Estimating and updating uncertainty with the GLUE methodology

Research report for flood forecasting procedures with an application to the Ve river

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Research report for flood forecasting procedures with an application to the Ve river

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Picture on the front page: a view on Ha Long Bay

Executive summary

This research was done within the framework of the Bachelor Thesis. The assignment of this research was to establish procedures to estimate and update uncertainty for flood forecasting using the WetSpa model. These procedures had to be made within the GLUE methodology, which takes into account the uncertainty of inputs and parameters of the WetSpa model. This model is a physically-based distributed hydrological model. The study area for this research is the Ve river basin located in central Vietnam (Quang Ngai province). The uncertainty analysis method used is the 'GLUE' methodology, which is an abbreviation for Generalised Likelihood Uncertainty Estimation.

The basis of the GLUE methodology, proposed by Beven and Binley (1992), is the premise that all model structures must, to some extent, be in error, and all observations and model calibration must also be subject to error. So there is no reason to expect that any one set of parameter values within a model will represent the true parameter set. When applying the GLUE-method one does not look for the optimum parameter set, but one makes an assessment of the likelihood of many parameter sets in a Monte Carlo analysis. This requires a goodness-of-fit index that must be chosen by the user. The calculated likelihoods are used in a GLUE-procedure to determine the uncertainty. The GLUE methodology also provides the possibility to update the likelihoods when new data become available and to evaluate these new data.

The results of this research are two procedures, one for estimating uncertainty and one for updating uncertainty. To this aim six Matlab scripts were designed. Three of these scripts have been designed to calculate the likelihood of simulations in different ways, by Nash-Sutcliffe, Model Efficiency and Error Variance. The advantage of multiple Matlab scripts for a procedure instead of one script for a procedure is that adjustments can be made more easily. So more likelihood measures can be incorporated, the procedures can also be used for other models and study areas, and one can switch easily between simulation mode and forecasting mode.

The procedures have been applied to the Ve river basin. Three data sets were available, dealing with three different floods. It was decided to use two data sets in simulation mode to test the estimating uncertainty procedure and the updating uncertainty procedure. The third data set has been used in forecasting mode. There are two main conclusions on the result for simulation mode. First, the hydrological responses of the two floods were not the same, due to parameter Ki. Secondly, the uncertainty bounds calculated by Nash-Sutcliffe were the most appropriate as compared to Model Efficiency and Error Variance. The result in forecasting mode for the third data set was poor, but this could be expected according to Doldersum (2009). He argued that this was due to the semi-open basin, a characteristic of the study area which is not incorporated into the model. Although the result was poor, it proved that the procedures work correctly in forecasting mode.

Preface

Hanoi- 27-June-2009

On 16 April I arrived at the Noibai Airport in Hanoi. This was the start of a 13-week experience of studying and travelling in Vietnam. First of all I want to thank Mr. Giang for this opportunity to work in his country on a very exciting topic. I also want to thank Mr. Van Oel for supervising my Bachelor thesis.

A great support to me has been Tom Doldersum, a fellow student from Enschede who worked on the same project. Together we discussed the data, the model, the progress of our reports, and we talked about the problems we faced during the project. Though we did not know each other very well before, we have become real friends. I appreciate his attitude, humour and mental attitude. But we were not just colleagues, we also spent leisure time together. We drove on the motorbike through Hanoi, played badminton with Vietnamese students, visited places inside and outside Hanoi and we explored Vietnam together after finishing our reports.
I want to thank Chi, a Vietnamese fellow student, who showed Tom and me many aspects of Vietnamese culture. She invited us to several weddings and one engagement party. Furthermore she showed us the beautiful landscape around the Perfume Pagoda. Another special moment to remember is the trip to the rural area where her family lived. Here we enjoyed Vietnamese kindness and hospitality and saw endless rice fields. She has also been a great help with our research. Without her knowledge and experience of Fortran and all her time spent on this part of the project, we couldn't have changed the WetSpa model, which was very important for our research.
I would like to thank Mr. Tuyet and Hoai, who took care of washing my clothes, cleaning my room, and who introduced me to the Vietnamese cuisine. I will always remember the good-humoured 'Goodmórning' from Mr. Tuyet.

Next to all the people I met in Vietnam, I want to thank my home front. Almost every day my parents and brother were available for a conversation. Thanks a lot for making this experience possible. Furthermore I want to thank my mother for supporting me with my English writing.
I also like to thank the other part of my home front: my girlfriend. We were blessed by the opportunities of Skype to keep in touch very well. Thanks for your support and listening ear.

Finally I want to thank God for all blessings during this whole experience.

Daniël

List of Abbreviations

DEM	Digital Elevation Model
EV	Error Variance
'EV'	Matlab script 'Error Variance'
GIS	GeoInformation System
GLUE	Generalised Likelihood Uncertainty Estimation
HUS	Hanoi University of Science
LHS	Latin Hypercube Sampling
'LHS'	Matlab script 'Latin Hypercube Sampling'
NS	Nash-Sutcliffe coefficient
'NS'	Matlab script 'Nash-Sutcliffe'
ME	Model Efficiency
'ME'	Matlab script 'Model Efficiency'
PET	Potential EvapoTransipiration
'RBS'	Matlab script 'Retain Behavioural Simulations'
'UE'	Matlab script 'Uncertainty Estimation'
WetSpa	Water and Energy Transfer between Soil, Plants and Atmosphere

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1 Introduction

Global climate change has been widely perceived as one of the main reasons leading to an increase in frequency and magnitude of hydro-meteorological extreme events as shown by Karl, Knight, and Plummer (1995) and Tsonis (1996). These extreme events can lead to flooding, which hinders the socio-economic development on both national and global scale. Flood prediction is an important instrument in reducing the damaging effects of flood events. But according to Krzysztofowicz (2001) flood prediction remains far from perfect, and falls short of society's expectations for timely and reliable warnings.

The Hanoi University of Science (HUS) started a flood forecasting project for the Ve river basin, an area in central Vietnam. This project contributes to the field of disaster prevention. The main goal of the project is to raise the degree of accuracy in flood forecasting of the study area. To this aim a sensitivity and an uncertainty analysis of the WetSpa model are made. The WetSpa model used within this research is the WetSpa Extension designed by Liu and De Smedt, which is based on the previously developed WetSpa model. It is called WetSpa in this report.
This report describes the uncertainty analysis applied to the Ve river. An uncertainty analysis shows the reliability of the model predictions. A reliable model contributes to a good prediction of flooding, which helps the people in charge to take effective measures to prevent flooding.

The aim of this thesis is:

"to establish procedures for estimating and updating uncertainty in flood forecasting that take into account the uncertainties of parameters and input data of the WetSpa model, using the GLUE methodology, with an application to the Ve River Basin"

In order to achieve this aim, several steps need to be taken, shown in Figure 1. The red boxes are done within this research, the black boxes are done within the research of Doldersum (2009).

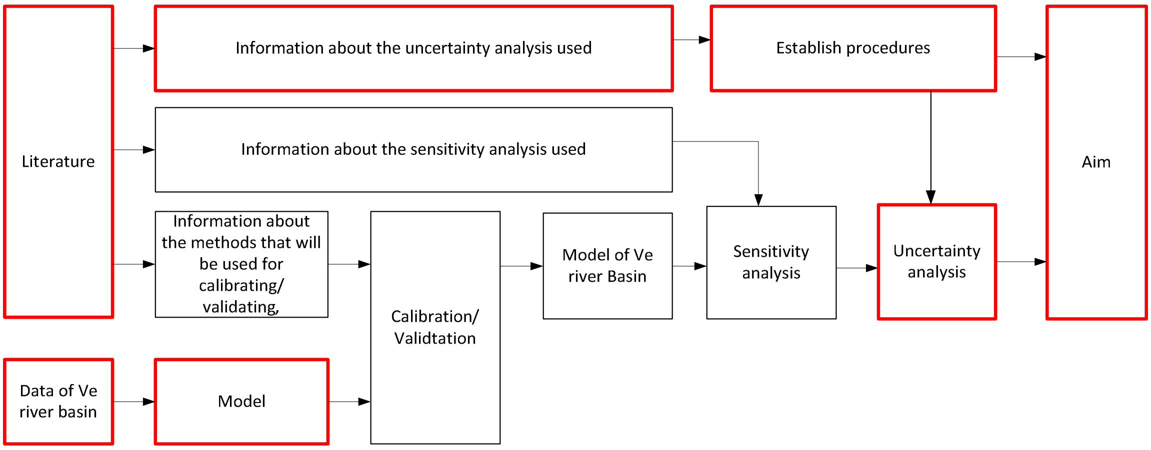

Figure 1: Scheme to achieve the aim

This scheme was the basis of the research questions. The four main research questions are stated below.

1. What is the input and output of the WetSpa model of the Ve River Basin?
2. How to use the GLUE methodology?
3. How to use the steps of GLUE within a procedure?
4. What is the uncertainty in the study area?

The structure of this report is based on the structure of the research questions.
Chapter 2 gives some general information about Vietnam, characteristics of the study area and a description of the WetSpa model. Afterwards Chapter 3 describes the data available. These data were provided by the Hanoi University of Science and KBR, an australian non-profit organization These two chapters provide the necessary information in order to answer the first research question. This provides the possiblity to use the WetSpa model.
The second research question is answered by Chapter 4, which describes the GLUE methodology, and the way it is used in this research. This is done by a literature study.
The results of this research are presented in Chapter 5. These are divided into two parts. The first part contains two procedures, one for estimating uncertainty, and the other for updating uncertainty when new data become available. These procedures were designed in Matlab. These procedures consist of six Matlab scripts. The procedures designed answer the third research question. The other part of the results answers the last research question by presenting the uncertainty in the study area. This is done by the use of the data available and the two designed procedures. A discussion of the results is given in the paragraph 5.4.
Finally in Chapter 6 the conclusions of this report and recommendations for further research are given. The last part of this report consists of the appendices.

2 Study area: The Ve river basin

The study area of this research is the upstream part of the Ve river basin. The Ve river is located in the central coast region of Vietnam. This chapter gives information about Vietnam, the study area and the model used.

2.1 *Vietnam*

Vietnam is situated in South-East Asia; its official name is the Socialist Republic of Vietnam. It is bounded by Laos to the west, Cambodia to the southwest, China to the north and the East Sea to the east (Figure 2).

Figure 2: Location of Vietnam in Asia (after Wikimedia Commons) and between its neighbouring countries (after NCBuy.com)

The capital Hanoi is located in the north of Vietnam. The other large city of Vietnam is located in the South, Ho Chi Minh City, and was previously called Saigon. Some general information about Vietnam is listed in Table 1. Vietnam consists of 63 Provinces. The study area of this research, the Ve river basin, is located in the Quang Ngai province.

Table 1: General information about Vietnam (Wikipedia, 2009)

Vietnam	
Capital city	Hanoi
Official language	Vietnamese
Area	
Total	331,690 km^2
Water	1,3 %
Population	
2008 mid-year estimation	86.116.559
Density	253/km^2

2.2 *The Ve river basin*

The Quang Ngai province is in the south central coast region of Vietnam. It is located 883 km south from Hanoi and 838 km north of Ho Chi Minh City. The Ve river is located south in the Quang Ngai province (Figure 3). The total Ve river basin has a surface area of 1300 km^2; the main stream is 91 km long. Within this project only the upstream part from An Chi is taken into account, which has a surface area of 757,32 km^2. The Ve River rises from the mountainous region Truong Son in the south and leaves the study area at An Chi. The study area is shown in the right part of Figure 3. The study

area is a semi-open basin. Under normal weather conditions it is a closed basin, but in extreme circumstances water can flow in and out of the Ve river basin.
For the Ve river basin, two problems in flood forecasting have priority. The degree of accuracy is very poor at the moment and the foreseeing time of predicting the water level has to be improved (Son, 2008). In the next paragraphs characteristics of the study are described.

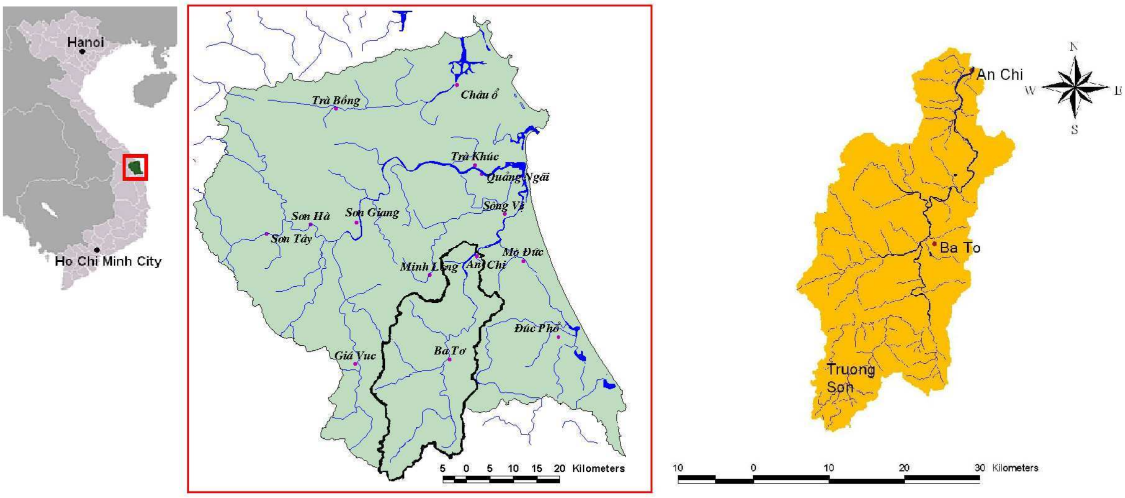

Figure 3: Location of the Quang Ngai Province in Vietnam (Wikipedia), and the Ve river upstream of An Chi inside Quang Ngai Province (Son, 2008)

2.2.1 Lithological characteristics

The study area consists of many different lithological structures. The most conspicuous lithological characteristic of Ve river basin is a rapid change in topographical gradient in profile from the south to the north, shown in the DEM (Digital Elevation Model) in Figure 4. Figure 5 shows the soil of the river basin. There are six different types of soil. In the mountainous region, sandy loam is the most common soil type and in the plain, sandy clay loam is the most common soil type (Son, 2008).

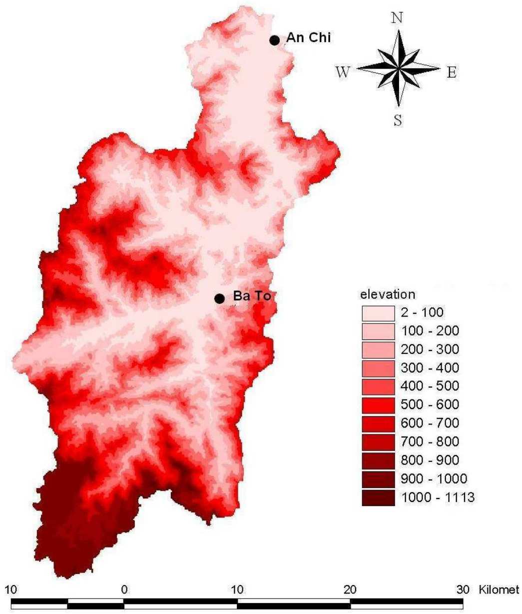

Figure 4: DEM of the study area

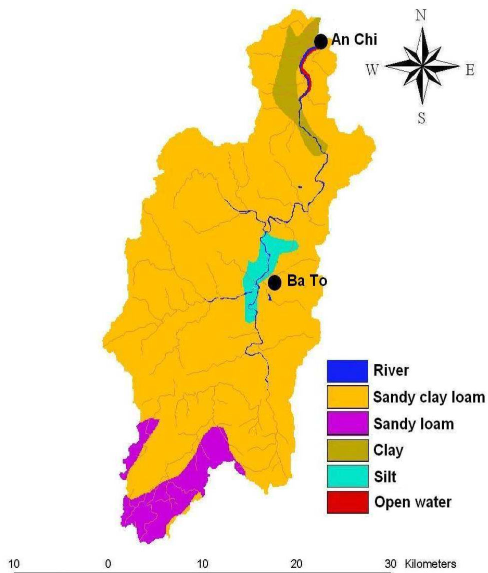

Figure 5: Soil type map of the study area

2.2.2 Land use

The dominant land use of the study is deciduous shrub. In the mountainous regions in the south evergreen broad leaf tree covers the surface. There is also a substantial amount of irrigated crop in the study area. An overview of the land use is shown in Figure 6.

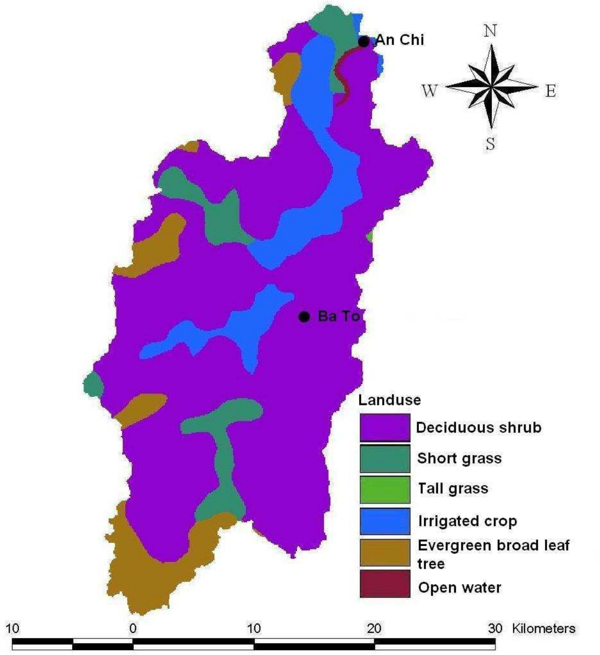

Figure 6: Landuse map of the study area

2.2.3 Climatic conditions

The Ve river basin is situated to the south of the Hai Van pass, which separates the two main climate regions of Vietnam. South of the Van Hai pass, there is a moderate tropical climate. In this region of Vietnam the average annual temperature is about 26^0C.
The precipitation in the plain is about 2000-2200 mm yearly, upstream it exceeds 3000 mm. During the year there are approximately 140 rainy days. The rainy season starts in September and ends in December. The amount of rainfall during this rainy season is 65-85% of the total amount of annual precipitation. So during the eight dry months there is only 15-35% precipitation of the total amount (Son, 2008).

2.3 *Model*

The model used within this research is the WetSpa model. Therefore this model is presented in the first part of this section. Next the different parameters and input variables are described in section 2.3.2.

2.3.1 WetSpa model

WetSpa is an acronym for "Water and Energy Transfer between Soil, Plants and Atmosphere". "The WetSpa (Extension) model is a GIS based-distributed hydrological model for flood prediction and water balance simulation on catchment scale" (Bahremand and De Smedt, 2008). It is a physically based model, and the hydrological processes considered in the WetSpa model are precipitation, depression storage, snowmelt, surface runoff, infiltration, evapotranspiration, percolation, interflow, groundwater flow, and water balance. For detailed information about the formulas used within these processes, the user manual of Liu and De Smedt (2004) can be read. A short description of some formulas which are relevant to this research is given in Appendix A-1.

WetSpa consists of two models: a semi-distributed model, and a fully-distributed model. The fully-distributed model has a large processing time. Therefore for calibration the simpler semi-distributed model can be used. For calculating the results the complex fully-distributed model is used within this research.
Paragraph 2.3.1.1 describes the necessary input for the WetSpa model. After this, paragraph 2.3.1.2 gives a brief description of the processes in the grid cells. Furthermore, a few assumptions and limitations of the model will be discussed in section 2.3.1.3.

2.3.1.1 ArcView and WetSpa

The WetSpa model is a GIS (GeoInformation System) based model, and consists of two parts. The first part, ArcView, is used to read the geographical data. This must be done before the second part of the model, the calculation with the WetSpa model, can be used. The process of loading the data in ArcView is timeconsuming, because the model has to save all the data of the study area. The maps loaded are used to calculate the values for new maps that are built in ArcView. This process is also timeconsuming, because all steps must be taken manually.
During this loading process a few input values have to be set. These different input variables are described in paragraph 2.3.2.2. It is important to choose these carefully because these maps are the basis for all calculations for the study area.

2.3.1.2 Grid cell

The model calculates the different types of discharges and the evapotranspiration for every grid cell separately. In Figure 7 the structure is presented at grid cell level. A short description of this process is given in the next part of this paragraph.

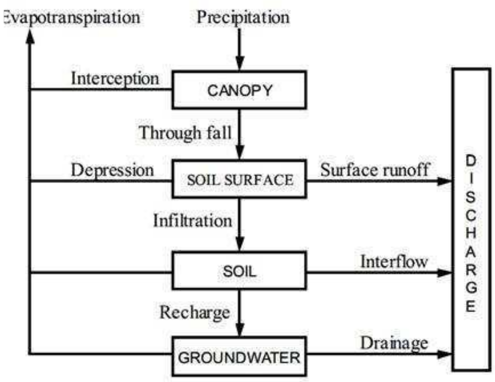

Figure 7: Structure of WetSpa Extension at a pixel cell level (Liu & De Smedt, 2004)

Incidental rainfall first encounters the plant canopy, which intercepts part or all of the rainfall till the interception storage capacity is reached. The rest of the water reaches the soil surface, where three different processes can take place. The water can infiltrate into the soil zone, it can enter the depression storage or it can divert as surface runoff. The depression storage is subject to evaporation and further infiltration. The initial losses at the beginning of a storm consist of the interception and depression storage. When the water infiltrates into the soil layer a fraction percolates to the groundwater and some diverts by interflow. Furthermore, the soil layer is subject to the evapotranspiration rate and the available soil moisture. The groundwater discharges are dependent on the recession coefficient and the amount of groundwater storage. The total discharge of a grid cell is the summation of drainage, interflow and surface runoff (Bahremand and De Smedt, 2008).

2.3.1.3 Limitations and assumptions

Liu and De Smedt (2004) describe twelve important assumptions and ten important limitations of the WetSpa model. In this section the relevant limitations and assumptions are discussed. Limitations and assumptions are considered relevant when they are interesting for a flood forecasting case, the topic of this research.

Assumptions

- Soil characteristics are isotropic and homogeneous for a single raster cell
- Precipitation is spatially homogeneous within a raster cell
    - It is important to be aware of these assumptions, it is clear that in fact reality is different. Furthermore, for the second assumption it is important to remember that there are a few meteorological stations used to generate the rainfall data. In this case this assumption looks reliable.
- Evapotranspiration does not occur during a rainstorm or when the soil moisture is lower than residual soil moisture
    - This seems a reliable assumption because during a rainstorm there cannot be a lot of evapotranspiration.
- Water flows along its pathway from one cell to another, and cannot be partitioned to more than one adjacent raster cell.
    - This is a major assumption because this proves that the model will not take into account an upstream flood.

Model limitations

- The WetSpa model runs with a continuous input of data.
    - The importance of this limitation can be explained by an example. In the case of the Ve river, there are four rainfall stations. One of them has measured data hourly, and the other six-hourly. Hourly data will produce a more accurate result, so it is preferable to use these. However, this means that the six-hourly data must be adapted. Furthermore, it is clear that the results will be influenced negatively when only few data are available.
- Values assigned to any raster or grid cell represent an average value over the area of each cell.
    - This limitation discusses the same point as the first two assumptions. There will be an error in the results, but this problem or limitation cannot not be changed.
- The impervious fractions for urban areas are set subjectively depending upon cell size, since no detailed measurements are available.
    - These fractions may cause an error in the model results, since these fractions may not reflect reality.

2.3.2 Parameters and input variables

The WetSpa model is a complex hydrological model and there are a lot of input variables and parameters. In the next paragraphs an overview of the parameters and input variables of the model is given. Furthermore, for every parameter and input variable a short description is given about how this parameter is incorporated into the model. First an overview of the input data is given, secondly the values that are requested during the loading of the WetSpa model are described and finally the global parameters are described.

2.3.2.1 Meteorological and geographical data

The model is GIS-based and needs five geographical inputs. These are DEM, soiltype, land use, the location of meteorological stations and the stream network. Apart from geographical information, hydro-meteorological information is also needed. Hydro-meteorological information consists of rainfall, PET (Potential EvapoTranspiration) and discharges. Temperature information is optional; it is only needed when snow occurs within the study area. The data used within this research are described in chapter 3.

2.3.2.2 Input variables during set-up time

As written in section 2.3.1.1 it is necessary to load the data of the study area in ArcView, before the WetSpa model can be used. During this set-up time in ArcView, some input variables have to be given. An overview of these input variables is given in Table 2.

Table 2: Input variables during set-up time

Variable	Description
Cell threshold for stream networks	Threshold value for creating a stream network
Threshold for minimum slope	Minimum slope
Setting a flood frequency	Choosing the flood frequency of the flood modelled, with options 1:2, 1:10 and 1:100 year
Cell threshold for the watershed	Determining into how many watersheds the study area is divided
A minimum ratio reflecting the moisture condition	Setting the initial moisture condition
Choosing a way to determine the Manning's coefficient	Choosing from three options the way Manning's coefficient has to be determined.
Percentage for urban area	Setting a value for the percentage of urban area.
Setting a flow limit	Choosing whether to set a flow limit (and determine the flow limit) or not

2.3.2.3 Global parameters

In the WetSpa model, twelve global parameters are compiled by the designers to simplify the calibration process. These parameters have physical interpretations. They are important in controlling runoff production and hydrographs at the basin outlet, but difficult to assign properly on a grid level. Therefore, it is preferable to calibrate these parameters against observed runoff data in addition to the adjustment of distributed model parameters (Liu and De Smedt, 2004). In Table 3 an overview of these different parameters is given.

Table 3: Overview of the global parameters (Liu and De Smedt, 2004 and Liu and Corluy, 2005)

Parameter	Description
Dt(h)	Time step in hours.
Ki	Scaling factor for interflow computation.
Kg	Groundwater recession coefficient
K_ss	Initial soil moisture
K_ep	Correction factor for potential evapotranspiration.
G0	Initial groundwater storage in water depth(mm)
G_max	Maximum groundwater storage in water depth (mm)
T0	Base temperature for snow melting.
K_snow	Degree-day coefficient (mm/°C/day) for calculating snowmelt.
K_rain	Rainfall degree-day coefficient (mm/mm/°C/day) for estimating snowmelt.
K_run	Surface runoff exponent when the rainfall intensity is very small
P_max	The threshold rainfall intensity (mm/d or mm/hour; depending on the timestep)

Seven global parameters are described more detailed in Appendix A-1. This appendix presents the physical meaning of these parameters and their influence in the WetSpa model. Only seven parameters are described, because these are the parameters used in the uncertainty analysis. Section 4.3.1 explains the choice for taking into account only these parameters.

3 Data

For this project data are available from two sources. The first source is KBR, a non-profit organization which receives funds from the Australian government. They set up the Quang Ngai Disaster Mitigation Project. The aim of the project was to mitigate the impact of natural disasters in the Quang Ngai province. The total funds received from the Australian government were A$ (Australian dollar) 13.5 million (Aid Activities).

The second source of data is the HUS (Hanoi University of Science). The description of data is divided into three parts: hydro-meteorological data, geographical data and tables.

3.1 *Hydro-meteorological data*

The hydro-meteorological data are provided by KBR. The main source for KBR for hydro-meteorological data is the Hydro Meteorological Service. Data are available for three floods, of which one took place in November 1999, and another one in December 1999 and the last one in October 2003. The hydro-meteorological data are divided into streamflow data, rainfall data, temperature and PET. These are described in the next paragraphs of the report.

3.1.1 Streamflow data

The streamflow data are provided by KBR, who got the data from the Hydro Meteorological Service. The data are measured at An Chi, where the Ve River leaves the study area. The discharge was measured hourly in November 1999 and December 1999. During the October 2003 flood not hourly discharges were measured, but only hourly water level data. For fifteen measurements discharges were also available. These were plotted, as shown in Figure 8.

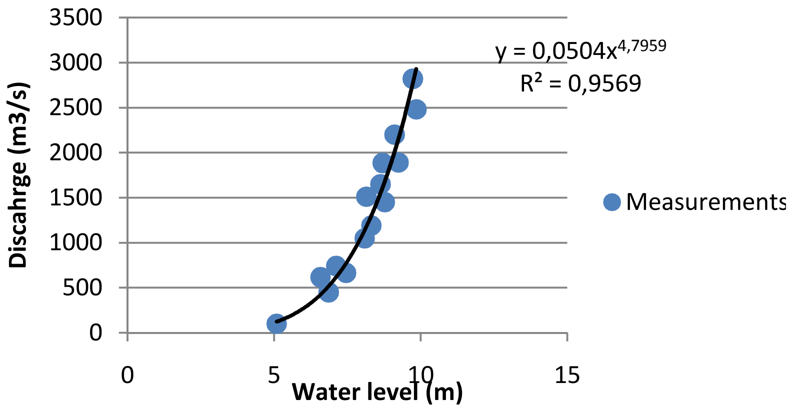

Figure 8: Relationship between discharge and water level for the October 2003 flood

To convert water level data into discharges, a trendline was added. This power-function had an R^2 of 0,9569, which indicates a good fit. The formula of the trendline was used to create discharges from the water level data. The result was checked with the fifteen original measurements in Figure 9, showing a good spread of data points during the time. It shows a good fit, and these calculated discharge data are therefore considered reliable.

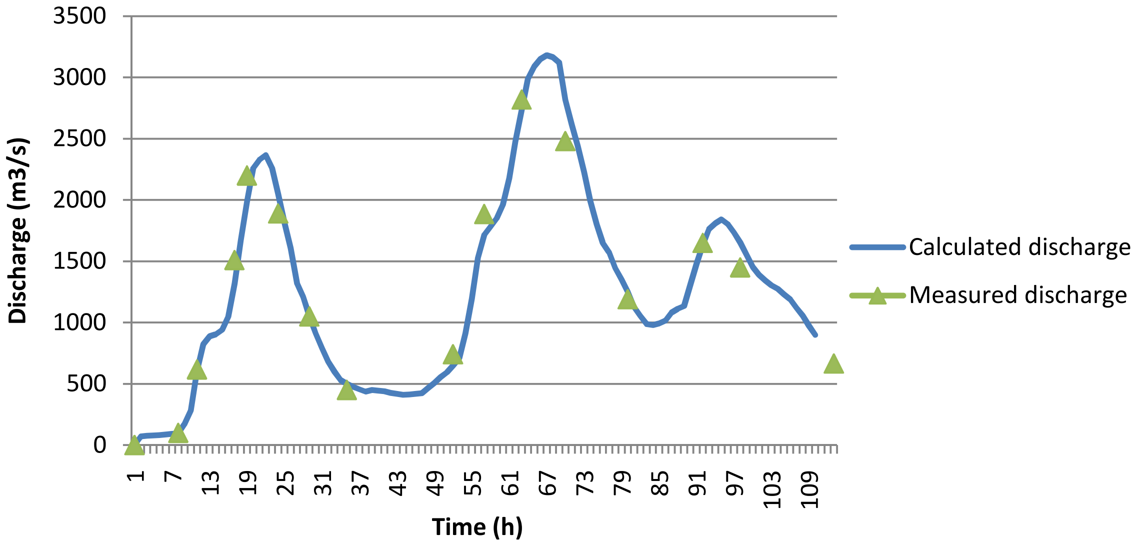

Figure 9: Calculated and measured discharge of the October 2003 flood

3.1.2 Rainfall data

The rainfall data are provided by KBR, who got the data from the Hydro Meteorological Service, and also from the Hydro Meteorological Forecasting Centre. For the rainfall five stations should be taken into account, because they cover the study area. However, one station lacks data, so it is not taken into account. The covering of this station is very small, about 0,02 % of the study area. So the effect of eliminating this station on the model output is very small. Figure 10 shows how the other four stations cover the study area. The division of the study area is done by Thiessen polygons, which is a standard procedure in WetSpa.

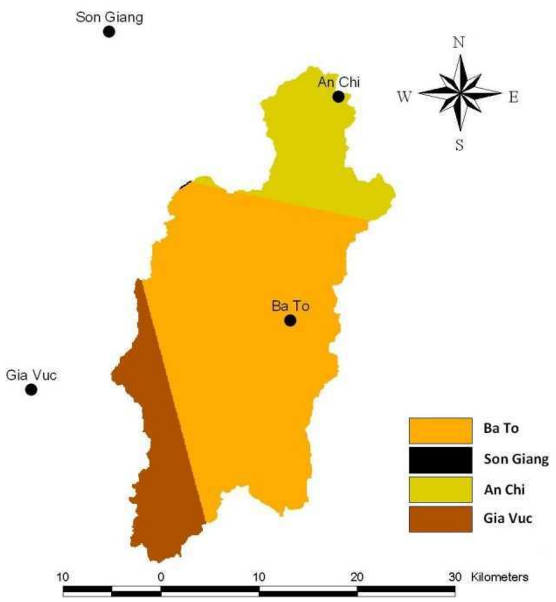

Figure 10: Meteo Stations covering the study area

At three stations (An Chi, Son Giang and Gia Vuc) the rainfall was measured with a six-hourly time step, at one station (Ba To) it was measured one-hourly. The data must be in accordance with the other ones, and therefore the data of the three six-hourly stations are changed into one-hourly data. The temporal (one-hourly) rainfall pattern of Ba To is used as a format for the temporal pattern of

the three other rainfall stations. So the percentage of every one-hour rainfall to the six-hour rainfall of Ba To is calculated and used to determine a one-hourly designed rainfall for the other stations.
In reality the temporal patterns of rainfall at the four stations are probably not exactly the same. To compensate this, a random factor could be implemented. However, the result of this can model reality better or worse. Therefore no random factor is implemented within this research.

3.1.3 Temperature

Temperature data in the WetSpa model are used only for the snowmelt and snow accumulation process (Liu and De Smedt, 2004). Within the study area snow melting does not occur, so the temperature values are irrelevant.

3.1.4 PET

PET-data (Potential EvapoTranspiration) were not available within this research. However, PET is so small during floods that it is almost negligible (Gash and Stewart, 1977). Therefore it is reasonable to use a PET of 0 during the flood period.

3.2 *Geographical information*

There are five geographical inputs available for this project. These are provided by the HUS. These inputs deal with DEM (Figure 4), soiltype (Figure 5), land use (Figure 6), measurement locations and the stream network. The DEM, land use and soiltype were available on a 90x90m grid cell size. Some improvements of the available data needed to be made, before using them in the model. The improvements made are described in the next paragraphs.

3.2.1 Boundaries

The original files of DEM, land use and soiltype covered a square around the study area. But the WetSpa model does not work when an area bigger than the study area is implemented. Therefore the geographical inputs were initially clipped by a boundary, also given by the HUS. However, this boundary was drawn in straight lines (Figure 11). This does not correspond with reality, because a watershed is a natural phenomenon. Therefore a second option is used to calculate the boundary. This is done by a function in ArcView, to calculate the boundary of a watershed from a DEM-map. This boundary is used to clip every map. Figure 12 shows the new soiltype input.

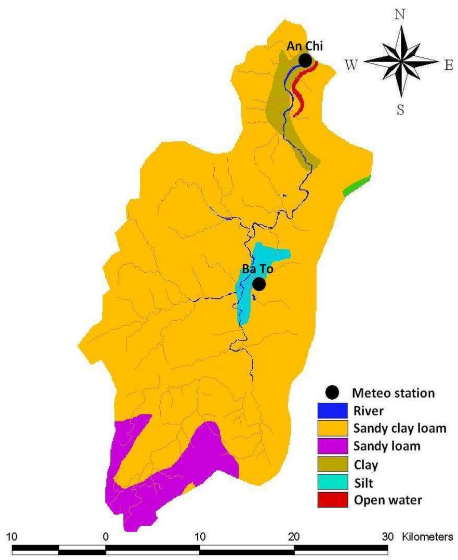

Figure 11: Original soiltype map

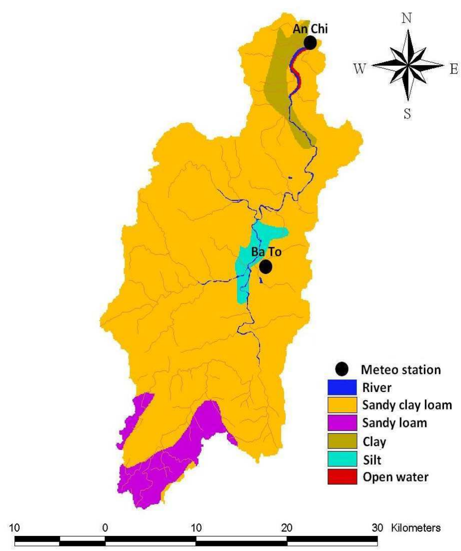

Figure 12: Referenced soiltype map with the correct boundaries

3.2.2 Georeference

The data were not georeferenced in the same way. The difference between the geographical inputs was approximately 10-15 grid cells. These were not a correct input for the model, and therefore not useful. Therefore the maps were referenced on the location of the river at An Chi. This is because the river at An Chi can be seen clearly on all maps. In Figure 11 and Figure 12 the river at An Chi is red, classified as 'open water'. Figure 12 is referenced correctly, because the river and the open water fall together. The referencing is done in ArcView.

3.2.3 Classification

The geographical information about land use and soiltype are related to tables in the WetSpa model. The (Vietnamese) information is classified in a different way from the (WetSpa) tables. Therefore some students from the HUS translated the Vietnamese classes into the WetSpa classes as well as they could. However, the classes of the model and the geographical information cannot be translated fully correctly, because the same classes do not exist. This translation can have impact on the output of the model, but it is impossible to measure this impact.

3.3 *Tables*

The tables used in the WetSpa model were provided by the model itself. More information about the tables can be read in the user manual from Liu and De Smedt (2004).

4 Uncertainty analysis method

According to Yang, Reichert, Abbaspour, Xia, and Yang (2008) distributed watershed models are increasingly used to support decisions about water management strategies. They state that for this reason it is important that these models pass through a careful calibration and uncertainty analysis. Uncertainty arises from incomplete process representation, uncertainty in initial conditions, input, output and parameter error (Blasone, Vrught, Madsen, Rosbjerg, Robinson, and Zyvolosky, 2008). Al these sources of error are handled within the GLUE methodology implicitly (Beven and Freer, 2001). In this chapter a description of this methodology is given.

4.1 *GLUE methodology*

The GLUE methodology, Generalized Likelihood Uncertainty Estimation, is a way to calibrate and estimate the uncertainty of models based on generalized likelihood measures, proposed by Beven and Binley (1992). They came up with this method originally to provide a strategy to calibrate and estimate uncertainty for physically-based distributed modelling. But as stated by Blasone et al (2008), the GLUE framework has found widespread application for uncertainty assessment in environmental modelling, including rainfall-runoff modelling, soil erosion modelling, groundwater modelling, flood inundation modelling and distributed hydrological modelling. As concluded by Beven and Freer (2001) the GLUE methodology implicitly takes into account all sources of uncertainty, i.e., input uncertainty, structural uncertainty, parameter uncertainty and response uncertainty.

The basis of the GLUE-method is the premise that all model structures must, to some extent, be in error, and all observations and model calibration must also be subject to error. So there is no reason to expect that any one set of parameter values within a model will represent the true parameter set.
When applying the GLUE-method one does not look for the optimum parameter set, but one makes an assessment of the likelihood of many parameter sets in a Monte Carlo analysis (Beven and Binley, 1992).
These likelihoods are used in a GLUE-procedure to determine the uncertainty. It is also possible to update these likelihood values when new data sets become available, and determine the value of these new data sets.

The GLUE methodology requires five steps, which are:

1. Specify a formal definition of a likelihood measure or a set of likelihood measures.
2. Make an appropriate definition of the initial range and distribution of parameter values.
3. A procedure for using likelihood weights in uncertainty estimation.
4. A procedure for updating likelihood weights as new data become available.
5. A procedure for evaluating uncertainty in such a way that the value of additional data can be assessed.

These five steps are explained separately in the next five sections of this report. Section 4.7 describes the difference between using the GLUE methodology in simulation mode and in forecasting mode.

4.2 *Formal definition of likelihood*

The first step is to define a formal definition of the likelihood of a parameter set. According to Beven and Binley (1992) the likelihood measure must have some specific characteristics. The value of the likelihood measure should be zero for all simulations that are considered to exhibit behaviour dissimilar to the system under study, and should increase monotonically as the similarity in behaviour increases. These are not restrictive requirements, and could be satisfied by many formulas. Therefore the modeller has to make a choice for a likelihood measure.
The resulting uncertainty bounds are influenced by the likelihood measure used. To investigate this influence multiple likelihood measures are used within this research. The resulting uncertainties are compared in Chapter 5.

A likelihood measure calculates the likelihood of a simulation, which is a way to evaluate how well the simulation simulates the study area. A likelihood measure is also named a goodness-of-fit index. In the past several goodness-of-fit indices are used within the context of GLUE. They mostly exist of two parts. The first is a goodness-of-fit formula; the second is a cut-off threshold. Both parts are explained in the next two sections.

4.2.1 Goodness-of-fit formula

A goodness-of-fit index calculates how well a simulation corresponds to reality. Within the context of GLUE several goodness-of-fit indices were used in the past. The Nash-Sutcliffe coefficient (NS) is the most frequently used likelihood measure for GLUE (Yang et al., 2008). This statement is also confirmed by the literature study, shown in appendix C-1. Because the NS is used most frequently as likelihood measure within GLUE, the first goodness-of-fit index within this research is NS. It is calculated as

$$NS_i = 1 - \frac{\sum_{j=1}^{M}(Qs_{i,j} - Qo_j)^2}{\sum_{j=1}^{M}(Qo_j - Qo_{ave})^2} \tag{1}$$

where i = 1, 2, ..., N is the number of simulations, NS_i is the likelihood of the i^{th} simulations, j = 1, 2, ..., M is the time step of the simulations, $Qs_{i,j}$ is the simulated discharge for the i^{th} simulation at time step j, Qo_j is the observed discharge at time step j, and Qo_{ave} is the average of the discharges observed.

The second is the model efficiency (ME) used by Blasone et al. (2008), Lamb, Beven and Myrabo (1998), and Thorndahl, Beven, Jensen, and Schaarup-Jensen (2007). This one is also a commonly used likelihood measure within GLUE (Blasone et al., 2008). Thorndahl et al. (2007) state that this likelihood measure is especially suitable in fitting the peak. In flood forecasting this is the most important derived output; therefore this likelihood measure is very appropriate for this research. The model efficiency is calculated as

$$L_i = \exp\left(-W\frac{\sigma_i^2}{\sigma_o^2}\right) \tag{2}$$

where i = 1, 2, ... N is the number of simulations, L_i is the likelihood of the i^{th} simulation, σ_i^2 is the variance of the residuals for the i^{th} simulation and σ_o^2 is the variance of the observations, W is a weighing factor that can be adjusted. Within this research W is incrementally increased from 1, 5, 10 to 100. It is concluded that the uncertainty bounds barely change between 1, 5 and 10. A weighing factor of 100 results in small uncertainty bounds, but these are also inconsistent, and therefore not useful. It is interpreted from Blasone et al. (2008) that W = 5 should lead to reasonable uncertainty bounds within the GLUE methodology.

The likelihood measure used by Beven and Binley (1992) is used within this research as a third goodness-of-fit index. This one is based on the variance of the residuals, within this research called error variance (EV). It is calculated as

$$L_i = (\sigma_i^2)^{-V} \tag{3}$$

where i = 1, 2, ... N is the number of simulations, L_i is the likelihood of the i^{th} simulation σ_i^2 is the variance of the residuals for the i^{th} simulation, and V is a weighing factor. Within this research V is increased from 1, 5, to 10. A weighing factor of 10 results in small but inconsistent uncertainty bounds. V = 1 gives a flat distribution of likelihoods, which results in relatively much weight to a poor simulation. Of course this results in consistent uncertainty bounds. However the bounds are very broad, so the predictive capability is small. *V* = 5 results in useful uncertainty bounds, with a slightly peaked distribution of likelihoods. Therefore this value is chosen.

4.2.2 Cut-off threshold

A cut-off threshold is used to separate behavioural from non-behavioural simulations. The likelihood values of non-behavioural simulations are set to zero, which means that they are not used in the procedure to estimate uncertainty. In literature the most common cut-off thresholds are a certain likelihood value (for example: NS > 0,8) or a certain percentage of the observations (for example: best 10% of all simulations), which can be seen in Appendix C-1.

Andersen, Refsgaard, and Jensen (2001) classified values of NS from poor, to fair, good and very good. NS-values below 0.7 are qualified as poor, whereas higher values are qualified fair or good. Within this research poor simulations can be qualified as non-behavioural, and fair or good simulations as behavioural. Therefore the cut-off threshold for the goodness-of-fit index NS is 'NS > 0.7'.

For the second goodness-of-fit index the threshold is the best 10% of the simulations. This looks a subjective choice, but it was tested within the research of Lamb, Beven and Myrabo (1998). They proved that taking more values into account than the best 10% resulted only in slight changes of the uncertainty bounds.

For the third likelihood measure no cut-off threshold is used at all, after Beven and Binley (1992). This means that all simulations are classified as behavioural and used in the procedure for using the likelihoods.

4.3 *Initial parameter range and distribution*

An initial range of the parameters and the distribution of parameter values must be determined. This is a very important part of the GLUE method, because the range must not be too wide, but also not too close. If the initial range is too wide, then many simulations are an unlikely simulator of the study area. If the range is too small, it can turn out that the observations are not covered by the uncertainty bounds. That means that the model used is not a good description of the watershed. (Beven and Binley, 1992)

Notice that only parameter uncertainty is taken into account within the GLUE methodology. Other sources of error and uncertainty (for example in input) are handled implicitly (Beven and Freer, 2001). The next section describes which parameters are selected to be taken into account within this research. Next the initial range and distribution of these parameters are described.

4.3.1 Parameter selection

The parameters in the WetSpa model are divided into two parts: parameters during set-up time in ArcView and global parameters (explained in paragraph 2.3.2). The parameters in ArcView could not be taken into account within the uncertainty estimation, because ArcView cannot run automatically. Doing the set-up in ArcView by hand takes approximately fifteen minutes, so for a large number of simulations it is impossible to take these parameters into account.

From the twelve global parameters seven are taken into account. The time step is the first parameter that is not taken into account within this research. The time step is one hour, and it doesn't make sense to change the time step. Three parameters, T0, K_snow and K_rain, are only used when snow melting occurs. Because no snow melting occurs in the Ve river basin, these parameters don't influence the discharges, and are therefore not taken into account. The fifth parameter not taken into account is K_ep, a correction factor for evapotranspiration. As already stated in paragraph 3.1.4, evapotranspiration is zero during a flood period. So K_ep cannot influence the model output and therefore it is not used in the uncertainty analysis. So all in all seven (global) parameters are taken into account within this research. A detailed description of the physical meaning and influence to the WetSpa model of these parameters is given in Appendix A-1.

4.3.2 Ranges and distributions

Defining the prior ranges and distributions of parameters is done by prior knowledge about realistic parameter values. These are often defined purely subjectively. In case of little prior knowledge, a uniform distribution function over a chosen wide range will be appropriate (Beven and Binley, 1992). Therefore the distributions of the parameters are chosen uniform within this research. The parameter ranges are determined and evaluated iteratively. This is done with the simpler semi-distributed model (designed for calibration), because the fully-distributed model is time-consuming (1000 runs take eight hour). Only the final result was evaluated with the fully-distributed model, because this is the real WetSpa model. All further calculations are done with the fully-distributed model.

The first parameter ranges were extracted from a manual calibration, done by Doldersum (2009). To this aim dotty plots of the parameters were drawn, which are shown in appendix C-2. The ranges extracted from these plots are evaluated by 1000 model simulations using a random sampling method. Paragraph 4.3.3 explains this sampling method. From the first evaluation new dotty plots of parameters were drawn. From these plots new parameter ranges were determined for the second time. This is done iteratively till the model outputs were reasonably good. This took nine iterative steps, and correspondingly 9000 parameter sets were evaluated. The final ranges were evaluated in the fully-distributed model. In this case not random sampling was used, but Latin Hypercube Sampling (LHS). This method is explained in the next paragraph. The final parameter ranges are shown in Table 4. The dotty plots for this final range are presented in Appendix C-3, confirming that the ranges are neither too small, nor too wide.

Table 4: Prior and final parameter ranges for the global parameters

Parameter	Prior range	Final range
Ki	0 - 12	0 - 10
Kg	0 - 0.5	0 - 0.07
Kss	0 - 2	0 - 1.5
G0	0 - 100	0 - 50
Gmax	25 - 125	50 - 100
Krun	0 - 12	0 - 12
Pmax	0 - 500	0 - 500

4.3.3 Sampling methods

For determining the parameter ranges two sampling methods are used. The first is random sampling, used with the semi-distributed model. The second is Latin Hypercube Sampling (LHS), used with the fully-distributed model. Both are explained in this section.

Random sampling generates a large number of realizations of model parameters according to their corresponding probability distribution (Saltelli, Chan, and Scott, 2000). In this way many parameter sets can be evaluated. This sampling method is suitable for simple models, with short processing time. Therefore this method was used for the semi-distributed model.

However, the fully-distributed model has a longer processing time, which makes the random sampling method inefficient. Therefore another sampling method is necessary, as was argued by Uhlenbrook and Sieber (2005).They used LHS, also a common sampling method within the context of GLUE.

LHS is a stratified sampling approach which efficiently estimates the statistics of an output. The probability distribution of each parameter is subdivided into N ranges with an equal probability of occurrence (1/N). Random values of the parameters are simulated in such a way that each range is sampled just once. The order of selecting the ranges is randomized and the model is executed N times with a random combination of parameter values from each prior defined range. (Yu, Yang, and Chen, 2001) Within this research N is set to five, and 200 parameter sets were evaluated for defining the parameter ranges. The processing time of the fully-distributed model for 200 model simulations took approximately two hours.

4.4 *The procedure of using likelihoods for uncertainty estimation*

After determining the formal definition of the likelihood measure and the initial range and distribution of parameters, a Monte Carlo analysis was done to evaluate many parameter sets. For this aim LHS was used, because the uncertainty analysis has been done in the fully-distributed model.

For every parameter set created by LHS, the WetSpa model calculates the discharges. This output of the model gets a likelihood value from the likelihood measure used. Within this research three likelihood measures are used, so every output gets three (different) likelihoods. However, the likelihood measures can only be used one at a time in this procedure, so the rest of the explanation is done for one likelihood measure. After the calculation of the likelihoods, the behavioural and non-behavioural simulations are separated by the cut-off threshold. Only the behavioural simulations are taken into account in the assessment of the uncertainty. For the non-behavioural simulations the likelihood is set to zero, so they are not taken into account in the uncertainty analysis.

The likelihoods of the behavioural simulations are rescaled so their sum is one, calculated as

$$RL_i = L_i/(L_1 + L_2 + \ \dots + L_N) \tag{4}$$

where RL_i is the rescaled likelihood of the i^{th} simulation, L_i is the original likelihood of the i^{th} simulation, L_1 and L_2 are the likelihoods of the 1st and 2nd behavioural simulation respectively, and L_N the likelihood of the last simulation qualified as behavioural.

At every time step, the discharges of the behavioural simulations are sorted from low to high. The likelihoods, associated with the simulations, are also sorted per time step, in the same way as simulated discharges per time step. Notice that for every time step the sequence of likelihoods, and therefore the distribution of likelihoods, can be different. For every time step, the discharge value of the 5% and 95% of the cumulative likelihood distribution are the uncertainty bounds of the prediction. (Beven and Binley, 1992)

The *n*% cumulative likelihood is found by the weighted average of the cumulative likelihoods of the nearest neighbours (of behavioural simulations) above and below the *n*% cumulative likelihood, calculated as

$$Q_{n\%} = Q_{nnb} + \frac{CL_{n\%} - CL_{nnb}}{CL_{nna} - CL_{nnb}} * (Q_{nna} - Q_{nnb}) \tag{5}$$

where $Q_{n\%}$ is the discharge calculated belonging to the *n*% cumulative likelihood, $CL_{n\%}$ is the *n*% step of the cumulative likelihood distribution, CL_{nnb} and CL_{nna} respectively are the cumulative likelihood of the simulation just below and above the *n*% cumulative likelihood, and Q_{nnb} and Q_{nna} respectively the discharge simulated, belonging to CL_{nnb} and CL_{nna} respectively.

For a better understanding, the whole process of determining the uncertainty bounds is visualised in appendix C-4. The first part of the process is determining the parameter ranges and likelihoods, and the second part is determining the uncertainty bounds.

4.5 *Procedure updating likelihoods*

Within the GLUE-procedure the uncertainty estimation can be updated when a new data set becomes available. Therefore not a totally new uncertainty analysis is required: only the likelihoods of the original data set must be updated. Therefore the new data set has to be analyzed.

To this aim the discharges for the new data set must be calculated in the WetSpa model, by using the original parameter sets. These simulated discharges get a likelihood, calculated with the likelihood measure. The results are likelihoods of the new data set, for the original parameter sets. Then the original likelihoods can be updated, using Bayes' equation, after Beven and Freer (2001) and Choi and Beven (2006):

$$L(\Omega \boldsymbol{y}) = L(\Omega|\boldsymbol{y})L(\Omega) \qquad (6)$$

where $L(\Omega \boldsymbol{y})$ is the posterior likelihood distribution of the parameter sets, $L(\Omega|\boldsymbol{y})$ is the likelihood distribution given the new set of observations $\boldsymbol{y}$ (before the cut-off threshold), and $L(\Omega)$ is the prior likelihood distribution of the parameter sets (before the cut-off threshold). So the likelihoods of the same parameter sets for the original and the new data set are multiplied.

The new likelihood distribution can be used in the procedure to determine the uncertainty bounds. When using these new likelihoods within the procedure described in paragraph 4.4, the uncertainty bounds of the hydrograph are updated. Notice that for ME and EV, the cut-off threshold can remain the same, whereas the cut-off threshold for NS must change. The new cut-off threshold for NS is

$$\mathrm{NS} > 0.7^{n} \qquad (7)$$

where *n* is the number of datasets taken into account. This way of multiplication of the cut-off threshold is similar to the multiplication of likelihoods in equation (6). Therefore the new cut-off threshold can be used for the updated likelihoods.

4.6 *Procedure evaluating new data*

The refinement of the uncertainty limits as new data become available provides a measure of the value of these data. To obtain an objective value for a new data set, some measure of the uncertainty associated with the predictions is required. Werner, Hunter, and Bates (2005), and Beven and Binley (1992), used the Shannon Entropy measure, H, calculated as

$$H = -\sum_{i=1}^{M} RL_i log_2 RL_i \qquad (8)$$

where i = 1, 2, ... M is the number of simulations, and RL_i is the rescaled likelihood of the i^{th} behavioural simulation.

The Shannon Entropy has a maximum when all realizations are equally likely. It has a minimum of zero when one single realization has a likelihood of 1 and all others have a likelihood of zero. A lower entropy value indicates more structure and therefore less uncertainty (Werner, Hunter, and Bates, 2005). It should be expected that by adding more and more data the uncertainty decreases, and the Shannon Entropy will also decrease. However, this is not always the case, especially when taking into account events with specific hydrological responses. (Beven and Binley, 1992)

A problem, noticed by Beven and Binley (1992), is that the number of behavioural simulations must be the same for a correct comparison of the original and updated Shannon Entropy. However, updating data sets by using NS, can increase and decrease the number of behavioural simulations, due to the cut-off threshold. Therefore the Shannon Entropy is not calculated for NS, but only for ME and EV, because the number of behavioural simulations is always the same for ME and EV.

4.7 *Forecasting mode and simulation mode*

The procedures of using and updating likelihoods can be used for both simulation mode and for forecasting mode. In simulation mode, rainfall and stream flow data already measured are taken into account. Starting with these data, all steps of the GLUE methodology are required to estimate and update uncertainty. The uncertainty bounds can be drawn with the discharges observed to check whether the uncertainty bounds are consistent.

In forecasting mode, stream flow data and rainfall data are not measured. The rainfall data are replaced by a design rainfall. This design rainfall is used to calculate discharges in the WetSpa model for the original parameter sets. These calculated simulations must get a likelihood value so they can be used in the GLUE-procedures. However, as no stream flow data were measured for the design rainfall, the likelihoods cannot be calculated by the likelihood measures. Therefore the likelihoods, calculated for a data set used in simulation mode, are used as likelihoods in the forecasting mode. So the uncertainty bounds are calculated with likelihoods from a measured data set and with the discharges produced in the WetSpa model from a design rainfall. So it is only possible to use the methodology in forecasting mode after having used the methodology in simulation mode.
The uncertainty bounds cannot be drawn with the discharges observed as in simulation mode, because no discharges observed exist. The discharges observed are replaced by the discharges related to the 50% cumulative time step (for each time step). Calculation of these discharges is done with the weighted average method from equation (5).

5 Results and discussion

In this chapter the results are presented. The results of this research are a procedure to estimate uncertainty, a procedure to update the uncertainty with new data, and the uncertainty of the flood prediction in the Ve river basin. All are described in the next three paragraphs. Afterwards in paragraph 5.4 a discussion of the results is given.

5.1 *A procedure for estimating uncertainty*

Within this research several Matlab-scripts are designed in order to determine uncertainty using the GLUE methodology. Figure 13 visualises how these scripts must be used. In the next part of this section every process is explained, and it is also explained how all the data must be stored. When not stated differently, data are stored in '.txt' extension.

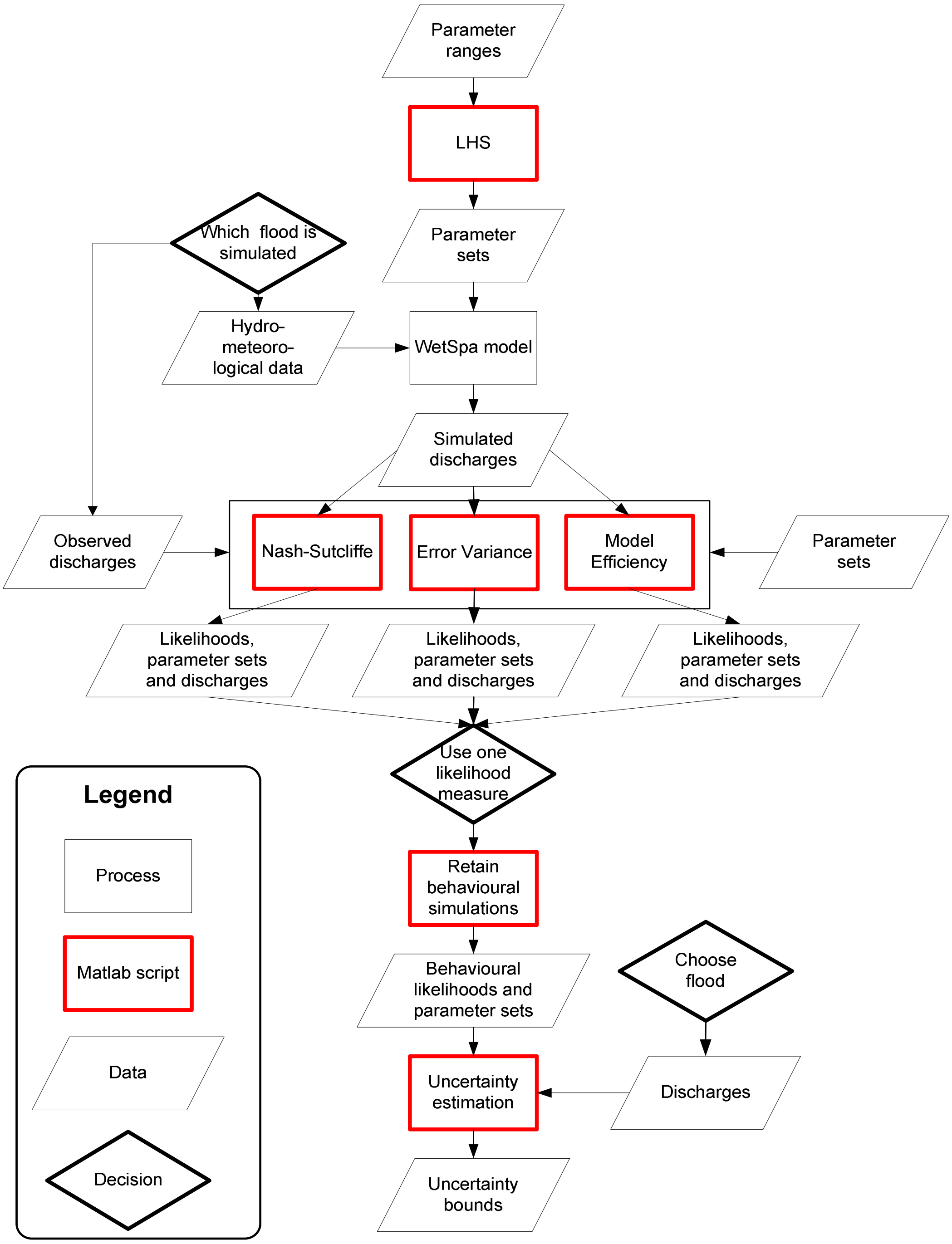

Figure 13: Process scheme to estimate uncertainty

5.1.1 Latin Hypercube Sampling

LHS is used to produce random parameter sets from parameter ranges, as was already explained in paragraph 4.3.3. The parameter ranges used, are presented in Table 4 (final ranges). These ranges are stored in the Matlab script 'Latin Hypercube Sampling' ('LHS'). So when the user wants to change the ranges, this has to be done in 'LHS'. The user determines the number of intervals and the number of parameter sets created.

5.1.2 WetSpa model

The WetSpa model needs two inputs from the user: the first input consists of hydro-meteorological data, as explained in paragraph 3.1; the second input consists of the parameter sets. Notice that it is assumed that the set-up in ArcView has already been done.
The WetSpa model can only take into account one flood at a time, so the user has to decide which flood is simulated, or run the model multiple times for multiple floods. How all hydro-meteorological data must be stored can be found in the User manual from Liu and De Smedt (2004). The parameter sets must be stored in the same format as Table 5, which shows an example-file for two parameter sets. The maximum number of parameter sets in one file is 1000, because the WetSpa model cannot handle more parameter sets.

Table 5: Example of a parameter sets file

	Ki	Kg	Kss	G0	Gmax	Krun	Pmax
p1	7.518	0.009	0.147	2.760	79.967	11.403	195.929
p2	10.512	0.028	1.034	16.797	69.195	5.412	354.722

5.1.3 Nash-Sutcliffe, Model Efficiency and Error Variance

The simulated discharges, the output of the model, get a likelihood from the formulas from equations (1), (2) and (3), within the Matlab scripts 'Nash-Sutcliffe' ('NS'), 'Model Efficiency' ('ME') and 'Error Variance' ('EV') respectively. These scripts need two input files, which consist of the discharges simulated from the WetSpa model and the discharges observed.

An example of the format of the output of the WetSpa model, the first input for the Matlab scripts here described, is shown in Table 6, for three time steps and four simulations. Every simulation is stored in a separate column, and for every time step the discharges are stored in separate rows.

Table 6: Example of the output file of the WetSpa model

	1	2	3	4
t1	984	622	828	1263
t2	906	520	713	1143
t3	846	462	643	1061

The observed discharges, the second input for these scripts, must be stored in the same way as the simulations. Of course, only one column is used, because per flood discharges are measured once.

Within these Matlab scripts the user can decide from what time step till what time step the NS, ME or EV must be measured. So it is necessary that the number of time steps of the observed dataset and of the simulation dataset is the same.

5.1.4 Retain Behavioural Simulations

In the Matlab script 'Retain Behavioural Simulations' ('RBS') the behavioural likelihoods are separated from the non-behavioural likelihoods. This script can handle one likelihood measure and one flood at a time. The user must decide whether to use this script for estimating uncertainty or for updating uncertainty. Because this paragraph describes the procedure for estimating uncertainty, the first option must be chosen. Updating uncertainty can also be done within this file, but this is explained in paragraph 5.2.1.

The input of this script is the output data of the Matlab scripts as described in the previous paragraph: the likelihoods, related parameter sets and related discharges. In Table 7 an example of such an output file is given.

Table 7: Example of the output file of the Matlab scripts from paragraph 5.1.3

	1	2	3	4
Li	1	0.53657	0.4065	0.26556
Ki	0	7.518	10.512	3.507
Kg	0	0.009	0.028	0.055
Kss	0	0.147	1.034	1.394
G0	0	2.76	16.797	36.551
Gmax	0	79.967	69.195	136.808
Krun	0	11.403	5.412	8.414
Pmax	0	195.929	354.722	413.862
t1	1263	984	622	828
t2	1143	906	520	713
t3	1061	846	462	643

In the first row the likelihoods are saved. In the second till eighth row the parameters are saved. From row nine till the end of the file the discharges are saved. This is done for all simulations, which are stored in separate columns. In the first column the data observed are stored, but these data do not have a likelihood or a parameter set. However, these cells need to be filled, because otherwise the '.txt'-file becomes unreadable for Matlab. Therefore the likelihood is given a value of one, and the parameters are given a value of zero.

5.1.5 Uncertainty Estimation

In the script 'Uncertainty Estimation' ('UE') all processes described in paragraph 4.4 are used, starting from the behavioural likelihoods. The final output of the script 'Uncertainty estimation' is a graph of the observed discharge, and the lower and upper uncertainty bound.
Two input files are necessary, which are the output file from the script 'RBS' and the discharges, observed and simulated, saved as in Table 7. Only one flood at a time can be handled in the script 'Uncertainty Estimation'.

An example of the output file of the script 'RBS', necessary as input for the script 'UE', is presented in Table 8, for the observed stream flow data and three simulations.

Table 8: Example of output file of the Matlab script 'RBS'

	1	2	3	4
Li	1	0.53657	0.4065	0.26556
BLi	4.32006	0.53657	0.00000	0.00000
Ki	0	7.518	10.512	3.507
Kg	0	0.009	0.028	0.055
Kss	0	0.147	1.034	1.394
G0	0	2.76	16.797	36.551
Gmax	0	79.967	69.195	136.808
Krun	0	11.403	5.412	8.414
Pmax	0	195.929	354.722	413.862

The data are stored in separate columns for all simulations, starting with the observed data set in column one. In the first row all the original likelihoods are stored, which are used for the purpose of updating, as explained in the next section. The second row contains the behavioural likelihoods. Behavioural likelihoods keep their own value, whereas the likelihood of non-behavioural simulations is set to zero. Furthermore the parameter sets are also stored in this file. In cell (1,2) the Shannon entropy (explained in paragraph 4.6) is stored.

The discharges, the second input for the Matlab script 'UE', must be stored as in Table 7, so beginning from row nine. From this file only the discharges are used, so the likelihoods and parameter sets stored in this file are irrelevant. Notice that the simulations from the discharges file and the related likelihoods from the behavioural likelihoods file must be saved in the same column number.

The output of the Matlab script 'Uncertainty Estimation' is a '*.tiff'-file, which shows a graph with the observed/forecasted discharges and the uncertainty bounds.

5.2 *A procedure for updating uncertainty*

Within the GLUE methodology the uncertainty bounds, estimated by the procedure previously described, can be updated when taking a new data set into account. Therefore only the likelihoods of the original data must be updated and used in the procedure to estimate uncertainty. In Figure 14 the procedure to update the likelihoods is shown, which has as a final result the newly drawn uncertainty bounds. The evaluation of new data is also incorporated into this procedure.

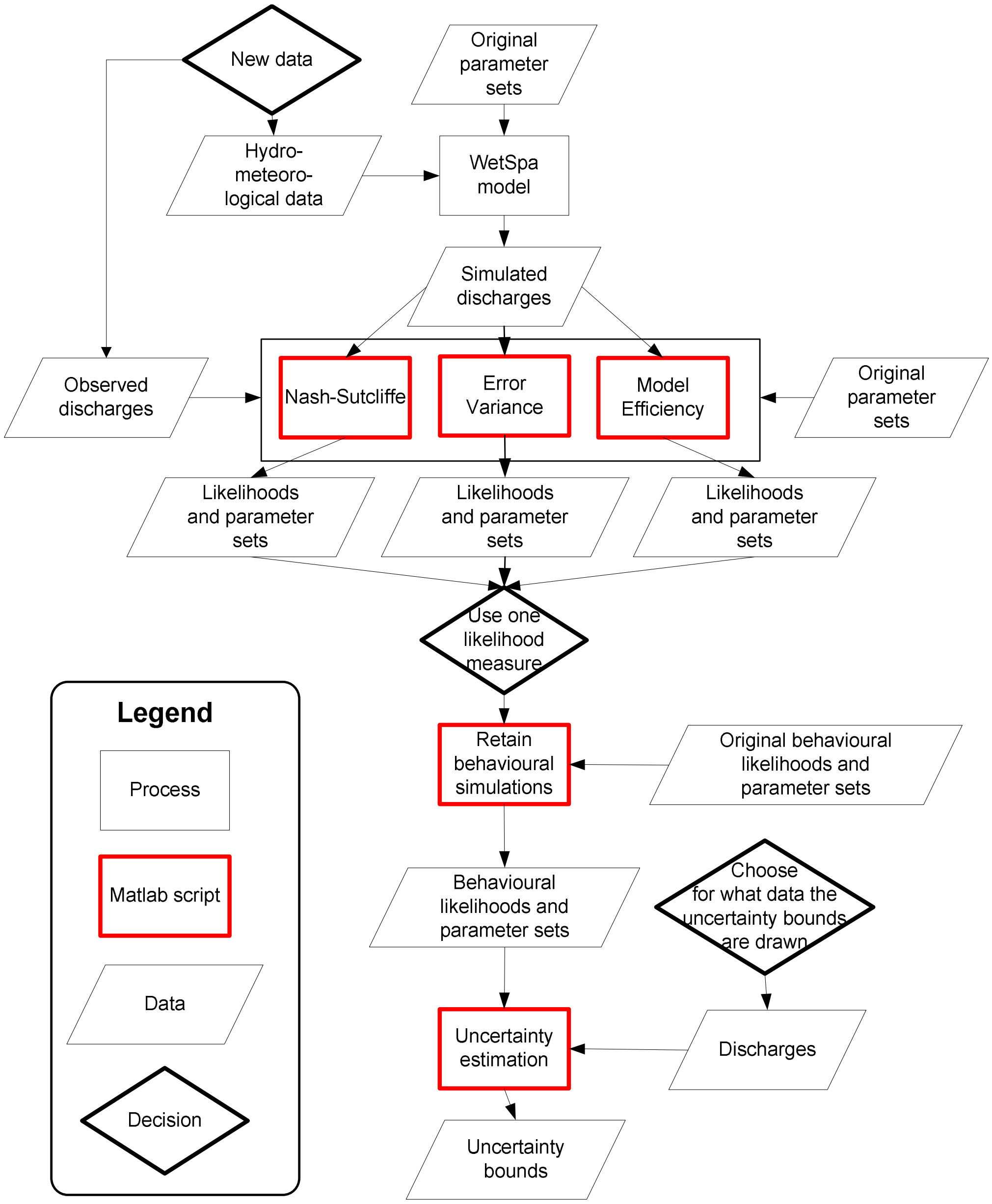

Figure 14: Process scheme to update the uncertainty estimation

The first processes, till the decision 'Use one likelihood measure', are similar to the steps of the uncertainty estimation procedure. The difference is that the WetSpa model has to simulate for different hydro-meteorological data. Notice that the same parameter sets which were used for the original data set are needed as input. The steps after the decision 'Use one likelihood measure' are described in the next paragraphs. Notice that the same Matlab-scripts used in the procedure to estimate uncertainty are used in the procedure to update uncertainty.

5.2.1 Retain Behavioural Simulations

In the Matlab script 'Retain Behavioural Simulations' ('RBS') the first question the user must answer is whether to use this script for estimating uncertainty or for updating uncertainty. As this procedure deals with updating, the second option must be chosen. Next the file where the original behavioural likelihoods ($L(\Omega)$ in Equation (6)) are saved is needed as input. This file must be stored in the format shown in Table 8. The second input is the likelihoods of the new data ($L(\Omega|\boldsymbol{y})$ in Equation (6)), which must be stored in the format shown in Table 7. When multiple new datasets exist, updating can only be done for one data set at a time.

Within this Matlab script the likelihood updating from equation (6) takes place. When NS is used as likelihood, the cut-off threshold is updated, using equation (7), within this script. The output of this script has the same format as Table 8.

In cell (1,1) of the output file of this script the number of datasets taken into account (*n* from Equation (7)) is stored. This number is used when taking more datasets into account to update the cut-off threshold for NS. In the uncertainty estimation procedure of paragraph 5.1, this number is automatically set to one. The Shannon Entropy for the updated project is stored in cell (1,2).

5.2.2 Uncertainty Estimation

The input for the Matlab script 'Uncertainty Estimation' ('UE') has already been explained in paragraph 5.1.5 , and consists of two parts. The first is the output from the Matlab script 'Retain Behavioural Simulations'. The other input is the discharges, simulated as well as observed, stored as in Table 7. For which flood the uncertainty bounds are drawn, must be chosen by the user. This is explained below.

In simulation mode, the updated likelihoods can be used to draw the uncertainty bounds for the original flood, using the discharges of the original data set (saved as in Table 7). Also these updated likelihoods can be used to draw the uncertainty bounds for the new data set, using the discharges of the new data set (saved as in Table 7). Of course, the uncertainty bounds can be drawn for both datasets. However, the Matlab script can only handle one data set at a time, so in that case the script has to be used twice.

Calculation of the uncertainty bounds in forecasting mode is also possible in this script. The input of the Matlab script 'UE' remains the same in forecasting mode: behavioural likelihoods and discharges (saved as in Table 7). As already explained in paragraph 4.7, to create discharges in forecasting mode, the WetSpa model is used to produce discharges from a design rainfall for the original parameter sets. From these simulated discharges no likelihoods can be determined with the likelihood measure, because no observed discharges exist. Therefore the likelihoods of a flood, (or multiple floods) calculated in simulation mode, are used as the likelihoods in forecasting mode.

5.2.3 Naming data files

Table 9 presents the way the names of the output files are stored for the different Matlab scripts. An explanation is given below.

Table 9: Naming output data

Process	Abbreviation	Explanation
LHS	'ps' 'x'	'parameter sets' 'x'
WetSpa	'myy' 'dis'	'month year' 'discharges'
NS, ME, EV	'myy' 'LM'	'month year' 'Likelihood Measure'
RBS	'myy' 'LM' 'bl'	'month year' 'Likelihood Measure' 'behavioural likelihoods'
UE	'myy' 'LM' 'o/u'	'month year' 'Likelihood Measure' 'original/updated'

The name of the output-file for LHS always starts with the two letter 'ps', followed by the x-th parameter set. Of course the starting value is one.

The output of the WetSpa model is stored as 'q_tot1.txt' by the mode itself, and this cannot be changed in the model. In order to understand from which flood the discharges are stored in this file, the file must be renamed to a three-character abbreviation for 'month year' and 'dis'. The three-character abbreviation for 'month year' is divided into one character to represent the month, and two to represent the year. Because the rainy season lasts from September till December, a flood can only occur in four months. These four months start with different letters (September – s, October – o, November – n, December – d). Therefore to make clear in which month the flood occurred, only one character is needed to represent the month. For the year two characters are needed.

The name of the output of NS, ME and EV starts with the three-character abbreviation for the 'month year'. Afterwards the likelihood measure used (NS, ME or EV) is stored.

The name of the output of RBS starts the same as the name of the output of NS, ME and EV. The two letters 'bl' are added afterwards, indicating that the behavioural likelihoods are stored in the file.

The graph of the Matlab script 'UE' starts like 'RBS' with the month, year and likelihood measure used. Afterwards an 'o' or a 'u' is added, to distiguish between an original situation or an updated situation.

Notice that this way of naming data files is not only used for the procedure of updating uncertainty. The data files used in the procedure of estimating uncertainty are named in the same way as described here.

5.3 *The uncertainty of the Ve river basin*

To estimate and update the uncertainty of the Ve river basin, the data sets of November 1999 and October 2003 are used in the procedures described in the previous paragraphs. These floods are used in simulation mode. These two floods have been chosen because they seem to produce the best results in comparison with the December 1999 data. Because a design rainfall was not available, the December 1999 data set is used in forecasting mode. The warming-up period of the three floods is twelve, seven and seven hours respectively. This is very short, but a great part of the flood is taken into account in this way. Increasing the warming-up period would leave very few data for analysis, as the data series is small, only about 100 time steps.

The number of model simulations is incrementally increased from 100, to 200, to 400. This is done to check if the uncertainty bounds change when taking more simulations into account. When 400 model simulations are taken into account, no significant differences in the uncertainty bounds can be seen compared to 200 model simulations. Therefore it can be concluded that 200 simulations are appropriate for this case.

First the results of the uncertainty for simulation mode are described in paragraph 5.3.1; afterwards the results for forecasting mode are presented in paragraph 5.3.2.

5.3.1 Simulation mode

The procedures are first used in simulation mode. To this aim the uncertainty bounds for the three likelihood measures are drawn. This is done for both the original likelihoods, and for the updated likelihoods. The next two sections present the results for November 1999 and October 2003 separately.

5.3.1.1 The uncertainty of the flood of November 1999

The uncertainty bounds are calculated by use of the procedures for estimating and updating uncertainty as described in the previous paragraphs. All plots are given in Appendix D-1. One example of these graphs is shown in Figure 15, to give an impression of the uncertainty bounds.

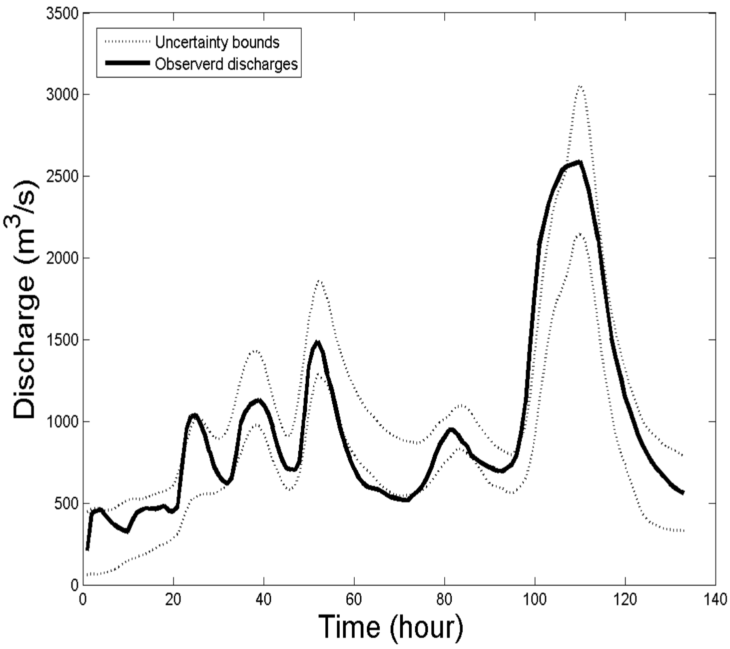

Figure 15: The updated uncertainty for the November 1999 flood, calculated with NS

The different likelihood measures, used in the original and in the updated situation, result in different uncertainty bounds. A survey of the characteristics is presented in Table 10. The original uncertainties are calculated while taking into account only the likelihoods of November 1999. For the updated uncertainties the updated likelihoods were used, using November 1999 data and October 2003 data.

Table 10: Characteristics of the uncertainty of the November 1999 flood

Characteristics	NS original	NS updated	ME original	ME updated	EV original	EV updated
Overestimation (at time step)	Slight (60-75)	Slight (55-70)	Slight (55-65)	Slight (58-62)	Slight (57-61)	Slight (55-62)
Underestimation (at time step)	Slight (98-102)	Slight (98-102)	Slight (98-102)	Slight (20-25, 98-105)	Slight (98-102)	Slight (98-105)
Uncertainty at peak (m^3/s)	1000	1000	500	700	800	700
Upper uncertainty at peak (m^3/s)	600	500	450	300	500	300
Behavioural simulations	128	87	20	20	200	200

5.3.1.2 The uncertainty of the flood of October 2003

The uncertainty bounds for October 2003 are calculated in the same way as the uncertainty bounds of November 1999. The plots are presented in Appendix D-2. An impression of the uncertainty bounds for October 2003 is shown in Figure 16. Table 11 gives a survey of the characteristics of the October 2003 flood.

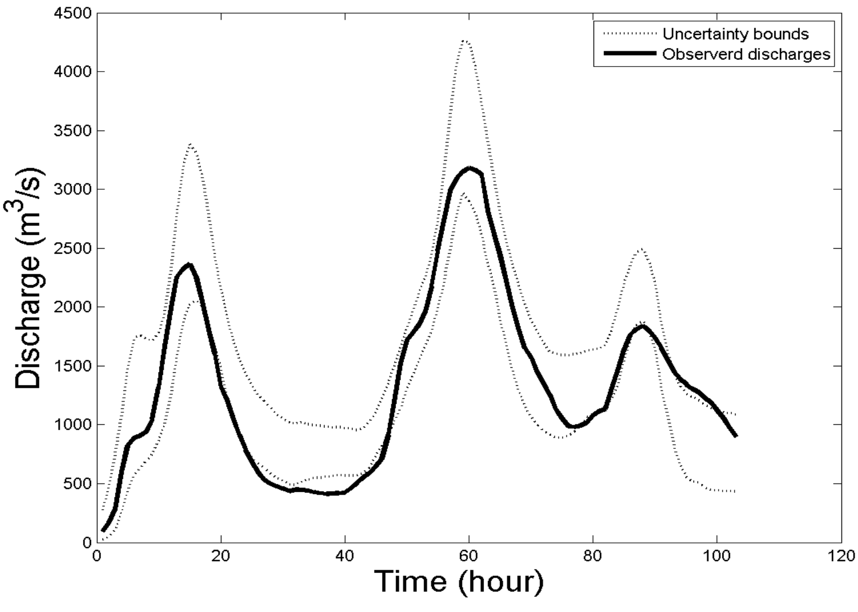

Figure 16: The updated uncertainty for the October 2003 flood, calculated with NS

Table 11: Characteristics of the uncertainty of the October 2003 flood

Characteristics	NS original	NS updated	ME original	ME updated	EV original	EV updated
Overestimation (at time step)	Slight (38-42)	Slight (25-45)	Modest (25-45)	Slight (35-40)	Slight (30-40)	Slight (35-45)
Underestimation (at time step)	Slight (95-100)	Slight (95-100)	Slight (96-99)	Modest (95-102)	None	Modest (90-102)
Uncertainty at peak (m^3/s)	1500	1300	1000	1100	1200	1100
Overestimation at peak (m^3/s)	1000	1100	800	900	800	800
Behavioural simulations	60	87	20	20	200	200

5.3.1.3 Shannon Entropy

The Shannon Entropy is a method to asses the value of data. Within this research this is calculated for the likelihoods of ME and EV, which is described in paragraph 4.6. Table 12 shows the Shannon Entropies for both floods separately and for the updated case.

Table 12: Original and updated Shannon Entropies

Likelihood measure	Original Nov 1999	Original Oct 2003	Updated
Model Efficiency	4.32006	4.32131	4.31362
Error Variance	6.477212	6.10924	4.78575

The Shannon Entropy has a maximum when all simulations are equally likely. Within this research for ME 20 likelihoods are taken into account, leading to a maximum entropy of 4.32193. For EV 200 likelihoods are taken into account, resulting in a maximum entropy of 7.64386.

5.3.2 Forecasting mode

After having used the procedures in simulation mode, the procedures are used in forecasting mode. Within this research no design rainfall was available. Therefore the rainfall of December 1999 is used as a design rainfall. This has the advantage that the discharges measured are available, so it is possible to check whether the uncertainty bounds are consistent.

5.3.2.1 The uncertainty for the December 1999 flood

The uncertainty bounds for December 1999 are drawn within the procedure of updating uncertainty. All likelihood measures were used in the updated situation, taking into account November 1999 and October 2003 likelihoods. These likelihoods and the simulated discharges of December were used as input for the script 'Uncertainty estimation'. All graphs are shown in Appendix D-3. An impression of the result is shown in Figure 17.

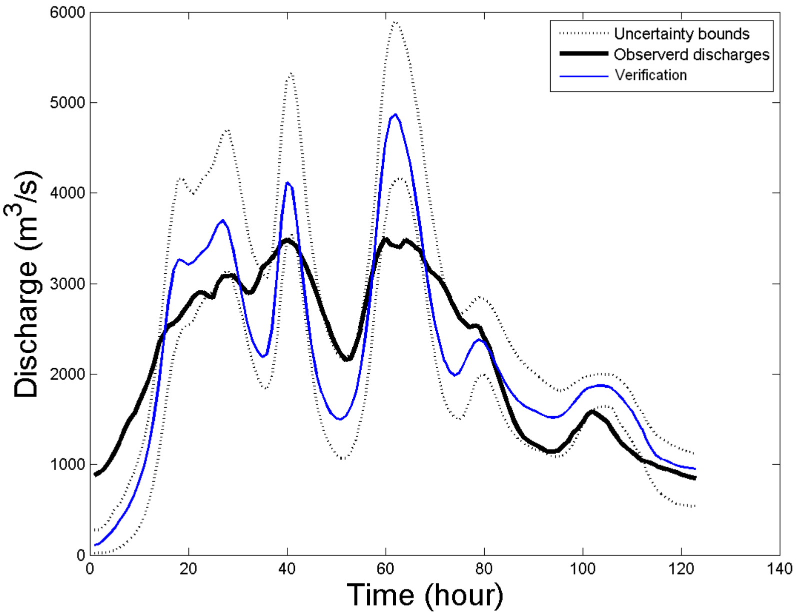

Figure 17: The uncertainty bounds for December 1999 calculated with NS, and the verification result of Doldersum (2009)

5.4 *Discussion*

In this section the results are discussed. Because there are no discussions on the procedures from paragraph 5.1 and 5.2, only the results from paragraph 5.3 are commented.

5.4.1 Simulation mode

Over- and underestimation

The uncertainty bounds are drawn for all likelihood measures used, both in the original and in the updated situation. The results show a slight to modest over- and underestimation for both floods in all situations. Though these occur at periods with low discharges, which are less relevant for flood forecasting, it shows that no likelihood measure or original/updated situation represent the uncertainty fully adequate. Some possible explanations for this problem are stated below.

- The underestimation for November 1999 around time step 100 (which is the upward to the peak) can be explained by the parameter insensitivity to time, argued by Doldersum (2009). Therefore no simulations have an earlier peak (nor an earlier rising to the peak) than the one observed . The result is that the uncertainty bounds from the upward discharges to the peak discharges are small, and a little inconsistent.

Another explanation of the over- and underestimation is the way the model is calibrated. This is done by the research of Doldersum (2009), and can influence the result. Three main problems of the calibration are stated here.

- First, the parameters during set-up time in ArcView were not calibrated due to model problems. Though the first input was chosen with care, calibrating these parameters would probably result in better uncertainty bounds. The chosen inputs for ArcView are presented in Appendix B-1.
- Secondly, the warming-up time for calibration was very short. This is due to data limitation, because only rainfall data during floods were available. Though this is not necessarily a problem, it could be one. A problem can arise when initial conditions of the floods are in reality different. Normally a long warming-up time would reduce the effect of parameters determining initial conditions. But with a short warming-up period, initial parameters have a great effect on the model output. When floods have different initial conditions, different

values of the initial parameters lead to a good representation of the floods. However calibration must lead to one parameter set for multiple floods.

- Thirdly, some data were not fully correct as input. The discharges of the October 2003 flood were not measured, but calculated from water level data. The geographical information and tables in WetSpa were not translated fully correct. Furthermore, the rainfall data were not measured hourly for all stations. These data problems can influence the over- and underestimations.

Updating uncertainty

Updating the uncertainty does not necessarily lead to a smaller uncertainty at the peak. This is true for both floods. For both floods, an increase can be seen when using likelihood measure ME. Using the other likelihood measures the uncertainty remains the same or decreases. The upper uncertainty at the peak decreases for all likelihood measures for the November 1999 flood. But for the October 2003 flood, the upper uncertainty increases for NS and Me, and remains the same for EV. Some possible explanations for these characteristics are stated below.

- For the November 1999 flood, an increase of the uncertainty at the peak is calculated when using likelihood measure ME. However, the upper uncertainty at the peak decreases for this likelihood measure. From the plots (Appendix D-1) it can be seen that in the original situation the lower uncertainty bound is very close to the value observed. So, in the updated situation the lower uncertainty bound becomes more consistent and the upper uncertainty at the peak decreases. Therefore it is concluded that despite the increase of uncertainty at the peak, updating gives better - because more consistent)-uncertainty bounds.

For the October 2003 flood this explanation is not sufficient. Updating the uncertainty leads to an uncertainty increase for ME. Though this is not expected at first, it is even more surprising that the upper uncertainty is higher with updating for NS and ME, and does not decrease for EV. Some explanations for this situations are stated below.

- The increase of the upper uncertainty with NS, can be explained by the increase of the number of behavioural simulations from 60 to 87. This means that simulations which were originally classified as non-behavioural (with a NS < 0.7) are classified as behavioural in the updated situation. So more simulations, which are poor for October, are taken into account in the updated situation. This normally leads to a higher uncertainty.

Though this is an explanation for NS, it is not an explanation for ME and EV. The fact is that the number of behavioural simulations for ME and EV remains the same.

- However, for ME the simulations qualified as behavioural can vary with updating, because the best 10% of the updated likelihoods is qualified as behavioural. Therefore it is expected that likelihoods, which are originally non-behavioural, are classified as behavioural in the updated situation.

Still, this is not an explanation for EV. The change of an uncertainty bound for EV can occur only when likelihoods get a new value.

- So only the distribution of likelihoods per time step can change, leading to different uncertainty bounds. The decrease of total uncertainty at the peak indicates that the discharge outside the uncertainty bounds got a lower updated likelihood. This is the reason for a change in the uncertainty bounds.

Though it seems that the increase of the uncertainty is a bad result, in fact it is not. It shows that the hydrological responses of November and October are different. The likelihoods of the same parameter sets show significant differences between the two floods, so combining the likelihoods would classify different parameter sets as behavioural. So it is expected that the uncertainty bounds change. For November 1999 updating results in smaller uncertainty bounds, which indicates that originally too many simulations were classified as behavioural. For October 2003 updating results in wider uncertainty bounds, indicating that the original uncertainty bounds were too small. This is already argued by Beven and Binley (1992), who stated that updating with an event that has specific hydrological responses should lead to an increase of the uncertainty.

In case of the Ve river basin, the difference of the two floods is caused by parameter Ki. The dotty plot patterns for the final ranges, shown in Appendix C-3, are different for both floods. According to Doldersum (2009), this parameter is very sensitive. This parameter influences the interflow and this indicates that the interflow of both floods is different. The driving force behind interflow is the effective hydraulic conductivity at soil moisture content. It is expected that in reality the initial conditions, specifically the initial moisture condition, for both floods were different. But this difference cannot be taken into account in the model, because the initial conditions and parameters must be the same for all simulations. As the warming-up periods were very small, the initial conditions have a great influence on the result.

Shannon Entropy

The Shannon Entropy is a way to measure the value of new data. It is expected that with more data less uncertainty exists. Though this is true for EV, it is not true for ME.

- For ME the entropies are approximately the same for the original and the updated situation. All three entropies are close to the maximum entropy, indicating that much uncertainty is present within the behavioural simulations. This could be expected looking at the increase of uncertainty for updating for October 2003.
- For EV, the original entropies show a small difference, indicating that more uncertainty exists forNovember 1999 than for October 2003. But especially the updated entropy is interesting, showing a significant decrease of uncertainty. This shows that the updated likelihood distribution is more peaked than the original likelihood distributions.

When comparing the Shannon Entropies it is expected that the likelihood distribution of all simulations is more peaked in the updated situation. However, the best 10% of the likelihoods show a similar likelihood distribution between original and updated situation. Therefore the Shannon Entropy for ME does not change significantly, whereas the Shannon Entropy for EV decreases significantly.

5.4.2 Forecasting mode

The results of the procedures in forcasting mode are very poor, although the discharges observed fall inside the uncertainty bounds most of the time. The pattern of the uncertainty bounds is also different from the pattern of the discharges observed. At the peak an overestimation between 700 m^3/s and 2600 m^3/s can be seen. Furthermore, the discharge observed switch from the lowest uncertainty bound at peaks (time step 30 and 40) to the highest uncertainty bound at a decrease of discharges (time step 35 and 50). This indicates that the pattern is not well modelled. Some possible explanations are stated below.

- This result could be expected from the research of Doldersum (2009). He showed that the verification on December 1999 was also poor. He calibrated for November 1999 and October 2003 with a result of a Nash-Sutcliffe for both floods of above 0.85, which is a good result. Verification was done for December 1999 but failed, with a Nash-Sutcliffe of 0.57, and a non-corresponding hydrograph. It was concluded that this was due to the ‘semi-open basin’, as explained in paragraph 2.2.

Therefore the verification result from Doldersum (2009) is also shown in Figure 17. This result shows a pretty good response with respect to the uncertainty bounds. The verification result remains within the uncertainty bounds during the whole flood. This indicates that the procedures for estimating and updating uncertainty work in forecasting mode, but it is also clear that the December 1999 flood is hard to model correctly.

6 Conclusions and recommendations

This chapter presents the conclusions of this research, and describes recommendations for further research. The conclusions and recommendation for the procedures and the use of the procedures are described separately.

6.1 *Procedures*

The procedures have already been described in paragraph 5.1 and 5.2. In this section conclusions and recommendations about the procedures are described.

6.1.1 Conclusions

The advantage of the procedures designed is that they consist of multiple scripts instead of one big script. This results in flexible procedures, which can be adjusted very easily. New likelihood measures can be incorporated into these procedures. Moreover it is possible to use the procedures for other models and study areas than the WetSpa model and the Ve river. Furthermore the procedures can be used in simulation mode and in forecasting mode. Because of these three advantages, it is concluded that the procedures are flexible. The advantages of multiple scripts are explained in more detail below. Some improvements could be made to the scripts. These are stated in paragraph 6.1.2.
The advantages of multiple scripts:

- To incorporate a new likelihood measure, a new script must be designed to calculate the likelihoods of simulations. The only requirements for such a script are that the input and output must be stored in the same way as the input and output of the scripts designed within this research, see paragraph 5.1.3. This way of expanding the procedure is more flexible in comparison to a procedure with one big script. In the case of one big script, that script has to be re-edited to incorporate more likelihood measures.
- When the procedures are used for a different model, the only requirements are that the input and output must be stored in the same way as done in this research. It can be necessary to modify the model used to simulate automatically for multiple parameter sets. This was also necessary for the WetSpa model, because it could not simulate multiple parameter sets automatically before.
- The difference between simulation mode and forecasting mode is the input and output of the last Matlab script ('UE'). In simulation mode the discharges-input must be the discharges produced by the WetSpa model from a measured rainfall and the likelihoods calculated from these discharges. The uncertainty bounds are drawn together with the discharges. observed. In forecasting mode the discharges-input must be the discharges produced by WetSpa from a design rain and the likelihoods calculated for a flood in simulation mode. The forecasted discharge is determined by the discharge of the 50% cumulative likelihood and drawn together with the uncertainty bounds.

6.1.2 Recommendations

- Parameters in ArcView have not been taken into account within these procedures. This is due to the model limitations of ArcView. It is recommended to use a model that can simulate map-data automatically. This could be realised by changing the WetSpa model, or by chosing another model. In that case all parameters can be taken into account.
- The procedures designed can handle only one data set at a time. This was not a problem within this research, because only three data sets were available. However, when more data sets are available, it is recommended to modify the Matlab scripts in order to handle more data sets at a time. This will save a lot of work and time.
- It is useful to give an ID (identification) to every simulation. This would make it possible to simulate only the behavioural parameter sets in forecasting mode. This will save processing time of the WetSpa model. However, this depends on the cut-off threshold. For ME only

twenty parameter sets need to be evaluated, which saves a lot of time in comparison to 200 model simulations. For EV all parameter sets need to be evaluated because it does not contain a cut-off threshold.

6.2 *Application of the procedures in the Ve river basin*

The procedures have been used for the Ve river basin. The results have been presented in paragraph 5.3. This section describes conclusions and recommendations. First, all conclusions are listed, afterwards the recommendations are described.

6.2.1 Conclusions

- The hydrological responses of the two analyzed floods were different. This is shown by the final dotty plots of parameter Ki. It is expected that the short warming-up time combined with different initial conditions is the reason of the different hydrological responses of both floods. This results in high Shannon Entropies and broad uncertainty bounds. Moreover the number of behavioural simulations for NS is signifcantly different between the November 1999 flood and the October 2003 flood.
- Almost all results show small over- and underestimation at the uncertainty bounds. For the November 1999 flood, the underestimation can be explained by the parameter insensitivity to the time till the peak. This conclusion is proved by Doldersum (2009), and is a drawback for the calculation of the uncertainty bounds. However, the other over- and underestimation cannot be explained in a similar way. Therefore it is concluded that the combination of model, data and parameter ranges is not fully adequate to represent the hydrological response of the study area. However, the inconsistency occurs at time steps with low discharges, so it is less relevant in case of flood forecasting.
- It is very important to update the likelihoods, because it increases the predictive capability of the model or it indicates that floods have different hydrological responses. The predictive capability of the model will increase when the uncertainty bounds become smaller with updating. When the uncertainty bounds do not become smaller, it shows that the hydrological responses are different. Within the Ve river, updating uncertainty did not result in smaller uncertainty bounds. This shows that the hydrological responses of the two floods were different.
- The comparison of the three likelihood measures shows that Nash-Sutcliffe is the most appropriate likelihood measure to produce uncertainty bounds. It produces the widest uncertainty bounds at the peak, and the highest upper uncertainty at the peak. This gives the impression of small predictive capability. However, the lower uncertainty bound is better when produced with Nash-Sutcliffe. Model Efficiency and Error Variance show a very high lower uncertainty bound especially in the original situation. At some time steps this bound is almost as high as the discharge observed. This shows that Nash-Sutcliffe produces the most adequate uncertainty bounds and is therefore the most appropriate to use.
- The Shannon Entropy for Error Variance is the most appropriate way to calculate the value of new data. This takes into account the likelihoods of all simulations, whereas Model Efficiency only takes into account the best 10% of all likelihoods. Updating resulted in a more peaked likelihood distribution for Error Variance, whereas the likelihood distribution of Model Efficiency remained approximately the same. A more peaked distribution indicates that there is less uncertainty. Notice that the difference between EV and ME is mostly caused by the cut-off threshold used.
- The result of the procedures in forecasting mode, for December 1999, is poor. The uncertainty bounds are inconsistent and show a pattern different from the discharges observed. This is a confirmation of the poor verification result of Doldersum (2009). He concluded that this was due to the semi-open basin, so water was flowing in and out of the study area. However, the verification result of Doldersum (2009) shows a good

correspondence with respect to the uncertainty bounds. This confirms that the procedures work correctly in forecasting mode, as well as in simulation mode.

6.2.2 Recommendations

- The initial conditions should be less relevant in order to reduce the effect of the difference in hydrological responses. This can be realised by taking into account a longer warming-up period. Therefore it is suggested to start earlier with measuring the rainfall before a flood, in order to increase the warming-up period.
- The comparison of likelihood measures is done for the cut-off threshold and weighing factors chosen. For a better comparison it is necessary to try multiple cut-off thresholds and weighing factors. Furthermore, more likelihood measures can be taken into account. When all this is practised, more characteristics can be determined for the different likelihood measures, cut-off thresholds and weighing factors. This will increase the reliablity of the conclusions.
- The comparison of the likelihood measures has been done for one study area and two (small) data sets. To check whether the characteristics of this comparison are correct on a global scale, more study areas and data sets need to be evaluated. It is also recommended to take into account more floods, to investigate the effect of multiple updating on the characteristics.
- To estimate the value of new data, more research must be done on the effect of the likelihood measure and cut-off threshold used. The difference of the Shannon Entropies of Model Efficiency and Error Variance are caused mostly by the cut-off threshold used. Therefore different cut-off thresholds must be evaluated in order to compare the Shannon Entropies.
- Within this research the ArcView part was not calibrated. Furthermore, the classes of the maps and tables were not related fully correctly, and the rainfall data were not measured hourly for all the stations. For a fully correct calculation of the uncertainty bounds, all these data problems must be solved. Therefore ArcView must be calibrated, the classes need to bem translated fully correctly and the rainfall data must be measured hourly for all stations.
- More research must be done to incorporate the characteristics of the semi-open basin into the model. The present WetSpa model can only simulate a closed basin. So the model has to be modified in order to take into account the semi-open basin. Furthermore, it must be clear when water flows in and out of the study area, to incorporate this effect into a flood forecasting procedure.

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A Study area: The Ve river basin

A.1 *Parameter description*

Seven global parameters are taken into account in the uncertainty analysis. These are Ki, Kg, Kss, G0, Gmax, Krun and Pmax. This paragraph describes the function and influence of these parameters in the WetSpa model, and the physical meaning of these parameters. This is an addition to the explanation of the processes in a grid cell, described in paragraph 2.3.1.2.

A.1.1 Ki

Ki is a scaling factor for interflow computation. Interflow or subsurface runoff is an essential runoff component for the humid temperate region, especially for the areas with sloping landscapes and a well-vegetated cover. Interflow is defined as the water which infiltrates the soil surface and moves laterally through the upper soil layers until it enters a channel, excluding the saturated groundwater flow. In the model a uniform soil matrix is considered. However, in fact, the porosity and permeability of soil tend to decrease with depth given the weight of overlying soil and the translocation of material in percolating water to lateral subsurface flow. Moreover, soil water passing quickly to a stream through root canals, animal tunnels, or pipes produced by subsurface erosion may become a critical component of peak flow. To account for theses effects, a scaling factor for lateral hydraulic conductivity in computing interflow is used in the model (Liu and De Smedt, 2004).
The quantity of interflow out of each cell is calculated from Darcy's Law and the kinematic approximation; i.e. the hydraulic gradient is equal to the land slope at each cell, with the formula:

$$RI_i(t) = K_i D_i S_i K[\theta_i(t)]\Delta t / W_i \tag{1}$$

where RI_i is the amount of interflow, D_i is the root depth, S_i is the cell slope, $K[\theta_i(t)]$ is the cell effective hydraulic conductivity at moisture content $\theta_i(t)$, W_i is the cell width, and Ki is the scaling factor depending on land use, used to consider stream density and the effects of organic matter and root system on horizontal hydraulic conductivity in the top soil layer (Liu and De Smedt, 2004). $K[\theta_i(t)]$ is the only variable in this formula, so can change during the time. The other factors are parameters, and remain the same at all time steps.

A.1.2 Kg

Kg is the groundwater recession coefficient. Groundwater flow is a very important part of the model. In WetSpa the simple concept of a linear groundwater reservoir is used to estimate groundwater discharge on a small subcatchment scale. A non-linear reservoir method is optional with storage exponent of 2.The groundwater outflow is added to any runoff generated to produce the total streamflow at the subcatchment outlet. The general groundwater flow equation can be expressed as

$$QG_s(t) = K_g [\frac{SG_s(t)}{1000}]^m \tag{2}$$

where $QGs(t)$ is the average groundwater flow at the subcatchment outlet, $SGs(t)$ is the groundwater storage of the subcatchment at time t, m is an exponent, $m = 1$ for linear reservoir, and $m = 2$ for non-linear reservoir, Kg is the groundwater recession coefficient taking the subcatchment area into account.

A.1.3 Kss

Kss is the initial soil moisture. Soil moisture content is a key element in the model controlling the hydrological processes of surface runoff production, evapotranspiration, percolation and interflow. A proper initial soil moisture condition may provide a much more realistic starting point for predictions. However, for a long-term flow simulation in a watershed, the initial soil moisture condition is less important, as it affects the hydrological processes only in the initial part of the simulation.

In the WetSpa model the (initial) soil moisture influences the excess rainfall, also named effective rainfall. Excess rainfall is that part of rainfall in a given storm, which falls at intensities exceeding the infiltration capacity of the land surface. Then water may stay temporarily on the soil surface as depression, or become direct runoff or surface runoff at the watershed outlet after flowing across the watershed surface under the assumption of Hortonian overland flow. Direct runoff forms the rapidly varying portions of watershed hydrographs and is a key component for estimating the watershed response. It is calculated as:

$$PE_i = C_i[P_i - I_i(t)][\frac{\theta_i(t)}{\theta_{i,s}}]^a \tag{3}$$

where $PE_i(t)$ is the rainfall excess on cell *i* over the time interval, P_i is the rainfall, $I_i(t)$ is the interception loss, $\theta_i(t)$ is the cell soil moisture content at time t, $\theta_{i,s}$ is the soil porosity, *a* is an exponent related with rainfall intensity, and C_i is the cell potential rainfall excess coefficient or potential runoff coefficient. Kss is the initial condition of θ_i(t).

A.1.4 G0

G0 is the initial groundwater storage. In equation (2) is explained what the function of the groundwater storage ($SG_s(t)$) is. The initial groundwater storage is the groundwater storage at the first time step of calculations.

A.1.5 Gmax

Gmax is the maximum groundwater storage in water depth. This parameter is used in calculating the evapotranspiration from the groundwater storage. The component of evapotranspiration from groundwater storage is produced by deep root system or by capillary drive in the areas with shallow groundwater table. The evapotranspiration from the groundwater is computed as

$$EG_i(t) = \frac{SG_i(t)}{Gmax}[EP_i(t) - EI_i(t) - ED_i(t)] \tag{4}$$

where $EG_i(t)$ is average evapotranspiration from groundwater storag, $EP_i(t)$ is PET, $SG_i(t)$ is the groundwater storage of the subwatershed at time t, and *Gmax* is the maximum groundwater storage capacity of the subwatershed, $EI_i(t)$ is the evaporation from interflow and $ED_i(t)$ is the evapotranspiration from depression storage.

A.1.6 Krun

Krun is a surface runoff exponent when the rainfall intensity is very small. In WetSpa, this exponent is assumed to be a variable starting from a higher value for a near zero rainfall intensity, and changing linearly up to 1 along with the rainfall intensity, when the predetermined maximum rainfall intensity is reached. So Krun is the value of the exponent in case of a near zero rainfall intensity.

The formula, in which the surface runoff exponent is used, is equation (3). 'a' is the surface runoff exponent in that equation.

A.1.7 Pmax

Pmax is the threshold rainfall intensity. This parameter is in fact spatially distributed, depending upon the cell characteristics, such as soil type, land use, and slope, etc. However, a constant value is assumed in WetSpa for simplification. This threshold value determines when the surface runoff exponent (explained in A.1.6) is one. In case of low rainfall intensity, the surface runoff exponent is equal to Krun. In case of a higher rainfall intensity, the surface runoff exponent changes linearly up to one. Pmax is the rainfall intensity related to a surface runoff exponent of one.

B Data

B.1 *ArcView inputs*

Table 1 shows the inputs for ArcView, calibrated by Doldersum (2009). These values are also used within this research.

Table 1: The calibration result for ArcView from Doldersum (2009)

Input variable	Result	Clarification
Stream network	400	After trying several times this threshold value produces the most realistic stream network.
Minimum slope	0.01%	Standard value and there isn't a reason to change it.
Flood return period	T2	Standard value and there isn't a reason to change it.
Watersheds	4000	It has to be a multiply of the stream network threshold value and therefore it is set to 4000 and produces 13 subwatersheds.
Saturation	0.8	The model will be utilized for flood prediction and there is no start up time therefore this value is set to 0.8.
Manning	Use lookup tables	This option is chosen because it seems to generate the best results.
Percentage urban are	30%	Standard value and there were no arguments available to change this value.
Flow limits	No	Because without limits Arcview produces good results.

C Uncertainty analysis method

C.1 *Literature review*

In Table 1 is shown a literature review to investigate what likelihood measures were used in different researches in the past.

Table 2: Used goodness-of-fit indices and cut-off thresholds in researches

Authors and year	Goodness-of-fit index	Cut-off threshold
Blasone, et al. (2008)	$L = \exp\left(-W \frac{\sigma_i^2}{\sigma_o^2}\right)$	Based on the number of simulations
Yang et al. (2008)	Nash-Sutcliffe	NS > 0,7
Beven, Smith, & Freer (2007)	Nash-Sutcliffe	None
Thorndahl, et al. (2007)	$L = \exp\left(-W \frac{\sigma_i^2}{\sigma_o^2}\right)$	L > 0,3
Mantovan & Todini (2006)	Nash-Sutcliffe	None
McMichael, Hope, & Loaiciga (2006)	Nash-Sutcliffe	NS > 0,8
Muleta & Nicklow (2005)	Nash-Sutcliffe	NS > 0,4
Uhlenbrook & Sieber (2005)	Nash-Sutcliffe	Best 10% of all simulations
Beven & Freer (2001)	Nash-Sutcliffe	NS > 0,6
Brazier, Beven, Freer and Rowan (2000)	$L = \sum \lvert Qi - Qo \rvert$	Certain value of *L*
Uhlenbrook, Seiber, Leibundgut and Rodhe (1999)	Nash-Sutcliffe	NS > 0,85
Lamb, Beven, & Myrabo (1998)	$L = \exp\left(-W \frac{\sigma_i^2}{\sigma_o^2}\right)$	Best 10% of all simulations
Beven & Binley (1992)	$L = (\sigma_e^2)^{-N}$	None

C.2 *Prior dotty plots*

In Figure 1 the dotty plots from the manual calibration on the November 1999 flood by Doldersum (2009) are drawn. From these plots were extracted the first parameter ranges. Notice that the vertical lines are due to the calibration method: only one parameter at a time was changed.

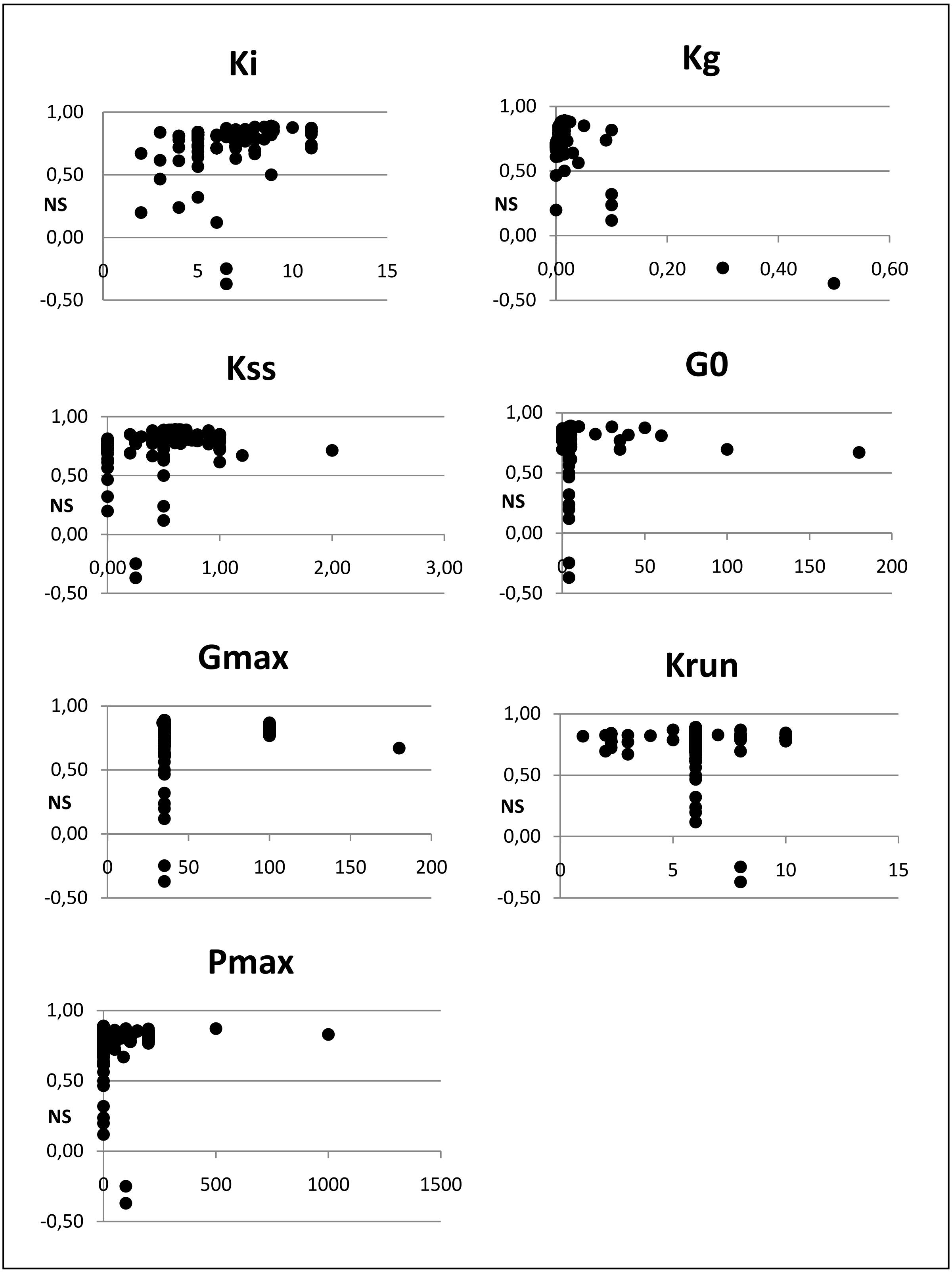

Figure 1: Dotty plots extracted from the manual calibration by Doldersum (2009)

C.3 *Final dotty plots*

Figure 2 and Figure 3 show the dotty plots for the seven global parameters. The dotty plots are drawn for the November 1999 flood and the October 2003 flood.

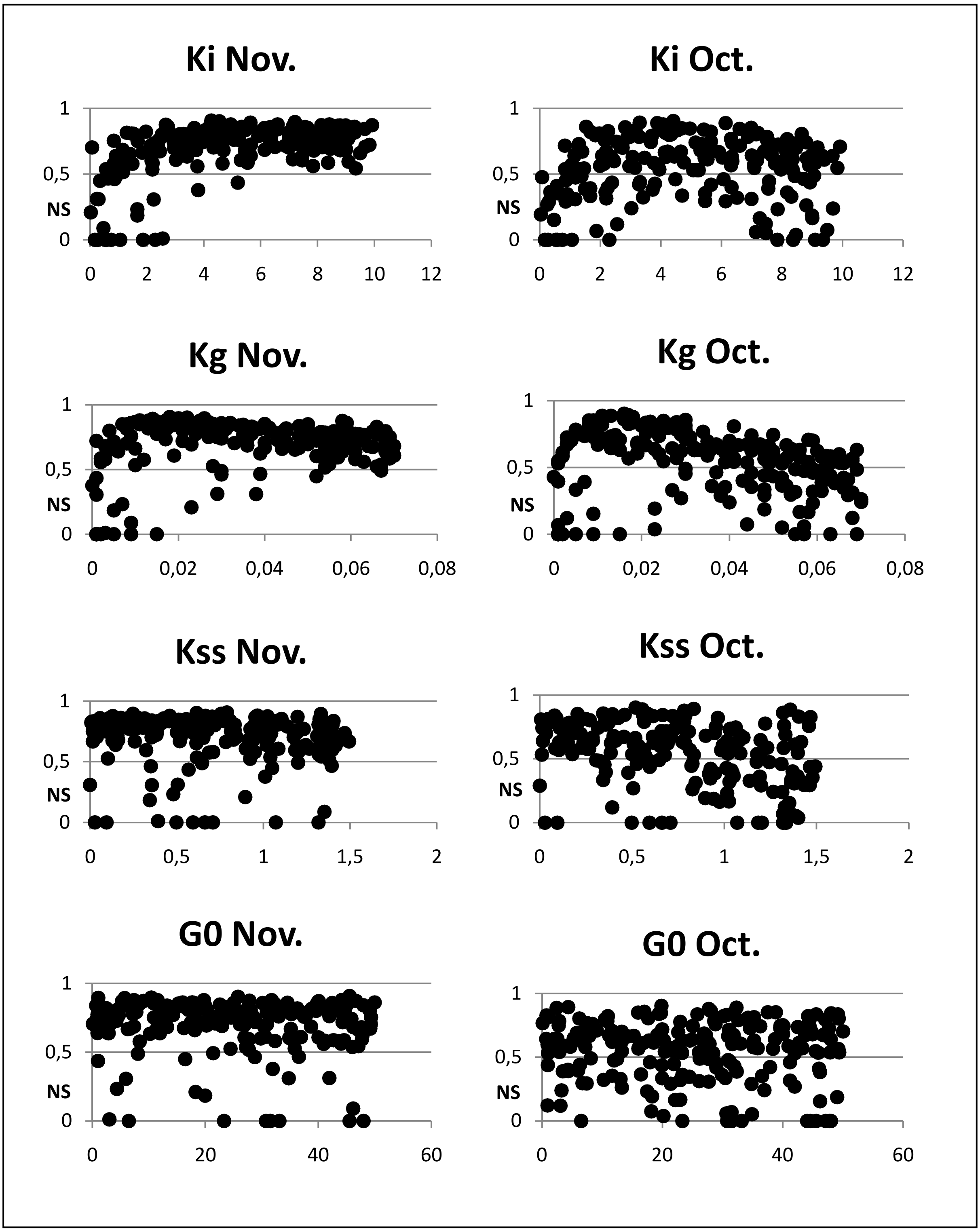

Figure 2: Dotty plots from the final ranges for Ki, Kg, Kss and G0 for both floods

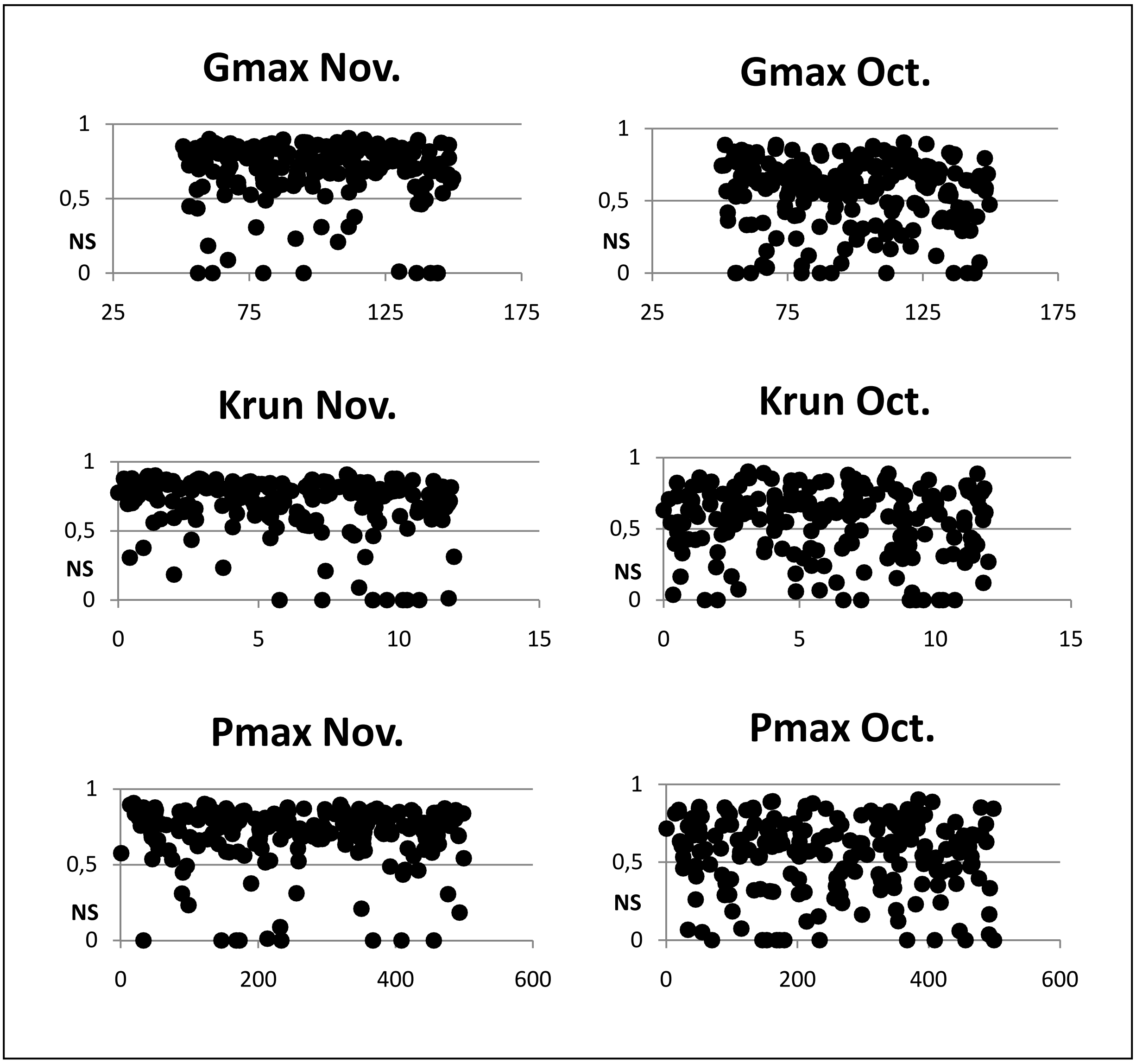

Figure 3: Dotty plots from the final ranges for Gmax, Krun, and Pmax for both floods

C.4 *Visualised procedure using likelihoods*

In Figure 4 is shown how to calculate likelihoods. The right part of the scheme is to determine the parameter ranges, the left part is the calculation of the likelihoods to use in the procedure of using likelihoods for uncertainty estimation (paragraph 4.4). The way to use the likelihoods, and determine the uncertainty bounds, is visualized in Figure 5.

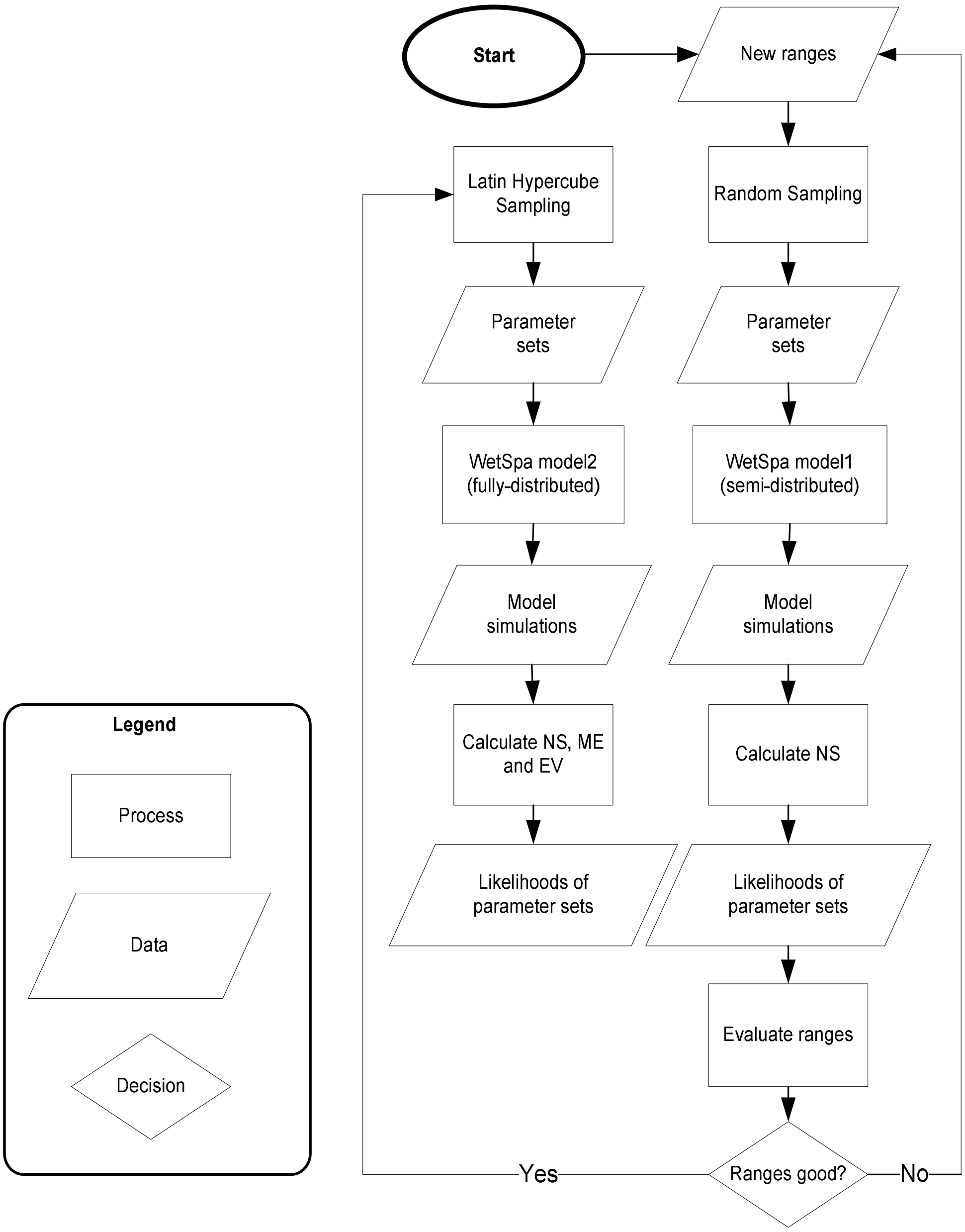

Figure 4: Process scheme to calculate likelihoods

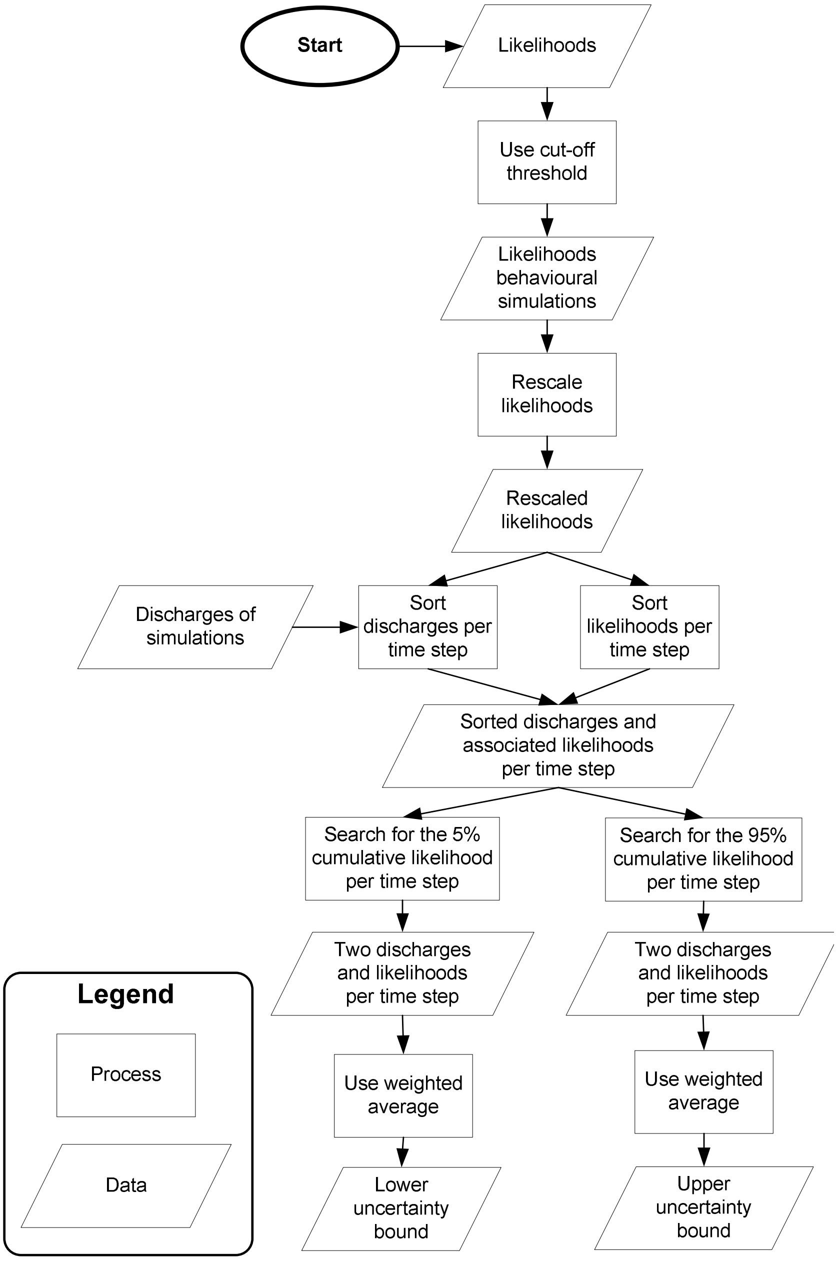

Figure 5: Process scheme of determine the lower and upper uncertainty bounds

The explanation of Figure 5 is given in paragraph 4.4. But the output of the process 'search for the 5% (or 95%) cumulative likelihood per time step' is not described very detailed, so is explained here.

The goal of this process is to find the 5% and 95% cumulative likelihood. However, the exact 5% and 95% cumulative likelihood is not expected to be found in the calculated likelihood distribution. To find this exact number, weighted average is used for the discharge belonging to the likelihood just above and below the exact number. So two discharges and two likelihoods are necessary for the weighted average method in order to find the discharge belonging to the exact 5% and 95% cumulative likelihood. Therefore the output of the script 'search for the 5% (or 95%) cumulative likelihood per time step', is not one likelihood and one discharge, but two of both.

D Results

D.1 *Uncertainty November 1999*

In Figure 6 till Figure 11 the original and updated uncertainty bounds are drawn for the November 1999 flood with likelihood measure NS, ME and EV.

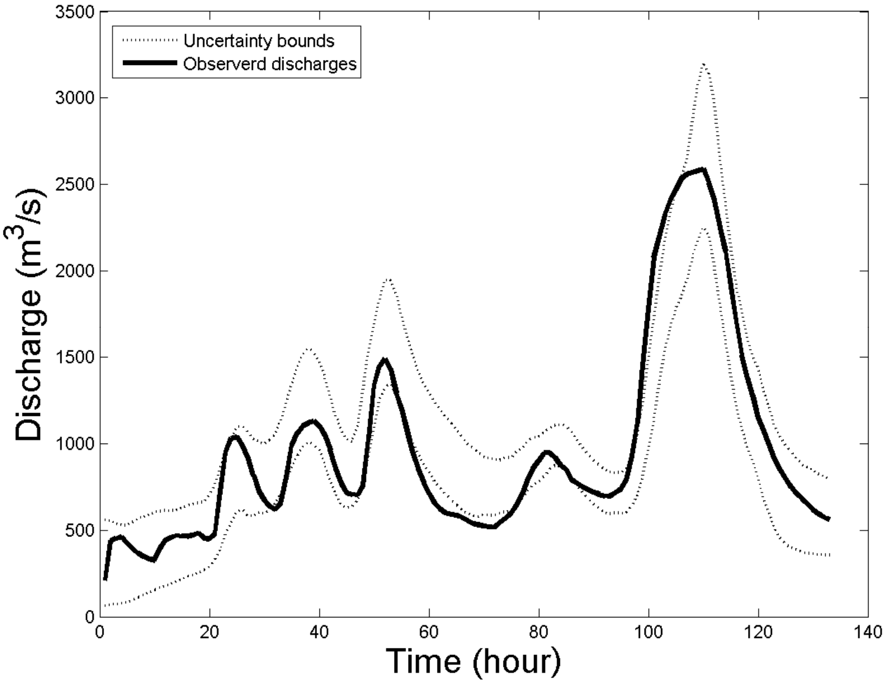

Figure 6: The original uncertainty for the November 1999 flood, calculated with NS

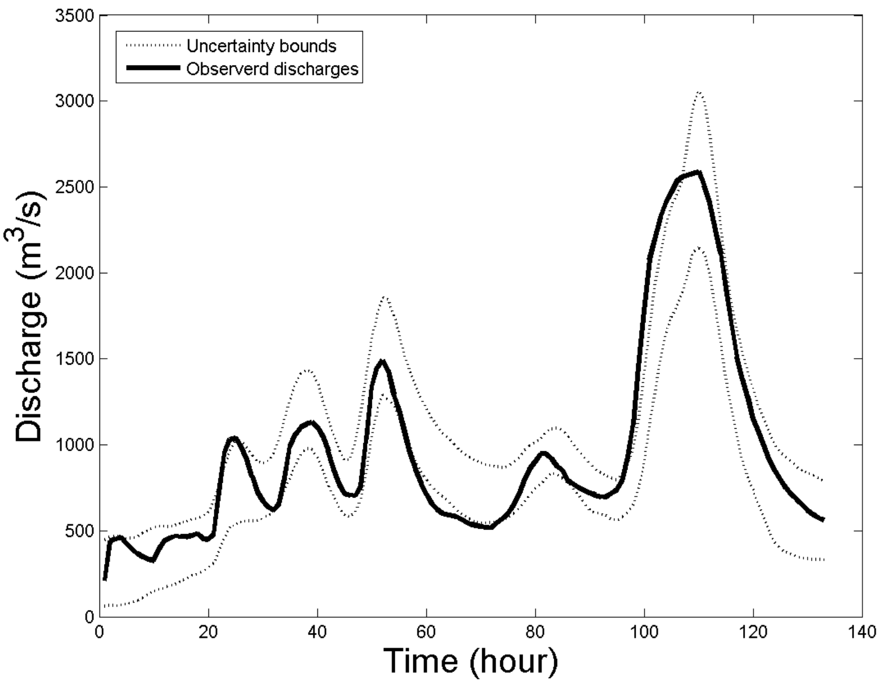

Figure 7: The updated uncertainty for the November 1999 flood, calculated with NS

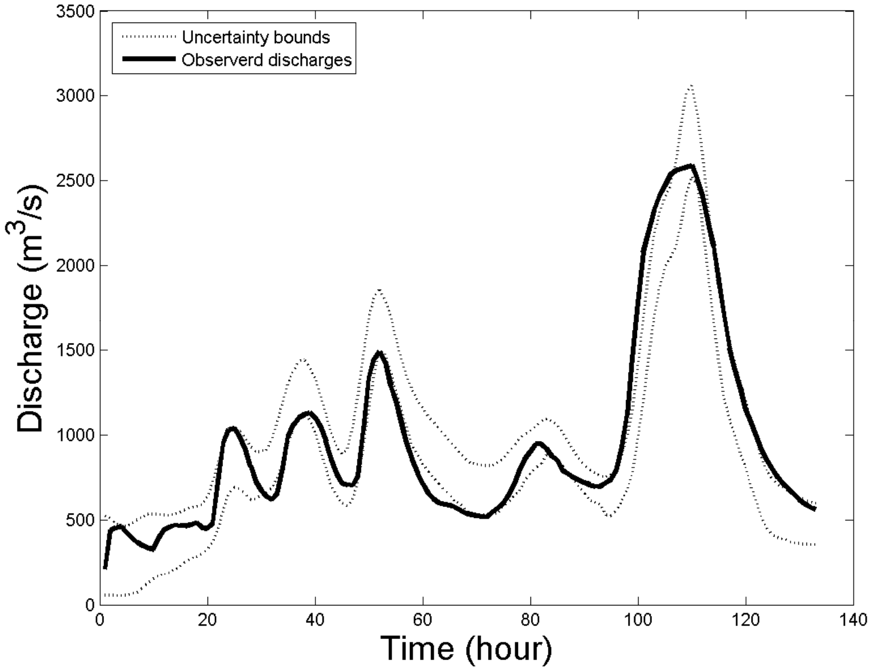

Figure 8: The original uncertainty for the November 1999 flood, calculated with ME

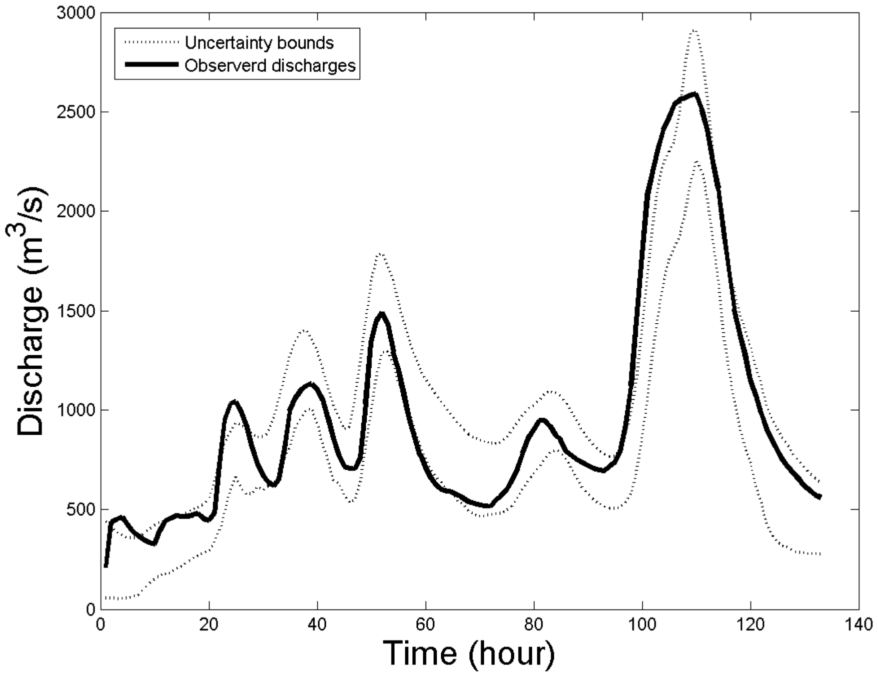

Figure 9: The updated uncertainty for the November 1999 flood, calculated with ME

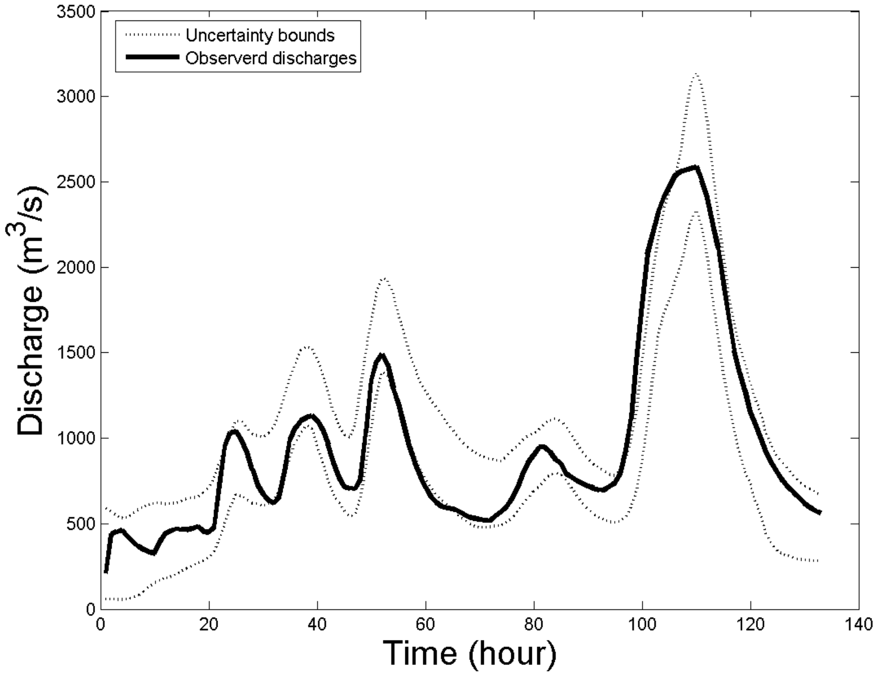

Figure 10: The original uncertainty for the November 1999 flood, calculated with ER

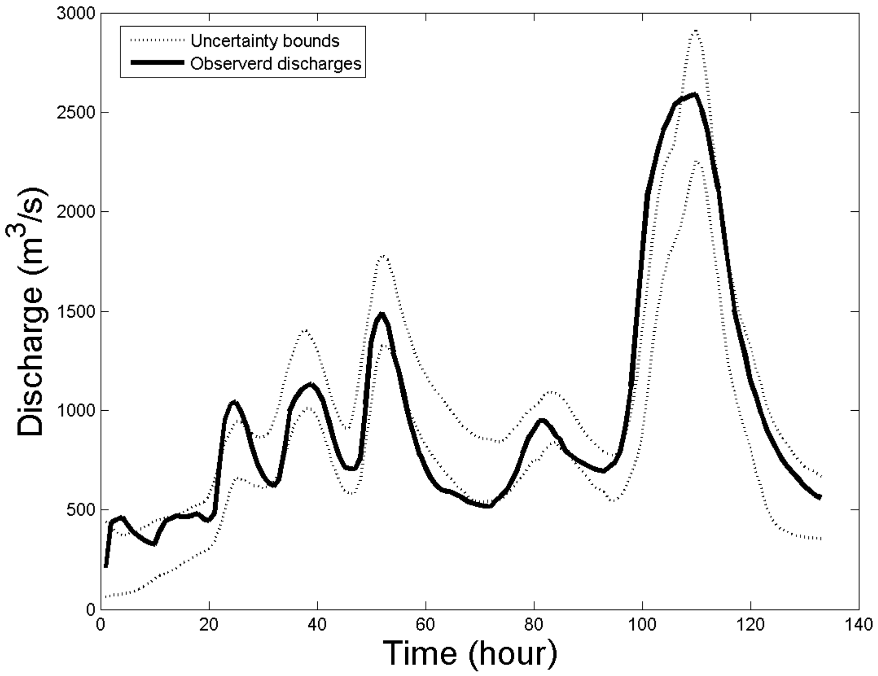

Figure 11: The updated uncertainty for the November 1999 flood, calculated with ER

D.2 *Uncertainty October2003*

In Figure 12 till Figure 17 the original and updated uncertainty bounds are drawn for October 2003 with likelihood measure NS, ME and EV.

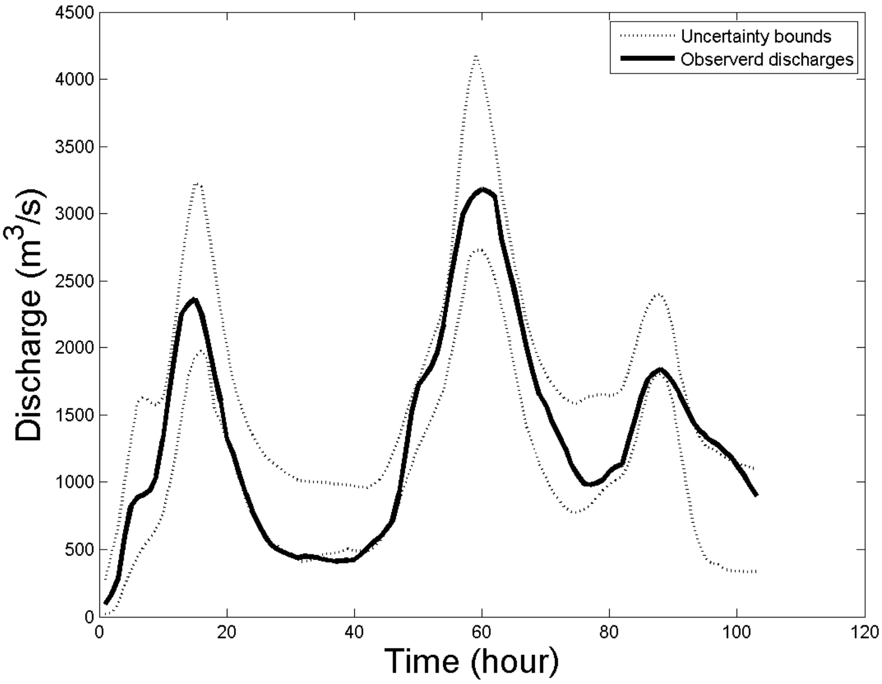

Figure 12: The original uncertainty for the October 2003 flood, calculated with NS

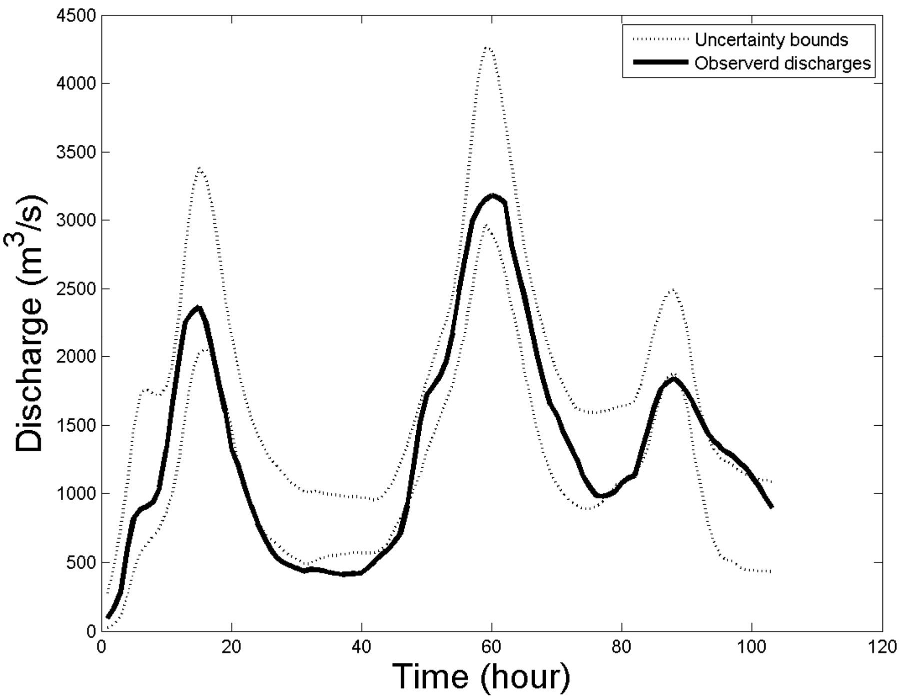

Figure 13: The updated uncertainty for the October 2003 flood, calculated with NS

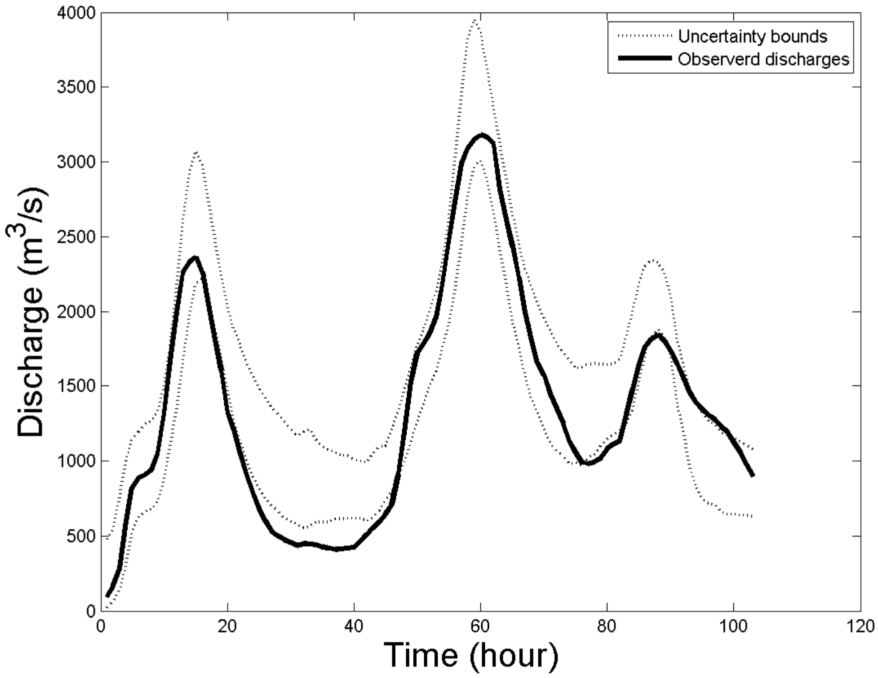

Figure 14: The original uncertainty for the October 2003 flood, calculated with ME

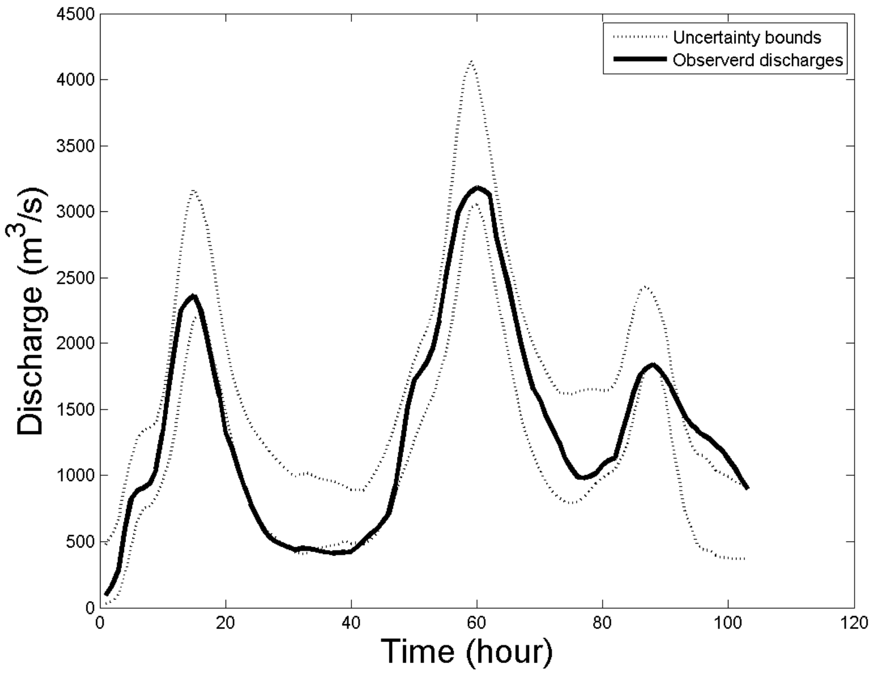

Figure 15: The updated uncertainty for the October 2003 flood, calculated with ME

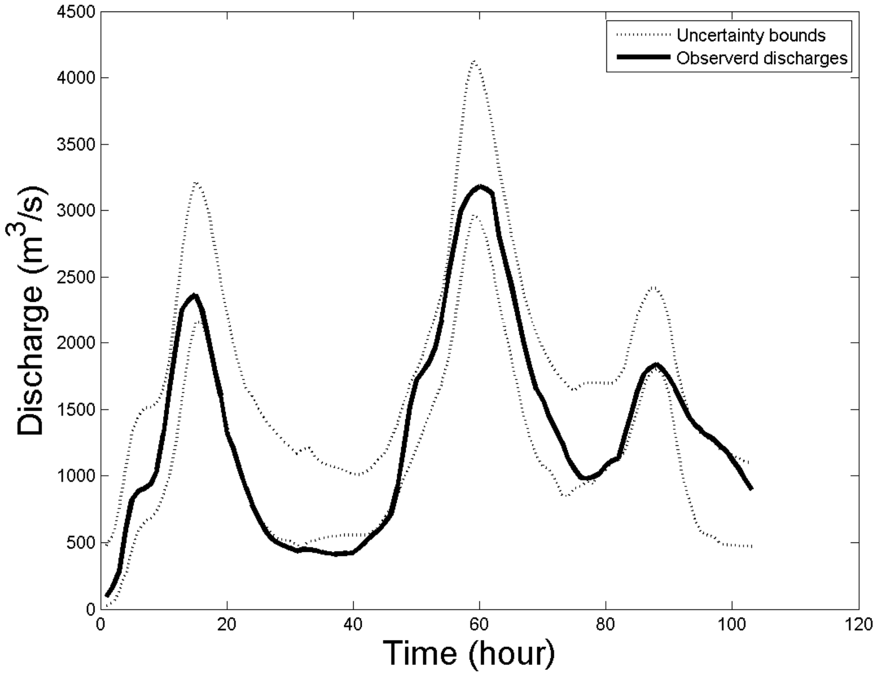

Figure 16: The original uncertainty for the October 2003 flood, calculated with ER

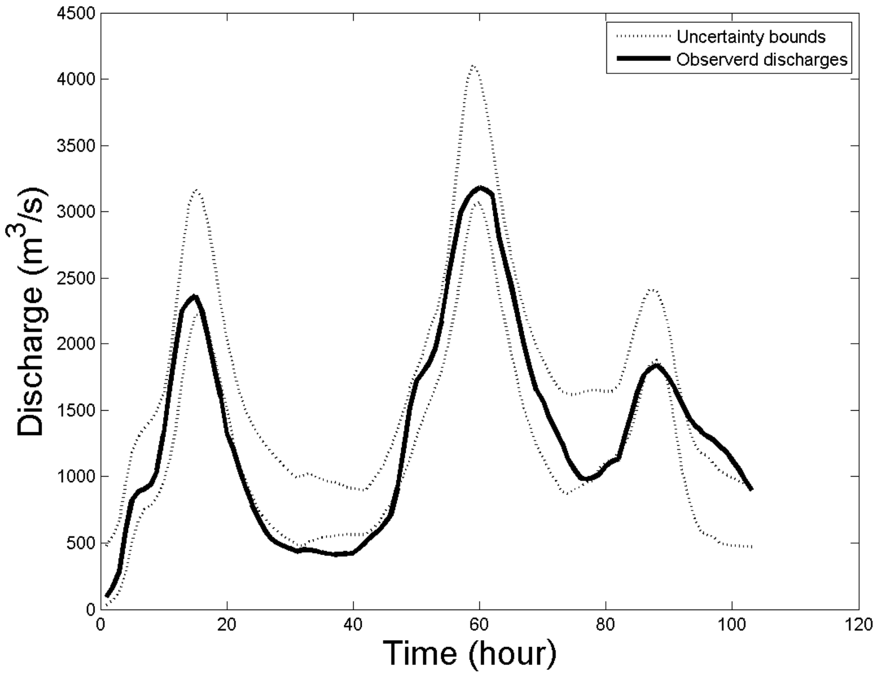

Figure 17: The updated uncertainty for the October 2003 flood, calculated with ER

D.3 *Forecasting mode*

Figure 18 till Figure 20 show the uncertainty bounds in forecasting mode for the December 1999 flood. This is calculated with NS, ME and EV.

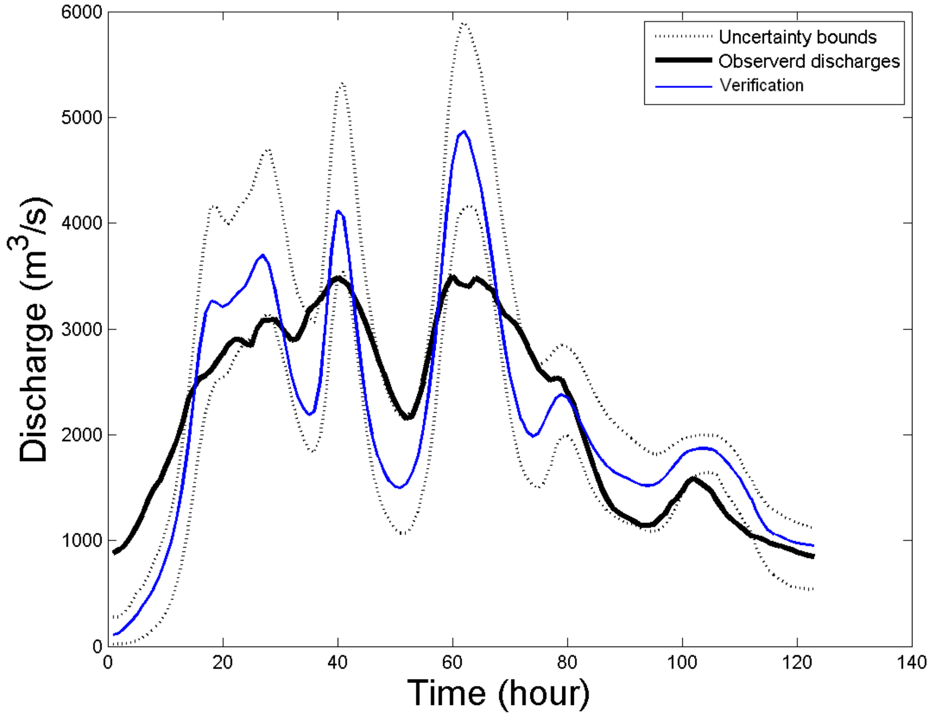

Figure 18: The uncertainty bounds in forecasting mode for the December 1999 flood, calculated with NS, with the verification result from Doldersum (2009)

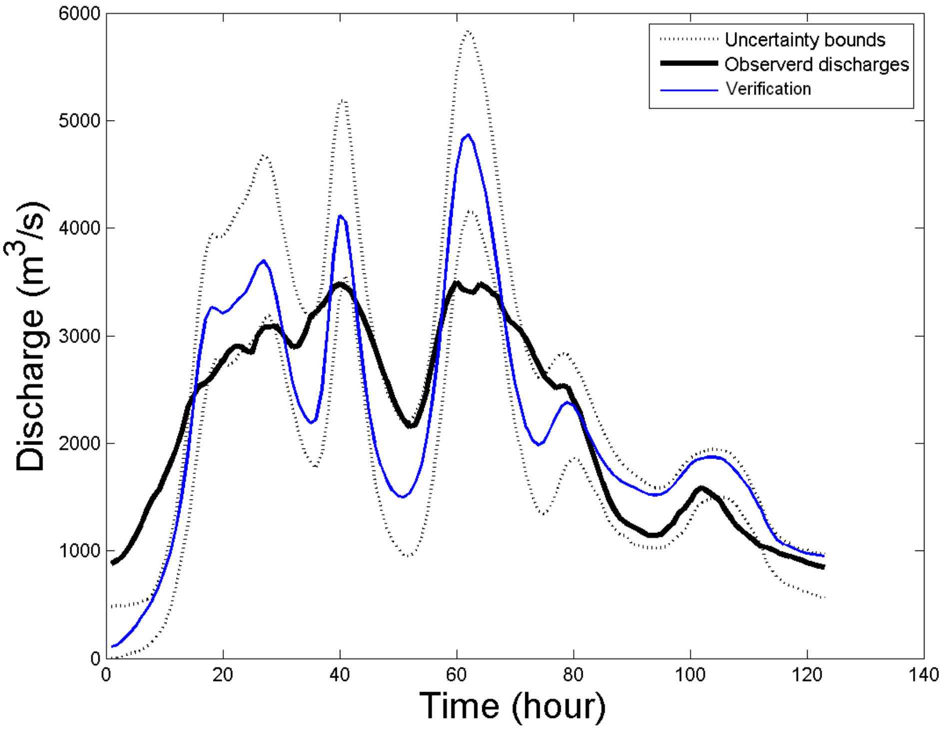

Figure 19: The uncertainty bounds in forecasting mode for the December 1999 flood, calculated with ME, with the verification result from Doldersum (2009)

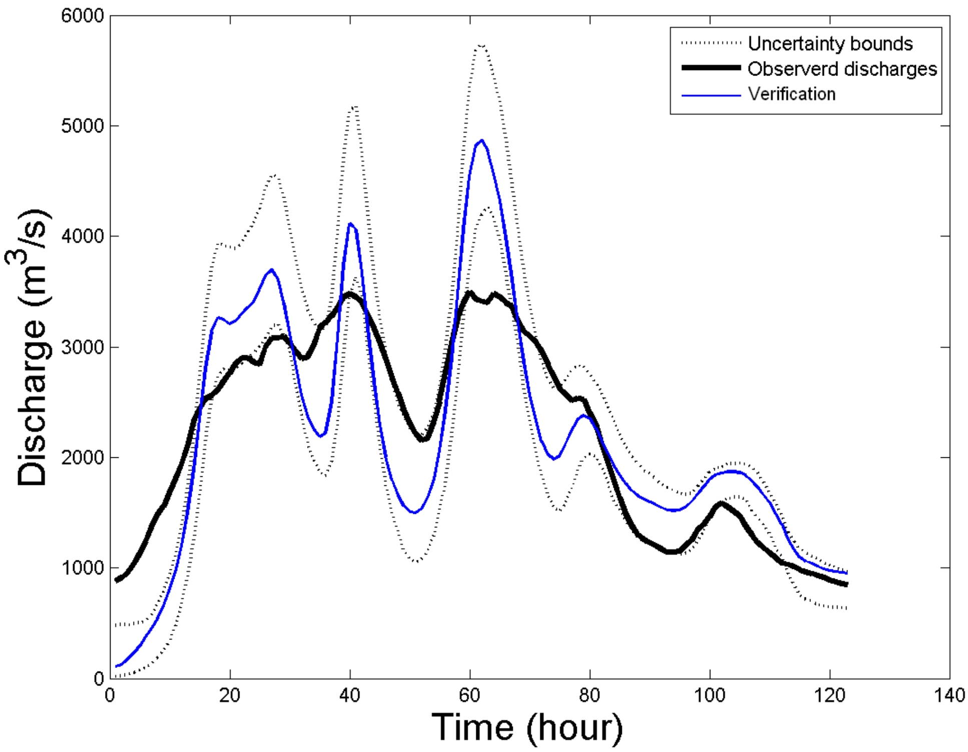

Figure 20: The uncertainty bounds in forecasting mode for the December 1999 flood, calculated with ER, with the verification result from Doldersum (2009)