Climate Change, Uncertainty and Investment in Flood Risk Reduction

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Climate change, Uncertainty and Investment in Flood Risk Reduction

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Contents

1. Introduction 1

1.1 Flood risk and climate change 1

1.2 Flood risk management 2

1.3 Economic analysis of flood risk management strategies under climate change 3

1.4 Research objective and research questions 5

1.5 Methods 6

1.6 Outline of the thesis 7

2. Economic analysis of adaptive strategies for flood risk management under climate change 9

2.1 Introduction 10

2.2 Climate change uncertainty and the climate change learning process 13

2.2.1 Current approaches for including climate change uncertainty in flood risk management decisions 13

2.2.2 Expert elicitation 15

2.2.3 Learning about the impacts of climate change 16

2.3 Economic models for flood risk management 20

2.3.1 Cost-benefit optimisation 20

2.3.2 Probabilistic modelling of climate change impact scenarios 22

2.3.3 Models of learning 24

2.4 Robustness analysis 28

2.5 Discussion 29

2.6 Conclusions 30

3. Optimal dike investments under uncertainty and learning about increasing water levels 33

3.1 Introduction 34

3.2 The optimisation problem 37
3.2.1 The deterministic base model 38
3.2.2 The benchmark model with uncertainty 40
3.3 Learning 41
3.3.1 Perfect learning with a given moment of learning 41
3.3.2 The expected value of information 46
3.3.3 Probabilistic learning 47
3.4 Implementation & results 49
3.5 Discussion 54
3.6 Conclusions 55
4. Impacts of rainfall variability and expected rainfall changes on cost-effective adaptation of water systems to climate change 57
4.1 Introduction 58
4.2 Rainfall variability 60
4.3 Mathematical representation of water system adaptations 62
4.4 Solution methods and case study 65
4.4.1 Solution methods 65
4.4.2 Case study 67
4.5 Results 70
4.6 Discussion 73
4.7 Conclusions 75
5. A dynamic minimax regret analysis of flood risk management strategies under climate change uncertainty with emerging information on peak flows 77
5.1 Introduction 78
5.2 Motivation 80
5.3 Static versus dynamic regret minisation 81
5.4 A flood risk management application 85
5.4.1 A conceptual flood risk management model 85

5.4.2 The primary dike problem 92
5.4.3 The floodplain problem 93
5.4.4 Investment selection and threshold-to-switch 94
5.5 Implementation and results 96
5.5.1 Implementation 96
5.5.2 Results 99
5.6 Conclusions and discussion 103
6. General discussion and conclusions 107
6.1 Research questions and summary of findings 107
6.2 General discussion 113
6.3 Model limitations and directions for further research 116
6.3.1 Limitations 116
6.3.2 Suggestions for further research 117
6.4 Conclusions 118
6.4.1 Modelling conclusions 118
6.4.2 Policy conclusions 121
Summary 124
Samenvatting 127
References 131
Acknowledgements 143
About the author 144
Education certificate 145

1. Introduction

1.1 Flood risk and climate change

In the domain of flood risk analysis, the term flood risk is commonly understood as the product of flood hazard and flood consequences (Plate 2002; Apel et al. 2004). Flood hazard is characterised by the frequency of occurrence of extreme events which cause flooding, and flood consequences consist of flood damages under these events. Flood consequences are defined by the product of flood exposure and vulnerability. Flood exposure consists of the people and resources at risk. Vulnerability is the predisposition to be adversely affected. Put simply, vulnerability to flooding is the lack of resistance when flooding would occur (Kron 2005; IPCC 2012).

In the past decades, exposure to riverine and coastal flooding has increased due to population growth, economic growth and urbanisation of flood-prone land. According to Jongman et al. (2012), over 800 million people in the world are exposed to a once in one hundred years (1/100) probability of river flooding, and more than 270 million people to 1/100 years of coastal flooding. Jongman et al. (2012) also estimated that at the global level asset exposure has increased from 1.8 trillion USD in 1970 to 35 trillion USD in river basins in 2005, and from 820 billion to 13 trillion USD in coastal zones. Low-lying coastal zones cover only 2% of the world's land surface, but 10% of the world population is living in these zones (McGranahan et al. 2007).

Global flood risk will continue to increase in the coming decades due to increasing flood exposure, increasing vulnerability and changing flood frequencies. The largest increase in economic flood exposure is projected to occur in Asia. In North America, Europe, Australia and Latin America, flood exposure will also continue to increase despite a slowing trend in population exposure (Jongman et al. 2012). Meanwhile flood frequencies will change due to soil subsidence and climate change induced impacts on weather patterns, river flows and sea levels (Syvitski et al. 2009; IPCC 2014).

Climate change has potential impacts on urban, riverine and coastal flood frequencies. The projected increases in intensity and frequency of rainfall extremes will decrease the performance of urban drainage systems (Mailhot and Duchesne 2010). Without additional investments, this will lead to more frequent system failures, which, amongst others, increase the incidence of surface flooding. Furthermore, peak river discharges and riverine flood frequencies are projected to increase in large parts of Europe, Southeast Asia, Northeast Eurasia, Eastern and low-latitude Africa, and some parts of Latin America (Feyen et al. 2012; Hirabayashi et al. 2013). Moreover, without effective adaptation sea level rise will lead to larger coastal flood risks worldwide, possibly reinforced by increasing storm intensities in some regions (Webster et al. 2005; Knutson et al. 2010; Nicholls and Cazenave 2010). Countries around the globe, therefore, have to reconsider their current flood risk management strategies.

1.2 Flood risk management

Without additional flood risk management measures, expected damages from flooding that can be ascribed to climate change will increase rapidly (Bosello et al. 2007; Ciscar et al. 2011). Expected damages from increasing flood risk can be mitigated by investment in flood risk reduction. The expected benefits of these investments, which can be expressed in terms of monetary damage reductions, are often higher than the costs to reduce flood risk. Flood risk management, therefore, can improve social welfare.

For long-term decisions, such as decisions on investments in infrastructure, anticipatory adaptation to climate change is needed (Smith 1997). Flood risk infrastructures have typically long technical lifetimes and often involve fixed costs of investment or modification (Gersonius et al. 2013). By anticipation of future flood regimes frequent re-investment, which is costly due to the fixed costs associated with every re-investment round, can be avoided. It is, for example, clearly suboptimal to heighten a dike on a yearly basis (van Dantzig 1956).

Anticipatory adaptation relies on climate change impact projections. There are, however, large uncertainties about climate change impacts on flood regimes. Until now, there is no scientific consensus on which climate projections to use, and how to use them for stormwater management and riverine and coastal flood risk management (Hall 2007; Kundzewicz 2010; Rosenberg et al. 2010). Despite climate change uncertainties, it is widely agreed that it is necessary to anticipate climate-induced changes in flood frequencies by upgrading storage and conveyance capacities of urban drainage systems and by updating fluvial and coastal flood risk management strategies (Nie et al. 2009; Merz et al. 2010; Katsman et al. 2011; Berggren et al. 2014).

There is a large variety of flood risk management measures for different types of flood risk. Coastal and fluvial floods can be classified as low-probability high-impact floods and may cause economic and societal disruption (Vrijling 2001; Jonkman et al. 2003). High probability-low impact floods from heavy precipitation at the local scale, in contrast, have less impact on society. Inundation depths are not comparable to those of fluvial and coastal flooding, but damages can still be substantial (Hoes and Schuurman 2006; Wu et al. 2012).

For any type of flood risk, control measures are either aimed at reducing flood frequencies or at mitigating flood exposure or flood vulnerability. Examples of measures that reduce flood frequencies are dune restoration in coastal areas, raising dikes in river basins, and upgrading drainage capacities in urban areas. Flood exposure mitigation can be achieved through spatial planning, and vulnerability can, for example, be reduced by implementing building codes and the development of emergency plans (Hooijer et al. 2004; Aerts and Botzen 2011; Wu et al. 2012; Hanley et al. 2014).

Due to climate change flood-related extremes can no longer be assumed to be statistically stationary for flood risk management practices (Khaliq et al. 2006; Milly et al. 2008; Merz et al. 2010; Rosenberg et al. 2010; Gilroy and McCuen 2012). It has, however, remained difficult to identify economically efficient and robust investment options, and to determine optimal investment levels and investment timing under climate change.

1.3 Economic analysis of flood risk management strategies under climate change

Flood exposure and flood frequencies will continue to change. As a consequence, investment in flood risk reduction will have to be repeated over time. Flood risk management strategies can be defined as sequences of investments in flood risk management measures. In order to identify economically efficient and robust strategies, both optimal strategies of single measures have to be identified, such as dike heights, as well as an optimal selection of investment options, for example the choice between raising a dike and creating a floodplain. Economic analysis of flood risk management strategies has become more complex, because uncertain climate change impacts have to be incorporated in the analysis (Zhu et al. 2007; de Bruin and Ansink 2011; Lickley et al. 2014).

Before an economic analysis of flood risk management strategies under climate change is carried out, first the applicable decision criterion needs to be considered. Cost-benefit analysis (CBA) aims at the maximisation of social welfare. CBA has been frequently applied to assess flood risk management strategies and to determine optimal flood protection standards (van Dantzig 1956; Zhu and Lund 2009; Eijgenraam et al. 2012; Kind 2014). Climate change increases the spread of possible outcomes. As a result, decision criteria that include risk aversion may lead to other optimal decisions than risk-neutral criteria. Risk-aversion has, for example, recently been studied by Kuijper and Kallen (2012) and Wang et al. (2015).

Decision-makers may also be regret-averse under climate change. This is for instance reflected by the search for 'no regret' or 'low regret' flood risk management options, which are relatively insensitive to different climate futures (IPCC 2012; Wilby and Keenan 2012). For flood protection studies, regret aversion may require an economic analysis that applies a regret-based decision criterion (Brekelmans et al. 2012). Other decision criteria, such as minimax, Laplace, Hurwicz or modified versions of these criteria can be considered as well (Clarke 2008; Gaspars-Wieloch 2014).

Once the decision criterion and the corresponding type of economic analysis have been chosen for the optimisation of flood risk management strategies, climate change uncertainty can be included in the analysis. The easiest way to include climate change uncertainty is to use a 'single future' approach, in which a single climate change scenario is applied to identify optimal investment strategies. Examples are CBA with a deterministic parameter for the rate of sea level rise, cost calculations of flood risk management strategies per design peak flow scenario, and the analysis of cost-effective compliance with a flood risk standard under a given rainfall scenario (van Dantzig 1956; Middelkoop et al. 2004; Mailhot and Duchesne 2010). Expected-value based economic analysis, in contrast, assigns subjective probabilities to different climate scenarios, or a probability distribution to possible climate change futures. The probabilistic information can then be applied to obtain estimates of the expected future flood risk (Purvis et al. 2008).

Climate change impact projections, furthermore, may be subject to change over time. For example, recent assessments report larger uncertainty ranges of sea level rise and extreme rainfall than in previous assessments (Wahl et al. 2013; KNMI 2014). Moreover, more extreme value observations and scientific progress may reduce or resolve climate uncertainties in the long run (Baker 2005; Khaliq et al. 2006). Uncertainty that can be reduced by acquiring new knowledge has been classified as epistemic (Merz and Thieken 2005). Possible changes in climate information, including the possibility that uncertainty is reduced, can be applied to study the value of flexibility and to develop adaptive flood risk management strategies (Gersonius et al. 2013). The arrival of new information, or learning, can be incorporated in an economic analysis of flood risk management strategies by real options methods (Woodward et al. 2011). Learning can also occur upon the arrival of new data, which can be analysed, for example, by means of Bayesian updating (Davis et al. 1972). However, learning, as induced by the arrival of new information, has received relatively little attention in economic flood risk management studies. This thesis is therefore concerned with the economic analysis of flood risk management strategies under climate change with learning.

Countries increasingly recognise that it is not only necessary to anticipate changes in flood risk, but that it is also important to be able to respond to new insights (Zevenbergen et al. 2013). The overall ability to adapt flood risk management investments to changing insights is part of the adaptive capacity of a water system (Pahl-Wostl 2007). Economic analysis of flood risk management with learning about climate change impacts is useful to study trade-offs between flexibility and costs, and to identify optimal strategies under possible changes in climate information.

1.4 Research objective and research questions

The overall objective of this thesis is to investigate the impact of climate change on investment in flood risk reduction, and to explore and apply optimisation methods to support identification of optimal flood risk management strategies. To this end, the following sets of research questions are addressed:

1. How can probabilistic extensions of cost-benefit analysis using climate and learning scenarios be applied to improve decision-making on flood risk management strategies? And what are advantages and limitations of such probabilistic extensions?

2. What are optimal dike investment strategies under uncertainty and learning about climate change impacts? What are the implications of the

assumed learning process and the use of subjective probability distributions to represent structural water level increase? And how large are the differences in optimal investment levels without and with learning?

3. What is the impact of new rainfall observations on cost-effective investment in detention storage? Can 'white noise' be distinguished from a structural shift of an extreme rainfall distribution? And what is the relationship between the fixed costs of investment and the statistical beliefs of a decision-maker about the risk of flooding?

4. What is the motivation for a minimax regret approach to study flood risk management investments? Can a consistent dynamic minimax regret procedure be developed, and can it be applied to practical flood risk management problems? What is the impact of 'learning scenarios' on optimal investment selection and optimal investment levels under a minimax regret decision criterion?

The research questions are addressed in Chapters 2-5 of this thesis.

1.5 Methods

This thesis applies three different types of economic analysis to study flood risk management strategies: (i) CBA with probabilistic extensions, (ii) a cost-effectiveness analysis for the case where a flood protection standard has been set and new rainfall data becomes available, and (iii) a dynamic robustness analysis based on regret. The appropriateness of a type of economic analysis is determined by the decision-context. It includes the decision-maker preferences regarding risk, loss and regret, the perspective of the decision-maker, and the relevant economic decision criterion.

To address the research questions, this thesis applies three main solution methods: (i) decision tree analysis, (ii) dynamic programming, and (iii) a novel dynamic minimax regret method. Decision tree analysis is applied throughout the thesis in Chapters 2, 3 and 5 to explore research question sets 1, 2 and 4. Dynamic programming methods are used to solve the economic models presented in Chapters 3 and 4 in order to study research question sets 2 and 3 in more detail.

In Chapter 4, moreover, stochastic dynamic programming is combined with simulation of rainfall and water levels. In Chapter 5, a dynamic minimax regret procedure is developed as well as a conceptual flood risk management model to address research question set 4.

Decision tree analysis has been advocated for its simplicity and is commonly used to explain the value of information and to study investment problems with information arrival (Copeland and Antikarov 2003). The method finds its origins in the binomial tree model of Cox et al. (1979) as an alternative model for financial option pricing in discrete time. Simplified tree models with scenarios for real options without risk-adjusted discounting followed shortly after (Conrad 1980).

The dynamic programming theory was developed by Bellman (1954). A deterministic application to the problem of optimal dike height for a single segment dike has been presented by Eijgenraam et al. (2012).

Rainfall-runoff-inundation simulation can be linked to an economic optimisation module. An example of a rainfall generator is described by Cameron et al. (1999). There are numerous software packages for the simulation of runoff, flow, water levels and inundation. The results may serve as an input to a damage model for CBA of upgrading urban drainage or regional surface systems, but this setting is not often studied in practice (Pathirana et al. 2011). Cost-effective compliance with a performance target under climate change can be studied in a deterministic setting (Mailhot and Duchesne 2010). This, however, does not account for randomness in the frequency of occurrence of extreme events. In Chapter 4 simulation-optimisation methods are applied to include these effects on optimal investment levels.

The minimax regret decision criterion has first been described by Niehans (1948) and Savage (1951). The problem of dynamic inconsistency, as a result of the dynamic application of the minimax regret decision criterion, has been studied by Hayashi (2011).

1.6 Outline of the thesis

The research questions are addressed in Chapters 2-5. Figure 1.1 displays an overview of the thesis chapters. Chapter 2 studies probabilistic extensions of CBA with climate scenarios and learning and explores the scope of such extensions. Chapter 3 revisits the problem of optimal dike height. An existing model is extended with an uncertain rate of structural water level increase and perfect learning. Chapter 4 develops a cost-effectiveness model with rainfall variability and climate change. It is applied to study the storage volume of a detention storage facility in a Dutch polder system. Chapter 5 develops and applies a consistent dynamic minimax regret procedure to a conceptual flood risk management model. The thesis ends with a general discussion of modelling approaches and results, and summarises the findings in Chapter 6.

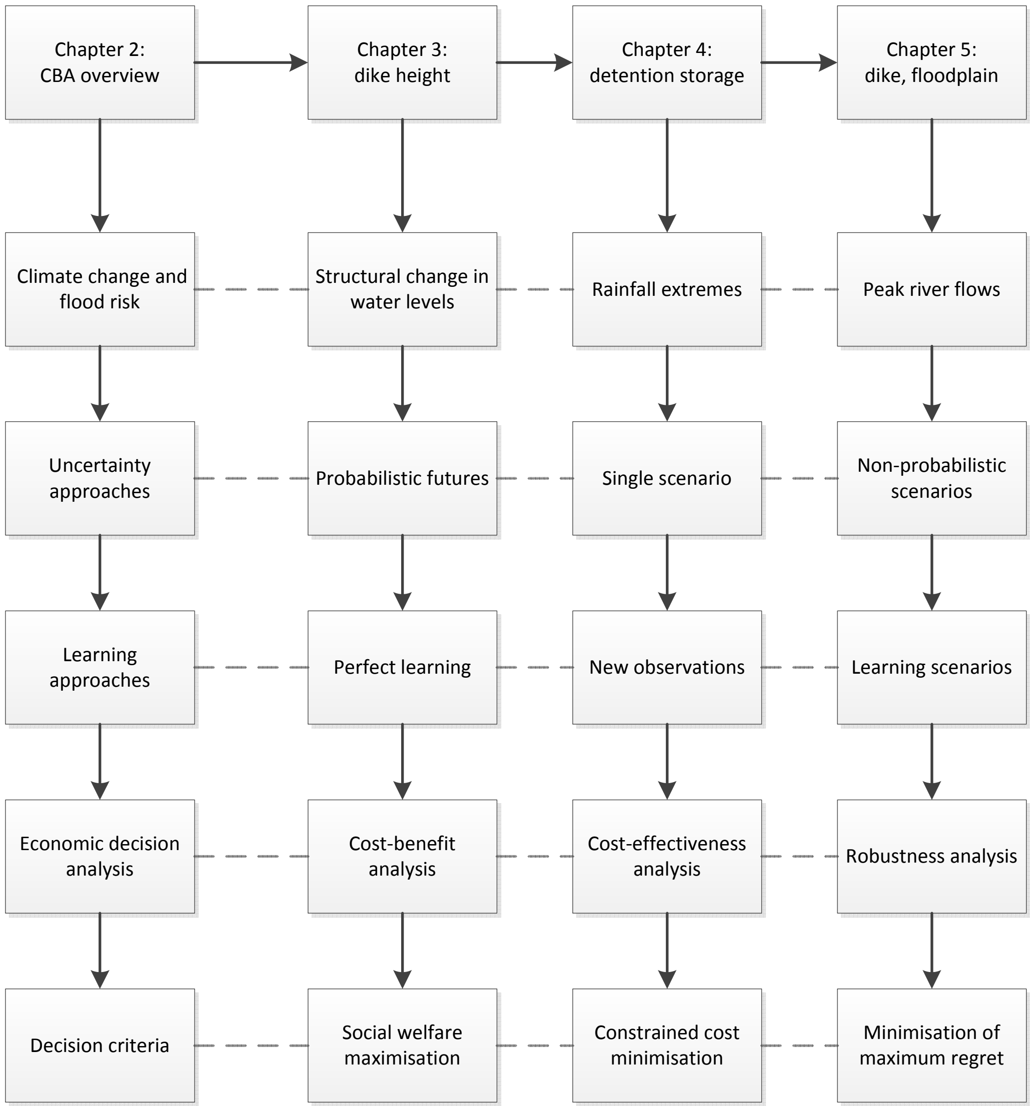

Figure 1.1 Thesis overview of Chapters 2-5

2. Economic analysis of adaptive strategies for flood risk management under climate change*

Climate change requires reconsideration of flood risk management strategies. Cost-benefit analysis (CBA), an economic decision-support tool, has been widely applied to assess these strategies. This paper aims to describe and discuss probabilistic extensions of CBA to identify welfare maximising flood risk management strategies under climate change. First, uncertainty about the changes in return periods of hydro-meteorological extremes is introduced by probability-weighted climate scenarios. Second, the analysis is extended by learning about climate change impacts. Learning occurs upon the probabilistic arrival of information. We distinguish between learning from scientific progress, from statistical evidence, and from flood disasters. These probabilistic extensions can be used to analyse and compare the economic efficiency and flexibility of flood risk management strategies under climate change. We offer a critical discussion of the scope of such extensions and options for increasing flexibility. We find that uncertainty reduction from scientific progress may reduce initial investments, while other types of learning may increase initial investments. This requires analysing effects of different types of learning. We also find that probabilistic information about climate change impacts and learning is imprecise. We conclude that risk-based CBA with learning improves the flexibility of flood risk management strategies under climate change. However, CBA provides subjective estimates of expected outcomes, and reflects different decision-maker preferences than those captured in robustness analyses. We therefore advocate robustness analysis in addition to, or combined with, cost-benefit analysis to support investment decisions for flood risk reduction.

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2.1 Introduction

Cost-benefit analysis (CBA) has been widely applied to flood risk management strategies, and its application has become more complex due to climate change (van Dantzig 1956; Zhu and Lund 2009; Kind 2014; Lickley et al. 2014). This paper discusses probabilistic extensions of CBA to identify welfare maximising strategies under climate change. Flood risk, here defined as the expected monetary loss from floods, is increasing in many regions of the world due to population growth, economic growth and urbanisation, and due to the impacts of climate change on weather patterns, peak river discharges, and sea levels (Milly et al. 2002; Groisman et al. 2005; Jongman et al. 2012). Flood risk is composed of the product of flood hazard, flood exposure, and vulnerability (Kron 2005; IPCC 2014). To mitigate flood risk locally, flood risk management strategies can be implemented that either mitigate flood hazard, exposure or vulnerability. Flood hazard mitigation is achieved by implementing flood protection measures over time which lower flood frequencies in vulnerable areas. Examples are restoration of sand dunes and beach nourishment in coastal areas, raising or relocating dikes in river basins, and extension of urban drainage capacities in urbanised areas. The harmful consequences of flooding are reduced by flood exposure mitigation through spatial planning, and by flood vulnerability mitigation, for example by implementing building codes and preparation of emergency plans (Hooijer et al. 2004; Wu et al. 2012; Stive et al. 2013; Hanley et al. 2014).

Flood protection measures, especially engineering-based measures, will continue to place a significant burden on national budgets and this trend is reinforced by climate change (Narain et al. 2011). Due to climate change, distributions of weather extremes, peak river discharges and water levels can no longer be assumed to be statistically stationary (Milly et al. 2008). Moreover, flood protection measures typically have long technical lifetimes and their protection levels are highly sensitive to climate change (Gersonius et al. 2013). It is therefore important to identify economically efficient flood risk management strategies, i.e.: welfare maximising investments in flood protection measures and other flood risk reducing measures over time, in response to current changes in climate and in anticipation of future climate change.

Economic analysis of flood risk management strategies aims to efficiently reduce the frequency and the consequences of various flooding events. These include low-probability high-consequence flooding events, typically coastal and fluvial floods, and high probability-low consequence flooding events, for example flash-floods in urbanised areas (Vrijling 2001; Wu et al. 2012). The latter may cause damages if storage and drainage capacities are insufficient to detain, retain or convey stormwater from heavy rainfall. From the perspective of a risk-neutral social planner, Net Present Value (NPV) estimates of the total expected damage costs from floods and the costs of protection determine the relative importance of investing in flood risk reduction.

The objective of CBA is to maximise the stream of discounted net benefits, or to evaluate whether or not an investment project improves social welfare (Boardman et al. 2011). CBA compares avoided damages of different flood risk management strategies, the monetised benefits of flood risk reduction, to their costs (Jonkman et al. 2008; Zhu and Lund 2009; Dierauer et al. 2012). It has, however, remained challenging to include climate change uncertainties in CBA of flood risk management strategies. There is, amongst others, hydrologic uncertainty about the effects of climate change on weather extremes, peak river discharges and sea levels, and about the possible emergence of new information about these changes over time. Furthermore, the outcomes of an economic analysis of flood risk management strategies are sensitive to a range of other uncertainties, including those originating from hydraulic, structural and economic uncertainties (Bao et al. 1987).

This paper restricts attention to the impacts of climate change on hydrologic uncertainty. Hydrologic uncertainty manifests, for example, through model uncertainty about the type of a peak flow distribution, and statistical uncertainty about its parameters over time. Moreover, hydrologic uncertainty is partly epistemic, which, in contrast to natural or inherent uncertainty, can be reduced or resolved by acquiring more knowledge (Merz and Thieken 2005).

The need to anticipate the possible emergence of new hydrologic information and to identify adaptive flood risk management strategies under climate change uncertainty is increasingly recognised; both in risk-based economic optimisation approaches, as well as in recently developed robustness approaches (Kwadijk et al. 2010; Woodward et al. 2011; Gersonius et al. 2013; Haasnoot et al. 2013). However, until now scientific consensus is lacking both on how to address climate change uncertainty and on how to incorporate learning in economic analysis of flood risk management and other climate change adaptation strategies (Watkiss et al. 2014). Moreover, probabilistic models to analyse efficient flood risk management strategies with new information are relatively scarce, and usually consider only one type of new information (Woodward et al. 2011).

The central research questions of this paper are as follows:

(i) How can probabilistic extensions of CBA using climate and learning scenarios be applied to improve decision-making on flood risk management strategies?

(ii) What are advantages and limitations of such probabilistic extensions?

These questions are relevant to inform flood adaptation decisions at different scales, from local decisions on flood risk management strategies to global decisions on, for example, the allocation of adaptation funds. This paper therefore informs adaptation strategies at different scales through economic analysis to mitigate flood risk under climate change.

In this paper, two types of probabilistic extensions of CBA are considered. First, uncertainty about the changes in return periods of hydro-meteorological extremes is introduced by probability-weighted climate scenarios. Second, CBA is extended by probabilistic arrival of new information, hereafter called learning, about climate change impacts to introduce two phenomena: (i) the reduction of epistemic uncertainty and (ii) the arrival of new data. We elaborate on different types of learning, from scientific progress, from statistical evidence, or from flood disasters, and discuss their reinforcing or opposite effects on optimal investment. The methods to implement these types of learning originate from statistics and the real options literature and have been widely used in many domains (Copeland and Antikarov 2003; Press 2003). We describe their generic implementation in a non-technical manner, and discuss the availability of the required probabilistic information and implications for the economic efficiency and flexibility of flood risk management strategies under climate change. Finally, we contrast cost-benefit approaches with robustness approaches, which follow a different line of analysis. We discuss the general findings and provide suggestions for the use of methods to support decisions on flood risk management strategies.

2.2 Climate change uncertainty and the climate change learning process

2.2.1 Current approaches for including climate change uncertainty in flood risk management decisions

Frequency analysis of extremes is required to estimate future flood risk, but is plagued by hydrologic uncertainty. In the literature, a variety of methods have been developed to assess return periods of extreme hydro-meteorological events under climate change. Examples are perturbation methods used to specify design rules or design storms with climate model simulations, and regression methods to remove effects of serial dependence and non-stationarity in hydro-meteorological observations (Khaliq et al. 2006; Willems 2013). Until now, however, it has remained unclear how the performance of flood defences and urban drainage systems should be assessed under climate change (Kundzewicz et al. 2010; Berggren et al. 2014). One approach is to exclude non-stationarity in the flood hydrology from the economic analysis of flood risk management strategies, which is still occasionally observed in theoretical work (Zhu and Lund 2009). However, in the adaptation literature it has been emphasised that anticipatory adaptation is required to support efficient decision-making on investments with fixed costs and long technical lifetimes (Smith 1997). Here, we provide a brief description of two important methods for water system design with the anticipation of climate change impacts; (i) a fixed-factor increase of design intensities, for example derived from the so-called delta-change method, for urban drainage design (Hay et al. 2000; Arnbjerg-Nielsen 2012), and (ii) the use of a prior distribution of, for example, sea level rise to estimate future coastal flood risk (Purvis et al. 2008).

Rainfall inputs used to evaluate the performance of urban drainage systems are design storms, either from frequency analysis of annual maxima, or partial duration series, or are obtained from continuous simulation (Cameron et al. 1999; Boughton and Droop 2003; Cameron 2006; Mailhot et al. 2013). With the design storm method a rainfall depth of an assigned duration with a given return period is applied to a site (De Michele et al. 1998). This method assumes that the average return period of the design storm coincides with the average return period of a flow rate, if an appropriate duration is selected, together with one or more representative synthetic storm hyetographs (Levy and McCuen 1999; Mays 2011).

To account for climate change, the design storm can be increased with a fixed factor (Waters et al. 2003). The appropriate uplift factor for the intensity of the design storm can be chosen pragmatically, or derived from the delta-change method, where rainfall events in a historical rainfall series are increased with delta-change factors. These factors, which are different for different rainfall intensities, are derived from the output of a regional climate model (Nilsen et al. 2011; Arnbjerg-Nielsen 2012). Uplift factors are, however, usually obtained per climate change scenario. Such studies usually do not provide estimates of total expected discounted costs of flood risk management strategies under multiple climate futures provided that a certain uplift factor is chosen for the design of flood protection measures.

Global climate change projections have remained highly uncertain. As a consequence, most projections are presented without probability distributions (Andronova and Schlesinger 2001; IPCC 2014). Prior distributions about regional climate change impacts are required to estimate the expected damage reduction over time associated with flood risk management strategies. It is, however, questionable whether or not such expected damage estimates can be obtained in the first place. Weitzman (2009), for example, argued that it may be inappropriate to perform CBA under uncertain fat-tailed extreme value distributions containing low probability but catastrophic events.

Nonetheless, some attempts have been made to estimate future flood risk with probabilistic methods. Purvis et al. (2008) defined a triangular distribution for sea level rise, where probabilities are set with IPCC scenarios based on the best estimate, and the lower and upper bound of the scenarios. This distribution, however, does not account for low-probability climate change scenarios, which, in expected terms, may be important to determine optimal flood risk management strategies. Van der Pol et al. (2014) showed this for a normal and log-normal distribution for dike investments. Flood risk uncertainty is even larger if socio-economic uncertainties are considered as well. Hall et al. (2005), for example, studied flood risk under climate change and socio-economic scenarios. Furthermore, Bouwer et al. (2010) constructed loss-probability curves for a range of climate and socio-economic scenarios under a range of flood scenarios.

2.2.2 Expert elicitation

Water defence systems are typically designed to withstand plausible high-end scenarios of flood-related frequency changes, which would require different flood protection measures and larger investments than under less severe climate change impacts (Katsman et al. 2011). Estimates of the likelihood of more extreme climate scenarios are therefore crucial to study the economic efficiency of flood risk management strategies with risk-based economic optimisation approaches using probability-weighted climate scenarios. In the previous section, we discussed that only few studies examining the economic efficiency of flood risk management strategies have applied prior probability distributions about climate change impacts. In addition, the design of many urban flood protection measures has been based on a single climate change scenario. Such pragmatic approaches do not seem satisfactory, as expected damage costs may greatly increase if the incidence of extreme weather events or high water levels is underestimated. This raises the question of whether or not it would be more appropriate to obtain prior distributions about climate change impacts from expert elicitation.

One could, for example, think of the Delphi method as a means to obtain priors from expert elicitation (Dalkey and Helmer 1963). Many climate experts reject participation in Delphi surveys and expectations of participants are too diverse to reach consensus and to arrive at a single prior distribution specifying likelihoods of rapid climate change (Arnell et al. 2005). Existing studies reveal that some high-end scenarios, for example the collapse of the West-Antarctic Ice Sheet, are considered to be unlikely in the near term (Vaughan and Spouge 2002). Satellite observations confirm this finding, although there is now strong evidence for partial ice-sheet thinning (Vaughan 2008). Despite the controversy of expert elicitation it might provide valuable insights on the physical processes that are more, or less likely to happen, which can be used to derive likelihood statements about climate change effects on, for example, the weakening of the Atlantic Meridional Overturning Circulation (Zickfeld et al. 2007). Expert opinion can also be used for, for example, defining climate model parameter ranges for perturbation purposes, or to distinguish between climate models based on quality (Stainforth et al. 2005; Knutti et al. 2010).

From the above we draw the following conclusions. First, decision-making on flood risk management strategies under climate change cannot be classified as decision-making under risk. This is because the probabilistic changes in the frequency of occurrence of the relevant hydro-meteorological extremes under climate change are not well-defined. Second, it can also not be classified as decision-making under ignorance, as there appears to be at least some consensus that some scenarios are less likely than others. This case is therefore best described as decision-making under uncertainty characterised by imprecise probabilities (Hogarth and Kuhnreuther 1995).

2.2.3 Learning about the impacts of climate change

In addition to uncertainty about climate change impacts, there is uncertainty about the detection of future climate change signals, and uncertainty about how decision-makers' investment decisions may respond to possible climate signals. In this section, we discuss different types of learning and their effects on climate change adaptation decisions. We distinguish between learning from scientific progress, from statistical evidence, and from flood disasters.

Information from scientific progress

Several authors have argued that climate change uncertainty cannot be expected to reduce or to be resolved any time soon. Leach (2007), for example, concluded that it may take hundreds if not thousands of years before reliable parameter estimates of climate models will become available. According to Roe and Baker (2007) uncertainty about climate change projections has not significantly decreased over the past decades, and showed, furthermore, that the probability of large temperature increases is relatively insensitive to reductions in climate change process uncertainties.

Information from scientific progress, in contrast, might reduce uncertainty about climate change impacts. Scientific progress can be modelled as probabilistic events of information. Uncertainty reduction introduces a trade-off between costs associated with immediate action, and increased exposure resulting from a learn than act strategy. The conditions required for immediate action to reduce emissions of a harmful pollutant such as CO_2 have been analysed by Gollier et al. (2000), in which the degree of risk-aversion, irreversibility and the information rate determines optimal action. Ingham et al. (2007) presented a model with both mitigation and adaptation, and showed that the possibility to adapt together with the prospect to learn tends to reduce climate change action today. In earlier work, Kolstad (1994) studied mitigation and adaptation decisions under perfect learning, and investigated trade-offs between the effects of irreversibilities associated with the accumulation of greenhouse gases, and the accumulation of abatement capital.

If uncertainty is epistemic, and expected to gradually reduce over time, flexible adaptation measures may be more economically efficient than inflexible measures. Flexible climate change adaptation with learning from scientific progress can be studied with risk-based optimisation approaches, such as real options analysis, as well as robustness approaches (Copeland and Antikarov 2003; Hallegatte et al. 2012). De Bruin and Ansink (2011), for example, distinguished between structural measures with relatively high fixed costs, such as dikes, and non-structural measures with relatively low fixed costs, such as beach nourishment. For analysis of an adaptation measure in isolation, the expected value of information is compared with the additional costs from immediate investment in the measure. Hence, future learning through scientific progress may have impacts on investment timing, size and portfolio of flood risk management measures, and may also have an impact on greenhouse gas mitigation strategies. Assumptions about the probabilities of learning in the near future, and the degree of uncertainty reduction are, however, determinants of initial investment strategies and the optimal responses to new information over time (van der Pol et al. 2014).

New hydro-meteorological observations: evidence-based learning

New hydro-meteorological observations are an important source of new information on changing flood risk. New hydro-meteorological observations may provide statistical evidence regarding climate change impacts on flood regimes in the future. It has, however, remained difficult to statistically detect changes in weather patterns, river flows and acceleration of mean sea level rise. Short-term trend detection is, amongst others, difficult due to multi-annual serial correlation, variability, and sample size. Fowler and Wilby (2010) reported that the detection of changes in seasonal precipitation may take several decades, and that this could motivate a precautionary approach to climate change adaptation. Zhang et al. (2004), furthermore, compared detection methods by simulations of 50 and 100 years of annual maxima. The simulation results show, in addition to differences in the ability to detect trends, that none of the methods guarantee trend detection, and that the probability of no-detection is much lower for larger sample sizes for any of these methods. Hamed (2008) showed that significant river flow trends found in earlier annual flow maxima may be false if scaling is considered. Wahl et al. (2013) reported that the rate of sea level rise over the past two to three decades has been high as compared to the long-run average, but that similar periods of high sea level rise have been observed at other times.

New hydro-meteorological observations can also be applied to evaluate water system performance over time. Because new weather and water level observations are not likely to reveal much information on structural climate change impacts in the near future, one might be tempted to think that it is irrelevant to consider the likelihood and effects of future observations on current decisions on flood protection measures. This is, however, a misconception. Weather variability and climate change uncertainty result in variability of best estimates of flood probability, which, in turn, results in uncertainty about the timing of new investments in flood protection measures, for example, through the need to meet a flood protection standard. However, evidence-based flood probability evaluation over time, and its effects on the economic efficiency of flood risk management strategies, has largely remained unexplored in flood risk management practices. It might, however, be highly relevant for efficient decision-making. First, in contrast to learning from scientific progress it is certain that new data will become available over time. Second, despite white noise, extreme value data may still be applied to analyse changes in flood risk and evaluate water system performance in the future. The underlying statistical beliefs, however, may deviate from actual frequency distributions. Whereas learning from scientific progress is about anticipation of better information by uncertainty reduction, learning from statistical evidence is about anticipation of new information that is not necessarily better. Effects of white noise can be opposite to the effect of uncertainty reduction on optimal investment; underestimation of a system's performance might trigger new investments, which can be anticipated by enlarging initial investments, while learning from scientific progress tends to reduce overall investment till better information becomes available. We will explain the latter in more detail in Section 2.3.3.

Disasters: incident-based learning

Historic flood observations show that large-scale flooding events often lead to large-scale investments in flood protection measures in developed countries that go far beyond repair. Examples that led to such large-scale investments include the 1953 flood in the Netherlands, the New Orleans flood by hurricane Katrina, and the flood by the 2011 tsunami in Japan. There are several explanations why investments in flood protection measures often take place after large-scale incidents, but the phenomenon remains intriguing. Clearly, a failure of a flood defence shows that a specific load has been greater than the resistance of the defence. In a statistical sense, however, any single observation has only a modest impact on extreme value estimates, even if its value is several times larger than ever measured before (Coles and Pericchi 2003).

In some cases, an incident may reveal new failure modes of, for example, a dike, and the flood probability estimate can be updated with this new information. This, however, does not explain large-scale investments for cases where a conventional failure mode, for example overtopping, was the primary cause of flooding. Neumayer et al. (2014) argued that both individuals and governments have incentives to underinvest in flood control. While this would explain large-scale re-investments after a disaster for cases with a maintenance backlog, it provides insufficient explanation for cases without backlog. Another motivation for re-investment is the “never again”-argument, often heard after large-scale disasters (Gerritsen 2005). A possibly related argument is victim pressure, where victims may have a disproportionate share in the decision process on flood control (Harries and Penning-Rowsell 2011).

Perhaps it is not important to understand why re-investment takes place after a disaster, as long as the likelihood of incidents occurring earlier than expected, together with the following investment response, are included in the economic analysis of flood risk management strategies. To illustrate this, consider that a decision maker can either invest in flood protection measure 1, with total expected discounted costs A consisting of both investment costs and total expected discounted damage costs, or in measure 2 with total costs B consisting of investment costs only and no expected damage costs. Furthermore, consider that $A < B$. At first sight, a risk-neutral decision maker would prefer measure 1. As an extension, consider that the public will demand to invest in never again-measure 2 if a disaster happens, and that the decision maker knows this in advance. Consider, furthermore, that the probability that a disaster happens during the technical lifetime of flood protection measure 1 is larger than zero. Now, despite that the decision maker is assumed to be risk-neutral, the risk-attitude of the public leads to a change in the expected economic efficiency of measure 1 through the probability of disaster during the lifetime of the infrastructure. As a result, measure 2 might be preferred.

2.3 Economic models for flood risk management

In this section we turn to economic models for analysing and comparing flood risk management strategies. We describe how a cost-benefit model can be extended with climate scenarios to include uncertainty about climate change impacts. We also provide a brief introduction to the modelling of the different types of learning that were introduced in the previous sections (2.3.1-2.3.3).

2.3.1 Cost-benefit optimisation

Benefits of flood risk management can be estimated in monetary terms by estimating the expected reduction in damages. Flood damage models can be used for this purpose (de Moel and Aerts 2011). An optimal investment strategy can be obtained by balancing discounted expected damages and costs of protection. In early work, van Dantzig (1956) applied this concept to determine optimal dike height. Improved versions of this model are still used today in the Netherlands to analyse optimal dike height strategies and to determine economically efficient flood protection standards (Brekelmans et al. 2012; Kind 2014). It is, furthermore, increasingly recognised that, especially in a context of climate change uncertainty, different types of flood protection measures have to be considered simultaneously (de Bruin and Ansink 2011; Woodward et al. 2011; Meyer et al. 2012).

Many urban drainage system elements have been designed with particular design storms and simple flow calculations instead of cost minimisation models, and only few stormwater models include an economic analysis of alternative stormwater management strategies (Zoppou 2001). Moreover, detailed CBA studies of urban drainage systems are rare (Pathirana et al. 2011). One possible explanation could be that in many countries CBA may not be legally required for such systems. In the Netherlands, for example, uniform flood protection standards have been defined for regional water systems per land use type, rather than setting flood protection standards at welfare maximising levels for every water system (NBW 2005; Hoes and Schuurmans 2006). Cost-effectiveness approaches are, hence, still predominant for urban drainage system design. However, if flood protection standards are set at economically efficient levels the solutions of cost-benefit analysis and cost-effectiveness analysis with an efficient flood protection standard will coincide. Therefore, in what follows, we continue with a cost-benefit model only.

In a CBA, the objective of a risk-neutral decision maker is to maximise the net present value of the total expected net benefits associated with a portfolio of flood protection measures over time (Eq. (2.1)):

$$W = \max_{z_{i,t}} E\left\{\int_0^T (B_t(x_{1,t}, x_{2,t}, \dots) - C_t(z_{1,t}, z_{2,t}, \dots))e^{-\delta t}dt\right\} \tag{2.1}$$

where $z_{i,t}$ is the decision variable, and $x_{i,t}$ is the stock of the flood protection measure m_i at system node $i = 1,2,\dots$. System nodes, for example, can be segments of a dike ring, open channels of a surface system, or pipe segments of a sewer system. B_t is a benefit function, C_t is a protection cost function, δ is the discount rate, and T represents the end of the considered time horizon. Benefits of flood risk management can be modelled as reduced damages, but expected damages from floods can also be interpreted as costs. By symmetry, minimisation of total expected discounted loss L yields the same optimal investment strategy as under Eq. (2.1):

$$L = \min_{z_{i,t}} E\left\{\int_0^T (D_t\left(x_{1,t}, x_{2,t}, \dots\right) + C_t(z_{1,t}, z_{2,t}, \dots))e^{-\delta t}dt\right\} \tag{2.2}$$

Consider a two-period model with a binary decision to invest (V_0) or not invest (N_0) at t_0, followed by the binary decision to invest (V_1) or not invest (N_1) at $t = T_1$. This is displayed in Figure 2.1.

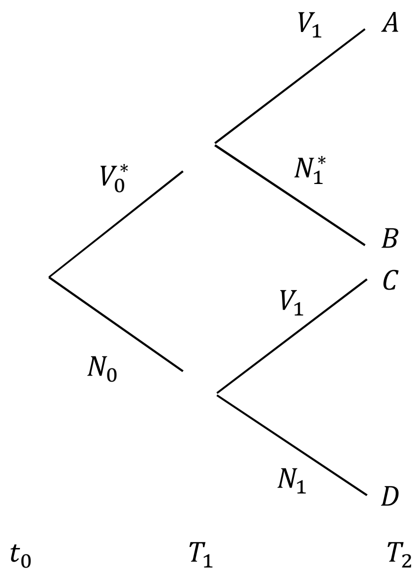

Figure 2.1 Example of a two-period decision tree with decisions to invest $(V_0; V_1)$ or not invest $(N_0; N_1)$ at $t = t_0$ and at $t = T_1$, respectively

The optimal strategy follows from outcome minimisation, i.e.: $\min\{A, B, C, D\}$, and results in investment strategy (V_0^*, N_1^*) in this example. This example represents a deterministic CBA, as the outcomes of different strategies are assumed to be known with certainty. However, a deterministic CBA is not suitable under climate change uncertainty, as multiple climate futures are possible (Watkiss et al. 2014). Therefore, we now turn to a probabilistic extension of CBA using probability-weighted climate scenarios.

2.3.2 Probabilistic modelling of climate change impact scenarios

Climate change impact scenarios can be introduced in the cost-benefit model through defining possible states of nature in order to account for uncertainty about climate change impacts. To illustrate this, consider that under a high climate change impact scenario the annual increase of the flood probability is ε_h and that probability P_h is assigned to this scenario, and that under a low climate change impact scenario flood probability increases with ε_l with probability

$P_l = 1 - P_h$. The corresponding decision tree for this problem is displayed in Figure 2.2.

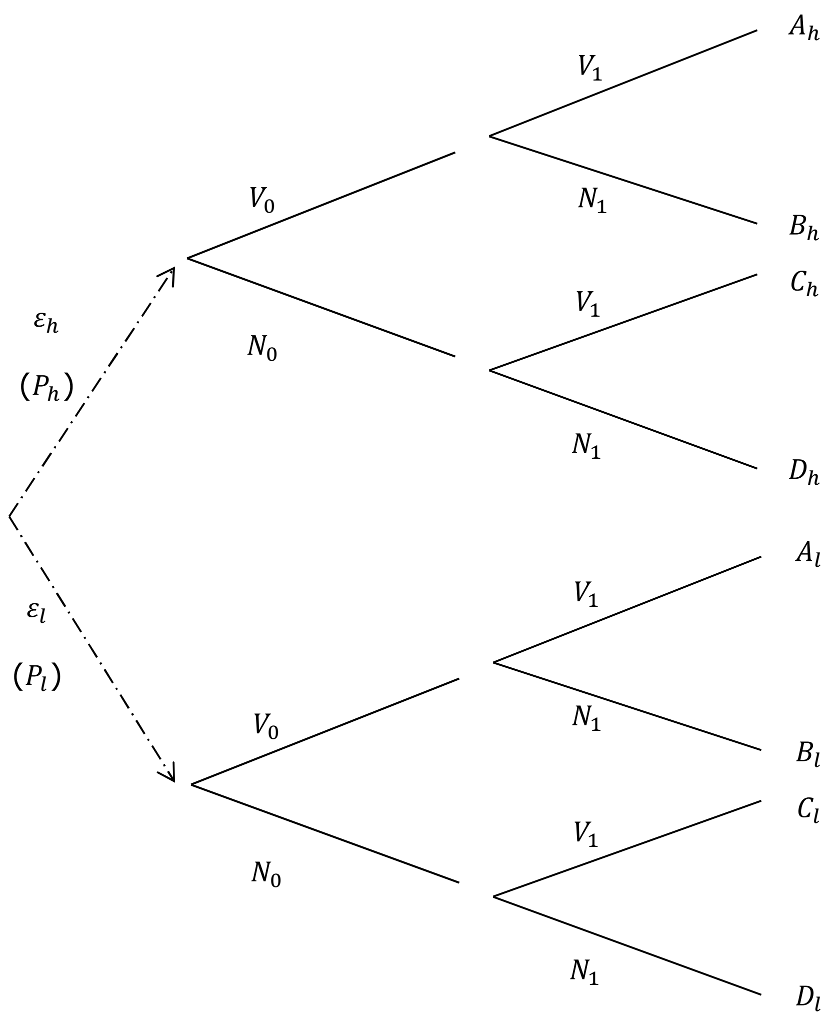

Figure 2.2 Decision tree for the two-period investment model extended with two possible climate change scenarios (ε_l and ε_h)

The expected outcome of a strategy is equal to the weighted average of the total discounted costs under the two scenarios. For strategy $\{V_0; V_1\}$ the total discounted expected costs are:

$$A = P_l A_l + P_h A_h, \tag{2.3}$$

and idem for outcomes B, C and D. Again, the optimal strategy follows from: $\min\{A, B, C, D\}$. In this example, only two climate scenarios are considered. The general case would require a continuous prior distribution of climate change impacts.

The importance of probability distributions for climate change adaptation has, for example, been explained in the UKCP09 projections, in which probabilistic climate projections of over-land changes have been derived for the UK (Murphy et al. 2009). However, probabilistic coastal projections are generally not available (Lowe et al. 2009; IPCC 2014). Without probabilistic impact projections, the above method can only employ probabilistic assumptions to derive expected flood damages under climate change for different flood risk management strategies. As a consequence, cost-benefit solutions may appear to be precise, while the discretised probabilities or densities to arrive at the solutions are not (Hall 2007). Risk-based cost-benefit optimisation using probability-weighted scenarios or distributions, therefore, cannot provide final answers to optimal flood risk management decisions. However, it supports the identification of economically efficient management strategies using information that is available to the best of our knowledge. Yet, this information is debatable. Sensitivity analysis can provide insights in the sensitivity of solutions to distributional assumptions.

2.3.3 Models of learning

Modelling of scientific progress

Scientific progress may eventually lead to a better understanding of the severity of climate change. This can be modelled as a probabilistic reduction of climate change uncertainty over time. Figure 2.3 displays a simplified example of the gradual reduction of sea level rise uncertainty over time. At t_0, sea level rise can be high or low, at T_1 the rate of sea level rise is approximately known, and at T_2 sea level rise uncertainty is fully resolved, and we know the outcome with certainty, for example B_1.

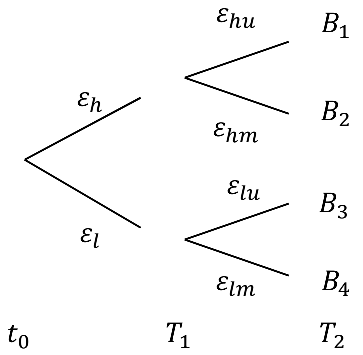

Figure 2.3 Graphical representation of gradual uncertainty reduction. Outcomes for strategy $\{V_0; N_1\}$ are displayed

The initial investment for this setting follows from:

$$\min_{\{V_0;V_1\};\{V_0;N_1\},\{N_0;V_1\},\{N_0;N_1\}} \left\{\sum_j P_j(\varepsilon_j)A_j, \sum_j P_j(\varepsilon_j)B_j, \sum_j P_j(\varepsilon_j)C_j, \sum_j P_j(\varepsilon_j)D_j,\right\}, \qquad (2.4)$$

and the investment at decision moment t_1 depends on the available information (ε_l or ε_h) at this moment. Larger problems with uncertainty reduction can be formulated recursively by dynamic programming, for example, applied in van der Pol et al. (2014). Clearly, future information has expected value. As a consequence, investment decisions may be changed by the probability of future information arrival, which has a general tendency to reduce overall investment before the arrival of new information, for example by postponing investment (deferral), changing the scale of investment (e.g. contraction), adaptive design or alternative portfolio choices (switching). These are typical examples of real options strategies from the real options literature. However, real options methods have not often been applied to economic flood risk management studies (Schwartz and Trigeorgis 2004; Woodward et al. 2011). This may be explained by the probabilistic assumptions needed regarding information arrival. In Section 2.3.1 we discussed that there is no consensus about the timing of uncertainty reduction, if reduced at all.

Belief updating with new observations

Evidence-based learning can be approached from a frequentist or a Bayesian perspective. Frequentist approaches interpret observations, for example of extreme water levels, as random realisations from a “true”, but unknown distribution. Re-sampling methods, such as bootstrapping, can be used to evaluate the robustness of the initial estimates. Climate change, however, introduces a trend in the data which can be studied with, amongst others, moving window analysis, or regression methods. In a moving window analysis, a part of the available observations is treated as if it is stationary (De Michele et al. 1998). For every time step, for example every year, an extreme value distribution f is re-estimated with the last N years of observations with standard statistical procedures such as maximum likelihood or the method of L moments. The likelihood of distributional estimates can then be studied by simulation of new observations based on climate scenarios.

Contrary to frequentist approaches, Bayesian inference methods assume that the unknown parameter θ is a random variable and can be expressed by means of prior beliefs $P(\theta)$. This is a probabilistic specification of the decision maker’s beliefs before new evidence has been observed. Prior beliefs can be updated with sample data using Bayes law:

$$P(\theta|y) = \frac{P(y|\theta)P(\theta)}{P(y)} \quad , \tag{2.5}$$

where $P(\theta|y)$ is the posterior belief after observing new event y, and $P(\theta)$ is the prior belief. $P(y|\theta)$ denotes the likelihood function, being the conditional probability distribution of observed data. Prior beliefs about, for example, extreme value distribution parameters, can either be based on subjective guesses (Huard et al. 2010), or can make use of existing information. Bayes law allows combining subjective beliefs with evidence gained from observed data, or simulated data y that can be added to original data, in order to arrive at posterior beliefs (Rajabalinejad and Demirbilek 2013). The posterior probability distribution characterises beliefs about the hypothesis θ (e.g. increase of mean temperature, sea level rise) after seeing the data. An early application of Bayes theorem to identify optimal protection levels for dike design under limited data and flood uncertainty is found in Davis et al. (1972).

As for the case of perfect learning, optimal investment strategies with evidence-based learning can be studied by formulating the general investment problem (Eq. (2.2)) recursively. The transition probabilities can be derived from the belief updating process which follows from dynamic application of Bayes law (Eq. (2.5)), and simulation of future hydro-meteorological observations. Implementation of this setting is, however, complex and goes beyond the scope of this paper. Note that variability in extremes is high relative to the expected changes in frequency of extreme weather events, which suggests that effects from variability in such settings may well be greater than the structural distributional changes due to climate change in the coming decades, and could increase optimal initial investment. So far, to our knowledge only few flood risk management studies explore the impacts of future weather variability and resulting transitions in beliefs on current investment decisions.

Modelling of disasters

In public choice theory the outcome of the net loss-minimising model (Eq. (2.2)) has been called the social planner's solution. It has, however, been argued that social planner solutions may not be implemented, because it differs from policy-makers' preferences which are subject to various factors including the discontent of voters (Hansen and Thisse 1981). Voter preferences for flood protection may differ from a social planner perspective, as voters may be risk-averse, or at least have a different planning horizon than the social planner.
Consider, as an example, voters who minimise total expenses on taxes and total costs from flood damages during their lifetime. Consider, further, that voters can observe whether or not flood disasters have occurred in previous years, and that the discounted costs associated with a single flood disaster are typically larger than the present value of total flood protection costs during the lifetime of a person. Two general implications from the objective function of individual voters can be deducted. First, the willingness-to-pay (WTP) for flood protection of an individual voter is not constant over time due to the probabilistic arrival of new information about the occurrence of disasters over time. As a result of the objective function, the WTP of an individual voter might decrease over time if no disaster occurs, but it might increase after the occurrence of a flood disaster. Second, a decision-maker cannot be sure about the timing of re-investment in flood protection, which now also depends on the stochastic nature of the

occurrence of flood disasters. Early or frequent re-investment in flood protection, furthermore, may be costly due to initial costs of flood protection measures. In this setting, therefore, a risk-neutral decision-maker has to account for the risk-averse preferences of voters.

2.4 Robustness analysis

The probabilistic extensions described in Section 2.3 require subjective probabilistic information on climate change impacts and the arrival of new information. However, climate change uncertainties have been classified as deep (Kandlikar et al. 2005). Several authors have argued that the optimality criterion should be abandoned in the presence of deep uncertainties and that research effort should focus on the identification of robust strategies that perform relatively well across a range of possible futures (Lempert et al. 2006; Hall et al. 2012).

Various kinds of robustness analysis have been developed, which appears to be the result of the normative nature of the robustness concept. Robustness analysis of adaptation strategies can be used to identify robust solutions in a narrow sense by employing alternative decision criteria, for example, minimax or minimax regret criteria (Clarke 2008). Other robustness methods analyse the performance of robust solutions under different degrees of uncertainty, for example info-gap theory (Hine and Hall 2010). Moreover, in recent robustness analysis, such as adaptation pathways, stakeholder participation is used to explore uncertainties, preferences, lock-ins and path-dependencies by qualitative methods (Haasnoot et al. 2013).

Robustness approaches differ fundamentally from risk-based optimisation approaches in at least two respects. First, they reject the assumption of risk-based approaches that probabilistic information can be identified for analysis of management strategies. Second, they reject the assumption that welfare maximising solutions can be identified, and are instead aimed at identifying solutions that are expected to perform relatively well under worst-case or a wide range of scenarios.

2.5 Discussion

The probabilistic extensions of CBA described in this paper can be used to analyse and compare the economic efficiency and flexibility of flood management strategies under climate change. They thereby support economic decision-making on flood risk management strategies. However, the results of a risk-based CBA of flood risk management and other climate adaptation strategies using probability-weighted scenarios have to be interpreted with care. Results can be misleading, as assigned probabilities may misrepresent uncertainty (Hall 2007).

We observe that the underlying scientific debate on whether or not climate change uncertainty should be addressed as subjective risk or deep uncertainty is increasingly polarised. In many papers, authors either motivate a risk-based or a robustness approach (Speijker et al. 2000; Hine and Hall 2010; Woodward et al. 2011; Brekelmans et al. 2012; Haasnoot et al. 2013). Clearly, both risk-based and robustness approaches are defensible. We argue that, due to differences in assumptions regarding decision-maker preferences and implementation of uncertainty, they may provide different but complementary insights.

A standard approach to expected-value based optimisation assumes risk-neutrality. The common use of CBA of flood risk management strategies reflects that expected outcomes provide an important decision criterion for flood risk management. However, expected-value optimisation is not the only relevant decision criterion. Even if probabilities would be properly defined decision-makers might, at least to some degree, be risk-averse. Risk aversion can be included in a risk-based economic analysis of flood risk management strategies if a certain degree of risk-aversion is assumed (Kuijper and Kallen 2012; Wang et al. 2015). However, given the imprecise probabilities associated with the impacts of climate change on flood frequencies and the high consequences of flooding, also other decision-maker preferences may be applicable, such as uncertainty aversion, loss aversion or regret aversion (Woodward and Bishop 1997; Clarke 2008; Weitzman 2009). These preferences do not fit in a standard cost-benefit framework (Hogarth and Kunreuther 1995; Yager 2004; Clarke 2008).

Both CBA and robustness approaches impose extreme assumptions. In a deterministic CBA uncertainty is largely ignored, while usually risk-neutrality with known probabilities is assumed in an expected value-based CBA (Watkiss et al. 2014). Robustness approaches usually put implicit or explicit weights on possible outcomes. For example, some decision criteria which are employed to obtain robust solutions, such as minimisation of maximum losses or maximum regret, focus only on outcomes under worst case-scenarios. Other robust decision criteria employ arbitrary scenario weights, or consider scenario outcomes to be equally likely (Gaspars-Wieloch 2014).

Yet, it may not always be the case that the outcomes from risk-based optimisation and robustness analysis diverge due to similarities between the overall decision objectives. For example, recently robustness methods and approaches have been developed to study adaptive flood risk management and other climate adaptation strategies that can be changed at relatively low costs over time (Kwadijk et al. 2010; Merz et al. 2010; Haasnoot et al. 2013). This refers to the overall objective of decision-robustness, which is important for flood risk management in addition to the robustness of a system to withstand disturbances (Mens et al. 2011). Risk-based optimisation models with events of information arrival also consider decision robustness by quantitative evaluation of the flexibility of management strategies under the emergence of new information.

To understand the quantitative effects of learning presented in this paper further applied economic analyses of flood risk management strategies is required, with extensions to implement the different types of learning. Sensitivity analysis allows the study of optimal long-run flood protection without the explicit modelling of information arrival (Zhu et al. 2007). However, anticipation of possible future information may help to avoid costly lock-in situations by giving weight to information scenarios in which non-incremental adaptation decisions would be required. Non-incremental changes in adaptation strategies tend to be costly, but early implementation could in some cases reduce long-run adaptation costs (Kates et al. 2012).

2.6 Conclusions

Climate change has introduced additional challenges for the economic analysis of flood risk management strategies. At the local level decisions need to be made on investment in flood risk reduction. At the global level strategies need to be defined on how to allocate adaptation funds for flood risk management in various regions of the world. This paper has discussed probabilistic extensions of cost-benefit analysis to identify economically efficient strategies under climate change. Uncertainty about the changes in return periods of hydro-meteorological extremes was introduced by probability-weighted scenarios. We revisited expert elicitation as a means to study climate change uncertainty. Expert elicitation is controversial. Yet, there appears to be some consensus that at least some of the more extreme climate scenarios are less likely than others in the near term.

Learning about climate change impacts has remained a largely unexplored domain in flood risk management. In the long run, uncertainty may be reduced because of scientific progress and longer time series of hydro-meteorological observations. Uncertainty reduction from statistical analysis of hydro-meteorological observations is, however, not very likely in the near term as trend detection tests may remain inconclusive in the coming decades, and convergence will be slow due to the high degree of variability in these observations. We have discussed that investment responses in the past have been strongly driven by actual observations, both to evaluate the performance of water systems, for example with a calibrated rainfall generator, and by the occurrence of disasters. The analysis of the likelihood of and investment responses to possible climate change signals, either as a result of transitions in beliefs about climate change impacts, or induced by incidents, may therefore improve the economic efficiency of decisions on flood risk management strategies. We have argued that risk-based approaches reflect different decision-maker preferences and implementations of climate uncertainty than robustness approaches. We have highlighted that flood risk practitioners and policy-makers are not merely concerned with subjective estimates of expected outcomes. We therefore advocate the use of robustness methods in addition to, or combined with, cost-benefit analysis for the economic analysis of flood risk management strategies to support decisions. For further research, it would be interesting to combine cost-benefit and robustness solutions in a meta-analysis.

Our paper contributes to the development of adaptation strategies through economic analysis of flood risk reduction under climate change. Local investments can be optimised, and global strategies on the allocation of adaptation funds can be enhanced if the costs and benefits of flood risk management strategies of individual countries are understood. Global strategies on the allocation of adaptation funds for flood risk management can then be derived from an economic analysis of costs and benefits of flood risk reduction that considers uncertainty under climate change.

3. Optimal dike investments under uncertainty and learning about increasing water levels*

Water level extremes for seas and rivers are crucial to determine optimal dike heights. Future development in extremes under climate change is, however, uncertain. In this paper we explore impacts of uncertainty and learning about increasing water levels on dike investment. We extend previous work in which a constant rate of structural water level increase is assumed. We introduce a probability distribution for this rate, and study the impact of learning about this rate. We model learning as a single stochastic event where full information becomes available. Numerical solutions are obtained with dynamic programming. We find that the expected value of information can be substantial. Before information arrives, investment size is reduced as compared to the benchmark without learning, but investment frequency may be increased. The impact of learning on the initial investment strategy, however, is small as compared to the impact of uncertainty about increasing water levels by itself.

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3.1 Introduction

Many countries are challenged to recurrently heighten their river and sea dikes for reasons of, for instance, economic growth, climate change impacts on water levels or soil subsidence. Estimated effects of climate change on peak river discharges (cf. Graham et al. 2007; Hurkmans et al. 2010; te Linde et al. 2010) as well as sea level rise predictions (cf. IPCC 2007; Guillerminet and Tol 2008; Katsman et al. 2008; Vellinga et al. 2009; Schaeffer et al. 2012) are, however, highly uncertain.

As expenditures on dikes place a significant burden on public budgets, economically efficient investment in dikes is of major importance to governments of countries with flood prone densely populated areas or low lying areas representing significant economic activity. The objective is to find a balance between investment costs and the reduction of expected damage costs of dike heightening over time. This is a cost-benefit approach which can be used to inform decision-makers on safety standards (e.g. Kind 2014). In a cost-effectiveness analysis, in contrast, social welfare is not maximised. Costs, for example, are minimised under a given safety standard or expected damages are minimised under a budget constraint.

Water level extremes for seas and rivers are crucial to determine optimal dike heights. In this paper we explore the impacts of uncertainty about increasing water levels and the resolution of the uncertainty on optimal dike investment and costs. It is likely that uncertainty about the structural increase in extreme water level observations and the related flood risk under climate change will be reduced over time as time series grow longer, as 'low-data' methods are developed and as model uncertainties in climate and hydrological models are reduced (cf. Wagener et al. 2003; IPCC 2007; Lenderink et al. 2007; Cunha et al. 2011). We refer to the event of obtaining new information as learning. We study the impact of uncertainty and learning on optimal dike investment strategies using a Bayesian approach applying informed priors for the structural water level increase. Structural water level increase is defined as the annual rate of the shift of the cumulative water level distribution (η) (van Dantzig 1956). For instance, if the exceedance probability of extreme water level x in year t is given, then in year $t+1$ the same exceedance probability applies to an extreme water level $x+\eta$.

A number of optimisation models have been developed to study the dike heightening problem (van Dantzig 1956; Speijker et al. 2000; Eijgenraam et al. 2012; van der Pijl and Oosterlee 2012). Van der Pijl and Oosterlee (2012) derive optimal increments from Hamilton-Jacobi-Bellman equations. The model is solved for stochastic economic growth. Evidence, however, is lacking that a stochastic process with drift can be used to represent water levels (cf. Booij 2005; Katsman et al. 2008).

Various other approaches have been used to deal with uncertainty, ranging from sensitivity analysis (Eijgenraam 2006) to minimisation of regret (Brekelmans et al. 2012) or mean-variance minimisation (Kuijper and Kallen 2012), and pragmatic approaches (Hoekstra and de Kok 2008). 'Robust' solutions perform best according to some regret minimising rule. Such solutions, however, rely on defined worst case scenarios and do not minimise expected costs (cf. Brekelmans et al. 2012). In Eijgenraam (2006) an illustration is provided how one would respond to the arrival of perfect information on the structural increase in extreme water levels. Hoekstra and de Kok (2008) propose an approach in which dike height is based on the worst case observation so far plus a safety margin. Figure 3.1 illustrates the recurrent heightening of a dike for a river dike ring in the Netherlands. It shows dike heightening strategies for different rates of structural water level increase (η): 'no climate change and no soil subsidence' ($\eta = 0$), 'low structural increase in extreme water levels' ($\eta_L = 0.5$) and 'high structural increase in extreme water levels' ($\eta_H = 1.0$). Note that even without climate change the dike will be recurrently heightened if positive economic growth in the area behind the dike is assumed.

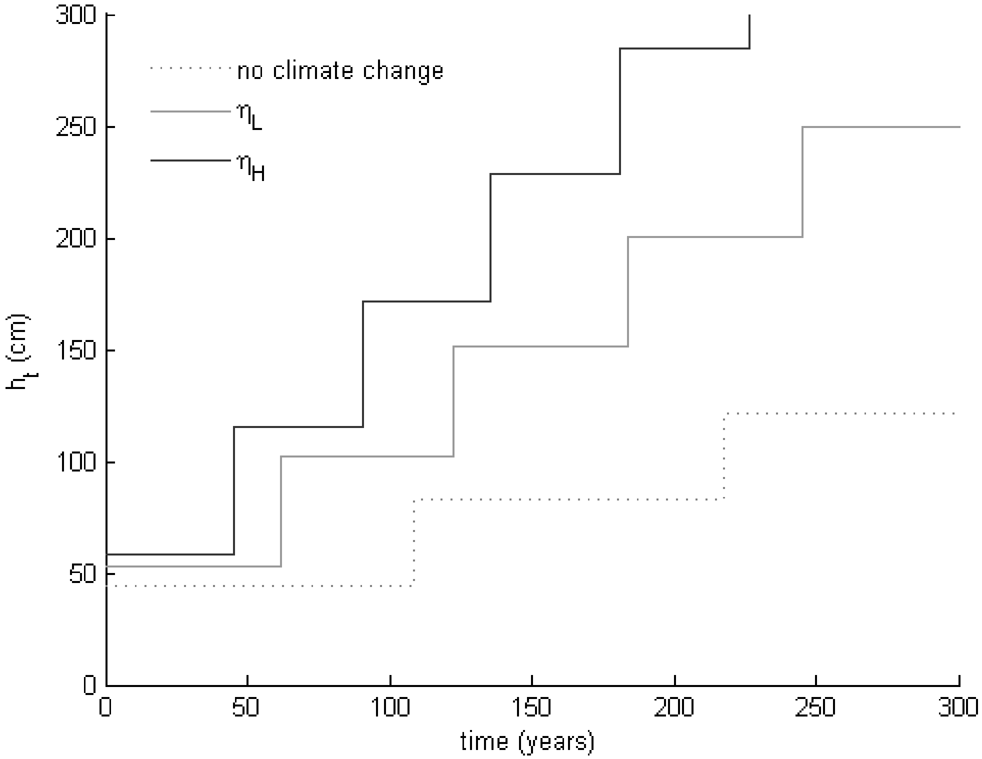

Figure 3.1 Base case solution with relative dike heights over time (h_t) for a homogeneous dike without uncertainty and without learning for different values of η with the model and calibration of den Hertog and Roos (2008) (dike ring 15: Lopiker- en Krimpenerwaard area, the Netherlands).

A probabilistic analysis which separates the effects of uncertainty about increasing water levels from uncertainty resolution is missing in the growing literature on optimal investment in dikes. The expected value of information from learning is positive for two reasons. Firstly, one can respond to information. For instance, if one would learn that ‘sea level rise is high’ dike heightening effort would be increased from that moment onwards. Secondly, total costs, i.e.: the aggregate of discounted expected damage and investment costs, may be reduced by changing initial dike investments before learning takes place.

Examples of methods to analyse ‘real’ investment decisions under uncertainty, irreversibility and learning are tree analysis, dynamic programming and methods related to optimal stopping problems. For an overview of real options literature see Schwartz and Trigeorgis (2004). The ability to change an investment project is in this literature referred to as ‘managerial flexibility’. In the dike heightening problem both the timing of consecutive dike heightening as well as investment size can be adapted over time. One could think of a discretised time horizon where there is an option to re-invest in the dike at every time step. Together, the decisions constitute the investment strategy.

We study the dike heightening problem with a homogeneous dike model. The problem of investment in a homogeneous dike was first described by van Dantzig (1956) after a large flooding event in the Netherlands in 1953. The problem has later been readdressed by Eijgenraam et al. (2012) by including economic growth and by Brekelmans et al. (2012) with a multi-segment dike and robust optimisation. The deterministic setting of the problem has been solved analytically, with dynamic programming and as an impulse control problem (cf. den Hertog and Roos 2008; Chahim et al. 2012; Eijgenraam et al. 2012). Results have been made available to policy makers (Duits 2010).

We use dynamic programming to obtain numerical results for the case with uncertainty and learning. Dynamic programming is similar to backwardly solving a discrete ‘tree’. The tool of tree analysis has been used by Cox et al. (1979) as an alternative model for financial option pricing in discrete time. The tool of tree analysis has also been adopted in real investment analysis (Conrad 1980). It is now widely applied (e.g. Copeland and Antikarov 2003).

3.2 The optimisation problem

To set the stage, we introduce the main elements of the deterministic exponential homogeneous dike model developed by van Dantzig (1956), Eijgenraam (2005; 2006), den Hertog and Roos (2008) and Eijgenraam et al. (2012). We extend this base model with a probability distribution for the rate of structural water level increase and we introduce perfect learning where full information on the structural water level increase becomes available. We distinguish between perfect learning at a given moment in time and perfect learning modelled as a stochastic event.

3.2.1 The deterministic base model

Cost-benefit analysis in the context of flood prevention goes to the 1936 US Flood Control Act and earlier. To our knowledge, van Dantzig (1956) was the first to provide a cost minimisation model for optimal investment in a 'homogeneous' dike. A homogeneous dike can be defined as a 'single segment' dike which can be represented by a single set of parameters. Clearly, water defence systems such as dikes are rarely homogeneous. An engineering level analysis encompasses assessment of complex failure probabilities (e.g. Kingston et al. 2011). Consider a risk-neutral decision maker who minimises total costs (Eq. (3.1)):

$$\min_{\boldsymbol{t},\boldsymbol{u}} C = \sum_{j=0}^{\infty} I_j e^{-\delta t_j} + \int_0^{\infty} D_t e^{-\delta t}\, dt \tag{3.1}$$

where C is the Net Present Value of the total expected costs composed of the sum of the construction costs of a sequence of dike investments (I_j) at moments t_j ($\boldsymbol{t} = \left(t_j\right)_{j\in\{0,1,2,..\}}$) and the expected damage costs (D_t) over time which are discounted at rate δ. In the sequel we define $t_0 = 0$. At t_0 the dike may or may not be heightened. The solution to the optimisation problem consists of two control variables: optimal dike heightening moments $\boldsymbol{t} = (t_0, t_1, ..)$ and amounts $\boldsymbol{u} = (u_0, u_1, ..)$ at those moments in time. When the dike is heightened it is assumed that it is raised without delay.

The expected damage at time t is equal to the sum of probability weighted flood losses at time t. We adopt the exponential expected damage cost function (D_t) for flooding events presented in den Hertog and Roos (2008) and Eijgenraam et al. (2012) (Eq. (3.2)):

$$D_t = P_{e,t} V_t = P_{e,0} e^{\,\alpha(\,\eta t - h_t)} V_0 e^{\gamma t + \zeta h_t} \tag{3.2}$$

The value of loss V_t depends on the economic value behind the dike at time t. The exceedance probability $P_{e,t}$ in Eq. (3.2) has been discussed by van Dantzig (1956). The initial flood probability $P_{e,0}$ can be estimated from water level observations, for instance annual maximum water levels or peak-over-threshold observations. High water levels will be observed more frequently over time due to soil subsidence and sea level rise or larger peak flows. The relationship between climate change impacts and increasing water levels at the local level is complex.

The structural increase in frequency of occurrence of extreme water levels is represented by a constant log-linear shift of the cumulative extreme value distribution over time. We refer to η as (the rate of) structural water level increase which, for example, can be expressed in cm/year. If only a single failure mode is considered, namely that the dike will fail when the water level reaches the 'critical dike height' and not otherwise, then there is no difference between exceedance and flood probability. h_t is the dike height at time t relative to $h_0 = 0$ and α is a shape parameter. When relevant we will distinguish between the dike height before heightening (h_j) and dike height after heightening ($h_{j+1} = h_j + u_j$). The annual growth of the economic value behind the dike is represented by parameter γ. Parameter ζ represents the additional losses incurred per cm dike height increase. The homogeneous dike model has been applied in the context of a sea dike and in the context of river dikes (cf. van Dantzig 1956; Eijgenraam et al. 2012).

We also adopt the exponential investment cost function of den Hertog and Roos (2008) and Eijgenraam et al. (2012) (Eq. (3.3)):

$$I_j = (c_f + bu_j)e^{\lambda h_{j+1}} \tag{3.3}$$

with $c_f > 0$ if $u_j > 0$. c_f is a fixed cost incurred every time the dike is heightened and b represents constant marginal heightening costs. λ is a constant for the marginal cost increase in dike height. Due to fixed costs it will never be optimal to continuously heighten a dike (van Dantzig 1956).

With exponential damage costs (Eq. (3.2)) and exponential investment costs (Eq. (3.3)) a periodic solution to the first order conditions of the problem (Eq. (3.1)) is obtained (den Hertog and Roos 2008). Periodicity implies that dike increments (Eq. (3.4a)) and periods of time between consecutive dike heightening moments are constant (Eq. (3.4b)), i.e.:

$$u_j = \bar{u} \ \ \forall j \geq 1 \tag{3.4a}$$

$$t_{j+1} - t_j = \tau \ \ \forall j \geq 1 \tag{3.4b}$$

Although numerical results suggest that periodic solutions are global minima, it remains as yet unproven (cf. Chahim et al. 2012; Eijgenraam et al. 2012).

When investment and damage costs are not balanced over time a dike will become 'unhealthy' at some moment in time. A dike is defined to be 'unhealthy' when the damage reduction at time t associated with dike increment $\bar{u}$ is larger than the costs of the investment accruing to that year (Eijgenraam 2006):

$$D_{t_j}(h_j) - D_{t_j}(h_j + \bar{u}) > \delta I_j(\bar{u}, h_j + \bar{u}) \tag{3.5}$$

Den Hertog and Roos (2008) provide an equivalent mathematical result. Thus, a 'healthy' dike is heightened when condition (5) holds with equality. The mathematics has been extensively dealt with by den Hertog and Roos (2008) and Eijgenraam et al. (2012). We will not repeat it here, but we will apply the analytical results to compute expected costs after perfect learning.

3.2.2 The benchmark model with uncertainty

In the base model the rate of the water level increase (η) is assumed to be known. Now we explore a benchmark model where we relax this assumption. We introduce a probability distribution for η which represents the beliefs about the structural increase in extreme water level observations. Let θ be the set of possible states of η, and define P_i the probability that $\eta_i \in \theta$ is the true state. If no new information arrives the state of η remains unobserved and beliefs are unaltered. Hence, the objective function of the benchmark model with uncertainty is:

$$C_{nl}^* = \min_{\boldsymbol{t},\boldsymbol{u}} \sum\nolimits_i P_i C(\boldsymbol{t}, \boldsymbol{u} | \eta = \eta_i) \tag{3.6}$$

where C_{nl}^* denotes the total discounted expected costs for the no learning case with a constant but unobserved state of η. The first-order conditions of (6) are:

$$\sum\nolimits_i P_i \frac{\partial}{\partial t_j} C(\boldsymbol{t}, \boldsymbol{u} | \eta = \eta_i) = 0 \tag{3.7a}$$

$$\sum\nolimits_i P_i \frac{\partial}{\partial u_j} C(\boldsymbol{t}, \boldsymbol{u} | \eta = \eta_i) = 0 \tag{3.7b}$$

Substituting (2) and (3) in (7a), and rearranging gives (cf. den Hertog and Roos 2008):

$$\sum_i P_i D_0 e^{(\alpha\eta_i+\gamma)t_j-(\lambda+\alpha-\zeta)h_j}\left(e^{(\alpha-\zeta)u_j}-1\right)=\delta(c_f+bu_j) \tag{3.8}$$

No time-independent $\bar{\eta}=\omega\sum_i P_i\eta_i$ can be identified to eliminate P_i from Eq. (3.8). Hence, no periodic strategy exists which is the certainty equivalent of the optimal strategy under the benchmark model. This result is confirmed by our numerical analysis (see Figure 3.3). This figure also includes results from the benchmark model extended with learning. We now turn to the issue of learning.

3.3 Learning

We introduce a single moment in time at which perfect information is received. This moment is referred to as the 'moment of learning' (t_l). We first analyse optimal investment when the moment of the information arrival is given. Subsequently, a setting is introduced where the moment of learning is stochastic.

3.3.1 Perfect learning with a given moment of learning

After uncertainty resolution at $t=t_l$ the dike heightening problem is reduced to the base model. The optimal dike heightening strategy is then conditional on the observed state of η and the height of the dike at t_l. We call the costs incurred after learning terminal costs (R):

$$R\left(h_{t_l},t_l,\eta_i\right)=\min_{\boldsymbol{t_2},\boldsymbol{u_2}}\sum_{j=j_2}^{Y} I_j(h_j,u_j)e^{-\delta t_j}+\int_{t_l}^{T} D_t(h_t|\eta_i)e^{-\delta t}\,dt \tag{3.9}$$

with $\boldsymbol{t_2}\subseteq\boldsymbol{t}$ and $\boldsymbol{u_2}\subseteq\boldsymbol{u}$ containing all t_j and u_j for which $t_j\geq t_l$ ($j\geq j_2$). We specify T as the end of the time horizon, and Y as the index of the final heightening. For every 3-tuple (h_{t_l},t_l,η_i) a unique 'best response' strategy exists. This is the optimal dike heightening strategy given the height of the dike at time of learning (h_{t_l}), the moment of learning (t_l), and the rate of water level increase (η).

Define $J_N(h_T)$ the total discounted costs incurred in period N on interval $[T, \infty)$. For the model to be applicable it must hold that $\lim_{T\to\infty} J_N(h_T) = 0$.[1] We choose T such that Eq. (3.10.1) is approximately true. We discretise time and dike height on interval $[0, t_l)$ and solve the investment problem backwards with dynamic programming (Eq. (3.10.1)-(3.10.3)):

$$J_N(h_T) = 0 \tag{3.10.1}$$

$$J_{N-1}\left(h_{t_l}\right) = \sum\nolimits_i P_i R(h_{t_l}, t_l, \eta_i) \tag{3.10.2}$$

$$J_k(h_k) = \min_{u_k}\left\{\left(\sum\nolimits_i P_i \int_{t_k}^{t_{k+1}} D_t(h_t, \eta_i) e^{-\delta t} dt\right) + I_k(h_k, u_k) e^{-\delta t_k} + J_{k+1}(h_{k+1})\right\} \tag{3.10.3}$$

where $k = 0,1,..,N-2$, and with dike increment steps of Δu and time steps of Δt. Hence, $u_k = \{0, \Delta u, 2\Delta u, .., h_{max}\}$ and $t_k = k\Delta t$.

Eq. (3.10.2) contains the expected terminal costs from t_l onwards. Total expected terminal costs are the weighted terminal costs of scenarios $\eta_i \in \theta$ $(i = 1,2,..)$ with prior probabilities P_i of occurrence. Eq. (3.10.3) is the Bellman equation. It is solved backwards in time. First Eq. (3.10.2) is calculated for $h_{t_l} = \{0, \Delta u, 2\Delta u, .., h_{max}\}$, followed by $J_{k=N-2}, J_{k=N-3}$ etc. Lastly, $C_l^* := J_0(0)$ is obtained.

If the timing of arrival of perfect information is given, the optimal height of the dike at the moment of learning is generally lower than the height of the dike at that moment for the case without learning. This is best understood by analysing a simple example. Consider the following case. At $t_1(s)$ a dike can be heightened with $\bar{u}(s)$. We use s to refer to some dike heightening strategy:

$$s(\boldsymbol{t}, \boldsymbol{u}) = \begin{pmatrix} t_0 & t_1 & t_2 & .. \\ u_0 & u_1 & u_2 & .. \end{pmatrix}$$

[1] This is satisfied when the discount rate is sufficiently high.

Assume, furthermore, that perfect information on the structural increase in extreme water levels will arrive at a given moment $t_l (t_1(s) < t_l < t_2(s))$ and that instead of heightening the dike at $t_1(s)$ one could wait for the information before heightening the dike. Which of the two strategies, waiting or heightening the dike at $t_1(s)$ with $\bar{u}(s)$, is less costly? The dilemma is graphically illustrated in Figure 3.2.

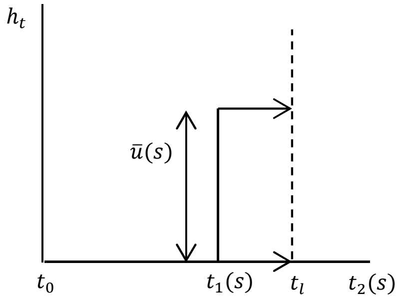

Figure 3.2 A simplified dike investment problem with two choices: construct a dike at t_1 with height $\bar{u}$ or postpone investment till learning at moment $t_l (t_l > t_1)$

Applying the dynamic programming equations (3.10.1-3.10.3) to this simplified investment problem gives:

$$C_l^* = \min\left[\left(\sum_i P_i \int_0^{t_l} D_t(h_t = 0|\eta_i) e^{-\delta t}\, dt + J_1(0)\right), \left(I_1(\bar{u}(s)) e^{-\delta t_1(s)} + \sum_i P_i \left(\int_0^{t_1(s)} D_t(h_t = 0|\eta_i) e^{-\delta t}\, dt + \int_{t_1(s)}^{t_l} D_t(\bar{u}(s)|\eta_i) e^{-\delta t}\, dt\right) + J_1(\bar{u}(s))\right)\right] \tag{3.11}$$

In Eq. (3.11), the discounted investment and damage costs incurred after learning are $J_1(0)$ if $h_{t_l} = 0$, or $J_1(\bar{u}(s))$ if $h_{t_l} = \bar{u}(s)$. Expected damage costs on interval $[t_0, t_l)$ are higher when investment is postponed till t_l. The difference in expected damage costs on the interval is:

$$\sum_i P_i \left(\int_{t_1(s)}^{t_l} D_t(h_t = 0|\eta_i) e^{-\delta t}\, dt - \int_{t_1(s)}^{t_l} D_t(\bar{u}(s)|\eta_i) e^{-\delta t}\, dt \right) \tag{3.12}$$

The savings on investment when waiting are:

$$\left(c_f + b\bar{u}(s)\right) e^{\lambda \bar{u}(s) - \delta t_1(s)} \tag{3.13}$$

The additional terminal costs due to postponement are:

$$\sum_i P_i R\left(h_{t_l} = 0, t_l, \eta_i\right) - \sum_i P_i R(\bar{u}(s), t_l, \eta_i) \tag{3.14}$$

Note that $J_1\left(h_{t_l} = 0\right) > J_1\left(h_{t_l} = \bar{u}(s)\right)$ because total expected terminal costs are strictly decreasing in dike height. Hence, it is less expensive to wait with heightening the dike if the gains from delaying the investment are higher than the sum of the expected additional damage costs before heightening, and the difference in expected terminal costs.

The above example illustrates that delaying a dike investment can be an effective strategy to account for the possible arrival of new information. Another simplified setting is one where waiting at $t_1(s)$ is not considered. Instead, imagine an alternative increment $u_1 < \bar{u}(s)$ at $t_1(s)$. Clearly, changing the investment size is another strategy to account for the possible arrival of information.

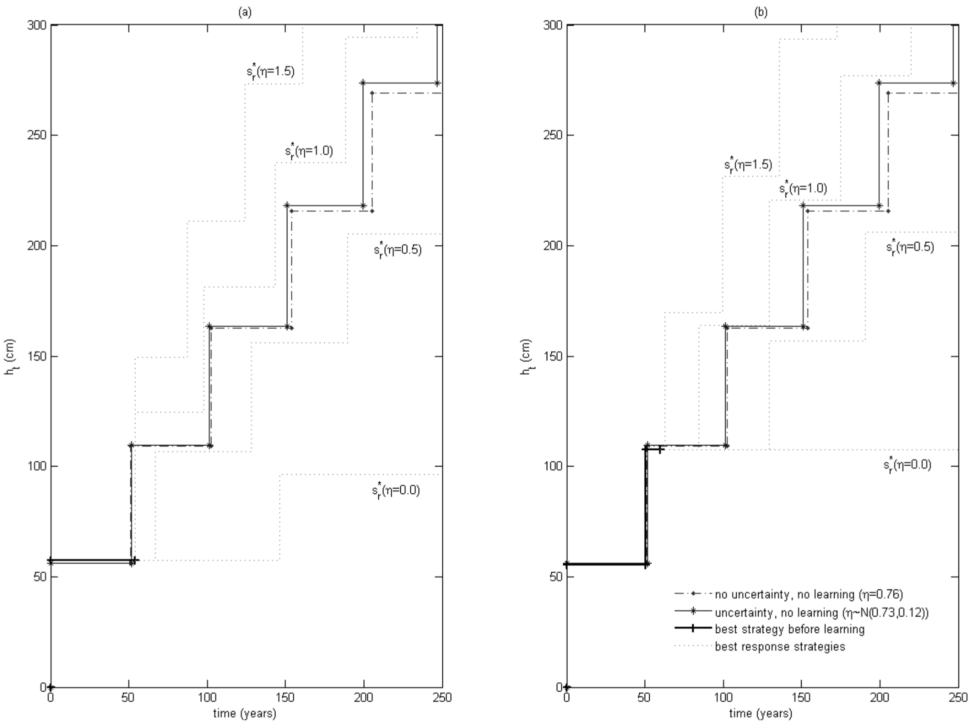

Figure 3.3 Case study (dike ring 15: Lopiker- en Krimpenerwaard area, the Netherlands): i) Deterministic base case strategy (no uncertainty, no learning) for $\eta = 0.76$. ii) Uncertainty benchmark with $\eta \sim N(0.73{,}0.12)$ and no learning. iii) Optimal strategy before learning for $t_l = 55$ (left panel) and $t_l = 60$ (right panel), which is followed by iv) a best response strategy after perfect learning (a selection of best response strategies is displayed)

Figure 3.3 displays flexible dike heightening strategies resulting from Eq. (3.10.1)-(3.10.3) with a given moment of learning at $t = 55$ years (left panel) or $t = 60$ (right panel) for a dike ring. It shows that for this ring the introduction of a probability distribution for the rate of structural water level increase enhances dike increments over time and decreases time intervals between consecutive increments as compared to the deterministic base case. The left panel shows an example for a case where the 'option to wait' is exercised. The adverse effects of waiting, however, are reduced by heightening the dike at t_0 more than for the uncertainty benchmark without learning ($h_1 = 57.5|\, t_l = 55$ versus $h_1 = 55.5|$ no learning). The right panel shows for learning at $t = 60$ that the dike is heightened for a second time before learning. This example illustrates that the possibility of learning in the future may have an effect on the entire dike heightening strategy before the information arrival. Comparing the left and the right panel also shows that differences in expected moment of learning result in different optimal dike heightening strategies. When $t_l = 60$ it is not worthwhile to wait for the information, and the dike is heightened at $t = 51$ but its height at t_l is lower ($h_2 = 107.5|\, t_l = 60$) than the optimal height under the uncertainty benchmark ($h_2 = 109|\text{no learning}$).

3.3.2 The expected value of information

The expected value of information is equal to the (quasi) option value of flexibility (Conrad 1980). Recall that minimum total discounted expected costs for the benchmark case without flexibility are defined C_{nl}^* (Eq. (3.6)). The minimum total discounted expected costs with a strategy adjustment after learning are C_l^* (Eq. (3.10.3)). Hence, the total expected value of information is equal to:

$$VOI_1 = C_{nl}^* - C_l^* \tag{3.15}$$

The expected value of information is monotonically decreasing in t_l:

$$\frac{\partial}{\partial t_l} VOI_1 \leq 0 \tag{3.16}$$

Eq. (3.16) implies that when perfect information on the structural water level increase arrives later in time its value decreases due to discounting. In the limit ($t_l \to \infty$) total expected costs can no longer be reduced whatever information is received.

Measure VOI_1 follows from a reference scenario where the decision maker never receives information (cf. Woodward et al. 2011). However, decision makers can adjust the initial investment strategy when new information becomes available *even* if the event of learning was not expected. Define C_r^* as the expected total costs resulting from an initial strategy derived from the uncertainty benchmark model (s^*) which is adapted optimally at t_l, i.e.:

$$C_r^* = \sum_i P_i \left(\int_0^{t_l} D_t(h_t(s^*)|\eta_i) e^{-\delta t}\, dt \right) + \sum_{j=0}^{L} I_j(h_j(s^*), u_j(s^*))\, e^{-\partial t_j} + \sum_i P_i R(h_{t_l}, t_l, \eta_i) \quad (3.17)$$

with $t_L < t_l \leq t_{L+1}$.

We distinguish between VOI_1, the total expected value of information defined as the difference in expected costs between the benchmark and the best strategy when it is known that information will arrive at t_l, and the expected value of information from *reactive* flexibility which is the difference between the benchmark and the best reactive strategy when it is not known that information will arrive at t_l:

$$VOI_2 = C_{nl}^* - C_r^* \quad (3.18)$$

We can, furthermore, compare reactive flexibility with an optimal flexible strategy:

$$VOI_3 = C_r^* - C_l^* \quad (3.19)$$

Measure VOI_3 is the expected value of information of knowing when we will learn. It is associated with changes in the initial investment strategy. Hence, we have disaggregated the total expected value of information (VOI_1) in two components:

$$VOI_1 = VOI_2 + VOI_3 \quad (3.20)$$

where the total expected value of information is separated in the expected value of learning the true η if the event of learning itself is not expected, and the value of knowing that we will learn in the future.

3.3.3 Probabilistic learning

It was shown that dike investment is changed by the timing of learning. It is, however, hard to identify the timing of learning about the structural increase in extreme water level observations. For this reason, we model perfect learning now as a probabilistic event. Figure 3.4 displays the discretised dike heightening problem with a probabilistic moment of learning (t_l). We assume an approximation of an exponential survival model where the conditional probability of perfect learning (P_l) is constant. A maximum moment of learning ($t_{l,max}$) is included. For simplicity, it is assumed that if learning has not occurred before $t_{l,max}$ learning will occur at $t_{l,max}$.

Extending Eq. (3.10.1)-(3.10.3) with conditional learning probabilities gives:

$$J_N(h_T) = 0 \tag{3.21.1}$$

$$J_{N-1}(h_{t_l}) = \sum_i P_i R(h_{t_l}, t_{l,max}, \eta_i) \tag{3.21.2}$$

$$J_k(h_k) =$$

$$\min_{u_k} \left\{ \begin{array}{c} (1-P_l)\left(\left(\sum_i P_i \int_{t_k}^{t_{k+1}} D_t(h_t, \eta_i) e^{-\delta t} dt\right) + I_k(h_k, u_k) e^{-\delta t_k} + J_{k+1}(h_{k+1})\right) \\ +P_l \sum_i P_i R(h_k, t_k, \eta_i) \end{array} \right\} \tag{3.21.3}$$

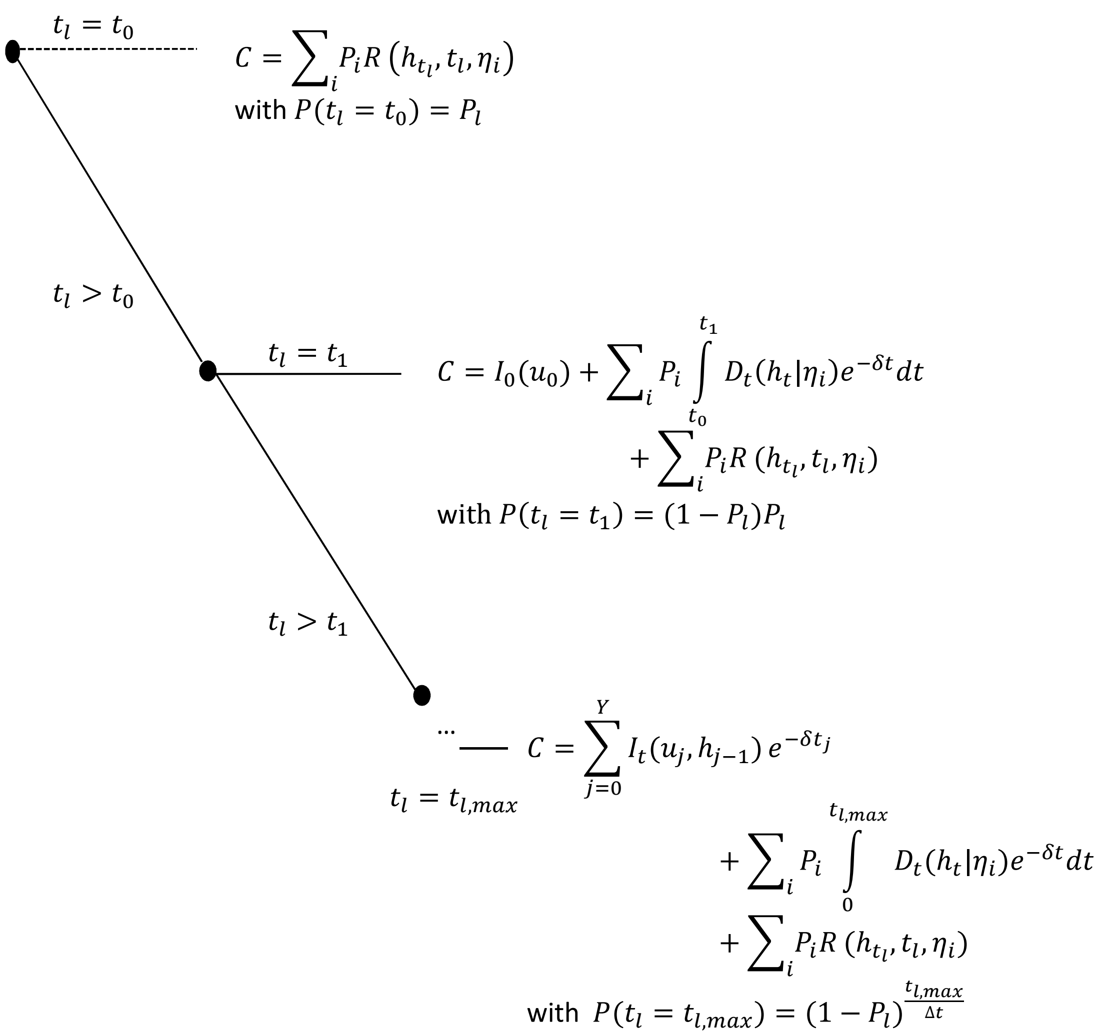

Figure 3.4 Event tree

3.4 Implementation & results

We use a hybrid method which combines dynamic programming and base case analytics after uncertainty resolution to find optimal investment strategies before and after perfect learning.[2] Eq. (3.21.1)-(3.21.3) are solved to determine

[2] The code is provided on request.

best flexible dike heightening strategies and total expected costs (C_l^*). To limit computation time we do not compute best response strategies (R) with dynamic programming. Instead, best responses are computed with analytical results of Eijgenraam et al. (2012) and built-in Matlab solvers 'fzero' and 'fminbnd'. Dike heightening strategies of the uncertainty benchmark without learning are found with dynamic programming (Eq. 3.10.1 and 3.10.3). We use a time horizon of 1500 years with 300 years being cut off ($T = 1200$) which closely approximates an infinite time horizon problem under the considered discount rates ($\delta = 0.025$ and $\delta = 0.04$). The computation of C_r^* is straightforward: the benchmark dike heightening strategy is combined with best responses when information arrives. The event of learning might take place at t_0, or at $t_0 + \Delta t$ etc. as described in Figure 3.4.

The implementation is executed in Matlab (R2012a; 64-bit) with local parallel computing on a pc with a processor with 4 cores and 16Gb internal memory. Solutions are obtained for a grid of $\Delta t = 0.5$ (year) and $\Delta h = 0.5$ (cm). To further reduce solution time we define a non-binding maximum increment (u_{max}) and a non-binding maximum dike height at $t_{l,max}$ (h_{max}). The maximum increment and maximum dike height are chosen sensibly with results from test-runs with a courser grid. Numerical results are presented for a river dike ring protecting the Lopiker- en Krimpenerwaard area in the Netherlands southwest of Utrecht; see Hoogheemraadschap De Stichtse Rijnlanden (2006) and ter Horst and Jongejan (2013). Table 3.1 contains the calibration of this ring.

Table 3.1 Calibration of ring 15

	ring 15*
p_o	0.001372
V_o	11810.4
α	0.0502
γ	0.02
ζ	0.003764
λ	0.0098
C	125.6422
b	1.1268

* Source: den Hertog and Roos (2008)

Currently, downscaled climate change projections and impact assessments are provided without probability distributions (e.g. van den Hurk et al. 2006; Hurkmans et al. 2010). We perform a sensitivity analysis with two distributions and two standard deviations. In Hurkmans et al. (2010) peak discharge estimates range from 1.1-1.6 $*10^4$ m^3/s for the river Rhine basin at the gauge station of Lobith for a return period of one hundred years. If these estimates would represent a 90% confidence interval of a normal distribution the standard deviation would be $1.5*10^3$ m^3/s. Longer return periods than one hundred year are applicable for primary water defences and standard deviation increases with return period. In the original base model a structural increase in extreme water levels of 0.76 cm/year is included for ring 15. From this a standard deviation in the order of 0.1 cm/year might be reasonable.

For comparison, the mean is calibrated such that the expected total costs of the benchmark model with uncertainty are approximately equal to the estimate found under the original base case (545 million €) with a discount rate of 4% and a standard deviation of 0.12. For ring 15 this results in $\bar{\eta} = 0.73$ with a normal distribution or $\bar{\eta} = 0.41$ for a lognormal distribution. We make use of equal bins of η with size 0.01 and truncate the distributions: two-sided at $\eta = 0$ and $\eta = 3.5$ for the normal distribution and right-sided at $\eta = 3.5$ for the lognormal distribution.

Perfect learning is a theoretical construct. Little is known about the process of learning about climate change. We use a constant biannual conditional learning probability of 1/100 and a maximum moment of learning at 400 years.

The impact of uncertainty and learning on dike heightening is demonstrated below for the dike ring protecting the Lopiker-Krimpenerwaard area in the Netherlands. This is a dike with a 'maintenance backlog' at t_0 which implies that the dike is heightened immediately. Figure 3.5 displays results for a lognormally distributed rate of water level increase. We already reported that a probabilistic rate increases dike height: time intervals between consecutive heightening decrease and dike increments increase over time. This is illustrated by the 'uncertainty, no learning' line in Figure 3.5. Probabilistic learning tends to decrease overall investment in dikes: dikes are generally lower when learning has not yet occurred compared to the base case with uncertainty but without learning. However, we find a tendency to heighten dikes more often. This finding is illustrated by the line 'best flexible strategy before learning' in Figure 3.5. For example, using a grid of 0.5 cm and 0.5 years the first increment with learning is found to be 0.5 cm lower than without learning. The third increment takes places at $t = 92.5$ with learning rather than at $t = 94$ but its increment size is smaller: 55.5 cm with learning rather than 63 cm without learning respectively.

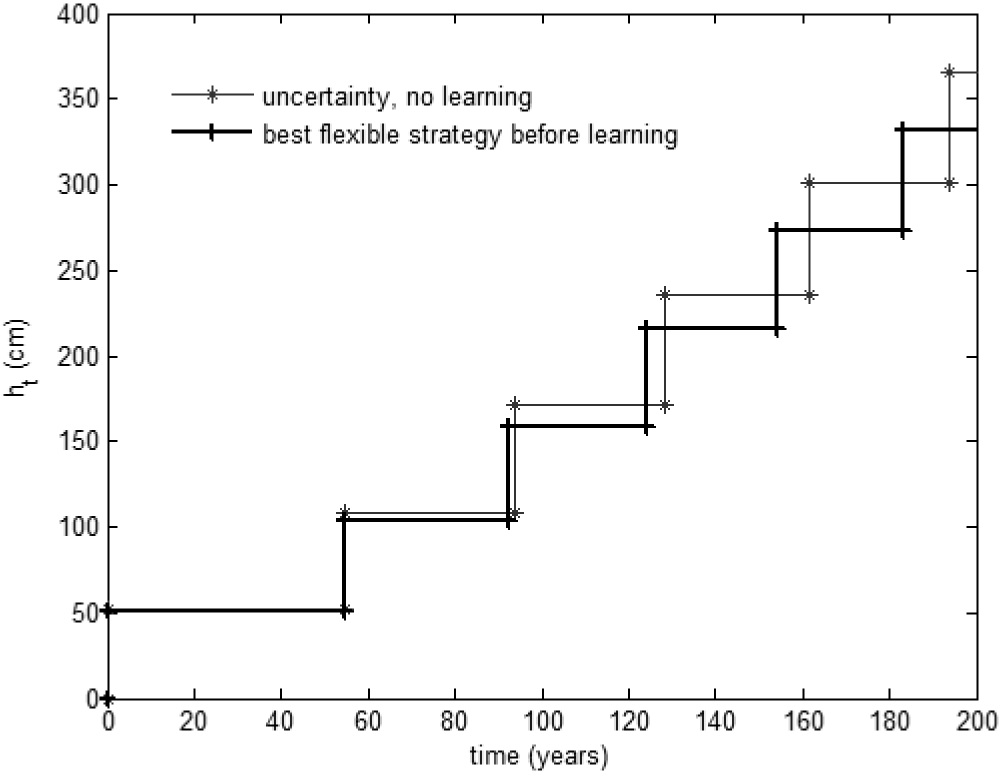

Figure 3.5 Optimal dike heightening strategy with a probabilistic η without uncertainty resolution (—∗—) and with probabilistic uncertainty resolution (—+—) for $\eta \sim logN(0.41,0.12)$ and $\delta = 0.04$

Table 3.2 displays the results of a sensitivity analysis with two standard deviations (σ), discount rates (δ), and distribution types. The following is observed. Firstly, a larger standard deviation increases total discounted expected costs both without and with learning. This finding is independent of the assumed discount rate and the assumed distribution type. Secondly, from Table 3.2 it can be concluded that the total value of information (VOI_1) is largest when the impact scenarios of the higher quantiles have significant probability mass and relatively low discount rates are used. This can be observed by comparing VOI_1 under a normal and lognormal distribution in Table 3.2. The total expected value of information can even exceed total expected costs (i.e.: $VOI_1 > C_l^*$) indicating that learning might reduce total expected costs with more than half as compared to total expected costs under the benchmark model. Thirdly, initial dike heightening strategies without and with learning largely coincide under a normal distribution. Gains of anticipation of information arrival are approximately zero (VOI_3) under a normally distributed η for the considered dike ring with the described calibrations. With a heavy-tailed distribution gains of expecting information arrival (VOI_3) are higher. We find a reduction in total discounted expected costs of 15.1 million Euro (1.0% of costs under the benchmark) for the probabilistic learning case with a relatively low discount rate ($\delta = 2.5\%$), a relatively high standard deviation ($\sigma = 0.14$) and a lognormal distribution for η.

Table 3.2 Total discounted expected costs under the learning case and the expected value of information in million € and as percentage of C_{nl}^{*} (in brackets) for two standard deviations, discount rates and distribution types (ring 15)

σ	δ		Normal		Lognormal	
0.12	0.025	C_l^*	863.8	(96.6)	723.4	(47.3)
		VOI_1	30.7	(3.4)	805.0	(52.7)
		VOI_3	0.0	(0.0)	1.6	(0.1)
	0.04	C_l^*	539.2	(99.1)	474.7	(87.3)
		VOI_1	4.7	(0.9)	69.2	(12.7)
		VOI_3	0.0	(0.0)	0.3	(0.1)
0.14	0.025	C_l^*	867.1	(95.2)	727.3	(46.1)
		VOI_1	43.8	(4.8)	850.9	(53.9)
		VOI_3	0.0	(0.0)	15.1	(1.0)
	0.04	C_l^*	540.1	(98.8)	475.5	(86.7)
		VOI_1	6.4	(1.2)	73.2	(13.3)
		VOI_3	0.0	(0.0)	0.4	(0.1)

3.5 Discussion

No prior distributions of beliefs about the likelihood of climate change impacts have been reported so far; only impact scenarios are available (cf. van den Hurk et al. 2006; IPCC 2007). The numerical results show that dike investment is increased under a lognormal distribution for the rate of structural water level increase as compared to a normal distribution. Impacts of learning are also larger under the former distribution. These findings illustrate the importance of distributional assumptions for increasing water levels to compute optimal dike heights. In the absence of consensus on likelihood of climate change impacts robust control approaches can be used instead (e.g. Brekelmans et al. 2012).

The process of learning has been represented by an exponential survival model with a constant conditional learning probability. When the probability of learning in the near future is high the optimisation problem approaches the case with a given moment of learning. When learning probabilities are close to zero, in contrast, the solutions of learning and no learning cases are approximately equal. An improved understanding of when new information might become available and of the degree of uncertainty reduction over time would support the analysis. Some authors have argued that climate change uncertainties have not decreased in the past decades despite improved understanding of the climate system and that, therefore, uncertainty may not be reduced in the short run (e.g. Hallegatte 2009). Learning about climate change impacts has been represented in a simplified manner. An alternative approach is to replace the assumption of probabilistic perfect learning with gradual learning through Bayesian updating.

We have used an existing base model which omits several real-world issues. For instance, it is assumed that the dike is homogeneous and that it has a single failure mode (van der Most and Wehrung 2005). Also river system interactions are not modelled (Markus et al. 2010). Our learning analysis can be extended with such features for real-world applications. The analysis in this paper can be used to obtain a first indication of impacts of uncertainty and learning on optimal dike heightening strategies. Further research on priors and the learning process about climate change impacts is needed.

3.6 Conclusions

It is unlikely that expectations about climate change impacts will remain as they are today, while climate change impacts are amongst the key determinants for decision making on optimal dike height. These two observations motivate our paper. We have extended an existing dike heightening model with a probability distribution for the rate of structural water level increase to study impacts of uncertainty and uncertainty resolution on dike investment and expected costs. The analysis contributes in three ways to the understanding of the problem.

(1) The analysis reveals important gaps in the current state of research. These gaps need to be filled to solve the dike heightening problem with a greater accuracy. It was shown that prior probability distributions constructed around climate change impact scenarios are needed, as well as an improved understanding of the learning process about climate change impacts.

(2) We show that a risk of overinvestment exists when learning is excluded from the analysis, and that uncertainty by itself tends to increase investment over time. We explain why initial investment in dikes is reduced when uncertainty is high but uncertainty is reduced in the near future as compared to a strategy where future learning is not expected. Our numerical findings also suggest that the initial investment frequency may be increased. The effect of uncertainty as such increases the first dike investment and for the presented cases it also accelerates and increases next investments.

(3) Learning may reduce total discounted expected costs, the aggregate of discounted costs of dike heightening and discounted damage costs, substantially. For the reported cases we find expected values of information (VOI_1) of $0.9\% - 53.9\%$ of total costs of the uncertainty benchmark. Hence, learning might even reduce total discounted expected costs by more than half.

(4) We find that first dike increments are similar before learning for the studied cases, whether or not the event of learning is expected from the start. The cost difference between a flexible strategy anticipating information arrival and a benchmark strategy which is adjusted in response to new information is small for most investigated cases ($VOI_3 < 1\%$).

Our results indicate that current and short-term dike height decisions are weakly affected by future learning and this suggests that it could be left aside in these decisions. Furthermore, it was shown that perceptions of the likelihood of climate impacts have a significant effect on initial investments and that the value of climate change impact information can be substantial especially when information may become available in the near future. We have modelled learning as an exogenous event. With research, however, it might be possible to influence the timing of learning in order to improve the quality of the information on which decision making will be based. That would make it possible to reduce the overall expected costs of adaptation.

4. Impacts of rainfall variability and expected rainfall changes on cost-effective adaptation of water systems to climate change*

Stormwater drainage and other water systems are vulnerable to changes in rainfall and runoff and need to be adapted to climate change. This paper studies impacts of rainfall variability and changing return periods of rainfall extremes on cost-effective adaptation of water systems to climate change given a predefined system performance target, for example a flood risk standard. Rainfall variability causes system performance estimates to be volatile. These estimates may be used to recurrently evaluate system performance. This paper presents a model for this setting, and develops a solution method to identify cost-effective investments in stormwater drainage adaptations. Runoff and water levels are simulated with rainfall from stationary rainfall distributions, and time series of annual rainfall maxima are simulated for a climate scenario. Cost-effective investment strategies are determined by dynamic programming. The method is applied to study the choice of volume for a storage basin in a Dutch polder. We find that 'white noise', i.e. trend-free variability of rainfall, might cause earlier re-investment than expected under projected changes in rainfall. The risk of early re-investment may be reduced by increasing initial investment. This can be cost-effective if the investment involves fixed costs. Increasing initial investments, therefore, not only increases water system robustness to structural changes in rainfall, but could also offer insurance against additional costs that would occur if system performance is underestimated and re-investment becomes inevitable.

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4.1 Introduction

There is growing evidence that climate change will lead to an increase of the intensity and frequency of heavy rainfall, the number and duration of droughts, and increasing peak river flows (Ekström et al. 2005; Frei et al. 2006; IPCC 2007; Lenderink et al. 2007; May 2008; Kirono et al. 2011; Vrochidou et al. 2013). Water systems, including stormwater drainage, flood defence and water supply systems, are vulnerable to changes in rainfall and runoff and need to be adapted (Hoes and Schuurmans 2006; Medellín-Azuara et al. 2008; Nie et al. 2009; te Linde et al. 2010). This paper studies impacts of rainfall variability and expected changes in the return periods of rainfall extremes on cost-effective adaptation of water systems to climate change given a predefined system performance target. System performance targets for water systems describe the minimum system performance that is required by law or institutional arrangements. Examples are flood risk standards for dike rings, flood risk standards for surface and urban drainage systems, and water quality limits for receiving waters (EC 2000; NBW 2005; Kind 2014).

Climate change impacts are uncertain, and technical lifetimes of infrastructure, such as sewers, open channels and dikes, are typically long (e.g. 100 years) and usually involve fixed costs (Read 1997; Arnbjerg-Nielsen 2012). An optimal mixture of initial climate change adaptation measures therefore accounts for the cost structure of available options (de Bruin and Ansink 2011). Moreover, it has been suggested to compare the expected decrease in performance during a portion of the expected lifetime of the infrastructure with a predefined performance target (Mailhot and Duchesne 2010). However, best estimates of extreme weather distributions, needed to evaluate infrastructure performance over time, are generally not reliable. This is due to the number of extreme value observations, weather variability, and uncertainty about the shift of extreme value distributions due to climate change (Huard et al. 2010; Rosenberg et al. 2010). Moreover, one or few new observations may change beliefs about the distribution parameters or distribution type, and hence about the return period of extreme events (e.g. Coles and Pericchi 2003). Hitherto, the stormwater and flood risk management literature has paid surprisingly little attention to the likelihood of investment responses induced by new hydro-meteorological observations, and to the implications for initial investment decisions (e.g. Fletcher et al. 2013).

This paper analyses optimal investment levels in water system adaptations to keep water system performance in line with a system performance target under climate change. Effects of rainfall variability and projected structural changes in rainfall on cost-effective investment levels are studied. To this end, the optimisation problem is described mathematically. In addition, a solution method is developed and applied to identify cost-effective investment strategies for stormwater drainage system adaptations.

Figure 4.1 summarises inputs and processes required for design decisions about elements of water systems. It includes: (i) hydro-meteorological observations from the case study area, for example weather, or peak flows observations, (ii) information about cost-structures and technical lifetimes, (iii) expected changes in extreme-value distributions, (iv) failure probabilities of the system before and after investment, (v) a system performance target, or other design rules, and (vi) an analysis of system failure probabilities over time based on simulated realisations of extremes. In the sequel, rainfall is used as observational input, failure probability is defined by flood probability, and a flood risk standard is applied to study cost-effective investment in stormwater infrastructure.

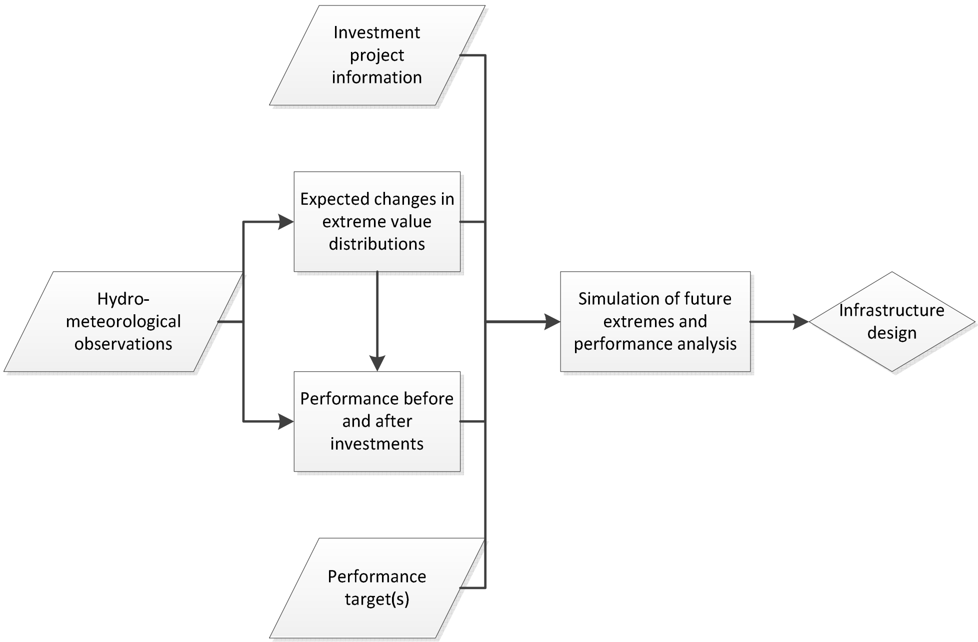

Figure 4.1 Flowchart with required inputs (trapezoids) and processes (rectangles) for decision-making on cost-effective infrastructure design

4.2 Rainfall variability

Traditionally, the design of stormwater infrastructure has been derived from so-called design storms. A critical design storm (CDS) specifies rainfall depth, i.e. rainfall quantity, for an assigned probability of occurrence and duration (e.g. De Michele 1998). Before simulation models were available, water system elements have often been designed separately with design storms, rather than by analysing the reliability of the system as a whole under a large number of rainfall events. System reliability is equal to one minus the joint failure probability of the system elements. For small water systems, system reliability ($\tilde{R}_t$) at moment t can be approximated by Eq. (4.1) if all individual system elements are designed for the same CDS. In Eq. (4.1), r_t is the average return period of the chosen design storm at moment t. Clearly, this is a rough approximation, for which an appropriate design storm duration, and representative synthetic rainfall events have to be selected (cf. Levy and McCuen 1999; Mays 2011).

$$\tilde{R}_t = \left(1 - \frac{1}{r_t}\right) \tag{4.1}$$

The CDS has to be chosen such that its average return period (r_t) in the future remains large enough to meet the reliability target under climate change. Analogue to the work of Mailhot and Duchesne (2010), the return period of the CDS could be chosen such that projected system reliability under a rainfall scenario intersects with the system reliability standard at the end of the compliance period. This is displayed in Figure 4.2, where the compliance period is assumed to end by the year 2050.

Rainfall variability, however, causes reliability estimates to be volatile. To illustrate this, a moving window analysis was applied where the last 50 years of observations were used to estimate the return period of the original CDS (cf. De Michele et al. 1998). Future rainfall was simulated by random draws from the shifted (24-hour) annual maximum rainfall distribution over time. Figure 4.2 shows three main differences between projected reliability and reliability estimates. Firstly, projected reliability decreases monotonically, but reliability estimates do not due to rainfall variability. Secondly, median reliability estimates are larger than projected reliability. Thirdly, the lower bound of the 95%-confidence interval intersects with the reliability standard well before the intersection of the projected reliability with the standard.

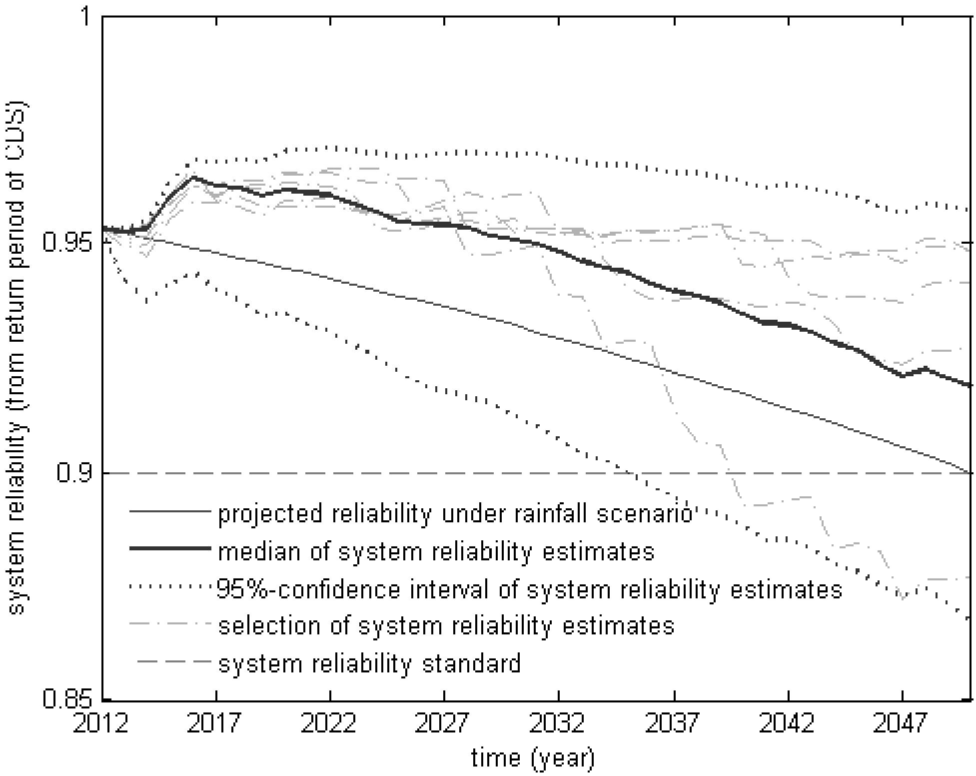

Figure 4.2 Comparison of projected system reliability and moving-window system reliability estimates, as derived from the expected or estimated return period of a critical design storm[3]

Re-investment in the system is required as soon as the best estimate of the system's reliability, following from the best estimate of the return period of the CDS (Eq. (4.1)), falls below the pre-defined reliability standard. This simplified example illustrates that due to rainfall variability the timing of re-investment in the system cannot be assumed to be known if a reliability standard has to be met. Future beliefs about the return period of rainfall extremes are partly based on new rainfall observations and may result in under- or overestimation of the *actual* flood probability, and hence in over- or underestimation of system reliability. Note that only overestimation of the flood probability can have unforeseen

[3] KNMI (2013) daily precipitation observations were used. The confidence interval has been obtained from 10000 simulations. The Matlab code is available on request.

financial consequences, as only experienced underperformance results in new investments. Such investments may incur additional costs due to the fixed costs of stormwater infrastructure. Cost-effective capacities of stormwater infrastructure are therefore not only determined by current beliefs about future return periods of rainfall extremes, but also by future beliefs about the return periods of the extremes.

4.3 Mathematical representation of water system adaptations

We now turn to a model specification and solution method to determine cost-effective water system adaptations. Consider the objective to find a cost-minimising investment strategy $(z_0, z_1, \dots, z_T)$ in a single water system element up to the last year of time horizon T:

$$C = \min_{z_0, z_1, \dots, z_T} E\left(\sum_{t=0}^{T} \frac{I(z_t) + O(x_t)}{(1+\delta)^t}\right) \tag{4.2}$$

where C is the Net Present Value of total investment, operation and maintenance costs. Annual investment costs are described by function I, and annual operation and maintenance costs by function O. Costs are discounted at rate δ. The decision variable z_t gives the level of investment in additional storage or conveyance capacity at year t, and x_t represents the total stock of the system element at year t before or, without construction time, directly after an investment. Investment z_t is realised in every year t at the beginning of that year, i.e.:

$$x_{t+1} := x_t + z_t \tag{4.3}$$

A reliability constraint is applicable during the compliance period $[0, T]$,

$$R(f_t, x_t, Q) \geq \alpha \qquad \forall \quad t \in [0, T] \tag{4.4}$$

where $R(f_t, x_t, Q)$ is the estimated system reliability, and α is the predefined reliability standard. Estimated reliability is a function of (i) probability density function f_t estimated with a historical time series, (ii) stock x_t and (iii) other elements of the system, Q. In what follows, Q is kept constant over time. Eq. (4.4) describes decision-maker behaviour. It reflects how the decision-maker implements legislation that specifies the system reliability standard (α). We consider that best estimates are used to evaluate system reliability, and that these estimates are not allowed to fall below the reliability standard at any year t after investment in that year. Alternative specifications, for example with a probabilistic constraint, could be considered to reflect alternative implementations of the reliability standard.

In the context of stormwater infrastructure, an annual system reliability estimate L follows from continuous simulation of rainfall, runoff and inundation:

$$L = 1 - \frac{\sum_{k=1}^{N} E_k}{N} \tag{4.5}$$

where N is the number of simulated years, and $E_k = 1$ if one or more flooding events occur during a year k of the simulated series, else $E_k = 0$. System reliability can be obtained from Eq. (4.5) before and after investment.

Continuous simulation of rainfall, runoff and water levels is computationally intensive even with stationary rainfall distributions. For this reason, an indirect procedure is developed to estimate system reliability over time based on annual maxima. As a first step, flood probability-rainfall curves $h(v, x_t, Q)$ are estimated for 24-hour annual rainfall maxima and for a range of x_t. These curves define the conditional probability that if some 24-hour annual maximum v has been observed in a year t, flooding has occurred in that year given x_t and Q. Note that this function is time-independent if there is a time-invariant upper bound on x_t. Furthermore, 24-hour annual maximum rainfall distributions are estimated. Rainfall maxima are described by a Generalised Extreme Value distribution (GEV) with cumulative distribution function (Jenkinson 1955):

$$F_t(v) = exp\left\{-\left[1 + \xi_t \left(\frac{v - \mu_t}{\sigma_t}\right)\right]^{-\frac{1}{\xi_t}}\right\} \tag{4.6}$$

where ξ_t is the shape parameter, σ_t is the scale parameter, and μ_t is the location parameter. It is estimated with rainfall of the past $\bar{t}$ years. Hence, the oldest observation is dropped when a new annual maximum becomes available. Moving-window analyses have previously been performed to study frequency changes in design storms and annual maximum floods (De Michele et al. 1998; Jain and Lall 2001). A full data set can also be used for frequency analysis if the trend in the data is removed; see Khaliq et al. (2006).

In a second step, reliability at the beginning of year t is estimated by:

$$R(f_t, x_t, Q) = 1 - \int_0^{\infty} f_t(v) h(v, x_t, Q) dv \tag{4.7}$$

where $f_t(v)$ is the density function of $F_t(v)$. In order to solve for the cost-effective investment strategy an investment cost function, and an operation and maintenance cost function for the water system element should be identified. A linear investment cost function I is applied with fixed costs a and variable investment costs of b per unit:

$$I(z) = \begin{cases} a + bz & if \;\; z > 0 \\ 0 & if \;\; z = 0 \end{cases} \tag{4.8}$$

where z is the decision variable, the level of investment in additional storage or conveyance capacity, in a given year t. For simplicity, the investment cost function is assumed to be linear. For the main purpose of this paper, it is sufficient to work with a simple investment cost function that accounts for fixed costs. The fixed costs component (a) in Eq. (4.8) motivates 'anticipatory' adaptation rather than 'reactive' adaptation (Smith 1997), as will be shown. Note that the investment cost function is assumed to be time-independent.

Marginal annual operation and maintenance costs are assumed to be constant:

$$O(x) = mx \tag{4.9}$$

where m denotes unit costs of operation and maintenance.

Annual rainfall transition probabilities can be described by a three-dimensional Markov process:

$$p(\xi_{t+1}, \sigma_{t+1}, \mu_{t+1} | \xi_t, \sigma_t, \mu_t)$$

We define the vector of distribution parameters as $\varphi_t = (\xi_t, \sigma_t, \mu_t)$. The conditional transformation probability can then be written as $p(\varphi_{t+1}|\varphi_t)$. This implies that distribution parameter estimates ξ_{t+1}, σ_{t+1} and μ_{t+1} are stochastic and depend on the parameter estimates at moment t. The optimisation problem can now be formulated recursively. The Bellman equation is:

$$J_t(\varphi, x) = \min_z \left(I(z) + O(x+z) + \frac{E\{J_{t+1}((\varphi_{t+1}|\varphi), x+z)\}}{1+\delta} \right) \tag{4.10}$$

$$s.t. \quad R(f, x + z) \geq \alpha \tag{4.11}$$

where J_t is the value function, and $(\varphi_{t+1}|\varphi)$ the stochastic transformation.

A practical way to implement the Bellman equation is to discretise the parameter state space of φ_t. Let $p_{ijt} := p_t(\varphi_j|\varphi_i)$, where φ_i contains values for distribution parameter estimates ξ_t, σ_t and μ_t, and φ_j contains the estimates of the next distribution. This gives:

$$J_t(\varphi_i, x) = \min_z \left(I(z) + O(x + z) + \frac{1}{1 + \delta} \sum_j p_{ijt} J_{t+1}(\varphi_j, x + z) \right) \tag{4.12}$$

where $t = 0,1,2, \ldots, T - 1$, and $z = 0, \Delta z, 2\Delta z, \ldots, x_{max} - x$. In this paper, transition probabilities (p_{ijt}) are evaluated by simulation. Combining the moving-window part of existing rainfall maxima (e.g. the last 40 years) with a simulated series (e.g. the next 20 years) determines the distribution estimates at a particular year. The oldest observation, e.g. an oldest annual maximum, is dropped to inform estimates of the next year. Rainfall extremes, i.e.: future realisations, of the next year can be simulated to estimate the new rainfall distribution. Many repetitions provide an estimate of the distribution of transitions of distributional beliefs. This method, however, is computationally intensive, and we therefore use an approximation using 'synthetic series' for every distribution state to derive transitions; see Section 4.1.

Terminal costs at the end of the time horizon are considered to be zero.

$$J_T(\varphi_i, x) = 0 \tag{4.13}$$

4.4 Solution methods and case study

4.4.1 Solution methods

The practical implementation of the solution method consists of three steps:

i. estimation of flood probability-rainfall curves for 24-hour annual rainfall maxima

ii. determination of lower and upper bounds of parameter estimates ξ_t, σ_t and μ_t of the 24-hour annual maximum rainfall distribution over time
iii. economic optimisation

To estimate flood probability-rainfall curves for 24-hour annual rainfall maxima, a rainfall generator was calibrated with an original hourly rainfall series as described in Cameron et al. (1999). Empirical rainfall duration and inter-arrival time distributions were obtained. Furthermore, empirical average intensity distributions per duration class were extrapolated with a Generalised Pareto Distribution (GPD). For exceedances over thresholds, the GPD was shown to be consistent for tail estimation under mild conditions (Pickands 1975). The GPD has a flexible functional form. The shape parameter provides a concave, or a convex plot, and a zero value reduces the GPD to an exponential distribution (Cameron et al. 1999).

Duration profiles per class were randomly selected, and 1000 years of rainfall were simulated. To reduce computation time, a selection of rainfall events from the simulated series was used for runoff and inundation simulation, instead of continuous simulation of runoff and water levels with the 1000 years of rainfall. For this purpose, 24 hours of maximum rainfall were selected from every simulated year of rainfall. Simulated rainfall in proceeding hours and in hours following the event were added. The number of hours added was based on a 'system recovery time', which we pragmatically defined as the time needed to restore the target water levels within the system after a one-hour rainfall event with a return period of 10 years. The simulation of runoff and inundation was repeated several times with the selected rainfall events, while changing system element dimensions in the hydrological model. Temperature and wind conditions were kept constant during all simulations. Finally, probit models were fitted to the binary inundation results to obtain flood probability-rainfall curves for 24-hour annual rainfall maxima.

To determine lower and upper bounds of parameter estimates ξ_t, σ_t and μ_t of the 24-hour annual maximum rainfall distribution for all yearly decision moments t, the original hourly rainfall series was transformed in a climate change scenario series, and 24-hour annual maxima were selected from both the original and the transformed series. Bootstrap samples were taken from the original 24-hour annual maximum series, and matched with corresponding bootstrap samples of the transformed 24-hour annual maximum series. GEV parameter estimates were obtained with maximum likelihood for every bootstrap sample. The GEV parameters of each original and transformed bootstrap sample were (log)linearly interpolated to find parameter estimates between $t = 0$ and the time horizon of the climate scenario (Kharin and Zwiers 2005). This was followed by simulation of times series of 24-hour annual maxima by random draws from bootstrap sample distributions to determine lower and upper bounds of moving-window parameter estimates of the 24-hour annual maximum distribution over time.

Cost-effective stormwater investment strategies are determined by solving the value function (Eq. (4.12)) backwards in time. For this purpose, synthetic time series of 24-hour annual rainfall maxima were created, which approximate parameter estimates of the GEV parameter state space $\varphi_t(\xi_t, \sigma_t, \mu_t)$ at decision moment t. The length of any synthetic series was kept fixed at 60 years, corresponding to the number of observations in the moving window, and percentile bins were used to construct the synthetic series. At every decision moment t, possible parameter state transitions were computed for every synthetic series. To achieve this, percentile bins of 24-hour annual maxima were estimated from simulated 24-hour annual maxima for year $t + 1$ which were obtained from random draws from the interpolated bootstrap samples of the GEV distribution parameters. One observation of each synthetic series approximating the oldest moving window observation of the original series, i.e.: the historical observation of year $t - 60 + 1$, was then replaced by one discretised percentile observation of $t + 1$, and this was repeated for all percentiles. The value function evaluation uses a grid interpolation to identify optimal action (z_k) at decision moment t given GEV parameter states $\varphi_t(\xi_t, \sigma_t, \mu_t)$ and total investment so far (x_t).

4.4.2 Case study

As an empirical application of the solution method, the volume of a storage basin in the Waalblok polder, the Netherlands, was studied. The Waalblok polder is located in the South-Western part of the Netherlands near the city of The Hague and has an area of 55 ha. Most of the area is covered by greenhouses. In contrast to a standard polder, water is pumped into the polder in dry periods and is discharged at sluices. Target water levels have been set at + 0.25 m above datum (A.D.) and, in a small area, at - 0.1 m A.D. (Delfland Water Board 2010). The

Waalblok is primarily used for greenhouse horticulture, and experienced regular inundation problems in the past. To resolve this, various measures were investigated (Gehrels et al. 2007). A pilot project was initiated which included the realisation of an off-line storage basin; it only fills if the water level rises above the crest level of the inlet. This storage basin, made of concrete, has been realised under a greenhouse upstream at the border of the lower lying area (- 0.1 m A.D.) to reduce flood risk in this sub-system.

Uniform flood risk standards, describing the maximum accepted annual flood probability within a water system, have been defined for Dutch regional water systems; see Table 4.1. First analysis showed that despite the realisation of a large storage basin (7142 m^3) the - 0.1 m A.D. subsystem of the Waalblok polder does not meet the horticulture flood risk standard of one inundation event per 50 years on average, see also Figure 4.4 in Section 4.5. We therefore applied the grassland flood risk standard to analyse the cost-effective volume of the storage basin in the - 0.1 m A.D. subsystem of the Waalblok polder.

Table 4.1 Dutch flood risk standards, describing maximum accepted annual flood probabilities, for regional water systems per land use type and failure definitions expressed as percentage of flooded land (source: NBW 2005)

Land use type	Standard	Failure definition
Grassland	1/10	>5%
Agriculture	1/25	>1%
Horticulture	1/50	>1%
Urban	1/100	>0%

The rainfall generator was calibrated with a homogenised hourly rainfall series of 106 years for gauging station ‘de Bilt’ (KNMI 2004).[4] We increased these observations with a fixed factor (10%) to correct for the ‘coastal effect’, a method which has also been applied by the water board responsible for the Waalblok polder system (Delfland Water Board 2005). We transformed the original hourly rainfall series into a climate change (W^+) scenario following the procedures of the KNMI transformation tool (Lenderink 2006; Bakker and Bessembinder 2012).

[4] We combined the KNMI (2004) data set with homogenised rainfall for 2005-2012 supplied by KNMI via personal communication.

To simulate water levels during heavy rainfall events we used hydrological model Sobek Rural. Detailed overland runoff and flow ‘schematisations’ of the Waalblok polder were provided by Water Board Delfland and RoyalHaskoning DHV. Sobek Rural allows detailed flow and water level simulation from many heavy rainfall events for real-world surface systems (Deltares Systems 2012). Inundation was defined to occur if the target water level (- 0.1 m A.D.) in the area increases with 60 cm or more, because the water level starts to exceed the surface level of the lowest lying land at this point. We adopted a number of system changes to increase the system performance. The water level in the - 0.1 m A.D. water level area tends to rise up to the water level of the + 0.25 m area during heavy rainfall events. We increased, therefore, the pumping station capacity at the downstream exit of the - 0.1 m A.D. subsystem with a factor 3; from 10 to 30 m^3/ min. Verhoeven (2010) proposed, furthermore, to change the storage inlet to increase storage capacity use.[5]

Table 4.2 shows cost parameter values used for the case study. These were derived from cost information that we obtained from Waterboard Delfland, and are used for illustrative purposes only. Gehrels et al. (2007) report values in the same order of magnitude as in Table 4.2.

[5] For our simulations the crest level of the orifice was lowered from + 0.65 m to + 0.3 m and its width was doubled from 1.5 m to 3.0 m.

Table 4.2 Cost parameter values used for the economic analysis of the case study

Parameter	Value (EUR)
a	1100000
b	88
m	1.3

Most of the three-step procedure was programmed in Matlab. We used Matlab R2013a with parallel computing and optimisation toolbox. The Matlab code is available on request.

4.5 Results

Storage basin volumes up to 10000 m^3 were considered in steps of 1000 m^3 (Δz). Figure 4.3 displays a selection of resulting flood probability-rainfall curves for 24-hour rainfall maxima and different storage volumes. Figure 4.3 shows that the storage basin effectively reduces flood risk in the studied subsystem of the polder. Marginal flood risk reductions were largest for small storage volumes, while increasing the storage basin beyond 5000 m^3 had little effect on flood probability. Although increasing the storage beyond 5000 m^3 still could prevent flooding in some of the simulation runs, other measures would be needed to reduce flood risk sufficiently to meet the horticulture flood risk standard (Figure 4.4).

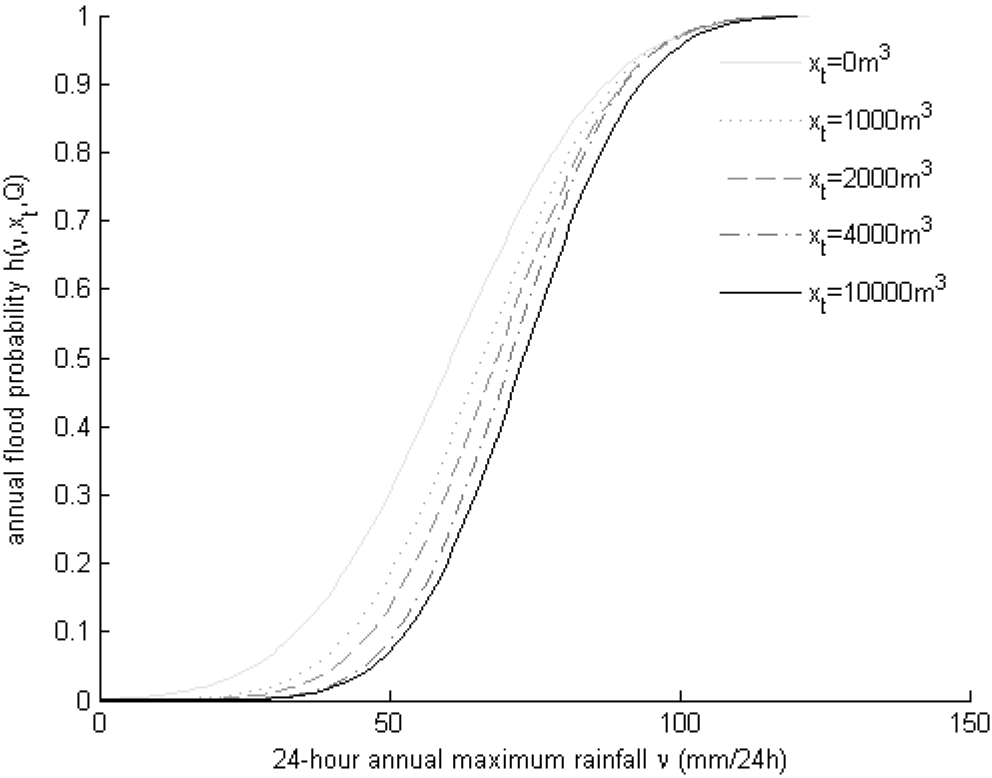

Figure 4.3 Selection of flood probability-rainfall curves for 24-hour rainfall maxima for different storage volumes

Figure 4.4 reports initial annual flood probabilities in the studied subsystem (-0.1 m A.D.) after an initial investment (z_0). These flood probability estimates can be obtained from the flood probability-rainfall curves presented in Figure 4.3. Note that the annual flood probability associated with the occurrence of some 24-hour annual rainfall event is the product of the probability of occurrence of this event and the probability that this event results in flooding. The flood probability is the sum of the probability products over all 24-hour events. As both the density function of annual rainfall, and flood probability-rainfall curves are continuous, estimates are obtained by numerical integration of flood probability-rainfall curves for given storage volumes (Figure 4.3) multiplied by the density function of annual rainfall. This is summarised by the integral in Eq. (4.7). A storage volume of 1000 m^3 meets the grassland flood risk standard at t_0. This is, therefore, the cost-effective storage volume if only immediate compliance is required, and future compliance is not considered. It is also the cost-effective initial volume for longer compliance periods in the absence of fixed costs ($a = 0$).

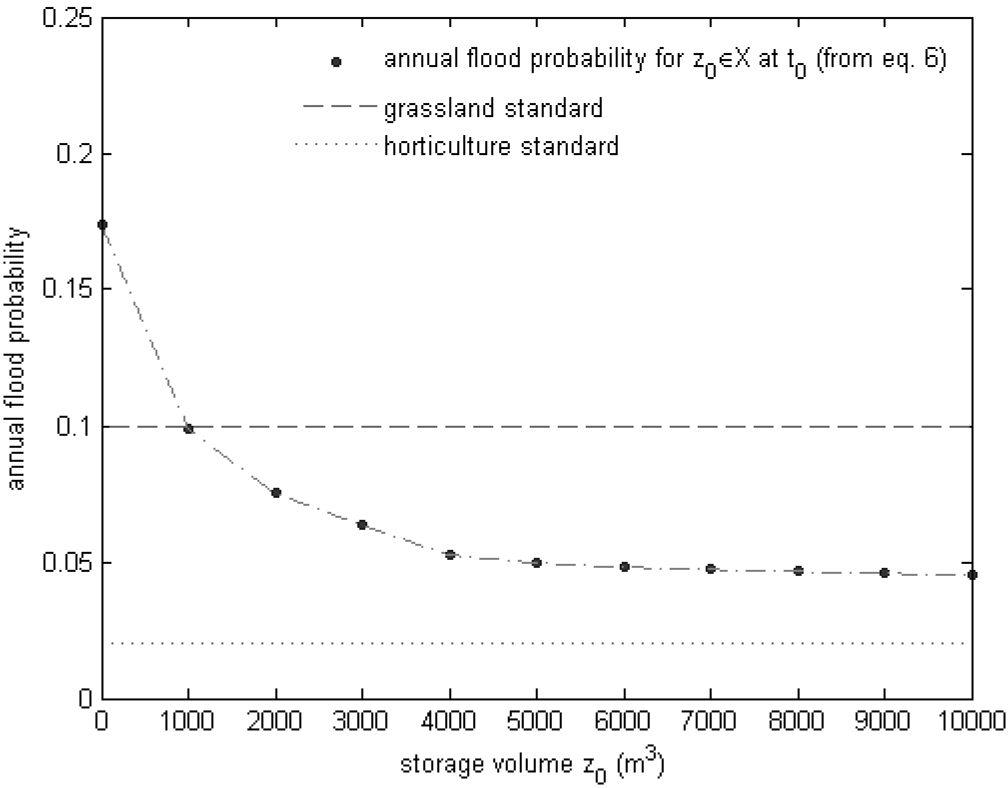

Figure 4.4 Initial annual flood probabilities for different storage volumes

Figure 4.5 shows total discounted costs for different storage volumes for a compliance period of 38 years. These costs include investment and operation costs. The minimum initial capacity is 1000 m^3 for compliance at t_0. However, 1000 m^3 is no longer cost-effective because there is a risk that the estimated subsystem reliability falls below the reliability standard somewhere in the coming decades, which would require re-investment. The cost-effective volume for this case is 2000 m^3, which we find for shorter compliance periods ($T \geq 2$) as well. We also find that the absolute cost difference between 1000 m^3 and 2000 m^3 is increasing, and between 2000 m^3 and 3000 m^3 is decreasing in T. This finding demonstrates that the cost-effective storage volume tends to increase when the compliance period is increased, although the effect is negligible for $T \geq 2$. There is, furthermore, a trade-off between operation costs and the risk of re-investment in storage volume. While a larger initial storage basin reduces the probability that re-investment is required, it goes along with increased costs of operation, and vice versa. Hence, cost-effective investment strategies are driven by the investment's cost structure and the time horizon of the performance target. The time horizon captures two effects: expected climate change impacts, and randomness in the re-investment moment due to rainfall variability.

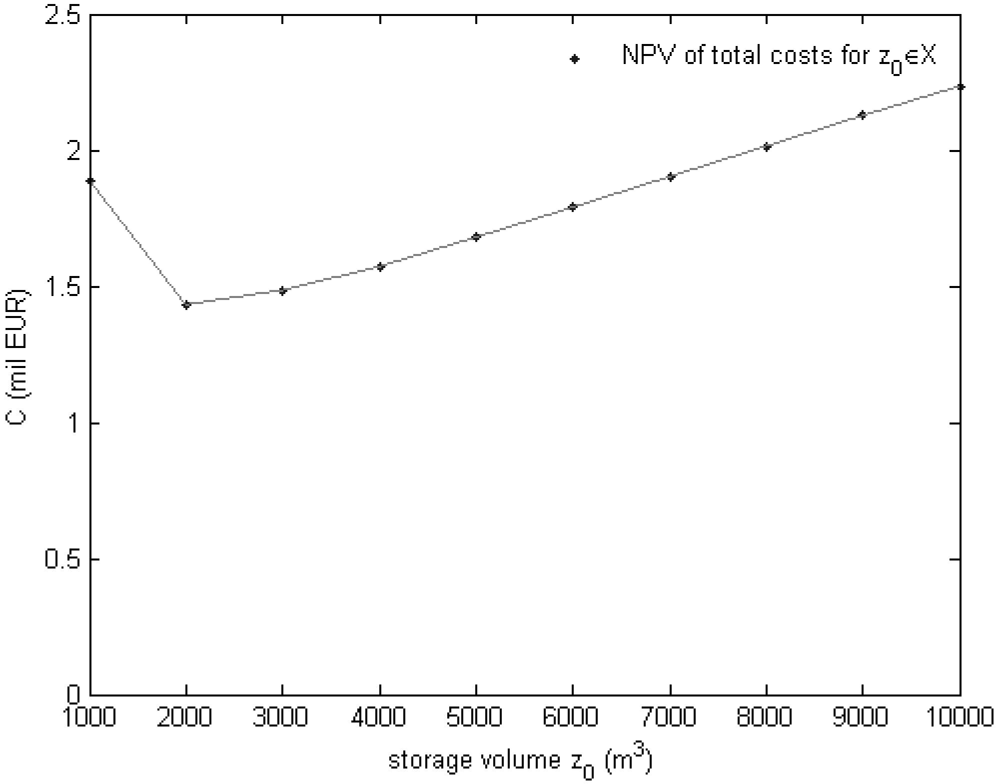

Figure 4.5 Total discounted costs for different storage volumes for a compliance horizon till 2050

4.6 Discussion

In the context of climate change cost-effectiveness analysis of water system adaptation options requires a performance target, for example a flood risk standard, and specification of expected revision moments of the performance target. In practice, explicit definitions of revision moments are often lacking, despite that economically efficient revision moments could be derived from a cost-benefit analysis (NBW 2005; Kind 2014). Moreover, initial performance targets are sometimes purposely set at economically inefficient levels (cf. Hoes and Schuurmans 2006).

A longer compliance period, during which the performance target remains unchanged, implies application of larger structural changes in rainfall to compute initial cost-effective water system adaptations. Long-term performance targets, therefore, increase the robustness of water systems to climate change. Moreover, when the likelihood of future beliefs about return periods of rainfall extremes is considered, a long-term performance target also reduces the probability of re-investments early in time. Yet, our case study results illustrate that cost-effective initial investments do not always change considerably when the time horizon of the performance target is increased. The numerical results are mainly driven by the cost structure of investment, expected rainfall changes, and the probability that costly re-investments are required in the short-run as a result of new rainfall observations. Other determinants are the initial state of the system, and the statistical updating process applied. For the case study analysis, only one climate change scenario was considered. So far, there is no scientific consensus on how to use multiple climate change scenarios (Kundzewicz et al. 2010; Berggren et al. 2014). In this study moving window estimates were used to recurrently evaluate performance. Alternatively, a statistical updating procedure could be applied on transformed data, which could improve the reliability of the distribution estimates over time (cf. Khaliq et al. 2006).

The three-step solution method described in this paper was designed to study cost-effective investment strategies for investments in a single element of a surface or urban drainage system. In certain cases, it may be reasonable to study an investment strategy in one water system element in isolation. The subsystem of the case study, for example, covers a relatively small area with a limited number of subsystem elements. In addition, the storage basin incurs relatively high costs compared to the other system elements, with no close substitutes for reducing flood risk in the subsystem. For other cases, however, these conditions may be different. Various algorithms could be used instead, for example, those applied to identify cost-effective sewer designs (e.g. Swamee and Sharma 2013).

The presented solution method can be extended to study multiple investments. This would, however, require integrated models that allow performance analysis of many system configurations at once (i.e.: the analysis of large-scale combinatorial problems with many investment options, and many investment levels). This was beyond the scope of this paper. Moreover, as water system investments will often have non-linear investment cost functions, their implications on cost-effective investment levels require further research. Furthermore, cost-benefit analysis could be considered, but this would require damage assessment (Jonkman et al. 2008; Pathirana et al. 2011).

4.7 Conclusions

Water systems, including stormwater drainage, flood defence and water supply systems, are vulnerable to climate change and often need to be adapted to keep system performance in line with performance targets, for example flood risk standards. In current practices, structural changes in rainfall are commonly anticipated in decisions on water system adaptations. In this paper, we argue that rainfall variability may have an impact on initial cost-effective investments on the basis of two premises. Firstly, it was assumed that decision-makers recurrently evaluate the performance of the water systems for which they are responsible. Secondly, it was assumed that decision-makers do not change the performance target during a specified time horizon.

We started this paper by showing that rainfall variability and the limited number of extreme value observations result in volatility of performance estimates. We demonstrated that if these estimates are used to evaluate whether or not a water system still complies with a predefined performance target, the timing of re-investment in the system cannot be assumed to be known. As a consequence, initial cost-effective investments are determined by current beliefs about the future return periods of rainfall extremes, and by future beliefs about the return period of the extremes. These beliefs will determine when re-investment is necessary, rather than the *actual* structural changes in rainfall, which cannot be observed in the short-run. So far, it has remained a challenge to link current management practices and investments with an analysis of possible rainfall realisations in the future. In this paper, an integrated solution method has been developed to show how such an analysis could be implemented.

The presented method has been developed to identify cost-effective investment strategies for stormwater drainage system adaptations. Runoff and water levels were simulated with rainfall from stationary rainfall distributions, and time series of annual rainfall maxima were simulated for a climate scenario. Cost-effective investment strategies were determined by dynamic programming. The results suggest that increasing initial investments increases water system robustness to climate change. For investments with large fixed costs shares this may also reduce the probability that costly re-investments are required in the short-run as a result of new rainfall observations. Increasing initial investments could therefore offer insurance against costs from underestimation of the system's performance.

Acknowledgements

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5. A dynamic minimax regret analysis of flood risk management strategies under climate change uncertainty with emerging information on peak flows[*]

Investment decisions on flood protection are often guided by considerations of regret. The ‘minimax regret’ (MR) decision criterion is used to identify investments in flood protection which minimise worst-case regret. In this paper, we study the dynamic application of the MR decision criterion to analyse robustness of flood risk management (FRM) strategies under climate change uncertainty with emerging peak flow information. The approach supports identification of adaptive FRM strategies by including ‘learning scenarios’ about peak flow development. We implement the MR decision criterion dynamically to study optimal dike height and floodplain development in a conceptual FRM model. Outcomes of static and dynamic MR analysis are compared. It is shown that the dynamic model offers greater flexibility than the static model, because it allows investments to be changed when new peak flow information emerges. We conclude that dynamic MR solutions are more robust than the solutions obtained from a static MR analysis of FRM investments due to ongoing changes in climate change impact projections.

[*]Chapter is based on a submitted manuscript and a working paper presented in a thematic session of the 21st Annual Conference of the European Association of Environmental and Resource Economists in Helsinki, June 24-27, 2015:
van der Pol TD, van Ierland EC, Gabbert S, Weikard HP and Hendrix EMT (2015) A dynamic minimax regret analysis of flood risk management strategies under climate change uncertainty with emerging information on peak flows

5.1 Introduction

Investment decisions on flood protection are often guided by considerations of regret, comparing an actual or a hypothetical outcome against a best achievable outcome. The 'minimax regret' (MR) decision criterion is used to support robust decision-making by identifying flood risk management (FRM) solutions with the least worst-case regret (cf. Hall and Solomatine 2008; Brekelmans et al. 2012). In its basic form, the MR objective is to minimise maximum regret for a defined set of scenarios (Niehans 1948; Savage 1951). In a one-shot or static MR application, this set is constant over time. However, recent literature advocates 'flexible' or 'adaptive' FRM strategies which can be adapted to new information at relatively low costs, motivated by the presence of 'deep' uncertainties, and the inherently limited capacity to predict the future and the possible emergence of new information (cf. Pahl-Wostl 2007; Kwadijk et al. 2010; Haasnoot et al. 2013). In this paper, we apply the MR decision criterion dynamically to FRM strategies under the possible emergence of new climate information.

Our starting point is an example of a static MR application to flood risk management to illustrate how climate change impact scenarios result in selection of flood protection measures using the MR criterion. Consider the choice between raising inland dikes and investment in a storm surge barrier.[6] Table 5.1(a) summarises total discounted costs, including investment and damage costs, associated with both investment options under a 'low' (s_L), 'high' (s_H) or 'extreme' (s_E) sea level rise scenario.

Table 5.1(a) Total discounted costs under different sea level rise scenarios: raising inland dikes versus construction of a storm surge barrier

Measure / Scenario	s_L	s_H	s_E
Storm surge barrier	C_1^*	C_2^*	C_3
Inland dikes	C_4	C_5	C_6^*

[6] Dutch policy makers were facing this dilemma in the 80s along the estuary of the "New Waterway" near Rotterdam. Raising the inland dikes would have required large-scale investments, which resulted in the decision to construct an innovative storm surge barrier (Bol 2005).

An optimal *ex-post* decision (*) minimises the costs of both flood protection measures for a given scenario. In this example, $C_1 < C_4$, $C_2 < C_5$ and $C_6 < C_3$. Corresponding *anticipated* regret values are displayed in Table 5.1(b).

Table 5.1(b) Corresponding regret values

Measure / Scenario	s_L	s_H	s_E
Storm surge barrier	0	0	$C_3 - C_6$
Inland dikes	$C_4 - C_1$	$C_5 - C_2$	0

The regret values in Table 5.1(b) are 'absolute' regret values obtained from subtracting the costs of an optimal *ex-post* alternative from the costs of the selected adaptation measure for the scenario.

Suppose that $C_3 - C_6 > C_5 - C_2 > C_4 - C_1$. MR of dike heightening is $C_5 - C_2$ and MR of investment in the storm surge barrier is $C_3 - C_6$. The optimal strategy, when applying the MR criterion, is to raise inland dikes if scenarios s_L, s_H and s_E are included in the MR analysis. Note that exclusion of extreme scenario s_E from the set of scenarios results in a decision to invest in the storm surge barrier rather than to raise the inland dikes. This implies that MR decisions are sensitive to the set of scenarios considered.

MR analysis of flood protection measures is challenged by climate scenario choices. Including scenarios that cover the complete uncertainty set, i.e. "the smallest closed set such that the probability of the data to take a value outside of this set is zero" (Ben-Tal et al. 2009), might include highly unlikely, but catastrophic climate scenarios and could lead to excessive investment costs or extreme outcomes, such as 'abandoning land' (cf. Clarke 2008; Londsdale et al. 2008). Instead, 'plausible high-end' climate change impact scenarios can be used for the analysis, as has been suggested for the updating of FRM strategies (Katsman et al. 2011).

In addition, the set of 'plausible' climate change impact scenarios may be subject to change over time. Examples are recent reports of larger uncertainty ranges of sea level rise and extreme rainfall than previously reported (Wahl et al. 2013; KNMI 2014). In the long run, more extreme value observations and scientific progress may reduce or resolve climate uncertainties (cf. Baker 2005; Khaliq et al. 2006). When new information emerges, anticipated regrets may change and investments can be adapted accordingly.

So far, few authors have discussed the dynamic application of the MR decision criterion with emerging information, and focus has mainly been on theoretical problems (Krähmer and Stone 2005; Hayashi 2011). To our best knowledge, no dynamic application of the MR decision criterion to FRM cases has been reported in the literature. This paper shows how the MR decision criterion can be applied dynamically to analyse practical FRM investment problems under climate change, and the important differences between static and dynamic MR analysis due to the possible emergence of new information. First, a procedure is developed to implement the MR decision criterion in a time-consistent manner building on the work of Hayashi (2011). Next, a conceptual FRM model is developed applying the dynamic MR procedure.

The structure of this paper is as follows. Section 5.2 provides a brief motivation for MR analysis. Section 5.3 introduces the MR decision criterion formally and develops a consistent procedure for its dynamic implementation. Section 5.4 describes a conceptual FRM model, and applies the dynamic MR procedure to this model. Section 5.5 presents results. Section 5.6 concludes and discusses implications of our findings.

5.2 Motivation

Management strategies are robust when they perform relatively well across a range of possible future states (Lempert et al. 2006). Robustness methods, including MR applications, are generally motivated by the presence of ‘deep’ uncertainties (Woodward and Bishop 1997; Dessai and Hulme 2007; Clarke 2008; Hine and Hall 2010; Green and Weatherhead 2014). Uncertainty is ‘deep’ when probability or outcome information is ambiguous or lacking. Decision-making under risk, in contrast, assumes known probabilities of possible outcomes (Hogarth and Kunreuther 1995). Climate change uncertainties have been classified as ‘deep’ (Kandlikar et al. 2005).

In this paper, robust solutions that minimise maximum regret are analysed (cf. Averbakh 2000). Regret is a context-dependent measure, because its value follows from outcome comparisons. Context-dependency implies that regret values may change under different scenarios or investment alternatives. As a result, no fixed relationship exists between a possible outcome and the objective variable assumed in standard economic theory (e.g. Yager 2004). Therefore, a decision-maker's ability to anticipate regret induces axiom violations of expected utility theory (Loomes and Sugden 1982).

Minimisation of maximum regret implies an infinite aversion against worst-case regret for a given set of investment opportunities and scenarios. In flood risk management, decision-makers are often regret- or loss averse. The common use of safety margins reveals loss aversion. The 'minimax' criterion analyses maximum losses. However, 'minimax' solutions may be associated with large regret, which advocates MR analysis. Regret arises both from under- and overinvestment. For example, a 'very high' dike may be robust to virtually any climate change impact scenario with barely any flood risk remaining. Therefore, the largest dike investment possible minimises maximum losses. Yet, this is not a low-regret solution, as these investment costs will largely outweigh damage reduction under any scenario (cf. Brekelmans et al. 2012).

MR analysis has several practical advantages over other robustness and expected-value methods. Application of the MR criterion does not require probabilistic information. The use of subjective probability distributions in expected-value approaches is controversial, and might result in 'bad' adaptation decisions (Hall 2007). It is generally considered easier to formulate a range of scenarios, for example by setting parameter intervals, than to attach probability distributions to these intervals. Furthermore, the MR decision criterion does not rely on arbitrary scenario weights such as the Laplace decision criterion, which uses equal scenario probabilities, the Hurwicz decision criterion, which employs weights for pessimism and optimism, or combined decision criteria (e.g. Gaspars-Wieloch 2014). Moreover, MR analysis usually yields a unique solution. More recent robust decision-making methods, such as info-gap theory, give insights in the robustness of solutions under different degrees of uncertainty (e.g. Hine and Hall 2010). Info-gap theory, however, does not prescribe which measures to implement.

5.3 Static versus dynamic regret minimisation

The MR decision criterion is mostly applied in static settings (Hayashi 2011). Let $C(s,z)$ be the Net Present Value (NPV) of the total costs of option z under climate scenario $s \in \theta$. The maximum absolute regret (R) for mutually exclusive adaptation investment options $z, y \in Z$ is mathematically defined by (e.g. Kasperski 2008)

$$R(z) = \max_{s \in \theta}\{C(s,z) - \min_{y \in Z} C(s,y)\}. \tag{5.1}$$

The MR objective is given by

$$R^* = \min_{z \in Z} R(z). \tag{5.2}$$

Hence, the investment option that minimises maximum regret is

$$z^* = \arg\min_{z \in Z}\{R(z)\}. \tag{5.3}$$

Sequential repetition of MR analysis over time could lead to dynamically inconsistent decisions as discussed by Hayashi (2011). However, no procedure was provided to resolve this problem. Dynamic consistency "imposes that the sequence of choice dispositions of the decision-maker's successive 'selves' has to be connected across date-events in a recursive manner" (Hayashi 2011). In other words, dynamic inconsistency arises when a decision-maker commits to an initial plan as his final, but would prefer to change it later on. Time-inconsistent decisions originate from context-dependency, as briefly explained in Section 5.2. Information arrival implies a change in scenarios. Therefore, regrets change on arrival of new information even if the scenario payoffs remain unchanged. This, in turn, may result in a change of the initial plan, which is dynamically inconsistent.

To address this problem, we suppose that a decision-maker is not only capable of anticipating regret, but also has the analytical capacity to anticipate future optimal decisions, i.e. future decisions which minimise maximum regret for any hypothetical sequence of previous decisions and events. In contrast to the time-inconsistent implementation of Hayashi (2011), our method removes any future suboptimal decision by a backward induction procedure. We will first illustrate the procedure by means of an example and formalise it in Section 5.4.2.

Consider forward-looking regret in the two-period investment problem of Figure 5.1.

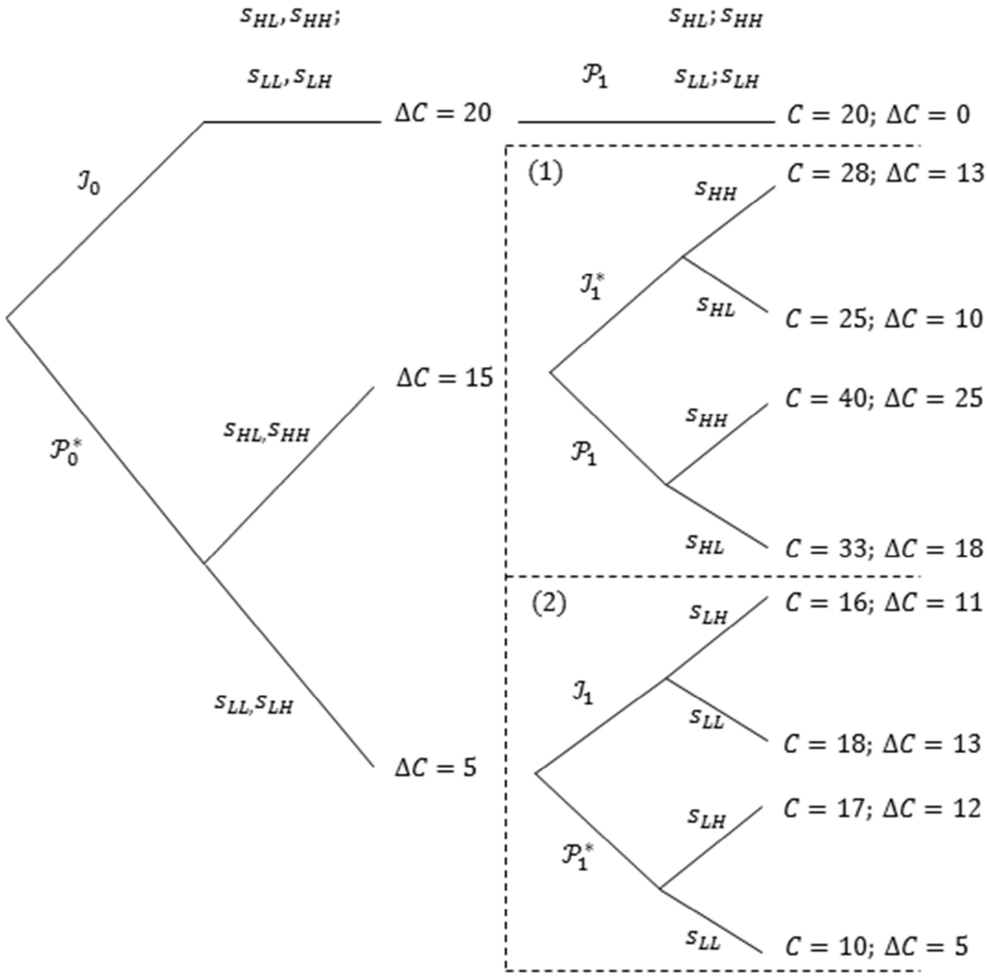

Figure 5.1 Decision-event-outcome tree for a two-period investment problem. The sub-trees, marked (1) and (2), are solved to determine optimal decisions at decision moment t_1 given that the initial decision is to postpone the investment

At moment t_0, the decision maker either chooses to invest ($\mathcal{J}_0$) or to postpone ($\mathcal{P}_0$) investment. The set of climate scenarios at decision moment t_0 is $\theta_0 = \{s_{LL}, s_{LH}, s_{HL}, s_{HH}\}$. Under strategy $(\mathcal{J}_0, \mathcal{P}_1)$, i.e. invest at t_0 and postpone investment at t_1, total costs are assumed to be scenario-independent, which is displayed in the upper branch of the tree in Figure 5.1. Consider that at decision moment t_1 it will be known whether or not climate change is severe or less severe with scenarios s_{HL}, $s_{HH} \in \theta_1$ or s_{LL}, $s_{LH} \in \theta_1$, respectively. If the investment decision is postponed to moment t_1, one can either invest ($\mathcal{I}_1$) at t_1 or postpone again ($\mathcal{P}_1$).

The anticipated regret at moment t_1 after decision $\mathcal{P}_0$ and new information s_{HL}, $s_{HH} \in \theta_1$ does not depend on the costs (15) incurred up to moment t_1, but only on the consecutive outcome changes from the decision at t_1 (respectively, $+13, +10, +25, +18$). The reader can verify that the minimising maximum regret decision at moment t_1 is $\mathcal{I}_1$ under climate information s_{HL}, $s_{HH} \in \theta_1$, and $\mathcal{P}_1$ under information s_{LL}, $s_{LH} \in \theta_1$. This result is obtained from the static application of the MR decision criterion to sub-trees (1) and (2) in Figure 5.1 respectively.

The initial optimal decision is derived from deleting outcomes of sub-optimal decisions from the next period. In the example, outcomes of decision $\mathcal{P}_1$ under scenarios s_{HL}, $s_{HH} \in \theta_1$, and outcomes of decision i_1 under scenarios s_{LL}, $s_{LH} \in \theta_1$ are removed. This results in the decision tree displayed in Figure 5.2. Applying MR Eqs. (1) and (2) to this problem leads to the optimal decision at t_0 to postpone investment. This is followed by investment at t_1 under climate information s_{HL}, $s_{HH} \in \theta_1$, and no investment under climate information s_{LL}, $s_{LH} \in \theta_1$. Note that this investment plan is dynamically consistent, because the decision-maker will stick to the initial plan throughout the time horizon under every course of events.

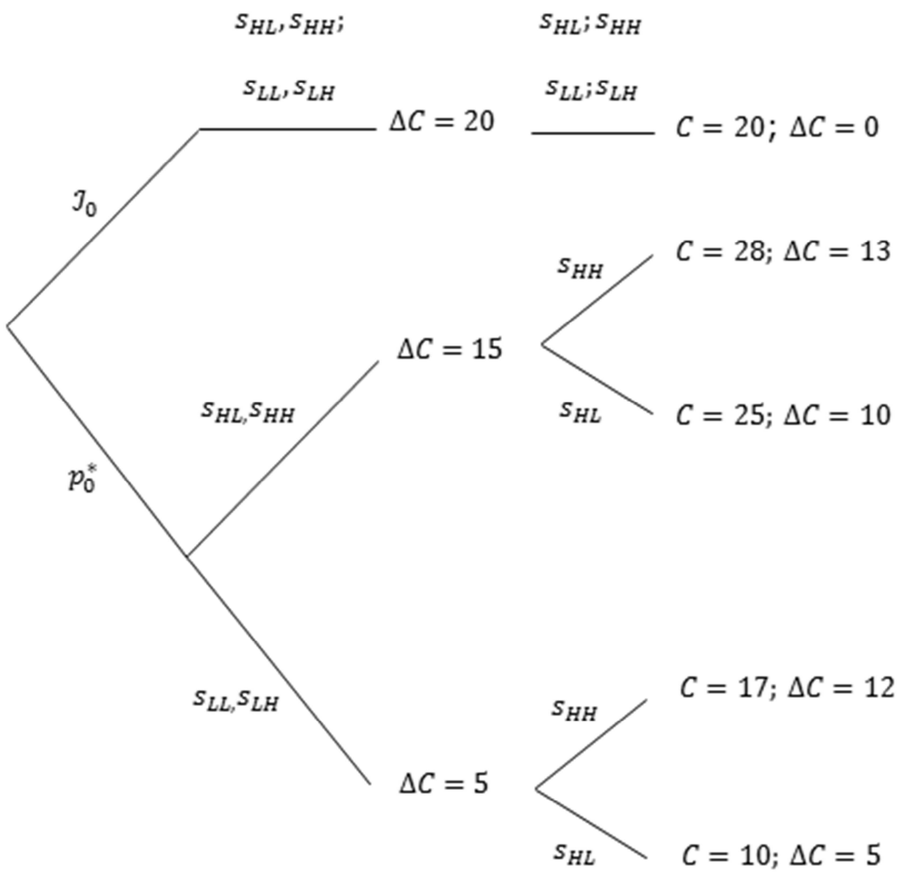

Figure 5.2 Decision-tree after removal of non-optimal branches of the second period

5.4 A flood risk management application

Section 5.4.1 describes a conceptual flood risk management (FRM) model for a stylised FRM investment problem. The dynamic MR procedure explained in the previous section is applied to this model in Sections 5.4.2-4.3.

5.4.1 A conceptual flood risk management model

Consider the problem of increasing river peak flows due to climate change and a river dike protecting agricultural land as well as urban area. The current river dike is expected to provide less flood protection in the future due to the impact of climate change on peak flows. A quick-scan of possible adaptation options suggests two alternative adaptation strategies: either raising the existing river dike, or creating detention compartments on agricultural land. In the latter case, agricultural land can be deliberately flooded in order to attenuate peak flows to prevent flooding of the downstream urban area. However, damages arise from yield losses when detention area is used. Figure 5.3 illustrates the problem setting studied in the remainder of this paper.

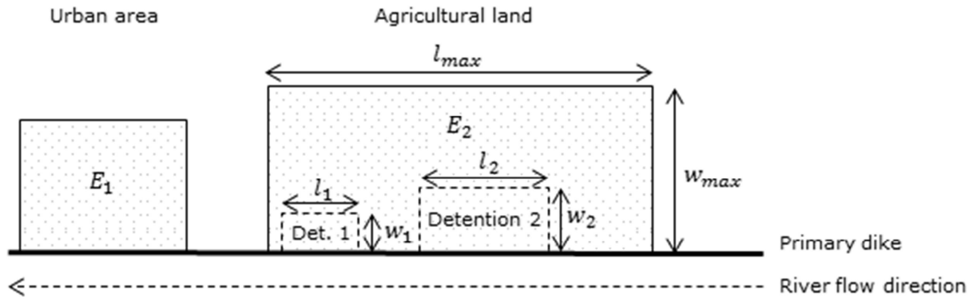

Figure 5.3 Graphical representation of the problem setting for two detention compartments

Figure 5.3 displays the length (l_{max}) and the width (w_{max}) of the agricultural land. The urban area is denoted by E_1, and the total area of agricultural land is denoted by E_2. Upstream of the urban area, the agricultural land can be used to create one or more rectangular detention compartments next to the existing primary dike. We assume that the existing dike can be used as one of the sides of the detention compartments. Detention compartment lengths are denoted by l_k, with $k = 1,2,\dots,K$ and $l_k \leq l_{max}$, and compartment widths are denoted by w_k with $w_k \leq w_{max}$. The compartments can be flooded in a cascading order such that the agricultural area that has to be flooded in order to prevent flooding of the urban area is minimised.

We study a two-period investment problem with an infinite time horizon divided into three parts: $[t_0, t_1)$, $[t_1, T)$, and $[T, \infty)$. At decision moments t_0 and t_1 investment can take place in either the primary dike or in detention storage. In the sequel, we denote these decisions moments by t_j $(j = 0,1)$. At the initial decision moment (t_0), three different peak flow projections are available: a low (s_L), a medium (s_M) and a high (s_H) peak flow scenario. We denote the set of peak flow scenarios at decision moment t_j by θ_j. At t_0 the set of peak flow scenarios consists of three scenarios, $\theta_0 = \{s_L, s_M, s_H\}$. Every peak flow scenario describes the development of an annual peak flow distribution, which is shifting over time due to climate change. The annual maxima of peak flows Q are distributed according to a Gumbel distribution, a subtype of the Generalised Extreme Value (GEV) distribution without shape parameter, with cumulative distribution function (Gumbel 1941)

$$F_t(Q,s) = \exp\left[-\exp\left\{-\left(\frac{Q-\mu_t(s)}{\sigma_t(s)}\right)\right\}\right], \tag{5.4}$$

where $\mu_t(s)$ is the location parameter, the mode, and $\sigma_t(s)$ is the scale parameter for peak flow scenario s at year t. Hence, a peak flow scenario s defines distribution parameters of the annual peak flow distribution for any year t: $(\mu_0(s), \mu_1(s), \dots; \sigma_0(s), \sigma_1(s), \dots)$. Note that mean and variance follow from the location and scale parameters (e.g. Forbes et al. 2011).

It is not only uncertain how peak flows will develop, but it is also hard to predict whether or not peak flow uncertainty will be reduced in the future. The future range of peak flow projections depends on future peak flow observations and new insights from improved climate models. We model possible futures by three ‘learning scenarios’, each represented by one or more information sets at t_1:

- ‘no learning’ scenario: the set of peak flow scenarios remains the same as today, with no-learning information set $\theta_1 = \{s_L, s_M, s_H\}$,
- ‘uncertainty reduction’ scenario: the set of peak flow scenarios becomes smaller, either s_L or s_H disappears from the original set, with uncertainty reduction set $\theta_1 = \{s_L, s_M\}$, or $\theta_1 = \{s_M, s_H\}$,
- ‘uncertainty resolution’ scenario: complete knowledge on the development of the annual peak flow distribution is obtained, with uncertainty resolution set $\theta_1 = \{s_L\}$, $\theta_1 = \{s_M\}$ or $\theta_1 = \{s_H\}$.

To capture the notion of information sets, consider information superset Θ_j, which contains possible information sets at decision moments t_j. At decision moment t_0 the superset contains only one set as θ_0 is given. At moment t_1, the information superset contains the information sets from the different learning scenarios, i.e. $\Theta_1 = \{\{s_L, s_M, s_H\}, \{s_L, s_M\}, \{s_M, s_H\}, \{s_L\}, \{s_M\}, \{s_H\}\}$.

Our conceptual FRM model contains a stage-discharge relationship and a peak flow attenuation function (cf. Westphal et al. 1999; Vis et al. 2003). These functions characterise the risk of flooding under different investment decisions.

The model also contains simple investment cost functions and damage cost functions. The model is described as follows:

Indices

$j = 0,1$	Decision moment index
$k = 1,2,\ldots,K$	Detention compartment index
$t = 0,1,2,\ldots,\infty$	Year

Data

$\theta_j \subseteq \Theta_j$	Set of peak flow scenarios at decision moment t_j
$s \in \theta_j$	Peak flow scenario describing an annual peak flow distribution over time
$\mu_t(s)$	Location parameter of annual peak flow distribution in year t under scenario s
$\sigma_t(s)$	Scale parameter of annual peak flow distribution in year t under scenario s
α_1, α_2	Stage-discharge function coefficients
$\beta_1, \beta_2, \beta_3$	Storage-attenuation function coefficients
c_1, c_2, λ	Investment cost function coefficients of primary dike
d_1, d_2, d_3	Investment cost function coefficients of detention storage
p_1	Damage value per unit of flooded urban area per flooding event
p_2	Yield loss per unit of flooded agricultural land per flooding event
l_{max}	Length of agricultural land
h_{max}	Maximum dike height of the primary dike
w_{max}	Width of agricultural land
E_1	Total urban area
E_2	Total agricultural area

Stock variables

h_j	Dike height of primary dike at decision moment t_j before heightening
x_{jk}	Storage volumes of existing compartments $k = 1, \ldots, K_1$ at moment t_j

Decision variables

u_j	Dike increment of primary dike at moment t_j
v_{jk}	Storage volume of new compartment $k = K_1 + 1, \ldots, K$ at moment t_j

l_{jk} Detention length of compartment k at moment t_j
w_{jk} Detention width of compartment k at moment t_j

Objective function at t_0
Minimisation of maximum regret at the initial decision moment (t_0) is defined by

$$R^* = \min\{R_A, R_B\}, \tag{5.5}$$

with R_A maximum regret under optimal investment in the primary dike (option A) and R_B under optimal floodplain investment in detention compartments (option B). Sections 5.4.2-5.4.4 describe how R_A and R_B are obtained.

Constraints
Detention compartment width and length:

$$w_{jk} \leq w_{max} \qquad \forall j, k \tag{5.6a}$$

$$\sum_{k=1}^{K} l_{jk} \leq l \qquad \forall j. \tag{5.6b}$$

Note that $l_{jk} = 2w_{jk}$, which maximises the surface of a rectangular detention area for a given detention dike length, as one of the compartment sides is covered by the existing primary dike. Detention volume is described by

$$x_{jk} = 2w_{jk}^2 g \qquad \forall j, k \qquad \Leftrightarrow \qquad w_{jk} = \sqrt{\frac{x_{jk}}{2g}}, \tag{5.7}$$

where g is the 'effective storage height' capturing the distance between the critical height of the floodplain dikes and the datum, i.e. the reference level of the surface, which is assumed to be constant, and a fixed amount of storage in the subsurface per surface unit.

Dike height is characterised by

$$h_{j+1} = h_j + u_j. \tag{5.8}$$

The case of mutually exclusive investment options is studied. At moment t_0 this is achieved by

$$u_0 v_{0k} = 0 \qquad \forall k, \tag{5.9a}$$

and at moment t_1 by

$$h_1 v_{1k} = 0 \quad , \quad u_1 x_{1k} = 0 \qquad \forall k. \tag{5.9b}$$

Damage cost functions

We assume that if river stage S exceeds critical level ($\bar{S}$), the primary dike fails, otherwise it does not. In case of primary dike failure, flood losses are assumed to be constant and independent of inundation depth[7]

$$D_1 = p_1 E_1 + p_2 E_2. \tag{5.10}$$

Annual use of detention compartments without primary dike failure gives damages from yield losses in the compartments approximated by:

$$D_2\left(n(Q, x_{jk}), w_{jk}(x_{jk})\right) = \sum_{k=1}^{n(Q,x_{jk})} 2w_{jk}^2 p_2 \, , \tag{5.11}$$

where $n(Q, x_{jk})$ is the required number of detention compartments for a given peak flow event Q.

Investment cost functions

The investment cost functions of dike construction or heightening are represented by an exponential function described by Brekelmans et al. (2012). Dike increments are denoted by u_j, and the cost function of heightening the primary dike by

$$I_A(h_j, u_j) = \begin{cases} c_1 + c_2 u_j e^{\lambda h_{j+1}} & if\ u_j > 0 \\ 0 & if\ u_j = 0 \end{cases} \tag{5.12}$$

where h_{j+1} is the relative dike height after heightening at t_j with $h_0 = 0$, parameter c_1 the per kilometre heightening costs, c_2 the variable costs of heightening the primary dike and λ the per centimetre incremental costs per kilometre of dike.

[7] In actual model applications more complex damage specifications can be included, e.g. damages depending on inundation depth and flood duration.

The storage cost function is represented by

$$I_B(v_{jk}) = \begin{cases} d_1 + d_2 \sum_{k=K_1+1}^{K} v_{jk} + d_3 \sum_{k=K_1+1}^{K} \sqrt{v_{jk}} & if \sum_{k=K_1+1}^{K} v_{jk_1+1} > 0 \\ 0 & if \sum_{k=K_1+1}^{K} v_{jk_1+1} = 0 \end{cases} \tag{5.13}$$

where d_1 are the fixed costs of investment in detention storage, and d_2 is a linear cost parameter, which includes a cost estimate of average infrastructure protection and land purchase costs per unit of detention. Construction costs of the floodplain dikes surrounding the detention compartments are captured in d_3. This term reflects 'economies of scale', which implies that increasing the capital investment in detention results in a more than proportional increase in detention volume. Note that $I_B(v_{jk})$ does not depend on previously constructed detention compartments (indexed $k = 1, \ldots, K_1$).

Stage-discharge relationship

Peak flow events result in increasing water levels, called surface water elevation, or stage. Stage can be studied in detail for peak flow events given the water bed form, roughness coefficients, and river bed elevation differences. An alternative is to identify a stage-discharge relationship, which can be directly applied to analyse FRM strategies (e.g. Hoekstra and De Kok 2008). Stage-discharge relationships are represented by a power function (e.g. Westphal et al. 1999)

$$S = \alpha_1 Q^{\alpha_2} \qquad \Leftrightarrow \qquad Q = \left(\frac{S}{\alpha_1}\right)^{\frac{1}{\alpha_2}}, \tag{5.14}$$

where S is the surface water elevation, Q is the annual maximum peak flow discharge, and α_1 and α_2 are constants.

Peak flow attenuation function

In order to attenuate peak flows to a given peak flow base level (Q_{base}) required detention storage volume $H(Q)$ is represented by a quadratic function of peak discharge Q (cf. Vis et al. 2003)

$$H(Q) = \begin{cases} \beta_1 + \beta_2 Q + \beta_3 Q^2 & if\ Q > Q_{base} \\ 0 & if\ Q \leq Q_{base} \end{cases} \tag{5.15}$$

5.4.2 The primary dike problem

We first derive optimal investment strategies for the primary dike. Consider the present value of the terminal costs V_2 from moment T onwards. Define a cumulative distribution function $G_t(S,s)$, which is obtained by substituting Eq. (5.14) into Eq. (5.4). For the terminal condition we will assume that $\mu_t(s) = \bar{\mu}(s)$ and $\sigma_t(s) = \bar{\sigma}(s)$ from T onwards. As a consequence, the annual flood probability $P_t(h,s)$ is constant on interval $[T,\infty)$ for a given dike height and peak flow scenario. Define this probability by $\bar{P}(h,s) = 1 - G_t(\bar{S}(h),s)$, where $\bar{S}(h)$ is the critical surface water elevation for a dike with height h. Terminal costs are given by

$$V_2(h,s,u=0) = \sum_{t=T}^{\infty} \frac{\bar{P}(h,s)D_1}{(1+\delta)^t} = \frac{\bar{P}(h,s)D_1}{\delta(1+\delta)^{T-1}} \tag{5.16}$$

For a given dike height h, peak flow development scenario s and dike increment decision u, the present value of the expected costs under scenario s from decision moment t_1 onwards is

$$V_1(h,s,u) = \frac{1}{(1+\delta)^{t_1}} I_A(h,u) + \sum_{t=t_1}^{T} \frac{P_t(h_2,s)D_1}{(1+\delta)^t} + V_2(h_2,s,0), \tag{5.17}$$

where $h_2 = h + u$. Given dike height h and information set $\theta \in \Theta_1$, the MR decision at moment $t_1$is

$$u^*(h,\theta) = \underset{u\in[0,h_{max}-h]}{\arg\min}\ \max_{s\in\theta} \left(V_1(h,s,u) - \min_{v\in[0,h_{max}-h]} V_1(h,s,v) \right). \tag{5.18}$$

For the perfect learning case, the MR computation (Eq. (5.18)) is trivial, as $\theta_1$contains only one scenario for this case (s_L, or s_M, or s_H). As a result, maximum regret is zero under the optimal strategy, which coincides with a deterministic cost minimising investment.

Once all regret minimising decisions $u^*(h,\theta)$ for decision moment t_1 have been identified, $V_1(h,s,u)$ is replaced by $V_1^*(h,s(\theta)) = V_1\big(h,s(\theta),u^*(h,\theta)\big)$, i.e.

any $u(h,\theta) \neq u^*(h,\theta)$ will not be implemented at decision moment t_1. If the primary dike is raised at the first decision moment (t_0) the optimal investment in the primary dike at this moment is

$$u^* = \underset{u\in[0,h_{max}]}{\arg\min} \max_{\theta_1\in\Theta_1} \max_{s\in\theta_1} \left(\left(I_A(h=0,u) + \sum_{t=0}^{t_1} \frac{P_t(u,s)D_1}{(1+\delta)^t} + V_1^*\big(h_1 = u, s(\theta_1)\big) \right) - \min_{v\in[0,h_{max}]} \left(I_A(h=0,v) + \sum_{t=0}^{t_1} \frac{P_t(v,s)D_1}{(1+\delta)^t} + V_1^*\big(h_1 = v, s(\theta_1)\big) \right) \right). \quad (5.19)$$

5.4.3 The floodplain problem

Next, we derive optimal investment strategies for the floodplain. Recall that $n(Q, x_{jk})$ is the number of required detention compartments for a given peak flow $Q > Q_{base}$. The number of required detention compartments is determined by

$$\sum_{k=1}^{n-1} x_{jk} < H(Q > Q_{base}) \leq \sum_{k=1}^{n} x_{jk} \ , \quad (5.20)$$

where $H(Q)$ follows from inserting Q in Eq. (5.15). Hence, the *maximum* peak flow Q for which the number of required detention compartments is equal to n is defined by

$$Q_{up}(n) = \frac{1}{2\beta_3} \left(-\beta_2 \pm \sqrt{{\beta_2}^2 - 4\beta_3(\beta_1 - \sum_{k=1}^{n} x_{jk})} \right). \quad (5.21a)$$

The *minimum* peak flow for which n detention compartments are required is

$$Q_{low}(n) = \frac{1}{2\beta_3}\left(-\beta_2 \pm \sqrt{{\beta_2}^2 - 4\beta_3(\beta_1 - \sum_{k=1}^{n-1} x_{jk})}\right) + dQ. \qquad (5.21b)$$

The probability P_{nt} that the number of used detention compartments is equal to n under peak flow scenario s in year t is

$$P_{nt}(s) = F_t\big(Q_{up}(n), s\big) - F_t(Q_{low}(n), s)\,, \qquad (5.22)$$

with $P_{nt}(s) = \bar{P}_n(s)$ on interval $[T, \infty)$. Define $Q_{max}(K_1) := Q_{up}(n = K_1)$, which is the maximum peak flow whose water can be stored in the existing K_1 detention compartments without causing flooding of the urban area. The present value of the total expected damage costs under scenario s on interval $[T, \infty)$ is

$$V_2(x_k, s, v_k = 0) =$$

$$\sum_{t=T}^{\infty}\sum_{n=1}^{K_1}\left(\frac{\bar{P}_n(s) D_2(n, w_k(x_k))}{(1+\delta)^t}\right) + \sum_{t=T}^{\infty}\frac{\Big(1 - F\big(Q_{max}(K_1)\big)\Big) D_1}{(1+\delta)^t}\,, \qquad (5.23)$$

where the first term of the right-hand side consists of expected damages due to the use of detention compartments to prevent flooding, and the second term contains expected damages due to failure of the primary dike.

The remainder of the floodplain problem follows the same lines as the primary dike problem. Given compartment volumes x_k and information set $\theta \in \Theta_1$, the MR decision at moment t_1 is

$$v_k^*(x_k, \theta) = \underset{v_k}{\arg\min}\max_{s\in\theta}\Big(V_1(x_k, v_k, s(\theta)) - \min_{u_k} V_1(x_k, u_k, s(\theta))\Big). \qquad (5.24)$$

Again, $V_1(x_k, s, v_k)$ is replaced by $V_1^*(x_k, s(\theta)) = V_1(x_k, s(\theta), v_k^*(x_k, \theta))$ and is substituted in the MR equation for moment t_0. This results in the optimal initial investment in the floodplain.

5.4.4 Investment selection and threshold-to-switch

The choice for either investment in the primary dike or in floodplain development follows from the cost differences *between* the options given the optimal investment strategies under the different learning scenarios. Between-option regrets are calculated as follows:

$$R_A = \max_{\theta_1 \epsilon \Theta_1} \max_{s \in \theta_1} \{V_A(\theta_1, s) - V^*(\theta_1, s)\} \tag{5.25a}$$

$$R_B = \max_{\theta_1 \epsilon \Theta_1} \max_{s \in \theta_1} \{V_B(\theta_1, s) - V^*(\theta_1, s)\} \tag{5.25b}$$

where $V_A(\theta_1, s)$ and $V_B(\theta_1, s)$ are the total discounted costs under scenario s and information set $\theta_1 \in \Theta_1$ for investment in the primary dike, and investment in detention compartments, respectively. The maximum regret minimising investment option is obtained by substituting R_A and R_B from Eq. (5.25a) and Eq. (5.25b) in Eq. (5.5).

To examine differences in flexibility between the two investment options, we will also study the threshold-to-switch from investment in the primary dike, to investment in the detention compartments based on adaptation capital accumulation. For comparison, the average of the total discounted capital investments under the specified learning scenarios is used as a negative measure of flexibility, i.e.

$$\bar{K}_A = I_A(u_0^*) + \frac{1}{L}\sum_{l=1}^{L} \frac{I_A(h_1 = u_0^*, u_1^*(\theta_1(l)))}{(1+\delta)^{t_1}} \tag{5.26a}$$

$$\bar{K}_B = I_B\left(v_{j=0,k}^*\right) + \frac{1}{L}\sum_{l=1}^{L} \frac{I_B\left(v_{j=1,k}^*(\theta_1(l))\right)}{(1+\delta)^{t_1}}, \tag{5.26b}$$

where $L = |\Theta_1|$, which is the number of learning scenarios. Next, the average total discounted capital is minimised under an acceptable maximum regret, where maximum regret is allowed to be higher than R^*. Thus,

$$\min(\bar{K}_A, \bar{K}_B) \quad s.t. \quad R_A \leq (1+\alpha)R^* \ , \ R_B \leq R^*(1+\alpha). \tag{5.27}$$

Switching can occur if $\bar{K}_A < \bar{K}_B$ and $R_A > R_B$, or if $\bar{K}_B < \bar{K}_A$ and $R_B > R_A$. The switching threshold $\tilde{\alpha}$ is:

$$\tilde{\alpha} = \frac{|R_A - R_B|}{R^*}. \tag{5.28}$$

Thus, $\tilde{\alpha}$ reflects the amount of additional maximum regret as a fraction of R^* that has to be allowed in order to reduce adaptation capital accumulation by switching between the investment options.

5.5 Implementation and results

In this section, results are presented of a numerical implementation of the conceptual FRM model. The results illustrate the effects of emerging information on optimal initial investment and on the optimal decisions after information arrival.[8] Outcomes of static and dynamic MR analysis are compared.

5.5.1 Implementation

The conceptual model of Section 5.4 is calibrated with peak flow information and information on dike and detention investment options from the lower Rhine River for which data was readily available from the literature (cf. Vis et al. 2003; Hoekstra and De Kok 2008; Hurkmans et al. 2010). We use our own assumptions where appropriate. Baseline annual peak flow distribution of the river Rhine at gauging station Lobith are reported by Hoekstra and De Kok (2008). They describe an 'extreme' peak flow scenario in which the design discharge with a return period of 1250 years increases from 16000 m^3 / sec. to 20000 m^3 / sec. by the year 2100. We adopt this scenario as an upper scenario for 2100 and define two other peak flow scenarios for 2050 and 2100. We consider that the design peak flow of 16000 m^3 / sec. today changes to 17000, 18500 and 19000 m^3 / sec. in 2050 under scenarios s_L, s_M and s_H, respectively, and to 16700, 18000 and 20000 m^3 / sec. in 2100. Note that the frequency of occurrence of peak flow extremes in the second half of this century decreases under scenarios s_L and s_M as compared to 2050. This is in line with the general findings reported in Hurkmans et al. (2010). Peak flow distribution parameter estimates are obtained for intermediate years by interpolation of the original and the scenario parameters (Kharin and Zwiers 2005).

Table 5.2 summarises the other parameters for the numerical case study. The investment cost function is taken from a Dutch dike ring at the Lobith-Westervoort-Doetinchem area (den Hertog and Roos 2008). Land use is assumed

[8] Note that optimal decisions after information arrival have been called 'optimal recourse' decisions in the operations research literature.

to be predominantly agricultural. Illustrative dimensions of the rural and urban areas are considered to describe the surface area of the case study. The effective distance between the datum and the water table is assumed to be small, which implies the retention capacity in the subsurface to be limited. The dimensions of the agricultural land (l_{max} and w_{max}) are calibrated such that the demand for storage capacity is not restricted by the area dimensions. In practice, this is not always the case at downstream river locations, for example, at the lower river Rhine.

Floodplain construction is usually relatively expensive in comparison with raising an existing dike. This is mainly due to the purchase of land and the costs of protection of infrastructure in the area (cf. Vis et al. 2003; Brouwer and van Ek 2004). We consider a Dutch average agricultural land price of 3.5 €/ m^2, and consider that 5% of the floodplain area has to be converted at this price with no alternative use. Note that farmers are compensated for inundation damages, which enters the model through the damage function. A fraction of 0.7 of the land acquisition costs is used to represent the average infrastructure protection costs per m^2, for example to protect roads and bridges within a detention area.[9] This results in an estimate of 0.3 €/ m^2, which is divided by the effective storage height (g), here assumed to be equal to 1 meter to obtain the value of parameter d_2. We consider that floodplain dikes are relatively inexpensive as compared to primary dikes, and assume 1.4 million € / km to calibrate parameter d_3. Fixed costs of detention are assumed to be lower than of the primary dike at 10 million €. A primary dike might involve more planning costs, because it stretches out over an entire dike ring (cf. den Hertog and Roos 2008). For flooding of residential and agricultural land constant value losses per square meter per flooding event are used, respectively, derived or taken from the literature (Vis et al. 2003; de Moel and Aerts 2011).

[9] These costs depend on local conditions. For example, in Brouwer and van Ek (2004) a fraction of 2445/1790=1.4 is reported.

Table 5.2 Default calibration

Parameter	Value	Units	Based on:
μ_0	$5.170 \cdot 10^3$	$m^3 s^{-1}$	Hoekstra and De Kok (2008): Rhine at Lobith
σ_0	$1.519 \cdot 10^3$	$m^3 s^{-1}$	Hoekstra and De Kok (2008): Rhine at Lobith
α_1	0.7953	$m^{1-3\alpha_2} s^{\alpha_2}$	Hoekstra and De Kok (2008)
α_2	0.3229	-	Hoekstra and De Kok (2008)
β_1	$1.093 \cdot 10^{10}$	m^3	Vis et al. (2003): quadratic regression
β_2	$-1.53 \cdot 10^6$	s	Vis et al. (2003): quadratic regression
β_3	53.43	$m^{-3} s^2$	Vis et al. (2003): quadratic regression
c_1	$3.5625 \cdot 10^7$	€	den Hertog and Roos (2008): ring 48
c_2	$1.425 \cdot 10^6$	€ cm^{-1}	den Hertog and Roos (2008): ring 48
λ	0.0063	cm^{-1}	den Hertog and Roos (2008): ring 48
d_1	$1.0 \cdot 10^7$	€	own assumption: see in-text explanation
d_2	0.3	€ m^{-3}	own assumption: see in-text explanation
d_3	4.0	€ m^{-3}	own assumption: see in-text explanation
l_{max}	$4.00 \cdot 10^4$	m	own assumption: see in-text explanation
w_{max}	$2.00 \cdot 10^4$	m	own assumption: see in-text explanation
E_1	$8.00 \cdot 10^7$	m^2	own assumption: see in-text explanation
p_1	75.60	€ m^{-2}	de Moel and Aerts (2011): residential value* damage factor (0.3)
p_2	0.11	€ m^{-2}	Vis et al. (2003)
δ	0.04	-	den Hertog and Roos (2008): risk-free rate + risk premium
g	1	m	own assumption: see in-text explanation

The decision space of dike height is discretised to steps of $\Delta u = 1$ cm with a maximum dike height of h_{max}. Dike increments of the primary dike (u_t), therefore, take values $0, \Delta u, \dots, h_{max} - h_t$. The detention volumes are discretised in steps of $\Delta v_k = 50\,(10^6 m^3)$ and the construction of a maximum of two detention compartments per period (2x2) are allowed. We implemented and solved the problem in Matlab R2013a. Running times are modest (seconds to minutes) due to the specified number of decision moments and the coarse grid. The code is available upon request.

5.5.2 Results

Figure 5.4 displays the optimal dike height strategy for the uncertainty base case without learning, and optimal strategies for the specified learning scenarios. The optimal increment at t_0 is 55 cm for the uncertainty base case without learning, followed by an increment of 33 cm at t_1. This strategy is optimal under the *static* minimisation of maximum regret, in which it is assumed that the information set remains unchanged over time ($\theta_0 = \theta_1 = \{s_L, s_M, s_H\}$). Interestingly, the initial optimal increment is 58 cm under the *dynamic* minimisation of maximum regret for the learning scenarios contained in $\Theta_1 = \big\{\{s_L, s_M, s_H\}, \{s_L, s_M\}, \{s_M, s_H\}, \{s_L\}, \{s_M\}, \{s_H\}\big\}$. This result of an increase of the initial investment due to future learning is counter-intuitive at first sight. However, it is a consequence of both the timing of the second decision, which is in the year 2050, as well as the optimal decisions that would follow at this decision moment after information arrival, which are zero (i.e.: no heightening) if peak flow increase turns out to be low ($\theta_1 = \{s_L\}$), or low or moderate ($\theta_1 = \{s_L, s_M\}$). Under the higher peak flow scenarios $\{s_M, s_H\}$, $\{s_M\}$ and $\{s_H\}$, optimal increments are 48 cm, 37 cm, and 58 cm at t_1, respectively. As a result, total discounted costs and regret decrease under worst-case scenarios by increasing the initial investment as compared to the base case strategy without learning.

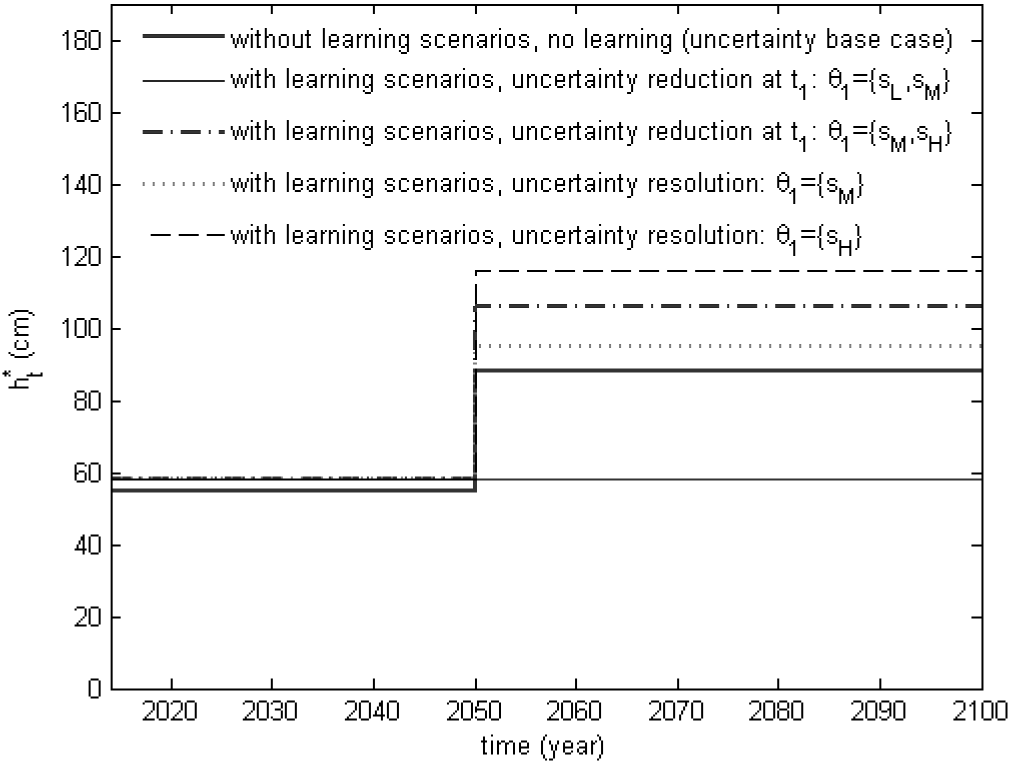

Figure 5.4 Optimal dike height strategy for the uncertainty base case without learning (static regret) and optimal strategies under a number of learning scenarios (dynamic regret)

The optimal floodplain development is to first invest in one detention compartment with a storage capacity of 250 million m^3 for the default calibration with economies of scale ($d_3 = 4.0$). Recall that parameter d_3 represents the economies of scale component of the investment cost function (Eq. (5.13)). For this case, the reduction in damages from yield losses by the creation of a second detention compartment does not outweigh the investment costs to create it. The optimal decisions after information arrival are displayed in Table 5.3. The investment pattern is similar to the one found for the dike height problem. Under scenarios $\{s_L, s_M\}$, $\{s_L\}$ and $\{s_M\}$ and $d_3 = 4.0$ no second investment would be required. For this case, information that peak flow increase is moderate or high ($\{s_M, s_H\}$), or just high ($\{s_H\}$) results in a second investment of 250 million m^3 and

400 million m^3, respectively. When uncertainty is not reduced at t_1, an additional 150 million m^3 is needed. Without economies of scale ($d_3 = 0.0$) two unequally sized detention compartments would be constructed at the initial decision moment (t_0) with volumes of 100 million m^3 and 200 million m^3. For any case, the total storage volume remains below the 2000 million m^3 that would be required at the end of the century to accommodate a peak flow event with a return period of 1250 years under peak flow scenario s_H. This implies that a higher flood probability will be accepted with time, which is caused by the relatively high investment costs. This effect is smaller when investment in the floodplain would be less expensive (for example, if $d_2 = 0$, or $d_3 = 0$), which results in larger optimal detention storage volumes; a total of 800 million m^3 of storage would be optimal under learning scenario $\theta_1 = \{s_H\}$ and $d_3 = 0$.

Table 5.3 Optimal investments in detention volume at decision moment t_1

	$d_3 = 4.0$		$d_3 = 0.0$	
θ_1	v_{12}^* $(x_k = 0, \theta_1)$ (million m^3)	v_{13}^* $(x_k = 0, \theta_1)$ (million m^3)	v_{13}^* $(x_k = 0, \theta_1)$ (million m^3)	v_{14}^* $(x_k = 0, \theta_1)$ (million m^3)
$\{s_L, s_M, s_H\}$	0	150	50	200
$\{s_L, s_M\}$	0	0	50	50
$\{s_M, s_H\}$	0	250	100	300
$\{s_L\}$	0	0	0	0
$\{s_M\}$	0	0	100	150
$\{s_H\}$	0	400	150	350

Table 5.4 displays a comparison of the NPVs of the total costs under different learning and peak flow scenarios associated with both investment options. Corresponding regret values are displayed as well. Based on the dynamic application of the MR criterion investment in the primary dike is the preferred option. This conclusion follows from the application of Eq. (5.5), i.e.: $\min\{7.3; 11.0\} = 7.3$.

Table 5.4 NPV of total costs under different learning and actual scenarios and corresponding regret values in million €

θ_1	Scenario	NPV dikes	NPV floodplain	R_A^*	R_B^*
$\{s_L, s_M, s_H\}$	s_L	288.7	285.1	3.6	0.0
	s_M	360.1	361.4	0.0	1.3
	s_H	420.2	428.2	0.0	8.0
$\{s_L, s_M\}$	s_L	278.2	271.2	6.9	0.0
	s_M	366.5	359.2	7.3	0.0
$\{s_M, s_H\}$	s_M	360.7	362.2	0.0	1.5
	s_H	411.2	422.2	0.0	11.0
$\{s_L\}$	s_L	278.2	271.2	6.9	0.0
$\{s_M\}$	s_M	359.5	359.2	0.3	0.0
$\{s_H\}$	s_H	409.9	419.0	0.0	9.1
				7.3	11.0

Despite that the primary dike is the maximum regret minimising investment option, more adaptation capital accumulates over time when the primary dike is raised as compared to the option to invest in detention storage. Table 5.5 reports the Present Value (PV) of dike and detention investment costs under the different learning scenarios. Due to the postponement of investment, as well as due to the relatively high unit costs of detention and the resulting reduction in investment, total discounted investment costs of floodplain investment are relatively low.

Table 5.5 Comparison of total discounted investment costs

θ_1	PV dike investments	PV floodplain investments
$\{s_L, s_M, s_H\}$	180.8	172.9
$\{s_L, s_M\}$	154.7	148.2
$\{s_M, s_H\}$	194.8	183.4
$\{s_L\}$	154.7	148.2
$\{s_M\}$	185.9	148.2
$\{s_H\}$	203.8	198.0
Average	179.1	166.5

Recall that the average of total discounted investment costs under the specified learning scenarios was defined as a negative measure of flexibility. The average PV of floodplain investments is lower ($\min\{179.1; 166.5\} = 166.5$). If a decision-maker would be willing to accept an additional maximum regret of $11.0 - 7.3 = 3.7$ million Euros, switching to investment in the floodplain would be optimal (Eq. (5.27)). The threshold-to-switch is $100\% * \frac{|7.3-11.0|}{7.3} = 51\%$ of R^* (Eq. (5.28)).

5.6 Conclusions and discussion

This paper presents a dynamic 'minimax regret' (MR) modelling approach for the analysis of flood risk management (FRM) investment problems under climate change. The approach supports the identification of adaptive FRM strategies by the inclusion of 'learning scenarios' about climate change impacts. We show how the MR decision criterion can be applied dynamically in order to analyse investments in flood protection. The important differences between static and dynamic MR analysis of FRM investments due to the possible emergence of new climate information are highlighted. The key message of this paper is that dynamic MR solutions are more robust than the solutions obtained from a static MR analysis of FRM investments due to ongoing changes in climate change impact projections.

In recent work the importance of the emergence of new information has been stressed for the successful adaptation to climate change, for example with the development of methods related to 'adaptation tipping points' and 'adaptive pathways' (cf. Kwadijk et al. 2010; Haasnoot et al. 2013). Unlike these methods, a dynamic MR analysis provides detailed economic advice on optimal management strategies based on regret aversion.

Robustness concepts are normative in nature. In this paper, a 'narrow' definition of robustness is employed, i.e.: minimisation of maximum regret. However, other robustness approaches, such as info-gap theory and analytic robustness methods, may give complementary insights in FRM strategies that perform relatively well across a wide range of scenarios (cf. Lempert et al. 2006; Hine and Hall 2010).

So far, applications of the MR decision criterion have mostly been restricted to static settings (Hayashi 2011). Whereas static MR analysis provides insights in the ability of a flood protection measure or a system to remain functioning under scenarios of future disturbances, it is implicitly assumed that this set of scenarios does not change over time. Dynamic MR analysis, in contrast, incorporates future information, which improves the robustness of decisions over time (cf. Mens et al. 2011).

The FRM problem solved in this paper could also be addressed from the perspective of a social planner with an expected-value based cost-benefit optimisation procedure (van der Pol et al. 2014). However, this approach assumes risk-neutrality and requires information on the probabilities of future states and events. In Europe, cost-benefit analysis is predominantly applied for economic appraisal of flood protection and other adaptation measures, although its use is controversial (Turner 2007; Watkiss et al. 2014).

We have shown that the implementation of the dynamic MR decision is complex, and that a backward induction procedure is required to ensure dynamic consistency. This procedure, however, is computationally intensive. The computation time is determined by the number of learning scenarios and the number of decision moments. Even if the number of learning scenarios is constant over time, computation time is exponential in the number of decision moments. However, the presented case illustrates that this is no obstacle to the application of the dynamic MR procedure to FRM problems as long as the number of decision moments is small. In this paper, the setting was restricted to two decision moments, and mutually exclusive investment options. For further research it would be interesting to study a multi-period case with complementary investment options.

The inspection of average adaptation capital accumulation might be a useful extension to obtain insights in the overall flexibility of dynamic MR solutions. We argue that adaptation capital accumulation is risky, as invested capital can lose some or all of its value under new information on climate change impacts. The concept of 'value-at-risk' originates from finance (Linsmeier and Pearson 2000). The value-at-risk, however, cannot be quantified in the absence of information on the likelihoods of value losses.

The conceptual FRM model presented in this paper is stylised regarding the cost functions and the risk of flooding. For example, fixed damages per flooding event were assumed independent of dike height, flood scenario and flood duration. Detention areas were assumed to be rectangular, and the infiltration potential was assumed to be constant independent of previous weather. For the dynamic MR approach to be applicable for decision support of real-world FRM investment decisions, the dynamic MR approach can be combined with a rainfall-runoff-inundation model.

6. General discussion and conclusions

This thesis investigates the impact of climate change on investment in flood risk reduction, and applies optimisation methods to support identification of optimal flood risk management strategies. The structure of this chapter is as follows. Section 6.1 summarises key findings. Section 6.2 provides a general discussion of modelling approaches and results. Section 6.3 presents model limitations and suggestions for further research. Section 6.4 ends with modelling and policy conclusions.

6.1 Research questions and summary of findings

1. *How can probabilistic extensions of cost-benefit analysis using climate and learning scenarios be applied to improve decision-making on flood risk management strategies? And what are advantages and limitations of such probabilistic extensions?*

Chapter 2 presents probabilistic extensions of cost-benefit analysis (CBA) to assess flood risk management strategies under multiple climate change impact scenarios and learning, and discusses the scope of such extensions. Probabilistic climate scenarios were used to model uncertainty about the changes in return periods of hydro-meteorological extremes. Learning was modelled by probabilistic events of information arrival. A distinction was made between learning from scientific progress, from statistical evidence and from flood disasters.

The principle advantage of assigning probabilities to climate change impact scenarios is that scenarios which are considered to be likely are given additional weight in the economic analysis, and that scenarios that are considered to be unlikely are still assigned relatively low but positive probabilities to optimise flood risk management strategies. There appears to be some consensus that some of the more extreme climate change impact scenarios are less likely. For example, local sea level rise scenarios beyond one meter by 2100 are often considered to be unlikely.

However, assigning probabilities to climate change impact scenarios is controversial. Climate model ensembles mostly provide non-probabilistic uncertainty ranges. Chapter 2 argues that expert elicitation methods are possible instruments to obtain probabilistic statements. Yet, climate change uncertainties prevent convergence of opinions with these methods. It was discussed that flood risk management under climate change is a case of decision-making under uncertainty. Risk-based approaches provide subjective estimates of expected costs. Subjective estimates of expected outcomes are arguably better than outcomes obtained with single scenarios due to non-linear damage cost and investment cost functions and their economic implications for the efficiency of flood risk management strategies. It was also discussed that robustness approaches may provide complementary insights to CBA, because they aim to find solutions that perform relatively well under worst-case or a range of scenarios and represent other types of decision-maker preferences, such as uncertainty aversion, loss aversion or regret aversion.

A key advantage of extending CBA with learning is that flood risk management strategies can be optimised under the possible arrival of new climate change information. Trade-offs between flexibility and expected costs are modelled, which could improve the flexibility of flood risk management strategies over time and could reduce total discounted expected costs. Chapter 2 briefly discussed that adaptive flood risk management is achieved in various ways, including adaptive design, investment timing and scale, and portfolio choice of flexible flood risk management measures. It was also discussed that different types of learning may have different effects on investment strategies, for example in terms of investment scale. For this reason, it may be useful to extend an economic analysis of flood risk management strategies with different types of learning.

The external validity of the discussed probabilistic learning models is limited by uncertainty about the learning process. It is, for example, unclear if and when hydrologic uncertainty will be reduced in the short-run. Outcomes are sensitive to the assumed learning process. In contrast, a learning analysis with new flood-related data does not rely on an exogenously defined learning process. Effects of flood-related extremes on flood risk management decisions can be introduced in an economic model by means of statistical updating and an analysis of possible future realisations of extremes, including flood events. Still, uncertain climate change impact projections are needed for this type of learning analysis.

2. *What are optimal dike investment strategies under uncertainty and learning about climate change impacts? What are the implications of the assumed learning process and the use of subjective probability*

distributions to represent structural water level increase? And how large are the differences in optimal investment levels without and with learning?

Welfare-maximising dike investment strategies minimise total discounted expected costs. In Chapter 3, total costs are assumed to consist of total discounted investment costs and total discounted expected damage costs. Expected annual damage costs are changing over time, and can be approximated by the sum of probability-weighted monetised expected flood losses in a year under climate change for a given dike height. Chapter 3 studies both cases of perfect learning with a given learning moment and probabilistic learning, where learning is implemented by a survival model. Chapter 3 demonstrated effects of uncertainty resolution on optimal dike investment strategies. It was shown that the original investment timing and size can be altered to anticipate and respond to new information on exceedance frequencies, respectively before and after information arrival.

The numerical results of Chapter 3 show that optimal dike investment strategies and total expected costs are sensitive to distributional assumptions of structural water level increase. However, subjective probability distributions of structural changes in water levels are often lacking. Chapter 3 also shows that an earlier investigated alternative, a model with a deterministic parameter for structural water level increase, is highly sensitive to the assumed parameter value due to the exponential investment and damage cost functions. The deterministic base model, therefore, overlooks the importance of climate change uncertainty.

Chapter 3 also demonstrated that the timing of information arrival is important for investment decisions. As a first step, investment in a dike was studied for a given moment of learning. Optimal investment in the limit ($t \to \infty$) coincides with the uncertainty benchmark without learning, which is applicable for the case where uncertainty reduction is expected to occur far away in the future. In contrast, earlier learning can both result in a lower or a higher dike before learning than under the benchmark without learning, depending on when the information is obtained. In some cases initial investment can be increased to be able to postpone investment later on, whereas for other cases multiple smaller investments may be optimal as compared to the benchmark without learning. This is due to trade-offs between the value of information, fixed costs of investment and additional damage costs, in expected terms, of waiting or reduced investment scale.

In a second step, the more general case of probabilistic learning was studied. The sensitivity of the outcomes to the assumed learning process led to the conclusion that further research on realistic representation of learning is needed to improve economic decision-making on dike height.

Moreover, Chapter 3 showed that learning may reduce discounted expected damage and investment costs. For the cases considered, expected values of information of 0.9–53.9% of total benchmark costs were reported. These estimates are highly sensitive to distributional assumptions and the applied discount rate. It was also shown that whether or not new information is expected from the start differences between first dike increments are small (e.g. ½ cm) for the studied cases. As a result, the expected cost difference between a flexible strategy anticipating information arrival and a reactive strategy that is only adjusted in response to new information is also small for most investigated cases. The results indicate that for the case of dike investment optimal recourse decisions are more important than the anticipation of new climate information, as studied from the perspective of a risk-neutral social planner.

3. *What is the impact of new rainfall observations on cost-effective investment in detention storage? Can 'white noise' be distinguished from a structural shift of an extreme rainfall distribution? And what is the relationship between the fixed costs of investment and the statistical beliefs of a decision-maker about the risk of flooding?*

Chapter 4 studies impacts of rainfall variability and changing return periods of rainfall extremes on cost-effective adaptation of water systems to climate change given a predefined system performance target. An example of a system performance target is a flood protection standard. It was shown that trend-free variability of rainfall, i.e. white noise, might cause re-investment to occur earlier than one would expect under projected changes in rainfall. Investment in flood risk and stormwater adaptations can be increased to reduce expected costs from underestimation of system performance. This was illustrated by a case study of the cost-effective volume of a storage basin in a Dutch polder system used to temporarily store stormwater from heavy rainfall.

It was shown that rainfall variability and the limited number of extreme value observations result in volatility of system performance estimates. Consequently, if these estimates are used to evaluate whether or not a water system still complies with a flood protection standard, the timing of re-investment in the system cannot be assumed to be known. Therefore, initial cost-effective investments are determined both by current beliefs about the future return periods of rainfall extremes, as well as by future beliefs about the return period of the extremes. These beliefs will determine when re-investment is necessary rather than the actual structural changes in rainfall, which cannot be observed in the short-run. This was demonstrated by applying a moving-window analysis. It is possible to increase the moving-window length. Yet, this reduces the probability of detection of climate change and increases the risk of overestimation of system performance. In contrast, reducing the length of the moving-window increases the probability of detecting climate change, but it also increases volatility of system performance estimates.

Chapter 4 showed that increasing initial investment reduces the probabilities of early re-investment. Frequent re-investment can be costly due to fixed costs of investment, and motivates anticipatory climate change adaptation in general. Flood risk infrastructure has typically a long technical life time and usually involves fixed costs. In Chapter 4 the timing of investment is determined by the statistical beliefs about the probability of flooding, which are compared to the predefined flood protection standard over time. Increasing the initial investment has two effects. Firstly, the actual flood probability will be lower than the accepted flood probability for a longer period of time, because the system is able to cope with larger structural changes in rainfall induced by climate change. Secondly, increasing initial investment offers insurance against additional costs that would occur in case of violation of the flood protection standard as a result of overestimation of the actual flood probability.

4. *What is the motivation for a minimax regret approach to study flood risk management investments? Can a consistent dynamic minimax regret procedure be developed, and can it be applied to practical flood risk management problems? What is the impact of 'learning scenarios' on optimal investment selection and optimal investment levels under a minimax regret decision criterion?*

Chapter 5 presents two arguments to motivate the application of the minimax regret decision criterion to study flood risk management investments. The first argument is about the general shortcomings of expected value-based optimisation approaches. Expected-value based approaches assume that risks are well-defined, and do not account for other decision-maker preferences under ambiguity or in the absence of probabilities. This type of argument motivates robustness analysis in general. The second argument focusses on the context-specific motivation for applying the minimax regret decision criterion, including evidence for regret aversion in the domains of flood risk management and climate change adaptation and the anchoring of worst-case outcomes in the decision-making on flood risk management strategies.

However, various theoretical and practical concerns have been expressed in the literature for applying the minimax regret decision criterion (Yager 2004; Hayashi 2011). Regret is a context-dependent measure, which implies that solutions are sensitive to specified scenarios and alternatives. This, for example, results in sensitivity to irrelevant alternatives (Yager 2004). A practical problem for dynamic application of the minimax regret decision criterion is that the dynamic analysis could result in time-inconsistent commitments (Hayashi 2011).

Chapter 5 develops a dynamic minimax regret procedure based on backward induction used to sequentially eliminate sub-optimal decisions. The developed procedure is computationally intensive. However, it remains tractable if the number of decision moments is kept low. In Chapter 5, a two-period investment case was studied.

The developed approach supports the identification of adaptive flood risk management strategies by including learning scenarios about peak flow development, and the dynamic minimisation of maximum regret over time under these scenarios. As a proof of concept, optimal dike height and floodplain development were studied with a conceptual flood risk management model. Numerical differences in investment levels were highlighted by comparing outcomes of static and dynamic minimax regret analysis. Also, thresholds-to-switch between investment in dikes and floodplain development were studied. The chapter concludes that dynamic minimax regret offers greater flexibility than static application of the decision criterion, because it allows investments to be changed at lower maximum regret when new peak flow information emerges. Dynamic minimax regret solutions may be more robust than the solutions obtained from a static minimax regret analysis of flood risk management investments due to ongoing changes in climate change impact projections.

6.2 General discussion

This section briefly compares modelling approaches and results of Chapters 2-5, and puts the contribution of the thesis in a broader flood risk management perspective.

- Modelling approaches

The need for adaptive flood risk management strategies has received increasing attention in recent years, for example by the analysis of adaptation tipping points and the application of quantitative learning methods to the flood risk management domain (Kwadijk et al. 2010; Woodward et al. 2011; Gersonius et al. 2013). However, the inclusion of climate change uncertainty and new information in economic models for flood risk management has remained challenging. The relevance and impact of new information on optimal strategies has often been overlooked. This thesis contributes to the existing research by implementing different types of learning processes in both probabilistic and non-probabilistic models to optimise flood risk management strategies under climate change uncertainty and the possible arrival of new information.

The models in Chapters 2-5 investigate several optimisation objectives. Chapters 2 and 3 present cost-benefit models aimed at maximisation of social welfare. In Chapter 3, economically efficient dike height is studied. Chapter 4 on cost-effective water system optimisation, in contrast, minimises expected costs in order to comply with a pre-defined flood protection standard. Hoes and Schuurmans (2006), for example, argued that application of equal protection standards to different systems may lead to economically inefficient investment strategies. Yet, CBA is not always useful for practical or legal reasons (NBW 2005; Pathirana et al. 2011). Equal protection standards have, next to practical implementation advantages, also advantages regarding transparency, insurance and flood risk communication. When such standards or other constraints are treated as given in the decision-making process on flood risk management strategies, the economic model has to reflect this as well for effective decision-support.

Chapter 5 on dynamic minimax regret departs from expected costs minimisation applied in Chapters 2-4. Robustness analysis provides an alternative to expected-value based approaches when climate change uncertainties are considered to be deep (Kandlikar et al. 2005; Lempert et al. 2006). The minimax regret decision criterion provides a narrow interpretation of robustness. Chapter 5 shows that for floodplain development and dike construction anticipated regrets are larger than zero, and that dynamic minimax regret analysis is useful to obtain insights in the robustness of flood risk management strategies over time.

Besides these differences the models in Chapters 2-5 consider several implementations of learning. Chapter 2 provides an overview of types of learning about climate change impacts that are relevant for the economic analysis of flood risk management strategies. Chapter 3 on optimal dike height studies the effects of probabilistic uncertainty resolution. Chapter 4 on cost-effective water system optimisation addresses the arrival of new rainfall data. Chapter 5 on dynamic minimax regret applies predefined learning scenarios.

The model in Chapter 3 on optimal dike height shows that even if a single investment option is studied, identification of optimal strategies is complex under the arrival of new information. It was shown that economic modelling is required for a detailed understanding of trade-offs between flexibility and expected costs. Recently, development of adaptive policy pathways under climate scenarios has been proposed as a tool to study dynamic adaptation strategies (Haasnoot et al. 2013). However, iterative pathway construction is limited by the human capacity to heuristically deal with high-dimensional problems, and therefore can only consider a limited number of investment options, investment levels, and climate and learning scenarios. In contrast, economic models with learning, as presented in Chapters 2-5, can provide detailed economic analysis of flood risk management strategies under climate change uncertainty and learning. These analyses can be used to identify economically efficient, cost-effective or robust flood risk management strategies.

- <u>Comparison of main results of the thesis chapters</u>

Throughout the thesis it was demonstrated that the outcomes of an economic analysis of flood risk management strategies are sensitive to possible changes in information about climate change. In Chapter 2, it was discussed that the type of learning has an effect on optimal investment strategies. This is confirmed by the findings in Chapters 3-5. In Chapter 3 on economically efficient dike height, initial dike investment is reduced by probabilistic learning from future uncertainty resolution, whereas in Chapters 4 (cost-effectiveness analysis) and 5 (minimax regret analysis) initial investment is increased by future learning, respectively from new observations and under predefined learning scenarios. Moreover, when the welfare maximising economic model of Chapter 3 and the maximum regret minimising model of Chapter 5 would be applied to the same investment problem on optimal dike height, results are likely to be different, because they use another objective and implementation of learning. The numerical results of Chapters 3 and 5 seem to suggest that the effect of learning on initial dike investment might be larger under minimisation of maximum regret than under minimisation of total discounted expected costs. This, however, might also be caused by the timing of new information and other learning assumptions. A comparison of identical cases would therefore be interesting for further research.

- <u>Wider context of the thesis</u>

The investment problems addressed in this thesis are based on Dutch flood risk management cases. In practice, large differences can be observed in flood exposure, definitions of acceptable flood risk and flood risk management strategies across countries. Many countries try to find effective portfolios of flood risk management measures that minimise flood frequencies, exposure and vulnerability under changing conditions, including climate change. In the Netherlands, a ‘multi-layer safety’ approach has been advocated in the domain of flood risk management (de Moel et al. 2014). It encompasses hazard, exposure and vulnerability mitigation. Historically, the Netherlands has invested in many structural flood protection measures, which is not surprising given the portion of land that is located below sea level and the proximity of rivers. Yet in other countries, for example in Germany, controlled flooding has been more common along rivers (e.g. Kreibich and Thieken 2009). In the United States, furthermore, accepted flood probability has historically been much higher than in the Netherlands (Kind 2014; Lickley et al. 2014). In developing countries, moreover, high vulnerability of the poor and governmental budget constraints may play an important role for flood risk management (Few 2003; Hanson et al. 2011). For the economic models developed in this thesis to be applicable elsewhere, local conditions need to be carefully considered for the economic assessment of flood risk management strategies.

The economic models with learning presented in this thesis are not limited to local investment decisions for flood risk management. The modelling of learning is also important to analyse global adaptation costs to climate change. Aggregation of national flood risk management costs can be used to obtain estimates of global flood risk management costs, including the economic effects of adaptive flood risk management practices under different climate change futures. Moreover, the understanding of differences in costs and benefits of flood risk management strategies across countries may also support the development and distribution of regional adaptation funds and improve international coordination of flood risk management strategies.

6.3 Model limitations and directions for further research

6.3.1 Limitations

Mathematical models, by definition, represent reality by simplification. The models presented in this thesis simplify reality at points where this was possible with no or limited loss of generality. For example, the distinction between exceedance probability and flood probability is clearly important for real-world decisions. However, it has not been included in the models throughout this thesis, as this distinction was not fundamental to the answering of the research questions. In the economic models of Chapters 3-5 various other modelling assumptions have been introduced, which have been summarised in the discussion sections of these chapters. Chapter 3, for example, considers dikes but no other flood risk management measures, and uses simple damage and investment cost functions. The learning process is considered to be exogenously given in this chapter, as well as a time-independent discount rate. Chapter 4 uses a simplified investment cost function, and modifies only one water system element. Chapter 5 employs a narrow definition of robustness and a stylised flood risk management model.

The primary focus on economics and flood risk under climate change provides an important limitation of the models in this thesis. Other societal objectives, such as equity issues or social justice, or impacts on landscape and biodiversity, and interests of actors and stakeholders were beyond the scope of the research.

6.3.2 Suggestions for further research

New research questions arise from my thesis. What is the best way to model learning by bad experience (e.g. disasters)? Why are regret calculations unpopular in practice? Can we combine robustness models for flood risk management to get even more robust answers? What is the impact of budget constraints on adaptive capacity over time in developing countries prone to flood risk? Next to alternative model specifications, including those that consider a broader scope or improve external validity, the following topics could be interesting for further study:

1. Disaster-based learning
   In Chapter 2 learning from disasters was discussed as a special case of learning from extreme-value observations. The model developed in Chapter 4 assumes that decision-makers behave rationally and use statistics to evaluate the performance of water systems. However, disasters have often led to large-scale investments that went beyond repair. The development of an expected-cost model that takes probabilities of disaster realisations into account would be interesting, especially for cases where annual flood probabilities are relatively high (e.g. 1/100).

2. Multi-type learning
   The numerical results of this thesis suggest that different types of learning may sometimes have opposite effects. It would be interesting to develop an economic model that combines different types of learning and to apply it to flood risk management case studies.

3. Economic and climate uncertainties
   In Chapter 2 it was mentioned that impacts of climate change on flood risk are increased under high scenarios of economic growth. The effects of learning may also be reinforced under these scenarios. The relevance of this issue would be interesting for further study.

4. Meta-analysis of economically efficient and robust strategies
   There are different robustness concepts and robustness decision criteria. Chapter 5 has restricted attention to the minimax regret decision

criterion. Moreover, solutions found with the minimax regret model of Chapter 5 are likely to be different from the solutions found with the expected-value based cost-benefit model of Chapter 3. Economic decision-making could be supported by developing meta-methods that help to identify solutions that perform relatively well both in terms of expected costs and under robustness definitions.

5. Adaptive capacity in developing countries
   Adaptive capacity is time-dependent. The adaptive capacity of developing countries is currently not only lower than the adaptive capacity of developed countries, but may also be improved or reduced by current adaptation decisions or reduced by disasters. Analysis of flood risk management strategies under climate change uncertainty and learning in developing countries could therefore be very interesting.

6.4 Conclusions

6.4.1 Modelling conclusions

Economic analysis of flood risk management strategies can be extended to include climate change uncertainty and new information. This thesis has demonstrated that concepts and methods from a number of disciplines are required to support the identification of economically optimal investment strategies. These disciplines include economics, operations research, statistics and hydrology. The work process applied to the modelling chapters of this thesis can be characterised by three main stages: (i) qualitative analysis of the decision problem, (ii) model development and (iii) implementation.

The qualitative research stage, in which the main characteristics of the decision problem are explored, is crucial. It starts from the notion that flood risk management under climate change is a case of decision-making under uncertainty, and that investment strategies can be adjusted over time on the basis of new information. This thesis has shown that different optimisation objectives can be considered for the economic optimisation of flood risk management strategies under climate change. In Chapters 2 and 3 an expected-value based cost-benefit analysis (CBA) was applied to identify welfare maximising strategies. In Chapter 4 the case of cost-effective compliance with a given flood protection standard was considered, and in Chapter 5 the objective was to minimise maximum regret over time.

Also determinants of optimal investment were explored. The cost-structure of available flood risk management measures is a determinant of optimal investment. Fixed costs of investment explain, for example, why dikes are raised in intervals of several decades, a result of Chapter 3, and why future changes in rainfall have to be included to determine initial investment in a storage basin studied in Chapter 4. Several other determinants of optimal investment were identified for the cost-effectiveness study in Chapter 4, including the projected changes in rainfall, the compliance period of the flood protection standard, and the likelihood of future rainfall realisations.

Optimisation models have been developed in Chapters 2-5. The economic objectives have been formalised, together with the state variables (e.g. dike height), decision variables (e.g. dike increments) and applicable constraints. Dynamic programming is a useful method to study flood risk management strategies under climate change, and was applied in Chapter 3 to dike investment and in Chapter 4 to investment in a storage basin. Chapter 4, furthermore, showed that for detailed economic analysis it is useful to combine stochastic dynamic programming with the simulation of rainfall and hydrodynamics. In Chapter 5 a conceptual flood risk management model was developed instead, but for real-world applications such models provide insufficient realism. The dynamic minimax regret approach developed in Chapter 5, however, could be linked to a detailed rainfall-runoff-inundation model in a similar fashion as in Chapter 4.

The implementation of the models in Chapters 3-5 was a time-consuming process. This may be a concern for real-world applications, especially when the model components required for the final optimisation are not readily available. Yet, the implementation itself is relatively straightforward. All model components, from rainfall-runoff-inundation simulation to dynamic programming, are well-described in the literature.

Learning can be implemented exogenously, for example by a survival model applied in Chapter 3, or predefined learning scenarios in Chapter 5. Learning from new observations, in contrast, can be introduced by simulation of extremes, as was done in Chapter 4.

The external validity of the numerical results presented in Chapter 3 is limited by probabilistic assumptions about climate change impacts and new information.

Expected-value based CBA was applied to dike investment with a normal and a lognormal distribution of structural water level increase and probabilistic uncertainty resolution. The numerical results heavily rely on the probabilistic assumptions about the learning process and the impacts of climate change on exceedance frequencies. Estimates of expected total costs and the value-of-information diverge, which suggests that sensitivity analysis is a requirement for expected-value based CBA of flood risk management strategies under climate change uncertainty with learning. The results of Chapter 3 also suggest that other aspects, such as discounting, have to be considered in the sensitivity analysis.

Chapter 4 shows that mere randomness in extreme value observations in the coming decades might trigger investment responses. Economic optimisation of flood risk management strategies goes beyond uncertainty from the natural system, for example, about the impacts of climate change on flood-related frequencies. New observations change decision-makers' statistical beliefs, which introduces social uncertainty. So far, research on flood risk management rarely addresses this type of uncertainty, while the economic consequences of early re-investment can be significant. Noisy observational evidence for climate change and changes in flood risk can be modelled in various ways, and the model in Chapter 4 provides one example of this.

The advantages of the dynamic minimax regret approach in Chapter 5 are that no probabilistic climate information is required, and that various learning scenarios can be introduced. However, still a plausible range of climate scenarios is needed, and learning scenarios have to be specified. Chapter 5 did not focus on methods to specify learning scenarios, and considered a two decision period model only. Upscaling the model to annual decision moments may be intractable, as computation time is exponential in the number of decision periods. Furthermore, the underlying assumption that decision-makers are merely concerned with worst-case regret is a narrow interpretation of regret-aversion. Yet, the overall information from a dynamic minimax regret analysis is useful to obtain insights in maximum regrets, rather than in total expected costs, under different flood risk management strategies that can be adapted over time on the basis of new information.

The models in this thesis can be used to analyse learning effects on initial investment and optimal recourse decisions, to support the identification of optimal flood risk management strategies, and to obtain expected cost estimates or estimates of maximum regret. For any of these models holds that the underlying model assumptions and model inputs together determine the quality of the results. Given the severity of climate change uncertainties any model, no matter how detailed, solved to economically optimise flood risk management strategies supports economic decision-making by providing a small part of the puzzle for the decision-making process on flood risk management strategies under climate change.

6.4.2 Policy conclusions

Economic analysis of flood risk management strategies has become more complex due to climate change. Despite severe climate change uncertainties, it is widely shared that it is no longer sufficient to only consider changes in flood exposure. Future changes in weather patterns, river flows and sea levels need to be considered to effectively and efficiently reduce flood risks. Flood risk infrastructures typically have long technical lifetimes and often involve fixed costs of investment. Wrong choices today can therefore result in high costs and regret in the future. An economic analysis of flood risk management strategies supports the identification of economically optimal flood risk management strategies under climate change, and provides insights in trade-offs between flexibility and expected costs or regret. To analyse these trade-offs, learning is introduced as the possible arrival of new information over time. Learning is particularly relevant to gain insights in the benefits and costs of flexible flood risk management strategies.

This thesis distinguishes between different types of learning, which were introduced in Chapter 2 and were summarised by learning from scientific progress and from new data. Learning from scientific progress was studied in Chapter 3 to determine optimal dike height under climate change uncertainty and uncertainty resolution. Uncertainty resolution is an extreme case of uncertainty reduction. Uncertainty resolution is not realistic, but more moderate versions of uncertainty reduction can be expected from reduction of epistemic climate uncertainties with time.

Chapter 3 demonstrates that learning from scientific progress has a large effect on optimal investment if we would know for sure that climate change uncertainty will be resolved, and if we would also know when it would be resolved. In some cases initial dike investment is postponed, while in other cases investment levels are reduced till uncertainty is resolved, or initial investment is increased in order to postpone investment later on. However, it is unclear how long it will take till we will have better information on climate change impacts on flood-related frequencies. Therefore, also solutions under probabilistic uncertainty resolution were studied in this chapter. The probabilistic learning cases show that learning could reduce expected costs significantly, for one case by an estimated 54% of total costs, as a result of implementing optimal response strategies as soon as new information becomes available.

The numerical results in Chapter 3 should be interpreted with care and mainly carry qualitative messages. It was found that optimal dike investment strategies are highly sensitive to probabilistic assumptions about climate change impacts on exceedance frequencies, and also the assumed probabilistic learning process could greatly influence the results. This highlights that there is a clear need for better underpinning of these probabilistic assumptions, and also that sensitivity analysis of these key uncertainties is necessary. The effects of probabilistic learning on initial dike height for the studied cases were less than a centimetre, which suggests that the modelling of learning from scientific progress for short-term dike investment could be left aside.

Chapter 4 investigates effects of new rainfall data on cost-effective water system investment under climate change. Unlike learning from scientific progress, learning from new data is certain: every day 24 new hourly rainfall observations will become available. These observations can be used to monitor the performance of a local water system over time. In the model it was assumed that if the estimated probability of flooding exceeds a predefined maximum accepted flood probability re-investment is required. One drawback of this approach is that the natural variation in rainfall observations is high, which results in volatility of performance estimates. If, for example, a water system element is designed for an event with a return period of 10 years in 2050, it is possible that somewhere along the way the return period of this design event is estimated to be smaller than 10 years due to mere natural variation. Resulting performance underestimation can be a trigger for new system investments, and this could be costly. Chapter 4 concludes that, if investments are associated with fixed costs, increasing initial investment not only increases water system robustness to future climate change impacts on rainfall, but it also provides insurance against costs that could arise in case of underestimation of system performance.

Chapters 2-4 consider expected cost minimisation as economic objective for flood risk management. Chapter 5, in contrast, focusses on minimisation of maximum regret as an alternative decision criterion. It has frequently been expressed in policy briefings and reports on climate change adaptation that adaptation should aim at no or low regret options. For flood risk management, however, these options do not always exist for structural investments. For example, if a low dike is constructed and sea level rise turns out to be high, this gives regret, and visa-versa. These regrets can be anticipated and quantified. This is explained in the introduction of Chapter 5. Whereas the concept of regret minimisation is well-established, the dynamic application of the minimax regret decision criterion has rarely been observed. In Chapter 5 it was shown that the decision criterion can be applied dynamically to analyse flood risk management strategies. By defining learning scenarios maximum regret minimising investment strategies can be identified, provided that these strategies are adapted as soon as new information becomes available. The results of a dynamic minimax regret analysis are more robust than of a static minimax regret analysis. A dynamic minimax regret analysis not only considers different climate scenarios, but also accounts for possible changes in information, and the costs of response strategies that would follow after information arrival under several informational scenarios.

Summary

Urban, riverine and coastal flood risks have been increasing globally, and flood risks will continue to increase in the coming decades as a result of growing flood exposure and higher flood frequencies. The adverse effects of climate change on flood frequencies can be mitigated by updating flood risk management strategies. Flood risk management poses a burden on national budgets. Yet, flood disasters may cause severe economic damages and social disruption. Economic analysis of flood risk management strategies supports the identification of economically optimal investments. Economic analysis of flood risk management strategies has become more complex due to climate change uncertainties. It is uncertain how weather patterns, river flows and sea levels will change in the future, and it is also hard to predict how the current information about these changes might alter over time. Learning, induced by the arrival of new information, has received relatively little attention in economic flood risk management studies. This thesis is therefore concerned with the economic analysis of flood risk management strategies under climate change with learning. The overall objective of this thesis is to investigate the impact of climate change on investment in flood risk reduction, and to explore and apply optimisation methods to support identification of optimal strategies.

Economic analyses applied throughout this thesis are cost-benefit analysis (Chapters 2 and 3), a cost-effectiveness analysis (Chapter 4) and a robustness analysis (Chapter 5). Studied flood risk management measures include dikes (Chapters 3 and 5), a storage basin of a polder system (Chapter 4) and floodplain development (Chapter 5). Learning is modelled as an exogenous process (Chapter 3), by simulation of new extreme-value data (Chapter 4) and by predefined learning scenarios (Chapter 5).

Chapter 2 provides an overview of cost-benefit analysis (CBA) of flood risk management strategies extended with climate change scenarios and learning, and discusses the scope of such extensions. Uncertainty about the changes in return periods of hydro-meteorological extremes is introduced by probabilistic climate scenarios. Learning occurs upon the arrival of new information. A distinction is made between learning from scientific progress, from statistical evidence and from flood disasters. It is concluded that these probabilistic extensions of CBA are

useful to support the identification of economically efficient flood risk management strategies. However, the required probabilistic information for such analyses, both on climate change impacts and on the learning processes, is ill-defined. Moreover, decision-makers may not be merely concerned with subjective estimates of expected outcomes. Robustness analysis can therefore be considered to complement insights obtained from CBA of flood risk management strategies.

Chapter 3 revisits the problem of optimal dike height. Whereas dike investment strategies have previously been studied in a deterministic setting, Chapter 3 extends the original problem with climate change uncertainty and probabilistic uncertainty resolution, an extreme case of uncertainty reduction. It is demonstrated that investment timing and investment levels can be changed in order to anticipate and respond to new information on exceedance frequencies, respectively before and after information arrival. Optimal strategies are determined by dynamic programming. It is found that the expected value of information can be substantial. However, the effect on initial investments is mostly small for the studied case of probabilistic learning. The results suggest that it is more important to respond to new information than to anticipate these changes. Moreover, it is found that optimal strategies are highly sensitive to the probabilistic assumptions about structural changes in water levels. Therefore, a better understanding about these probabilistic assumptions is needed and this highlights the importance of sensitivity analysis.

Chapter 4 studies impacts of rainfall variability and changing return periods of rainfall extremes on cost-effective adaptation of water systems to climate change given a predefined system performance target, for example a flood protection standard. Rainfall variability causes system performance estimates to be volatile. These estimates may be used to recurrently evaluate system performance. A model is presented for this setting, and a solution method is developed that combines rainfall simulation and a hydrological model with stochastic dynamic programming. It is demonstrated that if flood probability estimates are used to evaluate whether or not a water system still complies with a flood protection target, the timing of re-investment in the system cannot be assumed to be known. It is concluded that increasing initial investments not only increases water system robustness to structural changes in rainfall, but can also offer insurance against additional costs that would occur if system performance is underestimated and re-investment becomes inevitable. Cost-structure is an important determinant of cost-effective investment.

Chapter 5 departs from expected cost minimisation applied in Chapters 2-4. The minimax regret decision criterion is applied dynamically to identify minimax regret flood risk management strategies under the possible arrival of new information. New information is introduced through predefined learning scenarios, which are used to study dike investment and floodplain development. Dynamic minimax regret applications are scarce, and the chapter shows that it is possible to dynamically apply the decision criterion to practical flood risk management cases. The chapter concludes that dynamic minimax regret solutions are more robust than static solutions due to the ongoing changes in climate change impact projections.

The following main conclusions are drawn from this thesis:

- Several decision objectives can be considered to economically optimise flood risk management strategies, including expected welfare maximisation, constrained cost minimisation and minimisation of maximum regret;
- Probabilistic climate projections are useful for expected-value based economic optimisation of flood risk management strategies. However, solutions may be highly sensitive to assumed probabilities;
- For economic decision-support it is important to consider different types of learning, from scientific progress and from new data, as well as their effects on optimal investment.
- The explicit modelling of learning may improve an economic analysis of flood risk management strategies;
- Learning can be implemented in both probabilistic and non-probabilistic optimisation models;

Samenvatting

Wereldwijd zijn overstromings- en wateroverlastrisico's toegenomen en deze trend zal zich naar verwachting voortzetten door de groei van economische waarde in kwetsbare gebieden en de toenemende kansen op overstromingen. Daarbij kunnen de nadelige effecten van klimaatverandering worden beperkt door het verbeteren van strategieën die overstromingsrisico's verminderen. Dit risicomanagement is echter kostbaar voor nationale overheden, net zoals overstromingsrampen die grote economische schade en sociale ontwrichting kunnen veroorzaken. De economische analyse van overstromingsrisico's en managementstrategieën draagt bij aan het vinden van economisch optimale investeringen. Deze analyses zijn complexer geworden door klimaatonzekerheden. Niet alleen is het onzeker hoe weerpatronen, piekafvoeren en zeeniveaus zullen veranderen, het is ook moeilijk te voorspellen of en hoe de nu beschikbare informatie over deze veranderingen zal wijzigen met de tijd. Leren door het verkrijgen van nieuwe klimaat-gerelateerde informatie heeft relatief weinig aandacht gekregen in economische studies van overstromingsrisico's en managementstrategieën. Dit proefschrift richt zich daarom op de economische analyse van strategieën die overstromingsrisico's beperken onder klimaatverandering met speciale aandacht voor leereffecten. Het doel van deze studie is om onderzoek te verrichten naar de gevolgen van klimaatverandering voor investeringen in maatregelen die overstromingsrisico's beperken en om geschikte optimalisatiemethoden toe te passen die bijdragen aan het vinden van economisch optimale strategieën.

In dit proefschrift worden verschillende types van economische analyse toegepast. In hoofdstukken 2 en 3 wordt kosten-batenanalyse uitgewerkt, in hoofdstuk 4 wordt een kosteneffectiviteitsstudie gepresenteerd, en in hoofdstuk 5 een robuustheidsstudie. Daarbij worden diverse maatregelen die overstromingsrisico's beperken bestudeerd, inclusief het verhogen van dijken (hoofdstukken 3 en 5), de aanleg van kleinschalige detentieberging in een poldersysteem (hoofdstuk 4) en het creëren van meer ruimte voor rivieren (hoofdstuk 5). Leren wordt gemodelleerd als een exogeen proces (hoofdstuk 3), door middel van simulatie van extreme waarden (hoofdstuk 4) en met vooraf gedefinieerde leerscenario's (hoofdstuk 5).

Hoofdstuk 2 geeft een overzicht van uitbreidingsmogelijkheden van kosten-batenanalyse met klimaatscenario’s en leren om strategieën te analyseren die overstromingsrisico’s beperken. Ook wordt de externe validiteit van deze uitbreidingen beschouwd. Onzekerheid over de veranderingen in terugkeertijden van hydro-meteorologische extremen wordt geïntroduceerd door middel van kans-gewogen scenario’s. Leren vindt plaats na het verkrijgen van nieuwe informatie. Een onderscheid wordt gemaakt tussen leren door voortschrijdende wetenschappelijke inzichten, leren door het verkrijgen van nieuw statistisch bewijs en ervaringsleren uit het plaatsvinden van overstromingsrampen. Het hoofdstuk eindigt met de conclusie dat deze kans-gebaseerde uitbreidingen van kosten-batenanalyse bruikbaar zijn om economische efficiënte strategieën te identificeren. De benodigde kans-informatie met betrekking tot de huidige stand van kennis over de gevolgen van klimaatverandering en het leerproces is echter incompleet en onnauwkeurig. Bovendien zijn beleidsmakers niet alleen geïnteresseerd in subjectieve schattingen van uitkomsten. Robuustheidsanalyse kan worden overwogen om de inzichten van kosten-batenanalyse van strategieën voor het beperken van overstromingsrisico’s aan te vullen.

Hoofdstuk 3 gaat verder met het vraagstuk van optimale dijkhoogte. In een aantal eerdere onderzoeken zijn dijkophogingsstrategieën bestudeerd in een setting van volledige zekerheid. Hoofdstuk 3 breidt het ophogingsvraagstuk uit met klimaatonzekerheid en de probabilistische oplossing van onzekerheid, welke een extreem geval is van de vermindering van onzekerheden. Er wordt aangetoond dat zowel de investeringstiming als de omvang van dijkinvesteringen kunnen worden gewijzigd om nieuwe informatie over overschrijdingskansen voor te zijn of om adequaat te reageren na voortschrijdende inzichten over de werkelijke overschrijdingskansen. Optimale strategieën worden bepaald met behulp van dynamische programmering. De resultaten geven aan dat de waarde van informatie substantieel kan zijn. Echter is het effect van probabilistisch leren op de eerstvolgende investering in de meeste bestudeerde gevallen beperkt. De resultaten lijken vooral te wijzen op het belang om adequaat te reageren wanneer betere informatie beschikbaar komt, maar nuanceren de noodzaak om het beschikbaar komen van deze informatie voor te zijn. Bovendien zijn de optimale strategieën erg gevoelig voor kans-aannames over de structurele wijzigingen in de terugkeertijden van hoge waterniveaus. Een beter begrip over deze kansen is daarom wenselijk en dit benadrukt ook het belang om een kans-gevoeligheidsanalyse uit te voeren.

In hoofdstuk 4 worden de effecten van natuurlijke variatie in regenvalextremen en de structurele veranderingen in regenval bestudeerd op de kosteneffectieve aanpassing van watersystemen onder klimaatverandering en een gegeven doelstelling, bijvoorbeeld een wettelijk gedefinieerd maximaal toegestaan overstromingsrisico. Variatie in natuurlijke regenval veroorzaakt volatiliteit in faalkansschattingen van watersystemen. Deze schattingen kunnen worden gebruikt om het functioneren van een watersysteem te beoordelen over de tijd. Voor deze setting wordt een wiskundig model gepresenteerd en wordt een oplossingsmethode ontwikkeld, welke regenvalsimulatie combineert met een hydrologisch model en economische optimalisatie door middel van stochastisch dynamische programmering. In het hoofdstuk wordt uitgelegd dat onder een gegeven doelstelling de planning van investeringen in de tijd onzeker is. Het vergroten van investeringen die nu worden gedaan helpt niet alleen om beter in staat te zijn om grotere structurele veranderingen in regenval op te vangen, maar vormt ook een verzekering tegen extra kosten die kunnen ontstaan door overschatting van de faalkans van het systeem. Dat laatste kan resulteren in de wens om nieuwe systeemaanpassingen te maken. De kostenstructuur van een systeemelement is hierbij een belangrijke factor voor kosteneffectieve investering.

In hoofdstuk 5 wordt afgeweken van de minimalisatie van verwachte kosten, welke is toegepast in hoofdstukken 2-4. Het besliscriterium van minimalisatie van maximale spijt, zgn. ‘minimax regret’, wordt dynamisch toegepast om spijt minimaliserende managementstrategieën te vinden wanneer wijzigingen in de huidige klimaatinformatie kunnen optreden. Deze informatie wordt geïntroduceerd in het model met vooraf gedefinieerde leerscenario’s. Als case studie wordt de methode numeriek toegepast op een conceptueel model waarbij maximale spijt van dijkverhoging met maximale spijt van tijdelijke overstroming van compartimenten worden vergelijken. Dynamische toepassingen van de minimax regret beslisregel zijn tot op heden zeldzaam en dit hoofdstuk laat zien dat het methodisch mogelijk is om de regel dynamisch toe te passen op praktische case studies voor overstromingsrisicomanagement. Dynamische minimalisatie van maximale spijt kan robuustere oplossingen geven dan statische toepassing van de beslisregel, omdat dynamische toepassing kan omgaan met voortschrijdende inzichten over de gevolgen van klimaatverandering.

De volgende hoofdconclusies volgen uit dit proefschrift:

- Diverse besliscriteria kunnen worden overwogen voor de economische optimalisatie van strategieën die overstromingsrisico's beperken, inclusief de maximalisatie van de verwachte welvaart, kostenminimalisatie onder gegeven beperkingen of minimalisatie van maximale spijt;
- Kans-gewogen klimaatscenario's of kansverdelingen zijn nodig voor de economische optimalisatie van risicomanagementstrategieën op basis van verwachte waarden. De uitkomsten zijn hierbij gevoelig voor de kans-aannames over de effecten van klimaatsverandering;
- Voor economische beleidsondersteuning is het belangrijk om na te denken over informatieveranderingen over de tijd, inclusief voortschrijdende wetenschappelijke inzichten en het beschikbaar komen van meer data, en de gevolgen van deze informatie voor investeringen.
- Het explicit modelleren van leren kan de economische analyse van managementstrategieën verbeteren;
- Leren kan zowel in optimalisatiemodellen met als zonder kansen worden geïmplementeerd;

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About the author

Thomas David van der Pol was born on May 21st, 1984 in Nieuwegein, the Netherlands. He completed secondary school at the Christelijk Gymnasium in Utrecht in 2002. One year later he started with his ‘business and consumer studies’ at Wageningen University and gained expertise in environmental economics. This resulted in a BSc thesis on the principles of the European trade in carbon allowances in 2006. He obtained the MSc degree in 2009 for his thesis on the potential impact of altruism on the stability of international climate coalitions. The final results were published in Ecological Economics in 2012.

In November 2010 he started his work as a PhD student at the Environmental Economics and Natural Resources Group of Wageningen University. He addressed topics on the economic analysis of climate change adaptation measures geared towards challenges in flood risk management. Since March 2015 he has been employed as a junior researcher at the Netherlands Bureau for Economic Policy Analysis (CPB).

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- *Optimal Dike Investments under Uncertainty and Learning about Increasing Water Levels*. EAERE-FEEM-VIU Summer School "Uncertainty, Innovation and Climate Change", 1-5 July 2013, Venice, Italy
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