Large-scale uncertainties in river water levels

Literature report

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May 2018
Literature report:

LARGE-SCALE UNCERTAINTIES IN RIVER WATER LEVELS

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1 Introduction

The concept of ‘uncertainty’ is not easily explained. Any person can envision his own interpretation of uncertainty, but people’s interpretations of uncertainty are not equal. One of the reasons for this is the difficulty of understanding and accepting a non-probable outcome (Pappenberger and Beven, 2006). For example: on a summer day there is a 5% chance of rain. It is then difficult to approve of the weather forecast if it starts raining. Often the predictions will be blamed, however it could also be that the very unlikely event with a probability of 5% occurred. Also amongst scientists the concept of uncertainty is still under debate. There is no scientific consensus on the question ‘what is uncertainty?’ (Walker et al., 2003), let alone that there could be consensus on how to deal with uncertainty (Warmink et al., 2017; Pahl-Wostl et al., 2011; Hall and Solomatine, 2008; Pappenberger and Beven, 2006; Walker et al., 2003).

This literature review is part of the author’s PhD project. In this project the focus is on large-scale water level uncertainties on the river branches of the Rhine in the Netherlands. After the extreme discharges on the river Rhine in the years 1993 and 1995 the program ‘Room for the River’ was initiated. The aim of this programme, consisting of 34 individual projects in total, was to increase the safety against flooding by lowering the water levels on the Rhine branches. The construction phase of the program finished around 2017. The quantitative effects of the projects have been calculated on individual basis, despite of the likely presence of cumulative effects (Kok, 2015). The aim of this research project is to quantify, for a range of water levels, the cumulative effects and uncertainties of the Room for the River projects as well as their influence on and interaction with the discharge distributions at major river bifurcation points.

The purpose of this literature report is to gain insight into current knowledge on the topic. This comprises of several work fields such as uncertainty and risk frameworks, probability analyses and river dynamics. Below four research questions have been formulated which stand at the basis of this literature review.

1. What is uncertainty and how can it be dealt with?
2. What are the (main) causes and consequences of river water level uncertainties and how can these uncertainties be reduced?
3. Which factors determine how the discharge is distributed between the branches of the river Rhine and which factors influence the uncertainty of this distribution?
4. What are the most appropriate techniques to quantify uncertainties?

Following the outline of these research questions, chapter 2 deals with uncertainty in general; what is it and how can it be dealt with? Chapter 3 discusses the topic of river water level uncertainties. Subsequently, chapter 4 describes the phenomenon of discharge distribution with a focus on the river Rhine. Chapter 5 gives an overview of some useful statistical techniques in the context of this research project. Finally, this literature report is concluded in chapter 6.
2 What is uncertainty and how can it be dealt with?

2.1 What is uncertainty?

No common understanding of uncertainty has been achieved in the scientific community (Kwakkel et al., 2010; Warmink, 2009; Pappenberger and Beven, 2006; Walker et al., 2003). A general definition is given by the Cambridge Dictionary: “Uncertainty is a situation in which something is not known or something that is not known or certain”. In engineering practice the term uncertainty goes further than “the absence of knowledge” (Walker et al., 2003). There are many words which capture (other) elements of “uncertainty”, e.g. ignorance, doubt, risk, ambiguity and imprecision (Kwakkel et al., 2010; Warmink, 2009). The variety of words capturing part of the concept of uncertainty is also reflected in the many different definitions. This is mainly caused by another way of thinking between various fields of study (Refsgaard et al., 2007). They mainly vary in terms of perspective, which can be distributed into two categories: a definition as a property of the decision maker or as a property of the knowledge (Refsgaard et al., 2007). An example of a definition from the perspective of a decision maker is given by Refsgaard et al. (2007): a person is uncertain if he or she lacks the confidence about the specific outcomes of an event. Walker et al. (2003) give a model-based definition of uncertainty: any departure from the unachievable ideal of complete determinism. For its model-perspective this latter definition of Walker is adopted in this research.

The most obvious example of uncertainty is the throw of a dice. The outcome of the throw is unknown as it may range from 1 to 6. This is a form of inherent uncertainty: the process itself contains randomness. This type of uncertainty can also be categorized as natural variability or aleatory uncertainty. Examples of such uncertainty in the field of flood risk are future values of river discharges, local sea water levels and local wind speed. This type of uncertainty cannot be reduced. The primary other category of uncertainty is the uncertainty related to our knowledge of a situation: epistemic uncertainty. This type of uncertainty is related to our ability to understand, measure and describe the system (Merz and Thieken, 2009). For a fair dice the outcome of a throw does not contain any epistemic uncertainty as the possible outcomes and their probabilities are known from theory. In flood risk examples of epistemic uncertainties are statistical uncertainty due to a lack of data or uncertainty in an extrapolation process.

2.2 How to frame uncertainty?

Although no common understanding has been reached, large scientific effort has been put into defining, conceptualizing and framing uncertainties (e.g. Kwakkel et al., 2010; Hall and Solomatine, 2008; Refsgaard et al., 2007; Walker et al., 2003). For engineering problems often the uncertainty matrix of Walker, see table 2.1, is used for uncertainty classification. In this matrix the uncertainties are classified using three dimensions: their nature, level and location.

The nature dimension of uncertainties refers to aleatory versus epistemic uncertainty and is the prime subdivision of uncertainties (Warmink, 2009). After Brugnach et al. (2008) a third nature of uncertainty is often added: ambiguity (e.g. Warmink et al., 2017; Van den Hoek et al., 2014; Straatsma et al., 2013; Kwakkel et al., 2010). Ambiguity is the result of a deviant view or perspective on the issue under consideration (Brugnach et al., 2008). This may lead to uncertainties in the outcome as a decision maker may have to face unclarity, misunderstandings and value conflicts (Kwakkel et al., 2010). Ambiguity is also related to equifinality. Equifinality is the theory in which different methods, models or parameter
Table 2.1: The original uncertainty classification matrix by Walker et al. (2003)

<table>
<thead>
<tr>
<th>Location</th>
<th>Level</th>
<th>Nature</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistical uncertainty</td>
<td>Scenario uncertainty</td>
</tr>
<tr>
<td>Context</td>
<td>Natural, technological, economic, social and political representation</td>
<td></td>
</tr>
<tr>
<td>Input</td>
<td>driving forces</td>
<td>system data</td>
</tr>
<tr>
<td>Model</td>
<td>structure</td>
<td>technical</td>
</tr>
<tr>
<td>Parameters</td>
<td>Model outcomes</td>
<td></td>
</tr>
</tbody>
</table>

settings can be considered equally valid (Pappenberger and Beven, 2006). Methods to reduce uncertainties related to ambiguity vary significantly from generally applied uncertainty reduction measures.

The level of uncertainty is described as the determinacy of the uncertainty (Walker et al., 2003). This ranges from full understanding (known known) on one side to total ignorance (unknown unknowns) on the other side. This latter level of uncertainty is obviously the most difficult to take into account as we do not even know it exists (Merz et al., 2015). By attaining knowledge on such unknown unknowns the amount of uncertainty we should account for actually increases (Walker et al., 2003). Some of the critiques on the Walker uncertainty matrix are related to the indeterminable classes of the level of uncertainty (Kwakkel et al., 2010; Norton et al., 2006). Kwakkel et al. (2010) propose an adaptation of Walker’s matrix in which four levels of uncertainty are defined: shallow uncertainty, medium uncertainty, deep uncertainty and recognized ignorance. The levels are closely related to the possibility of quantifying the uncertainties. For example: for shallow uncertainties probabilities can be determined while for recognized ignorance no quantification is made, but the possibility of a wrong outcome is left open.

The location of uncertainty is where the uncertainty arises. Walker et al. (2003) define five possible locations: the context, input, model, parameters and outcomes. This characteristic is used similarly in subsequent studies (e.g. Warmink, 2009; Refsgaard et al., 2007). Similar to the level aspect, also for this characteristic alterations compared to Walker’s original matrix have been proposed (e.g. Netherlands Bureau for Economic Policy Analysis et al., 2008). After some of the critiques a synthesized framework was proposed (Kwakkel et al., 2010) in which the element ‘context’ was changed to the system boundary and in which the element ‘model’ is divided into a conceptual model and a computer model.

An important aspect which cannot be represented by the original Walker matrix is the interaction between various sources of uncertainty (Van den Hoek et al., 2014; Warmink, 2009; Norton et al., 2006). Van den Hoek et al. (2014) describe this interaction as the ‘cascades of uncertainty’, i.e. that an individual source of uncertainty affects the output differently when another uncertainty is involved. In this case also different natures of uncertainty (aleatory, epistemic and ambiguity) can be interrelated. An example following their theory is the weather conditions which affect sediment transport after a large beach nourishment project. The transport characteristics determine the effectiveness of the project and in its turn this affects the attractiveness for a constructor, which is ambiguous. This example also demonstrates the possibility of dealing with the most relevant uncertainty (the effectiveness of the project) in various ways. Before execution more in-depth research may be undertaken to increase the knowledge on the effectiveness of the nourishment. However, also more extensive participation with constructors in the planning phase of a project may increase the attractiveness of the project. It is important to be aware of such cascades of uncertainty when dealing with uncertainties (Van den Hoek et al., 2014).
CHAPTER 2. WHAT IS UNCERTAINTY AND HOW CAN IT BE DEALT WITH?

2.3 How to deal with uncertainty?

Before addressing methods dealing with uncertainty; first the question why do we want to deal with uncertainties must be answered. One of the primary reasons is the potential influence on preferred options in a decision process (Hall and Solomatine, 2008; Pappenberger and Beven, 2006). This can be illustrated with the example of potential rainfall introduced in Chapter 1. The predicted probability of rain in this example was 5%. However, if the weather model itself is very uncertain (an epistemic uncertainty) the likelihood that it may rain increases (see Bayesian theory in paragraphs 5.1 and 5.5). If the uncertainty related to the prediction itself is considered as well, a more robust choice on whether to take an umbrella or not can be made. A robust choice is the decision which continues to be the most appropriate choice under a wide range of uncertain future outcomes (Hall and Solomatine, 2008). Therefore, by addressing (more) sources of uncertainty a more robust decision can be made.

In risk management the "precautionary principle" is an old-fashioned but still widely applied mechanism of dealing with uncertainties (Tannert et al., 2007; Walker et al., 2003). This principle is related to the key question of how much uncertainty is allowed if a decision may have negative consequences. The tendency in risk management is to remain "on the safe side". An example of the application of the precautionary principle in flood risk is the safety height that is added when designing a flood defense, see paragraph 3.2. However, the precautionary principle remains under debate as it is not a constructive (i.e. optimal) way of dealing with uncertainty (Walker et al., 2003). Some of the arguments revolved in this debate are given by Morris (2000); the precautionary rule is: simple and effective on the one hand, while potentially overly conservative and used as an argument to omit an uncertainty analysis on the other hand. This (ongoing) discussion stretches a broad environment, e.g. from flood risk (De Waal, 2016) to European law (European Commission, 2000).

A more profound method to deal with uncertainty is by performing a structured uncertainty analysis. In a (quantitative) uncertainty analysis uncertainties are identified, quantified, their effects on the output are calculated and interpreted (Morgan and Henrion, 1990). Many different structures for uncertainty analysis have been proposed in literature (e.g. Baroni and Tarantola, 2014; Hall and Solomatine, 2008; Refsgaard et al., 2007; De Rocquigny, 2007), but their steps are very similar. The adopted structure is given in Figure 2.3. For each of the steps a description is given below.

1. **Formulate the goal**: the first step in an uncertainty analysis is the definition of the goal of the analysis (Baroni and Tarantola, 2014; Hall and Solomatine, 2008; Refsgaard et al., 2007). These goals may have an implication for the method of uncertainty analysis (De Rocquigny, 2007). De Rocquigny (2007) defines four primary goals of an uncertainty analysis: understanding the system, trusting results, optimization of a decision and complying with a threshold. In this research more of these goals are applicable, but 'Understanding the system' is the primary aim of this research. The chosen goal also affects the structure of the analysis. In this study for instance steps...
2. **Inventory:** In this step an inventory of all uncertainties is made. Although a complete inventory of uncertainties is impossible (Warmink et al., 2010), effort should be put into the inventory to decrease the probability of missing an important source of uncertainty. The unavailability of data or knowledge of a uncertainty source should not be a reason to omit the source from the inventory. An inventory of uncertainties can be attained by literature review and expert input.

3. **Classify:** The definition and classification of the listed uncertainties is done in step 3 of the uncertainty analysis. The main goal is to clarify which uncertainty is specifically meant. A relevant example in the context of this thesis is ‘the uncertainty in the discharge distribution’. Specification is required as many different interpretations are possible, e.g.: the variability at the bifurcation point for a certain (extreme) discharge, the uncertainty in the modeling of the bifurcation point or the uncertainty in the discharge distribution under future conditions. This example will be elaborated upon in paragraph 4.2.3.

4. **Local sensitivities:** A local sensitivity analysis is conducted to estimate the importance of individual sources of uncertainty. This allows for prioritizing. However, it must be kept in mind that a low sensitivity does not indicate low uncertainty as the source of uncertainty itself may have a wide probability distribution or that the source is strongly correlated with another source and thereby amplifying the total uncertainty (Pappenberger and Beven, 2006). Therefore, sources of uncertainty cannot be omitted without further evidence after this step.

5. **Quantify:** One of the main steps of the uncertainty analysis is the quantification of the sources of uncertainty, depending on the scope of the analysis, as comprehensive as possible. The outcomes of the uncertainty analysis highly depend on this quantification step. Different input probabilities, but equally plausible according to experts, can lead to dramatic changes in the outcomes and therefore also to the credibility of the analysis (Pianosi et al., 2016; Baroni and Tarantola, 2014; Hall and Solomatine, 2008). Input from various sources is needed in order to find the most suitable input functions. Model parameters can for instance be found in literature, but can also be quantified by expert elicitation or their physical meaning (Pianosi et al., 2016). Inverse modeling can also be applied to find input functions in which the input functions are derived from a comparison between the model outcomes and observations (Warmink, 2009).

6. **Correlations:** The next step in the uncertainty analysis is the estimation of correlations between the input functions found in the previous step. Ignoring these correlations can lead to a serious over- or underestimation of the total uncertainty (Van den Hoek et al., 2014; Pappenberger and Beven, 2006). However, quantifying the interaction may be difficult. In simple cases the interaction between two parameters can be described by a joint probability distribution (Mara et al., 2016; Hall and Solomatine, 2008). For more complex systems this may be impossible (Pappenberger and Beven, 2006). Pappenberger et al. (2006) give the example of the interaction between channel and floodplain roughness. Models are often calibrated without two-dimensional information. In that case the covariance between the floodplain and channel roughness cannot be estimated, making it practically impossible to estimate the uncertainty due to these sources.

7. **Propagate:** The final quantitative step of the uncertainty analysis concerns the propagation of uncertainties towards the output parameter. Uncertainty propagation is based on a form of sampling from the input functions and running the model using these samples. By performing these tasks multiple times insights are gained in the uncertainty of the outcomes. This step can be combined with a global sensitivity analysis (GSA) with minimal effort (Pianosi et al., 2016). In a GSA sensitivity indices are determined, thereby apportioning the uncertainty to the different sources. This gives valuable insights into which source of uncertainty should be prioritized for the largest reduction in total uncertainty (Pianosi et al., 2016; Hall and Solomatine, 2008).

8. **Communicate:** The final step of the uncertainty analysis is the communication of the results. An understanding of the results by decision-makers is the basis for more robust decision-making. Also for the other analysis goals defined by De Rocquigny (2007), a need for clear communication exists. Visual representations often allow for a clear interpretation of the results (Bonneau et al., 2014). Uncertainty bounds are often used to indicate the amount of uncertainty, see for instance Figure 3.3. The main alternative to these bounds is the Bayesian integration of uncertainties into the out-
come (Hall and Solomatine, 2008; Geerse, 2002), see paragraph 5.5. This integrated line indicates the ‘expected value’ including the effect of uncertainties. However, this technique has a downside as it may lead to confusion in changes of the outcomes. This can be illustrated by the following example: for a flood recurrence line a lowering of the line may both indicate a reduction of the deterministic value through a physical measure or a reduction of the uncertainty (Hall and Solomatine, 2008), but which of these two effects cause the lower line is not visible. The integration of uncertainties may also be a valuable tool in earlier stages of an uncertainty analysis in cases where the amount of stochastic variables should be limited for computational reasons (e.g. a GLUE analysis, see paragraph 5.4). Although state-of-the-art techniques are available, visualization of uncertainties is an ongoing topic of discussion (Bonneau et al., 2014).

Some of the statistical techniques required for the final four steps in the uncertainty analysis will be described in Chapter 5.
3 River water level uncertainties

This chapter will focus on the occurrence of river water level uncertainties. In the Dutch rivers design water levels are determined via hydraulic models. Both the original system as the modeled interpretation of the system involve numerous uncertainties (Warmink et al., 2013c). The chapter is divided into three sections: causes, consequences and reduction of river water level uncertainties. Although the focus of the literature review will be on the Dutch Rhine branches, international literature is evaluated as well, e.g. on the Thames river in the UK (Hall and Solomatine, 2008), on the Po river in Italy (Bozzi et al., 2015) and the Mississippi river in the USA (Criss and Luo, 2017). Furthermore, the literature review is not restricted to water level uncertainties as uncertainties of flood risk, flood extent and river discharge contain strong links with water level uncertainties.

3.1 Causes of river water level uncertainties

River flow is influenced by many processes, making it a very complex system. This is also expressed in the many sources of uncertainties. According to Walker et al. (2003) and Warmink et al. (2010) the classification of sources of uncertainty is useful as a starting point for an uncertainty analysis. However, because of cascades of uncertainty (Van den Hoek et al., 2014) a classification of sources of uncertainty neglects important interrelations and interactions. So besides being time-consuming, it might not be as useful to fill in the Walker matrix. Nonetheless, it is important to be aware of different dimensions of uncertainties. For instance, the discrimination between aleatory and epistemic uncertainties can be important when considering uncertainty reduction measures as aleatory uncertainties cannot be reduced. In the subsections below uncertainty sources have been identified from literature. The literature consists mainly of researches on alluvial, lowland rivers. Furthermore specific sources are added which originate from a modeling perspective, e.g. the downstream water level. The identified sources of uncertainty in the modeling of river water levels are listed in Table 3.1. The column “int” indicates whether the named uncertainty source interacts with the uncertainty in the river water levels. This is the case when the magnitude of the influence of the uncertainty source on the river water levels is a function of the water level itself. For instance, the discharge distribution is to a large extent determined by the (uncertain) water levels downstream of the bifurcation, while the uncertainty in the discharge distribution influences the downstream water levels by a change in the discharge. Furthermore, interactions between different uncertainty sources also exist, but have not been indicated in the table. For example, the lateral exchange of discharge between the floodplain and the main channel depends on both the hydraulic roughnesses of the floodplain and the main channel, but in its turn also affects the roughnesses.

3.1.1 Upstream discharge

Water level uncertainties due to an uncertain upstream discharge are generally a dominant source of uncertainty (Bozzi et al., 2015; Warmink et al., 2011; Pappenberger et al., 2006). The upstream discharge uncertainty has various dimensions (Merz and Thieken, 2009). A large portion of the uncertainties can be attributed to statistical uncertainties. These uncertainties are the result of fitting a distribution to a limited amount of observations (e.g. Zhong et al., 2016; Di Baldassarre et al., 2009; Merz and Thieken, 2009). To begin, it is not clear if the distribution of observed values is equal to the natural distribution of the upstream discharges. If fitting a distribution to the observations and sampling from this distribution, a new set of observations are found. These will give a different, but possibly equally valid representation of reality. Uncertainties may also be a result of measurement errors. Especially for out of bank flows errors in discharge data may be substantial (Hunter et al., 2007).

Furthermore when extrapolating towards very low exceedance probabilities
Table 3.1: Major uncertainty sources of river water level uncertainties identified from literature. *The column "int" indicates the possible interaction between river water level uncertainty and the tabulated uncertainty source. Other interactions between uncertainty sources have not been indicated in the table, but do exist **The "Reference" column lists literature in which the uncertainty source has been addressed and/or quantified.

<table>
<thead>
<tr>
<th>Uncertainty source</th>
<th>Int.*</th>
<th>Reference**</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>3.1.1 Upstream discharge</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Statistical errors</td>
<td></td>
<td>Zhong et al. (2016); Bozzi et al. (2015)</td>
</tr>
<tr>
<td>• Measurement errors</td>
<td></td>
<td>Hegnauer et al. (2014); Anouk Bomers</td>
</tr>
<tr>
<td>• Physical limit to the maximum discharge</td>
<td></td>
<td>Toonen et al. (2016)</td>
</tr>
<tr>
<td>• Long-term non-stationarity</td>
<td></td>
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<tr>
<td><strong>3.1.2 Hydraulic roughness</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Main channel roughness</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>- Occurrence of bedforms</td>
<td>X</td>
<td>Warmink et al. (2013a)</td>
</tr>
<tr>
<td>- Bed form roughness formulation</td>
<td>X</td>
<td>Warmink et al. (2013a)</td>
</tr>
<tr>
<td>• Floodplain roughness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Vegetation measurement errors</td>
<td></td>
<td>Straatsma and Huthoff (2011)</td>
</tr>
<tr>
<td>- Vegetation schematization</td>
<td></td>
<td>Straatsma et al. (2013)</td>
</tr>
<tr>
<td>- Vegetation discretization</td>
<td></td>
<td>Straatsma and Huthoff (2011)</td>
</tr>
<tr>
<td>- Roughness formulation of vegetation</td>
<td></td>
<td>Warmink et al. (2013b)</td>
</tr>
<tr>
<td>- Seasonality in vegetation cover</td>
<td></td>
<td>Makaske et al. (2011)</td>
</tr>
<tr>
<td>• Lateral exchange of discharge</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>3.1.3 Discharge distribution</strong></td>
<td>X</td>
<td>Ten Brinke (2013); Ogink (2006)</td>
</tr>
<tr>
<td><strong>3.1.4 Bathymetry</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Measurement errors</td>
<td></td>
<td>Neal et al. (2015)</td>
</tr>
<tr>
<td>• Discretization</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Seasonal and longterm variation</td>
<td></td>
<td>Van Vuren et al. (2010)</td>
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<tr>
<td><strong>3.1.5 Model structure and context errors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Model limitations due to assumptions</td>
<td></td>
<td>Bomers et al. (2017, 2018)</td>
</tr>
<tr>
<td>• Discretization onto a grid</td>
<td></td>
<td></td>
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<tr>
<td>• Downstream water level boundaries</td>
<td></td>
<td></td>
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<tr>
<td>• Extrapolation errors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Head loss formulations for structures</td>
<td>X</td>
<td>Domhof et al. (2018)</td>
</tr>
<tr>
<td>• Calibration strategy</td>
<td></td>
<td></td>
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<tr>
<td><strong>3.1.6 Human river interventions</strong></td>
<td>X</td>
<td>Berends et al. (2018)</td>
</tr>
<tr>
<td>• Unknown functioning</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>• Model implementation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Model calibration on old situation</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>3.1.7 Other sources, e.g.:</strong></td>
<td></td>
<td></td>
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<tr>
<td>• Time-dependency of uncertainty sources</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Shape of discharge wave</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Ice jams and sudden break ups</td>
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</tbody>
</table>
extrapolation uncertainty is introduced. Additional to statistical uncertainties, it is also not known how the upstream river system behaves under extreme conditions. For instance, flood events upstream (e.g. in Germany for the Dutch river Rhine) cause an upper limit to the discharge (Hegnauer et al., 2014). This type of uncertainty is addressed in the ongoing research project of Anouk Bomers in the STW-project *Floods of the past, design for the future*.

### 3.1.2 Hydraulic roughness

Another important source of uncertainty is hydraulic roughness. Uncertainty due to roughness is a collection of many different uncertainties. In theory roughness can be defined on a very small scale based on measurements in the field. However, as the modeled roughness is generally a representation of all kinds of energy losses, it is not feasible to determine physically based roughness coefficients on a small scale within a large domain (Hunter et al., 2007). A discrimination between uncertainty of the roughness in the main channel and the floodplain can be made as those uncertainties have different causes. Furthermore, uncertain overbank flow (exchange of discharge between main channel and roughness) may also be an important factor in the total amount of uncertainty (Warmink et al., 2011). This uncertainty is related to the water level as well as the roughness of the main channel and the floodplains.

Main components in the uncertainty of the roughness of the main channel are due to the formulation of the roughness and the occurrence of bedforms. The formulation of the roughness in a model is empirical and is often used for calibration. This introduces an epistemic uncertainty as the formulated roughness is factually only valid under calibration conditions and introduces uncertainties for all other conditions (Warmink et al., 2013a). Bedforms have a large, but uncertain influence on river water levels via a contribution in the roughness formulation, see Figure 3.1. A variation of the roughness of up to 20% between different roughness models may occur (Warmink et al., 2013a). Furthermore, Frings and Kleinhans (2008) have shown a large spatial variability of occurrence and size of bedforms. Additionally, flattening of bedforms may occur for extreme conditions (Naqshband et al., 2017; Duin et al., 2017). This Upper Stage Plane Bed (USPB) would cause a significant reduction of roughness and as a result a reduction of the river water levels. It is still unknown whether USPB can occur under Dutch design conditions (Hulscher et al., 2017). The most probable location of USPB occurring is in the river IJssel near the city of Kampen. Finally, there is a time-dependency of the roughness due to bed forms as it is related to the stage of the flood wave (hysteresis). (Warmink et al., 2013a).

In floodplains, vegetation is generally the main contribution to the hydraulic roughness.

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**Figure 3.1**: Uncertainty in the river water depths for a constant river Waal discharge. *Left* figure: Samples per roughness predictor model. *Right* figure: combined samples. Figure by Warmink et al. (2013a).
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Figure 3.2: Illustration of vegetation classification errors on two dimensions for an example in a section of a floodplain of the river Waal: incorrect classification and classification on a different scale. Figure by Straatsma and Huthoff (2011).

An important observation is the spatial variability of the hydraulic roughness in floodplains. Assuming heterogeneity could lead to significant discrepancies (Huang and Qin, 2014). Warmink et al. (2011) divides the uncertainty of roughness due to the presence of vegetation into four components: uncertainty due to: measurement errors, schematization, discretization and formulation. Measurement errors are related to inaccuracies in the actual observations of the vegetation. Secondly, the schematization is the step in which the observed vegetation is translated to the vegetation classes in the model. The classification uncertainty, illustrated in Figure 3.2 can have a significant influence on the water levels (Straatsma et al., 2013). Thirdly, the discretization makes the translation of the schematized floodplain vegetation onto the model grid, which will suffer from scaling errors, also illustrated in Figure 3.2. Finally, the vegetation roughness formulation is an empirical formula which determines the effect of the vegetation on the flow and. In all these steps uncertainties are involved. Additionally, the roughness due to vegetation is not stationary as there may be a seasonal variation in leaf cover, which is generally not accounted for (Warmink et al., 2010). In the Room for the River project nature rehabilitation was a secondary objective. The growth of this vegetation also causes uncertainties in the water level predictions (Makaske et al., 2011). Vegetation development also infers additional spatial variability.

3.1.3 Discharge distribution over bifurcations

The division of discharge at river bifurcations is a dominant source of uncertainty for the flood risk of downstream branches. For instance, Ten Brinke (2013) state that for the river Rhine it is not known whether the downstream branches are sufficiently robust in relation to the uncertainty of the discharge distribution. The distribution of discharge contains both aleatory and epistemic uncertainties. Examples of the large amount of uncertainty sources are: uncertain capacities of the downstream branches (in its turn being influenced by other uncertainty sources), floodplain roughness (Straatsma et al., 2013), presence of bedforms (Paarlberg et al., 2010), wind (Ogink, 2006) and control structures (Ten Brinke, 2013). Moreover, an interaction loop with the water levels increases the complexity of determining the uncertainties in the system. Due to the central focus of this research on the uncertain discharge distribution Chapter 4 is dedicated to this topic.
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3.1.4 Bathymetry

Uncertainties in the bathymetry can be an important source of water level uncertainty, especially in an one-dimensional model (e.g. Habert et al., 2016). Main causes of bathymetry uncertainty are the measurements of the actual bathymetry and the discretization of this bathymetry onto a grid (Warmink et al., 2011). An important aspect in this second step is the discrimination between main channel and flood plain as the roughness formulations for the two are sections are different. Generally, the uncertainties are more important for effect studies in which the effects of a river intervention are modeled (Warmink et al., 2011). Furthermore, the water levels are more sensitive to the floodplain topography in case of overbank flow, such that uncertainties in the topography of the floodplains are dominant over uncertainties in the main channel bathymetry (Robinson et al., 2017). By using high-resolution satellite data uncertainties due to measurement errors are reduced significantly (Robinson et al., 2017). In general, uncertainties in the cross-sectional geometry have a smaller impact on the river water levels compared to other errors (e.g. hydraulic roughness) encountered in real world application of hydraulic models (Neal et al., 2015). However, a poor estimation of the geometry may lead to physically unlikely values of the roughness coefficients after calibration (Neal et al., 2015).

Longterm variability in the bathymetry is usually accounted for by regular bathymetry measurements, but it may be hard to account for in predicting future flood water levels. Furthermore, the bathymetry may undergo seasonal variations. The influence of this seasonality on the uncertainty in the water levels is likely to be negligible (Van Vuren et al., 2010). Finally, Van Vuren et al. (2010) found a minor influence of dynamic morphology during a flood wave on flood water levels in the river Rhine.

3.1.5 Model context and model structure

In the context and structure of the model itself many more uncertainties arise. Although model context and model structure uncertainties are more complex to quantify, they may result in a significant underestimation of the total amount of uncertainty (Warmink et al., 2013b). A main uncertainty source in the model context is the calibration stage in the modeling process. River models are generally calibrated on one historic (extreme) event. When the calibrated model is applied to different conditions, e.g. low-water conditions, uncertainties are introduced. Even if the model is calibrated for several discharges, uncertainties remain for the conditions of which the discharge falls between the calibration discharges (Boyans’ werk citeren).

In the structure of the model numerical representations of physical processes cause uncertainties. Domain-wide this can be the simplification of the full Navier Stokes equation into the shallow water equations (SWE). Such equations should also be discretized onto a grid, which also causes some uncertainties. Discretization errors play a role in all parameters as for each grid cell one value must be assigned, which will always be an average of the spatially varying parameter. Depending on the location in the system the downstream (external) boundary condition in the form of a constant or dynamic water level or a rating curve may also add uncertainties (Karamuz et al., 2016). A downstream water level boundary can be an open body or water or a location in the river. Downstream water levels often cause a backwater effect which (generally) increases the water level compared to equilibrium flow for up to several tens of kilometers upstream. The water level boundaries can have a dynamic level such that both aleatory and epistemic uncertainties are introduced. Furthermore a fictional downstream boundary of a model domain may cause artificial backwater effects which are non-existent in reality. The influence of backwater effects is negligible for reaches far upstream of the boundary. Finally, also the modeling of structures introduces uncertainties: e.g. a weir formulation, a groyne formulation, head losses due to bridges and inlet formulations (Warmink et al., 2011).

3.1.6 Human river interventions

If we purposely change the system by implementing river interventions, the accuracy of the model outcomes is also affected (Berends et al., 2016). The effect of a river measure on
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water levels is always a coarse estimation as measurements are generally not available (yet). Consequently, the model is calibrated using "old" data, which corresponds to the river system before the measure was implemented. It is likely that this significantly increases the uncertainty in future predictions. Furthermore, the implementation introduces epistemic errors in itself as the model implementation deviates from reality. Also the future development of river interventions is uncertain, e.g. vegetation growth in widened floodplain after a dike-setback (Makaske et al., 2011) and the morphological development of a newly constructed side channel and the main channel (Van Vuren et al., 2015).

3.1.7 Other uncertainty sources

Although it is not the aim to be complete, which is practically impossible (Warmink et al., 2010), this section lists some other uncertainty sources of river water level uncertainty. Firstly, when estimating river water levels using hydraulic models one always applies simplifications with respect to time-dependent variables. Time-dependency is present in many of the listed uncertainty sources, e.g. changes in leaf cover over the seasons and change in discharge due to climate variability. Often it is assumed that the system is constant in time, i.e. stationarity. For the river Rhine Merz and Thieken (2009) found evidence of non-stationary flood behavior (Merz and Thieken, 2009). This may be a result of structural climate change or climate variability such as the North Atlantic Oscillation and the Atlantic Multi-decadal Oscillation (Toonen et al., 2016). Merz et al. (2015) names non-stationarity of the system, along with nonlinearity and interdependences as the complex factors in a risk analysis as it may be a prime source of surprise. =It is known that also short-scale temporal changes (i.e. the shape of the discharge wave) have an effect on uncertainty sources, e.g. the discharge distribution (Ogink, 2006) and the bedform roughness (Warmink et al., 2013a).

Another source of uncertainty is the possible occurrence and the effects of ice on the rivers (Dijkstra et al., 2012; Van der Wal, 2011). River ice is common for rivers around the worlds (Sene, 2016) and can also occur in the Netherlands (Van der Wal, 2011). Ice can accumulate at certain locations in the river system (e.g. at a bridge) and form obstructions, causing an increase of water levels upstream. Observations in the river Rhine have shown that water levels can increase by a few meters (Van der Wal, 2011). Over the past few decades the possibility of ice jams occurring has decreased in the Rhine as result of industrial use of river water for cooling and climate change (Van der Wal, 2011). Due to advances in the reuse of industrial cooling water it may be possible that the probability of ice jams occurring increases again (Van der Wal, 2011). The effect of ice is currently not accounted for in the Dutch design and assessment frameworks in the determination of river water levels (De Waal, 2016).

3.2 Consequences of river water level uncertainties

If uncertainties are present in a system it is up to the decision maker how to take them into account. Multiple strategies are possible; ranging from applying the precautionary principle to an explicit correction on the basis of quantified uncertainty levels. The choice on which strategy to follow is based on arguments such as: potential risk, complexity of an uncertainty analysis and the required effort to determine uncertainty levels explicitly.

In the end always a trade-off exists in dealing with uncertainties between optimizing and robust satisficing (Hall and Solomatine, 2003). On the one hand an optimal solution has the least construction costs, but it is minimally robust to conditions that depart from the conditions for which the optimal solution was designed. On the other hand a very robust solution has larger construction costs, but remains safe under a wide range of conditions. Depending on the outcomes of an uncertainty analysis and the potential for surprises a decision maker will be at either side of the spectrum. If the uncertainties are mapped (seemingly) very accurately an optimal solution is often the preferred option compared to robust satisficing.

In Dutch flood risk calculations the approach of taking uncertainties into account is different for design and assessment purposes. A main reason for this is the different time horizon
for the two procedures. In an assessment the current loads and strengths are evaluated while for a design one has to deal with the design life of the structure. This brings in time-dependent uncertainties, such as non-stationarities in the long-term discharge. Therefore, a design is fairly robust, such that it will easily pass the first round of assessment.

The required robustness of flood protections results in the practice of applying an ‘uncertainty margin’ (Rijkswaterstaat, 2017a), i.e. the precautionary principle. This margin expresses the addition to the hydraulic loads by which the uncertainties in the water level predictions can be accounted for. More specifically, these uncertainties are the model uncertainties and the statistical uncertainties. In the most recent Design Guideline (Dutch: Ontwerpinstrumentarium; Rijkswaterstaat, 2017a) the uncertainty margin assigned to the river system is 0.3 meters. Future climate change and a corresponding increase in design discharge is taken into account by applying the W+ scenario of the Dutch bureau of meteorology (Dutch: KNMI). This scenario is the most severe climate change scenario. This coping strategy is a typical example of a conservative approach in which it is “better to be safe than sorry” (Warmink et al., 2017). This strategy is related to the underlying system which is targeted at high predictability and controllability. Although this strategy leads to a very safe system, the related costs are high (Warmink et al., 2017). The strategy of being conservative might even lead to a lock-in situation. This is the situation that by being conservative an even more conservative approach is required in time. For example, in the Netherlands the flood protection system is very strong which causes floods to become rare but also decrease the awareness of the public. Consequences of flooding increase such that the protection standards should again be increased (Warmink et al., 2017).

In the new assessment guidelines of flood protections in the Netherlands, the Wettelijk Beoordelingsinstrumentarium 2017 (WBI2017), uncertainties are accounted for more explicitly (De Waal, 2016). No overly conservative safety margins are applied, but instead mainly actual quantifications of uncertainties are involved. For example, uncertainties in the upstream discharge of the Rhine are integrated into the actual discharge prediction (see Bayesian integration in paragraph 5.5). Such steps are taken as a first step towards less conservatism and also a step away from a lock-in situation (Warmink et al., 2017). As of the end of 2017, the WBI2017 does not account for all uncertainty sources in hydraulic loads explicitly. For the water levels at the upper reaches of the Rhine only the upstream discharge is taken as a stochastic variable (Diermanse, 2016). Other uncertainty sources, e.g. discharge distribution at the bifurcation, lateral inflow and bathymetry have been discounted into a more general “model uncertainty”. This model uncertainty for the river water levels has a normal distribution with a zero bias in WBI2017. The standard deviation is chosen such that it represents the underlying uncertainty sources. For the upper Rhine reaches the standard deviation due to model uncertainty is set to 15 centimeters (Diermanse, 2016). However, this practice assumes no non-linear effects of the uncertainty sources on the water levels and between the uncertainty sources themselves, but this assumption is to be tested during this research.

Internationally similar approaches exist. In the UK a certain allowance is added when designing a flood defense to account for any residual uncertainty (Robinson et al., 2017). This residual uncertainty is all the uncertainty that has not yet been accounted for, but will not be quantified exactly. Depending on the degree of confidence on a scale of 1 to 5 (5 being the most certain), a margin of 30 to 90 centimeters is added to the design water level. For assessment of existing structures a different approach is taken in which the safety standards are represented by a range of probabilities instead of a single value, e.g. the ultimate limit state is between the 10% lower percentile 1/100 years and the 90% upper percentile 1/300 years. This range acknowledges uncertainty in both the estimate of the flood modeling as well as in the acceptable limit states (Robinson et al., 2017).

In the USA uncertainties in a detailed flood risk assessment are explicitly incorporated into the analysis itself in a probabilistic fashion (U.S. Army Corps of Engineers, 2017). Amongst others uncertainties in relationships of discharge - frequency, stage - frequency, regulated - unregulated and stage - discharge are considered. In the most recent policy the USA has stepped away from conservative freeboards similarly to the Netherlands. Instead in the design of a flood defense the costs and benefits in a cost-benefit analysis are represented by a probability distribution in which the probability distribution is built up by the individual uncertainty source components.
3.3 Reduction of river water level uncertainties

The reduction of uncertainties is an important aspect of coping with uncertainties. From a Bayesian perspective uncertainty reduction even leads to a decrease in flood risk (see section 5.5). Epistemic (knowledge) uncertainties can generally be reduced by gaining more knowledge of the actual system and the modeled system (Merz and Thieken, 2009). This is a typical form of first-loop learning (Warmink et al., 2017). However, epistemic uncertainties can only be reduced when sufficient time and means are available (Hommes et al., 2009), i.e. research costs time and money. In certain cases more knowledge can also cause an increase of uncertainties as it might reveal unknown unknowns (Warmink et al., 2017). Ambiguity plays a role when there are multiple, possibly equally valid, interpretations are present. In the context of hydraulic modeling ambiguity is found in underlying modeling assumptions, choice of a hydraulic model and interpretations of the outcomes in relation to uncertainties. Such ambiguities are difficult to eliminate.

When the target is to reduce uncertainties it may be important to address the "cascades of uncertainty" (Van den Hoek et al., 2014). This theory predicts that in a system of interrelated processes and associated uncertainties, a reduction of one uncertainty source (both technical and social uncertainties) lead to decreased uncertainties throughout the entire cascade. A consequence is that there is no single, most effective approach of coping with uncertainties as the context is very important.

In the Netherlands, measures have been taken to reduce the uncertainty in the up-
stream discharge. For the river Rhine the GRADE model can estimate extreme discharges from a basin-wide rainfall-runoff model combined with an one-dimensional hydraulic model (Hegnauer et al., 2014). A significant uncertainty reduction was thereby achieved as the estimation has a more physical basis. The results of Prinsen et al. (2015) using the GRADE model for an analysis of the river Rhine discharges is shown in Figure 3.3. Statistical and model uncertainties remained, but they were much smaller compared to earlier extreme discharge predictions based on a statistical analysis of measured discharge series only.
4 Discharge distribution at bifurcation points

This chapter deals with discharge distribution at major river bifurcation points with a focus on the Dutch river Rhine bifurcations. The overall purpose of this chapter is to gain insight into the physical processes affecting the discharge distribution, such that the uncertainty associated with these processes can be addressed in the uncertainty analysis. Paragraph 4.1 gives a short introduction into the large-scale natural processes determining the formation and evolution of bifurcation points. Subsequently, paragraph 4.2 describes the bifurcation points and the discharge distributions of the Dutch river Rhine bifurcation points. The subparagraphs will address the policy (4.2.1), the natural processes affecting the discharge distribution in the Rhine (4.2.2), the uncertainties associated with the discharge distribution (4.2.3) and the regulation structures at the bifurcation points (4.2.4).

4.1 Natural processes

Any river system around the world is characterized by its network of combining branches and tributaries to form a larger river downstream. The shape of these confluences can differ from place to place, but one thing is certain: the discharge and sediment transport in the downstream branch is always the sum of the upstream branches. Where confluences are very common, bifurcations are more rare when looking at the entire river system (Kleinhans et al., 2013a). Nonetheless, studying their behavior is very important as the bifurcations often occur in the deltaic part of the river. These deltas are often more flood prone compared to upstream areas. The role of river bifurcations in flood risk is evident as they determine where the water will flow towards.

Whereas the basic physics of a confluence are quite well understood, this is not the case for bifurcations. The partitioning of discharge is mainly determined by the water level slopes of the downstream branches (Kleinhans et al., 2013b). The branch with a relatively steep water level slope will attract relatively more discharge. Whereas the division of discharge is mainly determined by downstream conditions, the division of sediment mainly depends on the conditions just upstream of the bifurcation point (Kleinhans et al., 2013b). Important factors are for example transverse bed slopes (Bolla Pittaluga et al., 2003) and cross-sectional spiral flows as a result of a river bend (Kleinhans et al., 2013b).

On the long-term any bifurcation point is theoretically instable; i.e., one of the downstream branches will always grow at the expense of the other branch (Kleinhans et al., 2013b). The morphological evolution of a river branch is determined by the ratio between sediment supply and sediment transport capacity. If the supply is larger than the transport capacity accretion will occur. In a stable situation the sediment supply equals the transport capacity for both downstream branches. If for whatever reason one of the branches receives more sediment, accretion will occur. This will result in a lower flow depth and a higher flow resistance, which will cause a slight decrease of discharge. This in turn decreases the sediment transport capacity. Due to the highly non-linear relation between flow velocity and sediment transport capacity, a slight decrease of flow velocity results in a significantly larger decrease of transport capacity. In the case that the branch suffering from accretion keeps receiving the same sediment load, the branch will keep accreting. This positive feedback loop causes relatively symmetrical bifurcation points, in which the dimensions of the downstream branches are almost equal, to be instable.

Studies have described the distribution of water and sediment over downstream branches by nodal point relations (e.g. Wang et al., 1995; Bolla Pittaluga et al., 2003). These nodal point relations capture the basic physics of river bifurcations. However, they neglect local conditions such as wind effects and river dunes. Especially the distribution of sediment depends heavily on local conditions: the topography, the sediment transport mode and the
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Figure 4.1: The Pannerdensche Kop at which the Upper Rhine splits into the Waal (right) and the Pannerdensch Kanaal (left). Source: Van Houdt (2007)

Figure 4.2: The IJsselkop at which the Pannerdensch Kanaal splits into the Nederrijn (left) and the IJssel (right). Source: Ministerie van I&M (2012)

three-dimensional flow conditions (Jagers, 2003). More recently multi-dimensional numerical studies have been applied to model river bifurcations (e.g. Zhang et al., 2017; Yossef and Becker, 2016; Yossef et al., 2008; Schielen et al., 2007). One-dimensional numerical models are not suitable as they still require a nodal point relation as it cannot model the partitioning itself. Numerical models introduce (epistemic) uncertainties as the real situation may differ from the modeled situation (Schielen et al., 2007).

4.2 Discharge distribution of the Rhine

4.2.1 Policy with regards to the distribution of discharge

The watershed of the river Rhine stretches over five different countries before it enters the Netherlands to form a delta. Only a few kilometers after entering the Netherlands at Lobith the Rhine bifurcates. This bifurcation, where the Bovenrijn (upper part of the Rhine) splits into the river Waal and the Pannerdensch Kanaal, stems back to 1745 and is named the Pannerdensche Kop and is seen in Figure 4.1. The Pannerdensch Kanaal is a six kilometer long channel which connects the first bifurcation to the next: the IJsselkop. At this second bifurcation the water is divided over the Nederrijn (lower Rhine) and the IJssel, see Figure 4.2. Ever since the current situation existed the distribution of discharge has always roughly been the same: 2/3 to the Waal, 1/3 into the Pannerdensch Kanaal, which again divides into 2/3 into the Nederrijn and 1/3 into the IJssel (1/9th of the Rhine discharge). This discharge distribution has been fixed in the Nationaal Waterplan, which is a product of the Dutch Waterwet. The exact distribution from the Nationaal Waterplan 2016-2021 is given in Figure 4.3. Maintaining this politically set discharge distribution is of vital importance for flood risk practice in the Netherlands as the flood protection system is designed on the design discharge of the branches (Schielen et al., 2008). If the discharge distribution is not as it is set, it may be possible that the rivers cannot safely transport the discharge towards the sea and lakes.

The discharge distribution set by policy is under ongoing debate. With a focus on the long term, the year 2050 and further, a different discharge distribution could increase flood safety and cost efficiency. In this context the task was posed by the Deltaprogramme 2015 (Ministeries van I&M en EZ, 2014) to reevaluate the discharge distributions of the Rhine. This reevaluation should consider the hydrodynamic effects and corresponding changes in the flood risk as well as the social impacts and political implications. Earlier studies gave
some insight into the hydrodynamic effects and the changing flood risk. The results of these studies lead to the decision of sparing the Nederrijn for upper Rhine discharges over 16,000 m$^3$/s (Ministeries van V&W, VROM en LNV, 2006). The main reason for this is that in the Nederrijn no space is available for sufficiently effective river measures. The part of the discharge over 16,000 m$^3$/s is distributed over the IJssel and the Waal in the same ratio as below 16,000 m$^3$/s, see the right figure of Figure 4.3. Whether a more severe change in the discharge distribution will remain an option with the scope of the year 2050 is under consideration. This decision is likely to be embedded in the Deltaprogramme 2019. This research project should contribute to the knowledge required to make such decisions in the future.

An additional challenging factor arises in the new flood risk framework (De Waal, 2016). In this framework the term “normative discharge” becomes factually irrelevant. Since all failure mechanisms are addressed the flood protection system is no longer designed for one single discharge. This also has consequences for the discharge distribution as the distribution of water becomes more relevant for discharges below the “normative discharge”. This aspect is one of the key drivers behind this research project.

### 4.2.2 Natural distribution of water and sediment in the Rhine

Human interventions such as channelization, normalization, flood protections and dredging have changed the Rhine branches significantly over the last centuries. Without these human interventions rivers naturally keep changing their paths. Obviously natural processes still determine how the water flows, sediment is transported and how these are divided between the branches. Although bifurcation points are theoretically almost always instable, the bifurcation points of the Rhine river seem to be relatively stable (Kleinhans et al., 2013b). This relative stability of the bifurcation points is for a large part due to coarse river beds. These coarse river beds are a result of selective erosion in which only the fine material erodes. To a large extent the gravel bed prevents the river IJssel from growing at the expense of the Nederrijn. It is not certain whether this gravel bed is stable under extreme flow conditions (Kleinhans et al., 2013b). However, if the gravel bed is removed, the discharge distribution is likely to change, thereby also affecting the stability of the bifurcation points. Any change in the discharge distribution might cause the bifurcation points to become instable as they balance on a “tipping point” (Kleinhans et al., 2013b).

For the river Rhine the discharge distribution at the bifurcation points is dominated by
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the downstream geometries and roughness conditions (Schielen et al., 2008), similar to bifurcation points at other rivers around the world. These factors are not fixed in time due to for instance human river interventions, natural aggradation and degradation and vegetation succession. Furthermore, dynamic bed forms are likely to have a strong influence on the discharge distribution (Paarlberg et al., 2010). These increase the main channel roughness and thereby also increase the water levels. The height of the bed forms varies as a function of water levels and therefore the bed forms and the discharge distribution interact via the downstream water levels. However, bed forms are not fully incorporated into the hydrodynamic river Rhine models (Schielen et al., 2008) and their effects on the discharge distribution are therefore not fully assessed. A complicating factor is that downstream branches may experience different sediment loads as well as different sediment characteristics. For the Dutch case due to bend sorting the Waal river experiences a higher sediment load and receives relatively fine sediment compared to the Pannerdenskanaal. The difference in sediment characteristics influence the bed forms in the downstream branches and consequently also influence the discharge distribution. Finally, the potential flattening of river bed forms under extreme conditions may cause a change in the discharge distribution for conditions with a large return period. This process is called "upper stage plane bed" (USPB). It is not yet known if USPB can occur for Dutch design conditions (Hulscher et al., 2017; Duin et al., 2017; Van Duin, 2015). But if it does, it might have a significant effect on the discharge distribution.

4.2.3 Uncertainties with regards to the discharge distribution over the Rhine branches

The discharge distribution over the Rhine branches experiences both aleatory and epistemic uncertainties. However, as mentioned by Ten Brinke (2013) it is first important to define which uncertainty is meant with "the uncertainty of the discharge distribution". There are two possibilities:

- The uncertainty of the discharges of the Rhine branches for an upper Rhine discharge with a certain probability of occurrence (e.g. 1/1250 years)
- The uncertainty of the discharges of the Rhine branches for an upper Rhine discharge of 16,000 m$^3$/s

A flood with a recurrence time of 1250 years was and is the norm, which had under the old norm been fixed on 16,000 m$^3$/s at Lobith. With the new norms, WBI2017, no single discharge is set as multiple failure mechanisms are taken into account. For that reason the discharges of the downstream Rhine branches also become variable under the same norm. In the second case with a fixed upper Rhine discharge the uncertainty of the discharge distributions is significantly less. In previous research often the second definition was used (Ten Brinke, 2013). However, in this integrative study the first definition becomes more relevant as the overall water level uncertainties are the goal instead of the uncertainties specifically regarding the discharge distribution. It must be kept in mind though that there is a clear distinction between the two definitions.

Several factors which influence the uncertainty of the discharge distribution have been identified in literature (Ten Brinke, 2013; Paarlberg et al., 2010; Ogink, 2006):

- Wind speed and direction; extreme wind speeds in the order of 25 m/s from the southwestern direction can induce a decrease of 200 m$^3$/s of discharge into the river Waal. Due to the orientation of the second bifurcation point, the IJsselkop, the discharge in the river IJssel increases severely Ogink, 2006.
- Shape of the discharge wave; for narrow discharge waves the river Waal receives more discharge in the order of tens of cubic meters. The opposite occurs for wide discharge waves when the river IJssel and Nederrijn receive more discharge (Ogink, 2006).
- Bed forms; Paarlberg et al. (2010) have estimated the bandwidth (which can be interpreted as a 90% confidence interval) of the uncertainty in the discharge distribution at the Pannerdendensche Kop due to uncertain bed forms to be 400 m$^3$/s. This analysis was performed with uniform bed material, which may have lead to inconsistencies.
in the results compared to the actual case in which the river Waal receives relatively finer material. Additionally, it is not known how river dunes influence the discharge distribution for conditions other than the design conditions.

- Hydraulic roughness; (realistic) changes in the hydraulic roughness can lead to variations in the discharge distribution up to 100 m$^3$/s Ogink, 2006. These errors have the same sources as listed in Table 3.1. In a study by Straatsma et al. (2013) a strong variability in the order of several tens of cubic meters in the discharge distribution is found as a result of vegetation classification errors.

- Statistical extrapolation; as the design conditions have never occurred yet in the Netherlands errors are introduced if the conditions are extrapolated towards extreme conditions. This not only holds for the discharge, but also for any other variable, e.g. the hydraulic roughness. Ten Brinke (2013) accounts a standard deviation of around 100 m$^3$/s to the discharge distribution as a result of extrapolation uncertainties.

- Modeling errors; examples of modeling errors are geometry and roughness schematization errors. Ogink (2006) mention a standard deviation in the discharge distribution as a result of modeling errors in the order of tens of cubic meters per second. However, this estimation is based on the considered uncertainty sources only and explicitly neglects interdependencies between the uncertainty sources. The uncertainty in the discharge distribution due to modeling errors can therefore be significantly different.

- Morphodynamic stability of the branches; it is not known whether large erosion events may occur during extreme events (Kleinhans et al., 2013b). This could occur in the Pannerdensche Kanaal, where a layer with coarse material acts as an armour layer and near the IJsselkop where a grass layer in the floodplain may suffer from erosion. These events certainly could affect the discharge distribution in the long term, but will not cause an immediate change in the discharge distribution. Also long-term degradation of the branches, especially when the degradation rates are different, can also cause uncertainties in the future prediction of the discharge distribution.

- Uncertainty due to the regulation structures, see paragraph 4.2.4.

Ogink (2006) estimates the 90% confidence intervals for the discharge distributions to be 500 m$^3$/s and 300 m$^3$ for the Pannerdensche Kop and the IJsselkop respectively. Ten Brinke (2013) suggests that these estimates still reflect the current uncertainty of the discharge distributions. These numbers will be reevaluated during this research project and extended towards lower discharges.

### 4.2.4 Regulation structures for the discharge distributions

Due to measures in the river branches the discharge distributions change. Within the scope of the Room for the River projects it was found that more influence over the distribution of water was desirable in order to keep the discharge distribution as it is set in policy. Therefore, two regulation structures were built near the bifurcation points. These structures allow for an adaptation of the discharge distribution during high water.

The regulation structure Pannerden (Figure 4.4) is located in the eastern floodplain of the Pannerdensch Kanaal, just downstream of the bifurcation point. It is a 175 wide and 5 meter high concrete structure. The structure is divided into several weirs of which the height can be changed by adding or removing concrete beams. With an increasing flow area (i.e. lower amount of beams), more discharge is let into the Pannerdensch Kanaal, while a decreasing flow area steers discharge towards the river Waal. The structure thus allows for semi-dynamic regulation of the discharge distribution; semi-dynamic because the beams cannot be placed during or just ahead of periods of high water. With the closure of the entire regulation structure an increase of the discharge with 480 m$^3$/s towards the Waal branch can be attained for an upper Rhine discharge of 16,000 m$^3$/s. Optimally, for this discharge the structure is approximately halfway closed such that a margin remains to regulate the distribution. The capacity of the regulation structure at the Pannerdensche Kop is barely sufficient to cope with the natural variability of the discharge distribution at this bifurcation point (Ten Brinke, 2013).

The other regulation structure, the Hondbroeksche Pleij (Figure 4.5), is located on the eastern bank of the river IJssel just downstream of the IJsselkop. It is slightly smaller than
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Figure 4.4: The regulation structure Pannerden at the Pannerdensche Kop after the completion of the construction in 2014. Source: Rijkswaterstaat (2014)

Figure 4.5: The regulation structure Hondsbroeksche Pleij at the IJsselkop during a high water event in January 2012. Source: Mönich (2012)

the structure of Pannerden with a width of 150 meters. The functioning of the Hondsbroeksche Pleij is very similar to the structure at Pannerden. However, one of the main tasks is not to regulate the fixed discharged distributions, but to relieve the Nederrijn for upper Rhine discharges above 16,000 m$^3$/s by redirecting discharge to the IJssel. Therefore in order to make use of its full potential the Hondsbroeksche Pleij is designed to remain (nearly) closed until 16,000 m$^3$/s. The regulating margin, i.e. the amount of discharge it can redirect to the IJssel, is 175 m$^3$/s. This is the case when all beams are removed. However, this margin is insufficient to cope with the (maximum) natural variability of the discharge distribution at the IJsselkop which is in the order of 300 m$^3$/s (Ten Brinke, 2013).

The height of both regulation structures is currently evaluated yearly using a river model study in WAQUA (Rijkswaterstaat, 2017b). In this river model the current heights of the structures are used as an input after which a discharge distribution is modeled. If necessary, when the model’s discharge distribution does not match the fixed distribution, the number of beams in the structures can be changed. One of the complicated (political) tasks is to choose for which Rhine discharge the optimal heights of the regulation structures are determined. In the new framework no single ‘normative’ discharge is given. Flood waves with peak values up to 20,000 m$^3$/s are taken into account. The functioning of the structures is different for various peak discharges. For instance, if the structures are set for a discharge of 16,000 m$^3$/s and a higher discharge occurs, too much water is diverted towards the Nederrijn. The uncertainties involved in these structures, mainly looking at conditions other than the design conditions, are a motivation for this research project.

For new river measures the functioning of the regulation structures may change. The policy with regards to river measures is that they may not negatively impact the regulating function of the structures. This means that the structures should still have a sufficient regulating margin. This is brought into practice in the current planning of measures (e.g. Klimaatpark IJsselpoort; Rijkswaterstaat, 2017b).
5 Statistical techniques

This chapter intends to give a short introduction of some statistical techniques which are likely to be applied at some moment during the research project.

5.1 General views of probability

To attain the correct background on the statistical techniques discussed in the next section first the two different, conflicting views of probability are shortly discussed: the frequentist or classical view and the Bayesian view. The statistical techniques are based on one of the views which must be kept in mind when analyzing the results. In the frequentist approach probability is the estimation of the long-term frequency of a certain event based on what you know about the event. In the Bayesian approach probability is linked to a hypothesis after which the probability of this hypothesis being true is updated by observations. In a more general sense in the Bayesian approach probabilities depend on the degree of belief of the observer that a certain event will occur given all known information. The essence is that not only the event itself is relevant, observations of the event are important as well in determining the probability of the event.

The difference between the two philosophies can be illustrated in an example on the average weight of a person in the global population. Both the frequentist and the Bayesian would agree on the fact that it is impossible to get the weight of every human on the globe. As of such the value must be estimated; however the approach differs between the two philosophies. The frequentist will take samples of a large and representative population and determine the mean of the samples. The Bayesian will define a probability distribution of the unknown mean of the average weight and will use samples to update this prior distribution. The Bayesian theorem revolves around Bayes’ Law which writes as follows:

\[ p(A|B) = \frac{p(B|A)p(A)}{p(B)} \]  

In this equation \( p(A) \) and \( p(B) \) are the probabilities of events A and B themselves and \( p(A|B) \) is the probability of event A occurring given the fact that event B occurs.

Bayesian updating of a prior distribution, \( p(A) \), makes use of Bayes’ Law. The prior distribution is the estimated distribution from the current knowledge. The updated distribution, i.e. the posterior distribution, gives the probabilities after the collected data has been taken into account, i.e. \( p(A|B) \) in which B is the evidence. The other term in Bayes’ Law is the conditional probability of the data following the prior distribution, i.e. \( p(B|A) \). This term is referred to as the likelihood function.

The Bayesian theory is applied in several statistical techniques of which the GLUE methodology and the Bayesian integration are discussed in paragraph 5.4 and 5.5 respectively.

5.2 Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a computational method which relies on repeated random sampling to obtain numerical results. The simulated process could be complex in itself in which the randomness is generated ‘naturally’, e.g. a road network, or the randomness can be introduced artificially to solve deterministic problems (Kroese et al., 2014). In the latter
case MCS is used to draw samples from given probability distributions. The philosophy behind a MCS is that many repetitions lead to a large amount of outcomes of the process from which relevant quantities can be deduced. In an uncertainty analysis MCS can be applied to propagate uncertainties through a model. The input for the model is generated randomly from the probability distributions which correspond to the uncertain parameters.

Monte Carlo methods are popular in all kinds of engineering practices (Kroese et al., 2014). The main reasons are their simplicity and large applicability while still giving in-depth insight into the behavior of a model. Regarding the applicability, MCS can deal with any shape of a probability distribution, as well as correlations and nonlinearities. However, a disadvantage of MCS is the possibility that many runs are needed to obtain the right characteristics of the output probability distribution, especially when looking at either tail of this distribution.

In order to overcome long runtimes advanced sampling techniques, replacing the crude sampling, have been developed. For instance, for stratified sampling the original (cumulative) probability function is divided into bins from which the samples are subsequently drawn. This avoids the possibility that crude samples are from the same local region of the probability distribution. However, it is uncertain whether stratified sampling significantly reduces the runtime compared to crude sampling in case of (highly nonlinear) hydrodynamic models (Van Der Klis, 2003). If the goal is to analyze the tails of the outcome distribution, for which many samples would be needed with crude sampling, importance sampling significantly reduces the required computational effort. With importance sampling a new probability distribution is constructed which has a mean closer to the tails of the original distribution. However, for non-trivial cases this requires a lot of expertise as well as numerical optimization.

5.3 Global Sensitivity Analysis

Global Sensitivity Analysis (GSA) is the analysis of how much the various sources of uncertainty in the model input contribute to the uncertainty in the model output. Contradictory to local sensitivity analyses, a GSA takes into account all sources at the same time instead of one at a time. In general, sensitivity analyses looks at the full range of plausible values and assesses the impact of a change of the variable on the outcomes. Objectives of a GSA include prioritization of input parameters, identification of unimportant parameters, mapping the output behavior and model calibration (Iooss and Lemaitre, 2015; Hall et al., 2009).

A screening approach is the most simple type of sensitivity analysis which is based on the derivative \( \frac{\partial Y}{\partial X_i} \), i.e. the change of the outcome Y with respect to the change of the input \( X_i \). Many formal and informal approaches exist which can evaluate this derivative (Hall et al., 2009). However, all approaches have in common that if the relation between the input and outcome is nonlinear a point-estimated derivative may not represent the actual sensitivity. A linear regression analysis is an extension to GSA in which input samples are regressed against outcomes in a multi regression model. This analysis is sufficiently accurate for linear models. For hydraulic models, which are generally nonlinear, the linear regression analysis can still give an indication of the sensitivity and is a good starting point for a more comprehensive sensitivity analysis method. Such sophisticated methods have not been widely applied in the context of river modeling, although they give the most accurate insight into the sensitivities (Hall et al., 2009). The basis for the methods is that they determine both first order sensitivities as well as higher order sensitivities. This is particularly useful if an input parameter influences the outcome indirectly via other parameters. What the methods actually determine is the amount of variance of the outcomes that remain as long as the input parameter \( X_i \) remains unknown.

5.4 Generalized Likelihood Uncertainty Estimation

Generalized Likelihood Uncertainty Estimation (GLUE) is a Bayesian, Monte-Carlo based, methodology for estimating the uncertainty of model predictions. The origins of the method
lie in 1992 when Beven and Binley (1992) seek an alternative to the optimization strategy in model calibration. Their philosophy is that potentially multiple models lead to the same acceptable results, i.e. equifinality. Also from practice it is known that various sets of parameters and model structures can be equally acceptable (Pappenberger et al., 2006). GLUE can then help to attain the overall aim of a modeling exercise: to have a high likelihood of obtaining a highly reliable model (Beven and Binley, 2014).

The possibility of equifinality is explicitly acknowledged in GLUE as the model under consideration is run for many different sets of parameters; both input variables as model structure parameters (Pappenberger et al., 2005). The choices of prior distributions of the parameters, either uniform with a specified range or a different distribution based on physical grounds, are often difficult. However, these choices do influence the results of the analysis (Beven and Binley, 2014). Along with the prior distributions any correlation between parameters should be explicitly included. In the next step of a GLUE analysis the model results are compared to data after which the performance of each parameter set is evaluated by the goodness of fit to the data. This goodness of fit is expressed in a likelihood of that set being representative for the data as well as a reflection of the belief of the modeler that the current set could predict the future conditions acceptability well. Often, but not necessarily, the parameter sets are then distinguished into behavioral and non-behavioral sets by a certain threshold for the likelihood.

Many different likelihood measures exist, e.g. sum of absolute errors and a Nash-Sutcliffe coefficient. The choice for a certain measure depends on the type of data, but remains a subjective choice. The subjectivity of choosing such a measure as well as choosing a threshold value for the distinction between behavioral and non-behavioral model is a main criticism on GLUE (Beven and Binley, 2014). A more objective likelihood measure is difficult to establish as this would require verified probabilities of future observations. In case a formal statistical model is used to assign likelihood weights certainty is needed on the quality of the underlying data. This effectively neglects the possibility of epistemic uncertainties in the data (Beven and Binley, 2014). Although being subjective, the choice for a likelihood measure does not necessarily influence the outcomes of the analysis (Jung and Merwade, 2012; Freer et al., 1996). The final step of a GLUE analysis is to construct a cumulative density function (CDF) using the output results of the behavioral parameter sets and the assigned likelihood weights. Furthermore, posterior distributions for the analyzed parameters can be estimated. These can be attained by Bayesian statistics.

An important restriction on the use of GLUE is the computational demand. The computational demand depends on the run time of the model under consideration, the number of parameter dimensions and the constraints on the acceptability of model predictions. The demand is especially increased in the case of spatially-varying values of a parameter. This is demonstrated by Pappenberger et al. (2005) who apply GLUE to spatially varying roughness values of the floodplains and the main channel in a 1D flow model. In that case the roughness parameters remained equifinal as many combinations of spatial distributions of the roughness gave the same simulation results. Moreover, it is not easy to determine the required amount of runs a priori. Convergence of the output CDF is one way of justifying the amount of runs (Pappenberger et al., 2005); once the CDF does not change shape with additional runs it can be assumed that the constructed CDF is applicable for prediction purposes based on the given information.

Decreasing the computational requirements for a GLUE analysis can be attained in various ways. For example, the model under consideration can be simplified such that the runtime of one single run is reduced. Also the number of stochastic variables can be reduced; this reduces the required amount of runs in the Monte Carlo analysis. Another option is to apply more advanced sampling methods instead of crude sampling. In a case where there is a strong belief in the prior distributions of the parameters Latin Hypercube Sampling might be a solid option. Also methods which look for the sample space with the highest likelihood values, such as artificial neural networks and Markov chain Monte Carlo, can reduce the computational demand of a GLUE analysis (Beven and Binley, 2014). Blasone et al. (2008). In the case of flood modeling, which is a computationally expensive practice, advanced sampling techniques are a must. For a flood inundation model, Yu et al. (2015) have shown the successful application of moving least squares in stochastic sampling to drastically decrease the computational demand, while the results stayed sufficiently
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5.5 Bayesian integration of uncertainty

Bayesian Integration (BI) of uncertainties can be an effective way of communicating uncertainties (Hall and Solomatine, 2008). Furthermore, it could also reduce the amount of stochastic variables in an uncertainty propagation analysis, thereby decreasing the computational requirements. This is achieved by transforming a probability density function into one value which then represents the process including uncertainties. The method is already applied in practice in the Netherlands in the determination of the working line for upstream discharges (Diermanse, 2016). In this case the epistemic uncertainties (e.g. extrapolation, choice for a distribution) cause an increase of the discharge for a certain return period (Geerse, 2002).

The statistical background of BI lies at Bayes’ rule, see Equation [5.1]. The method is explained below using a simple example of two options with equal probabilities of occurrence (see Figure 5.1 for a sketch). In classical statistics the expected values, i.e. the working line would lie exactly in the middle of the two options. In contrast, Bayesian statisticians will apply conditional probabilities to derive the working line. They calculate the probability of an event with magnitude X, as indicated in the figure, which corresponds to the calculation in equations [5.2] and [5.3].

\[
P(X) = P(X|Option1) \times P(Option1) + P(X|Option2) \times P(Option2) \quad (5.2)
\]

\[
P(X) = 0.02 \times 0.5 + 0.002 \times 0.5 = 0.011 \approx 90 \text{ years} \quad (5.3)
\]

As illustrated by the example Bayesian Integration causes a decrease in the return period for an event with equal magnitude if compared to the classical approach. An important
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consideration is that the constructed Bayesian working line is a replacement for any other uncertainty indicator (e.g. confidence intervals) as the single working line gives the expected values including the effect of uncertainties. This is an important advantage of the method.

One possible disadvantage is the introduction of statistical artifacts in the case of fairly horizontal working lines. In such a case events with lower return periods have a relatively large contribution to the integrated return periods, thereby strongly shifting the Bayesian working line. This is a known statistical artifact in cases of flood channels (Geerse et al., 2017). Furthermore, the Bayesian working line could also lead to communication problems with decision-makers (Hall and Solomatine, 2008), as a lowering of the working line can be both due to a system change as well as due to a decrease of the uncertainties. To a Bayesian theorist this is obvious, but it may pose a problem in formal procedure when assessing the effectiveness of reducing the flood risk by a flood mitigation measure. In this context a decision-maker might then ask: "have we decreased the flood risk to which people are exposed or have we merely been able to reduce the uncertainties in our flood risk assessment?" (Hall and Solomatine, 2008). This question originates from the fundamental difference in probabilistic views between "classic" and Bayesian probabilistics, addressed in section 5.1.
6 Conclusions

This literature report forms the base of the author's PhD research project with the title: Large-scale uncertainty in river water levels. The aim of this literature report was to find the state-of-the-art knowledge of river water level uncertainties and give an overview of useful quantification techniques. These steps form the basis for the PhD project and are the first steps in an uncertainty analysis. Here, the research questions for the literature review are answered.

1. What is uncertainty and how can it be dealt with?

In this research the definition of Walker et al. (2003) is used to define uncertainty: *any departure from the unachievable ideal of complete determinism*. The uncertainties can be aleatory (natural variability), epistemic (insufficient knowledge) or due to ambiguity (different perspectives). It is also noted that uncertainties are often interrelated and thereby form 'cascades of uncertainty' (Van den Hoek et al., 2014). The Dutch flood risk practice (De Waal, 2016) steps away from the more conservative precautionary principle and instead accounts for uncertainty more explicitly. In this research an 8-step uncertainty approach (Figure 2.3) is adopted in which: the goal is formulated, an inventory and classification of uncertainties is made after which these are quantified, propagated and communicated. The goal of the uncertainty analysis in this specific research project is to attain a better understanding of the river system through the analysis of uncertain factors. Furthermore, the resultant water level uncertainties can also help in future decision-making.

2. What are the (main) causes of river water level uncertainties and how can these uncertainties be reduced?

In Chapter 3 a provisional inventory of uncertainty sources was made. It is chosen to not make a formal classification of the uncertainty sources as the process would be time-consuming and the possibility exists that due to the formal classification important interrelations and interactions are neglected. Literature has shown that many uncertainty sources exist, but only few are likely to be dominant (Warmink et al., 2013c). Main components in the total amount of uncertainty are the upstream discharge and the hydraulic roughness in the main channel due to bed forms and in the floodplains due to vegetation. Furthermore, the discharge distribution over the bifurcation points also exhibits large aleatory and epistemic uncertainties.

3. Which factors determine how the discharge is distributed between the branches of the river Rhine and which factors influence the uncertainty of this distribution?

In this research project the uncertainty in the discharge distribution will be studied as it is a dominant source and one of the most relevant sources of water level uncertainty as the water levels and the discharge distribution interact strongly. 90% confidence intervals for the two major bifurcations of the Rhine in the Netherlands have been estimated to be 500 m$^3$/s for the Pannerdensche Kop and 300 m$^3$/s for the IJsselkop (Ten Brinke, 2013; Ogink, 2006). However, knowledge gaps are present on the influence of bed forms, river engineering works and regulation structures, both for extreme conditions as under less severe conditions (Ten Brinke, 2013). Due to the interaction between the water levels and the discharge distribution changes in the system, e.g. river engineering works, cause strong changes in the water levels of the entire system and not only locally.

4. What are the most appropriate techniques to quantify uncertainties?

For the propagation of uncertainties a Monte Carlo Simulation (MCS) will be applied as it is the most accurate and straight-forward technique. Stratified sampling is required as crude sampling would cause a high computational demand. Furthermore, MCS will be combined with GLUE if calibration is required and with GSA in uncalibrated situations. In order to
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communicate the resulting water level probabilities and uncertainties Bayesian integration of uncertainties can be used, but with care as it may lead to interpretation issues.
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