Merz, B., Thieken, A. H. (2009): Flood risk curves and uncertainty bounds. - Natural Hazards, 51, 3, 437-458

DOI: 10.1007/s11069-009-9452-6

Flood risk curves and uncertainty bounds

Bruno Merz[1] and Annegret H. Thieken[2]

[1]GeoForschungsZentrum Potsdam, Telegrafenberg, 14473 Potsdam, Germany

[2]Leopold-Franzens-University Innsbruck and alpS – Centre for Natural Hazard and Risk Management, Grabenweg 3, 6020 Innsbruck, Austria

Correspondence to: B. Merz (bmerz@gfz-potsdam.de)

Abstract

Although flood risk assessments are frequently associated with significant uncertainty, formal uncertainty analyses are the exception rather than the rule. We propose to separate two fundamentally different types of uncertainty in flood risk analyses: aleatory and epistemic uncertainty. Aleatory uncertainty refers to quantities that are inherently variable in time, space or populations of individuals or objects. Epistemic uncertainty results from incomplete knowledge and is related to our inability to understand, measure and describe the system under investigation. The separation between aleatory and epistemic uncertainty is exemplified for the flood risk analysis of the City of Cologne, Germany. This flood risk assessment consists of three modules, (1) flood frequency analysis, (2) inundation estimation, and (3) damage estimation. By the concept of parallel models, the epistemic uncertainty of each module is quantified. The epistemic uncertainty associated with the risk estimate is reduced by introducing additional information into the risk analysis. Finally, the contribution of different modules to the total uncertainty is quantified. The flood risk analysis results in a flood risk curve, representing aleatory uncertainty, and in associated uncertainty bounds, representing epistemic uncertainty. In this way, the separation reveals the uncertainty (epistemic) that can be reduced by more knowledge and the uncertainty (aleatory) that is not reducible.

1 Introduction

Decisions on flood mitigation and risk management are usually based on flood risk assessments. Such assessments may be associated with significant uncertainty. For example, Merz et al. (2004) quantified the uncertainty associated with flood damage estimates at the micro-scale, and Apel et al. (2004, 2008) assessed the uncertainty of flood risk estimates for a river reach. It is widely acknowledged that risk analyses should try to indicate the reliability of the risk quantification. Palmer (2000) and Downton et al. (2005) show that information on the uncertainty is important for more informed decisions, since decision makers may have differing perspectives, different risk attitudes (risk-neutral, risk-averse) or cost-benefit ratios of precautionary measures.

Furthermore, the available data do usually not suffice to validate flood risk assessments (Hall and Anderson, 2002). Events of large interest for a flood risk assessment, such as the 500-year flood and its consequences in terms of inundation areas and losses, may not have occurred during the available observation period. Or, events need to be assessed that are unrepeatable. An example is the failure of a dam. In such a case, the dam would either not be rebuilt, or it would be rebuilt with a much higher safety level. In such data-sparse situations, where the usual approaches for validation, i.e. comparing observed with simulated data, cannot be applied, formal uncertainty analyses are a means of better understanding the system under study. They force the analyst to consider a wider spectrum of assumptions. If the contribution of different uncertainty sources to the total uncertainty of the risk estimate can be quantified, additional resources can be used to effectively improve models, data or understanding. These resources will be allocated to the sources that dominate the overall uncertainty. In this way, uncertainty analysis is a guide for further information collection.

Uncertainty analyses usually distinguish between different kinds of uncertainty (e.g., Haimes, 1998, van Asselt and Rotmans, 2002, Helton and Oberkamp, 2004). In our view, a significant difference exists between aleatory and epistemic uncertainty. Aleatory uncertainty stems from variability of the process under study. It refers to quantities that are inherently variable in time, space, or populations of individuals or objects. Variability exists, for example, in the maximum runoff of a catchment in consecutive years, or in the infiltration capacity at different locations of a field. Aleatory uncertainty has also been termed (basic) variability, natural uncertainty, objective uncertainty, inherent variability, or (basic) randomness. Epistemic uncertainty results from incomplete knowledge about the system under study, e.g. a lack of knowledge about quantities that have fixed, but poorly known values. Terms for epistemic uncertainty are subjective uncertainty, lack-of-knowledge, (limited-)knowledge uncertainty, ignorance or specification error. Epistemic uncertainty depends on our ability to understand, measure, and describe the system under study.

In this paper the risk of the city of Cologne due to floods of the river Rhine is estimated. The maximum water level or discharge of the Rhine, for example in the next year, cannot be deterministically predicted due to the inherent variability of river flows. This variability can be described by a probability density function (pdf) of discharge based on observed runoff data. Since the observations represent a limited sample of the complete population, the choice of this frequency distribution and of its parameters is uncertain. This epistemic uncertainty is related to the available data and to our knowledge of the flood processes. It can be reduced, e.g. by sampling more data or by better understanding the flood processes in the catchment. This example illustrates the central issue in the differentiation between these two kinds on uncertainty. Epistemic uncertainty can be reduced whereas aleatory uncertainty is not reducible. As a consequence, many researchers argue that both types of uncertainty should be treated separately (e.g., Hoffman and Hammonds, 1994, Ferson and Ginzburg, 1996, Hora, 1996, Parry, 1996, Haimes, 1998, Cullen and Frey, 1999, Hall, 2003, Helton and Oberkamp, 2004, Merz and Thieken, 2005). The separation between these two kinds of uncertainty is particularly important in risk analyses, where aleatory uncertainty arises from the many possible failure scenarios that may occur, and epistemic uncertainty arises from a lack of knowledge with respect to the quantification of the frequency, evolution or consequences of failures.

There is no clear-cut boundary between aleatory and epistemic uncertainty. One analyst may have a detailed understanding of the system and may model a certain parameter as deterministic. Another analyst may choose a probabilistic description of the same parameter, since he/she has not enough information or insight to derive a deterministic model. For instance, the influence of flow velocity on building damage is usually not considered in flood damage models. On the basis of a hydraulic model and a damage model that accounts for the effects of flow velocity on the damage, one could derive a deterministic model that mimics local variations in velocity and associated variations in building damage. If this is not given, a certain part of the variation in damage data is unexplained and may be represented by a random component. Hence, the differentiation between aleatory and epistemic uncertainty depends on the context of the risk analysis, and is in most cases subjective. Although an objective differentiation would be preferable, model building is always a more or less subjective process.

In this paper, it is proposed to separate aleatory and epistemic uncertainty in flood risk analyses. The separation between aleatory and epistemic uncertainty is exemplified for the flood risk analysis of the City of Cologne. This flood risk assessment consists of three modules, (1) flood frequency analysis, (2) inundation estimation, and (3) damage estimation. The main sources of uncertainty are considered and treated either as aleatory or epistemic uncertainty. This results in the flood risk curve for Cologne, representing aleatory uncertainty, and associated uncertainty bounds, representing epistemic uncertainty. In a further step, the epistemic uncertainty associated with the risk assessment is reduced by introducing additional information in the risk analysis.

The paper extends former work published in Merz et al. (2002) and Merz and Thieken (2005). In particular, the flood risk and uncertainty analysis of Merz et al. (2002) is extended by considering a larger variety of uncertainty sources, such as the uncertainty due to non-stationary flood data, and by demonstrating how epistemic uncertainty of the estimated flood risk is reduced by means of additional information. Merz and Thieken (2005) separate aleatory and epistemic uncertainty for flood frequency analysis. The current paper extends this approach to the complete risk assessment, including inundation and damage estimation.

2 Study area Cologne/Rhine

The city of Cologne is situated at the Rhine River in Germany (Fig. 1). The Rhine basin is densely populated with approx. 50 million people living in the catchment. Nine states share the Rhine basin, and the Rhine receives flow from the Aare, Neckar, Moselle, Main, and several other tributaries. It is among the rivers with the highest streamflow in Europe (mean discharge at Cologne, 1891-1998: 2062 m^3/s) and one of the most important waterways in the world. The Rhine basin is divided in (1) the Alpine and High Rhine, a high mountain area partly covered by glaciers, (2) the Upper Rhine which flows through a lowland plain, (3) the Middle Rhine with meanders that have cut canyons of 200 to 300 m depth into the rocks, (4) the Lower Rhine, a typical lowland river, and (5) the Rhine Delta which is formed by Rhine branches. The flow regime of the Rhine River changes from the Alpine to the Rhine Delta: In the upper parts, the flow is dominated by snowmelt and precipitation runoff from the Alps in the summer, whereas the annual average hydrograph of the Lower Rhine peaks in the winter due to precipitation runoff from the middle mountain ranges.

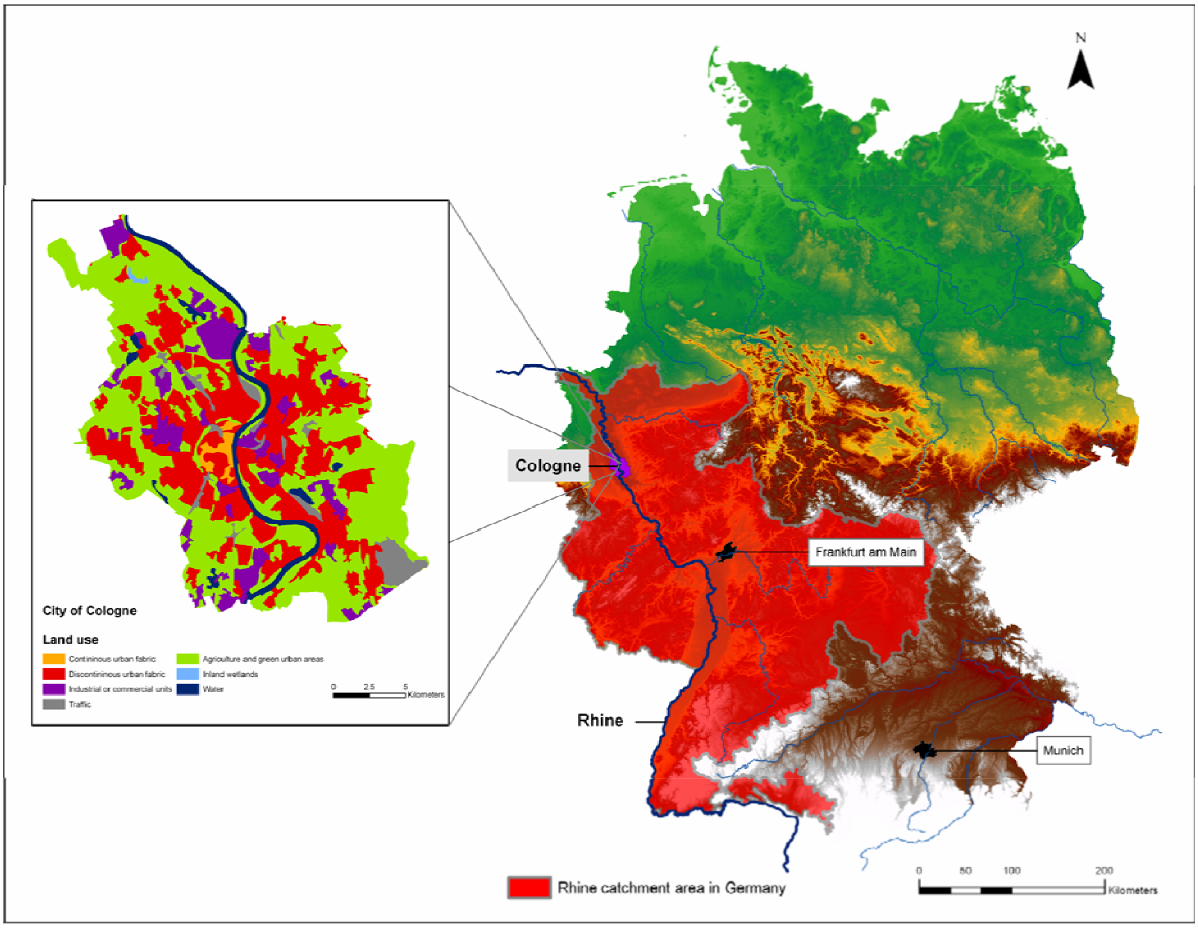
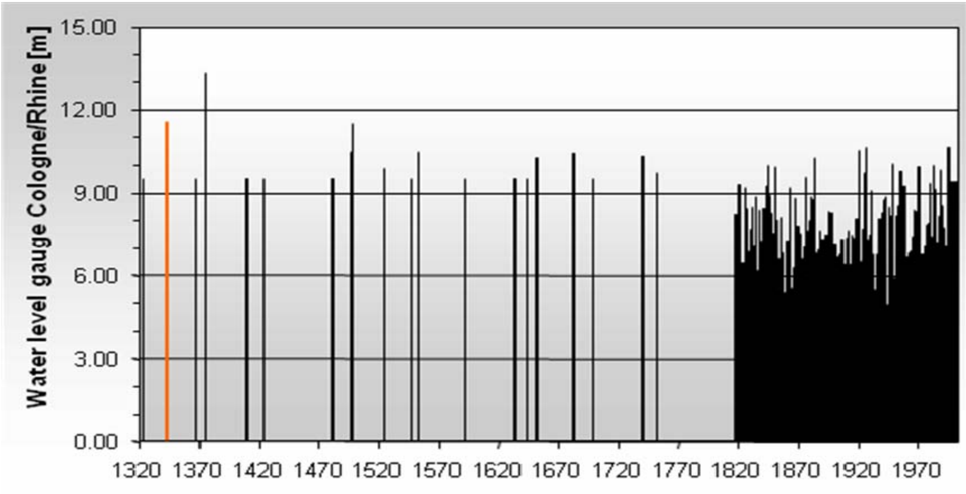


Figure 1: Map of the River Rhine, its catchment and location of study area Cologne.

Cologne is located at the Lower Rhine. At the gauge Cologne, the Rhine has a drainage area of 144232 km^2. Floods in Cologne are caused by rainfall events with long duration, typically in the range of 10 to 20 days. Most of the floods are winter floods, caused by rather moderate rainfall. Cologne has a long experience with floods. Fig. 2 shows the systematic flood observations at gauge Cologne as well as historic flood records. Recent floods occurred in December 1993 and in January 1995. Both floods had a similar genesis. The Christmas flood of December 1993 was caused by high antecedent soil moisture due to a first sequence of rainfall events, abundant rainfall following in a second sequence and snow melt. In January 1995, a similar effect was produced by melting snow and frozen soil in the uplands. Thus, heavy precipitation in the uplands of the Middle and Lower Rhine resulted in catastrophic flooding (Disse and Engel, 2001, Pfister et al., 2004). The damages reported for Cologne amounted to €76.7 million and €33.2 million in 1993 and 1995, respectively (Vogt, 1995, Fink et al., 1996).



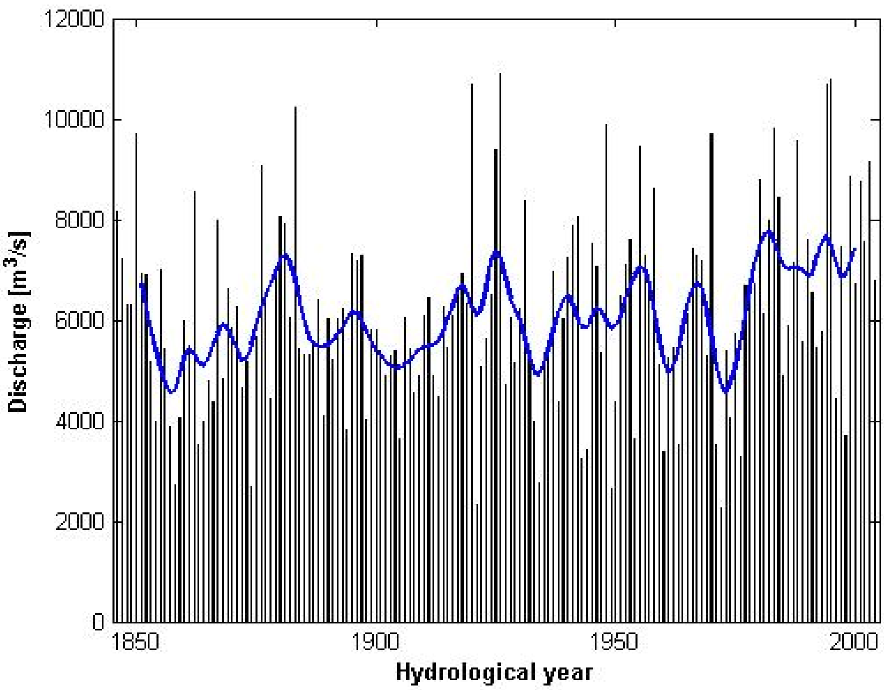


Figure 2: Flood time series at gauge Cologne/Rhine. Top: Historical and systematic water level observations; Bottom: Systematic discharge observations, 1846-2004 (annual maximum flood AMS 1846-2004), solid line: filtered time series with Hamming filter (bandwidth 10 years)

3 Outline of risk and uncertainty analysis

Flood risk is defined as damage due to inundation that is exceeded by a given probability. The flood risk analysis in this paper has a modular structure and consists of three modules: (1) flood frequency analysis at gauge Cologne, (2) transformation of flood discharge values to inundated areas in the City of Cologne, and (3) estimation of the direct economic flood damages. The modules and the quantification of uncertainty are described in section 4.

For the quantification of epistemic uncertainty the concept of parallel models is applied (Visser et al., 2000). We use the term model for a specific combination of model assumptions, structure (mathematical functions/algorithms) and parameters. For example, fitting a certain probability distribution function to two different historical periods yields different parameters sets and, consequently, two different models for flood quantile estimation. For each module a number of parallel models are used. Parallel models receive the same input and produce the same output variables. Each parallel model is regarded as a plausible description of the reality. If we had no epistemic uncertainty, we would apply just one model for each module, yielding one risk curve (probability of events with damage exceeding a certain value). Computing all parallel models simultaneously introduces epistemic uncertainty. The width of the model results is an uncertainty band that represents our incomplete knowledge.

To obtain a best estimate for the flood risk, we weight the results of all parallel models. To this end, a weight was assigned to each plausible model. Where data were available, the weights were derived from the agreement between observation data and values of the theoretical model. The resulting risk curve is seen as best estimate, and represents aleatory uncertainty. The uncertainty bounds around the risk curve represent epistemic uncertainty.

4 Risk and uncertainty analysis

Table 1 lists the important source of epistemic uncertainty. In the following, the sources of uncertainty are discussed, and the main sources are considered in the risk analysis.

Table 1. Sources of epistemic uncertainty in the flood risk analysis

Uncertainty source	Examples / remarks
(1) Flood frequency analysis	
Assumptions of extreme value statistics	Stationarity, homogeneity, independence
Choice of sample	Selection of time period; annual maximum series, peak-over-threshold, selection of 'independent' peaks
Choice of distribution function	GEV, Pearson Type 3, Lognormal
Choice of parameter estimation method	Method of moments, L-moments, Maximum Likelihood
Statistical inference uncertainty	Uncertainty associated with fitting and extrapolating, based on the given data
(2) Inundation estimation	
Use and extrapolation of rating curve as boundary condition for estimating inundation areas	Negligence of flood routing processes in the river for Cologne; uncertainty of extrapolation to extreme discharge values
DTM and representation of flood effecting urban structure	Horizontal and vertical resolution, representation of linear elements (e.g. road embankments) with inundation constraining effects
DFNK model: 0-dimensional hydraulic model for estimation of inundation areas	Negligence of propagation of flow in inundation areas; danger of overestimation of flooded areas; disregard of breaching and failure processes
HWSZ model: 2-dimensional hydraulic model without consideration of flood defence structures	Omission of flood defences
(3) Damage estimation	
Estimation of assets in flooded areas	Bias in spatial disaggregation; uncertainty of asset estimates derived from regional statistics
Stage-damage functions	Transfer of damage functions derived from other regions and other flood events; disregard of many damage influencing factors, such as flood experience, flood duration or flow velocity

4.1 Flood frequency analysis

The flood frequency analysis is based on the discharge observations at the gauge Cologne/Rhine. Discharge time series with mean daily streamflow data from 1846 to 2004

(159 years) was available. Older data were not taken into account since the quality of these data is not guaranteed.

Flood frequency analysis presumes that the observed flood discharges come from a parent population and can be described by a probability distribution. This probability distribution represents aleatory uncertainty. Flood frequency analysis is usually associated with large epistemic uncertainty.

Flood time series were derived from the available discharge data, i.e. from mean daily streamflow. Due to the large catchment and its slow response time, the difference between peak flows and maxima derived from mean daily flows is negligible. Firstly, for each hydrological year (from 1st November to 31st October), the maximum daily discharge was determined. This annual maximum series (AMS) is shown in Fig. 2. Secondly, three peak-over-threshold (POT) time series were derived. The thresholds were set at such a value that, on average, one, two and three flood peaks per year exceeded this threshold, respectively. To outrule dependence between successive flood events, two flood peaks were considered independent if the time interval between them was at least 20 days. We followed Svensson et al. (2005) who used thresholds which depended on catchment size: 5 days for catchments < 45000 km², 10 days for catchments between 45000 and 100000 km², 20 days for catchments > 100000 km².

As a first step, it was tested whether the derived flood time series fulfil the assumptions of extreme value statistics. Flood frequency analysis based on POT data requires the number of exceedences per unit time to be Poisson distributed and the time intervals between events to be exponentially distributed (von Storch and Zwiers, 1999). To test this assumption, the Kolmogorov-Smirnov goodness-of-fit test was applied. For a significance level of 5%, the hypothesis that the POT data follows a Poisson distribution was rejected for the three POT time series. AMS data is required to be independent. Applying Bartlett's test of independence for a significance level of 5%, the hypothesis of independence could not be rejected. As a consequence of these first statistical tests, it was decided to consider AMS values only.

Flood frequency analysis also assumes stationarity. The values are expected to fluctuate randomly around a constant mean. However, there is evidence for non-stationary flood behaviour in the Rhine catchment. Lammersen et al. (2002) analysed the effects of river training works and retention measures on the flood peaks. The construction of weirs along the Upper Rhine in the years 1955-77 accelerated the flood wave, leading to a higher probability that the flood peak of the Rhine coincides with the peaks of its tributaries, such as the Neckar. To reduce the flood risk along the Rhine, extensive retention measures have been planned and partially implemented. Lammersen et al. (2002) analysed these effects and concluded that, on average, the river training works have increased the flood peaks at Cologne and the retention measures have decreased the peaks, however to a smaller extent. Pinter et al. (2006) identified statistically significant increases in flood magnitude and frequency at gauge Cologne during the 20th century. Their analysis proposed that river engineering works caused little of the observed increase, and that climate and land-use related effects were responsible for increasing floods. Flood-producing precipitation events and runoff yields have increased in parallel to the upward flood trend. Pfister et al. (2004) summarized the impacts of climate change and land-use change in the Rhine catchment. They found no evidence for the impact of land-use changes on flood discharge, although the Rhine catchment has experienced widespread land-use changes. Petrow and Merz (2009) performed a Germany-wide flood trend analysis covering 145 gauges in Germany. They detected increasing flood trends for the period 1951-2002 for a considerable fraction of gauges in West Germany during the winter season which is the dominant season for floods in Cologne. Petrow et al. (2009) analysed the links between atmospheric circulation patterns and floods and concluded that significantly increasing persistence of flood-prone circulation patterns intensified the flood hazard during the winter season in West Germany.

Based on this evidence for an aggravated flood situation, AMS 1846-2004 was tested for an increasing trend by means of a resampling approach (Kundzewicz and Robson, 2004). The observed time series was resampled 1999 times, while the time history was destroyed: Each new time series contained the same values, however, the temporal order of the values was determined randomly. Using linear regression, a linear trend line was fitted to the observed time series and to each of the 1999 synthetic time series. Then it was tested, whether the slope of the observed time series deviates from the behaviour of the slope values of the synthetic time series. If there is no trend in the data (null hypothesis), the order of the data values should make little difference. If the observed slope lies somewhere in the middle of the generated values, it seems reasonable that the null hypothesis is correct (Kundzewicz and Robson, 2004). Since the hypothesis of no trend, versus the hypothesis of increasing trend, was rejected at the significance level of 5%, non-stationarity of AMS 1846-2004 has to be assumed.

This result leads to a dilemma: On the hand, flood frequency analysis benefits from longer time series; on the other hand, a very long time series may not be representative for the conditions for which the flood quantiles will be estimated. To account for this epistemic uncertainty due to non-stationarity, the flood frequency analysis was performed for two time periods: the complete period with reliable systematic discharge measurements (AMS 1846-2004), and the last three decades (AMS 1975-2004). The selection of the last three decades was grounded on the observation of a tendency for increased floods during the last 30 years (see Fig. 2).

A large source of epistemic uncertainty of flood frequency analysis arises due to the choice of the distribution function (e.g. Merz and Thieken, 2005). Often, different distribution functions agree well with the observed data, but give strongly differing extrapolation values. To take account of this uncertainty, seven distribution functions that are frequently used in flood frequency analysis were selected (e.g., Stedinger et al., 1992, Hosking and Wallis, 1997, Institute of Hydrology, 1999): GEV (Generalised Extreme Value), GL (General Logistic), LN3 (LogNormal 3-parameter-type), PE3 (Pearson type 3), GUM (Gumbel, GEV type 1), EXP (Exponential) and GP (Generalised Pareto). The parameters of the distributions were estimated by the method of L-moments given in Hosking and Wallis (1997).

Fig. 3 shows the fitted distribution functions for the two selected time series. In addition, empirical probabilities based on five plotting position formulas are plotted in Fig. 3. These formulas, namely Weibull, Cunnane, Hazen, Gringorden, Blom, are often used in flood frequency analysis (Stedinger et al., 1992). The distribution functions span a wide range and illustrate the epistemic uncertainty that may result from the application of different statistical models. The selection of the time series also influences the flood quantiles. AMS 1975-2004 results in higher quantiles than the longer time series.

For each of the 14 models (2 periods x 7 distribution functions), the Kolmogorov-Smirnov goodness-of-fit test was applied at significance level 5%. The test was performed for each plotting position formula, however, the choice of the plotting position formula did not influence the test result. In one case (AMS 1846-2004, EXP) the test rejected the null hypothesis that the theoretical distribution represented the data. However, conventional goodness-of-fit tests essentially test the model adequacy of the central range of the sample and not the adequacy of the tail (El Adlouni et al., 2008). They are frequently not powerful enough to discriminate between different distributions and the choice of the distribution function should not rely completely on such tests (Bobee and Ashkar, 1988).

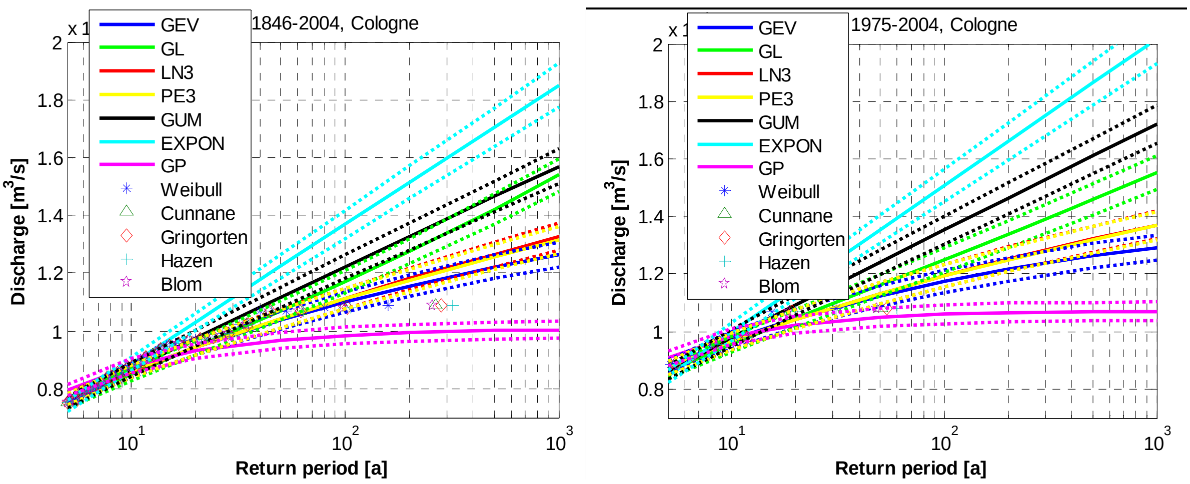


Fig. 3: Flood frequency curves and plotting positions for AMS 1846-2004 (left) and AMS 1975-2004 (right). Dotted lines illustrate +/- one standard deviation due to sampling uncertainty.

To reduce the range of epistemic uncertainty and to reject less plausible models, additional information was taken into account. One source of information was an envelope curve which is shown in Fig. 4. This envelope curve is based on flood data for catchments in Europe (Stanescu, 2002), and additional data from recent floods in Germany (in 1997, 1999, 2002 and 2005). The latter were provided by German Water Authorities. Fig. 4 shows also historic flood peaks in Cologne. The envelope curve may be considered as an upper limit for the specific discharge at Cologne, although it cannot be ruled out that a larger specific discharge could occur at Cologne.

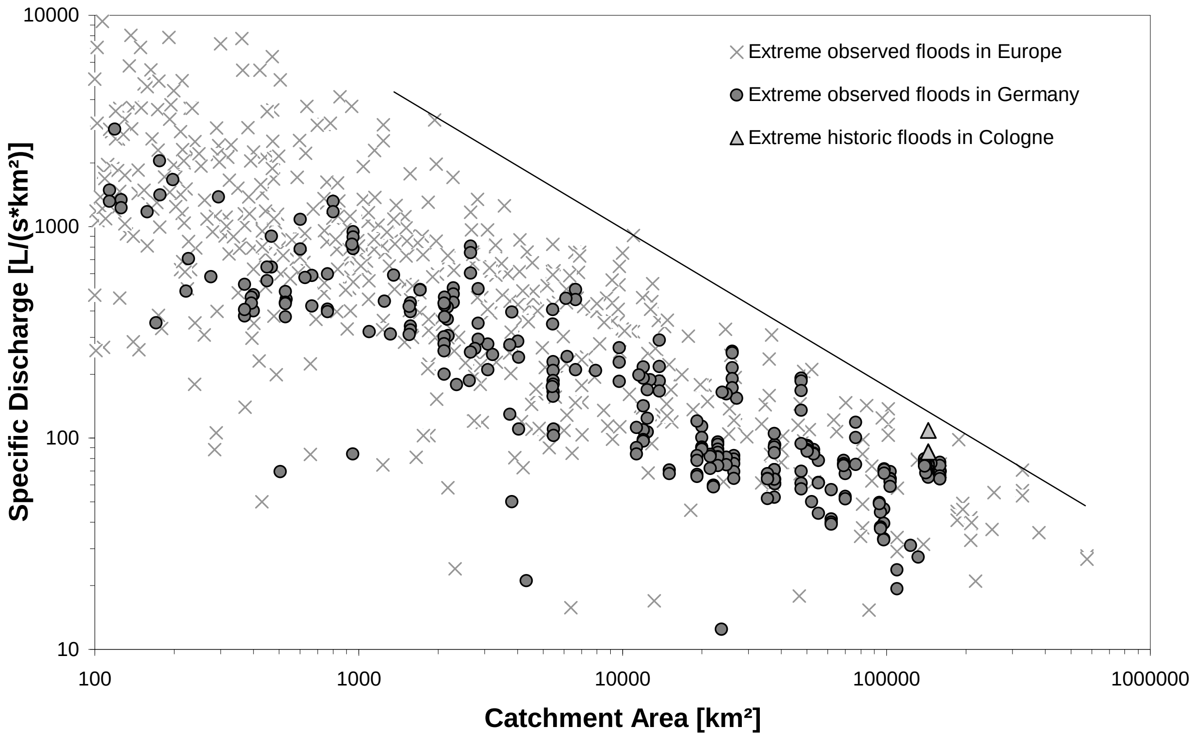


Figure 4: Specific peak discharge as function of catchment area for floods in Europe (data from Stanescu, 2002) and in Germany (data from several water authorities). Triangles show the historic flood peaks in 1342, 1374 and 1497 at Cologne (data from Krahe, 1997).

Besides the envelope curve, historical events were considered as further source of constraining uncertainty of the flood frequency curve. Krahe (1997) provides a list of historical floods in Cologne along with their water levels referred to the current gauge level. Floods in 1497, 1342 and 1374 clearly exceeded the largest flood events in the measured period. The discharges for these events were obtained using the current rating curve. Owing to the morphological and hydraulic changes in the river bed these discharges are very uncertain.

In order to assign a return period to these historic events the data gaps between the historic events and the continuous measurements have to be filled. In DVWK (1999) it is assumed that the statistical properties of the continuously measured data are representative for the whole time period. Therefore, the data gaps are filled by G times the flood events in the observed discharge series that undershoot the lowest historic flood water level. The factor G is determined by (DVWK, 1999):

$G = (N1 – M1)/(N2-M2) +1$

with:

N1:	Time period between the first historical event and the start of measurements
M1:	Number of historical events with water level ≥ $HISTFLOOD_{min}$
$HISTFLOOD_{min}$:	Lowest water level of historical event
N2:	Time period with measurements
M2:	Number of observed events with water level ≥ $HISTFLOOD_{min}$

Taking into account measurements from 1846 to 2004 , the first historical flood event in 1342 and $HISTFLOOD_{min}$ of 9.73 m, a factor G = 4 results. Accounting only for the measurements from 1975 to 2004 and treating all other data like historic information results in a factor G = 25. The total composite data series of all historical floods, all measured floods that exceeded $HISTFLOOD_{min}$ and G-times all floods below $HISTFLOOD_{min}$ was then used to estimate the empirical probabilities of three highest historic events by different plotting-position formulas (Weibull, Gringorden, Cunnane, Median, Blom and Hazen) given in Stedinger et al. (1992). The results are summarized in Tab. 2.

Furthermore, another approach for estimating the 1000-year was applied. Since flood frequency analysis is very uncertain for high return periods, Kleeberg and Schumann (2001) proposed a standard procedure for estimating discharges of return periods of 1000 years and more. Based on data from 1169 discharge gauges, they recommended a Pearson type III distribution with a maximised skewness of 4, which was found to be exceeded at 11 of the analysed gauges, i.e. in only 1 % of the analysed data. Therefore, this procedure prevents an underestimation of the 1000-year (Kleeberg & Schumann, 2001). To include the characteristics of the observed discharge series, they proposed the following approach:

$$HQ_{t2} = MHQ + (HQ_{t1} - MHQ) * k_{t2}/k_{t1},$$

where HQ_{t2} is the annual flood with return period $t2$, MHQ is the mean annual flood based on the observed series, HQ_{t1} is the 100-year-flood estimated by Pearson type III with statistical moments of the observed series, and k_{ti} is the parameter of the Pearson type III distribution with the maximised skewness of 4 and the exceedance probability according to $t1$ and $t2$. With this approach and the observed data series AMS 1846-2004 and AMS 1975-2004 the

1000-year flood at Cologne was estimated to be 15490 m³/s and 16090 m³/s, respectively (Tab. 2).

Table 2: Estimation of extreme floods at Cologne/Rhine

Return period [a] AMS 1846-2004	Return period [a] AMS 1975-2004	Discharge [m^3/s]	Data; method
204 - 244	225 - 269	12380	Flood 1497; method of DVWK (1999)
306 - 407	337 - 449	12440	Flood 1342; method of DVWK (1999)
612 - 1222	674 - 1346	14680	Flood 1374; method of DVWK (1999)
1000	---	15490	Method of Kleeberg and Schumann (2001) for AMS 1846-2004
---	1000	16090	Method of Kleeberg and Schumann (2001) for AMS 1975-2004
---	---	17000	Envelope curve shown in Fig. 4

Fig. 5 combines the estimates based on the systematic measurements (AMS 1846-2004, AMS 1975-2004) and on the additional information compiled in Table 2. Among the 14 models (2 periods x 7 distribution functions), five models were discarded, either due to rejection by the Kolmogorow-Smirnow test (AMS 1846-2004, EXPON) or, more importantly, by comparing their plausibility with the plotting positions and with the additional information of Table 2. Although the information in Table 2 may only be considered as indirect evidence, it helps to constrain the uncertainty. The remaining nine flood frequency models were kept. They cannot be ruled out from the comparison with the systematic flood data and they fit plausibly to the indirect evidence of Table 2. To obtain a best estimate, a weighted average of all plausible models was calculated. The weights were chosen according to the likelihood value of each frequency curve, given the observed flood data.

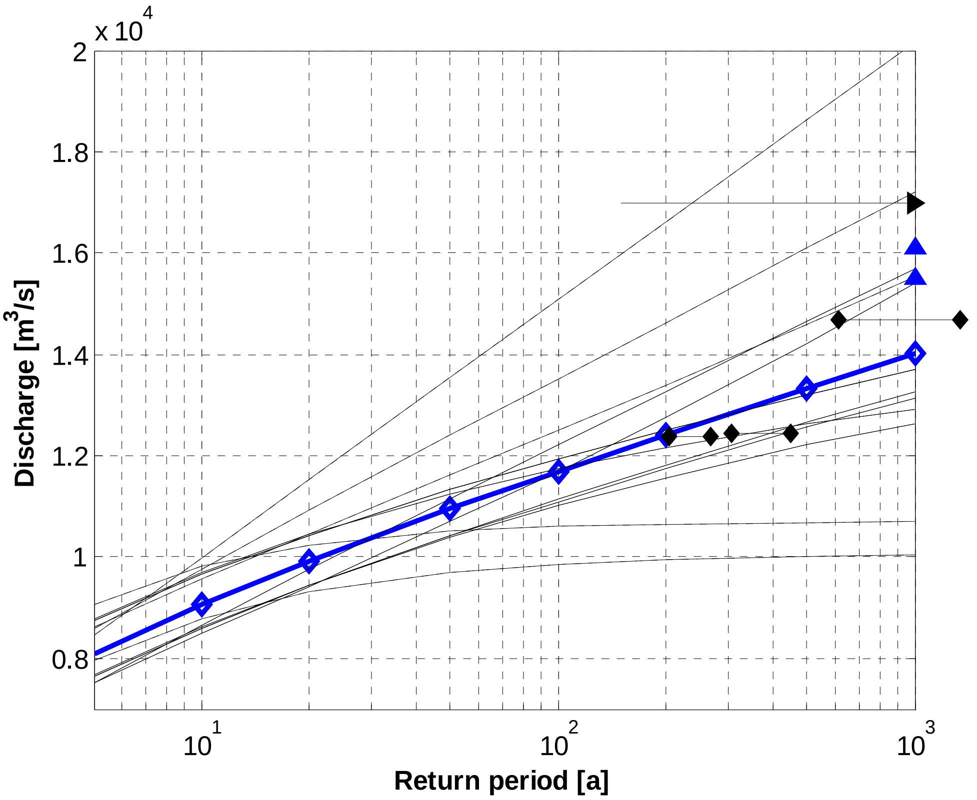


Fig. 5: Flood frequency curves and additional information from Table 2. Black solid lines show the flood frequency models that are assumed to be plausible models, black dashed lines show discarded models, and the blue line shows the best estimate. The arrow indicates the value derived from the envelope curve, the blue triangles the method of Kleeberg and Schumann (2001), and the horizontal bars the three historical floods.

There are other sources of epistemic uncertainty that are not considered in the further analysis, namely the sampling uncertainty and the choice of the parameter estimation method. The analysis of these uncertainties showed that they are of minor importance compared to the selection of the time period and distribution function. Fig. 3 illustrates sampling uncertainty which is considered by the variance $Var(q_T)$ of the flood quantile q_T. According to Stedinger et al. (1992), it is assumed that q_T follows a normal distribution with mean q_T and variance $s^2(q_T) = \frac{s_{AMS}^2}{n}\left[1 + K_T\, C_{SX} + \frac{K_T^2}{4}\left(K_X - 1\right)\right]$, where n is sample size of the discharge series AMS, s_{AMS} and $\overline{q}_{AMS}$ are the standard deviation and the mean of the discharge series AMS, respectively, K_X is the kurtosis, C_{SX} is the coefficient of skewness, and $K_T = \frac{q_T - \overline{q}_{AMS}}{s_{AMS}}$.

The observation that sampling uncertainty and choice of the parameter estimation method play a minor role is in line with Bardossy and Markovic (2002) who analysed the effects of different sources of epistemic uncertainty on the flood frequency for a number of gauges in the Rhine catchment.

4.2 Inundation estimation

For transforming flood discharges of certain return periods into inundated areas in the City of Cologne, two models were available. One model (in the following called DFNK) was developed by the authors on the basis of scenarios provided by MURL (2000; see Grünthal et al., 2006). The results of the second model (called HWSZ) were provided by the Flood Defence Centre of the City of Cologne. The HWSZ model was developed by the engineering company Rodriguez & Zeisler, Wiesbaden.

The first and identical step of the two models is the transformation of river discharge values into water levels at the gauge Cologne. To this end, the rating curve for the gauge Cologne, provided by the Flood Defence Centre, was used. Since measured pairs of water level and discharge were only available up to a discharge of 10656 m³/s and a water level of 10.61 m, the rating curve was extrapolated to extreme water levels that were necessary for a thorough risk analysis. By the methods of least squares, the function $Q = c\,(h+a)^b$ was fitted to the measurements, where Q is discharge, h is gauge water level, and a,b,c are coefficients (Mosley and McKerchar, 1992). Data and function correspond very well. Since the original river valley around Cologne is a slowly rising U-shaped valley, the extrapolation was assumed to be a good approximation for the unmeasured range of discharges and water levels.

The second step consisted in transforming water levels at gauge Cologne into inundation areas. For the DFNK model, water levels were overlaid with a digital elevation model (DEM) assuming the horizontal water surface to be perpendicular to the flow direction. A typical inundation scenario is shown in Fig. 6. This GIS-based approach builds on several assumptions and may yield unsatisfactory results, e.g., in case of high flow velocities and strong dynamic effects which may corrupt the assumption of horizontal water surface perpendicular to the flow velocity. Frequently, the flood extent is overestimated for lowland rivers since the methodology does not take into account the available water volume in the river system and hydraulic conditions of the floodplain. An overestimation may also occur if local depressions that are not connected with the main river are not excluded. Further, it may be important that hydraulic controls in the floodplain, such as embankments and elevated roads, are represented in the DEM. The DFNK model is based on a 25 m DEM which does usually not include such hydraulic controls. However, the major flood defences (dikes and flood walls) were considered in the DFNK model.

The second model HWSZ used FloodArea, a simplified 2-dimensional hydrodynamic model integrated in a GIS environment (Geomer, 2009). FloodArea simulates the propagation of flood water across the floodplain by using the Manning equation to calculate the flow between cells of an equidistant grid. It uses an explicit numerical scheme. To reduce the CPU time, FloodArea works with a time step adaptation, i.e. the time step is modified during the simulation depending on the current hydraulic gradients. The HWSZ model applied FloodArea on a very detailed Lidar-derived DEM with 5 m resolution including buildings and a digital model of the subway (Fig. 6). Further flow-influencing structures, such as culverts, were mapped and additionally included. Flood defences were not taken into consideration in the model. Inundation areas were assigned to certain river water levels by assuming a synthetic flood wave with a typical increase of discharge values for the Rhine River at Cologne.

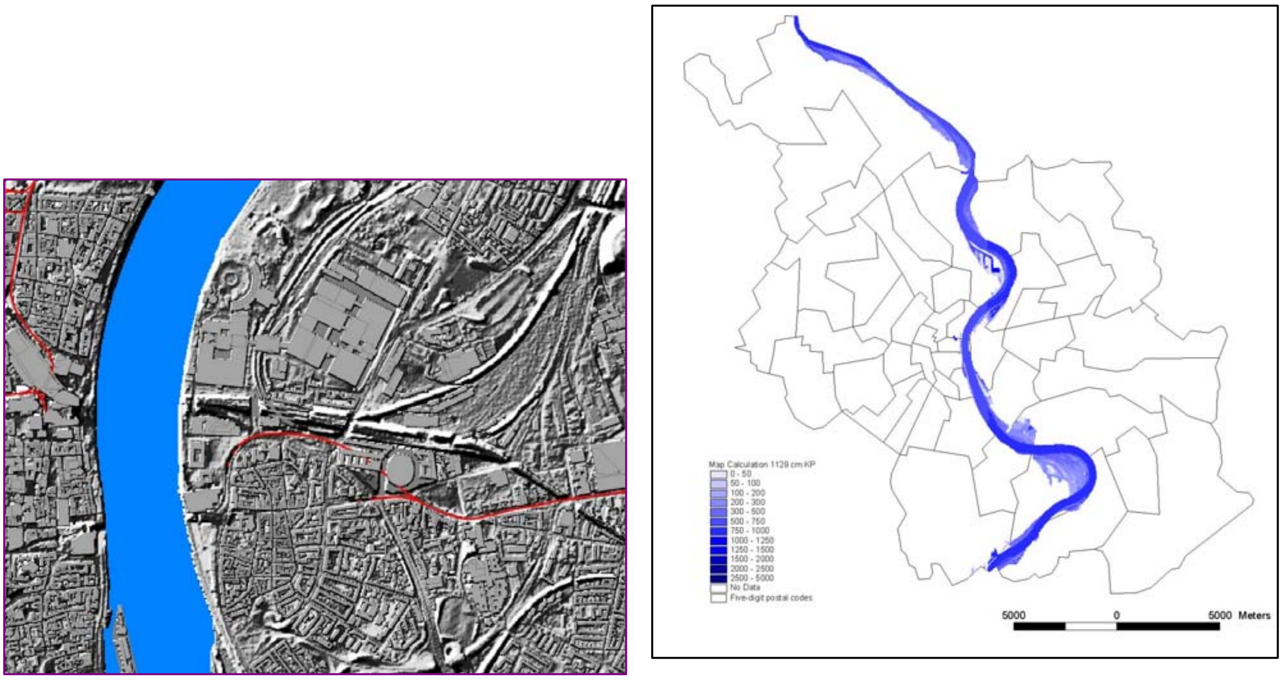


Fig. 6: High resolution DEM underlying the hydraulic model HWSZ (left) and inundation scenario of the model DFNK for water level of 11.29 m at gauge Cologne (bottom).

Fig. 7 plots the total inundated area as a function of the gauge water level. Large differences exist between the two models. Below a gauge water level of 12 m, the DFNK model yields smaller inundation extents. This can be explained by the consideration of major flood defence measures. Above 12 m, the situation is reversed. In this water level range, the flood defence measures are overtopped and assumed to fail, and they do not play any role in the calculation of the flood extent. Here, the coarseness of the DEM and the simplifying assumptions of the inundation estimation, in particular the negligence of the dynamic flow process, result in an overestimation of the flood extent of the DFNK model.

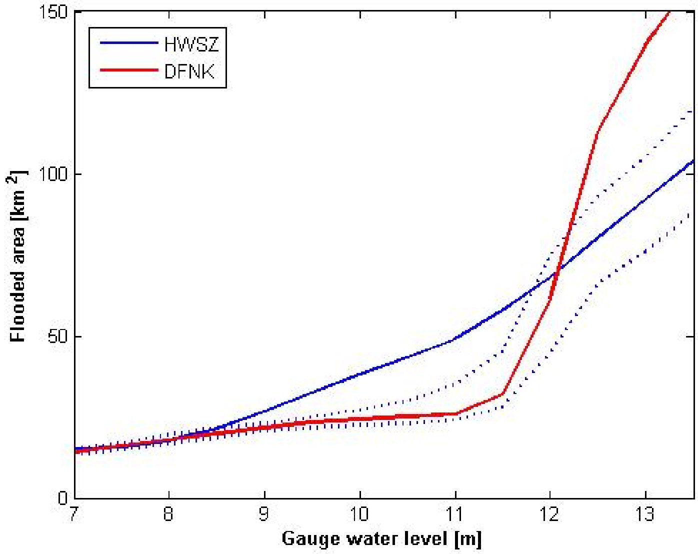


Fig. 7: Relationship between flooded area in Cologne as function of gauge water level for the two hydraulic models. The dotted lines represent the uncertainty band attached to the best estimate (DFNK for water levels below 12 m; HWSZ for water levels above 12 m).

Unlike the approach for the flood frequency estimation, where a number of different models were appraised as plausible and were, hence, selected to represent the uncertainty, both hydraulic models have severe shortcomings. On the one hand, the GIS-based DFNK model uses a coarse DEM and overestimates the flood extent for river water levels above approx. 12 m. On the other hand, the HWSZ model does not consider flood defences and leads to an overestimation for water levels below approx. 12 m. Therefore, the estimate for the module inundation estimation was decided to be a mixture of both models: for water levels below 12 m, DFNK was used; for levels above 12 m, HWSZ was used. In addition, an uncertainty band was assigned to this best estimate to represent epistemic uncertainty. Below 12 m river water level, the inundation extent is limited by the flood defences. Therefore, the uncertainty of the crude DFNK model should be rather low. Above 12 m, the 2-dimensional HWSZ model, based on very detailed topographical information, should deliver a good representation of the true inundation extent with rather low uncertainty.

Although the DFNK model considers the effect of major defence systems, the failure of flood defences is taken into account in a simplified way, namely by assuming that flood defences do not fail for water levels below their crest, and do fail completely for water levels above their crest. Failure of defences is usually not such a distinct threshold process. For example, dikes may fail by piping in the dike foundation at river water levels much below the dike crest. Recently, progress has been made in considering defence failure by means of fragility curves which give the probability of failure for a specific defence system as function of the system load (e.g. Gouldby et al., 2008). We did not explicitly consider defence failure, since the defence systems in Cologne were very well maintained, and we expected that failure probability at water levels below the crest was small. However, in determining the uncertainty bounds of the inundation model, this negligence was implicitly accounted for.

4.3 Damage estimation

In this study, damage estimation is restricted to direct financial damage at residential buildings. The damage estimation consists of two steps, (1) assessing the property values that are affected by a given inundation scenario, and (2) estimating the damage ratio. The damage ratio is the flood damage related to the total building value. To account for epistemic uncertainty, different damage ratio models were applied. No data were available for the assessment of the uncertainty of the assets. Therefore, this source of uncertainty had to be neglected. A rough comparison of asset assessment methods from the insurance industry and from governmental guidelines revealed that a factor of 2 might occur during asset estimations.

In total, six different models – three depth-damage-functions as well as three variants of the Flood Loss Estimation MOdel for the private sector FLEMO – were considered as candidates for damage estimation. All models have in common that they are meso-scale models, i.e. damage is not estimated for single buildings, but for land cover units that represent settlement areas. To estimate property values, the total asset value of all residential buildings in Cologne was taken from Kleist et al. (2006). Since only the total sum was provided, the assets were disaggregated on the basis of the CORINE land cover data 2000 by means of a dasymetric mapping approach that is outlined in Thieken et al. (2006). A damage ratio was determined for each inundated grid cell. Then, each ratio was multiplied by the specific asset value that was assigned to the corresponding grid cell.

Three different depth-damage functions were used, which have been applied in flood action plans or risk mapping projects in Germany. In the first model (MURL, 2000), the damage ratio to buildings is given by a linear function $y = 0.02x$ where y is the damage ratio and x the water level given in meter. For water levels of more than 5 m the damage ratio is set to 10 %. In the second model (ICPR, 2001), damage of residential buildings is estimated by the relation $y = (2x^2 + 2x)/100$, where y is the damage ratio and x is the water level given in meter. For some flood action plans in Germany, a third function has been used: $y = (27 \sqrt{x})/100$, where y is the damage ratio and x is the water level given in meter (HYDROTEC, 2001).

Although such depth-damage functions are the standard approach to assessing urban flood damage, estimations based on depth-damage functions may have a large uncertainty since water depth and building/land use only explain a part of the data variance (Merz et al., 2004). Therefore, the rule-based Flood Loss Estimation MOdel for the private sector FLEMO that accounts for more damage-influencing factors was developed. The model is based on a survey of 1697 private households that were affected by a flood in August 2002. In FLEMO, damage ratios were derived for five classes of inundation depths, three building types and two categories of building quality. In an additional modelling step (termed FLEMO+), the influence of the contamination of the floodwater and the precaution of private households are considered by scaling factors (Büchele et al., 2006). In addition, a scaling procedure was developed for model applications on the meso-scale (Thieken et al., 2008): By means of census data and cluster analysis the mean building composition and the mean building quality were derived per postal zone (and per municipality) in Germany. For each postal zone in Cologne, a mean damage model was set up by weighting the damage ratios of the three building types by the mean percentages of these building types in each zone considering all water level classes as well as the mean building quality in the zone under study.

The model was used in this study in three different ways: First, the meso-scale model FLEMO was used in its first model stage as described above. In the second and third variant, the effects of contamination and precaution were considered by a best case and a worse case. In the best case, very good precaution and no contamination of the floodwater were assumed (FLEMO+ P2C0), resulting in a scaling factor of 0.41. No precaution in combination with heavy contamination (FLEMO+ P0C2) and a scaling factor of 1.58 were used in the worst-case scenario.

Fig. 8 illustrates the differences of the six damage models for the inundation scenarios simulated by the HWSZ model. The variants of the new model FLEMO are within the range of the other three damage functions. However, the advantage is that FLEMO takes into account the building characteristics of the area under investigation. The six damage models span an unrealistically broad range. Especially for rather frequent floods (return period smaller approx. 10 years; river water level smaller approx. 9.5 m), four damage models yield very high damage in the order of magnitude of €100 million. Therefore, it was assumed that these four models were not plausible and were discarded. One model from the FLEMO family as well as the model from MURL (2000) were kept in the further analysis. There were additional arguments for these two models. The MURL model was deemed appropriate, since it is a damage model that was specifically developed for the Lower Rhine area. The decision to use one FLEMO model was also based on the fact that FLEMO uses more information on the damage situation than the depth-damage functions – especially about contamination and private precaution. Among the three FLEMO variants, the version FLEMO+ (P2C0) seemed the most appropriate for the application in Cologne. The high level of private precaution became evident during the flood in January 1995. Despite of the fact that the flood reached a very similar water level to the flood in 1993, the total amount of damage was cut down by almost 50%. Owing to continuous risk awareness campaigns, it has to be assumed that flood awareness is high. The flood authorities of the City of Cologne are well-known in Germany for their many activities to increase flood awareness and flood prevention in Cologne. Further, there is a citizens' initiative (Bürgerinitiative Hochwasser Köln-Rodenkirchen), which is also very active in distributing information on floods and in strengthening people's preparedness.

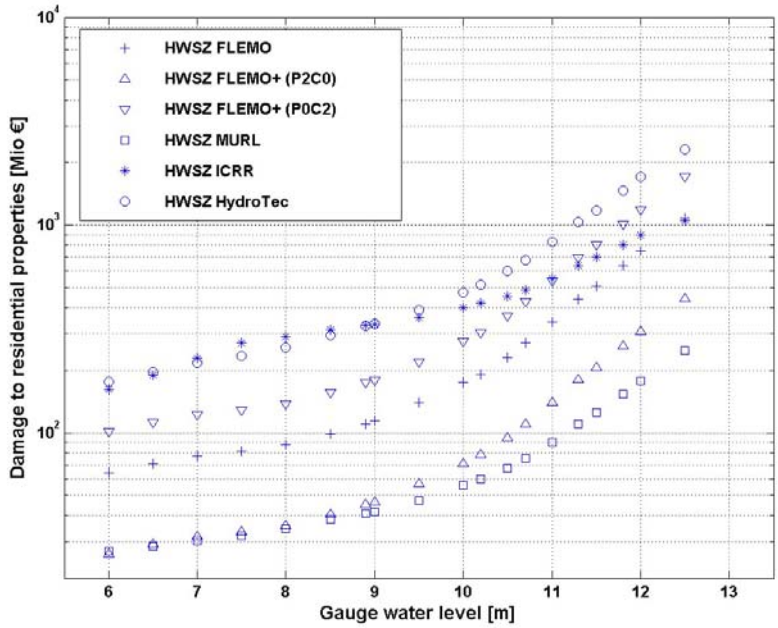


Fig. 8: Damage to residential properties as function of gauge water level for the HWSZ model and six damage models. The two lower damage functions (FLEMO+ P2C0, MURL) were rated as plausible damage models.

4.4 Result: Risk curve and uncertainty bounds

In the next step all parallel models of the three modules, which were considered to be plausible descriptions, were combined. In total, 36 models resulted from this combination (9 flood frequency curves x 2 inundation extent models x 2 damage models). Each model provides the flood damage for return periods from T = 10 to T = 1000 years. The results of the 36 models are plotted in Fig. 9 (also called spaghetti diagrams, Visser et al., 2000).

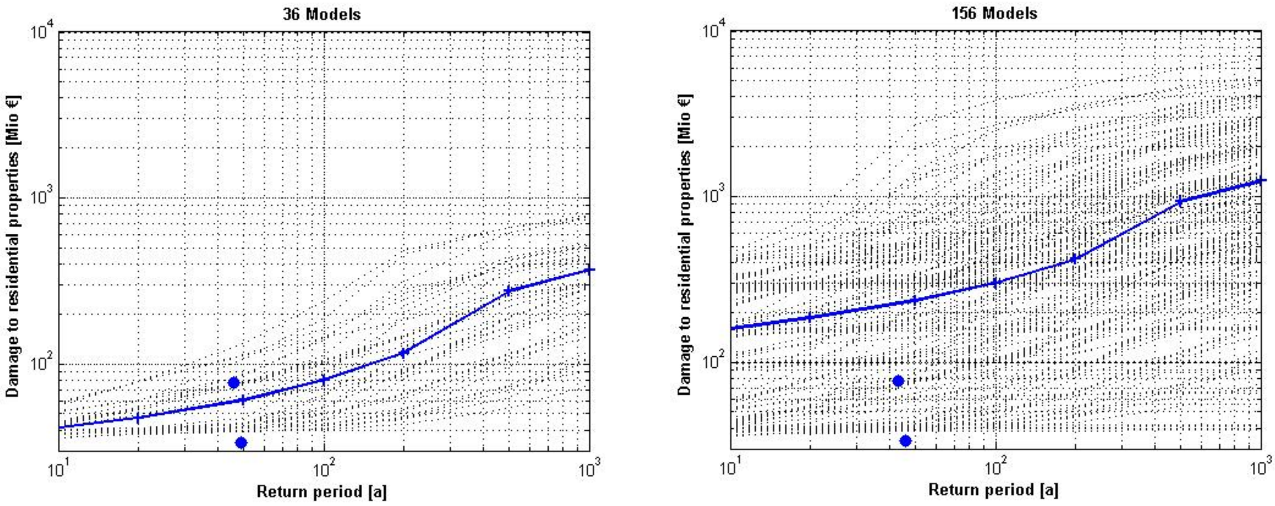


Fig. 9: Risk curve (blue solid) for the City of Cologne and associated uncertainty (black dotted), using 36 models (left). Same for 156 models including non-plausible models (right). The points show approximate estimates of the flood damages that occurred in 1993 (€76.7 million) and 1995 (€33.2 million).

Besides the uncertainty range provided by the combination of plausible models, Fig. 9 shows also the best estimate risk curve. It is a combination of the best estimate models of the three modules. For the flood frequency module, the best estimate was obtained by weighting all plausible models. The weights were chosen according to the likelihood value of each frequency curve, given the observation flood data. Since there were no data on inundation extent and very scarce data on damages for past floods, the weights for the plausible models of the modules inundation estimation and damage estimation had to be assigned by expert judgement. Taking into account the shortcomings of the two inundation models in different water level ranges, the model weights of the inundation models were linked to the water level. For the damage estimation both models deemed plausible obtained equal weight. The best estimate risk curve represents aleatory uncertainty, whereas the range of parallel models around the risk curve represents epistemic uncertainty.

As it is usually the case in flood risk assessments, there were not much data available to assess the plausibility of the risk estimates. The only available information on flood damage in Cologne were the very rough estimates of the direct damage for the floods in 1993 and 1995. The best estimate risk curve is between these damage estimates, indicating that the risk estimate is plausible, at least for return periods around 50 years. The uncertainty range is rather large. For example, for the 100-year flood, the maximum uncertainty ranges from €40 million to more than €200 million. Fig. 9 also illustrates the effect of discarding non-plausible models. The additional information that was introduced in the flood frequency estimation and the exclusion of damage models that yielded unrealistically high damages (1) provided a plausible risk curve and (2) narrowed considerably the uncertainty range.

4.5 Relative role of uncertainty sources

When different modules are combined into an overall result, it would be good to have information on the relative role of the different uncertainty sources. The concept of parallel models provides a simple way to quantify the relative role (Visser et al., 2000). Our risk estimates are composed of three modules. The contribution of a module i to the maximum uncertainty range $MUR_{c,T}$ of the complete chain of modules as function of return period T is calculated as follows (procedure slightly modified from Visser et al., 2000):

1. We calculate $MUR_{c,T}$ whereas all modules take into account all models that are considered as plausible description. For a specific return period T the maximum uncertainty range is given by subtracting the minimum from the maximum value.
2. We calculate the reduced uncertainty range $UR_{i,T}$, by using for module i the best estimate model, while all other modules are in full operation. The difference between $MUR_{c,T}$ and $UR_{i,T}$ may be seen as the uncertainty, caused by the module that was set to

$$R_{i,T} = \frac{MUR_{c,T} - UR_{i,T}}{MUR_{c,T}} \cdot 100\,\%.$$

3. We repeat step 2 for all modules.

Fig. 10 shows the result of this procedure applied to the three modules of the flood risk analysis of the City of Cologne. It is obvious that the damage module contributes a small share to the total uncertainty. In addition, this share is almost constant throughout the considered range of return periods. Of more importance for the total epistemic uncertainty are the modules flood frequency estimation and inundation estimation. Their shares are changing across the return period range. For return periods below 80 years the uncertainty of the inundation estimation contributes the largest share to the total uncertainty, whereas above 80 years, the total uncertainty is dominated by the uncertainty of the flood frequency analysis.

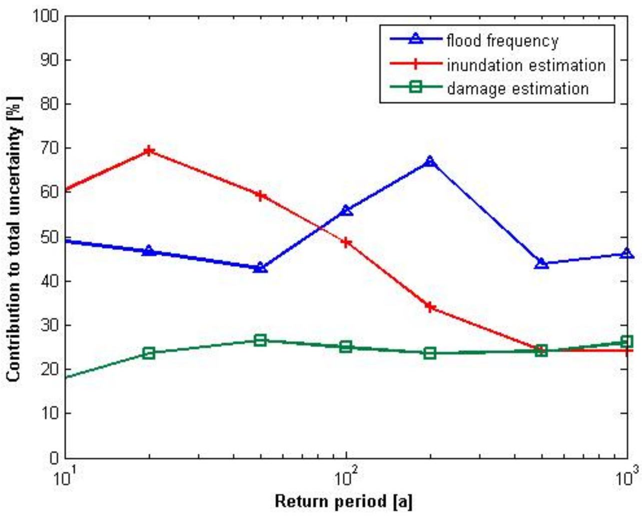


Fig. 10: Relative contribution of the three modules to the total maximum uncertainty range as function of return period.

5 Discussion and conclusions

Traditional validation approaches are based on the comparison of simulation results with observations. Flood risk analyses belong to those situations, where observations are not available to apply traditional validation approaches. Either the important events of a risk analysis, i.e., events with very small exceedance probabilities, have not occurred during the observation period. Or, if they occurred, information on such events is crude due to the difficulties to measure extremes, or the system likely has changed so that past extremes may only be partially representative for the situation for which the risk analysis is performed. Further, it has been shown that best estimates, i.e., estimates that are based on judgement and do not consider uncertainty aspects, may not really be good. There is a clear tendency (of experts and laypersons) to overestimate their knowledge (Hammitt and Shlyakhter, 1999). Given these problems of validation and over-confidence, an uncertainty analysis may improve a flood risk analysis. It identifies weak points in the risk analysis (e.g., which assumptions dominate the result?), and guides efforts for assembling further information and improving the risk analysis (e.g., what are the most valuable data for constraining uncertainty?).

We propose to distinguish between aleatory and epistemic uncertainty when performing a flood risk assessment. The risk curve, i.e., flood damage versus probability, represents aleatory uncertainty, and the uncertainty bounds around the risk curve represent epistemic uncertainty. The distinction between these two types of uncertainty reveals the part of the uncertainty that can be reduced from the non-reducible (aleatory) part. A difficulty with this approach is the need to classify uncertainty sources as aleatory or epistemic. This paper considered the occurrence of flood peaks as random (aleatory) process; all other uncertainties were classified as epistemic. This decision was based on the expected dominance of this random influence compared to other random effects. Additional aleatory elements could have been included in the risk analysis. For example, the damage to a certain building in a given flood situation is affected by many influences. A large floating object, such as a car or a tree trunk, may severely damage one house and may, by accident, spare the adjacent building. Currents and high flow velocity areas may occur very localized and may scour the foundation of one building leading to severe structural damage or total collapse, whereas a neighbouring building may only be inundated. Fast and effective help by disaster management and neighbours may secure a building against water inflow and may prevent large damage, whereas in a similar flood this external help may not be available. Such spatial-temporal variations in damage patterns contain large random influences, and, as a consequence, could be modelled as aleatory uncertainty. However, the damage module in this study does not assess flood damage at the micro-scale, i.e., the scale of single buildings, but at the scale of the (large) community Cologne. The aim is to estimate the mean damage for Cologne for the studied inundation scenarios. Hence, a large part of the randomness is expected to be cancelled out. However, the variation in the damage values, estimated by the City of Cologne for the 1993 and 1995 floods, shows that also at that scale some randomness occurs, since there was no deterministic model available that explains this variation. Concerning the inundation module, we were interested in an average inundation scenario for Cologne given a certain flood peak at gauge Cologne. Similarly to the damage module, the aim was not to model the range of possible inundation scenarios, influenced by random, mostly local effects, but to obtain inundation scenario that are realistic at the scale of the municipality Cologne.

Aleatory uncertainty was represented by the usual probabilistic approach, namely, the pdf of flood peaks. Traditionally, probability theory has also been used to describe epistemic uncertainty (Watson, 1994), however, with a different interpretation: probability distributions for quantities that are supposed to be inherently random represent the relative frequency of values from a specified interval, whereas probability distributions for quantities that are associated with epistemic uncertainty represent the degree of belief or knowledge that a value is within a specified interval. The appropriateness of probability distributions for describing epistemic uncertainty has been questioned. Ferson and Ginzburg (1996), Hall (2003), and Helton and Oberkamp (2004) discuss this issue in detail and provide examples how the representation of epistemic uncertainty by a probability distribution may lead to erroneous conclusions. All sources of epistemic uncertainty that were considered in this paper were represented by different models. In that way, a clear separation of both types of uncertainty was maintained.

In the course of such an analysis, it has to be decided which epistemic uncertainty sources are included and which are neglected. Again, this is no clear-cut decision. There are many uncertainty sources with different relevance to the total epistemic uncertainty. In order to decide objectively about the inclusion or negligence of uncertainty sources, their contribution to the overall uncertainty must be known. Since this is not the case, this decision has to be based on expert judgement. The approach taken in this paper follows the idea of including all available models that are seen as plausible representation of the process under study. Only in cases where the contribution to the total uncertainty is expected to be of minor relevance this uncertainty source is neglected. One example is the uncertainty due to different parameter estimation methods of flood frequency analysis.

This approach of including many models is not always feasible, due to the requirements for CPU time, data, pre-processing, model setup and calibration. This study used rather simple models in order to increase the number of models considered. The opposite approach is to use sophisticated models, and as compromise, to vastly reduce the number of models, or in the extreme case, to forego uncertainty considerations completely. We tried to apply models of comparable complexity at each of the three modules, i.e. models of low complexity with reduced demand for data and resources for implementing and running them. The decision on the model complexity depends strongly on the context of the flood risk analysis. We acknowledge that in many applications more sophisticated models are required. However, they do not always warrant better results. We feel that in many cases very sophisticated process models are applied to situations whereas the available data do not justify the detail. An example is a river dyke breach scenario with a 2-dimensional hydrodynamic model when there is very scarce knowledge on the boundary conditions of the inundation process, such as breach location and time, or breach mechanism.

The uncertainty bounds for the flooding risk of Cologne are quite large, but should be a realistic representation of the reliability of flood risk assessments. The inclusion of additional evidence, such as the envelope curve, reduced considerably the epistemic uncertainty. This reduction demonstrates the potential of including additional evidence for improving risk analyses. The usage of indirect evidence in flood risk analysis is the rule, rather than the exception. An advantage of an uncertainty analysis is that the analyst formalises the use of indirect evidence. Together with a systematic study of the contribution of different uncertainty sources to the overall uncertainty, such an uncertainty analysis helps to distinguish what is known from what is assumed.

Acknowledgements

We gratefully acknowledge the provision of data by Hochwasserschutzzentrale Köln (Flood defence centre Cologne).

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