Improvements of stream-flow predictions and flood forecasts

1. Error correction based on
   - Wavelet transformations of observed and simulated discharge series to capture errors caused by different time scales, resolutions
   - Vector AutoRegressive model with eXogenous Input (VARX) applied in the Wavelet domain (for each scale)
2. Predictive uncertainty estimation
   - Bayesian Uncertainty Processor of the forecast (Krzysztofowicz, 1999)
3. Forecast combination
   - Deriving optimal weights (e.g. Bayesian Model Averaging)

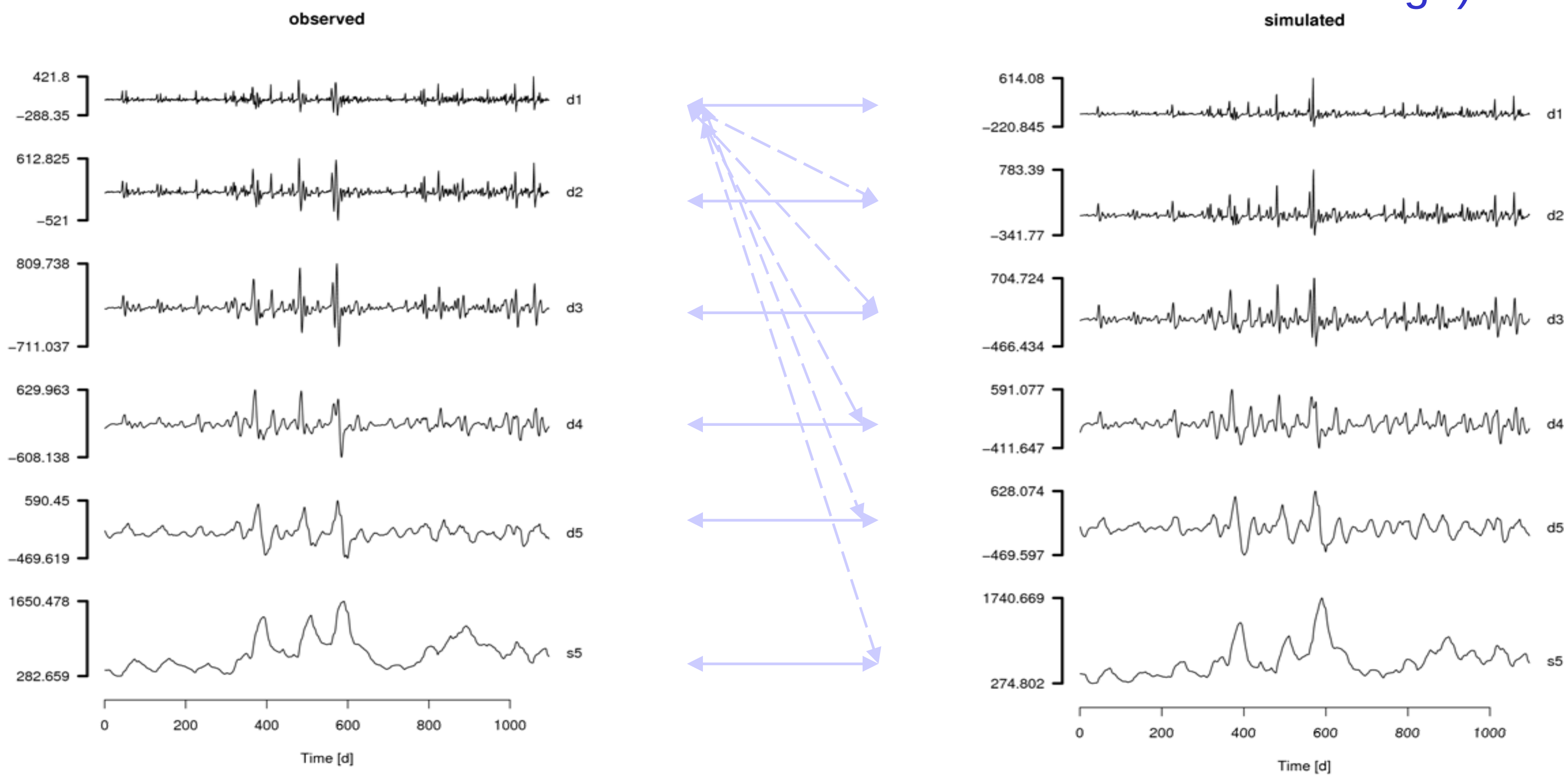
1.1 Wavelet transformation

Predictand

(observed discharge)

Predictor

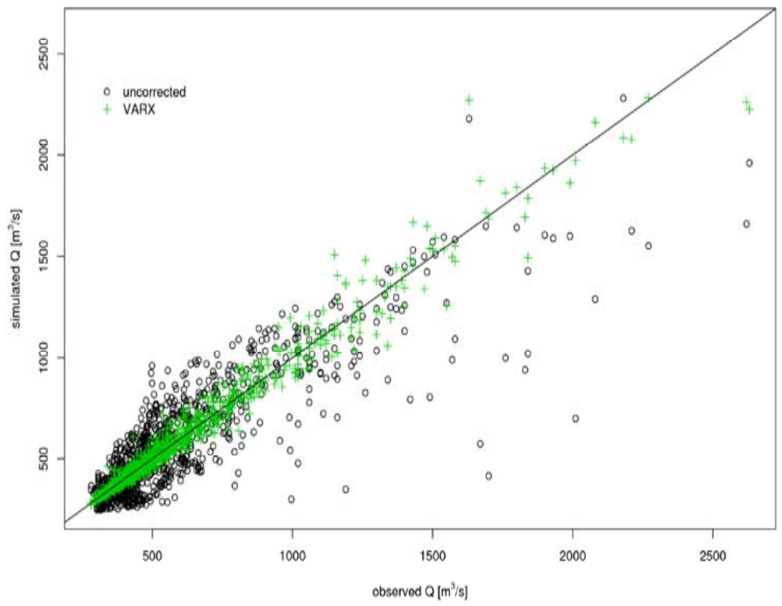
(simulated/forecasted discharge)

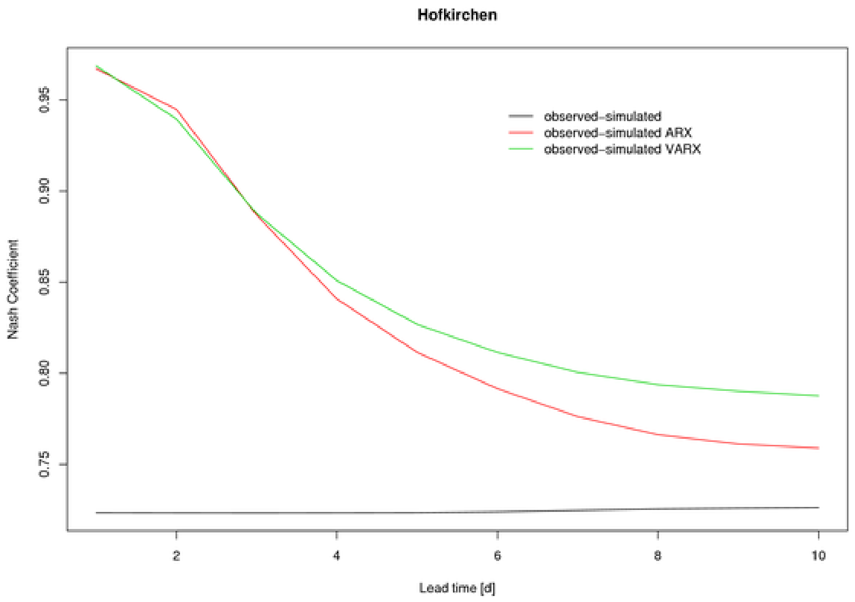


1.2. Fitting a Vector AutoRegressive model VARX in the Wavelet domain

(all levels of decomposition / resolutions simultaneously)

Post-processing: Validation





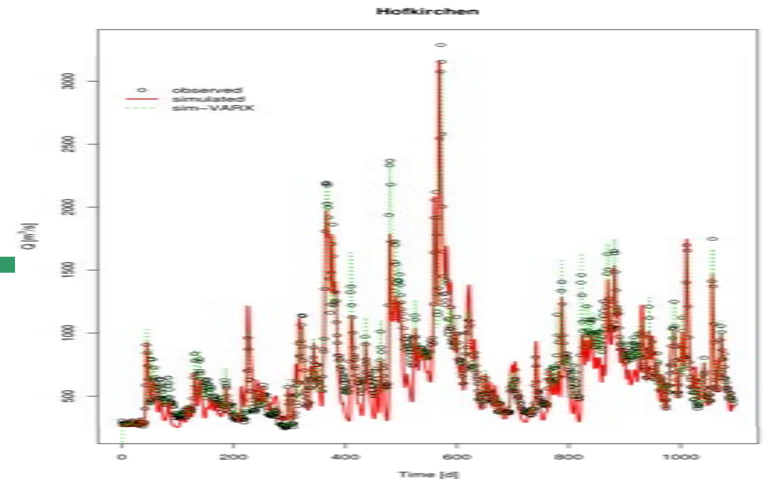
2. Predictive uncertainty estimation

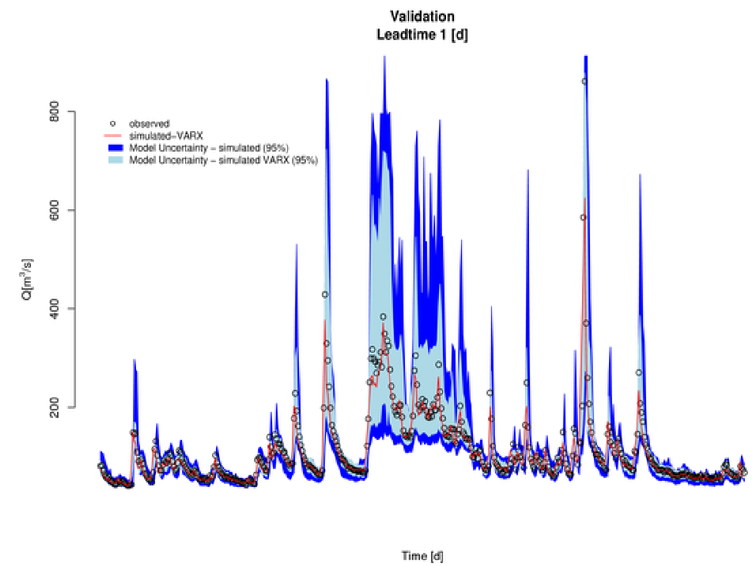
Normal quantile transform of the observed and simulated data

VARX predictions in the wavelet domain

Deriving Uncertainties for each lead time (Krzysztofowicz, R., 1999)

Back-transformation from Gaussian space

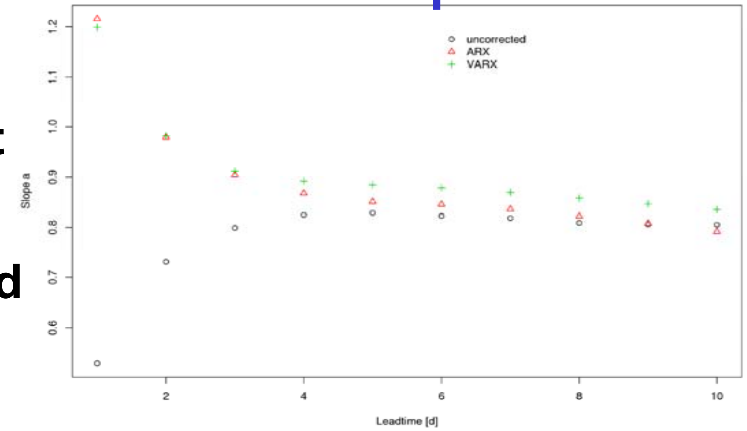




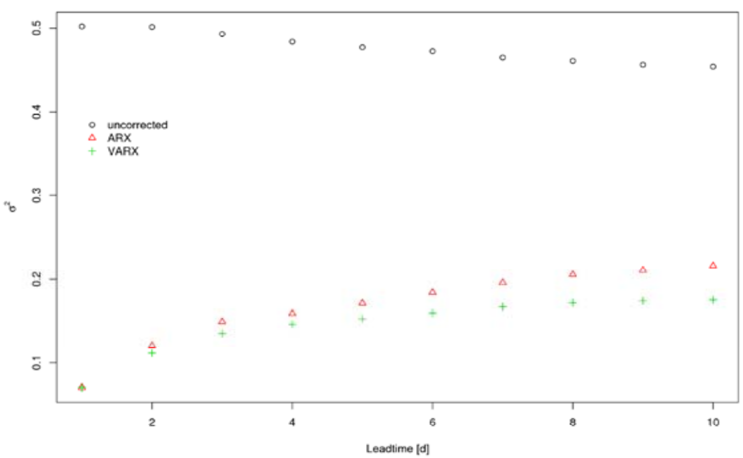
- **Slope *a* measures how much information is in the output**
- **σ^2 measures the "noise" of the output**
- **Informativeness Score (IS, (Krzysztofowicz (1992)) and is bounded between 0 (=uninformative predictor) and 1 (=perfect predictor)**

$$IS = \left[\left(\frac{a}{\sigma} \right)^{-2} + 1 \right]^{-\frac{1}{2}}$$

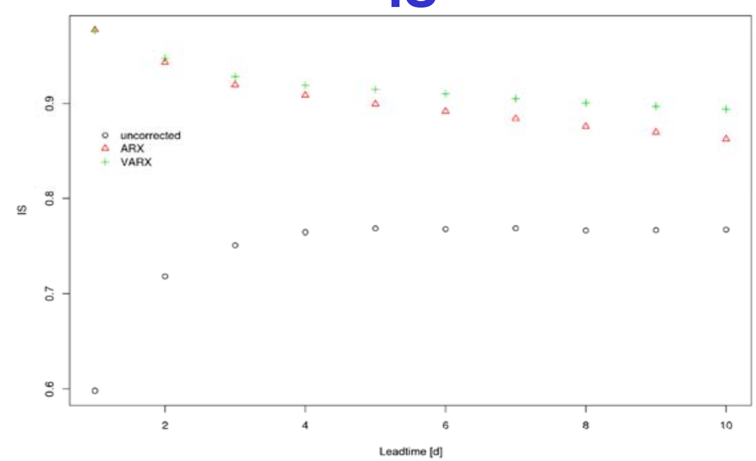
Slope a



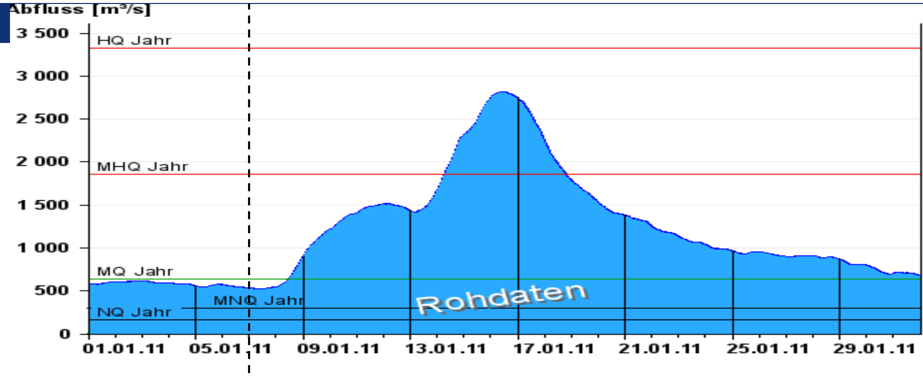
σ^2



IS



Example from January 2011



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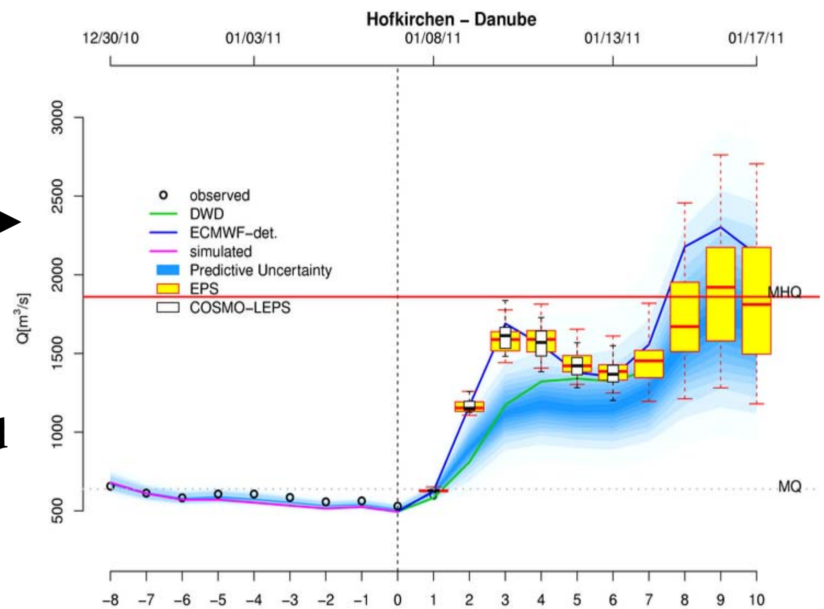
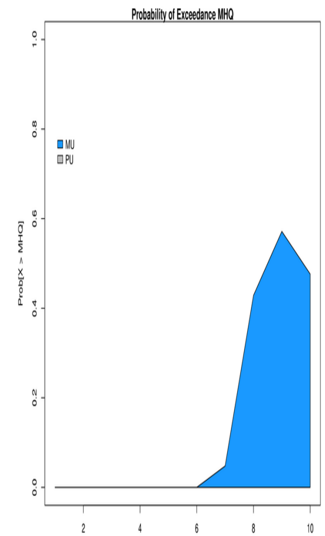
Measurements:

Observed discharge time series at station Hofkirchen (Danube, Germany)

EFAS discharge forecast (based on meteorological forecasts initiated at 01/07/2011 12:00

(9 days before the flood peak)





Exceedance probability of the mean annual flood discharge (MHQ) vs. leadtime

Hydrological Uncertainty
Input Uncertainty
Integrator (HU + IU)

At the moment the Input Uncertainty is simply estimated by giving each of the deterministic forecasts (DWD + ECMWF) 25% and each EPS member 1% -> ~100%: "empirical combination"

Possible improvements: Combining forecasts giving different weights according to the forecast quality in the previous days

- **Heteroscedastic Normal Regression or Nonhomogeneous Gaussian Regression (EnsembleMOS,** Gneiting et al. 2005)

$$E(X_n \mid u, v) = v_n,$$

$$Var(X_n \mid u, v) = \tau_n^2$$

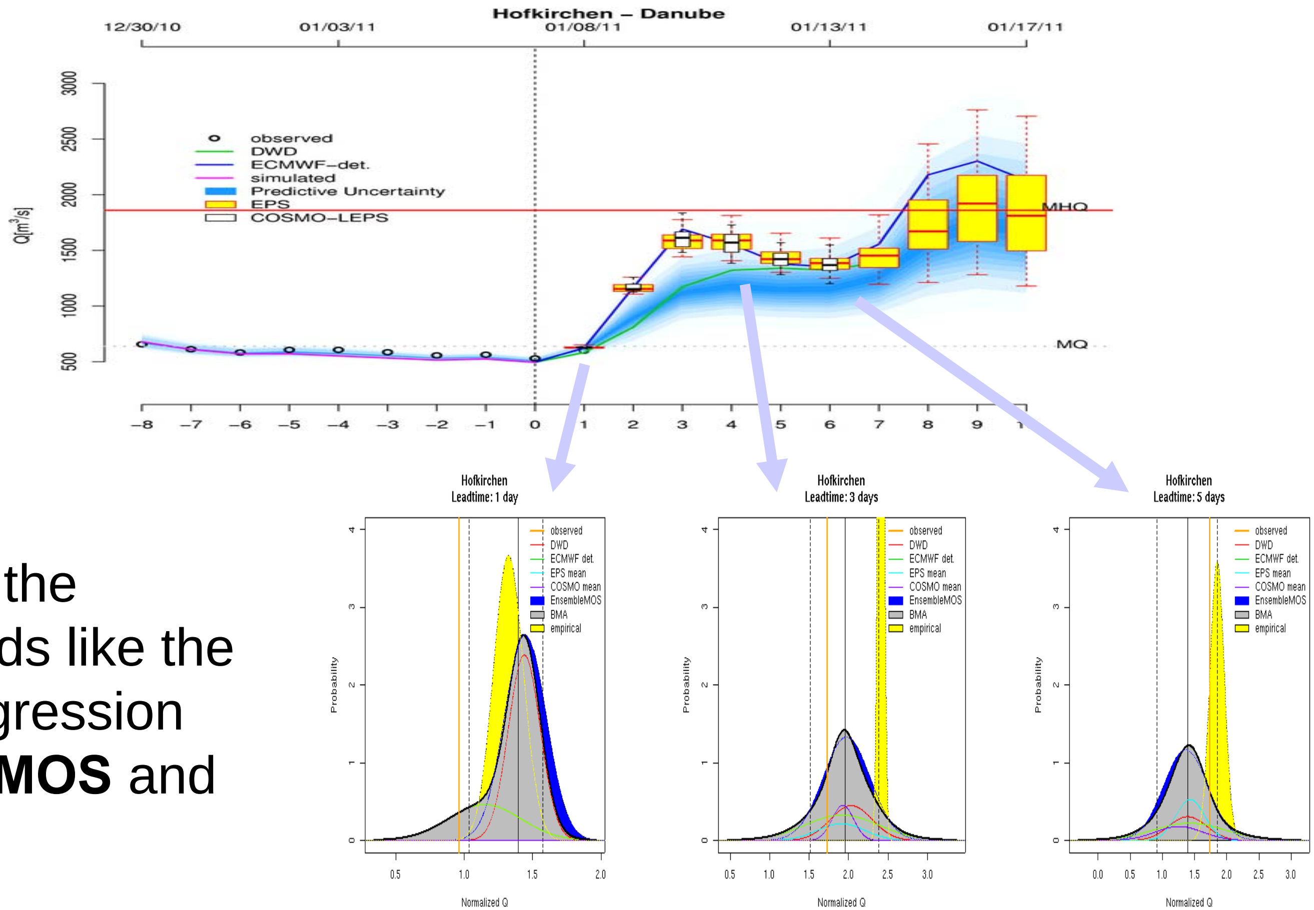
$$V_n = \beta_0 + \beta_1 X_{Det.DWD} + \beta_2 X_{Det.ECMWF} + \beta_3 \overline{X_{EPS}} + \beta_4 \overline{X_{LEPS}}$$

$$\tau_n^2 = g + hV_n$$

- **Bayesian model averaging**
  - **Dynamical updates -> quite intense in computing time**

- **Empirical method**

3. Forecast combination



Some examples of the investigated methods like the heteroscedastic regression model - **EnsembleMOS** and **BMA** method.

Conclusions

+ Improvements by re-weighting the various actual forecasts conditioning on their past forecast performance.

+ The combination by the use of static, empirical derived weights results many times in over- or underdispersive forecasts depending on the state of the stream-flow

References:

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