HORIX – DEVELOPMENT OF AN OPERATIONAL EXPERT SYSTEM FOR FLOOD RISK MANAGEMENT CONSIDERING PREDICTION UNCERTAINTY

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Funding

Project Management

Projektträger Forschungszentrum Karlsruhe (PTKA)

Coordination

GFZ Potsdam

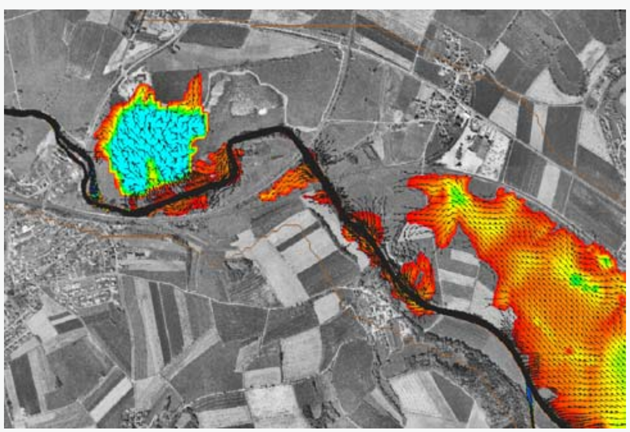
CEDIM

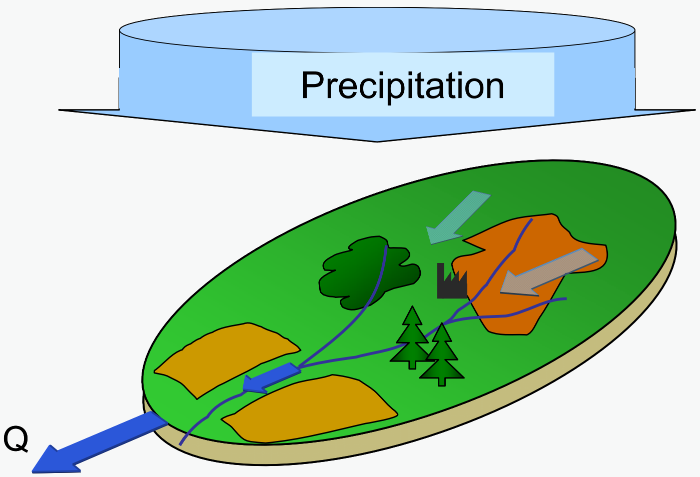
Content

- Objectives of HORIX
- Uncertainty of forecasted precipitation events
- Calibration of rainfall runoff models
- Uncertainty of hydrological models
- Fuzzy-based expert system for flood forecasting
- Inundation modelling
- WebGIS-Application with UMN MapServer
- Summary and outlook

Objectives of HORIX

www.rimax-hochwasser.de/projekte.htm

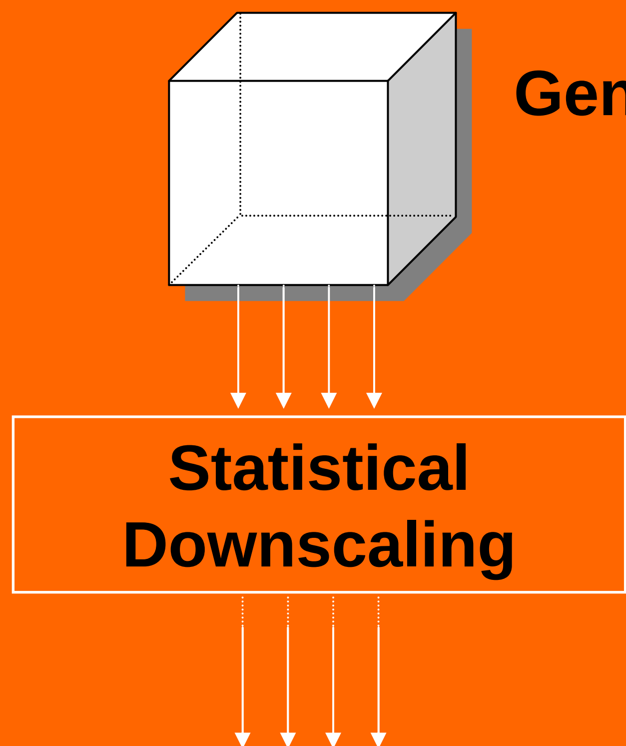




Objectives of HORIX

- Development of an efficient management tool for floods in meso-scale watersheds
- Analysis of the whole “flood chain”:
  rainfall events – rainfall-runoff-model – hydraulic model
- Quantification of uncertainties of the “flood chain”
- Development of an expert system, which
  - is operationally applicable,
  - is easy to use
  - establishes a flood forecast for the population
- Visualization of the current flood risk by WEB-based flood maps

Statistical Downscaling



General Circulation Model

(60 km x 60 km)

Hourly precipitation fields (1 km x 1 km)

Risk management of extreme flood events

Uncertainty of forecasted precipitation events

forecast uncertainty:

- statistical downscaling based on the analogue method (Obled et al. , 2002)

observation uncertainty:

- conditional simulation based on a three-dimensional turning bands method (Mantoglou and Wilson, 1987)

➡ focus on precipitation: dominant source of uncertainty

Analogue Method

Precipitation Forecast

(1) Past weather situation are identified, which are similar to the current situation

(2) The daily areal precipitation of past weather situations is chosen as forecast.

Predictors

- **Geopotential height of 1000 hPa-field**
- **Relative humidity of the 700 hPa-field**
- **Moisture flux of the 700 hPa-field**

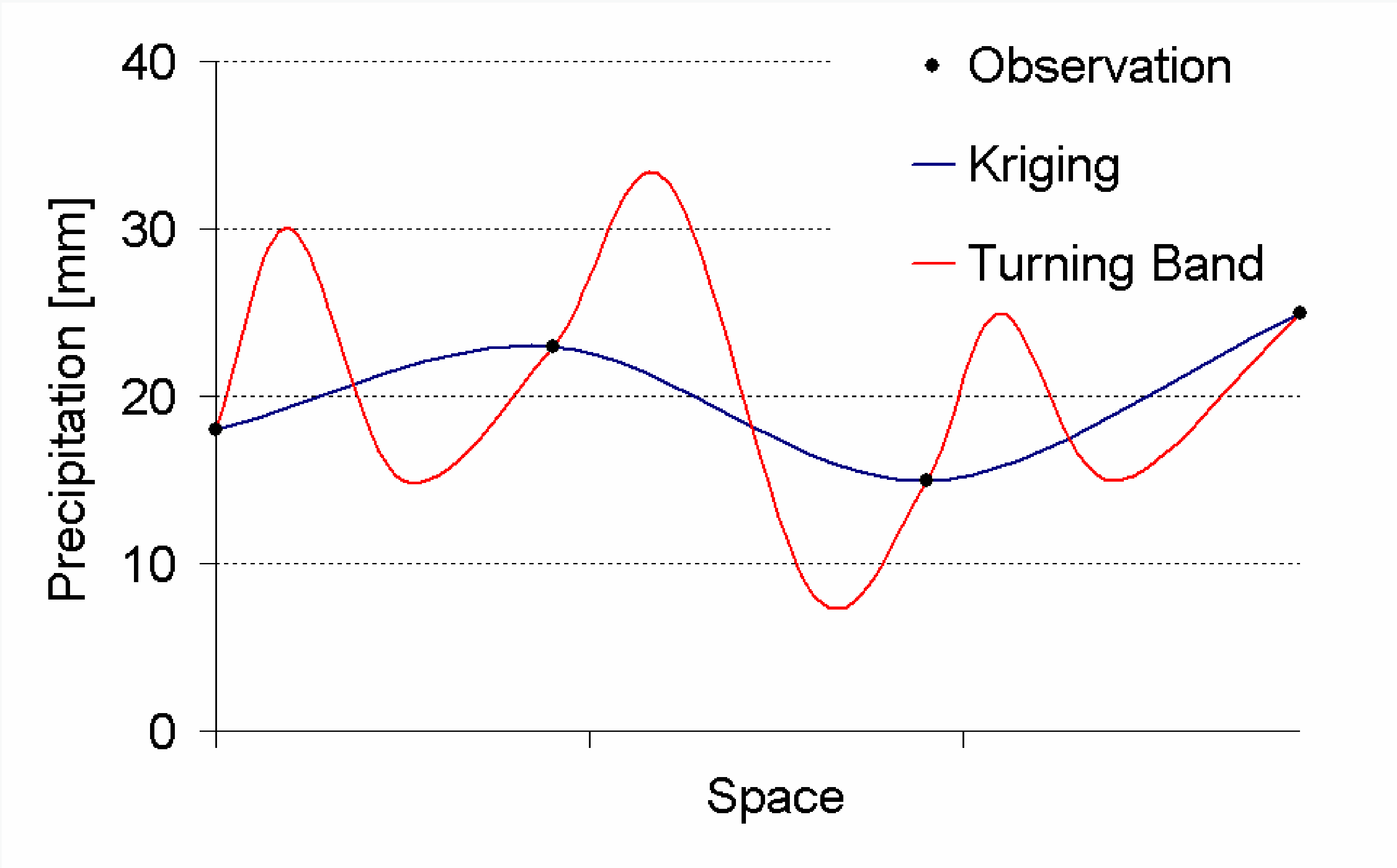
Generating precipitation scenarios

1. The temporal distribution and the moving direction of precipitation events are determined for each circulation pattern.

2. The daily areal precipitation is disaggregated in hourly time steps

3. Precipitation scenarios are determined using the turning bands method.

Concept of the turning bands method



Estimation uncertainty of precipitation observations

two different kinds of observations

- hourly observations (small number < 20) → good estimates of the temporal distribution
- daily observations (large number > 60) → good estimates of the spatial distribution

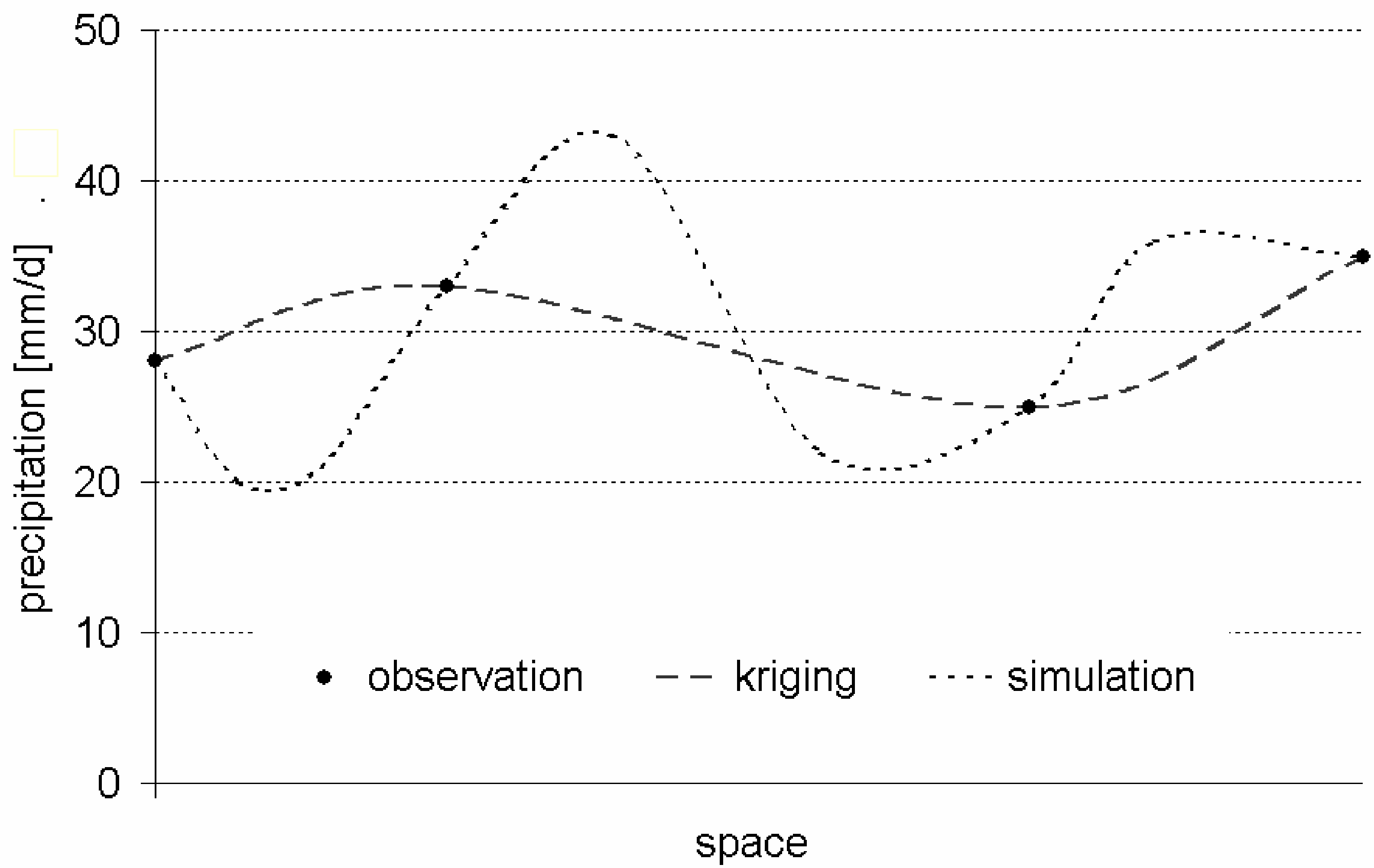
working steps of the methodologies:

1.) conditional simulation based on a three-dimensional turning bands method to derive n hourly precipitation fields

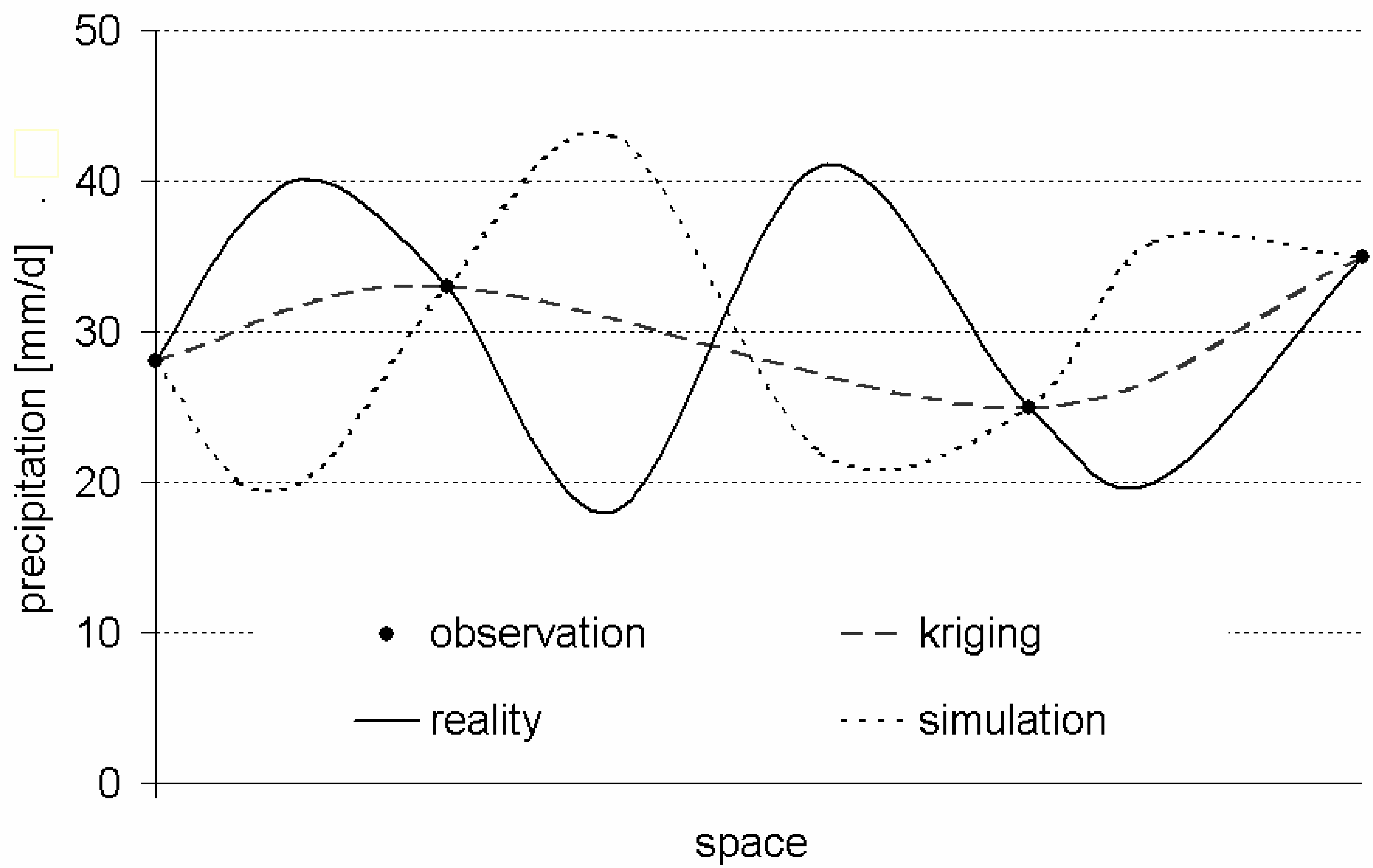
2.) interpolation of the daily areal precipitation by an external drift kriging

3.) disaggregation of the daily areal precipitation according to the temporal distribution of the hourly precipitation fields

simulation concept



Uncertainty of forecasted precipitation events

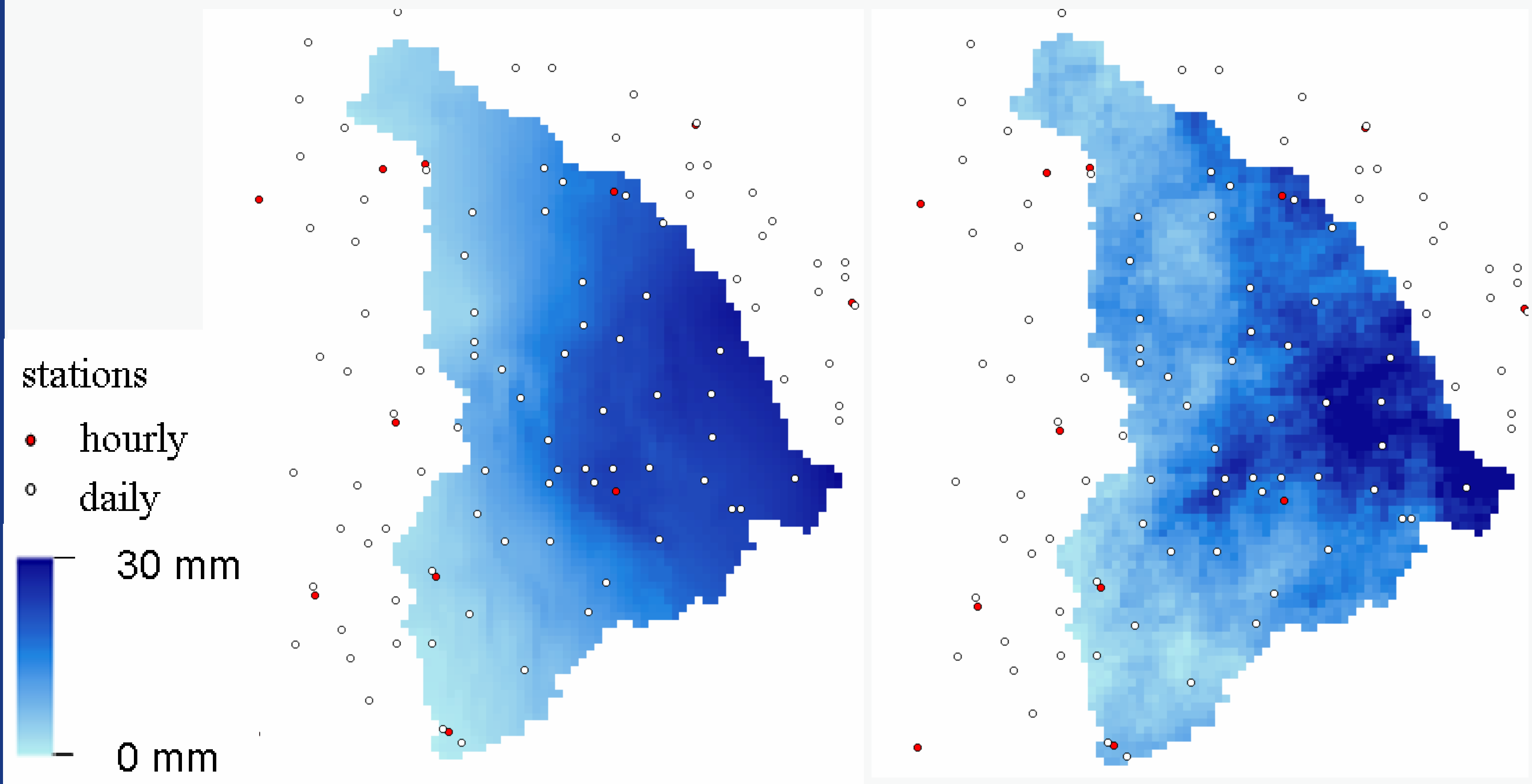


Risk management of extreme flood events

Interpolated and simulated hourly precipitation field

12. August 2002, 11 pm, Freiberger Mulde

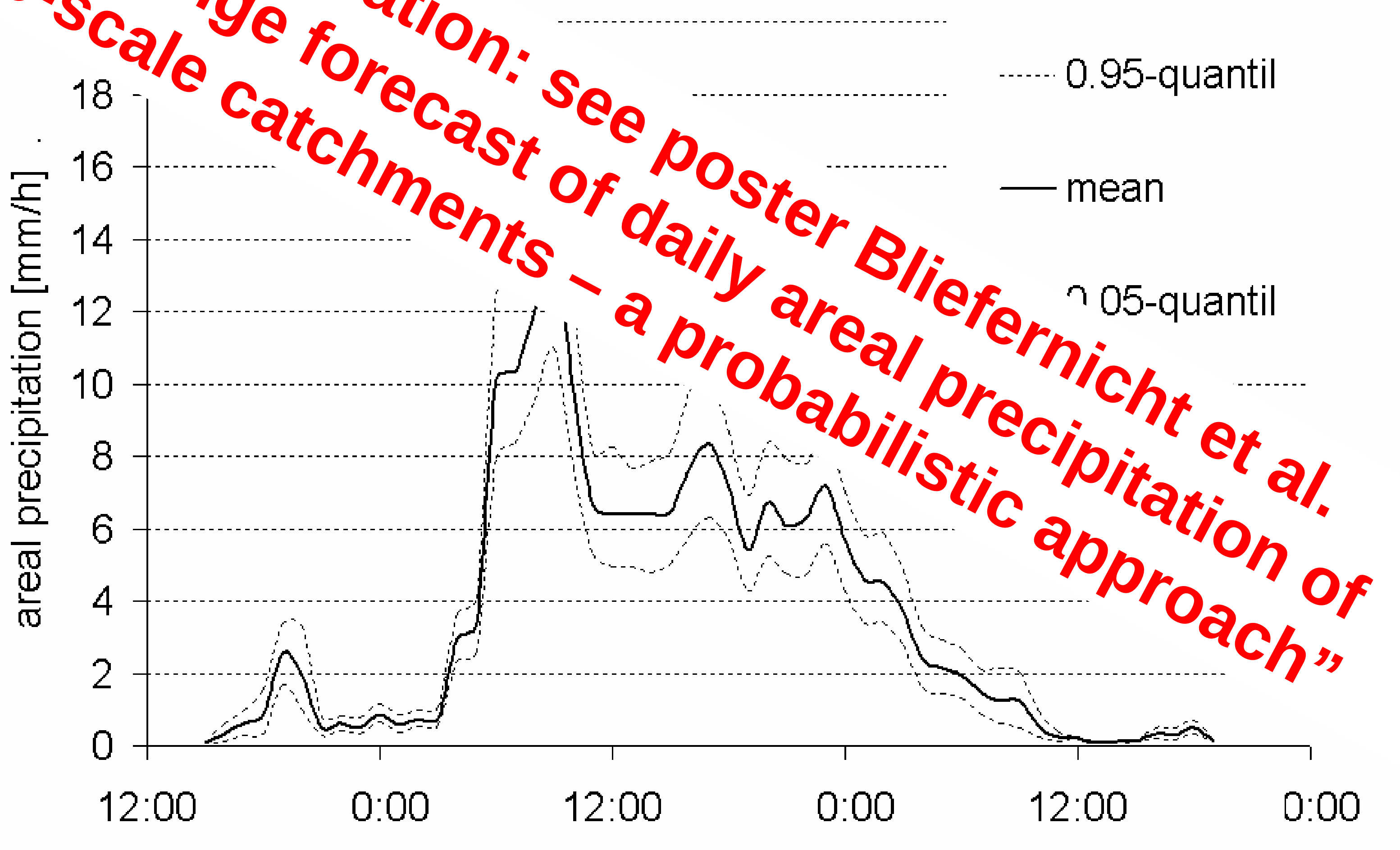
interpolation simulation



Risk management of extreme flood events

Uncertainty of hourly areal precipitation

02, Freiberger Mulde, 11. Aug. – 13. Aug.



Further information: see poster Bliefernicht et al. "Short-range forecast of daily areal precipitation of meso-scale catchments – a probabilistic approach"

Generation of extreme precipitation events

(1) Estimation of the amount of areal precipitation of an extreme event (extreme value distribution).

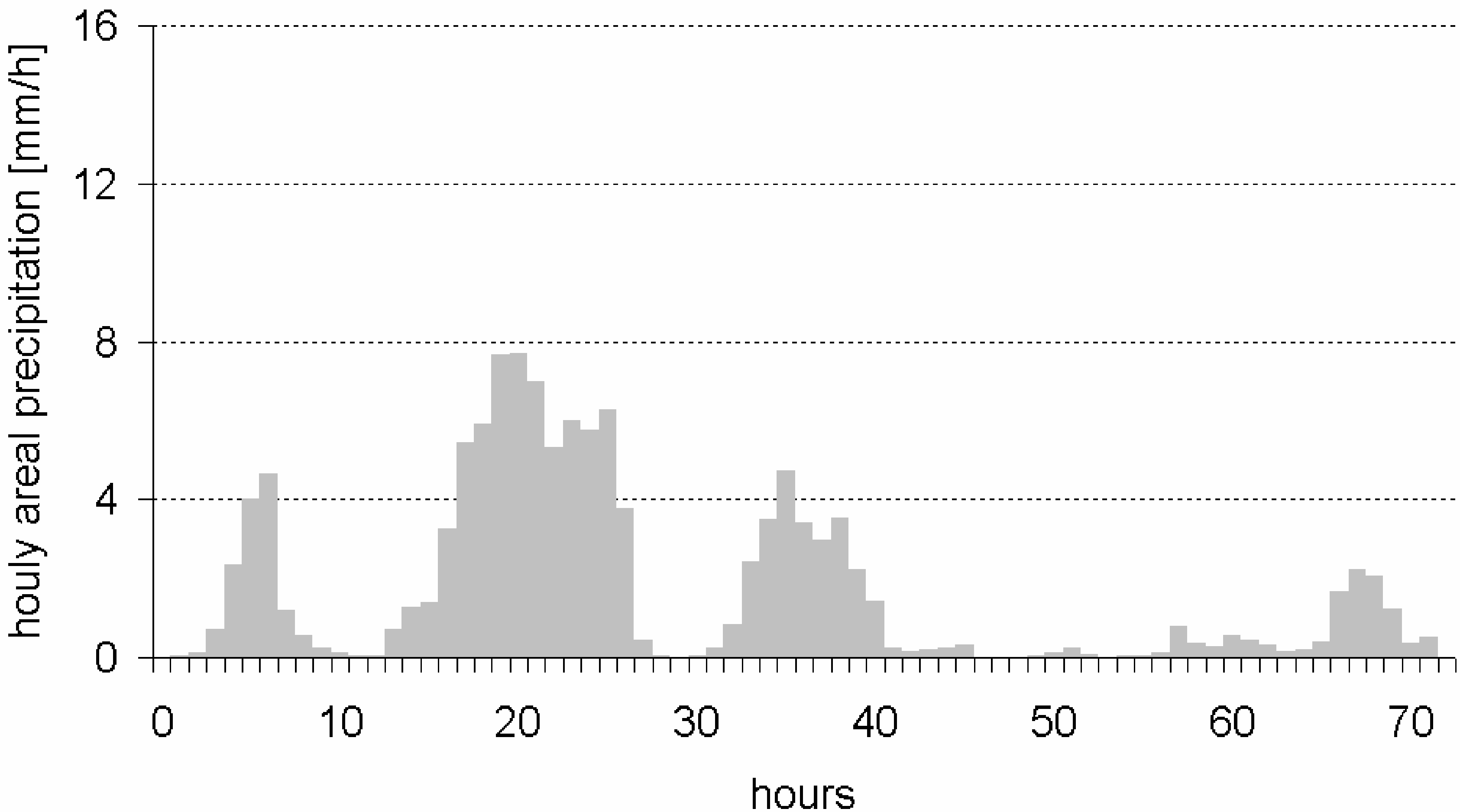
(2) Simulation of hourly precipitation fields in a spatial resolution of 1 km x 1 km (turning bands method).

(3) Disaggregation of the areal precipitation according to the spatial and temporal distribution of the hourly precipitation fields .

(4) Step 2 and 3 are repeated → n realisations

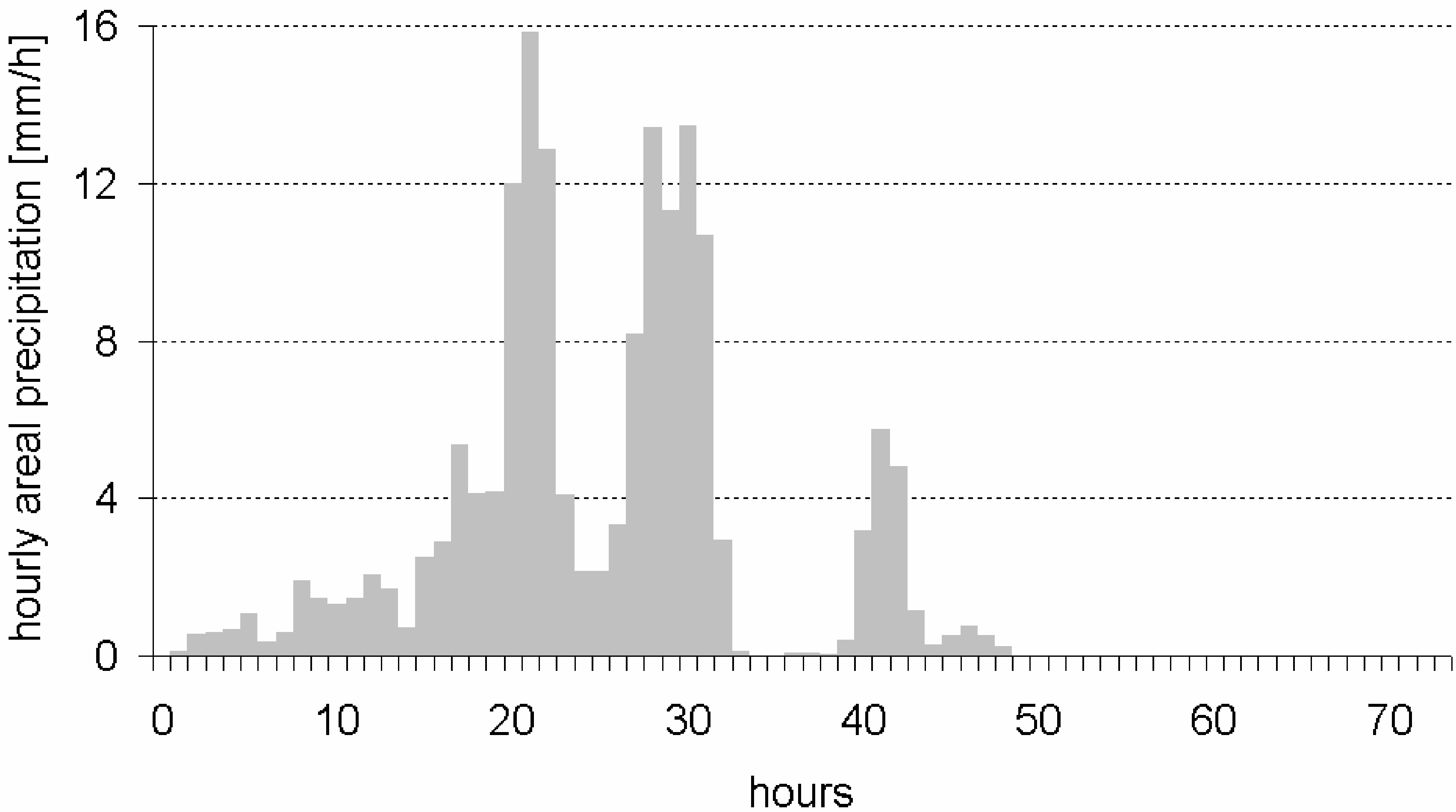
winter event
100-year return period

120 mm in 72 h, Freiberger Mulde, (Elbe basin, Germany)



summer event 100-year return period

163 mm in 48 h, Freiberger Mulde,Elbe basin, Germany.

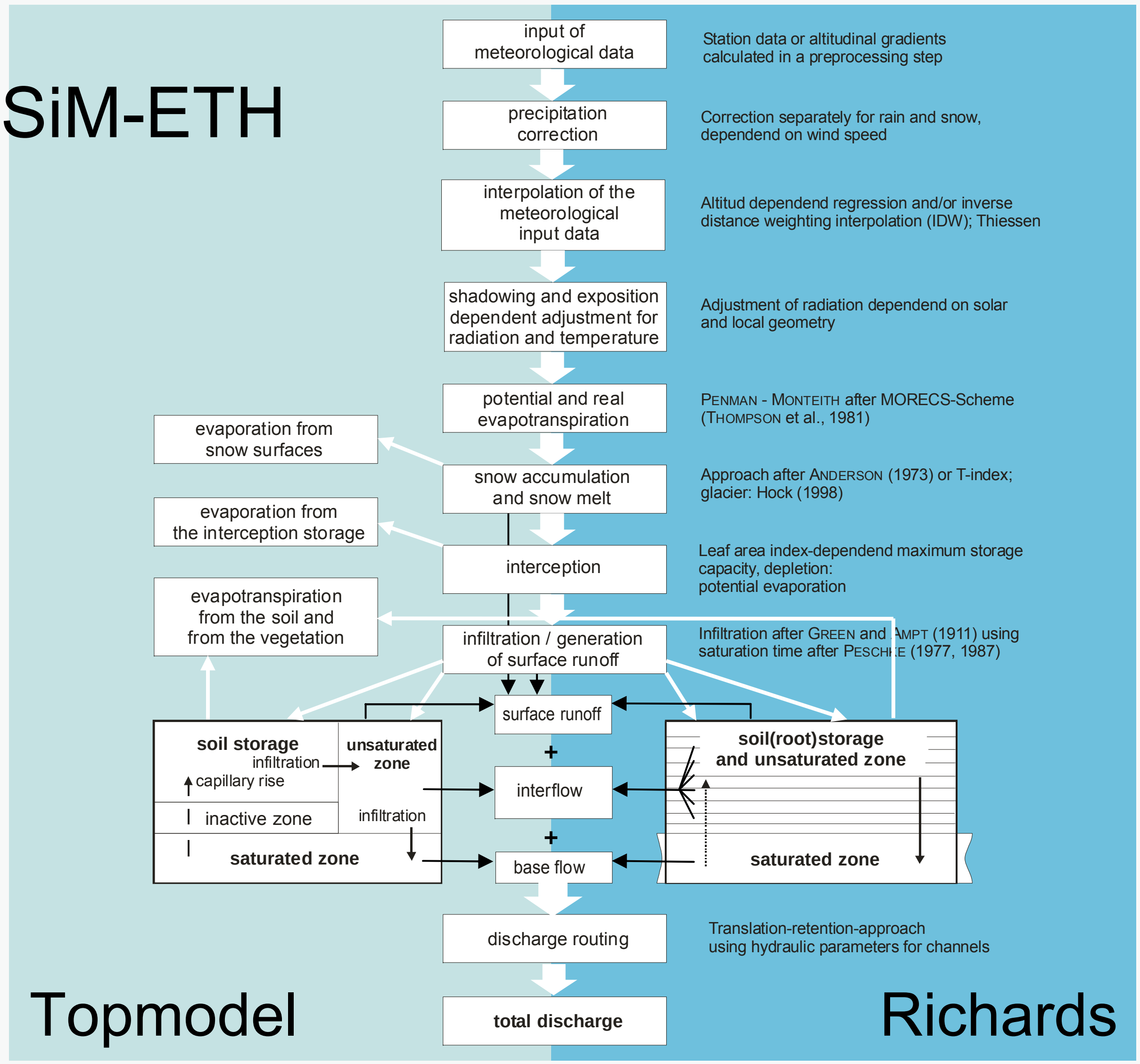


Calibration of rainfall runoff models

Risk management of extreme flood events

WaSiM-ETH

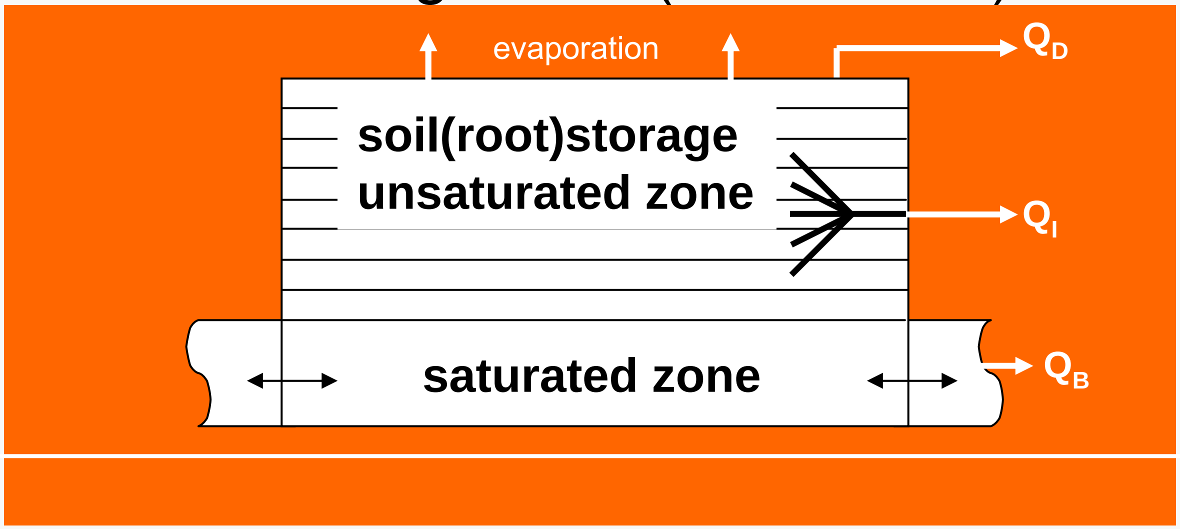
after Schulla (1998)



Modelling the vadose zone with Richards-equation:

$$\frac{\partial \Theta}{\partial t} = \frac{\partial q}{\partial z} = \frac{\partial}{\partial z}\left(-k(\Theta)\frac{\partial \Psi(\Theta)}{\partial z} \right)$$

- physically based approach
- modelling 1D vertically within a layer discretised soil column for each grid cell (FD method)



- Implementation of 2D groundwater model possible

- with groundwater model:
  → 4 parameter have to be calibrated

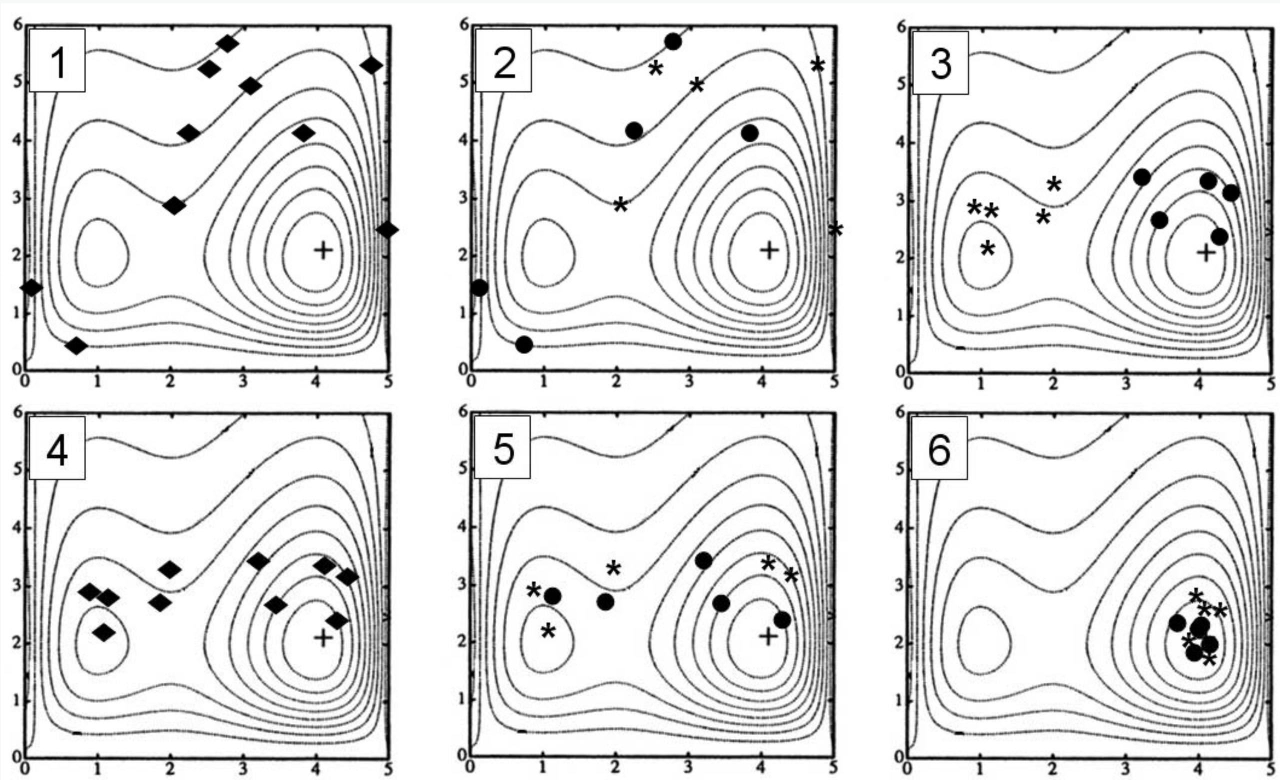
- without groundwater model:
  → conceptual approach for base flow
  → 6 parameter have to be calibrated

Calibration of rainfall runoff models

Parameter of WaSiM-ETH (Richards mode)

- k_d recession coefficient for the direct flow
- k_i recession coefficient for the interflow
- k_b recession coefficient for the base flow
- d_r scaling factor for the interflow $$q_{ifl} = K_s(\theta_m) \cdot \Delta z \cdot d_r \cdot \tan\beta$$
- Q_0 scaling factor for the base flow $$Q_B = Q_0 \cdot K_S \cdot e^{(h_{GW} - h_{geo,0})/k_B}$$
- k_{rec} scaling factor for the saturated hydraulic conductivity $$k_{S,z} = K_s \cdot k_{rec}^{z}$$

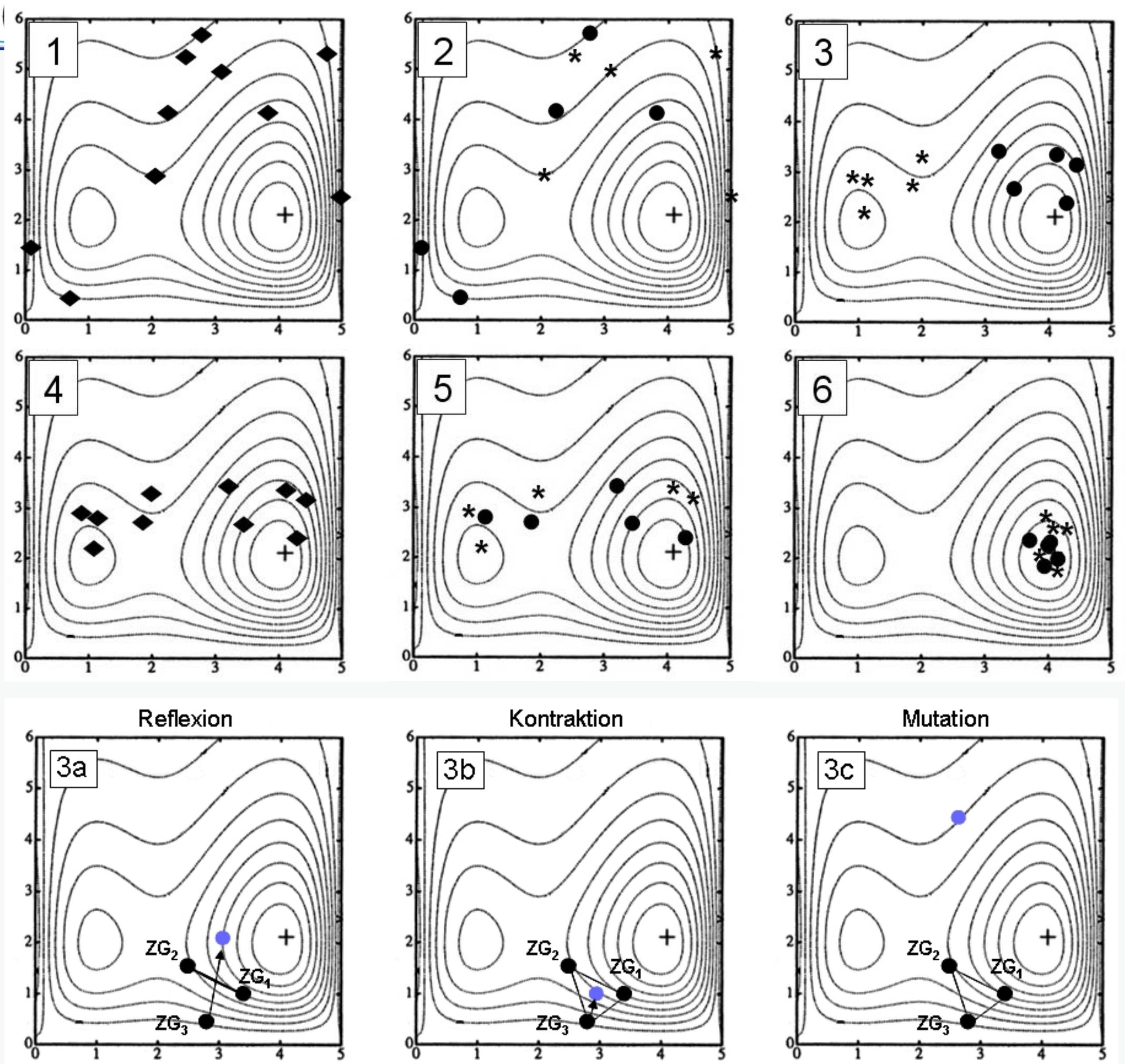
Calibration of rainfall runoff models



Genetic evolution algorithm SCE-UA (Shuffled Complex Evolution – University of Arizona)

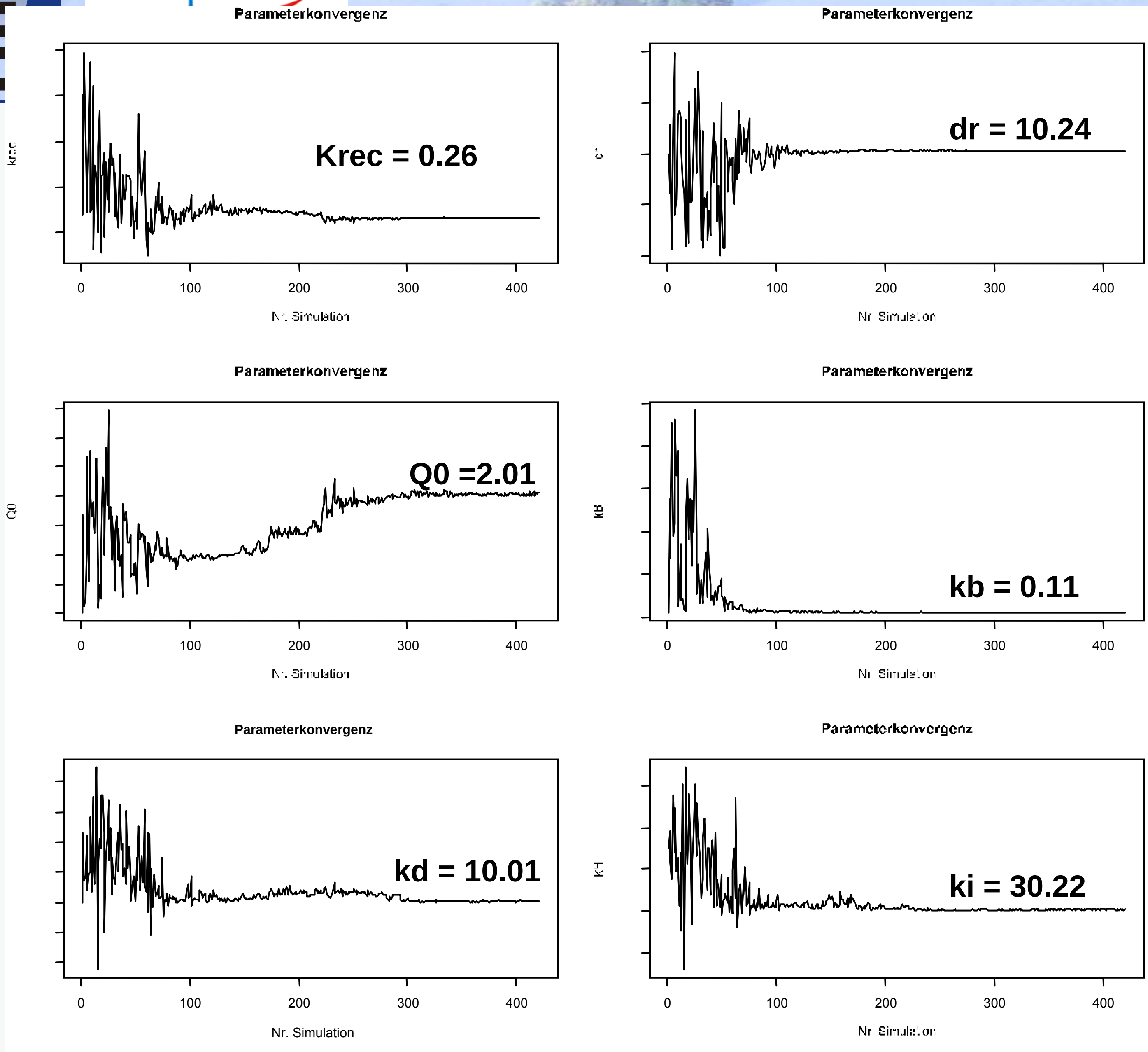
after
Duan et al. (1994)

Calibration of rainfall runoff models



Risk management of extreme flood events

Calibration of rainfall runoff models

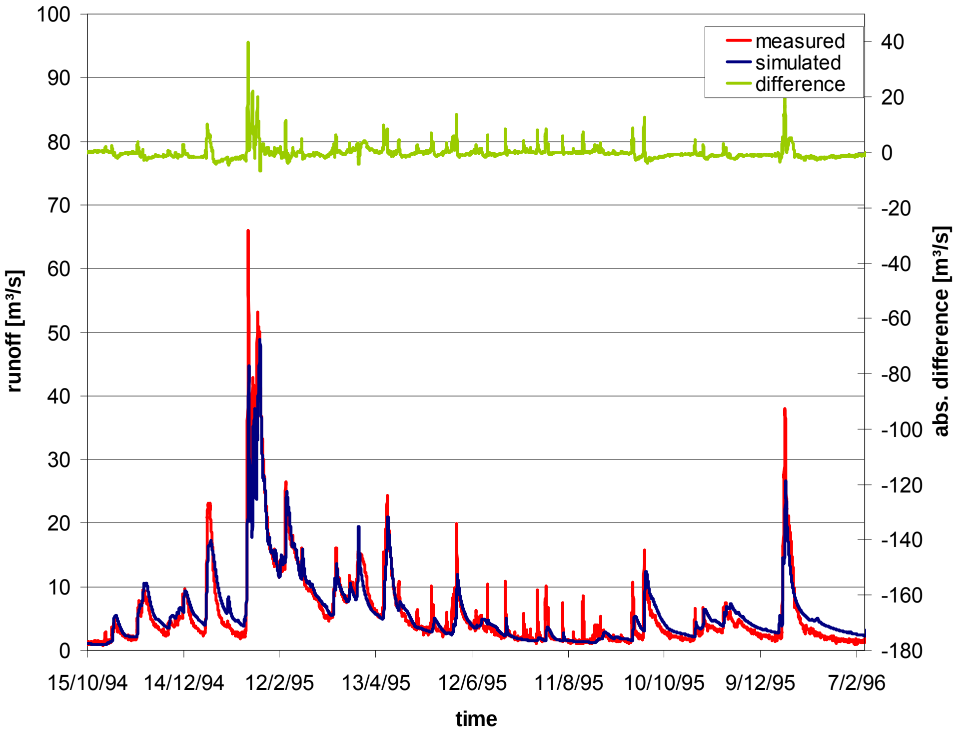


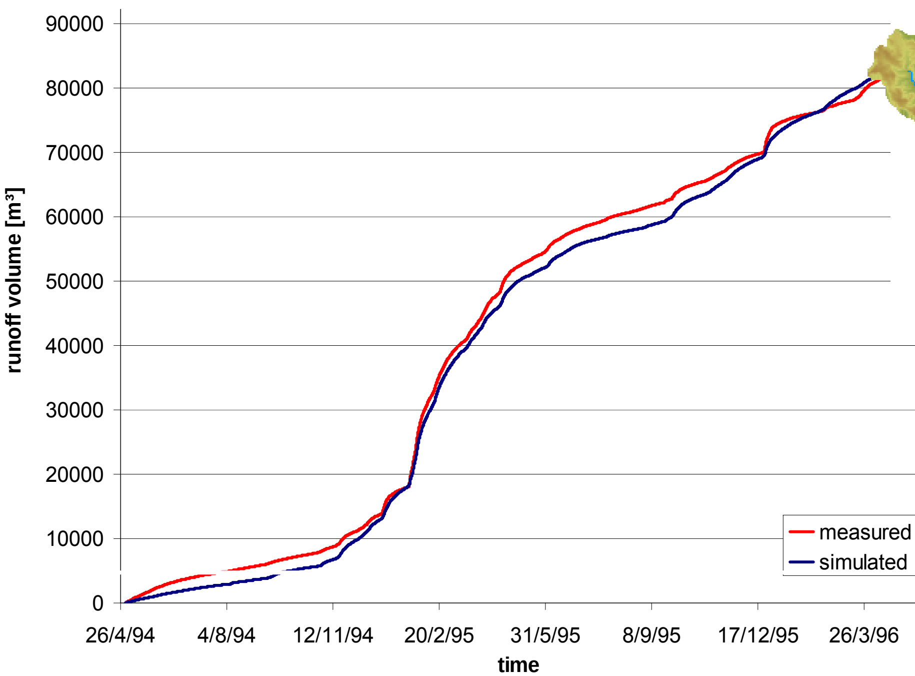
Automatic calibration by SCE (sub-catchment 5)

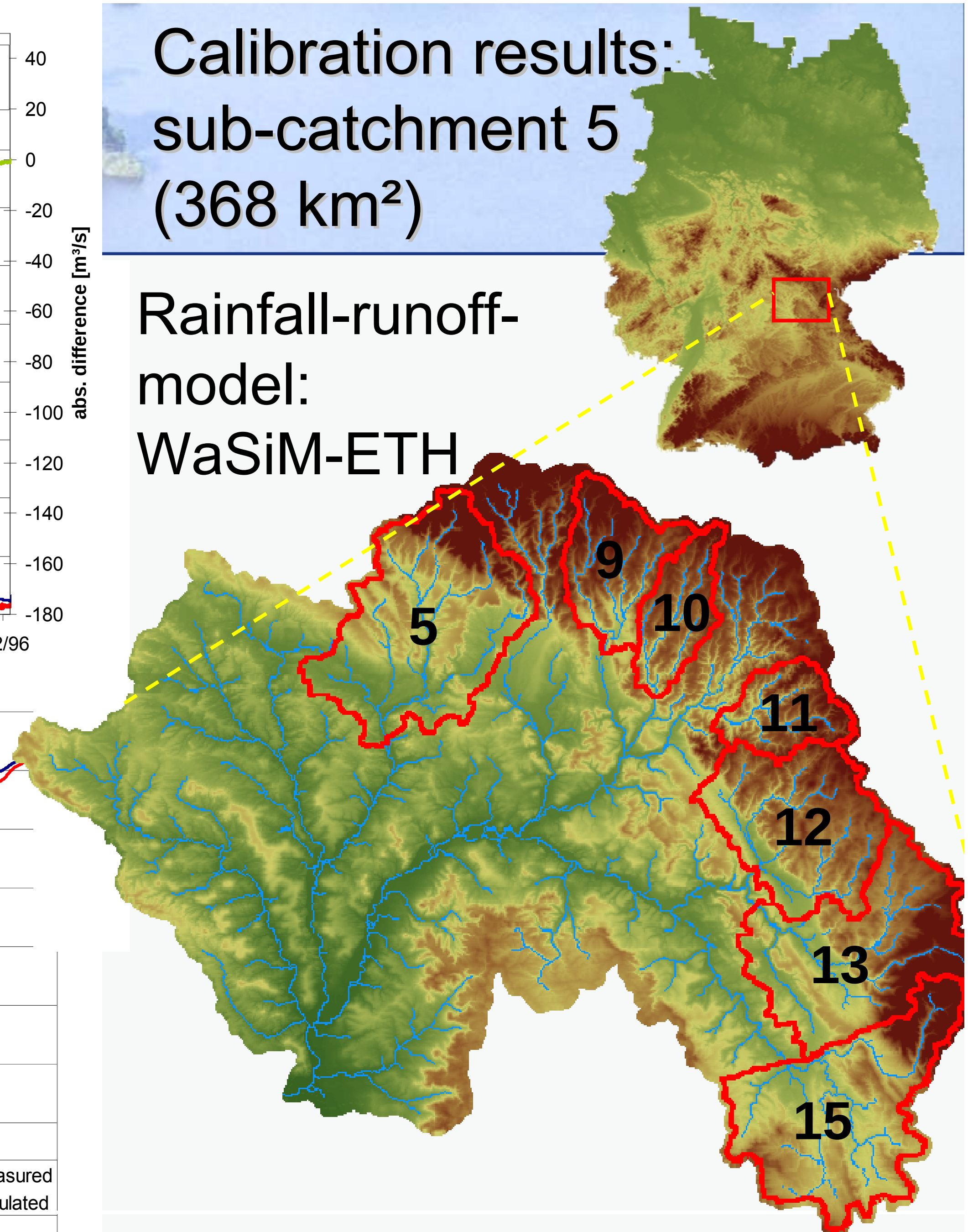
Objective function: RMSE

Calibration results: sub-catchment 5 (368 km²)

Rainfall-runoff-model: WaSiM-ETH







S. Pakosch and M. Disse

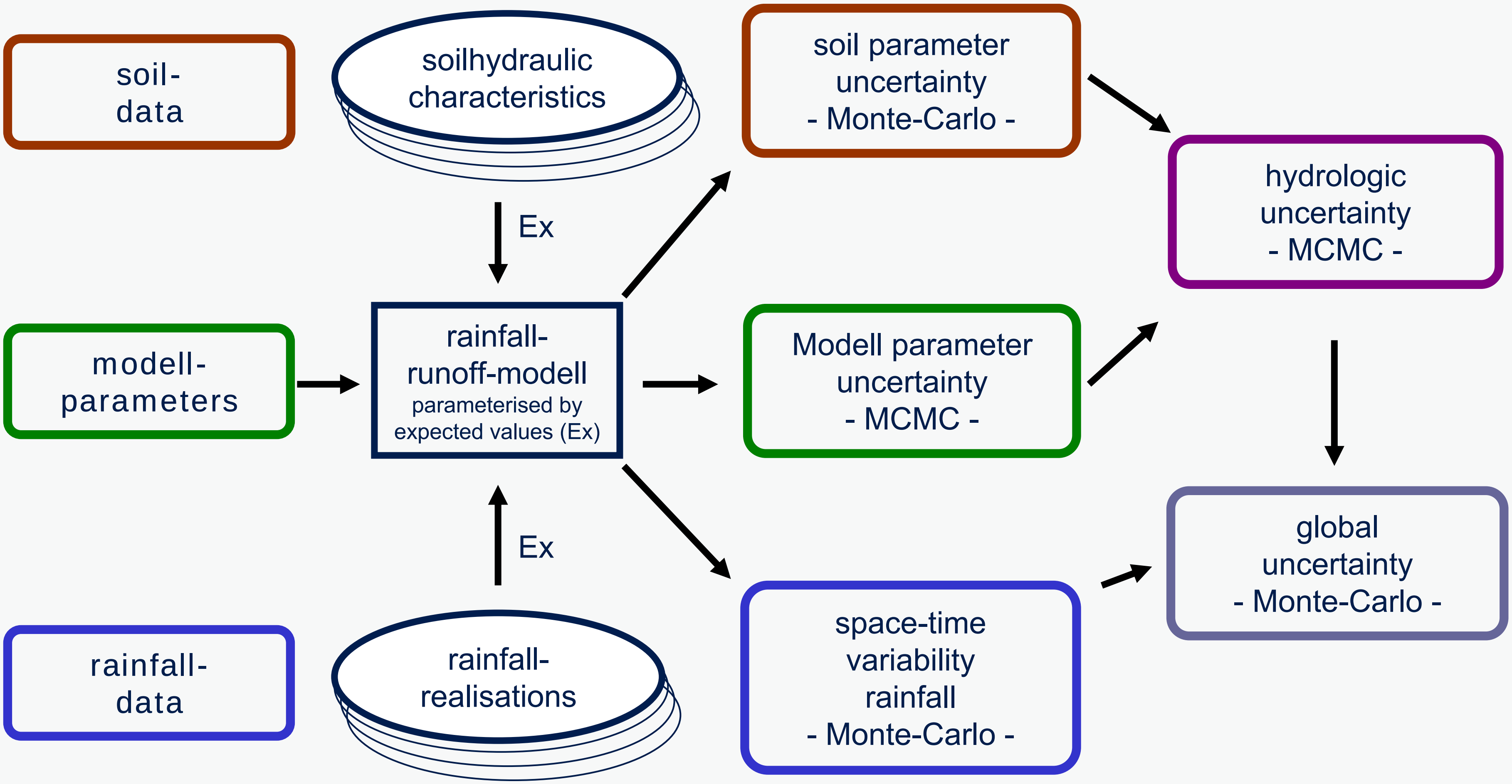
Results of the automatic calibration (SCE UA algorithm)

TEZG	A_{E0} [km²]	lin R²	log R²	lin EV	log EV	$\Sigma q_{bas}/\Sigma q_{ges}$	$\Sigma q_{sim}/\Sigma q_{gem}$	RMSE
15	332	0.814	0.689	0.819	0.710	0.137	1.109	0.6E-3
13	313	0.862	0.750	0.862	0.751	0.135	1.025	0.5E-3
12	245	0.872	0.712	0.872	0.714	0.081	1.008	0.7E-3
11	96	0.783	0.731	0.787	0.734	0.014	1.111	0.2E-2
10	96	0.843	0.639	0.843	0.639	0.017	1.007	0.2E-2
9	139	0.863	0.742	0.863	0.757	0.012	1.033	0.2E-2
5	368	0.824	0.646	0.828	0.761	0.332	1.093	0.6E-2

$$R^2 = 1 - \frac{\sum_i \varepsilon_i^2}{\sum_i \left(x_i - \bar{x}\right)^2} = 1 - \frac{\sum_i \left(y_i - x_i\right)^2}{\sum_i x_i^2 - \frac{1}{n}\left(\sum_i x_i\right)^2}$$

$$EV = 1 - \frac{\sum_i \left(\varepsilon_i - \mu_\varepsilon\right)^2}{\sum_i \left(x_i - \bar{x}\right)^2} = 1 - \frac{\sum_i \varepsilon_i^2 - \frac{1}{n}\left(\sum_i \varepsilon_i\right)^2}{\sum_i x_i^2 - \frac{1}{n}\left(\sum_i x_i\right)^2}$$

Uncertainty of hydrological models



Numerical solution: Markov-Chain-Monte-Carlo (MCMC) method
→ SCEM-UA (Vrugt, 2003)

Uncertainty of hydrological models

Bayesian inference

aim:
to determine the distribution of the model parameters, which are most likely to characterize the observed runoff

Bayes theorem

posteriori — likelihood — priori

$$f\left(\theta \mid y_{obs}\right) = \frac{f\left(y_{obs} \mid \theta\right) * f\left(\theta\right)}{f\left(y_{obs}\right)}$$

θ .. modell parameter
y_{obs} .. data

→ allows to include prior knowledge about the parameters

3.1.5. Methods of uncertainty analysis

Inferenz:

$$f\left(\theta \middle| y_{obs}\right) \propto f\left(y_{obs} \middle| \theta\right) * f\left(\theta\right)$$

Likelihood:

$$f\left(y_{obs} \middle| \theta\right) = \prod_{i=1}^{n} \left[\frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp\left(-\frac{1}{2} \frac{\left[y_{obs,i} - y_{M,i}\left(x_i ; \theta\right) \right]^2}{\sigma^2} \right) \right]$$

independent, normal distributed

θ .. modell parameter
y_{obs} .. obs. Output
y_M .. sim. Output
x .. obs. Input

Prior: uniform

Numerical solution: Markov-Chain-Monte-Carlo (MCMC) method
→ SCEM-UA (Vrugt, 2003)

Uncertainty of hydrological models

Bayes theorem

posteriori — likelihood — priori

$$f\left(\theta \mid y_{obs}\right) = \frac{f\left(y_{obs} \mid \theta\right) * f\left(\theta\right)}{f\left(y_{obs}\right)}$$

θ .. modell parameter
y_{obs} .. data

→ allows to include prior knowledge about the parameters

Likelihood:

$$f\left(y_{obs} \mid \theta\right) = \prod_{i=1}^{n} \left[\frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp\left(-\frac{1}{2} \frac{\left[y_{obs,i} - y_{M,i}\left(x_i ; \theta\right) \right]^2}{\sigma^2} \right) \right]$$

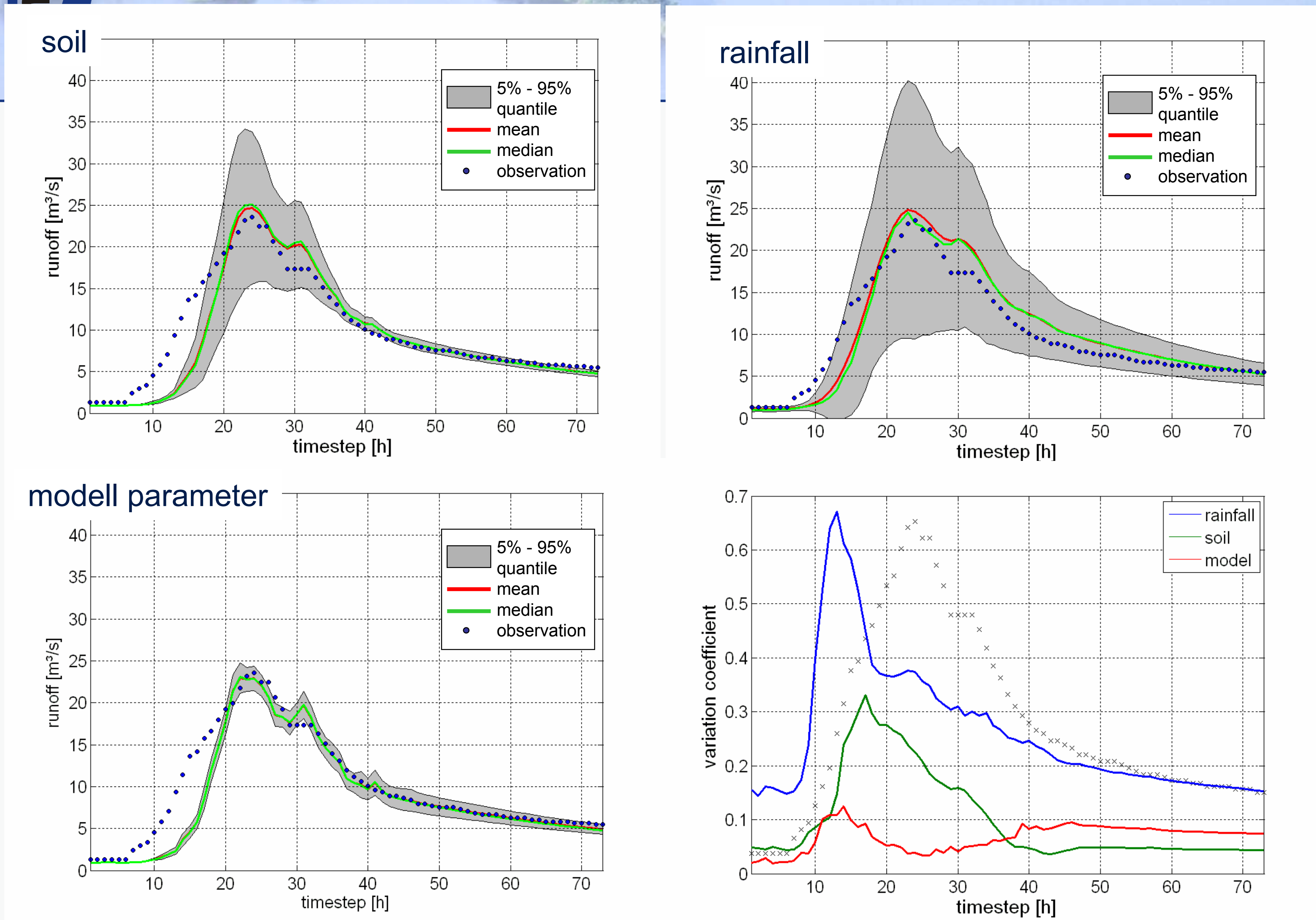
independent, normal distributed

θ .. modell parameter
y_{obs} .. obs. Output
y_M .. sim. Output
x .. obs. Input

Prior: uniform

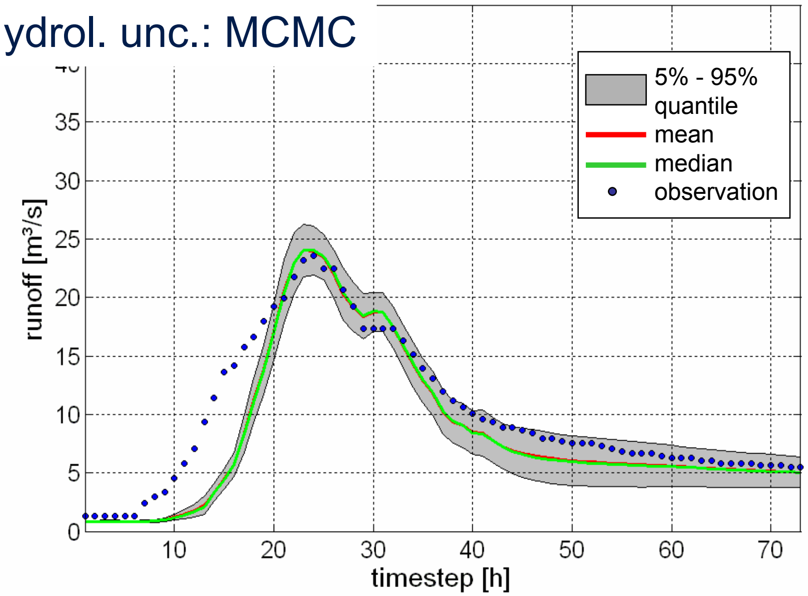
Risk management of extreme flood events

Uncertainty of hydrological models

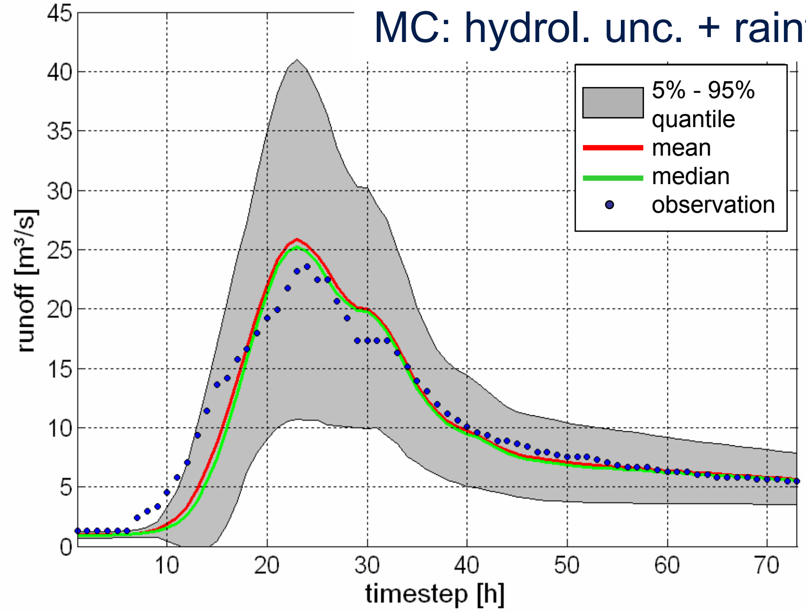


Uncertainty of hydrological models

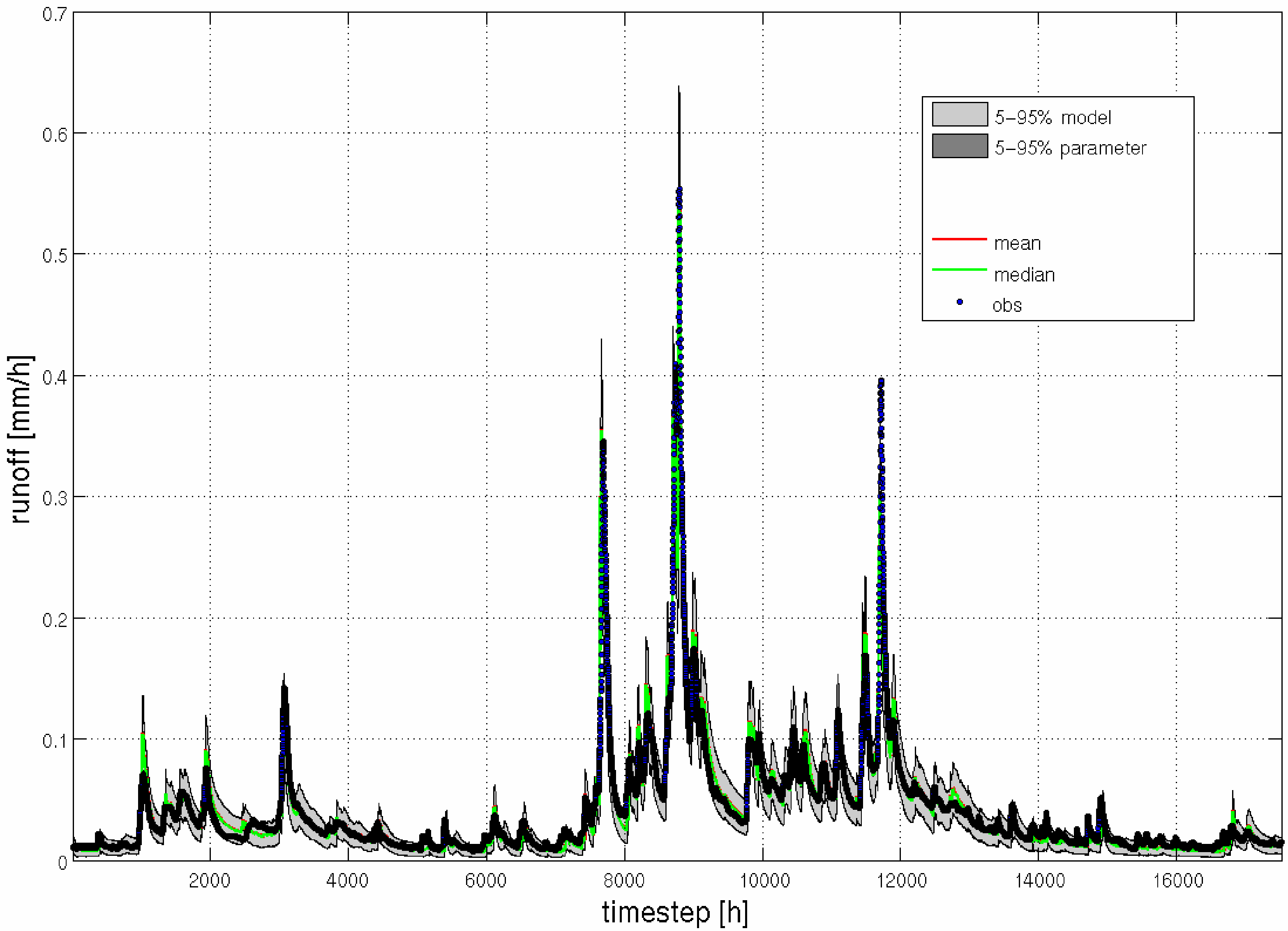
Hydrol. unc.: MCMC



MC: hydrol. unc. + rainfall



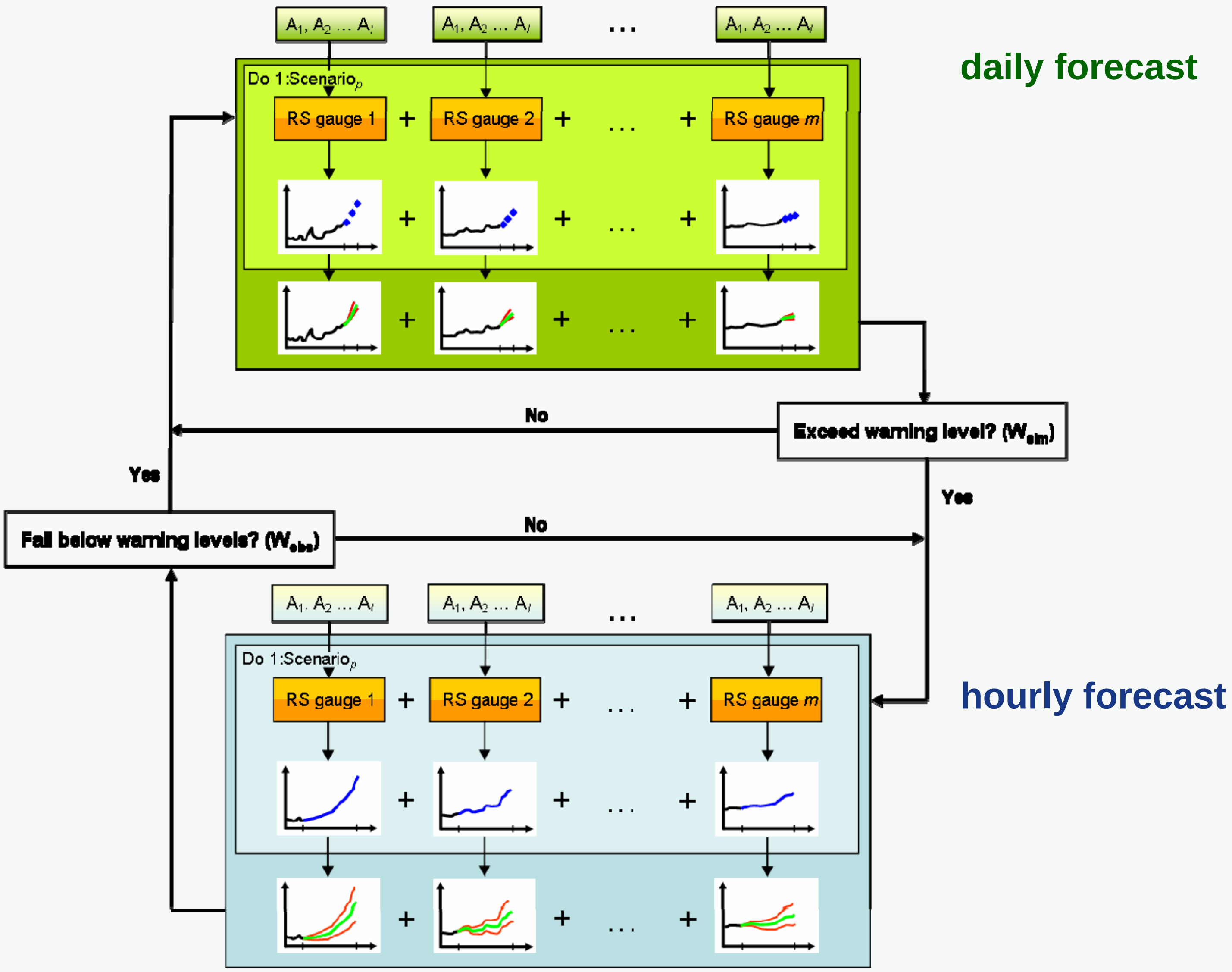
Parameter and model uncertainty Gauge Kemmern / Oberer Main



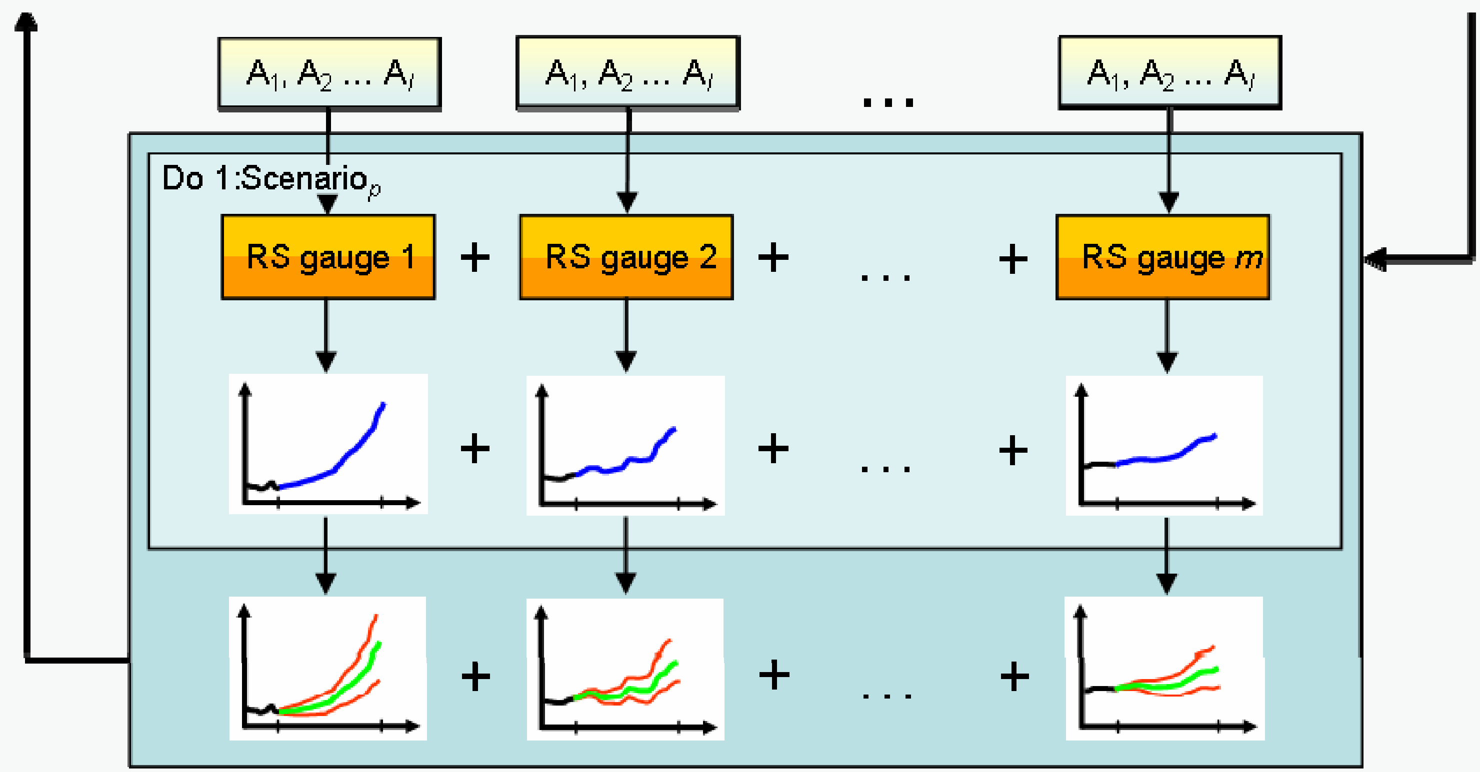
Fuzzy-based expert system

- normal discharge conditions
  - → daily based forecast of Q(t+1d), Q(t+2d), Q(t+3d) [m^3/s] and W(t+1d), W(t+2d), W(t+3d) [cm]
- if one forecasted water level exceeds given warning level 1
  - → switch forecast to a hourly base
  - → forecast of Q(t+1h), …, Q(t+12h), …, Q(t+24h) [m^3/s]
  - → get shape of hydrograph and discharge volume
  - → get corresponding inundation area (checking analogy)
- if observed water level W(t) [cm] falls below warning level 1
  - → switch forecast back to a daily base

Fuzzy-based expert system



Fuzzy-based expert system



hourly forecast

Fuzzy inference systems

- **M**AMDANI ‘S **M**ETHOD 1974

  IF x_1 is $A_{i,1}$ AND x_2 is $A_{i,2}$ AND … AND x_k is $A_{i,k}$ THEN B_i

  → DOF calculation: product operator

  → defuzzification method: centre of gravity method

- **T**AKAGI-**S**UGENOS ‘S **M**ETHOD 1985

  IF x_1 is $A_{i,1}$ AND x_2 is $A_{i,2}$ AND … AND x_k is $A_{i,k}$ THEN $y_i = f_i(x_1,...,x_k)$

  → DOF calculation: product operator

  → Response calculation: DOF weighting

use Simulated Annealing algorithm for the training

MAMDANI 'S METHOD 1974

IF x_1 is $A_{i,1}$ AND x_2 is $A_{i,2}$ AND … AND x_k is $A_{i,k}$ THEN B_i

→ DOF calculation: product operator

→ defuzzification method: centre of gravity method

$$B = \frac{\sum_{i=1}^{n} \left(DOF_i \cdot M(B_i) \right)}{\sum_{i=1}^{n} DOF_i}$$

Takagi-Sugenos 's Method 1985

IF x_1 is $A_{i,1}$ AND x_2 is $A_{i,2}$ AND … AND x_k is $A_{i,k}$ THEN $y_i = f_i(x_1,\ldots,x_k)$

→ DOF calculation: product operator

→ Response calculation: DOF weighting

$$y = \frac{\sum_{i=1}^{n} \left(DOF_i \cdot y_i \right)}{\sum_{i=1}^{n} DOF_i}$$

Fuzzy-based expert system

- Arguments

  → represent actual and forecasted meteorological situation: actual and predicted rainfall, temperature, etc.

  → represent actual discharge and catchment situation: antecedent precipitation index, etc.

- Responses

  → direct forecast of discharge $Q_F(t + x)$ [m³/s]

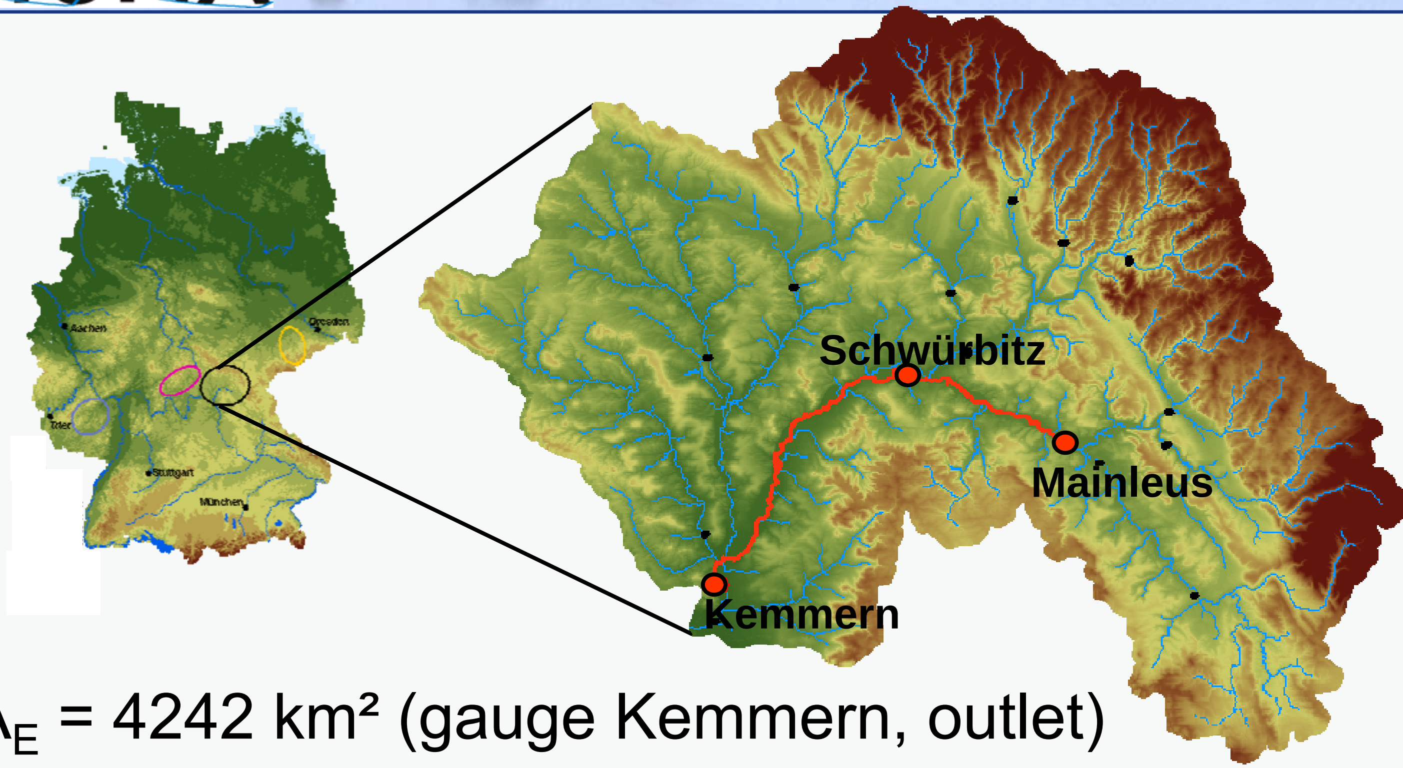
  → forecast discharge differences $\Delta Q_{F,x}(t)$ [m³/s]

training: $\Delta Q_{obs,x}(t) = Q_{obs}(t + x) - Q_{obs}(t)$

forecast: $Q_F(t+x) = Q_{obs}(t) + \Delta Q_{F,x}(t)$

Risk management of extreme flood events

Study area Upper Main, Germany

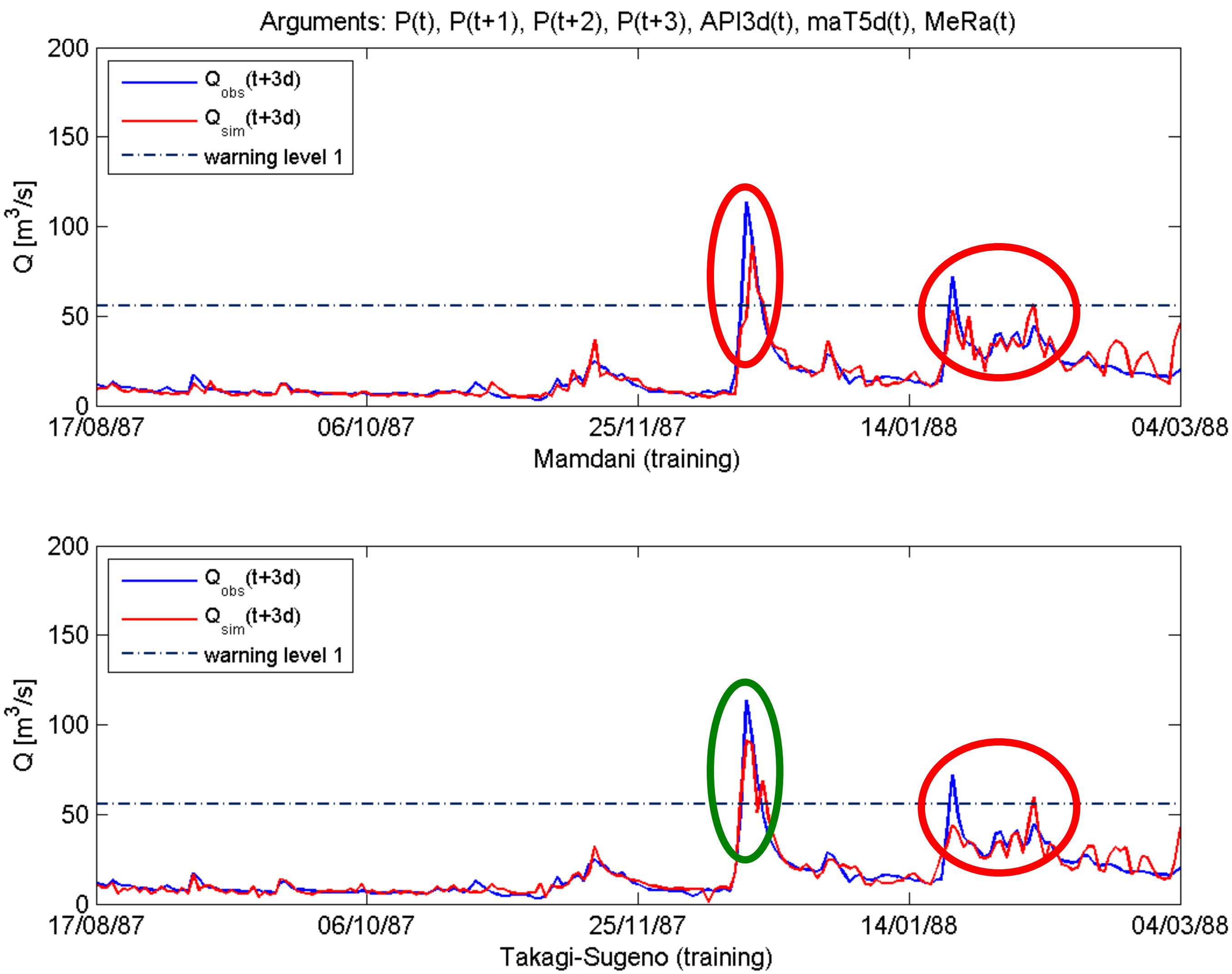


- A_E = 4242 km² (gauge Kemmern, outlet)
- characterised by high floods in winter
- Rainfall-runoff modell: WaSiM-ETH
- Hydrodynamic model: 1D/2D SOBEK

Database of the Upper Main

- Measured data: Q, T, P, etc.
  - → daily: 01.01.1964 – 31.12.2005
  - → hourly: 01.01.1991 – 31.12.2005
- simulated data:
  - → P-frequency: 10, 25, 50, 100, 250, 500 and 1000 years
  - → convective events with a duration of 48 h
  - → advective events with a duration of 72 h
  - → 100 realisations per precipitation frequency
  - → 2 different initial model conditions (dry / wet)
  - → extended database: 2800 possible discharge scenarios

Daily based forecast of Q(t+3d)



- Training

  01.01.1984 – 31.12.1994

- Validation

  01.01.1995 – 31.12.2004

- Mamdani

  50 rules

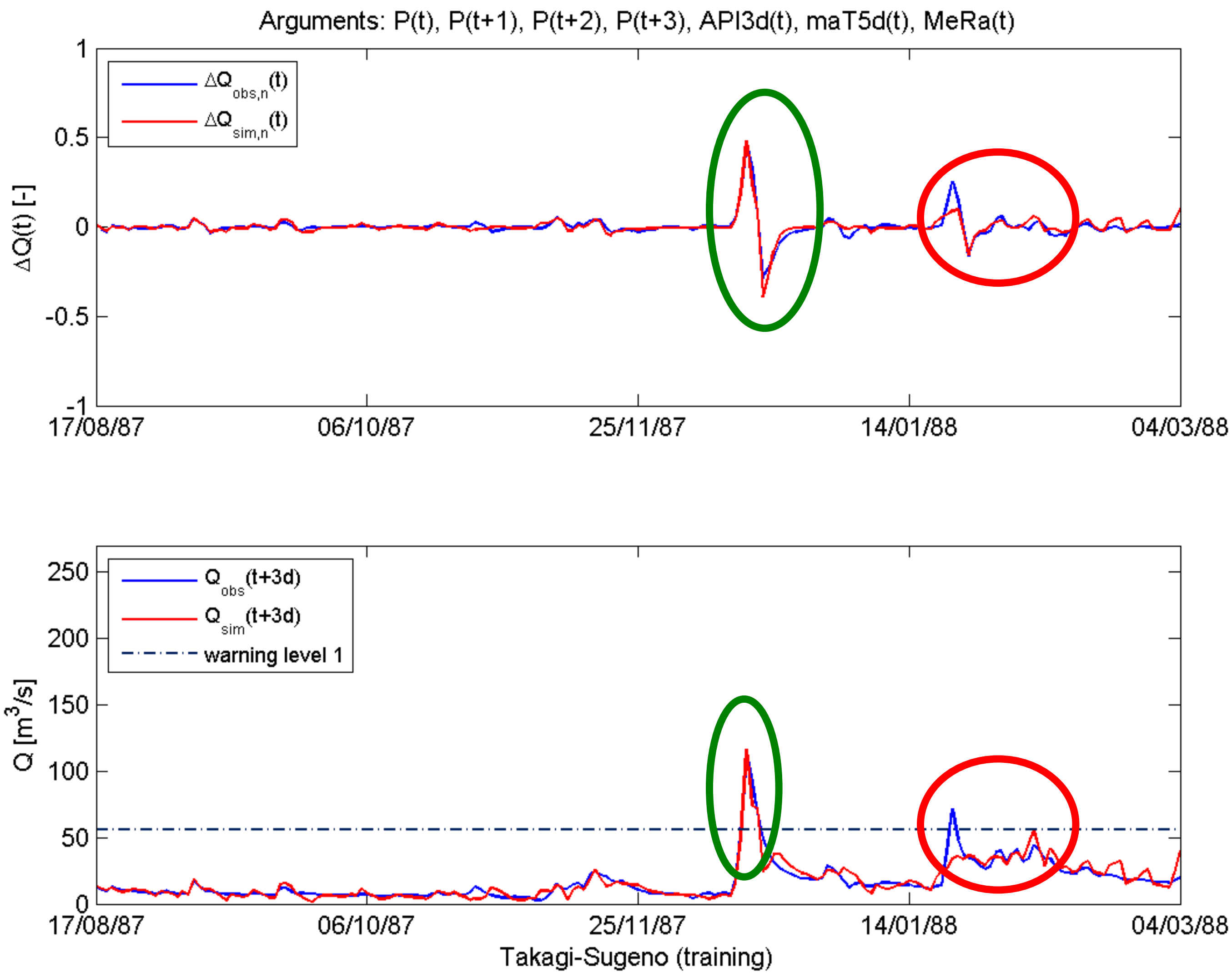
  $r_{val} = 0.89$

- Takagi-S.

  5 rules

  $r_{val} = 0.93$

Daily based forecast of ΔQ(t)



- Training

  01.01.1984 – 31.12.1994

- Validation

  01.01.1995 – 31.12.2004

- Mamdani

  55 rules

  $r_{val} = 0.74$

- Takagi-S.

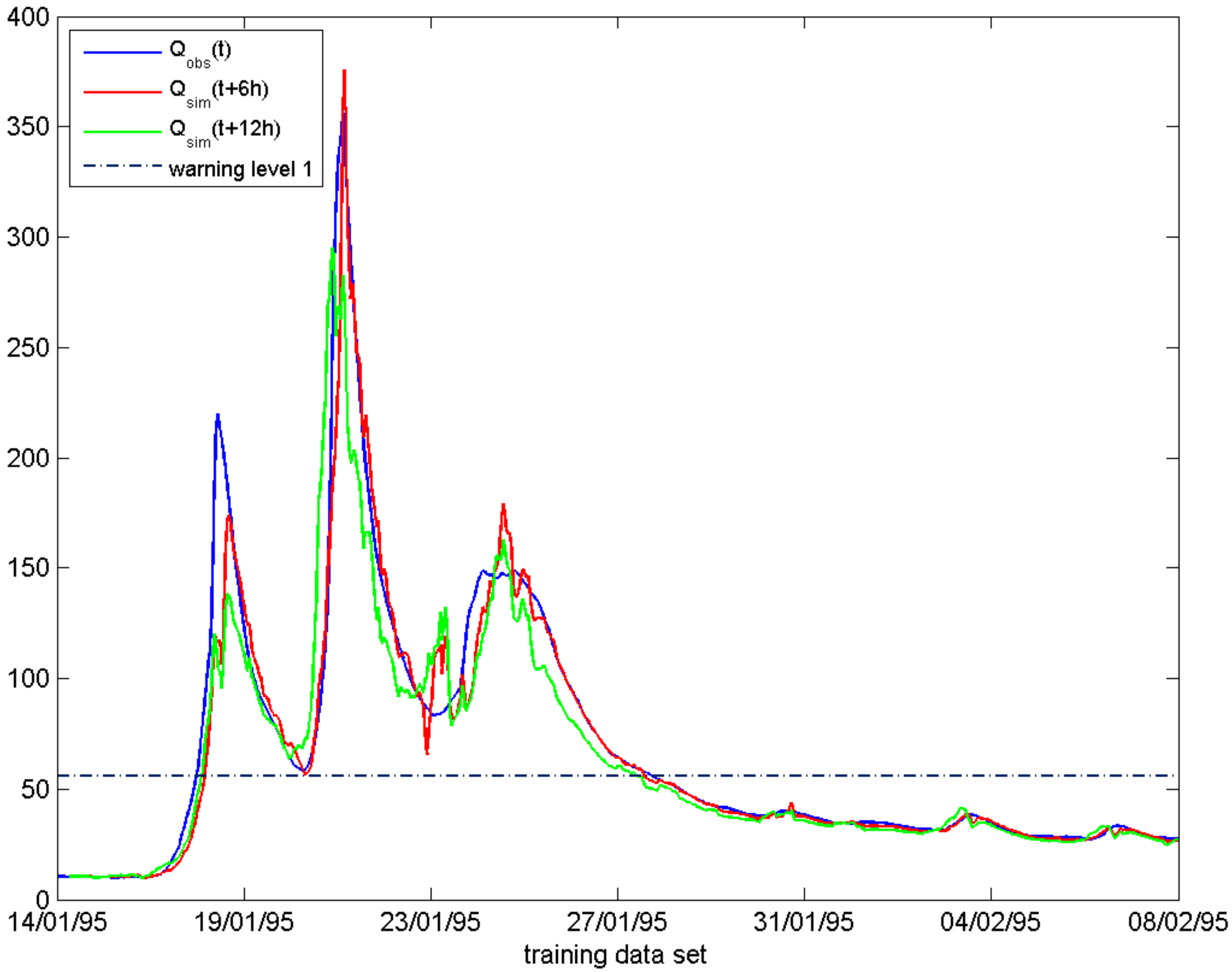
  5 rules

  $r_{val} = 0.70$

Hourly based forecast of Q(t+6h) and Q(t+12h)

Risk management of extreme flood events

Arguments: Q(t), API6h(t), maT6h(t), P(t-1), P(t-2), P(t-3), P(t-4) P(t-5), P(t-6), P(t), P(t+1), P(t+2), P(t+3), …, P(t+x), x= forecasting length



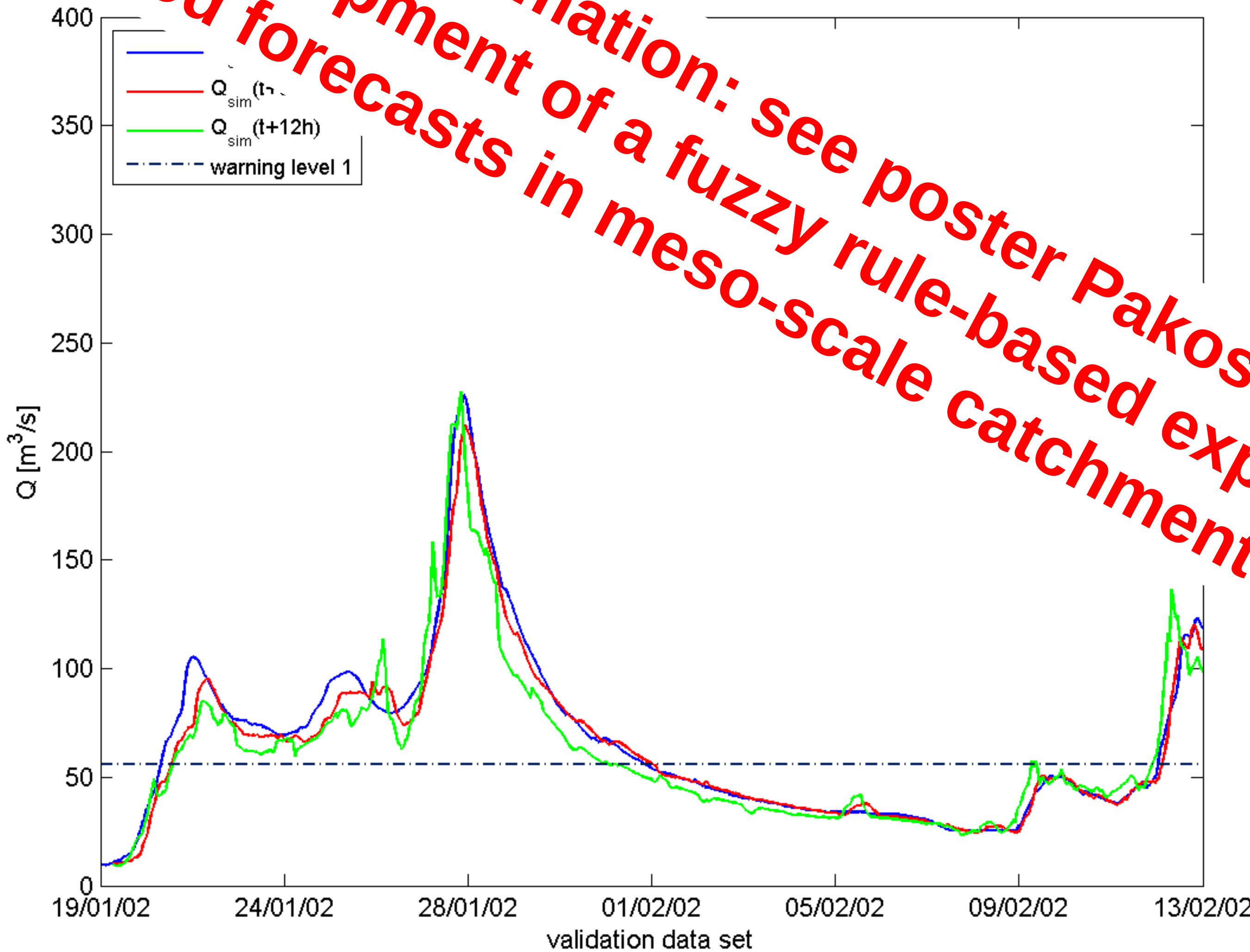
- Takagi-S.
  5 / 7 rules
  16 / 22arguments
- Training
  06.01.1991 –
  31.12.1999
- Validation
  01.01.2000 –
  31.12.2004
- correlation coefficient
  r_{train} = 0.98 / 0.97
  r_{val} = 0.98 / 0.98

Hourly based forecast of Q(t+6h) and Q(t+12h)

Risk management of extreme flood events

Further information: see poster Pakosch et al. "Development of a fuzzy rule-based expert system for flood forecasts in meso-scale catchments"

...maT6h(t), P(t-1), P(t-2), P(t-3), P(t-4) P(t-5), P(t-6), ... P(t+3), ..., P(t+x), x= forecasting length



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- correl... coefficient
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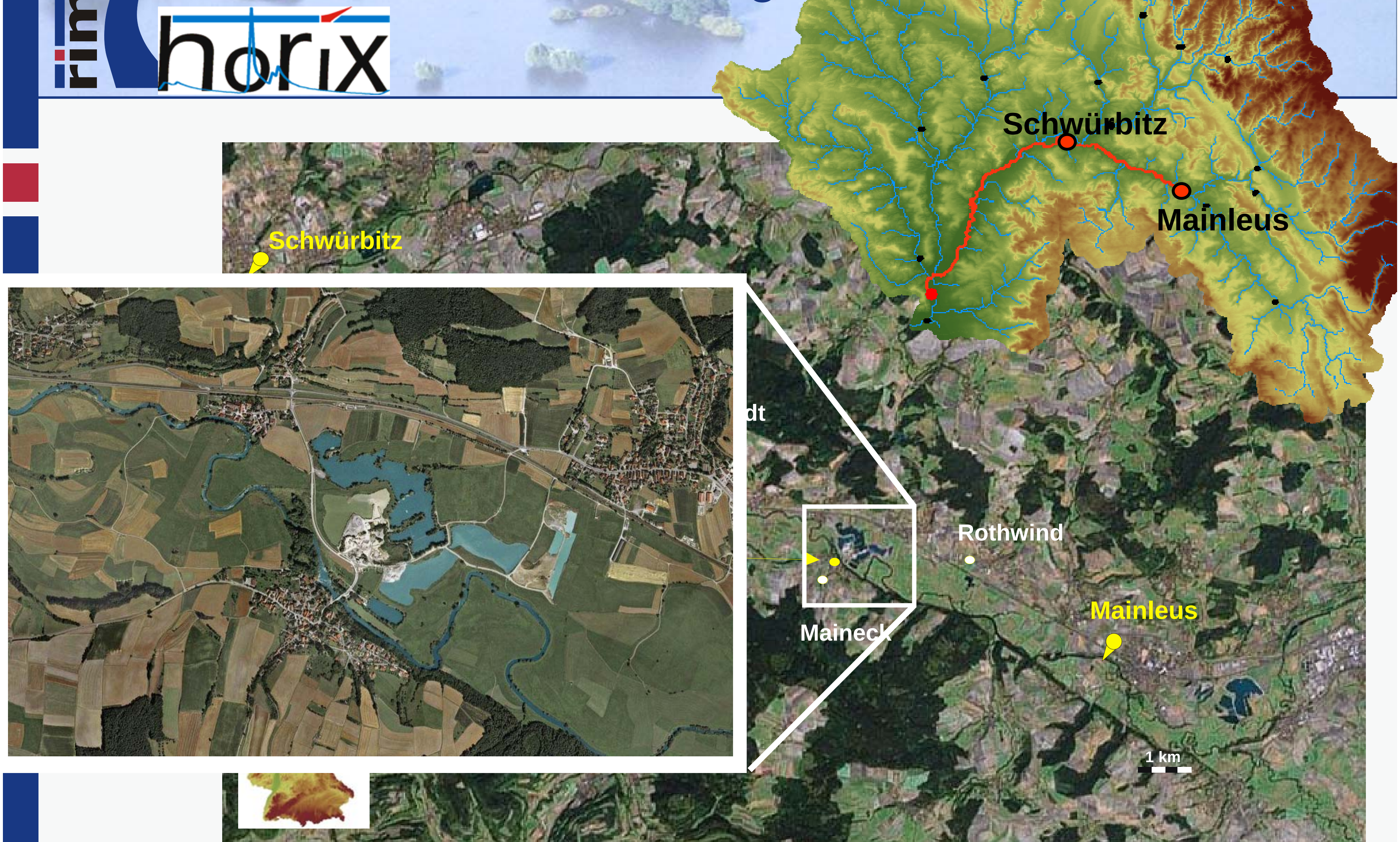
Risk management of extreme flood events

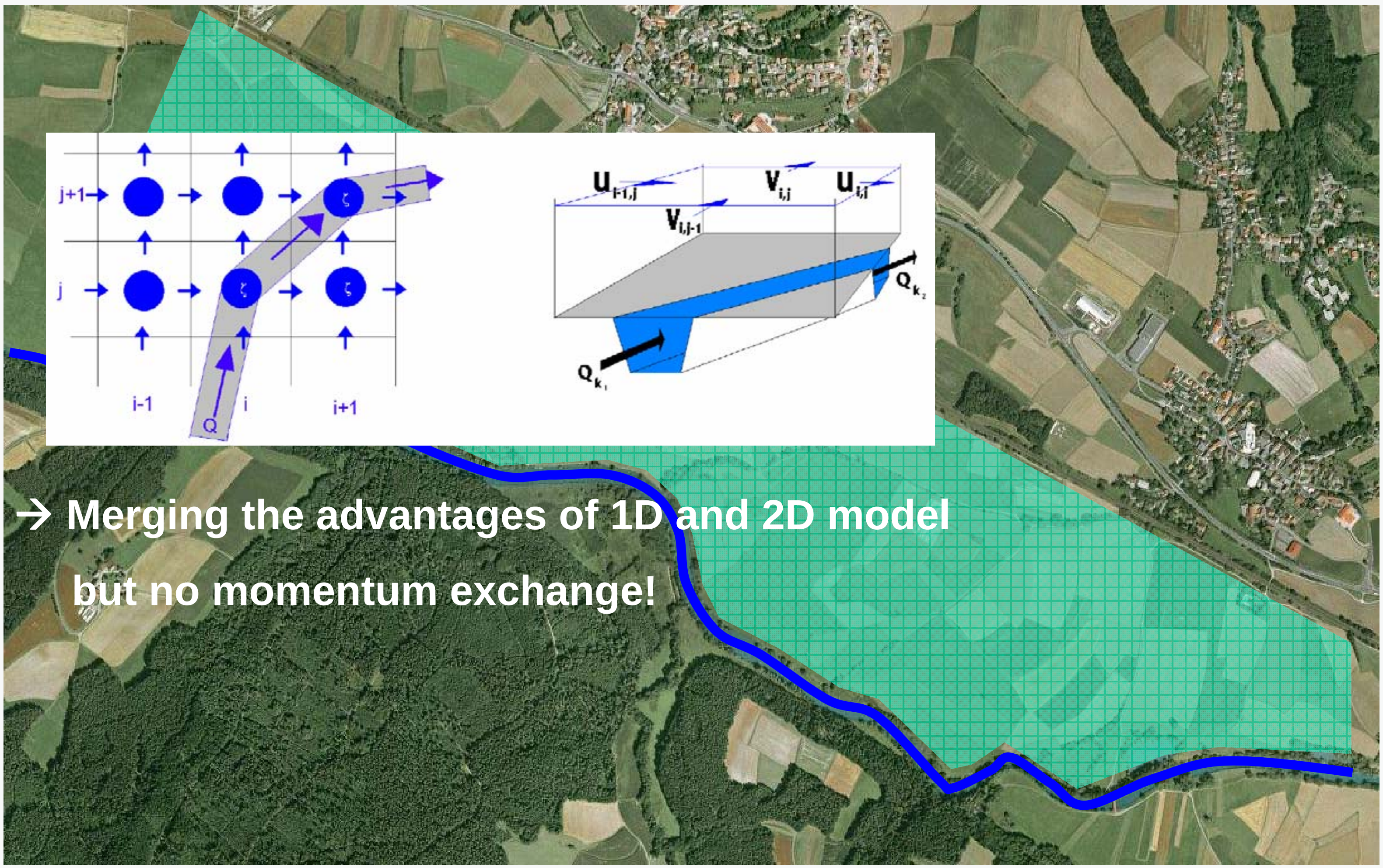
Inundation modelling



Inundation modelling

Deltares
Enabling Delta Life

1D/2D-Simulation (hybrid) SOBEK



→ **Merging the advantages of 1D and 2D model but no momentum exchange!**

Monte Carlo Simulation

Parameter	Range
Q	HQ100 ± 15 %
$k_{st}FS$	30 – 44 $m^{1/3}/s$
$k_{st}VL$	18 – 32 $m^{1/3}/s$
y_{FS}	± 0,2 m
y_{VL}	± 0,15 m

→ **Monte Carlo-Simulation**

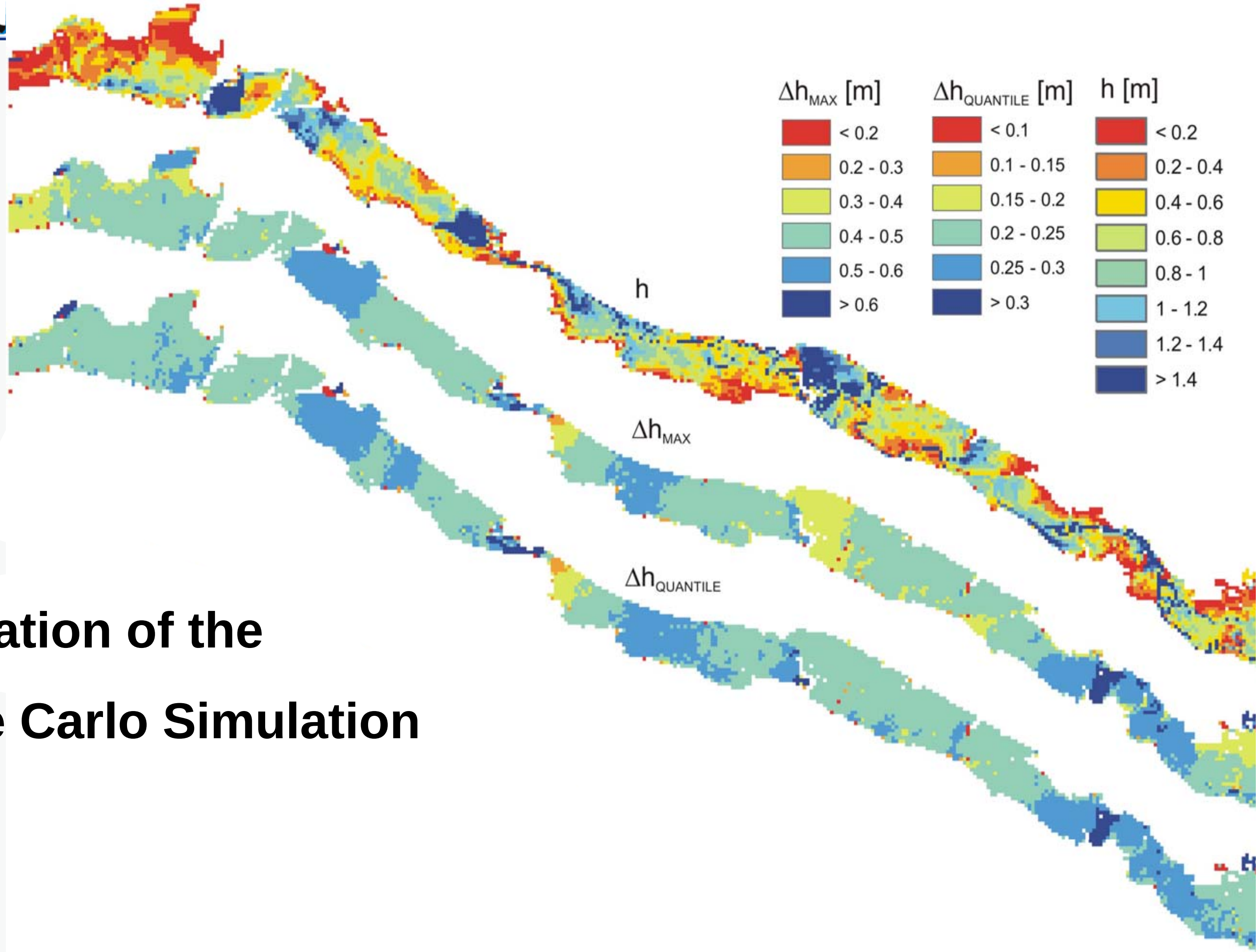
(3000 runs)

→ **Statistical analysis**

Target parameter: Water depth

- **stationary discharge**
- **non-stationary discharge**

Inundation modelling

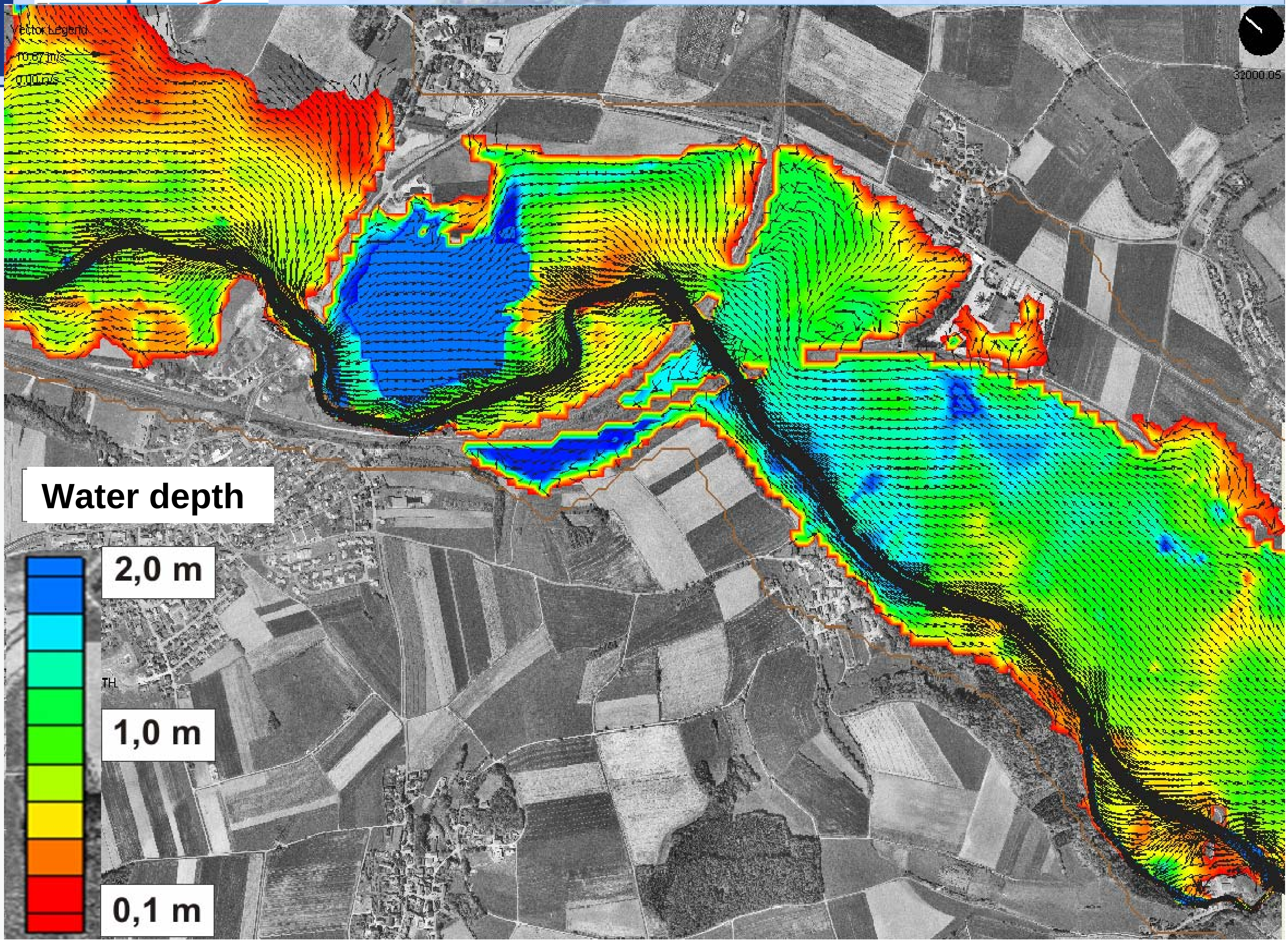


Evaluation of the

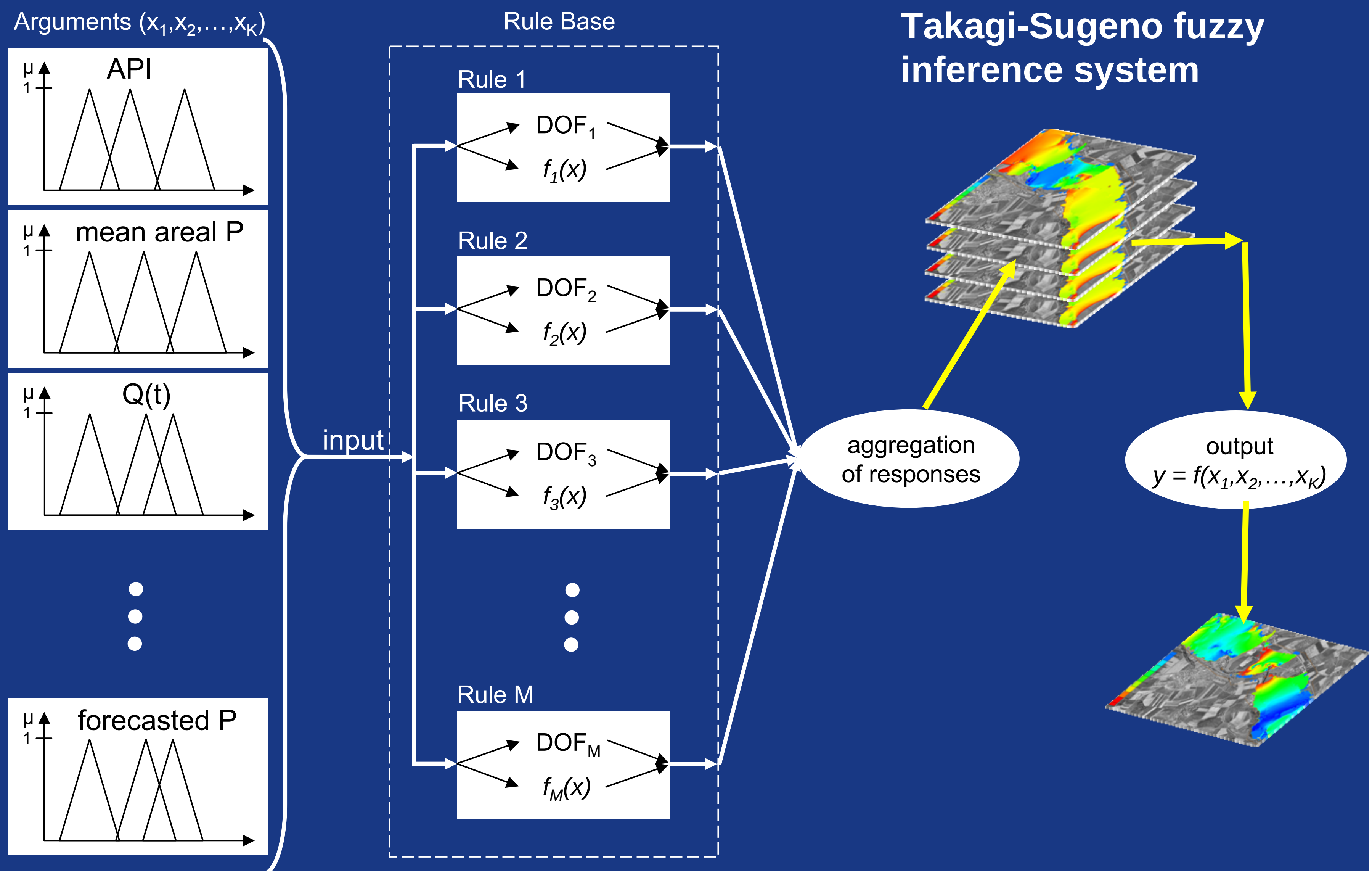
Monte Carlo Simulation

Risk management of extreme flood events

Uncertainties of hydrodynamic models



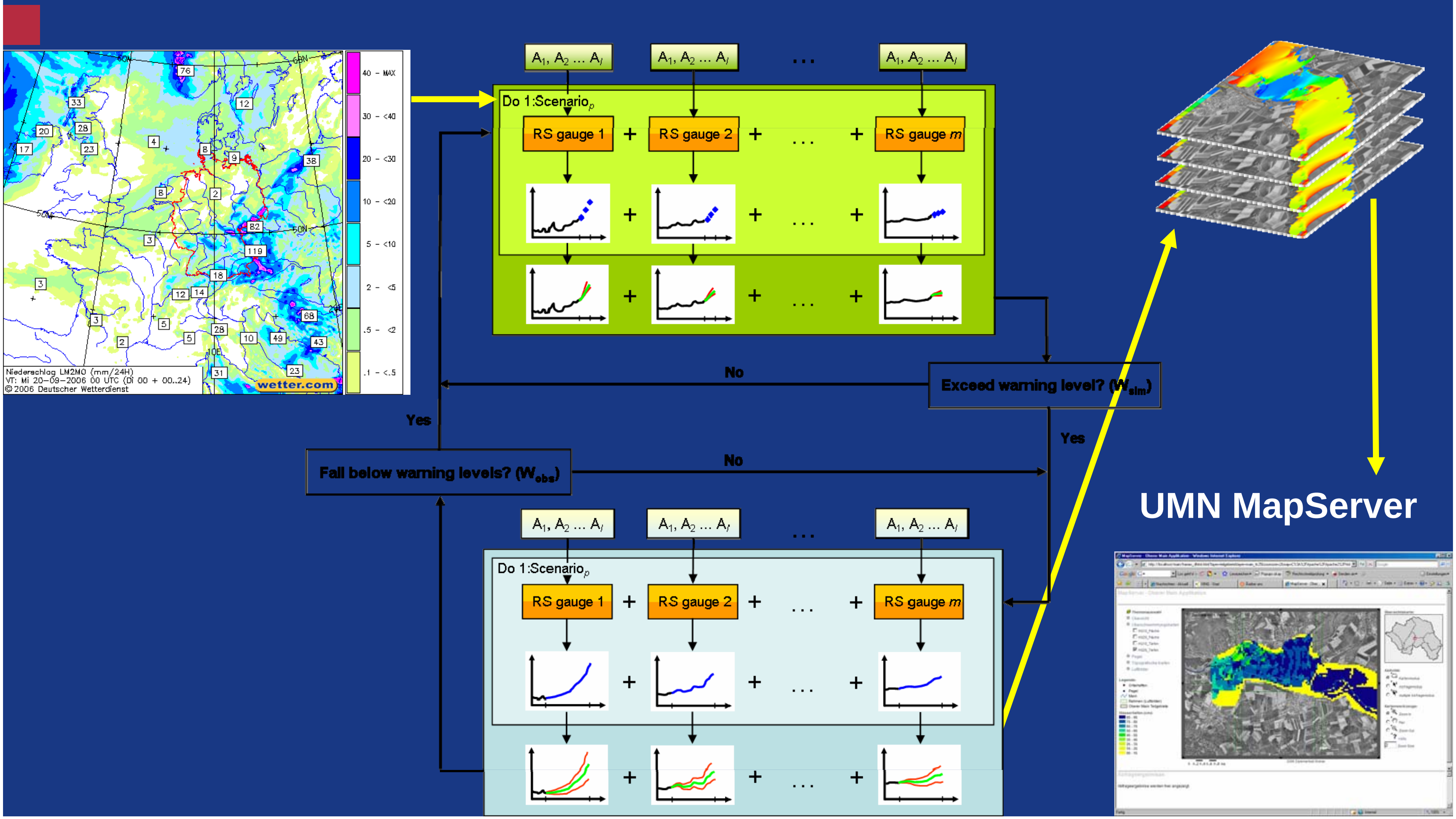
WebGIS-Application with UMN MapServer



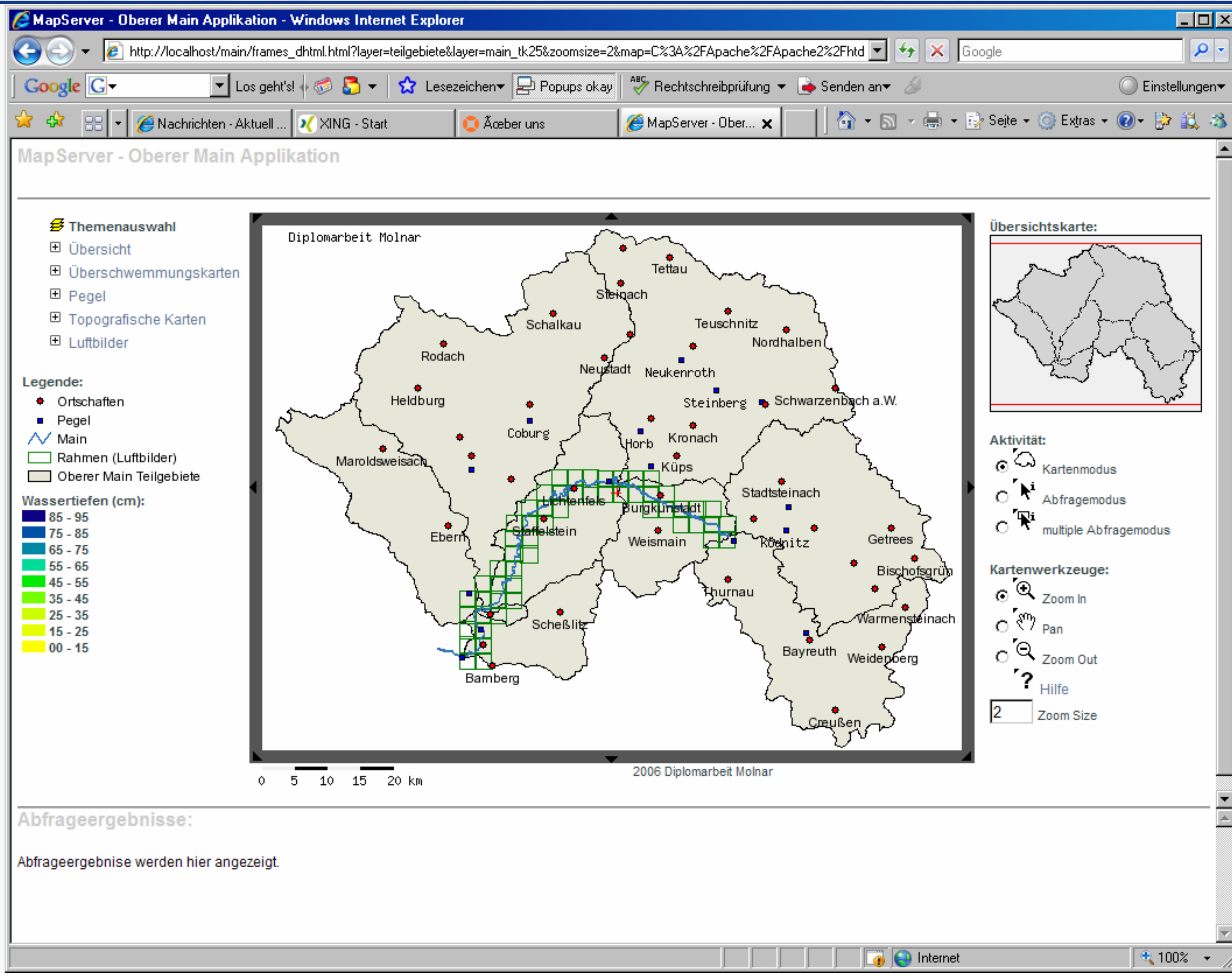
Risk management of extreme flood events

WebGIS-Application with UMN MapServer

Precipitation forecast | **Fuzzy inference system** | **Pre-calculated flood maps**

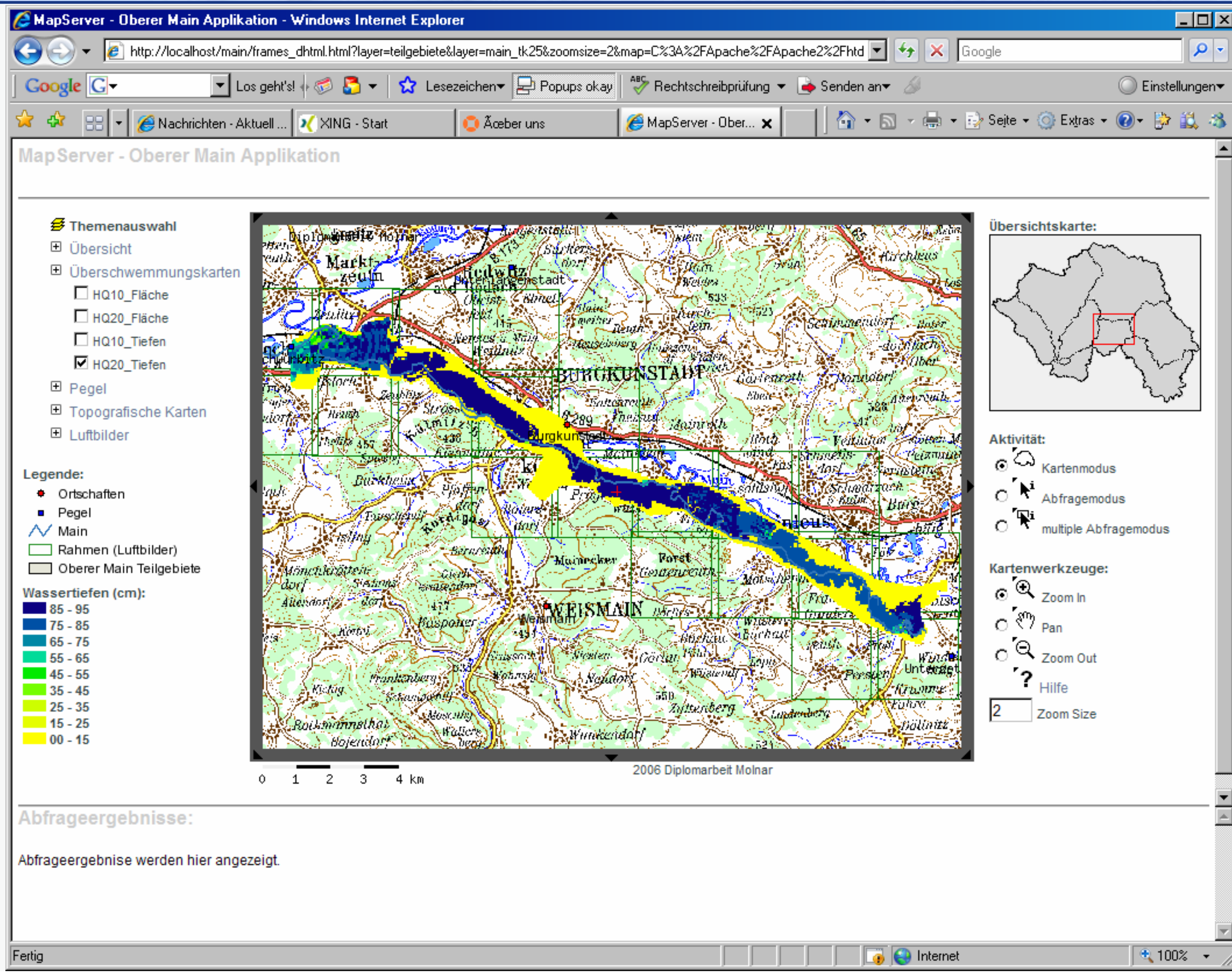


WebGIS-Application with UMN MapServer

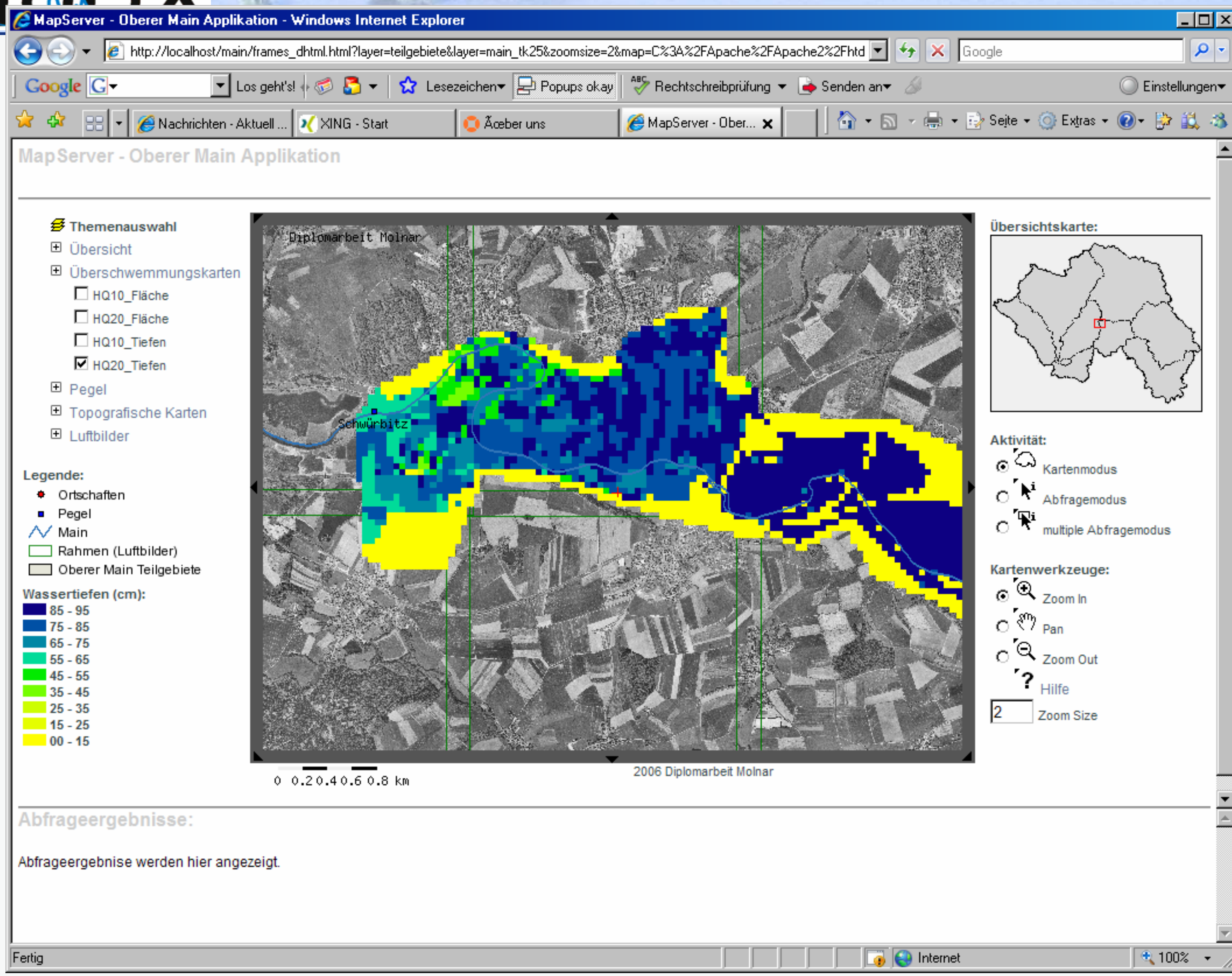


Risk management of extreme flood events

WebGIS-Application with UMN MapServer

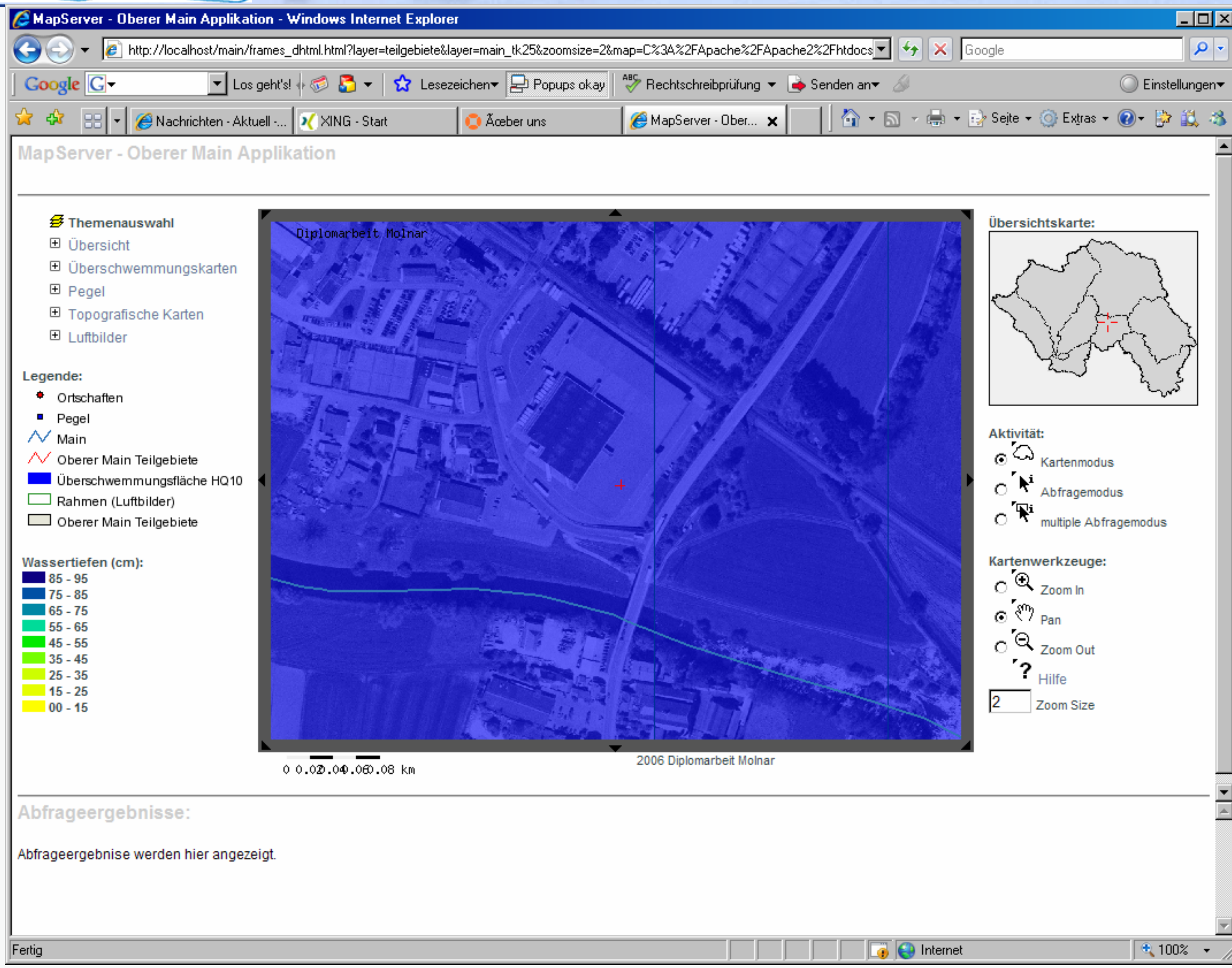


WebGIS-Application with UMN MapServer

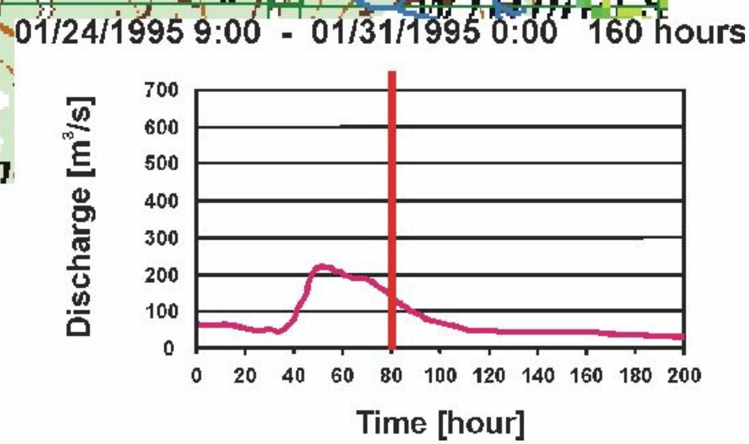


WebGIS-Application with UMN MapServer

Risk management of extreme flood events



Inun-
dation
movie
(Proto-
type!)



Conclusions

- Comparable performance of both fuzzy systems (daily base)
  - → training of Mamdani is faster than of Takagi-Sugeno
  - → Mamdani needs more rules than Takagi-Sugeno
- Comparable and good performance of daily $Q_F(t+x)$ and $\Delta Q_F(t)$ forecasts
- First results of hourly $Q_F(t+x)$ forecast are satisfying using Takagi-Sugeno
- Flood forecast is very fast
  - → precipitation ensembles can be evaluated statistically

Risk management of extreme flood events

Outlook

- investigate further arguments
  - → e.g. representing snow melting processes
  - → flood events mainly in winter
- investigate performance of both system on the hourly resolution further
  - → include investigation of $Q_F(t+x)$ and $\Delta Q_{F,x}(t)$ forecast
- integrate model uncertainty into the fuzzy system
- apply fuzzy system to 2 other study areas

Risk management of extreme flood events

Summary

- HORIX considers uncertainties of the whole „flood chain“
- Calibration of rainfall runoff models should be performed half-automatically
- Precipitation uncertainty is most important, followed by soil heterogeneity and parameter uncertainty of the models
- Flood forecasts, which are generated by the fuzzy-based expert system, are very fast
  → precipitation ensembles can be evaluated statistically
- The current inundation risk for the residents will be visualized by (dynamic) flood maps in the internet

Risk management of extreme flood events

rimax horix

Thank you for you attention!

Outlook

- **Integration of uncertainties into the inundation maps**
- **Presentation of complex information (dynamic flood maps, quantiles, confidence intervals,…) in an understandable manner**