Summary of SPATE sub-project 7

The predictability of extreme floods and the quantification of related uncertainties for unobserved locations in the coming decades will be the focus of investigation for sub-project 7, "Predictability of extreme floods". Through the prediction of floods, estimates of flood quantiles and return periods at unobserved locations and/or future time periods can be better understood. The predictability subsequently describes the quantification and attribution of uncertainty. A central component of this sub-project will be the improved prediction for unobserved locations and/or future time periods in terms of accuracy and robustness. The focus lies on the distinction of flood geneses, in other words, the flood causing processes. The attribution and reduction of uncertainties is of special consideration.

The sub-project contains two phases. The first phase will handle the investigation of peak floods under the assumption of stationarity within the German federal state of Lower Saxony containing the Aller-Leine catchment. This procedure is defined as univariate and stationary flood frequency analysis. In the second phase, non-stationary processes as well as flood volume and duration will be considered. This procedure is defined as multi-variate and non-stationary flood frequency analysis. The findings of the first phase will then be generalised and validated using data from the Neckar catchment of the German federal state of Baden-Württemberg.

The first phase is divided into three work packages. The first work package focuses on data-based flood predictability. The second work package is the development of a stochastic weather generator, the output of which will then be utilised as input for the third work package, model based flood predictability.

WP0 Data preparation

Available hydrological and metrological input data will be processed as a first step. The primary study area used for the first phase is the the German federal state of Lower Saxony containing the Aller-Leine catchment. Meso-scale catchments (100 – 1000km²) with low anthropogenic influence will be selected. In order to account for scaling effects, larger sub-catchments of the Aller-Leine will also be analysed.

The German federal state of Lower Saxony has an area of approximately 48,000 km². Elevations range from sea level up to 1140 m. The annual average precipitation varies between 500 – 1700 mm and average annual temperatures range from 6 – 10°C. In relative terms, the density of stream gauges and weather stations is high.

WP1 Flood predictability from data

WP1 will focus on data-based predictability of extreme floods. The quantification of uncertainties will be exclusively based upon the hydrological input data. In order to account for the varying flood drivers, a subdivision of the data ensemble will be performed by flood type (see Cunderlik & Burn, 2002; Ouarda et al., 2006; Salinas et al., 2013 or Fischer et al., 2016).

A local univariate flood frequency analysis will be performed. Here, stationarity will be assumed in relation to observed flood peaks. Long-term runoff time series will be coupled with varying flood driving factors, such as precipitation, temperature and catchment characteristics, to help distinguish between differing flood geneses. Estimated flood quantiles for specific return periods for the entire sample will then be compared to sub-samples classified by flood drivers. To aid the comparison, classical distribution functions will be fitted for all gauges within the study area. The uncertainties of the flood prediction will be quantified using a bootstrapping process (Schendel & Thongwichian, 2015).

In the next step the above mentioned procedure is adapted to the univariate, regional flood frequency analysis. This will be based upon the well established index-flood method using L-moments (Hosking & Wallis, 1997). To achieve this, homogeneous regions within the study area must first be determined. These regions will be based upon catchment characteristics. Findings about the dominant flood causing processes will play an important role within the regionalisation. The quantification of the uncertainty will be performed as per the local flood frequency analysis. Additionally, cross-validation will be utilized to evaluate the performance.

In a last sub-step, the estimated flood quantile uncertainties will be compared with the associated driving factors. This process will confirm dominate driving factors and enable a better process understanding. One particular problem is the uncertain reference. In particular, short time series exhibit higher uncertainties due to lower sample sizes. As such, these time series should not be selected as reference series. Instead, an application of simulation methods for an objective assessment is required.

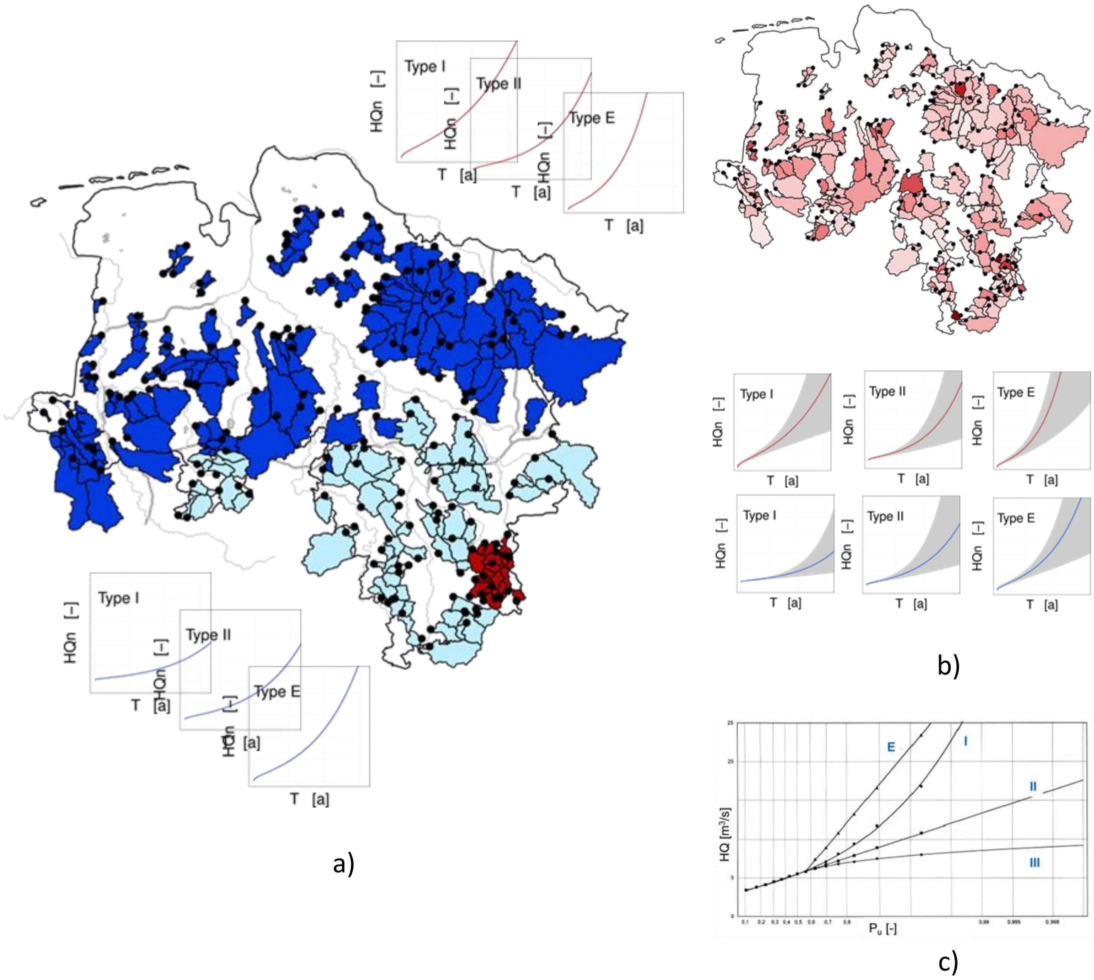


Figure 1: data-based predictability of floods: a) regional flood frequency analysis by flood type; b) Uncertainty analysis via a Monte-Carlo simulation based upon the sample extent of the observations in addition to the regionalisation; c) Summary of the regionswise, stratified distribution functions

WP2 Stochastic generation of climate input data for flood prediction

The aim of this work package is to develop a stochastic weather generator capable of simulating both space and time consistent weather variables (eg. precipitation, radiation, temperature) across a variety of spatial scales, from the lower mesoscale (10 km^2) up to the macroscale (10^4 km^2). The temporal scale will be hourly, in order to adequately simulate flood generation processes at lower scales.

In addition, the weather generator will be conditioned upon climate variables, allowing the model to be applied across a range of possible future climate scenarios.

The core of the weather generator will be based upon the stochastic space-time rainfall model developed previously by the LUH (Callau & Haberlandt, 2017). Previous applications include derived flood frequency analysis (Haberlandt et al., 2014), statistical downscaling of precipitation (Haberlandt et al., 2015) and high temporal resolution urban hydrology (Callau & Haberlandt, 2017).

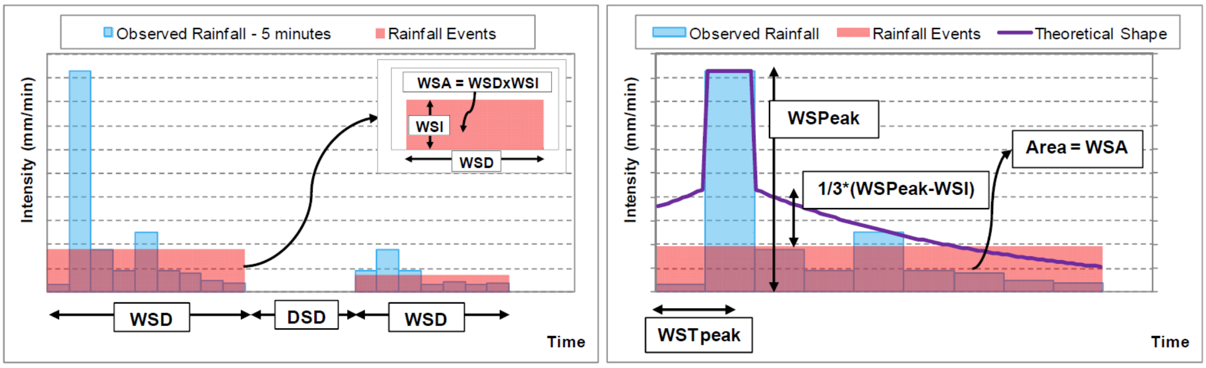


Figure 1 Schematic of the alternating renewal rainfall model of the LUH (Callau & Haberlandt, 2017)

The model is broadly based upon a two-step process, first modelling continuous rainfall time series for individual sites according to an alternating renewal process (wet and dry spells), and then applying cross-site spatial consistency via a simulated annealing approach. Interdependencies between rainfall event characteristics, for example rainfall duration to volume and event peak to average intensity, are handled using bi-variate Copula approaches. Regionalisation of model parameters using geo-statistical techniques is also possible to allow for modelling at ungauged locations.

The existing simulated annealing has been successfully demonstrated at limited spatial scales (Haberlandt et al., 2008), however new techniques will be required for an efficient model application at larger spatial scales. In order to improve performance of extreme events, it may also prove beneficial to split the model into a continuous part to simulate normal conditions, and an event based part to sufficiently model extreme events.

Other climate variables, such as temperature and radiation, will be simulated conditioned on the space-time event time series of the wet and dry state from the rainfall model. Alternatively, it may indeed prove more efficient to implement a reverse approach, whereby the rainfall model is conditioned on one or more of the other climate variables (temperature, radiation etc.). Cross correlations between the climate variables themselves and additionally precipitation will be preserved.

Different approaches for modelling are available. Parametric approaches (Fatichi et al., 2011) and non-parametric resampling from observed or simulated data (King et al., 2014) will be evaluated for both efficiency and performance.

Additional climate variables like cloudiness, humidity and wind may also be added to the weather generator according to the needs of other sub-projects. Regionalisation of the model parameters will also be investigated to allow for the generation of climate variable time series at ungauged locations. Performance of the regionalisation will be tested using cross-validation techniques.

Validation of the weather generator will be performed based on statistical characteristics and the correlations between the different modelled climate variables.

Conditioning of the weather generator on larger scale climate variables like sea level pressure and moisture fluxes is expected to improve its performance. It will allow for longer time scale oscillations and extrapolation into the future. A frequently applied strategy is to relate the weather generator parameters to circulation patterns (Burton et al., 2010). However, previous research has indicated that changes in circulation pattern frequency is unable to fully explain changes in precipitation over time (Haberlandt et al., 2015). Including additional climate variables such as temperature and moisture flux in the circulation pattern definition is expected to allow for a better explanation of rainfall. Circulation patterns will be classified using an objective fuzzy-rule based classification (Bárdossy et al., 1995). Of special focus will be climate conditions leading to extreme floods. To validate the selected approach, the performance of the climate conditioned model will be compared to the non-climate conditioned model.

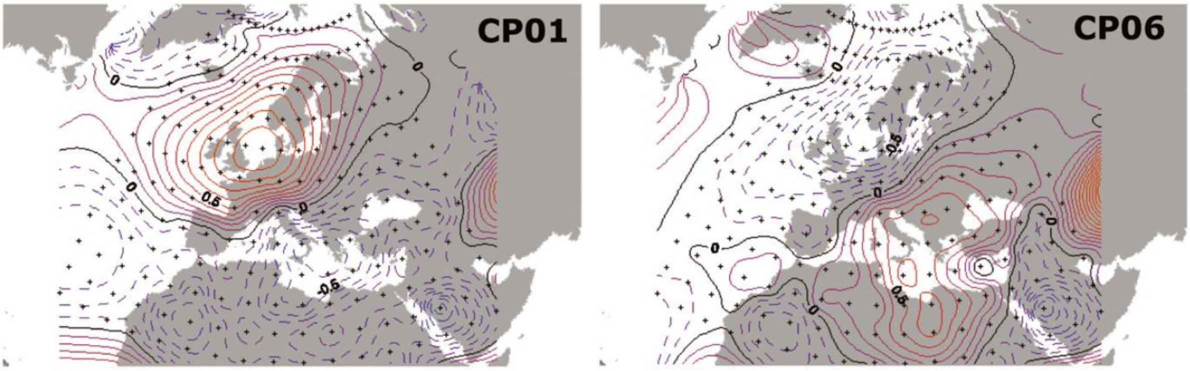


Figure 2 Examples of 'wet' (right panel) and 'dry' (left panel) circulation patterns (here, normalized sea level pressure anomalies over Europe are shown) based upon a Fuzzy-Rule classification (Haberlandt et al. 2015)

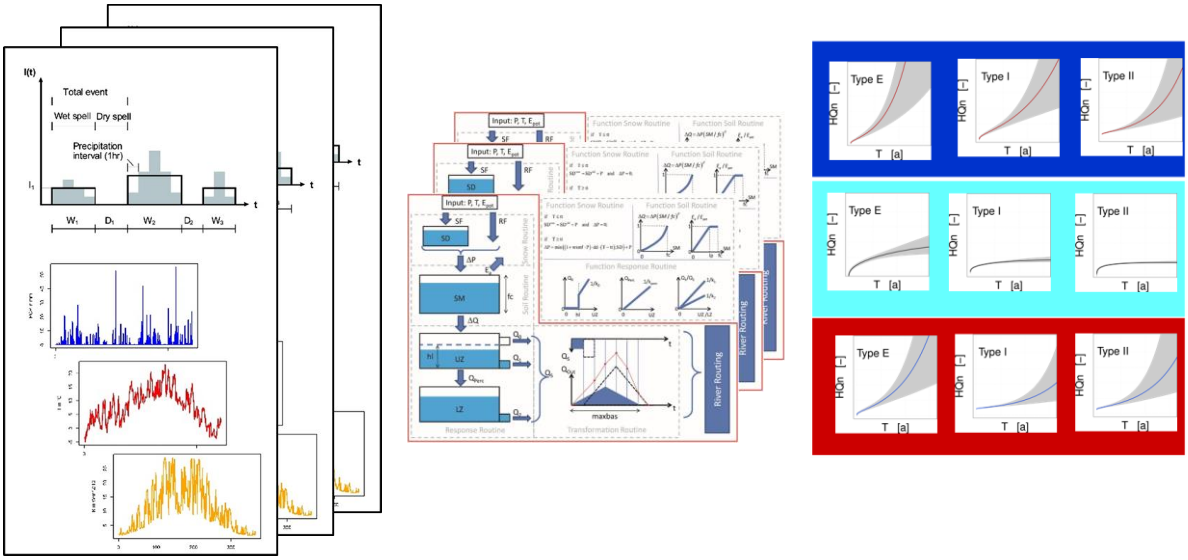
<u>WP3 Model-based predictability of floods</u>

The first step of the third work package will be the validation of the weather generator considering its suitability to varying climate data. The conceptual hydrological model, HBV-IWW, has been applied in the past for the application of derived flood frequency analysis (Ding et al., 2015 or Wallner & Haberlandt, 2015).

Individual meso-scale catchments will then be selected, modelled and evaluated, using the generated climate data as input. A simultaneous assessment of all catchments will then be undertaken, in order to asses scaling effects within the weather generator. The calibration of the hydrological model will be based on discharge statistics (Haberlandt & Radtke, 2014).

The second step will involve the generation of a reference simulation. For this, very long time series (10,000 years) of rainfall and other climate variables will be needed, as generated from the weather generator, for varying time and spatial scales. These time series will be utilised as climate input data for the hydrological model for many catchments with areas ranging from 100 to 10,000 km². Additionally, unobserved locations will be considered. The simulated discharge time series will then serve as a basis for the derived flood frequency analysis. The resulting flood quantiles and return periods will serve as a reference for the concluding uncertainty analysis.

As a last step, a Monte-Carlo simulation will then be performed to quantify the uncertainty. The assessment of hydrological model uncertainty will be based upon different hydrological model parameter sets. The complexity of the model structure will remain unchanged. The assessment of the uncertainty resulting from the driving factors will be realised through varying the parameterisation of the weather generator to create a range of possible scenario runs. The uncertainty analysis is undertaken both on an individual as well as a simultaneous basis, so that the sources of uncertainty can be ascertained. The simulated runoff of the varying scenarios will be used as the basis for the derived flood frequency analysis. These results can then be compared to the reference data. Learnings garnered relevant to flood genesis processes can be transferred from the data-based approach to the model-based approach. A comparison of the data-based and model-based prediction can then be used to detect relevant failure sources.



a) b) c)

Figure 4: Model-based predictability of floods: a) reference and Monte-Carlo simulations utilising the weather generator; b) Reference and Monte-Carlo simulations utilising the hydrological model; c) Predictability of floods utilising scenario modelling of varying parameter sets of the weather generator and the model parameterisation of the hydrological model.

Non-stationary processes will be considered in the second phase. Furthermore, a broadening of flood volumes and durations will be undertaken. In order to achieve a more generalised understanding of flood drivers, the findings will be validated against data from the Neckar catchment. This will allow the findings of the first phase to be tested and modified as necessary.

<u>In summary, the following core points will be assessed:</u>

- Improved flood prediction through a broadened process understanding due to catchment characteristics, flood types, atmospheric conditions etc.
- Multi-scale hydrological modelling for the provision of derived flood frequency analysis
- The significance of extreme floods in comparison to ordinary floods
- Optimal combination of data and model based approaches for flood prediction

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