Uncertainties in the impacts of Climate Change on extreme high Meuse discharges

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Preface

This report forms the completion of my study Civil Engineering & Management at the Department for Water Engineering and Management, which is part of the faculty of Engineering Technology at the University of Twente, The Netherlands.

The purpose of this report is to investigate the uncertainty of climate change on the extreme discharge of the Meuse, and to assess the degree of the uncertainty.

First of all, I would like to thank my graduation committee prof. dr. Ir. A.Y. Hoekstra and dr. ir. M.J.Booij for their enthusiastic support and supervision. Also, I would like to thank my room mates of the graduation room for the 'energy' and 'motivation' boosts they gave me. And of course for the endless discussions and fun during coffee breaks and lunches.
Finally, I would like to thank my parents for supporting me (not only financially), my brother Roland, the family of my girlfriend, friends and my football team for the distraction in the weekends. But most of all I would like to thank my girlfriend Jolanda, for supporting me in this sometimes "stressful" period.

Hope you like reading it, just like I did writing it.

Martijn Huisjes

Dronten, October 19Th 2006

Summary

The aim of this research is to assess the uncertainties of the climate change extreme high discharges of the river Meuse, identifying uncertainties in hydrological response and climate change. To do so the HBV Model has been used, the HBV-model is a rainfall-runoff model, which includes conceptual descriptions of hydrological processes at the catchment scale. The model has been developed by the Swedish Meteorological and Hydrological Institute. The schematization used was developed by Booij and has been modified to simulate extreme high discharges. The basis for the research consists of two studies performed by PRUDENCE, a project funded by the European Commission under its fifth framework programme. The results of these studies are climate change predictions for temperature and precipitation and uncertainties here in. The climate change data have been made applicable to the Meuse catchment with a climate change factor. The modified climate data set for the Meuse is expressed in the form of a normal distribution with a mean value and a standard deviation.

Before the modified climate data set has been put into the HBV-model and simulations have been made, an uncertainty analysis for the model has been performed. Out of previous studies the values for the important parameters were found. To investigate the uncertainty of the model a combination of different current method has been used. The combined method adopted in this research is based on the next the assumptions:

1. The uncertainty of a model can be expressed in a Nash Sutcliff coefficient, which is compareness between the observed and simulated discharge.
2. The uncertainty of a model can be simulated through parameters variation.
3. Through the variation of the parameters without correlation between them, different model world can be created. The range where in the parameters are varieted has been chosen in a certain a way that the average Nash Sutcliff coefficient out of the compares of the different model world is equal to the Nash Sutcliff coefficient mentioned at point 1.

It is also assumed that the uncertainty of the parameters expressed in the form of a standard deviation is the major source of the uncertainty of the model outcome. Through consideration of this parametric uncertainty, model structural and scale related uncertainties are not taken into account. However, these are assumed to be at least partly covered by the parametric uncertainty. After performing Monte Carlo simulations for the 4 sub-catchments in which parameter values are varied the uncertainty of the model can be seen in the standard deviation of the extreme high discharge output of the model.

The results for the period 2070-2100 show an average annual increase in temperature of 4,0 ºC for climate change conditions varying between 3,3ºC in DJF (December, January, February) and 5,1 ºC in JJA (June, July, August). Precipitation decreases slightly by 2,5 % on an annual basis varying between +24 % in DJF and -35 % in JJA. Uncertainties in climate change expressed as standard deviation vary between 1,3 ºC in DJF and 2,1 ºC in JJA for temperature and 11 % in MAM (March, April, May) and 16% in JJA for precipitation.

The results of performing the method for finding the uncertainty in the HBV model outcome are for the Vesdre a uncertainty percentage of 30.5% for the Ourthe 25,5% for the Ambleve 27% and for the Lesse 22%. For the other sub catchments the average is used and that is 25,8%. With these percentages a model simulation for the total catchment is made and a Nash-Sutcliffe coefficient is calculated. This Nash-Sutcliffe coefficient is 0,87 the Nash-Sutcliffe coefficient the calibrated model by Booij 2002 is 0.88. The very small difference between the two values indicates that the method is performed very well.

The first simulation performed is to compare the observed current climate discharge with the simulated current climate discharge. The lines for the observed discharge and simulated discharge are not equal. The difference between the lines is 17%. This indicates that the model prediction is 10% to high

Another simulation is performed to compare the simulated current extreme high discharge with the simulated climate change extreme high discharge. The simulated climate change extreme high discharge is 29% higher than the simulated current extreme high discharge. The standard deviation of the simulated climate change extreme high discharge is assumed to be the uncertainty of the discharge. It has a size of 933m^3/s or 20% of the extreme high discharge. This uncertainty range is build up of the four uncertainties groups that are present in the climate data and hydrological uncertainty. The uncertainty for the climate data is 453 m^3/s split up in 8,4% for the uncertainties of Sampling, in 18,3% for the emission scenarios, 15% for the GCM uncertainties and 10,7% for the RCM uncertainties. The other half is the uncertainty for the HBV-15 model. And can be divided in 16,6% for the soil moisture, 30,0 % for the quick runoff and 1,0 % for the baseflow.

For further research some recommendations can be given: one is about the climate data. A better and more certain method to obtain climate change data can be used. A possible method is probably the use of Regional Circulation Models (RCMs) specially developed for the catchment of the river Meuse. But there are more methods to obtain climate change data for a certain catchment. Another point is the uncertainty of the hydrological model. Now the uncertainty is quite large and is found with a new method. It is possible to develop the method further. Therefore more climatological data are necessary. When the data are available it is possible to perform the method for all the catchments instate of the 4 now and the different parameters. Or the use of an other method to find the uncertainty of the HBV-model.

Samenvatting (in Dutch)

Het doel van dit onderzoek is het inzichtelijk maken de toekomstige extreme hoge afvoer van de rivier Meuse en de onzekerheden in hydraulische en klimaatsverandering identificeren. Hiervoor is het HBV model gebruikt, het model is ontwikkeld door het Zweedse Meteorologische en Hydrologische Instituut. De gebruikte schematisatie is ontwikkeld door Booij en is in nu aangepast voor het simuleren van de extreme hoge afvoer. De basis voor het onderzoek zijn twee studies uitgevoerd door PRUDENCE, een project dat onderdeel uit maakt van de vijfde kaderrichtlijn van de Europese commissie. De resultaten van deze studies zijn voorspellingen van klimaatsveranderingen voor temperatuur en neerslag en de onzekerheden hierin. De gegevens zijn omgevormd tot voorspellingen voor het stroomgebied van de rivier de Maas met behulp van een climate change factor. De nieuwe klimaatsgegevens voor de Maas zijn weergeven in een in een normale standaard verdeling met een gemiddelde waarde en een standaard deviatie. Aangenomen wordt dat de onzekerheid in de klimaatdata uitgedrukt kan worden als de standaard deviatie

Voordat de aangepaste klimaatsgegevens in het HBV-model zijn ingevoerd en simulaties gemaakt zijn, is de onzekerheid van het model geanalyseerd. Uit eerder onderzoek zijn de waarden voor de belangrijkste parameters gevonden. Om de onzekerheid van het HBV-model te onderzoeken zijn er al bestaande methoden samengevoegd tot een nieuwe methode.

De gecombineerde methode is gebaseerd op de volgende aannames:

1. De onzekerheid van een model kan worden uitgedrukt als de Nash Sutcliff coëfficiënt, die en maat is van het verschil tussen de waargenomen en gesimuleerde afvoer.
2. De onzekerheid van het model kan worden gesimuleerd door middel van parameter variatie
3. Door middel van parameter variatie worden verschillende modelwerelden gecreëerd; de range (in %) waar binnen wordt gevarieerd wordt zodanig gekozen dat de gemiddelde Nash Sutcliff coëfficiënt die ontstaat uit de vergelijking van alle verschillende modelwerelden gelijk is aan de Nash Sutcliff coëfficiënt genoemd onder punt 1

De resultaten voor de periode 2070-2100 laten een de jaarlijkse gemiddelde toename in temperatuur van 4,0ºC afwisselend tussen 3,3 ºC in DJF(december, januari, februari) en 5,1 ºC in JJA (juni, juli augustus) zien. De neerslag neemt af met 2,5 % op een jaarlijkse basis wisselend tussen +24% in DJF en -35% in JJA. De onzekerheden in de klimaatveranderingen uitgedrukt in de standaard deviatie liggen tussen 1,31ºC in DJF en 2,1ºC in JJA voor de temperatuur. Voor de neerslag liggen die waarden tussen de 11% in MAM(maart, april, mei) en 116% in JJA.

De resultaten van het uitvoeren van de methode voor het vinden van de onzekerheden in de HBV- model uitkomsten zijn voor de Vesdre een onzekerheidspercentage van 30.5% voor de Ourthe 25,5% voor de Ambleve 27% en voor de Lesse 22%. Voor de andere sub stroomgebieden is het gemiddelde (25,8%) gebruikt. Met deze percentages is er een model simulatie voor het gehele stroomgebied gemaakt en een Nash-Sutcliffe

coëfficiënt berekend. Deze Nash-Sutcliffe coëfficiënt is 0,87. De Nash-Sutcliffe coëfficiënt van het gecalibreerde model (Booij 2002) is 0.88. het kleine verschil tussen deze waarden geeft aan het de methode goed is uitgevoerd.

De nieuwe klimaatdata voor de periode 2070 - 2100 is bepaald en de grote van de verschillende onzekerheidsgroepen zijn berekend. Nu is het mogelijk om de afvoer van de rivier de Maas te simuleren. Hiervoor zijn er verschillende Monte Carlo simulaties gemaakt.

De eerste simulatie die verricht is, is de simulatie voor het vergelijken van de gesimuleerde huidige afvoer met de gemeten huidige afvoer. Met de piekafvoeren van deze afvoeren is het mogelijk om een Gumbel plot te maken. De lijnen van gemeten huidige hoge afvoer en gesimuleerde huidige hoge afvoer zijn niet gelijk. Het verschil tussen de lijnen is ongeveer 10%.

Een andere simulatie die uitgevoerd is, is het vergelijken van de gesimuleerde huidige extreme hoge afvoer met de gesimuleerde climate change extreme hoge afvoer. De gesimuleerde climate change extreme hoge afvoer is 29% hoger dan de gesimuleerde huidige extreme hoge afvoer. De standaard deviatie van de gesimuleerde climate change extreme hoge afvoer waarvan aangenomen wordt dat deze een maat is voor de onzekerheid van de voorspelling heeft een grote van 933m^3/s of 20% van de afvoer. De onzekerheid is opgebouwd uit de vier onzekerheidsgroepen die aanwezig zijn in de klimatologische data en de Hydrologische onzekerheid. De onzekerheid voor de Klimaat data is 453 m^3/s verdeeld over 8,4% voor de onzekerheid in de Sampling, in 18,3% voor de onzekerheid in emissie scenario's, 15% voor de GCM onzekerheid en 10,7% voor de RCM. De andere helft van de onzekerheid is voor het HBV-15 model. Deze onzekerheid kan op gedeeld worden in 16,6% voor de soil moisture, 30,0 % voor de quick runoff en 1,0 % voor de baseflow.

Voor vervolg onderzoeken kunnen de volgende aanbevelingen gegeven worden: de eerste gaat over de klimaatsgegevens. Het moet mogelijk zijn om een betere meer zekerdere methode toe te passen voor het achterhalen van de data voor de klimaatveranderingen. Een methode daarvoor is vermoedelijk het gebruik van RCMs die speciaal ontwikkeld zijn voor het stroomgebied van de Maas. Maar er zijn waarschijnlijk meer methode die in aanmerking komen om toegepast te worden. Een ander punt is de onzekerheid van het hydrologische model. Nu is de onzekerheid van het HBV-model, die gevonden is met de nieuwe methode nog erg groot. Het is mogelijk om de methode nog verder te ontwikkelen en voor meer dan de 4 stroomgebieden die nu worden toegepast. Daar voor zijn meer gegevens over het stroomgebied en de deelstroomgebieden nodig. Wanneer er meer gegevens voorhanden zijn is het mogelijk de methode uit te voeren voor meerdere deelstroomgebieden en parameters.

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1 Introduction.

1.1 General

Human society adopts increasingly sophisticated and mechanized lifestyles; consequences are that the amounts of heat-trapping gases in the atmosphere have been increased. By increasing the amount of these gases, humankind has enhanced the warming capability of the natural greenhouse effect. It is the human-induced enhanced greenhouse effect that causes environmental concerns. It has the potential to warm the planet at a rate that has never been experienced in human history. This warming is called climate change. Climate change is more than a warming trend. Increasing temperatures will lead to changes in many aspects of weather, such as wind patterns, the amount and type of precipitation, and the types and frequency of severe weather events that may be expected to occur in an area. Not all regions of the world will be affected equally by climate change. Low-lying and coastal areas face the risks associated with rising sea levels. Increasing temperatures will cause oceans to expand (water expands as it warms), and will melt glaciers and ice cover over land – ultimately increasing the volume of water in the world's oceans (IPCC, 2001a).

Generally, higher temperatures lead to higher potential evaporation and decreased discharge (which also is a function of precipitation, storage, and topography). The storage of water in the soil serves as a buffer; in winter and spring, increasing precipitation normally generates higher discharges because the buffer is full and evaporation is low. During the summer, storage is reduced by evapotranspiration and must be refilled before discharge begins. Seasonal-to-interannual variability in precipitation and temperature also accounts for some of the variability in hydrological characteristics in European river basins. General Circulation Models (GCMs) -based analyses for the European continent (IPCC, 1996) give a range of possible responses of river runoff in a warmer global climate; decreases in some regions (e.g., Hungary, Greece) to increases in other regions (United Kingdom, Finland, Ukraine); these estimates are a function of precipitation, evapotranspiration, and soil moisture projections in the different GCMs. The results of catchment-scale simulations with conventional hydrological models driven by GCM data are highly variable. Arnell and Reynard (1996), for example, simulated changes of ±20% in annual runoff for 21 catchments in Great Britain-with a tendency toward lower amounts of discharge, especially in sensitive areas and during the summer months.

The uncertainties of climate model results, however, remain very large particularly at the regional scale. This limitation is particularly critical for water management practices in the future because water resource impacts occur at the local scale, not at regional or larger scales (Arnell 1999a).

Although the debate about changes in the frequency of floods is still open, an increase in rainfall during periods when soils are saturated (i.e., winter and spring), along with earlier snowmelt, could increase the frequency and severity in floods. An increase in large-scale precipitation might lead to increased flood risks on large river basins in Western Europe in winter. One of the main rivers of Western Europe is the Meuse. It is a large river with many tributaries. It is a rain fed river with a short reaction time. Two resent sent floods occurred in 1993 and 1995 (Wit, 2001). In future with climate change predictions that are more extremer, the discharge of the river Meuse will be higher. But of course there is a lot of uncertainty in the predictions of extreme discharges.

1.2 Problem / previous research

Because of the fact that climate change is a very hot issues for the future of the world many research is performed on this subject. The Intergovernmental Panel on Climate Change (IPCC,2001b) developed emissions scenarios to describe the relationships between the forces driving emissions and their evolution. The scenarios encompass different future developments that might influence greenhouse gas sources and sinks, such as alternative structures of energy systems and land-use. These scenarios are used for climate change prediction all over the world and are the main input in the investigation of climate change and the impact of climate change.

The behaviour of the climate system, its components and their interactions, can be studied and simulated using tools known as climate models. These models are made for studying climate change, weather forecasting and current climate and are called General Circulation Models (GCMs). Arnell (1999b) investigated climate change using different emissions scenarios and global circulation models. He found that global average precipitation will increase. Much of this increase occur over oceans and large parts of land surface. Also the temperature shall rise this will leads to a general reduction in the proportion of precipitation that falls as snow. These changes will have a impact on the discharge of rivers.

The climate change in combination with hydrological models made it possible to investigate the impact of climate change on the hydrological regimes. Dam (1999) investigated the impacts of Climate change and climate variability on hydrological regimes. Middelkoop et. al. (2001) investigated the impact of climate change on hydrological regimes and water resources management in the Rhine basin. He expected that due to climate change the river Rhine will shift from a combined rainfall-snowmelt regime to a more rainfall dominated regime. And that the frequency and height of peak flows will increase. Wit (2001) did research on the effect of climate change on the hydrology of the river Meuse. Out of this research can be concluded that the discharge in spring will increase and that the discharge in summer period will decrease.

In all research performed on climate change impacts on hydrological regimes, uncertainties were found in the results. Therefore it was important to do research on the uncertainties. Dickinson (1989) did research on the uncertainties in the estimations of climate change. Boorman and Sefton (1997) investigated the uncertainty in the quantification of the effects of climate change on hydrological responses. The key sources of uncertainty in climate change projections are identified by Visser et al. (2000). He found that the main uncertainty in climate change projects appears to be the uncertainty in the global circulation models. In the research of Middelkoop et. al. (2001), the bandwidth of the simulation results is primarily the result of uncertainty in climate scenarios. The uncertainties in the HBV model have been investigated by Wilby (2005). A model used for research of the impact of climate change on the hydrological system is the HBV model. The HBV model (Bergström and Forsman, 1976) is a rainfall-runoff model, which includes conceptual descriptions of hydrological processes at the catchment scale.

Wilby (2005) investigated the uncertainty in water resources model-parameters used for climate change impact assessment. A recommendations out of that research is that climate change impact assessments using conceptual water balance models should routinely undertake sensitivity analyses to quantify uncertainties due to parameter instability, identifiably and non- uniqueness. There are many ways to investigate the HBV uncertainty. Seibert (1997) investigated the uncertainty of a HBV-model performing a Monte Carlo simulation (section 3.2) resulting in a large number of models runs with randomly generated parameters sets. He studied how the measured runoff could be achieved at best with different parameter values. This procedure has the advantage that any interaction between parameters is implicitly taken into account since parameter sets are varied instead of individual parameters. Booij (2005) investigated the impact of climate change on river flooding assessed with different spatial model resolutions. Booij used the HBV model with different sub catchments for the Meuse. He found an increase of 10% in daily average river discharge with an uncertainty in river flooding of 40%. The uncertainties in extreme discharges due to precipitation errors and extrapolation errors are more important than uncertainties due to hydrological model errors and parameters errors.

All the main subjects that are important for the future predictions and uncertainties of the extreme discharge have been investigated. The studies described above are only a very small part of all the research performed on the subject of climate change and impacts of climate change on hydrological processes.

1.3 Objective and Research questions

The objective of this research is:

To assess the uncertainties in the impacts of climate change on future extreme high discharges of the river Meuse.

The objective has been split up into four research questions;

1). which uncertainties have to be considered in climate change predictions and what is the size of these uncertainties?

2). is there a method to investigate the uncertainty of hydrological models and is it possible to quantify this uncertainty?

3). what is the best way to propagate climatic and hydrological uncertainties through the HBV-15 model with as result the extreme high discharge for the river Meuse with all the uncertainties?

4). what are the most important sources of the uncertainties in the simulated extreme high discharge?

The research performed shall investigate the impact of climate change on the extreme high discharge on the river Meuse but, will also investigate the uncertainty in the extreme high discharge and investigate the size of the uncertainties. The goal is to split up the total uncertainties and quantify the uncertainty groups. The study will focuses on the upstream part of Borgharen on the river Meuse. The extreme discharge on the river Meuse shall be modelled with the HBV-15 model developed by Booij (2005). Not all the uncertainties are considered in this research. Only the uncertainties in the climatological data and the hydrological model are considered.

1.4 Report structure.

First in chapter 2 an overview is made of the properties of the Meuse catchment and the HBV-15 model. Catchment characteristics are considered and a description of the structure of the HBV-model and the HBV-15 model is given. Next in chapter 3 the methodology of the research is described, these are the methods for preparing the climate data and investigation of the HBV-uncertainty. In chapter 4 all the data necessary in this research are described. In chapter 5 the results of the study are considered. Finally in chapter 6 the discussion and conclusions are considered.

2 Meuse catchment: processes and modelling

2.1 Introduction

In this chapter the hydrological model is described. Before that the Meuse catchment is considered in section 2.2. The HBV-model is introduced in section 2.3. In section 2.4 the HBV-15 model that is used in the research is considered and in section 2.5 the calibration of the HBV model is described.

2.2 The Meuse Catchment

2.2.1 General characteristics

The Meuse is a river with a length of 880 km from the source Poulliy-en-Bassigny in France to the mouth the Holandsch Diep in The Netherlands. The Meuse can be divided into 493 km in France, 183 km in Belgium and 204 km in The Netherlands. Its catchment has an area of about 33.000 km^2. The Meuse catchment has a temperate climate, with tributaries that are dominated by a rainfall-evaporation regime, which generally produces high flows during winter and low flows during summer. The height of the river above sea level as a function of the distance is shown in figure 2-1. Therefore it can be concluded that the Ourthe, Vesdre, Viroin, Lesse and Amblève have a steep slope and that the Belgian Meuse has a relatively flat slope. The other tributaries are also shown in this figure.

An overview of the catchment of the Meuse is shown in figure 2-2. A good and complete description of the river Meuse and its tributaries is given by Berger (1992).

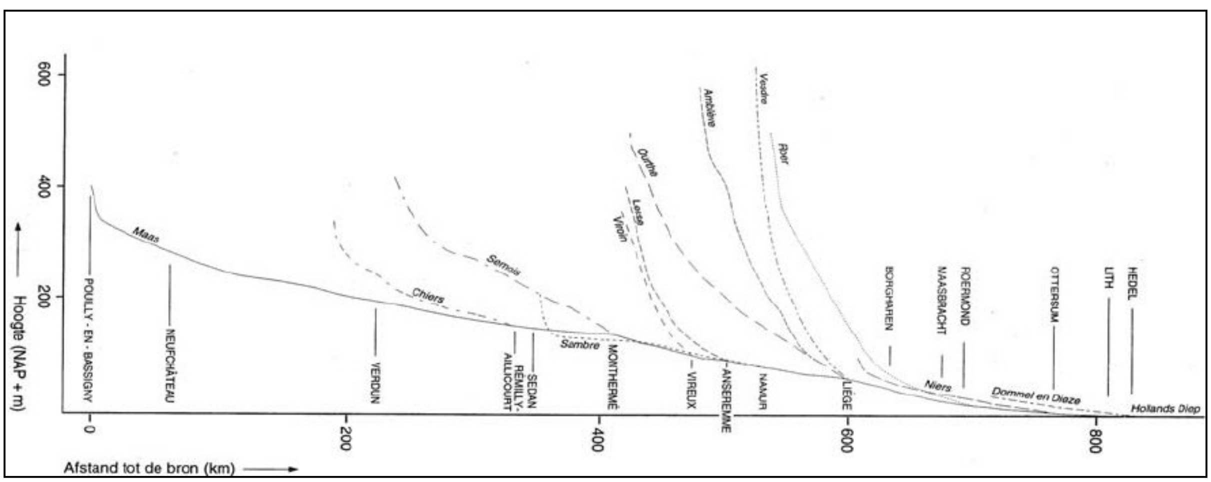

Figure 2-1: Gradient of the river Meuse and its tributaries (Berger, 1992).

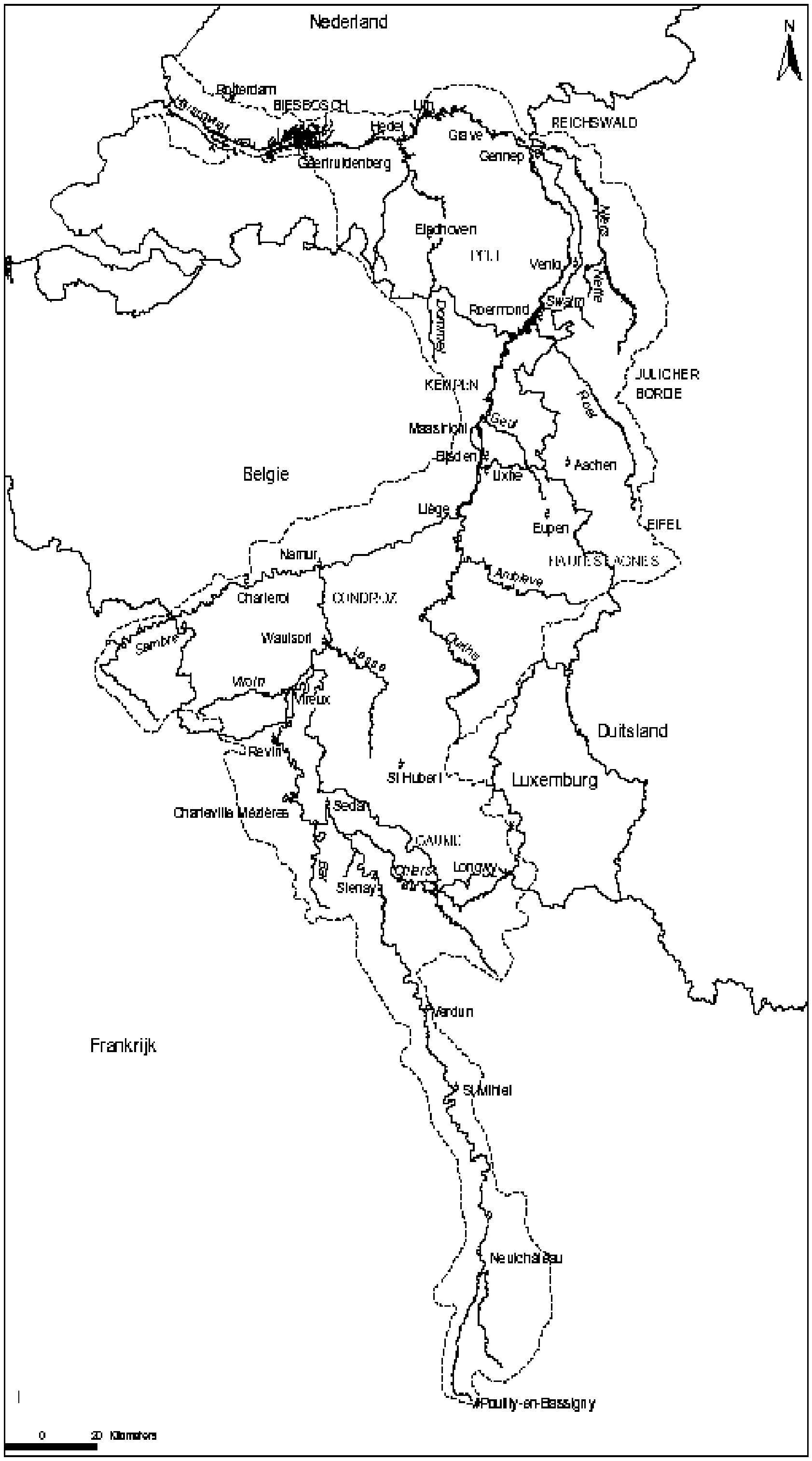

Figure 2-2: The catchment of the Meuse (Berger, 1992)

As far as the hydrologic properties are concerned, the Meuse can roughly be divided into three hydrological zones; the upper reaches, the central reaches and the lower reaches of the Meuse, (Berger, 1992).

- The upper reaches (Meuse Lorraine or Lotharingian Meuse), goes from the source at Poulliy-en-Bassigny to the mouth of the Chiers. Here the catchment is lengthy and narrow, the gradient is small and the major bed is wide. The discharge regime is therefore relatively flat.
- The central reaches of the Meuse (Meuse Ardennaise or Ardennes Meuse) is situated between the mouth of the Chiers and the Dutch border and transects Palaeozoic rock of the Ardennes Massif. This gives a narrow river valley and a big slope. Together with the poor permeability, this results in a quick response to precipitation. The main tributaries being the Viroin, Semois, Lesse, Sambre and Ourthe.
- The lower reaches of the Meuse correspond with the Dutch part of the river. The lower reaches themselves may be split into the stretches from Eijsden to Maasbracht and from Maasbracht to the mouth. In the former part the slope is still relatively large, for this reason it is occasionally reckoned to be part of the Meuse Ardennaise. The stretch that forms the border between Belgium and the Netherlands is called the Grensmaas. Below Maasbracht the river is provided with weirs to make it navigable. The main tributaries are the Roer, Niers and Dieze. In the Roer reservoirs are found, providing a certain minimum discharge. From Boxmeer the river is a typical lowland stream, with summer dikes, flood plains and winter dikes.

2.2.2 Precipitation

The mean annual precipitation in the catchment of the Meuse varies from 800 to 900mm in the south and west to locally 1400mm in the high Ardennes. In particular the total annual rainfall in the catchments of the Semois (1139mm), the Vesdre (1104mm) and the Amblève (1104mm) are high (Berger, 1992), see table 2-1.

2.2.2 Discharges

The variation of the mean discharges over the months is much higher than the variation of the precipitation. This is due to the influence of evaporation, which is highly related to the temperature. As a consequence, discharges in winter are high and discharges in summer are low. Almost all floods in the Meuse catchment have been observed during the winter season. One exception is the flood of July 1980 with a peak discharge of about 2000 m^3/s measured at Borgharen, see figure 2-3.
A flood arises when in a short period of time, approximately ten days; the amount of precipitation in the catchment is high. The highest known discharge ever measured at Borgharen was 3000 m^3/s during the floods of 1926 and 1993.
For precipitation to cause a flood there will have to be a minimum amount of 30-40 mm within a few days depending on the season, what kind of precipitation and other conditions. The amount of discharge depends on moisture content of the soil and geological components (Van der Wal, 2001).

Table 2-1 characteristics (size, gradient, mean discharge and mean annual precipitation) of the different tributaries. (Berger, 1992).

Tributary	Size (Km^2)	Gradient ($x\ 10^{-4}$)	Mean discharge (m^3/s)	Mean annual Precipitation (mm)
Meuse source- St.Mihiel	2540		26.3	
Chiers	2222	10	27	859
Meuse St. Mihiel-Stenay	1364		20	
Meuse Stenay- Chooz				
Semois	1358	15	27	1139
Viroin	593	20	6.9	940
Meuse Chooz-Namur				
Lesse	1314	50	16	954
Sambre	2863	7	28	825
Ourthe	5223	37	23	968
Vesdre	677	80	9.4	1104
Ambleve	1052	50	19	1104
Mehaigne	345		2.3	
Meuse Namur- Borgharen				
Jeker	463		1.7	

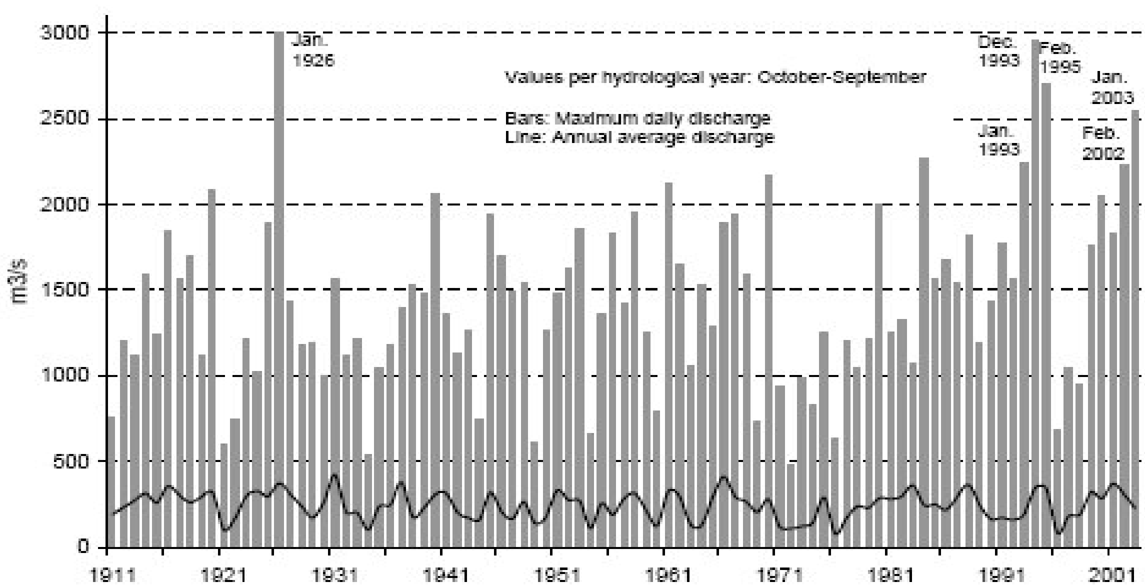

Fig 2-3: Discharge on the Meuse at Borgharen. (Bars: Maximum daily discharge. Line: Annual Average discharge) Arends 2005

The Meuse fulfils many functions, which are subject to droughts as well as to floods. These are: drinking water production, agriculture, recreation, water supply industry, inland navigation, nature, safety and cooling water.

2.3 HBV model

2.3.1 Introduction

Out of previous research is found that the HBV model is very appropriate for flood frequency analysis. Especially for assessments of climate change impacts on peak discharges (Booij, 2002). This and the fact that the model could be easily obtained, is the reason for using the HBV model in this research.

2.3.2 Background

The HBV model (Bergström and Forsman, 1976; Bergström et al., 1992) is a rainfall-runoff model, which includes conceptual descriptions of hydrological processes at the catchment scale (conceptual hydrological model). The HBV model has been developed by the Swedish Meteorological and Hydrological Institute (SMHI) in Norrköping, Sweden, by Bergström. The HBV-model is named after the abbreviation of **H**ydrologiska **B**yråns **V**attenbalansavdelning (Hydrological Bureau Water balance-section). This was the former section at SMHI where the model was originally developed. Different versions of the HBV model have been applied in more than 50 countries all over the world. It has been applied to countries with such different climatic conditions as for example Sweden, Zimbabwe, India and Colombia. HBV can be used as a semi-distributed model by dividing the catchment into sub catchments.

Input data are observations of precipitation, air temperature and estimates of potential evapotranspiration. The time step is usually one day, but it is possible to use shorter time steps. The evaporation values used are normally monthly averages although it is possible to use daily values. Air temperature data are used for calculations of snow accumulation and melt. It can also be used to adjust potential evapotranspiration when the temperature deviates from normal values, or to calculate potential evaporation. If none of these last options are used, temperature can be omitted in snow free areas. The model consists precipitation routine, soil moisture routine, quick runoff routine, baseflow routine, transformation routine and a routing routine It is possible to run the model separately for several sub catchments and then add the contributions from all sub catchments (Bergström, 1995) see section 2.3.2.

A comprehensive re-evaluation of the model was carried out during the 1990's and resulted in the present model version called HBV-96 (Lindström et al., 1997). The objectives were to improve the potential for making use of spatially distributed data in the model and to improve model performance. The model revision led to slight changes in the process descriptions for snow accumulation and melt, evapotranspiration, groundwater discharge and automatic calibration. When combined, the modifications led to significant improvements in model performance. The schematisation of the HBV-96 model with six routines for one sub-catchment is presented in figure 2-4.

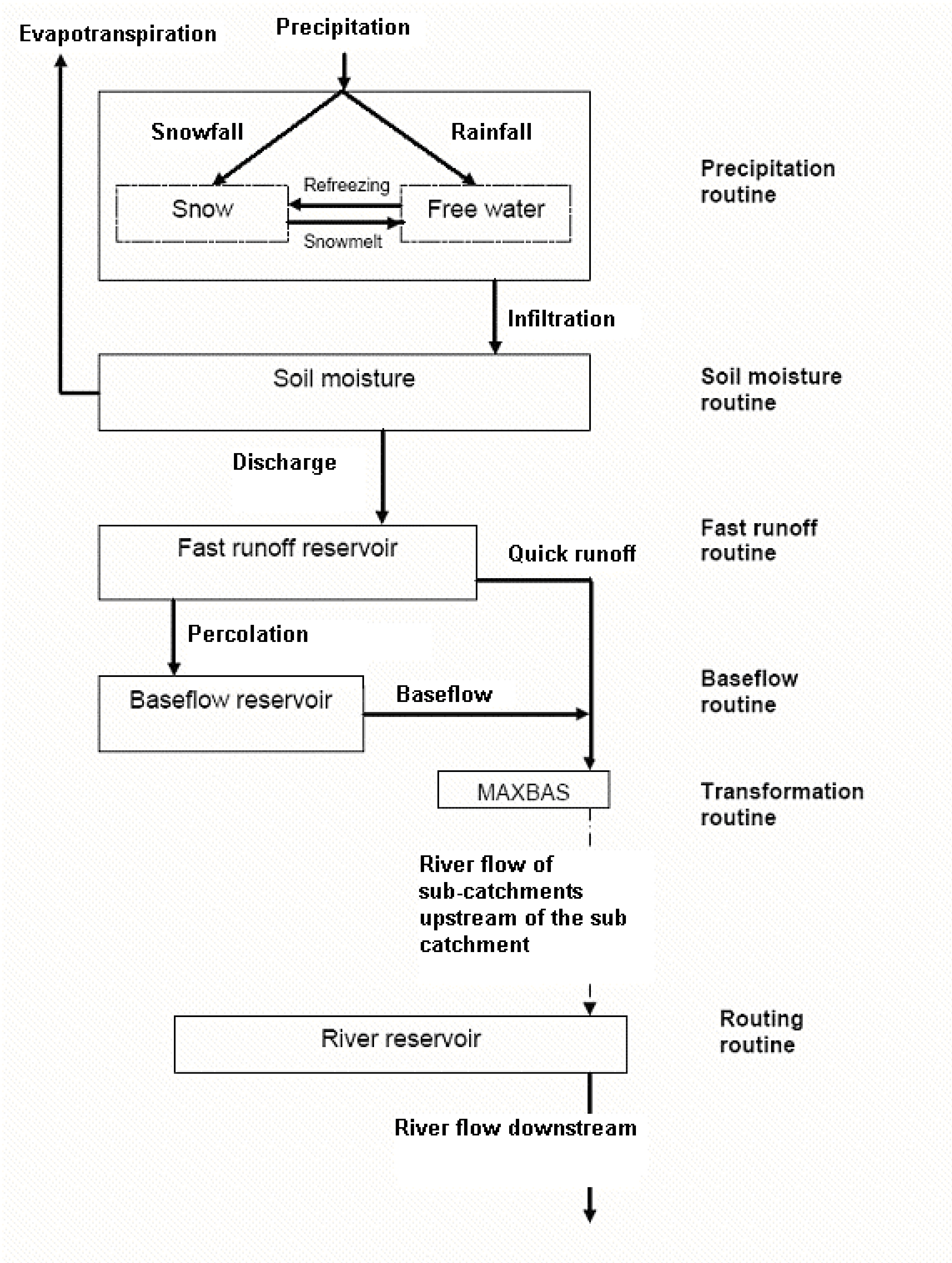

Figure 2-4 Schematization of the HBV model with six routines for one sub-catchment (Booij, 2002)

2.3.3 Structure HBV-model

A schematic sketch of the structure of the HBV-96 model is shown in figure 2-4. As can be seen from this figure the models consists the following six model routines:

- Precipitation routine
- Soil moisture routine
- Quick runoff routine
- Baseflow routine
- Transformation function
- Routing routine.

Each one of the sub-catchments has individual soil moisture accounting procedures and response functions. Therefore, the runoff is generated independently from each one of the sub catchments. The six model routines and their interactions that are illustrated in figure 2-4 for one sub catchment and are described below based on (Booij, 2002) and (Deckers, 2006).

Precipitation routine

Precipitation can occur as rainfall or snowfall. Snowfall occurs if the air temperature *T* [C^0] is below a defined temperature *TT* [C^o] and rainfall occurs if *T* >*TT*. Snowfall is added to the dry snow reservoir (within the snow pack) and rainfall is added to the free water reservoir, which represents the liquid water content of the snow pack. Interactions between these two components take place through snowmelt and refreezing, respectively shown in equation [2-1] and [2-2]:

$$P_{SNOW} = CFMAX \times (T - TT) \qquad [2\text{-}1]$$

$$P_{RAIN} = CFR \times CFMAX \times (TT - T) \qquad [2\text{-}2]$$

CFMAX = melting factor [mm/ (d C^0)]
CFR = refreezing factor [-]

Soil moisture routine

The soil moisture routine is the main part controlling runoff formation. Three output components are generated in this routine: direct runoff, indirect runoff and actual evapotranspiration

Direct runoff

The amount of soil moisture *(SM, [mm])* in the catchment is computed with a soil moisture reservoir, representing the unsaturated soil. It uses precipitation *(P, [mm/d])* as input which is supplied by the precipitation routine. As long as the maximum soil moisture storage *(FC, [mm])* is not exceeded, the precipitation infiltrates into the soil moisture reservoir. Otherwise the precipitation becomes directly available for runoff *(DR, [mm/d])* as shown in equation [2-3]:

$$DR = MAX\{(SM + P - FC),0\} \qquad SM = FC \Rightarrow DR = P \tag{2-3}$$

From equation [2-3] the volume of infiltrating water into the soil moisture reservoir *(IN, [mm/d])* equation [2-4] is:

$$IN = P - DR \tag{2-4}$$

A part of this infiltrating water will contribute to the soil moisture content SM; the other part will run through the soil layer as indirect discharge R.

Indirect runoff

The indirect discharge *(R, [mm/d])* through the soil layer is determined by the amount of infiltrated water *(IN)* and the soil moisture content *(SM, [mm*]), through a power relationship with parameter β. This is shown in equation [2-5]:

$$R = IN\left(\frac{SM}{FC}\right)^{\beta} \tag{2-5}$$

From this relation follows that the indirect discharge is increasing with increasing soil moisture content. For a smaller value of β, the increase is stronger. In equation [2-5] it is also assumed that as long as there is no infiltration, there is no indirect runoff. The amount of water that does not run off is added to the soil moisture.

Evapotranspiration

Actual evapotranspiration *(E_A, [mm/d])* which occurs from the soil moisture routine is related to the measured potential evapotranspiration *(E_P [mm/d])*, soil moisture state and a parameter value *LP, [-].* LP is a fraction between 0 and 1 and denotes the limit where above the evapotranspiration reaches its potential value. This relation is shown in equations [2-6] and [2-7]:

$$E_A = \frac{SM}{LP} \times E_P \qquad \text{With} \quad SM < (LP \times FC) \tag{2-6}$$

$$E_A = E_P \qquad \text{With} \quad SM \geq (LP \times FC) \tag{2-7}$$

The actual evapotranspiration is thus equal to the potential evapotranspiration if the actual soil moisture is above a specified threshold *(LP x FC).*

Quick runoff Routine

The runoff routine is the response function which transforms excess water from the soil moisture routine to runoff. In this transformation three processes can be distinguished which are; percolation to the base low, capillary transport from quick runoff reservoir back to the soil moisture routine and quick runoff.

Percolation

The outflow of the soil moisture routine, *DR+ R,* is available for the fast and base flow routine. The direct runoff *(DR)* and indirect runoff *(R)* together enter the quick runoff reservoir from which a specific amount percolates through to the underlying baseflow runoff reservoir. Percolation *(PERC, [mm/d])* only occurs when there is indirect and or direct runoff

Capillary rise

The second process in this routine is the capillary upward transport to the soil moisture reservoir from the quick runoff reservoir. The capillary flow [mm/d] depends on the amount of water stored in the soil moisture zone. The parameter *CFLUX* [mm/d], a maximum value of capillary flow, limits the capillary flow. The capillary flow depends on the soil moisture deficit, *FC- SM.* When there is no soil moisture deficit, no capillary rise will occur. Otherwise, a fraction of CFLUX will flow capillary upward. This is shown in equation [2-8]

$$C_f = CFLUX \times \left(\frac{FC - SM}{FC} \right) \qquad [2\text{-}8]$$

Quick runoff

When the yield from the soil moisture routine is higher than PERC and C_f allows and water is available in the quick runoff reservoir, quick runoff *(Q_0, [mm/d])* is determined through equation [2-9]

$$Q_0 = K_f \times UZ^{(1+\alpha)} \qquad [2\text{-}9]$$

Where UZ is the storage in the quick runoff reservoir [mm], α is a measure for the nonlinearity of the reservoir [-] and K_f [d^{-1}] a recession coefficient.

Baseflow routine

The baseflow Q_1 [mm/d] out of the Baseflow reservoir is the second part of the response function. The reservoir represents the groundwater contribution of the catchment.

The recession coefficient K_s [d^{-1}] is the only calibration parameter of this linear reservoir. The baseflow is represented by equation [2-10]:

$$Q_1 = K_S \times LZ \quad [2\text{-}10]$$

In which LZ is the water level in the reservoir [mm].

Transformation routine

The total discharge $Q = Q_0 + Q_1$ can be further transformed to get a proper shape of the hydrograph by using a transformation function. The transformation function is a simple filter technique with a triangular distribution of the weights, which is controlled by the parameter *MAXBAS.* For a value of 1 *MAXBAS*, distributes the runoff of a certain day over the same day. A higher value of *MAXBAS* will distribute the runoff of one day over a larger period of time. This procedure results in a delay of the sub-catchment discharge. (See figure 2-5) (Seibert, 2002)

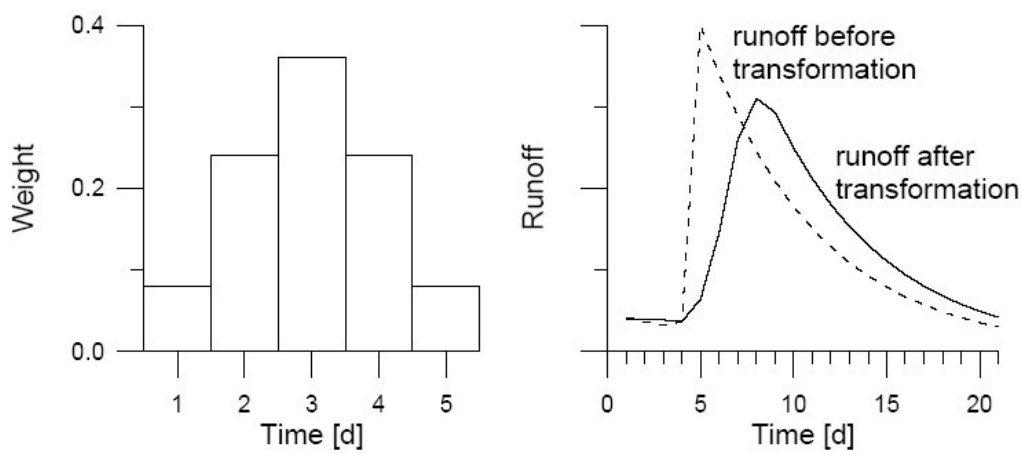

Figure 2-5. Example of the transformation function with MAXBAS =5 (Seibert, 2002)

Routing routine

With the transformation function, per sub catchment discharge runoff will be generated. In the routing routine HBV links the sub catchments to each other by adding the runoff from accompanying sub catchments to the local runoff. The inflow from another sub catchment is assumed to flow through a river channel from the outlet of the upstream catchment to the outlet of the current catchment where the local runoff is added. Besides plain linkage of the sub catchments, it is possible to delay the water in the river channel by using the parameters LAG and DAMP. A modified version of the Muskingum equation is used for this computation. This is shown in equation [2-11]. In brief, this equation simulates the attenuation of the wave amplitude (the parameter DAMP) and the passage time (the parameters LAG) of the discharge through the sub catchment.

By the parameters LAG, the river channel will be subdivided into a number of segments. When this parameter is an integer, each segment will refer to a delay of one day. If DAMP has a value of zero, the outflow from a segment equals the inflow to the same segment during the preceding time step, so that the shape of the hydrograph is not changed. If DAMP is not zero the shape will be changed, as the outflow from a segment will depend on the inflow during the same time step as well as the inflow and outflow at the preceding step. This is shown in equation [2-11]

$$Q_{OUT;t} = Q_{OUT;(t-1)} \times C_1 + Q_{IN;t} \times C_1 + Q_{IN;(t-1)} \times C_2 \qquad [2\text{-}11]$$

Where t is the current step and t -1 the previous time step. The coefficients C_1 and C_2 are defined through equations [2-12] and [2-13];

$$C_1 = \frac{DAMP}{(1+DAMP)} \qquad [2\text{-}12]$$

$$C_1 = \frac{(1-DAMP)}{(1+DAMP)} \qquad [2\text{-}13]$$

2.4 HBV-15 Model.

Booij (2002) developed a HBV model especially for the Meuse catchment and used is used in this study. This model called the HBV-15 model uses 15 sub-catchments upstream of Borgharen. The schematisation is shown in Figure 2-6. The model does not include locks, weirs, reservoirs or other man made structures. Calibration and validation of the model is performed for the whole catchment but also for the sub-catchments Vesdre, Amblève, Lesse and Ourthe. In section 3.4 the calibration results shall be used for the uncertainty analysis of the model parameters.

The HBV-15 model is available in an user interface from (SMHI) as well as in a FORTRAN code. In the user interface setting, simple standard simulation can be made. The model will simulate discharges that are the results of one run of the model. The FORTRAN model is especially useable for simulations with multiple runs. Furthermore it is easy to modify the model and make slight changes to the model setting. Therefore the FORTAN model shall be used to make the simulations runs in this research.

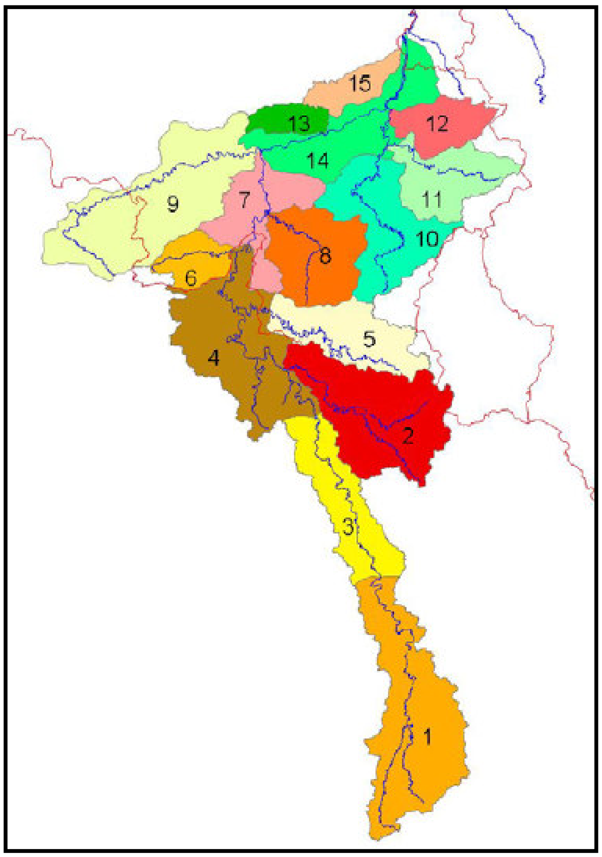

Figure 2-6 Schematisation of the upstream part of the river Meuse, used in the HBV-15 Model. *Legend;*
1. Meuse source-St.Mihiel 2. Chiers 3. Meuse St. Mihiel-Stenay 4. Meuse Stenay-Chooz 5. Semois
6. Viroin 7. Meuse Chooz-Namur 8. Lesse 9. Sambre 10. Ourhte 11. Amblève 12. Vesdre 13. Mehaigne
14. Meuse namur-Borgharen 15. *Jeke*r *(Arends*, 2005).

2.5 Calibration

A sensitivity analysis has been performed to asses the influence of individual or multiple parameters on the output of the model. This can be used to determine the parameter set that generates optimal model results. The six key parameters are FC, LP, β, α, K_S and K_h. This 6 different parameters shall be used in the research the others parameters out the HBV-model will stay constant. (All parameters are shown in table 2-2) This is because these parameters are not important to find the uncertainty of the HBV-model. In order to define the values of the 6 important parameters used in the HBV-model, these parameters are calibrated against observed discharge whereby the model parameters are adjusted until the observed natural system output showed an acceptable level of agreement (Booij, 2005). The calibration of the HBV-model has been performed by Booij (2005)

The optimality of the model output (discharge) has been assessed in different ways, namely by applying the Nash-Sutcliffe efficiency coefficient R^2 (Nash- Sutcliffe, 1970), the relative volume error RVE and the relative extreme value error REVE. They are outlined below presented by equations [2-14], [2-15] and [2-16]

- Nash-Sutcliffe coefficient, R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Q_{sim,i} - Q_{obs,i}\right)^2}{\sum_{i-1}^{n}\left(Q_{obs,i} - \overline{Q_{obs}}\right)^2} \qquad [2\text{-}14]$$

- Relative volume error, RV_E

$$RV_E = \left(\frac{\sum_{i=1}^{n} Q_{sim,i} - \sum_{i=1}^{n} Q_{obs,i}}{\sum_{i-1}^{n} Q_{obs,i}}\right) \times 100\% \qquad [2\text{-}15]$$

- Relative extreme value error REVE

$$REVE = 100 \times \frac{RV_{sim}(T) - RV_{obs}(T)}{RV_{obs}(T)} \qquad [2\text{-}16]$$

Where *i* is the time step, *n* is the total number of time steps, Q is the discharge. Subscripts *obs* and *sim* means observed and simulated and RV (T) is the t-year return value.

The Nash-Sutcliffe coefficient has been used in the identification method of the HBV-model parameter uncertainty. The degree of uncertainty in the hydrological model parameter value can be studied by testing the sensitivity of the model by calculating the Nash-Sutcliffe efficiency coefficient R^2 (Nash-Sutcliffe, 1970) see equation [2-14].

It compares the modelled discharge values ($Q_{sim,\ i}$) with the measured discharge values ($Q_{obs,\ i}$) and measured average value ($\overline{Q_{obs,i}}$). The range of the Nash-Sutcliffe value is from -∞ to 1. Hydrologic models are considered to be good when the coefficient is 0.8 or higher, (Booij 2005).

Table 2-2 HBV parameters.

Parameters
FC
β
LP
α
K_h
K_S
K_{HQ}
H_Q
Perc
Cflux

3 Methodology

3.1 Introduction

The methodology of the research is summarized in figure 3-1.

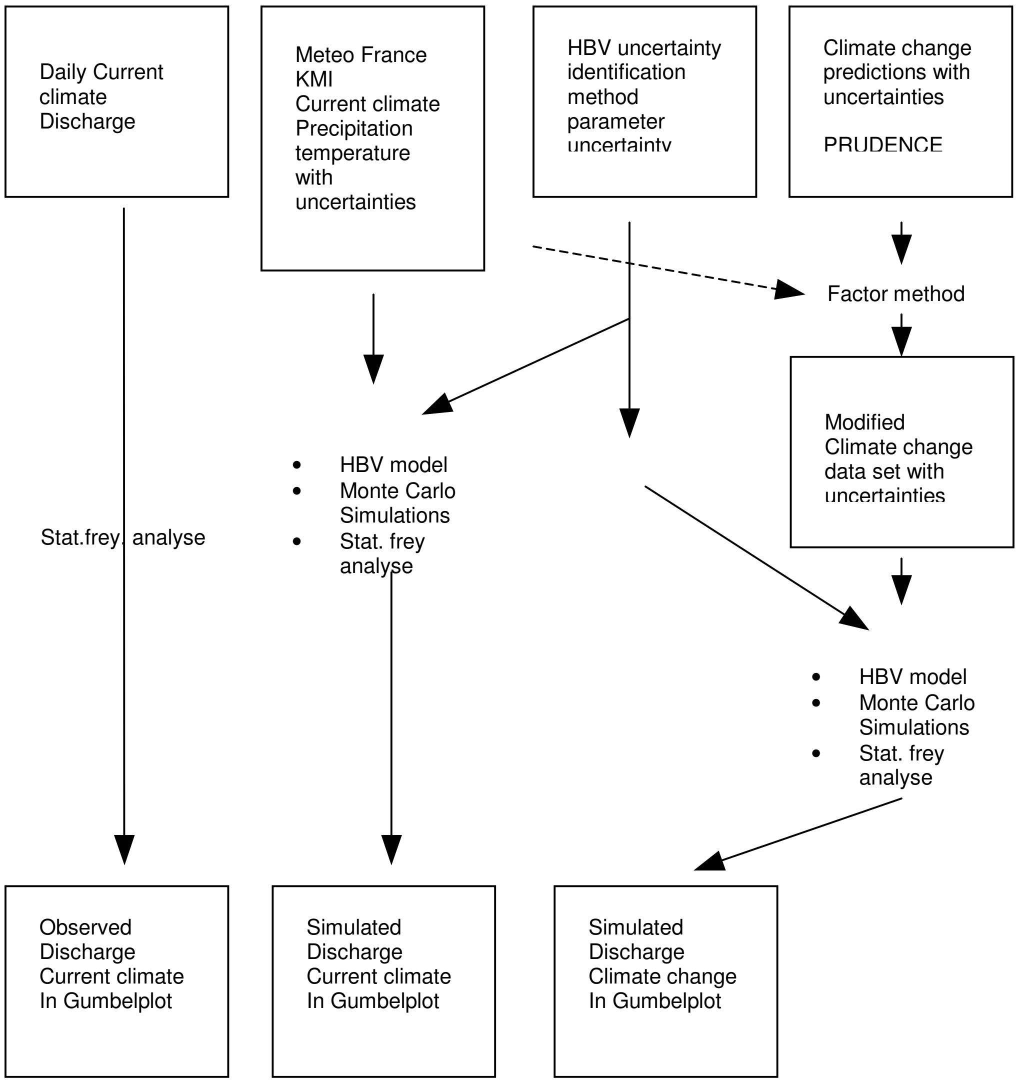

Figure 3-1 Flow diagram research methodology

The basis for this research are two studies performed by PRUDENCE. The results of these studies are climate change predictions for temperature and precipitation and uncertainties herein. These climate change data is transformed to the Meuse catchment with a climate change factor and the current climate for the Meuse catchment. The new climate data are presented in a normal distribution. The uncertainty in the data is expressed in the standard deviation. The different uncertainty sources are propagated through the HBV model using Monte Carlo simulations. Before the HBV-model is run, a special uncertainty analysis for the HBV-15 model is preformed. The output of the model is the extreme discharge of the river Meuse. In section 3.2 the Monte Carlo simulation is considered. The method for preparing the climate data is considered in section 3.3. The investigation of the uncertainty of the HBV-15 Meuse model is described in section 3.4. Finally in 3.5 the extreme discharge is considered.

3.2 Monte Carlo Simulation

The main aim of this research is to find the uncertainty in the extreme discharge on the Meuse. The discharge shall be simulated with the help of the HBV-15 model. That is why it is important to know how the different uncertainties develop during running the HBV - 15 model and how to quantify them in the output. There is chosen to propagate the modified climate data for the Meuse with all uncertainties through the model with a Monte Carlo analysis. There is chosen for a Monte Carlo analysis because it has been used in previous researches for the same kind of problems, (Booij, 2005).

In a Monte Carlo analysis, a value is drawn randomly from the distribution for each input. Together this set of random values, one for each input, defines a scenario, which is used as input to the model, computing the corresponding output value. The entire process is repeated n times producing n independent scenarios with corresponding output values. These n output values institute a random sample from the probability distribution over the output indicated by the probability distribution over the inputs, (Morgan and Henrion, 1990).

There shall be made 1000 runs in one Monte Carlo simulation. This amount of runs is bases on the fact that less runs will make the predictions not certain enough. More runs will take a lot more process time and the predictions are not more certain. So therefore there is chosen to do 1000 runs in a simulation. The model shall be run with different uncertainty groups. This way it becomes possible to investigate what the propagation of the different uncertainty groups through the HBV-15 model are and what the sizes of the uncertainty groups are according to the extreme discharge.

The uniform distribution is the simplest continuous statistical distribution in probability. It has a constant probability density on an interval (a, b) and zero probability density elsewhere. The continuous uniform distribution is a generalization of the rectangle function because of the shape of its probability density function. It is parameterized by the smallest and largest values that the uniformly-distributed random variable can take, a and b, (Morgan and Henrion, 1990). In this research the different parameters of the HBV-15 model are assumed to be distributed in an uniform distribution. This is assumed because of the fact that is it not for sure that kind of distribution the parameters will have so there for it is assumed that it will be a uniform distribution because it is the simplest. The uniform distribution is necessary for the investigation of the uncertainty of the HBV-model. See section 3.4.

The normal distribution is arguably the most important distribution of all. It is specified by two parameters: a mean μ and standard deviation σ. The normal distribution, also called Gaussian distribution, is an extremely important probability distribution in many fields. (Morgan and Henrion, 1990).The climatological data used in this research is assumed to be is in a normal distribution. This is because the fact that the sources (Déqué, 2004; Christensen, 2004), of the climatological data also assumed that the climatological data is in a normal distribution. (Déqué, 2004; Christensen, 2004) And the fact that it is a nature phenomenon. So through the normal distribution it was possible to use the climatological data as input for the HBV-15 model. This is because of the fact that during performing a Monte Carlo analyse the values are randomly chosen and the probability is the chance on a certain value. This chance is used to calculate the uncertainty in the data output of the HBV-model. See section 3.3.

3.3 Uncertainties in climate change variables

3.3.1 Predictions of temperature and precipitation

The basis for the research are two different studies performed within the framework of the EU-project PRUDENCE. PRUDENCE is a project funded by the European Commission under its fifth framework programme. It has 21 participating institutions from a total of 9 European countries, with several additional international collaborators, which have contributed to the project from their own funding. The PRUDENCE project is devoted to the study of climate changes over Europe. It has two main objectives: to estimate the uncertainties about the expected response, and to evaluate possible impacts in various fields of human activities (PRUDENCE, 2006).

The first study is performed by Christensen (Christensen, 2004). Christensen did research on the prediction of climate change for different countries in Europe. The analysis is based on all PRUDENCE simulations with RCMs and on a country-by-country basis. For each country (some of the larger countries are split in two sections) all available simulation data for temperature and precipitation have been aggregated into one number per field representing this country for each simulation. This number is scaled according to the global temperature change using the underlying global climate model, which has been used as a driver for the regional climate model. This way, more than 25 estimates of the change in temperature and precipitation has been provided for countries in Europe (Christensen, 2004).

The estimations for temperature and precipitation are given for the seasons: December, January and February *(DJF)*, March, April and May *(MAM)*, June, July and Augusts *(JJA)* and September, October and November *(SON)*. And are the averages of the whole country. The estimations for temperature are expressed as: $T_{CH,\ SEASON,}$ *[C^o]* and the estimations for precipitation are expressed as: $P_{CH,\ SEASON}$*, [%].*
The change in precipitation and temperature for a country expressed as: $P_{CHANGE,\ SEASON}$*, [%]* and temperature expressed as: $T_{CHANGE,\ SEASON,}$ *[C^o]* can be predicted when the estimations $P_{CH,\ SEASON}$ and $T_{CH,\ SEASON}$ are multiplied with the global average temperature change expressed as: T_{GA}, [C^o] as shown in equation [3-1] and [3-2]:

$$P_{CHANGE,SEASON} = P_{CH,SEASON} \times T_{GA} \qquad [3\text{-}1]$$

$$T_{CHANGE,SEASON} = P_{CH,SEASON} \times T_{GA} \qquad [3\text{-}2]$$

Uncertainties in the estimates still remain and are due to different formulations of the involved global and regional climate models as well as the different boundary forcing and model uncertainties (Christensen, 2004). Because of the fact that the predictions given by Christensen are independent of specific choices of emission scenario, the uncertainties of the different emission scenarios are not present in the estimates of the projected changes.

Christensen gives an uncertainty range of the predictions of temperature and precipitation change which is expected to be the standard deviation expressed as $\sigma P_{CH, SEASON}$, *[%]* for the precipitation and $\sigma T_{CH, SEASON}$, *[C^0]* for the temperature.

The total uncertainty in precipitation and temperature for a country expressed as: $\sigma P_{CHANGE, SEASON}$, *[%]* and temperature expressed as: $\sigma\ T_{CHANGE, SEASON}$, *[$C^o$]* can be estimated in the same way as the total change is estimated. Thus the estimations $\sigma P_{CH, SEASON}$ and $\sigma T_{CH, SEASON}$ are multiplied with T_{GA} as shown in equation [3-3] and [3-4]:

$$\sigma P_{CHANGE,SEASON} = \sigma P_{CH,SEASON} \times T_{GA} \qquad [3\text{-}3]$$

$$\sigma T_{CHANGE,SEASON} = \sigma P_{CH,SEASON} \times T_{GA} \qquad [3\text{-}4]$$

The sizes of the different uncertainty groups are not investigated by Christensen, but have been studied by Déqué (2004). Déqué investigated the uncertainty in the results of ten regional climate models (RCMs).
The objective of the study performed by Déqué is to focus on the response of a few General Circulation Models used in the PRUDENCE project. Déqué has restricted to 30-year seasonal means. Moreover, amongst the many fields archived in the PRUDENCE database, Déqué selected temperature and precipitation. These fields offer the triple advantage to be directly connected to human perception of the climate, to be comparable with reliable observations, and to exhibit regional-scale features that are not accessible to coarse resolution GCMs. In order to further reduce the size of his report, Déqué concentrated on the two extreme seasons winter (DJF) and summer (JJA).

Déqué used the ten RCMs available in the PRUDENCE seasonal database. The models are those of CNRM, DMI, ETHZ, GKSS, Hadley Centre, ICTP, KNMI, MPI, SMHI and UCM. Out of the ten RCMs, three models (CNRM, DMI and Hadley Centre) have produced three 30-year simulations. For the other seven, Déqué have triplicated the single simulation in order to give the same weight to each model. For the prediction of Europe two emission scenarios are used namely the A2 and B2 scenarios of the SRES emission scenarios of the IPCC.

The results out of the research of Déqué are the sizes of four different uncertainty groups namely, SD1: Sampling. These are uncertainties due to the sampling of data and other information necessary for predictions of climate change. SD2: Emission scenarios. These are uncertainties out of the different emissions scenarios of the IPCC. Because of the fact that there are several scenarios with different predictions for the future greenhouse gases makes the predictions for temperature and precipitation change very uncertain. SD3: GCMs. These are uncertainties that are present in the global circulation models. These uncertainties are due to the difficulty to simulate the nature responses. And SD4: RCMs. These are uncertainties out of the regional circulation models. The same models as the GCMs but now special build for smaller areas. The uncertainties are given for the season DJF and JJA for temperature as well for precipitation.

There is a problem because of the fact that there are used two different researches. But Christensen and Déqué used the same data sources namely PRUDENCE. Therefore it is possible to combine the result of both researches by only transforming the results of the research of Déqué to the results of Christensen. So it becomes possible to use the sizes for the different uncertainty groups found by Déqué (2004), to split up the total uncertainty found by Christensen (2004).

In the transforming process the sizes of the different uncertainties groups, are made usable for splitting up the total uncertainty in the predictions for temperature and precipitation ($\sigma\, T_{CHANGE,\ SEASON}$ and $\sigma P_{CHANGE,\ SEASON}$). The sizes of different uncertainty groups $\sigma T_{SDn,\ SEASON,}$ *[C°] and* $\sigma P_{SDn,\ SEASON,}$ *[%]* are necessary to investigate the contribution of one uncertainty group to the extreme discharge. The transformation process is shown in equations [3-5] and [3-6]:

$$\sigma T_{SDn,SEASON} = \left[\left(\frac{\overset{n}{\Sigma} SD_{SEASON}}{\sigma T_{CHANGE,SEASON}} \right) \times SD_n \right] \quad [3\text{-}5]$$

$$\sigma P_{SDn,SEASON} = \left[\left(\frac{\overset{n}{\Sigma} SD_{SEASON}}{\sigma P_{CHANGE,SEASON}} \right) \times SD_n \right] \quad [3\text{-}6]$$

The temperature uncertainty for one uncertainty group *n* can be calculated, when the sum of the four different uncertainties group divide by the total uncertainty out of Christensen(2004) is multiplied with the size of the group *n.* The size of the different groups is come out of Déqué (2004). This is the same for precipitation but that with the uncertainty for the precipitation.

The different uncertainty groups *n* should be propagated through the model one by one. The mean value shall be taken with the standard deviation value of one uncertainty group. This way it is possible to investigate what the contribution is of the different uncertainties groups to the total uncertainty of the extreme discharge

3.3.2 Modified data set

When the change in precipitation and temperature for a country ($P_{CHANGE,\ SEASON}$ and $T_{CHANGE,\ SEASON}$) is calculated with equations [3-1] and [3-2] and the sizes of the different uncertainty groups are calculated with equations [3-3] to [3-6], it becomes possible to calculate the modified data set. For this step a so called climate factor method *(CF)* is used. This CF is the same as used in Diaz-Nieto and Wilby, (2005). The CF method calculates climate series by adding (temperature) or multiplying (precipitation) with the observed series. The change in precipitation and temperature is transformed to the modified data expressed in $P_{NEW,\ SEASON}$ *[mm]* and $T_{NEW,\ SEASON}$ *[C^o]* with the help of the observed data expressed in $T_{CURRENT}$ *[C^o]* and $P_{CURRENT}$ *[mm]* shown in equations [3-7] and [3-8]:

$$T_{NEW,SEASON} = T_{CHANGE,SEASON} + T_{CURRENT} \quad [3\text{-}7]$$

$$P_{NEW,SEASON} = P_{CHANGE,SEASON} \times P_{CURRENT} \quad [3\text{-}8]$$

In the study performed by Déqué only two different emissions scenarios are used. So uncertainty for the different scenarios is not well investigated in the studies performed by Déqué (2004) and Christensen (2004). Therefore it is necessary to have a better look at the uncertainty for emission scenarios. To find the uncertainty for the emission scenarios figure 4-1 (section 4.2) from the IPCC shall be used.

The picture shows the impacts in temperature change for the years 2000 until 2100 for all the emission scenarios developed by the IPCC. In the picture there is given estimations with a certain range for each of the emissions scenarios. The total of this range is an indication for the uncertainty of the emissions scenarios. There is assumed that the standard deviation of this range is the uncertainty useable in this research as the uncertainty size of the emission scenarios. There for the 90% uncertainty interval of the range is calculated the get the standard deviation of the scenarios and so to the uncertainty size of the emissions scenarios.

3.4 Method to estimate parameter uncertainties.

The reliability of hydrological conceptual models is highly depending on the calibration procedure, which is the search for an optimal parameter set. See section 2.5

The method is bases on the next the assumptions:

1. The uncertainty of a model can be expressed in a Nash Sutcliff coefficient, which is compareness between the observed and simulated discharge.
2. The uncertainty of a model can be simulated trough parameters variation.
3. Through the variation of the parameters without correlation between them, different model world can be created. The range where in the parameters are verified is chosen shuts a way that de average NS coefficient out of the comparers of the different model world is equal to the ns coefficient mentioned at point 1.

It is also assumed that the uncertainty of the parameters expressed in the form of a standard deviation is the major source of the uncertainty of the model outcome. Through consideration of this parametric uncertainty, model structural and scale related uncertainties are not taken into account. However, these are assumed to be at least partly covered by the parametric uncertainty.

In previous research (e.g. Booij, 2002; Arends, 2005) the calibration and investigation of parameters for the HBV-15 models has been performed. The most important parameters are FC, LP and Beta in the soil moisture routine and Alpha, Kf and Ks in the fast flow routine, (Booij, 2002). This 6 different parameters shall be used in the research the others parameters out the HBV-model will stay constants. This is because this parameters are not important to find the uncertainty of the HBV-model. A Monte Carlo model simulation with these parameters values creates a Nash-Sutcliffe efficiency coefficient R^2 for the total Meuse catchment (NS_{Meuse}) for the calibration and the validation period of total 27 years (Booij, 2002). (See section 2.5) There are also Nash-Sutcliffe values for four sub catchments namely: Vesdre (NS_{Vesdre}), Ourthe (NS_{Ourthe}), Ambleve ($NS_{Ambleve}$) and the Lesse (NS_{Lesse}). The values of the main parameters and the Nash-Sutcliffe coefficients shall be used in this research for the uncertainty analysis of the HBV model.

To find the standard deviation ($\sigma_{parameters,\ sub\text{-}catchment}$) for the parameters there shall be calculated a certain percentage of the mean value of the parameters. This percentage (ξ) will create a certain range ($-\xi$;+ ξ) around the mean value of the parameter. This range could be considered as an uncertainty belt. So with a certain percentage of the mean value of a parameter a standard deviation for that parameter is created.

A Monte Carlo model simulation (see section 3.2) shall be made with the range of the parameters calculated with the chosen percentage and the mean value of the parameters. In one sub-catchment the percentage shall be the same for all the parameters. Because there are no observed discharge series for this method the normal equation for the Nash-Sutcliffe coefficient can not be applied (see section 2-5) for the calculation of the Nash Sutcliffe coefficients, in this case the different modelled discharge series are compared with each other instead of observed discharges. See equation [3-9].

$$NS_{Matrix} = 1 - \frac{\sum_{i=1}^{n}(Q_n - Q_m)^2}{\sum_{i-1}^{n}(Q_m - \overline{Q_m})^2} \qquad [3\text{-}9]$$

Q= Extreme discharge Series
n = 1 to 1000
m= 1 to 1000   n≠ m

When all the discharge series are compared with each other a matrix can be made of all the NS_{matrix} values. The matrix has the scale of n x n. So there are n^2 NS_{matrix} values in one matrix. The average Nash Sutcliffe value of the matrix expressed in $NS_{Subcatchment}^{Model}$ can be calculated with equation [3-10]. The diagonal out of the matrix is not used in the calculation of the average, this is because the diagonal are the results of the compares of the same discharges and the results are 1,0. When these values are also used for calculating the average, the value for the average will be to high.

$$NS_{Subcatchment}^{Model} = \left(\sum^{m+n} NS\right) - 1000/\left(1000^2 - 1000\right) \qquad [3\text{-}10]$$

The $NS_{Subcatchment}^{Model}$ value can be printed in a graph. When this process is performed for different percentages ξ it is possible to draw a graph of the $NS_{Subcatchment}^{Model}$ values as a function of the different percentage for specific sub- catchment.
When the $NS_{sub\text{-}catchment}$, value out of Booij 2002, is also printed as a horizontal line in the graph it becomes possible to read of the percentage at which the $NS_{Subcatchment}^{Model}$ is equal to $NS_{sub\text{-}catchment}$. See figure 3-2 as an example.

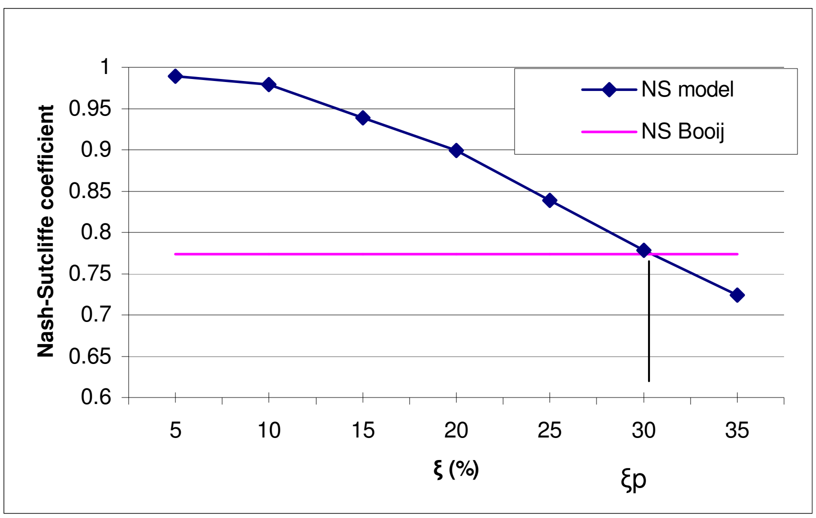

Fig.:3-2 Example of graph with NS Booij and NS model lines and point

The percentages expressed as *ξp [%]* (where the two values are equal) is taken to calculate the range and so the standard deviation of the parameters that are used for those sub-catchments. This process is performed for the sub-catchments the Lesse, Ambleve, Ourthe and the Vesdre. For the other 11 sub-catchments an average of the four catchments has been calculated. In the calculation of the average, the size of the discharge of the different sub catchments is used as weight. The found $P_{catchment}$ value for each sub-catchment is used to calculate the uncertainty range for the parameters of that sub-catchment. This range with the mean value shall be put into the model as the parameter uncertainty. A control Monte Carlo simulation shall be performed. With the results of this simulation a Nash-Sutcliffe coefficient (NS_{model}) shall be calculated. This value will be compared with the calibrated Nash-Sutcliffe coefficient for the Meuse catchment ($NS_{Meuse.}$) (This is the Nash Sutcliffe coefficient at Borgharen, calculated with equation *[2-17]*. When both values are almost equal the method of analysing the uncertainty of the HBV model is performed quite well. The HBV uncertainty expresses in the parameters shall be split up into the main routing processes of the HBV model. These routings are the soil moister, the quick runoff and the base flow.

3.5 Gumbel distribution, extreme discharge

In probability theory and statistics the Gumbel distribution (named after Emil Julius Gumbel (1891–1966)) is used to find the maximum of a number of samples of various distributions. For example it can be used to find the maximum level of a river in a particular year if we have the list of maximum values for the past ten years. It is therefore useful in predicting the chance that an extreme earthquake, flood or other natural disaster will occur. The Gumbel distribution, and similar distributions, are used in extreme value theory and is also known as the log-Weibull distribution, (Morgan and Henrion, 1990). In this research the Gumbel distribution is used for calculating the extreme discharge of the river Meuse.

To calculate the extreme high discharge with a certain return period and to make a figure with a Gumbel distribution of the extreme high discharge the equation 3-11 and 3-12 are used, (Shaw, 1994).

$$K(T) = -\frac{\sqrt{6}}{\Pi}\left(\gamma + \ln\ln\left[\frac{T(x)}{T(X)-1}\right]\right)$$ *K(T) is the frequency factor.* [3-11]

Thus if an estimate of the annual maximum discharge with a return period of 100 years is required, then T(X) = 100 years, K(T) = 3.14, *y*= 0,55772

The estimation of the extreme discharge expressed in $Q_{extreme}$ with a specific return period is shown in equation [3-12]:

$$Q_{extreme} = \overline{Q} + K(T) \times \sigma$$ [3-12]

Where $\overline{Q}$ is the mean of the annual maximum discharge and σ is the standard deviation of the sample of annual maximum flows. The return period that is chosen for this research is 100 years. This is because it is difficult to make predictions for a longer time step due to the uncertainties playing a role in the predictions.

4 Data

4.1 Introduction

In chapter 3 the methodology of the research has been considered. In this chapter all the necessary data and other values needed for performing the research according to the methodology are treated. In section 4.2 the findings out of the report of Christensen are described for the Meuse catchment and the global warming out of the report of the IPCC is described. The main points out of the report of Déqué, the different sizes for the uncertainty groups and the uncertainty for the emission scenarios are considered in section 4.3. Finally, in section 4.4 the HBV-15 calibration data needed for the calibration of the model and for performing the uncertainty analysis method are considered.

4.2 Change of current climate

The research area is the river basin upstream of Borgharen. The main countries in this area are Belgium, Luxemburg en France. The estimations for temperature and precipitation of Christensen (2004) are used. These are land average values. Because of the fact that France is a very large country with different climates, the data for France are not considered in this research. The data for Belgium and Luxemburg are considered for calculating the average that shall be used in the research

Table 4-1: Estimations for temperature and precipitation out of Christensen 2004

For each variable the results are shown as follows:
$T_{CH,SEASON}$: Estimate of the mean values from all models
$\sigma T_{CH,\ DJF}$: Estimate of standard deviation from all models

Temperature	$T_{CH,DJF}$	$T_{CH,MAM}$	$T_{CH\ JJA}$	$T_{CH,SON}$	$\sigma T_{CH,\ DJF}$	$\sigma T_{CH,MAM}$	$\sigma T_{CH,\ JJA}$	$\sigma T_{CH,SON}$
Belgium	1.0	1.0	1.5	1.3	0.3	0.4	0.5	0.3
Luxemburg	1.0	1.0	1.6	1.3	0.3	0.4	0.5	0.4
Averge	1.0	1.0	1.55	1.3	0.3	0.4	0.5	0.35

Precipitation %	$P_{CH,DJF}$	$P_{CH,MAM}$	$P_{CH\ JJA}$	$P_{CH,SON}$	$\sigma P_{CH,\ DJF}$	$\sigma P_{CH,MAM}$	$\sigma P_{CH,\ JJA}$	$\sigma P_{CH,SON}$
Belgium	6.5	0.0	-11.0	-2.3	3.1	2.6	4.4	3.0
Luxemburg	7.8	-0.2	-9.9	-2.0	2.7	2.8	3.7	3.1
Average	7.15	-0.1	-10.45	-2.15	2.9	2.7	4.05	3.05

Table 4-1 shows the data from Christensen (2004). The data are given seasonally DJF (Dec. – Jan. – Feb.), MAM (Mar. – Apr. – May), JJA (Jun. - Jul. – Aug.) and SON (Sep. – Oct. – Nov). The upper part gives the estimations for the temperature per 1 ℃ global warming for Belgium and Luxemburg. The lower part projects the estimations of relative change in precipitation for a 1℃ global warming for Belgium and Luxemburg. The uncertainty in the estimations as expressed in the standard deviation of the mean values. Due to the fact that the changes and the uncertainties are expressed relative to a 1 ℃ global warming, the change in precipitation and temperature for a country can be predicted when the given changes are multiplied with the global average temperature change expressed as: T_{GA} [C^{o}] (see section 3.3).

The change in precipitation and temperature for the countries Belgium and Luxemburg can be found when the given changes are multiplied with the global average temperature change expressed in: T_{GA}, [C°]. According to the IPCC, 2001a the average global warming for the year 2100 is about 3.3 °C (see figure 4-1 the dark gray section the mean value) (indicated by the straight black line). So the estimations from Christensen (2004) have to be multiplied with 3.3 to get the predictions expressed in: $P_{CHANGE,\ SEASON}$, *[%]* and $T_{CHANGE,\ SEASON}$, *[C°]* for the year 2100.

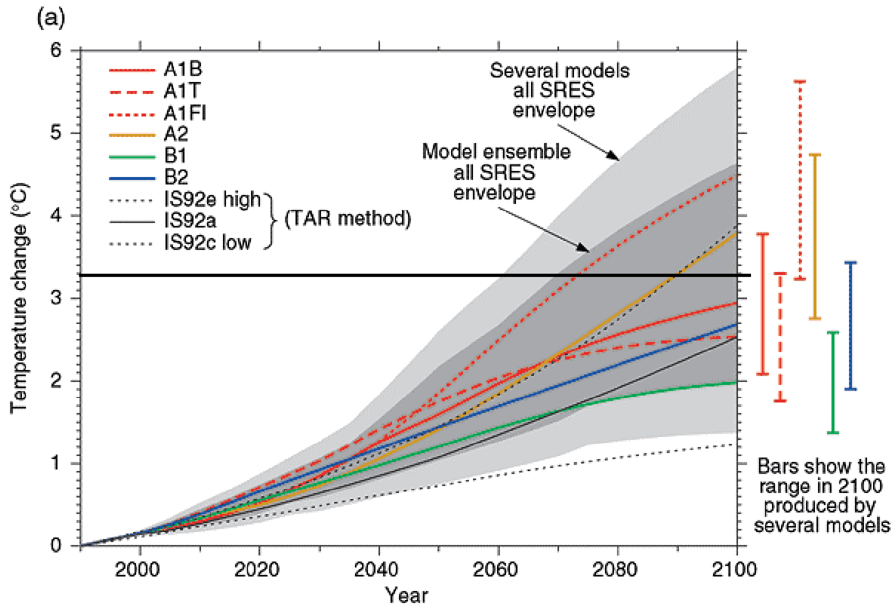

Figure 4-1 temperature change after 1990, six scenarios. (IPCC, 2001a)

4.3 Uncertainties in the climate change

In the predictions of Christensen (2004) is not given a distribution of the different uncertainty groups. Only a total uncertainty expressed as the standard deviation and mean values for temperature and precipitation change. Therefore the results of the study preformed by Déqué (2004) shall be used to get the size of the different uncertainty groups that must be considered in the climate change predictions.

In table 4-2 the size of the different uncertainties according to total uncertainty and climate impact are shown. The standard deviations due to sampling (SD1), emission scenarios (SD2), GCMs (SD3) and RCMs (SD4) are given. These sizes shall be used to split the total uncertainties in the predictions for temperature and precipitation ($\sigma\ T_{CHANGE,\ SEASON}$ and $\sigma P_{CHANGE,\ SEASON}$) into different uncertainty-groups. This way it becomes possible to create climate data with uncertainties expressed in different standard deviations for each uncertainty group expressed in $\sigma T_{SDn,\ SEASON}$, *[C°] and* $\sigma P_{SDn,\ SEASON}$, *[%].*

Table 4-2: the scales and size of the different uncertainties (Déqué, 2004)

	bias	impact	sampling	scenarios	boundary	RCM
DJF temperature (K)	1.7	3.3	0.3	0.7	0.7	0.5
JJA temperature (K)	1.4	3.7	0.3	0.9	0.9	0.7
DJF precipitation (mm/day)	0.8	0.5	0.2	0.2	0.3	0.2
JJA precipitation (mm/day)	0.5	0.4	0.2	0.2	0.3	0.3

Déqué did only investigate the uncertainties for the periods DJF and JJA. For the period MAM and SON no sizes are known for the uncertainties. Therefore is chosen to calculate the average of the period DJF and JJA and to use that value for the period MAM and SON.

$$MAM = SON = \frac{DJF + JJA}{2} \qquad [4\text{-}1]$$

The uncertainty for the different scenarios is not well investigated in the studies researches performed by Déqué (2004) and Christensen (2004). There for it is necessary to get the uncertainty for emission scenarios out of figure 4-1. The method here fore is described in section 3.5.

The range of the dark grey section in figure 4-1 is 2.9 ^{o}C. The 90 % uncertainty interval is used to calculate the standard deviation. This is in this case 2.9 divided by 4 is 0.73^{o}C. This is the average uncertainty for the whole year for the emission scenarios. Out of Déqué (2004) the uncertainty size for temperature 0.37 ^{o}C. So the values for DJF, MAM, JJA and SON have to be multiplied with 1.97 ^{o}C (0.73/ 0.37) to get an average of 0.73 ^{o}C

4.4 HBV-15 calibration data

The current HBV-15 model described in chapter 2 has been developed by Booij (2002). Booij calibrated the model for 4 sub-catchments (Vesdre, Ourthe, Ambleve and the Lesse) for the 11 others he used regionalization. For the calibration process Booij used the method and criteria described in section 2.5. Booij used climate data for the years 1970 to 1984 and 1985 to 1996, a total of 27 years. These data are used in this research as the current data expressed in $T_{CURRENT}$ and $P_{CURRENT}$. The current data has been provided by the KMI (Belgian Royal Meteorological Institute) and from Meteo France

Because of the fact that there are observed discharge series available for the sub catchments Vesdre, Ourthe, Ambleve and Lesse it is possible to calculate also NS values expressed as NS_{Vesdre}, NS_{Ourthe}, $NS_{Ambleve}$ and NS_{Lesse} for these sub-catchments. These values shown are in table 4-3 and shall be used in the uncertainty analysis of the HBV-15 model.

Table 4-3: Mean discharge and $NS_{Sub\text{-}catchment}$ values.

Sub catchment	**Average Discharge**	**$NS_{Sub\text{-}catchment}$**
Vesdre	9.4 m^2/s	0.774
Ourthe	23.0 m^2/s	0.881
Ambleve	19.0 m^2/s	0.847
Lesse	16.0 m^2/s	0.901

The optimal parameters sets for the different sub catchments found by Booij are shown in table 4-4. The Nash-Sutcliffe value for the complete Meuse catchment is equal to 0.88.

Table 4-4 parameters of the sub catchment of the River Meuse

		FC	BETA	LP	ALFA	Kf	Ks
Meuse nord	1	325	1.62	0.35	0.69	0.006	0.023
Jeker	2	270	1.97	0.4	0.15	0.046	0.023
Mehaigne	3	266	2.07	0.41	0.24	0.034	0.023
Vesdre	4	350	1.3	0.68	1.1	0.004	0.030
Sambre	5	365	1.42	0.28	0.27	0.031	0.023
Ourthe	6	180	1.5	0.71	1.1	0.003	0.024
Ambleve	7	202	1.9	0.68	1.1	0.002	0.024
Meuse midi	8	365	1.58	0.31	0.57	0.009	0.023
Lesse	9	253	1.5	0.65	1.1	0.002	0.018
Viroin	10	384	1.92	0.28	0.8	0.005	0.023
Semois	11	378	1.62	0.3	0.62	0.008	0.023
Bar-Vence-Sormonne	12	281	1.6	0.36	0.76	0.004	0.023
Chiers	13	321	1.48	0.36	0.61	0.013	0.023
Meuse Lorraine nord	14	318	1.73	0.35	0.68	0.007	0.023
Meuse Lorraine sur	15	293	1.39	0.39	0.73	0.006	0.023

5 Results

5.1 Introduction

In this chapter the results of the research are described. In section 5.2 the new climate data for the river Meuse catchment are considered. These data shall be used in the HBV-15 model to simulate the impact of climate change to the extreme high discharge for the river Meuse. In section 5.3 the uncertainty in the HBV-15 model is considered. In section 5.4 the results of the Monte Carlo simulations of the HBV-15 model with the uncertainty of the HBV-15 model and the climate data for 2070-2100 with their uncertainties are considered. The extreme discharge with a return period of 100 years for climate change conditions is shown. Finally the uncertainties in the extreme high discharges are considered in section 5.5

5.2 Climate change seasonal mean and uncertainties

The calculated values for $P_{CHANGE,\ SEASON}$, $T_{CHANGE,\ SEASON,}$ $\sigma P_{CHANGE,\ SEASON}$, and $\sigma\ T_{CHANGE,\ SEASON,}$ are shown in table 5-1. The data are given for the seasons DJF (December, January, February), MAM (March, April May), JJA (June, July, August) and SON (September, October, November). The upper part gives the predictions for temperature change for Belgium and Luxemburg. The lower part gives the predictions for the precipitation for Belgium and Luxemburg.

Table 5-1: Predictions of temperature and precipitation change and uncertainties

Temperature °C	$T_{CHANGE,\ DJF}$	$T_{CHANGE,\ MAM}$	$T_{CHANGE,\ JJA}$	$T_{CHANGE,\ SON}$	$\sigma T_{CHANGE,\ DJF}$	$\sigma T_{CHANGE,\ MAM}$	$\sigma T_{CHANGE,\ JJA}$	$\sigma T_{CHANGE,\ SON}$
Belgium	3.3	3.3	4.95	4.29	1.00	1.32	1.65	0.99
Luxemburg	3.3	3.3	5.28	4.29	1.00	1.32	1.65	1.32
Average	3.3	3.3	5.12	4.29	1.00	1.32	1.65	1.16

Precipitation %	$P_{CHANGE,\ DJF}$	$P_{CHANGE,\ MAM}$	$P_{CHANGE,\ JJA}$	$P_{CHANGE,\ SON}$	$\sigma P_{CHANGE,\ DJF}$	$\sigma P_{CHANGE,\ MAM}$	$\sigma P_{CHANGE,\ JJA}$	$\sigma P_{CHANGE,\ SON}$
Belgium	21.45	0	-36.3	-7.59	10.23	8.58	14.52	9.9
Luxemburg	25.74	-0.66	-32.7	-6.6	8.91	9.24	12.21	10.2
Average	23.6	-0.3	-35	-7.1	9.57	8.91	13.37	10.1

The average values are used to calculate the climate data for the river Meuse for climate change conditions (period 2070-2100).

The calculation of the different uncertainty groups is performed with equations [3-5] and [3-6]. The sizes of different uncertainty groups $\sigma P_{SDn\ SEASON}$ and $\sigma\ T_{SDn,\ SEASON}$ given in tables 5-2 and 5-3 are necessary to investigate the contribution of one uncertainty group to the extreme discharge.

Table 5-2 Modified data sets for Temperature

	Temperature	DJF	MAM	JJA	SON
	mean change	3.3	3.3	5.1	4.3
Uncertainty	Total	1.3	1.7	2.1	1.5
	SD1 Sampling	0.2	0.2	0.2	0.2
	SD2 Scenarios	0.6	0.7	1.0	0.6
	SD3 GCMs	0.3	0.5	0.5	0.4
	SD4 RCMs	0.2	0.3	0.4	0.3

Table 5-3 Modified data sets for precipitation

	Precipitation	DJF	MAM	JJA	SON
	mean change	23.6	-0.3	-35.0	-7.1
Uncertainty	Total	11.6	10.7	16.0	12.2
	SD1 Sampling	2.1	1.9	2.7	2.1
	SD2 Scenarios	4.2	3.7	5.3	4.2
	SD3 GCMs	3.2	2.8	4.0	3.2
	SD4 RCMs	2.1	2.3	4.0	2.7

The changes in precipitation and temperature are transformed to the new data expressed in $P_{NEW,\ SEASON}$ and $T_{NEW,\ SEASON}$ with the help of the current climate data expressed in $T_{CURRENT}$ and $P_{CURRENT.}$ The calculation is performed with equations [3-7] and [3-8]. In figure 5-1 the results of equation [3-7] and equation [3-8], in the form of the modified data set are shown. The new climate data for the River Meuse are shown as a normal distribution (dotted line). The current climate is also printed as a reference (solid line). The new climate data are shown for all four seasons for temperature (℃) and precipitation (mm/day). The results show an annual average increase in temperature of 4.0 ºC for climate change conditions varying between 3.3 ºC in DJF and 5.1 ºC in JJA. Precipitation decreases slightly by 2.5 % on an annual basis varying between +24 % in DJF and -35 % in JJA. Uncertainties with climate change (expressed as standard deviation) vary between 1.3 ºC in DJF and 2.1 ºC in JJA for temperature and 11 % in MAM and 16 % in JJA for precipitation.

In table 5-2 and 5-3 is the input to the HBV-15 model considered. These describe the changes for temperature and precipitation. The sizes for the different uncertainty groups are also pictured. It is now possible to make simulations with one uncertainty group at the time. Then the mean value is taken and a SD value of one uncertainty group is used.

In the climate change data different uncertainties sources can be considered. The first one are the boundary conditions or GCMs, 27% of the climatologically uncertainty is coming from this uncertainty source. The second uncertainty source are the emission scenarios, 36% of the climatological uncertainty is coming from this source. The contribution of the RCMS to the climatologically uncertainty is 18%. The last uncertainty sources considered in this research is sampling. Sampling creases a uncertainty percentage of 18% of the total climatological uncertainty.

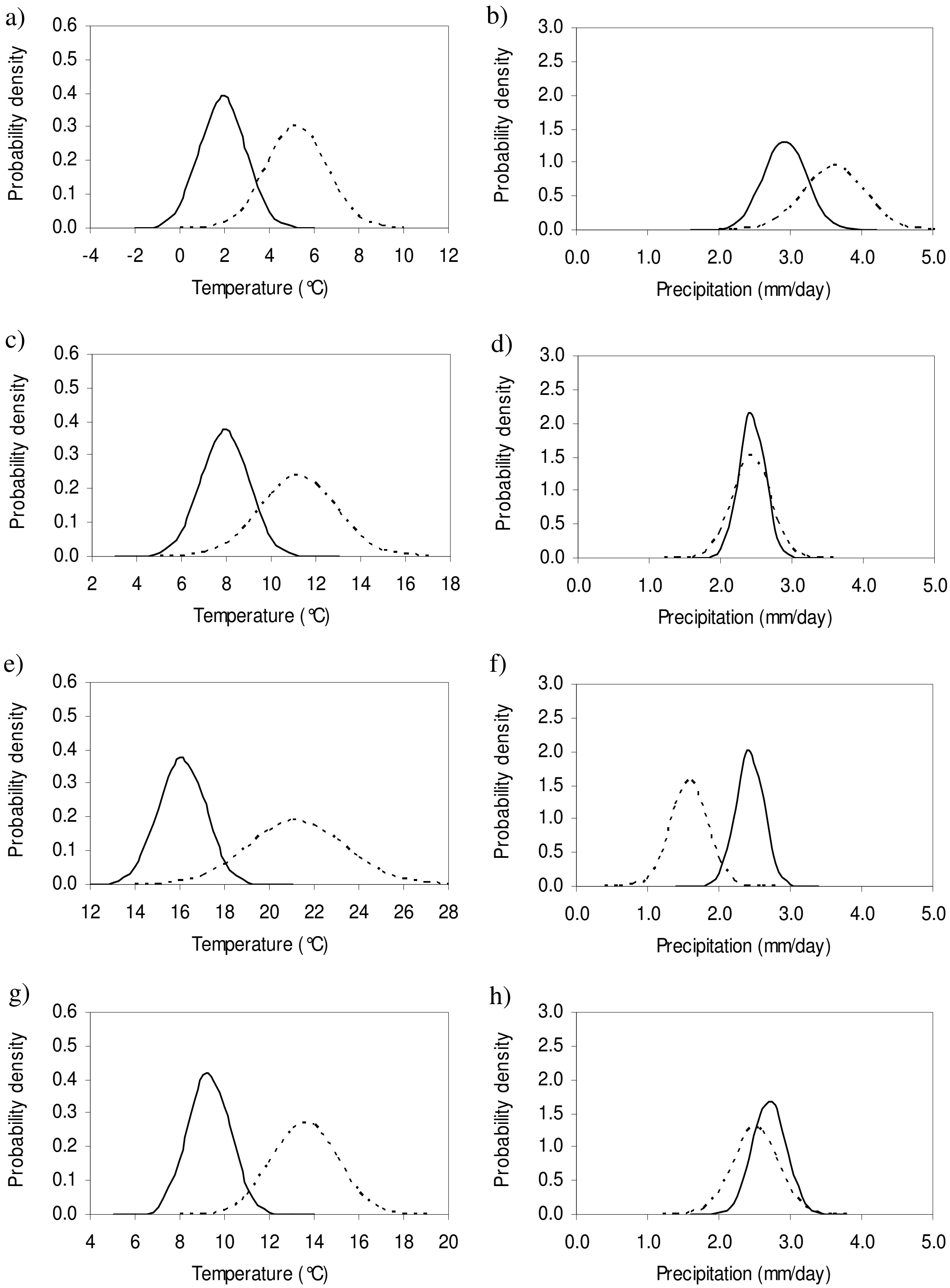

Fig. 5-1 Probability density functions as a result of different uncertainty sources for current climate (solid line) and changed climate (dotted line) for DJF (a), MAM (c), JJA, (e) and SON (g) temperature (°C) and DJF (b), MAM (d), JJA, (f) and SON (h) precipitation (mm/day).

5.3 Parameter uncertainties in HBV-15 model

5.3.1 Results parametric uncertainty

First the 4 sub-catchments (Vesdre, Ourthe, Ambleve and the Lesse) for which the values of *(NS_{Vesdre}), (NS_{Ourthe}),* ($NS_{Ambleve}$) and (NS_{Lesse}) are known are investigated with the method described in section 3.5. The Monte Carlo is performed for the percentage 5% 10%, 15%, 20%, 25%, 30% and 35%. The results expressed as $NS^{Model}_{Subcatchment}$ are shown in table 5-4.

Table 5-4 $NS^{Model}_{Subcatchment}$ for different sub catchments as a function of different related uncertainties in HBV parameters

Percentage	Vesdre	Ourthe	Ambleve	Lesse
5%	0.989	0.994	0.996	0.989
10%	0.979	0.985	0.986	0.977
15%	0.939	0.961	0.956	0.948
20%	0.899	0.933	0.921	0.908
25%	0.839	0.889	0.877	0.858
30%	0.778	0.848	0.821	0.786
35%	0.724	0.811	0.761	0.697

The $NS^{Model}_{Subcatchment}$ value can be printed in a graph. When this process is performed for all the percentages it becomes possible to draw a graph of the $NS^{Model}_{Subcatchment}$ values for different catchments as a function of different percentages. (Expressed in NS model) (see figure 5-2, 5-3, 5-4, 5-5) When the NS_{Vesdre}, NS_{Ourthe}, $NS_{Ambleve}$ and NS_{Lesse} values out of Booij 2002 (in figure expressed in NS Booij) (see table 4-3 for the values) are also printed as a horizontal line in the different graphs it is possible to read of the percentage at which the $NS^{Model}_{Subcatchment}$ is equal to the *NS* values out of Booij (2002).

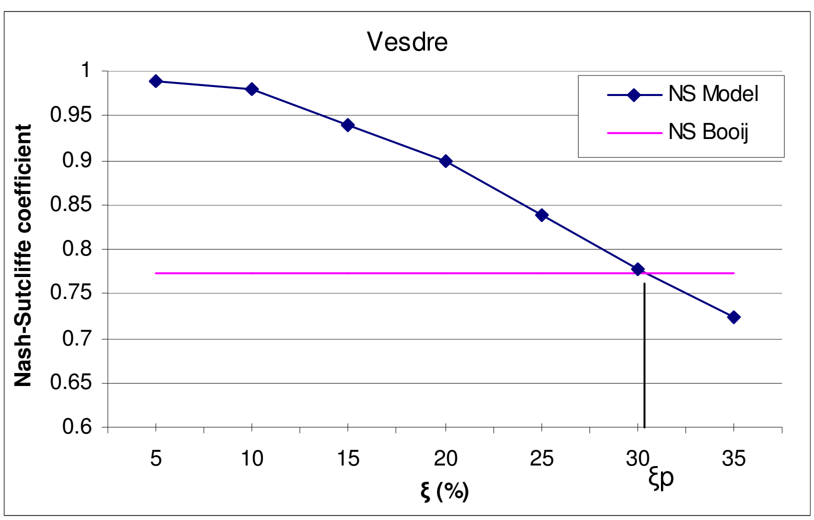

Fig.5-2 NS model and NS Booij values for Vesdre catchment as a function of different related uncertainties in HBV parameters.

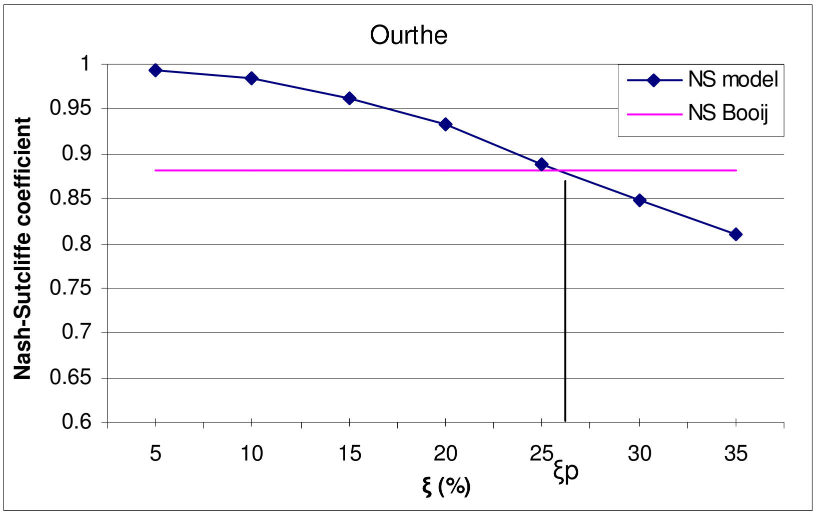

Fig.5-3 NSmodel and NS Booij values for Ourthe catchment as a function of different related uncertainties in HBV parameters.

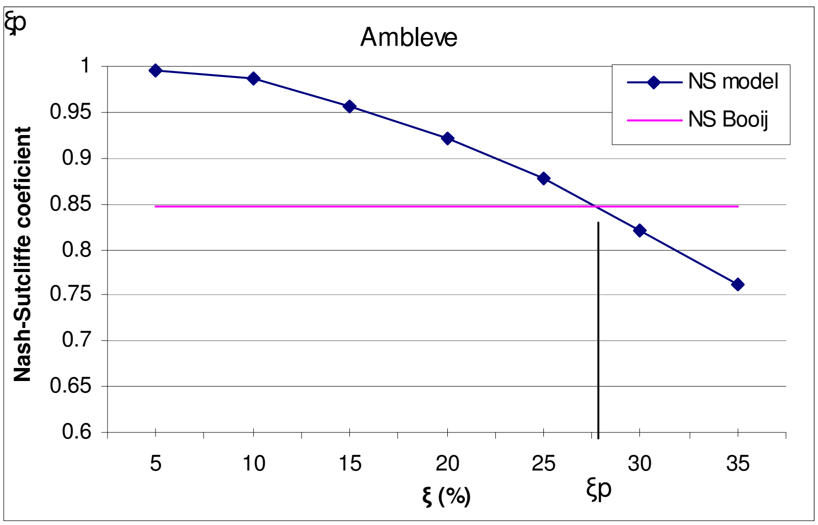

Fig.5-4 NSmodel and NS Booij values for Amblève catchment as a function of different related uncertainties in HBV parameters.

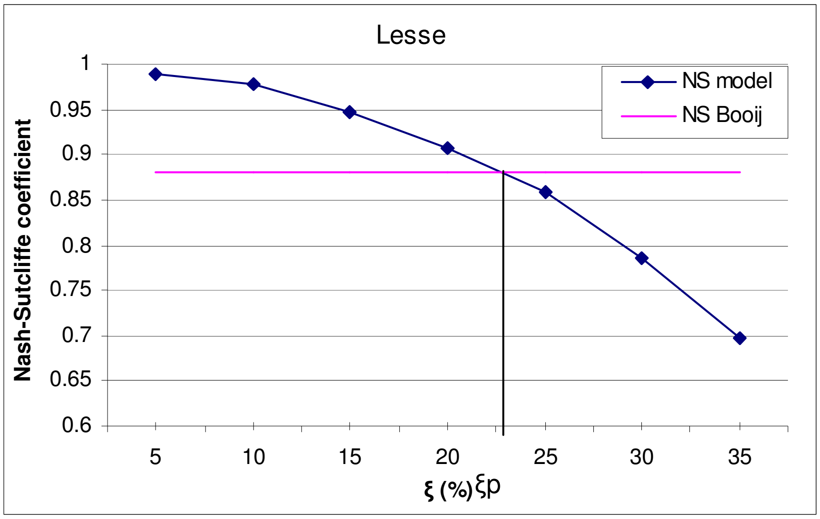

Fig.5-5 NS values for Lesse catchment as a function of different related uncertainties in HBV parameters.

The percentage at which NS_{model} is equal to the *NS* values out of Booij (2002) are taken to calculate the ranges and so the standard deviation of the parameters that are used for those sub-catchments. This process is performed for the sub-catchments Lesse, Ambleve, Ourthe and Vesdre. For the other 11 sub-catchments an average of the four

catchments is used. This is because of the fact that for the other 11 sub catchments no observed discharge values and NSbooij values are known. When calculating the average the size of the discharge (see table 4-3) of the 4 different sub catchments is used as weight. In table 5-5, the percentages for the uncertainties for all sub catchments are given

Table 5-5 Percentages for the uncertainties for all sub catchments

	ξp
Vesdre	30.5%
Ourthe	25.5%
Ambleve	27.0%
Lesse	22.0%
Others	25.8%

The found $P_{catchment}$ values for each sub-catchment (see table 5-5) are put in the model as the parameter uncertainty. Then 1000 model simulations are done. The average Nash-Sutcliffe coefficient is compared with the Nash-Sutcliffe coefficient for the Meuse catchment out of Booij (2002) expressed in NS_{Meuse}. When both values are equal, the method of analysing the uncertainty of the HBV-15 model is performed on the right way.

The average Nash-Sutcliffe coefficient for the calibrated model by Booij 2002 expressed in NS_{Meuse} is 0.88. The Nash-Sutcliffe coefficient of the model with the parameter uncertainty is 0.87

5.3.2 Conclusions

Conclusion after performing the method for identification and quantification of the parameter uncertainty of the HBV-15 model is that the method is suitable for the investigation of the parameter uncertainty of the HBV-15 model. The results are reasonably well; this can be concluded from the fact that the difference between NS_{model} (0.87) and NS_{Meuse} (0.88) (from Booij, 2002) is very small.
This small difference indicates that the method is suitable for identifying the uncertainty of the parameters is presented in the model. The uncertainty of the model shall be presented as the standard deviation of the output of the model.

When it is the case that $NS_{Meuse} < NS_{model}$, the uncertainties are not merely presented through the model parameters. This is because a higher NS_{model} value indicates a sharper model according to the observed and modelled discharge. The model with uncertainty is working better than the calibrated model without the uncertainty and that would be very strange. The second possibility $NS_{Meuse}>NS_{model}$. In this case the model is too uncertain. The main subject that in the uncertainty of the HBV model is the correlation between the different sub-catchments. Out of calculations can be said that there is no correlation between the different sub-catchments.

5.4 Extreme high discharges

Now it is possible to simulate the discharge of the river Meuse. Therefore different Monte Carlo simulation runs are made. The simulations performed are to investigate the high discharges. There are model output discharges for the current climate and the climate change period. But there is also observed current discharge data. These data is not coming out of the model.

Out of the model output discharge, the highest peak discharge, 1 each year, for 27 years is used to make the Gumbel plot which is shown in figure 5-6

The solid line is the line that corresponds with the simulated current climate and the dotted line is the line that corresponds with the simulated modified data set. The dashed line corresponds with observed current discharges at the Meuse for the same period as the simulated current climate line.

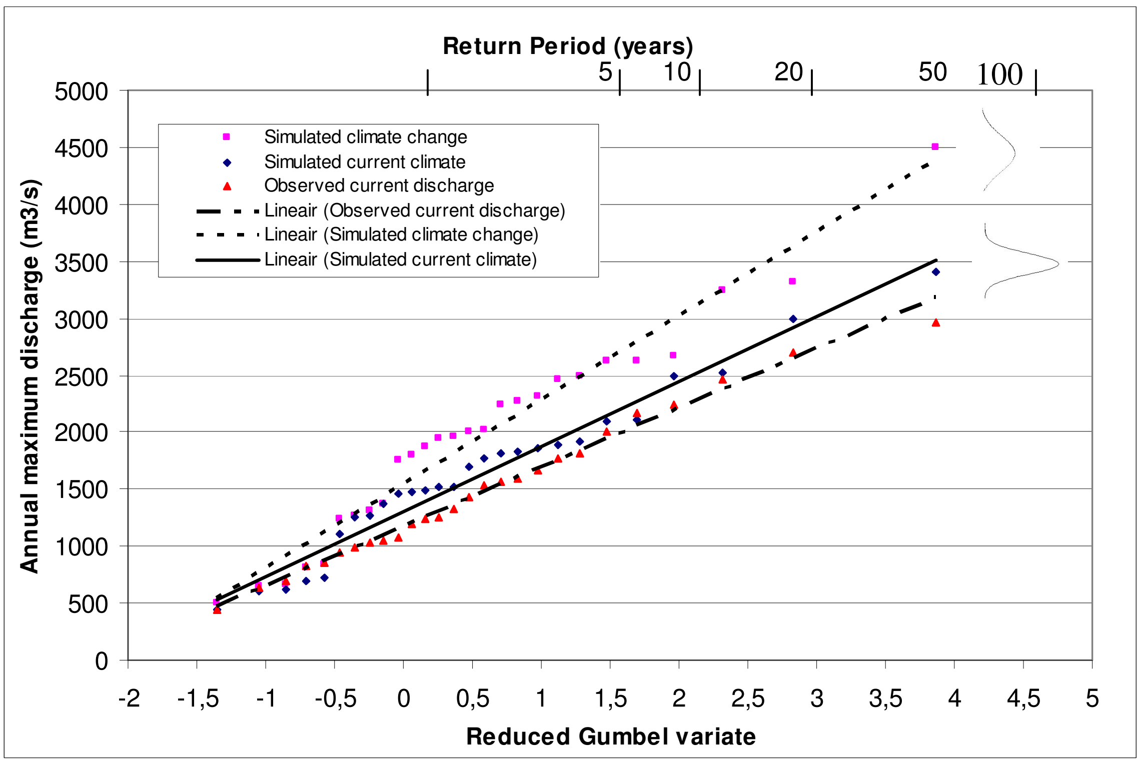

Fig. 5-6 Gumbel plot of the peak discharge of the river Meuse. For simulated climate change period, simulated current climate period and observed current discharge

The lines of observed discharge and modelled current discharge are not equal. This indicates that the HBV-15 model predicts a higher extreme discharge than observed. The consequence of that is that the line for the discharge for 2070 to 2100 should also be lower than the line pictured in figure 5-6.

The simulated peak discharge for the current climate with a return period of 100 years is 3865m^3/s. The observed current discharge with the same return period is 3465 m^3/s. This indicates that the model, as mentioned above is predicting a higher discharge than observed. The difference between the extreme discharges is 10%.

The simulated peak discharge under climate change conditions with a return period of 100 years is 4933 m^3/s. The difference between the simulated current climate period and the simulated climate change period is 29% what stands for almost 1100 m^3/s.

In figure 5-7 the extreme discharge for the river Meuse for period 2070-2100 is printed in a normal distribution function, also the current extreme discharge for the Meuse is printed. These are the average of 1000 Gumbel plots with a return period of 100 years. The discharges are simulated with the HBV-15 model what means that the predictions are like 10% to high.

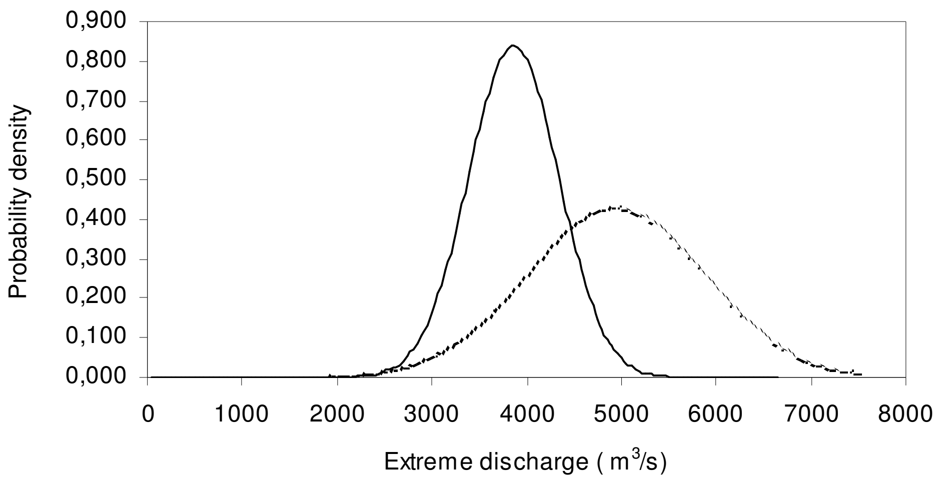

Fig.: 5-7Annual max discharge with return period of 100 years for current climate and climate change.
Soled line: current climate, dotted line: climate change.

The standard deviation is assumed to be the uncertainty of the predictions. In this uncertainty there is not considered the extrapolation uncertainties of calculating the probability function out of the Gumbel plot.

For the climate change period the standard deviation has a size of 933m^3/s. The standard deviation for the current climate is 450m^3/s. The standard deviation for the climate change period is thus 483m^3/s or 105% higher. This indicates a redoubling of the uncertainty.

5.5 Uncertainty

Figure 5-7 shows the total uncertainty size expressed as the standard deviation, this uncertainty can be split up into the different uncertainty groups. The different uncertainty groups: emission scenarios, sampling, boundary conditions (GCMs), RCMs, and HBV parameters.

The HBV uncertainty expresses in the parameters is split up in the same way as uncertainties in the climate data. The HBV uncertainty is split up into the main routing processes of the HBV model. These routings are the soil moister, the quick runoff and the base flow.

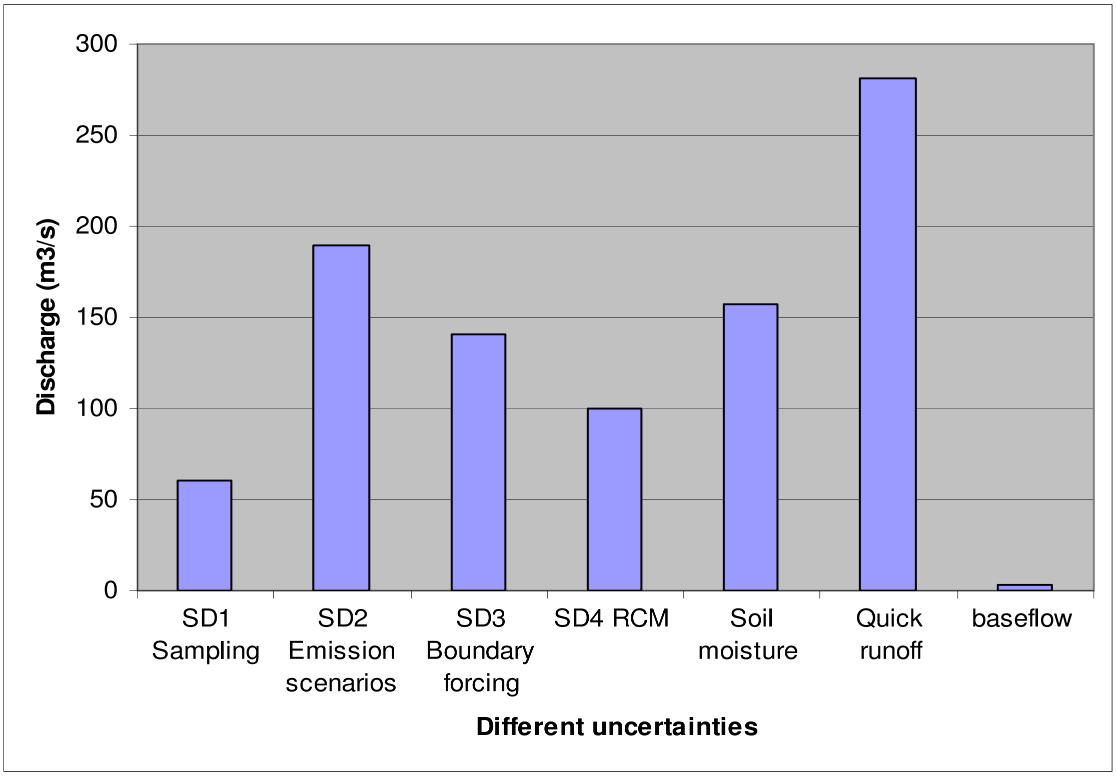

Fig.:5-8 Sizes of the different uncertainty groups in discharge (m^3/s)

When a simulation was made with all different uncertainty groups the total uncertainty was smaller (993 m^3/s) than when the uncertainty groups were propagated one by one through the model and then summed (1070 m^3/s). To give the uncertainty group the right size the different groups are scaled to the total uncertainty from the model.

The different uncertainty groups and there sizes in discharge (m^3/s) are shown in figure 5-8. In table 5-6 the apportionment of the climatological uncertainties and the hydrological uncertainties and the size of the two groups and the total uncertainty are shown in percentage.

Table 5-6 sizes different uncertainty groups in discharge

Source Apportionment	
Climatological Data uncertainties	**52,4 %**
Sampling	8,4 %
Emission scenarios	18,3 %
GCM	15,0 %
RCM	10,7 %
Hydrological uncertainties	**47,6 %**
Soil moisture	16,6 %
Quick runoff	30,0 %
Base flow	1,0 %
Total uncertainty	**100,0 %**

The uncertainty range of that extreme discharge is 933m^3/s. This uncertainty range is build up of the four uncertainties groups that are present in the climate data and hydrological uncertainty. In figure 5-8 the contribution in the discharge of the different uncertainties groups are shown according to the total uncertainty of 933m^3/s. The uncertainty for the climate data is 453 m^3/s split up in 61 m^3/s for the uncertainties of Sampling, in 153 m^3/s for the emission scenarios, 140 m^3/s for the GCM uncertainties and 100 m^3/s for the RCM uncertainties. The other half is the uncertainty for the HBV-15 model. And can be divided in 157 m^3/s for the soil moisture, 280 m^3/s for the quick runoff and 3 m^3/s for the baseflow.

6 Conclusion

6.1 Conclusion

The objective of this research was: To assess the uncertainties in the impacts of climate change on future extreme high discharges of the river Meuse. Four research questions where formulated in the introduction section 1.4.

1). which uncertainties have to be considered in climate change predictions and what is the size of these uncertainties?
2). is there a method to investigate the uncertainty of the HBV-15 model and is it possible to quantify the uncertainty?
3). what is the best way for propagating climate data through the HBV-15 model? With as result the extreme discharge for the river Meuse with all the uncertainties.
4). what are the most important sources of the uncertainties in the simulated extreme high discharge?

Based upon the research described in this report the following conclusions can be drawn with respect to these questions.

1). The five type of uncertainties that are considered in this research the uncertainties in the climate change data. These are the boundary conditions or GCMs. GCMs are the basis for the creation of climate predictions in case of climate change. They are very uncertain in their predictions for climate change. This is because of the response of the climate system in the future. 27% of the climatological uncertainty is coming from the GCMs. The second uncertainty source is the emission scenarios. Also a very uncertain source, this is because of the fact that future Green house gas concentrations are affected by societal, demographical and technological factors are present in the SRES scenarios and these are very uncertain for the future. 37% of the climatological uncertainty is coming from the emission scenarios. The other two uncertainty sources in the climate change data are RCMs and sampling. The contribution of the RCMS to the climatological uncertainty is 18%. For sampling is the uncertainty also 18%.

2). Another main uncertainty is the HBV-15 model, which is investigated in this research with a special method. Conclusion after performing the method for identification and quantification of the parameter uncertainty of the HBV-15 model is that the method is suitable for the investigation of the uncertainty in the HBV-15 model. (The structure, parameters, scales, etc.) The results are reasonably good. The uncertainty of the model shall be present in the standard deviation of the extreme high discharge output of the model. The hydrological uncertainty in the simulation has a size of 473m^3/s and can be divided in to 157m^3/s for the Soil moisture routine, 280 m^3/s for the quick runoff routine and 3 m^3/s for the base flow

3). The data are propagated through the HBV-15 model with a Monte Carlo simulation. The results of the simulations performed in the research are looking very well. The overall conclusion is that the Monte Carlo simulation is a good method for propagating the data through the model. The results of the different simulations are the extreme high discharges for the river Meuse. For the current climate data the extreme discharge with a return period of 100 years is 3865 m^3/s. The extreme discharge for the Meuse in the period 2070 to 2100 with also a return period of 100 years is a discharge of 4933 m^3/s. This is an increase of 29% according to the discharge now. The uncertainty of that extreme discharge is 933m^3/s. This uncertainty range is build up of the four uncertainties groups that are present in the climate data and the hydrological uncertainty

4). The uncertainties groups are showing a total uncertainty of 933m^3/s. The uncertainty for the climate data is 453 m^3/s, split up in 8,4% for the uncertainties of Sampling, in 18,3% for the emission scenarios, 15,0% for the GCM uncertainties and 10,7% for the RCM uncertainties. The other half is the uncertainty for the HBV-15 model. And can be divided in 16,6% for the soil moisture, 30,0% for the quick runoff and 1% for the baseflow.

The answer to the objective is: the future extreme high discharge for the river Meuse is 4933 m^3/s with an uncertainty of 933m^3/s. This will give a range of 4000 m^3/s to 5866 m^3/s. In this range the main uncertainties are the GCMs and the different emissions scenarios and the processes soil moisture and quick runoff out of the HBV-15 model.

6.2 Further research

For further research some recommendations can be given: one is about the climate data. A better and more certain method to find the climate change data can be used. A method therefore is probably the use of RCMs specially developed for the catchment of the river Meuse. But there are probably more methods to find the climate change data for a certain catchment. For example with the method used in the research, but than not the average change in temperature and precipitation for Belgium and Luxemburg, but precise calculated change for each sub catchment. A less uncertain method for finding the climate change data gives probably a smaller uncertainty range for the extreme high discharge. A point is this is the uncertainty of the GCMs which is now quite large. When it is possible to make the predictions of the GCMs better and less uncertain the climate change predictions are becoming better. This will result is less uncertain predictions for temperature and precipitation change for the future.

Another point is the uncertainty of the hydrological model. Now the uncertainty is quite large and is found with a new method. It is possible to develop the method further. Therefore more data are necessary. When these data are available it is possible to perform the method for all the catchments and so make the predictions of the method and the certainty of the HBV-15 better. It can be concluded that when the methods used in this research are developed further it is possible to make the uncertainty in the prediction of the extreme discharge for the future with climate change smaller.

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