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Model-based decision support for adaptation pathways: a proof of concept

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Model-based decision support for adaptation pathways: a proof of concept

Jan H. Kwakkel(1)
Wil A.H. Thissen(1)

(1) Delft University of Technology, Faculty of Technology, Policy and Management

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Summary

This report presents the results of applying exploratory modeling to a fresh water supply problem. Exploratory modeling is a way of using models for decision support in the presence of deep uncertainty. To demonstrate exploratory modeling, we use the fresh water supply for irrigation in Rijnland as a case study. The model is derived from the integrated assessment metamodel of the Rhine delta developed by Marjolijn Haasnoot. The Rijnland specific parameterization has been developed by Marjolein Mens. The case analyses the demand for fresh water for irrigation purposes in the presence of uncertainty regarding future runoff of the Rhine, rainfall, evaporation, and land use change. These uncertainties are quantified using the delta scenarios. For climate change, ten realizations have been used for both W+ and G, while for land use change we used maps describing the situation in 2050 and 2100. A crude interpolation turns these maps into transient scenarios.

As a first analysis, we considered demand for fresh water by farmers at the decade level. We compared the demand with Gouda closed, with the demand in case Gouda is open. We observed that irrespective of the climate change scenario or the land use scenario, demand during closure was below the currently available supply via the small-scale water supply. This suggests that there is no problem to be expected.

As a second analysis, we applied scenario discovery to a large database of model results for different policy options, land use scenarios, and climate scenarios. Scenario discovery is a critical part of the Robust Decision Making method developed at the RAND Corporation. Applying scenario discovery to this case showed, not surprisingly, that economic damages from lack of fresh water supply are most severe in case of W+ climate scenarios, irrespective of the exact realization considered.

Samenvatting

Dit rapport presenteert de resultaten van het toepassen van verkennend modeleren op een zoetwater case. Verkennend modeleren is een manier om modellen te gebruiken ter ondersteuning van besluitvorming onder diepe onzekerheid. Om deze methode te demonstreren gebruiken we de aanvoer van water voor landbouwdoeleinden in het Rijnland als case. Het model is gebaseerd op het Rijnmodel ontwikkeld door Marjolijn Haasnoot. De parameterisering voor Rijnland is gedaan door Marjolein Mens. In de analyses hebben we gekeken naar de vraag naar zoetwater, rekening houden met onzekerheiden omtrent de afvoer van de Rijn, neerslag, verdamping, en veranderingen in landgebruik. Deze onzekerheden zijn gekwantificeerd op basis van de deltascenario's. Voor de klimaatveranderingsscenario's W+ en G maken we gebruik van elk tien mogelijke realisaties op decade niveau. Voor de veranderingen van landgebruik hebben we de kaarten voor 2050 en 2100 gebruikt. Via een eenvoudige interpolatie zijn deze omgezet naar tijdreeksen op jaar basis.

In een eerste analyse is er gekeken naar de vraag naar zoetwater voor irrigatie op decade niveau. Hierbij is een vergelijking gemakt van de vraag als Gouda dicht is met de vraag als Gouda niet dicht is. Ongeacht klimaatverandering en veranderingen in landgebruik blijft de vraag als Gouda dicht is onder de maximumaanvoer beschikbaar via de KWA. Dit suggereert dat er geen probleem is te verwachten.

Als tweede analyse is *Scenario Discovery* toegepast. Dit is een innovatieve methode ontwikkeld door de RAND corporation in de context van *Robust Decision Making*. We hebben *Scenario Discovery* toegepast op een database van modelresultaten voor verschillende beleidsopties, klimaatveranderingsscenario's, en landgebruiksscenario's. Uit deze analyse kwam naar voren dat de economische schade als gevolg van een tekort aan zoetwater het meest extreem is in het geval van het W+ scenario, ongeacht de exacte realisatie.

Content

1 Introduction

The aim of this report is to provide a fresh water supply specific proof of concept of exploratory modeling and related methods and techniques. In the context of the uncertainty work package of Knowledge for Climate, a variety of methods and techniques have been developed to support decision-making under deep uncertainty. Deep uncertainty is encountered when the different parties to a decision do not know or cannot agree on the valuation of the outcomes of interest, the relationships within the system that relate actions to consequences, or plausible values or their prior probabilities of key developments external to the system that still influence the system (Lempert et al. 2003). In short, in decision-making under deep uncertainty one is able to enumerate multiple alternative ways of valuing outcomes of interest, alternative hypotheses for relationships within the system, or alternative external developments without explicating their plausibility or probability (Kwakkel et al. 2010b). Haasnoot et al. (2013) present a high level conceptual approach for the design of dynamic adaptive Policy Pathways. This conceptual approach builds on two disparate strands of literature. The first strand focused on adaptation tipping points and adaptation pathways (Haasnoot et al. 2012a; Kwadijk et al. 2010). The second strand emphasized dynamic policies and their adaptation over time through careful monitoring (Kwakkel et al. 2010a; Walker et al. 2001). Walker et al. (2013) present a comparison of various approaches including dynamic adaptation pathways (Haasnoot et al. 2013), robust decision making (Lempert et al. 2006), and adaptive policymaking (Kwakkel et al. 2010a; Walker et al. 2001). Kwakkel et al. (2014) present a model-based design approach for supporting the design of dynamic adaptation pathways. This design approach is demonstrated using a climate change specific case, but lacks a clear fresh water focus. This report aims to complement the foregoing work by demonstrating a model-based approach using a specific fresh water case.

Figure 1 shows the Dynamic Adaptive Policy Pathway approach. As in the other approaches, the DAPP approach begins with the identification of objectives, constraints, and uncertainties that are relevant for decision-making. The uncertainties are then used to generate an ensemble of plausible futures. These futures are compared with the objectives to see if problems arise or if opportunities occur. This determines if and when (reactive) policy actions are needed. To assemble a rich set of possible actions, the approach distinguishes among four types of actions, which are defined in the same way as in Adaptive Policy Making: shaping actions, mitigating actions, hedging actions, and seizing actions (Kwakkel et al. 2010a). In subsequent steps, these actions are used as the basic building blocks for the assembly of adaptation pathways. The performance of each of the actions and pathways is assessed in light of the defined objectives to determine its adaptation tipping point. Once a set of actions seems adequate, potential pathways (a sequence of actions) can be constructed, and subsequently one or more preferred pathways can be selected as input for a dynamic robust plan. The aim of this plan is to keep the preferred pathway(s) open as long as possible. For this purpose, contingency actions are specified and a trigger for each contingency action is specified and monitored. This approach is being tested on a fictitious case (Kwakkel et al. 2012), and is being applied in a real case involving the Lower Rhine Delta of the Netherlands (Haasnoot et al. 2012b).

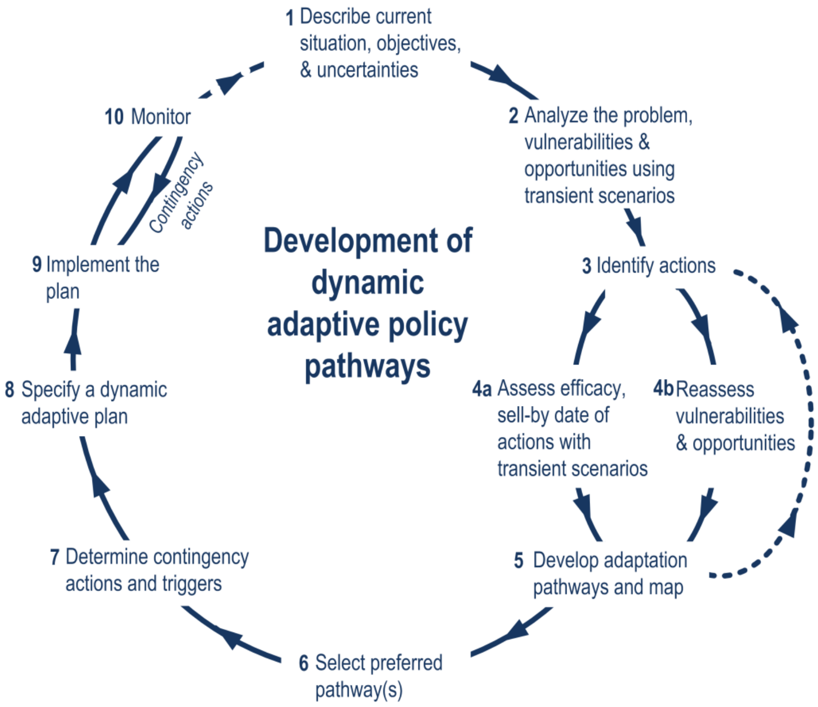
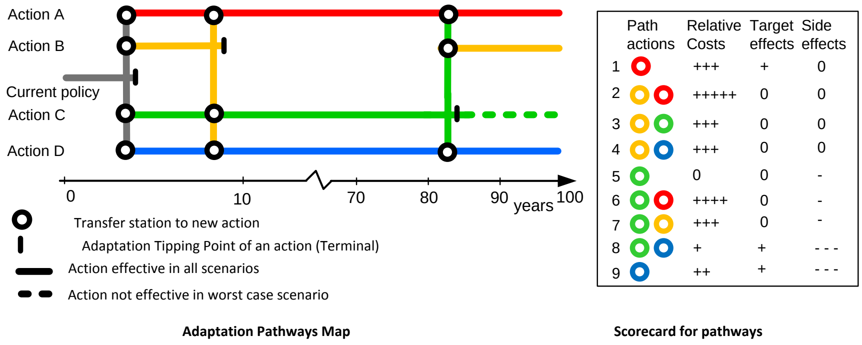


Figure 1: The Dynamic Adaptive Policy Pathway approach

In applying DAPP, typically, there is a portfolio of pathways that decision-makers would like to keep open for the future. This adaptation map forms the basis for the plan. Figure 2 shows an example of such a map. For a more detailed elaboration on DAPP, see Haasnoot et al. (2013).



Adaptation Pathways Map

	Path actions	Relative Costs	Target effects	Side effects
1	🔴	+++	+	0
2	🟡 🔴	+++++	0	0
3	🟡 🟢	+++	0	0
4	🟡 🔵	+++	0	0
5	🟢	0	0	-
6	🟢 🔴	++++	0	-
7	🟢 🟡	+++	0	-
8	🟢 🔵	+	+	- - -
9	🔵	++	+	- - -

Scorecard for pathways

Figure 2: A simple example of an Adaptation Pathways map (left) and a scorecard presenting the costs and benefits of the 9 possible pathways presented in the map.

In the map, starting with the current policy only, targets begin to be missed after four years. Following the grey lines of the current plan, one can see that there are four options. Actions A and D should be able to achieve the targets for the next 100 years in all climate scenarios. If Action B is chosen after the first four years, a tipping point is reached within about five years; a shift to one of the other three actions will then be needed to achieve the targets (follow the orange lines). If Action C is chosen after the first four years, a shift to Action A, B, or D will be needed after approximately 85 years in the worst case scenario (follow the solid green lines). In all other scenarios, the targets will be achieved for the next 100 years (the dashed green line). The colors in the scorecard refer to the actions: A (red), B (orange), C (green), and D (blue).

There are two challenges for DAPP: (i) identifying the most promising sequences of actions (those that are robust in some sense), taking into account a very large variety of plausible transient scenarios; and (ii) the combinatoric problem arising out of the multiplicity of ways in which actions can be sequenced over time, and the rules to be used to govern when new actions are to be triggered. To address these challenges, Kwakkel et al. (2014) propose to use multi-objective robust optimization. Algorithms for solving these types of problems are ideally suited for solving constrained non-linear problems with high dimensional decision spaces (Kasprzyk et al. 2013; Coello Coello et al. 2007; Reed et al. 2013). In this multi-objective robust optimization, the most promising sequences of actions are identified using a computational scenario-based approach (Lempert and Schlesinger 2000; Morgan and Dowlatabadi 1996), grounded in Exploratory Modeling and Analysis (Bankes 1993; Lempert et al. 2003; Bankes et al. 2013). Robustness of candidate pathways is assessed on multiple independent objectives, avoiding the need to make prior assumptions about decision-maker trade-off preferences.

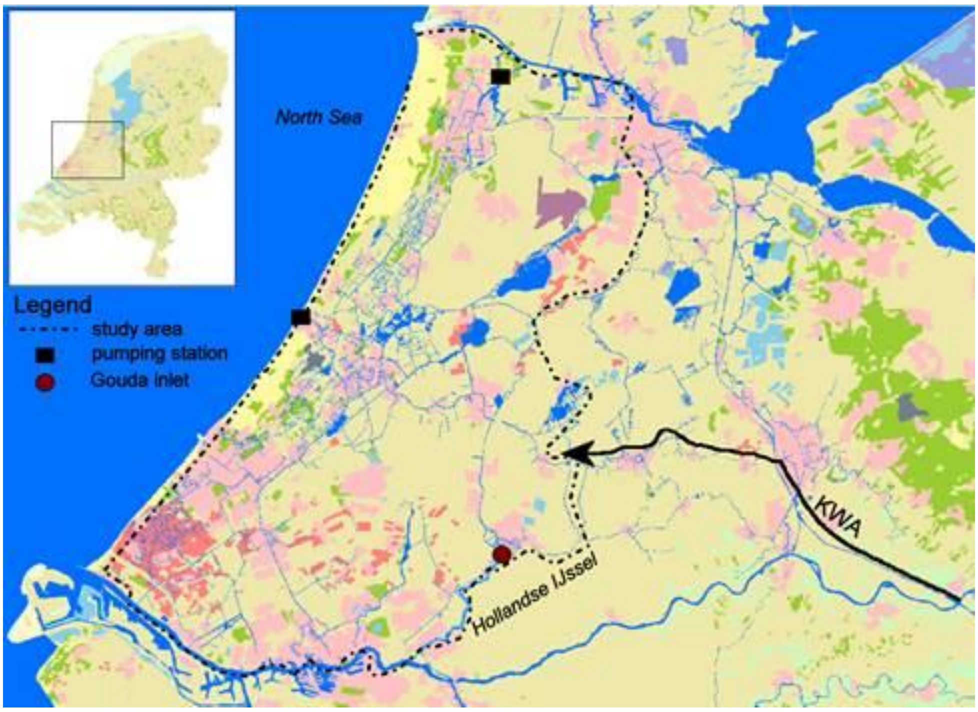
The aim of this report is to complement the foregoing work by offering a fresh water specific application. To this end, we apply exploratory modeling using a model of a particular region in the Netherlands. We investigate to what extent and under what conditions sever economic damages due to water shortages are expected. The analysis reveals that, for the specific case, based on the specific model used and the spectrum of uncertainties considered, no policy actions are necessary. We offer a reflection on these results.

The structure of this report is accordingly. Section 2 presents a general description of the model. Section 3 provides the case specific details. Section 4 discusses the uncertain factors taken into consideration. Section 5 and 6 contain results of various analyses. Section 7 contains the concluding remarks and reflection on the results.

2 Case study area

The case study area is shown in Figure 4. The focus is on the western part of the Netherlands. This is a system of low-lying polders. The main types of land use include agriculture, cattle breeding, urban areas including office space for the service industry, and recreational areas. Agriculture focuses on potatoes, horticulture, bulbs, and flowers. The water supply and drainage system is composed of canals, ditches, a few lakes and pumps and sluices. In winter there is excess water, which is pumped out. In summer, fresh water is pumped into the system. This is used for maintaining water levels, reducing salinity due to seepage and saline groundwater, and maintaining water quality standards. Fresh water is supplied via de Hollandse Ijssel using the inlet at Gouda (south-easterly) and the brackish water is pumped out using pumping stations in the north and east. The availability of the Gouda inlet depends on the salt concentration at the inlet. If the salt concentration exceeds 250 milligram per liter, the Gouda inlet cannot be used. A more limited emergency source of fresh water is then available from the east via the KWA (small scale water supply).

Figure 3: Case study area

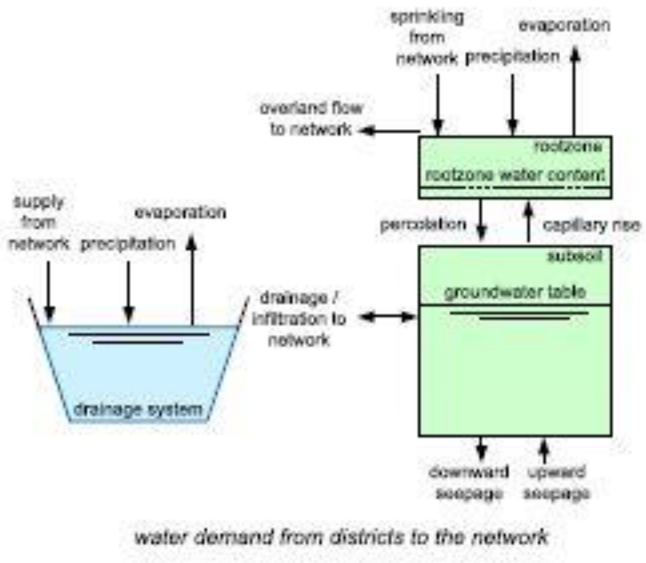


3 Model description

3.1 Water demand

The water demand module generates water demands for irrigation and water level control in rural areas and is a simple two layer grid base groundwater model with a resolution of 250 by 250 meter, taking into account a limited number of land use and soil types. For each layer in each grid cell, the model calculates the water balance. First, the potential evaporation is calculated by multiplying the reference evaporation with a crop factor that is specified for each crop and ten-day period. The actual evaporation is a function of the potential evaporation, the moisture in the root zone, and the soil moisture suction (pF value). Lateral flow from groundwater to local surface water and vice versa is a function of groundwater depth relative to surface water level. Water flowing from the root zone to the subsoil (percolation) depends on the root depth, porosity, and precipitation. Capillary rise (flow from subsoil to root zone) is calculated as a function of the groundwater depth below the surface level and the root zone suction (Kabat and Beekma 1994; Oosterbaan 2001). The lower boundary condition of each plot is an annual seepage flux taken from results of the complex model for an average year. In case the root zone and subsoil are saturated, excess water is moved through surface runoff. In urban areas surface runoff is a function of the net precipitation and a runoff coefficient of 0.8 (Urbonas and Roesner 1993). The water demand is determined from the difference between the actual and potential evaporation. The amount of water requested for maintaining the target water level in the local surface waters areas is derived from the net precipitation and the surface area of these waters. The grid cells are aggregated over a watershed area (called district).

Figure 4: Diagram showing the basic structure of the model



3.2 Salt intrusion

The salt intrusion module simulates the salt concentration at the Gouda inlet depending on river discharge and sea level. This module is based on empirical correlation between the Rhine discharge at Lobith and salt concentrations in the lower river reaches calculated using a 1D hydraulic model (SOBEK) (van den Boogaard and van Velzen 2012).

$$Salt = 1700 + (90 - 1700) \times \frac{e^{Fact}}{1 + e^{Fact}}$$

$$Fact = \left(\frac{Q_{lobith} - 600}{2.211}\right)^{0.309}$$

where Q_{lobith} is the discharce at Lobith in cubic meter per second and $Salt$ is the salt concentration at the Gouda inlet in milligram per liter. As discussed in Haasnoot et al. (2014), this relation will slightly underestimate the frequency of closure at Gouda.

3.3 Economic damages to crops

The focus of this analysis is on the economic damages to agriculture due to drought. For this, we use Agricom (Mulder and Veldhuizen 2014) which is an agro-economic model to estimate agricultural yield losses due to water shortage, saline soil moisture and water excess. Drought is defined in terms of

$$E_{ratio} = \frac{ET_{act}}{ET_{pot}}$$

Where ET_{act} is the actual evatranspiration and ET_{pot} is the potential evatranspiration. Given E_{ratio} and crop specific damage curves that take into account the growing season, the E_{ratio} is translated into a loss of yield in kilogram, which in turn is monetized. In our analysis, we calculate both the potential yield in Euro, assuming perfect conditions, and the actual yield in Euro's, allowing us to calculate the relative loss due to deficiencies in the system.

4 Uncertain Factors

The following uncertainties are taken into account

- River runoff in the Rhine
- Rainfall
- Land use
- Evatranspiration

For each of these uncertainties we use transient scenarios (Haasnoot et al. 2014). So, rather than looking at the system in e.g. 2050, we consider the change over time from the current system to the state of the system in 2100. For river runoff, rainfall, and evatranspiration we use different possible realizations of the climate scenarios W+ and G. These realizations are the same as those used by Haasnoot et al. (2014), although here we only use the parts relevant to the case study area. We use 10 possible realizations of both scenarios. For land use, we use the land use as described in the four delta scenarios as developed in the Deltaprogram. Maps were available for 2050 and 2100. I interpolated the maps in between. Given that we sum up over the region, a rather simple and crude interpolation has been used. Combining the different realizations with the delta scenarios gives us 40 scenarios. To assess the role of changing land use, we include, in addition to the changing land use also a no change case, giving us 60 scenarios in total (i.e. Warm, Druk, Rust, Stoom, No change W+, and no change G).

Note that in the current results land use has some influence on water demand, but the irrigation maps do not evolve with land use.

5 Results

5.1 100 years, Gouda always open or always closed

Before doing any more detailed analyses using the model, we need to assess whether the model is behaving as expected. To this end, we generate two 'policies'. In the one, Gouda is always open and in the other Gouda and the KWA are always closed. We ran these policies for 3 scenarios: 'warm', 'steam', and W+ without land use change. For each of the 3 scenarios, we considered ten possible realizations. Together, we thus ran 3 scenarios*10 realizations*2 ‘policies’ = 60 experiments. Next, we analyze the results at a decade level (3600 decades per experiment). Figure 5 shows a boxplot of water supply for irrigation. As expected, with Gouda and the KWA closed, no water is available for irrigation, while with Gouda open; there is water available for irrigation.

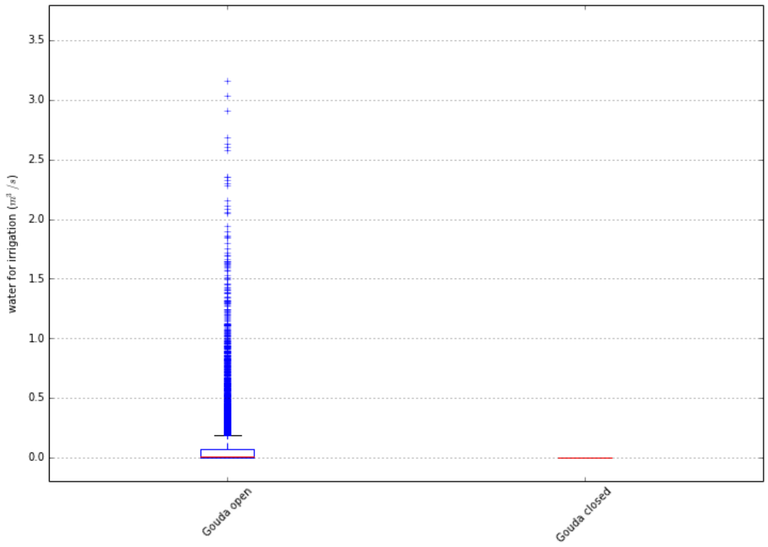


Figure 5: water supply for irrigation at decade level with Gouda and KWA open, and Gouda and KWA closed

Figure 6 shows the consequences of water availability on income loss. Income loss is accumulated over the year, this boxplot is thus based on 100 data points per experiment. In line with our expectations, the loss is higher in case of both Gouda and KWA being closed as compared to the Gouda open case. Note however, that the difference is minor, and mainly located at the high end of the spectrum. So, the lack of water availability results in slightly more years with income losses of 20% or higher. This demonstrates that the model (which is identical to the one used by Marjolein Mens) is behaving as expected.

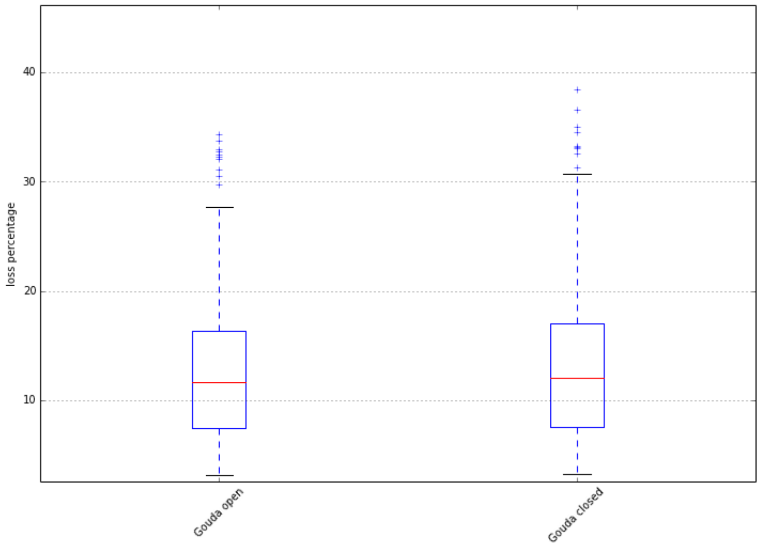


Figure 6: Percentage income loss

5.2 Water demand during Gouda closure for Warm

The next analysis focuses on the demand for irrigation when Gouda is closed in case of the Warm scenario. To this end, we ran the model for all ten realizations of the W+ climate scenario in combination with the land use scenario associated with Warm. Next, we identified for each decade the demand for irrigation. To get insight into the demand during closure we compare the overall demand for all decades with the demand during closure. The results are shown in Figure 7.

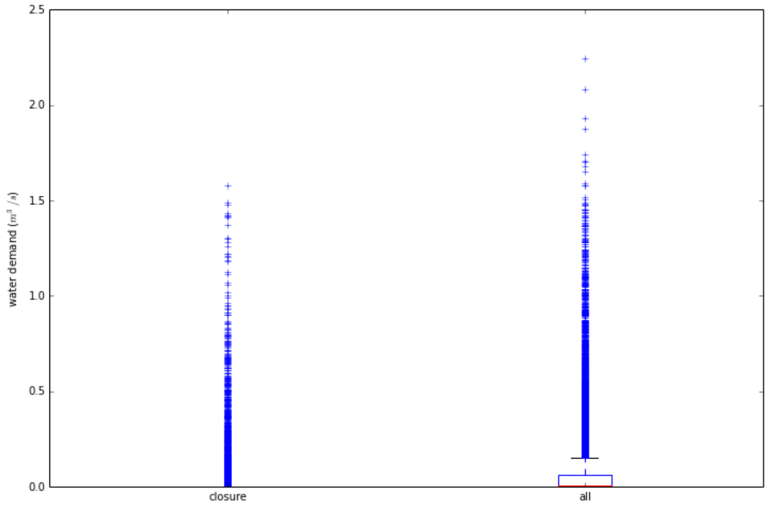


Figure 7: Water demand per decade for Warm, grouped by whether Gouda is closed

The maximum supply via the KWA is around 5 cubic meters per second. As can be seen in Figure 7 the demand for irrigation always is below this maximum. This implies that even for the most extreme scenario (i.e. warm), the current fresh water supply capacity through the KWA will be sufficient. There is thus no need for any further analysis of policy options.

5.3 Scenario discovery proof of concept

5.3.1 Background on scenario discovery

Scenario discovery is a relatively novel approach for addressing the challenges of characterizing and communicating deep uncertainty associated with simulation models (Dalal et al. 2013). The basic idea is that the consequences of the various deep uncertainties associated with a simulation model are systematically explored through conducting series of computational experiments (Bankes et al. 2013) and that the resulting data set is analyzed to identify regions in the uncertainty space that are of interest (Bryant and Lempert 2010; Kwakkel et al. 2013). These identified regions can subsequently be communicated through e.g. narratives to the decision makers and other actors involved. Scenario discovery is an analytical process which can be embedded in a participatory process supporting ”deliberation with analysis” (National Research Council 2009).

Although scenario discovery can be applied on its own (Rozenberg et al. 2013; Kwakkel et al. 2013; Gerst et al. 2013), it is also a key step in Robust Decision Making (RDM) (Lempert et al. 2006; Lempert and Collins 2007; Dalal et al. 2013; Hamarat et al. 2013). RDM aims at supporting the design of robust policies. That is, policies which perform satisfactorily across a very large ensemble of future worlds. In this context, scenario discovery is used to identify the combination of uncertain factors under which a candidate policy performs poorly, allowing for the iterative improvement of this policy. This particular use of scenario discovery suggests that it could also be used in other planning approaches that design plans based on an analysis of the conditions under which a plan fails to meet its goals (Walker et al. 2013).

Currently, the main statistical rule induction algorithm used for scenario discovery is the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999), although other algorithms, such as Classification and Regression Trees (CART) (Breiman et al. 1984), are sometimes used (Gerst et al. 2013; Lempert et al. 2008). PRIM can be used when one tries to find combinations of values for uncertain factors that result in similar characteristic values for the outcome variables. Specifically, one seeks a set of subspaces of the space spanned by the uncertain factors within which the values of a single output variable are considerably different from its average values over the entire uncertainty space. PRIM describes these subspaces in the form of ‘boxes’ of the uncertainty. The main merit of PRIM is its interactive usage, which helps to overcome its main weakness of restricting too many uncertain factors. Implementations of PRIM for scenario discovery are available in R (Bryant 2012) and in Python (Kwakkel and Pruyt 2013).

In current practice, PRIM is performed in an interactive manner. By keeping track of the route followed by the lenient hill climbing optimization procedure used in PRIM, the so-called peeling trajectory, a manual inspection can reveal how the number of uncertain factors that define the subspace varies as a function of density (precision) and coverage (recall). This allows for making a judgment call by the analyst balancing interpretability, coverage, and density. To avoid the inclusion of spurious uncertain factors in the definition of the subspace, Bryant and Lempert (2010) propose a quasi-p-values test. The quasi-p-value, essentially a one-sided binominal test, is an estimate of the likelihood that a given uncertain factor is included in the definition of the subspace purely by chance.

5.3.2 Scenario discovery results

The analysis below applies the scenario discovery approach to a dataset containing 6 policies and covering 10 realizations for each of the four delta scenarios. This is merely a proof of concept.

Figure 9 shows the tradeoff between coverage and density. Coverage and density are both ratios. Coverage is used to assess of all the cases of interest, how many there are inside the box found by PRIM. Density is used to assess of all the cases that are within the box, how many are of interest. In Figure 9, , each point represents a single candidate box found by PRIM. Ideally you want both as close as possible to one. As can be seen, we are unable to achieve this. Given that this is impossible, the analyst can use the figure to make a choice. For example, we can inspect box nr. 5, this is the first box with the maximum density, without giving up any coverage as compared to the other candidate boxes with the same density.

Figure 8: Trade off curve of coverage versus density

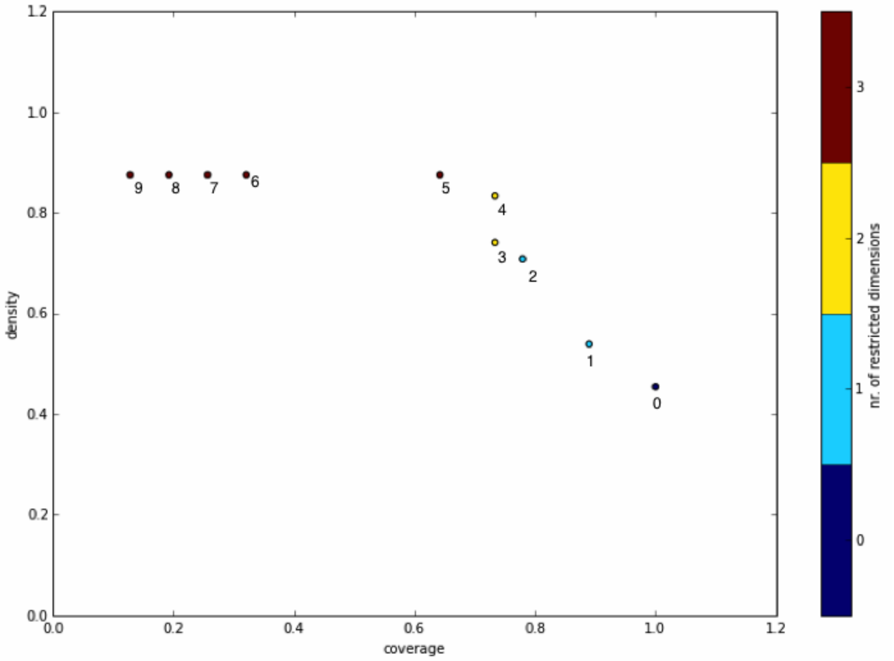


Table 1 shows the results for box 5. The top part of the table shows descriptive information of the box, while the bottom part shows the box definition and the quasi p values for each of the included uncertain factors. As can be seen, the box covers 65% of all the cases of interest. So 35% of the cases of interest is not being explained by this box. It is able to explain 65% of the cases of interest with a density of 88%. So 12% of the cases that fall within the box are not cases of interest. The box contains 33% of al the data. Looking at the definition of the box we see that the first two uncertain factors are statistically significant, while the third factor is not. Not surprisingly, we find cases with severe drought primarily in the warm and steam scenarios. More interestingly, we see that of the 10 realizations of W+, only numbers 1-8 are included. This suggests that even in W+ climate variability will have some influence on the severity of the droughts. The fact that the policy options are not significant is not surprising in light of the preceding analysis. In the do nothing case, there is hardly any problem, and the policy options therefore have no real effect.

Table 1: Prim results for box nr.5

	Restricted dimensions	**mass**	**coverage**	**density**
box nr. 5	3	0.33	0.65	0.88

Uncertain factors	**Box limit**	**quasi-p values**
Scenario	Warm, steam	$1.66e^{-9}$
Realization id for climate scenario	1-8	$4.66e^{-3}$
Policy option	Do nothing, kwa medium, kwa large, irrigation glass, more lenient Gouda norm,	$2.00e^{-1}$

6 Discussion of Results

Our analysis is rather reassuring: according to the model, the demand for water for irrigation even in future years and taking into account a wide set of uncertainties falls below the maximum capacity of the KWA. So, even when considering a wider range of uncertainties, the water supply system of the case study area appears to be robust. There are a few caveats worth mentioning.

First, the relation used to calculate closure of Gouda is known to underestimate the number of closures (Haasnoot et al. 2014). As such, a closer analysis on a different time scale might be needed. The current analysis uses decades, and it might be necessary to shift to a daily analysis to get a better insight into what is actually happening.

Second, the model does consider land use change. This land use change affects water demand. We have not translated the changes in land use into changes in the areas being irrigated. Doing so is possible. For example, we could use the procedure used in by ter Maat et al. (2013). However, implementing this inside the model is beyond my PC RASTER skills. Moreover, the analyses at the basis of this report took several weeks in runtime. Redoing them with the changing irrigation map would take too much time. We speculate that one of the reasons for the differences between the results reported here and those reported in ter Maat et al. (2013) are due to how changes in land use affect irrigation.

Third, it appears that the model at every time step resets the water levels to the norm height. Inspection of the source code of the model did not provide clarity as to where the water for this comes from. That is to say, it appears that a hidden assumption in the model is that the full capacity of the KWA is available for maintaining water levels. Based on ter Maat et al. (2013), I would question this assumption.

From a methodological point of view, the main conclusions of the analyses reported on are that it is possible to consider a wide range of different uncertainties simultaneously. Exploratory modeling offers an approach for systematically mapping out the consequences of various uncertainties. We also demonstrated that it is possible to do a variety of potentially useful further analyses on the exploratory modeling results. In some cases, it is sufficient to summarize the results of the experiments using boxplots, as done in the first part of the analyses. In other cases, it is necessary to trace back where experiments with undesirable results come from. That is, what combination of uncertain factors is causing these undesirable results? Scenario discovery provides insight into this and paves the way for designing and testing policy options that address the vulnerabilities revealed by these analyses. Moreover, these kinds of analyses can also help in assessing the usefulness of models, since they stress test the model and clarify the domain over which the model provides meaningful results.

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To develop the scientific and applied knowledge required for Climate-proofing the Netherlands and to create a sustainable Knowledge infrastructure for managing climate change

Contact information

Knowledge for Climate Programme Office

Secretariat:
c/o Utrecht University
P.O. Box 85337
3508 AH Utrecht
The Netherlands
T +31 88 335 7881
E office@kennisvoorklimaat.nl

Public Relations:
c/oAlterra (Wageningen UR)
P.O. Box 47
6700 AA Wageningen
The Netherlands
T +31 317 48 6540
E info@kennisvoorklimaat.nl

www.knowledgeforclimate.org