, being risk-averse, often focus on what might cause a system to fail when looking for deeply uncertain elements. The large number of academic and popular science books on why certain countries, societies or companies succeed or fail reflects our tendency to view the past in these binary, oversimplified terms.

Although researchers would argue that failure can be represented as a fixed threshold (Beck & Zuev, 2015), failure can also be thought of as a bandwidth that varies depending on the definition of benchmarks, variations in perception and even the boundaries of evaluation (McConnell, 2011). Haasnoot et al. (2012) have proposed the use of relative values to define systemic failure. For instance, in flood management, an Action A may prevent damage at a 1-meter sea level rise, while Action B is effective at 2 meters. In relative terms, Action B accommodates more change than Action A. Failure, seen as a loss of functionality, not only depends on the decisions made by decision makers, but also reflects the missed opportunities that could have materialized from alternative choices throughout history.

Such an expanded set of potential outcomes can be analysed with two concepts borrowed from the world of finance: downside risks (up to and including system failure) and upside profits. Deep uncertainties are usually associated with 'negative' risks: if sea level rises above our expectations, millions of people around the world may be displaced; if the frequency of droughts in croplands intensifies, there may be unmeasurable losses in income, jobs, land degradation and food scarcity; if a region overestimates future surface water availability, the resulting cascade effect can include water supply shortages, water quality deterioration and even the collapse of long-established ecosystems. However, this association is misleading, as ignoring deep uncertainties also means missing out on unpredictable potential profits (Figure 8). This way of thinking originates from finance and it acknowledges the existence of two dimensions of uncertainty for any asset, the upside potential and the downside risk (Chaigneau, 2023).

Either of these outcomes can materialize depending on how the future unfolds, with total system failure being the least desired extreme outcome. It is valuable to make a distinction between these situations because in the realm of decision making the preferences/priorities of a decisionmaker play an important role. For example, some critical infrastructure decisions might be governed by the priority to avoid losses and complete system failure (risk averse decision making), while other decisions might be aimed at maximizing gains and would focus on the potential upside profits. Such a distinction is not possible when only focusing on the 'average' outcome. In the drinking water sector objectives might be set in terms of requirements to be met, rather than potential profits or losses. It still worthwhile to acknowledge that as the unfolds these requirements might become excessively difficult, or easier, to meet.

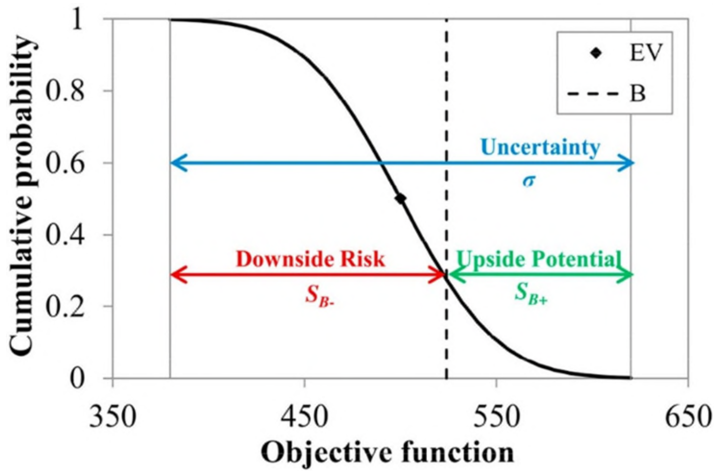


Figure 8 Simplified case to show the upside and the downside of the uncertainty of an objective function to be maximised. Standard deviation (σ) quantifies uncertainty, lower semi-deviation (SB−) quantifies downside risk, and upper semi-deviation (SB+) quantifies upside potential of a risk curve (in black). EV is the expected value, and B the benchmark. Image reprinted from (Santos et al., 2017).

Surface water in the Netherlands exemplifies this perspective. Because polders lack natural drainage, excess water is typically pumped into a higher elevated network of larger primary canals. Every year, millions of litres of rainwater are “lost” to the North Sea, particularly during the rainy winter months. During the drier summer months, water demand increases and there is increasing concern about the capacity of water utilities to consistently supply water without reaching unsafe groundwater levels (RIVM, 2020). This creates a future downside risk due to the system's inability to capitalize on previous extreme events (the excessive winter rainfall). The many combinations of engineering options available such as blue roofs, groundwater artificial recharge, underground pumped storage hydropower, transport to other provinces and provision of water to green hydrogen factories and other water-intensive industries, would incentivize collaboration between different sectors and allow Dutch water utilities to turn deep uncertainty into upside profits.

The broader view on system failure presented above does not intend to diminish the significance of identifying critical and inflection points. Tipping points are decisive in environmental sciences, as they can trigger a large-scale qualitative system change, with self-amplifying feedbacks that dominate the original behaviour (Wunderling et al., 2024). It is also is important to stress that engineering and societal projects cannot and should not blindly imitate methods derived from finance. Infrastructure projects are not merely assets, they also provide a service to people. Individuals and organizations tend to be risk averse and they avoid situations which offer the potential for significant gains but which also leave them even slightly vulnerable to losses below some critical level (Menezes et al., 1980). In most cases it is not possible for water utilities to accurately estimate uncertainties from available data, and reaching a critical level can mean the total failure of the system. Therefore, the goal of most DMDU methods is not to merely find decision paths with the highest expected values, but to envision and propose “No(Low)-Regret” strategies to decisionmakers.

2.6 Downside Risks and System Failure: a real world example

On the spectrum between upside profits and downside risk, system failure can be considered the most extreme outcome of downside risk. Due to the connotation of deep uncertainty with total system failure it is worth paying special attention to this potential outcome.

One of the best examples to understand our tendency to overlook uncertainties originates from the theory of evolution, as discussed by Taleb (2001). There has been widespread misunderstanding about why certain animals and businesses have survived over time. Just as an animal might survive due to sheer luck, the "best" businesses often emerge from a subset that thrived because they were overly adapted to a specific set of circumstances—a set that avoided rare catastrophic events. Ironically, the longer they go without encountering such rare events, the more susceptible they become to them. Extending time to infinity means, due to ergodicity, that the rare event will inevitably occur, leading to the species' extinction. Therefore, evolution represents adaptation to a single specific sequence of events, not an average of all possible environments.

The inclusion of epistemic uncertainty in decision making is not an easy task. Humans have a tendency to learn from past experiences and it can sometimes be difficult to overcome certain preconceptions about the robustness of a system. For example, in 2023, the country of Uruguay in South America experienced the worst water shortage in its history. The extended La Niña event from 2020 to 2023 almost depleted Uruguay's reservoirs, causing severe water shortages in the states of Montevideo, Canelones, and San José de Mayo. This crisis led the government-operated water utility to start incorporating brackish water from the La Plata River estuary into the supply system, which serves nearly 2 million people, roughly 60% of the country's population (Tocar, 2023). Both former president Jose Mujica and former Energy director Ramon Mendez have stated that the main reason for the unpreparedness of the system was the fact that nobody believed that Uruguay would run out of fresh water (Andreoni, 2023).

The country has six major watersheds: Uruguay River, Plata River, Atlantic, Merin Lake, Negro River and Santa Lucía River, and both its surface and ground water resources have been deemed relatively abundant by the Organization of American States (OAS). In 2004, Uruguay also became the first country in the world to recognize access to drinking water as a constitutional right (Martinez, 2023). Simultaneously, a series of blackouts in the early 21st century led Uruguay to prioritize its energy infrastructure, currently resulting in a remarkable 98% of its electricity being generated from renewable sources (Andreoni, 2023). However, this focus came at the expense of investing in the efficiency and resilience of a water supply system.

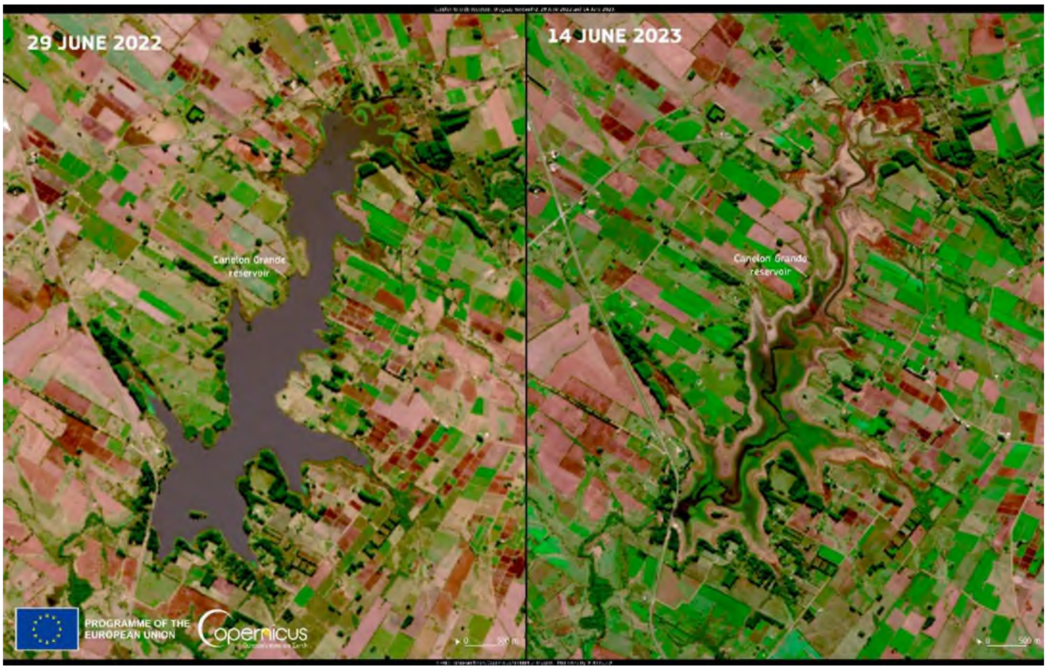


Figure 9: Satellite images, acquired by Copernicus Sentinel-2 satellites on 29 June 2022 and 14 June 2023, show the Canelon Grande Reservoir in Montevideo, Uruguay, which went through an unprecedented water crisis. On March 2023, the water level fell from 4 million m3 to a bit less of 300 thousand m3 within a week.

The effect of ignoring uncertainty and its extent can be seen in Figure 9. Poor planning and constant postponement of water infrastructure projects—the last major reform to Uruguay's water network was in 1987(Martinez, 2023) — led to a late identification of vulnerabilities and the large scale collapse of a system that had not been considered as fragile. However, some researchers had already pointed out that the crisis merely exposed the disconnect between civil-governmental organizations like the river basin commissions (11 in total, established in 2013) and the "real" decision-makers at higher levels of government, such as Parliament or the Executive Branch (Diaz, 2024).

Smaller drought episodes (2005, 2008, 2009, 2013 and 2015) had already alerted the national authorities. In 2016, the Uruguay government initiated the construction of a dam on the Casupá stream in the department of Florida. The rationale was clear: the Santa Lucia River typically has a surplus, and within 3 or 4 days, enough water flows to supply Montevideo for an entire year. However, this water is ultimately lost and ends up in the Atlantic Ocean, and an additional reservoir would enable storage more water for dry periods. Former Environment Minister Eneida de León noted that "during droughts, the river's water levels were insufficient, leading to the growth of cyanobacteria," and that "the construction of this dam would prepare Uruguay for the next 20 to 30 years"(GUB UY, 2016). By 2019, they had made progress in various technical studies and secured an $80 million loan from the Andean Development Corporation (CAF)(Cayota, 2023).

However, with the change of government in 2020, president Lacalle Pou chose to prioritize a different project: the Arazatí water treatment plant. While it would be three times more expensive than the reservoir, it would build new infrastructure for water purification, utilizing the brackish water of the Río de la Plata as its source, which is virtually unlimited for the needs of the metropolitan area. Additionally, most of the investment for this project would come from the private sector, allowing the government to avoid incurring additional debt.

Nevertheless, the treatment plant has faced criticism from the opposition. They argue that investing in water infrastructure should not be the role of the private sector and raise concerns about high salinity levels, which would turn water purification unfeasible. To address this, the project also includes the construction of a polder designed to store enough water for 87 days, the exact number of days with high salinity levels recorded in 2021.

Figure 10: Map of Uruguay's main rivers. 60% of the population live in the Montevideo metropolitan area. The proposed projects are the Casupá Reservoir (green cross) and the Azaratí water treatment plant (red cross).

The need for alternative options had already been outlined in a 1970 report titled “Development of the Water and Hydraulic Resources of the Santa Lucía River Basin”, a collaboration between the government of Uruguay, the

Organization of American States (OAS), and the Pan American Health Organization (PAHO). It wasn't until 1998 that the National Administration of State Sanitary Works (OSE) took into account future water supply and demand scenarios. They publicly announced that they had secured funds to explore the construction of a desalination water treatment plant, noting that "the current sources will only be sufficient until 2020" (Cayota, 2023), which coincided exactly with the beginning of the most recent drought crisis. The 1998 plant was even included in the 2002 national government budget, but it never materialized due to a lack of funding.

The case of Uruguay serves as a clear example of how even a country rich in water resources and research capabilities can face system failure if decisions are delayed and political and civil actors fail to collaborate effectively. The Uruguayan governments consistently undermined the need for innovation in the water sector. Nowadays, specialists say that both infrastructure initiatives will prove necessary and that a structural change of the water network is as unavoidable, as 50% of the potable water it produces is wasted due to damaged pipes, many of which are over a century old (Ambito, 2023).

Ongoing projects such as the Blue Deal, which involves a total of 34 countries all over the world, prove that the Dutch Water Authorities and Ministries are looking to help other countries gain access to clean, sufficient and safe water, while learning from their experiences (and their mistakes) to improve the water system in the Netherlands (Dutch Water Authorities, 2018).

2.7 Decision making under deep uncertainty (DMDU)

Once there is consensus about the presence of deep uncertainty and the need to apply non-traditional methods to deal with it the next challenge is to determine the most appropriate DMDU method. During the last decades, DMDU methods have evolved and grown in importance. Already in the 20th century, the governments of the United States, Japan and Germany explored the use of long-term policy analysis (LTPA), acknowledging that the policy options considered by decision makers and the choices they make would be significantly affected by events that may happen 30 or more years into the future (R. J. . Lempert et al., 2003). For that reason, they explored methodologies to combine expert knowledge from different fields and combine them to create narratives of the far future. These could be divided according to their objectives: either to obtain the most reliable consensus of opinion from a group of experts and translate it into policy, or to explore the deliberations themselves to support the discussion of uncertainty. However, a combination of specialists can only result in a limited array of futures and this division of methodologies resulted in an apparent paradox: such a process could not fully consider deep uncertainty and simultaneously provide practical policy recommendations (R. J. . Lempert et al., 2003).

Since then DMDU as a field has matured and should be considered as a collection of methods and concepts which aid decisionmakers in situation where the conditions for deep uncertainty are present; actions cannot be related to consequences, there is disagreement over inputs for models and the consequences to consider.

This section introduces the conceptual basis overarching all DMDU methods, highlights individual methods, and provides a starting point for choosing between them. In this section we first elaborate on the three key ideas that make up DMDU: exploratory modelling, adaptive planning, and decision support (J. H. Kwakkel, 2017; J. H. Kwakkel & Haasnoot, 2019a). Then the concept of 'robustness' as the goal of decision making is discussed.

2.7.1 Key ideas of DMDU

In the literature there are many methods and concepts that can be characterized as DMDU methods. Sometimes these methods and sub-methods build on each other, while others were developed independently. For the purposes of this research we consider the three high level description of the key ideas for DMDU provided by Kwakkel & Haasnoot: exploratory modelling, adaptive planning, and decision support.

Exploratory modelling

Exploratory modelling (EM) is a process in which computational models are used to explore a wide range of scenarios with the aim of establishing the potential consequences of certain actions/decisions in the face of a deep uncertainty. When there is consensus that it is impossible to predict the future with sufficient certainty the alternative is to use 'what-if' scenario development. When scenario development methods are combined with modern computational capabilities it becomes possible to explore the consequences of a wide range of decisions under many sources of uncertainty. Computational models are needed for this because the complexity of the involved systems makes it nearly impossible to systematically create the set of scenarios. Mental models/expert judgement have been shown to be flawed when dealing with complex systems in which nonlinear interactions play a significant role.

EM attempts to create a set of 'what-if' scenarios that is as complete at possible for the system under investigation. Analysis of this set of scenarios aims to establish if there are patterns under which a set of decisions fails or is successful. This search for 'robust' options within the complete set of 'what-if' scenarios can be complemented with optimization algorithms. However, applicants of exploratory modelling methods must remain aware that a truly comprehensive set of scenarios cannot be guaranteed.

Exploratory modelling is also a valuable tool to explore conditions under which tipping points occur in a system. In natural systems tipping points are boundaries, which if crossed, do not allow a system to return to a previous equilibrium state without external inputs or effort. For human systems it is also possible to define tipping points as boundaries which policymakers are unwilling to cross.

Adaptive planning

There is a tendency to think that the application of DMDU methods means trying to solve tomorrow's problems today. This can lead to the application of "passive" methods, in which the main goal is to design solutions that reduce the risk of system failure in a long term, but with the additional risk of restricting future action within a system of changing needs and uncertainties. For example, even with today's computational tools and an increased capacity to describe complexity, it is always possible that current conclusions will be wrong or at least lack valuable future information.

As the future unfolds and conditions change it is intuitive that previous plans or decisions should be adapted to fit the new reality. Adaptive planning acknowledges this but also explicitly considers this from the start. Plans are developed in such a way that adaptations over time are expected and possible. In addition, the conditions under which deviations from the original plan are needed are established before implementation. This is complemented with insight into suitable courses of action for different futures and mechanisms that warn decisionmakers that adaptations are needed. This type of approach is only possible in combination with EM because a such wide range of possible futures must be explored.

The need for adaptive planning is well illustrated by historical example in the Netherlands. After the great floods of 1953 the Delta Act was put into force, which proposed shortening the coastline by 700 kilometres and raising the primary sea and river flood defences. The catastrophe led to an inclusion of the protection against floods to the political agenda without a previous political process, and decisions were made to guarantee safety as the only existing public value (Correljé & Broekhans, 2015). The new policy made a clear emphasis on the planning of a 50 year long civil engineering project to carry out dike improvements and the construction of dams, retaining walls, floodgates and coastal inlets. However, already in the 1960s and early 1970s, the Dutch government was confronted with the limits of the preventive measures, as conservationists raised awareness among people against the closure of the Oosterschelde estuary and promoted the necessity of safeguarding the delta and river landscape, its natural resources and its distinctive tidal habitat. This led to an adaptation of the Delta Plan to serve these multiple values, and in 1976 it was decided that the Oosterschelde barrier would be constructed with storm-surge barriers that are normally open but can be closed during a storm (Nienhuis & Smaal, 1994). This meant a turning point for Dutch decision-making, as the presence and inclusion of informed citizens forced an initially “passive” and centralized methodology to create space for proactive methods that allow for adaptation to the future situation and needs of society.

The need for adaptive planning under conditions of deep uncertainty is illustrated in Figure 11. The appropriateness of a static or adaptive approach depends on the degree of uncertainty, the flexibility of potential solutions, the rate of change of the system and time horizon required to implement adjustments (Maier et al., 2016). If the time required to implement a solution is long relative to the system's rate of change, a single, static strategy that performs well under a range of plausible futures is likely to be a better option, as adaptation may not occur quickly enough to prevent system failure. In contrast, if the system can adapt quickly relative to the rate of change it needs to address, an adaptive approach is likely to be more attractive (Maier et al., 2016). This also explains and justifies why DMDU methods are needed to cope with increasingly complex societies. The rate of change of the world and society (climate change, technological innovation and implementation, artificial intelligence, etc.) is arguably higher for today’s societies compared to societies in the past. As a result the degree of uncertainty over the planning horizon increases, which makes adaptive approaches (based on DMDU methods) necessary. At the same time technological innovations can increase the flexibility of solutions which enable adaptive approaches. In highly urbanized settings/countries such as the Netherlands implementation time (permits, environmental audits, etc.) might be limiting factor for adaptive approaches.

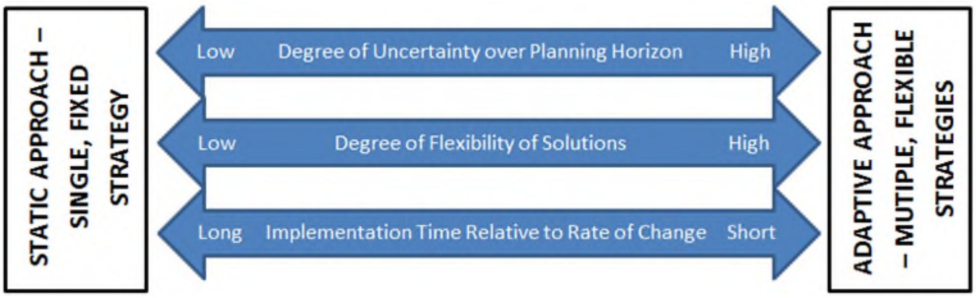


Figure 11 Conceptual representation of how to choose between static and adaptive approaches under uncertainty, Image reprinted from (Maier et al., 2016).

Decision support

The type of complex systems for which DMDU is used will mostly involve multiple stakeholders that must come a joint decision. This complexity, in combination with diverging preferences and requirements of the different stakeholders, benefits from an iterative approach to decision making. Arriving at robust decisions ideally takes the form of a learning process involving the stakeholders and the analysts (J. H. Kwakkel & Haasnoot, 2019a). The aim of the process should not be to establish the ‘right’ or ‘best’ choice, but rather to facilitate interaction and understanding between the involved parties. To achieve this the focus moves from agreeing on the assumptions and objectives towards and understanding of the trade-offs between different goals/objectives.

2.7.2 Robustness and flexibility: two confusing goals for DMDU

The scientific literature on system planning and design often distinguishes between the concepts of robustness and flexibility as a way to deal with unexpected shocks to a system. Especially when optimization is involved in the design process the distinction between the two is often highlighted, and made explicit in the objective. These two concepts can be complemented with resilience, agility and changeability. For the purpose of this report we use the approach proposed by Kwakkel and Haasnoot linked to adaptive planning as a key idea for DMDU (J. H. Kwakkel & Haasnoot, 2019a) Rather than choosing between one concept or another they argue that the aim should be to arrive at a robust *decision*, rather than a robust or flexible *design* (see Figure 12). Flexibility, and/or other concepts, can then be used as performance metrics during system design to achieve this goal. In the rest of this section we highlight flexibility and robustness because they do play a big role in the exploratory modelling phase of DMDU as a way to quantify the performance of scenarios. See Appendix I and Appendix II for an elaboration on the ways to increase the robustness and flexibility of a system.

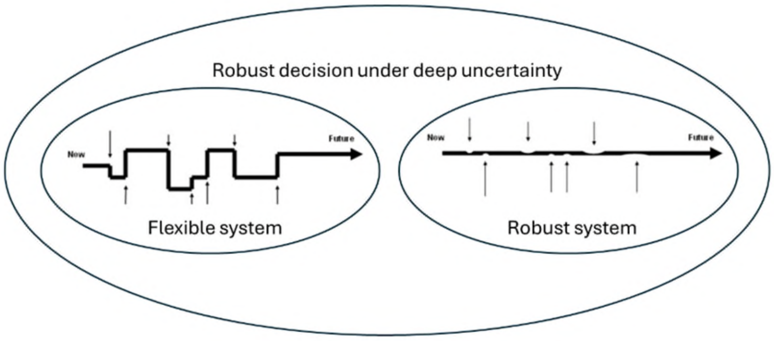


Figure 12 System flexibility and system robustness within a robust decision (adapted from (Husdal, 2004))

Robustness

Robust design aims to make systems functions more consistently and invariantly to changes in the environment, manufacturing, deterioration, and customer use patterns (Cardin, 2014). As it has already been stated throughout the report, there is no clear answer on how to quantify "robustness". Irrespective of which metric is used, robustness generally requires the specification of (McPhail et al., 2018):

1) The decision alternatives (e.g. policy options, designs, solutions, management plans);

2) The outcome of interest of the decision alternatives (e.g. cost, reliability);

3) The plausible future conditions (scenarios) over which the outcomes of interest is to be evaluated.

Robustness measures can be broadly divided between the categories of regret or satisfice. Regret quantifies the cost (not necessarily monetary) of choosing incorrectly. These measures can either focus on the difference between a single solution and the baseline performance, or on its deviation from the "best" solution in the prevailing state of the world. This means that the decision maker can choose to either emphasize on which assumptions were incorrect and led to major mistakes in the modelling process, or on the identification of lost opportunities and the incorrect choice of decision alternatives (Herman et al., 2015). We will describe two regret-based measures named R1 and R2, and one satisficing-based measure named S (Herman et al., 2015). R1 is defined for each decision alternative as the 90th percentile deviation from the baseline, maximized over all objectives:

$$R1 = max_i[D_{i,90}: P\left(D_i \leq D_{i,90}\right) = 0.90]$$

$$D_{i,j} = \frac{|F(\boldsymbol{x})_{i,j} - F(\boldsymbol{x})_i^*|}{F(\boldsymbol{x})_i^*}$$

Where $F(\boldsymbol{x})_i^*$ represents the value of objective i in the baseline state of the world; and $F(\boldsymbol{x})_{i,j}$ represents the value of objective i calculated in state of the world j. Similarly measure R2 calculates regret as the deviation from the best solution in each state of the world:

$$R2 = max_i[D_{i,90}: P\left(D_i \leq D_{i,90}\right) = 0.90]$$

$$D_{i,j} = \frac{|F(\boldsymbol{x})_{i,j} - F(\boldsymbol{x_s})_{i,j}|}{F(\boldsymbol{x})_{i,j}}$$

The best value of each objective i is taken across solutions s. This measure depends on the other solutions in the set as it incorporates all of them. It is important to note that in this case the deviation is normalized by the objective value itself rather than the best value because the latter often approaches zero.

As for the satisficing measures, they refer to the tendency of decision makers to fulfil minimum performance thresholds rather than look for an optimal set of solutions. Measure S will be defined as the fraction of N states of the world in which a solution meets stakeholders' performance requirements in one or more objectives:

$$S = \frac{1}{N}\sum_{j=1}^{N} \Lambda_{s,j}$$

Where $\Lambda_{s,j} = 1$ if solution s meets requirements in state of the world j and $\Lambda_{s,j} = 0$ otherwise. The results for these metrics largely depend on what is considered as acceptable by the stakeholders. The development of simulation-based decision support frameworks such as Many-Objective Robust Decision Making (MORDM) has allowed decision makers to identify trade-offs in conflicting performance measures like system reliability, efficiency, costs and benefits (Kasprzyk et al, 2013).

Flexibility
It has also been stated that certain methods take specific care of flexibility, but what does it mean to be flexible? Which indicators should we try to maximise? Flexibility can be defined as the ability to adapt, change and be reconfigured, if needed, in light of uncertainty realizations (Cardin, 2014). It is especially important for water planners who analyse large, irreversible infrastructure investments, and it differs from most system indicators due to its absolute character, rather than relative to a particular hazard or stressor (IPCC, 2007). Difrancesco & Tullos (2014) summarized the flexibility characteristics for water resources as:

1. Slack: surplus capacity to cope with uncertain and changing conditions.

2. Redundancy: refers to multiple options performing the same function in a system. In flood management systems, repetitiveness and diversity of options increase the system's ability to cope or adapt to uncertain, future conditions. It ensures that slack is complemented with a variety of options.

3. Connectivity: ensures that a system is capable of fully utilizing its redundancy by employing the options available to meet system objectives. For water resources management, the term applies to the linkages between infrastructure that promote reliability of moving water across networks and the capacity to run a treatment plant from different locations

4. Coordination/compatibility: coordination and information sharing between scientists, water managers and various levels of government in planning efforts.

5. Adjustability: ability to add, modify and remove any component of the system and/or its operations with ease and with no major overall effect. It describes the ease with which managers can modify the previous flexibility characteristics to adapt to changing conditions.

The first four characteristics are linked to the ability to cope with uncertainty and change whereas adjustability is directly related to the system's ability to adapt. Although the grade of flexibility is inherent to all management systems, the mathematical description of the aforementioned characteristics may differ depending on the final purpose of the infrastructure. Table 2, based on Difrancesco & Tullos (2014), exemplifies some of the metrics that can assess flexibility in flood management systems.

Table 2: Examples of flexibility characteristics for water resources

Characteristic	Metric's Description	Metric's Formula
Slack	Excess reservoir capacity: dam's flood storage capacity in excess of the amount of water stored in the reservoir to attenuate a 100-year flood event.	$E = C - S(100y\ event)$ E is the excess reservoir capacity, C is the dam's capacity and $S(100y\ event)$ is a flood with a 1% chance of occurring yearly.
Redundancy	Surface storage options: number of reservoirs and bypasses per major tributary.	$S_{total} = \sum_{i=1}^{N} S_i = \sum_{i=1}^{N} (R_i + B_i)$ Where S_i is the total surface storage options for major tributary i, R_i is the number of reservoirs along major tributary i, B_i is the number of bypasses along major tributary i and S_{total} is the total surface storage options for all major tributaries.
Connectivity	Groundwater and surface water connections: percent of reservoirs operated conjunctively with groundwater.	$P = \left(\frac{R_c}{R}\right) * 100$ Where P is the percentage of reservoirs operated conjunctively, R_c is the number of reservoirs operated conjunctively and R is the total number of reservoirs.
Compatibility/coordination	Intra-basin coordination of operations: percentage of reservoirs with coordinated operating agreements.	$P = \left(\frac{P_{co}}{P_{total}}\right) * 100 = \left(\frac{P_{co}}{\binom{R}{2}}\right) * 100$ Where P is the percentage of reservoirs with coordinated operating agreements, P_{co} is the number of coordinated pairs of reservoirs and P_{total} is the total number of possible pairs of R reservoirs.
Adjustability	Ability to expand storage and conveyance capacity with levee setbacks: calculated as the percent of levees with greater than an x m buffer to infrastructure.	$P = \left(\frac{L_x}{L}\right) * 100$ Where P is the percentage of levees with an x m buffer, L_x is the number of levees with an x m buffer and L is the total number of levees.

2.8 DMDU methods

DMDU researchers have developed a wide range of methods to analyse and evaluate systems where deep uncertainty is present (Table 3). This development process has been evolutionary, in which additions and extensions by different researchers is very common. After evaluation similarities and overlaps five main DMDU methods can be distinguished: Robust Decision Making (RDM), Dynamic Adaptive Planning (DAP), Dynamic Adaptive Policy Pathways (DAPP), Info-Gap Theory (IG) and Engineering Options Analysis (EOA) (Marchau et al, 2019). There is no standardized way to say that a case qualifies for a specific DMDU method. In this report RDM, DAPP and EOA, are highlighted to show the main differences between the approaches on a conceptual level.

Table 3 Overview of DMDU methods

Method (* denotes that it is explained in detail in the text)	Short description
Robust Decision Making*	Iterative process that uses “scenario discovery” to find vulnerabilities in the system and develop robust plans. RDM runs a model several times and assumes no ranking of the projected futures. The main goal is to avoid system failure during vulnerable periods.
Dynamic Adaptive Planning	It involves specifying goals and objectives, developing an initial plan to meet these goals and objectives, identifying the vulnerabilities of the plan, adding to the plan a set of initial actions to be taken immediately upon implementation to protect it against some of these vulnerabilities, and establishing signposts to monitor the remaining uncertain vulnerabilities.
Dynamic Adaptive Policy Pathways*	Designed to avoid making inappropriate and unnecessary adaptation decisions under certain climate, technological, socio-economic and political states. A plan is conceptualized as a series of pathways, including initial actions and long-term options that are triggered if and when the action is needed in the future.
Info-Gap Theory	It is a non-probabilistic decision theory for prioritizing alternatives and making choices and decisions under deep uncertainty. Focuses on the disparity between what you do know and what you need to know for making a reliable or responsible decision. It introduces the opportuneness function, the lowest horizon of uncertainty at which that decision enables better-than-anticipated outcomes.
Engineering Options Analysis*	Process of assessing the value of including flexibility in the design and management of technical systems. It consists of procedures for calculating the value of options in terms of the distribution of additional benefit due to the options. Heavily based on the idea that “The forecast is always wrong”, which leads to periodically build smaller, less capable infrastructure to avoid overbuilding and lock-in on old technology.

2.8.1 Robust Decision Making (RDM)

RDM (R. J. . Lempert et al., 2003): is an iterative process for developing robust rather than optimal strategies based on four key concepts: Decision Analysis (DA), Assumption-Based Planning (ABP), Scenario Analysis (SA) and Exploratory Modelling (EM). Traditional DA is based on expected utility theory and looks to seek an agreement regarding the likelihood of future states of the world and rank the policy alternatives ("agree-on-assumptions"). RDM employs DA in a different way, as it seeks to use models and data to stress test the strategies over a wide range of scenarios and then use the resulting information to characterize vulnerabilities of the proposed strategies ("agree-on-decisions").

ABP sets the organization's plans and identifies explicit and implicit assumptions that, if wrong, could cause the plan to fail. It links the identification of vulnerabilities with shaping actions (those designed to make assumptions less likely to fail), hedging actions (those taken if assumptions begin to fail) and signposts (trends and events to monitor in order to detect whether any assumptions are failing). SA includes the concept of a multiplicity of plausible futures to characterize and communicate deep uncertainty (R. J. . Lempert et al., 2003). The main characteristic is that these projected futures are not ranked according to probabilistic forecasts and relative likelihood. By using a sense of possibility rather than probability, it allows researchers to expand the space of futures and communicate a wide range of futures to audiences.

RDM integrates these concepts through EM, which runs a model numerous times and maps a wide range of assumptions onto their consequences without privileging one set of assumptions over another. If researchers are capable of defining an appropriate set of questions and cases designed to address these questions, the large database of results can prove useful toward informing policy choices. Finally, RDM follows a learning process called "deliberation with analysis", shown in Figure 13, in which parties to a decision deliberate on their objectives and options'; analysts generate decision-relevant information using system models; and the parties to the decision revisit their objectives, options, and problem framing influenced by this quantitative information.

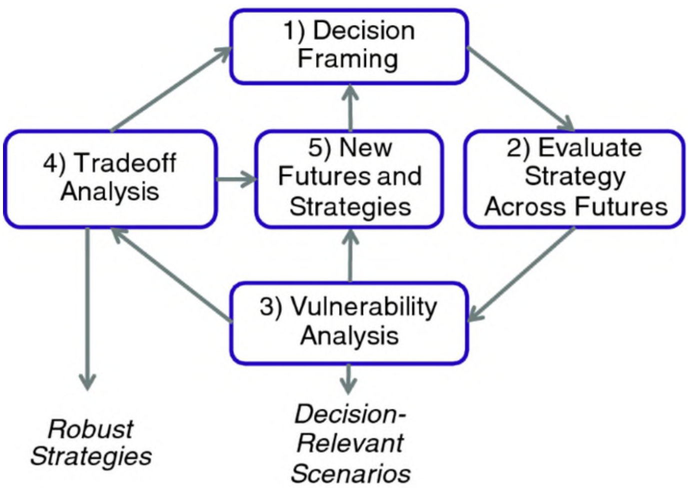


Figure 13 Iterative, participatory steps of a RDM Analysis. Image reprinted from the RDM chapter of the DMDU book.

But what if the future turns out to be different from the range of hypothesized scenarios? What if new technologies arise in the long term? Can we really simulate the occurrence of events such as wars and financial crises? Environmental conditions as well as societal perspectives and preferences may change over time. Investments in "hard-path" infrastructure with high capital expenditures, once considered robust, could be reevaluated by a society with different needs than initially estimated.

2.8.2 Dynamic Adaptive Policy Pathways (DAPP)

DAPP(Walker et al., 2013): aims at building flexibility into an overall plan by recognising that decisions are made over time in dynamic interaction with the system of concern. The central parameter which determines if adaptation should take place is the degree of change in the environment. DAPP aims to explicitly sequence the implementation of actions over time in such a way that the system can be adapted to changing conditions, with alternative sequences specified to deal with a range of plausible future conditions. Therefore, a plan is conceptualized as a series of actions over time (pathways), including initial actions and long-term options activated by the identification of signals.

The approach starts from the premise that policies/decisions have a design life and might fail when operating conditions change. Once (not if) actions fail, additional actions are needed to ensure that the original objectives are still achieved, and a set of potential pathways emerges, as shown in Figure 14. The preference for specific pathways over others is actor specific and will depend on the trade-offs, such as the costs and benefits of different pathways. In this sense, pathways can focus on adapting to changing conditions (development pathways), enabling socio-economic developments (development pathways), or transitioning to a desired future (transition pathways).

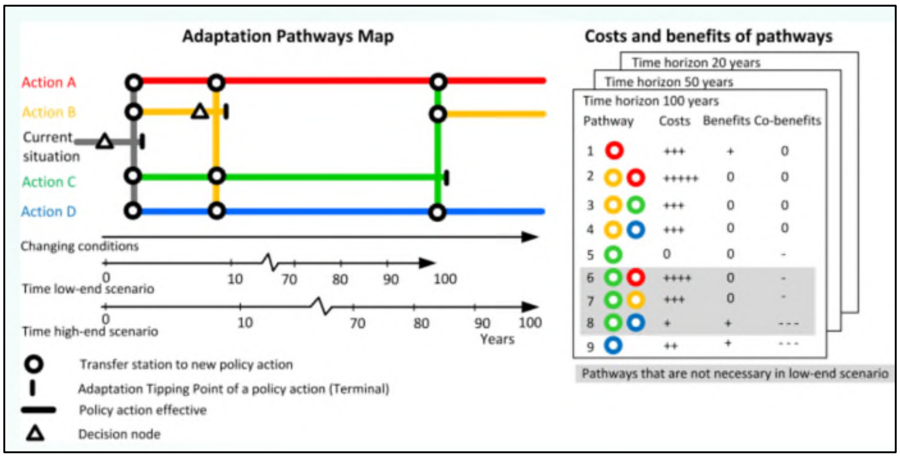


Figure 14 Example of an Adaptation Pathways Map and a scorecard for each of the pathways. With the current situation, targets begin to be missed after four years, and an adaptation tipping point is reached. Actions A and D should be able to achieve all targets for the next 100 years in all scenarios. Actions B and C have tipping points in the following years and they would need to shift paths. Image reprinted from the DAPP chapter of the DMDU book.

2.8.3 Engineering Options Analysis (EOA)

EOA is a methodology to assess the value of including flexibility in the design and management of technical systems (de Neufville & Smet, 2019). It provides procedures for calculating the value of options in terms of additional benefits. An option in this context is defined as: the right, but not the obligation, to undertake a specific action (like expanding a plant) at a certain cost within a specific time period. These additional benefits can be communicated to decision-makers through average expectations, extreme scenarios, and initial capital investments. It's important to note that in EOA, calculating an expected price is secondary; it's merely a tool to identify the most effective designs and strategies. Engineers have the task to complement these values with the downside risks and trade-offs of all options.

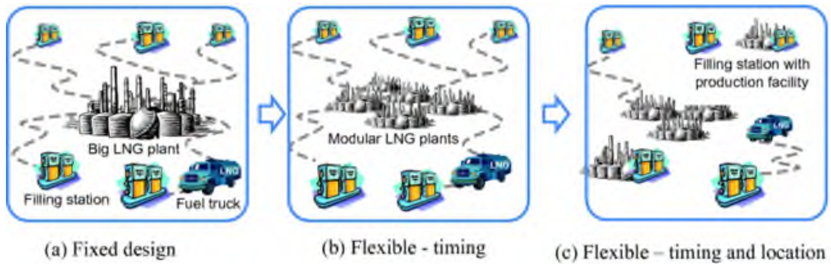


Figure 15 Alternative design configurations of a LNG (Liquified Natural Gas) production and distribution system. Option (a) represents the conventional design that creates an optimal single large facility, taking advantage of economies of scale. Option (b) represents a flexible strategy that deploys capacity at the central site according to how demand does or does not grow. Option (c) is a more flexible strategy that allows for gradual deployment of capacity both over time and geographically to the demand sites. Image reprinted from Cardin et al, 2015.

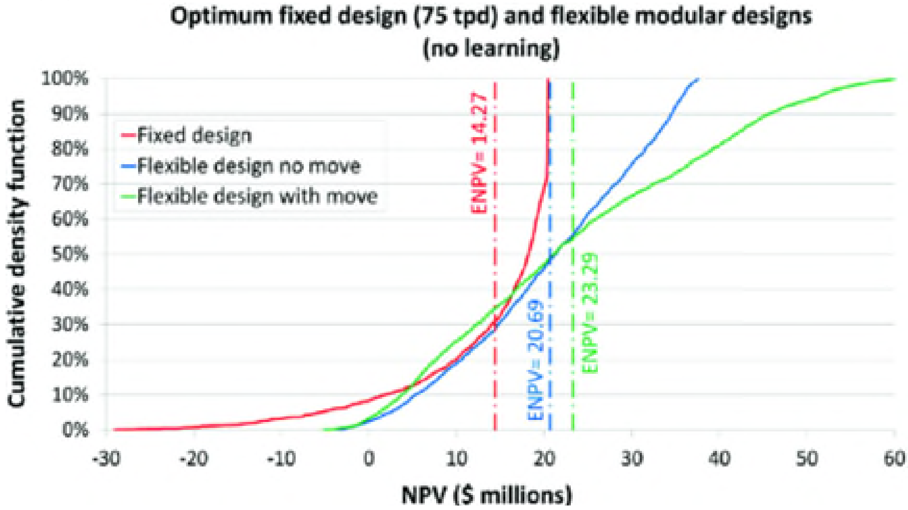


Figure 16 Net protected value (NPV) target curves for the optimum fixed design and for the flexible modular design (no move option). Image reprinted from Cardin et al, 2015.

EOA focuses on the investment, design and management of technical system. This is a main difference with other methods, which can be used more broadly to develop adaptive strategies for both infrastructural and non-technical applications. As shown in Figure 16, EOA allows managers to deal explicitly with many strategies to alter the capacity of an engineered system by sampling the space (sizes, times, locations, etc) with computer simulations and obtain a useful distribution of the possible outcomes. This way, the interaction of the possible uncertainties, and of the managerial responses are taken into account. It finally compares the range of possibilities, and proposes the strategies that are most likely to be successful. As the future clarifies, the EOA can be extended and a revaluation of the initial goals and options is required.

2.9 Choosing a DMDU method

The overlaps, similarities and evolution of DMDU methods makes it unwise to connect or assign specific methods to specific sectors/cases a priori (J. H. Kwakkel & Haasnoot, 2019c). Researchers and DMDU practitioners must acknowledge and weigh the advantages, disadvantages and merits of the different approaches for the specific case in question. This also entails being conscious about the limitations of the methods one is most familiar with and to be aware of the potential cognitive bias this may elicit. Or as the saying goes: "If the only tool you have is a hammer, it is tempting to treat everything as if it were a nail." The taxonomy in Figure 17, developed by J. H. Kwakkel & Haasnoot, can be used as a guide to match a specific case with a suitable DMDU method. In Figure 17 the main methods discussed in the previous section are highlighted. A preliminary set of steps which can be used to guide the implementation of DMDU methods is shown in Appendix III. Further method development to use the taxonomy together with stakeholders for joint definition of a suitable DMDU method within a specific sector is suggested for future work.

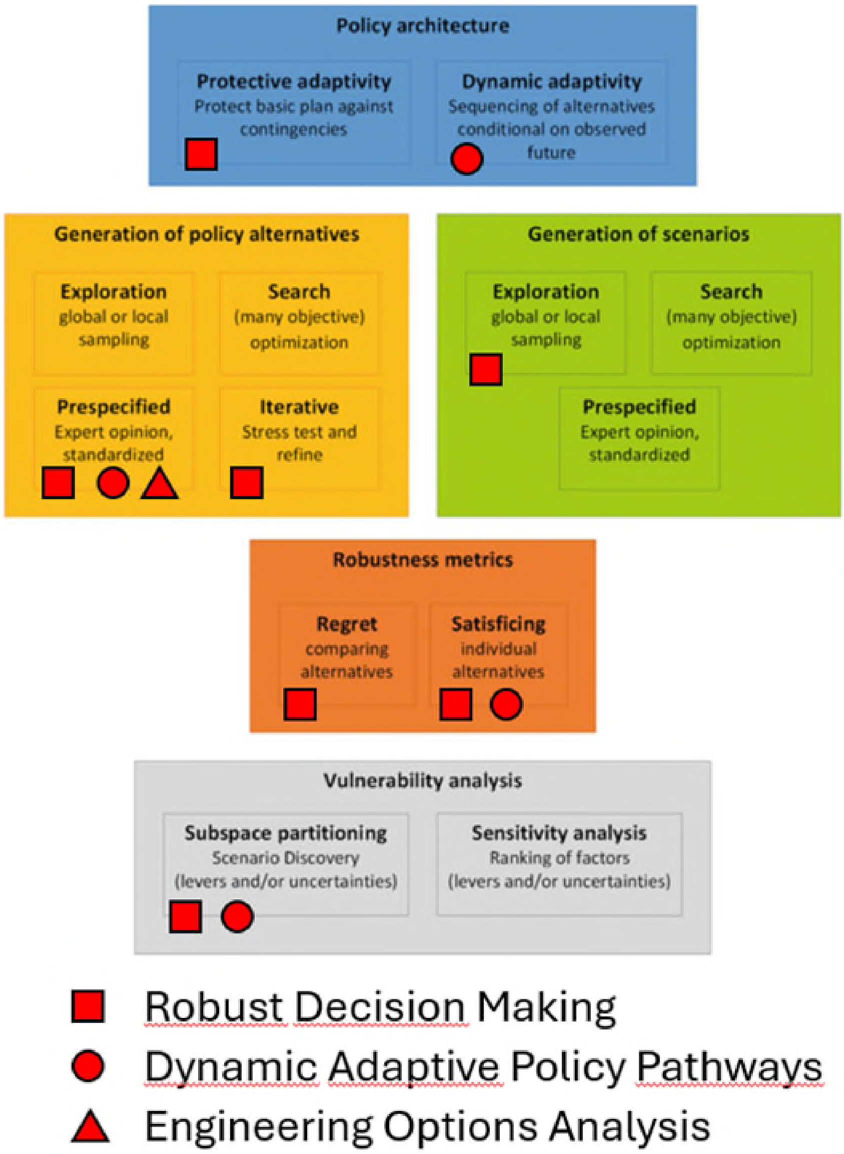


Figure 17 Taxonomy of components that make up the DMDU approaches. Adapted from (J. H. Kwakkel & Haasnoot, 2019a). The methods highlighted in this section (RDM, DAPP and EOA) are depicted within the taxonomy. Icons missing from some categories means that classification for that category is impossible, or a method specific approach is used.

3 Deep uncertainty in the drinking water sector

Water managers and planners must handle a large number of uncertainties. In the case of the water sector their job mostly revolves around assuring water availability, quality and the reduction of variability, their actions have a big effect on the development of societies, economies and ecosystems. Water resource systems are considered to include three subsystems (Loucks & van Beek, 2017):

- The Natural Resource System (NRS), consists of the streams, rivers, lakes, their embankments and bottoms, the groundwater aquifers, and the water itself. This includes the physical, biological and chemical components in and above the soil. It also includes the infrastructure needed to collect, store, treat, and transport water, and the policies or rules for operating them.
- The Socioeconomic System (SES) is the water use and water-related activities. This component can also include the stakeholders.
- The Administrative and Institutional System (AIS) component are the institutions responsible for the administration, legislation and regulation of the supply and the demand components of the water resource system.

Any attempt to model a water resource system implies describing the infinite interactions between the “connected hydrologic, infrastructure, ecologic and human processes that involve water” (C. M. Brown et al., 2015), i.e. the components of the previous three subsystems. It also includes the characterisation of policies and decisions made throughout the years by a number of actors.

In Section 2.3 we described the different levels of uncertainty, and more specifically, deep uncertainty, which included the identification of many plausible futures (Level 4a) and the acknowledgement of a space of unknown future states (Level 4b). It is important to remember that decision-making in the context of deep uncertainty does not follow the "predict-then-act" paradigm. Instead, it aims to prepare and adapt by monitoring how the future unfolds and allowing for adjustments over time as new knowledge is gained to implement long-term strategies (Marchau et al., 2019). This approach, known as the "monitor and adapt" paradigm, relies heavily on the analyst’s ability to not only quantify but, most importantly, visualize the vulnerabilities and needs of the system in the future.

During recent years, the water sector has begun to pay more attention to this paradigm shift. As the impacts of deep uncertainties become increasingly evident in both climate and society, experts can no longer set priorities without developing and examining multiple plausible scenarios. There has been a notable increase in white papers and case studies highlighting the growing interest in DMDU techniques and their real-life applicability. Decision makers are mostly interested in detecting sign points that indicate that changes are already occurring in the system, and developing management actions that assure robustness across all potential futures. In the context of water companies, robustness includes but is not limited to: water supply, water quality and the prevention of disasters. It should also be recognized that this awareness might be different among researchers compared to professionals working in practice. In this section the literature on deep uncertainty in the water sector is compared with the results of a limited questionnaire.

3.1 Deep Uncertainties and DMDU methods in the drinking water sector

In the energy sector (Paredes-Vergara et al., 2024) and in the water sector (Stanton & Roelich, 2021a) recent studies have made an inventory of the main sources of uncertainty and the prevalence of applied methodologies to cope with these (deep) uncertainties. The systematic review by Stanton & Roelich is taken as a starting point to investigate which sources of uncertainty are prevalent in the scientific literature in relation to water supply, which management steps of the water supply system are investigated most often, and which DMDU methods are used (Figure 18).

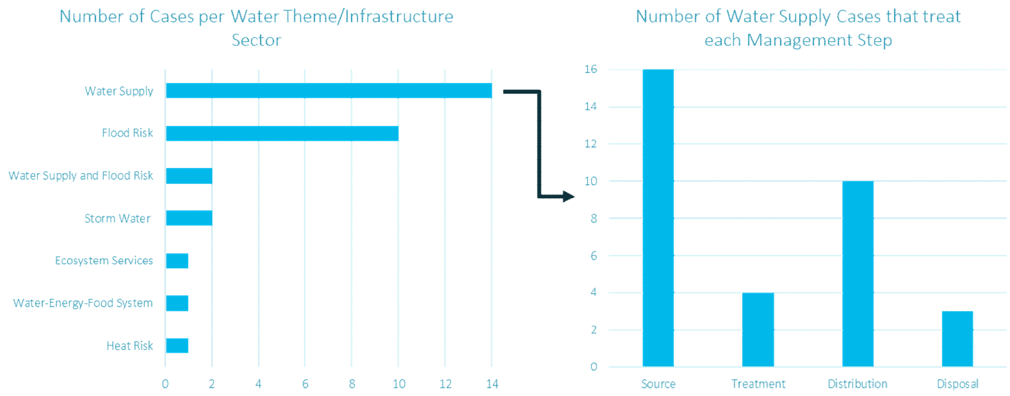


Figure 18 Topics of interest for papers related to DMDU and the water sector (left) and the water management steps analysed by papers that study future water supply (right). Data derived from Stanton & Roelich, 2021.

When examining the underlying papers for the water supply and flood risk sectors (see Appendix IV) the underlying deep uncertainties can be globally grouped (Table 4). Based on this analysis climate change, water demand, and population change can be identified as the most prevalent sources of uncertainty in literature where DMDU is brought to practice.

Table 4 Sources of deep uncertainty identified in the water supply and flood risk sectors of (Stanton & Roelich, 2021a). Sources of uncertainty were copied literally from the case studies in the paper and were then grouped into overlapping themes as indicated with the fill color in the table. For example: Future Water Demand, London Demand, and Water Demand were the uncertainties mentioned in separate papers, but they fall under a similar category, indicated with the blue colour.

Source of deep uncertainty	Count	Source of deep uncertainty	Count
Achievement of Management Strategies	1	Local Water Supply	1
Climate Change	5	London Demand	1
Climate Change (Rainfall, Evapotranspiration)	1	Market Pricing	1
Climate Change (water supply reliability)	1	Nature's Water Demand	1
Climate Change Flow Perturbation	1	Population and Economic Growth	1
Climate Key Factors	1	Population Growth	3
Delta Water Flows	1	Population Pressures	1
Energy Prices	1	Response of Groundwater Basin to Changes in Precipitation	1
Financial Risks	1	Response of Groundwater Basin to Urbanization	1
Future Climate Conditions	1	Runoff conditions	1
Future Costs	1	Societal Preferences	1
Future Feasibility	1	Socio-Economic Conditions	1
Future Stream Flow	1	Sociopolitical Context	1
Future Water Demand	1	Socio-Political Decision Making Context and System Response	1
Global Climate Models	1	Storm Surges (Climate Change)	1
Hydrological Models	1	Tidal Surges	1
Hydrological Variability	1	Water Availability	2
Impact of Climate Change on Imported Supplies	1	Water Availability (Climate included)	1
Interaction Climate Change Risks	1	Water Demand	4
Irrigation Requirements	1	Water salinity	1
Knowledge and Innovation	1	Water scarcity	1

When examining the methods used by researchers in the field it can be seen that a broad range of methods is used, and that in several cases methods are combined (Table 5). The use of a wide range of methods is in accordance with the general sentiment within the DMDU community, that method selection should be done on a case by case basis to match the requirements of the specific situation.

Table 5 Overview of DMDU methods used within the water supply and flood risk papers in (Stanton & Roelich, 2021a)

DMDU method	Water Supply	Water Supply and Flood Risk	Total
Adaptive Planning	2	1	3
Dynamic Adaptive Policy Pathways		1	1
Engineering Options Analysis and Robust Decision Making	1		1
Multi Objective Robust Decision Making	5		5
Multi Objective Robust Decision Making and Info-Gap	1		1
Robust Decision Making	4		4
Robust Adaptation	1		1
Total	14	2	16

3.2 Questionnaire

A questionnaire was distributed amongst Dutch drinking water professionals to investigate their perception of uncertainty and deep uncertainty within several aspects of the drinking water system. The investigated aspects were; sourcing, treatment, transport, governance and other. In addition participants were asked to evaluate the current practices to deal with uncertainties and to propose potential cases studies to test DMDU methods.

The understanding of *uncertainty* by water utility experts can be summarized as follows:

There is an inherent uncertainty in predicting future events and their impacts, which is represented in probability distributions for potential scenarios. This uncertainty is partly due to a lack of knowledge or insight into changing conditions, and partly due to the limited resources and knowledge available to address future issues. In the context of a water supply company, this uncertainty manifests as a lack of insight into certain situations or parameters, leading to doubts about the adequacy of current actions and the inability to accurately predict the nature and extent of changes and their consequences. Additionally, this uncertainty may necessitate stepping out of comfortable frameworks, potentially pushing the boundaries of conventional approaches.

The understanding of *deep uncertainty* by water utility experts can be summarized as follows:

The concept of deep uncertainty encompasses an array of unpredictable aspects, events, consequences, and effects that defy standard probability distributions. It involves not knowing which actions to take or which contextual factors, including data, can be relied upon for decision-making. The term reminds one respondent of 'unknown unknowns'—areas of ignorance about potential influences on us that we cannot anticipate. Deep uncertainty arises from a multitude of compounding uncertainties: unclear questions, directions, solutions, and a complex and variable environment. Unlike the general definition of uncertainty, deep uncertainty specifically refers to situations or parameters that are influenced by other stakeholders or factors beyond the water supply company's control. This complexity might lead to crossing multiple comfortable boundaries, within which it becomes impossible to distinguish between different scenarios.

Respondents were asked to indicated the level of uncertainty within different areas of the drinking water system and to provide additional comments where applicable. A total of 7 respondents out of 11 contacted drinking water companies filled out the questionnaire.

Water sourcing

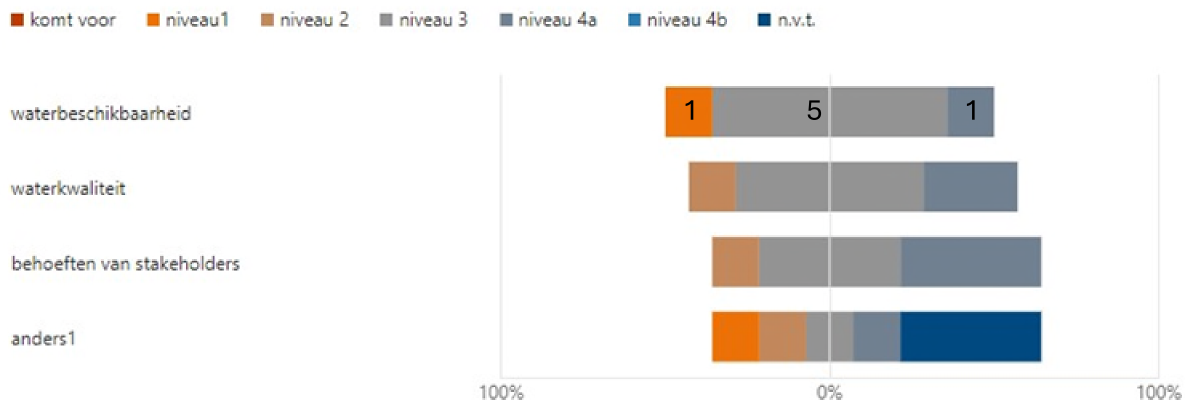


Figure 19 Questionnaire responses related to water sourcing. Each row represents a total of 7 responses, for example: for 'waterbeschikbaarheid' 1 response indicated a level 1 uncertainty, 5 indicated level 3, and 1 indicated level 4a.

Several additional sources of deep uncertainty were identified. There is a recognition of the challenges faced due to the maintenance of resources (level 1), political interference (level 3), and the varying preferences of management regarding resource extraction (level 2). Furthermore, the availability and cost of energy are essential factors since energy is expended in the process of extracting water (level 4a). There is also an acknowledgment of the difficulty in isolating various uncertainties from one another due to the complexity of the problems, which are interconnected and influenced by multiple factors, such as water quality dependence on availability, forced choices of source due to this dependency, and the overarching impact of climate change. Adding to this complexity is the role of legislation and regulations.

Current practices of dealing with these deep uncertainties in the field of water sourcing include the following. Water companies manage deep uncertainty through a multifaceted approach. They forecast water availability years in advance by developing various building blocks and applying operational risk (OR), non-operational risk (NOR), and asset strategy values (ASVs). In terms of water quality, they implement redundancies and allow space for additional purification steps such as activated carbon filtration (ACF) and reverse osmosis (RO), focusing on preventing source pollution and conducting broad screenings. Stakeholder engagement involves analyses, maintaining public affairs staff, intensifying lobbying through organizations like Vewin, and keeping in close contact with stakeholders. Operational strategies include periodically exploring new source options, assessing them against expected demand growth, and considering the climate impact on current sources like the Rhine and IJsselmeer. For water quality, they advocate for clean sources and develop predictive models for quality changes, such as the salinization of the IJsselmeer. Plans for water transition involve creating prognostic scenarios, building operational water reserves, engaging in dialogue with local communities, and compiling area dossiers. This process entails gathering information, reviewing and analyzing data, writing scenarios, and performing calculations. Companies are also applying for water permits, utilizing brackish water or effluent from water treatment plants as sources, and employing reverse osmosis purification to address both water availability and quality. However, there seems to be a lack of focus on stakeholders' needs within the water company framework. In addressing these complexities, the companies aim to explore as many alternatives as possible and start with what they can model.

Solutions are further sought in the use of tools to refine the margins in forecasts, pointing out that projections often include wide safety margins to account for the possibility of underestimating budgets or hours, which can impact other plans. They note the significant effect of costs associated with acquiring extraction areas and developing new pumping stations. Regarding water availability, they propose the use of reverse osmosis purification, applying for water permits from the province, and utilizing brackish water or water from wastewater treatment plants as sources. For water quality, the implementation of reverse osmosis purification is again mentioned.

Water treatment

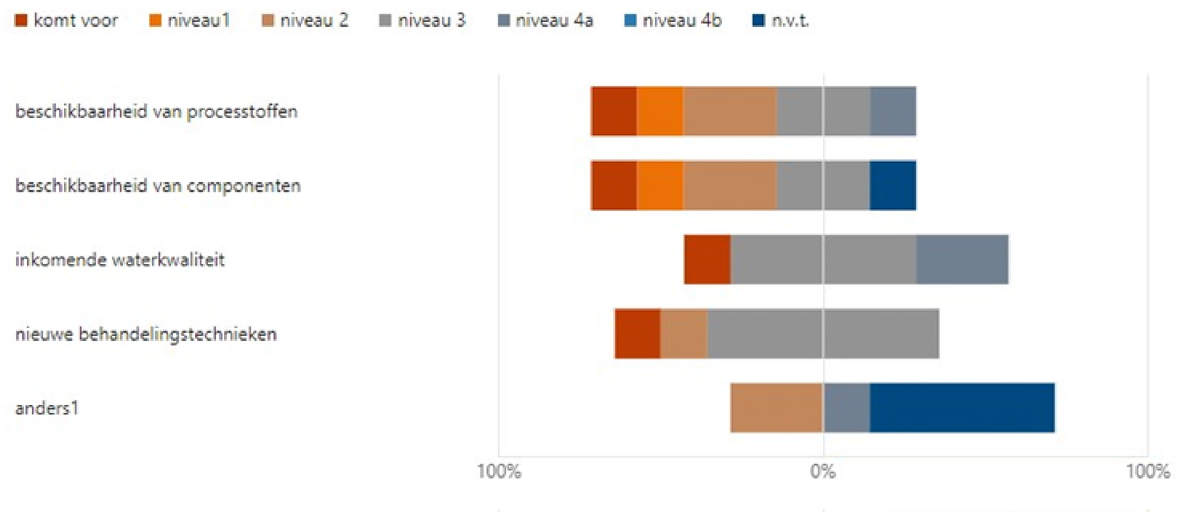


Figure 20 Questionnaire responses related to water treatment.

Additional sources of uncertainty that were identified include the influence of management's opinions (level 2) and focuses on the importance of quality standards for drinking water and infiltration water (level 2). They suggest an uncertain shift towards model-based process control rather than rule-based management (level 4a). Additionally, the necessity of dedicated individuals with the right competencies is emphasized, noting that the requirements may differ between the north and the Randstad region.

Respondent utilities are addressing deep uncertainties in water treatment by adopting more sustainable practices and state-of-the-art technologies. These utilities are reducing their dependence on raw materials and chemicals, favouring electrical purification methods like reverse osmosis and ultrafiltration. In dealing with regulatory challenges, such as the EU's restrictions on mercury UV lamps for disinfection (although the water sector is exempted), they are exploring alternative technologies, including LED lamps. The balance between self-sustaining energy provisions and their associated costs is also a focal point for these utilities as they plan for the future, with an eye on maintaining quality even when substituting components due to availability issues.

To address additional solutions for water treatment uncertainties, there's an emphasis on capturing the knowledge possessed by current operators through the use of artificial intelligence. Moreover, to ensure the availability of process materials and components, strategies include creating strategic reserves in collaboration with other drinking water companies. This involves providing transparency in inventory levels to facilitate the sharing of resources and engaging in joint procurement efforts to bolster supply chain resilience.

Water distribution

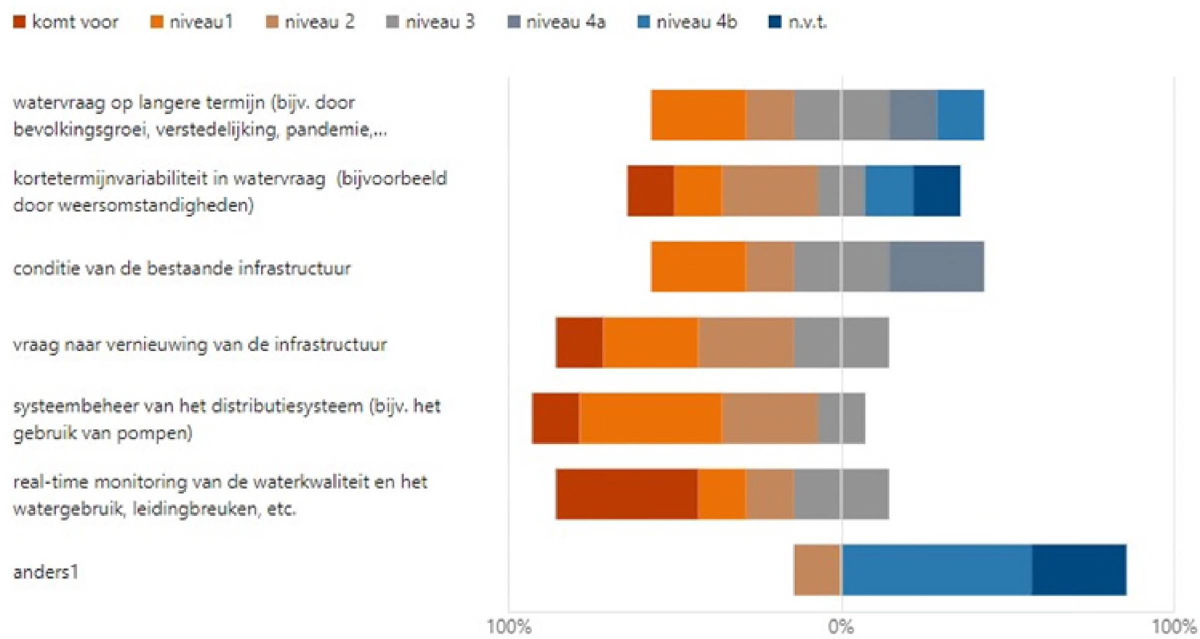


Figure 21 Questionnaire responses related to water distribution.

An additional source of uncertainty mentioned is flexible routing, for instance, by utilizing diversely located extractions such as brackish water sources (between level 2 and level 4a).

Addressing deep uncertainty in water distribution involves a multi-faceted approach. There is an acknowledgment of the complexity of the task, with some respondents uncertain about the solutions. The difficulty in forecasting population growth and economic activities was highlighted, emphasizing their substantial impact on costs. Long-term water demand is managed using predictive models, strategic reserves, and capacity expansion. For short-term variability, peak factors methodology is applied. Condition assessment of existing infrastructure appears to lack a formal program; cathodic protection is used as a mitigation measure. Renewal demands are tackled by setting a yearly minimum replacement target for main pipelines, informed by data-driven analyses. System management for the distribution system is reactive, with broken pumps being replaced as needed. Real-time monitoring is evolving, with ongoing pilots for digital water meters, digital twins, and pressure sensor installations.

To enhance the response to water distribution challenges, an increase in the accuracy of forecasts is being pursued. For long-term water demand, the implementation of multiple models is suggested. This multi-model approach is also applied to address short-term variability. Assessing the condition of existing infrastructure involves using tools like USTORE and sharing experiences with other drinking water companies. For system management of the distribution system, predictive maintenance strategies are being emphasized.

Governance

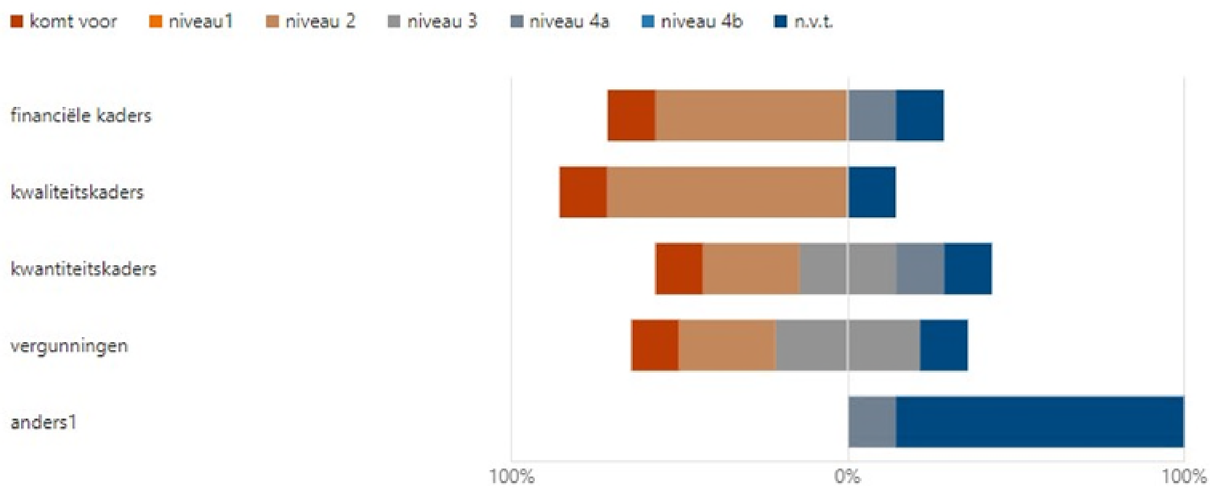


Figure 22 Questionnaire responses related to governance.

An additional factor that was mentioned is the development of the labour market (level 4a).

Dealing with sources of deep uncertainty in governance related to water resources, there is an admission of limited knowledge and a lack of expertise among some respondents. However, it is observed that various stakeholder groups are increasingly forming stronger opinions and asserting their rights to water resources. This includes farmers' organizations uniting to highlight drought damage and environmental groups aiming to prevent desiccation or acidification. The discourse is reflective of a densely populated nation with a keen sense of environmental and resource stewardship. In terms of governance frameworks, while financial frameworks remain unspecified, quality frameworks are being addressed through Waterwijs research. Quantity frameworks involve the use of models and scenario studies, and for permits, environmental management is indicated. Addressing additional solutions for long-term planning is challenging; the further we look into the future, the greater the degree of uncertainty becomes.

Other uncertainties

Other sources of uncertainty not yet addressed include the management of organizational portfolios (level 3), which involves prioritizing and executing activities cohesively, and the preservation of knowledge within the organization (exists, level '0'). Additionally, ensuring a sufficient number of personnel with relevant knowledge, training, and experience is mentioned, alongside the pressures of increasing regulatory demands and legal obligations.

In the organizations, portfolio management for activities with an ICT component is practiced but does not always align with the overall ambition. Recruitment efforts are focused on hiring in-house talent, and eliciting knowledge to incorporate it into decision-support systems is a priority. Addressing the need for adequately knowledgeable, educated, and experienced personnel is approached through strategic staff planning. However, the response to the increasing regulatory burden and legal obligations remains unspecified.

Evaluation of current uncertainty management practices

In considering which sources of uncertainty in water utility management receive adequate attention and which do not, it's observed that the degree of uncertainty largely depends on the time horizon being considered. Generally, uncertainty increases as the future is projected further out, making near-term uncertainties more manageable. In terms of sufficient focus, lifecycle management of corporate assets and awareness of climate change (guided by KNMI scenarios) and CO_2 footprint are noted as being adequately addressed. However, knowledge preservation is deemed insufficiently attended to. Concerns are raised about the broader impact of the energy transition in the Netherlands, such as the potential shift to a hydrogen economy demanding large-scale water for electrolysis, which poses both risks and opportunities. The future industrial landscape in the Netherlands and Germany and its effects on water quality is also uncertain. Workforce development, particularly competencies in digitalization, face uncertainties. Financial uncertainties are amplified by geopolitical tensions affecting energy, chemical prices, components, and labour costs, coupled with legal limitations on water pricing. There's an acknowledgment that while all sources of uncertainty receive some level of attention, it is unclear whether it is the appropriate amount. The criteria for judging the adequacy of current attention are not well-defined. It is mentioned that uncertainties that can be comprehended can also be modelled; however, explaining more complex issues remains challenging, leading to a focus on more readily understandable and modellable problems.

In response to what should be done regarding sources of uncertainty that are currently receiving insufficient attention, there's a consensus that more focus is needed. Enhanced information-supported working practices, increased efforts for knowledge elicitation, and greater automation of non-knowledge-related or lower-quality (administrative) tasks are suggested. One water company indicated that there is an ongoing debate concerning uncertainties and the requirement of more capacity and expertise that is not internally available. The labour market presents challenges, particularly in making the northern regions more attractive, but the specifics of how to do this are complex. Adjusting legislation to allow water pricing based on geopolitical scenarios is proposed, with the realism of scenarios potentially supported by modelling. The idea of making the issue more tangible through a case study is suggested, without preference for any specific source of uncertainty at this moment, but with intentions to inquire further within the company for insights.

Overall the value of modelling and scenario building (often based on expert knowledge) to explore potential solutions for future challenges is present amongst all, if not most, of the uncertainty categories. However, there was no specific mention of the application of DMDU method or approaches. This confirms that DMDU methods have not yet found their way to widespread adoption in practice. If drinking water utilities can agree on the perceived increasing rate of change of socio/technical developments, and therefore increasing uncertainty, the logical next step is to increase the use of DMDU methods within the drinking water sector.

3.3 Comparison of literature and Questionnaire

Based on the investigated literature and the results of the questionnaire there seems to be a disconnect between the sources of uncertainty which are investigated or considered relevant in the drinking water sector compared to those that receive attention from the scientific community. Within the scientific community the sources of uncertainty which are most often characterised as deeply uncertainty are related to large global or regional changes, such as climate change and population changes. Based on the limited number of questionnaire responses it seems that while these sources of uncertainty are recognized but are not overwhelmingly seen as deeply uncertain. It is therefore not surprising that the implementation of DMDU methods in practice is lacking, for there is a disconnect between simulation models aimed at global patterns and effective downscaling towards local consequences.

Until now, the rate of change, flexibility of solutions, and planning horizon within the water sector have remained relatively aligned. This is shown by the success that Dutch water utilities have had in ensuring a reliable supply of clean water. However, as demonstrated throughout this report, the water sector is now confronting increasingly dynamic and complex challenges, characterized by greater uncertainty. Consequently, the need for adaptive DMDU methods is expected to arise sooner rather than later. Actions to deal and prepare for these uncertainty is being taken by several drinking water companies in separate initiatives without a clear overarching methodology.

It is also relevant to remember that if the time required to implement a solution is long relative to the system's rate of change, adaptation may not occur quickly enough to prevent system failure. Therefore, water utilities must not only focus on diversifying their water sources but also on enhancing connectivity with other utilities and improve coordination to reduce response times during emergencies.

Both Dynamic Adaptive Policy Pathways (DAPP) and Engineering Options Analysis (EOA) present themselves as potential candidates to enhance the flexibility of sociotechnical systems. But, what are their key differences and similarities? Which of them is more sensitive to the researcher’s input? When provided with the same set of simulations, will they yield identical results? In other words, will they recommend the same set of actions as the “best” strategy to address future challenges? This exploratory case study aims to provide insights into these questions.

3.4 Case Study Description

Due to a lack of a readily available case study from the involved drinking water companies it was decided to build a hypothetical case study. This was done in an iterative process based on an exploration of areas in the Netherlands where drinking water provision is subject to sources of deep uncertainty. The final case study was inspired by the groundwater system in North Brabant.

The Netherlands has experienced episodes of climate stress in recent years, with the back-to-back dry summers of 2018, 2019, and 2020 highlighting the pressing need to understand how droughts impact freshwater availability (Figure 23). From a hydrological perspective, drought involves two aspects: a lack of precipitation, which leads to reduced soil moisture, low groundwater levels, and decreased stream flows; and a diminished water supply in major rivers (Bierkens & Wanders, 2022). In particular, The 2018–2019 meteorological drought caused record groundwater drought throughout the south-eastern Netherlands, and higher-elevation areas suffered from severe drought well into 2020 (Brakkee, Van Huijgevoort, et al., 2022).

Addressing these challenges goes beyond implementing specific restrictions and innovations to manage climate change. Some experts have begun to question the overall approach to Dutch groundwater management (Utrecht University, 2020):

> *“…as it currently stands, groundwater can be pumped up at practically no charge. All you need is a pump and you can extract as much water as you like. Both commercial farmers and private citizens take advantage of this for irrigation purposes. If we invest in increasing our water reserves, we must prevent those additional reserves from being pumped out as fast as we can store them.”*

Therefore, it will be essential to implement a coordinated set of measures to strengthen the security of the groundwater supply, while ensuring that groundwater levels are maintained at safe levels for both nature and the future development of the region. These measures should consider new sources of water for consumption or aquifer replenishment, as well as initiatives to reduce water demand across various sectors.

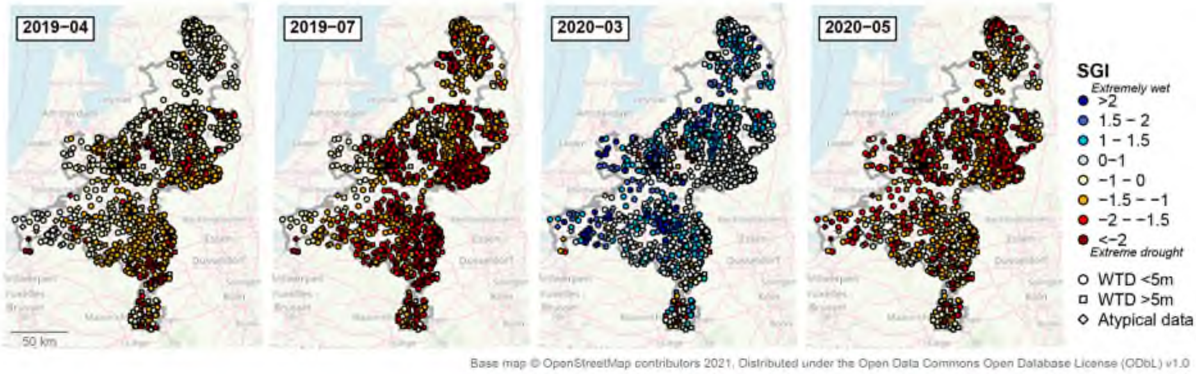


Figure 23: Groundwater drought over 2019-2020. SGI stands for Standardized Groundwater Index and WTD denotes Water Table Depth (Brakkee, van Huijgevoort, et al., 2022).

3.5 Exploratory modelling methodology

In this case study, we will explore the application of initiatives to reduce water consumption in urban and rural areas, along with the construction of potential brackish water and wastewater treatment plants for agricultural use. The goal is to identify the combination of measures most likely to succeed in maintaining healthy groundwater levels and ensuring water security for people, agriculture, nature, and industry, while remaining adaptable to sudden shocks or unforeseen scenarios. As this is an exploratory study with relatively experimental interventions, we will not consider costs as a variable of interest.

We create and simulate an yearly system dynamics case study exploring the consequences of land use change in the groundwater levels until 2100. We examine a current square of land with sides of 10 km (totalling 100 km²) and a spatial resolution of 100 m. Each pixel represents a hectare of land classified as urban, natural, or agricultural. The agricultural pixels are further divided into specific crop: grass, green maize, corn, cereals, potatoes, and beets. The initial proportions for each type of land of the map are based on data from the Dutch Central Bureau of Statistics. Because each land type has a different annual groundwater recharge rate, the land use map results in a recharge rate map, as seen in Figure 24. The recharge rate equations for each land type at location (x,y) are the following (Witte et al., 2019):

$$r_{(x,y)}[t] = \begin{cases} 0.75 * P[t] - 0.66 * E_{urban} \; if \; (x,y) = urban \\ P[t] - E_{nature}[t] \; if \; (x,y) = nature \\ P[t] - \left(T[t] + E_{agriculture}[t]\right) if \; (x,y) = \; agriculture \end{cases}$$

Where P: Precipitation, E_{urban}, $E_{agriculture}$ and E_{nature}: Evaporation, T: Transpiration. Both the evaporation and transpiration rates differ between crops (Witte et al, 2019).

The primary driver of change in this system is urbanization: both the initial urban area- 6 km² - expands, and the population density (people per pixel) increases at an uncertain rate. Consequently, the city's total water demand is likely to rise, and land previously designated for nature and agriculture is converted into urban areas, leading to a lower groundwater recharge rate per pixel. It is important to note that, although this model is inspired by real-life data, there is no geographic link between the original data and the model’s figures, and therefore it should not be considered a geographic information system (GIS) analysis.

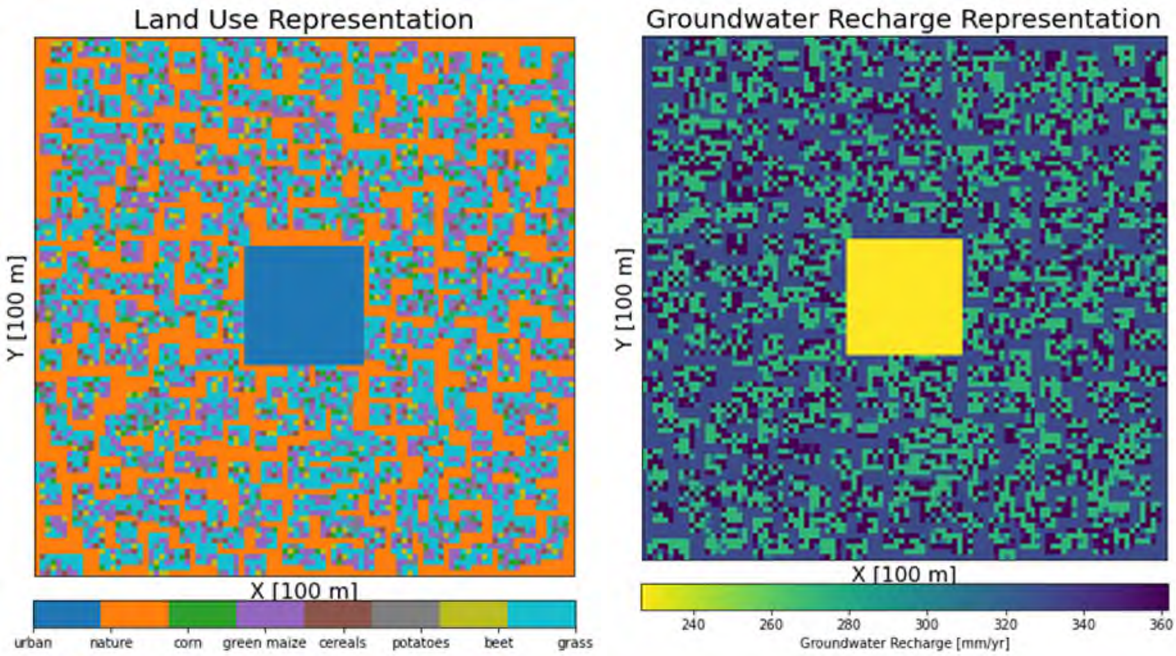


Figure 24: Graphical representation of land use within the simulation model (left). Land use translates to a specific groundwater recharge rate per location (right). The central urban square grows throughout time and lowers the potential recharge rate of the system.

To model annual groundwater changes, we used a simple bucket model (Figure 25). The aquifer has a depth of 10 m and an uncertain porosity characteristic of sandy materials (ranging from 0.25 to 0.5). The water balance is defined by the annual vertical recharge rate and total demand, assuming that horizontal groundwater flow remains constant (inflow equals outflow). The equations which describe the changes to the groundwater system over time are described below:

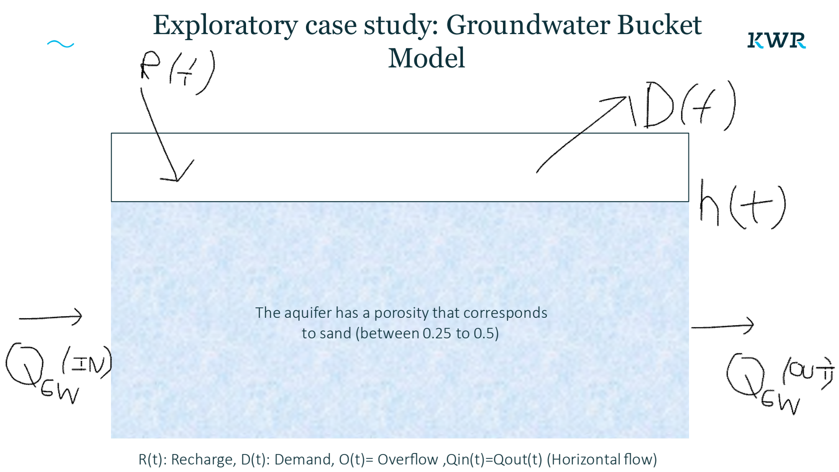


Figure 25 Aquifer Bucket Model. Based on Stuurman et al. (2020)

$$D[t] = D_{agriculture}[t] + D_{urban}[t] + D_{industry}$$

$$\mathrm{R}[t] = \sum_{(x,y)\in Map} r_{(x,y)}[t, land\ type]$$

$$O[t] = Max(W[t-1] + R[t] - V, 0)$$

$$W[t] = Max(W[t-1] + R[t] - D[t] - O[t], 0)$$

$$h[t] = Max\left(h[t-1] + \frac{(W[t] - W[t-1])}{area * porosity}, 0\right)$$

Where $D[t]$: Demand, $R[t]$: Total Recharge, $r_{(x,y)}[t, land\ type]$: Recharge per pixel, $W[t]$: Water in aquifer, V: Volume aquifer, $O[t]$: Overflow, $h[t]$: height. The horizontal flow/flux is should remain unaffected.

In a system dynamics model, the groundwater level will depend on multiple factors. A causal loop diagram of our model can be seen in Figure 26. This diagram uses arrows to illustrate how various system components affect one another, with the symbols '+' or '-' indicating whether the influence is positive or negative. It has been plotted on Vensim only for visualization purposes. The actual model was built on Python and run with the Exploratory Modelling and Analysis (EMA) workbench (J. Kwakkel, 2024). EMA aims to offer computational support for decision making under uncertainty: it provides help to design the experiments, perform them, and analyse their results.

In exploratory modelling, there is an uncertainty space, a decision space and an outcome space. The uncertainty space is made up of external factors, variables outside the control of policy makers. The decision space is composed by levers (mitigation and adaptation measures) to be evaluated by the model. These two spaces are connected through relationships, i.e. the model structure and its functions. Finally, the performance metrics of interest define the outcome space.

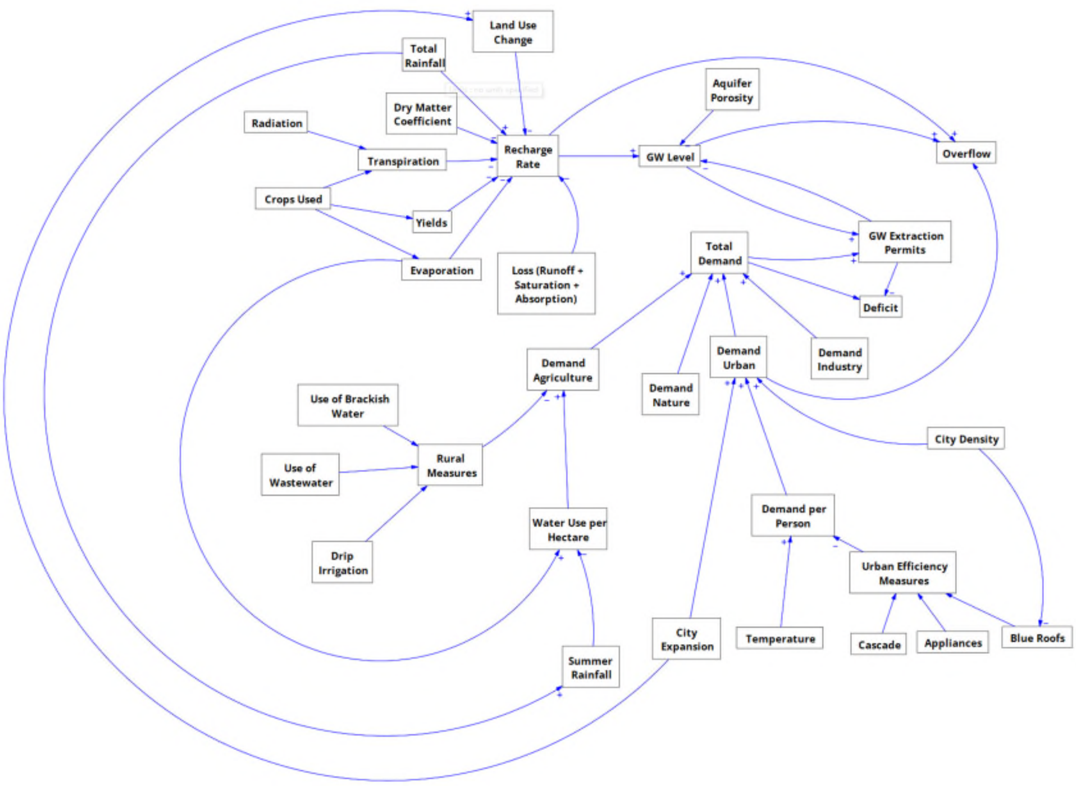


Figure 26: Visualization of the System Dynamics Model for this case study. Plotted with Vensim.

As mentioned, all models are merely attempts to capture the complexity of real-world systems. The focus is not necessarily on achieving an extremely accurate representation, but rather on uncovering new relationships, identifying critical points, and understanding rates of change. In this context, the relevant variables (uncertainties, levers and outcomes) can be broadly divided between the following groups:

- Land use (urban, nature, and agriculture) and population density: These are the primary drivers of demand— their rate of change is uncertain in this model. Water use for industry is the same for all scenarios and remains constant throughout time.
- Groundwater characteristics (volume of water, porosity, recharge, overflow): As described by the water balance equations—uncertainties and outcomes affected by levers.
- Climate (rainfall, temperature, radiation, evaporation, and summer droughts): They influence the entire system—uncertainties.
- Measures to reduce urban water demand: cascade systems, more efficient appliances, and blue roofs—levers with uncertain outcomes.
- Measures to reduce agricultural water demand: brackish water plants (KWR, 2020 & 2024), urban wastewater treatment plants (van Wasteren, 2019; Nairain-Ford et al, 2020), and drip irrigation (KWR, 2024)—levers with uncertain outcomes.

In the DMDU literature a commonly used framework to structure modelling approaches is the XLRM matrix (R. J. . Lempert et al., 2003). This framework was designed to distinguish among the uncertain factors (X); the (water)management strategies (L) that make up the response packages; the relationships (R) among these elements that are reflected in the planning models; and the performance metrics (M) that are used to evaluate and compare response packages. The XLRM framework for the case study is shown in Table 6.

Table 6: Summary of Uncertainties, Policy Levers, Relationships and Metrics identified in the study (XLRM Matrix)

Uncertainties or Scenario Factors (X)	Management Strategies and Response Packages (L)
• Demographic and land-use scenarios • Climate change scenarios • Effect of the response packages	• Alternative water sources for agriculture (brackish and wastewater) • Implementation of drip irrigation for agriculture • Urban efficiency measures (cascade, blue roofs and new appliances) • Implementation of GW restrictions
Relationships or System Model (R)	**Performance Metrics (M)**
System Dynamics Model composed by: • Groundwater Bucket Model • Urbanization (Land Use) Model • Links between climate change and changes in water demand	• Groundwater level (height) • Deficit relative to the demand

The set of possible measures are described in detail in Table 7. All factors and innovations are interconnected, either directly or indirectly. For instance, groundwater extraction primarily depends on climatic (both part of the Natural Resource System) and population factors (Socioeconomic System), but the actual changes are also influenced by decisions made by the authorities, such as the total extraction permits granted by provincial authorities (Administrative and Institutional System). These decisions, in turn, may be influenced by the success of the alternative sources, the definition of 'healthy' aquifer level ranges and the government's willingness to risk not meeting consumer water demands.

In such systems, clearly identifying critical points is often challenging and ultimately depends on the decision-makers' priorities. However, in the Results we will show why placing too much emphasis on a single objective, such as ensuring a reliable water supply, ultimately leads to the system's long-term collapse.

Table 7: Set of measures to improve the system's performance. The first three measures, along with drip irrigation, focus on improving the system's efficiency through demand-side efforts. The brackish and wastewater plants represent supply side improvements through infrastructure innovations. All information, except for the wastewater data (Narain-Ford et al, 2020), derives from previous KWR reports.

Measure	Setting	Type	Effect	Adoption of the measure
Cascading/grey-water reuse	Urban	Efficiency	Shower water used for toilet and washing machine	Linear. Rate is uncertain
New water-efficient Appliances	Urban	Efficiency	More efficient shower, garden, toilets, washing machine and dishwasher	Linear. Rate is uncertain
Blue Roofs	Urban	Efficiency	Capture of grey water for toilet and garden	Linear. Rate is uncertain
Brackish Water Plant	Agriculture	Infrastructure	Use for agriculture	Every 15 years a plant can be built with a capacity between 438000 and 1752000 m^3
Wastewater Plant	Agriculture	Infrastructure	Use for agriculture	Every 15 years a plant can be built. Capacity = [333000, 1000000] m^3
Drip Irrigation	Agriculture/Efficiency	Efficiency	Reduction of water needs for agriculture	Linear. Maximum savings are 40% of irrigation. Rate is uncertain

3.5.1 Uncertainty Characterization

In this section the representation of climate and population as sources of uncertainties over time is explained.

Population growth (Table 8 and Figure 27), which is largely driven by the periodic expansion of the city's area every 4, 5, or 6 years (growth interval). In 2024, the city occupies around 6% of the total region, but by 2100, it is projected to cover between 13% and 18%. City density increases due to a rise in the number of houses per roof, which starts at a value of 2. This increase is influenced by two factors: a continuous sigmoid-shaped growth pattern and the potential for a sudden interannual shock, which could raise the average by 2 to 8 additional houses per roof. By 2100, this could result in an average of up to 18 houses per roof:

$$houses_{roof}(t) = C_1 * \frac{1}{1 + e^{-\frac{t}{\tau}}} - C_2 + \begin{cases} n_{shock}\ if\ shock = True\ and\ t \geq t_{shock} \\ 0\ if\ t < t_{shock} \end{cases}$$

$$population\ (t) = urbanpixels * roofs_{pixel} * houses_{roof}(t) * people_{house}$$

Table 8: Important parameters for the population growth

Parameters	Description	Constant or Uncertainty?	Values
T	Growth interval of area	Uncertainty	[4, 6]
τ	Rate of change of density	Uncertainty	[5, 25]
C_1	Scaling factor of density	Constant	16
C_2	Vertical offset of density	Constant	6
n_{shock} (density shock increase)	Shock of population density	Uncertainty	[2, 8]
t_{shock} (year of shock)	Year of density shock	Uncertainty	[4, 70]
$roofs_{pixel}$	Roofs per pixel	Constant	5
$people_{house}$	People per house	Constant	2

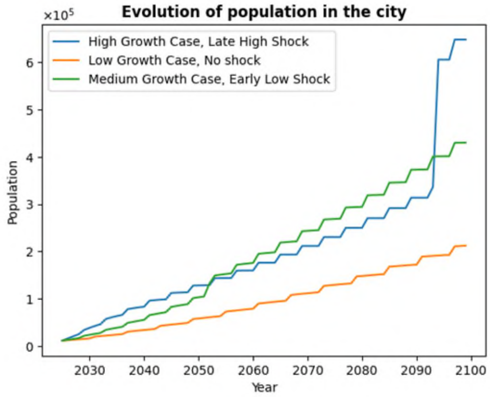


Figure 27 Population Evolution, it is a function of the size of the urban square (stepped growth), the increase of density (sigmoid function with uncertain growth) and a possible density shock. The later this shock happens, the higher the impact due to the spatial growth of the city

The detailed descriptions and effects of climate variables are presented in Table 9. In summary, total yearly rainfall is considered random within "stretched" ranges based on historical data from KNMI of a Dutch region. Similarly, summer rainfall is treated as random within ranges, but it is also subject to variability due to consecutive "summer drought" years, which occur randomly (Figure 28). For average temperature, evaporation, and radiation, current values are connected to a final value within the 2100 IPCC projections. This transition is modeled through a linear increase, with random noise of up to 5%.

These climate variables directly influence other factors, such as aquifer behavior and water demand. In the case of crops, water demand increases proportionally to the severity of drought conditions. In some instances, the effects of climate on these variables involve not only value uncertainty but also structural uncertainty. For example, there may be a correlation between average temperature and water demand per capita (Xenochristou et al., 2018), but we currently lack sufficient information to fully describe this relationship. As a result, water demand per capita can be modeled in various ways: it may increase linearly with rising temperatures, grow as a square root function, or even remain constant throughout the simulation (Figure 29).

Table 9: Description of the climate variables and its effect on other variables

Variable/Uncertainty	Temporal Evolution	Minimum Value	Maximum Value	Effect on:
Rainfall (year)	Random	[400, 500]	[1000, 1200]	Recharge Rates
Summer Rainfall (year)	Random with shocks	0.05*Rainfall (drought years)	0.6*Rainfall	Agricultural Water Demand
Average Temperature (year)	Linear with 5% noise	10.5 °C (in 2024)	[11.3, 14.7] °C (in 2100)	Water Demand per Capita
Average Evaporation (year)	Linear with 5% noise	286 mm (in 2024)	[303, 346] mm (in 2100)	Crops Recharge Rates and Agricultural Water Demand
Average Radiation (year)	Linear with 5% noise	206 W/m^2 (in 2024)	[214,229] W/m^2 (in 2100)	Crops Recharge Rates

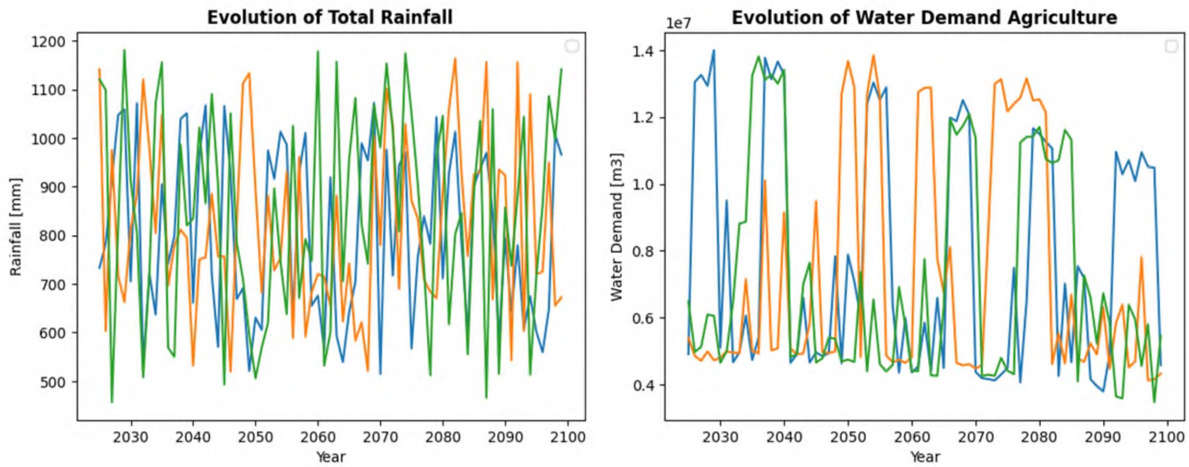


Figure 28 Total rainfall per year (left) is random in a range and ultimately defines the water recharge, but the agricultural water demand (right) is driven by summer rainfall, which is modelled with consecutive drought shocks

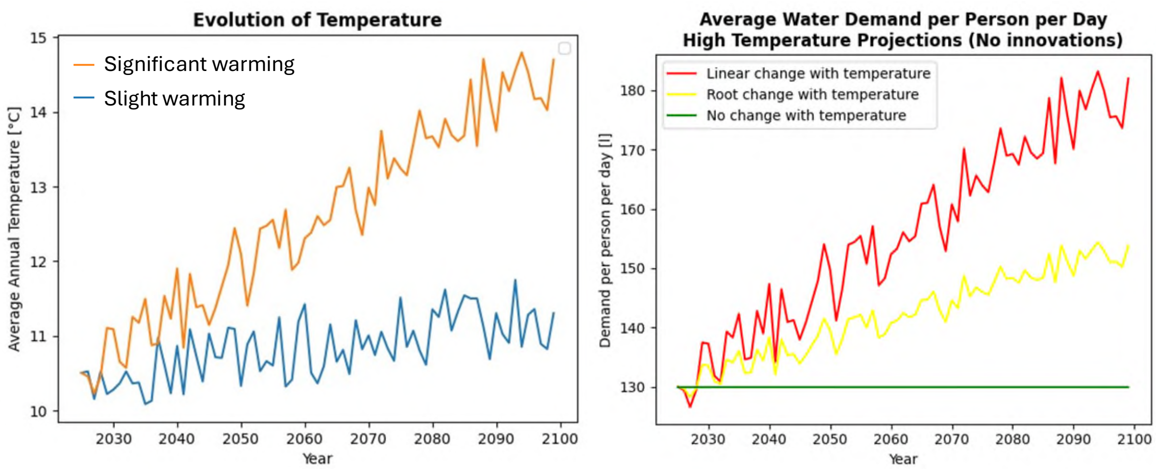


Figure 29 The average temperature is modelled as a linear growth from the current value to 2100 projection values, with a 5% random noise at each point. Temperature may affect the average daily water intake per person (linear or root growth).

3.5.1 DMDU Method 1: EOA

When discussing flexibility in DMDU, while DAPP is the methodology most commonly employed by Dutch researchers, Engineering Options Analysis (EOA) represents the MIT school of thought. First introduced by Richard de Neufville in 2011, EOA is an adaptation of real options analysis (ROA), a decision-making process from financial economics, which extends the principles of cost–benefit analysis to allow for learning based on an uncertain underlying parameter. EOA's objective is to offer explanations for why and how flexible approaches to engineering design are appropriate, providing decision-makers with arguments for adopting flexible designs (Cardin et al, 2015). In brief, EOA involves the following steps:

Table 10: Traditional steps of the EOA methodology

Step	Description	DMDU Phase
1	Formulate the (engineering system) problem or opportunity	Frame the analysis
2	Specify the objectives and outcomes of interest	Frame the analysis
3	Develop a computationally efficient analytic model of the system	Frame the analysis
4	Generate a set of options	Exploratory uncertainty analyses
5	Specify the relevant uncertainties, and generate a sufficient number of future scenarios (typically in the thousands, for instance)	Exploratory uncertainty analyses
6	Calculate system performance across the range of scenarios, using computer simulation to couple the variation in external forces and the management responses in terms of exercising their options along the way (i.e., engage in “Exploratory Modeling”)	Exploratory uncertainty analyses
7	Reduce the resulting data for stakeholder consideration, using suitable target curves and multi-objective tables to illustrate trade-offs	Exploratory uncertainty analyses
8	Support the choice of a preferred starting decision and plan for its adoption, using the insights the analysis provides	Choose short-term actions
9	Implement a monitoring system that tracks variables that may trigger future adjustment of the current decision	Choose long-term contingent actions

EOA is not the same as ROA. It is a systems engineering approach tailored to the realities of design practice. This distinction is made because key financial assumptions, like path-independence (managers constantly reconfigure the system over time) and market comparables, are not applicable in systems engineering. Additionally, the vast number of design options and limitations in computational power make finding optimal solutions impractical (Cardin et al, 2015).

3.5.2 DMDU Method 2: DAPP

For this case study, we are mostly interested in finding a series of decisions that will build flexibility to deal with a range of plausible futures. As it has already been stated, Dynamic Adaptive Policy Pathways (DAPP) helps us envision a plan, conceptualized as a series of actions over time (pathways), including initial actions and long-term options activated by the identification of signals. In this case, we will attempt to define the signals according to the definition of a healthy groundwater level, the minimization of water supply deficits, and the overall reduction of urban and rural water demand.

In subsection 5.4, we described that there are challenges in choosing a case-appropriate method for DMDU. In one of their first papers, the authors of the DAPP methodology emphasized its particular usefulness for dynamically exploring a wide range of relevant uncertainties, linking short-term targets with long-term goals, and identifying immediate actions while preserving future flexibility (Haasnoot et al., 2013). This can be achieved by the implementation of the following steps:

Table 11: Traditional steps of the DAPP methodology

Step	Description	DMDU Phase
1	Decision Context: Participatory scoping, analyse objectives; describe the system and uncertainties	Frame the analysis
2	Assess vulnerabilities and opportunities: Identify adaptation tipping point condition of status quo; assess timing tipping points with (transient) scenarios	Frame the analysis (qualitative) / Exploratory uncertainty analyses (quantitative)
3	Identify and evaluate actions: assess efficacy of actions, tipping points and timing; reassess vulnerabilities and opportunities	Exploratory uncertainty analyses
4	Develop and evaluate adaptation pathways: explore pathways; generate a pathways map; evaluate pathways in scorecard	Exploratory uncertainty analyses
5	Design adaptive plan: select preferred strategies, short-term actions and long-term options; identify signposts and triggers.	Exploratory uncertainty analyses
6	Implement the plan: short-term actions	Choose short-term contingent actions
7	Monitor: implement next actions if an adaptation tipping point is approaching: implement corrective, preparatory, or new signposts if needed to stay on track; reassess in case of signals for reassessment	Choose long-term contingent actions

It is also worth noting that DAPP was developed by researchers in the Netherlands and has since been widely adopted and adapted for numerous water-related case studies, both within the Netherlands—where Deltares is its leading proponent—and internationally. Its integration into various projects serves as strong evidence of the added value DAPP brings to uncertainty and action analysis, as well as the clarity and interpretability of its results.

3.6 General Results

First, one of our key premises is that the rate of city growth and the occurrence of density shocks through 2100 are major drivers of water deficit. Figure 30 supports this, showing that the most critical changes occur in the second half of the century. By 2100, larger cities meet more than 90% of demand in less than 50% of the scenarios. This raises the question of how sustainable it is to continue growing the city indefinitely without implementing major changes to the system.

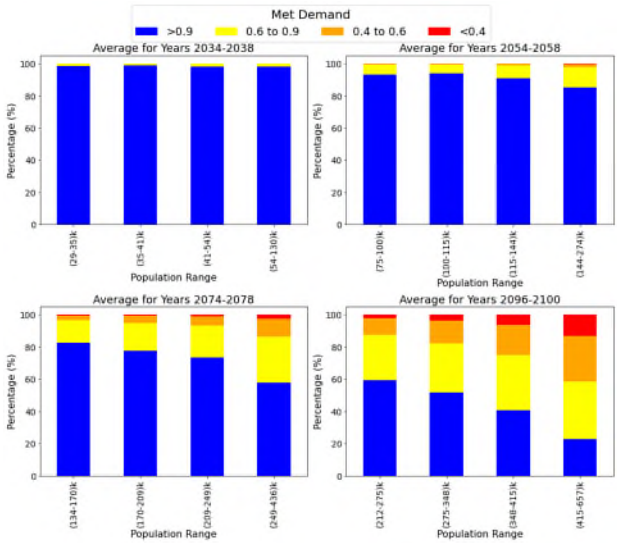


Figure 30: Met demand for different population ranges throughout time. Because of the quadratic nature of city growth, system failure grows quickly during the second half of the century. The population range at each time was defined to have equal size representation at each range.

Then, it was time to analyse the urban efficiency measures (cascade, blue roofs, and new appliances). Once again, the most significant changes emerge in the second half of the century (see Figure 31). For blue roofs, as population density increases, more people occupy the same urban area. Therefore, even if the technology's implementation expands, there comes a point where the actual water savings become negligible. Cascading is the most effective intervention in the long term. The reason is that it involves using shower water for washing machines and toilets, it does not rely on the evolution (or potential increase) of per capita water demand, which doesn't distinguish between specific water uses. As for the new appliances, the estimated savings may be somewhat conservative, eventually "losing" against rising water demands.

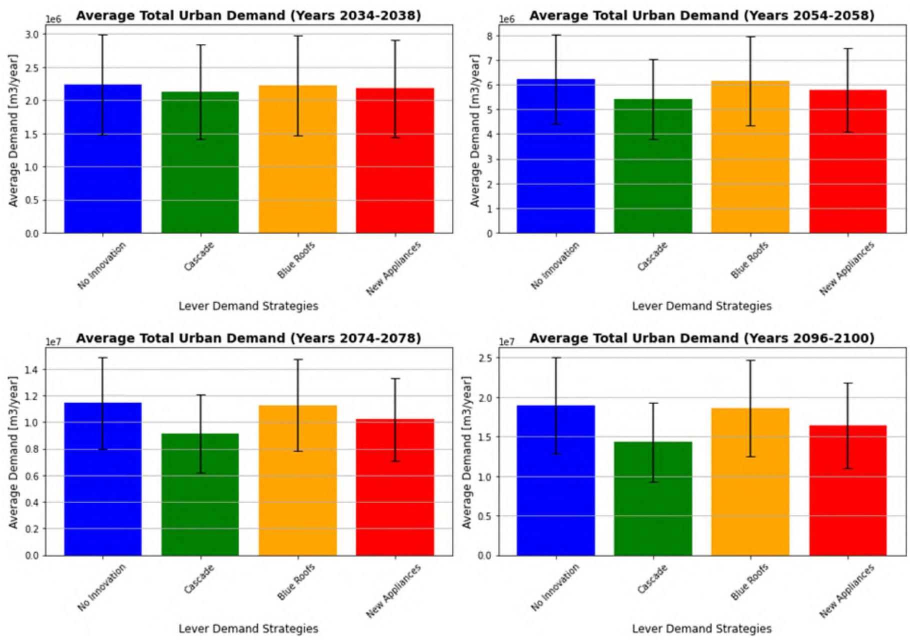


Figure 31: 5-year average and standard deviation of total urban water demand at different stages of the system.

To simplify comparisons between the rural measures and groundwater extraction restrictions, the following simulations assume that half of the alternative city versions implement cascade technology, still, at an uncertain rate, and the other half don't. As outlined in the XLRM matrix (Table 6), the two most relevant metrics are the annual aquifer depth (with 10 representing a full aquifer and 0 an empty one) and the water deficit relative to actual demand.

As a first step, we ranked feature importance (top 5 model parameters) for the years 2050, 2075, and 2100 (Table 12). This allows us to quantitatively understand which factors most influence the system at different points in time. Several noteworthy patterns emerge. Firstly, the features related to shocks to the aquifer are significant at every stage, but their relative importance shifts over time. For instance, the year the shock occurs is the most critical factor for aquifer depth and relative deficit in 2050. However, as time passes, the system seems to exhibit a kind of "memory loss," becoming more sensitive to the percentage of loss rather than the timing of the shock.

It's also worth noting that the aquifer's porosity and initial depth are important up to 2050. However, by 2075, factors related to the shocks themselves and groundwater management become more significant. Specifically, by 2100, the aquifer depth is highly sensitive to the definition of the critical depth (ranked second in importance, only after the occurrence of a previous aquifer shock). Interestingly, when it comes to the system's relative deficit, critical depth ranks only fifth, with the groundwater extraction restriction rate (*rate_restriction_gw*) being more influential. This will become clearer in the cumulative distribution function graphs.

Lastly, the appearance of the parameter *shock_density* only in the year 2100 is linked to the quadratic nature of city growth. A sharp increase in population density (people/km²) at this later stage not only affects the system when it is more "vulnerable," but also represents a much larger total influx of people on the land use map.

Table 12: Ranking of the 5 most important parameters influencing Aquifer Depth and Relative Deficit in the years 2050, 2075 and 2100.

Parameters (type)/Metric	Aquifer Depth			Relative Deficit		
	2050	2075	2100	2050	2075	2100
year_shock_aquifer (Year)	1st	4th	-	1st	4th	-
shock_aquifer (Boolean – Sudden Decrease of Aquifer's Surface)	2nd	1st	1st	3rd	1st	1st
porosity_aquifer (Percentage)	3rd	-	-	-	-	-
loss_shock_aquifer (Percentage)	4th	2nd	5th	4th	2nd	4th
depth_initial (Depth Aquifer Year 2024)	5th	-	-	-	-	-
critical_depth (Depth for GW Restrictions)	-	3rd	2nd	2nd	3rd	5th
evaporation_nature_2024 (mm of evaporation of nature)	-	5th	-	5th	5th	-
shock_density (Boolean - Sudden Increase of people/km^2)	-	-	3rd	-	-	3rd
rate_restriction_gw (Rate of GW Restrictions)	-	-	4th	-	-	2nd

3.6.1 EOA

A commonly used tool in EOA studies is the cumulative distribution function (CDF), defined in Equation 7. The right-hand side represents the probability that the random variable X takes on a value less than or equal to x. One of the main advantages of CDFs is their applicability to any type of random variable—whether discrete, continuous, or mixed.

$$F_X = P(X \leq x), for\ all\ x \in \mathbb{R}\ \ (1)$$

They can easily extract key values such as the minimum, maximum, median (CDF=0.5), and other percentiles directly from the graph. In this particular case, both the depth and relative deficit have predefined ranges, but CDFs also facilitate the quick identification of outliers. Additionally, they are useful for detecting clusters, as regions with horizontal lines indicate ranges with a low population density. This will be particularly evident in the graph of Relative Deficit.

Figure 32 shows the CDFs of 5-year average depths for 2050, 2075, and 2100. Once again, a clear gap only appears in 2075 between strategies that restrict water at 5 meters versus 8 meters. The CDFs also help illustrate the "Flaw of Averages". The 2100 graph further displays the expected depth for each strategy. Although the largest expected depth difference (1.74 m) is not negligible, relying on single values overlooks the broader distribution and misses the bigger picture.

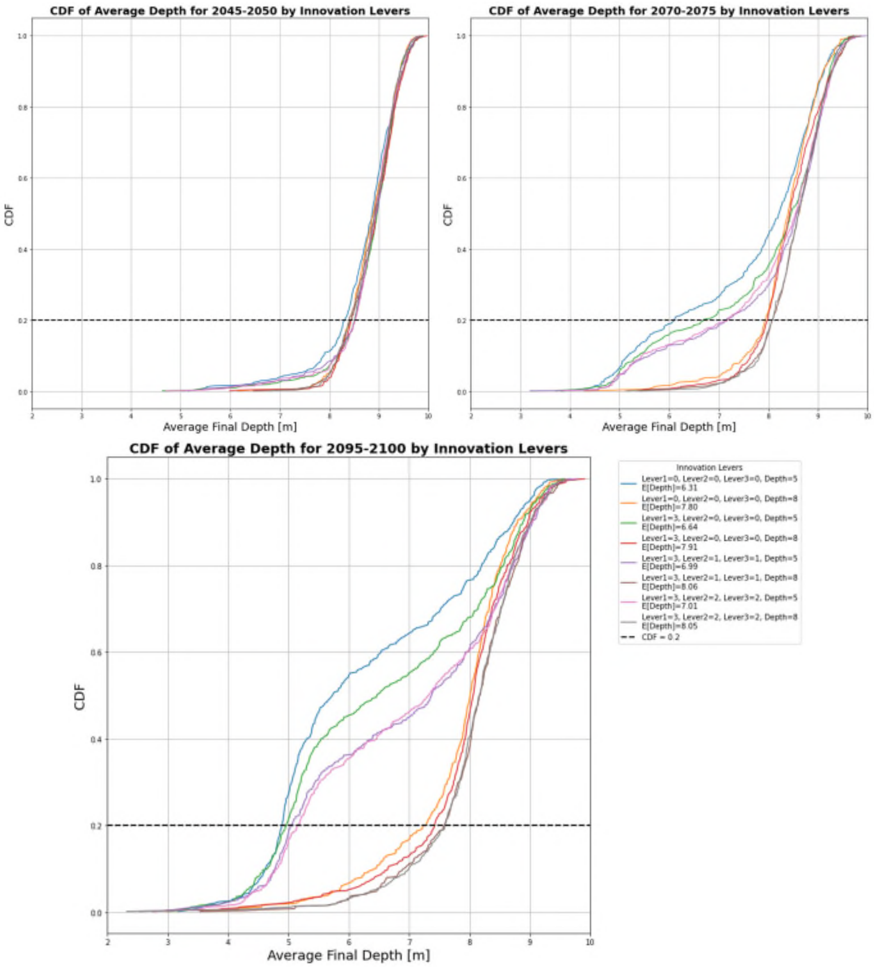


Figure 32: CDF of average depth for various strategies over 5-year periods before 2050 (upper left), 2075 (upper right), and 2100 (lower). A higher aquifer final depth is better. The blue line represents the most extreme strategy, which involves not introducing renewable water sources, avoiding drip irrigation, and only restricting water use when the aquifer depth reaches 5 meters. As before, significant differences between strategies are most evident in 2075, primarily driven by the restriction policies. However, in 2050, a small gap appears below CDF = 0.2, indicating that under extreme shocks, restrictive policies are more effective at maintaining healthy water levels.

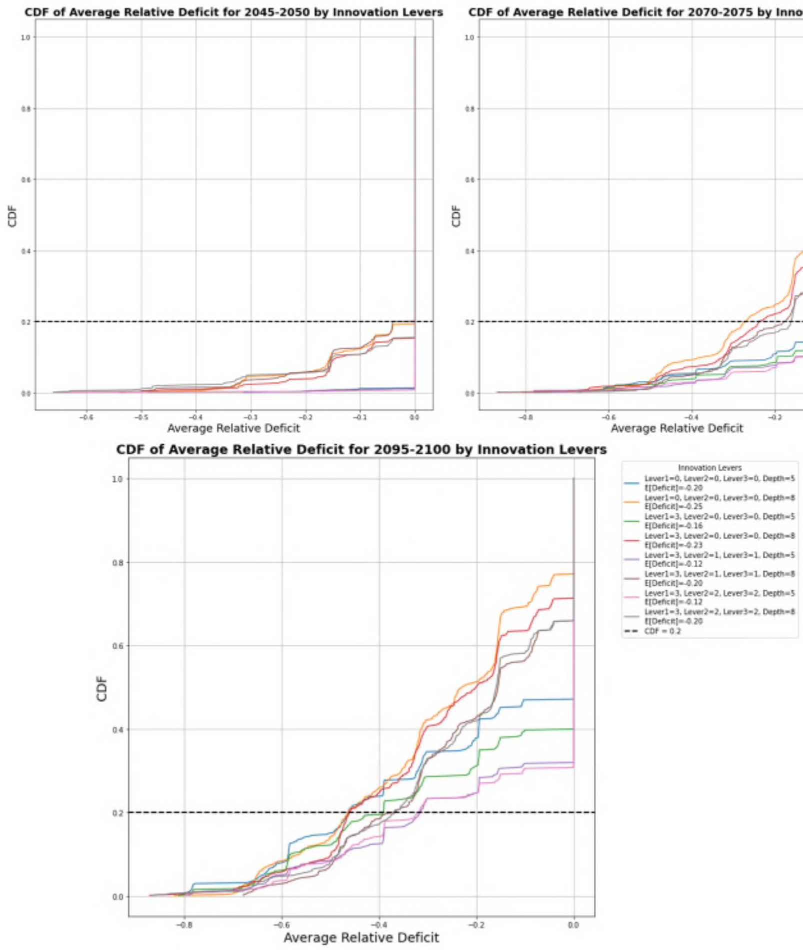


Figure 33: CDF of Relative Deficit for various strategies over 5-year periods before 2050 (upper left), 2075 (upper right), and 2100 (lower). The horizontal lines represent ranges of values with no population. Again, larger differences between strategies appear after 2050. There is a clear difference between the percentage of scenarios with no deficit, but afterwards the lines come close to each other.

Figure 33 shows the CDFs of 5-year average relative deficits for 2050, 2075, and 2100. In particular, for the period 2095-2100, all policies that initiate restrictions at a depth of 5 meters result in zero deficit in over 50% of scenarios. In contrast, the other four policies show no deficit in only about 30% of scenarios, with a more gradual decline in performance thereafter.

The outcomes of the above EOA approach are mainly suitable to gain an understanding of the conditions under which groundwater levels will irreversibly deteriorate. The next steps in the decision making process would be to weigh the importance of the water level in the aquifer against the requirements/possibilities for implementation of the preventive measures. For the implementation of the technical measures this will likely entail a different process and set of criteria compared to the implementation of strict water use restrictions.

3.6.2 DAPP

The dynamic adaptive policy pathways are usually envisioned in terms of time, emphasizing the survival time of a policy, the conditions under which it remains effective, and the system's flexibility to transition from one policy to another. Alternatively, they can be conceptualized in terms of a variable, illustrating how far a policy can take you. In this case, the connections between pathways focus less on their immediate viability and more on the added value of implementing additional measures or making alternative decisions.

Still, in all cases, the ability to alternate between pathways depends on the identification of signposts or tipping points. As discussed in the literature review, defining these points is not always straightforward, and often cannot be done in a purely quantitative way. In many instances, signals are predefined by experts, and the entire modeling process relies on these choices.

In this case study, we aimed to avoid relying on expert-based decisions to identify a “natural” point of no return. Also, given the synthetic nature of the case, such decisions would not have had much correlation with reality. However, upon analyzing the outcomes of the exploratory modelling exercise, we found it impossible to pinpoint a specific time or water level at which most scenarios fell below the point of return. Further analysis showed that creating subway-map styled adaptation pathways benefits, or even requires, a control parameter which does not experience feedback loops with the implemented measures. The implications of such feedbacks for the creation of DAPP is elaborated on in the discussion section. An alternative, DAPP inspired, visualization of the results, and an alternative approach are presented in Appendix VIII.

3.6.3 General comments on EOA and DAPP

One key challenge in using EOA results to build pathways is that it limits the ability to answer one of our core research questions: How do the two methods compare when it comes to selecting the "best" strategy for addressing future challenges? This largely depends on the specific case study and the perspectives of both the analysts (who design the model) and the stakeholders.

In situations where expert opinion plays a significant role, or where tipping points are predefined before exploring scenarios, pathways offer an excellent tool for visualizing which policies can "take you further" while minimizing losses along the way. This case study only considers two metrics, ongoing research is expanding DAPP into a Multi-Risk framework to evaluate pathway performance across multiple objectives (Schlumberger et al., 2024). This development represents a step forward, but it still requires clearly defined goals or tipping points, and in cases where trade-offs between objectives exist, clear rules to prioritize one over the other are necessary.

EOA, on the other hand, may be more data-driven and straightforward to implement, especially when integrated with tools like EMA Workbench. Once the model, uncertainty space, and decision space are defined, the process is relatively straightforward. However, interpreting the results raises other questions: What does it mean if 20% of scenarios show water levels below 5 meters by 2100? How do these results translate into possible policy transitions? While EOA isn't designed to answer these questions, it does encourage decision-makers to explore their initial range of options and demonstrates the value of adding flexibility in the long term. This reinforces the general advice within DMDU that methods should be selected based on the specific case study at hand.

4 Discussion

4.1 DMDU, adaptation or mitigation, and agency

An aspect which is discussed less explicitly in the DMDU literature is the relationship between DMDU methods and their relationship with adaptation as opposed to mitigation strategies. This distinction is very prevalent in the area of climate change research (Vijayavenkataraman et al., 2012) and a significant body of research is dedicated to navigate a balance between the two. In the context of deep uncertainty, and DMDU methods, this distinction requires more attention to guide decisionmakers in their choice of DMDU methods. This is especially the case when the implemented measures have an effect on the source of uncertainty for which they are implemented. For this we propose a framework in which the decisionmaker considers the degree of influence they have over the source of uncertainty to guide their choice in DMDU methods (Figure 34). The more control the decisionmaker has over the source of uncertainty the more likely it is that mitigation strategies can effectively be employed. As the source of uncertainty moves further away from the circle of control the only remaining option is to employ adaptation strategies. This realization might influence the preferred choice in terms of DMDU methods.

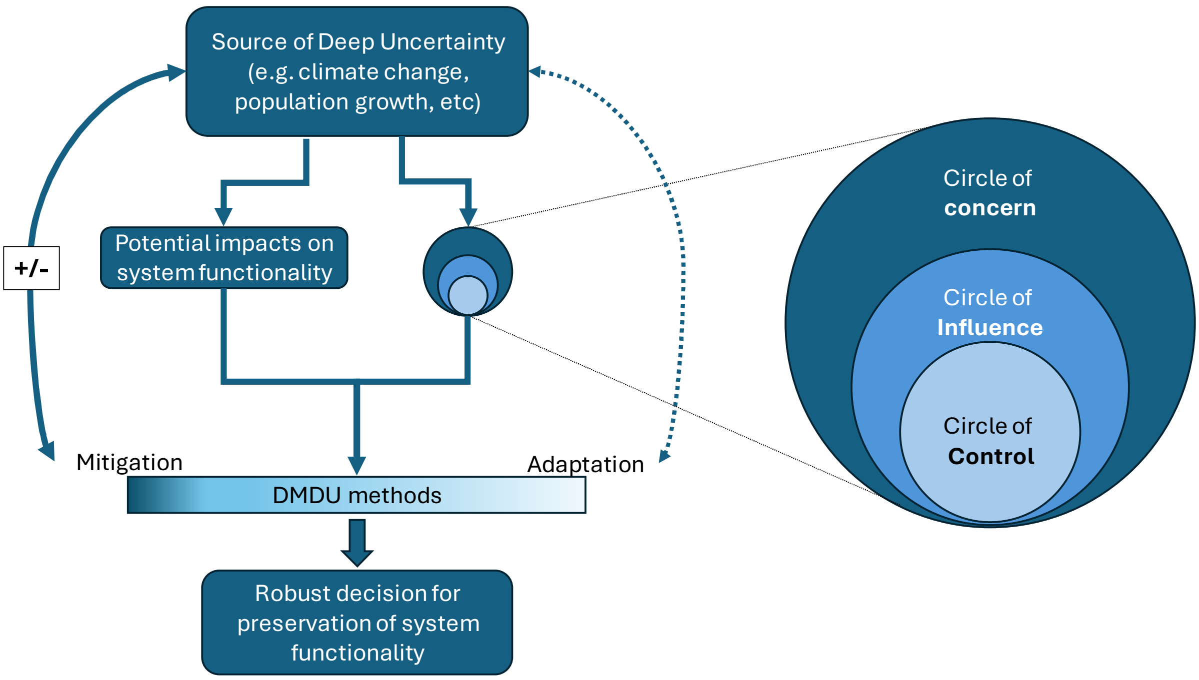


Figure 34 Relationship between sources of uncertainty, circles of influence and DMDU method selection

When applying DMDU methods it is important to acknowledge that potential actions a decisionmaker can take are mainly related to the circle of control, and slightly less so to the circle of influence. The circle of concern on the other hand has a strong connection to the control parameter, the developments which will occur irrespective of the (local) measure taken by the decisionmaker. The relationship between the circles of influence, the potential measures for a decisionmaker and the control parameter are shown in Figure 35. The adaptation measures (small ships, medium ships, small dredging, large dredging) are sufficiently disconnected from the source of deep uncertainty (climate change induced sea level rise). That is to say, they won't interfere with the control parameter (the sea level, expressed in terms of years in the future).

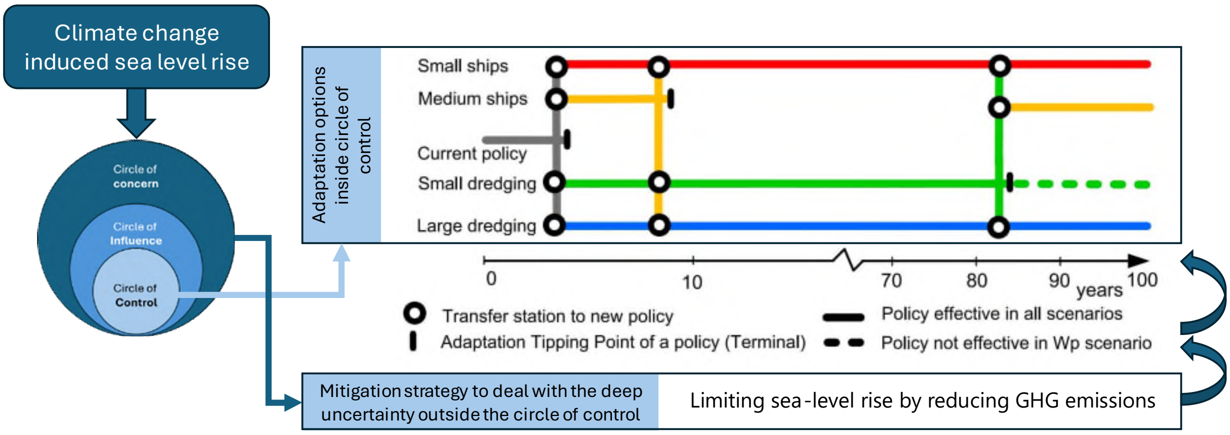


Figure 35 Visualisation of the potential complications when using DAPP in combination with interventions that influence the source of deep uncertainty for which a decision is being made, adapted from (Haasnoot et al., 2012).

Using the above framework also implies that that the level of agency of the decision makers is important in the choice of DMDU method and subsequent strategies. A government with the power to introduce new legislation would classify sources of uncertainty differently compared to a single company devising a suitable strategy (Figure 36).

Dimension	Subsystem	Deep uncertainty source
Political	Policy objectives	Renewable shares
		Carbon emissions
	Policy instruments	Subsidies and incentives
	International context	Energy transfers
	National context	Social opposition
Socio-technical	Technology diffusion	Technology diffusion
	Regimes and niches	Consumers behaviour
		Support mechanisms for emergent technology

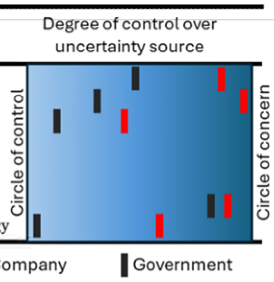


Figure 36 Example of deep uncertainty classification by decisionmakers with different levels of agency, adapted from (Paredes-Vergara et al., 2024)

4.2 Semantics in DMDU and application

As it happens with any new theory, or with any sector that rapidly gains relevance, new authors tend to incorporate frameworks and methodologies in the way that best suits their interests. For example, an analyst from the water sector and another one from transport sector can both decide to use DMDU tools like exploratory modelling to ultimately enhance their system's flexibility. However, the definitions of what being flexible means for them can be slightly different. Not only that, but even within sectors, definition discrepancies can also arise. For example, literature reviews have found that there are as much as 50 different definitions for flexibility in the context of manufacturing processes (Sánchez-Silva & Calderón-Guevara, 2022).

Furthermore, words and concepts can overlap with each other depending on the authors. For example, Ben Haim, the creator of Info-Gap theory, considers robustness to be a necessary combination of five proxies: resilience, redundancy, flexibility, adaptiveness, and comprehensiveness. Therefore, a decision, policy, action, or system is highly robust against uncertainty only if it is strong in some or all of these attributes; it has low robustness if it is weak in all of them (Ben-Haim, 2019). Concepts such as robustness and flexibility that initially seemed to be contrasting and that could potentially create trade-offs, are now a necessary element of the other.

The adoption of DMDU by various sectors should certainly be encouraged. However, for newcomers, developing a DMDU application for their system of interest can feel overwhelming. While coming researchers are encouraged to explore and adapt DMDU methods, it's important to first agree on basic common terminology to make it easier to apply these methods to real case studies.

Marchau's book (Marchau et al., 2019) represents a major step forward in this regard, offering realistic examples and practical guidelines that clarify what decision-making under deep uncertainty entails and how it can be applied. A dedicated section in the book presents and explains a taxonomy of the components that constitute the different approaches and tools for supporting decisions under deep uncertainty.

All components can be divided in 5 categories: policy architecture, generation of scenarios, generation of alternatives, definition of robustness, and vulnerability analysis (J. H. Kwakkel & Haasnoot, 2019b). However, when trying to connect these components with the various approaches (like RDM, DAPP and EOA), we quickly realize that many are not explicitly considered, therefore allowing researchers to implement them as they may deem adequate.

For those interested in exploring DMDU methods, it is highly recommended to read the aforementioned taxonomy. During the last 5 years, there have been advances in expanding the exploration and description of components, such as the inclusion of multi objective evolutionary algorithms (Gupta et al., 2020) and reinforcement learning (Jiang et al., 2024) for the construction of policies. However, this taxonomy serves as a valuable starting point for discussing the combination of tools that may be useful, depending on the nature of the system (J. H. Kwakkel & Haasnoot, 2019b).

4.3 Expert knowledge and scientific focus

The results of the questionnaire show that there is awareness about the presence of (deep) uncertainty amongst experts in the drinking water sector. However, this awareness does not seem to match the prevalence of the sources of deep uncertainty as described in the scientific literature. This discrepancy can have various causes and is likely linked to the limited sample size of the questionnaire but it does pose some research topics for the future.

- Operationalization of deep uncertainty for the drinking water sector: the definition of deep uncertainty allows for significant room of interpretation when a single person is asked to identify sources of deep uncertainty. For this reason a procedure or checklist which can be used to evaluate the different potential sources of uncertainty could be helpful. Which indicators show that parties do not agree on the system model, the probability distributions, and consequences? Ideally this procedure is performed an interactive and iterative process to establish the underlying reasoning of decisionmakers.

- Excessive focus on global phenomena within the scientific community: it is unclear whether there is a bias for research on global phenomena by the scientific community with a simultaneous blindness to non-local phenomena amongst local practitioners. It is therefore important to further investigate if expert knowledge is sufficient to classify global changes as less uncertain for the Dutch drinking water sector.

- Lessons from other countries: how do the results of the questionnaire compare to the perception of deep uncertainty of drinking water experts in other countries? Do the effects of climate change need to start materializing for a sector to recognize it as a source of deep uncertainty?

4.4 Static vs adaptable approaches

The degree to which a static or adaptive approach is suitable depends on the degree of uncertainty over the planning horizon, the degree of flexibility of the solutions, and the implementation time relative to the rate of change (Maier et al., 2016). It is worth investigating the extent to which the drinking water sector has the agency to affect their position on these three criteria. Investments in modelling and simulation could reduce the uncertainty over the planning horizon. Development of new technologies and organisational structures could increase the flexibility of potential solutions. Arguing for simplification of permitting procedures through lobbying could reduce the implementation time.

4.5 Multi-Objective Flexibility: The Path to Multiple Pathways

The case study presented in this report proposes a simplified decision making process, featuring four distinct time windows for implementing changes and a groundwater extraction restriction based on uncertain but predefined thresholds. This approach was deliberately chosen to introduce DMDU (Decision Making Under Deep Uncertainty) through a straightforward narrative, while establishing a baseline system performance that is subject to external shocks.

The definition of the most relevant metrics and indicators is essential in any planning process. However, in real-life dynamic planning problems, the continuous search for alternatives based on new observations over time is a continuous task. While defining indices or metrics is a crucial first step, complete policy design requires optimizing the sequence, timing, and/or threshold values that trigger adaptations (Herman et al., 2020). Ideally such a process should be flexible enough to provide decision makers with insight on the interactions between multiple competing objectives. The presence of multiple risks, and the interactions between multiple sectors, has shown to pose a challenge for at least the DAPP method (Schlumberger et al., 2022). Dealing with multiple objectives in optimisation (see Appendix VII for a brief introduction) has long been on the agenda in several field and is an area for further exploration in DMDU.

5 Conclusions and recommendations

This project set out to establish the current status of knowledge on deep uncertainty and methods to deal with it within the context of the drinking water sector, specifically within the Netherlands.

Through a questionnaire amongst Dutch drinking water professionals in combination with a literature review it was established that deep uncertainty is perceived differently between practitioners and DMDU scientists. The main discrepancy that was identified is a focus on global sources of deep uncertainty in the scientific literature, while practitioners tend to characterize local sources of uncertainty the main sources of deep uncertainty. For example, climate change is a predominant source of deep uncertainty in the scientific literature on water sector DMDU, while local uncertainties such as political sentiment were identified in the questionnaire responses. It is worthwhile to further investigate and close this gap between science and practice to allow for the implementation of DMDU methods in real cases.

While there is a discrepancy between the underlying sources it is unmistakable that the water sector faces several deep uncertainties which will influence system planning and operation. Sources of deep uncertainty related to climate change, water availability, water demand, population growth, and the sociopolitical context have already been investigated with DMDU methods in the context of the drinking water sector case studies. It is important to note that the sources of deep uncertainty can rarely be completely isolated; climate change influences water availability, and population growth influences water demand. Nonetheless, it is apparent that a plethora of deep uncertainties is already impacting the drinking water sector to such an extent that decision making based solely on non-DMDU methods is no longer suitable.

The DMDU methodology toolbox has grown in the last decades to contain more than ten distinctive methods. Methods have evolved over time and the mixed use of methods, or aspects of methods, is a common strategy to deal with case specific situations. Out of the many DMDU methods a set of five seem most common: Robust Decision Making, Dynamic Adaptive Planning, Dynamic Adaptive Policy Pathways, Info-Gap Theory, and Engineering Options Analysis. The common aspects between DMDU methods are a focus on exploratory modelling, adaptive planning, and decision support. The focus on adaptive planning encourages practitioners to evaluate their current position in relation to stative vs. adaptive approaches and the possible strategies which make it possible to switch between them.

Relatively recently efforts have been made to create a framework to guide method selection based on the characteristics of the case at hand. Method selection remains an important skill for DMDU practitioners because there no ‘Swiss army knife’ amongst DMDU methods which can be applied to virtually every case. Method selection not only requires knowledge on the availability of data and models for a case, but also an exploration of the preferences and needs of local stakeholders and decisionmakers. Further elaboration of DMDU selection procedures, which can be explored together with stakeholders, would be a valuable addition to bring DMDU closer to (Dutch drinking water sector) practice.

The synthetic case study performed in this project shows that model building and the exploratory modelling part of DMDU methods is only the first step in formulating adaptive strategies which can actually be implemented by decisionmakers. The transition from exploratory modelling, towards adaptive planning, and finally decision support benefits from an iterative process with stakeholders. The employed modelling approach was able to show what would happen to groundwater levels based on the implementation of different strategies. However, translating these findings into an actionable set of flexible strategies resembling Dynamic Adaptive Policy Pathways would have benefitted from an iterative process with stakeholders to define a suitable metric to define tipping points which is not influenced by the implementation of adaptation strategies. This lesson is incorporated into the follow-up of this research, where expert knowledge and joint learning process are emphasized to create DAPP under multiple risks and cross sectoral interactions; DAPP-MR.

6 References

Abdelmoaty, H. M., Papalexiou, S. M., Rajulapati, C. R., & AghaKouchak, A. (2021). Biases Beyond the Mean in CMIP6 Extreme Precipitation: A Global Investigation. Earth's Future, 9(10). https://doi.org/10.1029/2021EF002196

Ahmed, Y., Choudhury, G. A., & Ahmed, Md. S. (2017). Strategy Formulation and Adaptation Pathways Generation for Sustainable Development of Western Floodplain of Ganges. Journal of Water Resource and Protection, 09(06), 663–691. https://doi.org/10.4236/jwarp.2017.96045

Ambito. (2023, June 19). Uruguay desperdicia casi el 50% del agua corriente por roturas de cañerías. Ambito.

Andreoni, M. (2023, August 15). No se suponía que Uruguay se quedara sin agua. New York Times.

Baggelaar, P. and P. Kuin (2022) Prognoses drinkwatergebruik in Nederland t/m 2040. https://www.vewin.nl/sitecollectiondocuments/publicaties/cijfers/vewin-rapport_2022_prognoses_drinkwatergebruik_nl.pdf

Babovic, F. (2018). Development and assessment of adaptive urban flood risk infrastructure under conditions of deep uncertainty. Imperial College London.

Barnett, J., Graham, S., Mortreux, C., Fincher, R., Waters, E., & Hurlimann, A. (2014). A local coastal adaptation pathway. Nature Climate Change, 4(12), 1103–1108. https://doi.org/10.1038/nclimate2383

Beck, J. L., & Zuev, K. M. (2015). Rare-Event Simulation. In Handbook of Uncertainty Quantification (pp. 1–26). Springer International Publishing. https://doi.org/10.1007/978-3-319-11259-6_24-1

Béen, F., & Beernink, S. (2020). Early Warning Systems for drinking water sources-Assessment of available and innovative monitoring techniques. www.kwrwater.nl

Bellman, R. (1956). DYNAMIC PROGRAMMING AND LAGRANGE MULTIPLIERS. In The Rand Corporation. https://www.pnas.org

Ben-Haim, Y. (2019). Info-Gap Decision Theory (IG). In Decision Making under Deep Uncertainty (pp. 93–115). Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2_5

Bhave, A. G., Conway, D., Dessai, S., & Stainforth, D. A. (2018). Water Resource Planning Under Future Climate and Socioeconomic Uncertainty in the Cauvery River Basin in Karnataka, India. Water Resources Research, 54(2), 708–728. https://doi.org/10.1002/2017WR020970

Bierkens, M., & Wanders, N. (2022, April 29). Extreme droughts almost three times more frequent with climate change. Utrecht University.

Bloemen, P. J. T. M., Hammer, F., van der Vlist, M. J., Grinwis, P., & van Alphen, J. (2019). DMDU into Practice: Adaptive Delta Management in The Netherlands. In Decision Making under Deep Uncertainty (pp. 321–351). Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2_14

Brakkee, E., Van Huijgevoort, M. H. J., & Bartholomeus, R. P. (2022). Improved understanding of regional groundwater drought development through time series modelling: The 2018-2019 drought in the Netherlands. Hydrology and Earth System Sciences, 26(3), 551–569. https://doi.org/10.5194/hess-26-551-2022

Brakkee, E., van Huijgevoort, M. H. J., & Bartholomeus, R. P. (2022). Improved understanding of regional groundwater drought development through time series modelling: the 2018–2019 drought in the Netherlands. Hydrology and Earth System Sciences, 26(3), 551–569. https://doi.org/10.5194/hess-26-551-2022

Brown, C., Boltz, F., Freeman, S., Tront, J., & Rodriguez, D. (2020). Resilience by design: A deep uncertainty approach for water systems in a changing world. Water Security, 9. https://doi.org/10.1016/j.wasec.2019.100051

Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., Hall, J., Characklis, G. W., Yu, W., & Brekke, L. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable

water management. Water Resources Research, 51(8), 6110–6124. https://doi.org/10.1002/2015WR017114
Buishand, T. A. (1989). Statistics of extremes in climatology. Statistica Neerlandica, 43(1), 1–30. https://doi.org/10.1111/j.1467-9574.1989.tb01244.x
Cardin, M. A. (2014). Enabling flexibility in engineering systems: A taxonomy of procedures and a design framework. Journal of Mechanical Design, Transactions of the ASME, 136(1). https://doi.org/10.1115/1.4025704
Castelletti, A., Galelli, S., Restelli, M., & Soncini-Sessa, R. (2010). Tree-based reinforcement learning for optimal water reservoir operation. Water Resources Research, 46(9). https://doi.org/10.1029/2009WR008898
Castelletti, A., Pianosi, F., & Soncini-Sessa, R. (2008). Water reservoir control under economic, social and environmental constraints. Automatica, 44(6), 1595–1607. https://doi.org/10.1016/j.automatica.2008.03.003
Cayota, D. (2023, May 15). ¿Arazatí o Casupá? Ventajas y desventajas de las obras que analizó OSE para mejorar abastecimiento de agua potable. El Observador.
CBS. (2024). Population Counter. Central Bureau Voor de Statistiek (CBS).
Clark, M. P., Kavetski, D., & Fenicia, F. (2011). Pursuing the method of multiple working hypotheses for hydrological modeling. Water Resources Research, 47(9). https://doi.org/10.1029/2010WR009827
Correljé, A., & Broekhans, B. (2015). Flood risk management in the Netherlands after the 1953 flood: A competition between the public value(s) of water. Journal of Flood Risk Management, 8(2), 99–115. https://doi.org/10.1111/jfr3.12087
de Neufville, R., & Smet, K. (2019). Engineering Options Analysis (EOA). In Decision Making under Deep Uncertainty: from Theory to Practice. Springer Nature.
Decision Making under Deep Uncertainty Society (2024) https://www.deepuncertainty.org/about-us/, visited on January 9, 2024
Der Kiureghian, A., & Ditlevsen, O. (2009). Aleatory or epistemic? Does it matter?. *Structural safety*, *31*(2), 105-112.
Diaz, G. (2024, February 26). Fin de tres años de sequía: Uruguay hace balance de la peor crisis hídrica en 70 año. El Pais.
Difrancesco, K. N., & Tullos, D. D. (2014). Flexibility in Water Resources Management: Review of Concepts and Development of Assessment Measures for Flood Management Systems. Journal of the American Water Resources Association, 50(6), 1527–1539. https://doi.org/10.1111/jawr.12214
Dutch Water Authorities. (2018). Blue Deal. https://dutchwaterauthorities.com/blue-deal/
Erkens, G. (2021, June 23). Updated land subsidence maps show the effects of climate change and water level management. Deltares.
European Environment Agency. (2024, September 20). Observed annual mean temperature trend from 1960 to 2023 (left panel) and projected 21st century temperature change under different SSP scenarios (right panels) in Europe. Https://Www.Eea.Europa.Eu/En/Analysis/Maps-and-Charts/Observed-Annual-Mean-Temperature-Trend-3?ActiveTab=570bee2d-1316-48cf-Adde-4b640f92119b.
Gallopín, G. (2018). Back to the future. Energy Policy, 123, 318–324. https://doi.org/10.1016/j.enpol.2018.08.060
Galloway, D., Jones, D., & Ingebritsen, S. E. (1999). Land subsidence in the United States.
Gleick, P. H. (2003). Global Freshwater Resources: Soft-Path Solutions for the 21st Century. Science, 302(5650), 1524–1528. https://doi.org/10.1126/science.1089967
Groves, D., & Bloom, E. (2013). Robust Water-Management Strategies for the California Water Plan Update 2013.
Groves, D., Bloom, E., Johnson, D., Yates, D., & Mehta, V. (2013). Addressing Climate Change in Local Water Agency Plans: Demonstrating a Simplified Robust Decision Making Approach in the California Sierra Foothills.
Groves, D., Fischbach, J., Knopman, D., Johnson, D., & Giglio, K. (2014). Strengthening Coastal Planning: How Coastal Regions Could Benefit from Louisiana's Planning and Analysis Framework.
Guarino, M. V., Sime, L. C., Schröeder, D., Malmierca-Vallet, I., Rosenblum, E., Ringer, M., Ridley, J., Feltham, D., Bitz, C., Steig, E. J., Wolff, E., Stroeve, J., & Sellar, A. (2020). Sea-ice-free Arctic during the Last Interglacial supports fast future loss. Nature Climate Change, 10(10), 928–932. https://doi.org/10.1038/s41558-020-0865-2

GUB UY. (2016). Futura obra de presa de arroyo Casupá garantiza reservorio de agua para área metropolitana.

Gumbel, E. J. (1958). Statistics of Extremes. Columbia University Press. https://doi.org/10.7312/gumb92958

Gupta, R. S., Hamilton, A. L., Reed, P. M., & Characklis, G. W. (2020). Can modern multi-objective evolutionary algorithms discover high-dimensional financial risk portfolio tradeoffs for snow-dominated water-energy systems? Advances in Water Resources, 145, 103718. https://doi.org/10.1016/j.advwatres.2020.103718

Haasnoot, M., Kwakkel, J. H., 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. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Haasnoot, M., Middelkoop, H., Offermans, A., van Beek, E., & van Deursen, W. P. A. (2012). Exploring pathways for sustainable water management in river deltas in a changing environment. Climatic Change, 115(3–4), 795–819. https://doi.org/10.1007/s10584-012-0444-2

Hall, J., & Murphy, C. (2012). Adapting water supply systems in a changing climate. In Water Supply Systems, Distribution and Environmental Effects. Nova Science Publishers.

Hewitt, H., Fox-Kemper, B., Pearson, B., Roberts, M., & Klocke, D. (2022). The small scales of the ocean may hold the key to surprises. Nature Climate Change, 12(6), 496-499.

Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate Adaptation as a Control Problem: Review and Perspectives on Dynamic Water Resources Planning Under Uncertainty. In Water Resources Research (Vol. 56, Issue 2). Blackwell Publishing Ltd. https://doi.org/10.1029/2019WR025502

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). https://doi.org/10.1061/(asce)wr.1943-5452.0000509

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. https://doi.org/10.1002/2014WR015338

Hublart, P., Ruelland, D., Dezetter, A., & Jourde, H. (2015). Reducing structural uncertainty in conceptual hydrological modelling in the semi-arid Andes. Hydrology and Earth System Sciences, 19(5), 2295–2314. https://doi.org/10.5194/hess-19-2295-2015

Hurford, A. (2016). Accounting for water-, energy- and food-security impacts in developing country water infrastructure decisionmaking under uncertainty. University College London.

Husdal, J. (2004). Robustness and flexibility as options to reduce uncertainty and risk. www.husdal.com/gis/flexibility.htm.

Intergovernmental Panel on Climate Change (IPCC). (2023). Future Global Climate: Scenario-based Projections and Near-term Information. In Climate Change 2021 – The Physical Science Basis (pp. 553–672). Cambridge University Press. https://doi.org/10.1017/9781009157896.006

IPCC (2007). Uncertainty Guidance Note for the Fourth Assessment Report

IPCC (2021) Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change[Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, doi:10.1017/9781009157896.

Jansen, E., Christensen, J. H., Dokken, T., Nisancioglu, K. H., Vinther, B. M., Capron, E., Guo, C., Jensen, M. F., Langen, P. L., Pedersen, R. A., Yang, S., Bentsen, M., Kjær, H. A., Sadatzki, H., Sessford, E., & Stendel, M. (2020). Past perspectives on the present era of abrupt Arctic climate change. Nature Climate Change, 10(8), 714–721. https://doi.org/10.1038/s41558-020-0860-7

Jeuland, M., & Whittington, D. (2014). Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile. Water Resources Research, 50(3), 2086–2107. https://doi.org/10.1002/2013WR013705

Jiang, Q., Li, J., Sun, Y., Huang, J., Zou, R., Ma, W., Guo, H., Wang, Z., & Liu, Y. (2024). Deep-reinforcement-learning-based water diversion strategy. Environmental Science and Ecotechnology, 17, 100298. https://doi.org/10.1016/j.ese.2023.100298

Kaatz, L., Water, D., Raucher, K., & Raucher, R. (2015). Embracing Uncertainty: A Case Study Examination of How Climate Change is Shifting Water Utility Planning.

Kalra, N., Groves, D. G., Bonzanigo, L., Perez, E. M., Ramos, C., Brandon, C., & Rodriguez Cabanillas, I. (2015). Robust Decision-Making in the Water Sector: A Strategy for Implementing Lima's Long-Term Water Resources Master Plan. The World Bank. https://doi.org/10.1596/1813-9450-7439

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2012, July). Many-Objective Robust Decision Making for Water Supply Portfolio Planning Under Deep Uncertainty. 6th International Congress on Environmental Modelling and Software.

Katz, R. W. (2010). Statistics of extremes in climate change. Climatic Change, 100(1), 71–76. https://doi.org/10.1007/s10584-010-9834-5

Katz, R. W., Parlange, M. B., & Naveau, P. (2002). Statistics of extremes in hydrology. Advances in Water Resources, 25(8–12), 1287–1304. https://doi.org/10.1016/S0309-1708(02)00056-8

Ke, Q., Haasnoot, M., & Hoogvliet, M. (2016). Exploring adaptation pathways in terms of flood risk management at a city scale – a case study for Shanghai city. E3S Web of Conferences, 7, 21002. https://doi.org/10.1051/e3sconf/20160721002

Kingsborough, A. (2016). Urban climate change adaptation pathways for short to long term decision-making . University of Oxford.

Kwakkel, J. (2024, September 9). Exploratory Modelling and Analysis (EMA) Workbench�. Https://Emaworkbench.Readthedocs.Io/En/Latest/.

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. Environmental Modelling and Software, 96, 239–250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., & Haasnoot, M. (2019a). Decision Making under Deep Uncertainty. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), Decision Making under Deep Uncertainty. Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2

Kwakkel, J. H., & Haasnoot, M. (2019b). Supporting DMDU: A Taxonomy of Approaches and Tools. In Decision Making under Deep Uncertainty (pp. 355–374). Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2_15

Kwakkel, J. H., & Haasnoot, M. (2019c). 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. Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2

Lawrence, J., Bell, R., & Stroombergen, A. (2019). A Hybrid Process to Address Uncertainty and Changing Climate Risk in Coastal Areas Using Dynamic Adaptive Pathways Planning, Multi-Criteria Decision Analysis & Real Options Analysis: A New Zealand Application. Sustainability, 11(2), 406. https://doi.org/10.3390/su11020406

Lempert, R. J. (2003). Shaping the next one hundred years: new methods for quantitative, long-term policy analysis. RAND Corporation.

Lempert, R. J. ., Popper, S. W. ., & Bankes, S. C. . (2003). Shaping the next one hundred years : new methods for quantitative, long-term policy analysis. RAND.

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. https://doi.org/10.1016/j.techfore.2010.04.007

Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). Ensuring Robust Flood Risk Management in Ho Chi Minh City. The World Bank. https://doi.org/10.1596/1813-9450-6465

Lendering, K. T., Jonkman, S. N., & Kok, M. (2015). Flood Risk of Regional Flood Defences.

Lijdsman, L. (2019). Inverting Ecosystem Service Assessment as a Planning and Design Instrument for Decision-Makers to Develop Sustainable Eco-Based Solutions in an Uncertain Region. TU Delft.

Loew, A., Holmes, T., & De Jeu, R. (2009). The European heat wave 2003: Early indicators from multisensoral microwave remote sensing? Journal of Geophysical Research Atmospheres, 114(5). https://doi.org/10.1029/2008JD010533

Loucks, D. P., & van Beek, E. (2017). Water Resource Systems Planning and Management. Springer International Publishing. https://doi.org/10.1007/978-3-319-44234-1

Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environmental Modelling and Software, 81, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014

Manocha, N., & Babovic, V. (2017). Development and valuation of adaptation pathways for storm water management infrastructure. Environmental Science & Policy, 77, 86–97. https://doi.org/10.1016/j.envsci.2017.08.001

Manocha, N., & Babovic, V. (2018). Real options, multi-objective optimization and the development of dynamically robust adaptive pathways. Environmental Science & Policy, 90, 11–18. https://doi.org/10.1016/j.envsci.2018.09.012

Martinez, B. (2023, October 20). Running Dry: The Battle for Water Security in Uruguay and Why It Foreshadows a Greater Issue. Harvard International Review.

Matrosov, E. (2015). Planning water resource systems under uncertainty. University College London.

Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. (2019). Decision making under deep uncertainty: from theory to practice (p. 405). Springer Nature.

McCarthy, G. D., & Caesar, L. (2023). Can we trust projections of AMOC weakening based on climate models that cannot reproduce the past? Philosophical Transactions of the Royal Society A, 381(2262), 20220193.

McConnell, A. (2011). Success? Failure? Something in-between? A framework for evaluating crisis management. Policy and Society, 30(2), 63–76. https://doi.org/10.1016/j.polsoc.2011.03.002

McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? Earth's Future, 6(2), 169–191. https://doi.org/10.1002/2017EF000649

Menezes, C., Geiss, C., & Tressler, J. (1980). Increasing Downside Risk (Vol. 70, Issue 5).

Moerman, A., E.J.M. Blokker and C.M. Agudelo-Vera (2017) Drinkwaterverbruik in Nederland. TVVL Magazine. https://forms.tvvl.nl/l/library/download/9028/tm0117+-+drinkwaterverbruik+in+nederland+-+een+overzicht+van+ontwikkelingen.pdf

Nienhuis, P. H., & Smaal, A. C. (1994). The Oosterschelde estuary, a case-study of a changing ecosystem: an introduction. Hydrobiologia, 282–283(1), 1–14. https://doi.org/10.1007/BF00024616

Paredes-Vergara, M., Palma-Behnke, R., & Haas, J. (2024). Characterizing decision making under deep uncertainty for model-based energy transitions. In Renewable and Sustainable Energy Reviews (Vol. 192). Elsevier Ltd. https://doi.org/10.1016/j.rser.2023.114233

Peters, J., Ulling, K. M. ¨, Altün, Y., & Altün, A. (2010). Relative Entropy Policy Search. Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence (AAAI-10). www.aaai.org

Pickering, E., Guth, S., Karniadakis, G. E., & Sapsis, T. P. (2022). Discovering and forecasting extreme events via active learning in neural operators. Nature Computational Science, 2(12), 823–833. https://doi.org/10.1038/s43588-022-00376-0

Ranger, N., Reeder, T., & Lowe, J. (2013). Addressing 'deep' uncertainty over long-term climate in major infrastructure projects: four innovations of the Thames Estuary 2100 Project. EURO Journal on Decision Processes, 1(3–4), 233–262. https://doi.org/10.1007/s40070-013-0014-5

Recht, B. (2019). A Tour of Reinforcement Learning: The View from Continuous Control. The Annual Review of Control, Robotics, and Autonomous Systems, 2, 253–279. https://doi.org/10.1146/annurev-control-053018

Ren, K., Huang, S., Huang, Q., Wang, H., Leng, G., & Wu, Y. (2019). Defining the robust operating rule for multi-purpose water reservoirs under deep uncertainties. Journal of Hydrology, 578, 124134. https://doi.org/10.1016/j.jhydrol.2019.124134

Renard, B., Kavetski, D., Kuczera, G., Thyer, M., & Franks, S. W. (2010). Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors. Water Resources Research, 46(5). https://doi.org/10.1029/2009WR008328

Sánchez-Silva, M., & Calderón-Guevara, W. (2022). Flexibility and adaptability within the context of decision-making in infrastructure management. Structure and Infrastructure Engineering, 18(7), 950–966. https://doi.org/10.1080/15732479.2022.2038642

Santos, S. M. G., Botechia, V. E., Schiozer, D. J., & Gaspar, A. T. F. S. (2017). Expected value, downside risk and upside potential as decision criteria in production strategy selection for petroleum field development. Journal of Petroleum Science and Engineering, 157, 81–93. https://doi.org/10.1016/j.petrol.2017.07.002

Savage, S. (2012). The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty (Wiley, Ed.; 2nd ed.).

Schlumberger, J., Haasnoot, M., Aerts, J. C. J. H., Bril, V., van der Weide, L., & de Ruiter, M. (2024). Evaluating Adaptation Pathways in a Complex Multi-Risk System. Earth's Future, 12(5). https://doi.org/10.1029/2023EF004288

Schlumberger, J., Haasnoot, M., Aerts, J., & de Ruiter, M. (2022). Proposing DAPP-MR as a disaster risk management pathways framework for complex, dynamic multi-risk. IScience, 25(10). https://doi.org/10.1016/j.isci.2022.105219

Siddika, A. (2019). Development of a livelihood adaptation decision model for southwest coastal region of Bangladesh. Bangladesh University of Engineering and Technology .

Sornette, D. (2006). Critical phenomena in natural sciences (2nd ed.). Springer.

Stanton, M. C. B., & Roelich, K. (2021a). Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171. https://doi.org/10.1016/j.techfore.2021.120939

Stanton, M. C. B., & Roelich, K. (2021b). Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171. https://doi.org/10.1016/j.techfore.2021.120939

Stuurman, R., Verhagen, F., van Wachtendonk, A., & Runhaar, H. (2020). Een verkenning naar de Watervraag van de Noord-Brabantse Natuur.

Taleb (2007) The Black Swan. The Impact of the Highly Improbable. Random House.

Taleb, N. N. (2022). Statistical Consequences of Fat tails: Real world Preasymptotics, Epistemology, and Applications (2nd ed.). STEM Academic Press.

Tannert, C., H.-D. Elvers and B. Jandrig (2007) The ethics of uncertainty. EMBO reports, 8(10), 892-896.

Tocar, M. (2023, July 15). Drought leaves millions in Uruguay without tap water fit for drinking. The Guardian.

Van Campenhout, J., Houbrechts, G., Peeters, A., & Petit, F. (2020). Return Period of Characteristic Discharges from the Comparison between Partial Duration and Annual Series, Application to the Walloon Rivers (Belgium). Water, 12(3), 792. https://doi.org/10.3390/w12030792

van Engelenburg, J., Hueting, R., Rijpkema, S., Teuling, A. J., Uijlenhoet, R., & Ludwig, F. (2018). Impact of Changes in Groundwater Extractions and Climate Change on Groundwater-Dependent Ecosystems in a Complex Hydrogeological Setting. Water Resources Management, 32(1), 259–272. https://doi.org/10.1007/s11269-017-1808-1

van Gaalen, F., Franken, R., Kirkels, F., Ibrahim, S., van Minnen, J., Bouwman, A., & Vonk, M. (2024). Klimaatrisico's in Nederland.

Vijayavenkataraman, S., Iniyan, S., & Goic, R. (2012). A review of climate change, mitigation and adaptation. In Renewable and Sustainable Energy Reviews (Vol. 16, Issue 1, pp. 878–897). https://doi.org/10.1016/j.rser.2011.09.009

Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or perish: A review of planning approaches for adaptation under deep uncertainty. Sustainability (Switzerland), 5(3), 955–979. https://doi.org/10.3390/su5030955

Walker, Warren E., Robert J. Lempert, and Jan H. Kwakkel (2013) Deep Uncertainty, in Gass, S. and M. Fu (eds.), Encyclopedia of Operations Research and Management Science, Third Edition, Springer, DOI 10.1007/978-1-4419-1153-7.

Wigley, T. M. L. (2009). The effect of changing climate on the frequency of absolute extreme events. Climatic Change, 97(1), 67–76. https://doi.org/10.1007/s10584-009-9654-7

Witte, J.-P. M., Zaadnoordijk, W. J., & Buyse, J. J. (2019). Forensic Hydrology Reveals Why Groundwater Tables in The Province of Noord Brabant (The Netherlands) Dropped More Than Expected. Water, 11(3), 478. https://doi.org/10.3390/w11030478

Wunderling, N., Von Der Heydt, A. S., Aksenov, Y., Barker, S., Bastiaansen, R., Brovkin, V., Brunetti, M., Couplet, V., Kleinen, T., Lear, C. H., Lohmann, J., Roman-Cuesta, R. M., Sinet, S., Swingedouw, D., Winkelmann, R., Anand, P., Barichivich, J., Bathiany, S., Baudena, M., … Willeit, M. (2024). Climate tipping point interactions and cascades: A review. In Earth System Dynamics (Vol. 15, Issue 1, pp. 41–74). Copernicus Publications. https://doi.org/10.5194/esd-15-41-2024

Yakowitz, S. (1982). Dynamic Programming Applications in Water Resources. In WATER RESOURCES RESEARCH (Vol. 18, Issue 4).

Yan, D. (2017). Water allocation under future climate change and socio-economic development : the case of Pearl River Basin. Wageningen University.

Yan, D., Ludwig, F., Huang, H. Q., & Werners, S. E. (2017). Many-objective robust decision making for water allocation under climate change. Science of The Total Environment, 607–608, 294–303. https://doi.org/10.1016/j.scitotenv.2017.06.265

Yeh, W. W.-G. (1985). Reservoir Management and Operations Models' A State-of-the-Art Review. In WATER RESOURCES RESEARCH (Vol. 21, Issue 12).

7 Appendices

I Increasing robustness of a system

Risk can be minimized but never eliminated. One common criticism of robust strategies is that they tend to adopt a static approach. Strategies are often tested against a wide range of scenarios, but it is not possible to dynamically represent decision-making in the face of changing conditions (Murgatroyd, 2020). Simultaneously, multi-objective static planning can lead to conservative decisions, which are likely to incur high economic, social, and/or environmental costs when the level of uncertainty over the planning horizon is high (Maier et al., 2016).

All models that attempt to describe societal systems, no matter how rich and complex, are likely to fail at some point. This is because they typically require human input to determine which events can occur and how best to address them. However, our understanding of potential events and the development of tools to address them is inherently limited by our imagination. Some DMDU researchers have early stated that all forecasts of infrastructure systems are wrong (de Neufville et al, 2005). It is important to also remember that our worst-case scenarios are based on incomplete information. In most cases, the level of uncertainty is so high that any attempt to pre-plan solutions capable of "surviving" any given situation without a minimum degree of adaptability is likely to eventually fail.

Implementing adaptability in long-term infrastructure investments is always a challenge. For example, consider a region that needs to plan its water supply for the next 50 to 100 years. The region, located by the coast, has experienced rising salinity levels due to sea level rise and decreasing surface water from river flows and rainfall during summer months. The water company is concerned that the recent increases in both population and demand may prevent them from reliably supplying water during extremely dry summers. Reliability analysis can be performed to evaluate the probability of total supply failure. This probability can be expressed as:

$$\mathrm{P_f} = \int_{\mathrm{x}\in\Omega_\mathrm{F}} \mathrm{q(x)\ dx} = \int_{\mathrm{x}\in\Omega} \mathrm{I}_{\Omega_\mathrm{F}}\mathrm{(x)q(x)\ dx}$$

Where $\mathbf{x}$ is a random vector of the system's uncertain parameters having joint probability density $q(\mathbf{x})$, and Ω is the set of all possible system states. Ω_F represents the set of system states that correspond to failure and can be expressed as $\Omega_F = \{\boldsymbol{x}: I_{\Omega_F}(\boldsymbol{x}) = 1\}$, where the indicator function I_{Ω_F} equals 1 for states $\mathbf{x}$ that correspond to failure and is 0 otherwise. For real-world systems, this integral is nearly always analytically intractable due to dimensionality and/or complex failure domains, but it can be approximated through Monte Carlo methods (Chakroborty et al, 2022).

It is also relevant to take into account the duration of these failures. The water company believes that due to multiple sources of uncertainty in the initial water quality, the usual water treatment processes may prove to be unfeasible for consecutive days. Along with the municipalities, they have established a threshold of half a day without water supply. Consequently, they plan to build new treatment plants equipped with state-of-the-art desalination technology in new locations next to alternative water sources. These plants represent investments of millions of euros, but the water company, committed to the communities and local governments, considers diversification as a necessary step. The new plants have the potential to double water production by 2050 and triple it by 2100.

In the coming years, these investments would prove their worth during unpredictable summer months. However, despite the government's initial concerns, the population did not grow; instead, it stagnated. Additionally, due to increasing efficiency of home appliances and industrial processes, water demand per capita significantly decreased. Consequently, during the rainy winter months, water planners face a dilemma: keep all plants open and functional, resulting in an excessive amount of water production and pumping to sustain self-cleaning processes in the new pipelines while preventing floods, but generating large and seemingly unnecessary costs; or seasonally close some plants, which could compromise the quality of the network and necessitate temporarily laying off a large number of employees.

The new network is robust in terms of its primary goal: enhancing water supply reliability during summer months. However, in this theoretical scenario, the water company risked its financial stability and core functions by being overly ambitious and neglecting adaptability. Instead of constructing smaller, more flexible plants or sources, they overbuilt and committed to current technology. If they had sacrificed capacity but developed flexible and dynamic pathways maps linked to signposts, such as those described by DAPP, they could have scaled their infrastructure as needed—right time, right size, right technology, and for the right needs. By doing so, they would have also promoted sustainability by avoiding the unnecessary deployment of resources.

II Increasing flexibility of a system

Timing and location

In practice, the degree of flexibility of infrastructure solutions that form part of urban water supply expansions is generally low, favouring a static approach (Maier et al, 2016). The Environmental Protection Agency of the USA (EPA) created a handbook for water and wastewater utilities to ensure that water infrastructure investments are cost-effective over their life cycle, resource efficient and support other relevant community goals. Figure Figure 37summarizes the core elements to carry out this quest.

The completion of these processes can be time-consuming, which is why planners and decision-makers often seek to gather the relevant specialists early in a project lifetime to define these elements. Additionally, the creation and development of infrastructure projects can be influenced by a country's political agenda. Objectives and strategies are sometimes not established systematically but rather aim to fulfil simplified campaign promises. This can lead to a focus on finding appealing, robust and long-term infrastructure solutions, potentially resulting in initial budget underestimations. Consequently, this can cause overspending and/or unmet expectations in later stages of a project.

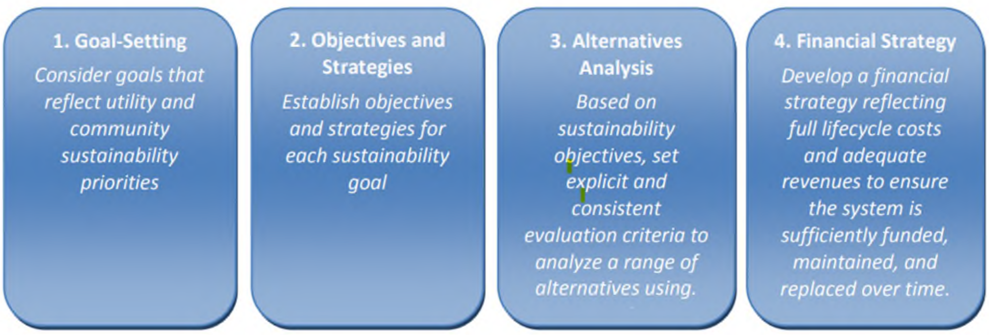


Figure 37 Core planning elements for sustainability. They are intended to build on each other as water utilities go through a planning process. Image reprinted from EPA's handbook (2024).

Planning is necessary when the speed of change of the business environment is faster than your own speed of reaction (Wack, 1993). The structural incorporation of flexibility can help organizations prevent some of the previous cases. In order to do so, Figure X needs to be executed in a cyclical manner. The frequency of redefining goals, objectives, strategies, alternatives, and budget constraints will vary depending on the project. While decision makers often cannot control the speed of external changes, they can enhance the organization's ability to respond quickly and systematically. The identification of the spatial and temporal scales of relevant processes (see Figure X) can help planners define the operational scope, optimize reaction times, and establish necessary coordination with other stakeholders.

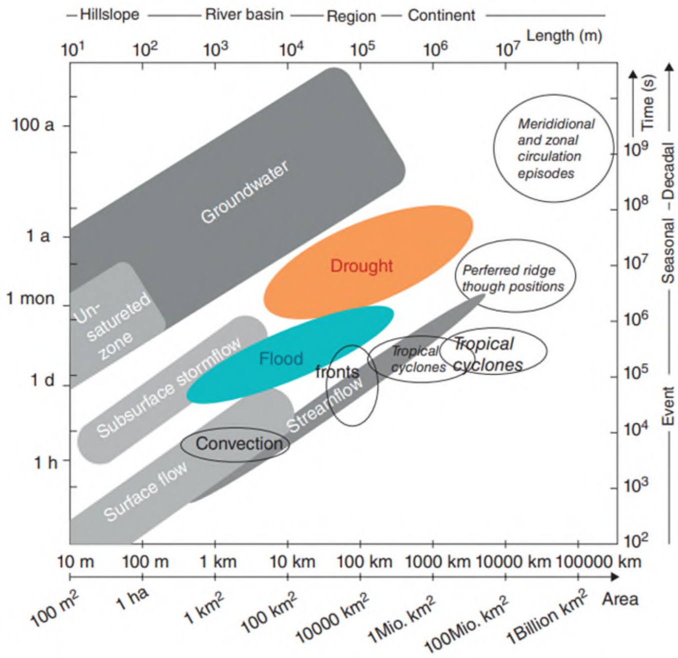


Figure 38 Spatial and temporal scales of hydrological processes. Image reprinted from Stahl and Hisdal, 2004.

Black-swan protection

By definition, all black-swan accidents or rare events share three characteristics: they are unpredictable, they carry a massive impact, and after the fact, we tend to rationalize explanations to make them seem less random (Taleb, 2007). The problem is that due to their unpredictability, no two of these events are alike. To complicate matters further, their behaviour is non-linear, and many collateral factors can come into play in their evolution. As humans, we fall into an illusion of understanding, believing we fully comprehend a world that is far more complex and random than we realize. Therefore, these post factum explanations, although valuable for the thought processes they involve, will not help us with the exact forecast of future extreme events.

This does not aim to diminish the value of creating future scenarios but rather to emphasize that focusing too much on an accurate description of the variables is of limited worth. It is more important to challenge our understanding of what may happen within and outside of the system, both in terms of our frame of reference and unlikely possibilities. Thus, scenario planning should not only be seen as a technical procedure to reach a set of goals but rather as an exercise in creative thinking, complemented by all relevant models and data.

At the same time, it is necessary to explore alternatives and mechanisms to cope with anticipated and unanticipated tail risk events. One concept that has been widely adapted across different sectors is operating flexibility (Christie et al., 2024). In finance, this involves maintaining buffers of financial resources, such as a cash reserve or a reserve fund above minimum capital requirements, to be used during periods of stress. In the context of the renewable energy market, it can refer to the ability of a power system to respond to changes in electricity demand and generation, sudden transmission failures, and coupling with other sectors.

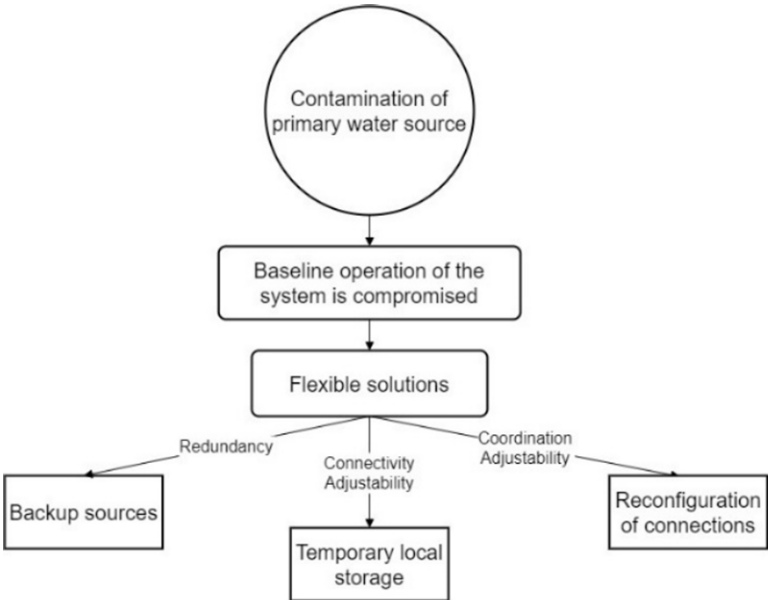


Figure 39 Illustration of a theoretical "black swan" event for a water network, and the solutions required to deal with it.

In the context of water networks, we have previously outlined key characteristics of a flexible system: slack, redundancy, connectivity, coordination, and adjustability. Each of these elements represents a facet of operational flexibility crucial to the water sector. Given the unpredictability of "black swan" events, it is essential for a water network to possess all these characteristics to some extent. For example, in the event of a sudden contamination of a primary water source, the baseline operation of the system could be compromised if several key requirements are not met (Figure 39): there are no backup reservoirs or alternative sources (redundancy), temporary local storage capacity is insufficient (redundancy, connectivity), and there is a lack of effective coordination among stakeholders to reconfigure connections and mitigate the spread of contamination (coordination and adjustability).

All of these risk management measures may reduce the return in the majority of scenarios in which no tail risk materializes, but the potential economic, social and human costs of not implementing them far outweigh the short term cost (Christie et al, 2024).

Multiplicity of functions

Water resource systems can only be considered as sustainable if they are "designed and managed to fully contribute to the objectives of society, now and in the future, while maintaining their ecological, environmental, and hydrological integrity" (UNESCO, 1999). Multi-objectivity includes goals related to environmental quality, flood control, recreation, among many others that cannot or should not be simply converted to monetary units (Tilmant et al, 2002). In a world with an overload of new information and a constant revaluation of objectives, inflexibility is an indication of reduced system sustainability (Loucks, 2000). Therefore, multi-purpose is inherently connected to how flexible a system is.

Let's consider for example the case of hydropower reservoirs. Nowadays, an ideal multipurpose hydropower reservoir looks like the one described in Figure X (Wyrwoll & Grafton, 2021). There are a number of potential interconnected services related to water, energy, nature and recreation. Hydropower energy is one of the oldest sources of renewable energy, and it accounts for 29.9% of the EU's renewable electricity provision (Eurostat, 2024). It is widely considered to be both flexible and reliable, as it helps integrate significant amounts of variable renewable energy, such as from solar and wind sources, into the energy system. Additionally, it offers much longer storage capabilities compared to other technologies, providing storage for hours or days instead of just minutes or seconds.

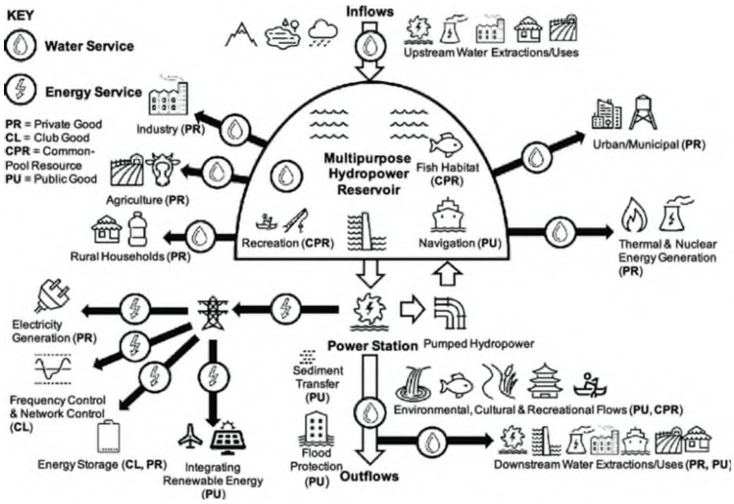


Figure 40 The potential water and energy services provided by a multipurpose hydropower reservoir. Image reprinted from Wyroll & Grafton, 2021.

Unfortunately, the Netherlands is almost flat and lacks the required space for traditional pumped hydro storage facilities (PHS). This is why the Dutch Government has historically seen no alternative to gas- and coal-fired backup capacity (Energierapport, 2016). However, since the 1980s, a number of researchers have explored the possibility to use underground water reservoirs for pumped hydro storage (U-PHS). The central hypothesis is that this innovation is one of the key elements to achieve the agreed CO_2 emission reduction targets and resolve any future intermittency problems in the Netherlands (Huynen, 2018).

A U-PHS is fundamentally a storage system that is based on the conversion of potential energy in electrical energy and vice versa. Generally, when electricity supply is higher than demand, excess electric generation capacity is used to pump water from the lower reservoir to the upper reservoir. When electricity demand exceeds the typical supply, the stored water is released from the upper reservoir to the lower reservoir through a turbine to generate electricity (Huynen, 2018). They can also work as “water batteries”, separating the production time of other renewable electricity sources from its consumption. This creates a buffer that helps manage fluctuations in the availability of wind and solar energy throughout the day and between days (Huynen, 2018).

The main difference with a traditional PHS comes in the design, as they are mostly built underground and don’t take up that much space (see Figure 14). Researchers in Belgium have even explored the possibility to reuse old gas mines, but the prediction of plant operation capacity is difficult due to the complex geometry of available underground volume and its aeration conditions (Kitsikoudis et al, 2020). The adaptation of old caverns and the creation of new ones could minimize the need for water pumping during the flooding season and, if water quality remains uncompromised, provide an additional source in times of droughts for agriculture and natural water bodies.

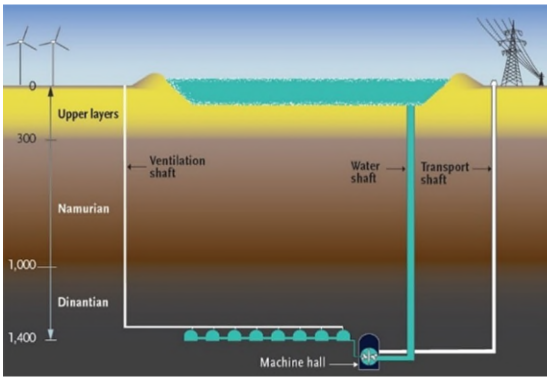


Figure 41 The Ondergrondse Pomp Accumulatie Centrale (O-PAC) is an example of a U-PHS. It pumps cheap surplus power to a high-lying basin at night and produces new, more expensive power during the day by emptying this basin via turbines in a lower location. The greater the difference in height between basins, the more energy can be produced with the same amount of water. Image reprinted from Huynen, 2018.

The key takeaway from this example is to encourage the exploration of existing local structures and foreign technologies for adaptation to the Dutch context. Innovations like U-PHS can significantly increase a whole system's flexibility and robustness, as well as facilitate the integration of fundamental functions and services from different sectors. For a thorough explanation of U-PHS, please refer to Huynen's thesis.

III Twelve steps for DMDU implementation

It is not an easy task to plan the future. And it may even look more challenging to systematically include new methods, such as those of DMDU, to the decision-making process. We have chosen a set of 12 steps to help decision-makers include DMDU into their processes:

Step	Objective	Action
Define the Primary Focus	Determine whether the primary focus is on water supply, water quality, or both.	
Creation of the Systems Dynamics Models	Conceptualize the system and identify differences between stakeholders and researchers.	Develop two system dynamics models—one by researchers and another collaboratively with stakeholders. Compare and evaluate assumptions to align perspectives.
Identify System Boundaries and Variables	Outline the system boundaries and categorize variables.	Utilize spheres of influence to delineate uncertainties, levers, and transitional variables. Colour-code for clarity (Green = Internal System, Yellow = Transactional Space, Red = External System). Conduct this jointly with researchers and stakeholders and evaluate differences.

Describe the Variables and their Interactions in a long term	Identify the most accurate functions to represent the evolution and interactions of variables over time.	Evaluate the availability and quality of historical data, including variability and randomness. Extend historical data ranges where feasible. Balance detailed and simplified functions to uncover knowledge gaps.
Establish Metrics	Choose metrics that prioritize flexibility and adaptability.	Define metrics such as slack, redundancy, connectivity, coordination, and adjustability, alongside robustness metrics. Involve both researchers and stakeholders, followed by an evaluation of trade-offs between flexibility and robustness.
Scenario Analysis with EMA Workbench	Explore a wide range of scenarios and lever combinations.	Use the EMA Workbench to simulate numerous scenarios (space of uncertainties) and test various lever combinations (space of levers). Experiment with different time scales and implementation sequences to understand dynamic responses.
Assessment of the Rate of Change	Ensure planning aligns with the pace of environmental, social, and economic changes.	Recognize that planning is essential when environmental changes outpace the system's response capability. EMA helps identify thresholds, but also assess if changes occur too rapidly (characteristic times). Involve a diverse range of experts to provide comprehensive insights and avoid underestimating the pace of change.
Explore Worst-Case Scenarios	Test system resilience under extreme conditions.	Identify the worst-case scenarios (the what-ifs), prioritizing stress testing over realism. Measure the extent of system failure as a critical metric.
Transition Feasibility	Evaluate the practicality of switching between different policy paths.	Choose a preferred starting decision from the data obtained. Extend the decision over time, and assess the feasibility of transitioning between different options in terms of cost, rigidness, and alignment with flexibility measures. Analyse challenges and expenses associated with each transition to ensure the system can adapt effectively.
Identify Infrastructure Options Amid Threats	Discover new levers or strategies.	Link threats to potential infrastructure opportunities, possibly identifying additional levers. Re-run steps 6 to 9 to assess the impact of these new levers on the system.
Create your Pathways	Plan the options in order according to the previous steps.	Present the results and pathways to stakeholders for review, ensuring the identification and resolution of any inconsistencies.

Future Monitoring System	Set up a monitoring system to follow key variables that may trigger future adjustments.	Implement sensors, systematic surveys, updates on climate and population projections, etc. Track the transformation of existing or new risks and the rise of unexpected new levers that can change decision pathways. Measure structural changes in the system and restart the process if significant change occurs and enough information is available.

These steps are recommendations and even the inclusion of some of them in a more qualitative manner can be useful for companies and organizations. For example, only steps 1 through 4 can help decision-makers estimate the characteristic times of processes, and visualize the existing links and trade-offs between variables and interested parties, without the need of much computational power. If complemented with scenario planning and the creation of a simple monitoring system to detect changes in the system, it can already help managers to include flexibility in their traditional planning models.

IV Overview of DMDU methods in different sectors

Data in this table comes from (Stanton & Roelich, 2021a).

Case Study Label	Theme/Infrastructure sector	Main Uncertainties (as described by authors)	DMDU Method
1 (Ahmed et al., 2017)	Flood Risk	Water Logging, Salinity Intrusion, Floods, Freshwater Availability, Environmental Degradation	DAPP
2 (Babovic, 2018)	Flood Risk	Population Growth, Urbanisation, Climate Change	AP
3(Barnett et al., 2014)	Flood Risk	Change in Environmental Conditions, Social Awareness and Response	AP
4 (Bhave et al., 2018)	Water Supply	Climate Change (water supply reliability), Sociopolitical Context	AP
5 (Bloemen et al., 2019)	Water Supply and Flood Risk	Climate Change, Socio-Economic Conditions, Societal Preferences, Knowledge and Innovation	AP
7 (Groves et al., 2014)	Flood Risk	Rate of sea level rise, land subsidence, erosion rates, future hurricane activity, hydrologic fluctuations and trends, ecosystem and species'	RDM

		responses, and development and industrial activities	
8 (Groves & Bloom, 2013)	Water Supply	Population and Economic Growth, Climate Change, Irrigation Requirements, Nature's Water Demand	RDM
9 (Groves et al., 2013)	Water Supply	Population Growth, Local Water Supply, Climate Change	RDM
10 (Haasnoot et al., 2013)	Flood Risk	Climate Change, Sea Level Rise, Population Growth, Economic Growth, Societal Changes	DAPP
11 (Hall & Murphy, 2012)	Water Supply	Global Climate Models, Hydrological Models, Water Availability	Robust Adaptation
12 (Herman et al., 2014)	Water Supply	Population Pressures, Climate Change, Financial Risks	MORDM
13 (Hurford, 2016)	Water-Energy-Food System	River Flows, Abstraction Demands, Environmental Flow Releases (for water availability), Construction Cost, Discount Rate, Plant Lifetime, Electricity Price (socio-economic)	MORDM
14 (Jeuland & Whittington, 2014)	Water Supply	Climate Change, Water Demand	EOA and RDM
15 (Kalra et al., 2015)	Water Supply	Future Water Demand, Future Stream Flow, Future Feasibility	RDM
16 (Kasprzyk et al., 2012)	Water Supply	Future Climate Conditions, Population Growth, Market Pricing	MORDM
17 (Ke et al., 2016)	Flood Risk	Socio-economic Developments, Sea Level Rise, Climate Change, Land Subsidence	AP
18a (Kingsborough, 2016)	Water Supply	Interaction Climate Change Risks, Socio-Political Decision Making Context and System Response, Population Growth, Water Availability	AP
18b (Kingsborough, 2016)	Heat Risk	Future Temperatures, Heat Waves, Real Vulnerability of populations	AP

18c (Kingsborough, 2016)	Flood Risk	Climate Change and the Relationship with Social, Institutional, Physical uncertainties	AP
19 (Lawrence et al., 2019)	Flood Risk	Sea Level Rise (Rate and Magnitude), Maintenance of Coastal Protection Structures	DAPP and ROA
20 (R. Lempert et al., 2013)	Flood Risk	Hazard-related uncertainties (Rainfall Intensity, River Height), Exposure-related uncertainties (population, geographic distribution, poverty rate, economic growth, wealth distribution), Vulnerability-related uncertainties (population, economic)	RDM
21 (R. J. Lempert & Groves, 2010)	Water Supply	Climate Key Factors, Water Demand, Impact of Climate Change on Imported Supplies, Response of Groundwater Basin to Urbanization, Response of Groundwater Basin to Changes in Precipitation, Achievement of Management Strategies, Future Costs	RDM
22 (Lijdsman, 2019)	Ecosystem Services	Sea Level Rise, Ground Level Height for New Buildings, River Discharge (Averages and Extremes), Temperature Rise	“Preferred Pathways”
23a (Manocha & Babovic, 2017)	Storm Water	Climatic Scenarios, Land Use Scenarios, Socio-Economic Trends, Political Atmosphere	DAPP
23b (Manocha & Babovic, 2018)	Storm Water	Future Climate (Rainfall), Land-Use	DAPP and ROA
24 (Matrosov, 2015)	Water Supply	Hydrological Variability, Climate Change Flow Perturbation, London Demand, Energy Prices	MORDM and Info-Gap
25 (Ranger et al., 2013)	Flood Risk	Climate Projections, Socioeconomic scenarios, Real Flood Consequences	AP
26 (Ren et al., 2019)	Water Supply	Runoff conditions, water demand	MORDM
27 (Siddika, 2019)	Water Supply and Flood Risk	Water salinity, water scarcity, Tidal Surges, Storm Surges (Climate Change)	DAPP
28a (Yan et al., 2017)	Water Supply	Climate Change (Rainfall, Evapotranspiration), Delta Water Flows	MORDM

28b (Yan, 2017)	Water Supply	Water Availability (Climate included), Water Demand	MORDM

V Questionnaire

BTO VO DMDU - Enquête Diepe Onzekerheid

In het BTO Verkennend Onderzoek 'Methoden voor besluitvorming onder diepe onzekerheid' kijken we naar een extreme vorm van onvoorspelbaarheid in de watersector: 'diepe onzekerheid' ('deep uncertainty'). We spreken van diepe onzekerheid in een systeem wanneer er nog geen overeenstemming is over de uitgangspunten, processen en (sociale) dwarsverbanden die in het systeem van belang zijn. Een dergelijk systeem heeft een brede waaier van mogelijke uitkomsten waarvan we het bereik niet goed kunnen overzien, laat staan het doen van een voorspelling (zoals bijvoorbeeld wel mogelijk is bij statistische onzekerheid).

In dit project brengen we in kaart waar diepe onzekerheid zich voordoet in de drinkwatersector en beschouwen we welke aanpakken het meest geschikt zijn voor besluitvorming onder diepe onzekerheid (decision making under deep uncertainty, DMDU) in de drinkwatersector.

We kijken daarbij naar de literatuur, maar er zouden jullie ook graag een aantal vragen stellen om ons te helpen vormen van diepe onzekerheid in de watersector te identificeren. Mogelijk wordt dit nog gevolgd door een interviewverzoek. Ook zal er in de tweede helft van het project een casus toegespitst op een voor jullie relevant voorkomen van diepe onzekerheid worden uitgewerkt. Hiervoor zullen wij nog een aparte uitvraag doen.

Bij voorbaat dank voor jullie medewerking en reacties!

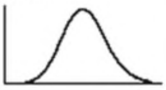
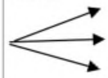
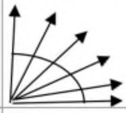
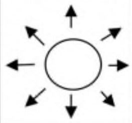
Xin Tian en Peter van Thienen

Voor meer informatie (niet noodzakelijk om deze enquête in te vullen!), zie:
- https://iwa-network.org/publications/digital-water-the-importance-of-knowing-what-we-do-not-know/ (algemene inleiding onzekerheid in water)
- https://link.springer.com/book/10.1007/978-3-030-05252-2 (boek over diepe onzekerheid)

Vragen:

1. Naam
2. Functie/rol
3. Organisatie
4. E-mailadres
5. Ben je eventueel bereid om mee te werken aan een vervolginterview?
6. Wat versta jij onder "onzekerheid" in de context van het drinkwaterbedrijf?
7. Wat versta jij onder "diepe onzekerheid" in de context van het drinkwaterbedrijf?

Er worden in de literatuur verschillende niveaus van onzekerheid onderkend. Een veelgebruikte indeling is de volgende (overgenomen uit Marchau et al., 2019):

	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	

8. Welke bronnen van onzekerheid zie jij op het gebied van **winning**, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.
9. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?
10. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?
11. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op het gebied van **winning**? (optioneel). Graag per bron benoemen.

12. Welke bronnen van onzekerheid zie jij op het gebied van **zuivering**, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.
13. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?
14. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?
15. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op het gebied van **zuivering**? (optioneel). Graag per bron benoemen.

16. Welke bronnen van onzekerheid zie jij op het gebied van **distributie**, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.
17. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?
18. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?
19. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op het gebied van **distributie**? (optioneel). Graag per bron benoemen.

20. Welke bronnen van onzekerheid zie jij op het gebied van de **bestuurlijke context**, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.
21. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?
22. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?
23. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op het gebied van de **bestuurlijke context**? (optioneel). Graag per bron benoemen.

24. Welke bronnen van onzekerheid zie jij op andere gebieden, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.
25. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?
26. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?
27. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op andere gebieden? (optioneel). Graag per bron benoemen.

28. Welke bronnen van onzekerheid krijgen naar jouw mening voldoende aandacht, en welke onvoldoende?
29. Wat zou er volgens jou moeten/kunnen worden gedaan m.b.t. de bronnen die naar jouw mening onvoldoende aandacht krijgen?
30. Is er in jouw bedrijf een (systeem)ontwerp dat in de afgelopen jaren is gemaakt of in de komende jaren zal worden gemaakt, dat wellicht flexibeler kan worden ontworpen om in de toekomst met diepe onzekerheden om te kunnen gaan? Zou dit ontwerp mogelijk een interessante casestudy in de tweede fase van het project kunnen zijn?

31. Zijn er nog andere zaken die je met ons wilt delen?

VI Full questionnaire responses (anonymized)

1. Functie/rol

7 antwoorden

ID	Naam	Antwoorden
1	anonymous	Strategisch adviseur
2	anonymous	Afdelingsmanager Informatiemanagement
3	anonymous	projectleider onderzoek
4	anonymous	processtechnologist
5	anonymous	Informatie analist
6	anonymous	Specialist Assetmanagement
7	anonymous	Data scientist

2. Wat versta jij onder “onzekerheid” in de context van het drinkwaterbedrijf?

7 antwoorden

ID	Naam	Antwoorden
1	anonymous	Een waarschijnlijkheidsverdeling voor het optreden van gebeurtenis en voor het effect, voor bedachte aspecten, gebeurtenissen, gevolgen en effecten.
2	anonymous	Niet weten of huidige acties binnen de huidige context afdoende zijn.
3	anonymous	De toekomst die zich niet laat voorspellen.
4	anonymous	Veranderingen die moeilijk te voorspellen zijn, zaken waarvan ik weet dat ze zullen veranderen maar waarbij het lastig is om zowel de aard als de omvang van hun impact te beoordelen.
5	anonymous	Onzekerheid is het hebben van onvoldoende mensen, middelen en kennis om toekomstige vraagstukken of scenario's aan te kunnen.
6	anonymous	Onzekerheid in de context in de praktijk en context van het drinkwaterbedrijf zou ik voornamelijk willen omschrijven als een gebrek aan kennis of inzicht in een bepaalde situatie of parameter waar het drinkwaterbedrijf zelf van invloed op is. Je weet iets niet je weet niet hoe het zich gaat ontwikkelen of je meet iets niet precies genoeg.

ID	Naam	Antwoorden
7	anonymous	het niet kunnen voorspellen van de toekomst. Mogelijk buiten comfortabele kaders kunnen moeten treden.

3. Welke bronnen van onzekerheid zie jij op het gebied van winning, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.

7 antwoorden

ID	Naam	Antwoorden					
		waterbeschikbaarheid	waterkwaliteit	behoeften van stakeholders	anders1	anders2	anders3
1	anonymous	niveau 3	niveau 4a	niveau 2	niveau1	n.v.t.	n.v.t.
2	anonymous	niveau 3	niveau 2	niveau 3	niveau 3	n.v.t.	n.v.t.
3	anonymous	niveau1	niveau 3	niveau 4a	niveau 2	n.v.t.	n.v.t.
4	anonymous	niveau 3	niveau 3	niveau 4a	n.v.t.	n.v.t.	n.v.t.
5	anonymous	niveau 3	niveau 3	niveau 4a	niveau 4a	n.v.t.	n.v.t.
6	anonymous	niveau 4a	niveau 4a	niveau 3	n.v.t.	n.v.t.	n.v.t.
7	anonymous	niveau 3	niveau 3	niveau 3	n.v.t.	n.v.t.	n.v.t.

4. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?

6 antwoorden

ID	Naam	Antwoorden
1	anonymous	ander1: onderhoud winmiddelen
2	anonymous	Politieke inmenging.
3	anonymous	Wisselende directies die sterke winningsvoorkeuren hebben
4	anonymous	Anders 1: beschikbaarheid energie (of de kosten er van). Je pompt er immers energie in en krijgt er water uit.
5	anonymous	Veranderende wetgeving
6	anonymous	Ik denk dat het lastig is om verschillende onzekerheden van elkaar los te trekken. Natuurlijk kunnen we dat proberen en dit gaat tot op zekere hoogte maar de problemen zijn juist zo complex omdat het aan veel dingen raakt. Bijv, de waterkwaliteit is afhankelijk van de waterbeschikbaarheid, daardoor gedwongen bronkeuzes en dus ook weer deels van klimaatverandering. gooi daar de wetten en regelgeving bij.....

5. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?

7 antwoorden

ID	Naam	Antwoorden
1	anonymous	Waterbeschikbaarheid: 10% OR, 10% NOR, ASV's, meerdere bouwstenen ontwikkelen, jaren vooruit prognosticeren Waterkwaliteit: redundantie, ruimte voor aanvullende zuiveringsstappen, AKF, RO, inzetten op voorkomen van vervuiling van de bron, brede screening Stakeholders: stakeholder-analyse, matrix, medewerker public affairs, intensiveren lobby, vewin,
2	anonymous	Onderzoek, contacten met betrokkenen en omgeving.
3	anonymous	Zo goed mogelijk in kaart brengen en vervolgens een vaak financieel gedreven besluit nemen.
4	anonymous	waterbeschikbaarheid: 1. periodiek verkenning/inventarisatie van opties voor nieuwe bronnen en dat toetsen tegen de verwacht groei in vraag. 2. de impact van klimaat op huidige bronnen (Rijn en IJsselmeer) waterkwaliteit: 1. inzetten voor schone bron (via lobby RIWA en Vewin). 2. voorspel modellen maken voor kwaliteit veranderring, bijv. verzilting van IJsselmeer.
5	anonymous	Plannen voor de watertransitie, prognose scenario's, operationele (water)reserve op bouwen, dialoog met de omgeving, gebiedsdossiers. Met andere woorden, informatie vergaren, dan terugkijken en analyseren, vervolgens scenario's schrijven en doorrekenen.

ID	Naam	Antwoorden
6	anonymous	Waterbeschikbaarheid: inzetten reverse osmose zuivering, watervergunningen aanvragen bij de provincie, brak water of water vanuit een AWZI inzetten als bron. Waterkwaliteit: inzetten revers osmose zuivering. Behoefte van stakeholders: ik denk dat hier momenteel weinig aandacht voor is binnen het drinkwaterbedrijf.
7	anonymous	We proberen naar veel alternatieve te zoeken en beginnen met wat we wel kunnen modeleren

6. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden te verkleinen op het gebied van winning? (optioneel). Graag per bron benoemen.

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Tools die helpen om de bandbreedtes op prognoses aan te scherpen. Vaak zitten er ruime 'veiligheid'-marges in. Want, liever wat te veel budget or uren ergens voor rekenen dan te weinig. Terwijl die best een impact kan hebben op andere plannen. Kosten om wingebieden aan te kopen en nieuwe pompstations te ontwikkelen hebben een extreme impact.
2	anonymous	Waterbeschikbaarheid: inzetten reverse osmose zuivering, watervergunningen aanvragen bij de provincie, brak water of water vanuit een AWZI inzetten als bron. Waterkwaliteit: inzetten revers osmose zuivering.

7. Welke bronnen van onzekerheid zie jij op het gebied van zuivering, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan 'komt voor')? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.

7 antwoorden

ID	Naam	Antwoorden						
		beschikbaarheid van processtoffen	beschikbaarheid van componenten	inkomende waterkwaliteit	nieuwe behandelingstechnieken	anders1	anders2	anders3
1	anonymous	niveau1	niveau1	niveau 4a	niveau 3	n.v.t.	n.v.t.	n.v.t.

ID	Naam	Antwoorden						
2	anonymous	niveau 2	niveau 2	niveau 4a	niveau 3	n.v.t.	n.v.t.	n.v.t.
3	anonymous	niveau 2	n.v.t.	niveau 3	niveau 3	niveau 2	n.v.t.	n.v.t.
4	anonymous	niveau 3	niveau 2	niveau 3	niveau 2	niveau 2	n.v.t.	n.v.t.
5	anonymous	niveau 4a	niveau 3	niveau 3	niveau 3	niveau 4a	niveau 4a	n.v.t.
6	anonymous	niveau 3	niveau 3	niveau 3	niveau 3	n.v.t.	n.v.t.	n.v.t.
7	anonymous	komt voor	komt voor	komt voor	komt voor	n.v.t.	n.v.t.	n.v.t.

8. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?

4 antwoorden

ID	Naam	Antwoorden
1	anonymous	wederom mening van directies
2	anonymous	anders1: kwaliteit norm voor drinkwater en infiltratie water
3	anonymous	Anders 1: Modelmatige proces aansturing in plaats van aansturing op basis van regels. Anders 2: Devote mensen met de juiste competenties. In het noorden is anders dan in de randstad.
4	anonymous	N.v.t.

9. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?

5 antwoorden

ID	Naam	Antwoorden
1	anonymous	er is nog geen duidelijk standpunt ingenomen. Sommigen denken dat we overal geavanceerde technologie moeten toepassen; sommigen hopen op de KRW en innovaties.

ID	Naam	Antwoorden
2	anonymous	beschikbaarheid van processtoffen: in het algemeen is de richting van PWN om minder grondstoffen te gaan gebruiken . De voorkeur is voor technologieën die "elektrisch" zuiveren, RO en UF, en minder chemicaliën gebruiken. beschikbaarheid van componenten: een concrete voorbeeld is de beschikbaarheid van UV kwik lampen voor disinfectie. In principe verboden door de EU maar er is een vrijstelling voor een paar sectoren waar onder de watersector. Het woord overwogen bij het bouwen van nieuwe installatie tegen de optie van LED lampen.
3	anonymous	Net als bij de winning is energie de grondstof die alles processen doet leven. Hoe betaalbaar is deze in de toekomst en wat voor impact heeft dit op de organisatie en keuze in zuiveringstechnieken? Er wordt geprobeerd om als bedrijf een deel van de energie voorziening zelf te organiseren, maar hoe ver moet je daar in gaan tegen welke kosten?
4	anonymous	Beschikbaarheid van processtoffen & Beschikbaarheid van componenten: bij onvoldoende beschikbaarheid van de gevraagde stoffen of componenten worden er alternatieven ingezet. Dat kan ertoe leiden dat er daardoor ingeboet wordt op de -in eerste instantie- gevraagde kwaliteit. Met als gevolg dat er mitigerende maatregelen genomen moeten worden. Inkomende waterkwaliteit: reverse osmose inzetten voor de zuivering eventueel aangevuld met traditionele technieken voor bepaalde stoffen zoals ammonia.
5	anonymous	ik heb hier te weinig verstand van

10. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden op het gebied van zuivering te verkleinen? (optioneel). Graag per bron benoemen.

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Kennis in de hoofden van de huidige operators proberen te vangen met behulp van AI.
2	anonymous	Beschikbaarheid van processtoffen: strategische voorraden aanleggen met andere drinkwaterbedrijven. Beschikbaarheid van componenten: strategische voorraden aanleggen met andere drinkwaterbedrijven, inzicht geven in de voorraden van elkaars magazijn om makkelijker voorraden te delen. gezamenlijke inkoop.

11. Welke bronnen van onzekerheid zie jij op het gebied van distributie, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan ‘komt voor’)? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.

7 antwoorden

ID	Antwoorden								
	watervraag op langere termijn (bijv. door bevolkingsgroei, verstedelijking, pandemie, industrialisatie)	kortetermijnvariabiliteit in watervraag (bijv oorbeeld door weersomstandigheden)	conditie van de bestaande infrastructuur	vraag naar vernieuwing van de infrastructuur	systeembeheer van het distributiesysteem (bijv. het gebruik van pompen)	real-time monitoring van de waterkwaliteit en het watergebruik, leidingbreuken, etc.	anders 1	anders 2	anders 3
1	niveau 3	niveau1	niveau1	niveau1	niveau1	niveau 2	niveau 4b	niveau 4b	niveau 4b
2	niveau 3	niveau 2	niveau 2	niveau1	niveau 2	niveau 3	niveau 2	niveau 4b	niveau 4b
3	niveau1	komt voor	niveau 3	komt voor	niveau1	komt voor	niveau 4b	niveau 4b	niveau 4b
4	niveau 2	n.v.t.	niveau1	niveau 2	niveau1	niveau 1	niveau 4b	niveau 4b	niveau 4b
5	niveau 4a	niveau 3	niveau 4a	niveau 2	niveau 2	niveau 3	n.v.t.	n.v.t.	n.v.t.
6	niveau 4b	niveau 4b	niveau 4a	niveau 3	niveau 3	komt voor	niveau 4b	niveau 4b	niveau 4b
7	niveau1	niveau 2	niveau 3	niveau 3	komt voor	komt voor	n.v.t.	n.v.t.	n.v.t.

12. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Variabele routering, bijvoorbeeld door anders gesitueerde winningen (zout water).
2	anonymous	N.v.t.

13. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?

4 antwoorden

ID	Naam	Antwoorden
1	anonymous	ik heb geen idee
2	anonymous	dit is niet echt maar vakgebied (ga het nog checken met collega)
3	anonymous	Eigenlijk al een beetje bij winning benoemd. Voorspellen van bevolkingsgroei en economische activiteiten zijn lastig in te schatten maar hebben een grote impact op de kosten.
4	anonymous	Watervraag lange termijn: gebruik van modellen voor voorspelling watervraag, strategische reserve, capaciteitsuitbreiding Korte termijn variabiliteit: piekfactoren methodiek Conditiebepaling bestaande infra: er is hier naar mijn weten geen programma voor, Kathodische bescherming Vernieuwingsvraag: jaarlijkse vervangingsopgave van min. 1% van de hoofdleidingen, vervangingsvraag voorspellen op basis van analyses van Spatial Insight Systeembeheer distributiesysteem: als een pomp stuk is wordt deze vervangen Real-time monitoring: zijn nog bezig met pilots voor digitale watermeters, digital twin en het plaatsen van druksensoren

14. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden op het gebied van distributie te verkleinen? (optioneel). Graag per bron benoemen.

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Verhogen van accuratesse van prognoses.
2	anonymous	Watervraag lange termijn: multi-modellen toepassen Korte termijn variabiliteit: (multi-)modellen toepassen Conditiebepaling bestaande infra: USTORE, ervaringen delen met andere drinkwaterbedrijven Vernieuwingsvraag: --- Systeembeheer distributiesysteem: predictive maintenance Real-time monitoring: ---

15. Welke bronnen van onzekerheid zie jij op het gebied van de bestuurlijke context, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan ‘komt voor’)? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.

7 antwoorden

ID	Naam	Antwoorden						
		financiële kaders	kwaliteitskaders	kwantiteitskaders	vergunningen	anders1	anders2	anders3
1	anonymous	niveau 2	niveau 2	niveau 3	niveau 3	n.v.t.	n.v.t.	n.v.t.
2	anonymous	niveau 2	niveau 2	niveau 3	niveau 3	n.v.t.	n.v.t.	n.v.t.
3	anonymous	niveau 2	niveau 2	niveau 2	niveau 2	n.v.t.	n.v.t.	n.v.t.
4	anonymous	n.v.t.	n.v.t.	n.v.t.	n.v.t.	n.v.t.	n.v.t.	n.v.t.
5	anonymous	niveau 4a	niveau 2	niveau 4a	niveau 2	niveau 4a	n.v.t.	n.v.t.
6	anonymous	komt voor	komt voor	komt voor	komt voor	n.v.t.	n.v.t.	n.v.t.
7	anonymous	niveau 2	niveau 2	niveau 2	niveau 3	n.v.t.	n.v.t.	n.v.t.

16. Welke andere factoren zie je nog en heb je bij de vorige vraag onder anders1-3 ingevuld?

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Anders 1: arbeidsmarkt ontwikkeling.
2	anonymous	N.v.t.

17. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?

4 antwoorden

ID	Naam	Antwoorden
1	anonymous	ik weet er weinig van
2	anonymous	weet ik niet (niet mijn expertise)

ID	Naam	Antwoorden
3	anonymous	Voor kwantiteitskaders zien we wel dat steeds meer groepen die gebruik maken van water hier een wat sterkere mening over vormen over de rechten op dat water. Denk aan boeren organisaties die samen spannen om droogte schade op de agenda te zetten, of milieu organisaties die verdroging, of verzuring willen tegen. Denkend aan de tekst van Fluitsma en van Tijn 18 miljoen mensen op dat hele kleine stukje aarde.
4	anonymous	Financiële kaders: onbekend Kwaliteitskaders: BTO onderzoek Kwantiteitskaders: modellen en scenariostudies Vergunningen: Omgevingsmanagement

18. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden op het gebied van de bestuurlijke context te verkleinen? (optioneel). Graag per bron benoemen.

1 antwoorden

ID	Naam	Antwoorden
1	anonymous	Heel lastig, hoe verder de horizon waar je naar kijkt hoe hoger de mate van onzekerheid wordt.

19. Welke bronnen van onzekerheid zie jij op andere gebieden, en om wat voor niveau van onzekerheid gaat het? (Is iets een belangrijke bron van onzekerheid, maar weet je niet zeker welk niveau, kies dan ‘komt voor’)? Mis je nog bronnen, beschrijf deze dan bij de volgende vraag en geef ze een niveau onder anders1-3 in deze tabel.

3 antwoorden

ID	Naam	Antwoorden		
		anders 1	anders 2	anders 3
1	anonymous	niveau 3	niveau 3	
2	anonymous	n.v.t.	n.v.t.	n.v.t.
3	anonymous	komt voor	komt voor	komt voor

20. Welke factoren heb je bij de vorige vraag onder anders1-3 ingevuld?

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Organisatieportfoliomanagement ofwel het in samenhang prioriteren en uitvoeren van activiteiten. Kennisbehoud.
2	anonymous	Voldoende persoon met relevante kennis, opleiding & ervaring, Toenemende regeldruk en wettelijke verplichtingen,

21. Kun je voor de belangrijkste van bovenstaande bronnen van onzekerheid aangeven hoe er in jouw bedrijf hiermee wordt omgegaan?

2 antwoorden

ID	Naam	Antwoorden
1	anonymous	Portfoliomanagement voor activiteiten met een ICT-component bestaat, maar is niet altijd in sync met de totale ambitie. Werving van eigen mensen; kenniselicitatie en onderbrengen in beslissingsondersteunende systemen.
2	anonymous	Voldoende persoon met relevante kennis, opleiding & ervaring: strategische personeelsplanning Toenemende regeldruk en wettelijke verplichtingen: onbekend

22. Welke oplossingen/opties kunnen nuttig zijn om de impact van de genoemde onzekerheden op andere gebieden te verkleinen? (optioneel). Graag per bron benoemen.

1 antwoorden

ID	Naam	Antwoorden
1	anonymous	N.v.t.

23. Welke bronnen van onzekerheid krijgen naar jouw mening voldoende aandacht, en welke onvoldoende?

7 antwoorden

ID	Naam	Antwoorden
1	anonymous	Algemene bespiegeling. De matig van onzekerheid (level 0-4) hangt in sterke mate af van de tijdshorizon waarop wordt gekeken. In algemene zin: voor ieder aspect zal het level van onzekerheid stijgen naarmate er verder in de toekomst wordt gekeken. Maw, voor de meeste bronnen is de onzekerheid voor de komende maand laag. In de vragen is niet duidelijk op welke horizon moet worden gekeken, sterker nog, in de vragen wordt zelfs gevraagd naar korte termijn en lange termijn. Voor wat betreft de voldoende of onvoldoende aandacht: dit zou ik ook risicogestuurd willen doen. Grote onzekerheid (met potentieel hoog risico) op

ID	Naam	Antwoorden
		korte termijn wil je voldoende aandacht geven om meer zekerheid te krijgen, en daarmee hoog risico uitsluiten of mitigeren.
2	anonymous	Voldoende: levenscyclus van bedrijfsmiddelen. Onvoldoende: kennisborging.
3	anonymous	ik denk dat waterbedrijven zich goed bewust zijn van hun onzekerheden
4	anonymous	voldoende: klimaatverandering (KNMI scenario's) en CO2 footprint. onvoldoende: de bredere impact van de energietransitie op NL: krijgen we een Hydrogen economie die water nodig heeft op grote schaal? (electrolysis needs ~10kg of water for 1kg H2). is dit een kans of risico? wat voor industrieën zien we in de toekmost in Nederland en Duitsland en wat zijn de effecten op waterkwaliteit.
5	anonymous	Arbeidsmarkt ontwikkeling, competenties op het gebied van digitalisering. Financiën: geopolitieke spanningen zorgen voor stijgingen in energie, chemie, componenten prijzen en arbeidsloon. Wettelijke limitering waterprijs.
6	anonymous	Alle bronnen krijgen in zekere mate aandacht. De vraag is alleen of het per bron van onzekerheid de juiste mate van aandacht krijgt. En op basis van welke criteria kan je beoordelen of je in het nu voldoende aandacht besteed? (N.B. Het was handig geweest om hier een overzicht te plaasten van de bronnen van onzekerheid)
7	anonymous	alles wat we kunnen bevatten daar kunnen we ook voor modeleren. Als het complexer word is het lastig om uit te leggen. aangezien we ook genoeg te bevatten modeller vraagstukken hebben word hier meer aandacht aan gegeven.

24. Wat zou er volgens jou moeten/kunnen worden gedaan m.b.t. de bronnen die naar jouw mening onvoldoende aandacht krijgen?

7 antwoorden

ID	Naam	Antwoorden
1	anonymous	Meer aandacht geven.
2	anonymous	Informatie-ondersteund werken. Verhoogde inspanning voor kenniselicitatie. Sterkere automatisering van niet-kennisgerelateerde of minder kwalitatieve (administratieve) activiteiten.
3	anonymous	nvt
4	anonymous	binnen PWN hebben hier nog discussie over, het vraagt meer capaciteit en expertise die we zelf niet hebben. Mijn persoonlijk opinie is ook aanwezig zijn bij algemene chemical engineering conferences om een beeldvorming te krijgen van wat de grote industrieën voor plannen hebben.

ID	Naam	Antwoorden
5	anonymous	Arbeidsmarkt is een lastig punt. Het noorden aantrekkelijker maken maar hoe? Wetgeving zodanig aanpassen dat waterprijs op basis van geopolitieke scenario's bepaald kan worden. Het realistisch krijgen van de scenario's kan mogelijk met modellen ondersteund worden.
6	anonymous	Zie suggesties op de vorige pagina.
7	anonymous	Ik denk dat het interessant is om voor een casus te laten zien hoe je er mee om kan gaan zodat het tastbaar word. geen voorkeur op dit moment voor een specifieke bron maar ik zal nog in het bedrijf eens rondvragen.

25. Is er in jouw bedrijf een (systeem)ontwerp dat in de afgelopen jaren is gemaakt of in de komende jaren zal worden gemaakt, dat wellicht flexibeler kan worden ontworpen om in de toekomst met diepe onzekerheden om te kunnen gaan? Zou dit ontwerp mogelijk een interessante casestudy in de tweede fase van het project kunnen zijn?

5 antwoorden

ID	Naam	Antwoorden
1	anonymous	In algemene zin wordt er rekening mee gehouden op de volgende manieren: * redundatie inbouwen in allerlei systemen (meerdere winlocaties, OR, NOR, ASV, meerzijdige voedingen, ruim gedimensioneerde zuivering en distributie, ...) * buffer inbouwen om stappen toe te voegen (financieel, ruimte op zuiveringslocatie reserveren voor toekomstige (aan te treffen) verontreinigingen, ...) * planningen maken waarbij keuzeopties voor de toekomst worden opgehouden
2	anonymous	niet dat ik weet
3	anonymous	weet ik niet. gaat dit checken bij collega's
4	anonymous	Ik denk dat het toevoegen van verschillende scenario's van geopolitieke wanorde, aan allerlei verschillende documenten en studies, waardevol kan zijn. De kern van grote onzekerheden ligt denk ik op dat vlak. Wat kunnen we en willen we doen met welke energie.
5	anonymous	1. Een gebied dat wordt voorzien door een ander drinkwaterbedrijf waarbij de vraag is of dat op de lange termijn houdbaar is; 2. Een deelvoorzieningsgebied waar de verwachtte groei van de watervraag de capaciteit op korte termijn gaat overstijgen; 3. De transitie van de huidige infrastructuur met deelvoorzieningsgebieden met verschillende waterkwaliteiten naar een opzet met reverse osmose zuiveringsstations aangesloten op en ringstructuur met 1 waterkwaliteit; Voorstel bedrijfsoverstijgende studiecase: In deze case ga je uit van een gebied met drinkwaterbedrijven met verschillende bronnen (zoals Evides, Dunea en Oasen) en onderzoek je in welke mate het systeemontwerp van de

ID	Naam	Antwoorden
		individuele waterbedrijven aangepast zou moeten worden om de buurtbedrijven maximaal te ondersteunen. Het idee erachter is dat de individuele bedrijven de belangen van de buurtbedrijven meenemen in hun beslissingsproces gegeven de sterke punten en uitdagingen voor de individuele bedrijven.

26. Zijn er nog andere zaken die je met ons wilt delen?

4 antwoorden

ID	Naam	Antwoorden
1	anonymous	Mooi onderzoek! Succes!
2	anonymous	nvt
3	anonymous	nee
4	anonymous	lastig om dit zo in te vullen. Merk dat ik meer sparring had moeten zoeken.

VII Multiple objectives: an optimization perspective

Herman et al. (2020) reviewed extensively the different approaches to face dynamic water resources planning under a deeply uncertain future, organized under the framing of an optimal control problem. By a control problem, they refer to the design of a policy that maps observed and projected information to actions. System states are modelled as continuous, actions are discrete and exogenous forcing is considered to be stochastic and non-stationary, i.e., random outside shocks or trends that cannot be exactly forecasted. Mathematically, it can be thought of in the following way:

$$\boldsymbol{x}_{t+1} = f_t(\boldsymbol{x}_t, a_t, \boldsymbol{e}_{t+1})$$

There are several things to note from this equation. Firstly, the system state and the stochastic forcing are vectors, which means that a set of variables are evaluated throughout the process. Secondly, the forcing can be defined by either a scenario ensemble or a (nonstationary) probability distribution. Finally, the set of state, action, and forcing variables of the system over the time history at time step t is called the system trajectory $\tau_t = (\boldsymbol{x}_0, \dots, \boldsymbol{x}_t, a_0, \dots a_t, \boldsymbol{e}_1, \dots, \boldsymbol{e}_t)$. At each time step t, the decision problem is to select one action from the set of possible actions, $a_t \in \mathrm{A}$, by applying the policy function π to the current information: $a_t = \pi(\boldsymbol{I}_t)$, where $\boldsymbol{I}_t$ can include a combination of observed or forecasted states and fluxes in the system.

The objectives will include multiple cost functions computed from the trajectory at each time step, $\boldsymbol{J}_t(\tau_t)$, which allows for time-variant cost functions. Therefore, the optimization problem is to choose the policy π that minimizes the expected sum of costs over a finite planning horizon H:

$$\min_{\pi} E_{\boldsymbol{e}_1,\dots,\boldsymbol{e}_{H+1}} \left[\sum_{t=0}^{H-1} \boldsymbol{J}_t(\boldsymbol{x}_t, a_t, \boldsymbol{e}_{t+1}) + J_{H+1}(\boldsymbol{x}_{H+1}) \right]$$

$$\text{subject to: } \boldsymbol{x}_{t+1} = f_t(\boldsymbol{x}_t, a_t, \boldsymbol{e}_{t+1}),\ a_t = \pi(\boldsymbol{I}_t)$$

Solving this equation results in a Pareto-optimal set of policies. Optimal control problems have long been applied across various areas of water resources management, particularly in reservoir operations(Castelletti et al., 2008; Yakowitz, 1982; Yeh, 1985). However, climate adaptation involves managing an open system over several decades into the future, making it impossible for a modeled representation of $\boldsymbol{e}_t$ to capture all sources of uncertainty comprehensively. Moreover, the selection of options is crucial to the optimization's outcome, including their interactions with chosen scenarios. Many solutions will evolve over time or are currently unforeseeable, adding further complexity to the process.

Herman's review delves deeper into this matter, and anyone interested in optimal control problems and deep uncertainties is highly encouraged to read it. For our purposes, we will only summarize the numerical methods used to solve these dynamic planning problems in the water resources field: open loop, dynamic programming, and policy search.

Open loop control directly optimizes the sequence of actions over the time horizon, $a_t = \pi(t)$. The actions are based only on time and are not updated as a function of new observations of states or forcing variables. Open loop problems can therefore be solved with any type of optimization method, including linear or nonlinear programming, heuristics, or even enumeration.

In the case of dynamic programming, the most common variant is SDP, in which the value function Q for each state at time t can be found from the recursive Bellman equation (Bellman, 1956):

$$Q_t(\boldsymbol{x}_t) = \min_{\boldsymbol{a}_t} E_{\boldsymbol{e}_{t+1}} [\boldsymbol{J}_t(\boldsymbol{x}_t, a_t, \boldsymbol{e}_{t+1}) + \gamma\, Q_{t+1}(\boldsymbol{x}_{t+1})]$$

Where γ is a discount factor. Then the optimal policy can be found by minimizing the Q function:

$$\pi = \operatorname*{argmin}_{\boldsymbol{\pi}} Q_t(\,\boldsymbol{x}_t)$$

The optimal policy is limited by the precision of the state, control and forcing variables. In many dynamic programming approaches, the sequence of actions is optimized on a finite rolling horizon, which is repeated at each time step. This results in a closed loop control, because new information about the system state is included at time $t+1$ based on the outcome of the optimized decision and the realization of the stochastic forcing $\boldsymbol{e}_t$ during the time step $[t, t+1)$.

By contrast, a policy search approach assumes a specific structure for the function $\pi(\cdot)$ with parameters θ such that $a_t = \pi(\boldsymbol{I}_t, \theta)$. The optimization problem then becomes:

$$\min_{\theta} E_{\boldsymbol{e}_1,\dots,\boldsymbol{e}_{H+1}} \left[\sum_{t=0}^{H-1} \boldsymbol{J}(\boldsymbol{x}_t, \pi(\boldsymbol{I}_t, \theta), \boldsymbol{e}_{t+1}) + J_{H+1}(\boldsymbol{x}_{H+1}) \right]$$

$$\text{subject to: } \boldsymbol{x}_{t+1} = f_t(\boldsymbol{x}_t, \pi(\boldsymbol{I}_t, \theta), \boldsymbol{e}_{t+1})$$

The outcome is a parameterized function that maps observations to actions, with the parameters serving as the decision variables to be optimized. The optimal policy is constrained by the type of function selected and the numerical convergence of the optimization process. The relationship between policy parameters and the objective functions may be complex, exhibiting multimodal or discontinuous behavior, which can affect the effectiveness of gradient-based techniques. Consequently, heuristic methods like evolutionary algorithms have become popular for assisting in policy search (Herman et al., 2020). It is important to clarify that these methods resemble an online setting, where solutions stay close to the previous policy (e.g., policy gradient methods with only small incremental policy updates). This way, there is not a disconnect between finding an optimal policy and staying close to the observed data (Peters et al., 2010).

Dynamic programming methods are drawn from optimal control, while policy search aligns more with reinforcement learning (Recht, 2019), which has had some application in the water resources literature (Castelletti et al., 2010). A key distinction between the two is that dynamic programming methods search an approximation of the cost function to find the optimal policy, while reinforcement learning searches the exact cost function (e.g., a simulation model) for an approximation of the optimal policy.

VIII Subway-map representation of EOA results

The EOA graphs were used to generate subway-map like pathways (see Figure 42 and Figure 43). We defined the 20th percentile as our threshold of interest (CDF=0.2). This value was chosen because it includes both "catastrophe" scenarios and mid-level shock cases, and it establishes a baseline functionality for the system at that stage.

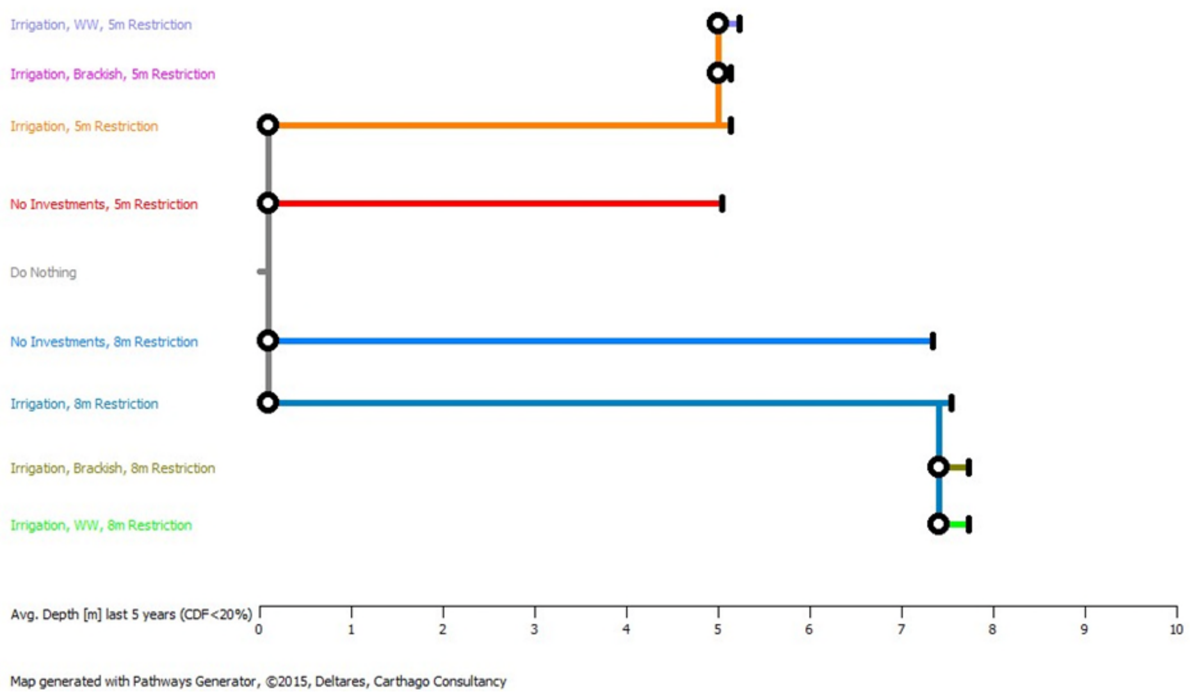


Figure 42: Dynamic Adaptive Policy Pathways for the Average Water Level (Depth) of the last 5 years (2095-2100)

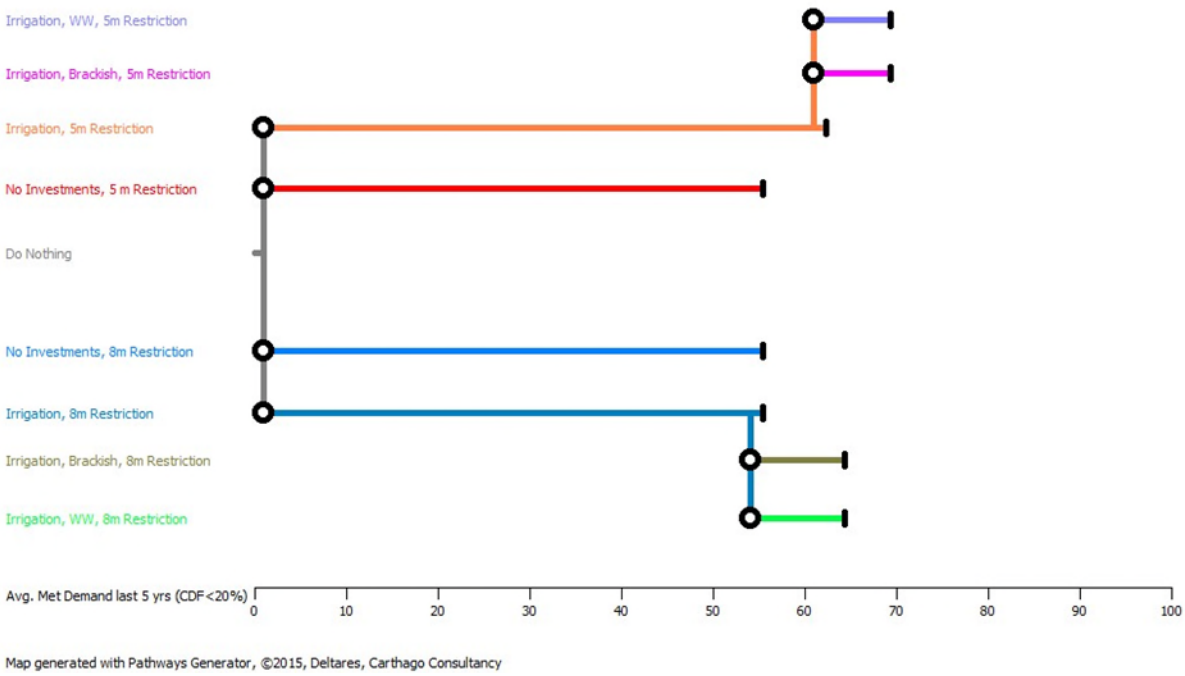


Figure 43: Dynamic Adaptive Policy Pathways for the Average Met Demand (Relative Deficit) of the last 5 years (2095-2100)

This methodology to build the pathways differs from the original final step of the pathways, as described in Table 11: *"implement next actions if an adaptation tipping point is approaching: implement corrective, preparatory, or new signposts if needed to stay on track; reassess in case of signals for reassessment".* Instead, the pathways work as a tool to help us visualize the added value of flexibility.

There are several important details to consider in the graphs. First, there is a clear difference in water levels due to the restriction policies (Figure 42). Policies that begin restrictions at 8 meters result in water levels reaching up to 7.2 meters, whereas those starting restrictions at 5 meters stabilize around that level. However, when additional water sources (brackish and wastewater) are introduced, the difference compared to no-investment policies is minimal, with only a 0.2-meter variation.

The situation changes somewhat in Figure 43. While there is still a difference between the two restriction strategies, the trade-off is not as pronounced as the variation in depth: a 7% difference with no investments versus 5% difference when implementing irrigation and additional water sources for agriculture. Additionally, within the 8-meter restriction scenarios, there is a 9% increase in met demand when developing new water supplies.
This suggests that it may be beneficial to restrict water extraction earlier, considering potential ecosystem dependencies (van Engelenburg et al., 2018), the need for surplus water supplies during consecutive shock events, and preventing aquifer compaction (Galloway et al., 1999), while simultaneously seeking new water sources to minimize the water deficit and meet demand.

In this case study, we created a system dynamics model from scratch, challenging ourselves to identify tipping points, propose solutions, and build dynamic adaptive policy pathways. As the system became more detailed, evolving over time and adding interconnections, decisions began to interact with key metrics, which makes tipping point identification more challenging.

However, as noted, models don't need to be overly detailed to be useful. We create a straightforward "accounting" system in Excel, which includes four monthly demands (city, agriculture, industry, and nature), a recharge based on historical Dutch rainfall patterns, and a set of measures, drip irrigation (DI), brackish water plants (BW), wastewater plants (WW), and cascade technologies, that activate if specific goals are unmet. To simplify, we set an arbitrary 8-meter aquifer depth, assuming it would be significant for both surface ecosystems and general soil and groundwater integrity in our synthetic system.

In this simplified model, we only adjusted city population in Excel, observing how the measures helped maintain the threshold while still meeting 100% of water demand until 2100. This approach contrasts with the original case study, where we allowed the system to evolve by defining numerous relationships and analysing the resulting trade-offs.

As shown in Figure 44, this method makes it relatively easy to build pathways for whatever system and time of interest. The system can then be iteratively expanded to increase realism: testing scenarios with the EMA Workbench, incorporating climate change projections, or linking these to sector-specific water demand (see Table 13). Nonetheless, it is crucial to remember that with added intricacy, results often become less clear. In this case, adding too much detail may lead to difficulties in finding a stable urban water demand (population size) that satisfies both goals (the 8-meter threshold and 100% demand fulfilment).

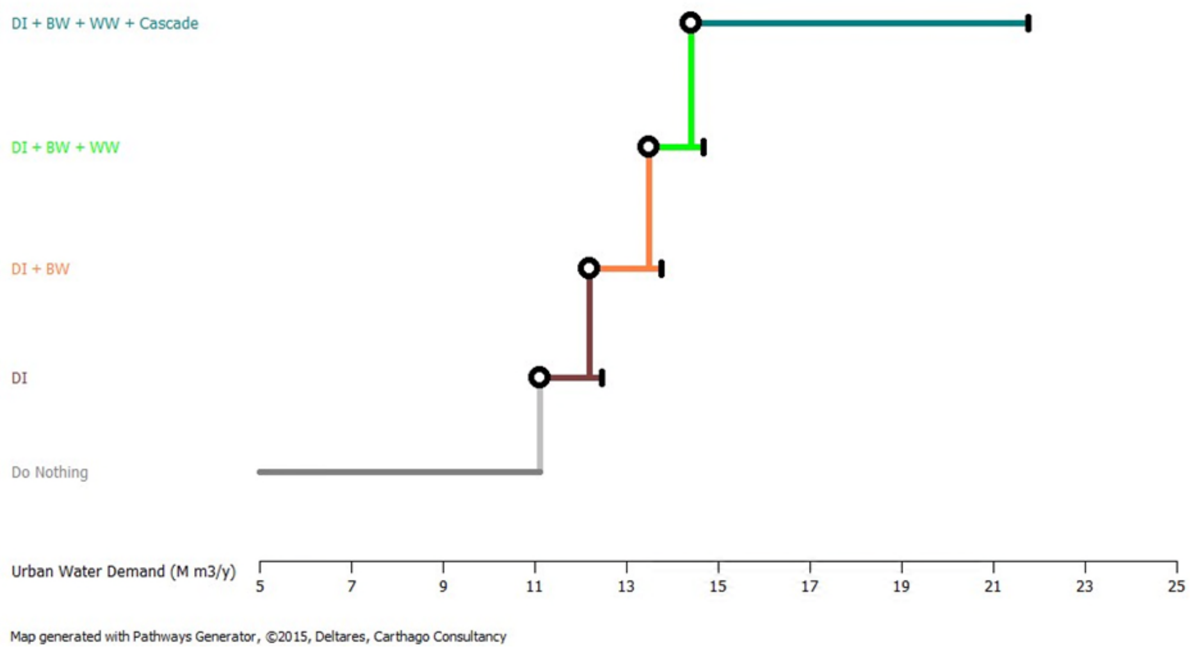


Figure 44: Dynamic Adaptive Model for the Excel Model. The paths show the maximum urban water demand for each measure, while respecting the 8 meter level boundary for the aquifer and a 100% met demand until 2100. Urban water demand is in millions of cubic meters per year. The corresponding population sizes for these urban water demands are: 233000, 255000, 282000, 302000 and 450000 (left to right).

Table 13: Columns/Variables in the Excel Model, with a short description of how they were defined and what can be improved in future iterations of the model

Column/Variable (m3/month)	How is it defined?	What can improve?
Urban Water Demand	Direct relationship with population. Peaks in the summer	Connect water demand per capita it to future temperatures

	months, annual average of 130 l/person/day	or define scenarios of high and low consumption
Agriculture Water Demand	Distributed from April to September (productive months)	Water demand per hectare can be connected to future precipitations and droughts. Connect it to types of crops
Industry Water Demand	Distributed throughout the year	Connect it to the population size. Find seasonal patterns
Nature Water Demand	Distributed from April to September	Connect it to precipitations and droughts. Add data of different types of plants/trees
Groundwater Recharge	Proportional to monthly precipitation in the Netherlands. With a loss factor of 30%	Test different rainfall future scenarios. Connect recharge to land use changes
Drip Irrigation Savings	Activated when there is a time step below 8 meters of depth	Implementation should not be immediate. Efficiency may vary between crops
Brackish and Wastewater Plants Production	Activated when there are 3 and 6 time steps below 8 meters of depth	Implementation should not be immediate. Wastewater plant capacity can be connected to the urban water demand