

Special Session S2: Ensemble predictions in a decision making context



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What is a „good“ forecast?

Murphy (1993) specifies a good meteorological forecast as follows:

- **Consistency**
 - degree to which a forecast corresponds to the **forecaster's best judgement** about the situation
- **Quality**
 - agreement of the forecast conditions with the **observed conditions** during the valid time of the forecast
- **Value**
 - degree to which a forecast helps users to realise some incremental **economic and other benefits**

Ensemble forecasts: Why?

Bertrand Russel in his contribution about the “Theory of Knowledge” for the Encyclopaedia Britannica (published in 1926):

“All knowledge is more or less uncertain and more or less vague: These are, in a sense, opposing characters: vague knowledge has more likelihood of truth than precise knowledge, but is less useful.”

==> Maximizing this likelihood with ensemble predictions?

==> More and more studies are dedicated to uncertainties (e.g. in data, models or even uncertainties of uncertainties).

But: Can uncertainties be handled by end-users ?

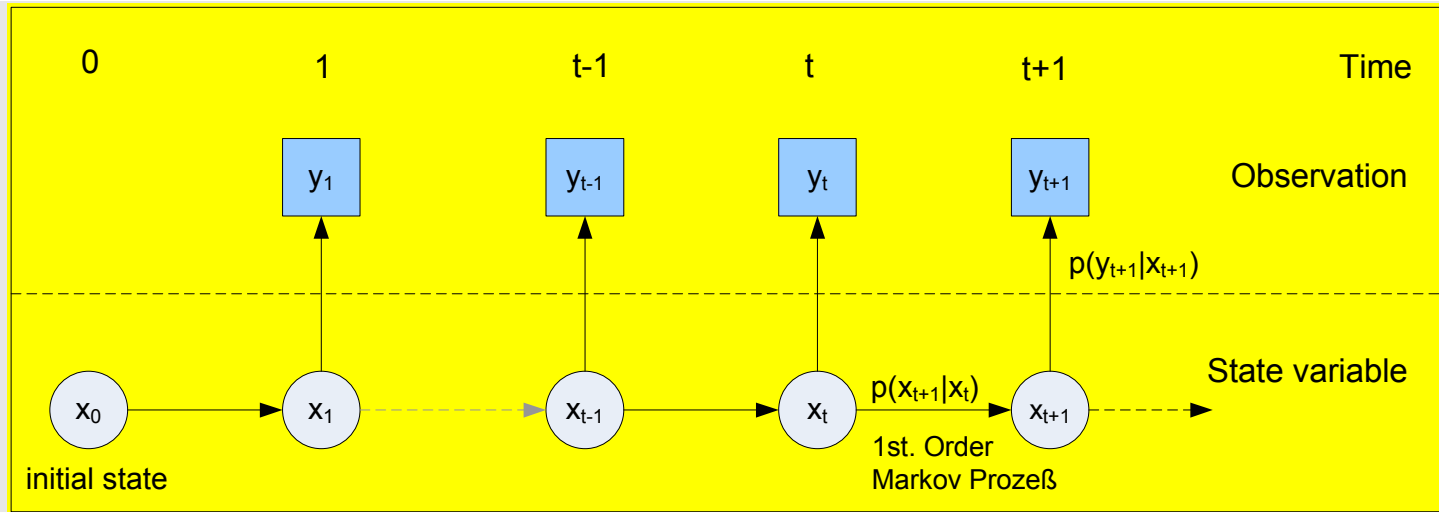
Ensemble forecasts: How?

Ensemble forecasting is a method to integrate a deterministic forecast with estimates of uncertain characteristics

Types of ensemble forecasts:

- **Single system ensembles**
 - **perturbation** of initial and boundary conditions, different model components (e.g. convection schemes in weather forecasts models) (physically based ensembles)
 - perturbation of model parameters
- **Multiple systems ensembles**
 - Combination of forecasts from **different models**
- **Lagged average ensembles**
 - Combination of actual forecasts with forecasts from **earlier model runs**

Separation of sources of uncertainties



Hydrological model in a dynamic state-space formulation:

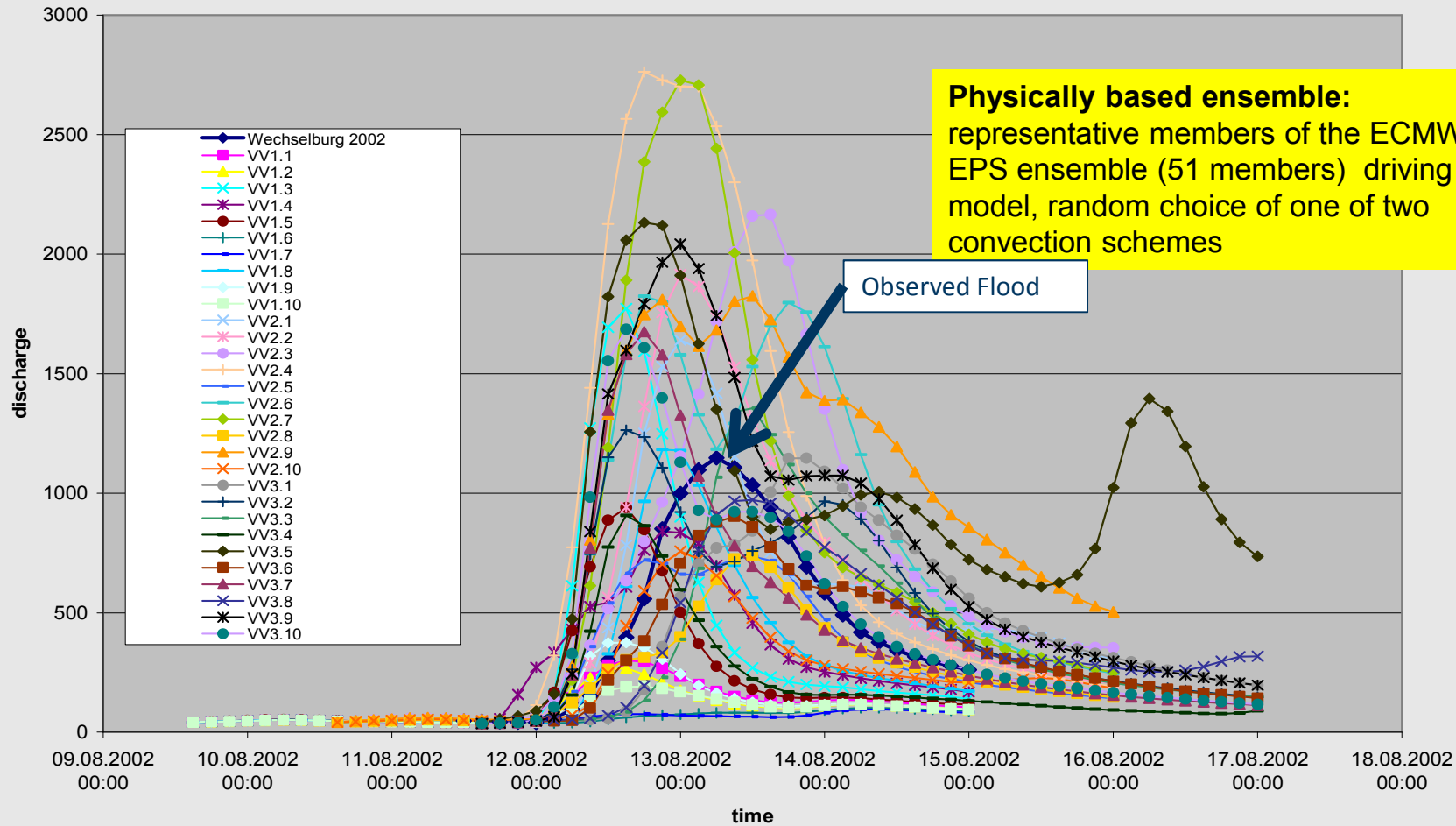
$$\text{Runoff } y_{t+1} = x_{t+1}$$

System state transition

$$x_{t+1} = f(x_t, u_t, \theta)$$

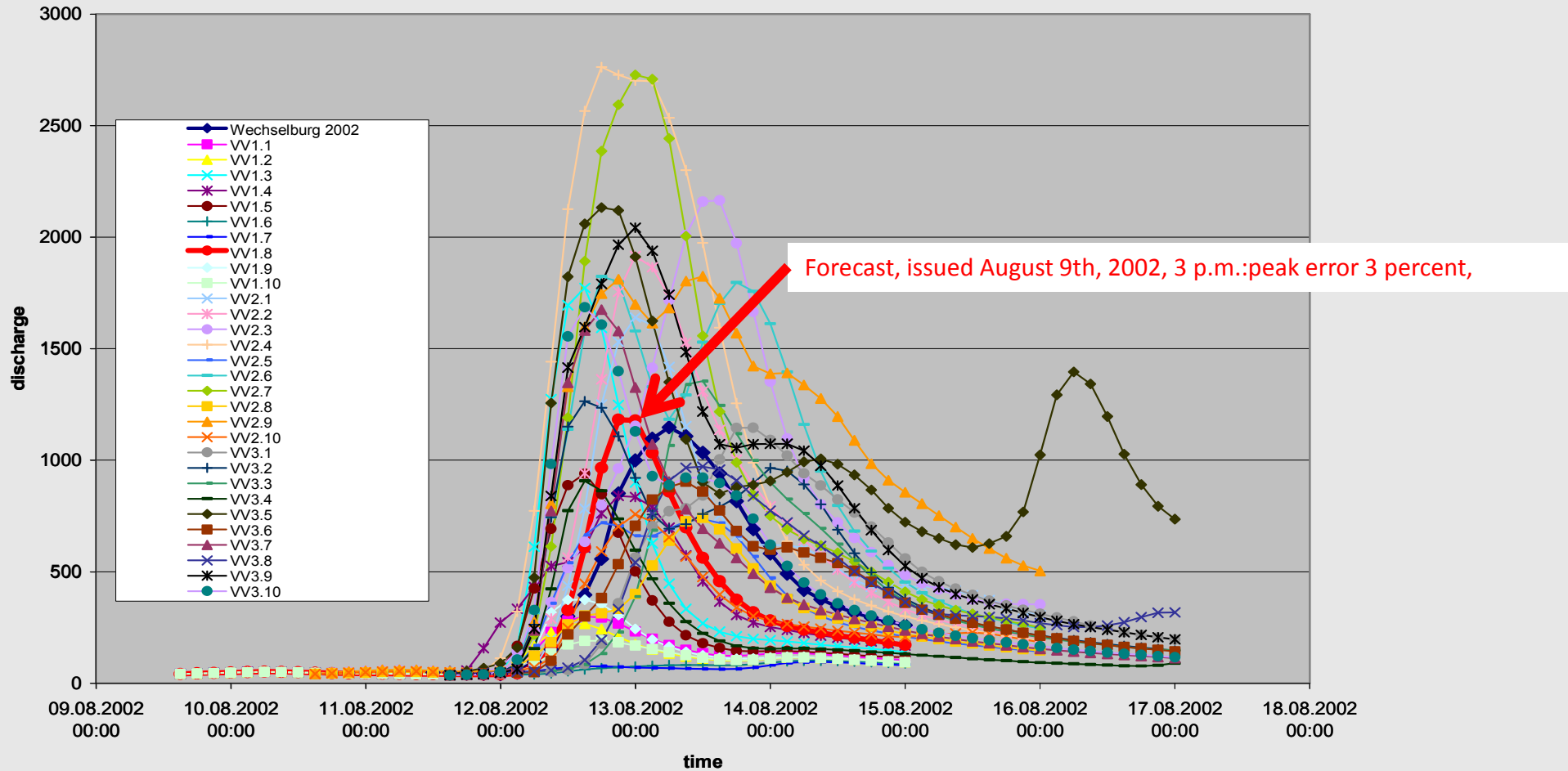
- | | | | |
|--------------------------------------|---|---|------------------------|
| 1. System state uncertainty | → | x: System state variable; | Ensemble Kalman-Filter |
| 2. Observation uncertainty | → | y: Observation (Measured system response); | |
| 3. Precipitation (input) uncertainty | → | u: Input data (precipitation); | Ensemble forecasts |
| 4. Parameter uncertainty | → | Θ: Model parameter; | Parameter Ensemble |
| 5. Model structural uncertainty | → | f(): System equation (hydrological model). | Multi-model Ensemble |

How can we use ensemble forecasts in the decision making process?



30 Ensemble forecasts for the flood at August 13th, 2002, gauge Wechselburg/ Mulde River, issued at August 9th (Re-analysis)

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Key question:

Have ensemble forecasts a probabilistic meaning?

Basic assumption of a probabilistic approach:

The ensemble should be a **statistical representative sample** from the basic population of **all** possible states in future and should map the space of uncertainties completely.

What Type of „Probabilities“ are characterized by ensembles?

Difference between objective (empirical) and subjective (epistemic) probabilities:

- **Empirical probabilities**: result of a random process, which can (theoretically) be repeated many times to review the frequency of this outcome

- **Subjective probabilities** describe the logical or psychological based **belief** in a statement, result etc.

How to quantify this belief?

Belief in Bayesian Model Averaging

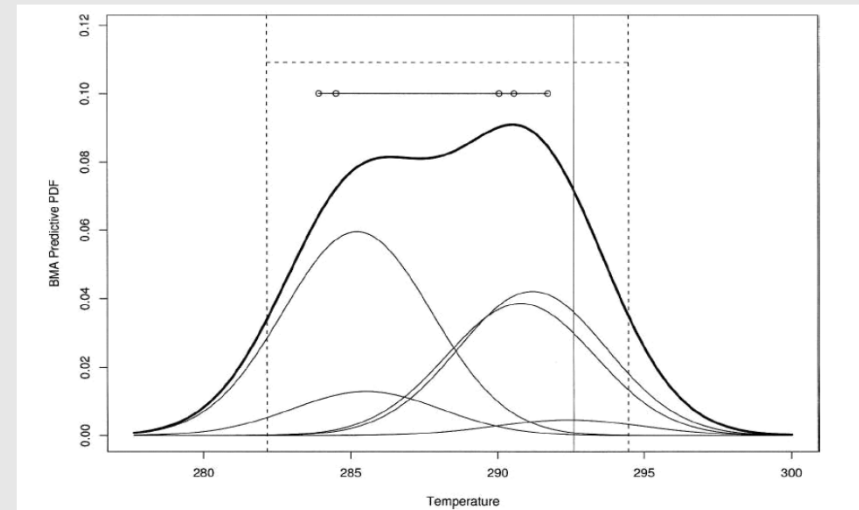
Bayesian Model Averaging assigns **weights** to ensemble members based on training period:

- Each ensemble member forecast f_k is associated with a conditional PDF $h_k(y|f_k)$ (PDF of quantity y given f_k , conditional on f_k being the best forecast in the ensemble)
- The BMA predictive PDF is then

$$p(y|f_1, \dots, f_k) = \sum_{k=1}^K w_k \cdot h_k(y|f_k)$$

where w_k is the **posterior probability** of forecast k being the best one, based on forecast k 's relative performance in a training period.

The w_k 's are probabilities and add up to 1.



(Raftery et al. 2005)

Traditional Uncertainty Assessment in Hydrological Modelling (Ajami et al. 2007)

Parameter uncertainty

$$\tilde{y} = M(\tilde{X}, \theta) + e(\theta)$$

↑ residuals (assumption additive)

Bayesian statistics

Hydrological model parameters θ are treated as probabilistic variables with the posterior probability distribution $P(\theta | \tilde{X}, \tilde{y})$

$$P(\theta | \tilde{X}, \tilde{y}) \propto P(\theta) \cdot \text{Likelihood}$$

Box and Tiao [1973]:

$$L(\theta | \tilde{X}, \tilde{y}) = \frac{1}{\sigma_y^T} \exp\left(-\frac{1}{2\sigma_y^2} \left(\sum_{t=1}^T (e(\theta)_t)^2\right)\right)$$

Contributions to this session

Three main topics:

- **Operational flood forecasting**
- **Seasonal streamflow forecasting**
- **Estimation of Design Floods considering Climate Change**

Contributions to this session

E. Todini (invited):

From data assimilation to multi-temporal uncertainty processors to improve real time flood forecasting and emergency management

A Conditional Model Processor (CMP) is presented. It aims to assess:

- The predictive uncertainty for each forecasting time step
- The probability of occurrence of flooding (or of exceeding a threshold) within a given time horizon
- The probability of the most likely time of occurrence of flooding (or threshold exceedance).

O.C.S. Valeriano, M. Ryo, T. Koike, T.D. Ngoc

Ensemble forecasts to support decision making at basin scale during heavy precipitation

Ensemble approach to consider the inaccuracy of the quantitative precipitation forecast (QPF) for flood control. The evaluation of recent forecasts with real time in situ measurements is used to determine the prediction bias from previous time steps.

D.C. Garen:

Ensemble streamflow prediction in western North America: Experience, development, and questions

Historically, statistical models have been used. Ensemble streamflow prediction is the alternative methodology that can provide fuller hydrologic information for these more complex decisions. At present, both statistical and ensemble prediction methods are used together. There is work yet to be done in developing robust ensemble prediction systems and in understanding forecast uncertainty. Continued work is also needed in the incorporation of forecast uncertainty into decision making.

Contributions to this session

S. Das, S.P. Simonovic (invited):

Assessment of uncertainty in flood flows under climate change - the Upper Thames River basin (Ontario, Canada)

This study investigates the climate change related uncertainty in the flood flows for the Upper Thames River basin (Ontario, Canada) using a wide range of climate model scenarios. The use of large number of climate models and scenarios also permits a probabilistic assessment of future flood flow uncertainty.

S. Bergstrom, J. Andréasson:

Ensemble simulations for climate change adaptation of the Swedish guidelines for design floods for dams

A method for climate change adaptation of the Swedish guidelines for design floods for dams has been developed. This includes a method for adjusting regional climate scenarios used as input to a hydrological model, the so called DBS method. The simulations are based on 16 regional climate scenarios. In this process the climate uncertainty was also discussed in perspective of other uncertainties in a design study for high hazard dams.

G.M. Midttomme, E. Holmquist, D. Lawrence:

Climate change and design flood calculation for dams in Norway

The design flood for large dams in Norway, which is a 1000-year flood, is calculated by using historical flood and precipitation data. The study is based on ensemble modeling using multiple climate scenarios and methods for interpreting these so that some of the uncertainties underlying projected changes can be quantified.