Simulating flood-peak probability in the Rhine basin and the effect of climate change

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ABSTRACT: Extreme value analysis, rainfall generator, climate change, flooding.

Impacts of land use change, flood defence measures and climate change on peak discharges are studied at different scales in the Rhine basin. Few studies, though, have studied the combined effect of these variables in scenarios and how these scenarios change the return period of flood peaks. Also, it is recognized that uncertainty is inevitable when performing flood risk analysis within climate change scenario studies. In the current paper we introduce a method to combine simulations of the effect of upstream flooding and climate change on flood-peak probability. We argue that in the Rhine basin, both statistical extrapolation and the assumption of no upstream flooding introduce large uncertainties when estimating (future) flood-peak probabilities

1 INTRODUCTION

1.1 *Background*

Flood management activities in the Rhine basin already started in the beginning of the 19th century. Since the flood events of 1993 and 1995, and the growing evidence that climate change does significantly affect the runoff regime of the Rhine (Middelkoop et al., 2001), flood risk management has gained attention in the region. This has, among others, resulted in the EU Flood Directive.

Models, datasets and understanding of the hydrological system continue to improve and quite a few studies have reported on the effects of land use change, flood defence measures and the impact of climate change on peak discharges. Few studies, though, have studied the combined effect of these variables in scenarios and how these scenarios change the return period of flood peaks.

Both scientists and policy makers recognize the inherent uncertainty when performing flood risk analysis within climate change scenario studies. This uncertainty finds its origin in the uncertainty in climate models and scenarios. Furthermore, historical time series are too short to derive a statistically sound extrapolation of return periods of flood peaks with a low probability. In addition, in case of an extreme flood event, large floodings occur upstream, which reduce the peak that enters the Rhine delta. It appears that most studies on climate change and floods in the Rhine use hydrological models without simulating floodings.

We argue that these aspects introduce large uncertainties when estimating (future) flooding probabilities. In the current paper we introduce a method to combine simulations of low probability floods, the effect of upstream flooding and climate change on peak discharges. As a result, we are able to compare the relative impacts using extreme value analysis. We use a combination of a rainfall-runoff model to implement climate scenarios, a hydraulic model to simulate the effect of flooding and a rainfall generator to optimize extreme value analysis.

1.2 *Rhine basin*

The Rhine is a cross-boundary river located in NW-Europe. It originates in the Alps in Switzerland, flows through parts of Germany, France and Luxembourg before it enters the Netherlands at Lobith. The basin area is 160,800 km^2, the average discharge at Lobith is 2200 m^3/s and the maximum observed discharge is 12,600 m^3/s. Both rainfall and melt water contribute to discharge generation, depending on the season (Pinter et al., 2006). The Rhine has a length of 863 km from Basel in Switzerland to Lobith. Kaub is located at the Middle Rhine at river kilometre 546. The Rhine can be separated in three parts. First, the Upper Rhine from Basel up to Mainz, where the former flood plain is used for agriculture and several cities exist along the Rhine branch. Second, the Middle Rhine between Mainz and Bonn, where the Rhine flows through a narrow gorge. Third, the Lower Rhine, which is densely urbanized and where the flood prone area widens to become a delta river in the Netherlands.

The safety levels of embankments vary along the main branch of the Rhine. In Germany these safety levels are 1 / 200 to 1 / 500 years, while in the Netherlands the 1250-year flood is the base for the design discharge of 16,000 m3/s (Lammersen, 2002).

2 METHOD

2.1 *Hydrological models*

2.1.1 *Rainfall runoff*

All modelling steps are visualized in Figure 1. We used the semi-distributed conceptual HBV model (Hydrologiska Byråns Vattenbalansavdelning) (Bergström, 1976; Lindstöm et al., 1997) to simulate discharge on a daily basis. The HBV model for the Rhine is applied to 134 sub-basins and was developed in 1999 (Eberle et al., 2005). The model uses different routines in which snowmelt is computed by a day-degree relation, and groundwater recharge and actual evaporation are functions of the water storage in a soil box. Discharge formation is presented by three linear reservoir equations and the sub-basins are linked with a simplified Muskingum approach to simulate routing processes.

2.1.2 *1D-Hydrodynamic*

Because the Rhine is a regulated river, the routing scheme in HBV is not sufficient to simulate peak discharge. Therefore, the 1D-hydrodynamic model SOBEK was used to re-calculate all yearly maximum peak discharges (Delft Hydraulics, 2005). This model allows the implementation of structural measures, such as dike heightening, dike relocation, weirs and detention areas. In the current research, SOBEK1D is also used to simulate the effect of flooding. The floods are schematized as large detention areas with regulated inlet and outlet structures. The 1D modelled flood simulations were calibrated using results of 2D-hydrodynamic simulations of flooding events (Gudden, 2004; Lammersen, 2004). All cross-sections, dike locations, dike heights and detention areas as they currently exist are schematized in the model.

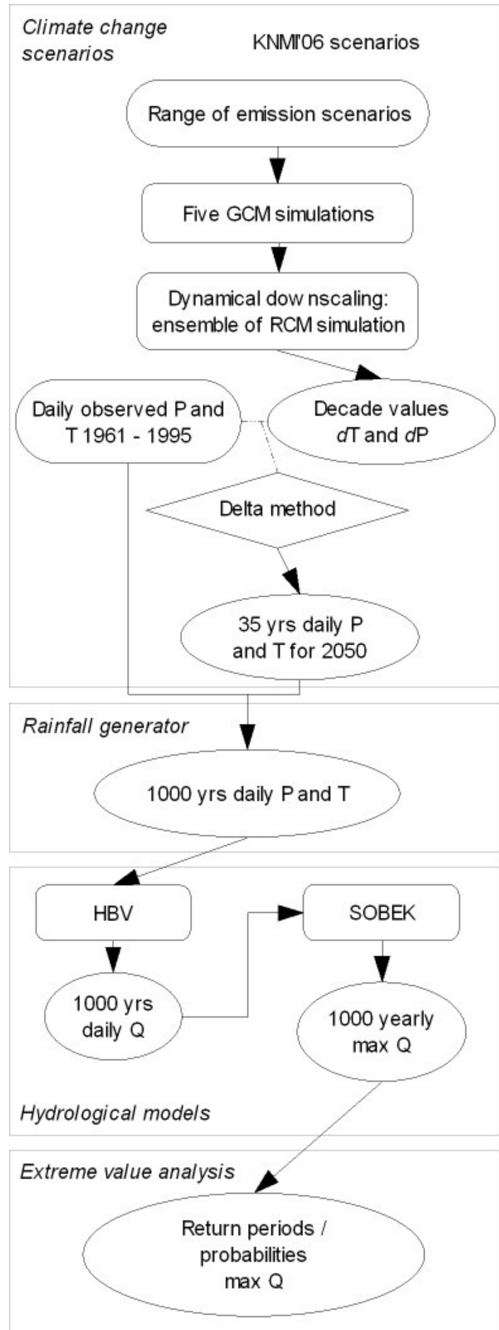

Figure 1. Scheme displaying all modelling steps

2.2 *Rainfall generator*

Because safety levels in the Rhine basin vary from 1 / 200 to 1 / 1250 years, estimated associated design discharges using extreme value distributions are uncertain since observation records only include 110 years. To produce discharge series of at least 1000 years, a stochastic rainfall generator for the whole Rhine basin was developed by Beersma (Beersma, 2001). This instrument uses a nearest-neighbour resampling for generating long time series of daily rainfall and temperature at 36 stations spread across the Rhine basin. These time series have the same statistical properties as the historical measured data.

2.3 *Climate change scenarios*

In 2006, the Royal Netherlands Meteorological Institute (KNMI) presented four new climate scenarios for the Netherlands (Van den Hurk et al., 2006). These scenarios are based on five different General Circulation Models (GCMs) and an ensemble of Regional Climate Models (RCMs). Due to the spatial scale of the GCMs, they also apply to the north westeren part of Germany. The simulation results show variable changes in projected strength of westerly winds in the area around the Netherlands. A strong change in atmospheric circulation is expected to result in milder and wetter winters due to more westerly winds, and in warmer and drier summers due to more easterly winds, when compared to scenarios without atmospheric circulation change. Hence, besides temperature, the atmospheric circulation is used as steering parameter to discriminate four climate change scenarios. They are summarized in Table 2 and are all equally probable.

We constructed specific climate scenarios for the Rhine basin by applying the delta change approach on the historical dataset. (Lenderink, 2007; Te Linde, 2007). This method adds the projected temperature increase to the observed temperatures and precipitation is perturbed by a fraction. KNMI provided decade values of changes in precipitation and temperature for all four climate change scenarios for the year 2050. We applied this to a historical data set for the period 1961-1995 of daily temperature and precipitation and then applied the rainfall generator to generate 1000 years of daily rainfall and temperature describing the change projected for 2050. But this approach has some limitations. First, the present day variance of temperature and the coefficient of variation of precipitation are left unchanged, while changes can be expected. Also, possible changes in the number of precipitation days are not considered. Finally, the transformation was uniform applied to the whole Rhine basin, not taking into account possible geographical differences.

Table 2. Changes in precipitation and temperature corresponding to the KNMI'06 scenarios for the year 2050. G is moderate and W is warm. 'p' Indicates scenarios with a strong change in atmospheric circulation.

	Winter			
Variable	G	Gp	W	Wp
Mean T (K)	+ 0.9	+ 1.1	+ 1.8	+ 2.3
Mean P (%)	+ 3.6	+ 7.0	+ 7.3	+ 14.2

	Summer			
Variable	G	Gp	W	Wp
Mean T (K)	+ 0.9	+ 1.4	+ 1.7	+ 2.8
Mean P (%)	+ 2.8	- 9.5	+ 5.5	- 19.0

2.4 *Extreme value analysis*

Three types of extreme value distributions are combined into the Generalized Extreme Value distribution (GEV) (Smith, 2004):

$$F(x) = \exp\left\{ -\left(1 + \beta \frac{x-\lambda}{\delta}\right)^{\frac{1}{\beta}} \right\} \tag{1}$$

where λ is the location parameter, δ is the scale parameter and β is the shape parameter.

When the limit $\beta = 0$ the GEV corresponds to the Gumbel distribution, $\beta < 0$ corresponds to the Fréchet distribution and $\beta > 0$ corresponds to the Weibull distribution and has a finite upper limit.

At Lobith, the current practice is to extrapolate yearly maximum discharges using the Gumbel distribution (Diermanse, 2006). We applied fitting the Gumbel distribution to the 1000 years of generated yearly maxima for the reference and the climate change scenario at Lobith. In the analysis of flooding probabilities we used only the Wp climate change scenario, which is the most extreme of the four scenarios. The Gumbel fit failed to describe the upper tail of the distribution of the 1000 years of generated data. We therefore introduced the shape parameter and also applied the Weibull distribution. We used the maximum likelihood approach to estimate distribution parameters.

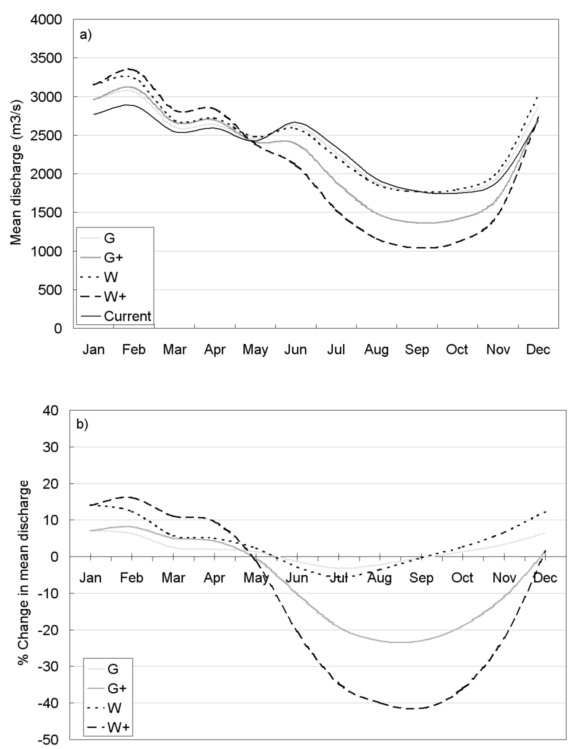

Figure 2. Mean change in discharge at Lobith according to KNMI'06 scenarios for 2050, a) absolute values, b) relative values

3 RESULTS

3.1 *Effect of climate change*

When applying the KNMI06 scenarios, mean winter discharge is expected to increase from 2850 m^3/s to 3200 m^3/s according to the G scenario and to 3400 m^3/s according to the Wp scenario (Figure 2a). Also notable, though, is the simulated decrease of 40% during the summer months for the Wp scenario, while the G and W scenarios indicate up to 5% decrease of mean discharge (Figure 2b).

3.2 *Effect of flooding (select several flood events)*

In Figure 3 a discharge wave of an artificially constructed flood peak event of 16,000 m^3/s at Lobith in case no upstream flooding would occur. At Lobith, this is the present design discharge. We constructed this wave by upscaling the historical flood peak event of 1995 with 34%. Under the current conditions, flooding upstream from Lobith would occur for such an event. Hence, this flood peak would be lowered with 1000 m^3/s at Kaub and 2000 m^3/s at Lobith.

In Figure 4 yearly maximum peak discharges over 10,000 m^3/s at Lobith for the situation without flooding is plotted in a scatter diagram against the situation with flooding. Results of 1000 years of the reference situation as well as results of the 1000-year run of the Wp scenario are shown. In Table 3 the 10 highest peaks are selected from both runs and the percentage of change due to flooding is displayed per event. It ranges from 1.5 – 12.6% in the reference situation and from 9.6 – 18.7% for the Wp scenario, as a result of increased peak discharges in this scenario.

Figure 4 and Table 3 show that the decrease of peak discharge due to flooding is variable. This can be explained by the heterogeneity of the Rhine basin and the flood generation process. Timing and volume of sub-basin contribution, timing of flooding, peak volume and duration, differ from event to event.

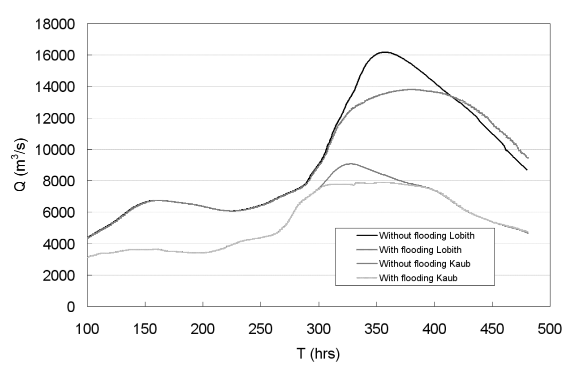

Figure 3: Effect of upstream flooding on a synthetic discharge wave

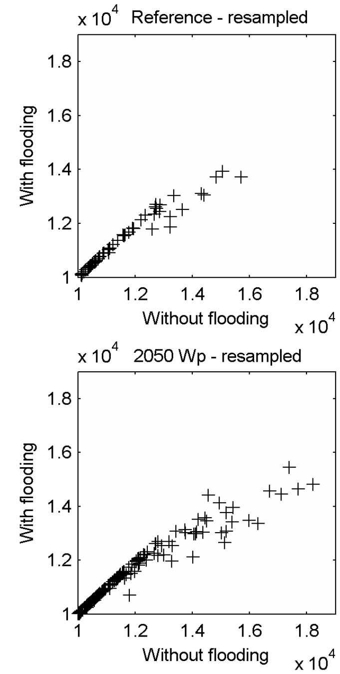

Figure 4: Effect of upstream flooding on the maximum discharge (m3/s) of all events > 10,000 m3/s at Lobith, in the reference situation and under the Wp scenario for 2050

Table 3: Decrease of peak discharge due to flooding at Lobith of the 10 highest peak events

Reference			Wp		
Without flooding	With flooding	*d*	Without flooding	With flooding	*d*
m^3/s	m^3/s	%	m^3/s	m^3/s	%
15,694	13,717	12.6	18,215	14,809	18.7
15,047	13,918	7.5	17,696	14,644	17.3
14,825	13,719	7.5	17,384	15,445	11.2
14,402	13,052	9.4	17,106	14,457	15.5
14,321	13,102	8.5	16,704	14,561	12.8
13,648	12,520	8.3	16,288	13,369	17.9
13,358	13,037	2.4	15,971	13,480	15.6
13,230	11,864	10.3	15,427	13,945	9.6
13,226	12,240	7.5	15,384	13,421	12.8
12,880	12,681	1.5	15,186	13,077	13.9

3.3 *Flood-peak probabilities*

Next, we have used the resample scenarios as input for our models to derive return periods of peak discharge in the future. All results displayed and discussed apply to Lobith. The simulation results are presented in Figure 5. Figure 5a shows a Gumbel distribution fitted through 100 years of observed peak discharges. Also shown are the 95% confidence intervals that visualize the uncertainty as a result of this fit. At a return period of 100 years, the estimated peak discharge is 13,000 m^3/s, +/- 1750 m^3/s according to the width of the confidence interval. The narrowing effect of increasing the sample size from 100 – 1000 years is displayed in Figure 5b, where the confidence interval is 75% smaller. The Gumbel fit agrees very well with the fit in Figure 5a, but the ten most extreme peak discharges in Figure 5b lie around the lower 95% confidence interval and the 2 most extreme discharge peaks even fall outside the confidence intervals. The Gumbel distribution seems a good fit at historical data, but apparently fails to describe the upper tail of the actual distribution, as is plotted in Figure 5b.

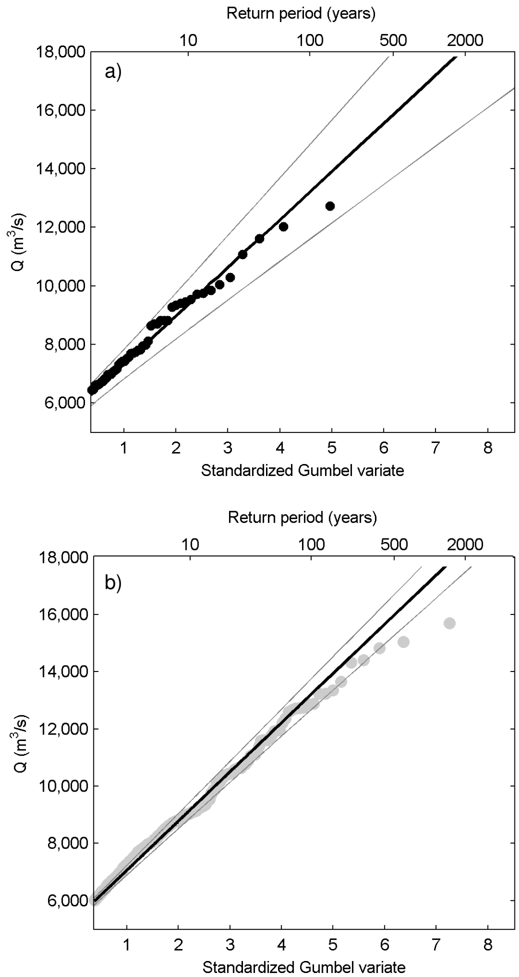

Figure 5: Extreme value distribution of yearly maximum at Lobith. The Gumbel distribution fit is projected as a straight line with 95 % confidence intervals. Displayed are 100 years of observed data (a) and 1000 years of resampled and modelled data (b).

We therefore introduced the shape parameter as explained in Section 2.4 and fitted the Weibull distribution, of which the result is shown in Figure 6a. Weibull fits well to the situation without flooding (dotted line), but due to flooding, the system behaviour changes and also Weibull does not suffice (black line). Weibull also fits the increased maximum discharges due to climate change for the situation without flooding (dotted line in Figure 6b). And due to the increased number of flooding events, the distribution fit is more influenced by these extreme events and the Weibull fit improves for the situation with flooding (black line), compared to the reference situation, but still overestimates the highest peak events.

According to Figure 6, the flood frequency will increase as a result of climate change. For the situation without flooding, a peak discharge of 15,000 m^3/s with a return period of 500 years (Gumbel variate is 6.2) in the reference situation will shift to a return period of 100 years (Gumbel variate is 4.6) in the Wp scenario. Also, the 1 / 1250 year event of 16,000 m^3/s in the reference situation will shift to approximately 18,000 m^3/s in 2050. If we do take into account the simulated effect of flooding, these differences in peak discharges and return periods between the reference and the Wp scenario for 2050 are less dramatic. The 1 / 1250 year event will then shift from 14,000 m^3/s in the reference situation to 15,000 m^3/s in 2050.

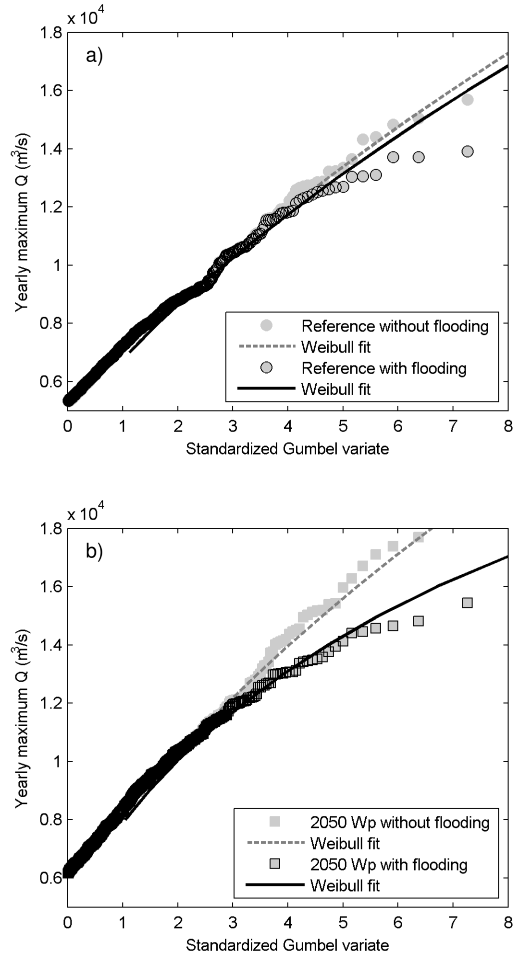

Figure 6: Extreme value distribution of yearly maximum at Lobith The Weibull distribution fits are shown without confidence intervals. Displayed are the reference situation (a) and 2050 according to the Wp scenario (b).

To improve the distribution fit and therefore estimates of extreme return periods and accompanying discharges, one might choose to introduce a threshold below which all yearly maximum discharges are discarded. The location of such a threshold, however, is arbitrary. Instead of a further attempt to statistically model the tail of the distribution of our modelling results, we therefore chose to use the straightforward method of ranking the peak events according to size and linking return periods to the ranks. For example, in our dataset of 1000 years of daily discharge values, we took the maximum simulated peak value as the discharge with a return period of 1000 years. The 10th value in our dataset was adopted as the discharge with a return period of 100 years, etcetera. The thus obtained estimated discharges at several return periods, with and without flooding, are presented in Table 4.

Of the discharges shown in Table 4, the increase of peak discharge as a result of climate change ranges from 16 – 19% in case of no flooding and from 8 – 11% when flooding is taken into account. Looking at both Figure 6 and Table 4, it can be seen that flood-peak probabilities do increase due to climate change, but decrease as a result of flooding. The relative effect of those impacts varies depending on event size. Climate change increases all peak events by a more or less constant percentage, which is a direct consequence of the delta change method (Te Linde, 2007). Flooding occurs above a threshold value of approximately 12,000 m^3/s at Lobith. The effect of flooding increases from that point onwards with increasing discharge, but does not neutralize the effect of climate change. The maximum simulated discharge at Lobith in case of flooding increases from 13,900 m^3/s to 15,445 m^3/s according to the Wp scenario for 2050. In other words, an increase in peak discharge due to climate change remains when the effect of flooding is taken into account.

Table 4: Estimated return periods obtained by ranking the peak events at Lobith according to size and linking return periods to the ranks. A dataset of 1000 years was used.

Rank	Return period	Reference		Wp	
		Without flooding	With flooding	Without Flooding	With flood-ing
	year	m^3/s	m^3/s	m^3/s	m^3/s
1	1000	15,694	13,918	18,215	15,445
2	500	15,047	13,719	17,696	14,809
5	200	14,321	13,052	16,704	14,457
10	100	12,880	12,554	15,186	13,576
20	50	11,938	11,807	14,147	13,025

4 UNCERTAINTY

In this section we reflect on the inherent uncertainty when estimating flood-peak probabilities and the effect of climate change, and discuss our results in relation to uncertainty. The debate on quantifying uncertainties in climate change impact studies is necessarily restricted to uncertainties that can be expressed in terms of probabilities, such as the measurement error, variability and model structure. There is no common technique available to quantify how uncertainty propagates through all steps in our modelling exercise (Katz, 2002). Although it does not identify the uncertainty, the use of scenarios at least allows for describing the bandwidth of projected changes and is therefore quite popular. Some studies aim to develop probability distributions for regional climate change scenarios (Dettinger et al, 2007; Hingray et al., 2005), but the KNMI'06 scenarios that we applied are stated as equally probable.

We assume that parameter uncertainty and uncertainty due to scaling and model structure of our hydrological models, is the same for the reference situation and the climate change scenarios. Based on this assumption and hydrological model calibration results (Te Linde, *in press*) we are confident that the simulated relative change in peak discharge is not a substantial source of uncertainty.

Also the final steps in our method, fitting of extreme value distributions, have a number of uncertainties (Perrichi & Rodriguez-Iturbe, 1985):

1 System uncertainty, which includes the measurement error.
2 Parameter uncertainty, which is the uncertainty related to the estimation of parameters of the stochastic model.
3 Stochastic model uncertainty, which is the lack of certainty that a particular probabilistic model of the stochastic process is true.

When applying extreme value analysis, uncertainty can also be quantified in terms of a probability distribution. The relatively small number of observations result in wide confidence intervals, such as displayed in Figure 5a. Resampling the data reduces parameter and stochastic model uncertainty, which narrows the 95% confidence interval significantly as can be seen in Figure 5b. Resampling, on the other hand, introduces a new stochastic uncertainty related to the resampling model (Beersma et al., 2001). Since the Gumbel fits in Figure 5 for the observed and resampled discharges agree so well, we can assume that uncertainty related to resampling of the reference situation is low. We argue that resampling significantly reduces uncertainty related to the extreme value distribution fit, and therefore overall uncertainty related to simulating flood-peak probabilities.

The system behaviour of extreme discharges is mainly influenced by the effect of flooding that will occur under current conditions of the Rhine basin. We analyzed the impact of flooding and have shown that the decrease of flood peaks ranges from 2 – 19%, depending on event size. Due to flooding, the system behaviour changes dramatically, which affects the extreme value analysis as is visualized in Figure 6. We therefore identify the impact of flooding as a key source of uncertainty in estimating flood-peak probabilities in the Rhine basin.

5 CONCLUSIONS

Historical time series are too short to derive a statistically sound extrapolation of return periods of flood peaks with a low probability. In addition, in case of an extreme flood event, large floodings occur upstream, which reduce the peak that enters the Rhine delta at Lobith. We have shown that the decrease of peak discharge due to flooding is variable and ranges from 2 – 19%, which can be explained by the heterogeneity of the flood generation process. We used a rainfall generator and hydrological models to derive resampled time series of 1000 yrs of daily discharges. The confidence intervals of the extreme value fits reduced significantly due to the resampling method, but in the situation with simulated upstream flooding, the Weibull fit did not satisfactorily model the upper tail of extreme discharges. We then used the straightforward method of ranking the peak events according to size and linking return periods to the ranks.

Results show that the flood-peak probabilities will increase as a result of climate change. At Lobith, for example, a 500-year event in the reference situation will shift to a 100-year event in 2050. When no upstream flooding us assumed, the simulated 1000-year discharge event at Lobith increases from 15,700 m^3/s to 18,200 m^3/s according to the Wp scenario for 2050.

We then compared the relative impacts of climate change and flooding on flood-peak probabilities of extreme events. We have seen that flood-peak probabilities do increase due to climate change, but decrease as a result of flooding. Climate change increases all peak events by a more or less constant percentage, while flooding occurs above a threshold value of approximately 12,000 m^3/s at Lobith. The effect of flooding increases from that point onwards with increasing discharge, but does not neutralize the effect of climate change. The maximum simulated discharge at Lobith in case of flooding increases from 13,900 m^3/s to 15,445 m^3/s according to the Wp scenario for 2050. In other words, an increase in peak discharge due to climate change remains when the effect of flooding is taken into account.

In Section 2.3 we explained the limitations of applying the KNMI'06 scenarios to the Rhine basin. Further work is in progress on creating basin specific climate change scenarios, including geographical differences and adding more statistical descriptive parameters to the currently used mean decade changes in precipitation and temperature. The use of direct RCM output is also considered.

We have shown that in the Rhine basin, both statistical extrapolation and the assumption of no upstream flooding introduce large uncertainties when estimating (future) flood-peak probabilities. A combination of a resampling method and a hydrological model capable of simulating flooding resulted in a valuable description of the river system, which is used for simulating flood-peak probability and the effect of climate change.

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