

Data- and Predictive Uncertainties in Flood Forecasting: How to Decide under Uncertain Information

D.E. Reusser¹, G. Bürger¹, E. Zehe², and **A. Bronstert**¹

1 University of Potsdam , Institute for Geoecology

2 TU München, Institute for Water and Environment

(dreusser@uni-potsdam.de)

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- Uncertainty often missing in (German) flood prediction systems
- May affect decisions taken. e.g. Reservoir management
- Balance between information content and ease of communication
- Exceedence probabilities and corresponding flood loss estimation





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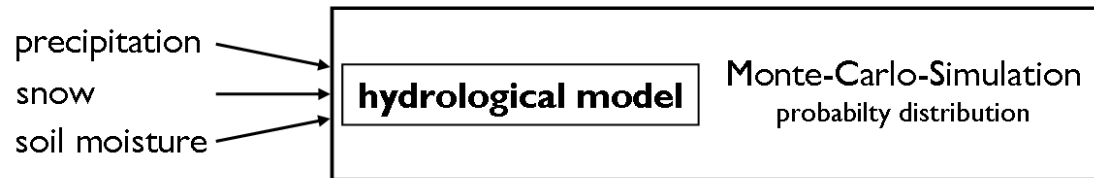
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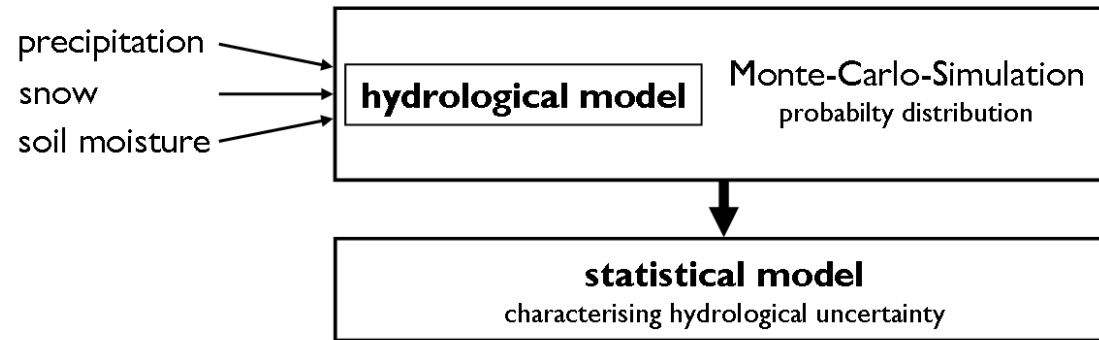
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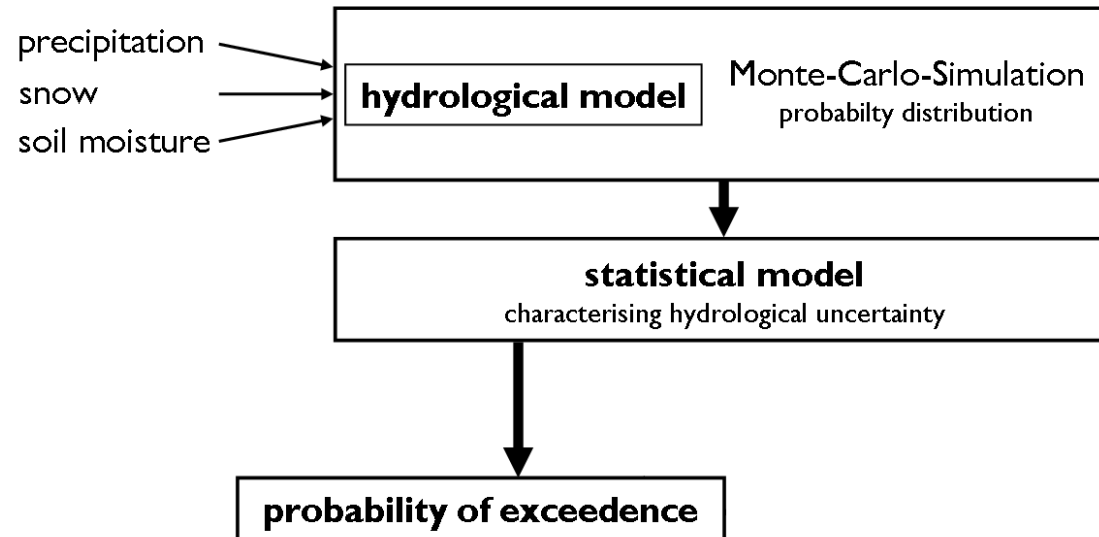
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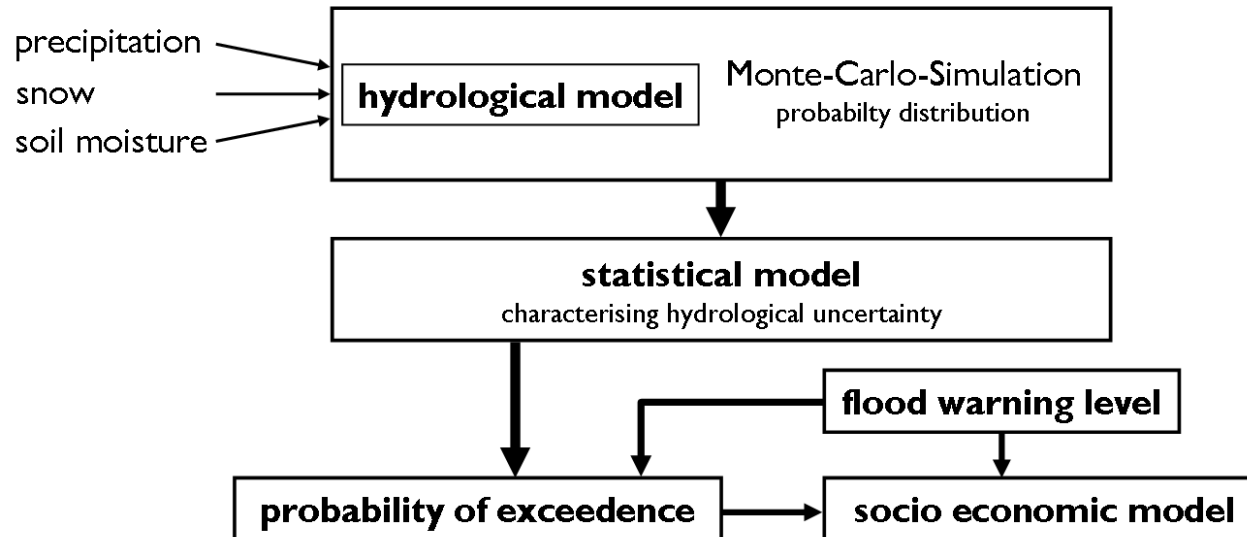
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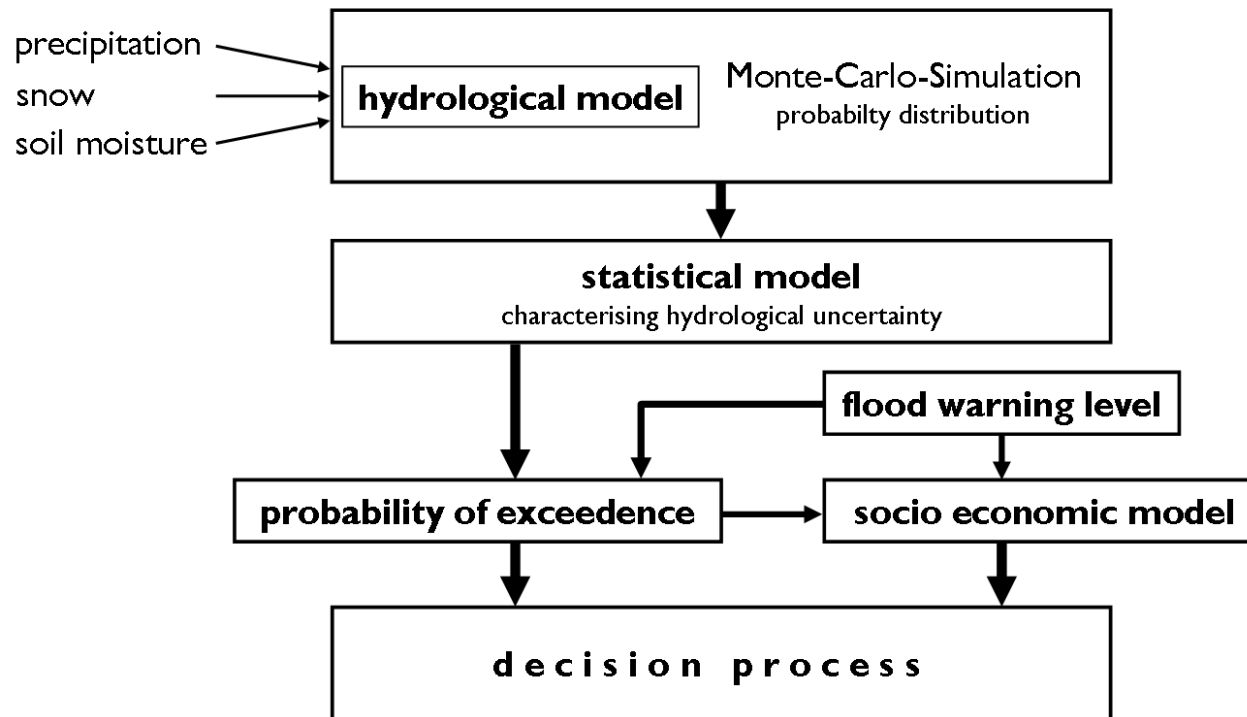
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■ Initial states

◆ Snow

◆ Soil Moisture

■ Rainfall predictions

◆ Radar now-casting

◆ COSMO-DE (Previously LMK)

◆ Medium Range: ECMWF Ensemble





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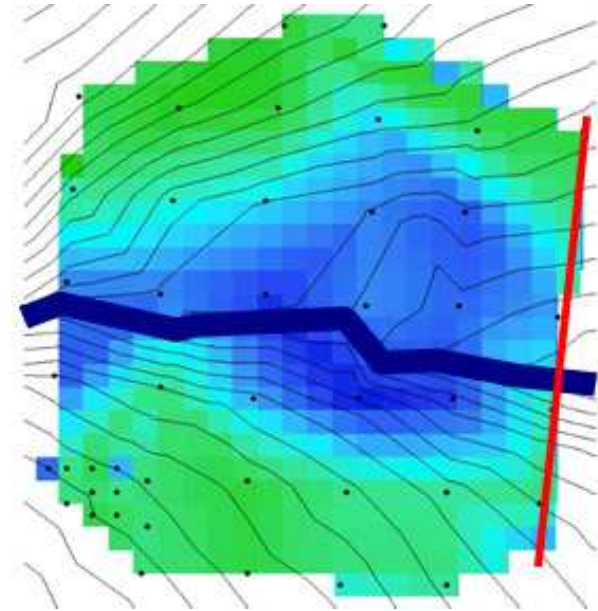
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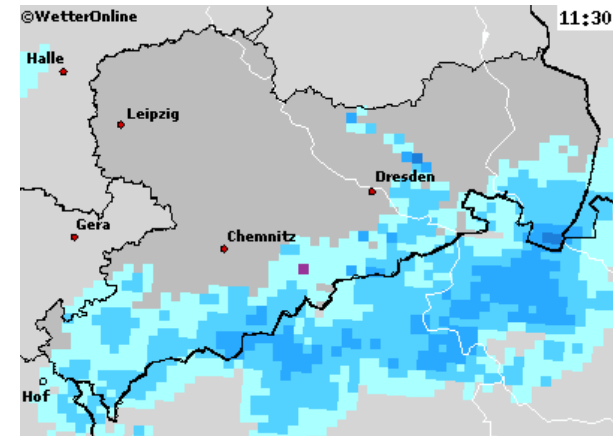
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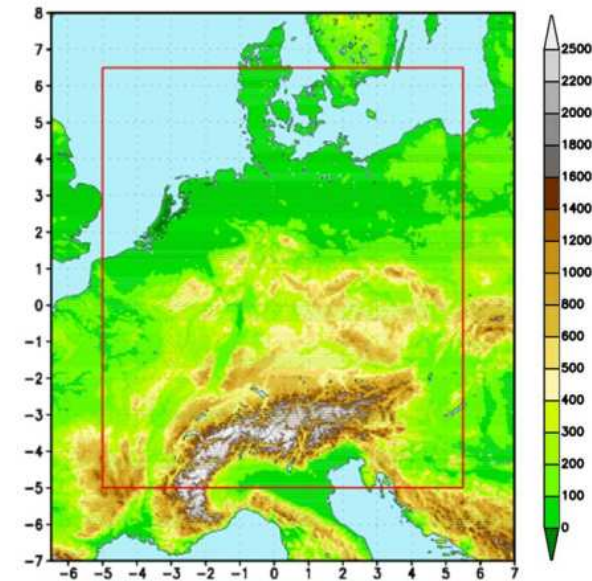
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Source: www.dwd.de



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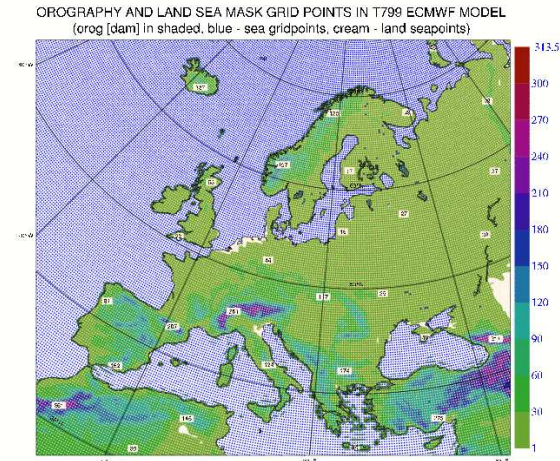
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Source: www.ecmwf.int

Example: Medium range forecast

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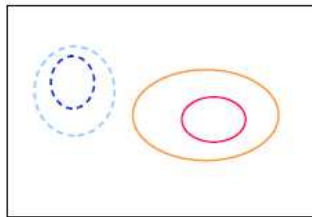
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- Downscaling
- ECMWF ensemble forecasts
- Linear regression between circulation patterns and local weather
- Constraint: Preserving local covariance structure

global/NA circulation g
(Z_{500} , T_{850} , Q_{850} , ...)



transfer function f

$$g \xrightarrow{f} l$$
$$l = f(g) + \varepsilon$$

local weather l



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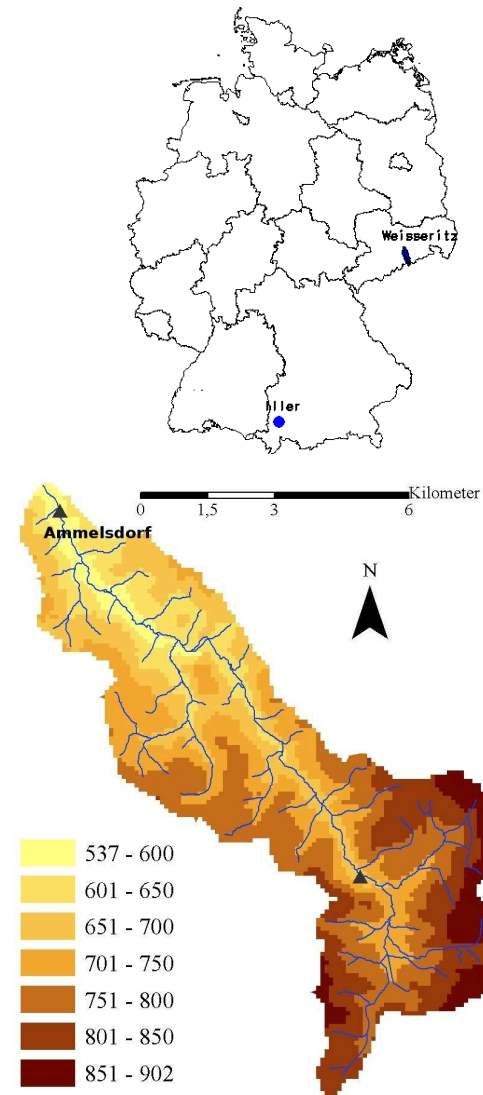
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- Eastern Ore mountains at the Czech-German border
- Total area of 384 km²
- Two large multipurpose reservoirs in the Wilde Weisseritz
- August 2002: severe flooding: Dresden main train station and villages along the river.



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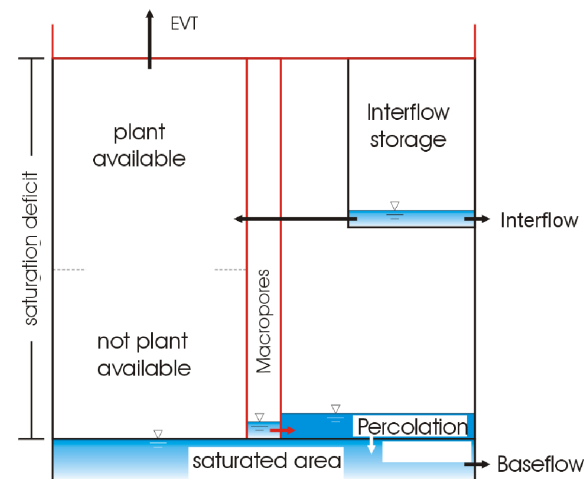
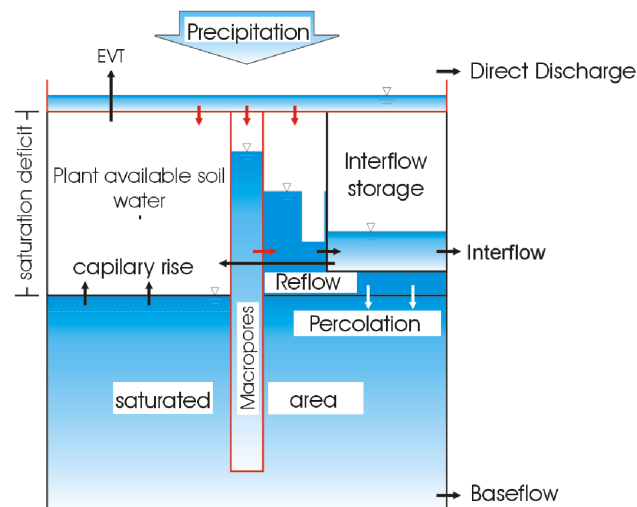
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- Deterministic, distributed rainfall-runoff model (Schulla & Jasper 1999)
- Provides methods for the interpolation of meteorological input
- Describes the soil water based on the TOP-model approach (Beven & Kirkby 1979)
- Macro pores are described with an extension by Niehoff et al. (2000)



after NIEHOFF, 2001



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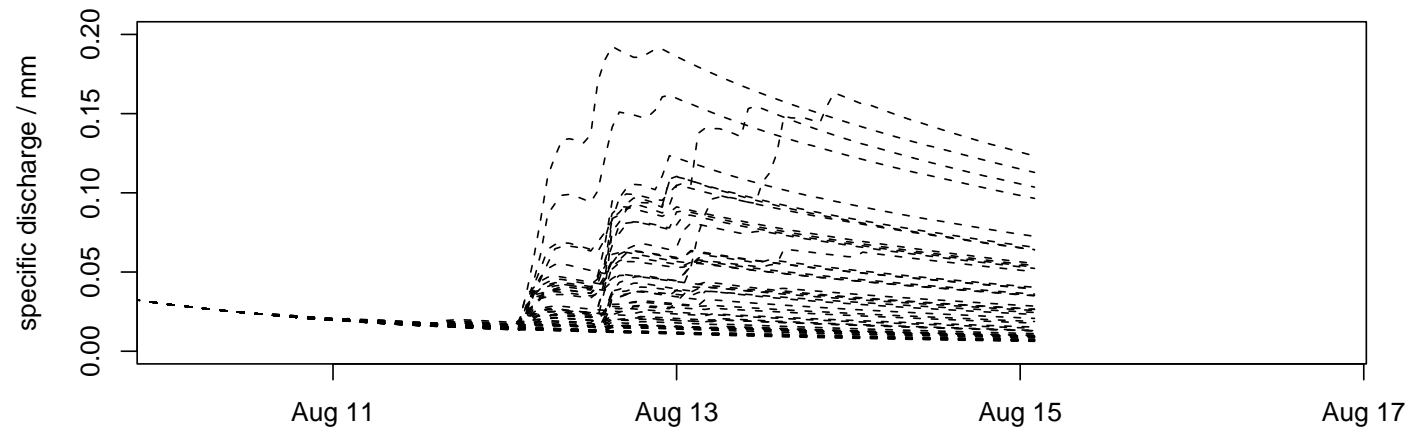
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- Range of the ensemble prediction is small for times with predictable conditions
- Range much wider for the time of the extreme rainfall event
- Uncertainty clearly larger with increasing prediction times



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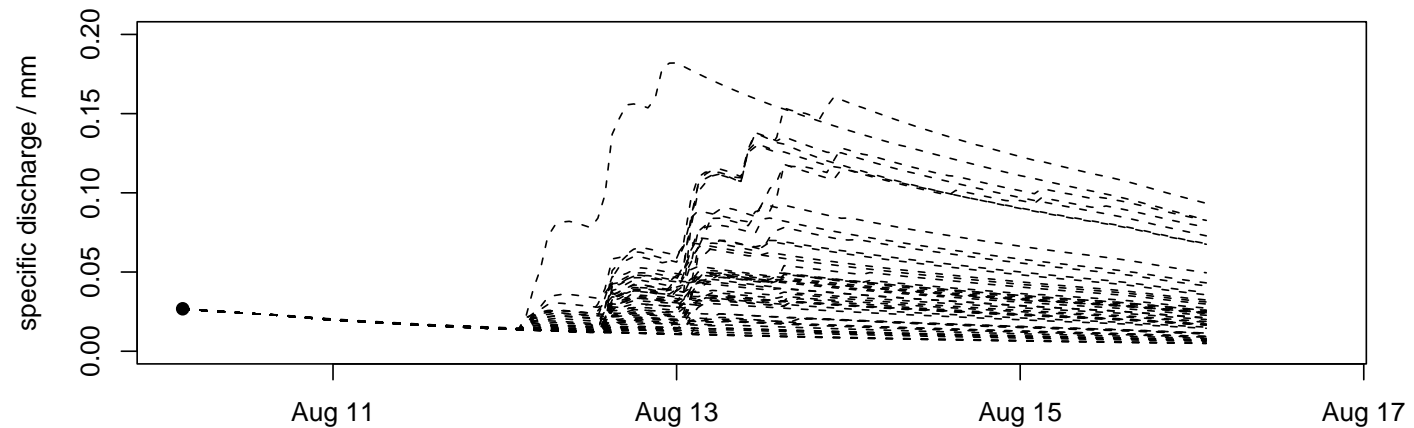
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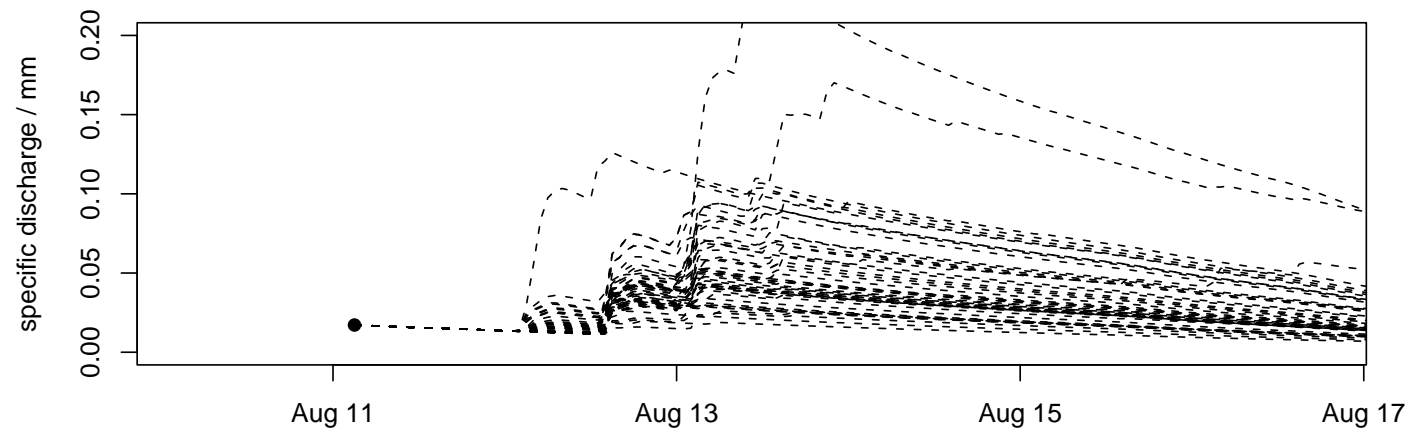
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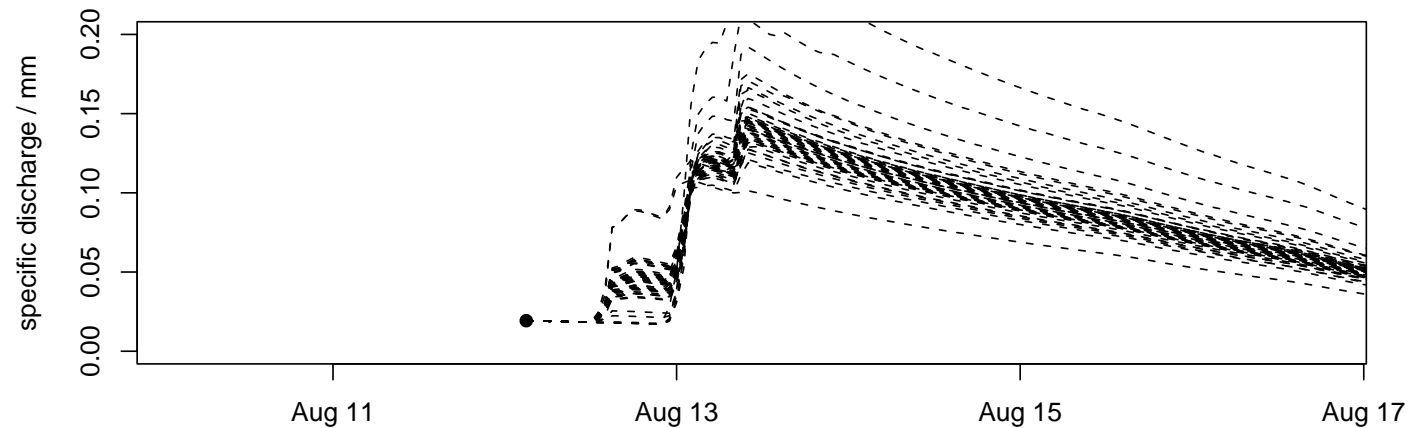
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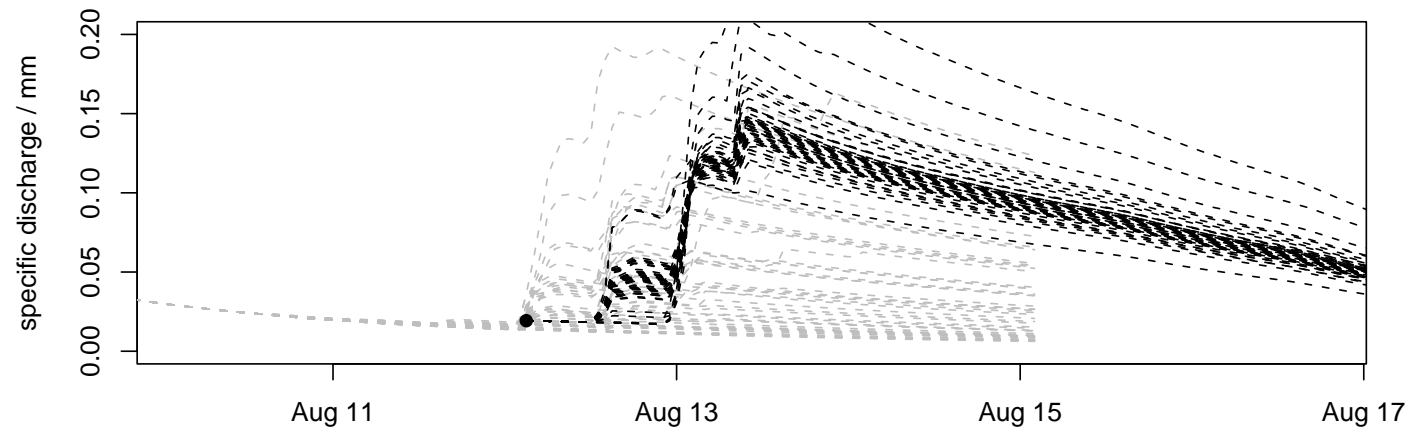
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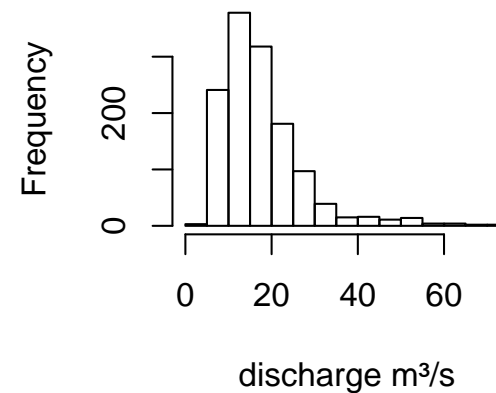
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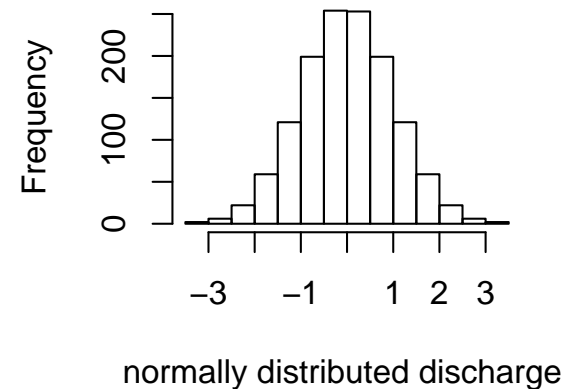
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- Based on transformation of data to normal distributions.
- First order transition probability
- Likelihood function for forecast and observation
- R-package soon published

Before transformation



After transformation





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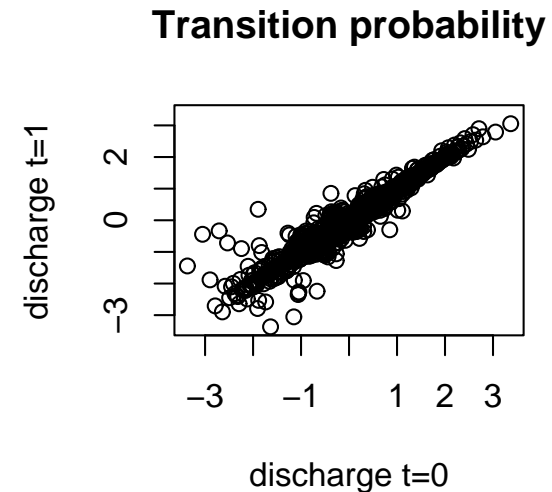
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R. Krzysztofowicz and K. S. Kelly. Hydrologic uncertainty processor for probabilistic river stage forecasting. *WATER RESOURCES RESEARCH*, 36(11):3265–3277, 2000

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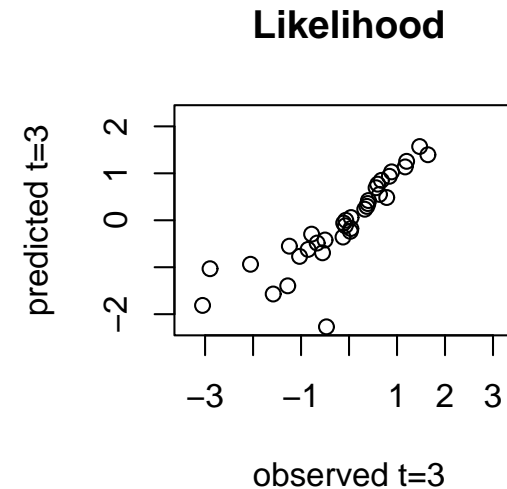
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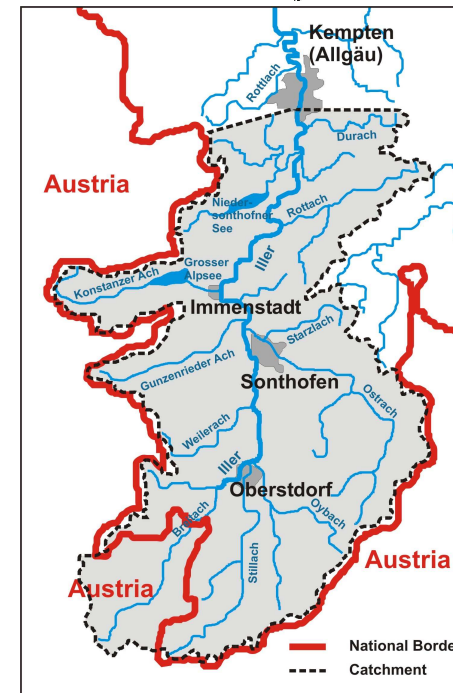
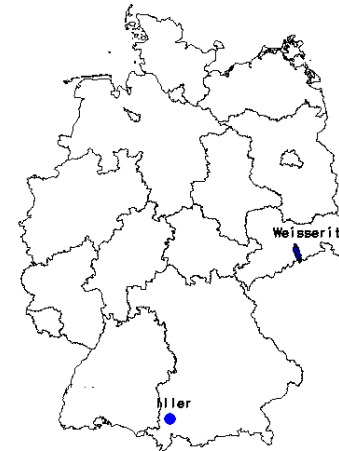
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- Alps at the German-Austrian border
- Total area of 954 km²
- 650 to 2700 m asl
- highest recorded floods (in 100 years) in May 1999 and August 2005 (850 and 900 m³)



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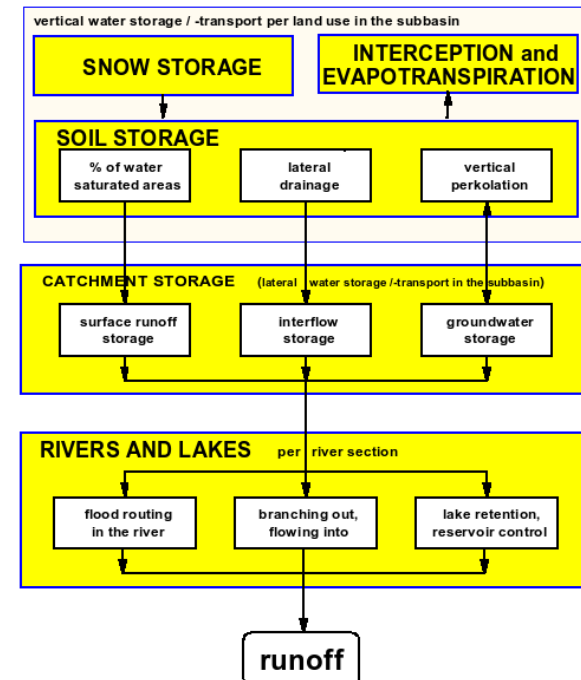
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- Conceptual, distributed rainfall-runoff model (Ludwig and Bremicker, 2007)
- Provides methods for operational flood forecasting
- Flood predictions calculated at the Bavarian Flood Warning Center





Prior expected discharge level

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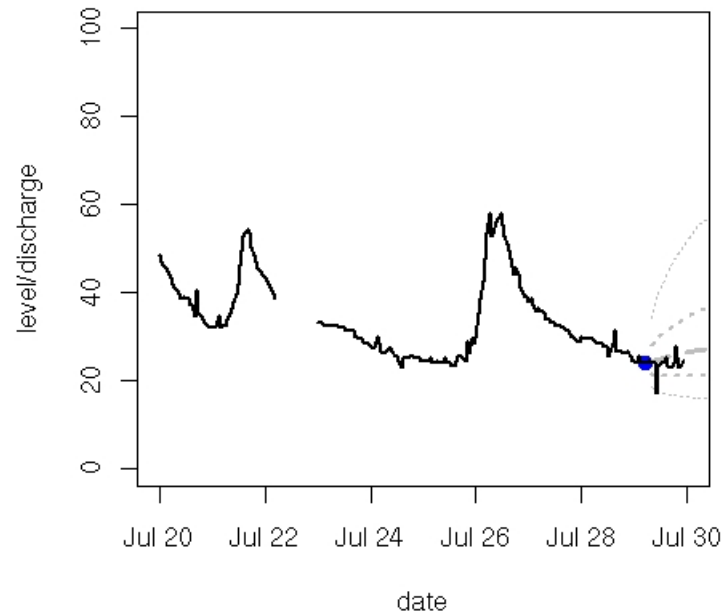
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- Without prediction: First order Markov process
- Converging to probability distribution of observed discharge level for a given month



Posterior expected discharge level

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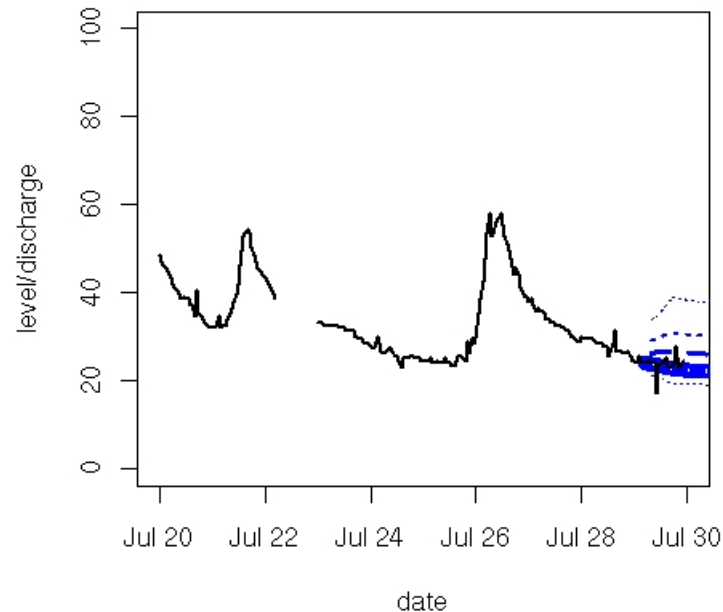
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- Combination of forecast and Markov process
- Converging to probability distribution of observed discharge level for a given month



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Socioeconomic Model:FLEMO

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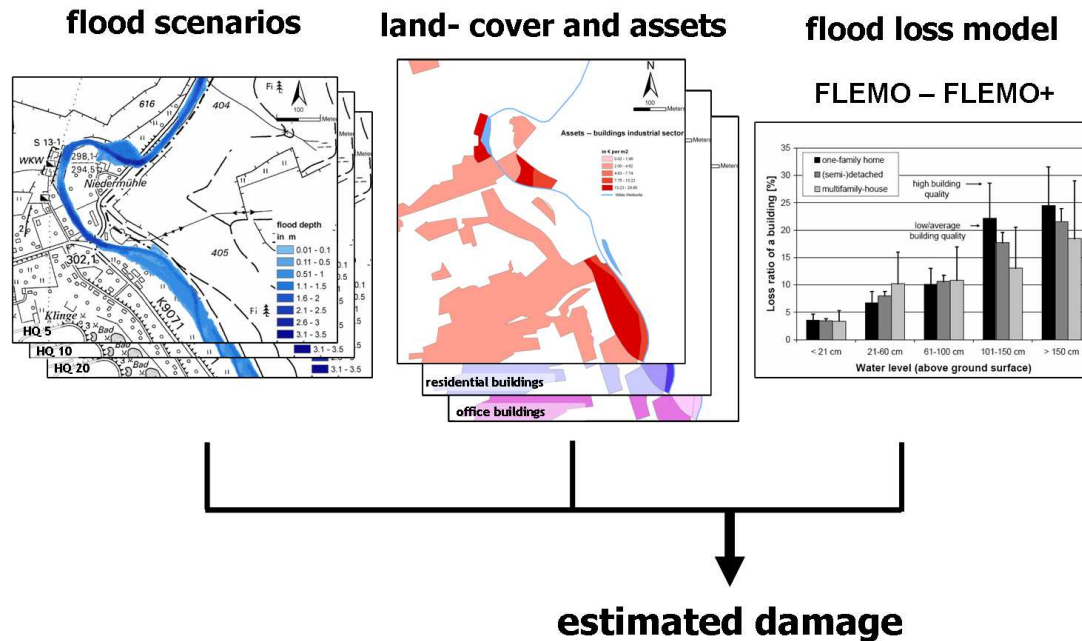
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- FLEMO: losses depending on water level, building type and building quality/size.
- Second stage: effects of private precautionary measure and contamination of the floodwater.

H. Kreibich, I. Seifert, et al. *Hydrological Sciences Journal*, submitted.

A.H. Thieken and H. Kreibich. *Journal of Hydrology*, submitted.



Reservoir management

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- Uncertainty based management
- Probability to cause damage greater threshold (e.g. 50%) triggers scenario testing
- Scenario range:
 - ◆ Maximum damage free release
 - ◆ Maximum reduction of peak discharge
- Expected (from prediction ensemble) damage for
 - ◆ Pre-event release
 - ◆ Event itself





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- Quantification of input uncertainties (for ECMWF ensemble)
- Quantification of model uncertainties
- Neither source of uncertainty can be excluded a priori
- Next steps:
 - ◆ combination of approaches with flood loss model
 - ◆ uncertainty of radar now-casting
 - ◆ precipitation dependent hydrological uncertainty processor



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Thank you for your attention

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