Prepared for:

DG Rijkswaterstaat RIZA

Baseline Study Uncertainty in Flood Quantiles

Report

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Appendix

1 Introduction

In the past couple of years in a cooperation between the Dutch Royal Meteorological Institute (KNMI) and the Institute for Inland Water Management and Waste Water Treatment in the Netherlands (RIZA) a rainfall generator has been developed for the Rhine basin (Beersma & Buishand, 2003). With this rainfall generator it is possible to generate long time series of rainfall and temperature (e.g 10,000 years), which serve as input for hydrological and hydraulic models.

With these models, developed in cooperation with the Federal Institute of Hydrology in Germany (BfG), discharges with a return period up to 1000 years can be calculated using a computer tool FEWS Extreme Discharges (FEWS-ED), developed by Delft Hydraulics in commission from RIZA (Werner & Reggiani, 2002). Currently, several projects are of have been carried out to determine extreme discharge scenarios. Recently a rainfall generator for the Meuse basin has also been developed by KNMI (Leander and Buishand, 2004). This rainfall generator is currently being tested with a hydrological model for the river basin.

A short overview of the setup of the FEWS system is given in Eberle et al. (2001).

In the end, the usefulness of this approach to determine the design discharge needs to be evaluated. Important questions to be answered are:

- What is the uncertainty bandwidth of the calculated discharges?
- How accurate are the calculated discharges at high return period?

To perform this evaluation and address the above questions the work will be carried out stepwise. A first step in this process is to carry out an inventory of the uncertainties in the extreme discharges tool (rainfall generator, hydrological model, hydraulic models).

The accuracy of the method to calculate flood quantiles is determined by the quality of the 3 elements: rainfall generator, hydrological model and hydraulic model. In this inventory the following issues will be addressed:

- research into available methods for uncertainty analysis;
- evaluation of these methods;
- to provide a research plan for carrying out the uncertainty analysis.

The proposed approach has been presented and discussed during a workshop held 12 November 2004 at WL|Delft Hydraulics.

Acknowledgement

The various chapters in this report on the rainfall generator were made available by Mr. A. Buishand of the KNMI. He has also reviewed the draft version of the report.

2 Short description extreme discharge frequencies tool

2.1 Generating Synthetic Rainfall and Temperature series

The first step in the extreme discharge frequency tool is to generate synthetic temperature and precipitation series using the KNMI rainfall generator (Buishand & Brandsma, 2001). Long synthetic sequences are produced by reshuffling the daily data from 34 stations in the Rhine basin, taking into account the temporal correlation, and preserving the spatial correlations and the correlation between precipitation and temperature. The output of the KNMI rainfall generator is a single file with a series of indices corresponding the chosen length of the series (e.g. 10,000 years). Each of these indices refers to a unique day in the observed series of 134 subbasins that were distinguished in the Rhine basin (see next Chapter).

2.2 HBV Rainfall Runoff model

The second step is to calculate the runoff due to the synthetic rainfall and temperature series through application of HBV models of the Rhine basin as calibrated by the Bundesanstalt für Gewasserkunde (BfG, 1999). The HBV model for the Rhine basin is divided into 134 subbasins. A detailed description of the HBV model is beyond the scope of this report and can be found in BfG (1999). In Chapter 4.2 a short overview is given of the model setup and the various parameters.

Figure 2-1 shows the lay-out of the HBV subbasins.

2.3 Hydraulic models

The final step is to calculate the flow in the river channels modelled with routing modules of different physical approximation. There are three routing modules:

- SYNHP;
- SOBEK;
- Muskingum routing.

The first two modules are used in the modelling system itself. The SYNHP model is a hydrological routing module with evidently restricted representation of the physical reality. The SOBEK model is a full 1-D hydrodynamic model that is capable of a physically correct representation of the movement of a flood wave.
The Muskingum routing is only used to emulate the SYNHP and SOBEK modules in order to make a selection of certain flood peaks that should be included in the analysis.

It is important to remark that the routing in the modelling system is restricted to the main river, i.e. the various major tributaries are represented by the HBV model which has a very simple transfer module for the river routing.

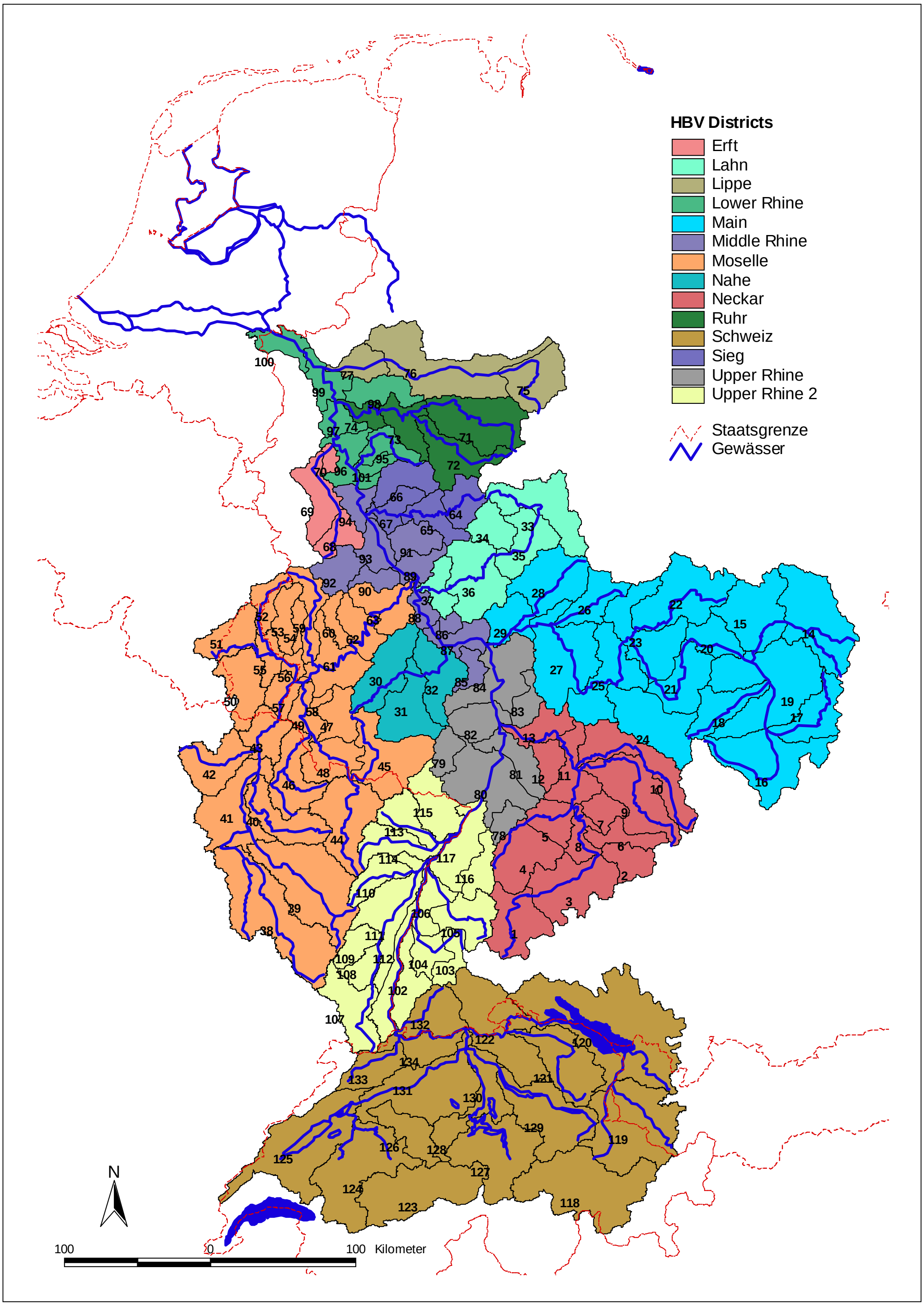


Figure 2-1 Map of the HBV basins of the Rhine

2.3.1 SYNHP/SOBEK

SYNHP

For the reach between Basel and Maxau the model SYNHP is used. This model describes the routing of the flood wave through a series of linear reservoirs, and although the model exists for the Rhine downstream of Maxau, it is applied only to the reach between Basel and Maxau.

SOBEK

The SOBEK model developed for the Rhine between Maxau and Lobith is applied for routing the runoff calculated with HBV through the river network. There is also a small branch on the Mosel river up to Cochem. The upper boundary of the model is being fed with the SYNHP output series. For a detailed description of these models we refer to Barneveld & Meijer (1997) and Ritter et al. (2003).

2.3.2 Muskingum Routing model

A 2 layer Muskingum routing model is applied to emulate the SYNHP/SOBEK model between Basel and Lobith. This model is run prior to the full SYNHP/SOBEK models and provides the routed discharge series at the same stations. The results of the Muskingum routing model are then used to sample interesting events that should be run with the SYNHP/SOBEK models. The SOBEK model is only run for events where the discharge at Lobith exceeds a given threshold or for each yearly maximum.

3 Uncertainties

3.1 Introduction

Presenting a definition of uncertainty is not trivial. Baecher and Christian (2003) give a review of definitions used by different authors. Van Asselt (2003) provides a historical perspective of uncertainty. Bedford and Cooke (2001) discuss that in practical scientific and engineering contexts, certainty is achieved through observations, implying that uncertainty concerns the result of *possible* observations. Walker et al. (2003) adopt a general definition of uncertainty as being "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system".

To answer the type of questions raised in chapter 1, an inventory must be made of all uncertainties of potential importance. We will make use of a classification method to order the uncertainties per element. This classification method was developed by van Asselt (2000) and van Asselt and Rothmans (2002). It was also used by van der Klis (2003). For background on different ways of classifying uncertainties we refer to these three references. In this chapter we will follow the approach taken by van der Klis (2003) in detail and therefore the few first paragraphs shows much resemblance with Chapter 3 of van der Klis (2003).

3.2 Classification of uncertainties

3.2.1 Taxonomy of uncertainties

Van Asselt (2000) distinguishes between two main sources of uncertainty: variability and limited knowledge:

- Variability: A process or system behaves in different ways or has a random character. A number of sources of variability can be distinguished (see Figure 3-1). Uncertainty due to variability is inherent to the particular process, elimination is not possible;
- Limited Knowledge: This is a property of the modeller or of the general state of knowledge. Limited knowledge partly results from variability, but knowledge of deterministic processes can also be incomplete and uncertain.

To make this taxonomy of uncertainties concrete, we apply it to the rainfall runoff generator, the hydrological model HBV, and the hydraulic models Muskingum/SYNHP/SOBEK. In gathering these uncertainties, we focussed on long-term river discharge processes modelled by a numerical model.

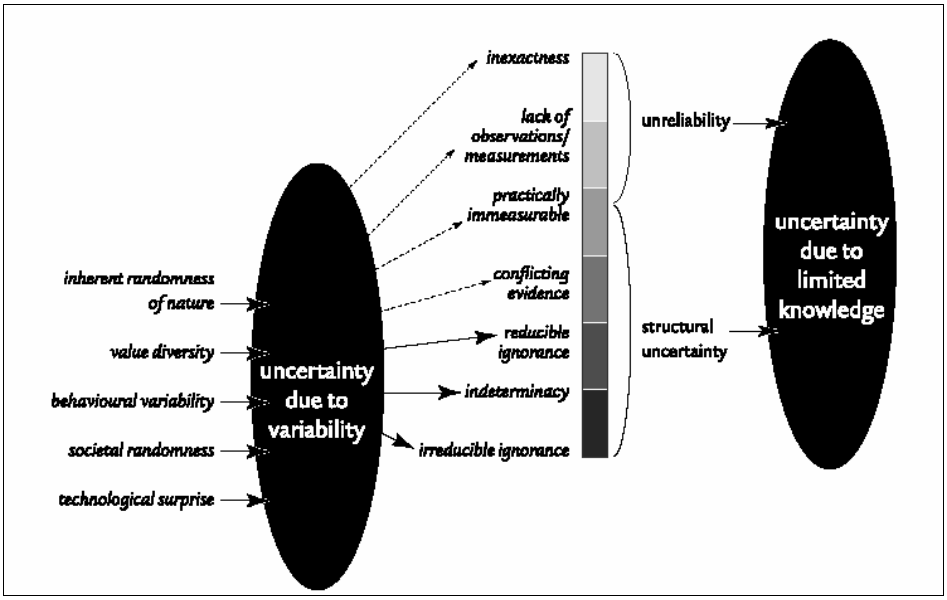


Figure 3-1 Taxonomy of sources of uncertainties (Van Asselt, 2000)

3.2.2 Manifestation of uncertainties of models

The ordering of uncertainties of a particular problem according to the taxonomy of their sources reveals to what extent the uncertainties can be quantified or eliminated. When, however, a method has to be chosen to assess the effect of uncertainties on model results, a classification in terms of the manifestation of uncertainties of the particular model is desired. Van Asselt and Rothmans (2002) distinguish between four levels at which uncertainties manifest themselves in computer simulation models (van der Klis, 2003). Here we use a slightly different but very similar approach bases on van Asselt et al. (2001):

Model uncertainties, which are uncertainties in model quantities (model empirical parameters, model domain parameters, model structure, and technical implementation). An individual uncertainty at this level can be caused both by variability and limited knowledge (Ragas, 2000). The model quantities can be subdivided (Van der Klis, 2003) as:

- Model structure, which are uncertainties due to the assumptions underlying the model structure and model equations. Uncertainties at this level primarily result from limited knowledge. A nuance of the term ’limited knowledge’ is appropriate here, since available knowledge is sometimes intentionally omitted from a numerical model. In such a case the modeller assumes that the omitted knowledge is of minor influence to the model results. To verify this assumption, the omitted knowledge can be considered to be the source of an uncertainty due to limited knowledge and as such be included in an uncertainty analysis;
- Implementation technical model, which are uncertainties due to numerical and implementation errors. These uncertainties are due to limited knowledge;
- Model empirical parameters, which are, in principle, measurable properties of the real world system being modelled. Morgan and Henrion (1990) suggest that this is the only type of quantity that can appropriately be represented in terms of a probability distribution function, since it is the only type that is both uncertain and can be said to have a *true*, as opposed to an *appropriate* or *good*, value.

In a numerical model, empirical quantities are often used for calibration purposes. Van der Klis (2003) also defines probability distribution parameters as empirical quantities. These may be indirectly measurable through data describing the empirical quantities;

- Model domain parameters, which specify the domain of the system being modelled, generally by specifying the range and increments for the spatial and temporal grid. It is common to be uncertain about what values are *appropriate* for them, but they have no *true* values.

Data ***uncertainties***, which are uncertainties related to the measured quantities. These uncertainties relate to variability, but also to limited knowledge in case the measurements are being used for interpolation and transformation.

Context uncertainties, which are uncertainties about model completeness and validity. This type of uncertainty refers to whether the model is an adequate or at least relevant representation of the system under concern. These uncertainties result from limited knowledge (due to structural uncertainty) and variability.

Rainfall Generator

Table 3-1 presents the application of the classification system to the rainfall generator developed by KNMI (Buishand & Brandsma, 2001). These issues are further discussed in Chapter 4.1.

Table 3-1 Classification of uncertainties of the rainfall generator ordered by taxonomy and manifestation level

Location		Source of uncertainty due to variability	Source of uncertainty due to limited knowledge
Model	*Model Structure*		• representation of physical reality in model structure • composition feature vector (inclusion of lagged variables) • choice distance metric • conversion from station precipitation and temperatures to values for 134 HBV subbasins
	Technical model		• uncertainty due to implementation errors
	Model empirical parameters		• number *k* of nearest neighbours and width of moving window from which days are resampled
	Model domain parameters		• spatial resolution (34 stations with daily precipitation and temperature)
Data		• non-homogeneities in precipitation and temperature records	• relatively short base period 1961-1995 (with relatively wet 1960s)
Context		• climate variability	• no information about daily values outside the range of observed data

HBV

Table 3-2 presents the application of the classification system to the HBV rainfall runoff model. These issues are further discussed in Chapter 4.2.

Table 3-2 Classification of uncertainties of the HBV rainfall runoff model ordered by taxonomy and manifestation level

Location		**Source of uncertainty due to variability**	**Source of uncertainty due to limited knowledge**
Model	*model structure*		• lumped rainfall runoff concept • soil and evapotranspiration routine • snow routine • response function • overland flow • river flow
	technical model		• uncertainty due to implementation errors • uncertainty due to propagation of errors through the model • uncertainty due to truncation errors
	model empirical parameters		• HBV model parameters
	model domain parameters		• time step • spatial aggregation level (division in subbasins, division in height zones, division in land use)
	model input		• degree of reality of synthetic rainfall and temperature series
Data (used in calibration)		• temperature measurements • precipitation measurements • evaporation estimates • water level measurements	• rating curves • temperature as a function of height • interpolation error temperature, rainfall, evapotranspiration • inadequate measurement locations
Context		• climate variability • future river basin management • new measurement techniques	• conflicting results model calibration • validity of the model under extreme conditions

3.2.3 Muskingum/SYNHP/Sobek

Table 3-3 presents the application of the classification system to the hydraulic models (Muskingum, SYNHP and SOBEK). These issues are further discussed in Chapter 4.3.

Table 3-3 Classification of uncertainties of the hydraulic models ordered by taxonomy and manifestation level

Location		Source of uncertainty due to variability	Source of uncertainty due to limited knowledge
Model	*model structure*		• selection high peaks Muskingum, • restrictions of 1-D model, • model relations of SYNHP, • method to couple HBV-results to SOBEK/SYNHP (multiplier), • location downstream boundary SOBEK, • modelling controllers in Mosel, • neglecting groundwater interaction
	technical model		• implementation errors, • truncation errors, • propagation of errors through the model
	model empirical parameters		• hydraulic roughness • conveyance versus storage width • SYNHP model parameters
	model domain parameters		• numerical spatial steps (river geometry) • numerical time steps
	model inputs		• degree of reality of HBV discharge series
Data (used in calibration)		• water level measurements • Q-h relationships	• rating curves (extrapolations) • inadequate measurement locations
Context		• future river management • future climate change • new measurement techniques	• validity of the model under extreme conditions

Some uncertainties in Table 3-3 require explanation:

- The Muskingum routing model affects the uncertainty about the model results through the selection of high discharge peaks at Lobith: it is uncertain whether the routing model selects all high discharge peaks;
- To decrease the required calculation time, the downstream boundary of the SOBEK model is situated at Lobith, by means of a rating curve. Both the extent to which this rating curve corresponds to reality and the location of this boundary determines whether it affects significantly the accuracy of the modelled discharge peaks at Lobith;
- Before the HBV results are coupled to the SOBEK model they are multiplied by a constant factor, which is applied linearly to all discharges in order to compensate for the difference between the contributing area at the gauging station (used in the calibration) and the real basin area at the basin outlet. It is not clear to which extent this affects the accuracy of the model results (Werner and Reggiani, 2002);
- A set of hydraulic roughness parameters is used to calibrate the SOBEK model. Therefore, the uncertainty about this set of parameters must be considered differently than the uncertainty in parameters which are directly related to measurements. Reasoning from the model calibration, it is improbable that one optimal parameter set exists. This results in the uncertainty how well the chosen roughness suits the model and what would be the model result in case of other ‘evenly well suitable’ roughness settings.

4 Relative importance of uncertainties

4.1 Rainfall Generator

The performance of the rainfall generator has been extensively tested by comparing statistical properties of observed rainfall with those of generated data. Table 4-1 presents an overview for the first two moments. The differences are small, and, with the exception of those in the lag 1 autocorrelation coefficient, statistically not significant. For the Rhine basin, the standard deviation of the monthly rainfall amounts is underestimated by 3.8 %. This bias is not found for the Meuse basin, probably as the result of a 4-day memory term in the rainfall generator (see below). It was further found that the extreme-value distributions of the multi-day rainfall amounts were well reproduced within the range of the historical data.

Table 4-1 Differences between observed and simulated statistics for the winter half-year (October – March), averaged over the entire drainage area (M stands for the monthly mean rainfall, s_D for the standard deviation of the daily rainfall amounts, s_M for the standard deviation of the monthly rainfall amounts, and r_1 and r_2 are the lag 1 and 2 autocorrelation coefficients of daily rainfall).

	Rhine[1]	Meuse[2]
M (mm/month)	–0.4	–2.5
s_D (%)	–0.4	0.3
s_M (%)	–3.8	0.5
r_1	–0.035	–0.022
r_2	–0.011	–0.009

[1] Average of ten 1000-year simulations based on observations for the period 1961-1995 (Beersma, 2002)
[2] One 3000-year simulation based on observations for the period 1961-1998 (Leander and Buishand, 2004)

4.1.1 Model

Model structure

Composition feature vector. The inclusion of a 4-day memory term can have a marked influence on the standard deviation of the monthly rainfall amounts (increase of about 5% for the Ourthe basin) and the distribution of the annual maxima of multi-day rainfall amounts (Leander and Buishand, 2004). It might be of interest to investigate the effect on flood quantiles.

Distance metric. Most simulations have been based on a weighted Euclidean distance. The sensitivity to the choice of weights is low (Buishand and Brandsma, 2001). The use of the Mahalanobis distance does not give better results.

Conversion of station precipitation to area-averages. For the Meuse basin the properties of extreme multi-day basin-average rainfall were adequately reproduced, even though resampling was based on the precipitation from only 7 stations. For the Rhine basin there might be difficulties with high-altitude regions in Switzerland, because the set of 34 stations does not include stations above 1500 meters.

<u>Technical Model</u>
Implementation errors are improbable. The only point is that the length of the simulation should be in the order of 10 times the return period of interest, i.e. about 10 000 years for the 1250-year event.

<u>Model empirical parameters</u>
The number k of nearest neighbours should be about 10. Spurious results may be obtained, e.g. repeatedly sampling of the same day within short intervals, if $k \leq 5$ (Buishand and Brandsma, 2001; Leander and Buishand, 2004). Biases in autocorrelation coefficients and standard deviations tend to increase if $k > 20$. The sensitivity of the model results to the number of nearest neighbours is low for k between 5 and 20. It is further expected that the influence of the width of the moving window is small. The differences between the use of windows of 61 and 121 days are currently investigated for the Meuse basin.

<u>Model domain parameters</u>
The daily precipitation and temperature data at 34 stations form the basis of the rainfall generator for the Rhine basin. The sensitivity to the density of stations has not been explored. For the Meuse basin the use of 7 stations has been compared with the use of 14 stations. The differences were small regarding the simulation of extreme multi-day basin-average rainfall (Leander and Buishand, 2004).

4.1.2 Data

Base period. The use of a relatively short base period of 35 years for resampling causes the largest uncertainty. An additional difficulty is that winter rainfall over the Swiss and German parts of the basin exhibits a significant increasing trend over the 20th century (Rapp and Schönwiese, 1995; Widmann and Schär, 1997, Schmidli et al., 2002). Different explanations for this trend have been given.

Nonhomogeneities. Changes in the measurement conditions may cause nonhomogeneities. For the Rhine basin the homogeneity of the precipitation and temperature records has not been tested. A nonhomogeneity in a single record will generally have a limited effect on the mean and other statistical properties of the generated rainfall series. Note that the rainfall generator in its present form always generates a homogeneous sequence even if the observed data are nonhomogeneous.

4.1.3 Context

Climate change. The rainfall generators for Rhine and Meuse have been developed to generate realistic sequences for the present-day climate. The extension to future climate conditions will be studied in the coming years. An important source of uncertainty is the change in precipitation. Apart from a change in the mean winter rainfall amounts, it turns out that flood quantiles of the Rhine are very sensitive to changes in the variability of these rainfall amounts (Shabalova et al., 2003).

Values outside the range of observed data. A resampling technique cannot generate larger daily values than the highest observed daily value.

The form of the extreme upper tail of the daily rainfall distribution determines how far this influences large quantiles of the simulated multi-day rainfall amounts. Buishand (2003) shows that this influence is small for the 10-day rainfall amounts (less than 5%).

4.2 HBV

The HBV model is a conceptual model that by its very nature can only approximate the real rainfall-runoff generation processes that occur in nature. As such it is very important to determine the impact of the imperfection of this representation of the natural processes in order to estimate the reliability of the outcome of the model.

For this analysis, the classification of uncertainties of the HBV model, as given in Table 3.2 has been used as a guideline. In this Chapter the various error sources are discussed in order to find the most likely sources that will dominate any error occurrence in the outcome of the model.

As reference to the discussion in this Chapter, an overview of the model structure and the various parameters of the model are shown in Figure 4-1.

Experience with the HBV model in flood generation

There are a number of studies on the use of the HBV model for flood generation. The publications by the original developers at SMHI are generally positive on the performance of the model. There are, however, also a number of ‘external’ studies. An example is the study by Roald et al. (2002) from the Norwegian Meteorological Institute. They mention that: “The model is generally able to simulate the mean annual runoff quite well. The standard deviation of the daily runoff is generally moderately underestimated. The model tends to underestimate the floods substantially in most cases. Some models are capable of representing the annual cycle quite well, other have marked deviations. An underlying assumption is that the control series used for verification (1980-1999) should have similar statistical properties as the observed series for the same period. The statistics of the observed series and the control series are shown in Table 4.6 *(in original publication, not reproduced here*). The table shows that the model usually simulates the mean values quite well, with a small underestimation of the standard deviation, and that the model tends to underestimate the floods quite in many catchments”.

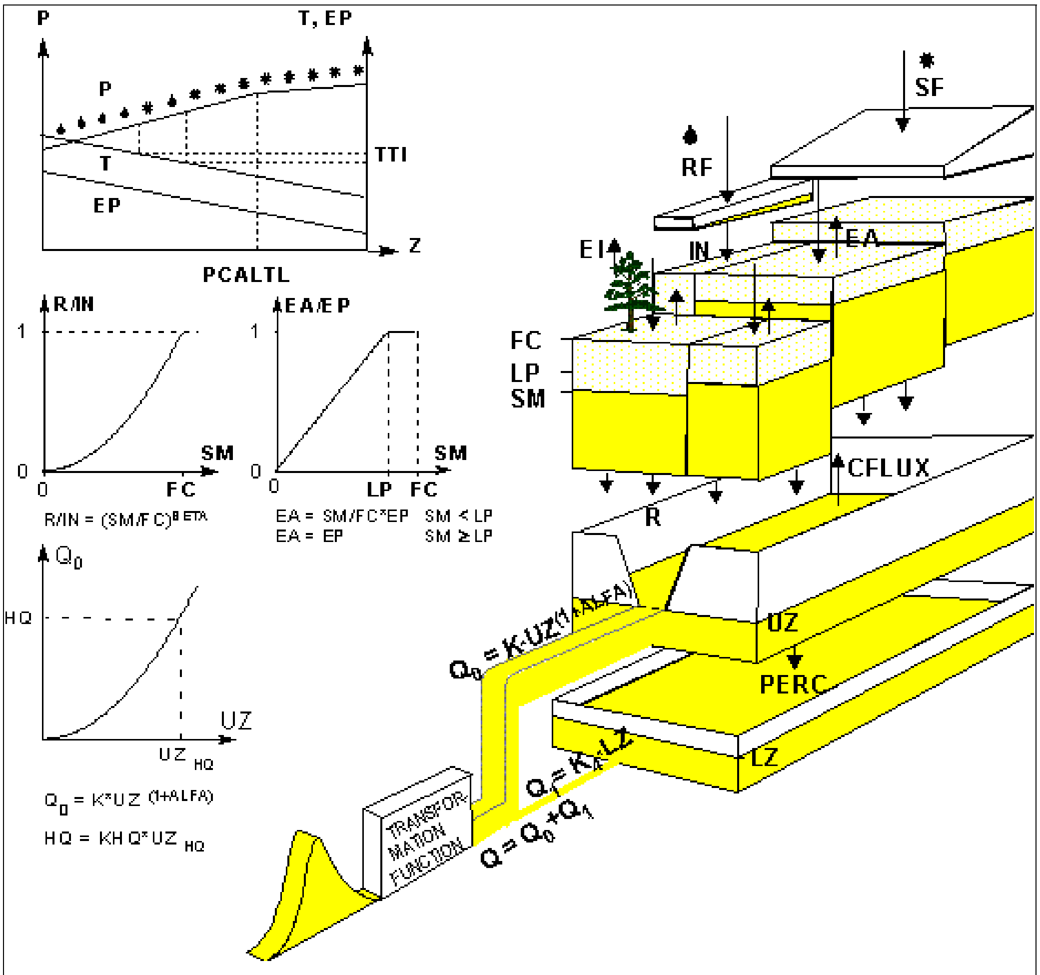
However, in a study by Bruen (1999) a comparison was made of 5 model concepts:

- Unit hydrograph with prior information;
- SMAR (conceptual, quasi-physical, lumped, Soil Moisture Accounting);
- HYRROM (conceptual, lumped);
- HBV (conceptual, semi-distributed);
- ARNO.

In the conclusions Bruen stated that:

- Overall: all models appear to underestimate the peak flows;
- HBV is best, particularly for peak flows.

There are many other studies incorporating HBV and it is impossible to come to a general conclusion either in favour or against the use of HBV for flood generation purposes. However, the conclusion that the models appear to underestimate peak flows is found in many occasions and should be born in mind when using the HBV model for the simulation of floods in the Rhine basin.



P = Precipitation
T = Temperature
SF = Snow
RF = Rain
Z = Elevation
PCALTL = Threshold for altitude correction
TTI = Threshold temperature interval
IN = Infiltration
EP = Potential evapotranspiration
EA = Actual evapotranspiration
EI = Evaporation from interception
SM = Soil moisture storage
FC = Maximum soil moisture storage
LP = Limit for potential evapotranspiration

BETA = Soil parameter
R = Recharge
CFLUX = Capillary transport
UZ = Storage in upper response box
LZ = Storage in lower response box
PERC = Percolation
K, K_4 = Recession parameters
ALFA = Recession parameter
Q_0, Q_1 = Runoff components
HQ = High flow parameter
KHQ = Recession at HQ
HQ_{UZ} = UZ level at HQ

Figure 4-1 Structure of the HBV model and its parameters

4.2.1 Model

Model structure

The most important item in this group is the representation of the physical reality. It is evident that a conceptual model such as HBV has to make a large concession in this respect and it can be safely stated that any resemblance of the processes in the model with the physical reality is largely due to chance. Nevertheless it is also well-known that conceptual models are capable of reproducing very well the rainfall-runoff process (e.g. the Sacramento model that is already being used since the 1970s). The question remains whether such models, that might produce excellent results in both calibration and verification of historical floods, are able to reproduce faithfully extreme flood situations outside the measuring range. Various tests with the HBV model are encouraging in this respect, but it is not possible to give a final answer to this question as there are no possibilities to simulate and verify extreme events with high return periods such as T = 1250 year.

A very important aspect is the routing module in HBV. At present the flood routing in the tributaries is done by the hydrological routing module in HBV, which by its very nature is not able to represent correctly the flow processes in the channels. Any physical limitations of flood conveyance in the channels, especially those due to dikes and/or flood planes, can not be taken into account and may result in gross overestimation of the contribution of the flood waves from the tributaries. Errors in the routing of the flood waves may also lead to errors in the timing of the flood wave, which is very important for the generation of the flood wave on the main river.

Another aspect is the lumped character of the HBV model. This issue is directly related to the one discussed below on the spatial aggregation level.

Technical model

As shown in Table 3-2 there are 3 items that belong to this group. These are uncertainty due to:

- implementation errors;
- propagation of errors through the model;
- truncation errors.

Implementation errors, i.e. technical errors in the model itself, are still possible, but the HBV model has been used for many years now worldwide and it can be assumed that simple ‘bugs’ have by now been eliminated Although the uncertainty created by the possibility of implementation errors cannot be quantified, we expect it to be smaller than uncertainties in the model structure and in the model empirical and domain parameters and model inputs. However, since the HBV model of the Rhine is a relatively new model one must be alert to this type of errors and review the results critically.
Propagation of errors through the model: Errors will namely be present in the input data and while propagating through the model system this may results in significant errors.
Truncation errors: No numerical schemes have to be solved and therefore these truncation errors are not relevant for the HBV model.

Model empirical parameters

It is evident that for a hydrological rainfall-runoff model, and probably for most models, the impact of the choice of the model parameters has a large impact on the outcome of the modelling. Here there are two issues that are important:

1. the parameter choice according to the model calibration and verification;
2. the relative sensitivity of the model parameters.

The calibration process and outcome of the HBV model for the Rhine river in Germany is described by the BfG (1999) and is further discussed in Chapter 4.2.3. In general this calibration has not let to satisfactory results, because there are many errors in the peak values. At present a re-calibration of the model is being carried out by the BfG and it is important to use this result as the starting point for the uncertainty analysis.

Regarding the relative model parameter sensitivity, a number of studies are already available. The results of these studies are summarized below and have been used to arrive at the most sensitive parameters that should be incorporated in the reliability study. For the meaning of the various model parameters, reference is made to Figure 4-1.

In Roald et al. (2002): a total of 15 calibrated model parameters were selected that are listed in Table 4-2. The choice of parameters to calibrate and calibration method are based on suggestions from an earlier study (Kolberg et al. 1999, ref. in Roald et al., 2002). The range of variation for the parameter values is based upon physical interpretation and tentative recommendations in Sælthun et al. (1996).

Table 4-2 Parameters chosen in the study of Roald et al. (2002)

Parameter	**Description**
TX	Threshold temperature snow/ice
TS	Threshold temperature for snow melt
CX	Melt index
PKORR	Precipitation correction for rain
SKORR	Additional precipitation correction for snow
TTGRAD	Temperature gradient for days without precipitation
TVGRAD	Temperature gradient for days with precipitation
PGRAD	Precipitation altitude gradient
FC	Maximum soil water content
BETA	Non-linearity in soil water zone
KUZ2	Quick time constant upper zone
UZ1	Threshold quick runoff
KUZ1	Slow time constant upper zone
KLZ	Time constant lower zone
PERC	Percolation to lower zone

In a research project by WL | Delft Hydraulics on the HBV implementation in the Rhine basin (Stone, 2002) a detailed evaluation was made of the sensitivity of the model parameters. An extensive summary is given of this study in the following paragraphs.

In order to quantify the parameter sensitivity (and also uncertainties in model predictions and likelihood values of parameter sets), objective functions were defined. In total six objective functions are applied. As we are interested in the extreme discharges range five objective functions were selected specifically for extreme events. The results are analysed as a total and per sub-basin. In addition the results are analysed per objective function to evaluate the effect of the different functions when applying to extreme the discharge ranges. From each measured discharge time series a threshold was derived, such that on average one peak per year is selected, i.e. the analysis is carried out on a peak-over-threshold series. The following characteristics of the discharge peaks were used:

- Time over Threshold; the time of a peak discharge;
- Volume over Threshold; the volume of a peak discharge;
- Number of Peaks over Threshold; the total number of discharge peaks;
- Time to Peak; the time from the moment the discharge reaches the threshold till;
- The time of the peak;
- Mean average error.

In addition to the criteria above, the Nash/Sutcliffe criterion (R^2, see Nash and Sutcliffe, 1970) was also applied.

Expected results

According to the basin characteristics and the model structure the following physically-based parameters are expected to react in a sensitive manner:

FC: The field capacity is a parameter which describes the soils characteristics such as waterholding capacity and soil depth. The discharge depends greatly on these characteristics. A larger field capacity provides extra soil storage which in turn decreases the amount of water available for runoff. The parameter is used at many stages of the model and this parameter is expected to be a sensitive parameter under all circumstances.

KHQ (HQ): The Quick runoff rises linearly when KHQ increases. HQ is related to KHQ and although it is a physically based parameter, it will not be considered in the sensitivity analysis. KHQ is expected to react sensitively especially under extreme conditions.

Alpha: The quick runoff rises exponentially when alpha increases and therefore is expected to be very sensitive for mediate to high runoff discharges.

K4/Perc: The amount of water which is passed on from the lower zone to slow runoff is defined by K4 in a linear manner. If K4 increases by a factor 2, the baseflow becomes twice as large too. The effect of K4 though also depends on the available supply of the lowerzone which in turn is replenished through percolation defined by the percolation rate.

The parameters PERC and K4 are expected to be moderately sensitive in general runoff situations, though under extreme conditions the quickflow will exceed the baseflow by far and these parameters will not be very sensitive.

Maxbas: maxbas defines the amount of routing steps. The larger maxbas is, the more the runoff will be lowered and broadened. Especially for elongated basins like the Nahe, Mosel and Ruhr sub-basin this parameter is of great importance. Under all conditions this parameter is expected to be relatively sensitive.

CEVPFO, Icfo and Icfi: In areas with a considerable amount of forests like the Ruhr sub-basin it is expected that CEVPFO and Icfo will be of influence. CEVPFO determines the amount of evaporation in forested area's and Icfo the amount of interception. Though the effect of CEVPFO will also depends largely on the amount of potential evaporation. Icfi will be of influence in areas with a small area of forest. Under extreme conditions the evaporation is only a fraction of the total runoff and these parameters will then not be very sensitive.

TT: This parameter represents the temperature threshold at which precipitation falls as snow or as rain. This parameter is only expected to be of influence in area's with considerable snowfall.

In Figure 4-2 the results are shown of the sensitivity analysis for each of the five subbasins in the Rhine basin. The degree of sensitivity increases from left to right. The full results for the various parameters are given in Appendix A-1.

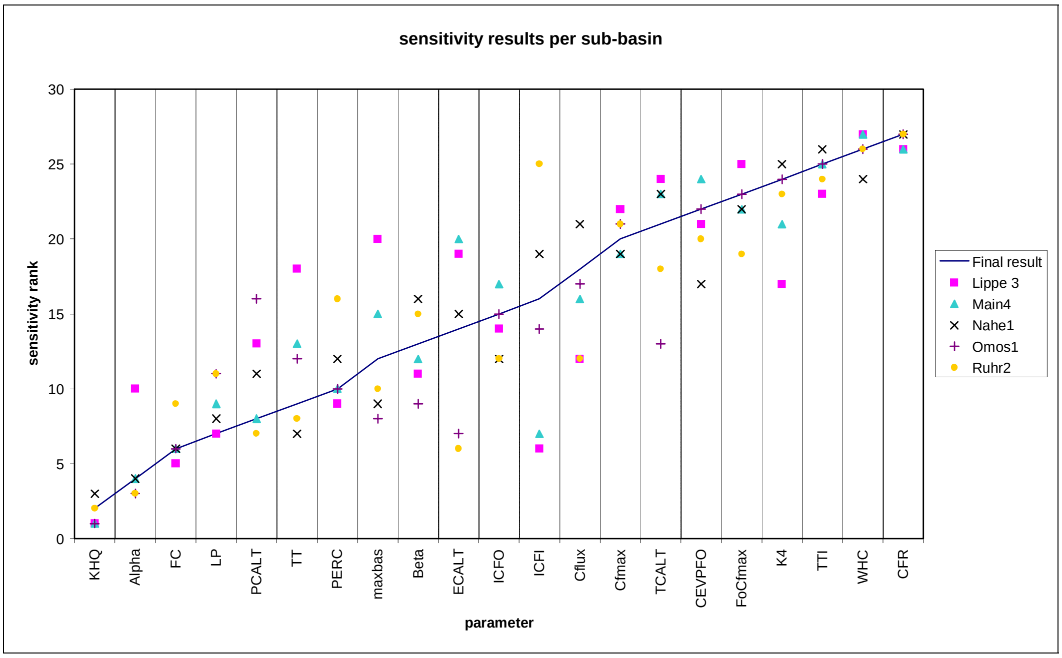


Figure 4-2 Sensitivity analysis results per sub-basin

The parameters which were discussed in the forgoing section plus other eye catching parameters are evaluated in relation to the sub-basin characteristics:

K4/Perc: K4 is not a very sensitive parameter unlike Perc which is quite sensitive. It seems that the value of Perc determines the amount of baseflow, while K4 has little influence.

Maxbas**:** Maxbas is a relatively sensitive parameter and as expected it seems to be more sensitive for the elongated basins (Nahe, Mosel and Ruhr).

CEVPFO, Icfo and Icfi: Icfi en Icfo turn out to be moderately sensitive and show quite some variation between the different sub-basins. Especially Icfi is highly related to the amount of (lack of) forest in an area. The results for the Ruhr sub-basin with a large forested area show that Icfo is moderately sensitive and Icfi shows no sensitivity. CEVPFO is not sensitive.

TT**:** TT is quite sensitive, specifically in the basins with a large amount of their area at higher altitudes.

LP: LP, the parameter which defines the soil moisture threshold above which the actual evaporation reaches the potential evaporation, shows a high sensitivity. Apparently the evaporation under the meteorological conditions as applied to these model runs is a considerable share compared to the amount of runoff. It can be expected that the parameter will be less sensitive when the rain intensity increases.

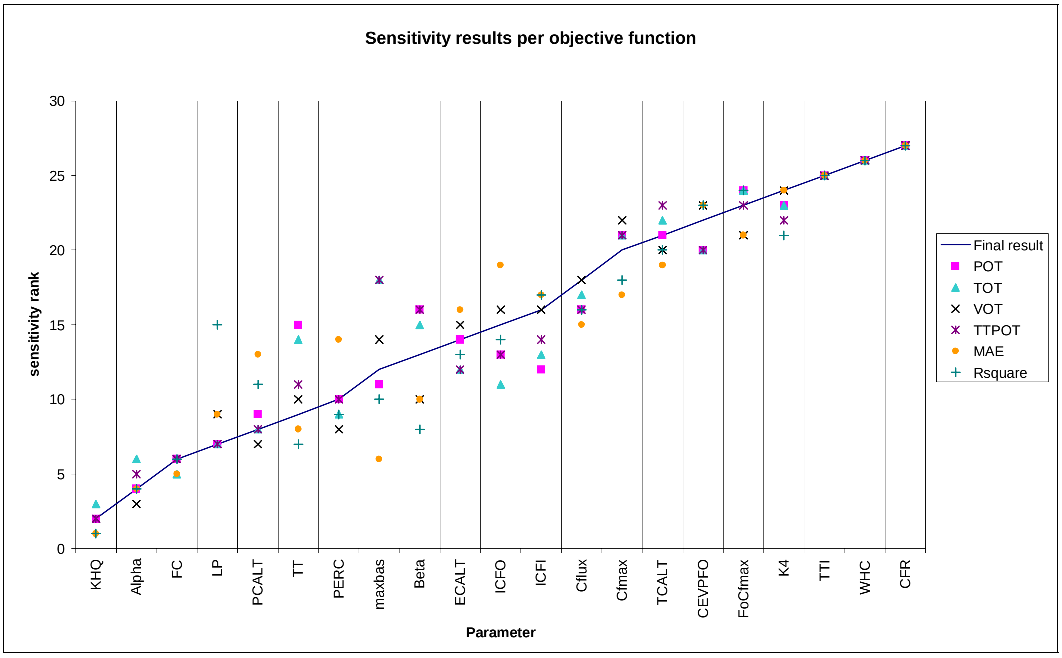


Figure 4-3 Sensitivity results per objective function

These results too show that independent of the objective function the parameters KHQ, Alpha and FC are the most sensitive and TTI, WHC and CFR show hardly any sensitivity at all. Figure 4-3 shows the range of results per objective function.

In Table 4-3 the results of the analysis of the sensitivity of the various parameters is summarized with a sorting in degree of sensitivity.

Table 4-3 Summary of analysis of parameter sensitivity of HBV model

Parameter	**Rank**
RFCF	**1**
KHQ	**2**
Pcorr	**3**
Alpha	**4**
HQ	**5**
FC	**6**
LP	**7**
PCALT	**8**
TT	**9**
PERC	**10**

This table indicates the order by which the parameters should enter the analysis of the reliability of the HBV model. Note however, that the parameters Pcorr and RFCF are correction parameters (e.g. for systematic errors in the rainfall record) and are therefore not considered to be suitable to include in an uncertainty analysis.

A second study towards the sensitivity of the model parameters of HBV (Weerts, 2003) leads to similar results, with the highest values for **Alpha, FC, KHQ and PERC**.

Evidently for the present study, the focus is set completely on extreme events, i.e. with many of the parameters used in the outer boundaries of their (probable) range. This is an issue that is directly related to the model structure (see next Paragraph) as it can be stated that a model structure is also valid only within a certain ‘range’ of external conditions (rainfall intensity/depth, temperature, etc.).

Model domain parameters

There are two main issues in this topic:

- time step;
- spatial aggregation level (division in subbasins, height zones, land use, etc.).

<u>Time step</u>

The basis time step of the model is daily. However, in a number of cases a shorter timestep is used, often hourly, in order to have either a better representation of the actual process or to avoid model instabilities. All output, however, is always aggregated again to the standard daily time step.

The choice of the daily time step is logic given the limitations of the meteorological input. A shorter time step would also put a tremendous weight on the performance of the system and it is fair to say that at present the daily time step is a good compromise between precision and usefulness.

Spatial aggregation level

The various issues under this title refer to the setup and calibration of the HBV model. Details on the calibration can be found in the report by BfG (1999).

Division in Subbasins

The HBV model is a lumped model and as such the spatial variation within a subbasin is represented in the model as a unity. The essence of a lumped model is that there is supposedly no internal variation in physical characteristics that might hamper the application of a lumped approach. In the case of the setup of the HBV model of the Rhine basin, many subbasins were chosen such that they can be represented by a discharge gauging station. Whether or not such subbasins also correspond well with homogeneous areas that can be represented by a lumped hydrological model is not clear.

The actual subbasin boundaries are based on the work of the ‘Geographic Information Systems’ workgroup of the CHR. No further information is available on the actual method of delineation.

As with many of the ‘initial choices’ of the model setup, it is nearly impossible to assess the impact of the choice of spatial aggregation and for this reason this issue can only be mentioned rather than the impact determined.

Division in land use

In the HBV model, only two land use classes have been distinguished:

- forest;
- open land.

The land use information has been derived from Landsat-TM data for the period 1984-1990. The original spatial information with a resolution of 30m x 30m was aggregated to a resolution of 1km x 1km. It is evident that the decision to distinguish only two classes of land use, as well as the aggregation of the information, introduces a certain error in the model setup and parameter values. However, also this issue can hardly be translated to the possible impact on the outcome of the model simulations.

Division in altitude zones

For the benefit of the snow modelling, it is necessary to use altitude zones that are given a certain temperature value during the simulations on the basis of the values from the Rainfall Generator and the lapse rate of temperature with altitude.

The altitude ranges themselves are based on the digital elevation model of the USGS, available with a resolution of 1km x 1km. It is not known whether any editing has been done on this model and/or checking of the topography.

The final impact of the choice of altitude zoning and the temperature value assigned to each zone during the modelling is nearly impossible to establish, but it is unlikely that this will be a major issue given the small contribution of snowmelt in the flood generation process.

Division in soil groups

For the determination of the root depth and the corresponding field capacity (an important parameter in HBV), use is made of the soil map of the EU with a scale of 1:1,000,000. It is evident that this can only lead to a rather coarse distinction in soil regions. Values of the field capacity are based on the land use and soil types as given in Table 4-1 of the original BfG report (BfG, 1999).

However, this table makes a much finer distinction in land use types than the two types mentioned above and it is also based on the FAO soil map. This is a confusing issue that is unlucky as the field capacity (FC) parameter in HBV proves to be rather sensitive and thus important in the rainfall-runoff process. Nevertheless no effort has been made here to address the possible impact of this issue on the reliability of the model as this would mean a reassessment of both the setup of the subbasins as well as the calibration of the model.

Model inputs
The degree of reality of the synthetic rainfall and temperature series is evidently an issue that is discussed already in the Chapter on the Rainfall Generator.

4.2.2 Data

The most important time series, as mentioned above, are produced by the rainfall generator. However, there are a number of additional data sources that need attention for the determination of the reliability of the HBV model application:

- Calibration data (discharge, precipitation, snow depth, etc.);
- Estimate of evapo(transpi-)ration;
- The assessment of the temperatures for various height zones based on temperature-altitude relationship;
- Interpolation of various data types;
- Transposition of measured data from measuring location (gauging station) to basin outlet;
- ***Input data*** (precipitation and temperatures).

It is important to distinguish between calibration data and input data. The former are historical series that are used to calibrate the model parameters such that the model represents as faithful as possible to actual rainfall-runoff process in the basin. The input data are the precipitation and temperature values generated by the Rainfall Generator.

Calibration data
It is evident that calibration data such as discharge series contain errors. The problem with the calibration for the higher discharges is that especially those values often contain large errors due to the fact that the highest historical discharges are often outside the measured values of the rating curve. Extrapolation of the rating curve can introduce large errors, although a sophisticated method such as the use of a hydrodynamic model for the extrapolation may reduce such errors substantially.
Precipitation is the most important input variable of the HBV model and any error in either the intensity/depth and/or the spatial pattern of the rainfall has a direct impact on the reliability of the model output. Here the issue of possible new measurement techniques may be important. Such improvements might occur in the future, but the impact of such changes on the calibration are difficult to quantify. Evidently it is supposed that such changes will improve the accuracy of the rainfall and temperature data available for the setup and calibration of the model. It is fair to say, though, that the measurement of rainfall and especially temperature has a long record of improvements and it is doubtful whether major improvements are still possible. However, improvements may occur in the assessment of areal rainfall/temperature from the point measurements.

As the calibration of the HBV model is already done in an earlier stage, it is very difficult to determine now the impact of any errors in the higher discharge values and/or errors in the precipitation on the model calibration and subsequently the correct performance of the model. For this reason it should be acknowledged that it is nearly impossible to study the impact of errors in the historical precipitation and discharge series used for calibration of HBV models on the final outcome of the simulations with the same model. It is suggested that any such error is in fact indirectly studied by the assessment of the impact of uncertainty in the model parameters on the reliability of the model output. It is unlikely, though, that this will have a major impact on the final outcome of the modelling system.

Estimate of evapo(transpi-)ration

Any estimate of a hydrological parameter will evidently contain errors, but in the case of the estimation of the evapo(transpi-)ration this is a minor issue as this variable has a very small impact on the simulated discharge in extreme situations. For this reason this item is disregarded in the study of the uncertainty in the modelling.

Variation of temperature with height

The variation of temperature with height is only important for the snow production and melt. The relationship temperature – altitude is often well-established, but normally one relationship is used for the entire basin, despite the fact that other factors, such as aspect, land and land cover, may locally alter this relationship. The error in the relationship is translated directly into an error in snow cover and thus both in amount of direct runoff and in amount of snowmelt contributing to the flood events.

It is very difficult to estimate the exact impact of such an error on the final outcome of the flood simulations, but given the fact that snow melt plays only a minor role in this flood generation it is likely that a small difference in snow cover will hardly be noticed in the resulting flood hydrograph, not only in Lobith but most likely even in the various major tributaries in Germany. Therefore this aspect can be disregarded in the analysis.

Interpolation of various data types

The most important data type that needs interpolation from point values to spatial values is the precipitation. In general errors in the rainfall intensity and depth are the main sources of error in rainfall-runoff modelling and a good knowledge of the spatial distribution of the rainfall is of utmost importance. For the present project, the rainfall field is produced by the rainfall generator and it is in the corresponding chapter that this aspect is further discussed.

Transposition of measured data from measuring location (gauging station) to basin outlet

It is nearly always necessary to transpose the measured discharge values at a gauging station to the basin outlet of a river basin in order to account for the difference in basin area. A similar correction should be made for difference in rainfall in the two areas, but this has not been applied. As long as the transposition is done on the same river basin (i.e. not transposed to a neighbouring basin), difference in climate and/or basin characteristics can be disregarded. The method of transposition is liable to discussion as it is not clear whether this can be done by a linear relation or whether another function should be used. Apart from the linear relation, which is used most often, a power law is used with a factor in the order of 0.6 to 0.9. In the Rhine modelling a linear relationship has been used.

There is no agreement in the literature on this issue, but the difference between the use of a linear or a power relation will be very small as long as the difference between the basin areas and the contributing areas at the gauging stations are small.

It is possible to find the actual relationship for different basins by deriving the formula for a basin that has various gauging basins along the same river.

Input data (precipitation and temperature)
Although possible errors in the input data are already discussed in the Chapter on the Rainfall Generator, its is important to remark that there may still be errors in the representation of the 134 generated series that correspond with the same amount of subbasins in the model. It is difficult to judge whether these series correctly represent the areal rainfall in each of these basins, also given the fact that the basins were selected on the basis of the location of discharge gauging stations, not on position of rainfall stations. However, it seems impossible at present to assess the impact of any possible error in the areal rainfall series.

4.2.3 Context

Climate variability
Evidently climate variability reflected in the precipitation and temperature input series of HBV are part of the Rainfall Generator and are not further discussed here.

Future river basin management
Another unknown factor is the future river basin management. This includes changes in the physical characteristics of the basin (especially land use) as well as operation of structures etc.
Evidently it is difficult to take into account the impact of such changes, but on the other hand it can be expected that under very extreme conditions that will be faced during the generation of floods the impact of changes in the land use as well as the operation of structures (e.g. weirs) will hardly have any effect on the flood generation. For the present study it is assumed that the impact of future river basin management on the design discharge can be disregarded as long as those are minor changes, i.e. not large-scale canalization, etc. A different issue is the use of retention areas and/or failure of dikes of large inundation areas. The impact of these events can, however, be simulated effectively with the hydrodynamic model SOBEK.

New measurement techniques.
Similarly to the comments on this issue for the rainfall generator, the impact of improvement in measurements can not be quantified. For the HBV model the most important input variables are the rainfall and temperature that are produced by the rainfall generator. For the calibration of the model, measured discharges are used. Here substantial improvement is possible in the future as the most important values for the model are the extreme values that are difficult to measure accurately at present. Improvements in the measurement of extreme discharges will definitely improve the accuracy of the model outcome, although this is an issue that can’t easily be quantified.

Behaviour of rainfall-runoff processes under extreme conditions
Already during the past few years attention is given to the issue whether the HBV model is still a valid concept for the simulation of rainfall-runoff generation under extreme hydro-meteorological conditions. This refers to a combination of extreme high rainfall intensities and very wet initial conditions in the basin.

The model has been developed for ‘average’ conditions, but for the simulation of design discharges it may well be that the model is applied outside its range of validity.

As part of an internal research of WL | Delft Hydraulics to the behaviour of the HBV model (Stone, 2002), the model was tested under extreme conditions for the two subbasins of the Rhine (Main 4 and Ruhr 2) that were also used in the analysis of the sensitivity of the various model parameters (see above). The question was raised at which stage of a rainstorm the reservoirs of the HBV model would become saturated and all precipitation would be transformed to form direct runoff. And in addition to this question a short analysis was made to which extend the most sensitive parameters were expected to continue to play a dominant role even when certain model reservoirs would be fully saturated and become a source of steady output irrespective the values of their parameters.

The model was tested by applying constant rain intensities to the two sub-basins for a period of ten days. The main difference between these two areas lies in their field capacity and percolation value. The Ruhr 2 basin has a field capacity of 305 mm which is one of the highest found in the area modelled by the BfG, and the Main 4 area has a field capacity of 100 mm which is one of the lowest values found in this area. In the HBV model the field capacity is a measure for the amount of water which the rootzone of the soil can store. A high field capacity stands for soils with root zones with high water storing capacities. The Ruhr 2 basin has a percolation rate of 1 mm/day where the Main 4 area has a percolation rate of 0.5 mm/day. The percolation rate gives the amount of water which flows from the upper to the lower zone. It is expected that the time to reach a saturated state will be larger for the Ruhr with its higher field capacity and a higher percolation rate.
The two sub-basins were subjected to ten days rainshowers with constant rain intensities of 2, 5 and 10 mm/hour. During this period the temperature and potential evaporation were kept to a constant value of 5 °C and 0.0083 mm/hour (0.2 mm/day) respectively.
The initial state of the sub-basins was varied. The simulation was started under dry, intermediate and wet initial conditions. For the dry state all reservoirs were empty at the start of the calculations. For a wet initial state the reservoirs with a maximum capacity (interception and soil moisture) were set to their maximum value and for the reservoirs with no maximum (Upper and Lower zone) a high value was derived from the calculations made for the initially dry conditions. Also calculations were carried out for an initially intermediate state of the sub-basins where the reservoirs were half filled. Details on this study are given in Appendix A.

Table 4-4 shows an overview of the different calculations which were executed for both basins.

The results show an almost immediate filling of the interception storage for both area’s under all condition. After a certain time the soilmoisture content approaches its maximum capacity (field capacity) and the quick runoff approaches the amount of maximum rain intensity. In almost all calculations the upper zone, lower zone (reservoirs without a defined maximum capacity) and baseflow reach equilibrium within a timeperiod of ten days. It is seen that the equilibrium value for the upper zone has the same value for a certain rain intensity independent of the initial conditions. The equilibrium values for the lower zone and the baseflow are always the same, independent of the precipitation intensity and initial conditions.

Table 4-4 Overview of calculations with different conditions

Initial state	**Rain intensity (mm/hour)**
dry	2
intermediate	2
wet	2
dry	5
intermediate	5
wet	5
dry	10
intermediate	10
wet	10

The conceptual HBV model works in such a way that when a constant input of precipitation is given for indefinite time all reservoirs will eventually fill up to their maximum and an equilibrium is reached when the inflow in the upperzone (seepage and direct runoff from the Soil moisture reservoir) is equal to the outflow from the upper zone (Quickflow, Percolation to the lower zone and capillary flux to the soil moisture reservoir). The difference between the two basins is found in the time to reach this equilibrium. It is seen that the Ruhr area with its high value for the field capacity reaches this equilibrium in a later stage then the Main area. However this difference becomes smaller when the rain intensity increases. The initial situation also influences the time to reach the equilibrium. As can be expected it is found that the wetter the initial conditions, the faster equilibrium is reached.

The results show that when applying a constant input of precipitation for indefinite time equilibrium will always be reached. But in reality a rainshower will not be of indefinite time. An (extreme) time horizon of two and of three days was chosen to evaluate the effects of a constant precipitation input. A system was considered to be saturated if the soilmoisture and the quick runoff had reached their maximum. The results are shown in Table 4-5.

Table 4-5 Results of the time horizon evaluation

Initial state	**Rain intensity (mm/hour)**	**Main 4**		**Ruhr 2**	
		2 days	**3 days**	**2 days**	**3 days**
dry	2				
	5				
	10	?	X		?
intermediate	2				
	5		X		
	10	X	X		X
wet	2	X	X	X	X
	5	X	X	X	X
	10	X	X	X	X

X = saturation of system reached
? = border situation

As can be seen in Table 4-5 the Ruhr sub-basin with its thicker rootzone reaches equilibrium later then the Ruhr area. This result is according to what can be expected. It is obvious that full saturation is reached within this period when the initial conditions are wet, even for a situation of only 2 mm/hour rainfall intensity and 2 days duration (total rainfall depth 96 mm). For dry and intermediate initial conditions no equilibrium was reached within 24 hours.

In addition to the study of the sensitivity of the HBV model parameters, the most sensitive ones (FC, alpha, KHQ and Perc) were studied again to see whether they remain sensitive under extreme conditions with all model reservoirs filled to their maximum capacity. This gave the following results:

Alpha and KHQ: both alpha and KHQ determine the amount of quick runoff. So even when all reservoirs are filled to their maximum capacity, these parameters will still be highly sensitive.
FC: the parameter FC will be less sensitive. The soil moisture is already saturated and all net precipitation will go to the upper zone reservoir.
Perc: the percolation rate determines the amount of water available for the baseflow. This parameter can be expected to be a sensitive parameter, though the higher the rain intensity will be, the smaller the sensitivity will be. With a higher rain intensity, the amount of quick runoff will be much greater then the amount of baseflow and the effect of varying the percolation will be small.

These results form the basis for the setup of the analysis of the reliability of the HBV model with respect to model structure and behaviour under extreme hydrometeorological conditions. Although in the paragraph above the sensitivity of Perc is considered small, it will still be included in the analysis. Evidently the parameter FC can be omitted, which leaves three parameters to be included in the reliability analysis: **Alpha, KHQ** and **PERC.**

Application in the uncertainty analysis

The variation in the HBV model parameters should in principle be applied to all of the 134 river subbasins. However, this is in practice a major task and not always efficient. There are many of the 134 subbasins that are relatively small and/or far from the main river. Therefore a grouping of the subbasins is suggested based on the main subbasins as shown in Figure 2-1. This means that there will be a total of 14 groups for the analysis.

Conflicting results of model calibration
The calibration of the HBV models of the various subbasins was done using two criteria:

- Nash/Sutcliffe;
- Accumulated differences.

Evidently the second criterion is not very useful in the case of calibration for flood purposes as it only shows errors in accumulative volume of the total hydrograph.
The Nash/Sutcliffe criterion is more useful, but the results of the calibration process shown in BfG (1999) makes clear that even a high value for this criterion does not mean that the peak discharges are well represented.

Although it is mentioned that a visual inspection of the modelling results versus the measured values was also used as a criterion, this seems to have been a minor factor in the calibration process.
The calibration was done over the period 1976 – 1985. Evidently this leaves out some of the major flood occurrences in the 1990es, such as 1993 and 1995.
Whether or not there have been many incidences of conflicting results is not known and therefore this issue can not be taken into account in the assessment of the model reliability.

4.3 Muskingum/SYNHP/Sobek

The routing of the flood wave through the main channels of the model is done by several routing modules that each have a specific river stretch and/or purpose in the system. The stretch Basel – Maxau is represented by the SYNHP routing module. The second stretch downstream from Maxau to Lobith is represented by the SOBEK 1-D model. A third routing module, based on muskingum routing, is only used to select flood peaks out of the total series of 1000 years of discharge series from the HBV modelling.

The various uncertainties that have been distinguished are given in Table 3-3. The order that is used in this table has been adopted for the structure of this Chapter.

4.3.1 Model

Model structure
Under the issue of model structure, a large number of topics need attention (see Table 3-3):

- selection high peaks Muskingum;
- restrictions of 1-D model;
- model relations of SYNHP;
- method to couple HBV-results to SOBEK/SYNHP (multiplier);
- location boundary HBV – routing modules;
- modelling controllers in Mosel.

<u>Selection of high peaks by the Muskingum Routing</u>
The Muskingum routing is applied over the full stretch from Basel to Lobith in order to have a first insight in the occurrence of major flood peaks in the 1000 year time series. Major floods are defined as floods with a discharge of more than 7000 m^3/s at Lobith. This is a rather arbitrarily set value mainly determined by the need to avoid large running time of the model and the impact of the choice on the model outcome (and thus reliability) is unknown. It was recognized that this threshold approach might lead to the exclusion of some yearly maxima if they remained below the threshold. Therefore a second ‘yearly maxima’ criteron was added which is function satisfactory.

The Muskingum routing module has been calibrated against the two other (more sophisticated) routing modules and the agreement is very good. Although in theory it is possible that floods are either included or excluded due to an error in the Muskingum routing, this seems a very small percentage of the total number of floods and it can safely be assumed that the impact of such an error is negligible on the final outcome of the model application.

Restrictions of 1-D model

The use of the SOBEK model for flood routing is most likely a minor issue in the study of the reliability of the full modelling system. In a hydrodynamic model the two main input values that may cause errors are the river geometry and the roughness of the wet section. In principle the river geometry can be known precisely, but this is evidently normally not the case due to the choice of cross profiles, changes in the river bed since the date of measurement, etc. Especially the time of measurement is important as floods may produce major changes in the bed level due to erosion/sedimentation. Although it seems necessary to use the latest river geometry, care should be taken that this does not lead to a mixture of input data from different measuring periods. In the present calibration of the model, a number of different time periods have been used (e.g. HBV calibration period 1976-1985) that do no correspond with each other.

Model relations of SYNHP

The SYNHP routing module is used for the stretch Basel – Maxau. For this module, different river geometries are available:

- Situation before the start of the major river works in the 19th century;
- Situation before 1977, after completion of the river works in the Oberrhein;
- Situation of 2002 (“Current situation”);
- Projected situation on completion of all river works.

For the present application of the model, the situation of 2002 is used. This illustrates again the presence of input data from different time periods.

Method to couple HBV-results to SOBEK/SYNHP (multiplier)

This issue has already been discussed in the Chapter on the HBV model dealing with the ‘Data’ issue. The conclusion is that this multiplier an unknown source and does need to be studied as part of the uncertainty analysis of the modelling system.

Location boundary HBV – routing modules

An issue that is often overlooked is the need for a ‘variable boundary’ between the HBV model and the routing modules. For low and medium discharge values the division between the hydrological modelling stretches and the hydrodynamic stretches will be different than during (extreme) flood events. During the latter, the ‘boundary’ between the two modelling approaches will move upstream and hydrodynamic effects will become dominant in stretches that can easily be represented by a hydrological model during low and medium flows.

This is an important issue that, however, can not easily be addressed in the present reliability study. It should though obtain sufficient attention during the application of the model, because it may be a major source of error in the routing of the flood waves, especially in the major tributaries of the Rhine.

A related issue is the downstream boundary of the SOBEK model at Lobith. Here a Q-h curve is used as boundary condition and it is evident that any error in this relation will negatively affect the outcome of the modelling exercise.

Modelling controllers in Mosel

In the study by Werner & Reggiani (2002) a problem is mentioned with the use of controllers on the Mosel tributary. However, for the present use of the model, a new option has been chosen that eliminates this problem. In any case it is likely that the problems that are limited to situations with a discharge at Cochem up to 1250 m^3/s are not relevant to this study of reliability.

Technical model

The following issues will be discussed under this heading:

- Implementation errors;
- Truncation errors;
- Propagation of errors through the model.

Implementation errors

Implementation errors in the Muskingum routing module can safely be assumed absent as this is a very straightforward approach that is well-known by now. Apart from that, the Muskingum routing module does not enter directly in the modelling system, but only for selection of flood peaks.

It is more difficult to assess the possible errors in the SYNHP module, which has been developed by the BfG and other German partners. Again this is not a very complicated routine and most likely major errors will be spotted very quickly. The module has also been used already since the 1980es.

The SOBEK hydrodynamic model has by now a long record of applications and it is unlikely that there are still any major errors in the model that would have an important impact on the outcome of the total modelling system.

For these reasons this issue is not included in the uncertainty analysis.

Truncation errors

As far as known, truncation errors will not be important in the application of the routing modules.

Propagation of errors through the model

Although it is clear that errors in the input will simply have a direct effect on the outcome of the modelling activities, it is not easy to assess the exact propagation of errors through the model. It can safely be assumed, though, that any major error in the routing module (e.g. error in the geometry of the river and/or in the roughness values) will directly relate to errors in the output. As long as a proper calibration of the hydrodynamic model is performed with the correct geometry, this aspect will have a minor impact on the output of the model.

Model empirical parameters

For most routing models, the hydraulic roughness is the most important (and sensitive) parameter. This is especially the case for 1-D hydrodynamic models such as SOBEK. Although the model has many other parameters, most of these parameters are used for the proper functioning/stability of the model and do not influence the final outcome of the model simulations.

For the Muskingum routing the parameters are found by calibration against the results of the SOBEK and SYNHP model and therefore the estimation of these parameters is not relevant in this context.

Model domain parameters
For the routing models, two domain parameters are important:

- Numerical spatial steps (river geometry, distance between cross-sections);
- Numerical time steps.

Numerical spatial steps
The main advantage of a hydrodynamic model is that one of the most important input data, the river geometry, can in principle be perfectly known. In practice, of course, this is never the case, apart from the fact that such knowledge is outdated continuously due to ongoing changes in the river bed. For practical reason also the river geometry is only well-known at certain locations (the cross-sections) and between these locations an interpolation is made for intermediate points. This implies that the choice of the location of the cross-sections is very important as well as the time of measurement. As will be discussed for the SYNHP module, it is often the case that input data refer to different dates and in principle should not be mixed. Evidently this is often disregarded out of practical reasons, especially the measuring of new sets of cross-sections is far too costly to perform very regularly (compared to e.g. waterlevel recording).
Despite the clear importance of the possible errors in the representation of the river geometry in the hydrodynamic model this issue can not easily be evaluated in the uncertainty analysis. It is suggested that only obvious errors (that will be evident by gross errors in local waterlevels) are corrected whenever found during the analysis of the modelling system, but that this issue is not included in the uncertainty analysis.

Numerical time steps
The numerical time step, another issue relevant to hydrodynamic modelling, will not be an important issue in the uncertainty analysis. The choice of the time step is often based on either the required output / purpose of the project and/or the time step of the input data. In this case only daily input is available from the HBV model and as such a daily time step is the logical choice for the modelling system.

Model inputs
The main input to the routing models, either as point inflow or as diffuse inflow, are the discharge series produced by the HBV models of the various subbasins. A discussion of the possible sources of error is given in Chapter 4.2. The issue of the inflow towards the SOBEK model as diffuse flow may introduce an error as it is evident that in reality the inflow will not be linearly distributed along the river stretch. However, it is unlikely that this issue will produce noticeable errors in the model output and therefore this issue can be disregarded in the uncertainty analysis.

4.3.2 Data

Under this heading, there are three groups of data that need attention:

- Water level measurements;
- Rating curves;
- Inadequate measurement locations.

These three issues are intimately related and will be discussed as a whole.
Calibration of a hydrodynamic model is done by comparison with measured discharges and waterlevels. Errors in the estimation of the water levels will not only lead to direct misinterpretations of the behaviour of the model, but also to errors in the discharge values for which waterlevels are converted through the use of a rating curve. It is evident that any error in the location of a measuring station will have the same negative impact on the accuracy of the model as the measurements themselves. A most common source of error is the position of a gauging station within the influence of the discharge of another river (or structure) downstream, i.e. within the reach of the backwater effect. However, in the Rhine basin these effects are well-known and it is unlikely that these types of errors will be widespread, despite the fact that the most important calibration data are the highest measured values that will be most vulnerable to backwater effects. Obvious errors in measured water levels will have been eliminated as there have been numerous data validation checks and smaller errors are probably without major consequences for the output of the modelling. For this reason this issue will not be used in the uncertainty analysis.

4.3.3 Context

The last main group of uncertainties includes four possible sources:

- Future river management;
- climate variability;
- Validity of the model under extreme conditions;
- New measurement techniques.

Future river management
It is clear that any major change in the river management will affect the outcome of the modelling system. This issue has already been discussed for the HBV model. For the routing modules, changes in the river geometry and/or operation of structures are important in this context. Changes in river geometry also include the implementation and use of detention basins and this will need a lot of attention in the application of the total modelling system. In fact this is less an issue of uncertainty as well as planning and management of the Rhine river system in situations of extreme rainfall. Therefore it is suggested to study these aspects separately, i.e. as scenarios of optimal management of the system, and not in the uncertainty analysis.

Future climate changes

Evidently future climate change has only an indirect impact on the routing modules, beside the minor input source of direct rainfall on the water bodies. Most of the climate change effects will be passed on to the routing modules through the Rainfall Generator – HBV system and therefore this issue will not need to obtain additional attention in the uncertainty analysis.

Validity of the model under extreme conditions

For the hydrodynamic model there is no problem using the model in extreme conditions as there is no upper limit to its applicability, provided that the cross-sections have been measured to above the maximum flow level and as long as the flow remains subcritical (and this can be safely assumed). The validity of the input data is a different issue (especially the river geometry), but this belongs to a different class of uncertainty (see data issue). Therefore the validity of the model concept will not need to be included in the uncertainty analysis.

For the SYNHP module the validity in extreme conditions is not clear, but it is evident that a hydrological routing module will always have a larger error than a well-applied hydraulic model.

New measurement techniques

For the routing modules the most important data are the river geometry, bed roughness and discharges measurements for the calibration.

In principle it is hardly possible to improve on the measurement of the river geometry; the geometry can be known with very high accuracy and the main problem is the representation of the geometry in the model by using cross-sections with a certain precision and with a certain distance between them.

Bed roughness has always been a major source of error simply due to the difficulty to measure the value. It is normally either derived from indirect sources (e.g. comparison with known values for other similar river beds) or by optimization in the calibration process, although for major rives such as the Rhine measurement of bed features such as large scale dunes on the river bed are also used. Improvements in the assessment of the bed roughness will improve the accuracy of the model, although similar to the situation for the rainfall generator and the HBV model the actual impact on the outcome of the simulations are difficult to quantify.

The impact of the improvement of discharge measurements, i.e. the combination of improved water level measurements and assessment of the rating curves, has already been discussed for the HBV model. This is an important issue as there is normally a relatively high error in the extreme values that are difficult to measure. Again, the quantification of the improvement in the modelling output, through the improvement of the model calibration, is not easy to quantify.

5 Inventory uncertainty analyses methods

5.1 Introduction

Uncertainty analysis is a fast growing science. New methods and insight are being found nearly everyday and therefore it is not possible to give a complete overview. Therefore, we will attempt to describe those methods that are being used in field of hydraulics and hydrology or methods that will be used in the near future in the next paragraph. In paragraph 5.3 the method that is judged most appropriate to be used is described in detail.

5.2 Uncertainty analysis methods

GLUE

Beven and Binley (1992) developed the Generalized Likelihood Uncertainty Estimation (GLUE) method. The philosophy behind this method is to award all uncertainty (input, model structure, model domain parameters) to the model empirical parameter. Since its introduction, a wide variety of applications of the method have been published (Beven & Freer, 2001). This method is based upon Monte Carlo simulation were each parameter set is assigned a likelihood ratio on the basis of comparing modelled and measured responses.

Strong points: Easy to implement and use.

Weak points: Many simulations needed. All uncertainty is awarded to the model empirical parameters, which is unrealistic.

Markov Chain Monte Carlo Methods

Only recently have methods for realistic assessment of parameter uncertainty in hydrological models begun to appear in the literature. These include for instance multi-normal approximation to parameter uncertainty (Kuzcera & Mroczkowski, 1996), parametric bootstrapping and Markov Chain Monte Carlo (MCMC) methods (Kuzcera & Parent, 1998). An MCMC method is a stochastic simulation that successively visits solutions in the parameter space with stable frequencies stemming from a fixed probability distribution. These algorithms originally arose from statistical physics were they were used as models of physical systems that seek a state of minimal free energy. More recently, MCMC algorithms have been used in statistical inference and artificial intelligence.
Recently, Kuzcera & Parent (1998) used the Metropolis-Hastings algorithm (Metropolis et al., 1953, Hastings, 1970) in a Bayesian framework to describe parameter uncertainty in conceptual catchments models. Vrugt (2004) developed an efficient MCMC-algorithm for optimization and uncertainty assessment of hydrological model parameters.

Weak Point: Many simulations necessary, input uncertainty normally ignored leading to unrealistic narrow parameter distributions, slow convergence.

Strong Points: Well known.

Combined data assimilation-parameter estimation

There is a growing consensus that during model calibration all sources of uncertainty should be accounted for (Vrugt, 2004, Kavetski et al, 2002). In rainfall-runoff modelling, this has led to an approach of using data assimilation methods in combination with parameter estimation techniques (Vrugt, 2004, Liu & West, 2001). The data assimilation methods are being used to take into account all uncertainties such as data uncertainties and model structural uncertainties.

Strong points: Take into account most (hopefully all) uncertainties, obtain unbiased estimates of model empirical parameters that may be linked with easily measurable variables;

Weak Points: Many simulations needed, error models of input data and model are not known; being developed at the moment.

5.3 Application of uncertainty analysis to FEWS-ED HBV

From the methods mentioned in paragraph 5.2 GLUE is probably the asiest to be used and to be implemented. There may be a possibility to seek cooperation with the the University of Amsterdam were they developed a parallel version of the MCMC-sampler developed by Vrugt (2004), to allow for an efficient application of the MCMC method. However for this project Glue has been choosen.

The GLUE approach can be used to derive model ensembles and associated likelihoods. This realisation is the basis of the Generalised Likelihood Uncertainty Estimation method proposed by Beven and Binley (Beven and Binley, 1992). The basis of the method is to consider an ensemble of parameter sets instead of identifying a single parameter set that after calibration is considered as the parameter set that together with the selected model structure optimally describes the system. The ensemble is obtained during the calibration period, where parameter sets are sampled from prior distributions of the constituent parameters. For each parameter set the model performance is measured using a selected likelihood function (or objective function). The ensemble is then formed by selecting all models giving a performance above a set threshold. The selected models can be given a likelihood weight according to their relative performance, and predictions made with each model in the ensemble are weighted with this likelihood to determine the likelihood distribution of model predictions. To describe it in a more formal way, the principle of the GLUE method (Beven and Binley, 1992) is to approximate the posterior parameter distribution $\pi(\theta|Y)$, where Y is the vector of measurements, by a discrete probability distribution (θ_i, p_i), I=1,…,N, $\sum p_i=1$, where p_i is the probability associated with the parameter vector θ_i.

The method proceeds as follows:

1. Randomly generate N vectors θ_i, i=1,…,N, from the prior parameter distribution $\pi(\theta)$;
2. Calculate the likelihood values $\pi(Y|\theta_i)$ and the prior density $\pi(\theta_i)$, I=1,…,N, associated with the different generated parameter vectors;
3. Calculate the a posteriori probability density p_i:

$$p_i = \frac{\pi(Y|\theta_i)\pi(\theta_i)}{\sum_{j=1}^{N} \pi(Y|\theta_j)\pi(\theta_j)} \tag{5.3.13}$$

The pairs (θ_i,p_i), i=1,…,N, can be used to determine various characteristics of the posterior distribution, for instance, the posterior means.

It is clear that the choice of likelihood (objective) function will impact the resulting likelihoods of parameter sets. Several likelihood measures have been used in the past (Beven and Freer, 2001). For instance, one can use the explained variance according to the Nash-Sutcliffe criteria as likelihood measure and expressed as:

$$\pi(Y|\theta_i) = \left(1 - \frac{\sigma_\varepsilon^2}{\sigma_0^2}\right) = R^2 \tag{5.3.14}$$

where σ_ε^2 is the error variance $(\Sigma(Q_{modelled}-Q_{measured})^2)$ and σ_0^2 is the variance of the observations $(\Sigma(Q_{measured}-Q_{measured\_mean})^2)$.

Resulting uncertainties can also be constrained through applying multiple objective functions, this being particularly relevant in some models where different parameters affect different parts of model response and can as such be identified using different parts of the observed data (e.g. peaks, recession curves and low flows). The result of using these different options is in essence the same and consists of an ensemble of model parameter sets and/or structures that simulate the behaviour of the system acceptably, where acceptable is defined by the objective function or multiple objective functions selected. This holds also for considering different model structures or even different model types.

6 Proposal plan uncertainty analysis tool extreme discharge frequencies

6.1 Introduction

The aim of the research into the uncertainsy analysis of the extreme discharge frequency tool is to provide an answer to the question mentioned in Chapter 1:

- What is the uncertainty bandwidth of the calculated discharges?
- How accurate are the calculated discharges at high return period?

To achieve this one needs to derive the uncertainties for each component and finally combine these uncertainties to derive the uncertainty bounds for the flood frequency estimation. Such an approach was also followed by Cameron et al. (2000a,b). Below a short outline of the proposed uncertainty analysis is given:

- Rainfall generator → assess uncertainty of rainfall generator (description Chapter 6.2) and generate 6 rainfall and temperature series reflecting the uncertainty in the generated rainfall.

- HBV → assess uncertainty in HBV using the observed daily rainfall and flow data (description Chapter 6.3) and generate X HBV model parameter sets reflecting the uncertainty in the hydrological modelling.

- Muskingum/SYNHP/SOBEK → assess uncertainty in SOBEK and Muskingum using the measured flow data of the tributaries and the measured flow data of the Rhine (description Chapter 6.4) and generate X SOBEK/SYNHP model parameter sets and/or X Muskingum model parameters sets and X parameters for translating the measured discharge to the tributary outlets reflecting the uncertainty in the hydraulic modelling.

- Combine all rainfall and temperature series and the X HBV and routing model parameter sets to do Y 10000 year simulations giving the uncertainty bounds of the flood frequency curve.

The amounts X and Y need to be determined before proceeding with the uncertainty analysis. One may think in the order of about (X=Y=)1000 simulations.

6.2 Rainfall Generator

Two points are of interest for the rainfall generator:

- The simulations in Beersma (2002) for the Rhine could be repeated with an extra memory term in the feature vector ($10 \times 1000 = 10\,000$ years of rainfall and temperature).
- A study of the sensitivity of flood quantiles to the base period used for resampling.

For the Meuse basin the use of a relatively short base period (1961-1998) is currently compared with that of a longer base period (1930-1998). Results are expected by the end of 2004. Data before and after the period 1961-1995 are not available for the Rhine basin. Nevertheless the sensitivity of flood quantiles to the base period can be studied by comparing the generated sequences from different sub series of the historical record , e.g.

- a 10 000-year sequence from the odd historical years,
- a 10 000-year sequence from the even historical years,
- a 10 000-year sequence from a sub series with relatively wet winters, and
- a 10 000-year sequence from a sub series with relatively dry winters.

The selection of sub series of wet and dry winters should be done with care. It is further advisable to extend the 34 records used for resampling and the records for the 134 HBV sub basins with data after 1995.

6.3 HBV

A GLUE analysis is proposed because of its simplicity and easiness to implement. It is clear that a full GLUE analysis of the HBV model with 134 subbasins will take many simulations. Therefore, to carry out a GLUE analysis for the HBV model of the Rhine basin spatial aggregation is necessary as was mentioned in Chapter 4. This can be done in two ways. The first is to leave the HBV model as it is, but aggregate only the model parameters which are considered in the uncertainty analysis. This approach was followed by Weerts (2003). Another approach is to model the subbasins of one catchment as one basin. That this can lead to satisfactory results as was demonstrated by Winsemius (2004) who modelled the Neckar, Moesel and Lippe as one basin.

This GLUE analysis must be carried out at least for Switzerland and the 9 major basins in Germany taking into account the HBV model parameters Alpha, KHQ and PERC (see Chapter 4). For these 10 areas long series of observation are available (30-40 years). The ranges of variation in the GLUE analysis must be:

- Alpha: 0 – 3;
- KHQ: 0.15 - 0.25;
- PERC: 0 – 1.

From an independent uniform distribution a large amount (+/- 5000) of parameter sets must be generated. For each of these parameter sets a single continuous simulation using the measured daily rainfall must be carried out. The performance of each parameter set must be evaluated using a likelihood function. Before carrying out the GLUE analysis an investigation into the appropriate likelihood function is advised. Cameron et al. (2000a) used a log likelihood function to evaluate the fit of maximum likelihood of a extreme value distribution to the simulated annual maxima versus the maximum likelihood fit of the same distribution to the measured annual maxima data. Cameron et al. (2000) also tested the parameter sets retained under flood peak criterion via a χ^2-statistic calculated between the observed and simulated flow duration curves.
It is clear that calculation time is a limiting factor for this study. One HBV simulation of 25 years takes about 90 seconds (on a Pentium 4, 2.8 GHz, 512 Mb), so 5000 simulations will take about 450 000 s or nearly 6 days.

6.4 Muskingum/SYNHP/SOBEK

A GLUE analysis is also proposed for the routing module of FEWS-ED. As a SOBEK simulation is the most time-consuming step in the simulation process, it is proposed to start with a GLUE analysis for the Muskingum routing module. In this routing model there are 22 branches each having two parameters: a weighting factor between inflow and outflow (wich must be between 0-0.5) and a factor representing the travel time through the reach. A third parameter is the coefficient that is used for translating the measured discharge to the tributary outlets. All 3 parameters must be included in the GLUE analysis.
From an independent uniform distribution a large amount (+/- 10000) of parameter sets must be generated. For each of these parameter sets a single continuous simulation using the measured outflows must be carried out. The performance of each parameter set must be evaluated using a likelihood function. Measurements of the water level (and discharge) are available along the river, so this analysis can be done independently for each stretch that ends (and begins) with a measurement location. Before carrying out the GLUE analysis an investigation into the appropriate likelihood function is advised. A similar approach as mentioned for HBV can be used. Calculation time is not likely to be a problem because the runtime is in the order of seconds.

6.5 FEWS-ED as a total

After analysis of the elements of FEWS-ED the combined effect must be calculated. For the total uncertainty analysis of the flood frequency calculated with FEWS-ED as many runs as possible must be done, taking a sample from the 6x10000 year meteorological time series, combined with a sample from the HBV model parameter sets and a sample of the Muskingum routing parameters. The 10000 year simulation requires the use of a combined measure, which assumes equal weightings between the HBV and Muskingum routing parameter sets (see Cameron et al. 2000a). The weight factors of the rainfall scenarios are uniform (1/6).
It is clear that calculation time is a limiting factor. One run will take about 3 hours (on a Pentium 4, 2.8 GHz, 512 Mb) , so if 1000 simulations are done this will take 125 days, or 31 days if 4 of such computers are being used. Evidently, if these calculations must be done it might be worthwhile to invest in an increase of computing power (more PC's or maybe even a Linux cluster).

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A Results of sensitivity analysis of HBV model parameters in the Rhine Basinin the Rhine Basin

Table A-1 shows the ranking results of the parameters per sub-basin. The first three *physically-based* parameters are highlighted in grey. The last column shows the overall results.

Lippe 3	Rank	**Main4**	Rank	**Nahe1**	Rank	**Omos1**	Rank	**Ruhr2**	Rank
KHQ	1	KHQ	1	RFCF	1	KHQ	1	RFCF	1
RFCF	1	RFCF	2	Pcorr	2	RFCF	2	KHQ	2
Pcorr	3	Pcorr	3	KHQ	3	Alpha	3	Alpha	3
Ecorr	4	Alpha	4	Alpha	4	Pcorr	4	Pcorr	4
FC	5	HQ	5	HQ	5	HQ	5	HQ	5
ICFI	6	FC	6	FC	6	FC	6	ECALT	6
HQ	7	ICFI	7	TT	7	ECALT	7	PCALT	7
LP	7	PCALT	8	LP	8	maxbas	8	TT	8
PERC	9	LP	9	Ecorr	9	Beta	9	FC	9
Alpha	10	PERC	10	maxbas	9	PERC	10	maxbas	10
Beta	11	SFCF	10	PCALT	11	LP	11	LP	11
Cflux	12	Beta	12	ICFO	12	TT	12	Cflux	12
PCALT	13	TT	13	PERC	12	TCALT	13	ICFO	12
ICFO	14	Ecorr	14	SFCF	14	ICFI	14	SFCF	14
SFCF	15	maxbas	15	ECALT	15	ICFO	15	Beta	15
EPF	16	Cflux	16	Beta	16	PCALT	16	PERC	16
K4	17	EPF	17	CEVPFO	17	Cflux	17	Ecorr	17
TT	18	ICFO	17	EPF	18	Ecorr	18	TCALT	18
ECALT	19	Cfmax	19	Cfmax	19	EPF	19	FoCfmax	19
maxbas	20	ECALT	20	ICFI	19	SFCF	19	CEVPFO	20
CEVPFO	21	K4	21	Cflux	21	Cfmax	21	Cfmax	21
Cfmax	22	FoCfmax	22	FoCfmax	22	CEVPFO	22	EPF	22
TTI	23	TCALT	23	TCALT	23	FoCfmax	23	K4	23
TCALT	24	CEVPFO	24	WHC	24	K4	24	TTI	24
FoCfmax	25	TTI	25	K4	25	TTI	25	ICFI	25
CFR	26	CFR	26	TTI	26	WHC	26	WHC	26
WHC	27	WHC	27	CFR	27	CFR	27	CFR	27

Parameter	**Rank**
RFCF	**1**
KHQ	**2**
Pcorr	**3**
Alpha	**4**
HQ	**5**
FC	**6**
LP	**7**
PCALT	**8**
TT	**9**
PERC	**10**
Ecorr	**11**
maxbas	**12**
Beta	**13**
ECALT	**14**
ICFO	**15**
ICFI	**16**
SFCF	**17**
Cflux	**18**
EPF	**19**
Cfmax	**20**
TCALT	**21**
CEVPFO	**22**
FoCfmax	**23**
K4	**24**
TTI	**25**
WHC	**26**
CFR	**27**

Table A-1Results of the sensitivity analysis per sub-basin and totalled

Table A-2 shows the results per objective function. The first three physically based parameters are highlighted in grey. The last column shows the overall results.

POT	Rank	TOT	Rank	VOT	Rank	TTPOT	Rank	MAE	Rank	Rsquare	Rank
RFCF	1	RFCF	1	RFCF	1	RFCF	1	KHQ	1	KHQ	1
KHQ	2	Pcorr	2	KHQ	2	KHQ	2	RFCF	2	RFCF	2
Pcorr	3	KHQ	3	Alpha	3	Pcorr	3	Pcorr	3	Pcorr	3
Alpha	4	HQ	4	Pcorr	3	HQ	4	Alpha	4	Alpha	4
HQ	5	FC	5	HQ	5	Alpha	5	FC	5	HQ	4
FC	6	Alpha	6	FC	6	FC	6	maxbas	6	FC	6
LP	7	LP	7	PCALT	7	LP	7	HQ	7	TT	7
Ecorr	8	PCALT	8	PERC	8	PCALT	8	TT	8	Beta	8
PCALT	9	PERC	9	LP	9	Ecorr	9	LP	9	PERC	9
PERC	10	Ecorr	10	Beta	10	PERC	10	Beta	10	maxbas	10
maxbas	11	ICFO	11	TT	10	TT	11	SFCF	10	PCALT	11
ICFI	12	ECALT	12	Ecorr	12	ECALT	12	Ecorr	12	Ecorr	12
ICFO	13	ICFI	13	SFCF	13	ICFO	13	PCALT	13	ECALT	13
ECALT	14	TT	14	maxbas	14	ICFI	14	PERC	14	ICFO	14
TT	15	Beta	15	ECALT	15	SFCF	15	Cflux	15	LP	15
Beta	16	SFCF	16	ICFI	16	Beta	16	ECALT	16	Cflux	16
Cflux	16	Cflux	17	ICFO	16	Cflux	16	Cfmax	17	ICFI	17
SFCF	18	maxbas	18	Cflux	18	EPF	18	ICFI	17	Cfmax	18
EPF	19	EPF	19	EPF	19	maxbas	18	ICFO	19	SFCF	18
CEVPFO	20	CEVPFO	20	TCALT	20	CEVPFO	20	TCALT	19	TCALT	20
Cfmax	21	Cfmax	21	FoCfmax	21	Cfmax	21	FoCfmax	21	EPF	21
TCALT	21	TCALT	22	Cfmax	22	K4	22	EPF	22	K4	21
K4	23	K4	23	CEVPFO	23	FoCfmax	23	CEVPFO	23	CEVPFO	23
FoCfmax	24	FoCfmax	24	K4	24	TCALT	23	K4	24	FoCfmax	24
TTI	25	TTI	25	TTI	25	TTI	25	TTI	25	TTI	25
WHC	26	WHC	26	WHC	26	WHC	26	WHC	26	WHC	26
CFR	27	CFR	27	CFR	27	CFR	27	CFR	27	CFR	27

Parameter	Rank
RFCF	**1**
KHQ	**2**
Pcorr	**3**
Alpha	**4**
HQ	**5**
FC	**6**
LP	**7**
PCALT	**8**
TT	**9**
PERC	**10**
Ecorr	**11**
maxbas	**12**
Beta	**13**
ECALT	**14**
ICFO	**15**
ICFI	**16**
SFCF	**17**
Cflux	**18**
EPF	**19**
Cfmax	**20**
TCALT	**21**
CEVPFO	**22**
FoCfmax	**23**
K4	**24**
TTI	**25**
WHC	**26**
CFR	**27**

Table A-2Results of the sensitivity analysis per objective function