Unraveling Uncertainties

the effect of hydraulic roughness on design water levels in river models

Jord Warmink

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THE EFFECT OF HYDRAULIC ROUGHNESS ON DESIGN WATER LEVELS IN RIVER MODELS

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This research is supported by the Technology Foundation STW, applied science division of NWO and the technology programme of the Ministry of Economic Affairs of the Netherlands as part of the VICI project 'Roughness modelling for managing natural shallow water systems' (project number TCB.6231).

Cover design: Willemijn Warmink-Perdijk

Printed by GildePrint

DOI: 10.3990/1.9789036532273

ISBN 978-90-365-3227-3

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PROEFSCHRIFT

ter verkrijging van
de graad van doctor aan de Universiteit Twente,
op gezag van de rector magnificus,
prof.dr. H. Brinksma,
volgens het besluit van het College voor Promoties
in het openbaar te verdedigen
op vrijdag 2 september 2011 om 14:45 uur

door

Jord Jurriaan Warmink
geboren op 14 mei 1980
te Zuidwolde

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'If the sun shines every day, it can not be good wheather.'

Frank Schleck (July 1, 2011)

Preface

A PhD project is like unraveling a knot, it requires both patience and persistence. At the start of my PhD project, I became more and more entangled by the topic of uncertainties until the point where I asked myself "if everything is uncertain, why bother?". Then, confused by my own thoughts, I heard of the legend about Alexander the Great.† In 333 B.C. in Gordium stoot an ox-cart, which had been put there by the King of Phrygia over 100 years before. The staves of the cart were tied together in a complex knot. Legend said that whoever was able to release the knot would be successful in all his future conquests. For 100 years nobody had been able to unravel the knot. Then Alexander asked Aristander, his seer, does it matter how I do it?. Aristander couldn't provide a definitive answer, so Alexander took his sword and cut through the knot. This legend illustrated to me that thinking outside the box and being practical sometimes leads to better results than diving in deeper while keeping the beaten track.

In 2007, during my internship at WL|Delft Hydraulic, I met Jos Dijkman, who told me that there was an opportunity for a PhD position at the University of Twente. He was the first in a long line of people who helped me to finish my PhD research. Here, I want to thank these people.

In the first place my supervisors, Suzanne Hulscher, Martijn Booij and Hanneke van der Klis. Thank you for the support, motivation and pushes in the right direction. Suzanne, you always made me feel appreciated and you always pointed out the added values of my work. Martijn, thanks for our interesting discussions and for always being available to help me out. Your numerous corrections greatly improved my work. Hanneke, thanks for our discussions during my 'bimonthly' visits at Deltares. I always left with renewed energy and many new plans for my research.

I am grateful to all my collegues at the Department of Water Engineering and Management, especially my (former) roommates Judith Janssen and Bas Borsje. Judith, when I arrived at the university, you made me feel welcome, the mug you gave me that first day is still in use. Our many inside and outside discussions about life, the universe, and everything even led to a joint publication. Bas you joined our room a year later, which makes you still the Benjamin of the room. Judith tought me to drink tee, but after she left you learned me to drink coffee again. Anke, Joke, Brigitte, René, and the IT support team thank you for all your assistance and hallway chats.

†Lucius Flavius Arrianus (AD 86–160). Anabasis of Alexander

During my travels to conferences and summerschools, I met many people. Peter van der Keur was always there. Peter, thank you for the nice time in Basel, Venice and Copenhagen. Also, thank you for giving me the opportunity to write a paper together.

At Deltares, I had a second working place at the water safety department. Although, my visits were somewhat irregular, I greatly enjoyed being there and enjoyed the hospitality of the department of water safety. Special thanks go to Frank van Stralen for your quick support when I had remote problems and for always being so 'aardig'. Furthermore, I want to thank Erik Mosselman, Kathryn Roscoe, Sophia Caires and Anke Becker for their help and fruitful discussions.

Many thanks go to the experts from Deltares, HKV, Haskoning and Rijkswaterstaat. Besides your greatly valued expert opinions you introduced me in practically dealing with uncertainties in river modelling practice.

Freek, I greatly enjoyed our trip to Canada. This was the start of the work that led to the last chapter of this thesis, together with Menno. Menno, it was my pleasure to work together again after you supervised my MSc thesis. Thank you for your sharp and valuable comments on the paper.

Brother Marijn and Michiel Schaap, it is an honour to have you by my side at the day of the defence. Michiel thank you for all substantive (and less substantive) talks and all overnight sleeps during my visits to Delft. I hope there will be many more in the future. Marijn, thanks for always being there and putting life into perspective with your never-ending stories.

The second last words are for my parents. Gerhard en Loura, you always showed what is most important in life. Loura, ik weet dat je niet alles meer mee zult maken, maar ik ben je meer dan dankbaar voor al je wijze levenslessen. Gerhard, toen ik ging promoveren waren je eerste woorden: "promotieonderzoeken gaan zo diep dat ze geen link meer hebben met de werkelijkheid, dat moet je niet laten gebeuren". Ik hoop dat dit een beetje gelukt is. Ik ben je woorden nooit vergeten. Dank voor jullie interesse, ondersteuning en liefde.

Willemijn, jij bent buitencategorie en verdient meer dan woorden kunnen zeggen. Dankjewel voor je steun en liefdevolle kopjes thee als ik weer eens op onze avonden en in onze weekenden moest werken. Ik ben je dankbaar voor je taak als eerste reviewer. Jij bent mijn alles.

Jord Warmink

Dedemsvaart, 11 July 2011

Contents

Summary

Flooding is a serious threat in many regions in the world and is a problem of international interest. Hydrodynamic models are used for the prediction of flood water levels to support flood safety. Two-dimensional river models are often applied in a deterministic way. However, the modelling of river processes involves numerous uncertainties. Previous research has shown that the hydraulic roughness is one of the sources of uncertainty that contributes most to the model outcome uncertainty of hydrodynamic river models. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model outcomes and the usefulness of model outcomes in decision making. Quantification of the uncertainty in model outcomes is carried out by means of an uncertainty analysis. An uncertainty analysis consists of five steps: identification, importance assessment, quantification of the sources of uncertainty, propagation to the model outcomes and the communication of uncertainty.

There are several problems in current studies about uncertainty analysis in river models. Firstly, these studies often only consider uncertainties in input and parameters, thereby omitting the uncertainties in model structure and model context. Secondly, little research has been done on the quantification of the uncertainty in the hydraulic roughness. Thirdly, in flood safety computations we deal with design conditions. The problem is that these circumstances rarely or never occur. Therefore, the magnitude of the uncertainties cannot be determined by measurements only. Finally, in current modelling practise it is assumed that the physical processes in the model are also valid under design conditions, which is not always the case. The objective of this thesis is *to quantify the uncertainties in the hydraulic roughness that contribute most to the uncertainty in the water levels and quantify their contribution to the uncertainty for a 2D hydrodynamic model for a lowland river under design conditions.*

The research consists of four steps, that are the first four steps of an uncertainty analysis. In chapter 2, I present a method to identify the sources of uncertainty in an environmental model. In chapter 3, I used expert opinion elicitation to determine the sources of uncertainty that contributed most to the uncertainty in the design water levels. Chapter 4 describes the quantification of the uncertainty in the bedform roughness, being an important uncertainty source, by data analysis and statistical extrapolation. Finally, in chapter 5 the uncertainty in bedform roughness is combined with the uncertainty in the vegetation roughness. Furthermore, the effect of the combined uncertainties on the design water levels is assessed for the 2D hydrodynamic model, WAQUA (Rijkswaterstaat, 2001), of the river Waal in the Netherlands.

Identification of uncertainties (Chapter 2)

In this chapter a method for a structured identification and classification of uncertainties in the application of environmental models is presented. I adapted the existing uncertainty framework of Walker et al. (2003) to enhance the objectivity in the uncertainty identification process. The method comprises two steps. Firstly, sources of uncertainty are globally identified using expert opinions, following the locations of uncertainty according to the adapted Walker matrix. During interviews all possible sources of uncertainty are listed. In the second step, the sources are iteratively classified in the Walker classification matrix. The sources of uncertainty are more specifically described until classification is possible along the three dimensions of uncertainty. Using this new approach, a complex source of uncertainty can be broken down in smaller components, and a list of unique and complementary uncertainties is created.

Two case studies demonstrate how the method helps to obtain an overview of unique uncertainties encountered in a model. The presented method improves the comparability of the results of an uncertainty analysis in different model studies and leads to a coherent overview of uncertainties that affect the model outcomes. This overview of sources of uncertianty is a sound basis for quantification or qualification of the sources of uncertainty in environmental models

Importance assessment (Chapter 3)

In this chapter, expert opinion elicitation is used to identify the uncertainties that contribute most to the uncertainty in water level computations for the river Waal in the Netherlands that is currently used in practise for the design water level computations. The use of a Pedigree analysis (Funtowicz and Ravetz, 1990) assured an objective selection of experts and gave confidence that the outcomes of the expert interviews are reliable. The uncertainties in two applications of the WAQUA model for the river Waal have been studied: 1) the computation of the design water levels and 2) effect studies, which are studies about the effect of measures taken in the floodplain areas. In the effect studies case, the effect of measures taken in the floodplain areas that change the geometry of the cross section are computed.

The aggregated expert opinions showed that the upstream discharge and the empirical roughness equation for the main channel contribute most to the uncertainty in the design water levels. The ranking of the uncertainties from important to less important was strengthened by the combination of qualitative and quantitative information from the expert opinions about the uncertainties. In the effect studies case, the ranking given by the experts was less clear, because the case study of the river Waal was not specific enough to get a reliable ranking for the effect studies case. Further research is required with more specific case studies to assess the importance of the various sources of uncertainty for effect studies.

Quantification of uncertain bedform roughness (Chapter 4)

The hydraulic roughness in the main channel of many lowland rivers is dominated by the resistance due to bedforms that develop on the river bed. However, the relation between roughness and the development of bedforms is not yet fully understood and is highly uncertain. In this chapter, it is shown that different models to compute bedform roughness resulted in a large range of bedform roughness values for the same measurements of bedform dimensions and flow characteristics for the river Rhine in the Netherlands.

I quantified the uncertainty in the bedform roughness under design conditions using statistical extrapolation of the roughness values from five different roughness models. The results showed that the 95% confidence interval of the Nikuradse roughness length for the main channel of the river Rhine under design conditions ranged from $k_N = 0.32$ m to $k_N = 1.03$ m, which is a range of 0.71 m. Propagation of this uncertainty range to the water levels for a idealised WAQUA model for the river Waal showed that the uncertainty due to the choice of the roughness model (a model structure uncertainty) may significantly contribute to the uncertainty in the design water levels.

Combination and propagation of uncertain bedform and vegetation roughness (Chapter 5)

In this chapter, the quantified uncertainty in the bedform roughness from chapter 4 is combined with the uncertainty due to the vegetation schematization, which was quantified in an earlier study by Straatsma and Huthoff, and the uncertainty due to the vegetation roughness model. The individual and combined uncertainties have been propagated through the WAQUA model for the river Waal to assess the effect on the design water levels.

A Monte Carlo Simulation using the WAQUA model for the river Waal showed that the uncertainty range of the bedform roughness of 0.71 m resulted in a 95% confidence interval of the design water levels of 49 cm. The results showed that the 95% confidence interval increased from 49 cm and 34 cm, for uncertain bedform roughness and vegetation roughness, individually, to 61 cm if they were combined. However, these values have not been corrected for the effect of calibration on the uncertainty in design water levels. The uncertainties in the vegetation roughness model proved to have little influence on the uncertainties in the design water levels. It has been shown that positive outliers in the vegetation roughness increase the uncertainty in the design water levels due to uncertain bedform roughness. This showed that interactions between the various sources of uncertainty are important for the uncertainty in the design water levels.

Conclusions

In this thesis, an uncertainty analysis has been carried out for a case study of the two-dimensional WAQUA model of the river Waal that is used to predict the design water levels for flood safety purposes in the Netherlands. This research showed that

the uncertainty of a complex model factor, such as the hydraulic roughness, can be quantified explicitly. The hydraulic roughness has been unravelled in separate components, which have been quantified separately and subsequently, the uncertainties of the individual sources were combined and propagated through the model.

The final uncertainty range is significant in view of Dutch river management practise. This thesis describes, which measures should be taken to reduce the uncertainties and what benefits in terms of reduced uncertainty in water levels can be accomplished. However, the uncertainty has not been corrected for the effect of calibration. This thesis demonstrates that the uncertainties in a modelling study can be made explicit. The process of uncertainty analysis helps in raising the awareness of the uncertainties and enhances communication about the uncertainties among both scientists and decision makers.

Samenvatting

Het overstromen van rivieren is een bedreiging in grote delen van de wereld en veroorzaakt grote sociale en economische schade. Om overstromingen te voorkomen worden hydrodynamische riviermodellen gebruikt voor het voorspellen van hoogwaterstanden. Riviermodellen worden vaak deterministisch gebruikt, maar deze modellen bevatten veel onzekerheden. Eerdere onderzoeken hebben aangetoond dat de hydraulische ruwheid een van de bronnen van onzekerheid is die het meest bijdragen aan de onzekerheid van de modeluitkomsten. Kennis van de grootte en het type van deze bronnen van onzekerheid is cruciaal voor een betekenisvolle vertaling van de modeluitkomsten in beleid. De kwantificering van de onzekerheid in modeluitkomsten wordt gedaan in een onzekerheidsanalyse. Een onzekerheidsanalyse bestaat uit vijf stappen: (1) identificatie, (2) bepaling van de belangrijkste bronnen van onzekerheid, (3) kwantificering van de bronnen van onzekerheid, (4) voortplanting van de onzekerheden naar de modeluitkomsten en (5) de communicatie van onzekerheiden naar beleidsmakers.

Aan de huidige aanpak van onzekerheidanalyses in riviermodellen zitten verschillende beperkingen. Ten eerste, deze studies beschouwen vaak alleen onzekerheden in de modelinvoer en parameters. Onzekerheden in de structuur van het model en de context worden dan dus niet meegenomen. Ten tweede is er weinig onderzoek gedaan naar de kwantificering van de onzekerheid in de hydraulische ruwheid. Dit betekent dat we niet weten hoe nauwkeurig onze modellen zijn. Ten derde bestuderen we in hoogwatervoorspellingen vaak de toestand van de rivier onder maatgevende condities. Het probleem is dat deze condities zelden of nooit voorkomen en dat er dus geen metingen beschikbaar zijn. De grootte van de onzekerheid in de bronnen kan dus niet direct door metingen worden bepaald. Daarom wordt in de praktijk aangenomen dat de fysische processen die in het model zitten ook geldig zijn onder maatgevende condities. Dit is niet zonder meer het geval. Het doel van dit proefschrift is dan ook: het kwantificeren van de onzekerheden in de hydraulische ruwheid die het meest bijdragen aan de onzekerheid in de waterstanden en het kwantificeren van hun bijdrage aan de onzekerheid in de maatgevende waterstanden voor een 2D hydrodynamisch model van een laagland rivier.

Het onderzoek bestaat uit vier stappen. Dit zijn de eerste vier stappen van een onzekerheidsanalyse. In hoofstuk 2 presenteer ik een methode om bronnen van onzekerheid te identificeren in hydrodynamische modellen. In hoofdstuk 3 gebruik ik expert meningen om de bronnen van onzekerheid te bepalen die het meest bijdragen aan de onzekerheid in de maatgevende waterstanden. Hoofdstuk 4 beschrijft het kwantificeren van de onzekerheid in de ruwheid van beddingvormen door ge-

bruikt te maken van historische metingen en statistische extrapolatie. In hoofdstuk 5 wordt de onzekerheid in de ruwheid door beddingvormen gecombineerd met de onzekerheid in de ruwheid door vegetatie in de uiterwaarden en wordt het effect van beide onzekerheden op de maatgevende waterstanden berekend voor het 2D model, WAQUA (Rijkswaterstaat, 2001), van de rivier de Waal.

Identificatie van onzekerheden (Hoofdstuk 2)

In dit hoofdstuk wordt een methode gepresenteerd voor een gestructureerde identificatie en classificatie van onzekerheden in de toepassing van hydrodynamische modellen. Het bestaande raamwerk van (Walker et al., 2003) (de matrix) is aangepast en aangescherpt om de objectiviteit te verbeteren tijdens het identificatieproces. De methode bestaat uit twee stappen. Ten eerste worden de bronnen van onzekerheid globaal geïdentifieerd met behulp van experts. Hierbij wordt gebruik gemaakt van de locaties van onzekerheid volgens de aangepaste Walker matrix. Tijdens de interviews met de experts worden alle mogelijke bronnen van onzekerheid verzameld. Vervolgens wordt geprobeerd om de verzamelde onzekerheden iteratief te classificeren in de Walker matrix. Als classificatie niet mogelijk blijkt voor de drie de dimensies van onzekerheid in de Walker matrix, worden de onzekerheden opgebroken in kleinere componenten en wordt de onzekerheid dus specifieker gedefinieerd. Dit proces wordt herhaald totdat alle onzekerheden geclassificeerd zijn. Deze nieuwe aanpak maakt het mogelijk dat een complexe bron van onzekerheid in unieke componenten wordt verdeeld en dus nauwkeuriger beschreven is.

Twee case studies laten zien dat de methode resulteert in een overzicht van unieke onzekerheden in een model. De gepresenteerde methode zorgt voor een betere vergelijkbaarheid van de bronnen van onzekerheid en van de resultaten van een onzekerheidsanalyses voor verschillende model studies. Het zorgt het voor een overzicht van unieke en onafhankelijke onzekerheden die invloed hebben op de modeluitkomsten. Door zo uitgebreid en nauwkeurig mogelijk te zijn is een sterke basis gelegd voor het verder kwantificeren en kwalificeren van de bronnen van onzekerheid.

Bepaling van de belangrijkste bronnen van onzekerheden (Hoofdstuk 3)

In dit hoofdstuk worden expert meningen gebruikt om te bepalen welke bronnen van onzekerheid het meest bijdragen aan de onzekerheid in de maatgevende waterstandsberekeningen voor de rivier de Waal. Het gebruik van een Pedigree analyse (Funtowicz and Ravetz, 1990) zorgt voor een objectieve selectie van experts. Een objectieve selectie geeft het vertrouwen dat de uitkomsten van de expert interviews betrouwbaar zijn. De onzekerheden in twee toepassingen van het WAQUA model voor de Waal zijn onderzocht: (1) een berekening van de maatgevende waterstanden voor de hydraulische randvoorwaarden en (2) de berekening van effect studies. Effect studies zijn berekeningen die het effect bepalen van een ingreep in de uiterwaarden van de rivier. Hierbij wordt het effect berekend van een veranderingen in de riviergeometrie.

De gecombineerde meningen van de experts laten zien dat de bovenstroomse afvoer en de empirische ruwheidsvoorspeller voor de hoofdgeul van de rivier het meeste bijdragen aan de onzekerheid in de maatgevende waterstanden. De ordening van de onzekerheden van belangrijk naar minder belangrijk wordt versterkt door de combinatie van kwantitatieve en kwalitatieve inschattingen van de bijdrage van de onzekerheden door de experts. De ordening door de experts voor de effect studies was minder duidelijk, omdat de afbakening van de case studie van de Waal niet specifiek genoeg bleek te zijn. Verder onderzoek is nodig, waarbij gebruik wordt gemaakt van kleinere en specifieker beschreven case studies, om de ordening van verschillende bronnen van onzekerheid in het geval van effect studies duidelijk te maken.

Kwantificering van onzekerheid in de beddingvorm ruwheid (Hoofdstuk 4)

De hydraulische ruwheid van de hoofdgeul van veel laaglandrivieren wordt bepaald door de weerstand van beddingvormen die zich ontwikkelen op de rivierbodem. De relatie tussen ruwheid en de ontwikkeling van beddingvormen is echter nog grotendeels onbekend. In dit hoofdstuk worden bestaande ruwheidsmodellen om de ruwheid van beddingvormen te berekenen vergeleken op basis van veldmetingen van de dimensies van beddingvormen en karakteristieken van de waterstroming. Deze vergelijking laat zien dat verschillende ruwheidsmodellen resulteren in een grote spreiding in de ruwheid.

De onzekerheid in de beddingvormruwheid tijdens maatgevende condities is gekwantificeerd door gebruik te maken van statistische extrapolatie van de ruwheid berekend door vijf verschillende ruwheidsmodellen. De resultaten laten zien dat het 95% betrouwbaarheidsinterval van de Nikuradse ruwheidslengte (k_N een maat voor de ruwheid) van de hoofdgeul tijdens maatgevende condities ligt tussen $k_N = 0.32$ en $k_N = 1.03$ m. Dit is een range van 0.71 m. De voortplanting van deze onzekerheid met behulp van een geïdealiseerd WAQUA model voor de Waal laat zien dat de keuze die gemaakt wordt voor een bepaald ruwheidsmodel (een onzekerheid in de modelstructuur) significant kan bijdragen aan de onzekerheid in de maatgevende waterstanden.

Combinatie en voortplanting van onzekerheid in beddingvorm en vegetatieruwheid (Hoofdstuk 5)

In dit hoofdstuk wordt de gekwantificeerde onzekerheid in de beddingvormruwheid uit hoofdstuk 4 gecombineerd met de onzekerheid in de schematisering van vegetatie die is gekwantificeerd door Straatsma en Huthoff in een eerdere studie en de onzekerheid door het vegetatieruwheidsmodel. De afzonderlijke en gecombineerde onzekerheden zijn voortgeplant door het WAQUA model van de Waal om het effect op de maatgevende waterstanden te bepalen.

Een Monte Carlo Analyse van een realistisch WAQUA model van de Waal laat zien dat een onzekerheidsrange van 0.71 m in de beddingvormruwheid resulteert in een 95% betrouwbaarheidsinterval in de maatgevende waterstanden van 49 cm. De resultaten laten verder zien dat het 95% betrouwbaarheidsinterval toeneemt van 49 cm en 34 cm voor de beddingvorm- en vegetatie schematisering afzonderlijk naar 61 cm voor de combinatie van deze twee bronnen. Deze waarden zijn echter niet gecorrigeerd voor het effect van kalibratie van het WAQUA model op de onzekerheid in maatgevende waterstanden. De onzekerheid door de keuze voor het vegetatieruwheidsmodel liet weinig invloed zien op de onzekerheid in de maatgevende waterstanden. De voortplanting van beddingvormruwheid en de schematisering van vegetatie liet zien dat er positieve uitschieters voorkomen door de schematisering van vegetatie die zorgen voor een toename van de onzekerheid in de waterstand in combinatie met een hoge beddingvormruwheid. Dit laat zien dat interacties tussen de verschillende bronnen van onzekerheid belangrijk kunnen zijn voor de onzekerheid in de maatgevende waterstanden.

Conclusies

Dit proefschrift beschrijft een onzekerheidsanalyse van het tweedimensionale WAQUA model voor de rivier de Waal. Dit model wordt gebruikt voor de bepaling van de maatgevende waterstanden voor de bescherming tegen overstromingen in Nederland. Dit onderzoek heeft aangetoond dat de onzekerheid in een complexe factor in het model, zoals de hydraulische ruwheid, expliciet kan worden gekwantificeerd. De hydraulische ruwheid is ontrafeld in afzonderlijk componenten die zijn gekwantificeerd. Vervolgens zijn de belangrijkste gekwantificeerde componenten gecombineerd en is het effect op de maatgevende waterstanden bepaald.

De uiteindelijke onzekerheid is significant binnen het Nederlandse riviermanagement. De analyse laat zien welke maatregelen er genomen kunnen worden om de onzekerheden te verkleinen en hoeveel winst er in termen van gereduceerde onzekerheid, behaald kan worden. Er is echter geen rekening gehouden met het effect van kalibratie op de uiteindelijke onzekerheid. De toegevoegde waarde van dit proefschrift is dat er is aangetoond dat de altijd aanwezige onzekerheden in een modelstudie expliciet gemaakt kunnen worden. Het proces van onzekerheidsanalyse helpt om het bewustzijn te vergroten, onzekerheden inzichtelijk te maken en de communicatie over onzekerheden te verbeteren voor zowel wetenschappers als beleidsmakers.

Chapter 1

Introduction

1.1 Modelling of rivers for flood management

Flooding is a serious threat in many regions in the world and is a problem of international interest (Dilley et al., 2005). In the past few years river flood events occurred all around the world, such as in the Elbe and the Oder in Germany, the Oder and the Vistula in Poland, the Indus river in Pakistan, the Jamuna river in Bangladesh, the Yangtze in China and the Mundau river in Brazil. These kind of river floods costs many lives every year and cause large economic damages. In the Netherlands, (near) flood events occurred in 1993 and 1995, which led to large scale evacuations and large economic damages (Middelkoop and Van Haselen, 1999; Van Stokkom et al., 2005).

To prevent rivers from flooding, flood protection measures need to be taken. Flood protection is carried out by, amongst others, river regulation. In Europe, the main human interventions in relation to river regulation consist of damming, building and management of reservoirs, river channelisation, building of weirs and dredging of river channels (Scheidleder et al., 1996). In the Netherlands, dramatic and repeated flooding of some rivers in the 19th century led to a widespread movement to channel them and to straighten their courses (Van Stokkom et al., 2005). However, after the 1993 and 1995 (near) flood events, a more sustainable approach has been adopted: the "room for the river" strategy (Ministry of Transportation, Public Works and Water Management, 1998; Silva et al., 2001; Van Vuren et al., 2005). Instead of raising the dikes, the discharge capacity is increased by increasing the space for the river by, amongst others, moving the dikes further inland or lowering the floodplains (Ministry of Transportation, Public Works and Water Management, 1998). Accurate modelling is required to determine the location and dimensions of the flood protection measures that are to be constructed.

1.1.1 River modelling

Models and model outcomes play an essential role in river management decisions. Much of the effort in environmental sciences is spent on the development of quantitative models (Heuvelink, 1998). Quantitative models are an aid in the understanding of processes and the prediction of future behaviour and are used in different

(a) Vistula river, Poland

(b) Rhine river near Nijmegen, the Netherlands

(c) Mississippi river, New Orleans, USA

(d) Pannerdensche Weir, Rhine river, the Netherlands

Figure 1.1: River flooding around the world. Picture courtesy: (a) REUTERS, 2010, (b) www.beeldbankVenW.nl, 1995, (c) REUTERS, 2005, (d) www.beeldbankVenW.nl, 1993

working fields, such as policy making and engineering. In engineering, environmental models are used mainly to simulate physical processes for prediction purposes (Harremoës and Madsen, 1999; Brown, 2004). In river management, hydrodynamic models are used to predict flood water levels and support navigation, water quality monitoring and ecological rehabilitation. The water levels that occur as a result of a flood wave should be predicted accurately. River models describe the interactions between bed topography and water motion in a simplified way, but these processes are highly complex.

River flood protection measures are designed to withstand floods with a certain return period. The return period is an expression for the interval in time between (extreme) events. Typical return periods for design floods range from around 20 years for the Mississippi river (Storesund (Ed.), 2008) to 1250 years for the upper part of the river Rhine in the Netherlands (Ministry of Transportation, Public Works and Water Management, 1995). The water levels and flow velocities need to be computed for design conditions, but these conditions rarely or never occur. This complicates the computation of the design water levels, because the behaviour of fluvial systems under design conditions is to a large extent unknown.

1.1.2 Classification of river models

In river management practise, different types of environmental models are used for various purposes, on different scales and with different dimensions (figure 1.2). Brugnach and Pahl-Wostl (2008) describe four different model purposes: learning, communication, exploratory analysis and prediction. These different model purposes aim at other model outcomes and, therefore, have other structures and characteristics. The prediction model class is subdivided by Klemes (1986) in: simulation, prediction and forecasting models. Simulation models aim at the understanding of the physical processes, while forecasting models aim at the prediction of the value of a quantity (water levels or discharges) for the next couple of days. Prediction models aim at the prediction of changes in the behaviour of a system under circumstances that are not yet observed. In this thesis I will focus mainly on the subclass prediction models.

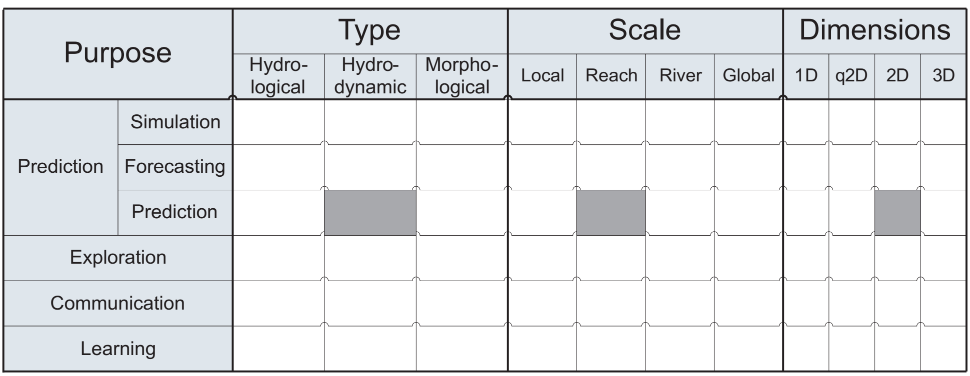


Figure 1.2: The model matrix. A model is defined along four dimensions. Model purpose, type, scale and model dimension. The grey classes show the models that I focus on in this thesis.

Besides different model purposes, also different types of models are used for river management. For example, hydrological models predict discharges based on, amongst others, precipitation in rainfall-runoff models or use simple streamflow routing models to propagate the discharge through a river network. Hydrodynamic river models are based on the shallow water equations and compute water levels and flow velocities based on the discharge in a more detailed way. Furthermore, hydrodynamic models drive morphological and water quality models, where the water flow controls the transport of sediment and pollutants respectively.

Common hydrodynamic prediction models for river management have different scales. A river can be schematized at the local scale (up to ±5 km), reach scale (±5–100 km) or river scale (±100–1000 km). Although flow in compound channels is known to be fully three-dimensional, the detailed numerical treatment of such processes is not (yet) a viable option at scales larger than the local scale, which are of interest for river flood management. Spatial scales are linked to temporal scales (De Vriend, 1999). Models at reach and river scale typically deal with time scales of days to months, respectively.

River flood problems can be modelled in one, two or three spatial dimensions. One dimensional river models, such as MIKE11 (DHI, 2010b), HEC-RAS (USACE, 2008) or SOBEK (Deltares, 2010) still form the majority of traditional numerical hydrodynamic models used in practical river engineering (Pappenberger et al., 2005). However, two-dimensional, depth averaged (2D) models are used more often nowadays.

It is generally believed that two-dimensional representation of flow gives more accurate predictions of flood wave propagation than 1D (Cunge, 1975; Anderson et al., 1996; Pappenberger et al., 2008). Commonly used 2D models are MIKE21-C (DHI, 2010c), DELFT3D (Deltares, 2010), TELEMAC-2D (Galland et al., 1991; Sogreah, 2010) and WAQUA (Rijkswaterstaat, 2009). Between 1D and 2D models are the quasi-2D models, such as LISFLOOD-FP (Bates and Roo, 2000) or MIKE-FLOOD (DHI, 2010a), which compute the water levels in the main channel in 1D, but use a simple storage cell concept for floodplain flow. Quasi-2D models are most suitable if the interest lies in the spatial extent of a flood in the river region (Werner, 2004; Hunter et al., 2007). However, the drawback of quasi-2D models is that they do not compute the water flow in the floodplain region and, therefore, are not suitable to study physical processes in the floodplain. In this thesis, I focus mainly on fully 2D models that explicitly compute the depth-averaged hydrodynamics in the main channel and floodplain region.

1.2 Uncertainty and uncertainty analysis

Two-dimensional river models for the purpose of safety against flooding are often applied in a deterministic way (e.g. Sauvaget et al., 2000; Rijkswaterstaat, 2001). However, the modelling of river processes involves numerous uncertainties. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model outcomes and the usefulness of model outcomes in decision making. Therefore, a full understanding of the model and its uncertainties is important (Pappenberger and Beven, 2006). Information about the uncertainty in model outcomes can increase the reliability of a decision. Without knowledge of this uncertainty, the reliability and usefulness of model outcomes can not be fully known.

1.2.1 Defining uncertainty

In scientific literature, uncertainty is used to comprise different terms (Zimmermann, 2000), such as model error, prediction error, conflicting evidence, randomness and as the opposites of adequacy, accuracy, precision, reliability, robustness and confidence. Therefore, it is of main importance to frame the concept of uncertainty. Many authors recognised the need for a framework to clarify the meaning of uncertainty (Van Asselt and Rotmans, 1996, 2002; Van der Sluijs, 1997; Zimmermann, 2000; Walker et al., 2003; Refsgaard et al., 2007). However, they all use other definitions and concepts of uncertainty.

A general definition of uncertainty in modelling is given by Walker et al. (2003), who define uncertainty as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system". However, many other definitions exist. Sigel et al. (2007) define uncertainty as: "a person is uncertain if he/she lacks confidence about his/her knowledge relating to a concrete question". According to Zimmermann (2000) and Brugnach et al. (2007), "uncertainty implies that in a certain situation a person does not dispose about information which quantitatively and qualitatively is appropriate to describe, prescribe or predict deterministically and numerically a system, its behaviour or other characteristics". Brugnach et al. (2007) and Sigel et al. (2007) studied uncertainty by decision makers in water management, while Walker et al. (2003) considers uncertainty in modelling. These different views on uncertainty result in ambiguity between working fields and even between different research groups within a working field.

In this thesis I define uncertainty according to Walker et al. (2003), because this definition has its background in modelling and it evolved from many years of research (e.g. Janssen et al., 1990; Van Asselt and Rotmans, 1996, 2002; Harremoës and Madsen, 1999). This definition implies that uncertainty is the absence of knowledge, so it depends on the available amount of information to the observer (figure 1.3) and the general state of knowledge. Uncertainty is introduced in the perception of the observer of the real world and the model. All interactions with the real world and the model introduce uncertainty. This comprises that (Heuvelink and Brown, 2009):

- Uncertainty arises when we are not sure about the "true" state of the environment; it is an expression of confidence based on limited knowledge
- Uncertainty is an acknowledgement of error: we are aware that our representation of reality may differ from reality itself and express it by being uncertain
- Uncertainty is subjective, one person can be more uncertain than another about the same phenomenon
- In the presence of uncertainty, we cannot identify a true "reality", but perhaps we can identify possible realities and a probability for each one

So, the definition of uncertainty states that it is a subjective concept that is used with different meanings by different people. In this thesis, I deal with uncertainties in modelled water levels. Uncertainty is, therefore, considered to be the difference between the predicted model outcome under consideration and its "true" value, which we do not always know.

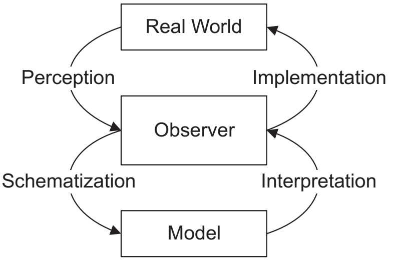


Figure 1.3: Definition of uncertainty. Uncertainty is introduced in all interactions between the observer, the real world and the model (based on Zimmermann, 2000)

1.2.2 Uncertainty analysis

Quantification of the uncertainty in the model outcomes is carried out by means of an uncertainty analysis (Morgan and Henrion, 1990; Refsgaard et al., 2007). An uncertainty analysis consists of five steps (Van der Sluijs et al., 2005b): identification, importance assessment, quantification of the sources of uncertainty, propagation to the model outcomes and the communication of uncertainty (see figure 1.4). To avoid distinctions between uncertainties in input, parameters, model structure and model context all inputs of an uncertainty analysis are collectively referred to as the sources of uncertainty.

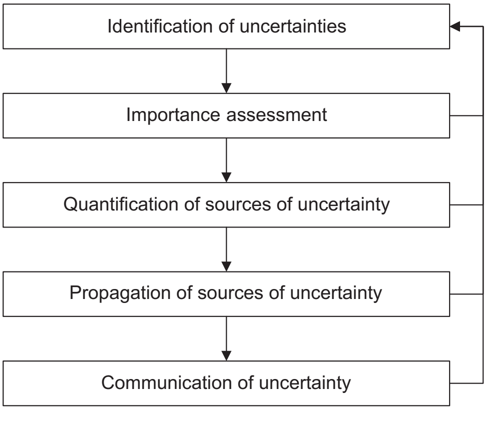


Figure 1.4: The five steps in an uncertainty analysis

The first step in an uncertainty analysis is to identify the sources of uncertainty in the model. All locations of uncertainty in a model, such as input, parameters, model structure and model context (Walker et al., 2003), should be taken into account in an uncertainty analysis. Otherwise, there is the risk of omitting important sources of uncertainty, which results in underestimation of the uncertainty in model outcomes.

The second step in an uncertainty analysis, the importance assessment, determines the uncertainties that contribute most to the uncertainty in the model outcomes. In this step the change in model outcomes is determined due to differences in the model input (Saltelli et al., 2000, 2004). Importance assessment is an essential aspect of responsible model use, particularly at a time when models are becoming more complex and are being coupled in order to address multidisciplinary problems (Hall et al., 2009).

The third step is the quantification or qualification of the individual sources of uncertainty in the model. The sources of uncertainty need to be explicitly quantified by means of, for example, a coefficient of variation (CV, standard deviation divided by the mean) or a probability distribution function (PDF). If quantification is not possible, the uncertainty should be described as a scenario or qualified. The reliability of the uncertainty analysis is highly sensitive to the assumed quantification (or qualification) of the sources of uncertainty (Johnson, 1996). The problem is that information about the magnitude or probability distribution functions for these sources is usually not available or insufficient (Johnson, 1996; Van der Sluijs, 2007).

The fourth step is to propagate the quantified uncertainties in the model to the model outcomes. Many different methods exist for the propagation of uncertainties. Refsgaard et al. (2007) list seven methods for uncertainty propagation. The authors state that for different types of uncertainties different methods of uncertainty propagation are available. Which method to use depends on the level (e.g. quantitative, scenario or qualitative Walker et al., 2003) of the source of uncertainty under consideration.

Finally, the results of an uncertainty analysis need to be communicated to the intended audience. Communication of uncertainties aimed at policy makers, as well as other parties involved in policy making, is important, because uncertainties can influence the policy strategy that is selected. Furthermore, it is a matter of good scientific practise, accountability and openness toward the general public (Wardekker et al., 2008).

1.3 Uncertainty analysis in river modelling practise

Uncertainty analyses are part of the modelling cycle (Jakeman et al., 2006; Refsgaard et al., 2007; EPA, 2009). However, in current modelling practise, uncertainty analysis is often considered a burden. Many studies about uncertainty analysis have been carried out for hydrological models (e.g. Beven, 2006b; Choi and Beven, 2007; Huang and Lee, 2009), 1D hydrodynamic models (e.g. Chang et al., 1993; Van der Klis, 2003; Pappenberger et al., 2005) and quasi-2D hydrodynamic models (e.g. Aronica et al., 2002; Bates et al., 2004; Pappenberger et al., 2007), but rarely for fully 2D hydrodynamic models. Two-dimensional river models are assumed to be more accurate than 1D models (e.g. Pappenberger et al., 2008), but little attention is paid to the uncertainties. Two-dimensional models are computationally demanding. Therefore, uncertainty analysis is often not carried out for 2D models. To get insight in the uncertainties in the model outcomes of detailed 2D river models, a structured and reliable uncertainty analysis is required. In this section, a literature review is presented for the five steps of the uncertainty analysis.

1.3.1 Identification of uncertainties

In recent uncertainty analysis studies about river modelling, often only the uncertainties that can easily be quantified are taken into account, such as uncertainties in model input and parameters (e.g. Refsgaard et al., 2006a; Hall et al., 2005; Bates et al., 2004). The uncertainties in model context and model structure are often omitted in the analysis. In such cases, it is likely that the model outcome uncertainty is underestimated (Refsgaard et al., 2006b). Pappenberger and Beven (2006) stressed that it is important to frame the model outcomes and associated uncertainties to the model context.

Another problem is that the identification of uncertainties is often carried out in an unstructured manner. The conclusions of the uncertainty analysis are then a result of a suboptimal identification, which might result in an inaccurate uncertainty analysis. For example, Van der Sluijs et al. (2005a) and Krayer von Krauss et al. (2004) identified the uncertainties in various environmental impact studies. The authors used an unstructured identification, which did not guarantee that all possible sources of uncertainty are taken into account. However, they accounted for uncertainties in model context and model structure. In their study, it strongly depended on the expert, which uncertainties were considered. So, besides accounting for all locations of uncertainty according to Walker et al. (2003) in a model, also a structured identification is essential for a reliable uncertainty analysis.

1.3.2 Importance assessment

Sundararajan (1998) stated that in the importance assessment step, next to the sensitivity of the model for a source of uncertainty, also the "quality" of the uncertainty should be assessed. This "quality" was determined by quantifying the scientific consensus on the assumptions underlying the uncertainty. The author used expert elicitation with three experts to assess this quality and the importance of 12 parameters in a nuclear plant risk assessment. The author showed that, although expert opinions are subjective, the results were useful to select the important uncertainties in an uncertainty analysis.

There is a difference between sensitivity analysis and importance assessment. In an importance assessment, the contribution of a source of uncertainty to the uncertainty in the model outcomes is assessed. In a sensitivity analysis the change of the model outcomes as a result of a change in a model input, parameter or other model component is assessed. In the latter case, a source of uncertainty does not need to be quantified, but a simple deviation (e.g. $\pm$ 20%) can be assumed. In the first case, the source of uncertainty needs to be explicitly quantified as the effect on the model outcome uncertainty is required. This makes the importance assessment practically the same as the uncertainty analysis. Sensitivity analysis is an essential step in responsible model use to understand the behaviour of the model. However, it is not a replacement for an uncertainty analysis.

A sensitivity analysis is useful to explore the impact of initial conditions (Bates and Anderson, 1996) and model structure (Pappenberger et al., 2006) on flood inundation predictions. Bates and Anderson (1996) showed that a uniform change in floodplain topography and upstream inflow produced a complex model response, non-uniform in both space and time. This resulted in significant variation between flood events for uniform model inputs. Pappenberger et al. (2006) showed how the results of the sensitivity analysis can be used to suggest how the effective values of the Manning surface roughness could be spatially disaggregated based on local model performances. This revealed that several of the imposed parameter set combinations resulted in failure of the model. Ideally, a physically-based model should not fail for all evaluation criteria justified by the goal of the model (Pappenberger et al., 2006), as it is supposed to be a representation of reality. However, in practise, this is not always the case due to anomalies in the model. These studies showed that a sensitivity analysis is useful to get insight in the behaviour of non-linear models and to identify anomalies in models.

Sensitivity analyses also provide information for the calibration process by determining the influential model factors (Bates and Anderson, 1996). Sensitivity analysis is useful for model understanding and determination of suitable parameters for model calibration. However, it is not a replacement for an uncertainty analysis. In some studies (e.g. Hall et al., 2009; Pappenberger et al., 2008; Saltelli et al., 2004; Ratto et al., 2001) the term global sensitivity analysis is used to address the issue of how the uncertainties in output can be apportioned to different sources of uncertainty. If the sources of uncertainty are reliably quantified, such a study actually is an uncertainty analysis.

1.3.3 Quantification of sources of uncertainty

The critical step in an uncertainty analysis is to quantify the sources of uncertainty based on the available evidence. The rigour of this step and use of appropriate peer review is of utmost importance to the credibility of the analysis (Hall and Solomatine, 2008). The quantification of the sources of uncertainty is often carried out by data analysis. Refsgaard et al. (2006a) quantified sources of uncertainty for a groundwater model for the Odense (Denmark) region. They showed that the uncertainty in the model output was caused, amongst others, on the difference between the measured and modelled spatial scale of the sources of uncertainty (e.g. precipitation, climate factors and discharge measurements). This revealed that the scale of the measurements used for the quantification of uncertainties is of main importance.

Pelletier (1988) carried out a literature review of uncertainties in discharge measurements in Canada. The author showed how the combination of many different sources of uncertainty resulted in a total uncertainty in discharge measurements. However, she noticed that quantification of uncertainty is highly complex, especially, because the estimates of uncertainty are uncertain themselves. Johnson (1996) carried out a review that aimed at quantifying the uncertainty in hydraulic parameters that are reported in literature (e.g. Chow, 1959; Knighton, 1998). These values in text books are often unquestioningly used in practise. Van der Klis (2003) and Van Vuren et al. (2002; 2005) quantified the effect of uncertain discharge hydrographs on river morphology. To quantify the source of uncertainty, they generated multiple variations of the discharge hydrograph based on the uncertainty in a 100 year measured discharge series. Van Gelder (2008) used statistical extreme value analysis for the extrapolation of historically measured discharges to design conditions. The author showed that at extreme design conditions the uncertainty in the design discharge was considerable. It was shown that besides the uncertainty due to the measurements, also the uncertainty due to the extrapolation method played a role. These studies showed how data analysis has been used for the quantification of the sources of uncertainty. The measurements themselves are, however, also uncertain, especially if they are extrapolated to design conditions.

Another approach was used by Van der Sluijs et al. (2005b), who quantified the uncertainties in the VOC (Volatile Organic Compound) emission of paint using expert opinion. The authors elicited PDFs for all inputs by asking the expert to state the extreme minimum and maximum plausible values for the variable. Also, the 5%, 50% and 95% quantiles and the shape of the distribution were elicited from the experts. This method required detailed knowledge from the experts, which made it difficult to get reliable estimates of these values. In the study of Van der Sluijs et al. (2005b) most of the estimated PDFs were based on the opinion of a single expert, which introduced uncertainty in the elicited PDFs. The advantage of expert opinion is that experts are able to estimate the uncertainty if no measurements are available. Furthermore, expert opinions enable the estimation of the uncertainties due to model structure. For example, Zio and Apostolakis (1996) quantified the uncertainty due to the model structure for the tracing of nuclear waste through groundwater flow. They used experts to define plausible alternative models for the transport of nuclear waste in groundwater.

Ogink (2003) quantified the uncertainties in the computation of design water levels and effect studies for the river Rhine in the Netherlands. In impact studies, the effect of measures taken in the floodplain areas that change the geometry of the cross section are computed. The author quantified the uncertainties in the hydraulic roughness of the main channel, the floodplains and the intermediate region influenced by groynes, the uncertainties in the magnitude and shape of the discharge wave, uncertainties in river bed geometry and uncertainties due to extrapolation to design conditions. This study gives an indication of the magnitude of these sources of uncertainty and their effect on the design water levels. The quantification of the uncertainties is based on rules of thumb and strong assumptions. However, in case of limited measurements, this is the only information that is available.

1.3.4 Propagation of sources of uncertainty

In the propagation of uncertainty the effect of the quantified sources of uncertainty on the model outcomes is determined. Propagation of uncertainties is mostly carried out by means of error propagation equations (e.g. Vrijling et al., 1999; Maurer et al., 1998; Van der Klis, 2003; Maskey and Guinot, 2003; Kunstmann and Kastens, 2006) or Monte Carlo Simulation (MCS) (e.g. Kuczera and Parent, 1998; Bates and Campbell, 2001; Van der Klis, 2003; Van Vuren et al., 2005; Krupnick et al., 2006; Booij et al., 2007; Refsgaard et al., 2007). Error propagation equations (Morgan and Henrion, 1990) are fast to compute, but difficult to apply for complex models (Van der Klis, 2003). Monte Carlo Simulation (MCS) is computationally more demanding, but easier to apply. It does not impose any assumptions on the model or the probability distribution of the sources of uncertainty. Therefore, MCS is commonly used for uncertainty propagation in river modelling (e.g. Gates and Al-Zahrani, 1996b; Bates and Campbell, 2001; Van der Klis, 2003; Van Vuren et al., 2005). However, MCS requires a detailed description of the sources of uncertainty, usually by means of a probability distribution function (PDF). Also, the correlations between the sources of uncertainty need to be quantified.

Van der Klis (2003) compared error propagation equations with MCS, with and without Latin Hypercube Sampling, for a 1D morphological model. She concluded that MCS is the most suitable method to propagate the uncertainty through this model. Latin Hypercube Sampling did not significantly reduce the required computational time for highly non-linear models.

Another uncertainty propagation method is scenario analysis. For this method logically and internally consistent sequences of events are described to explore how the future could evolve. By scenario analysis, the different alternative futures are explored and in this way the uncertainties are addressed. As such, scenario analysis is a tool to deal explicitly with different assumptions about the future (Van der Sluijs et al., 2004), thereby addressing uncertainties in both model context and the assumptions about which environmental processes are involved.

1.3.5 Communication of uncertainty

The goal of quantifying uncertainty in modelling is to provide knowledge in a form that is accessible and useful to decision makers and other stakeholders (Pappenberger et al., 2006). Sayers et al. (2002) suggested that it may be effective communication that is the major problem. Communicating results to users is probably the most critical and important step in the entire code of practise as without it our scientific analysis will not be used by anyone else beside ourselves.

Scientific assessments of environmental problems, and policy responses to those problems, involve uncertainties of many sorts. Potential impacts of wrong decisions can be far-reaching (Wardekker et al., 2008). Uncertainty communication should meet the information needs of the target audiences, and therefore should be context dependent and customised to the audience. The implications of the uncertainties for the policy context and for different risk management strategies should be addressed (Kloprogge et al., 2007).

Communication of uncertainties is not merely a matter of reporting the uncertainties themselves, but they also need to be properly reflected in the formulation of the main messages that are conveyed. Moreover, it can be of importance to inform the audiences on the implications of the uncertainties and what can be done about it (Kloprogge et al., 2007). It will often be relevant to inform them with insights in how the uncertainties were dealt with in the assessment and additionally offering them educational information on uncertainties in general. Overall, a responsible communication of uncertainty information leads to a deeper understanding and increased awareness of the phenomenon of uncertainty and its policy implications. It is expected that this understanding and awareness may result in a more responsible, accountable, more transparent and ultimately more effective use of intrinsically uncertain science in decision making (Wardekker et al., 2008).

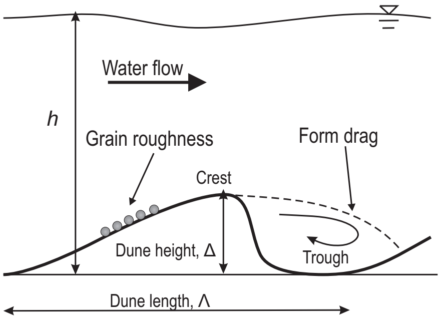
1.4 Hydraulic roughness

Previous research has shown that the sources of uncertainty that contribute most to the model outcome uncertainty are the upstream discharge and hydraulic roughness for hydrodynamic models (e.g. Dijkman et al., 2000; Ogink, 2003; Kok et al., 2003; Hunter et al., 2005; Pappenberger et al., 2008) of lowland rivers. The discharge is an input of these models, which is imposed as an upstream boundary condition. The hydraulic roughness is integrated into the model as a constant parameter or as an equation in the model structure. The hydraulic roughness is often considered a bulk parameter, used for calibration and then does not represent a single physical process. Therefore, the hydraulic roughness is a complex uncertainty that has both a physical background and is used for calibration. For these reasons, it is difficult to quantify the uncertainty due to hydraulic roughness.

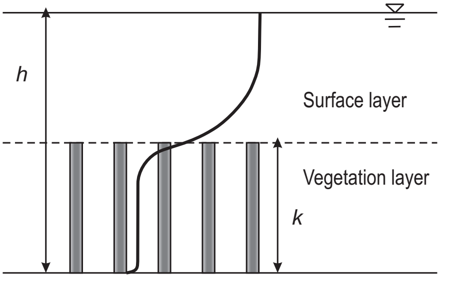
1.4.1 Defining hydraulic roughness

Hydraulic roughness is defined by Chow (1959) as the resistance to flow by all objects protruding into the water flow. Hydraulic roughness has many sources, such as grain resistance, resistance due to subaqueous bedforms, vegetation resistance, resistance due to man-made obstacles in the flow, resistance due to channel shape and bends and resistance due to velocity differences in the flow (Knighton, 1998).

The resistance in the main channel of many lowland rivers is dominated by bedforms that develop on the river bed (figure 1.5(a); Gates and Al-Zahrani, 1996b; Julien and Klaassen, 1995; Julien et al., 2002). The relationship between roughness and the development of bedforms is not yet fully understood. It is often represented by an empirical relation that has been derived from flume studies. This roughness model is then applied to a 'real' river case. These empirical relations or parameters that are used to represent the hydraulic roughness of the main channel are largely uncertain. This may lead to considerable uncertainties in the model outcomes.



(a) Bedform roughness



(b) Vegetation roughness

Figure 1.5: Illustration of bedform and vegetation roughness. (a) Sketch of a series of bedforms. Resistance is, amongst others, caused by the energy losses due to turbulence in the bedform troughs (after Paarlberg, 2008). (b) Sketch of water flow through and over vegetation (after Huthoff, 2007)

The hydraulic roughness of floodplains is dominated by resistance due to vegetation (figure 1.5(b); Mason et al., 2003; Baptist et al., 2004; Straatsma et al., 2008). Vegetation in floodplain areas in many lowland rivers consists of a mixture of low and high vegetation with different densities. The vegetation roughness is locally highly variable and changes with time. This spatial and temporal variability is difficult to represent accurately in the model and, therefore, may cause large uncertainties in the model outcomes (Augustijn et al., 2008; Straatsma and Huthoff, 2011; Straatsma and Huthoff, 2010).

1.4.2 Uncertainties in hydraulic roughness

Little research has been carried out to assess the uncertainty in the hydraulic roughness in river models. In this section, the literature on uncertainties in hydraulic roughness in river models is presented.

Noordam et al. (2005) showed that the uncertainty in the bed roughness is, amongst others, caused by the uncertainty due to the empirical roughness model. The authors compared the empirical roughness models for grain and form roughness by Van Rijn (1984), Vanoni and Hwang (1967) and Engelund (1966) for flume data from Blom et al. (2003). They showed that these roughness models resulted in different roughness values for measured bedform characteristics. However, the authors only base their analysis on flume data and do not consider bedforms in natural rivers. Van der Mark et al. (2008a) quantified variability in bedform characteristics from bed level surveys during high discharges in the river Rhine. The authors showed that the variability in bedform shapes is large and Van der Mark (2009) suggested to use four correction factors to account for physical processes that are not included in most existing roughness models. Also, Wilbers (2004) showed that including more bedform characteristics increased the predictive capacity of roughness models.

Paarlberg et al. (2010) stated that the uncertainty in the roughness model of Van Rijn (1984) for the river Rhine is partly caused by omitting physical processes. The author showed that for a simplified channel using a composite 1D approach, the influence of hysteresis between bed roughness and discharge on the computed water levels is large. Julien et al. (2002) estimated the hydraulic roughness of bedforms in the main channel during the peak discharge of 1998 in the Dutch river Rhine. They showed that including bedforms had a significant effect on the computed water level using the DELFT3D model.

Aberle et al. (2010) applied the random field approach for the analysis of bedforms in the river Elbe in Germany. They concluded that the measured bed elevation spectra are characterised by more than one dominant length of the bedforms. This indicates that hysteresis and antecedent flow conditions are important to bedform dynamics. Also, an effect of groyne arrangement appeared in the data. Shimizu et al. (2009) showed with numerical experiments that stage-discharge relationships significantly depend on the pattern of discharge variation with time. Furthermore, they showed that discharge waves with steep rising and falling limbs have a more pronounced hysteresis effect. These studies show that hysteresis in hydraulic roughness is an important source of uncertainty in many rivers, where the hydraulic roughness is dominated by bedforms. Furthermore, the above mentioned studies show that the hydraulic roughness due to bedforms is highly uncertain even for discharges that often occur.

Hall et al. (2005) and Pappenberger et al. (2005) demonstrated the dominant influence of the Manning roughness coefficient for the main channel on the modelled water levels. This conclusion is shared by many authors (e.g. Chang et al., 1993; Bates et al., 1996; Aronica et al., 1998). Gates and Al-Zahrani (1996a,b) reviewed the hydraulic roughness values from previous research. They determined the mean, coefficient of variation (CV, standard deviation divided by the mean) and probability distribution of the Manning roughness coefficient. They concluded that these statistical characteristics of the hydraulic roughness were non-homogeneous in space and time. Furthermore, they showed that for 1D models, the computed water depths and flow velocities are more sensitive to cross-section geometry than to the roughness coefficient.

Vegetation roughness is often modelled by a uniform and constant roughness parameter (Mason et al., 2003). In floodplain regions, vegetation is spatially highly variable, which makes it difficult to accurately map the vegetation characteristics that are required for roughness computations (Straatsma et al., 2008). Several models have been proposed to compute vegetation roughness (e.g. Petryk and Bosmajian, 1975; Klopstra et al., 1997; Kouwen and Fathi-Moghadam, 2000; Fisher and Dawson, 2003; Baptist et al., 2004; Huthoff, 2007). For non-submerged vegetation, literature showed that there is a high degree of consensus about the equations used for roughness prediction (Baptist et al., 2004). However, if the vegetation becomes submerged, the energy losses above the canopy of the vegetation become important and this process is poorly understood (Nepf and Vivoni, 2000)

1.4.3 Roughness as a calibration coefficient

In current modelling practise the hydraulic roughness is often used as a calibration coefficient. The problem is that the calibrated value of the roughness is only valid for the conditions used for the calibration (Klemes, 1986). Therefore, predictions for situations other than the calibration situation are inherently uncertain (Hunter et al., 2007). This holds in particular for flood safety modelling, where design floods are considered that rarely or never occurred and little or no measurements are available of the flow and bedform characteristics.

Roughness in models is often a bulk parameter, because it represents a range of different sources of energy loss, whose explicit treatment within a particular model varies with code dimensionality and process representation decisions (Morvan et al., 2008; Hunter et al., 2007). Hall et al. (2005) compared the uncertainty due to the choice of the model to the uncertainties that are attributable to measurement errors and calibration. They showed that the uncertainty in the calibration parameter has the largest influence.

Calibration cannot be carried out for design conditions that have never occurred, due to the lack of observations. Therefore, the hydraulic roughness is calibrated for a situation close to the design conditions and then extrapolated. By calibration, errors in the hydrodynamic model are compensated, however, during extrapolation the circumstances change and new uncertainty is introduced.

1.5 Problem description

The previous sections describe literature that showed that the outcomes of hydrodynamic river models are uncertain and that the hydraulic roughness is an important contributor to this uncertainty. Most uncertainty analysis studies about river models only consider uncertainties in input and parameters, thereby omitting the uncertainties in model structure and model context. Uncertainties in model input and parameters are often easier to quantify, because for model structure and context the model itself and its underlying assumptions should be varied, which is more difficult than varying the input or parameters. Omitting the uncertainties in model structure and context might result in a significant underestimation of the uncertainty in the model outcomes.

The reliability of an uncertainty analysis is determined mainly by the accuracy of the quantification of the individual sources of uncertainty (Johnson, 1996). Especially, for complex sources of uncertainty such as the hydraulic roughness of the main channel and floodplains, this quantification is difficult. Hydraulic roughness is computed by the model in a simplified way, but its integration in most 2D models is highly complex. Many river models lack an accurate description of the hydraulic roughness, but little research has been done about the quantification of the uncertainty in the hydraulic roughness. Studies that consider hydraulic roughness in fully 2D models have a highly simplified roughness description and often consider roughness as a uniform and constant parameter. This results in uncertainties in the modelled (design) water levels.

In the computation of water levels for design conditions, the problem is that these circumstances rarely or never occurred. Therefore, the magnitude of the sources of uncertainty cannot be determined by measurements only, because no or very limited measurements are available. Furthermore, it is often assumed that the physical processes that are schematized in the model are also valid under design conditions. In such cases, the uncertainty in the model structure is recognised by many authors to be the main source of uncertainty in model predictions (Refsgaard et al., 2006b; Hojberg and Refsgaard, 2005). For these reasons the uncertainty in the hydraulic roughness under design conditions might by large. The uncertainty in the hydraulic roughness results in an uncertainty in the design water levels, which is expected to be significant.

1.6 Objective and research questions

The objective of this research is to quantify the uncertainties in the hydraulic roughness that contribute most to the uncertainty in model outcome and quantify their contribution to the model outcome uncertainty in a 2D hydrodynamic model for a lowland river under design conditions.

The research is divided in the following research questions (RQ):

1. In what way can the uncertainties in a 2D hydrodynamic river model be identified, specifically concerning hydraulic roughness?

2. Which uncertainties contribute most to the uncertainty in water levels for design conditions and effect studies, taking all types of uncertainties into account?

3. How large is the uncertainty in bedform roughness of a lowland river under design conditions?

4. What is the effect of the uncertainty in the bedform roughness on the design water levels?

5. What is the combined effect of the uncertainties in bedform and vegetation roughness on the uncertainty in the design water levels?

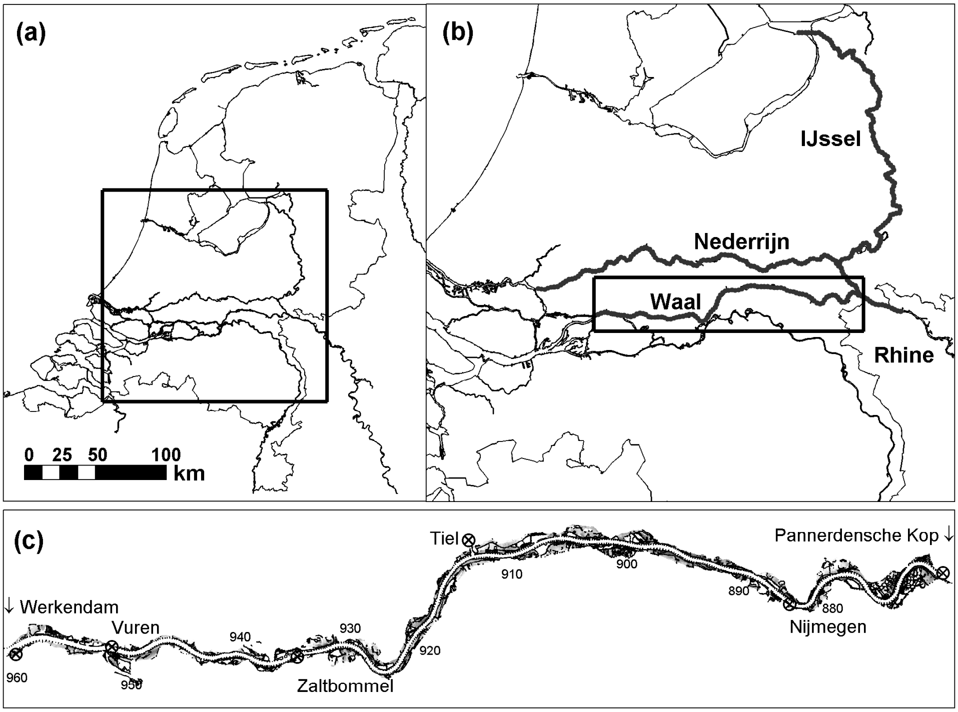


Figure 1.6: Study area. (a) the Netherlands, (b) location of the Rhine tributaries in the Netherlands, (c) the WAQUA model for the Waal branch

1.7 Research approach and outline

As stated in section 1.1, in this thesis 2D hydrodynamic models are considered for prediction purposes at reach scale. The WAQUA model (Rijkswaterstaat, 2009) of the river Rhine in the Netherlands is used as a case study. Specifically, the focus lies on the river Waal, a tributary of the river Rhine in the Netherlands (figure 1.6). The WAQUA model is used for two different applications. Firstly, for the computation of the design water levels for the 1250 year return period. Secondly, the model is used for the computation of the effect of measures taken in the floodplain areas that change the geometry of the cross section, the so called effect studies. The design-water-levels case is used throughout the thesis, while the effect-studies case is used for comparison in chapter 3. Although I focus on a single case study, the conclusions of this thesis are not limited to the WAQUA model or the study area as will be discussed in chapter 6.

In the study area, the uncertainty in the design discharge is agreed to have a large contribution to the uncertainty in the design water levels (e.g. Silva et al., 2001; Ogink, 2003; Van Vuren et al., 2005; Van der Klis et al., 2006; Van Gelder and

Mai, 2008). However, in Dutch river management practise, the design discharge can be considered a political decision even though it is computed from statistical extrapolation to a given return period of 1250 years, which is laid down by law (Ministry of Transportation, Public Works and Water Management, 1998). In government protocols (e.g. Rijkswaterstaat, 2007; Delta Committee, 2008), the design discharge for the river Rhine at Lobith, the location where the Rhine enters the Netherlands, is assumed fixed at 16000 m^3/s, although in the future a new design discharge of 18000 m^3/s is anticipated. In this thesis the design discharge is assumed deterministic even though it is subject to considerable uncertainty. This uncertainty is often not considered in Dutch river management practise.

In this thesis I combine different levels of uncertainty (see section 1.2.1), both quantitatively and qualitatively, and I carry out the first four steps of an uncertainty analysis. The last step, communication of uncertainties, is beyond the scope of this thesis. However, in the discussion (chapter 6) attention is paid to this subject. The chapters 2–5 are published or submitted for publication as individual papers. This results in some overlap in the chapters, but the papers form a sequence in which most of them refer to a step in the uncertainty analysis.

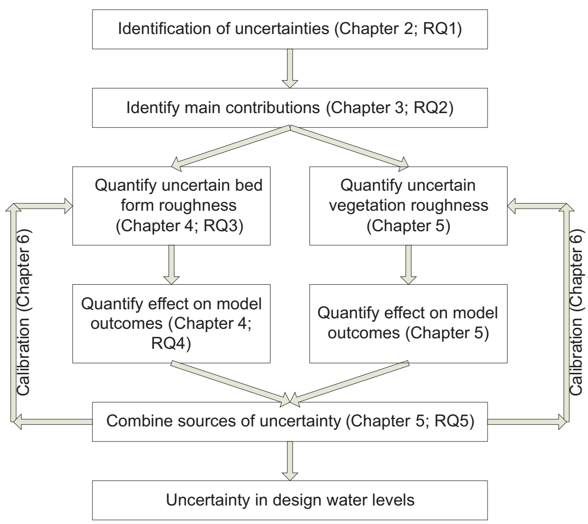


Figure 1.7: Research methodology and thesis outline

Figure 1.7 shows the methodology and outline of this thesis. The identification of uncertainties (RQ1) is based on an adapted version of the uncertainty classification matrix of Walker et al. (2003) that is a framework to classify uncertainties. In chapter 2, I use this framework to identify the uncertainties in a river model in a unique and consistent manner. In chapter 3, the identified uncertainties in the river model are ranked, based on their contribution to the uncertainty in the design water levels (RQ2) using expert opinions. The experts rank the uncertainties for two applications of the 2D river model, WAQUA, for the Waal river. Chapter 4 comprises the quantification of the uncertainties in bedform roughness under design conditions (RQ3) and the propagation of this uncertainty to the design water levels (RQ4) is computed for a simplified schematization of the river Rhine. In chapter 5, the quantified uncertainties in bedform roughness are combined with the dominant source of uncertainty in vegetation roughness and propagated to the design water levels for the case study of the river Waal (RQ5). This results in an estimation of the uncertainty in the design water levels for the Dutch river Waal. In chapter 6, the approach followed in this thesis is discussed. Also, the (qualitative) effect of calibration on the uncertainty in the design water levels is discussed. Finally, in chapter 7 the research questions are answered and the main conclusions of this work are given. Also, the recommendations for dealing with uncertainty in river management practise and recommendations for future research are presented in this concluding chapter.

Chapter 2

Identification and classification of uncertainties in the application of environmental models

Abstract

In the support of environmental management, models are frequently used. The outcomes of these models, however, rarely show a perfect resemblance to the real world system behaviour. This is due to uncertainties, introduced during the process of abstracting information about the system to include it in the model. To provide decision makers with realistic information about these model outcomes, uncertainty analysis is indispensable. Because of the multiplicity of frameworks available for uncertainty analysis, the outcomes of such analyses are rarely comparable. In this paper a method for structured identification and classification of uncertainties in the application of environmental models is presented. We adapted an existing uncertainty framework to enhance the objectivity in the uncertainty identification process. Two case studies demonstrate how the method helps to obtain an overview of unique uncertainties encountered in a model. The presented method improves the comparability of uncertainty analyses in different model studies and leads to a coherent overview of uncertainties affecting model outcomes.

This chapter is published as: Warmink, J.J., Janssen, J.A.E.B., Booij, M.J. & Krol, M.S. (2010). Identification and classification of uncertainties in the application of environmental models. Environmental Modelling and Software 25(12) 1518–1527. DOI: 10.1016/j.envsoft.2010.04.011

2.1 Introduction

In the support of environmental management, models are frequently used. A continuous interaction exists between the water management process and the modelling process (see for example Refsgaard et al., 2007; EPA, 2009). The modelling process involves several phases and actors (Refsgaard et al., 2007). The phases consist of model development, model evaluation and model application (EPA, 2009). However, the outcomes of these models rarely show a perfect resemblance to the real world. Environmental systems show behaviour which is to a large extent difficult to predict or simulate. To assess the inaccuracies or imperfections in model predictions, uncertainty analysis is often recommended (Refsgaard et al., 2007; Ascough II et al., 2008). Furthermore, an uncertainty analysis is an important step in the development and evaluation of all kinds of environmental models (Jakeman et al., 2006; Welsh, 2008; Robson et al., 2008).

A model is by definition an abstraction of reality. Computer simulation models comprise mathematical relations, data and a calculation core to simulate or explore the behaviour of a real world system. The development, evaluation and application of these models involves numerous choices and simplifications (EPA, 2009), resulting in uncertain model outcomes. This means that because we do not know what the best choices and simplifications are, or because we are either technically or intellectually unable to represent the complexity found in the natural system, the model outcomes will show a certain degree of randomness. Uncertainties are introduced in all stages of this modelling process. Next to uncertainties in the model itself, also during the interaction with the actors uncertainty is introduced. However this paper focuses on uncertainties in the model.

The uncertainty in the model outcomes has implications for the usefulness of these outcomes in the policy or decision making process. According to Morgan and Henrion (1990), decision makers make less than optimal decisions without information on the uncertainties in outcomes. Knowledge of the magnitude of model uncertainties is crucial for a meaningful interpretation of model results. Therefore, there is a need for structured analysis of the uncertainties in environmental management practise. In the model evaluation process, an uncertainty analysis should be carried out (Jakeman et al., 2006). Starting with an inventory of the uncertainties involved in the model, quantifying them as far as possible, estimate their (relative) effect on the model output and interpreting the resulting uncertainty in the model outcomes (Morgan and Henrion, 1990).

In uncertainty analysis, the identification of the uncertainty in a model is a crucial step. Ideally, the identification leads to a comprehensive list of unique and complementary uncertainties. In this context, complementary means that all resulting uncertainties are unique and do not overlap. This uniqueness also assures that uncertainties are comparable. A list of unique uncertainties simplifies the uncertainty assessment that follows the identification. A structured identification of uncertainties can help to acquire these unique uncertainties. The ideal of comprehensiveness is, however, not reachable, because we cannot cover all possible uncertainties that influence the model outcomes (Walker et al., 2003).

In the practical application of existing uncertainty analysis studies we often see that the identified uncertainties are only the ones that can be quantified (e.g. Hall et al., 2005; Bates et al., 2004) or originate from unstructured and aggregate identification using expert elicitation (e.g. Van der Sluijs et al., 2005a; Van der Keur et al., 2008; Hall and Solomatine, 2008). In the first case, it is likely that the model outcome uncertainty is underestimated (Refsgaard et al., 2006b). In the second case, it strongly depends on the expert, which uncertainties are taken into account. Also different aggregation levels of the resulting uncertainties will occur (Kloprogge et al., 2009). This means that some identified uncertainties are very detailed, while other uncertainties consist of many aggregated uncertainties (Risbey et al., 2001; Kloprogge et al., 2009). In the assessment of these uncertainties this may lead to an unbalanced comparison of the different uncertainties. In traditional identification of uncertainties it may happen that the same uncertainty is included more than once, because the uncertainties that are identified are not unique.

Over the past years the number of model applications in environmental management proliferated, and along with it the number of studies focusing on uncertainties in these applications (Jakeman et al., 2006). Quite a few frameworks have been proposed to identify and classify uncertainties (e.g. Van Asselt and Rotmans, 1996; Walker et al., 2003; Brown, 2004; Krupnick et al., 2006; EPA, 2009). The NUSAP methodology (Funtowicz and Ravetz, 1990) is a methodology for a structured uncertainty analysis that accounts for quantitative and qualitative uncertainties. The NUSAP methodology identifies the different sorts of uncertainty in quantitative information and enables them to be displayed in a standardised way (Van der Sluijs et al., 2004). However, even in this structured methodology, little attention is paid to the identification of the uncertainties. The uncertainties that are considered using the NUSAP method can have different aggregation levels and do not need to be unique and complementary, because no guideline is given how to frame the individual uncertainties. This may limit the assessment in the next steps of the uncertainty analysis. The studies by Krayer von Krauss et al. (2004) and Van der Sluijs et al. (2005a) comprise a structured expert elicitation study to quantify the uncertainties in two models. However, the identification of uncertainties does not provide a method to assure that the resulting uncertainties are unique. Apparently, even though the importance of uncertainty identification is acknowledged in literature (Refsgaard et al., 2007), it rarely takes place in a structured and consistent manner.

To describe and identify uncertainties in a structured and consistent manner, a classification scheme or matrix can be used. We used the uncertainty classification matrix from Walker et al. (2003) to identify the uncertainties in two different models. This Walker matrix is developed with models (specifically decision support systems) in mind and has a solid background. The purpose of this matrix is to provide a tool by which to get a systematic and graphical overview of the essential features of uncertainty in relation to the use of models (Walker et al., 2003). The

Walker matrix distinguishes three dimensions of uncertainty, which are all defined in different classes. All uncertainties should be classified along all three dimensions. Van der Sluijs et al. (2004) and Refsgaard et al. (2007) present a similar matrix that shows for each class the possible methods to use for an uncertainty analysis.

Although many uncertainty frameworks exist, their application to existing models is not as straightforward as one might think. During our application of the Walker matrix many uncertainties could not be uniquely classified. We often encountered that an uncertainty could be classified in different classes within one dimension. If this is the case, then the uncertainty is an aggregation of various sources of uncertainty. Furthermore, it was not clear which uncertainties should be included in the analysis. Consider, for example, a measured input to a model. Should also the uncertainty in the measurement instrument be included as a separate uncertainty source or is this already included in the uncertain measured input? This decision also affects the class to which the uncertain measured input is assigned. Furthermore, it is not clear when to stop with including uncertainty in the analysis. The result of our identification was that we had a list with uncertainties that included double counted uncertainties with different aggregation levels. The resulting list of uncertainties may not be suitable to serve as the start of a further uncertainty analysis without addressing the identification. These difficulties in the identification affect and complicate the further uncertainty analysis, because, for example, it is not clear which methodology should be used to study the effect on the model outcomes. Also, elicited uncertainties from an expert opinion study (e.g. Krayer von Krauss et al., 2004; Van der Sluijs et al., 2005a) do not necessarily match well with techniques for quantification or description of uncertainties.

The aim of this paper is to provide a structured procedure for the identification and classification of uncertainties in the application of environmental models as a first step to a structured uncertainty analysis. We do not focus on structural difficulties in the quantitative description of uncertainties, but rather try to reveal theoretical dilemmas which trouble the identification of uncertainties. If even the identification of uncertainties turns out to be difficult, it should come as no surprise that a further analysis of uncertainties in models is rarely achieved.

To be able to distinguish the uncertainties, it is necessary to work with a set of highly specified definitions. The definitions in the framework of Walker et al. (2003) are tested on our case studies and turn out to be insufficiently accurate to identify unique dimensions for each uncertainty. Therefore, we here present a set of more specific and mutually exclusive definitions, which we will use in the method for uncertainty identification. The definitions need to be able to distinguish more clearly between the different classes and must address all uncertainties in a model in a more unique way. We also implemented some small changes in the Walker matrix in accordance with state of the art literature.

The presented procedure is based on the existing uncertainty analysis framework by Walker et al. (2003) (section 2.2), which is further specified and refined (section 2.3). We demonstrate the proposed procedure using two case studies. The first case study is a hydraulic model for stage-discharge relations (section 2.4). The second case study is a fuzzy set model for agriculture suitability of floodplains (section 2.5). The completely different nature of the models underpins our claim of broad applicability of the proposed procedure. Finally, section 2.6 and 2.7 comprise the discussion and conclusions.

2.2 Definitions and dimensions of uncertainty

2.2.1 Definitions of uncertainty

Definitions of (model) uncertainty vary from "any departure from the unachievable ideal of complete determinism" (Walker et al., 2003) to "the degree of confidence a person has about the specific outcome of an event or action" (Klauer and Brown, 2004; Refsgaard et al., 2007) and "(uncertainty refers to) the situation in which a decision maker does not have a unique and complete understanding of the system to be managed" (Brugnach et al., 2007). Zadeh (2005) and Klir and Yuan (1995) stated that uncertainty is considered as an attribute of knowledge or of (the state of) information. All these definitions are based on a concept in which uncertainty deals with people's knowledge about the natural system.

Chang et al. (1993) state that uncertainty inherently resides in all physical processes and therefore cannot be eliminated. Similarly, other authors state that uncertainty is inherent to the natural system (Oreskes et al., 1994; Harremoës and Madsen, 1999). This seeming contradiction between the opinion that uncertainty is a property of information and that uncertainty is a property of the natural system results from the lack of distinction between the natural system and the information about the natural system. Zimmermann (2000) stated that "whether uncertainty is an objective feature of physical real world systems seems to be a philosophical question." In the following we also shall not make this distinction, but we will focus on the human-related, subjective interpretation of uncertainty which depends on the quantity and quality of information that is available to a human being about a system or its behaviour that the human being wants to describe, predict or prescribe (Zimmermann, 2000).

We follow the definition of uncertainty by Walker et al. (2003), because this definition concerns uncertainty in models. Also, the definition evolved from many years of research (Janssen et al., 1990; Van Asselt and Rotmans, 1996; Harremoës and Madsen, 1999; Walker, 2000). Following Beck (1987) and Van der Perk (1997), uncertainty consists of both inaccuracy and imprecision (which Van der Perk referred to as uncertainty). Inaccuracy is defined as the difference between a simulated value and an observation, while imprecision refers to the possible variation around the average simulated and observed values. Here, both are considered uncertainty.

Figure 2.1 shows the knowledge production in the modelling cycle. A conceptual model is created, based on the natural system. In this step processes in the natural system are delineated and uncertainty is introduced, due to the perception of this natural system. When the conceptual model is next translated into an

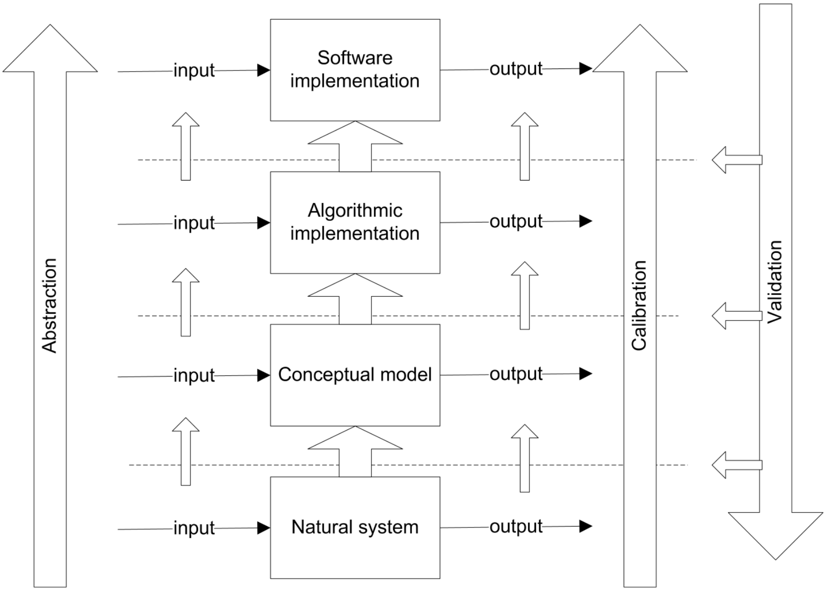


Figure 2.1: Knowledge production in the modelling cycle (Kolkman et al., 2005, adapted after Dee (1995)). The steps of the cycle are: delineation of the part of the natural system to be studied, construction of a conceptual model, algorithmic (mathematical) implementation of the conceptual model, implementation of the algorithm in software, calibration of the model parameters and validation of the model results (Kolkman et al., 2005).

algorithmic implementation, and after that into a software implementation, more choices are made, and further uncertainties are introduced.

2.2.2 Dimensions of uncertainty

Sources of uncertainty can be found at numerous locations in a model. These locations are related to the steps in the modelling cycle (figure 2.1), and the choices and simplifications made during the ongoing process of model development.

Uncertainty is typically characterised along different dimensions. Walker et al. (2003) developed a conceptual basis for uncertainty management in model-based decision support, which covers the relevant dimensions in the model without becoming overly complex. Three different dimensions of uncertainty are distinguished: 1) the location, which is where the uncertainty manifests itself in the model, 2) the level, which is where the uncertainty manifests itself along the (continuous) spectrum between deterministic knowledge and total ignorance, and 3) the nature of the uncertainty.

Walker et al. (2003) described five possible locations of uncertainty: a) context uncertainty, b) input uncertainty, c) model uncertainty, which consists of model structure uncertainty and model technical uncertainty, d) parameter uncertainty, and e) uncertainty in the model outcomes. The levels of uncertainty range from statistical uncertainty and scenario uncertainty through recognised ignorance to total ignorance. For the last dimension, they distinguish between epistemic uncertainty (due to a lack of knowledge) and variability uncertainty (due to the variability in the behaviour of the natural, social, economic or technical system).

2.3 Methods

In the introduction we stated that the Walker matrix proved to be insufficient for the identification of the uncertainties in two different environmental models. It was not always clear in which class a source of uncertainty should be placed and identification resulted in double counted uncertainties with different aggregation levels. We will resolve these issues by refining the definitions of the different classes in the Walker matrix and presenting a methodology to frame uncertainties in a unique and consistent manner.

2.3.1 Adapted uncertainty matrix

Location

We define the following locations of uncertainty: context, input, model structure, model technical and parameters. We omitted the model outcome uncertainty, because it results from the uncertainties in the other locations.

Model context is defined as anything outside the model boundary. It therefore relates to the assumptions and choices underlying the model, which define the boundaries of the model. Context uncertainties affect the extent to which model outcomes resemble the natural system. Model context uncertainties are introduced mainly in the first step of the modelling cycle (see figure 2.1), or in the choice for a particular kind of model. Here, the delineation of the part of the natural system to be modelled takes place and choices about the model scale and the range of model application are taken.

Input is defined as all data to define or describe the geographical location and time-dependent driving forces for a specific model run. Uncertainty in model input results from uncertainties in measurements, uncertainties in outcomes of preceding models (used as input) and uncertainties due to scaling that occurs during the ongoing abstraction in the modelling cycle.

Model structure is defined as the mathematical relations between the variables or model components which are chosen to describe the system located within the model boundaries. The model variables are considered to be part of the model structure. In the modelling cycle, the relations between the model components are determined during the construction of the conceptual model. Subsequently, appropriate equations are chosen during the algorithmic implementation of the conceptual model. The decisions regarding which processes are included in the model are therefore referred to as model context, while the relations between the model components inside the model are regarded as model structure.

Model technical refers to the technical and numerical aspects related to the software implementation of the model and the numerical implementation of the algorithms. These are the two final steps in the modelling cycle. Also uncertainties due to software and hardware errors belong to model technical.

Parameters are defined as the a priori determined values, which do not change as an effect of causal relations within the model. They differ from input in the way that they do not directly depend on or refer to the geographical location and the period to be modelled. Parameters are supposedly invariant within the chosen context and algorithmic representation. Constants that control the software implementation of the model, such as time step or grid size are considered at the "model technical" location. Parameters do not directly refer to the natural system, but can have a physical background.

Level

We distinguish four levels of uncertainty: statistical, scenario, qualitative and recognised ignorance. Following Refsgaard et al. (2007), we added a level of uncertainty to the original levels as defined by Walker et al. (2003): qualitative uncertainty, which lies between scenario uncertainty and recognised ignorance. Furthermore, the level of total ignorance is omitted in the classification scheme of uncertainties, because we cannot identify what we do not know. This means that in practise we will never encounter total ignorance, as we will never encounter complete determinism.

Statistical uncertainty is any uncertainty which can be characterised in probabilities or numbers. This comprises the uncertainties that are traditionally addressed in model uncertainty assessments (Morgan and Henrion, 1990; Refsgaard et al., 2007). The second level, scenario implies that there is a range of possible outcomes, but the mechanisms leading to these outcomes do not enable the definition of the probability of any particular outcome. Qualitative uncertainty is defined as any uncertainty that cannot be expressed in terms of nominally measurable values. This level of uncertainty comprises opinions of experts, linguistic probabilities, and ambiguities between people. In the case of recognised ignorance, uncertainty exists about the relations and mechanisms being studied. In this case, it is not possible to outline different possibilities or give any qualification on the value of the uncertainty.

Nature

We define three natures of uncertainty. Epistemic uncertainty is due to imperfection of our knowledge. This includes limitations in appropriate measurement methods due to limited knowledge, leading to measurement errors. Natural variability is caused by inherent random natural system behaviour. Brugnach et al. (2007) discriminates a third nature of uncertainty: ambiguity. Ambiguity is the simultaneous presence of multiple equally valid frames of knowledge (Dewulf et al., 2005), where we add that these multiple frames need to be reflected in the model. Therefore, it often relates to expert subjectivity. Ambiguity is considered by Walker et al. (2003) as an epistemic uncertainty. This presupposes that more knowledge will reduce ambiguity. However, in decision making practise, there is seldom a single truth. Therefore, gathering more knowledge does not necessarily converge to a single truth and hence more certainty. We hence follow Brugnach et al. (2007) who see it as an additional nature of uncertainty.

The distinction between epistemic and natural variability is not always clear. Natural variability is defined by Walker et al. (2003) as uncertainty due to random system behaviour. Furthermore, it is often stated that the uncertainty due to natural variability cannot be reduced, compared to lack of knowledge which can. One can argue that up to a certain level, random system behaviour is also a lack of knowledge. However, in practise, the available resources (time and money) limit the possibility to reduce an uncertainty by more observations. Therefore, we define natural variability as random system behaviour that cannot be adequately explained given the available resources.

2.3.2 Global identification of uncertainties

The dimensions of uncertainty provide the starting point for our uncertainty identification. The first step to identify uncertainties is to gather the initial uncertainties in the model environment. To acquire a more comprehensive list of uncertainties, the uncertainties are identified following the locations according to Walker et al. (2003). This is done by elicitation of expert opinions. During interviews, the model components, such as assumptions, input data and parameters are listed. These listed model components are then compared to the processes that occur in the natural system, following the locations in the uncertainty matrix. By means of considering all locations of uncertainty, the list with identified uncertainties will be more complete than if only quantifiable uncertainties are taken into account.

2.3.3 Detailed identification of uncertainties

We argue that to obtain a list of unique and complementary uncertainties, every uncertainty needs to be described so accurately, as to specify it along all three dimensions in a unique manner. In this second step, we attempt to uniquely identify the listed uncertainties from the first step by classification of the uncertainties into a single class for each dimension. This means that an uncertainty can for instance not be at the level of "statistical uncertainty" and "scenario uncertainty" at the same time. If the uncertainty falls into two classes at the same time, the uncertainty needs to be described in more detail that is broken down into smaller parts. The resulting uncertainties are unique and form a consistent set (figure 2.2).

Three decision trees (one for each dimension) are created to clarify the classification criteria based on the set of definitions (figure 2.3). For each uncertainty source the analyst needs to go through each of the three decision trees. The first question

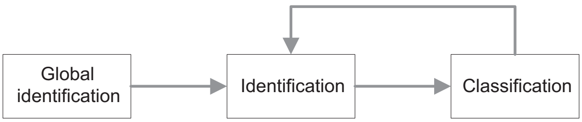


Figure 2.2: Method to identify uncertainties. First a global identification of uncertainties is carried out. Subsequently, these uncertainties are classified in a unique class in the adapted Walker matrix. If this does not succeed, the uncertainty needs to be broken down in smaller parts until it can be uniquely classified.

is whether the uncertainty falls inside the model boundaries. If the answer to this question is positive, continue to the next question, if the answer is negative the uncertainty is classified as a context uncertainty. If one cannot make a decision, because both "Yes" and "No" are valid, the uncertainty is broken down into separate parts, which are more accurately defined. Then, the analyst needs to follow the decision trees again from the start for all these newly defined uncertainties. If all three decision trees are finished successfully, the uncertainties are identified and classified. This procedure assures that all uncertainties are unique and that all uncertainties have the appropriate levels of aggregation.

During the uncertainty identification, the source of uncertainty must be well-framed. That means that one must be aware not to apply backward reasoning. Backward reasoning is the process of considering the background of an uncertainty. For example, if we attempt to identify a model input uncertainty, the uncertainty in the measurement instrument which was used to measure the input must not be considered. Otherwise, backward reasoning will lead to an endless chain of uncertainties and identification and classification becomes impossible.

We apply this methodology to identify uncertainties in two different types of models. The first model is a physically-based, two-dimensional deterministic model, used for the prediction of design water levels and the computation of the effects of engineering measures taken in the Dutch branches of the river Rhine. The second model is a fuzzy set model evaluating the impact of river engineering interventions on the agriculture suitability of floodplains, applied to part of the Dutch river Meuse. The models and the uncertainties in the models have different characteristics. By using such different models we underpin our claim of a broad applicability of the developed method.

2.4 Case study I: hydraulic model

2.4.1 Model description

River flooding is a serious threat in the Netherlands. Strong dikes have been constructed to protect the land from flooding. After the 1993 and 1995 (near) flood events, the Dutch government laid down that every 5 years the safety of the primary

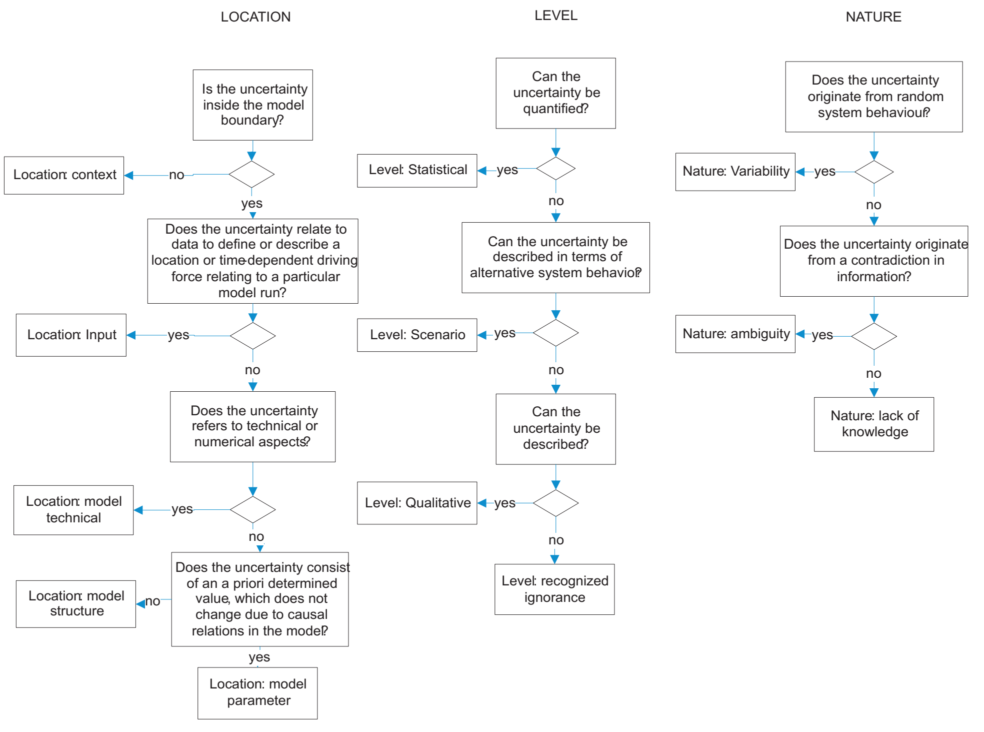


Figure 2.3: Three decision trees for the process of breaking down uncertainties until the appropriate level of aggregation is reached. These trees are based on the set of definitions and on the classification scheme based on Walker et al. (2003)

dikes has to be evaluated against a design discharge (Van Stokkom et al., 2005). This design discharge is based on the statistical analysis of historical discharge series.

The design water levels for the upper part of the Dutch river Rhine are calculated using the two-dimensional hydrodynamic model WAQUA. This model uses the depth-averaged shallow water equations to compute the design water levels along the Dutch part of the rivers Rhine and Meuse, based on the design discharge as upstream input. The model consists of: 1) the program environment SIMONA (see Rijkswaterstaat, 2009), which contains the shallow water equations to simulate water flow and the empirical stress model to approximate the energy losses, and 2) the schematization for a certain period with corresponding input, such as measured stage-discharge relations, upstream discharge, the geometry of the river bed, and mapped characteristics of the flow channel (e.g. vegetation and structures, such as weirs and spill-ways). The model has been calibrated on the highest recorded discharge, which occurred in 1995 (Van den Brink et al., 2006).

2.4.2 Results for the hydraulic model

Global identification of uncertainties

The first step is to assess the uncertainties in all components (i.e. context, input, model structure, model technical, parameters) of the model. The initial uncertainties for the WAQUA model are obtained from the elicitation of opinions of experts involved in the development and application of this model. Figure 2.4 shows some examples of the uncertainties for the hydraulic model case, organised following the classification on location.

The purpose of the model is to predict water levels under design conditions and therefore related model boundaries are chosen. In case of an event outside the model boundaries, context uncertainties arise. For instance, it is assumed that peak discharge events occur in the winter period. However, the 1988 peak discharge occurred in spring. Therefore, the density of the vegetation was much higher than assumed in the model, which introduces a large uncertainty due to the chosen model context. The assumption that the circumstances during calibration are similar to the circumstances during the design discharge introduces uncertainty in the model outcomes. Furthermore, the WAQUA model neglects (local) variations in the height of the river bed during the peak discharge and 3D effects in the river bed are also omitted or included in a constant parameter.

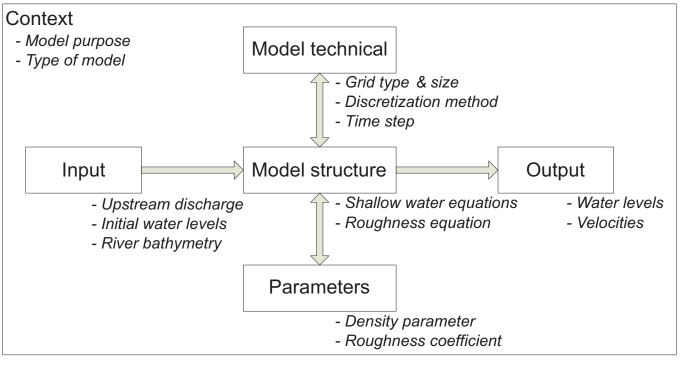


Figure 2.4: Global identification of uncertainties in the hydraulic model

The input for the WAQUA model is also uncertain to some extent. The upstream discharge, for a return period of 1250 years, is obtained by the extrapolation of an historical discharge series. Also, the measured geometry and vegetation differ from the actual situation in both floodplain and main channel. This is caused by measurement errors and errors in the discretisation of the measurement data onto a grid. The model structure comprises, amongst others, the mathematical equations that compute the water flow and the empirical equations that describe the local energy losses: the roughness equations. Hydraulic roughness is defined as the resistance to flow by all objects protruding into water flow (Chow, 1959). All kinds of local energy losses are present in the model, such as the roughness of the bedforms in the main channel, roughness due to vegetation and roughness due to accelerations of flow over a bank, groyne or weir. Model technical uncertainties comprise the type of computational grid, the discretisation method of the shallow water equations onto this grid and the choice of the time step.

Parameters in the model comprise empirically determined parameters in the roughness equations, physically based parameters in the shallow water equations and the calibration parameters. All these parameters are more or less uncertain. Their degree to which they represent a physical process varies considerably. For example, the parameter that describes the acceleration of gravity, which has a strong evidence base and accuracy, is much more physically based than the eddy-coefficient, that describes the energy loss due to differences in flow velocity. Both are considered constants in the model.

Detailed identification of uncertainties

The initially identified uncertainties can be classified in the uncertainty matrix using the decision trees (figure 2.3). However, some of the uncertainties cannot be classified in a unique manner. This is for instance the case for the hydraulic roughness, which is often mentioned in literature (amongst others by Chang et al., 1993; Bates et al., 1996) and by experts as the main uncertain parameter. If we follow the decision tree for location, the uncertainty will be inside the model boundaries. Next, the answer to the question if it relates to data to define or describe a geographical location or driving force, is partly yes and partly no. If a question can not be answered, the uncertainty needs to be broken down into smaller pieces. In this case, roughness in the model consists of roughness of the main channel, vegetation roughness, energy losses over weirs and a turbulent eddy viscosity parameter. Now, the decision tree has to be followed again for these new uncertainties. For the roughness of the main channel, the answers on the first question is still “Yes”. Next, this uncertainty does not relate to data to define or describe a geographical location or driving force and neither does it relate to technical or numerical aspects. It can however not be said whether it concerns a constant or not. Therefore, further breaking down is required. The roughness of the main channel consists of an empirical equation and of parameters within this equation. This distinction enables the classification of the empirical equation as a source of uncertainty in the model structure and the parameters as sources of uncertainties in the model parameters.

Subsequently, the decision trees of level and nature need to be addressed. The uncertainty in the equation of the roughness of the main channel cannot be quantified, but can be described in alternative system behaviour, because different equations can be compared. Therefore, the level of this uncertainty is scenario. A parameter in the roughness equation can be quantified and therefore its level is statistical. The nature of the uncertainty in the roughness equation of the main channel does not originate from random system behaviour, neither does it originate from ambiguity. Therefore, its nature is lack of knowledge. One can argue that the equation is simplified and it is uncertain because it does not explain the natural variability. However, within "reasonable limits", it is possible to improve the equation so that the roughness is better predicted. The definition of "reasonable limits" is highly subjective. This can best be done by experts that have an idea of the scientific background of the uncertainty. Furthermore, because the selection of the equation of the roughness of the main channel represents a physical process and if it is not caused by random system behaviour, there should be a single truth. Therefore, the nature of this uncertainty is not ambiguity, despite the fact that different experts may have a different view on the "best" equation of the main channel roughness. Table 2.1 shows the identification and classification of the uncertainties related to roughness in the hydraulic model.

2.5 Case study II: fuzzy set model

2.5.1 Model description

When evaluating the impacts of different river management strategies, numerous functions of the riparian zone need to be considered. Among these is the agriculture suitability in the floodplains. The relation between river engineering measures and agriculture suitability in the floodplains has been described by Klijn and De Vries (1997) and Van Eupen et al. (2003) for the river Meuse in the Netherlands. However, the only measure they considered was floodplain excavation. The method they used involves numerous steps to be undertaken in different models. The development of a fuzzy module facilitates easy iteration between different types of measures, at different geographical locations along the river and under different climate scenarios. By modelling the relation between water levels and agriculture suitability in fuzzy rules, the model can be linked to a hydraulic calculation core and the water level changes (due to measures such as excavation of the main channel) can be accounted for.

A range of daily water levels, averaged over multiple years, is used as an input for the model, along with floodplain elevation data. The conceptualisation of the relation between floodplain elevation levels and agriculture suitability is considered to be valid for Dutch lowland rivers without tidal influence. A single (fixed) soil type is assumed for the entire study area.

2.5.2 Results for the fuzzy set model

Global identification of uncertainties

The uncertainties are initially indicated by an expert following the classification based on location. Figure 2.5 shows these initial uncertainties.

In the step from the natural system to the conceptual model, a number of assumptions have been made resulting in uncertainties in the model context. The assumption that there is no tidal influence will (from a certain geographical location onwards) only be partially true, since tidal influence in a lowland river increases gradually in downstream direction. This means that the assumptions on the one

Table 2.1: Identification and classification of uncertainties related to roughness in the hydraulic model. The uncertainties in bold are classified in more than one class for a dimension. Therefore, they do not have the appropriate aggregation level and need to be broken down

Description	Location					Level				Nature		
	Context	Input	Model structure	Model technical	Parameter	Statistical	Scenario	Qualitative	Recognised ignorance	Natural variability	Epistemic	Ambiguity
Roughness:	**x**	**x**	**x**	**x**	**x**	**x**	**x**		**x**	**x**	**x**	**x**
Main channel roughness			**x**		**x**	**x**	**x**				x	
Main channel roughness equation			x				x				x	
Parameters in this equation					x	x					x	
Vegetation roughness	**x**	**x**	**x**	**x**	**x**	**x**	**x**		**x**	**x**	**x**	**x**
Vegetation roughness equation			x				x				x	
Parameters in this equation					x	x					x	
Observed vegetation type		x					x			x		
Discretisation of observed vegetation type				x			x			x		
Period of peak discharge	x								x			x
Energy losses due to weirs		**x**	**x**	**x**	**x**	**x**	**x**			**x**	**x**	
Weir equation			x				x				x	
Flow contraction parameters					x	x					x	
Measured height of weirs		x				x				x		
Discretisation of weir heights				x			x			x		
Eddy viscosity parameter					x	x				x		

hand specify the application domain of a model, on the other hand they may introduce uncertainties when it is uncertain to what extent the assumptions are true. Other context uncertainties include for instance climate change, which may impact the input (water levels), but is located outside the model boundaries.

Input uncertainties involved are soil type, floodplain elevation levels and water levels. The soil type is in practise unlikely to be homogeneous, as it is currently modelled. Floodplain elevation levels provide a second important input uncertainty. Water levels account for the third input uncertainty, owing to measurement errors in the underlying discharge data and uncertainty in the subsequent hydraulic computations.

The model structure comprises the relation between floodplain elevation, water levels and agriculture suitability, and all the intermediate variables used to describe this relation. Some of the intermediate variables are the result of fuzzy relations between them, some are described in a non-fuzzy way. Particularly the fuzzy sets contribute to the uncertainty in the model output, due to their inherent imprecise character.

Model technical uncertainties, related to the software implementation of the model, comprise, amongst others, possible errors made in the programming work and (in some instances) necessary truncations or other mathematical operations required to fit the algorithmic model into a programming language. For the fuzzy modelling case, the implication and aggregation method (see e.g. Klir and Yuan, 1995) introduce model technical uncertainty. Also the choice of calculation steps (e.g. daily discharges, averaged over multiple years) is regarded to add to model technical uncertainty. Like in the hydraulic model, the discretisation of the area description introduces further uncertainties in the model. The discretisation of the floodplain elevation level is the most important one in this case.

The majority of the parameters in the model are used in the description of the fuzzy sets. These sets are based on classification schemes as used in Van Eupen et al. (2003) and Klijn and De Vries (1997). The uncertainty in the fuzzy parameterisation essentially represents the imprecision in the knowledge that is used in the model.

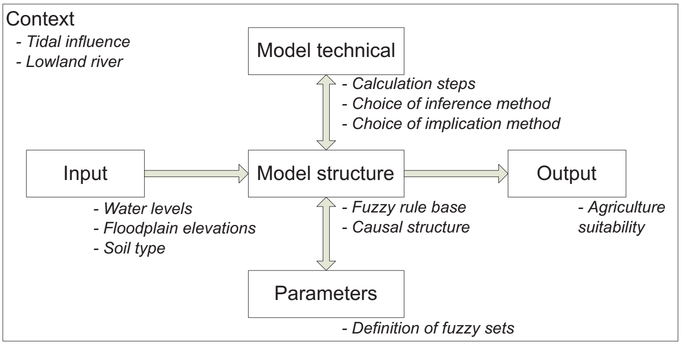


Figure 2.5: Initial identification of uncertainties in the fuzzy model

Detailed identification of uncertainties

The initially identified uncertainties can be classified using the decision trees depicted in figure 2.3. Again, some of these uncertainties cannot be classified in a unique manner, and therefore need to be specified more accurately. Here, the method is demonstrated for the uncertainty introduced by the inclusion of "soil type" in the model. Starting from the "location" decision tree, the soil type uncertainty is within the model boundaries, and does relate to data describing the geographical location for a particular model run; it is an input uncertainty. When proceeding to the "level" tree, we find that the uncertainty cannot be quantified, but that the uncertainty can be described in terms of alternative system behaviour; its level is therefore scenario.

When addressing the "nature" tree, we find that the uncertainty in the "soil type" is not merely due to random system behaviour; to some extent the variability in the soil plays a role, but on the other hand also a lack of knowledge (measurements or accurate data) apply to this situation. Therefore, we apparently need to further specify the uncertainty related to the soil type. The epistemic nature of the soil type uncertainty refers to the lack of data or accurate measurements. The variability refers to the way in which the soil type information is discretized in the model. These are the two newly specified uncertainties: soil type data and discretisation of soil types.

We propagate these new uncertainties through the location tree. The soil type data is inside the model boundary, and again relates to the description of a particular geographical location in the model. In the level tree, it can be quantified, so its level is statistical: it is theoretically possible to derive distributions of different soil types in a single sample. In practise, however, it will be easier to work with different scenarios. We classify this uncertainty as statistical, because the choice for a method to address it can easily be made in a later stage. As far as the nature is concerned, the uncertainty now originates from a lack of knowledge, so its nature is epistemic. We also applied the three trees again to the "discretisation of soil types"; the result is summarised in table 2.2.

As a second example we address the uncertainty in the parameters describing the fuzzy sets in the model by going through the location tree. The definition of fuzzy sets is within the model boundaries, not relating to a particular model run or geographical location, not referring to technical or numerical aspects, and is relating to a priori determined values which do not change during the model run. The uncertainty in the definition of fuzzy sets is therefore indeed defined as a parameter uncertainty. In the level tree, we cannot say that the uncertainty can be described in a quantitative way, but it can be described in terms of alternative system behaviour (scenario uncertainty). The nature of the uncertainty is not due to random system behaviour, but the second question cannot be answered unambiguously. Part of the uncertainty is epistemic, namely the shape and extent of the fuzzy sets, but part is also caused by ambiguity, namely the part where a single value can be attributed to different fuzzy sets. Thus, we need to further specify our description of the fuzzy set definition (table 2.2) and go through the trees again. The resulting description of the uncertainties is summarised in table 2.2. When analysing all the uncertainties identified in step 1, a comprehensive overview of the uncertainties will emerge.

2.6 Discussion

We propose a method to identify and classify unique and complementary uncertainties in environmental models. We adapted the classification scheme of Walker et al. (2003), according to state of the art literature, by adding a class to the level-dimension: the qualitative uncertainty (Refsgaard et al., 2007), which makes the classification on the level-dimension more detailed, and adding a class to the nature-dimension: ambiguity (Dewulf et al., 2005), to acknowledge the existence of uncertainty due to different equally valid opinions. Furthermore, we specified the definitions of the classes in the matrix. This was needed because the distinction between classes made in the Walker classification scheme was not clear enough. We put a strong focus on model development as the point of view of the definitions. We defined the uncertainty due to the choices that are made regarding which processes to include in the model in the model context. In many papers, the decision which processes to include is stated model structure uncertainty (see for example Hankin and Beven, 1998; Refsgaard et al., 2006b). However, this distinction cannot be made explicitly, because other processes (often at a larger scale) that are not included are considered in the model context, such as climate change in a forecasting model. We argue that to make a clear distinction between the context and structure class, the decision which processes are included belongs to the model context, because omitted processes are located outside the model boundaries. The included processes belong to the model structure, because they are located within the model boundaries. This also means that different alternative descriptions that are available for a certain process that is included belong to the model structure uncertainty.

We encountered three important problems in the identification of uncertainties for the two case studies. Firstly, during the process of breaking down uncertainties, it is important to be aware of the risk of "backward reasoning". This is a very important pitfall, because eventually, everything is uncertain to a larger or smaller degree. For example, with regard to the hydraulic model, one can argue that the level of uncertainty of the parameters in the main channel roughness equation is statistical, because the uncertainties in the flume and river measurement data, that underlie the equation, have a statistical level. This is of course true, but when reasoning further backward, these measurements itself are uncertain due to inaccuracies in the measurement instrument, and so on. This leads to an endless chain of uncertainties, making it impossible to identify uncertainties at all. If one is reasoning too far backward, the uncertainties do not have a direct effect on the model outcomes. Therefore, the process of breaking down uncertainties must be stopped when the uncertainties do no longer influence the model or the model boundaries. However, for the application of the methodology it is not important where one puts the threshold to stop backward reasoning, as long as it is defined in a consistent manner during the study.

Table 2.2: Identification and classification of uncertainties related to the fuzzy model. The uncertainties in bold are classified in more than one class for a dimension. Therefore, they do not have the appropriate aggregation level and need to be broken down

Description	Location					Level				Nature		
	Context	Input	Model structure	Model technical	Parameter	Statistical	Scenario	Qualitative	Recognised ignorance	Natural variability	Epistemic	Ambiguity
Soil type		**x**		**x**		**x**	**x**			**x**	**x**	
Soil type data		x				x					x	
Discretisation of soil types				x			x			x		
Definition of fuzzy sets					x	**x**	**x**				**x**	**x**
Parameterisation of fuzzy sets					x	x					x	
Simultaneous membership to multiple sets (overlap)					x		x					x

Secondly, contrary to common suggestions in literature, the distinction between natural variability and lack of knowledge (Beck, 1987; Van der Sluijs, 1997; Walker et al., 2003) and between lack of knowledge and ambiguity (Zimmermann, 2000; Brugnach et al., 2007) is not always obvious. In many cases, what seems to be natural variability at first sight, may well comprise a lack of a knowledge component. If more knowledge or data, or better empirical relations would be available, the system can be more accurately described in a model. At the bottom of this issue is the philosophical discussion described in section 2.2.1 about "coincidence" and the question of what is knowable and what is not. Also with regard to ambiguity, one can discuss the question whether ambiguity can always be resolved, or whether it is a fundamental property of information about a system. These questions hamper the process of uncertainty analysis in models. We chose to advocate a pragmatic stance, in which lack of knowledge and ambiguity are interpreted in the light of the available resources (time and money), state of the art knowledge, and the complexity of the system at hand.

Thirdly, also with respect to the level of uncertainty, there is a tension between what is fundamentally possible (e.g. to describe the uncertainty in the soil type in statistical terms) and what is practically plausible (in this case, the uncertainty is practically easier described on a scenario level). Again, we here plea for pragmatism: when starting from the best theoretically possible description, the approach to uncertainty can always be adjusted to a less detailed level in a later stage of the analysis.

Although, the new set of definitions is more strict than the definitions given by Walker et al. (2003), the distinction between classes is still influenced by the opinion of the analyst and therefore remains subjective. This is hard to prevent, because the background of a source of uncertainty is not always clear. For example, the distinction between input data and model parameters is defined by the dependence of the data on a certain river and period. However, also physically based parameters are often only valid for a certain river. A parameter is then distinguished from an input because it could also be valid for other rivers than the modelled river. This definition therefore depends on the subjective estimate by the expert or analyst. This is also the case for the level of uncertainty, which classes are distinguished in view of the available resources. Again for the application of the method it is not important where to lay the boundary between the classes, as long as it is consistent throughout the analysis.

The presented approach results in a list of uniquely identified uncertainties that are classified according to their location in the model, level and nature of uncertainty. This filled matrix is the first step in an uncertainty analysis. The matrices shown in Van der Sluijs et al. (2004) and Refsgaard et al. (2007) present for each class the possible methods to use for an uncertainty analysis and can be used to select the method for quantification or qualification of the uncertainties themselves or the propagation to the uncertainty in model outcomes. Furthermore, the uncertainties in the matrix do not overlap. This assures that uncertainties are not double counted in the analysis of the propagation of the uncertainties. For uncertainty propagation, the fact that the identified uncertainties are unique and do not overlap assures that the resulting uncertainties in the model outcomes are more comparable. Finally, a main advantage of the described approach to identify uncertainties is that they are better described and framed. This enhances the communication about the uncertainties, because all actors know better what is meant by the uncertainties.

2.7 Conclusions

In this paper we described a structured approach to identify and classify uncertainties, which is the first step in the uncertainty analysis of models. Existing methods for the identification of uncertainties in environmental models are limited, because uncertainties can overlap and have different aggregation levels. Therefore we adapted the existing framework by Walker et al. (2003) using Refsgaard et al. (2007), to enhance the objectivity in the uncertainty identification process. The new sets of definitions that were used to distinguish the uncertainties for classification make the classification scheme better applicable for identification and classification of uncertainties in practise. Furthermore, it leads to a more balanced description of uncertainties.

Although a number of issues remain to be discussed, a mixture of theoretical accuracy and practical thoroughness leads to a consistent identification of unique uncertainties. This was demonstrated in the two case studies. The identification becomes more robust when it takes the form of an iterative process with multiple model experts.

The proposed approach to uncertainty identification by means of classification improves the comparability of the outcomes of uncertainty propagation studies. Classification of uncertainties according to their unique dimensions leads to a coherent overview of uncertainties affecting model outputs. By being as accurate and comprehensive as possible, a sound basis is laid for quantification or description of uncertainties. Moreover, an analysis of model uncertainties will only be useful to decision makers if they know which uncertainties are included, and how these uncertainties are defined or described. The effort it takes to do a comprehensive uncertainty analysis is considerable, and with the detailed description of this framework for identification and classification of uncertainties it certainly does not decrease. The alternative however, namely neglecting uncertainties affecting model outcomes, leads to decision makers being provided with incomplete information. Continuous effort to improve uncertainty identification contributes to a better communication of model validity to decision makers and to a better underpinning of their decisions.

Acknowledgements

This research reported in this paper was supported by the Technology Foundation STW, applied science division of NWO, the technology program of the Ministry of Economic Affairs, and the Cornelis Lely Stichting. We thank the Dutch Centre for Water Management (Rijkswaterstaat) for providing the hydraulic model for the analysis.

Chapter 3

Identification and quantification of uncertainties in a hydrodynamic river model using expert opinions

Abstract

Hydrodynamic river models are applied to design and evaluate measures for purposes such as safety against flooding. The modelling of river processes involves numerous uncertainties, resulting in uncertain model outcomes. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model results and the usefulness of results in decision making processes. The aim of this study is to identify the sources of uncertainty that induce the largest uncertainties in the model outcomes and quantify their contribution to the uncertainty in the model outcomes. Experts have been selected based on an objective Pedigree analysis. The selected experts are asked to quantify the most important uncertainties for two model applications: (1) the computation of design water levels and (2) the computation of the hydraulic effect of a change in the river bed. For the computation of the design water levels, the uncertainties are dominated by the sources that change between the calibration and the prediction. The experts state that the upstream discharge and the empirical roughness equation for the main channel have the largest influence on the uncertainty in the modelled water levels. For effect studies, the floodplain bathymetry, weir formulation and discretization of floodplain topography induce the largest uncertainty. Finally, the contribution of the uncertainties to the model outcomes show that the uncertainties have a significant effect on the predicted water levels, especially under design conditions.

This chapter is published as: Warmink, J.J., Van der Klis, H., Booij, M.J. & Hulscher, S.J.M.H. (2011) Quantification of uncertainties in a river model using expert opinion elicitation. Water Resources Management 25(2) 601–622. DOI: 10.1007/s11269-010-9716-7

3.1 Introduction

Hydraulic-morphological river models are applied to design and evaluate measures for purposes such as safety against flooding. These numerical models are all based on a deterministic approach. However, the modelling of river processes involves numerous uncertainties, resulting in uncertain model outcomes. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model results and the usefulness of results in decision making processes.

Uncertainty is defined by Walker et al. (2003) as "any deviation of the unachievable ideal of complete determinism". Uncertainty consists of inaccuracy and imprecision. Inaccuracy refers to the difference between the model outcomes and reality, while imprecision deals with the variation around the model outcome and observations. Model uncertainty can be classified according to Walker et al. (2003) along three dimensions: the location, level and nature of an uncertainty.

The uncertainty in model outcomes can be quantified by propagation of the quantified uncertainty in all parts of the model. Monte Carlo simulation is a commonly used method for uncertainty propagation (Morgan and Henrion, 1990), especially for highly non-linear models (Van der Klis, 2003). Monte Carlo simulation requires a quantification of the uncertainties in all parts of the model as input. Therefore, to determine the uncertainty in the model outcomes, a structural analysis and quantification of the sources of uncertainty in a model is required. Many uncertainty studies are based on strong assumptions of the variation of the underlying uncertainties. However, the reliability of the uncertainty analysis is very sensitive to the assumed coefficient of variation (Johnson, 1996). The problem is that information about the magnitude and probability distribution functions of this input is usually not available or insufficient (Johnson, 1996; Van der Sluijs, 2007). Furthermore, the magnitude of the sources of uncertainty strongly depends on the case study and the model under consideration (Warmink et al., 2010b).

In recent uncertainty analysis studies about river modelling, uncertainties have often been studied in isolation. Often, only uncertainties that can easily be quantified are taken into account, such as uncertainties in model input and model parameters (e.g. Refsgaard et al., 2006a; Hall et al., 2005; Bates et al., 2004). In such a case, it is likely that the model outcome uncertainty is underestimated. The uncertainties in the model context and model structure are often neglected. Although, Refsgaard et al. (2006b) present a method to deal with uncertainties in model structure, the authors do not consider other sources of uncertainty.

Pappenberger et al. (2005) and Hunter et al. (2007) presented a structured overview of uncertainties in river models. They reviewed the recent developments in reduced complexity of river models to determine the extent to which such techniques are capable of reliable and practical application. However, they only focused on uncertainties in the input, parameters and model structure of river models. They did not include the uncertainties in the context and application of the model in the review. Hall and Solomatine (2008) and Van der Keur et al. (2008, 2010) described and identified the individual sources of uncertainty in a broader context. They focused on uncertainties in water resources management, including flood risk management. However, they did not quantify the sources of uncertainty, nor did they quantify the uncertainty in the model outcomes.

A substitute for the information about the magnitude and probability distribution functions of the input for an uncertainty analysis is the use of subjective probability functions, which can be obtained by the systematic combination of expert judgements (Cooke and Goossens, 2000; Ayyub, 2001). In environmental modelling, especially for health risk analysis, expert opinion has been used for the identification and quantification of uncertainties (Krayer von Krauss et al., 2004; Van der Sluijs et al., 2005b; Refsgaard et al., 2006b).

Krayer von Krauss et al. (2004) conducted detailed expert interviews to formally explore the uncertainty in the risk assessment on genetically modified crops. They interviewed seven leading experts in this research field to obtain qualitative and quantitative information from their understanding of the uncertainties associated with the risks. Van der Sluijs et al. (2005b) studied the emission of volatile organic compounds (VOC) from paint in the Netherlands. The authors used expert elicitation to identify key sources of error, critical assumptions and bias in the monitoring process. Both these studies by Krayer von Krauss et al. (2004) and Van der Sluijs et al. (2005b) comprise an uncertainty assessment, combining quantitative and qualitative data in a risk assessment. In our study we assess the uncertainty in the outcomes of a hydrodynamic river model, thereby focusing on quantification of the uncertainties in the model outcomes.

In this study we want to identify and quantify the uncertainties in a two-dimensional river model for flood safety computations in a structured manner by using expert opinion elicitation to identify and rank the most important uncertainties in the river model. These ranked uncertainties will be used in a future study as the first step in a Monte Carlo analysis. The reliability of the outcomes of a Monte Carlo analysis depend on the reliability of the ranking of the identified sources of uncertainty. The aim of this study is to identify the sources of uncertainty that contribute most to the uncertainties in the model outcomes and quantify their contribution to the uncertainty in the model outcomes using expert opinion elicitation.

This paper is organised as follows. Section 3.2 describes the study area and model. The method for the selection of the experts and the approach for the interviews is presented in section 3.3. In section 3.4 the results are given and discussed in section 3.5. Finally, conclusions are drawn in section 3.6.

3.2 Study area and model

River flooding is a serious threat in the Netherlands. Strong dikes have been constructed to protect the land from flooding. After the 1993 and 1995 (near) flood events of the rivers Rhine and Meuse, the Dutch government laid down that every 5 years the safety of the primary dikes has to be evaluated (Ministry of Transportation, Public Works and Water Management, 1995). The Ministry of Transport, Public Works and Water Management publishes every five year the Hydraulic Boundary conditions. These comprise the water levels that are used in the safety assessment. They are determined using statistical and deterministic models (Van den Brink et al., 2006).

The design water levels in the main rivers in the Netherlands are computed based on a design discharge (Ministry of Transportation, Public Works and Water Management, 1995). This design discharge is based on the statistical analysis of historical discharge series. Subsequently, the heights of the dikes are compared to the computed design water levels in the river. These design water levels are the main components of the dike safety evaluation.

The design water levels in the upper part of the Dutch river Rhine in the Netherlands are calculated using the two-dimensional, depth-averaged river model WAQUA. The WAQUA model has been developed in the late sixties, based on the work of Leendertse (1967). WAQUA is used for two-dimensional hydrodynamic and water quality simulation of well-mixed estuaries, coastal seas and lowland rivers. The WAQUA model is used and maintained by the Dutch Centre for Water Management in cooperation with Deltares (former WL | Delft Hydraulic). WAQUA accounts for flooding and drying of individual cells and can account for energy losses due to weirs. These features are essential for channelised rivers, such as the river Rhine. The model is applied mainly to the Dutch Rhine tributaries and for several studies of the river Rhine in Germany.

WAQUA consists of: 1) the program environment SIMONA (Rijkswaterstaat, 2009) which holds the discretized shallow water equations to simulate the water flow and the empirical equations to approximate energy losses, and 2) a schematization of the river Rhine region for a certain period with corresponding input parameters (e.g. stage-discharge relations, river bed roughnesses, upstream discharge, etc.). The schematization consists of a computational grid, the bathymetry of the river bed and mapped characteristics of the flow channel (e.g. grain size, vegetation, and other objects such as houses, bridges, barriers, spillways, etc.). The vegetation is represented by a hydraulic roughness that is calibrated for different classes of vegetation types (Van Velzen et al., 2003). Aerial photography is used to determine the vegetation type for each polygon in the floodplain area. Subsequently, these data are converted onto the computational grid. In this study, the 2006 version of the WAQUA model (HR2006_4) was used, which has grid sizes of approximately 40 m (Rijkswaterstaat, 2007). The time required to simulate one full day for the Dutch tributaries is approximately one hour using a time step of 15 seconds.

The WAQUA model is used for two different applications. Firstly, for the computation of the design water levels (DWL) as described above. Secondly, the model is used for the computation of the effect of measures taken in the floodplain areas that change the geometry of the cross section, so called effect studies. This is the case if, for example, someone wants to exploit the floodplain for building or clay excavations. In this case the changes in the floodplain region are not allowed to result in a rise in the water level in the river. Therefore, the plans are tested using the WAQUA model by schematising the plans in the model and computing the effect. Another example of effect studies is that the Ministry of Transport, Public

Works and Water Management wants to lower the design water levels in the Dutch rivers by increasing the discharge capacity of the floodplains. Therefore, the effect of different measures on the design water levels are compared using the WAQUA model.

The main differences between DWL computations and effect studies are that the DWL case uses a design discharge wave as input, while the effect studies use a constant discharge as upstream input. Furthermore, the result from a DWL computation is an absolute water level in the river, while for the effect studies case, the result is a difference in water levels. This means that for effect studies, two model runs are subtracted, which has large implications for the uncertainties. For both applications the effect at the river axis (the centre line of the main channel) and near the dike are computed.

Calibration of the WAQUA model has been carried out using the measured discharge peak of 1995, with corresponding schematization and measured water levels at several locations along the river Rhine (Van den Brink et al., 2006). The 1995 peak is used as it is the highest measured discharge peak in the river Rhine in recent history and is, therefore, closest to the design discharge of 16000 m^3/s. The 1995 peak had a maximum discharge of 12000 m^3/s at Lobith (the location where the Rhine enters The Netherlands). During this calibration only one linear parameter in the equation that relates the hydraulic roughness of the main channel to the water level is adapted so that the computed water levels of the seven stations along the river Waal match the measured water levels. In the setup of the model, also optimal values for several other parameters, such as the eddy viscosity are determined.

The experts were asked to consider only the WAQUA model for the Waal branch for the two above mentioned applications. The Waal river is the largest branch of the river Rhine in the Netherlands. Figure 3.1 shows the location of the Waal branch in the Netherlands and the schematization of the WAQUA model. This model was well known to all interviewed experts.

3.3 Methods

The first step in an expert opinion study is to select the experts. Van der Sluijs (1997) noted that the results of an expert opinion study are sensitive to the selection of the experts whose estimates are gathered. In this study, the experts have been selected based on their expertise that has been measured using a Pedigree analysis. Next, eleven face-to-face interviews have been conducted with the selected experts and the experts' opinions have been aggregated.

3.3.1 Pedigree analysis

In this study the experts are selected using objective criteria in a Pedigree analysis. Pedigree is a method to convey an evaluative account of the production process of information and indicates different aspects of the underpinning of the numbers and scientific status of the knowledge used (Funtowicz and Ravetz, 1990). Pedigree

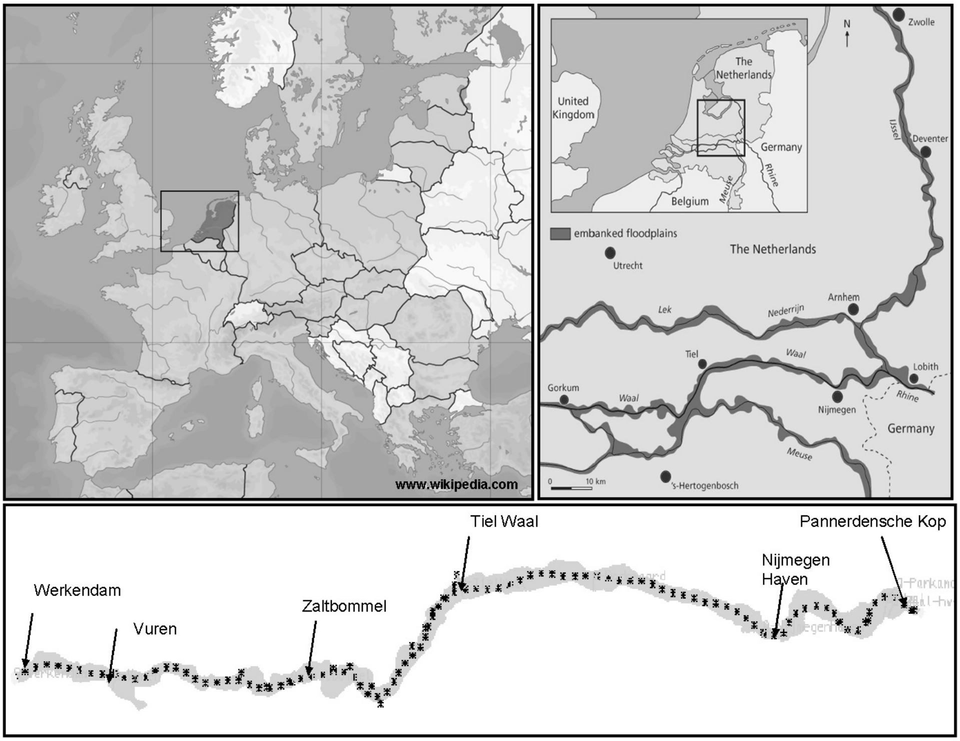


Figure 3.1: Location of the Rhine tributaries in the Netherlands. The Waal model is shown below with the measurement stations indicated by the arrows and the river kilometres as black crosses

is expressed by means of a set of pedigree criteria to assess these different aspects (Van der Sluijs et al., 2005b).

Pedigree analysis has been used in uncertainty analysis, commonly as part of the NUSAP methodology (Van der Sluijs et al., 2005a). NUSAP is a notational system proposed by Funtowicz and Ravetz (1990), which aims to provide an analysis and diagnosis of uncertainty in science for policy. It captures both quantitative and qualitative dimensions of uncertainty and enables one to display these in a standardised way. The basic idea is to qualify quantities using the five qualifiers of the NUSAP acronym: Numerical, Unit, Spread, Assessment and Pedigree. By well describing and framing the uncertainties (Numerical and Unit) and adding expert judgement of reliability (Assessment) and systematic multi-criteria of the production process of numbers (Pedigree), NUSAP has extended the statistical approach (Spread) (Van der Sluijs et al., 2004). The Pedigree part of NUSAP is developed to describe and quantify the background of different types of information.

Pedigree is used to assess the 'strength' of an assumption, input or parameter. The strength means that the assumption underlying the quantity is 'weak' or 'strong'.

Different criteria are defined on which this strength is evaluated. To minimise arbitrariness and subjectivity in measuring strength, a Pedigree matrix is used to code qualitative expert judgements for different criteria into a discrete numerical scale from 0 (weak) to 4 (strong) with linguistic descriptions (the criteria) of each level on the scale. Each special sort of information has its own aspects that are key to its Pedigree (Van der Sluijs et al., 2004). The criteria may vary, depending on the audience and case at hand. Common criteria include: quality of proxy, empirical basis, theoretical understanding, methodological rigour, validation, and value-ladenness (Wardekker et al., 2008). Assessment of Pedigree involves qualitative expert judgement and is therefore commonly used in combination with expert opinion elicitation.

Pedigree has been applied in several uncertainty analysis studies in combination with expert opinion elicitation. Groenenberg and Van der Sluijs (2005) used Pedigree analysis for determining the strength of uncertain assumptions, input and parameters in an emission reduction targets model as an addition to a sensitivity analysis. They concluded that in the identification of the major uncertainties in their model, one should not only consider the variance in the outcome, but also pay attention to the strength of various inputs. This means that the values of the parameters with the lowest strength need to be chosen based on maximal research and consultation of stakeholders (Groenenberg and Van der Sluijs, 2005), because a quantitative sensitivity analysis might show that these parameters only have little influence on the model outcomes. However, a low strength indicates that the background of these parameters is potentially highly uncertain. Therefore, they may have a large effect on the uncertainty in the model outcomes, which is not revealed by the quantitative analysis only.

Van der Sluijs (2002) showed the experiences in applying Pedigree, as an addition to quantitative methods in an uncertainty analysis to four cases: a policy case, a complex model case, a chain of models and an interactive assessment of uncertainty in environmental health risk science and policy. In both model cases they used expert opinions to assess Pedigree scores to determine the strength of the underlying assumptions and model input and parameters. They concluded that Pedigree is a useful addition to quantitative sensitivity analysis to prioritise uncertainties. Wardekker et al. (2008) analysed a series of experiments evaluating uncertainty communication in the yearly reports that describe the state of the (Dutch) environment and evaluate policy influences. They showed that policy advisers find qualitative information on uncertainty presented by Pedigree scores useful to put the presented data in perspective. In this study, we used Pedigree to determine the strength of the experts and assess their level of expertise.

3.3.2 Application of Pedigree for expert selection

The first reason to select an expert was its familiarity with the case study. Initially 42 possible experts have been selected who were familiar with the WAQUA model. All experts have been either involved in research activities related to the WAQUA model or in WAQUA project execution. Most experts had “hands-on” experience with the WAQUA model, that is they have been working on setting up and running the model personally.

From these 42 initially selected experts we needed to select between 10 and 15 experts for a face-to-face interview given the available time. Expert opinions are sensitive to the selection of experts (Van der Sluijs, 1997), therefore, an objective method to select the experts was required. We used the Pedigree method to measure the expertise of the experts and selected the experts with the highest expertise. A Pedigree matrix has been developed for measuring the expertise for this particular case. We chose four different criteria that we considered most appropriate to determine the experts' expertise. Subsequently, for each criterion five possible answers have been prepared ranging from 0 (low expertise) to 4 (large expertise). A short questionnaire has been send to the experts to get the input for the Pedigree analysis.

The four criteria in the Pedigree matrix are: 1) experience with code development of the WAQUA model, 2) number of years experience with research and consultancy projects regarding the WAQUA model, 3) number of years experience with the WAQUA model applied to the rivers Rhine or Meuse and 4) number and type of publications about research projects with the WAQUA model concerning the rivers Rhine or Meuse. The Pedigree matrix is shown in table 3.1.

Table 3.1: Pedigree matrix for the selection of experts, based on Funtowicz and Ravetz (1990)

Question	Code development	Project experience	Model experience	Publications
Weights:	4	3	2	1
4	Yes $\geq$ 10 years	Yes, $\geq$ 10 years	$\geq$ 10, Rhine	Journal paper
3	Yes long time ago	Yes, $\leq$ 10 years	$\geq$ 10, No Rhine	Conference
2	Yes, some	Only related models	$\geq$ 5, Rhine	Report
1	Few	Only 1D models	$\geq$ 5, No Rhine	Few
0	No	No	No	No

We gave the criteria within the Pedigree matrix a relative weight, because not all criteria are considered equally important. The criteria have been given a weight between 1 and 4. We considered experience with code development the most important criterion, because it has been assumed that people that have information about the code background have more insight in the model and can therefore better judge the uncertainties in the model. The second most important criterion was experience with WAQUA projects for the same reason, followed by "hands-on" experience. Number of publications was considered to be the least important criterion. The Pedigree score for each expert was determined by:

$$P = \frac{\sum_{i=1}^{4} col_i \cdot w_i}{40} \tag{3.1}$$

where col_i is the number of points in column i and w_i is the weight of that column. To normalise P between 0 and 1, we divide here by 40, which is the maximum number of points that can be scored. A sensitivity analysis on the influence of the weights on the selected experts showed that only two experts would be excluded (have a P value below 0.65) if the weights were omitted and all criteria would have the same weight. So, the weights do not have a large influence on the selection of the experts, but it improves the representation of the expertise of each expert by the Pedigree score.

Thirty-one experts returned the questionnaire and have been given a Pedigree score, based on their answers of the questionnaire. Figure 3.2 shows the results of the Pedigree analysis. The 17 experts with a Pedigree score above 0.65 were selected and invited for an interview. The threshold of 0.65 was chosen because the trend of the Pedigree scores shows a clear drop after expert 17 and time was available for 10 to 15 experts. Experts 25-31 did not complete the questionnaire, but answered that they were not the intended expert, therefore they were assigned a zero Pedigree score.

Subsequently, 11 of the 17 selected experts are actually interviewed. The interviewed experts all had a Pedigree score of 0.75 or higher, which indicates that all these experts have enough experience with the WAQUA model to reliably give estimates of its uncertainty.

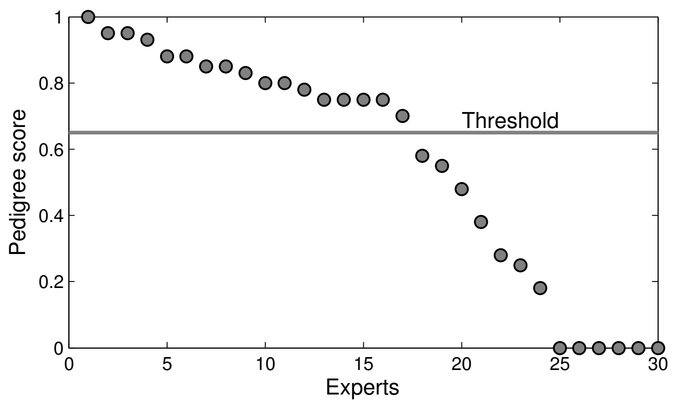


Figure 3.2: Pedigree scores of all experts that returned the questionnaire. 17 experts with a Pedigree score above 0.65 have been selected for an interview

3.3.3 Identification of uncertainties

The uncertainties are identified following the method described in chapter 2. Walker et al. (2003) describe five possible locations of uncertainty: a) context uncertainty, including uncertainties that are located outside the model boundary and relate to the assumptions and choices underlying the model, b) input uncertainty, c) model uncertainty, which consists of model structure uncertainty and model technical uncertainty, d) parameter uncertainty, and e) uncertainty in the model outcomes.

The levels of uncertainty (second dimension) range from statistical uncertainty and scenario uncertainty through recognised ignorance to total ignorance. For the last dimension, the nature, they distinguish between epistemic uncertainty (due to a lack of knowledge) and variability uncertainty (due to the variability in the behaviour of the natural, social, economic or technical system).

The first step in the identification of uncertainties is to elicit a global list of uncertainties. This is done by asking the experts, which uncertainties play a role in this case study. By considering all locations of uncertainty, including model context and model structure the global list with identified uncertainties will be more complete than if only uncertainties in input and parameters are taken into account.

The next step is to go through this list again and check if the identified uncertainties are unique and complementary (Warmink et al., 2010b). To assure this, every uncertainty needs to be described accurately and specified along all three dimensions in a unique manner. This methodology is presented in Warmink et al. (2010b). In this step of the identification, we attempt to classify the listed uncertainties from the first step into a single class for each dimension. This means that an uncertainty can, for instance, not be at the level of 'statistical uncertainty' and 'scenario uncertainty' at the same time. If the uncertainty falls into two classes of any dimension, the uncertainty needs to be broken down into smaller parts and described in more detail. This methodology assures that the resulting uncertainties are unique and form a consistent set.

3.3.4 Aggregation of expert opinions

The aggregation of expert opinions for the drafting of probability distributions for Monte Carlo analysis, brings several important methodological difficulties (Van der Sluijs, 1997). Firstly, the fraction of the experts having a certain view is not proportional to the probability of that view to be correct. This implies that the spreading in the expert opinions can not be used to describe the uncertainty and as a result the expert opinions cannot be averaged. However, Cooke and Goossens (2000) state that if appropriate weights are given to the experts, averaging can be conducted. Also, Keith (1996) states that averaging of expert opinions can be safely conducted, but only if the experts refer to the same model. In expert opinion practise, this is hardly the case (Keith, 1996). Weighting and combining the individual estimates of distributions is only valid if the opinions are weighted with competence of the experts making the estimate. To account for the above mentioned difficulties, the experts are given a weight using the Pedigree scores to be able to average the experts estimates.

3.3.5 Interviews

In a face-to-face interview of approximately one hour, the experts were asked to indicate the parts of the model that had the most influence on the uncertainty of the model outcomes. This means that either an uncertainty has a high degree of uncertainty itself, or it has a large influence on the model outcomes, or both. This question was asked for the computation of the design water levels (DWL), and for the computation of the effects of measures taken in the river bed. This resulted in two (partly overlapping) lists with uncertainties.

For each list, the uncertainties were broken down into uncertainties with an equal level of detail, using the classification matrix by Walker et al. (2003). Next, the experts have been asked to identify the major sources of uncertainty. In many cases these uncertainties overlapped between the different experts. However these lists were not comparable, because some experts mentioned small (negligible) uncertainties, while other experts omitted these uncertainties. Therefore, it was not possible to compare the number of times a source of uncertainty was mentioned.

Furthermore, the experts were asked to comment on each uncertainty source and to give a value for the contribution of that uncertainty to the uncertainty in model outcomes in terms of water levels. The uncertainty is therefore expressed as a value that represents the maximum uncertainty range, which ranges from plus or minus the given value. For the effect studies case, the uncertainty was expressed as a percentage of the effect. For example, if a floodplain excavation of 1 m has an effect of 10 cm on the water level on the river axis and the uncertainty was chosen to be 50%, this means that the uncertainty range of the effect of this excavation is from 5 to 15 cm.

In many cases the experts were not able to give a single number for the uncertainty. Sometimes a range was given or an order of magnitude (millimetres, centimetres, or decimetres). In case an expert mentioned a range in which the value of the uncertainty was located, the average of that range was taken for further analysis. If the experts were not able to give a numerical value, sometimes they expressed the uncertainty in qualitative terms, such as “small” and “large”. Other experts were not able to give any value at all. No guidance was given how to interpret the terms “large” or “small”, so the experts made their own subjective judgement in this respect. The experts identified 16 different sources of uncertainty for both applications of the WAQUA model. For each source of uncertainty, a maximum of 5 experts were able to quantify the uncertainty.

3.4 Results

3.4.1 Identification of uncertainties in design water levels

Each expert identified at least seven different uncertainties. The identified uncertainties are shown in table 3.2. The uncertainties in this table are sorted with decreasing importance according to the weighted average of the expert opinions. The terms measurements, schematization, discretisation and formulation are used to denote the different steps in the setup of the model. Firstly, the uncertainty due to measurements is caused by the measurement instrument and measurement method in the field. Secondly, the schematization represents the method that is used to translate the measurements to different classes that are used in the model. For example, the schematization of the vegetation is the decision in which of the three

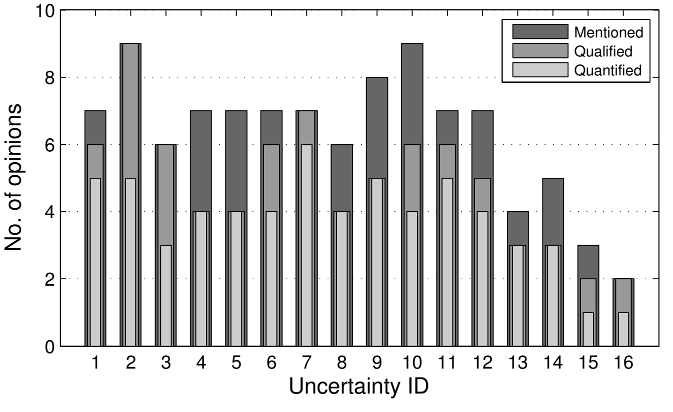


Figure 3.3: Number of expert opinions for each source of uncertainty for the design water level case. Specified as mentioned uncertainties, qualified uncertainties or quantified uncertainties. The numbers on the horizontal axis refer to the uncertainty ID's listed in table 3.2

classes of forest an observed forest would fit best. This depends on the type of trees, the average tree-height and the density of the trees in the forest. Next to these data, also the actual average density of the trees in the forest is an input parameter. The vegetation manual (Van Velzen et al., 2003) is used as the guideline to discriminate between the different vegetation classes. Thirdly, the discretisation represents the method that is used to discretize, for example, the vegetation classes onto a grid. The uncertainty is caused by the delineation of these observed vegetation patches and depends on the grid size. Finally, the uncertainty due to formulation stems from the structure of the equation that is used in the model.

3.4.2 Quantification of uncertainties in design water levels

Figure 3.3 shows the number of times an uncertainty is mentioned by an expert compared to the number of times an uncertainty is qualified and quantified. The values are given cumulative, which means that every quantified uncertainty is assumed qualified and, of course, mentioned. This figure shows that almost all uncertainties are mentioned equally often and most uncertainties are quantified by more than four experts. Uncertainties 15 and 16 both are only quantified by one expert, but they stated this uncertainty as very uncertain, therefore these were included in the analysis. The results from other uncertainties that were mentioned by only one or two experts were considered to be not important and are not shown.

Figure 3.4 shows only the opinions of the experts that were able to quantify the uncertainty. The left panel of this figure shows that the sources of uncertainty number 1 and 2, upstream discharge and main channel roughness predictor have the largest contribution to the uncertainty in the model outcomes. Both the weighted average and the maximum value given by an expert are large compared to the

Table 3.2: Identified sources of uncertainty in design water levels. FP represents floodplain and MC represents main channel. The uncertainties are sorted with decreasing importance

ID	Short name	Description
1	Upstream discharge	Discharge that is imposed as upstream discharge. The design discharge is derived by extrapolation of a historical discharge series. Subsequently, a design discharge wave is constructed with a return period of 1250 years.
2	MC roughness predictor	The empirical roughness predictor for the main channel.
3	Vegetation schematization	The schematization of the vegetation in the floodplain area.
4	Weir formulation	The formulation of the energy losses, due to acceleration and deceleration of the water flow over weirs, embankments or slopes in the landscape.
5	Calibration data	The data used for the calibration of the model. These data consist of measured water levels and discharges, both of which are uncertain.
6	MC bathymetry discretisation	Discretisation of the measurements of the main channel bathymetry onto the computational grid.
7	FP roughness predictor	Empirical roughness equation for the floodplain vegetation and other objects in the floodplain area.
8	FP vegetation measurements	Measurements of the floodplain vegetation. This represents the variability within the floodplain ecotopes and the accuracy of the classification.
9	Weir discretisation	The discretisation of the weirs on the computational grid.
10	MC bathymetry measurements	Measurements of the bathymetry of the main channel.
11	FP bathymetry measurements	Measurements of the bathymetry of the floodplain area.
12	Eddy viscosity	Eddy viscosity parameter that accounts for energy losses due to velocity differences.
13	SWE discretisation	Numerical method to discretize the shallow water equations.
14	Discharge distribution	Distribution of the discharge over the three branches of the river Rhine.
15	Groyne formulation	The method that is used to compute the energy losses due to groynes.
16	Season of peak discharge	Currently, it is assumed that a peak discharge will occur in winter when the vegetation has no leafs. However, if a peak discharge occurs in spring the circumstances, especially of the vegetation, are different.

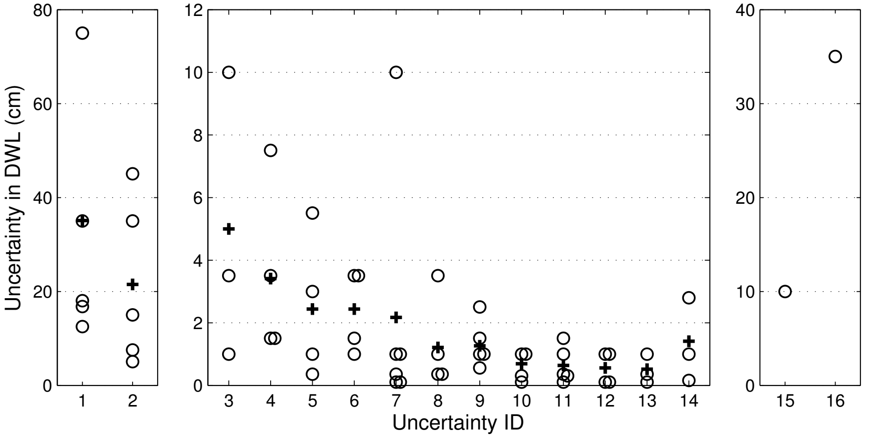


Figure 3.4: Quantitative results of the expert opinions for the design water level case. Weighted average (+ symbols) and individual expert opinions (open circles) are shown. Note the differences in the scale of the vertical axes. The numbers on the horizontal axis refer to the uncertainty ID's listed in table 3.2

other uncertainties. The range of the individual expert opinions for the upstream discharge lies between 12.5 cm and 75 cm for the computed water levels under design conditions. The uncertainty due to the main channel roughness predictor ranges between 5 and 45 cm. Additionally, one expert states that the upstream discharge has a "large" influence on the design water levels (see figure 3.5). Furthermore, three experts state that the main channel roughness equation has a "large" contribution to the uncertainty in the design water levels.

The centre panel of figure 3.4 shows that the sources of uncertainty 3–6 result in a weighted average uncertainty between 2 and 5 cm in the computed water level. These uncertainties clearly have a smaller contribution than uncertainties 1 and 2, but still are considered to be important. For the sources of uncertainty 7 and 8, only one expert has the opinion that the uncertainty is larger than 2 cm. None of the experts have the opinion that uncertainties 9–14 have an uncertainty larger than 2.8 cm. Therefore, these uncertainties are considered to be less important. As a first step, these uncertainties can be excluded from an uncertainty analysis. In the computation of the Hydraulic Boundary conditions the computed water levels are usually rounded on 5 cm. Therefore, uncertainties below 5 cm are considered not important. However, the cumulative contribution of these uncertainties can be significant.

Uncertainties 15 and 16 (groyne formulation and the season of high discharge) in the right panel of figure 3.4 are quantified by one expert only. Therefore, it is not possible to say anything about the average uncertainty and its importance. However, both uncertainties are qualified as important. Therefore, it is possible

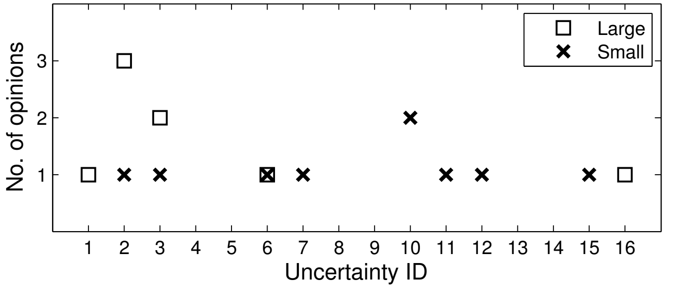


Figure 3.5: Qualitative results of the expert opinions for the design water level case. The numbers on the horizontal axis refer to the uncertainty ID's listed in table 3.2

that these uncertainties have a large contribution to the uncertainty in the model outcomes. Future study on these uncertainties is therefore required.

Some experts were not able to express the uncertainty in a value. They expressed the uncertainty for a certain source qualitatively as "large" or "small". Figure 3.5 shows these results. It must be noted that these opinions do not overlap the quantified uncertainties. For each uncertainty the number of times the uncertainty was qualified as "large" or "small" is shown. This figure shows the same trend as the quantified results. Uncertainties 1–3 were qualified more often as "large" than as "small". Furthermore a trend of decreasing uncertainty is shown with increasing uncertainty ID number, because the uncertainties are sorted on their quantified weighted average values. This indicates that the qualitative results show the same behaviour as the quantified uncertainties. The uncertainty in the season of peak discharge is also considered "large" in addition to the value of 35 cm estimated by one other expert. This may be an indication that this might be an important source of uncertainty. The similarity between the qualitative and quantitative results increases the confidence in the quantified uncertainties.

3.4.3 Identification of uncertainties in effect studies

Table 3.3 summarises the identified uncertainties in the computation of effect studies. Only the largest eight uncertainties are shown. The experts identified in total 18 different uncertainties. Next to the uncertainties in table 3.3 they mentioned, for example, the choices made by the modeller, the eddy viscosity parameter and the measurements of the main channel bathymetry as uncertainties. However, these uncertainties could not be quantified and were only qualified by one or two experts. For clarity, these results are not shown in the analysis. However, in addition to these uncertainties the natural succession of vegetation is mentioned by four experts as a large uncertainty. This uncertainty however could not be quantified and is therefore omitted from this list as well.

Table 3.3: Identified sources of uncertainty in effect studies. FP represents floodplain and MC represents main channel. The uncertainties are sorted by decreasing uncertainty according to the weighted average quantified expert opinions

ID	Short name	Description
1	Schematization FP vegetation	The schematization of the vegetation in the floodplain area. This source of uncertainty comprises the uncertainty in the measurements and the uncertainty due to the variability within each class of vegetation.
2	Groyne formulation	The groyne formulation is uncertain, because groynes are modelled as weirs. Therefore, amongst others, the 3D effects around the tip of the groynes are ignored.
3	FP bathymetry measurements	Measurements of the bathymetry in the floodplain area.
4	Weir schematization	The schematization of the weirs is uncertain. This is caused by the uncertainties in the measurements in the heights of the weirs. Also, steep slopes in the floodplain area are computed by means of a weir formulation if the slope is above a certain threshold. This causes that energy losses due to some slopes are computed as weirs, while energy losses due to smaller slopes in the landscape are omitted. Furthermore, the slopes classified as weirs are then assumed to have a fixed slope.
5	Weir formulation	Formulation of the energy losses, due to acceleration and deceleration of the water flow over weirs. The equation used for these weirs is empirically derived.
6	FP roughness equation	Empirical roughness equation that computes the energy losses due to vegetation and other objects in the floodplain area.
7	Discretisation FP bathymetry and vegetation	Discretisation of the bathymetry and vegetation onto a grid.
8	Discharge distribution FP-MC	The discharge distribution between the floodplain an the main channel.

3.4.4 Quantification of uncertainties in effect studies

Figure 3.6 shows that about half of the experts that mentioned an uncertainty were able to quantify it. Furthermore, more uncertainties are mentioned and quantified for the design water level computations than for the effect study computations. The ranking in the sources of uncertainty in effect studies is less pronounced.

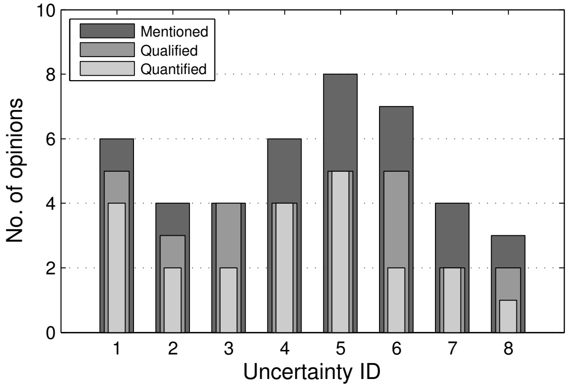


Figure 3.6: Number of expert opinions for each source of uncertainty for the effect studies case. Specified as mentioned uncertainties, qualified uncertainties or quantified uncertainties. The numbers on the horizontal axis refer to the uncertainties listed in table 3.3

The uncertainties are quantified by the experts as a percentage of the computed effect on the water level in the river of a measure taken in the river bed. Figure 3.7 shows the individual expert opinions and the weighted average for each uncertainty that the experts were able to quantify. The uncertainty that causes the largest uncertainty in the computed effect is the discharge distribution over the floodplain and the main channel. However, this source of uncertainty is actually a variable within the model, which is the result of the ratio of the aggregated roughness between the floodplain and the main channel. The weighted average due to the schematization of floodplain vegetation is larger than the other values. However, no clear distinction in the weighted averages is visible between the sources of uncertainty.

Figure 3.8 shows that for each of the uncertainties 1–3, one additional expert qualified the uncertainty as “large”. For uncertainty 7 one expert qualified it as “large”, while two experts qualified it as “small”. For the effect studies case, the quantitative and the qualitative results both show no clear distinction between the different uncertainties. Next to these listed uncertainties, four experts identified the natural succession of the floodplain vegetation as an additional uncertainty with a “large” contribution. However, no expert was able to quantify the contribution of this source of uncertainty to the effect on the computed water levels.

The uncertainties in the effect studies case are more difficult to quantify than the uncertainties in the DWL case, because the uncertainty highly depends on local cir-

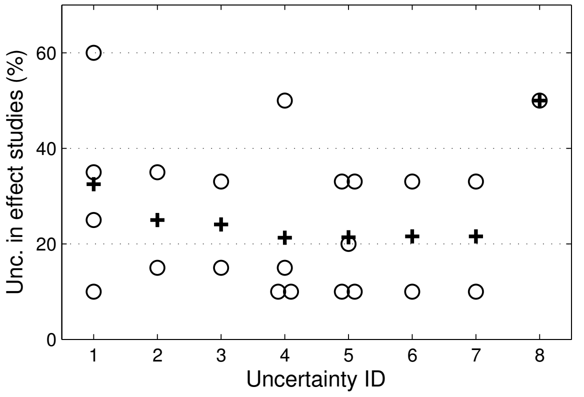


Figure 3.7: Quantitative results of the expert opinions for the effect studies case. Weighted average (+ symbols) and individual expert opinions (open circles) are shown. The numbers on the horizontal axis refer to the uncertainty ID's listed in table 3.3

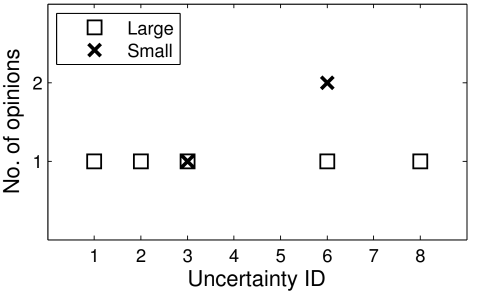


Figure 3.8: Qualitative results of the expert opinions for the effect studies. The numbers on the horizontal axis refer to the uncertainties listed in table 3.3

cumstances. Local circumstances are, for instance, the local topography of a floodplain due to the construction of a small channel or the vegetation characteristics of a floodplain. The experts gave generic statements to qualify the uncertainty for a given situation. Firstly, if a characteristic of the floodplain in the modelled region is changed between the two model runs, it might be important. For example, if the effect of a small channel in the floodplain is modelled this channel is included in the schematization. The uncertainty in the schematization of that channel can be very important. However, if this channel was already in the schematization, the uncertainty might not be important. In general, the experts stated that characteristics that do not change between two model runs generally have little contribution to the uncertainty. Furthermore, if a characteristic of the modelled region is also in a region with large flow, this uncertainty could have a large contribution to the model outcome uncertainty. The locations with a large flow are locally highly variable. The experts stated that if a part of the floodplain has a large discharge capacity and therefore a large flow, the uncertainties in that part of the floodplain are more important than in low flow regions. Therefore, quantification of individual sources is only possible for a specific situation if all other uncertainties are assumed deterministic. Especially for the effect studies case, there is a strong correlation between the sources of uncertainty and the flow field, because uncertainties are highly sensitive to that flow field.

3.5 Discussion

Firstly, the influence of calibration on the answers given by the experts is addressed, because it was often mentioned in the interviews as a complication of the uncertainty assessment. Secondly, the different sources of bias in expert opinion research are discussed that may have played a role in this study. Finally, the aggregation of the expert opinions and the methodology that was used during the elicitation of the expert opinions is discussed.

3.5.1 Calibration

Calibration plays an important role in the quantification of the sources of uncertainties. The method used to calibrate the WAQUA model for the DWL computations and effect studies case is described in section 3.2. According to the experts many uncertainties are reduced by calibration. This effect is taken into account in the experts' estimation of the uncertainties. The uncertainties that are influenced by calibration are uncertainties in the measurement data, uncertainties in the discretisation of these data onto a grid and the uncertainties in the computational parameters, such as the eddy viscosity, because it is assumed that these parts of the model do not change between the situation used during calibration and the design conditions. For example, the experts state that for a floodplain that has the same topography and vegetation in 1995 and in 2006, the uncertainty in the topography is reduced by calibration, because all errors that are compensated by the calibration on the 1995 case are still compensated in the 2006 case if nothing has changed. However, the interactions between the flow through the floodplain and a small dike that did change between the two schematizations, might have an effect on the uncertainty.

The uncertainties that are not compensated for by calibration are valued by the experts to have a larger contribution to the uncertainty in the model outcomes for the DWL case. These uncertainties comprise the upstream discharge and the main channel roughness formulation. Furthermore, some experts stated that the extrapolation from the calibrated situation to design conditions also introduces uncertainty in other parts of the model. This uncertainty mainly comes from the difference in water levels between the calibration conditions and the design conditions. This difference is especially large in the floodplain area and becomes apparent in the roughness formulations. Therefore, the floodplain roughness formulation and the weir formulation are also stated as uncertain. For example, some experts question the validity of the weir formulation in the case that a large water level is present above the top of the weir.

The major difficulty in the determination of the main uncertainties is that all uncertainties are correlated. Therefore, many experts state that the discharge distribution between the floodplain and the main channel is of main importance. The ratio between both discharges expresses the ratio between the aggregated roughness of the main channel and the aggregated roughness of the floodplain area. In future studies, this characteristic should be taken into account in the calibration and validation of 2D hydrodynamic models. The uncertainty in this characteristic also expresses the uncertainty in the aggregated roughnesses.

3.5.2 Expert bias

Experts opinion research is known to have several difficulties. One has to cope with judgemental heuristics and the biases, which are produced in the expert opinions (Van der Sluijs et al., 2004). Sources of bias are: anchoring, availability, coherence, representativeness, satisficing, overconfidence and motivational bias (Van der Sluijs et al., 2004).

Anchoring is the bias of experts to weigh their opinions toward the conventional value or the first given value. In this study, most experts refer to previous research that is known to the expert. For example, the experts frequently refer to the research reports of Stijnen et al. (2002) and Ogink (2003). Also, unpublished memos and other small studies are the sources of the experts opinions. Therefore, also availability bias plays a role in the results by giving too much weight to the available data. These reports and memos are assumed to give a good approximation of the uncertainties, because the aim of their studies was to give an overview of some of the important uncertainties. However, these reports and memos only focused on a limited number of uncertainties. Also, these documents are not easily available and only the involved experts know of their existence.

Coherence bias means that events are considered more likely if many scenarios can be created that lead to an event, or if some scenarios are particularly coherent (Van der Sluijs et al., 2004). In this study coherence bias did not play a role, because only a single scenario was considered. Representativeness bias is caused by placing confidence in a single piece of information that is considered to represent a larger process and satisficing bias refers to the tendency to search through a limited number of solutions and select the most appropriate. In this study these sources of bias have little influence on the results, because the case study was strongly framed by the specific model and the experts were asked to indicate which part of this model was uncertain and to quantify this uncertainty. Therefore, the list of options was considered equal for all experts.

Overconfidence is that experts tend to over estimate their ability to make quantitative judgements. This bias is difficult for an individual to guard against (Van der Sluijs et al., 2004) and probably played a role in this study. Overconfidence may result in too narrow uncertainty bands (Cooke, 1991). The effect of overconfidence in this study is that the stated uncertainties may be smaller than the actual uncertainties. The uncertainties are therefore considered to be on the lower end of the “true” uncertainty.

Motivational bias probably was important during the interviews. The experts all had their own area of expertise. For example, some experts had most experience with the input data used for the model. These experts had the tendency to give most uncertainty to the part of the model with which they were most familiar. In this study, there is no indication that a certain part of the model is better represented by the experts than other model parts. This gives confidence that most important uncertainties are represented by several of the experts. This is shown in figure 3.3 and 3.6 in which uncertainties 1-12 for the DWL are mentioned all approximately seven times, also the uncertainties for the effect studies are mentioned approximately seven times. Thereby, it is assumed that experts who were not familiar with a certain topic omitted the uncertainty or stated a small value. This also has the effect that the weighted average uncertainties are biased toward the lower end.

Furthermore, analysis of the results shows that there is a weak correlation ($R^2 = 0.22$) between the Pedigree scores of the experts and the weighted average quantified uncertainty. This indicates that the experts with more expertise do not give higher or lower estimates of the uncertainty. Also, a weak correlation was found between the individual experts and the magnitude of the quantified uncertainty. So, we may safely state that high values of the uncertainty cannot be attributed to one or a few experts only. The maximum values for the uncertainties are stated by different experts, which means that most experts do not agree, which uncertainty is most important. However, the weighted average values for the DWL case show that some uncertainties are more important.

3.5.3 Aggregation of expert opinions

Aggregations of expert opinions are prone to bias from the selection of experts and to the creation of the impression of consensus where none exists (Krayer von Krauss et al., 2004). However, to facilitate the comparison of experts the weighted average of the values given by the experts is taken. It is not attempted to present the values as single truth, but merely as an order of magnitude, which is similar to the significance of the experts opinions. Nor is it attempted to give the impression of consensus among experts. However, the discussion of biases in expert opinion elicitation above indicates that the elicited uncertainties are more likely to be on the lower end of the “true” uncertainty.

The discussion of the appropriateness of aggregating expert opinions has a long history; see for example Cooke (1991) and Rowe (1992). In the discussion there are two camps, those who consider aggregation of expert opinion absurd and those who do not. Krayer von Krauss et al. (2004) and Keith (1996) have the opinion that the appropriateness depends on the specific circumstances and what is meant to be accomplished. Due to the objective selection of experts, the equal levels of detail of the uncertainties, the framed case study, and the aim to compare the uncertainties relatively to each other, we argue that in this case, averaging of expert opinions is valid.

We have shown that in accordance with Van der Sluijs et al. (2005b) and Krayer von Krauss et al. (2004) expert opinion elicitation can be a good method to identify and, to a certain degree, quantify uncertainties. Including expert opinions in an uncertainty analysis is valuable in the first steps of an uncertainty analysis. Experts were able to identify, rank and quantify to a certain degree the uncertainties in the model outcomes of the WAQUA model. The main difference with the studies by Van der Sluijs et al. (2005b) and Krayer von Krauss et al. (2004) is that we use an objective method to select the experts. This gives confidence that the outcomes of the expert interviews are reliable, because the results of an expert opinion study are sensitive to the selection of the experts (Van der Sluijs, 1997).

The interviews with the experts have been conducted individually, which gives a good representation of the expert opinions and is good for the identification of the uncertainties by the experts. It is recommended to organise a workshop with all elicited experts to discuss the results and try to reach a consensus. However, in this study it was not possible to organise the workshop, due to time limitations. If consensus is reached during a workshop that will make the results more reliable and it can be used to further specify and quantify the uncertainties in the model outcomes.

The first objective of this study was to identify the different uncertainties the WAQUA model has for the DWL and effect studies case. Tables 3.2 and 3.3 show that for both cases the uncertainties are identified. By comparing the uncertainties stated by the different experts, we clearly identified the sources of uncertainty. The distinction between the different uncertainties is strengthened by the quantification, because for the quantification the uncertainties need to be well-framed and unambiguous. The ranking of the uncertainties from important to less important is strengthened by the combination of qualitative and quantitative information about the uncertainties.

Figure 3.4 shows that the weighted average values of the uncertainties have the same trend as the maximum values. Also, the relative spreading in the expert opinions (the maximum minus the minimum divided by the average) has a constant value of approximately 2 with a decrease in the average value for the uncertainty. This suggests that the weighted average value gives the right trend in the experts opinions. Therefore, we argue that it is valid to use the weighted average to aggregate the expert opinions with the note that the average values can only be compared relatively and no consensus among the experts is suggested.

For the effect studies case, the quantitative and the qualitative results (figure 3.7 and 3.8) both show no clear distinction between the different uncertainties. This is because for effect studies the uncertainties are dominated by local circumstances and the local flow field. However, the experts stated that all uncertainties are in the order of magnitude of 25 % of the computed effect. Therefore, this can be considered a good approximation of the uncertainties in effect studies computations. Furthermore, the uncertainties are dominated by the method to formulate, schematize and discretize weirs, bathymetry and vegetation. Therefore, to reduce the uncertainties in effect studies, these uncertainties need to be further addressed.

In this study, we quantified the uncertainties in the outcomes of a two dimensional river model for different sources of uncertainties in the model. Although it is not possible to give exact values for the uncertainty, the order of magnitude of the uncertainty due to different sources can be determined. We want to stress that it is not attempted to present the values as single truth, but merely as an order of magnitude, which is similar to the significance of the experts opinions.

We attempted to quantify the uncertainty of the different sources themselves, which is needed as input for an uncertainty propagation analysis. However, the experts were not able to give a reliable estimate for the uncertainty of the different sources. Therefore, in a future study, the uncertainties in the DWL and effect studies case that have a large influence on the model outcomes, need to be quantified. For example, the experts were not able to give an uncertainty range for the roughness in the main channel. This is due to the fact that the hydraulic roughness is not a truly physical parameter, but it is lumped and therefore, the experts cannot give reliable estimates. In a future study we will address this issue and try to quantify the uncertainty in the most important parts of the model. Subsequently, this uncertainty is propagated through the model to yield the uncertainty of the computed water levels. These results will be compared to the expert opinions.

3.6 Conclusions

The aim of this study was to identify the sources of uncertainty that induce the largest uncertainties in the model outcomes and quantify their contribution to the uncertainty in the model outcomes. Therefore, we used expert opinion elicitation for two case studies. The experts stated that the sources of uncertainty are different for the computation of the design water levels and effect studies. The use of a Pedigree analysis assured an objective selection of experts and gives confidence that the outcomes of the expert interviews are reliable. The ranking of the uncertainties from important to less important was strengthened by the combination of qualitative and quantitative information about the uncertainties.

In the design water level computations case, the uncertainties were dominated by the sources that change between the calibration and the prediction. The results from the expert opinions showed that the upstream discharge and the empirical roughness equation for the main channel contribute most to the uncertainty in the design water levels. It was not possible to give exact values for the uncertainty, however, the order of magnitude of the uncertainty due to different sources of uncertainty was determined from the aggregated expert opinions.

For effect studies, the floodplain bathymetry, weir formulation and discretisation of floodplain bathymetry induces the largest uncertainty. However, the ranking for the effect studies case was less clear than for the design water level case, because the uncertainties for effect computations are dominated by the local flow field.

The contribution of the uncertainties to the model outcomes show that the uncertainties have a significant effect on the predicted water levels under design discharge conditions and for effect studies. The experts were not able to quantify the uncertainties themselves, only the contribution to the model outcomes could be assessed. Future research will focus on the quantification of the most important uncertainties and on the propagation of these uncertainties to the model outcomes.

Acknowledgements

The research reported in this paper was supported by the Technology Foundation STW, and the technology program of the Ministry of Economic Affairs. The authors thank all the experts for their time and constructive input in the preparation stage and during the interviews.

Chapter 4

Quantification of uncertainty in design water levels due to uncertain bedform roughness in the Dutch river Rhine

Abstract

Hydrodynamic river models are applied to design and evaluate measures for purposes such as safety against flooding. The modelling of river processes involves numerous uncertainties, resulting in uncertain model results. Knowledge of the type and magnitude of these uncertainties is crucial for a meaningful interpretation of the model results. Uncertainty in the hydraulic roughness due to bedforms is one of the main contributors to the uncertainty in the modelled water levels. The aim of this study is to quantify the uncertainty in the bedform roughness under design conditions and quantify the effect on the design water levels for a two-dimensional river model. Five roughness models that predict bedform roughness based on measured bedform and flow characteristics have been extrapolated to design conditions. The results show that the 95% confidence interval of the predicted Nikuradse roughness values under design conditions ranges from 0.32 m to 1.03 m. This uncertainty is propagated through the two-dimensional hydrodynamic model, WAQUA by means of a Monte Carlo Simulation for a simplified schematization of the Dutch river Waal. The uncertain bedform roughness results in an uncertainty in the design water levels, with a 95% confidence interval of 0.71 m, which is significant for Dutch river management practice. The uncertainty in the bedform roughness is mainly caused by a lack of knowledge about the physical processes of the hydraulic roughness due to bedforms. An improved estimation of bedform roughness can significantly reduce the uncertainty in the design water levels.

This chapter is submitted for publication as: Warmink, J.J., Booij, M.J., Van der Klis, H. & Hulscher, S.J.M.H. Quantification of uncertainty in design water levels due to uncertain bed roughness in the Dutch river Rhine.

4.1 Introduction

River flooding is an international problem, which causes large economic damages and costs many lives every year (Dilley et al., 2005). For the construction of flood protection measures, the water levels that occur as a result of a flood wave should be predicted as accurate as possible. Hydrodynamic river models are applied to design and evaluate measures for purposes such as safety against flooding. The numerical models used to predict water levels are often based on deterministic approaches. However, the modelling of river processes involves numerous uncertainties, which consequently result in uncertain water levels. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model results and the usefulness of model results in decision making processes for flood protection measures and the robustness of flood defences. A full understanding of the model and the uncertainty in the modelling strategy is therefore important (Pappenberger and Beven, 2006).

Uncertainty in models have many different sources, such as uncertainties in model input, parameters or model structure. One of the main uncertainties in hydrodynamic river models is the hydraulic roughness (Warmink et al., 2011; Pappenberger et al., 2008; Pappenberger and Beven, 2006; Hall et al., 2005; Mason et al., 2003). Hydraulic roughness is defined by Chow (1959) as the resistance to water flow by all objects protruding into the water flow. The hydraulic roughness of the main channel of many lowland rivers is dominated by the resistance due to bedforms that develop on the river bed and increase in height with increasing discharge (Julien et al., 2002). However, the relation between the development of bedforms and their resistance is not yet fully understood. In his review paper, Best (2005) highlighted the need to better understand the development of bedforms for the prediction of, amongst others, hydraulic roughness. Horritt and Bates (2001) concluded that model validation of quasi-2D and fully 2D river models is difficult due to the lack of friction parameterisation data. Uncertainties in the hydraulic roughness are, therefore, difficult to quantify.

Hydraulic roughness is described in river models as a model parameter or in the model structure. The ideal of a single good roughness model to predict hydraulic roughness does not exist as roughness is different for each model (Morvan et al., 2008). In hydrodynamic models with grid sizes larger than the size of the bedforms, hydraulic roughness is often modelled by reach scale effective empirical relations or parameters that are subject to significant uncertainty (Pappenberger et al., 2006). In current modelling practise, the hydraulic roughness is often used as a calibration parameter. The problem is that the calibrated value of the roughness is only valid for the conditions used in the calibration (Klemes, 1986). Therefore, predictions for situations other than the calibration situation are inherently uncertain. Especially, the uncertainty due to model structure (i.e. conceptual model uncertainty) is important in case of extrapolations beyond the dataset used for calibration (Rojas et al., 2010). In computations for the robustness of flood defences, often design floods are considered that have never occurred. This implies that measurements of the flow and bedform characteristics are not available for validation. Therefore, the water levels that are modelled for design floods are inherently uncertain, amongst others, because the hydraulic roughness under design conditions is uncertain.

In the Netherlands, design water levels are computed for a design discharge with a return period of 1250 years, using the two-dimensional, hydrodynamic model, WAQUA (Rijkswaterstaat, 2009). Elicitation of expert opinions showed that for the WAQUA model, the uncertainties in the imposed design discharge and the hydraulic roughness of the main channel contribute most to the uncertainty in the modelled water levels (Warmink et al., 2011). This conclusion is supported by many authors. For example, Pappenberger and Beven (2006) state that the uncertainty in the input boundary conditions and the uncertainty in the bed roughness are of main importance. The uncertainty in the design discharge and its effect on the design water levels have often been studied (Silva et al., 2001; Van der Klis, 2003; Van Vuren et al., 2005; Van Gelder, 2008). In this paper we will focus on the uncertainty in the hydraulic roughness, because it is the second most important contributor to the uncertainty in the design water levels and its integration in the model is highly complex. Also, the uncertainty in the hydraulic roughness of the main channel has a large influence on the modelled water levels Aronica et al. (2002); Mason et al. (2003); Bates et al. (2004); Hall et al. (2005); Hunter et al. (2007).

Many approaches exist that relate flow and bedforms characteristics to hydraulic roughness. See, for example Alam and Halim (2002) and Wilbers (2004) for a comparison. Noordam et al. (2005) showed that different roughness models resulted in different roughness values up to 20% for data of bedform and flow characteristics measured in flumes. Also, Van der Mark (2009) showed that different roughness models resulted in different roughness predictions for uniform and alluvial flume data. However, Noordam et al. (2005) and Van der Mark (2009) considered only laboratory and alluvial flume data. Under field conditions the uncertainty in the hydraulic roughness models is probably larger, due to the large variation in natural rivers. Julien et al. (2002) and Wilbers (2004) used data of bedform dimensions to compare different roughness models for field measurements in the Dutch river Rhine. They both showed that under field conditions different approaches for estimating roughness resulted in a large variation in the predicted roughness values for the measured high discharges of 1995, 1997 or 1998. However, they used data from a discharge wave with a peak discharge that is only half of the design discharge.

The objective of this paper is to quantify the uncertainty in the bedform roughness under design conditions and quantify the effect on the design water levels for a two-dimensional model of the river Rhine in the Netherlands. The outline of this paper is as follows. Firstly, we describe the study area and the available field measurement data. Secondly, the method for the selection of the roughness models, the quantification of the uncertainty in the bedform roughness and the propagation of the uncertain roughness to the design water levels are presented. Subsequently, the results are given and discussed and, finally, conclusions are drawn.

4.2 Data and model

4.2.1 Study area

In the Netherlands, river flooding is a serious threat. Strong dikes have been constructed to protect the land from flooding. In 1993 and 1995 the river Rhine experienced maximum discharges of 11200 m^3/s and 12000 m^3/s, which are amongst the highest recorded. These discharge waves led to extremely high water levels in the Dutch tributaries, and the surrounding lands were nearly flooded, which led to large scale evacuations. After the 1993 and 1995 (near) flood events of the rivers Rhine and Meuse, the Dutch government required that every 5 years the safety of the primary dikes has to be evaluated (Ministry of Transportation, Public Works and Water Management, 1995). Therefore, the design water levels are required as an input for the computations of dike failure probabilities. In this way, the robustness of the river flood defences is monitored. Also in other countries, such as the U.K. or the U.S.A. river models are used to compute design discharges, but often with a smaller return period. The Dutch flood defences along the river Rhine are designed to withstand a design flood with a return period 1250 years. This design discharge is based on a statistical analysis of historical discharge peaks (Parmet et al., 2001). The Ministry of Transportation, Public Works and Water Management publishes every five years the Hydraulic Boundary Conditions (Rijkswaterstaat, 2007). These comprise, amongst others, the water levels that are used in the safety assessment. The hydrodynamic river model, WAQUA is used to compute the design water levels for the upper part of the river Rhine in the Netherlands.

The study area is a tributary of the river Rhine in the Netherlands, the Waal river. The river Rhine enters the Netherlands at the Dutch-German border near the city of Lobith. It has an average discharge of 2250 m^3/s and an average water level gradient of 0.11 m/km (Julien et al., 2002). In the Netherlands, the river Rhine bifurcates into the Pannerdensche Kanaal and the river Waal (figure 4.1), where approximately two third of the discharge enters the river Waal. The river Waal is relatively straight with an average sinuosity of 1.1 (Julien et al., 2002). The width of the main channel of the Waal between the groynes is relatively constant and is 280 m on average, with a standard deviation of 35 m (Yossef, 2005). The cross-sectional width between embankments varies between 0.5 and 2.6 km, with an average width of 1 km. (Straatsma and Huthoff, 2010; Straatsma and Huthoff, 2011). Flow velocities range between 0.5 to 1.5 m/s up to a maximum of 2 m/s at peak discharges. Approximately two-third of the discharge is conveyed through the main channel under peak discharges.

4.2.2 WAQUA model

The design water levels in the river Waal (figure 4.1) are calculated using the numerical, two-dimensional river model WAQUA. This model is based on a staggered curvilinear grid with grid sizes of approximately 40 m. Currently, the 2006 version of the WAQUA model (HR2006_4) is used for the computation of the design water

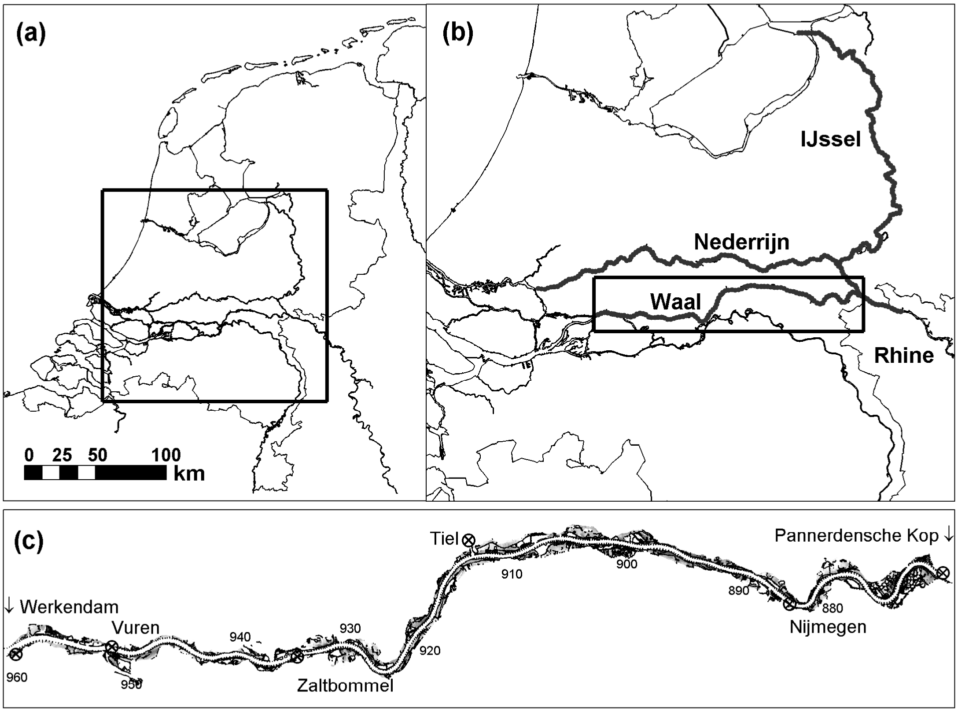


Figure 4.1: Study area. (a) the Netherlands, (b) location of the upper part of the river Rhine in the Netherlands with its major tributaries, (c) WAQUA schematization of the river Waal. The numbers refer to the river kilometres and the names in (c) refer to the water level measurement stations

levels. The water flow is computed by solving the shallow water equations using a finite difference method. The WAQUA model consists of: 1) the program environment SIMONA (Rijkswaterstaat, 2009), which contains the discretized shallow water equations to simulate the water flow and the empirical equations to approximate energy losses, and 2) a schematization of the upper river Waal for a certain period in time with corresponding input parameters (e.g. stage-discharge relations, river bed roughnesses, upstream discharge, etc.). The digital elevation model of the river Waal is based on two-dimensional bathymetry scans of the river bed, using, amongst others, echo soundings for the main channel and laser altimetry and photogrammetry data for the floodplain area. The vegetation in the floodplains is represented by a hydraulic roughness using a drag force approach for different classes of vegetation types (see Van Velzen et al., 2003). The hydraulic roughness of the main channel is predicted using a roughness model. This roughness model is based on the Van Rijn (1984) roughness model and assumes a constant relation between dune height and water depth (Rijkswaterstaat, 2009) that is calibrated for each section between subsequent measurement stations (see figure 4.1c) by minimising the difference between predicted and measured water levels. The time required to simulate a 72 hour flood wave for the schematization of river Waal is approximately two hours on a 2.6 GHz computer with 4 Gb of memory. We used an idealised schematization for the WAQUA model, to reduce the computational time, which is described in section 4.4.5.

4.2.3 Field measurements

We used the data from the studies of Julien et al. (2002) and Wilbers (2004). The Julien data were measured during the 1998 flood wave in the river Rhine 200 m upstream of the first bifurcation in the Netherlands (Pannerdensche Kop). Longitudinal and cross-sectional profiles of the bed elevation were recorded by single-beam and multi-beam echo sounding. These data were recorded about twice a day for ten days during the flood wave and about every three days for the next twelve days. The bathymetry data were processed and classified into primary and secondary dunes using the procedure described in Ten Brinke et al. (1999). This resulted in an average height and length of the bedforms for each of the recordings. Next to the bedform measurements also the size of the bed material was recorded. Simultaneously, velocity measurements were taken using an ADCP, for six days of the 1998 flood wave. Furthermore, hourly stage measurements were available at the Lobith, Pannerdensche Kop and Nijmegen measurement stations. Local water surface slopes were computed from detailed laser altimetry data between river kilometres 866 and 869, upstream of Pannerdensche Kop.

The data from Wilbers were measured during the flood waves of 1995, 1997 and 1998. The measurements were carried out in the river Rhine just upstream of Pannerdensche Kop (at the same location as the Julien et al. data) and in the river Waal 400 m downstream of Pannerdensche Kop. We used only the measurements upstream of Pannerdensche Kop in this study, as these are of better quality than the Waal data (Julien et al., 2002). Longitudinal and cross-sectional profiles of bed elevation were recorded using a single-beam echo sounder for the 1995 flood wave, a single- and multi-beam echo sounder for the 1997 flood waves and only a multi-beam echo sounder for the 1998 flood wave. For the 1995 measurements, bedform data were recorded about once a day for twelve days during the flood wave and about every three days for the next twelve days. The 1997 measurements consist of seven daily measurements and one measurement after three days. The measurements of the bedform characteristics of the 1998 flood wave of Julien et al. and Wilbers are the same. However, Julien et al. reported the local water surface slope that is required to compute the local roughness based on the local energy slope.

Hysteresis plays an important role in the relation between the measured dune characteristics and measured flow characteristics (Julien et al., 2002; Paarlberg et al., 2009, 2010). To minimise the effect of hysteresis, we take only the data from the rising limb of the flood waves into account. The rising limb was defined as the data up to the highest measured discharge for each discharge wave. We took the rising limb data instead of the falling limb, because the bedform characteristics at the peak of a discharge wave are determined by the increase in discharge. Using only these data, the hysteresis effect is not fully eliminated, but the variability in the data due to differences between the rising and falling limb is reduced. This variability is not of interest for the uncertainty at the peak of the discharge wave. The effect on the results is that we might underestimate the maximum water level, because the bedform height and length still increase after the peak of the discharge wave has passed. We will further discuss the effect on the computed uncertainties in section 4.6.2.

4.3 Bedform roughness models in literature

Bed roughness consists of, amongst others, the energy losses due to grain friction and form drag due to bedforms or other objects protruding into the flow. Hydraulic roughness is commonly expressed by some roughness coefficient (e.g. Manning, n (–), Chézy, C ($m^{1/2}/s$), Darcy-Weisbach, f (–), Nikuradse, k_N (m)). These different coefficients all describe hydraulic roughness and can easily be converted into each other (Van Rijn, 1990). These roughness coefficients are based on a relation between water level, flow velocity and energy slope and all describe the total energy losses. The hydraulic roughness of the main channel in case of bedform dominated rivers can be determined by summation of the grain friction and form drag. Thus, the bed roughness consists of a grain shear friction factor, c'_f, and the form drag friction, c''_f, due to local energy losses on the lee side of bedforms.

We analysed ten roughness models that were found in literature and predict bedform roughness based on bedform and flow characteristics. These roughness models can be analytical, semi-analytical or empirical (Van der Mark, 2009). The analytical models (Yalin, 1964; Engelund, 1966) are based directly on the mass and momentum conservation laws. They assume abrupt flow expansion after the bedform crest and they do not account for the effects of nearby bedforms. Furthermore, these roughness models assume that the brink point height (that is the point where the flow no longer touches the bed) is equal to the mean bedform height.

The semi-analytical roughness models (Engelund, 1977; Haque and Mahmood, 1983; Karim, 1999; Van der Mark, 2009) are also based on the conservation laws, but are calibrated to fit measured (flume) data. The Engelund (1966, 1977) model is calibrated on alluvial flume data and is, therefore, (partly) corrected for the above mentioned effects, for as far as present in the calibration data. The Van der Mark (2009) model is based on the Yalin model (see also Van der Mark et al., 2008b), but has additional parameters to account for gradual flow expansion, effects of nearby bedforms, spatial variability in bedform distribution and the fact that the brink point height differs from the mean bedform height. The roughness model of Haque and Mahmood (1983) is based on numerical simulations in which bed pressure is integrated along a bedform. Haque and Mahmood (1983) calibrated the relation between the flow separation height and the bedform height on laboratory flume data and validated their roughness model for data from the Missouri river. The Karim (1999) model assumes that the water depth at the dune crest is equal to the

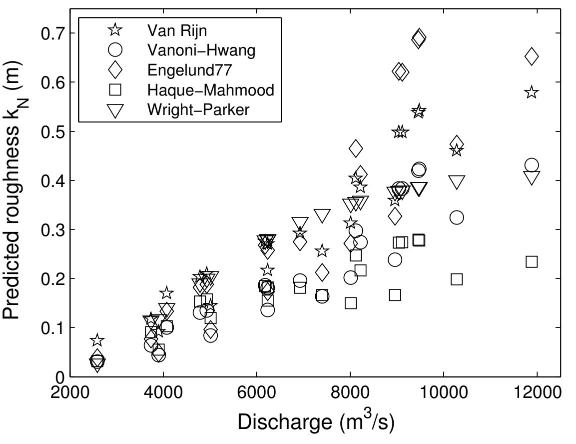


Figure 4.2: Nikuradse roughness for various discharges computed by five roughness models

mean depth, minus a half bedform height and that the water depth downstream of the influence zone of the bedform is equal to the mean depth plus a half bedform height. Furthermore, this equation uses the first order of the dune height (see discussion in Van der Mark, 2009), while the other bedform models use the square of the dune height.

The empirical roughness models (Vanoni and Hwang, 1967; Van Rijn, 1984, 1993; Engelund and Hansen, 1967; Wright and Parker, 2004) are empirical relations between bedform or flow characteristics, and measured bed roughness. These models have been calibrated mainly on flume data. However, the Van Rijn and Wright-Parker models have also been calibrated on extensive field data. The Engelund-Hansen and Wright-Parker models are sensitive to the flow velocity and grain characteristics, whereas the other empirical models are sensitive to bedform characteristics. Table 4.1 lists the assumptions underlying the models. The equations are given in appendix A.

Figure 4.2 shows the predicted k_N values using the data from Wilbers for five roughness models. This figure shows that, generally, the k_N values increase with increasing discharge. This was expected and has also been stated by Julien et al. (2002), because the bedforms increase in height with increasing discharge. Furthermore, there is a large scatter in roughness values, especially for larger discharges. At discharges between 9000 m^3/s and 12000 m^3/s, which is 56% to 75% of the design discharge, the predicted roughness values range from 0.22 m for the Haque-Mahmood roughness model to 0.65 m for the Engelund77 roughness model. This large range shows that there is a large variation due to the different approaches used in the roughness models.

Table 4.1: Roughness models used for the performance assessment for the measured data of Julien et al. (2002). A short description with the type of model and the assumptions that underlie the different models is given

Model	Type	Assumptions
Yalin (1964)	Analytical	Abrupt flow expansion, no effects of nearby bedforms, brink point height is equal to mean bedform height. Grain friction only accounts for energy loss due to grain friction along the stoss face of the bedform.
Engelund (1966)	Analytical	Same as Yalin.
Engelund (1977)	Semi-analytical	Same as Yalin, but calibrated on alluvial flume data from experiments as reported by (Guy et al 1966 in Engelund, 1977).
Haque and Mahmood (1983)	Semi-analytical	Abrupt flow expansion, but calibrated the relation between flow separation height and bedform height. Validated against data of Missouri River and other field channels.
Karim (1999)	Semi-analytical	Water depth at the dune crest is equal to the mean depth minus a half bedform height.
Van der Mark (2009)	Semi-analytical	Same as Yalin, but calibrated to account for gradual flow expansion, effects of nearby bedforms, brink point height differs from mean bedform height, spatial variability in bedforms.
Vanoni and Hwang (1967)	Empirical	Empirical relation determined from Moody diagram. The grain and form drag relations are based on laboratory and alluvial flume data.
Van Rijn (1993)	Empirical, update of Van Rijn (1984)	Dimensions of bedforms are determined by maximum value of bed-load transport. Relation based on extensive flume and field data.
Engelund and Hansen (1967)	Empirical, only based on flow characteristics	Based on an approximation of the Engelund (1966) equation to compute grain roughness. Empirically relates the form drag to this grain roughness.
Wright and Parker (2004)	Empirical, update of Engelund-Hansen	Adaptation of Engelund-Hansen using new field data from six North American rivers, such as the Rio Grande and Mississippi.

4.4 Methods

To quantify the uncertainty in bedform roughness under design conditions, we consider two sources of uncertainty. Firstly, the uncertainty due to the choice of the roughness model, that is the variability between the k_N values under design conditions. Secondly, uncertainty is introduced by the extrapolation from the measured to the design conditions. This uncertainty also accounts for the variability in the historically recorded discharge data. The uncertainty in the measurements of the dune and flow characteristics are not taken into account. We quantified these two sources of uncertainty and combined them to quantify the total uncertainty in the bedform roughness under design conditions.

4.4.1 Selection of roughness models

The first step in the quantification of the uncertainty due to the choice of the roughness model is to select the roughness models that are appropriate to predict bedform roughness for the river Rhine. We used the data from Julien et al. (2002) to compare the roughness models listed in table 4.1 for the 1998 flood wave. The measurements of local flow velocity, water depth and local water surface slope were used to compute the dimensionless Darcy-Weisbach friction factor,f, for different time steps during the discharge wave and convert this value to a Nikuradse roughness length k_N (m), similarly to Julien et al. (2002):

$$f = \frac{8ghS_e}{u^2} \tag{4.1}$$

$$\frac{1}{\sqrt{f}} = 2.03 \log \frac{12.2h}{k_N} \tag{4.2}$$

where g is gravity acceleration (m/s^2), h is water depth at river axis (m), S_e is local water level slope (m/m), and u is local flow velocity (m/s). This “measured” k_N value was compared to the predicted k_N for ten roughness models that predict bed roughness due to grains and bedforms.

The performance of the roughness models for the Julien et al. data is expressed by the Root Mean Squared Error (RMSE) of the predicted versus the measured k_N values for each roughness model. The performance has been combined with an assessment of the assumptions that underlie the different roughness models resulted in the selection of five roughness models that are used in the further analysis.

4.4.2 Parameterisation of roughness against discharge

To quantify the uncertainty in the bedform roughness under design conditions, the roughness at the design discharge needs to be determined. Therefore, we extrapolated the predicted roughness values in figure 4.2 to the design return period. For this extrapolation a series of independent annual maximum roughness values was required. We used the historically recorded discharges for the river Rhine available from Parmet et al. (2001). These discharges are the (daily averaged) annual maximum values at Lobith over the last 100 years. This series has been corrected for the changes in the river geometry upstream of the Netherlands that have occurred in the last 100 years. Parmet et al. (2001) used these data to compute the design discharge for a return period of 1250 years for the Dutch tributaries of the river Rhine by extrapolation of the weighted average of three statistical distributions (Gumbel, Pearson III and Log-Normal). These data are independent annual maxima and can be described by an extreme value distribution.

If we assume that every discharge corresponds to a characteristic shape of the bedforms that is independent of the shape of the discharge wave and antecedent flow conditions, it is possible to relate the discharge to the observed bedform dimensions and flow characteristics. Furthermore, we assumed that the data measured during the three discharge waves from Wilbers (2004) are independent and we corrected for hysteresis by taking only the rising limb data into account. By making these assumptions, we were able to relate the predicted roughness values, based on the observed bedform dimensions, for each of the selected roughness models to the observed discharge values. These relations (see figure 4.3a for an example) were used to generate a series of independent annual maximum roughness values, using the historically recorded annual maximum discharge series for the river Rhine, by determining the predicted roughness for each of the annual maximum discharges.

For the fitted relations between the observed discharge and the predicted k_N values for the five selected roughness models, we tried a linear, cubic and power equation and determined for each of the roughness models the best fit of the k_N-Q relationship using the Non-linear Least Squares method where the mean-squared-error is minimised. Subsequently, for each roughness model, the fitted relation has been used to compute a k_N value for each discharge, resulting in five sets of 100 roughness values, one set for each of the roughness models. These sets contain independent, annual maximum roughness values. This approach assumes that for a certain discharge a corresponding single roughness value exists and that this roughness value is valid for the whole river. Thereby, we consider the hydraulic roughness no longer as a physical process, but merely as a value that belongs to a certain discharge, given the parameterised relations between the annual maximum discharges and the predicted roughness values.

4.4.3 Extrapolation of roughness

Statistical distributions have been fitted through the annual maximum roughness values, because we do not know the characteristics of the bedforms under design conditions. It is uncertain which processes in the development of the bedforms are dominant and, therefore, how the bedforms will develop. Although, the studies by Julien et al. (2002) and Wilbers (2004) suggest that bedforms might flatten and secondary bedforms might develop, there is little evidence if this occurs under design conditions and how this affects the hydraulic roughness.

We fitted a Generalized Extreme Value (GEV) and a Gumbel (G) distribution (Coles, 2001) to the generated sets of independent annual maximum roughness val-

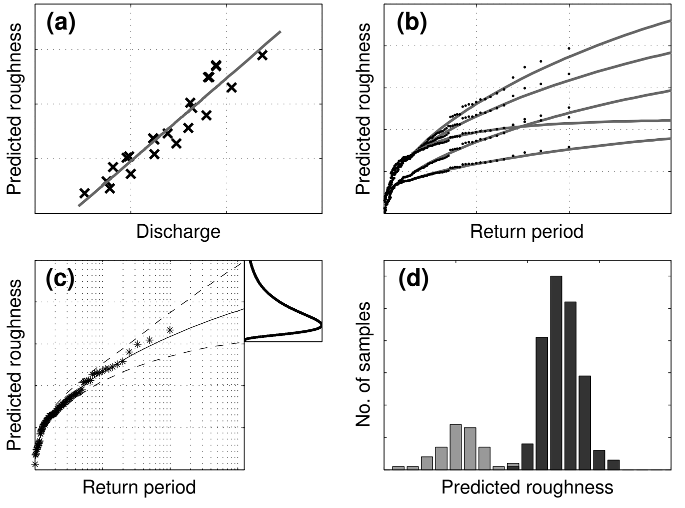


Figure 4.3: Method used to compute the uncertainty in bedform roughness. (a) parameterisation: for each selected roughness model a relation between roughness and discharge has been fitted, (b) extrapolation: independent annual maximum roughness values have been extrapolated to design conditions, (c) probability density functions of the roughness at the design return period have been computed for each roughness model and, (d) the five distributions are combined by Monte Carlo Simulation

ues for each roughness model.

$$GEV(x) = \exp\left\{ -\left[1 + \kappa_{GEV}\left(\frac{x - \mu_{GEV}}{\sigma_{GEV}} \right) \right]^{-1/\kappa_{GEV}} \right\} \tag{4.3}$$

$$G(x) = \exp\left\{ -\exp\left[-\left(\frac{x - \mu_G}{\sigma_G} \right) \right] \right\} \tag{4.4}$$

where μ_{GEV}, μ_G are the location parameters of the GEV and G distributions, σ_{GEV}, σ_G are the scale parameters and κ_{GEV} is the shape parameter. The GEV distribution is based on the extreme value theory of Fisher and Tippitt (1928). The three types of the GEV distribution for $\kappa_{GEV} > 0$ (Fréchet distribution), $\kappa_{GEV} < 0$ (Weibull distribution) and $\kappa_{GEV} = 0$ (Gumbel distribution) have distinct forms of tail behaviour. The Gumbel distribution is a special case of the GEV distribution for which the shape parameter approaches zero and, therefore, only has two degrees of freedom instead of three for the GEV distribution. For the Gumbel distribution, the shape of the tail is linear on any logarithmic x-axis, while for the GEV distribution the data themselves determine the most appropriate type of tail behaviour and there is no need to make an a priori judgement about which of the three extreme value distributions to adopt (Coles, 2001).

For each set of roughness values, the optimum values for the parameters of the GEV and Gumbel distributions have been determined. The fitting of these distributions has been carried out using the "ORCA routines", a MatLab package for extreme value statistics (Deltares 2010) using probability weighted moments. The fitted GEV and Gumbel distributions are extrapolated to the return period of 1250 years.

The confidence intervals have been computed by the ORCA routines using parametric bootstrapping, given the variances of the fitted parameters of the distributions. The confidence intervals, therefore, assume that the distributions appropriately describe the data. To test if this is a valid assumption we use the Probability Plot Correlation Coefficient test (Stedinger et al., 1993). The variability between the k_N values gives the uncertainty between the roughness models (source 1). The 95% confidence interval comprises the uncertainty due to extrapolation (source 2). Figure 4.3 shows the subsequent steps in this method.

4.4.4 Total uncertainty in bedform roughness

The extrapolation resulted in a probability distribution of the roughness values at the design return period for each roughness model. The five probability distributions have been combined to yield the uncertainty in the hydraulic roughness due to bedforms. A weight has been assigned to each of the roughness models, based on their performance for the Julien et al. data (see section 4.4.1). The performance of the roughness model, i is expressed by the RMSE. The weights are then computed by:

$$w_i = \frac{\left(\frac{1}{RMSE_i}\right)}{\sum_{i=1}^{5}\left(\frac{1}{RMSE_i}\right)} \tag{4.5}$$

This equation is a standardisation, in which we take the inverse of the RMSE as a measure for the performance, because the roughness models with low RMSE values are assigned a large weight. We assume that the weights increase linearly with the inverse of the RMSE.

The probability distributions have been combined using crude sampling Monte Carlo. Random samples have been drawn from each of the five probability distributions. The number of samples is different for each roughness model, and is determined by their performance. A total of 1000 samples has been drawn. The number of samples (M) for every selected roughness model, i, is computed by:

$$M_i = Nw_i \tag{4.6}$$

where $N = 1000$ is the total number of samples drawn from the distributions. The number of samples for each roughness model was rounded toward the nearest integer, so that the sum of the samples equals N. The drawn samples from the different distributions yielded the combined uncertainty in the bedform roughness due to the three different sources of uncertainty. The same samples have been used for the propagation to the design water levels. A thousand samples proved to be sufficient as re-sampling ten times showed that the average differed only 0.2% and the 2.5% and 97.5% quantiles differed 0.6% and 0.7%, respectively, for the resampled samples.

4.4.5 Propagation of uncertainties to the design water levels

The final step is to compute the effect of the uncertain bedform roughness on the computed water levels. Therefore, the sampled roughness values are propagated through an idealised schematization of the WAQUA model. A simplified schematization has been set-up for the WAQUA model. Bends and variations in the width of the floodplains are eliminated by defining a straight compound channel. This idealised schematization enabled us to isolate the uncertainty in the roughness of the main channel from most other sources of uncertainty in the model. This assures that the resulting variation in the water levels is mainly caused by the uncertainty in the hydraulic roughness of the main channel, because the interactions with other sources of uncertainty are minimised.

The idealised WAQUA model was created with dimensions similar to those of the river Waal (figure 4.1). We constructed a straight compound channel with floodplains, which has a constant width in the flow direction. We use grid cells of 40 m and the model represents a straight river reach of 60 km long (figure 4.4). The depth of the main channel is 8 m with respect to the floodplains. The dikes are assumed to be infinitely high. The bed slope was set to 0.0002 m/m. The Nikuradse roughness of the floodplains was set to a uniform and constant value of 0.6 m, which is approximately the average of the vegetated floodplains of the river Waal model.

The upstream boundary condition is set as a constant discharge equal to 2/3 of the Dutch design discharge of 16000 m^3/s (Parmet et al., 2001). The downstream boundary condition was set as a fixed water level. A 60 km long reach is required so the results for the equilibrium depths are not influenced by the downstream boundary condition. The constant discharge upstream and the constant water level downstream leads, in combination with a variable roughness, to different backwater curves. The effect of the adaptation length can be computed using a first order approximation of the Bélanger equation. To illustrate, for an average slope of 0.0002 and an average water depth of 12 m, this means that at the upstream end of the model the error in the water levels is about 6% of the difference between the equilibrium depth and the imposed water depth at the downstream boundary condition. We consider an error of 6% acceptable for the analysis and consider the length of 60 km, therefore, sufficient.

A Monte Carlo Simulation (MCS) consists of a large number of deterministic simulations where the value for the roughness is randomly drawn from the distribution computed in the previous steps. The advantage of MCS is that the method maintains the non-linear character of the model and, therefore, there are no limitations on the shape of the distribution (Morgan and Henrion, 1990). The combined

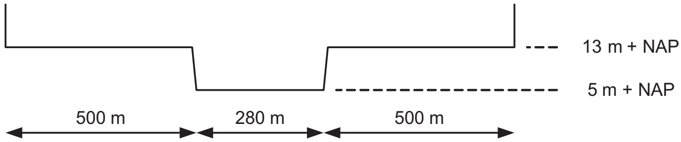


Figure 4.4: Cross-section of the idealised WAQUA model at the upstream location. The dimensions are similar to the river Waal

samples from the quantified bedform roughness uncertainty were used as input distribution for the Monte Carlo Simulation. The idealised WAQUA model has been run 1000 times where for each run, one sample from the bedform roughness distribution was assigned to the main channel as a uniform Nikuradse roughness. This resulted in 1000 water levels. The distribution of the water levels is shown 1 km (25 cells) downstream of the upstream boundary. At this location, there is little effect ($\pm$ 6%) of the fixed downstream boundary condition and there is no effect of the upstream boundary condition.

4.5 Results

4.5.1 Selection of roughness models

The first step in the quantification of the uncertainty in bed roughness is to select appropriate roughness models. Figure 4.5 shows the performance of ten roughness models. The analytical and semi-analytical roughness models perform worse than the empirical models. This was expected, because the (semi-)analytical models do not account for variability in the bedform characteristics. The Vanoni-Hwang, Van Rijn, Yalin, Engelund (1966), Engelund (1977), Wright-Parker and Haque-Mahmood models yield the best results.

Most of these roughness models have been calibrated (partly) on field measurements of lowland rivers, therefore, they are assumed to be able to predict the bedform roughness in lowland rivers, such as the river Rhine. The Yalin and Engelund roughness models are not calibrated, but perform quite well for these data. However, these roughness models are omitted from this analysis, because the assumptions of abrupt flow expansion are not valid under field conditions (Wilbers, 2004). Furthermore, these models have been improved by Engelund (1977) by calibration of the analytical roughness models on irregular bedforms. Therefore, we only consider the updated version of the model. The Wright-Parker model is based on the Engelund-Hansen model and adapted using field measurements. Therefore, the Wright-Parker model is more appropriate to predict bed roughness for the river Rhine. The Karim and Van der Mark roughness models are not taken into account, because they have only been calibrated on flume data and perform poorly for the

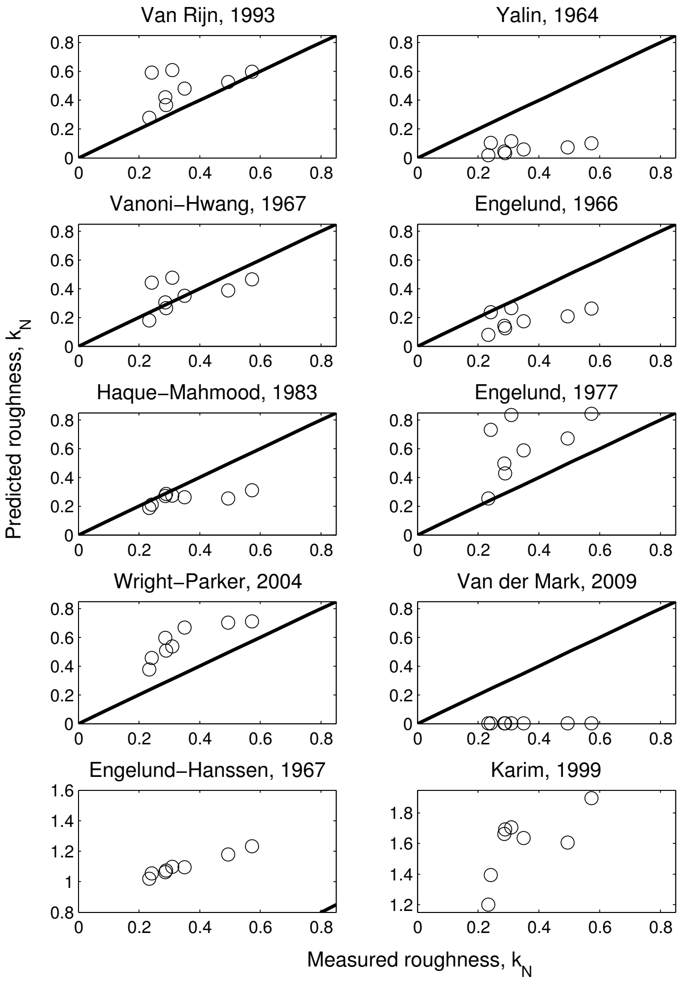


Figure 4.5: Performance of the roughness models for the rising limb data measured during the 1998 flood wave in the river Rhine, from Julien et al. (2002). The line represents the line of perfect agreement. Note the different scale of the vertical axis for the two bottom figures

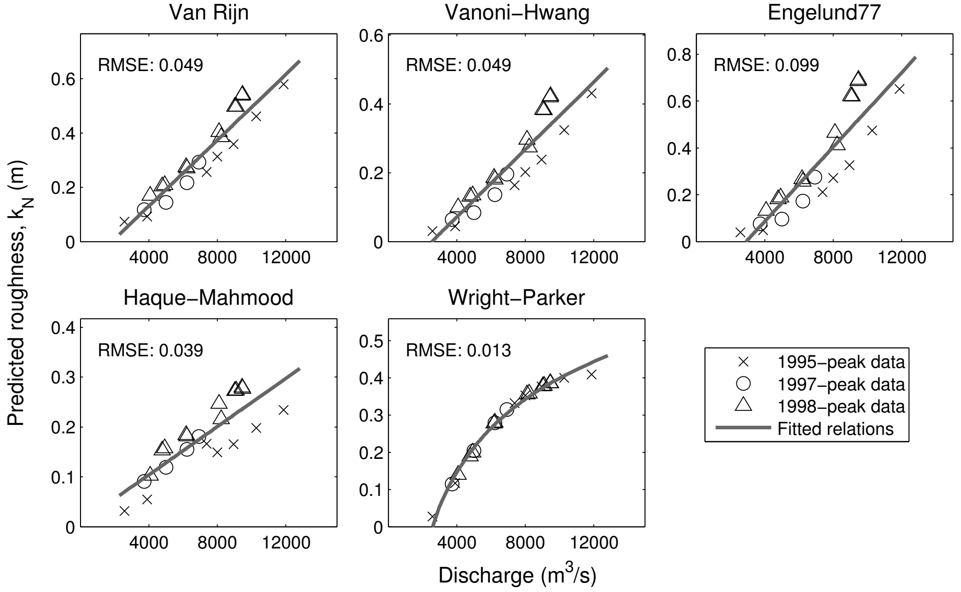


Figure 4.6: Parameterisation of the five selected roughness models against discharge and RMSE (Root Mean Squared Error) for the fitted relation

data in this case study. Therefore, we selected the Van Rijn, Vanoni-Hwang, Engelund (1977), Haque-Mahmood and the Wright-Parker roughness models.

4.5.2 Parameterisation of roughness against discharge

Figure 4.6 shows the fitted relations between the measured discharge and the roughness based on measured bedform and flow characteristics from Wilbers (2004). The Wright-Parker roughness model shows a convex shaped trend, while other roughness models show a linear increase of the roughness. A power function is used to parameterise the Wright-Parker model and a linear function for the other models. The Wright-Parker model shows less scatter, because this roughness model is based only on flow characteristics instead of bedform characteristics. Clearly, the variability in the bedform measurements is larger than the uncertainty in the flow measurements. The uncertainty in the data is expressed in figure 4.6, but is not taken into account. Furthermore, the data from the different discharge peaks show that the observed bedform dimensions for the 1998 discharge wave resulted in slightly higher roughness values than for the other discharge waves. However, the differences are small compared to the variability with discharge. This shows that the assumption that the data measured during the three discharge waves is independent is valid.

4.5.3 Extrapolation of roughness

The uncertainty due to the choice of the roughness model is expressed by the differences between the extrapolated roughness values at the design return period. Figure 4.7 shows the fitted GEV distributions for the five selected roughness models extrapolated to the return period of 1250 years. The extrapolated roughness values under design conditions range from $k_N = 0.36$ m for the Haque-Mahmood model to $k_N = 0.92$ m for the Engelund (1977) model. All roughness models show an increase in the hydraulic roughness with increasing return periods. However, the GEV distributions slightly underestimate the roughness values at higher return periods.

For the fitted Gumbel distributions (figure 4.8), the extrapolated roughness values range from $k_N = 0.47$ m for the Haque-Mahmood model to $k_N = 1.28$ m for the Engelund (1977) model. The roughness values predicted by the Wright-Parker model are not described well at higher return periods as figure 4.8 shows a significant overestimation of the roughness for higher return periods. Furthermore, the fitted Gumbel distributions slightly overestimate the roughness values.

We carried out a Probability Plot Correlation Coefficient (PPCC) test (Stedinger et al., 1993) to test if the roughness values could have been drawn from the fitted distributions. This analysis showed that for both the GEV and Gumbel distributions, there is no reason to reject these distributions for the Van Rijn, Vanoni-Hwang, Engelund (1977) and Haque-Mahmood roughness models. For the Wright-Parker roughness model the Gumbel distribution was rejected at the 95% confidence interval, but the GEV distribution was not rejected.

Figure 4.7 and 4.8 also show the 95% confidence intervals for the fitted distributions. Both figures show that the 95% confidence intervals increase with increasing return period. The confidence intervals represent the extrapolation uncertainty (source 2). These confidence intervals assume that the predicted roughness values could have been drawn from the distributions, which is confirmed by the PPCC test.

For the GEV distributions the width of the confidence intervals compared to the extrapolated roughness at the design discharge is about 50% of the extrapolated roughness value for the first four models, ranging from 43% for the Haque-Mahmood model to 55% for the Engelund (1977) model. The width of the confidence interval for the Wright-Parker roughness model is only 18% of the extrapolated roughness at design discharge. The width of the confidence interval for the Gumbel distribution is around 20% of the extrapolated roughness at the design return period for all roughness models. The confidence intervals for the Gumbel distributions are smaller than the confidence intervals for the GEV distribution, because the Gumbel distribution has only two degrees of freedom and therefore has a smaller variance. This results in a smaller value for the extrapolation uncertainty.

In the further analysis, we only take the GEV distribution into account, because the tail behaviour of the GEV is determined by the data and is not fixed a priori. The trend in the GEV distribution is in accordance with the expectation that the

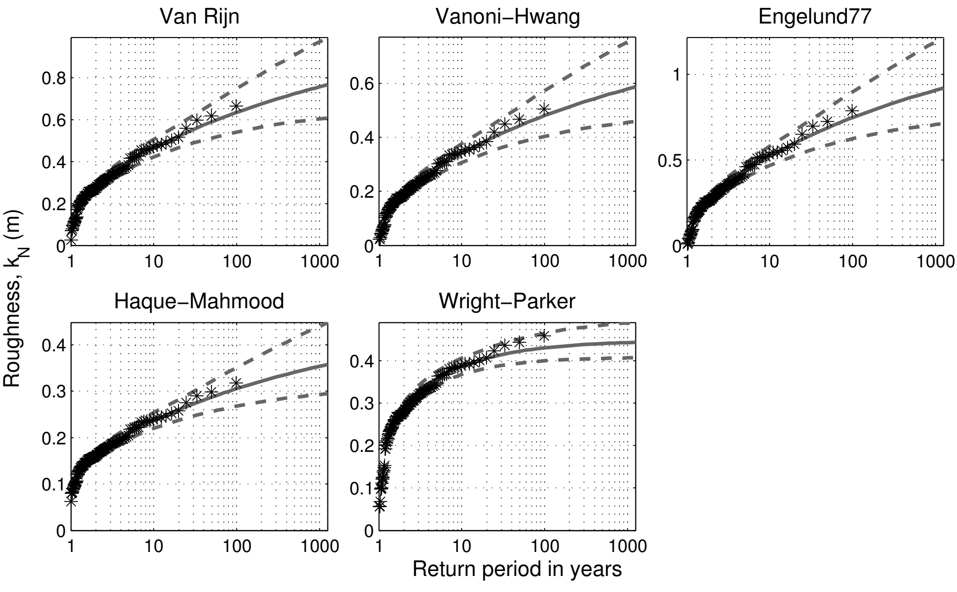


Figure 4.7: Fitted GEV distributions for the five roughness models. The dashed lines show the 95% confidence interval. Note the different scales of the vertical axes

hydraulic roughness does not infinitely grow with increasing discharge (Van Rijn, 1984; Julien and Klaassen, 1995).

4.5.4 Total uncertainty in bedform roughness

Figures 4.9a and 4.9b show the combined distributions at the design return period for the five roughness models, which represent the combined uncertainty due to the two sources. The number of samples has been determined based on the performance of the models for the Julien et al. data (equations 5 and 6; figure 4.5). Thereby, we accounted for the probability of each roughness model. The number of samples ranges from 121 samples for the Engelund (1977) model, which performed worst to 292 samples for the Vanoni-Hwang roughness model, which performed best, for a total of 1000 samples.

Figure 4.9a shows that the Nikuradse roughness values for the GEV distribution overlap. The peak on the left side of the right panel is caused by the Haque-Mahmood and Wright-Parker models that predict lower roughness values than the Vanoni-Hwang, Van Rijn and Engelund (1977) models. The relatively small confidence limits for the Haque-Mahmood and Wright-Parker roughness models at the design return period result in small high peaks.

Figure 4.9b shows the combined samples for the five distributions. In this figure

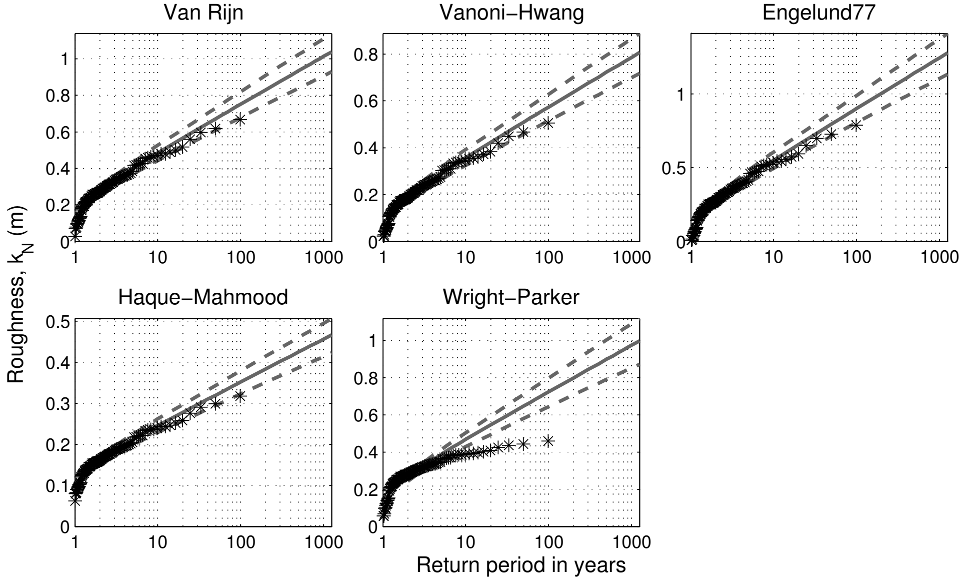


Figure 4.8: Fitted Gumbel distributions for the five roughness models. The dashed lines show the 95% confidence intervals. Note the different scales of the vertical axes

all three sources of uncertainty are integrated and the results show that the maximum and minimum roughness values range from $k_N = 0.28$ m to $k_N = 1.24$ m. The 95% confidence interval is between $k_N = 0.32$ m and $k_N = 1.03$ m with a mean of $k_N = 0.59$ m, which is a range of 0.71 m.

4.5.5 Propagation to the design water levels

The WAQUA model has been run for the 1000 sampled k_N values to determine the effect on the water levels for the design discharge. Figures 4.10a and 4.10b show the uncertainty in the water levels 1 km downstream of the upstream boundary condition. Figure 4.10a shows the uncertainty in the computed water levels due to the individual roughness models showing the extrapolation uncertainty, represented by the width of the 95% confidence interval for each roughness model, and the between roughness model uncertainty, represented by the variability of the average of the predicted roughness values for each model. Figure 4.10b shows the combined samples where all uncertainties are integrated. The left peak is caused by the Haque-Mahmood and Wright-Parker models. The wider peak on the right is the combination of the other three roughness models.

The figures reveal that the uncertainty in the water level has a maximum range of 80.4 m. If we only take a single roughness model into account, the 95% confid-

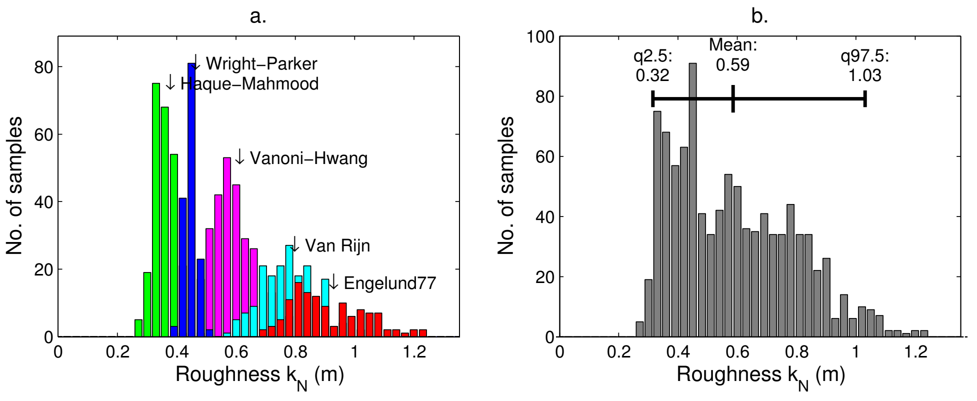


Figure 4.9: Uncertainty due to various roughness models for the GEV distributions. The samples are drawn from the distribution at the design return period, (a) samples by roughness model, (b) combined samples

ence interval is between 7 and 24 cm for the Wright-Parker and Engelund (1977) roughness models respectively. The uncertainty between the five roughness models results in a range of 41 cm, which is the difference between the average of the Engelund (1977) and the Haque-Mahmood model. The uncertainty between the roughness models is larger than the uncertainty in the modelled water levels compared to the extrapolation uncertainty. Furthermore, figure 4.10 shows that with 95% confidence the water levels (given a mean of 16.57 m) at the observed location are between 16.32 m and 16.85 m above NAP (Dutch ordnance datum), which is a range of 53 cm.

4.6 Discussion

4.6.1 Sensitivity of the results

In this section we will discuss the assumptions that are taken in this study and their effect on the uncertainty in the water levels.

A strong assumption in the propagation of the uncertain bedform roughness to the design water levels is that the floodplain roughness is set to an uniform and constant value of $k_N = 0.6$ m. Although this floodplain roughness is the average of the floodplain roughness as set in the model that is used for the computation of the design water levels, it is a large simplification. Green (2005) showed that for flexible vegetation, there is a non-linear relationship between the total resistance of a compound channel system and the proportion of the channel occupied by vegetation. To assess the effect of the value of the floodplain roughness on the uncertainty in

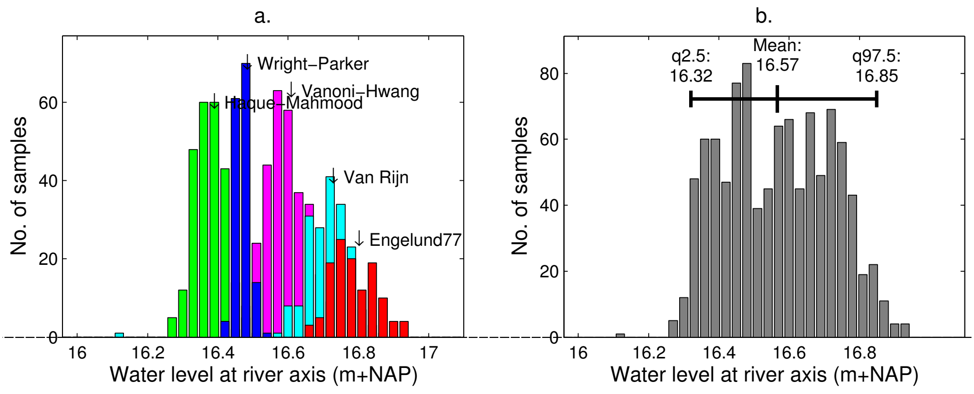


Figure 4.10: Uncertainty in water levels in the river Rhine under a constant design discharge, (a) samples by roughness model, (b) combined samples

the computed water levels, the sensitivity of the resulting uncertainty for the value of the floodplain roughness was assessed.

The Monte Carlo Simulation is repeated with floodplain roughness values of 50% and 200% of the default value. Figure 4.11 shows the results of this sensitivity analysis for a constant floodplain roughness of $k_N = 0.3$ m, 0.6 m and 1.2 m for the same sampled bedform roughness values. This figure shows that the shape of the uncertainty distributions is relatively constant for different floodplain roughness values, but the average of the water levels changes. Furthermore, the range between the minimum and maximum water level increases for increasing values of the floodplain roughness. If the floodplain roughness increases, the flow conveyance through the main channel increases and, therefore, the water levels are more sensitive to the uncertainty in the main channel roughness.

An idealised schematization of the WAQUA model has been used for the propagation of uncertain roughness. The simplifications cause the bedform roughness uncertainty to be isolated from most other sources of uncertainty that are present in any model. In this way interactions between uncertainties are minimised. The idealised model also required less computational time. However, due to the simplifications in the model, a comparison with field data was not possible and the uncertainty range only gives an indication of the effect of the uncertainty in bedform roughness on the design water levels. The dimensions of the cross section can be assumed representative for the river Waal. Therefore, it is expected that the effect on the water levels is of the same order of magnitude as the results of a realistic schematization. Based on the analysis we can conclude that the uncertainty in the bedform roughness has a significant influence on the design water levels for the Dutch river Rhine.

The comparison of the predicted bedform roughness values to the calibrated

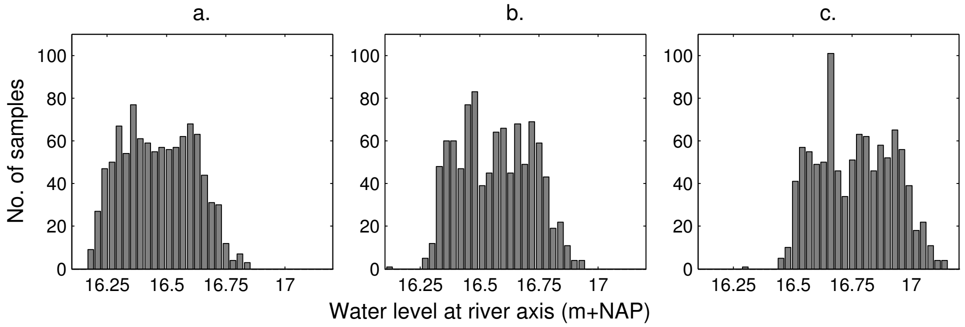


Figure 4.11: Sensitivity of the uncertainty in the design water levels to the floodplain roughness. Uncertainty in water levels with (a) a uniform and constant floodplain roughness of 0.3 m, (b) a uniform and constant floodplain roughness of 0.6 m and (c) a uniform and constant floodplain roughness value of 1.2 m

bedform roughness in the WAQUA model shows that the physically-based roughness values are larger than the calibrated roughness. This indicates that the other roughnesses in the model, such as vegetation roughness or roughness due to groynes are overestimated.

The selection of the hydraulic roughness models has been carried out with care by using only models that are calibrated or validated for field data and perform well for the river Rhine. The field data used for calibration and validation of the models have also been measured in other rivers than the river Rhine and these rivers may have different dominant physical processes and hydrodynamic conditions. So this does not assure that these models perform well for the river Rhine. Therefore, also the performance of the roughness models for the river Rhine is compared. Although only a limited number of measurements are available, clear differences have been shown between the different roughness models, which enabled us to determine the roughness models that are appropriate to predict roughness for the case study.

The performance of the bedform roughness models, compared to the "measured" roughness, influenced the probability of each of the five distributions. This affects the number of samples that are drawn from each distribution and, therefore, the distribution of the roughness. The performance is computed based on a limited number of measurements. However, relatively small differences are shown between the numbers of samples, ranging from 121 samples for the Engelund (1977) model to 292 samples for the Vanoni-Hwang roughness model. Changing the number of samples will not significantly affect the maximum range of the roughness values and, therefore, of the water levels, but it will affect the shape of the final distribution. Furthermore, measurements of dynamic bedform characteristics in the field are rare. Therefore, it is recommended to carry out more field measurements to better understand the bedform dynamics, especially under high discharges to get a better estimate of its uncertainty.

Another factor that influences the results is the selected distribution that is used to extrapolate the roughness to the design conditions. This choice determines the values of the predicted roughness and the 95% confidence interval. Other distributions will result in other values of the roughness at the design discharge. However, this might result in unrealistic values of the roughness. This is shown in figure 4.8, where the predicted k_N values are higher than reported in literature (Julien et al., 2002) and expected based on extrapolation of the linear trends in figure 4.6. Including other distributions in the analysis will result in an increase of the 95% confidence interval, which might then comprise unrealistic values. In this case, the GEV distribution was the most appropriate one, because it has been developed for extreme values and the tail behaviour is not fixed, but is determined by the roughness values.

For the extreme value analysis we used the historically recorded annual maximum discharges of the last 100 years. Hundred years is a limited number of measurements for an extreme value analysis. This has the result that the distribution is weighted toward the lower discharges with return periods of around 10–20 years. The extreme value distribution corrects for this effect, but a longer series of measurements would improve the accuracy of the analysis and reduce the uncertainty due to extrapolation.

The accuracy of a Monte Carlo Simulation is determined by the number of samples. The MCS results consist of independent random samples from the probability distribution of the output. This means that the required number of samples depends on the probability distribution of the output and on the required accuracy of its estimate (Van der Klis, 2003). Morgan and Henrion (1990) present a simple method to estimate the confidence interval for the p^{th} fractile. This confidence interval gives the accuracy of the resulting distribution. It states that the given value for the p^{th} fractile lies with 95% confidence in the given confidence range. This method assumes that the probability of the number of samples multiplied by the fractile represents the actual value of this fractile, is normally distributed. In this study we carried out a MCS with 1000 samples. Using the Morgan and Henrion method, the mean of the resulting distribution (16.57) lies with 95% confidence between 16.552 m and 16.582 m. The lower and upper limits of the 95% confidence level (16.32 m and 16.85 m), as shown in section 4.5, lie with 95% confidence between 16.305–16.327 m and 16.836–16.866 m, respectively. Compared to the total uncertainty range of 53 cm in the water levels and the sensitivity of the results for the above mentioned assumptions, an increase of the number of samples will not significantly increase the accuracy of the results.

4.6.2 Hysteresis

The study by Julien et al. (2002) showed that hysteresis has a large effect on the relation between roughness and discharge. In natural rivers with relatively steep discharge waves, such as the river Rhine, bedforms will never be in equilibrium with the flow conditions under design conditions. Therefore, bedform dimensions will be different for the rising and falling limb for the same discharge. We avoided for this effect by taking only the rising limb data into account. This reduced the variability during the parameterisation and assumes that bedform dimensions during the peak discharge are determined by the grow according to the rising limb. However, after the peak of the discharge wave has passed, the bedforms continue to grow and the roughness increases. We did not account for this effect, which resulted in slightly underestimated maximum roughness values.

The effect on the computed uncertainties is that we underestimated the magnitude of the uncertainty due to variations in the shape of the discharge wave. In case of a steeper discharge wave, the bedforms will be smaller for a same discharge, because there was less time to grow. Also, the opposite might occur, if a discharge wave is less steep bedforms are closer to their equilibrium conditions for a same discharge and the roughness will be higher. This effect is shown in figure 4.6, where for the same discharge, the bedform dimensions measured in 1995 and 1998 result in slightly different roughness values. This effect has not been accounted for and adds to the uncertainty in the roughness due to bedforms. However, the difference between the k_N values for the 1995 and 1998 discharge waves are on average 0.11 m as shown in figure 4.6, which is small compared to the difference between the roughness models. In future research this source of uncertainty should be accounted for.

The hysteresis effect has a large influence on the predicted roughness values if we consider a discharge wave and it should be accounted for in future research on the prediction of bedform roughness in natural rivers. This is important if the water levels during the discharge wave are of interest instead of only the maximum. Including more physical processes, such as hysteresis, can increase the accuracy of water level predictions by reducing the uncertainty between roughness models.

4.6.3 Bedform development toward design conditions

The parameterisation of the predicted roughness values assumes a linear relation between predicted roughness and discharge for four of the five models. However, at increasing flow velocities, bedforms will at a certain point flatten and eventually develop into a plane bed (Van Rijn, 1993) and as a result the roughness will decrease. This effect was not present in the data and is, therefore, not included in the extrapolation. However, for the measured discharges during the rising limb there is no indication that flattening of the dunes might occur, because no decrease in roughness is shown in figures 4.2 and 4.6 with increasing discharge for the Van Rijn, Vanoni-Hwang and Engelund (1977) models. Also, Julien and Klaassen (1995) suggested that this flattening of bedforms might not occur under design conditions in the river Rhine. The Wright-Parker and to a lesser degree also the Haque-Mahmood roughness models show a decrease in roughness growth with increasing discharge. The conditions when this effect will occur are however unknown. Therefore, the uncertainty in the bedform roughness under design conditions might be larger, because lower roughness values could also occur if the flattening proves to be an important process toward design conditions. All the above mentioned uncertainties in the development of the bedforms toward design conditions indicate that the uncertainty might be even larger than the range between the five selected roughness models, because this effect is not included in the roughness models. It is highly recommended to further develop the existing roughness models and to get insight in the development of bedforms toward design conditions.

The uncertainty analysis showed that the uncertainty due to the used roughness model significantly contributes to the uncertainty in the design water levels. To reduce the uncertainties, more research is required on the physical processes in lowland rivers that cause the development of bedforms and resulting hydraulic roughness. In future research, we recommend to include more physical information in the extrapolation of the bedform roughness. Also, more measurements are required to give insight in these processes both in flume studies and under natural conditions. An improved bedform roughness estimation can significantly reduce the uncertainties in the water levels, especially under design conditions.

4.7 Conclusions

The aim of this study was to quantify the uncertainty in the bedform roughness due to the chosen roughness model for design conditions and quantify the effect on the design water levels for a two-dimensional model of the river Rhine. The uncertainty in the bedform roughness consisted of the uncertainty due to the choice of the roughness model and the uncertainty due to extrapolation to design conditions. Five roughness model have been selected that predict bedform roughness based on a comparison of the performance of these roughness models for measurements of bedforms characteristics and water levels under varying discharges. The selected models were the Van Rijn, Vanoni-Hwang, Engelund 1977, Haque-Mahmood and Wright-Parker bedform roughness models. It was shown that these roughness models resulted in different roughness values for the same measurements of bedform and flow characteristics under design conditions.

The Generalized Extreme Value and Gumbel distributions were used to extrapolate the predicted roughness values for each roughness model to design conditions. The GEV distribution showed the best fit to the data, because it followed the convex shape of the data for most roughness models. The two different sources of uncertainty have been quantified and combined to show that the 95% confidence interval of the Nikuradse roughness for the main channel of the river Rhine under design conditions ranges from 0.32 m to 1.03 m, which is a range of 0.71 m.

A Monte Carlo Simulation using an idealised schematization of the WAQUA model for the river Rhine, showed that the uncertain hydraulic roughness of the main channel has a significant influence on the modelled design water levels for the Dutch river Rhine. Although some strong assumptions were made and the number of measurements was limited, we have shown that the absolute values of the computed roughness and water level ranges might change due to the simplifications in the method, but the assumptions do not have a large influence on the order of magnitude of the uncertainty for both the roughness and the water levels. Furthermore, it was shown that the effect of the uncertain bedform roughness depends on the difference between the main channel roughness and the roughness of the floodplains.

The analysis of the uncertainties in design water levels due to uncertain bedform roughness leads to insights in the possibilities to reduce uncertainties. We showed that the uncertainties are caused by a lack of knowledge of the physical processes in lowland rivers that cause the development of bedforms and resulting hydraulic roughness. In future research, we recommend to improve the existing roughness models by including more physical processes in the computation of the hydraulic roughness. Also, more measurements are required to get insight in these processes and the associated uncertainties. An improved estimation of the hydraulic roughness can significantly reduce the uncertainties in the hydraulic roughness, especially under design conditions.

Acknowledgements

This research is supported by the Technology Foundation STW, applied science division of NWO and the technology program of the Ministry of Economic Affairs. We thank the Dutch Centre for Water Management for providing the WAQUA model for the analysis. Furthermore, the authors thank the experts at Deltares for their constructive comments during the research and advice on the draft of this paper.

Chapter 5

Combination of bedform and vegetation roughness uncertainty to assess the uncertainty in design water levels for a lowland alluvial river

Abstract

River flooding is a problem of international interest. Hydrodynamic models are used frequently for flood protection studies and risk management to compute flood risk and reduce economic damage. However, the modelling of river processes involves numerous uncertainties. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model outcomes and the usefulness of model outcomes in decision making. In this study the effects of combined uncertainty in channel and floodplain roughness on the uncertainty in the design water level for an 2D hydrodynamic river model are quantified. We combined three uncertainty sources by means of a Monte Carlo Simulation: bedform roughness of the main channel (MC), classification error of floodplain vegetation (FP1) and choice of vegetation roughness model (FP2). By combining the main contributors to the uncertainty in design water levels we showed that the 95% confidence interval of the design water levels is approximately 0.7 m, which is significant in view of Dutch river management practice. However, this estimate should be considered as an order of magnitude as the effect of model calibration was not taken into account. The combination of the uncertainties due to MC and FP1 resulted in a larger confidence interval than the separate sources. The uncertainty due to FP2 had a minor influence on the uncertainty in the design water levels.

This chapter is submitted for publication as: Warmink, J.J., Huthoff, F., Straatsma, M.W., Booij, M.J., Van der Klis, H. & Hulscher, S.J.M.H. Combining uncertainty in channel and floodplain roughness to assess the uncertainty in design water levels for a lowland alluvial river.

5.1 Introduction

River flooding is a problem of international interest, which costs many lives and causes large economic damage every year. To prevent rivers from flooding, flood protection measures need to be taken. The main human interventions in Europe in relation to river regulation consist of damming, building and management of reservoirs, river channelisation, building of weirs and dredging of river channels (Scheidleder et al., 1996). Hydrodynamic models are used frequently for flood protection and risk management to compute flood risk and reduce economic damage. They are used to predict flood extent, water levels and flow velocities for purposes such as flood safety, navigation, water quality monitoring and ecological rehabilitation. However, current models are imperfect as they cannot reproduce satisfactorily measured data at every location in time and space (e.g. Pappenberger et al., 2006, 2007). So, models are inherently uncertain, but model outcomes are often interpreted in a deterministic way. Knowledge of the type and magnitude of uncertainties is crucial for a meaningful interpretation of the model outcomes and the usefulness of model outcomes in decision making. Therefore, a full understanding of the model and its uncertainties is important (Pappenberger and Beven, 2006).

Many studies have been carried out to quantify uncertainties in hydrological (e.g. Huang and Lee, 2009; Beven, 2006b) and one-dimensional river models (e.g. Pappenberger et al., 2007, 2005; Bates et al., 2004; Aronica et al., 2002). However, hydrodynamic models based on the two-dimensional shallow water equations are rarely used in uncertainty analyses. One exception is the study by Horritt (2006), who shows a method to propagate uncertainty through a two-dimensional model by means of an uncertainty finite volume (UFV) model. In this study it is shown that a stochastic model is able to estimate the uncertainty due to the main channel and floodplain roughness parameters for three simplified case studies. However, as the case study becomes more realistic, the model behaves increasingly non-linear and supporting Monte Carlo Simulation exposed clear shortcoming of the UFV method. Pappenberger et al. (2006) studied the effect of uncertain boundary conditions and model structure on the uncertainty of inundation predictions using the GLUE method for a 1D model on the river Alzette. They concluded that the relative importance of any source of uncertainty depends largely on the hydraulic conditions in the reach. Therefore, decisions to omit factors from further analysis due to low sensitivities or the attempt to decrease the overall model uncertainty through knowledge gain of the most sensitive factors should be based on a large variety of hydraulic scenarios. They conclude that it is of vital importance to consider the uncertainty in rating curves, channel roughness and downstream boundary conditions in flood forecasting and flood mapping.

One of the main uncertainties in hydrodynamic river models is the hydraulic roughness (Warmink et al., 2011; Pappenberger et al., 2008, 2006; Hunter et al., 2007; Hall et al., 2005; Chang et al., 1993). According to Morvan et al. (2008) "hydraulic roughness appears in fluid mechanics as a consideration at wall boundaries, to account for momentum and energy dissipation that are not explicitly accounted for in the simplified equations used in numerical engineering and science." Therefore, roughness is a model of the physical processes that are omitted (e.g. Huthoff, 2007; Morvan et al., 2008). Hydraulic roughness has many sources, such as vegetation resistance, resistance due to other obstacles in the flow, resistance due to channel shape and bends, resistance due to velocity differences in the flow, grain resistance and resistance due to subaqueous bedforms (Knighton, 1998). Roughness parameterisation is a daunting task given the number of processes that are involved in energy dissipation (e.g. Julien et al., 2002; Van Rijn, 1984; Kouwen and Li, 1980). The hydraulic roughness in the main channel of many lowland rivers is dominated by the resistance due to bedforms that develop on the river bed and increase in height with increasing discharge (Julien et al., 2002; Van Rijn, 1984). The relation between roughness and the development of bedforms is not yet fully understood (see Paarlberg et al., 2010). Therefore, hydraulic roughness is often modelled by empirical relations or parameters that are largely uncertain.

Another source of uncertainty that is important in modelling flood water levels in lowland rivers is the floodplain roughness parameterisation (Straatsma and Huthoff, 2011; Straatsma and Baptist, 2008; Horritt, 2006; Mason et al., 2003). Floodplain roughness is often parameterised by a single roughness value (Horritt and Bates, 2002) or derived from a remote sensing based land cover map (Straatsma and Baptist, 2008). An assessment of the effects of the uncertainties in the land-cover map or the vegetation structures have rarely been carried out, particularly for two-dimensional hydrodynamic models. Recently, Straatsma and Huthoff (2010) quantified the uncertainty in 2D hydrodynamic models from uncertainties in remotely sensed roughness parameterisation. Two-dimensional hydrodynamic models have some degree of non-linearity (e.g. Horritt, 2006; Van der Klis, 2003). Dynamic effects may also have to be taken into account, and these may introduce significant non-linearity. For example, friction parameters affect flood wave travel times and thus the time of arrival of an irregular flood hydrograph (Horritt, 2006). Furthermore, Horritt (2006) states that more research is required to determine whether spatial variability of roughness is significant relative to other sources. Little research has been carried out on combining various sources of uncertainty in hydrodynamic models. Previous research has shown that independent uncertainties can be added in case of a linear model (Morgan and Henrion, 1990). However, in case of highly non-linear models combining sources of uncertainty may lead to interactions and unexpected behaviour.

The objective of this study is to determine the effects of combined uncertainty in channel and floodplain roughness on the design water level for an alluvial river using a 2D hydrodynamic model. We address the following sources of uncertainty: (1) bedform roughness of the main channel, (2) classification error of floodplain vegetation, (3) choice of vegetation roughness model. For this purpose we carried out a case study of the river Waal, a tributary of the river Rhine in the Netherlands. In the next section details of the case study are explained. The uncertainty sources were assessed separately and in combination. The outline of this paper is as follows. Firstly, the case study and the used model are presented. Then, a brief review is given on the state of the art of uncertainties in hydraulic roughness for both the main channel and floodplain areas. Thirdly, the methods are presented followed by the results. This paper ends with a discussion and conclusions.

5.2 Study area and model

5.2.1 Study area

The chosen study area of the river Waal is one of the tributaries of the river Rhine in the Netherlands (figure 5.1). At the Dutch-German Border, the river Rhine has an average discharge of 2250 m^3/s. In the Netherlands, the river Rhine bifurcates into the Pannerdensche Kanaal and the river Waal at Pannerdensche Kop, where approximately two thirds of the discharge enters the river Waal (Ogink, 2006). The width of the main channel of the river Waal between the groynes is 250 m on average. The cross-sectional width between the embankments varies between 0.5 and 2.6 km. The Waal has an average water level gradient of 0.11 m/km (Middelkoop and Van Haselen, 1999). The total embanked area of the total river Rhine is about 112 km^2, divided between the main channel fixed with groynes and the floodplain areas. The vegetated floodplain area including the groynes takes up 69% of the total embanked area. The land cover of the floodplains is dominated by meadows, but recent nature rehabilitation has led to increased areas with herbaceous vegetation, shrubs and forest (Straatsma and Huthoff, 2011).

5.2.2 WAQUA model

In the Netherlands, the hydrodynamic river model WAQUA is used to calculate the design water levels (DWL) for flood protection measures based on the design discharge (Rijkswaterstaat, 2009), which corresponds to a return period of 1250 years and an estimated discharge magnitude of 16000 m^3/s. In this study we use this model for the Waal branch only (figure 5.1). The WAQUA model with an equivalent design discharge of 16000 m^3/s is based on a staggered curvilinear grid with 148,334 grid cells with a cell size of approximately 40x40 m. The water flow is computed by solving the shallow water equations using a finite difference scheme. The WAQUA model consists of: 1) the program environment SIMONA (Rijkswaterstaat, 2009) which contains the discretized shallow water equations to simulate the water flow and the empirical equations to approximate energy losses, and 2) a schematization of the upper river Waal for a certain period in time with corresponding input parameters. The used digital elevation model of the river Waal is based on two-dimensional bathymetry scans of the river bed using, amongst others, echo soundings for the main channel and laser altimetry and photogrammetry data for the floodplain area. Furthermore, the WAQUA model includes several hydraulic structures, such as characteristics of the flow channel (e.g. grain size and vegetation). The vegetation is schematized by a map with roughness codes. A constant discharge, equal to the maximum design discharge of 16000 m^3/s is set as the upstream boundary condition, and a corresponding water level as downstream

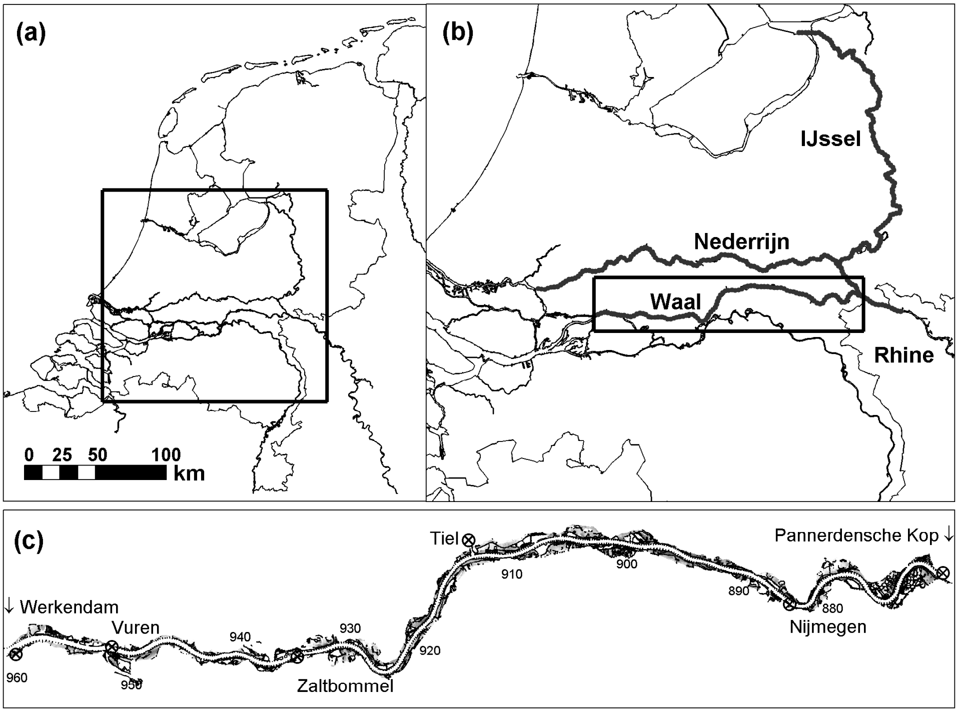


Figure 5.1: Study area. (a) the Netherlands, (b) location of the river Rhine tributaries. (c) WAQUA model of the river Waal, the numbers refer to the river kilometres and the names in the bottom figure refer to the water level measurement stations

boundary condition. We used the 2006_4 version of the WAQUA model with the schematization of the river that is currently used for the computation of the design water levels (Rijkswaterstaat, 2007).

5.2.3 Hydraulic roughness

In the WAQUA model, the roughness of the main channel is expressed as an equivalent grain roughness length (Nikuradse, k_N) and may be used to represent the combined effect of grain roughness and roughness due to bedforms (ripples and subaqueous dunes) (Van Rijn, 1984). This roughness is calculated according to a roughness model that is simplified after Van Rijn (1984):

$$k_N = \alpha h^{0.7} \left[1 - \exp\left(-\beta h^{-0.3}\right)\right] \tag{5.1}$$

where α ($m^{0.3}$) and β ($m^{0.3}$) are empirically determined parameters and h is the water depth (m). Parameter β is fixed at 2.5 $m^{0.3}$ (Van den Brink et al., 2006) and the model is calibrated by adapting α in equation 5.1 (Van den Brink et al., 2006) for each section between the measurement stations (Vuren, Zaltbommel, Tiel, Nijmegen, Pannerdensche Kop). In the calibration procedure, the difference between the measured and computed water levels is minimised by adapting α for every section separately at the peak of the highest recorded discharge wave, which occurred in 1995.

The roughness of the floodplains is derived from ecotope maps (Jansen and Backx, 1998), which are transformed into vegetation types following the method proposed in the vegetation handbook of Van Velzen et al. (2003). In the model implementation, vegetation types are linked to average vegetation structural parameters, such as vegetation height and density, and a drag coefficient. Next, the structural parameters are used as input in the vegetation roughness equation proposed by Klopstra et al. (1997, see appendix B).

5.3 Review on uncertainties in hydraulic roughness

Hydraulic roughness in models is computed in a simplified way, but its integration in most 2D models is highly complex. Many river models lack an accurate description of the hydraulic roughness. Previous research has shown that the uncertainties in the hydraulic roughness of the main channel and the floodplain area are important contributors to the uncertainty in model outcomes (e.g. Straatsma and Baptist, 2008; Pappenberger et al., 2008; Hunter et al., 2007; Mason et al., 2003). In this section we give an overview of important uncertainty sources in the hydraulic roughness and explain our rationale behind closing and omitting certain uncertainty sources.

5.3.1 Uncertain bedform roughness

The hydraulic roughness of the main channel of many lowland rivers is dominated by resistance due to bedforms (Julien et al., 2002; Alam and Halim, 2002; Aberle et al., 2010). Julien et al. (2002) and Wilbers (2004) compared different roughness models for field measurements in the Dutch river Rhine. Both studies showed that under field conditions different roughness models result in large differences between the predicted roughness values for measured high discharges. Aberle et al. (2010) applied the random field approach for the analysis of bedforms in the river Elbe in Germany. They concluded that the measured bed elevation spectra are characterised by more than one scaling region. This indicates that hysteresis and antecedent flow conditions are of importance to bedform dynamics. The above mentioned studies show that the hydraulic roughness due to bedforms is highly uncertain even for commonly occurring discharge scenarios.

In flood safety modelling extreme discharge scenarios are considered, which have seldom or never occurred. Due to the lack of observations, the uncertainties in the modelled water levels for these extreme scenarios, are therefore even larger (for the river Rhine see Ogink, 2003; Kok et al., 2003). A rough estimate by Ogink (2003) yielded that the uncertainty in the development of the bedforms during design conditions results in a 95% confidence interval of 40 cm for the design water levels. In chapter 4 (Warmink et al., 2010a) three sources of the uncertainty in the roughness due to bedforms were considered: the uncertainty in the data, the uncertainty due to extrapolation of the roughness to design conditions and the choice for the roughness model. These sources have been quantified based on measured bedform characteristics and result in a 95% confidence interval for k_N from 0.32 to 1.03 m. In this study, we will use this uncertain bedform roughness and explain the quantification of the uncertainty in more detail in section 5.4.1.

5.3.2 Uncertain vegetation roughness

Several models have been proposed to describe vegetation roughness of floodplains in terms of vegetation structure parameters (Huthoff et al., 2007; Baptist et al., 2007; Klopstra et al., 1997; Kouwen and Fathi-Moghadam, 2000; Kouwen and Li, 1980; Petryk and Bosmajian, 1975). Vegetation roughness models can be distinguished between models for non-submerged and submerged vegetation. For non-submerged vegetation, literature shows that there is a high degree of consensus about the equation used for roughness prediction (Baptist et al., 2004). The existing roughness predictors all are based on an analytical derivation of the conservations of mass and momentum (e.g. Huthoff et al., 2007; Baptist et al., 2007; Van Velzen et al., 2003; Klopstra et al., 1997) that are based on Petryk and Bosmajian (1975). Another approach for non-submerged vegetation is to model it as a porous medium (Hoffmann, 2004). However, this approach is only valid in densely vegetated channels. In the study area, tree-type, non-submerged vegetation covers less than 5% of the floodplains. Therefore, the porous medium approach is not applicable and the widely-used drag force approach is adopted.

If the vegetation becomes submerged, the energy losses above the canopy of the vegetation become important. This process is poorly understood (Nepf and Vivoni, 2000) and many different roughness models exist to account for these energy losses. Relationships are developed between roughness and the product of velocity (V) and the hydraulic radius (R) and some measure for the coverage of vegetation (e.g. vegetation height) (Fisher and Dawson, 2003). However, these so called VR-methods have little scientific justification (Bakry et al., 1992; Smith et al., 1990; Kouwen and Li, 1980). Other vegetation roughness models represent vegetation as flexible elements (e.g. Järvelä, 2004; Mason et al., 2003; Fischenich and Dudley, 2000; Kouwen and Fathi-Moghadam, 2000). These models often require a species-specific vegetation index. However, it is difficult to measure this vegetation index because of the heterogeneity of natural vegetation (Straatsma and Baptist, 2008). Therefore, these models have limited practical applicability until values of the species-specific vegetation index are available for typical species of natural vegetation (Järvelä, 2004). Alternatively, vegetation may be represented by rigid cylinders. This assumption is only valid if the flow velocity is low, which is the case in many floodplain regions and the vegetation is not deflected. Different models exist to predict roughness due to submerged, rigid vegetation (e.g. Huthoff et al., 2007; Baptist et al., 2007; Van Velzen et al., 2003; Klopstra et al., 1997).

One of the main uncertain parameters in these vegetation roughness models is the drag coefficient (C_D). This is evident from the wide range of values that are stated in the literature. For submerged vegetation, a wide variety of values for the drag coefficient is found in literature of flume and field measurements (Baptist, 2005). These values range from 0.1 up to 3.0 (Nepf and Vivoni, 2000). However, most values are larger than 1.0. The Klopstra vegetation roughness model in the WAQUA model uses a C_D value of 1.8 for submerged vegetation and 1.5 for non-submerged vegetation.

For non-submerged vegetation Mertens (1989) and Nuding (1991) (in Järvelä, 2004) assumed that a constant C_D value of 1.5 is valid for most practical cases and Klaassen and Zwaard (1974) reported a mean C_D coefficient of 1.5 for small, branched fruit trees. DVWK (1991, in Järvelä, 2004) and BWK (1997, in Van Velzen et al., 2003) recommend C_D values of 1.5 for practical computations, which is well in line with the reported experimental values. It is assumed that $C_D = 1.5$ can be used as a base value, which is analogous to the typically made assumption of $C_D = 1.0$ for cylinders (Järvelä, 2004). For non-submerged vegetation, Järvelä (2002a) computed C_D values for leafless willows for 46 test runs in a flume study under varying discharges with a stem density of 512 stems/m^2. The average C_D with standard deviation in parentheses was 1.43 (0.12). The coefficients include the effect of the other willows, i.e. are dependent on the willow pattern and density.

The uncertainty in the hydraulic roughness due to floodplain vegetation is quantified in a study by Straatsma and Huthoff (2011), also reported in Straatsma and Huthoff (2010) for the Dutch river Rhine branches. This uncertainty consists of three sources: the uncertainty due to the classification error of the ecotopes, the uncertainty due to mapping scale of the land cover map and the uncertainty due to the parameterisation of the vegetation characteristics within an ecotope. Straatsma and Huthoff (2011) quantified these uncertainties due to the classification error, the mapping scale and the vegetation characteristics. They showed that the resulting 68% uncertainty range in the design water levels had a maximum of 32 cm, 5 cm and 1 cm, respectively along the river Upper Rhine and Waal. The authors noted that the overall classification accuracy was low, only 69% of the ecotopes were correctly classified. Furthermore, the validation of the classification error has been disputed. Due to differences in support and discernibility of the different ecotopes in the field it is argued that the classification error is overestimated during the field measurements. Straatsma and Huthoff (2011) concluded that even if the classification accuracy is increased to 95% the classification error was still the largest contributor to the uncertainty in the design water levels. Another important uncertainty source that was not included in the study by Straatsma and Huthoff (2011) is the uncertainty due to the vegetation roughness model.

5.4 Methods

The literature shows that uncertainty in hydraulic roughness consists of many different sources. For a structured and reliable uncertainty analysis, it is required to identify the individual sources of uncertainties before quantification is possible (Warmink et al., 2010b). In this study we combined three different sources of uncertainty: the uncertainty due to bedform roughness of the main channel (MC), quantified by Warmink et al. (2010a), the uncertainty due to the classification error (FP1) that is the dominant source of vegetation roughness uncertainty, quantified by Straatsma and Huthoff (2011) and finally the uncertainty due to the choice of the roughness model for the prediction of vegetation roughness (FP2), which is quantified in this study.

5.4.1 Uncertain bedform roughness

The quantification of the uncertainty due to bedforms has been carried out by Warmink et al. (2010a). They compared ten roughness models that predict the hydraulic roughness of the river bed of the Dutch river Rhine, based on measurements of bedforms characteristics and water levels. The data from Wilbers (2004) and Julien et al. (2002) have been used. These data consist of detailed bedforms and flow characteristics under various discharges. Five roughness models have been selected, based on their performance for the measured data and assumptions. These roughness models are the equations of Van Rijn (1984), Vanoni and Hwang (1967), Engelund (1977), Haque and Mahmood (1983) and Wright and Parker (2004). Next, for each roughness model a Generalised Extreme Value distribution has been fitted through the predicted roughness values. The five fitted GEV distributions were then extrapolated to the return period of 1250 years, which resulted in a 95% confidence interval for the roughness for each roughness model. The spread of the data around the fitted distributions gave a measure for the uncertainty within each of the roughness models, while the differences between the extrapolated roughness values gave the uncertainty between the roughness models. These sources of uncertainty were combined by random sampling from the distributions, where each of the roughness models was given a weight based on its performance for the measured data. Figure 5.2 shows the samples drawn from the distributions at the design return period. The 95% confidence interval of the Nikuradse roughness length (k_N) for the main channel of the river Rhine under design conditions ranges from 0.32 m to 1.03 m, with a positively skewed distribution. In the Monte Carlo Simulation one uniform roughness value is applied to the main channel for each sample.

5.4.2 Vegetation classification error

The classification error of the floodplain vegetation was identified as the main source of uncertainty in floodplain roughness (Straatsma and Huthoff, 2011) and is included as an error source in this study. Figure 5.3 shows the results of the Straatsma and Huthoff (2011) study for the river Upper Rhine and Waal. Straatsma and Huthoff (2011) showed that the contribution of the classification error is much larger than the other two sources of uncertainty: the mapping scale of the land cover map and the uncertainty due to the parameterisation of the vegetation characteristics. The classification error of the Rhine branches has been determined by Knot-

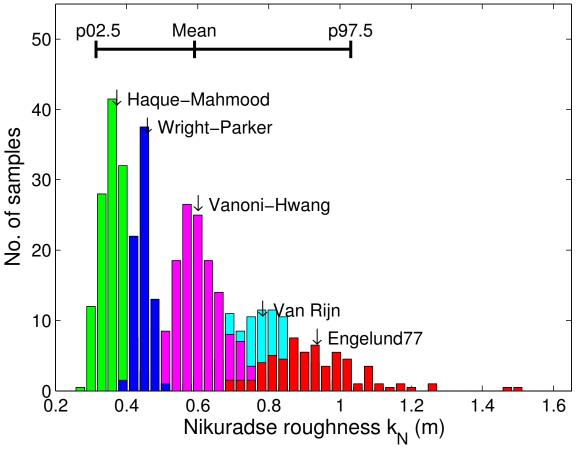


Figure 5.2: Samples for the Monte Carlo Simulation for source MC, showing the uncertainty in the hydraulic roughness due to bedforms under design conditions. These data are quantified in chapter 4. The five distributions represent the uncertainty due to the five bedform roughness models. Furthermore, the mean and 95% confidence interval of the combined distribution are shown

ters et al. (2008) as "map purities". Table 5.1 shows the aggregated map purities table that Straatsma and Huthoff (2011) constructed from the field measurements of Knotters et al. (2008). This table shows the percentage of the total map that is correctly classified. The map purities sum up to one per row. The classification error should be interpreted as a maximum value (Straatsma and Huthoff, 2011), which results in an estimate of the maximum uncertainty range in design water levels.

Following the approach by Straatsma and Huthoff (2011), the map purities table is used as probabilities that an ecotope polygon is classified correctly. For each polygon in the ecotope map, a random number was drawn from a uniform distribution, and based on the ecotope probability assigned a new ecotope code to each of the polygons. Straatsma and Huthoff (2011) used 15 samples for their Monte Carlo Simulation. In this study we followed this approach, but used 500 samples for the Monte Carlo Simulation and generated 500 realisations of the ecotope map. These maps were recoded to WAQUA roughness codes and used in the 2D hydrodynamic model.

5.4.3 Quantification of vegetation roughness model uncertainty

As described in section 5.3, many models exist to predict vegetation roughness. This study followed the approach of Klopstra et al. (1997), which is used for Dutch river management practise and characterised vegetation as rigid elements. For this purpose, we selected the four roughness models from Klopstra et al. (1997), Van Velzen et al. (2003), Huthoff et al. (2007) and the model derived from genetic pro-

Table 5.1: Purity matrix for ecotopes in the Rhine tributaries, after Straatsma and Huthoff (2011). The rows show the vegetation type on the map and the columns show the field reference data. So agricultural area is correctly classified in 78.2% of the field validations. Also, the total areas of the different ecotopes are given, where reference km^2 is the coverage in the reference situation, after PM km^2 is the coverage of the ecotopes after the application of the purity matrix and dA is the change in surface area

Description	Roughness code	reference km^2	after PM km^2	dA km^2	Groyne field / sand bar	Build-up area / paved	Agricultural area	Pioneer vegetation	Production meadow	natural grass / hay land	Dry herbaceous veg.	Reed-grass	Reed	Softwood shrubs	Willow plantation	Thorny shrubs	Softwood production forest	Hardwood forest	Softwood forest
Equivalent grain roughness types																			
Groyne field / sand bar	111	3.4	4.1	+0.7	85.7%									14.3%					
Stone protection	113	0.5	0.0	-0.5		80%								20%					
Build-up area / paved	114	13.8	18.2	+4.4		91.6%			4.9%					1.7%			1.7%		
Agricultural area	121	35.3	32.9	-2.5			78.2%			21.3%	0.3%	0.2%							
Submerged vegetation (grass-type)																			
Pioneer vegetation	1250	0.8	2.5	+1.7	53.1%	24.4%		7.6%		15%									
Production meadow	1201	135.4	102.8	-32.6	0.5%		2.2%		51.7%	32.5%	6.7%			3.1%			2.9%		
Natural grass / hay land	1202	71.8	77.8	+6.0		0.7%	2.5%	2.2%	33.3%	43.1%	7.7%	2.7%	5.5%				2.3		
Submerged vegetation (herb-type)																			
Dry herb. vegetation	1212	22.4	29.9	+7.5		9.9%	2.3%	4.3%	1.7%	7.6%	52.8%	3.9%	2.2%	5.2%	4.6%	4.3%	1.8%		
Reed-grass	1804	3.7	3.7	0.0						22%	58.9%			16%					3%
Reed	1807	3.4	6.8	+3.4								26.3%	64.7%	9%					
Non-submerged vegetation (tree-type)																			
Softwood shrubs	1231	4.0	11.1	+7.1		0.4			3.0%	3.0%	10.1%		3.0%	43.3%	12.1%		16.0%	0.8%	8.3%
Willow plantation	1232	0.1	1.0	+1.0										14%					100%
Thorny shrubs	1233	1.6	2.3	+0.7		9.2%				5.4%	15.8%			19.6%		21.4%	2%	10.5%	16.2%
Softwood production	1242	2.6	8.7	+6.2		12%			6%					0.4		7.8%	43.2%		30.7%
Hardwood forest	1244	5.9	2.1	-3.8		29.8%								11.7%			11.6%	31.8%	15.2%
Softwood forest	1245	11.2	12.0	+0.8							5.9%			11.3%		3.3%			79.4%

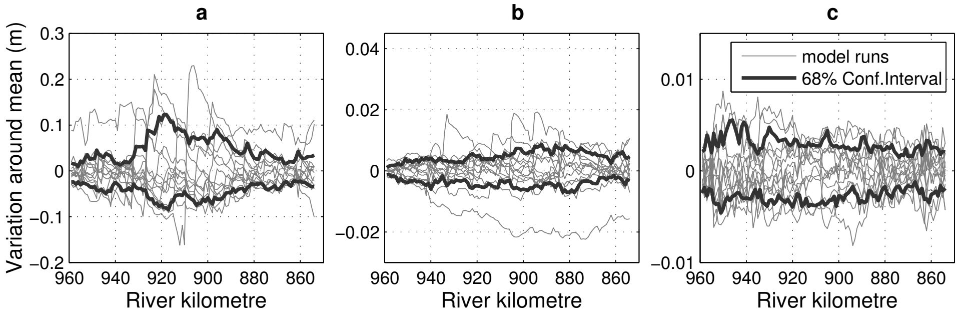


Figure 5.3: Variations in water levels and 68% confidence interval (1 standard deviation) for different error sources: (a) classification errors, (b) uncertainty due to mapping scale and (c) uncertainty due to vegetation characteristics (from Straatsma and Huthoff, 2011).

gramming from Baptist et al. (2007) that are all based on the rigid approach. For non-submerged vegetation these equations are all the same and are based on Petryk and Bosmajian (1975). The equations differ only for emergent vegetation and are shown in appendix B.

Figure 5.4 shows the performance of these four roughness models for the flume data series of Meijer (1998a) and Meijer (1998b). These data result from flow studies with rigid cylinders and natural reed. The flume was 100 m long, 3 m wide and vegetation was placed over a length of 22 m. The water depths ranged between 1 m and 2.5 m, vegetation height between 0.45 m and 1.65 m and vegetation densities (A_r), which is the product of the number of stems per square meter, m and the average diameter of the stems, D, between 0.5 m^{-1} and 2 m^{-1}. Figure 5.4 shows that all four roughness models perform well for this data set. NS is the Nash-Sutcliffe coefficient (Nash and Sutcliffe, 1970), which represents the predictive power of the roughness models. Possible values for NS vary between 1, indicating a perfect match between observed and predicted values, via 0, indicating that the model predictions are as accurate as the average of the observed roughness values, to minus infinity, which indicates that the average is a better predictor than the model. The NS values show that the Van Velzen model performs slightly better than the other models. All models show a small underestimation of the roughness. It should be noted that the Meijer data are part of the calibration data set for the vegetation roughness models of Klopstra, Huthoff and Van Velzen.

Figure 5.5 shows the same four roughness models for varying water depths. This figure shows that the Klopstra, Van Velzen and Huthoff models have a similar trend. The Baptist roughness model has a different trend then the other three roughness models. The four models show that hydraulic roughness increases with increasing water depth, up to the point where the vegetation becomes submerged. At that point, the Klopstra, Van Velzen and Huthoff models show an initial increase of the roughness up to approximately two times the vegetation height, and then a decrease of the roughness with discharge. The Baptist roughness model shows a

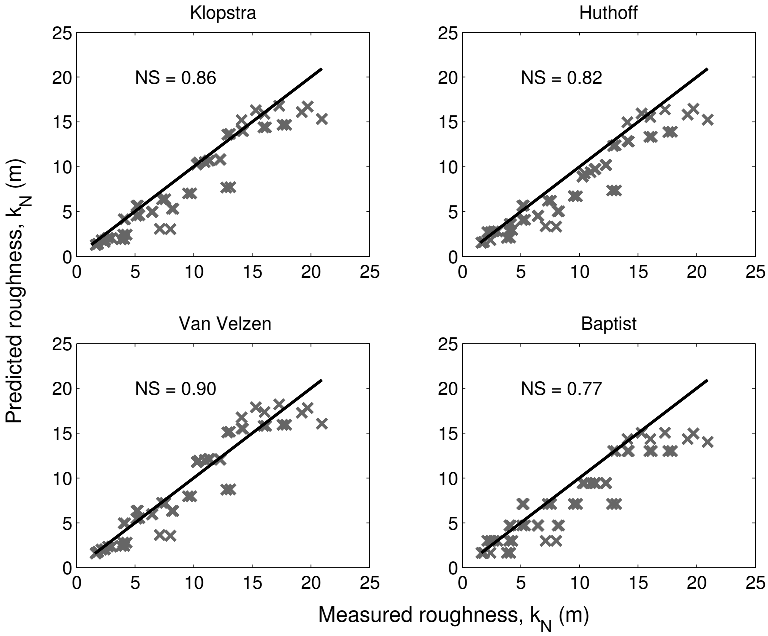


Figure 5.4: Performance for the four vegetation roughness models for the Meijer (1998a, 1998b) data of submerged vegetation. The solid line represents the line of perfect agreement $y = x$ and NS refers to the Nash-Sutcliffe coefficient

constant roughness with water depth in case of submerged vegetation. Effectively, this roughness model relates the vegetation height to an equivalent roughness.

The literature described in section 5.3 shows that there is little information on the validation of these models for natural vegetation. All models perform well for the flume data that are used for their development, calibration and validation. However, little information is available for the roughness of vegetation for water depths that are much larger than the vegetation height. Therefore, we cannot assign one model to be better (more probable) than another model. Instead, we treat all models as a single expert opinion, with equal probability. So we assume that these four roughness models are equally valid to predict the roughness of floodplain vegetation for the Dutch river Rhine branches and give all models an equal weight.

The WAQUA model that is used for flood simulation in the study area only allows utilisation of Klopstra's vegetation roughness model. Therefore, the Van Velzen and Huthoff models are approximated by changing the parameters in the Klopstra formulation and the Baptist model is approximated by applying a constant bed roughness. We adapted the vegetation drag (C_D) and vegetation height (k) for each vegetation type. The set of C_D and k values is determined by minimising the Mean Squared Error (MSE) between the Van Velzen and Huthoff models and

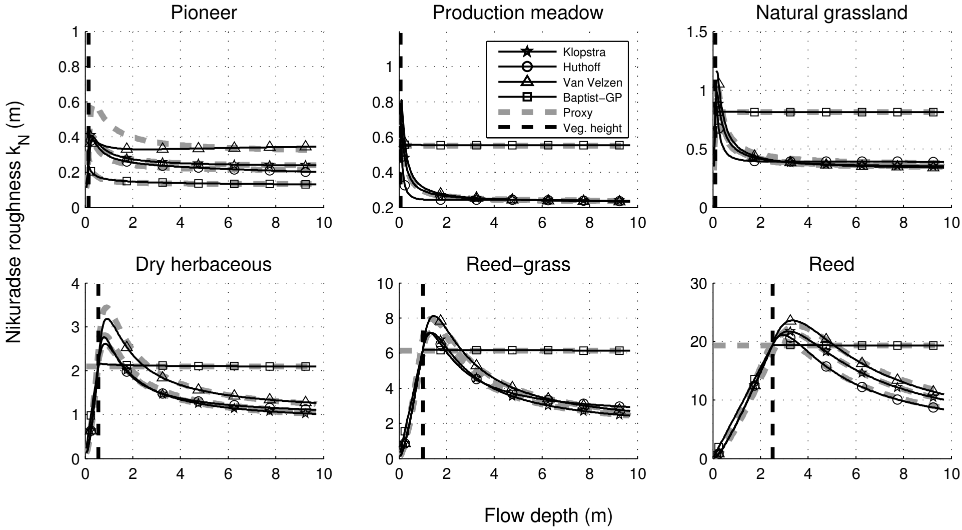


Figure 5.5: Difference between the vegetation roughness models for six submerged vegetation types. The solid lines with the symbols represent the four vegetation roughness models, the grey, dashed lines show the proxy (i.e. the fitted model) that is implemented in the WAQUA model. The vertical, dashed lines represent the vegetation height

the adapted Klopstra models. The MSE is computed for the water depths that occur under design conditions. The water depths in the floodplain area under design conditions are analysed for different vegetation types. This showed that the water depth in the floodplains is on average 6.1 m and is distributed approximately normal with a 95% confidence interval of 3.3–9.7 m. Therefore, we computed the MSE between a water depth of 3.3 and 9.7 m. The Baptist model could not be approximated by changing the C_D and k parameters in the Klopstra model, because it has a different trend. Therefore, we imposed a constant Nikuradse roughness length (k_N) and fitted this value in the same way to approximate the Baptist model.

Table 5.2 shows the sets of parameters that are used to approximate the Van Velzen, Huthoff and Baptist vegetation roughness models and figure 5.5 shows the behaviour of the roughness models for the six vegetation types and their proxy values. For example, for pioneer vegetation the Huthoff model predicts a slightly smaller roughness than the original Klopstra model, which is approximated by a decrease in the k and C_D values from 0.15 m and 1.8 for the Klopstra model to 0.135 m and 1.45 for the proxy of the Huthoff model. In the approximation of the Van Velzen model, the roughness predicted by the proxy overestimates the original Van Velzen model for low water depths, but slightly underestimates the roughness for high water depths. However, these small water depths rarely occur under design conditions. Therefore, the error that is made in the proxies has little influence on the computed uncertainties. In total 81% of the surface area in the WAQUA model is taken into account. The remaining 19% is assumed deterministic as this consists of a large number of vegetation types with small coverage or special vegetation types, such as single trees or hedges, which are computed in a different manner.

For non-submerged vegetation, the four considered roughness models predict the same behaviour for a chosen drag coefficient. Furthermore, the variation in the drag coefficient reported in literature (Järvelä, 2004) is relatively small. Therefore, for the non-submerged vegetation types we assume no uncertainty in the vegetation roughness model.

5.4.4 WAQUA modelling

The time required to simulate one full day for the schematization of the upper part of the Dutch Rhine branches is approximately one hour on a single node on the Deltares (www.deltares.nl) computer cluster, which has a 2.6 GHz dual core processor with 4 Gb internal memory. To reduce the computational time, only the Waal branch is modelled, which reduces the computational time by half. The modelled branch has a length of 95 km. We ran the model with a constant discharge of 10667 m^3/s as the upstream boundary condition. This discharge magnitude is two third of the current design discharge at Lobith, the location where the Rhine enters the Netherlands. As approximately two third (the exact value is uncertain and depends on many factors) of the discharge flows into the river Rhine, this discharge corresponds to a return period of approximately 1250 years. The corresponding design water level is approximately 4.8 m above Dutch Ordnance Datum (NAP), which is set as the downstream boundary condition near Werkendam (Rijkswaterstaat, 2007).

The water levels in the downstream part of the river Waal are influenced by the downstream boundary condition. This is caused by the differences in the equilibrium depth between the different simulations, because the hydraulic roughness is adapted. In this section, the water levels are influenced by the backwater effect of the fixed downstream boundary condition. As a consequence the range in water levels between the simulations at the downstream boundary condition is zero and increases upstream. The results show that the downstream 25 km (up to Zaltbommel) are dominated by this effect. The uncertainties in this region are, therefore, underestimated and unreliable. The results are presented for the whole Waal stretch and at a single location at river kilometre 893 (close to the city of Ewijk), which is 67 km upstream of the downstream boundary condition. This stretch of the river is relatively straight and the effect of the downstream boundary condition is negligible.

5.4.5 Monte Carlo Simulations

Firstly, we carried out the reference run, in which all variables have been set to their default value. This run is therefore equal to the calibrated model that is used for the computation of the design water levels for the Dutch governmental Centre

Table 5.2: Parameters for the Klopstra vegetation roughness model and adapted parameters as proxy for the Huthoff, Van Velzen and Baptist models. The default vegetation-structure parameters A_r, k and C_D are taken from Van Velzen et al. (2003). Also, the fractional coverage (cov) of each ecotope type is shown.

Ecotope	r_code	Cov (%)	k_N (m)	A_r (m^{-1})	k (m)	C_D (–)	Error range proxy: Huthoff	Error range proxy: Van Velzen	Error range proxy: Baptist
Bedform roughness							Variable		
Main channel	102	31.0	var.				0.28 – 1.24		
Equivalent grain roughness							Deterministic		
Groyne field / sand bar	111	1.4	0.15						
Stone protection	113	0.0	0.30						
Build-up area / paved	114	2.7	0.60						
Agricultural area	121	3.6	0.20						
Submerged vegetation (grass-type)									
Pioneer vegetation	1250	0.4	0.1	0.15	0.15	1.8	k:0.135 C_D:1.45	k:0.195 C_D:2.65	k:0.06 C_D:2.50
Production meadow	1201	13.2	0.1	45	0.06	1.8	k:0.063 C_D:2.30	k:0.061 C_D:2.35	k_N:0.55
Natural grass / hay land	1202	15.5	0.1	12	0.1	1.8	k:0.11 C_D:1.60	k:0.1 C_D:1.15	k_N:0.81
Submerged vegetation (herbaceous-type)									
Dry herbaceous veg.	1212	4.2	0.1	0.23	0.56	1.8	k:0.56 C_D:2.10	k:0.62 C_D:2.45	k_N:2.1
Reed-grass	1804	0.6	0.1	0.4	1.0	1.8	k:1.00 C_D:2.60	k:1.10 C_D:1.60	k_N:6.15
Reed	1807	1.0	0.1	0.37	2.5	1.8	k:2.25 C_D:1.30	k:2.75 C_D: 1.30	k_N:19.3
Non-submerged vegetation (tree-type)							Deterministic		
Softwood shrubs	1231	3.0	0.4	0.13	6	1.5			
Willow plantation	1232	0.1	0.4	0.041	3	1.5			
Thorny shrubs	1233	0.5	0.4	0.17	5	1.5			
Softwood production for.	1242	1.4	0.3	0.01	10	1.5			
Hardwood forest	1244	0.1	0.4	0.023	10	1.5			
Softwood forest	1245	2.4	0.6	0.028	10	1.5			

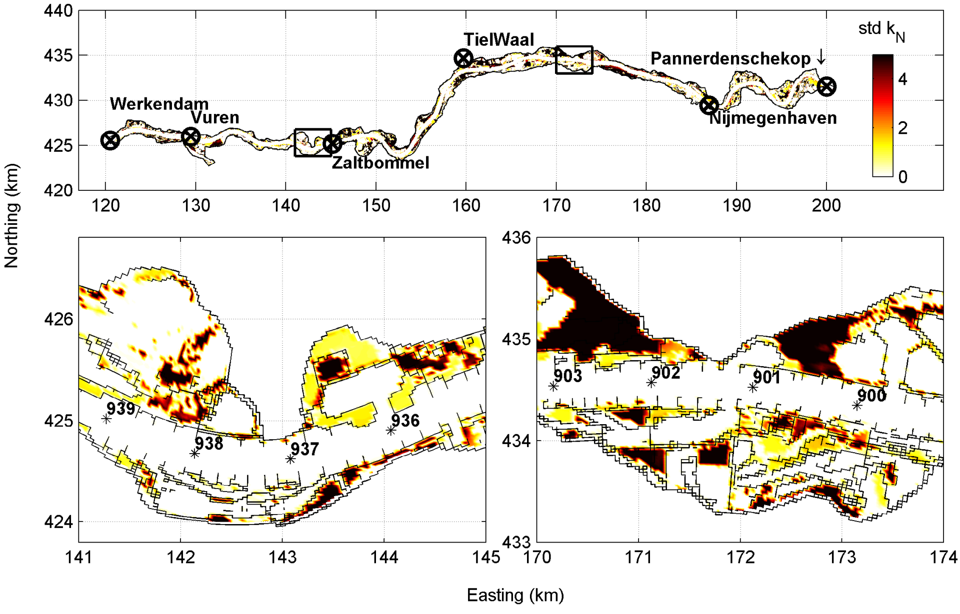


Figure 5.6: Standard deviation of roughness length (k_N) used as input for the Monte Carlo Simulation for all three sources of uncertainty. Model of the river Waal branch (top) with the Gamerensche Waard (lower left) and Afferdensche en Deestsche Waarden floodplains (lower right)

for Water Management (Rijkswaterstaat, 2007). Five sets of Monte Carlo simulations have been carried out with 500 simulations each. One set of 500 simulations is carried out for each of the uncertainty sources: the bedform roughness, vegetation classification error and vegetation roughness model, separately. For latter set of simulations, a vegetation roughness model is drawn randomly with an equal probability of 25%. Then a set of simulations is carried out with both the bedform roughness and the vegetation classification error set variable. Finally a set of simulations is carried out with all three sources of uncertainty set variable. The samples for the uncertain bedform roughness and classification error are drawn once. The samples for the bedform roughness are shown in figure 5.2. The combined sets of runs are, therefore, based on the same samples as the individual sets of runs.

The sampled roughness values including the three sources of uncertainty show large differences in spatial distribution between the 500 realisations. Figure 5.6 shows the standard deviation of the Nikuradse roughness length for all 500 realisations with all sources of uncertainty set variable. This figure shows that the standard deviation of the hydraulic roughness is locally very high, up to a standard deviation of 25 m. However, these regions are sparse compared to the large areas with lower standard deviations.

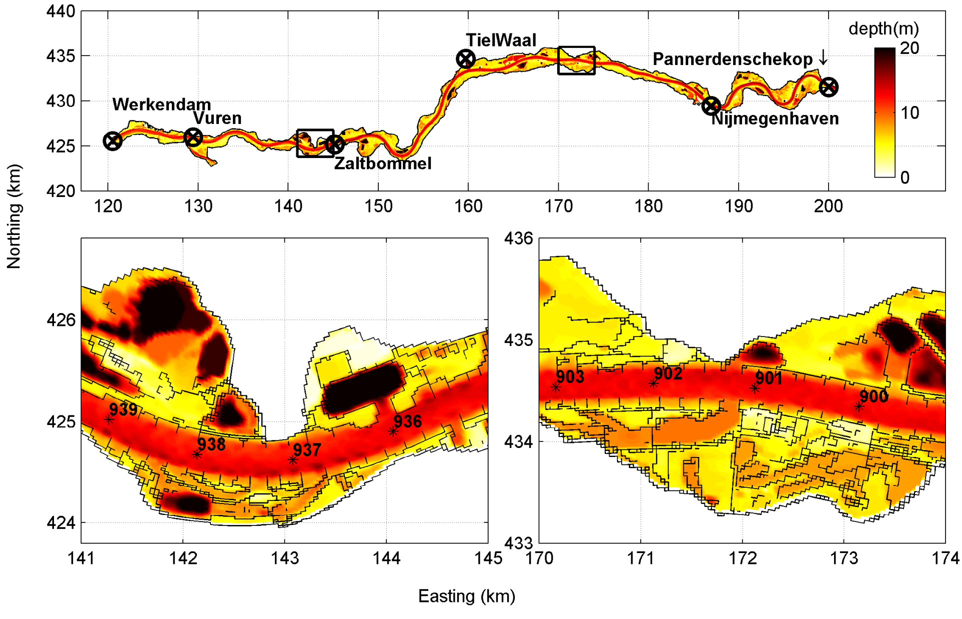


Figure 5.7: Results of the reference run for the calibrated WAQUA model. Water depths in the main channel are around 13.5 m, while water depths in the floodplain areas are on average 6 m. The dark spots in the floodplain area are deep pools with water depths of more than 15 m

5.5 Results

Firstly, we present the reference run and the contribution of each of the three sources of uncertainty separately. Then we will present the results of all three sources of uncertainty combined. The uncertainty ranges in the design water levels are presented along the river axis (the centre part of the main channel of the river) and as a histogram at a single point. The uncertainties are expressed as 95% confidence intervals of the water levels at the river axis and at river kilometre 893. Table 5.3 summarises the results and shows the contribution of the individual sources and the combined sources of uncertainty to the uncertainty in the design water levels.

5.5.1 Reference run

The reference run computes the water depths in the river Waal using the calibrated main channel roughness and the deterministic values for the vegetation roughness. Figure 5.7 shows the water depths for the reference run. This figure shows that the water depth in the main channel is about 14 m, while the water depth in the floodplains varies from 20 m for some deep lakes to around 6 m for the vegetated areas. A comparison of the standard deviation in the hydraulic roughness realisations

Table 5.3: Water levels (m) from the five Monte Carlo Simulations and the reference run. The values of the 2.5% and 97.5% quantiles, mean water level at river axis, 95% confidence interval, standard deviation and skewness are shown, computed at river kilometre 893

Simulation	Q2.5	Mean	Q97.5	95% CI	STD	Skewness
Reference run		13.95				
Bedform roughness	14.07	14.29	14.56	0.49	0.14	0.15
Classification error	13.93	14.03	14.27	0.34	0.087	1.87
Veg. roughness model	13.90	13.93	14.01	0.12	0.057	1.15
Bedform + Classification	13.98	14.23	14.59	0.61	0.16	0.71
All variable	13.99	14.26	14.66	0.68	0.18	0.60

(figure 5.6) and the water depth (figure 5.7) reveals that a high standard deviation in the roughness occurs in regions with a relatively small water depth.

5.5.2 Uncertainty due to bedform roughness

Based on the 500 sampled roughness values of the main channel shown in figure 5.2, the variation in water level is computed. Figure 5.8a shows the water levels from the 500 simulations and the 95% confidence interval. This figure shows that the uncertainty range is relatively constant over the length of the river upstream of river kilometre 940. This is because for each simulation, the roughness value of the main channel is adapted with a fixed value for the whole river stretch. It indicates that the uncertainty in the main channel is equally important along the river stretch. However, slightly smaller ranges in water levels are positively correlated to regions with relatively wide floodplains. The regions between river kilometre 920 and 900 have slightly wider floodplains than the regions between 940–920 and 900–880 (see lower frame in figure 5.1) and these regions show a 5 cm smaller uncertainty range.

Figure 5.8b shows the histogram of the water levels at river kilometre 893. The histogram shows that the 95% confidence interval of predicted water levels ranges from 14.07 to 14.56 m above mean sea level (NAP) with a mean of 14.29 m. This is an interval of 49 cm. The histogram of the input samples (figure 5.2) shows a positively skewed distribution. Skewness is the third moment of a distribution and is a measure of the asymmetry of the data around the sample mean. The skewness of the roughness samples in figure 5.2 is 0.68, while the skewness of the water levels, based on these samples is 0.15. This indicates that high roughness values for the main channel do not result in extreme water levels, but are partly compensated by a higher discharge through the floodplain regions.

5.5.3 Uncertainty due to vegetation classification errors

The results of the Monte Carlo Simulation of the classification error of the floodplain vegetation led to a spatial variation of the 95% confidence interval of the variation in water levels along the river axis (figure 5.8c). The 95% confidence interval at river kilometre 893 is shown in Figure 5.8d and ranges from 13.93 to 14.27 m+NAP

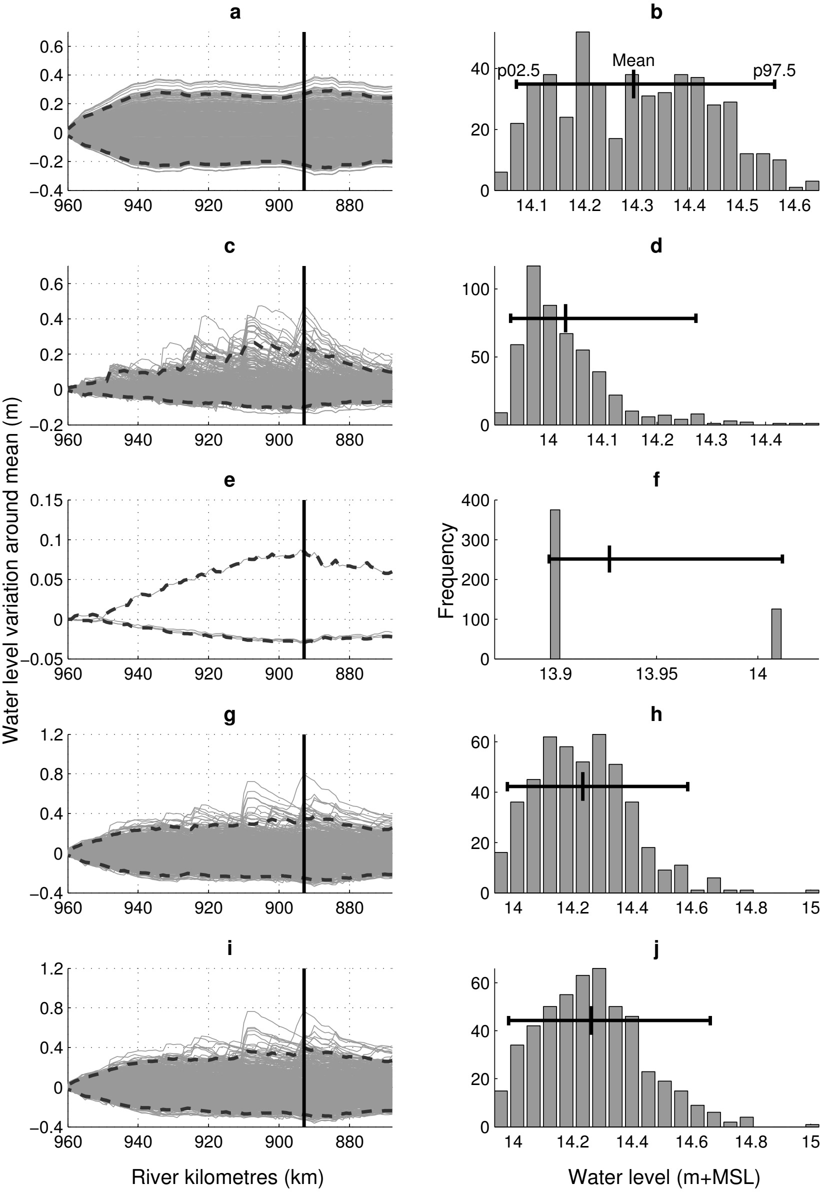


Figure 5.8: Variation in the design water levels. (a,b) uncertain bedform roughness, (c,d) uncertain classification of vegetation type, (e,f) uncertain vegetation roughness models, (g,h) uncertain bedform roughness and classification error, (i,j) results for all sources combined. Left column figures show the variation of the water levels around the average along the river axis, the right column figures show the histograms of the water levels at river kilometre 893.

with a mean of 14.03 m. This is an interval of 34 cm, which is smaller than the effect due to bedform roughness, but in the same order of magnitude. Figure 5.8d also shows that most samples are clustered around the mean, except for some outliers, resulting in a distribution with a skewness of 1.6. The positive outliers are observed along the river between river kilometre 890–935. These outliers can be explained because the polygons are changed in a spatially distributed manner, instead of uniformly as is the case for the bedform roughness. The outliers are caused by randomly sampled combinations of vegetation types that result in a strong increase of the aggregated roughness. Combinations of drawn vegetation types that extremely smoothen the floodplain areas, on the other hand, have little influence on the design water levels, which is observed as no negative outliers are shown in figure 5.8c. Another explanation for the outliers is that polygons with a very low roughness value are changed to an extremely high roughness value. For example, the map purity matrix (table 5.1) shows that approximately 20% of the polygons that are classified as groyne field, sand bar or stone protection in the reference run, have tree-type vegetation. Some of these polygons lie close to the river and may have a high specific discharge. This may significantly increase the water level if this occurs for many polygons in a certain sample.

We assumed that in the classification, the individual polygons have no spatial correlation and that the classification error is random without bias. As a result, the classification errors might cancel each other out, because at a certain location a polygon is assigned a higher roughness, while in the same realisation at another location a polygon is assigned a lower roughness. Omitting the spatial correlation and bias might, therefore, results in an underestimation of the uncertainty in the design water levels. On the other hand, Straatsma and Huthoff (2011) noted that the overall classification errors reported in table 5.1 might be overestimated, due to flaws in the validation design, resulting in an overestimation of the uncertainty.

5.5.4 Uncertainty due to the vegetation roughness model

The application of four roughness models led to different design water levels (figure 5.8e,f). For each of the 500 samples, we randomly selected one of the four roughness predictors with an equal probability. This enabled us to compute a 95% confidence interval of 12 cm, which is small compared to the uncertainty due to main channel roughness and vegetation classification. The proxies for the roughness models of Klopstra, Huthoff and Van Velzen resulted in a variation in the water levels of 0.003 m, which is negligible. This was expected as there is little variation between the predicted roughness values from these models. Only the Baptist model resulted in a maximum increase of the water levels of 12 cm. Obviously, the results are influenced by the choice to include the Baptist model. However, by lack of solid arguments to discard the Baptist model it should be treated as a valid alternative to the other models and therefore be included in the uncertainty analysis. Also, even if we assume that the Baptist model is more reliable than the other models, the uncertainty due to the vegetation roughness model is still relatively small, because the effect of the vegetation roughness model on the design water levels is relatively small.

5.5.5 Combined uncertainty in design water levels

Figure 5.8g shows the variation in design water levels due to the combined effect of uncertainty in main channel roughness and classification error. In this set of simulations, the Klopstra vegetation roughness model is used. This figure shows a combination of the relatively constant 95% confidence interval for uncertain bedform roughness and the irregular 95% confidence interval due to classification error. Figure 5.8h shows the 95% confidence interval at river kilometre 893, which ranges from 13.98 to 14.59 m with a mean of 14.23 m. The combined uncertainties resulted in an increase of the 95% confidence interval from 49 cm and 34 cm for the bedform and vegetation classification error, individually, to 61 cm for both sources combined.

The standard deviation of the design water level variation for a stretch of the river Waal varied between 0.15 m and 0.2 m (figure 5.9a). The standard deviation increased in upstream direction, but locally small differences in the standard deviation occur. These local increases in the standard deviation were caused by the different vegetation types that are sampled at that location. Figure 5.9b,c show the roughness realisations for the samples that cause the highest and lowest water level. A comparison revealed that in this particular floodplain section a large area that was classified as meadows in the sample shown in the right frame is replaced by softwood forest in the sample shown in the left frame. This causes a significant rise in the hydraulic roughness and results in a large increase in the water levels. Figure 5.6 shows that also at other locations the standard deviation of the Nikuradse roughness length is large. However, this does not result in a large variation in water levels at all of these locations. The hydraulic roughness in the floodplain that is outlined in figure 5.9 is by chance changed for the whole floodplain area. This has the effect that the discharge is conveyed to the main channel and a bottleneck is formed. Therefore, the uncertainty in the hydraulic roughness has a large effect on the water level at this location.

Figure 5.8i,j show the simulated water levels for all three sources of uncertainty combined. Figure 5.8j and table 5.3 show that the 95% confidence interval ranges from 13.99 to 14.66 m at river kilometre 893, which is a range of 68 cm, with a skewness of 0.60. These results are similar to the results where the vegetation roughness model was set deterministic. Therefore, the uncertainty due to the vegetation roughness models has little influence on the uncertainty in the design water levels and we can conclude that the uncertainty due to the vegetation roughness model is not of high importance for the uncertainty in the design water levels. To reduce the uncertainties in the design water levels, the effort should be focused on improvements to the roughness model for the prediction of bedform roughness under design conditions and to the classification accuracy of the land cover map used for roughness parametrisation.

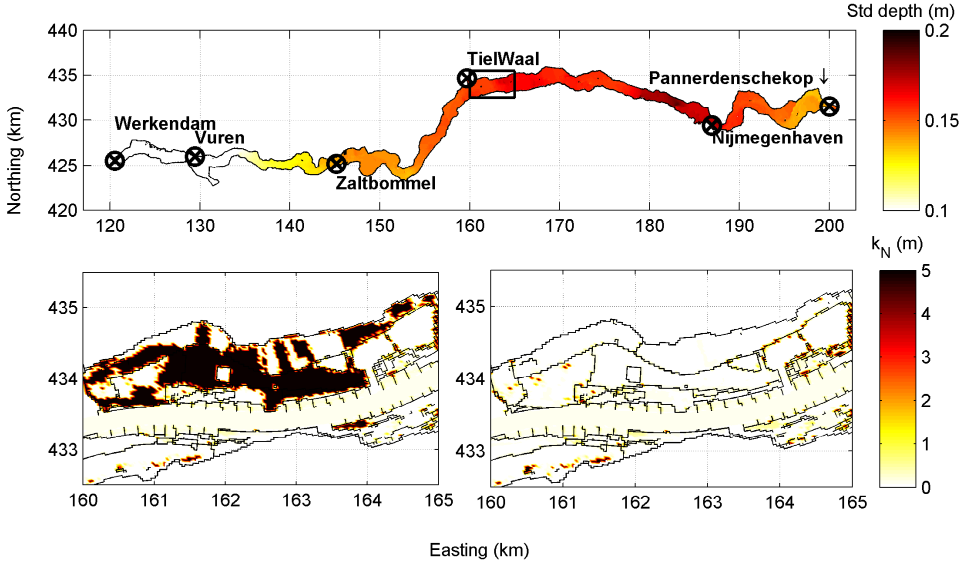


Figure 5.9: (Top) Standard deviation of the water depth due to all three sources of uncertainty. The lower frames show the Nikuradse roughness, k_N of two individual samples that caused (left frame) the highest water level and (right frame) the lowest water level

5.5.6 Accuracy of Monte Carlo Simulation

Both the width of the confidence intervals in figure 5.8 and the relatively constant standard deviation in figure 5.9a in longitudinal and cross-shore direction show that the location for reporting the uncertainty is not important. Only the results for uncertainty source FP1 show a small variation in the width of the confidence interval in longitudinal direction. This is caused by the outliers that are located only in the centre part of the study area.

The number of simulations that is used for the Monte Carlo Simulation influences the accuracy of the results (figure 5.10). The mean, and the 2.5 and 97.5 quantiles of the 95% confidence interval are shown in the left panel for the set of simulations for the combined uncertainty. The right panel shows the standard deviation of the mean, the 2.5 quantile and the 97.5 quantile. The standard deviation gives a measure of the precision of these estimates. This figure shows that the standard deviation of the mean, lower quantile and upper quantile of the confidence interval is 0.01 m, 0.021 m and 0.047 m respectively for 500 simulations. Morgan and Henrion (1990) present a simple method to estimate the accuracy of the resulting distribution. If we assume that the probability of the number of samples multiplied by the fractile represents the actual value of this fractile is normally distributed, this means that we are 95% confident that the values for the mean and lower quantile are within $\pm$ 2 cm and $\pm$ 4 cm. This precision is small compared to the width of

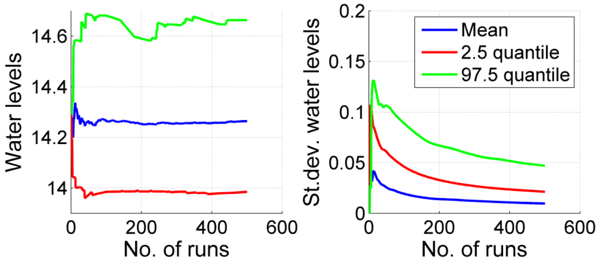


Figure 5.10: Stability analysis of the Monte Carlo Simulation for the three combined sources of uncertainty. Left: values of the mean, lower and upper quantile of water levels (m+NAP) as function of the number of simulations. Right: standard deviation of the mean and the quantiles for an increasing number of simulations

the confidence interval and shows that the number of simulations was sufficient to accurately determine the mean and lower quantile. For the 97.5% quantile, the standard deviation is relatively large, which is caused by the heavy tail of the distribution and results in a larger uncertainty of the value of the upper tail. Therefore, the 500 samples used in this study are considered rather low to accurately predict the 95% confidence interval. However, for a reliable estimate of the upper quantile many more simulations should be carried out, which is not feasible considering the large computational time. Furthermore, the uncertainty range can, with 95% confidence, maximally be about 6 cm larger. The large effort of increasing the number of simulations, therefore, has little added value to the analysis.

5.6 Discussion

5.6.1 Assumptions in the quantification of the sources

The results showed the effects of three sources of uncertainty in roughness on the design water levels. We showed that explicit quantification is possible for complex sources of uncertainty and combined these uncertainties in a Monte Carlo Simulation setting. We included the uncertainty due to bedforms, vegetation classification and the choice for the vegetation roughness model. For inclusion of the uncertainty due to the vegetation roughness model, we used an approximation of three roughness models due to technical restrictions of the hydrodynamic model. In the approximation of the Huthoff and Van Velzen roughness models, we used an equal weight for the 95% most frequently occurring water levels. Although some assumptions of the quantification of the vegetation model uncertainty are not ideal, the effect of this uncertainty proved to be small compared to the other sources. Therefore, we did not focus more attention on improving the manner in which the various roughness models are approximated in the computations.

We omitted the uncertainty in the C_D value, which might be significant for submerged vegetation according to literature (Baptist, 2005; Nepf and Vivoni, 2000). However, for grass vegetation types, the drag coefficient is of minor importance, because flow through the vegetation is negligible and the flow over vegetation is more sensitive to the vegetation height. Also, we used C_D values between 1.15 and 2.65 (in combination with adapted vegetation height) as proxy for the Huthoff and Van Velzen roughness models. This variation had only a small effect on the roughness for all submerged vegetation types (see figure 5.5) and a negligible effect on the design water levels (see figure 5.8e). Therefore, we may also conclude that omitting the uncertainty in the drag coefficient has little influence on the presented results. For non-submerged vegetation, we assumed the uncertainty in the drag coefficient to be zero. Fathi-Maghadam and Kouwen (1997) and Järvelä (2002b) have shown that the pattern and distribution of sparse trees and bushes do not have a significant effect on the friction factor, i.e. the C_D value should be practically constant in natural woody vegetation types. Järvelä (2002a) presented the average drag coefficients for two different willow patterns equal to 1.55 and 1.43, respectively. However, a sensitivity analysis carried out by the authors (not reported in this paper) showed that a change in the drag coefficient of 50% for non-submerged vegetation has a significant effect (3 cm) on the design water levels, even though the fractional coverage of woody vegetation is small (7%). This indicates that an error in the C_D value might be important. However, we could not find any evidence in the literature showing that the default value of 1.5 has a high degree of uncertainty and it is therefore assumed to be deterministic.

The exposure of the grid cell containing the vegetation to the flow (i.e. the specific discharge (m^2/s) in a cell) plays a role and should ideally be taken into account in the determination of the classification error. This requires an extensive field study where classification errors should be related to the exposure of the polygon to the flow. These data are not available and therefore this effect is not taken into account. Figure 5.9 shows that a randomly drawn sample leads to areas with extremely increased roughnesses. Whether these samples are realistic or caused by the assumptions in the methodology is subject to further research. This is worth looking into, because these extreme cases largely determine the upper tail of the confidence interval even in combination with the other sources of uncertainty.

5.6.2 Uncertainty in design water levels

We showed that it is possible to quantify the uncertainty in the roughness that is used as input for an uncertainty analysis. Previous Monte Carlo studies of roughness parameterisation (Bates et al., 2004; Aronica et al., 2002, 1998; Romanowicz and Beven, 1998) suggested uniformly distributed Manning's n values for the main channel as best describing uncertainty in their values. However, Horritt (2006) stated that other sources of Manning's n values may mean that a Gaussian description is quite suitable, for example as a result of a calibration process. We showed that it is possible to quantify the uncertainty in the hydraulic roughness explicitly and get spatially variable estimates of the uncertainty in water levels. There was no need to make strong a priory assumptions on the shape and magnitude of the distribution of the roughness values as these were explicitly quantified.

Horritt (2006) also stated that more research is required to determine whether uncertainty in the spatial variability of roughness is significant relative to other sources, such as the main channel roughness or the upstream boundary condition (Hall et al., 2005). Our study shows that uncertainty in spatially distributed vegetation has a smaller influence on the uncertainty in water levels than the main channel roughness. However, some sources of uncertainty that cause outliers (e.g. extremely dense vegetation in a region with high flow conveyance) are still important. Especially in combination with other uncertainties, such as the roughness of the main channel, this leads to an increased uncertainty in water levels.

Aronica et al. (2002) computed the uncertainty in the main channel and floodplain roughness by inverse modelling for the rivers Imari (Italy) and Thames (UK). They used the GLUE method of Beven and Binley (1992) to determine the range of roughness values for which modelled flood extent fitted the measured extent. Their results showed in concordance to our study that the main channel roughness was the largest contributor to uncertainty in flood extent. This gives confidence that the general picture is valid for a wider variety of lowland rivers than only the studied area.

The combination of the three sources of uncertainty shows the contributions of the uncertainty due to bedforms and the uncertainty due to vegetation. The results showed that the 95% confidence interval in the water levels for the case study is approximately 68 cm if we do not account for calibration. The reference run has been calibrated on the highest recorded discharge peak of 1995. In the extrapolation from the calibration conditions to the design conditions the errors that are not compensated during the calibration will cause uncertainty. In the calibration of the WAQUA model, the bedform roughness is adapted. Figure 5.11 shows the water level from the calibrated, reference run compared to the results from the uncertainty analysis. There is a difference of 31 cm between the water level from the reference run and the average of the Monte Carlo Simulations. This difference is mainly attributed to the higher roughness values for the main channel, which increased from about 0.3 m for the set of simulations with deterministic bedform roughness to on average 0.6 m for the simulations with variable bedform roughness. The calibrated bedform roughness is thus much smaller than the roughness that is expected based on the physically-based bedform roughness models. This means that the aggregated roughness of the other regions (e.g. the floodplains) is overestimated. This observation is supported by Paarlberg et al. (2010), who developed a model to predict bedform roughness and applied it to a 1D model for the river Rhine and showed that the bedform roughness can be up to 10% higher than roughness coefficients based on calibration. Furthermore, figure 5.11 shows that calibrated roughness lies within the uncertainty range of physically-based roughness values.

It is important to accurately predict the extreme water levels, because policy decisions, such as the relocation of a dike, are based on these computed water levels. In the Netherlands, the required accuracy is in the order of centimetres or deci-

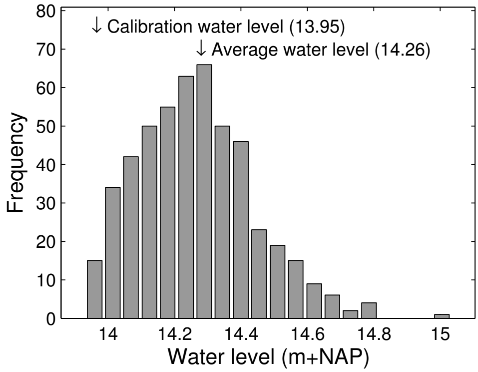


Figure 5.11: Histogram of the water levels at river kilometre 893 for all sources of uncertainty combined, compared to the water level from the reference run

metres. Although we did not account for the effect of calibration on the uncertainty, it is not expected that this uncertainty will be much larger given the fact that we included the most important sources of uncertainty. Further research is required on the possible reduction of the uncertainties due to calibration. Besides information about the magnitude of the uncertainty, also the sources of uncertainty that contribute most to the uncertainty in the design water levels and the method that is used to acquire the uncertainty range are shown. This knowledge is valuable to decision makers (Kloprogge et al., 2007). It gives the decision makers the opportunity to value the model outcomes and the associated uncertainty and gives leads for reduction of the uncertainty.

5.7 Conclusions

The objective of this study was to determine the effects of combined uncertainty in channel and floodplain roughness on the design water level for an alluvial river using a 2D hydrodynamic model. We addressed the following uncertainty sources: (1) bedform roughness of the main channel, (2) classification error of floodplain vegetation, (3) choice of roughness model. We show that combining the main contributions to the uncertainty in the design water levels results in a 95% confidence interval of approximately 68 cm, which is significant in view of Dutch river management practise. However, given that we did not account for calibration and several assumptions underlie the quantification of the uncertainties, this estimate should not be considered as an absolute value of the uncertainty in the design water levels.

The uncertainty due to the classification error is spatially distributed and caused positive outliers in the design water levels, due to clustering of rough vegetation types. These outliers increased the uncertainty, especially if they occur simultaneously with a high bedform roughness. This resulted in extreme water levels, but with a low probability. Combining the uncertainty in the bedform roughness and vegetation roughness resulted in an increase of the 95% confidence interval in the design water levels compared to the individual sources. Adding the uncertainty due to the choice of the roughness model was of minor importance. Therefore, the ranking of the uncertainties based on their contribution to the uncertainty in model outcomes is of main importance. It is not necessary to quantify all sources of uncertainty as only the most important sources determine the majority of the uncertainty in the design water levels.

The goal of quantifying the uncertainty in modelling is to provide knowledge in a form that is accessible and useful to decision makers and other stakeholders. More research is required to assess the effect of calibration on the uncertainty in the design water levels, because then an estimate of the total uncertainty can be made. Next to information about the magnitude, decision-makers also want information about the background of an uncertainty. The presented work results in this kind of information that can be used by decision makers in water management practise.

Acknowledgements

The research reported in this paper was supported by the Technology Foundation STW, applied science division of NWO and the technology program of the Ministry of Economic Affairs. We thank the Dutch Centre for Water Management for providing the WAQUA model to do the analysis. Furthermore, the authors thank Deltares for the use of their facilities. This research was also supported by the Flood Control 2015 program. For more information please visit http://www.floodcontrol2015.com.

Chapter 6

Discussion

The work presented in this thesis consists of a structured analysis of uncertainties of the two-dimensional river model WAQUA for the prediction of the design water levels for a complex source of uncertainty: the hydraulic roughness. I carried out the first four steps of an uncertainty analysis (figure 1.7): identification of uncertainties, importance assessment, quantification and propagation. In this chapter, firstly, I will reflect on the most important assumptions in each step of the uncertainty analysis. In the previous chapters it has been pointed out that calibration was not explicitly accounted for. Therefore, the effect of calibration on the quantification of the uncertainties is discussed. Finally, I will discuss the implications of the research presented in this thesis for further research and management.

6.1 Reflection on the assumptions of the uncertainty analysis

Pappenberger et al. (2008) showed that the results of an uncertainty analysis are often highly uncertain themselves and are to a large extent dependent of the assumptions made in the analysis (see also Beven, 2006a). The reliability of the outcomes of an uncertainty analysis depends on the reliability of all steps in an uncertainty analysis. Therefore, to determine the total uncertainty in the design water levels, a structural analysis and quantification of the sources of uncertainty in a model is required. Furthermore, the uncertainties in the model strongly depend on the case study and the model under consideration. This requires a structured analysis of the uncertainties for a specific case study. I used the case study of the WAQUA model for the river Waal in the Netherlands. In the following sections, the assumptions that were made in this thesis and their effect on the conclusions of the individual chapters are discussed.

6.1.1 Identification of sources of uncertainty (Chapter 2)

In chapter 2, a method is presented to identify the uncertainties in the WAQUA model in all locations as presented by Walker et al. (2003), in the model. I used classification as a method to identify the individual sources of uncertainty, which requires a clear distinction between the various classes in the Walker uncertainty matrix. However, these classes are not uniquely defined and applied in literature.

For example, Hojberg and Refsgaard (2005) refer to uncertainty about the geological structure of a groundwater model (i.e. the description of the study area) as model structure uncertainty, while according to the definitions in chapter 2 and Hunter et al. (2007) the uncertainties in the description of the study area are classified as input uncertainties. This difference in terminology hinders the discussion about uncertainties. However, for the methodology in chapter 2 the name of the class in which an uncertainty is put is not of main importance, as long as clear and consistent distinctions are made for each case study.

The limits of the model context class remain subjective, but are of main importance as they define the framing of the case study. Model context is defined in chapter 2 as: "it relates to the assumptions and choices underlying the model, which define the boundaries of the model." This implies that the context defines the model boundaries. Often model context uncertainties are omitted in an uncertainty analysis, because they are considered outside the model boundary. However, some context uncertainties do affect the extent to which model outcomes resemble a natural system. In the quantification of uncertainties in this thesis, model context uncertainties are not included, because they were not important according the aggregated expert opinions. However, experts are prone to be biased and are known to take the context of the model, which they work with, for granted (Van der Sluijs, 1997). This is shown, for example, by the few experts that mention the season in which a peak discharge occurs as an important contribution to the design water level uncertainty. These uncertainties are "recognised ignorances" and are often omitted. It proved to be difficult for the experts to consider the uncertainties in the context of the model. This is an important pitfall and may lead to an underestimation of the uncertainty. Experts are able to identify these sources. But in future studies, firstly, the experts should be made aware of the existence of uncertainties in model context. Then they should be asked explicitly about these kind of events, which has not been done in this research. Additionally, there are uncertainties that we do not know they exist (the so called "total ignorance" (Walker et al., 2003) or "unknown unknowns"). So, we know that there are factors that affect the model outcome uncertainty, but recognise that we are not able to quantify or even take them into account.

6.1.2 Importance Assessment (Chapter 3)

The goal of chapter 3 was to select the uncertainties that are taken into account in the uncertainty analysis. Experts have been interviewed and were asked which uncertainties contribute most to the uncertainty in the design water levels and to the quantify their contribution for two applications of the WAQUA model. The sources of uncertainty that were included in chapter 4 and 5 are based on the importance ranking of the uncertainties from the aggregated expert opinions. Three important sources of uncertainty have been selected: the main channel roughness, vegetation schematization and vegetation roughness model. The ranking based on the expert opinions in chapter 3 has a strong influence on the combined uncertainty in the design water levels.

The selection of the experts is known to have a large influence on the results of an expert opinion study (Van der Sluijs, 1997). Therefore, a strict selection was carried out. Only experts from the Netherlands were selected, because only Dutch experts were familiar with the WAQUA model. As shown in chapter 3 it is essential that experts are familiar to the case study. However, these experts are probably overconfident in the model and uncertainties in model structure and context might have been underestimated. This might eventually result in an underestimation of the uncertainty in design water levels.

The uncertainties due to the main channel roughness, the vegetation schematization and the vegetation roughness model have been quantified by both the experts, in chapter 3 and by data analysis, in the chapters 4 and 5. Table 6.1 shows the ranking made by the experts is the same as the ranking of the quantified values. The values given for the expert opinion data are the width of the maximum range, while the values given for the quantified data are 95% confidence intervals. The fact that the quantified uncertainties are ranked in the same way as the expert ranking gives confidence in the ranking in chapter 3. However, the absolute values of the uncertainty ranges differ a factor three for the vegetation schematization and vegetation roughness model. The difference indicates that the experts were conservative in their estimate and tend to underestimate the uncertainty.

Only three sources of uncertainty have been included in the analysis. The uncertainties in the main channel roughness and vegetation schematization both proved to have a significant influence. The uncertainty in the vegetation roughness model had little influence on the uncertainty in the design water levels. The uncertainties in the weir formulation, calibration data and main channel bathymetry discretisation were omitted, but according to the experts, the magnitude of their contribution to the uncertainty in the design water levels lies between the vegetation schematization and the vegetation roughness model. Including these sources of uncertainty will increase the uncertainty in the design water levels, however, no significant influence is expected. By making some strong assumptions I will give a crude estimate of the effect of omitting these sources on the total final uncertainty range. If we assume that the effect on the design water levels for each of the omitted sources is the average of the quantified uncertainties of the sources 3 and 7 (i.e. 34 and 12 cm; table 6.1), then each of the sources individually results in a range of 23 cm in the design water levels. If we then combine these ranges with the ranges given in table 6.1 by adding up variances, the combined uncertainty range increases by 10 cm. This crude estimate gives an indication for the effect that omitting these uncertainties might have on the reported uncertainty range. This increase is significant for a reliable estimate of the uncertainty range. Therefore, it is recommended to quantify these sources explicitly in a future study. The other sources of uncertainty (8–14; figure 3.4) have, according to the aggregated expert opinions, a smaller effect on the design water levels than the uncertainty due to the floodplain roughness model. Therefore, these sources probably have little effect on the uncertainty in the design water levels and can be omitted.

Table 6.1: Comparison of uncertainties quantified by expert opinions (chapter 3) and data analysis (chapters 4 and 5). The values for the experts show the width of the maximum water level range in cm, the quantified values show the width of the 95% confidence intervals (cm)

ID	Name	Experts (cm)	Data analysis (cm)
2	Main channel roughness	43	49
3	Vegetation schematization	10	34
7	Vegetation roughness model	4.3	12

In chapter 3, the ranking of the uncertainties from two different case studies is presented: the design water level case and the effect studies case. The same study area has been selected for both case studies. The ranking for the effect studies case that comprises the computation of the effect of changes in river geometry, was less pronounced than the ranking for the design water levels case. This is caused by the large spatial variation within the floodplains in the effect studies case. The experts could only give some general rules (see section 3.4.4), which means that the case study was not well-framed. The study area was the Waal branch of the river Rhine in the Netherlands. This section is too large to identify and rank the uncertainties for a case study in which local effects are the main outcome of interest as is the case for effect studies. Ideally, the importance of the sources of uncertainty should be assessed for a single floodplain. However, this is not feasible in practise. Experts should be able to group floodplains with similar geometry and vegetation cover characteristics with a corresponding ranking of the uncertainties. This will be less time consuming, but give a more reliable insight in the ranking of uncertainties in effect studies.

I carried out 11 interviews, which resulted, on average, in only five values for the uncertainty of each source. The number of opinions is considered on the lower end for reliable aggregation of the results, where six is considered a minimum (Van der Sluijs et al., 2004). To increase the number of opinions, without increasing the number of experts or prior identification by the interviewer, the elicitation of the experts should be carried out in two steps. Firstly, the uncertainties need to be identified by the experts and a list should be made containing all possible sources of uncertainty. Secondly, the same experts should comment on each of these identified sources, thereby also encourage them to comment on sources identified by other experts. A clear identification is of main importance for the comparison between the experts and, therefore, for the aggregation of their opinions.

6.1.3 Quantification of bedform roughness uncertainty (Chapter 4)

In chapter 4, I quantified the uncertainty based on measured bedform characteristics and extrapolation of various bedform roughness models to design conditions. This resulted in a 95% confidence interval of 0.7 m, which was dominated by the variation between the bedform roughness models.

In the quantification of the bedform roughness by data analysis a problem is that the parameters or model structure in a model do not always represent a single physical process (Cunge, 2003). For example, the parameter of the effective hydraulic roughness of the river bed in a 1D model accounts for the spatial and temporal variability and other sources of resistance in the model. Therefore, the measured roughness of the main channel does not correspond to the parameter value in the model, even in ideal circumstances. Quantification by data analysis is only useful if the uncertainty represents a physical process or parameter. In practise, the bedform roughness in the WAQUA model is calibrated and then extrapolated to design conditions. Using only the calibrated model, it is not possible to get insight in the development of the bedform roughness toward design conditions. Therefore, a physically-based approach was adopted to get insight in the processes that might occur toward design conditions. The predicted bedform roughness by the roughness models is assumed to be the same as the roughness value imposed in the WAQUA model. The physically-based roughness results in a larger value of the bedform roughness, compared to the calibrated value and enables us to quantify the uncertainty range.

The measurements of bedform characteristics and most roughness models consider only primary bed forms, so the effect of secondary bedforms is neglected. Julien et al. (2002) and Wilbers (2004) showed that secondary bedforms might significantly contribute to the hydraulic roughness of the main channel. This simplification results in an underestimation of the hydraulic roughness, as the secondary bedform roughness can be added to the primary bedform roughness (Julien et al., 2002). This might affect the uncertainty of the bedform roughness as the effect of the secondary bedforms is the same as for primary bedforms, because the same roughness model is used. Including secondary bedforms will results in a larger bedform roughness under design conditions and will also increase the uncertainty range, because the Engelund (1977) model will result in a larger increase than the Haque-Mahmood model. Furthermore, it is unknown if or how secondary bedforms will develop toward design conditions. This results in a larger uncertainty range. However, quantification of this uncertainty is difficult and can only be achieved by a better physical understanding of bedform development under peak discharges.

Another factor that is not included in the analysis is the possible transition from the "dune" regime that occurs under relatively low energy conditions (low flow velocities) to the "upper plane bed" regime that occurs during higher energy conditions (high flow velocities) where dunes are washed out (see Knighton, 1998). Currently, it is assumed that the upper plane bed is not present in the river Rhine (Julien et al., 2002). However, this assumption is under debate. This uncertainty is, therefore, a recognised ignorance, of which we know it exists, but information is not available and more research is required. The transition to upper plane bed is expected to reduce the hydraulic roughness of the main channel. This is the opposite effect as shown in chapter 4, where all roughness models show an increase of the roughness due to bedforms from calibration to design conditions. If upper plane bed conditions would occur, the average value of the predicted roughness would change. This does not mean that the uncertainty range will necessarily decrease. Because according to current knowledge both upper plane bed and bedform regimes are possible, this increases the uncertainty range, as lower roughness values might also be possible.

6.1.4 Combination and propagation of bedform and vegetation roughness uncertainty (Chapter 5)

In chapter 4, the sensitivity of the uncertainty range for the aggregated roughness of the floodplains has been determined. This showed that the uncertainty range of the design water levels due to uncertain bedform roughness increased if the aggregated floodplain roughness increased for the idealised model. This means that the water levels are more sensitive to the uncertainty in the bedforms, as the main channel has a higher discharge conveyance, because the floodplain roughness increases. This interaction between the uncertainty in vegetation and bedform roughness is also shown in the results of the realistic schematization. As numerous interactions are present between all model factors, the quantification of this interaction is difficult. This shows that the uncertainty in the water levels due to uncertain bedform roughness is mainly determined by the discharge conveyance of the floodplains.

For management practise, it is useful to know if the results of the idealised model are valid for a realistic case as the idealised model significantly reduces the computational time. In chapter 4, I used an idealised schematization of the WAQUA model for the Rhine, while in chapter 5 a more realistic schematization has been used for the Waal branch only. Figure 6.1 compares the results of the two Monte Carlo Simulations. The samples of bedform roughness were drawn randomly between the simulations. For the idealised model 1000 samples were drawn, while for the realistic model 500 samples were drawn. The figure shows that the width of the confidence interval was 53 cm and 49 cm for the idealised and realistic schematization, respectively. So, the idealised and realistic model give similar results. Differences are caused by an overestimation of the effect of the bedform roughness uncertainty by the idealised model. This is because the relative width of the main channel where bedforms are present was larger in the idealised model for two reasons. Firstly, the roughness in the region dominated by groynes between the floodplain and main channel is schematized as bedform roughness in the idealised model, but is not schematized as bedform roughness in the realistic model. Secondly, immobile layers are present in the realistic model (Tuijnder et al., 2010; Sloff, 2010) that are not schematized as bedform roughness, but by a constant roughness value, while this has not been accounted for in the idealised model. This leads to an overestimation of the region dominated by bedform roughness and, therefore, to an overestimation of the effect of the uncertainty in bedform roughness. The uncertainty from the idealised model can be used for an initial estimate of the effect of the uncertainty in the bedform roughness, as it requires significantly less computer time (4 minutes per run instead of 2.5 hours). However, based on this study, the width dominated by bedforms and the aggregated roughness of the other

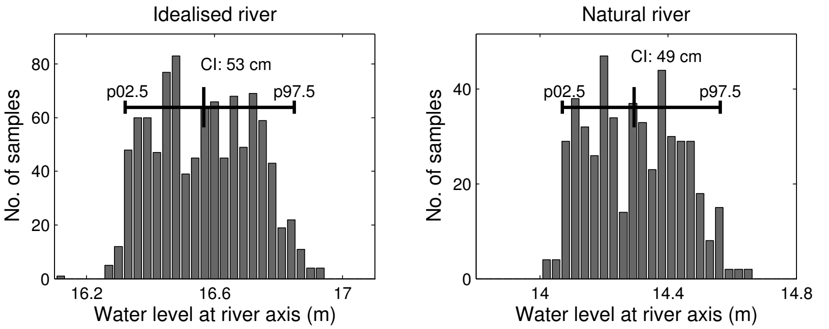


Figure 6.1: Comparison of uncertainty in design water levels due to uncertain roughness. Left: results for the idealised schematization of the Waal, right: results for the realistic schematization of river Waal. Note that the reported water levels have different reference levels

model factors should be set with care as these might affect the resulting uncertainty range in the water levels.

6.2 Effects of calibration on uncertainty in design water levels

Almost all river models require calibration to a certain extent. In the quantification and propagation of uncertainties in chapters 4 and 5, I did not take into account that in practise the WAQUA model is calibrated. In this section I discuss the effects of calibration on the uncertainty in the design water levels.

6.2.1 Calibration of the WAQUA model

In the application of the WAQUA model for design water level predictions, the relation between hydraulic roughness of the main channel and the water depth is calibrated. This relation is a simplified version of the Van Rijn (1984) roughness model for predictions of bedform roughness (see equation 5.1 in section 5.2.3). The parameters are optimised for the highest measured discharge peak, which occurred in 1995. This discharge peak had a maximum discharge of approximately 12000 m^3/s, which is 75% of the design discharge of 16000 m^3/s.

Warmink et al. (2007) studied the effect of the discharges and water levels used for calibration on the value of the calibrated roughness for the main channel. The authors calibrated the WAQUA model for eight different discharges, with correspondingly measured water levels. The results are shown in figure 6.2 and table 6.2. Figure 6.2 shows the uniform Nikuradse roughness values for the Waal section between Nijmegen and Tiel if the model is calibrated on different discharge peaks. The discharges shown on the horizontal axis are the discharge values at Lobith (where the Rhine enters the Netherlands), which are used for calibration. These

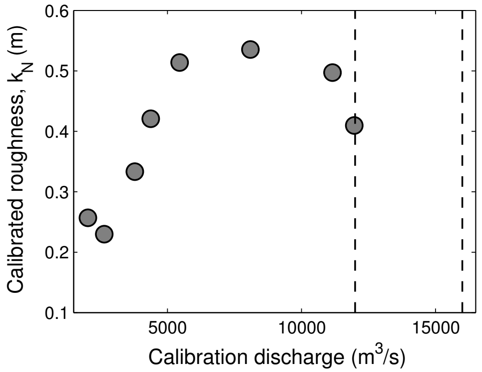


Figure 6.2: Variability in calibrated roughness values for the river stretch Nijmegen-Tiel if the model is calibrated for various discharges. The vertical lines represent the calibration (12000 m^3/s) and design (16000 m^3/s) discharges

eight calibrations resulted in eight α values, which are adapted during calibration. The α are converted to Nikuradse roughness values, k_N,using equation 5.1 and an average water depth under design conditions at the river axis of 13.2 m.

The k_N values in figure 6.2 show an increasing trend for discharges up to 8000 m^3/s, but no clear trend is shown for higher discharges. This indicates that the expected increase in the main channel roughness with increasing discharge, which is predicted by the five roughness models in chapter 4, is not represented in the calibrated roughness. The calibrated k_N values are not the same as the physically expected roughness as described in chapter 4, but they represent an "effective" roughness. This "effective roughness" includes the uncertainties due to various sources and, therefore, has no direct physical meaning (Morvan et al., 2008; Cunge, 2003). A possible trend in figure 6.2 can, therefore, not be physically explained, but should be explained by a model analysis. This study shows that there is a large variability in the bedform roughness if it is calibrated on different discharges. So, the calibrated roughness is highly uncertain and it is significantly different from the physically-expected value for the main channel roughness.

6.2.2 Effects of calibration on the uncertainty

The average k_N predicted by the five bedform roughness models in chapter 4 is 0.59 m, while table 6.2 shows that the calibrated k_N value under design conditions ranges spatially between 0.34 m and 0.67 m, with an average of 0.47 m. This is a difference of 0.12 m between the calibrated and physically expected roughness, which is caused by both the errors in the roughness models and the aggregated effect of errors in the model, such as erroneous vegetation schematization, weir formulation, errors in the calibration data, main channel bathymetry discretisation and the vegetation roughness model. The physically-based roughness is probably

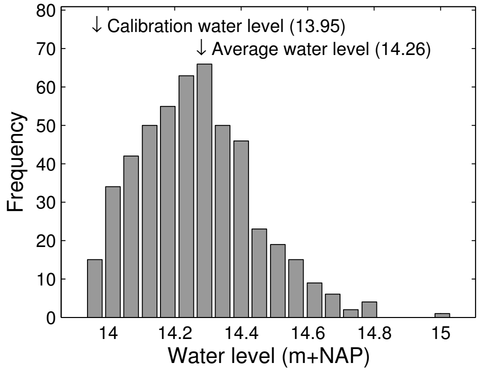


Figure 6.3: Calibration water level, computed using the calibrated roughness and the design discharge, compared to the computed water level distribution based on uncertain bedform and vegetation roughness from chapter 5 at river kilometre 893

a better estimate of the main channel roughness than the calibrated roughness. In this case, the aggregated roughness of the floodplain area and the groyne region is overestimated compared to reality. Figure 6.3 shows that the difference in roughness between the spatially averaged calibrated and average of the physically-based roughness realisations results in a difference of 23 cm in the design water levels.

The error in the calibrated roughness also results in an erroneously modelled amount of discharge through the main channel. This affects the discharge distribu-

Table 6.2: Roughness values from calibration on the 1995 discharge wave that are applied for the computation of the design water levels from (Warmink et al., 2007) compared to the physically-based roughness values from chapter 4. The bottom rows of both tables show the increase in k_N from the calibration water level (CWL) to the design water level (DWL)

Calibration (Warmink et al., 2007)					
Station	Pan.Kop	Nijmegen	Tiel	Zaltbommel	Vuren
α_{cal}	0.0561	0.0573	0.0751	0.0898	0.111
$k_{N,CWL}$ (m)	0.306	0.313	0.410	0.491	0.605
$k_{N,DWL}$ (m)	0.340	0.347	0.455	0.544	0.671
Increase in k_N	0.034	0.034	0.045	0.054	0.066

Chapter 4					
Model	Van Rijn	Vanoni-Hwang	Engelund	Haque-Mahmood	Wright-Parker
$k_{N,CWL}$ (m)	0.74	0.48	0.75	0.31	0.43
$k_{N,DWL}$ (m)	0.77	0.59	0.92	0.36	0.44
Increase in k_N	0.03	0.11	0.17	0.05	0.01

tion between the main channel and floodplains. An error in the ratio between the aggregated roughness of the main channel and the aggregated floodplain roughness has little influence on the modelled water levels under calibration conditions, but might result in significant uncertainties for effect studies, such as the "Room for the River" measures. Errors in this ratio result in an erroneous discharge distribution between main channel and floodplain. The goal of an effect study is to quantify the effect of changes in the geometry or vegetation mainly in the floodplain region on the water levels. If the discharge through the floodplain region is erroneously modelled, then the effect of a change in the floodplain geometry is uncertain. Therefore, it is important for effect studies to have a reliable ratio between main channel and floodplain roughness. To avoid this problem, the discharge distribution should also be used for calibration and ideally be validated before effects of measures are computed. To do this, measurements of the discharge distribution between main channel and floodplain should be made available.

6.2.3 Effects of extrapolation of the calibrated roughness

In the extrapolation of the calibrated model to design conditions it is assumed that the bedform roughness increases according to the WAQUA roughness model (equation 5.1). However, table 6.2 reveals that the calibrated and physically-based roughness models show a different increase of the k_N values from calibration to design conditions. The table shows an increase in k_N, according to the (calibrated) WAQUA roughness model, of around 0.046 m. This value is the difference between the predicted roughness for a calibrated α at the calibration water depth (11.4 m) and the design water depth (13.2 m). This increase is lower than expected based on the bedform roughness models. The average increase according to the five physically-based roughness models is around 0.074 m. This difference in the increase of the WAQUA and physically-based roughness models is not accounted for during calibration and can, to a large extent, be attributed to the assumed relation between water depth and bedform characteristics, that is defined by the chosen roughness model in the WAQUA model.

The magnitude of the aggregated roughness of the model factors, such as the vegetation roughness model or energy losses due to velocity differences in the flow, is not calibrated. This value is assumed constant between the calibration and design conditions. In the previous section it is shown that the calibrated bedform roughness is 0.12 m lower than the physically-based roughness. This has the effect that the aggregated roughness of the floodplains and groyne region is overestimated by a certain value, which is assumed constant between the calibration and design conditions. However, this assumption is not always valid, because the aggregated roughness of the floodplains and groyne regions is not constant from the calibration to the design conditions. Two examples will show that this assumption is not always valid.

Firstly, if we look at the vegetation roughness models (figure 5.5), this figure shows that the vegetation roughness is not constant with the water depth. This

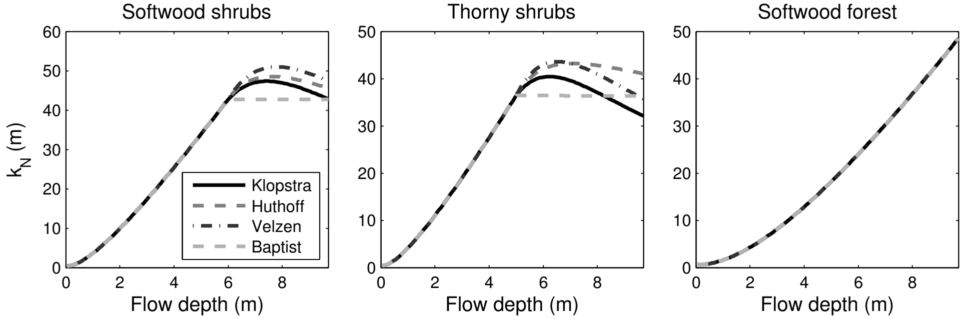


Figure 6.4: Predicted roughness k_N (m) for the four vegetation roughness models described in chapter 5 for three mainly non-submerged vegetation types

means that the hydraulic roughness changes with the water level. For example, the roughness of submerged vegetation slightly decreases with the water depth, which results in a decrease of the design water levels. For non-submerged vegetation, the roughness strongly increases with increasing water depth (see figure 6.4), which will result in an increase of the design water levels. The combined effect of these opposite trends in the development of the vegetation roughness on the aggregated floodplain roughness is unknown, because it depends on the local circumstances. Further research is required on the spatially variable aggregated roughness of the floodplains. The results of chapter 5 indicate that this effect is limited, as the contribution of the vegetation roughness model is limited. However, the example shows that the aggregated roughness in which the uncertainties are calibrated is not constant, but changes between calibrated and design conditions. Further research should be carried out to see if this effect is important to the uncertainty in design water levels.

The second example considers the energy losses due to shear layers. Shear layers exist due to differences in flow velocity, mainly between the main channel and floodplain section. The energy losses are accounted for in the model by means of an eddy-viscosity parameter. Uittenbogaard et al. (2005) showed that, instead of the calibrated value of 0.5 m^2/s, a physical derivation of the eddy viscosity for the Dutch river Waal ranged between 1.37 and 1.78 m^2/s for discharges of 16000 m^3/s and between 1.42 and 1.75 m^2/s for discharges of 12000 m^3/s. The eddy viscosity depends on the grid size, the hydraulic roughness, the water depth, the flow velocity and the slope of the river bed (Uittenbogaard et al., 2005). If the hydraulic roughness of the main channel is underestimated by calibration and consequently, the roughness of the floodplain area is overestimated, then also the velocities in both regions are erroneous. Consequently, the energy losses due to shear layers are computed erroneously, even if they were based on an "error-free" value of the eddy-viscosity. This error is compensated for during calibration. Under design conditions, i.e. higher discharge and thus higher flow velocities, the energy losses due to shear layer are different than under calibration conditions. Therefore, the error in the energy losses due to shear layers will also differ, resulting in a different aggregated roughness. Besides these two examples, the uncertainty in many other model factors, such as weir formulation or discretisation of bed levels can have similar effects that interact with the calibrated roughness, in addition to their own uncertainties.

These two examples illustrate that due to the numerous interactions between the various sources of roughness and other model factors, the extrapolation to design conditions results in an aggregated roughness that is not constant with increasing discharge. A source of uncertainty in the aggregated roughness, which is compensated for by calibration contributes to the uncertainty in the design water levels if the model is extrapolated to design conditions. This uncertainty is not corrected for by calibration. Therefore, the uncertainty after extrapolation is larger than the uncertainty during calibration conditions. In this thesis, I did not account for the possible reduction of the uncertainty by calibration. However, the two examples show that calibration does not necessarily reduce the uncertainties.

The magnitude of the uncertainty under calibration conditions is unknown as strong interactions exist between the various sources of uncertainty in the model. The magnitude of these interactions is changed by the calibration. This makes tracing of the uncertainty sources under calibration conditions highly complex. In literature, the quantification of uncertainties in calibrated river models is often carried out by inverse modelling (e.g. Romanowicz and Beven, 2003; Bates et al., 2004; Pappenberger et al., 2008). For example, the commonly used GLUE method, developed by Beven and Binley (1992), determines the uncertainty of the input and parameter space based on the performance of the model output. Therefore, a model is run with a randomly sampled set of input and parameter values. Given a certain threshold for the performance measure, the performance is qualified as behavioural or non-behavioural. The distribution of the parameter of the behavioural model runs is then used as its uncertainty. The disadvantage of GLUE is that many model runs are required, about 10 times as much as MCS, because the non-behavioural runs are not used to estimate uncertainty. Furthermore, GLUE only accounts for uncertainties in model input and parameters. In this thesis, I consider roughness in a physical context. The advantage of this approach is that model structure and context uncertainties are considered, while in a GLUE-like setting these uncertainties are omitted. However, the disadvantage of the physical approach is that uncertainties that are present under calibration conditions are not taken into account.

A combination between GLUE and the uncertainties from the used physically-based approach can be highly useful. For example, by including the various roughness models as variables in the GLUE analysis. This gives information on the uncertainty in model input and parameters and their uncertainty under calibration conditions, which can be useful in addition to the uncertainties from the physical approach. Future research on combining these approaches looks promising and may lead to an even better estimate of the uncertainty in the water levels under design conditions.

6.3 Applicability of this research

In current modelling studies, uncertainty is often not taken into account. Although the analysis of uncertainties is an essential step in the modelling cycle (Jakeman et al., 2006), it is often considered a burden (Matott et al., 2009; Refsgaard et al., 2007). In this thesis I showed that uncertainties can be explicitly quantified. This leads to an estimate of the magnitude of the uncertainty in design water levels and gives information on the range of applicability of the model and the value of the model outcomes.

6.3.1 Applicability of the methods

The identification and importance assessment approaches used in chapters 2 and 3 are generally applicable to all kinds of rivers all around the world. The reliability of the approach depends on the available number and quality of the experts. The important steps to which most attention should be paid are the selection of the experts and the framing of the case study. Expert selection should be based on objective criteria and sufficient expert opinions are required. Expert opinion studies remain subjective, amongst others, due to the selection of experts. Experts selection should be aimed at the study area. Thus, for another river or other models, other experts are required. If only a limited number of experts is available (i.e. one or two), the biases, discussed in section 3.5.2 will have a larger effect on the results. This limitation will propagate through the whole uncertainty analysis as the selected uncertainties are important for the quantification of the uncertainty range.

The methodology presented in chapter 2 helped in framing the uncertainties and the case study. This approach can be used for all types, scales and dimensions of environmental models. For model purposes, the identification and importance assessment approaches presented in chapters 2 and 3 are applicable to prediction and exploration models. However, for models aimed at communication and learning, the uncertainties in the social system, i.e. between the stakeholders, are more important than the uncertainties in the model. Therefore, the Walker uncertainty matrix is less suitable, because other locations of uncertainty should be defined, focusing on location of uncertainty in a social system (e.g. Hommes, 2008; Raadgever and Mostert, 2007).

The quantification of the uncertainties in chapters 4 and 5 is carried out for the sources of uncertainty that contributed most to the uncertainty in the design water levels. The quantification is based on available measurements. The results are, therefore, only valid for the studied section of the river Rhine. In this case, the bedform roughness proved to be important. More generally, this is the case for all rivers where 1) bedforms are the dominant resistance in the main channel and 2) where the main channel has a large discharge capacity compared to the floodplain.The experts stated that the effect of bedform roughness for the river IJssel is smaller than for the river Rhine, because the main channel is small compared to the width of the river. Therefore, the floodplain roughness has a larger contribution to the uncertainty in the design water levels (see, for example, Straatsma and Huthoff, 2011). Other rivers, such as the river Elbe (Aberle et al., 2010) or Ganges (Alam and Halim, 2002) have relatively small floodplains and the roughness of the main channel is dominated by bedforms. Therefore, the approach presented in chapter 4 can also be applied to these rivers if sufficient data are available. The selection of valid roughness models depends on the local circumstances and should be carried out thoroughly.

The extrapolation to design conditions should be carried out with care, as the transitional regime from bedforms to upper plane bed might occur and has a large influence on the uncertainty, but is not accounted for in all roughness models. In the river Ganges, measurements show that the upper flow regime often occurs (Alam and Halim, 2002). Therefore, other roughness models might be appropriate for the prediction of hydraulic roughness. Unfortunately, the ideal of a single good roughness model to predict hydraulic roughness under both low and high flow conditions does not exist, because roughness is different for each model (Morvan et al., 2008). Furthermore, measurements should be available of the bedform characteristics under varying discharges, especially for peak discharges. As discussed in Morvan et al. (2008), the roughness is expressed as a Nikuradse roughness height, k_N, which gives a lumped value of the hydraulic roughness, in which channel geometry and flow characteristics are encompassed. This means that by using the measurements for the river Waal, information about the geometry of the river is also included in the predicted k_N values. The absolute k_N values are, therefore, only applicable to the study area, but the approach is applicable to quantify uncertainties in the physically-based bedform roughness for other rivers and models.

The Monte Carlo Simulation method used in chapter 4 and 5 is straightforward and can, therefore, be applied to most rivers and models. On the other hand, the method used for the quantification of bedform and vegetation roughness is specific for the model scale. Bedform and vegetation roughness approximated by a roughness model are only relevant on a reach and small river scales. At local scales often 3D models are used in which bedform roughness should be solved explicitly. For detailed 3D models, the methods presented in chapters 4 and 5 are, therefore, not relevant. However, for larger scale 3D models, where roughness is computed by roughness models, the results of the research are relevant. The hydraulic roughness in 1D and quasi-2D models are often represented in another way, for example as a constant coefficient. The assumption that the quantified physically-based roughness refers to the same process as the roughness coefficient in the model is not valid for 1D and quasi-2D models (Morvan et al., 2008) and can be debated for fully 2D models. Therefore, the determination of physically-based roughness is not useful for 1D models, but a thorough calibration method should be used to determine the roughness values. An uncertainty analysis in 1D or quasi-2D models is often carried out using a method such as GLUE for the uncertain input and parameters, but should be combined with a method to account for model structure uncertainty, such as MMS (Multiple model simulation Matott et al., 2009; Refsgaard et al., 2007), BMA (Bayesian model averaging Todini, 2008) or model comparisons (e.g. Werner and Lambert, 2007; Horritt and Bates, 2002).

6.3.2 Applicability of the results

The ranking of the uncertainties in chapter 3 is only valid for this model and study area. Other rivers, even within the Netherlands, may result in another ranking of the uncertainties. Similarly, other models may have different model structures and context, which will result in another ranking of the uncertainties.

In this thesis, I omitted the uncertainty in the design discharge due to statistical extrapolation of the measured discharge series. This choice was made, because the design discharge is assumed deterministic in practise in most government protocols (Rijkswaterstaat, 2007; Delta Committee, 2008) and the focus of this research is the uncertainty within the model and less on the boundary conditions. The uncertainty in the design discharge has been quantified by (Parmet et al., 2001). The IPCC report (IPCC, 2007) indicated that there is a high confidence that river discharges will increase in the future due to climate change. The Delta Committee (Delta Committee, 2008) followed this advice and recommended to take a design discharge of 18000 m^3/s into account. In future research, the effect of the uncertainties in bedform roughness and vegetation roughness should also be studied for this discharge. It is expected that the uncertainty in the design water levels will increase as the design discharge increases, because other physical processes might occur that are not considered in the model. Also, the discussion in section 6.1.3, about the occurrence of a transitional regime will be increasingly relevant. Finally, due to the increase in flow velocities, the circumstances at a design discharge of 18000 m^3/s might be significantly different, so other “recognised ignorance” uncertainties should also be reconsidered.

Ogink (2003) quantified the uncertainties in the design water levels. However, the analysis was based on strong assumptions and linear combination and propagation of the sources of uncertainty. The author concluded that for the river Waal, the 95% confidence intervals were 20 cm, 20 cm and 40 cm for representativeness (i.e. extrapolation), schematization and physical processes, respectively. Combined (by summing up variances), the author showed that this results in a total uncertainty range of 48 cm. This uncertainty range is in the same order of magnitude as the uncertainties computed in chapter 5, where a range of 68 cm was determined. Ogink (2003) also omitted the uncertainty in the design discharge, but accounted for 13 sources of uncertainty and calibration. His quantification is less thorough than the quantification in the chapters 4 and 5, but gives a good estimation of the order of magnitude of the uncertainties. The interactions between uncertainties are not considered and non-linear effects have not been accounted for. This more simple approach can be used to select the important uncertainties or use a rough estimate of the uncertainties in a model.

If time is limited, the ranking of the sources of uncertainty based on their contribution to the uncertainty in the water levels is the most important step, because this determines which uncertainties should be focused on. The uncertainties that are less important can then be omitted. Besides the ranking, the quantification of the most important sources of uncertainty should be the main point of focus.

6.3.3 Implications for management

In the newly developed Delta Programme (Delta Committee, 2008), the Delta Model plays an important role. This Delta model is the collection and standardisation of models used for the Dutch water management. I recommend to include uncertainty analysis in all studies that are carried out in the scope of the Delta Program. Besides the uncertainty in input and parameters, different models and model schematizations should be compared, to account for model structure uncertainty. The Delta Model, in which multiple models are collected, is an opportunity to do this as sometimes different models are available for a study area. Ideally, multiple models are used to compute a result for a single case study and the results from these models are combined to yield a single outcome with an associated uncertainty. This multi-model approach has the potential of increasing the knowledge about uncertainty and, therefore, the reliability of the model outcomes.

An uncertainty analysis should not be an "end of the pipeline" analysis, which is carried out after model development, calibration and validation. Uncertainty analysis should be considered in the initial stages of each model development or modelling study. This has the advantage that the identification increases the awareness of the modeller/developer of the possible pitfalls that might occur during the modelling. Identification also helps in the communication between experts, modellers and stakeholders about uncertainties and assures that people refer to the same subject. Furthermore, quantification of uncertainty requires more detailed information than a deterministic model. If the uncertainty analysis is considered in advance, the data required for the uncertainty analysis can be accounted for in future measurement campaigns, which may largely increase the reliability of the uncertainty analysis. Finally, the uncertainty analysis increases the reliability of the results and gives a better view on the range for which the model outcomes are valid.

The goal of quantifying uncertainty in modelling is to provide knowledge in a form that is accessible and useful to decision makers and other stakeholders (Pappenberger et al., 2006). I quantified the uncertainty in the design water levels and gave insight in the background of the uncertainties. This background is required as part of the communication about uncertainties (Kloprogge et al., 2007). This information can be used by the decision maker to value the uncertainty range, look for opportunities to reduce the uncertainty and to better judge the applicability of the model. The research in this thesis gives insight in the causes of the uncertainties in water levels and also gives directions to reduce the uncertainties. The results of this thesis also give an estimate of the magnitude of the uncertainty in design water levels due to uncertain roughness. Although there are some limitations, the results are considered to be representative and the most reliable estimate for the case study. Furthermore, it is shown how to apply uncertainty analysis in practise for a single study area. Although the magnitude of the various sources of uncertainty are different for each study area and model, the approach is more generally applicable.

Chapter 7

Conclusions

The objective of the research presented in this thesis was to quantify the uncertainties in the hydraulic roughness that contribute most to the uncertainty in model outcomes and quantify their contribution to the model outcome uncertainty of a 2D hydrodynamic model for a lowland river under design conditions. In this chapter, first the answers to the five research questions that are defined in the introduction are given and I will reflect upon the objective. Subsequently, recommendations for future research and management practice are given.

7.1 Conclusions

Q1 In what way can the uncertainties in a 2D hydrodynamic river model be identified, specifically concerning hydraulic roughness? (Chapter 2)

Identification is the first step of an uncertainty analysis. The reliability of the results of an uncertainty analysis strongly depends on the included uncertainties. An unreliable identification may lead to an unbalanced comparison of the different uncertainties. Therefore, there is a need for a list of unique and complementary uncertainties. Often only uncertainties in model input and parameters are considered, but uncertainties are also present in the context and structure of a model. It is important to be aware of these sources of uncertainty and consider them in uncertainty analysis studies. In chapter 2, I show a general method for a structured identification of uncertainties to acquire this list of unique and complementary uncertainties. This method consists of iterative classifying the sources of uncertainty in the adapted classification matrix of Walker et al. (2003) and in each step more specifically specifying the uncertainties until classification is possible along all three dimensions of uncertainty. If this is achieved, then the uncertainties are uniquely identified.

To enhance the objectivity in the uncertainty identification process, the existing uncertainty framework by Walker et al. (2003) has been adapted. New sets of definitions are formulated that are used to distinguish the classes and make the classification scheme better applicable for identification and classification of uncertainties in environmental modelling practice. It is impossible (and often not feasible) to be complete in the identification of all uncertainties, but by being as accurate and comprehensive as possible, a sound basis is laid for quantification or description of the uncertainties in environmental models for prediction and exploratory purposes.

Using this approach, I show that the hydraulic roughness, which is a complex source of uncertainty can be explicitly unravelled. The hydraulic roughness consists of uncertainties in all locations, as defined by Walker et al. (2003) in the model. Its quantification comprises quantitative methods, qualitative methods or scenario analysis method. Using the new approach, this complex uncertainty is broken down in smaller components, which simplified the quantification and propagation of the uncertainties, because a consistent overview is given.

Q2 Which uncertainties contribute most to the uncertainty in water levels for design conditions and effect studies cases, taking all types of uncertainties into account? (Chapter 3)

Expert opinion elicitation has been used to identify the uncertainties that contribute most to the uncertainties in the design water levels for the river Rhine as the second step in the uncertainty analysis. The use of a Pedigree analysis assured an objective selection of experts and gave confidence that the outcomes of the expert interviews are reliable. I used the approach presented in chapter 2 to assure that all locations of uncertainty in the model are considered, including uncertainties in model structure and context. The uncertainties in two applications of the WAQUA model have been studied: 1) the computation of the design water levels and 2) effect studies, which are studies about the effect of measures taken in the floodplain areas that change the geometry of the cross section. The expert opinions show that different uncertainties are the dominant contributors to the uncertainty in water levels. In the design water level case, the uncertainties in the water levels are dominated by the sources of uncertainty that change between the calibration conditions and the design conditions.

The aggregated expert opinions showed that the upstream discharge and the empirical roughness equation for the main channel contribute most to the uncertainty in the design water levels. The ranking of the uncertainties from important to less important was strengthened by the combination of qualitative and quantitative information from the expert opinions about the uncertainties. The experts were able to give a range for the uncertainties in terms of water levels. The values for the uncertainty in design water levels stated by the experts should not be used directly, but merely as an indication. Therefore, the elicited values are only used to rank the uncertainties from high to low contribution to model outcome uncertainty.

In the effect studies case, the sources of uncertainty that are subject to the strongest flow conveyance contribute most to the uncertainty in the water levels. For example, the uncertainty caused by a small forest in a floodplain is only important if it is located in a region with a large water flow. This has the result that the uncertainties for effect studies are dominated by the local flow field. Therefore, the ranking given by the experts to the importance of the various sources of uncertainty was less clear. It is revealed that the case study of the river Waal was not specific enough to get a reliable ranking for the effect studies case. Further research is required with more specific case studies to asses this ranking.

Q3 How large is the uncertainty in the bedform roughness of a lowland river under design conditions? (Chapter 4)

The hydraulic roughness in the main channel of many lowland rivers is dominated by the resistance due to bedforms that develop on the river bed. However the relation between roughness and the development of bedforms is not yet fully understood and is highly uncertain. In chapter 4, I showed that the predicted roughness values vary under design conditions for different bedform roughness models (empirical equations to predict resistance) for the same measurements of bedform dimensions and flow characteristics. To quantify the uncertainty in the roughness due to bedforms under design conditions, I unravelled the uncertainty due to bedforms into three sources of uncertainty: the uncertainty due to the choice of the roughness model, the uncertainty in the data and the uncertainty due to extrapolation from calibration to design conditions.

The three sources of uncertainty due to bedform roughness are quantified and combined. The combined uncertainty is quantified by statistical extrapolation of historical measurements of bedform characteristics under high discharges. This shows that the 95% confidence interval of the Nikuradse roughness length for the main channel of the river Rhine under design conditions ranged from $k_N = 0.32$ m to $k_N = 1.03$ m, which is a range of 0.71 m. It is shown that from the three sources of uncertainty, the uncertainty due to the choice of the roughness model (a model structure uncertainty) contributes most to the uncertainty in the design water levels. The reported value of the uncertainty range of the bedform roughness should not be considered as an absolute value as few measurements were available and some assumptions are taken in the quantification process. However, it is the best available estimate. Furthermore, other factors are not included in the analysis, such as the presence of secondary bedforms or possible transition to upper plane bed. These factors might increase or decrease the bedform roughness under design conditions. If these factors were included, the uncertainty range would increase.

Q4 What is the effect of the uncertainty in the hydraulic roughness on the design water levels? (Chapters 4 and 5)

The Monte Carlo Simulation using a simplified schematization of the WAQUA model (chapter 4) shows that the quantified uncertainty due to bedforms result in a 95% confidence interval for the design water levels with a range of approximately 70 cm. However, this value should not be considered as an absolute value, but merely as an order of magnitude as strong assumptions underly the simplified model and the surface area dominated by bedforms is overestimated.

The Monte Carlo Simulation using a realistic WAQUA model of the river Waal showed that the uncertainty in bedform roughness results in a range of design water levels with a 95% confidence interval of 49 cm with a uniform width in longitudinal direction. This value is more realistic than the simplified schematization. However, we did not account for calibration. A comparison between the results of these two models showed that the uncertainty from the simplified model had the same order of magnitude, but differed 21 cm. It is concluded that the simplified model can be used in practice for an initial estimate (order of magnitude) of the effect of sources of uncertainty. However, for a realistic estimate of the uncertainty a realistic model is required.

Q5 What is the combined effect of the uncertainties in bedform and vegetation roughness on the uncertainty in the design water levels? (Chapter 5)

In chapter 5, the uncertainties in bedform roughness (quantified in chapter 4) are combined with the vegetation classification error (quantified in Straatsma and Huthoff, 2011) and the uncertainty due to the vegetation roughness model (quantified in chapter 5). The uncertainties in the vegetation roughness model proved to have little influence on the uncertainties in the design water levels. However, only four vegetation roughness models were included in the comparison.

The uncertainties in the bedform roughness resulted in a uniform confidence interval in longitudinal direction. The uncertainties due to the vegetation classification error resulted in spatially variable uncertainties in the roughness, which caused a positively skewed distribution of design water levels. This revealed that outliers in the vegetation classification are important. However, the statistical probability of these outliers is small and whether these realizations are realistic should be subject to further research.

The combination of both uncertain bedform roughness and vegetation roughness showed that the 95% confidence interval increased from 49 cm and 34 cm, for both sources individually, to 61 cm if they were combined. Including the uncertainty in vegetation roughness resulted in an uncertainty range of 68 cm. However, these values have not been corrected for the effect of calibration on the uncertainty in design water levels. It has been shown that positive outliers in the vegetation roughness increase the uncertainty in the design water levels due to uncertain bedform roughness. This showed that interactions between the various sources of uncertainty are important for the uncertainty in the design water levels.

General objective to quantify the uncertainties in the hydraulic roughness that contribute most to the uncertainty in model outcomes and quantify their contribution to the model outcome uncertainty of a 2D hydrodynamic model for a lowland river under design conditions.

In this thesis, an uncertainty analysis has been carried out for a case study of the two-dimensional WAQUA model of the river Waal that is used to predict the design water levels for flood safety purposes in the Netherlands. The first four steps of an uncertainty analysis have been carried out from identification of the uncertainties to the quantification of the combined effect of three important sources of uncertainty in hydraulic roughness on the design water levels. This research showed that the uncertainty of a complex model factor, such as the hydraulic roughness, can be quantified explicitly. Therefore, the hydraulic roughness has been unravelled in separate components, which have been quantified separately and then the uncertainties of the individual sources were combined and propagated through the model. The quantified uncertainties are presented as 95% confidence intervals of the sources of uncertainty and of the design water levels.

The final uncertainty range of 68 cm is significant in view of Dutch river management practice. However, the results of an uncertainty analysis are inherently unverifiable and I did not account for calibration. The thorough analysis ensures that the reported uncertainty ranges are the best estimates of uncertainty in the design water levels. The added value of this thesis is that it is shown that the uncertainties in a modelling study can be made explicit. This showed that the process of uncertainty analysis helps in raising the awareness of the uncertainties and enhances communication about the uncertainties. Furthermore, it is shown, which measures should be taken to reduce the uncertainties and what benefits in terms of reduced uncertainty in water levels can be accomplished. Finally, to get to a better estimate of the uncertainty further research is required into the effect of the weir formulation, discretization of the main channel bathymetry and the effect of calibration on the uncertainty range.

7.2 Recommendations

In this research some further challenges were identified. As this research is both scientific and might have practical implications for water management in the Netherlands, recommendations are given for both.

7.2.1 Recommendations for further research

A thorough identification using, for example, the adapted Walker matrix, is required in the early stages of any modelling study. The methodology presented in chapter 2 can be used in uncertainty analyses in water resources management studies. In these kind of studies not only models play a role, but also the interactions with stakeholders are important and cause uncertainties (Van der Keur et al., 2008, 2010). Therefore, the matrix needs to be adapted with some other locations that are oriented towards management instead of modelling. In further research the applicability of the iterative classification method to these kind of uncertainty analysis studies should be investigated. This enables an explicit assessment of uncertainties, which is useful in water resources management. Furthermore, the methods for uncertainty quantification and qualification (as described in Van der Keur et al., 2010) can then be linked to the classified uncertainties.

The ranking of the sources of uncertainty in the effect studies case showed that the case study was not well framed. In future research the ranking of the uncertainties for effect studies should be carried out for a more specific case study of, for example, a single floodplain development plan. The Delta Committee (Delta Committee, 2008) recommended to implement the measures in the "Room for the River" program as soon as possible. It is recommended to carry out a separate importance assessment for each study area, where measures will be implemented, to get insight in the important uncertainties. This may be cumbersome, so to avoid a separate importance assessment for every study area, experts may be able to group floodplains with similar geometry and vegetation cover characteristics for which the uncertainties are comparable.

In this research only three important sources of uncertainty are quantified. The effect of the weir formulation, the discretization of the main channel bathymetry and the effect of uncertainties in the calibration data have not been quantified, but may also contribute to the uncertainty in the design water levels. Therefore, it is recommended to quantify these sources of uncertainty in a similar manner as shown in chapter 4 and 5 and assess the effect on the design water levels.

Chapter 5 showed that the largest uncertainty is caused by the uncertainty in the bedform roughness. To reduce this uncertainty and, thereby, the uncertainty in the design water levels, more knowledge should be included in the prediction of roughness due to bedforms. Furthermore, the relation to predict main channel roughness should not be subject to calibration, because knowledge is available about the bedform roughness that is not taken into account in current practice. However, calibration remains necessary. Therefore, an additional parameter should be included in the model, that does not represent a physical process, but is only a calibration coefficient. This enhances the transparency of the model and includes more physical knowledge in the model.

Further research is also required into the development of the bedform roughness. A main source of uncertainty is the occurrence of the transition of bedforms to upper plane bed under design conditions. As this deals with circumstances that have never occurred, research into the circumstances that will occur during design conditions and research into the development of bedforms under these conditions is required. As little is known about this transition, firstly, the physical processes that drive the transition to flat bed should be studied by flume measurements. Only then it might be possible to predict if this transition actually occurs under design conditions.

The possible reduction of the uncertainties under design conditions due to calibration have not been taken into account when quantifying the uncertainty ranges in the design water levels. However, calibration does not necessarily mean that the uncertainty is reduced nor that it is increased. Therefore, more research should be carried out to study the effect that calibration has on the uncertainty in the design water levels. This is a necessary step in the goal to get a realistic estimate of the uncertainty in design water levels. GLUE is a promising method for quantification of the sources of uncertainty under calibration conditions. However, GLUE needs to be extended to account for model context and model structure uncertainty that have been quantified in this thesis.

7.2.2 Recommendations for management

A thorough identification using, for example, the adapted Walker matrix, is required in the early stages of any modelling study, for example, in the scope of the Delta Program and Delta Model (Delta Committee, 2008). In future research about uncertainty analysis, identification and framing of the uncertainties is of utmost importance. Uncertainties should be thought of in advance, so the data required for an uncertainty analysis should be accounted for in measurement campaigns. Then, the data that are required in the uncertainty analysis are already available, which increases the reliability of the uncertainty analysis and reduces the effort required to conduct an uncertainty analysis afterwards.

A clear identification of uncertainties in the early stages of any modelling study increases the reliability of the results and gives insight in the application range of the model. Another advantage is that communication is improved between the modeller and the client. The identification leads to better understanding of the uncertainties that are associated with the model outcomes.

The ratio between the discharges in the floodplain and main channel expresses the ratio between the aggregated roughness of the main channel and the aggregated roughness of the floodplain area. In future modelling, this characteristic should be used for calibration and validation of 2D hydrodynamic models to reduce equifinality.

The Delta Program states that we should account for a higher design discharge of 18000 m^3/s. I recommend to carry out the quantification of the uncertainties also for this design discharge. This will probably result in an increase of the uncertainty in the design water levels. Furthermore, the quantification of bedform roughness is even more important for an increased design discharge, as the gap between the calibration discharge and design discharge increases.

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Appendix A

Equations of the used bedform roughness models

Yalin, 1964

Yalin (1964) developed an analytical friction model. The grain friction is computed by:

$$c'_f = \frac{\Lambda_{st}}{\Lambda} \left(\frac{1}{\kappa} \ln \frac{11h}{k_{N|Y}} \right)^{-2} \tag{A.1}$$

$$\frac{\Lambda_{st}}{\Lambda} = 1 - \frac{\Delta}{\Lambda} \cot \theta \tag{A.2}$$

where Λ_{st} (m) is the length of the bedform stoss face, Λ (m) is the average bedform length, h (m) is the average water depth, κ is 0.4, the Von Karman constant, and $k_{N|Y} = D_{50}$ (m) is the Nikuradse grain roughness height as applied by Yalin (1964), Δ (m) is the mean bedform height and θ is the angle of the bedform lee face. Van der Mark et al. (2008a) measured the θ parameter for field data from the Rhine & North Loup River, Nebraska, USA. This data showed a range of 0.01–0.22 for the lee face slope with an average of 0.13 (Van der Mark et al., 2008a).

The form drag model of Yalin (1964) is also used by Engelund (1966) and is based on the momentum and energy conservation equations applied to expansion of a pipe flow, i.e., the Borda-Carnot equation (Van der Mark, 2009, e.g. Borda, 1766; Daugherty and Franzini, 1965 in), rather than those applied to expansion of a free surface flow. It is assumed that (a) the depth at the crest is equal to the mean depth minus half a bedform height, and (b) the water depth downstream of the influence zone of the bedform is equal to the mean depth plus half a bedform height. The form drag model of Yalin (1964) is given by:

$$c''_f = \frac{\Delta^2}{2h\Lambda} \tag{A.3}$$

Yalin (1964) used the square of the dune height. The data used to derive equation A.3 comes from flume and river data (e.g. Rio Grande & Lower Mississippi).

Engelund, 1966

In the grain friction model of Engelund (1966) first grain shear velocity u'_f is solved using:

$$\frac{u}{u'_f} = 6 + \frac{1}{\kappa} \ln \left(\frac{u'^2_f}{g S_e k_{N|E}} \right) \tag{A.4}$$

where S_e (-) is the energy slope, which can be approximated by the slope of the river bed, i, and g is the acceleration of gravity 9.81 $\mathrm{m/s^2}$. The Nikuradse grain roughness height equals $k_{N|E} = 2D_{65}$. We used the D_{50} instead as the D_{65} is unknown. Grain friction then equals:

$$c'_f = \left(\frac{u'_f}{u} \right)^2 \tag{A.5}$$

Equation A.3 is used to solve form drag.

Engelund, 1977

Engelund (1977) used the same grain friction model as Engelund (1966), but extended the analytical form drag model of Yalin (1964) with a calibration coefficient:

$$c''_f = c_E \frac{\Delta^2}{2h\Lambda} \tag{A.6}$$

in which $c_E = 2.5 \exp \frac{-2.5\Delta}{h}$. Engelund (1977) used flume data and alluvial channel data to determine the calibration coefficient. This coefficient accounts for abrupt flow expansion, effects of other bedforms, difference between brinkpoint height, variability in bedforms and others (Van der Mark, 2009).

Haque & Mahmood, 1983

Haque and Mahmood (1983) apply the following grain friction model (as reported in Van der Mark, 2009):

$$c'_f = \left(5.75 \log \left(\frac{12.27h}{D_{65}} \right) \right)^{-2} \tag{A.7}$$

and the form drag model of Haque and Mahmood (1983) is:

$$c''_f = 0.6125 \left(\frac{0.8\Delta}{\Lambda} \right)^{1.477} \left(\frac{0.8\Delta}{h - \frac{1}{2}\Delta} \right)^{0.176} \tag{A.8}$$

Haque and Mahmood (1983) based their calibration of the roughness model on flume data, canal data (30-100 m wide) and data from the Missouri River.

Karim, 1999

The grain friction model and form drag model of Karim (1999) are:

$$c'_f = 0.016875 \left(\frac{D_{50}}{h}\right)^{0.33} \tag{A.9}$$

$$c''_f = C_{K,1} \cdot C_{K,2} \frac{\Delta}{\Lambda} \tag{A.10}$$

where

$$C_{K,1} = 0.55 \left(\frac{\Delta}{h}\right)^{0.375} \left(\frac{\Lambda}{h}\right)^{-0.2} \tag{A.11}$$

where $C_{K,2} = 0.85$.

The Karim roughness model is valid for the ripple, dune, transitional and anti-dune regime (Karim, 1999). The ripple/dune regime was calibrated on flume data only, while the alluvial river data (Missouri River) was used to calibrate the transitional regime.

Van der Mark 2009

Van der Mark (2009) developed a semi-analytical form drag model, which consists of two components, (1) an expression for the form drag and (2) four calibration coefficient accounting for gradual flow expansion γ_s, bedform interactions, γ_i, the flow separation zone height deviating from the bedform height, γ_f, and the effect of variability in bedform geometry on form drag, γ_v.

$$c''_f = \gamma_s \gamma_i \gamma_f \gamma_v \frac{C_{M,1} g h^3 H''_a}{q^2 \Lambda} \tag{A.12}$$

where

$$\gamma_s = \tanh\left[1.6 \tan\left(\frac{\theta\pi}{180^o}\right)\right] \tag{A.13}$$

$$\gamma_i = 1 - 1.4 \exp\left[\frac{-\Lambda/\Delta}{12.75}\right] \tag{A.14}$$

$$\gamma_f = 0.8 \left(\frac{\Delta_f}{\Delta}\right) + 0.2 \left(\frac{\Delta_f}{\Delta}\right)^4 \tag{A.15}$$

$$\gamma_v = 1.2 + 0.0047 \exp\left[9.4 \frac{\Delta}{h}\right] \tag{A.16}$$

$$H''_a = \Delta + d_t - d_2 + \frac{q}{2g}\left(\frac{1}{d_t^2} - \frac{1}{d_2^2}\right) \tag{A.17}$$

where H''_a is the analytical energy loss due to expansion of a free surface flow, $C_{M,1} = 2.0$ is a calibration coefficient relating the analytical energy loss to the measured energy loss, Δ_f (m) is the height of the flow separation zone (m), q (m^2/s) is the specific discharge, d (m) is the mean water depth, and d_t and d_2 are the water depth at the bedform crest and the water depth downstream of the influence zone of the bedform, respectively. For a known average water depth these are derived from:

$$\frac{1}{2}\rho g(d_t + \Delta)^2 + \rho\frac{q^2}{d_t} = \frac{1}{2}\rho g d_2^2 + \rho\frac{q^2}{d_2} \tag{A.18}$$

$$d_t = h - \frac{1}{2}\Delta \tag{A.19}$$

Vanoni & Hwang, 1967

Vanoni and Hwang (1967) determined the value of the grain friction, c'_f from a graph of the friction factor against Reynolds number for several values of the relative roughness (i.e. Moody diagram). (Colebrook, 1939) applied the following expression for the grain friction, which yielded the same values of the grain friction for their data as Vanoni and Hwang (1967) determined from the Moody diagram:

$$c'_f = \frac{1}{8}\left(1.8\log\left(\frac{Re_{VH}}{7}\right)\right)^{-2} \tag{A.20}$$

where $Re_{VH} = 4uR/\nu$ denotes the Reynolds number, R the hydraulic radius related to the bed, and ν the kinematic viscosity. The ν is taken from Van Rijn (1990, tab 2.1; p.14) and depends on the temperature. For rivers often a T of 10^oC is used ($\nu = 1.307 \cdot 10^{-6}$).

The form drag model of Vanoni and Hwang (1967) is based on the hydraulic radius, the square of the average dune height and the average dune length (Noordam et al., 2005):

$$c''_f = \frac{1}{8}\left(3.3\log\frac{\Lambda R}{\Delta^2} - 2.3\right)^{-2} \tag{A.21}$$

The data used by Vanoni and Hwang (1967) to construct the Moody diagram originated from numerous laboratory and alluvial flume studies.

Van Rijn, 1993

The Van Rijn (1984) roughness model, is based on the idea that grain roughness and form roughness can be summed. This is physically wrong (Ogink, 2005), but works quite well in practise and the Van Rijn approach is one of the most commonly used roughness models for bedform roughness.

$$k_N = k'_N + k''_{N,p} + k''_{N,s} \tag{A.22}$$

$$k'_N = D_{90} \tag{A.23}$$

$$k''_{N,p} = 1.1\Delta_p(1 - e^{-25\Delta_p/\Lambda_p}) \tag{A.24}$$

$$k''_{N,s} = 1.1\Delta_s(1 - e^{-25\Delta_s/\Lambda_s}) \tag{A.25}$$

$$c_f = \frac{1}{8}\left(2.03\log\frac{12.2h}{k_N}\right)^{-2} \tag{A.26}$$

where k'_N is the Nikuradse grain roughness, k''_{Np} is the roughness due to primary dunes and k''_{Ns} the roughness due to secondary dunes. Equation A.23 is a modification of the Van Rijn (1984) approach by Van Rijn (1993) and Kleinhans and Van Rijn (2002). Equation A.22 provides the values of the Nikuradse roughness length that approach the dune height for short dunes and approach grain roughness when the dune length approaches infinity (Julien et al., 2002).

Engelund & Hansen, 1967

In the Engelund and Hansen (1967) bed resistance model firstly the water depth due to grain friction, h' is solved using:

$$\frac{u}{\sqrt{gh'i}} = 9.45\left(\frac{h'}{k_{N|EH}}\right)^{1/8} \tag{A.27}$$

where $k_{N|EH} = 2.5D_{50}$. This equation is an approximation of equation A.4. Dimensionless grain shear stress, τ'_* is then determined:

$$\tau'_* = \frac{h'S}{(\rho_s/\rho - 1)\,D_{50}} \tag{A.28}$$

where ρ is the water density and ρ_s is the sediment density. Where $\rho = 1000\,\mathrm{kg/m^3}$ and $\rho_s = 2655\,\mathrm{kg/m^3}$.

Dimensionless shear stress τ_* now follows from:

$$\tau_* = \sqrt{\frac{\tau'_* - 0.06}{0.4}} \tag{A.29}$$

Note that the dimensionless bed shear stress becomes a complex values if the dimensionless grain shear stress is smaller than 0.06. The grain friction c'_f and bed resistance coefficient c_f then become:

$$c'_f = \frac{\tau'_*(\rho_s/\rho - 1)D_{50}}{u^2} \tag{A.30}$$

$$c_f = \frac{\tau_*(\rho_s/\rho - 1)D_{50}}{u^2} \tag{A.31}$$

Engelund and Hansen (1967) used only a correction factor for the grain friction to account for form drag. Their roughness model is based only on flow characteristics. They state that they only present empirical results used for engineering purposes. Their empirical relation is based on extensive flume experiments carried out at Fort Colins by Guy, Simons and Richardson. This resulted in the relation for τ_* (eq. A.28).

Wright & Parker, 2004

The bed resistance model of Wright and Parker (2004) is an extension of the Engelund and Hansen (1967) model. The water depth due to grains friction, d' is first solved using:

$$\frac{u}{\sqrt{gh'i}} = \frac{8.32}{\alpha_s}\left(\frac{h'}{k_{N|WP}}\right)^{1/6} \tag{A.32}$$

where $k_{N|WP} = 3D_{90}$ and α_s is a stratification coefficient for which Van der Mark (2009) applies $\alpha_s = 1$ as information on sediment concentration is not available. Dimensionless τ_* is then determined:

$$\tau_* = \frac{\left(\frac{\tau'_* - 0.05}{0.7}\right)^{5/4}}{F_r^{0.7}} \tag{A.33}$$

The bed resistance coefficient is then determined using equation A.31. The data used for development of their roughness model originates from six different rivers in North America, e.g. the Rio Grande, Mississippi and Atchafalaya.

Appendix B

Equations of the used vegetation roughness models

Here we give the equations for the Klopstra, Van Velzen, Huthoff and Baptist models.

Nikuradse equivalent roughness

In this thesis we expressed roughness as an equivalent Nikuradse roughness, k_N. Therefore, the Chézy values (C_r) are converted to k_N values:

$$k_N = \frac{12h}{10^{\frac{C_r}{18}}} \tag{B.1}$$

Equation for non-submerged vegetation

The equation for non-submerged vegetation is equal for all roughness predictors.

$$C_r = \sqrt{\frac{1}{C_b^{-2} + \frac{C_D m D h}{2g}}} \qquad \text{for} \qquad h <= k \tag{B.2}$$

where C_b is the roughness of the bed below the vegetation, m, D, C_D and k are vegetation characteristics and h is the water depth. Here m is the number of stems per square meter (m^{-2}), D is the average diameter of the stems (m), C_D is the drag coefficient, k is the vegetation height (m) and $g = 9.81$ ($\mathrm{m/s^2}$) is the acceleration of gravity.

Klopstra (1997)

The equation proposed by Klopstra et al. (1997) for submerged vegetation is:

$$
\begin{aligned}
C_{r,K} = {} & \frac{2}{h^{3/2}\sqrt{2A}}\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} - \sqrt{C_1 + u_{v0}^2}\right) + \\
& \frac{u_{v0}}{h^{3/2}\sqrt{2A}} \ln\left[\frac{\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} - u_{v0}\right)\cdot\left(\sqrt{C_1 + u_{v0}^2} + u_{v0}\right)}{\left(\sqrt{C_1 e^{k\sqrt{2A}} + u_{v0}^2} + u_{v0}\right)\cdot\left(\sqrt{C_1 + u_{v0}^2} - u_{v0}\right)}\right] + \\
& \frac{u_*}{h^{3/2}\kappa\sqrt{S_b}}\left[(h-(k-h_{s,K}))\ln\left[\frac{h-(k-h_{s,K})}{z_{0,K}}\right] - h_{s,K}\cdot\ln\left[\frac{h_{s,K}}{z_{0,K}}\right] - (h-k)\right]
\end{aligned}
\tag{B.3}
$$

where

$$A = \frac{C_D m D}{2\cdot\alpha_K} \tag{B.4}$$

$$u_{v0} = \sqrt{\frac{2g}{C_D m D}} \tag{B.5}$$

$$u_* = \sqrt{g\,(h-(k-h_{s,K}))\,S_b} \tag{B.6}$$

$$h_{s,K} = g\frac{1+\sqrt{1+\frac{4E^2\cdot\kappa^2(h-k)}{g}}}{2E^2\cdot\kappa^2} \tag{B.7}$$

$$z_{0,K} = h_{s,K}\cdot\exp\left[\frac{-\kappa\sqrt{C_1/S_b\cdot e^{k\sqrt{2A}} + u_{v0}^2}}{\sqrt{g(h-(k-h_{s,K}))}}\right] \tag{B.8}$$

$$E = \frac{\sqrt{2A}\cdot C_1 \exp k\sqrt{2A}}{2\sqrt{C_1 \exp k\sqrt{2A} + u_{v0}^2}} \tag{B.9}$$

$$C_1 = \frac{2g\,(h-k)}{\alpha_K\sqrt{2A}\left(\exp k\sqrt{2A} + \exp -k\sqrt{2A}\right)} \tag{B.10}$$

The hydraulic roughness can be computed if vegetation characteristics m, D, C_D and k, the water depth h and a characteristic length scale according to Klopstra et al. (1997) α_K are known. Here $\kappa = 0.4$ (-) is the Von Karman constant, A is a constant depending on the vegetation characteristics, S_b (–) is the bed slope, u_{v0} (m/s) is the characteristic constant flow velocity in non-submerged vegetation divided by the square root of the water level slope, $h_{s,K}$ (m) is the distance between the top of the vegetation and the virtual bed of the surface layer, $z_{0,K}$ (m) is the length scale for bed roughness of the surface layer according to Klopstra et al. (1997) and E and C_1 are assisting coefficients.

This characteristic length scale α_K has been calibrated on data from flume studies by Tsujimoto and Kitamura (1990), Shimizu and Tsujimoto (1994), Starosolsky (1983), Tsujimoto et al. (1993) Nalluri and Judy (1989) and Kouwen et al. (1969), referred to in Klopstra et al. (1997). This resulted in the following best-fit relation:

$$\alpha_K = 0.0793k \cdot \ln\frac{h}{k} - 0.00090 \qquad \text{and} \qquad \alpha_K >= 0.001 \tag{B.11}$$

Van Velzen (2003)

The equation proposed by Van Velzen et al. (2003) for submerged vegetation is:

$$C_{r,V} = \frac{kU_v + (h-k)\,U_0}{h\sqrt{hS_b}} \tag{B.12}$$

where U_v is the average flow velocity in the vegetation layer (m/s) and U_0 is the average flow velocity above the vegetation. These are computed by:

$$\begin{aligned} U_v = & \frac{2}{k\sqrt{2A}}\left(\sqrt{C_2 e^{k\sqrt{2A}} + u_{s0}^2} - \sqrt{C_2 + u_{s0}^2}\right) + \\ & \frac{u_{s0}}{k\sqrt{2A}} \ln\left[\frac{\left(\sqrt{C_2 e^{k\sqrt{2A}} + u_{s0}^2} - u_{s0}\right)\left(\sqrt{C_2 + u_{s0}^2} + u_{s0}\right)}{\left(\sqrt{C_2 e^{k\sqrt{2A}} + u_{s0}^2} + u_{s0}\right)\left(\sqrt{C_2 + u_{s0}^2} - u_{s0}\right)}\right] \end{aligned} \tag{B.13}$$

$$U_0 = \frac{u_*}{\kappa\,(h-k)}\left[(h-(k-h_{s,V}))\ln\left[\frac{h-(k-h_{s,V})}{z_{0,V}}\right] - h_{s,V}\ln\left[\frac{h_{s,V}}{z_{0,V}}\right] - (h-k)\right] \tag{B.14}$$

where

$$A = \frac{C_D m D}{2 \cdot \alpha_{VV}} \tag{B.15}$$

$$u_{s0} = \sqrt{\frac{kS_b}{C_b^{-2} + \frac{mDkC_D}{2g}}} \tag{B.16}$$

$$u_* = \sqrt{g\,(h-(k-h_{s,V}))\,S_b} \tag{B.17}$$

$$h_{s,V} = \frac{1+\sqrt{1+\frac{4F^2\kappa^2(h-k)}{gS_b}}}{\frac{2F^2\kappa^2}{gS_b}} \tag{B.18}$$

$$z_{0,V} = h_{s,V}\exp\left[\frac{-\kappa\sqrt{C_2 e^{-k\sqrt{2A}} - C_2 e^{k\sqrt{2A}} + u_{s0}^2}}{\sqrt{g\,(h-(k-h_{s,V}))\,S_b}}\right] \tag{B.19}$$

$$C_2 = \frac{-2gS_b\,(h-k)}{\alpha_{VV}\sqrt{2A}\left(e^{k\sqrt{2A}} + e^{-k\sqrt{2A}}\right)} \tag{B.20}$$

$$F = \frac{\sqrt{2A}\left(-C_2 e^{-k\sqrt{2A}} - C_2 e^{k\sqrt{2A}}\right)}{2\sqrt{C_2 e^{-k\sqrt{2A}} - C_2 e^{k\sqrt{2A}} + u_{v0}^2}} \tag{B.21}$$

and

$$\alpha_{VV} = 0.0227 k^{0.7} \tag{B.22}$$

The hydraulic roughness can be computed if vegetation characteristics m, D, C_D and k, the water depth h, the roughness of the unvegetated bed C_b and a characteristic length scale according to Van Velzen et al. (2003) α_{VV} are known. Here A is a constant depending on the vegetation characteristics, S_b (–) is the bed slope, u_{s0} (m/s) is the characteristic flow velocity in the vegetation layer, u_* is the shear velocity at the transition from the vegetation to the surface layer, $h_{s,V}$ (m) is the penetration length of the turbulence in the vegetation layer, $z_{0,V}$ (m) is the length scale for bed roughness of the surface layer and F and C_2 are assisting coefficients.

Huthoff (2007)

The equation proposed by Huthoff et al. (2007) for submerged vegetation is:

$$C_{r,H} = \frac{U_T}{\sqrt{hS_e}} \tag{B.23}$$

where

$$U_T = U_{r0}\sqrt{\frac{k}{h} + \frac{h-k}{h}\left(\frac{h-k}{s}\right)^{2/3}} \tag{B.24}$$

$$U_{r0} = \sqrt{\frac{1}{C_b^{-2} + \frac{2gh}{C_D m D}}} \tag{B.25}$$

and

$$s = \sqrt{m} - D \tag{B.26}$$

where U_T (m/s) is the depth-averaged flow velocity over the total flow depth, U_{r0} is the depth averaged flow velocity in the vegetation layer in case of submerged vegetation and s is the separation length between neighbouring stems. Huthoff et al. (2007) noted that since U_{r0} is a depth-averaged value, the parameters m, D, and C_D should be treated accordingly.

Baptist (2007)

Based on the method of effective water depth, Baptist et al. (2007) developed an analytical formula for the representative roughness of vegetation. This approach includes the zero-plane displacement of the logarithmic velocity profile. This approach is similar to the method by Van Velzen et al. (2003) and is rather complex, because it needs an estimate for the zero-plane displacement (Baptist et al., 2007).

The authors applied genetic programming to approximate the analytical formula, which resulted in a simple equation and showed a good approximation for the representative roughness, valid for a wide range of vegetation properties and flow conditions (Baptist et al., 2007):

$$C_{r,B} = \sqrt{\frac{1}{C_b^{-2} + C_D m D k/(2g)}} + \frac{\sqrt{g}}{\kappa} \ln \frac{h}{k} \tag{B.27}$$

where C_b is the roughness of the bed below the vegetation. Note that for non-submerged vegetation the right-hand term approaches zero and the equation is equal to equation B.2.

Notation

Roman

A	Constant depending upon vegetation characteristics
A_r	Vegetation density (m^{-1})
C_D	Vegetation drag coefficient (–)
C	Chézy coefficient ($m^{1/2}/s$)
C_b	Chézy coefficient of the bed (below the vegetation)
$C_{r,X}$	Representative Chézy value for vegetation model X
$C_{X,x}$	Coefficient number x for the X bedform roughness model
c_f	Friction factor, defined as $f/8$ (–)
c_E	Calibration coefficient for the Engelund (1977) model
D	Average diameter of stems (m)
D_{xx}	Grain size fraction, where xx% is smaller (m)
d_t	Water depth at bedform crest (m)
d_2	Water depth downstream of the influence of the bedform (m)
F_r	Froude number
f	Darcy-Weisbach
g	Acceleration of gravity (9.81 m^2/s)
H_a''	Analytical energy loss due to expansion of free surface flow (m)
h	Water depth
h'	Water depth due to grain friction (m)
h_s	Penetration length, distance between top of vegetation and virtual bed of surface layer (m)
k_N	Nikuradse roughness length (m)
k	Vegetation height (m)
M	Number of samples for each bedform roughness model
m	Number of stems per square meter (m^{-2})
N	Number of samples
n	Manning's' n (–)
P	Pedigree score (–)
q	Specific discharge (m^2/s)
R	Hydraulic radius (m)
Re	Reynolds number

S_e	Energy slope (–)
S_b	Bed slope (–)
s	Separation length between neighbouring stems (m)
U_0	Average flow velocity above the vegetation (m/s)
U_{r0}	Depth-averaged flow velocity in the vegetation layer in case of submerged vegetation (m/s)
U_T	Depth-averaged flow velocity over the flow depth (m/s)
U_v	Average flow velocity in vegetation layer (m/s)
u	Flow velocity (m/s)
u'_f	Grain shear velocity (m/s)
u_{s0}	Characteristic constant flow velocity in non-submerged vegetation (m/s)
$u_{*,v}$	Shear velocity at the transition from the vegetation to the surface layer (m/s)
w_i	Weight factor
z_0	Length scale for bed roughness of the surface layer (m)

Greek

α	Calibration parameter in the WAQUA main channel roughness model ($m^{0.3}$)
α_s	Stratification coefficient used in the Wright-Parker roughness model
α_K	Characteristic length scale according to Klopstra
α_{VV}	Characteristic length scale according to Van Velzen
β	Calibration parameter in the WAQUA main channel roughness model ($m^{0.3}$)
γ_x	Correction factor, x, for the Van der Mark (2009) roughness model
Δ	Bedform height (m)
Δ_f	Height of the flow separation zone (m)
Λ	Bedform length (m)
Λ_{st}	Length of the bedform stoss face
θ	angle of the bedform lee face
κ	Von Karman constant = 0.4
κ_{GEV}	Shape parameter of Generalized Extreme Value distribution
μ_{GEV}	Location parameter of Generalized Extreme Value distribution
μ_G	Location parameter of Gumbel distribution
ν	Kinematic viscosity (m^2/s)
σ_{GEV}	Scale parameter of Generalized Extreme Value distribution

σ_G	Scale parameter of Gumbel distribution
ρ	Density of the water (kg/m^3)
ρ_s	Sediment density (kg/m^3)
τ_*	Dimensionless shear stress

Additions to symbols

superscript $'$	considers grain roughness
superscript $''$	considers form roughness
subscript $_p$	considers primary bedforms
subscript $_s$	considers secondary bedforms
subscript $_{\vert E}$	used for the Engelund (1966) bedform roughness model
subscript $_{\vert EH}$	used for the Engelund-Hansen bedform roughness model
subscript $_{\vert K}$	used for the Karim bedform roughness model
subscript $_M$	used for the Van der Mark bedform roughness model
subscript $_{\vert VH}$	used for the Vanoni-Hwang bedform roughness model
subscript $_{\vert Y}$	used for the Yalin bedform roughness model

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- Warmink, J.J., Booij, M.J., Van der Klis, H., Hulscher, S.J.M.H. (submitted) Quantification of uncertainty in design water levels due to uncertain bed roughness in the Dutch river Rhine. Submitted for publication

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About the author

Jord Warmink was born on 14 May 1980 in Zuidwolde (DR). He received his VWO diploma in 1998 from the 'OSG De Groene Driehoek' in Hoogeveen. In 1999, he started his study Physical Geography at Utrecht University.

During his study Jord carried out field work in the Netherlands, France and joined an excursion to the Coast of Denmark. He chose the Coastal and River Systems track, and later specialised in River Systems. He carried out his internship at the research institute Deltares (former WL| Delft Hydraulics), where he studied the effect of data assimilation by means of Ensemble Kalman Filtering for the Delft FEWS system for the river Rhine. In 2007, Jord received his Masters degree. For his graduation project he developed two novel methods for field measurements of the hydrodynamic density of different types of floodplain vegetation using terrestrial laser scanning and digital parallel photography. His work was presented at a conference in Vienna and published in an international journal. During his Masters project, he became enthusiastic about doing research and developed the ambition to get his Ph.D.

In February 2007, he started his Ph.D. research at the Department of Water Engineering and Management at the University of Twente. The research was performed in close cooperation with Deltares in Delft. The results of this work are described in this thesis. During his PhD, he assisted in several courses and supervised a MSc student.

At this moment, Jord is employed as postdoc at the University of Twente. He is working on the project River Bed Form Evolution Modelling for Flood Management.