



UNIVERSITAT
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Instituto de Ingeniería del
Agua y Medio Ambiente



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA



DIPARTIMENTO DI SCIENZE della TE
e GEOLGICO-AMBIENTALI

Predictive uncertainty estimation at ungauged basins in a Bayesian framework

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Introduction

- Flow simulations and forecasts from models **are not error free**
- Implications in **decision making** process
 - => Growing interest in assessing **uncertainty** of predictions
- Several developed methods for gauging stations:
 - Hydrologic Uncertainty Processor (Krzysztofowicz, 1999)
 - Bayesian Model Averaging (Raftery, 1993; Raftery et al, 2003; 2005)
 - Meta-Gaussian error model (Montanari and Brath, 2004)
 - Model Conditional Processor (Todini, 2008)
 - Some others statistical approaches...
- How to estimate PU at **ungauged sites?**

Introduction

- Two different approaches for Predictive Uncertainty estimation:

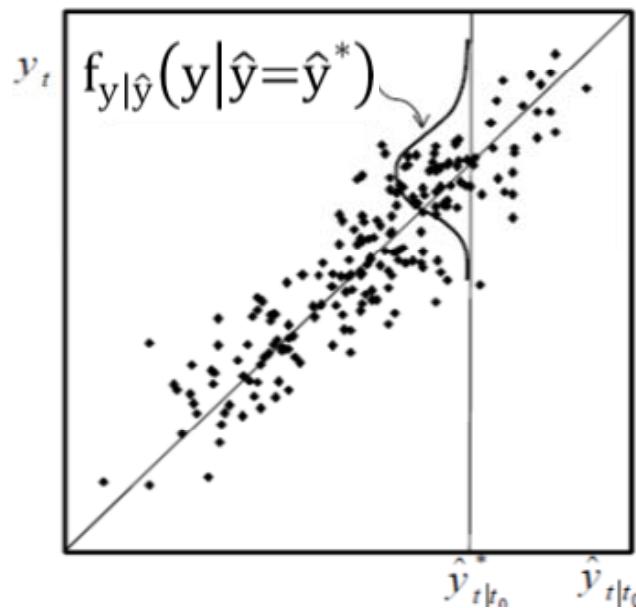
1st proposal: One hydrological model and multi-site data assimilation using a Kalman filter based algorithm **MISP** (*Mutually Interactive State-Parameter Estimation*)

Presented at "Floods in 3D" Leonardo EGU Conference. Bratislava, November 2011

2nd proposal: Multi-site and multi-model approach using the bayesian post-processor **MCP** (*Model Conditional Processor*) by combining historical simulations from various hydrological models at several sites on a region, in a regionalization framework

Predictive Uncertainty definition

- Probability density function (pdf) of the predictand given our model prediction (simulation or forecast).



From Todini (2011)

- NQT transformation (Krzysztofowicz, 1999):

➤ Observations:

y

➤ Models predictions:

$\hat{y}_1, \hat{y}_2, \dots, \hat{y}_N$



$$\left[\begin{array}{l} \eta \\ \hat{\eta}_1, \dots, \hat{\eta}_N \end{array} \right]$$

MCP with one prediction model

- The predictive distribution of an event conditional on the prediction of a model in the Gaussian space:

$$f(\eta/\hat{\eta}) = f(\eta, \hat{\eta}) / f(\hat{\eta}) \quad (1)$$

- The joint distribution in the Normal space has moments:

- Mean: $\mu_{\eta,\hat{\eta}} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

- Variance: $\Sigma_{\eta,\hat{\eta}} = \begin{bmatrix} 1 & \sigma_{\eta,\hat{\eta}} \\ \sigma_{\eta,\hat{\eta}} & 1 \end{bmatrix} = \begin{bmatrix} 1 & \rho_{\eta,\hat{\eta}} \\ \rho_{\eta,\hat{\eta}} & 1 \end{bmatrix}$ Marginals of η and $\hat{\eta} \approx N(0,1)$

- The predictive conditional pdf resulting from (1) is Normal with moments:

$$\mu_{\eta/\hat{\eta}} = \rho_{\eta,\hat{\eta}} \cdot \hat{\eta}$$

$$\sigma_{\eta/\hat{\eta}}^2 = 1 - \rho_{\eta,\hat{\eta}}^2$$

MCP with multiple prediction models

- The predictive distribution of an event conditional on the prediction of more than one model in the Gaussian field:

$$f(\eta/\hat{\eta}_1, \dots, \hat{\eta}_N) = f(\eta, \hat{\eta}_1, \dots, \hat{\eta}_N) / f(\hat{\eta}_1, \dots, \hat{\eta}_N) \quad (2)$$

- The predictive conditional pdf from eq. (2) is Normal and it has moments:

➤ Mean: $\mu_{\eta/\hat{\eta}} = \sum_{\eta\hat{\eta}} \sum_{\hat{\eta}\hat{\eta}}^{-1} \hat{\eta}$

➤ Variance:
$$\begin{aligned} \sigma^2_{\eta/\hat{\eta}} &= \sum_{\eta\eta} - \sum_{\eta\hat{\eta}} \sum_{\hat{\eta}\hat{\eta}}^{-1} \sum_{\eta\hat{\eta}}^T \\ &= 1 - \sum_{\eta\hat{\eta}} \sum_{\hat{\eta}\hat{\eta}}^{-1} \sum_{\eta\hat{\eta}}^T \end{aligned}$$

where:

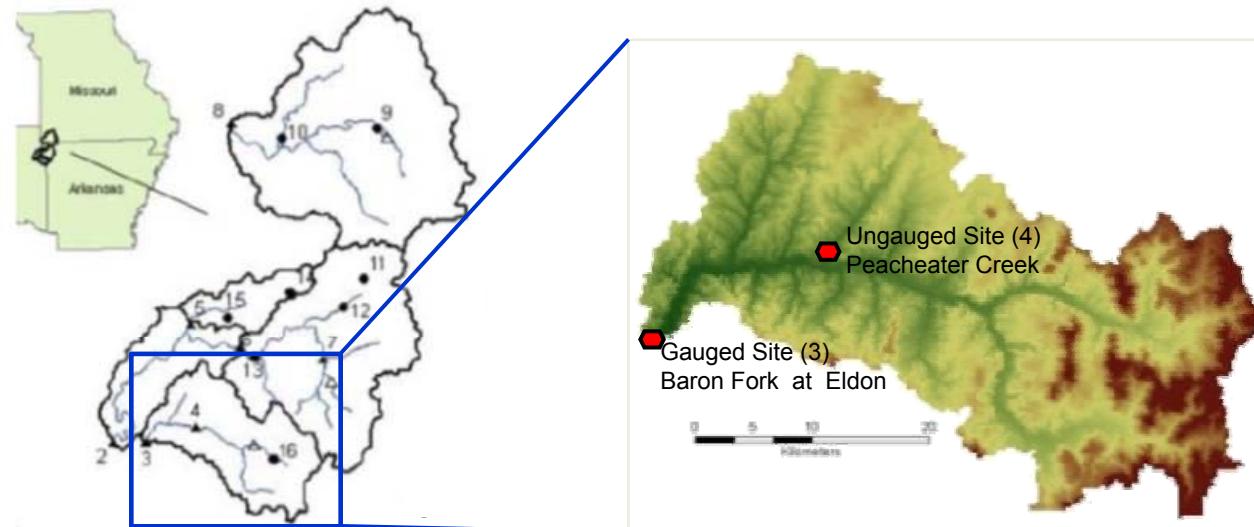
$$\sum_{\eta\eta} = 1$$

$$\sum_{\eta\hat{\eta}} = [\rho_{\eta\hat{\eta}_1} \quad \rho_{\eta\hat{\eta}_2} \quad \dots \quad \rho_{\eta\hat{\eta}_N}]$$

$$\sum_{\hat{\eta}\hat{\eta}} = \begin{bmatrix} 1 & \rho_{\hat{\eta}_1\hat{\eta}_2} & \cdots & \rho_{\hat{\eta}_1\hat{\eta}_N} \\ \rho_{\hat{\eta}_2\hat{\eta}_1} & 1 & \ddots & \rho_{\hat{\eta}_2\hat{\eta}_N} \\ \vdots & \ddots & \ddots & \vdots \\ \rho_{\hat{\eta}_N\hat{\eta}_1} & \cdots & \rho_{\hat{\eta}_N\hat{\eta}_{N-1}} & 1 \end{bmatrix}$$

Case study

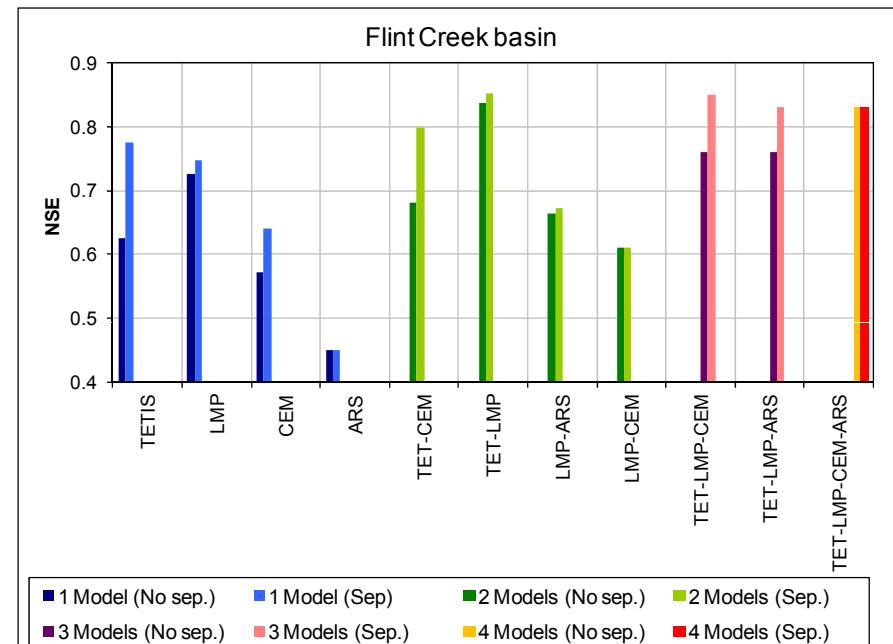
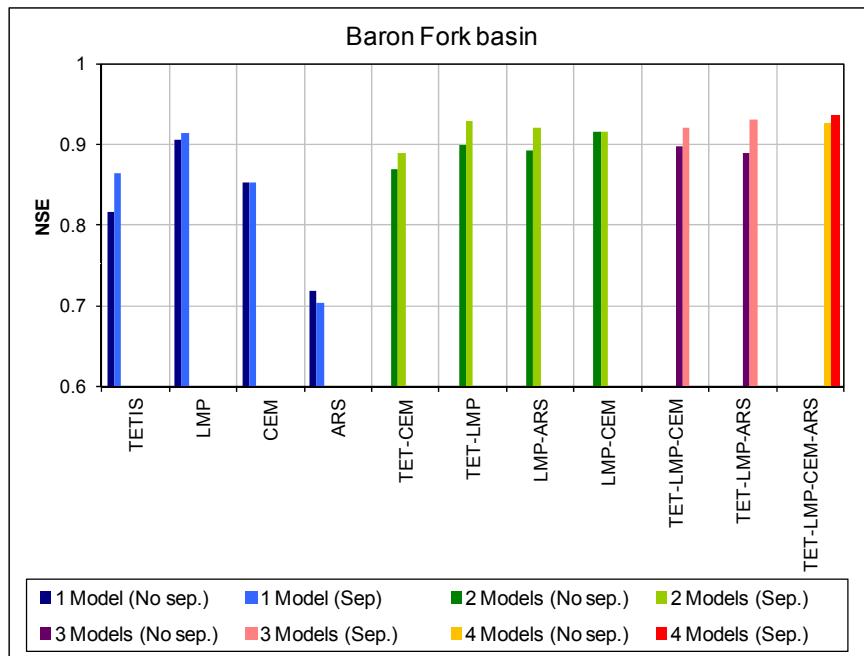
- Distributed Model Intercomparison Project (DMIP2) by NOAA/NWS.
- Four Hydrological models selected from DMIP2 participants: TETIS (UPV), LMP SAC (NWS), SWAT (ARS), GR4J (CEM)
- We are using 13 gauge stations:
 - Calibration at Baron Fork (3) 795 km²
 - Ungauged basin: Peacheater Creek (4) 65 km²



Results at gauged sites

□ Nash Sutcliffe efficiency index

One single model (blue) and combination of two (green), three (purple-pink) and four (orange-red) models.

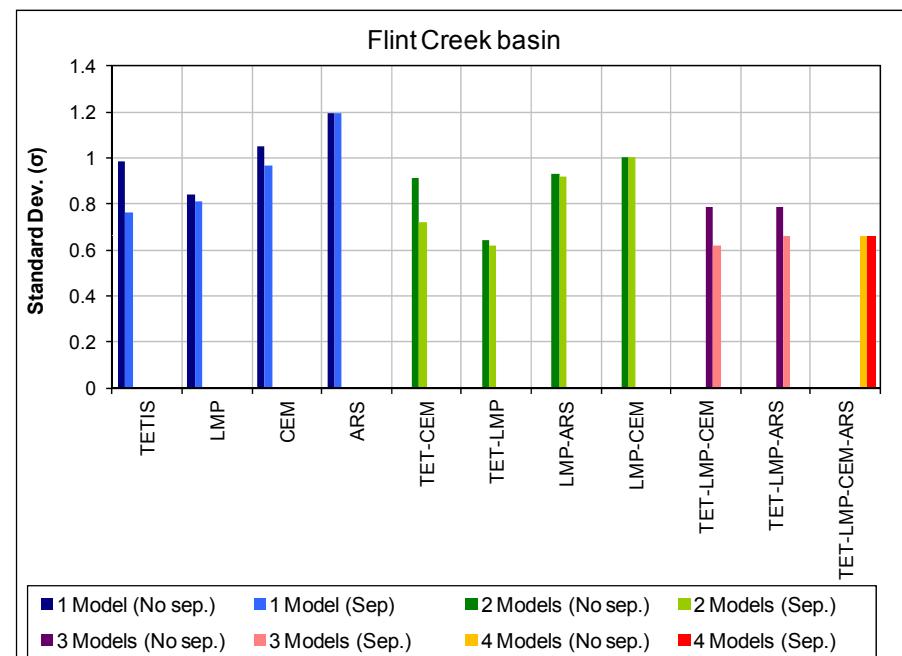
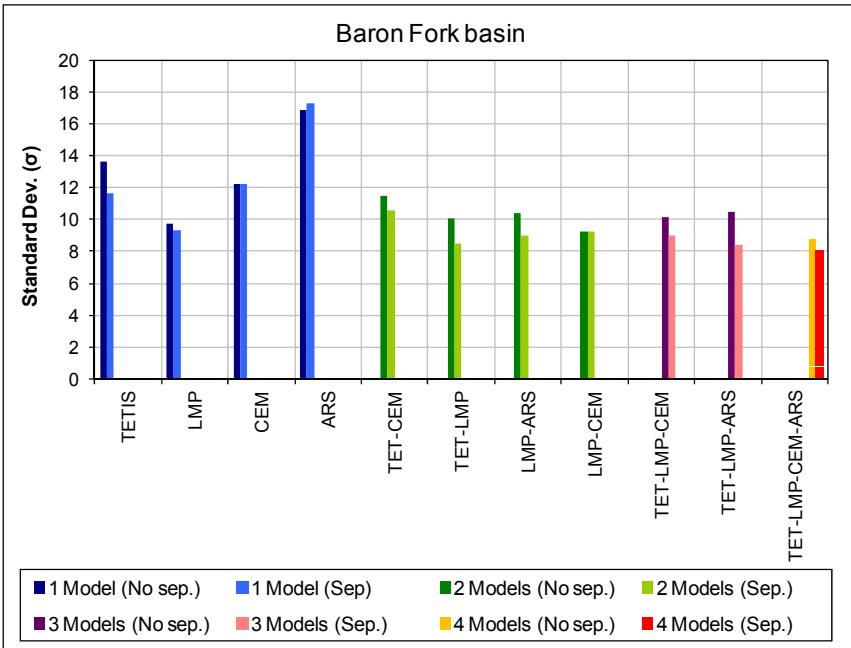


Left bar: all data in a single sample

Right bar: separation of data in two Truncated Normal Joint distributions

Results at gauged sites

- Standard deviation (σ) of model errors

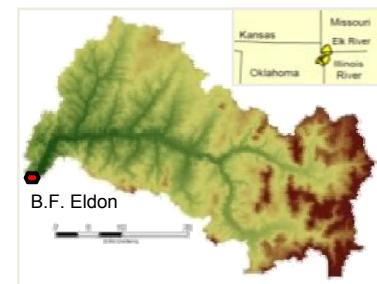
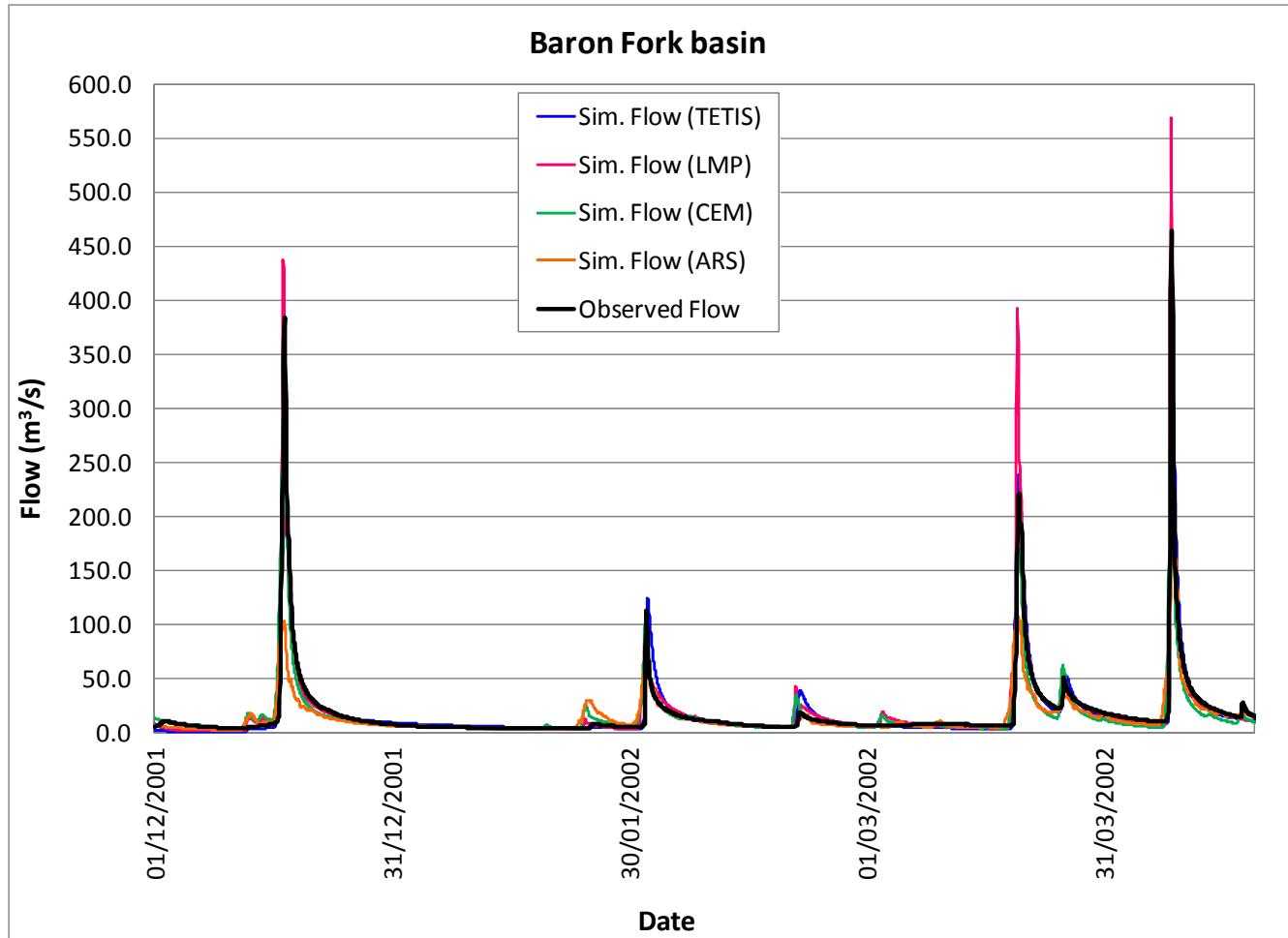


Left bar: all data in a single sample

Right bar: separation of data in two Truncated Normal Joint distributions

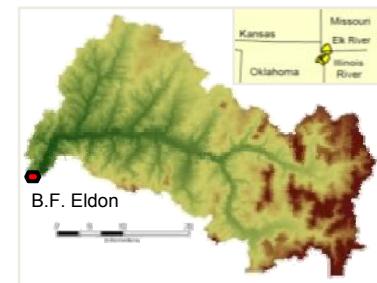
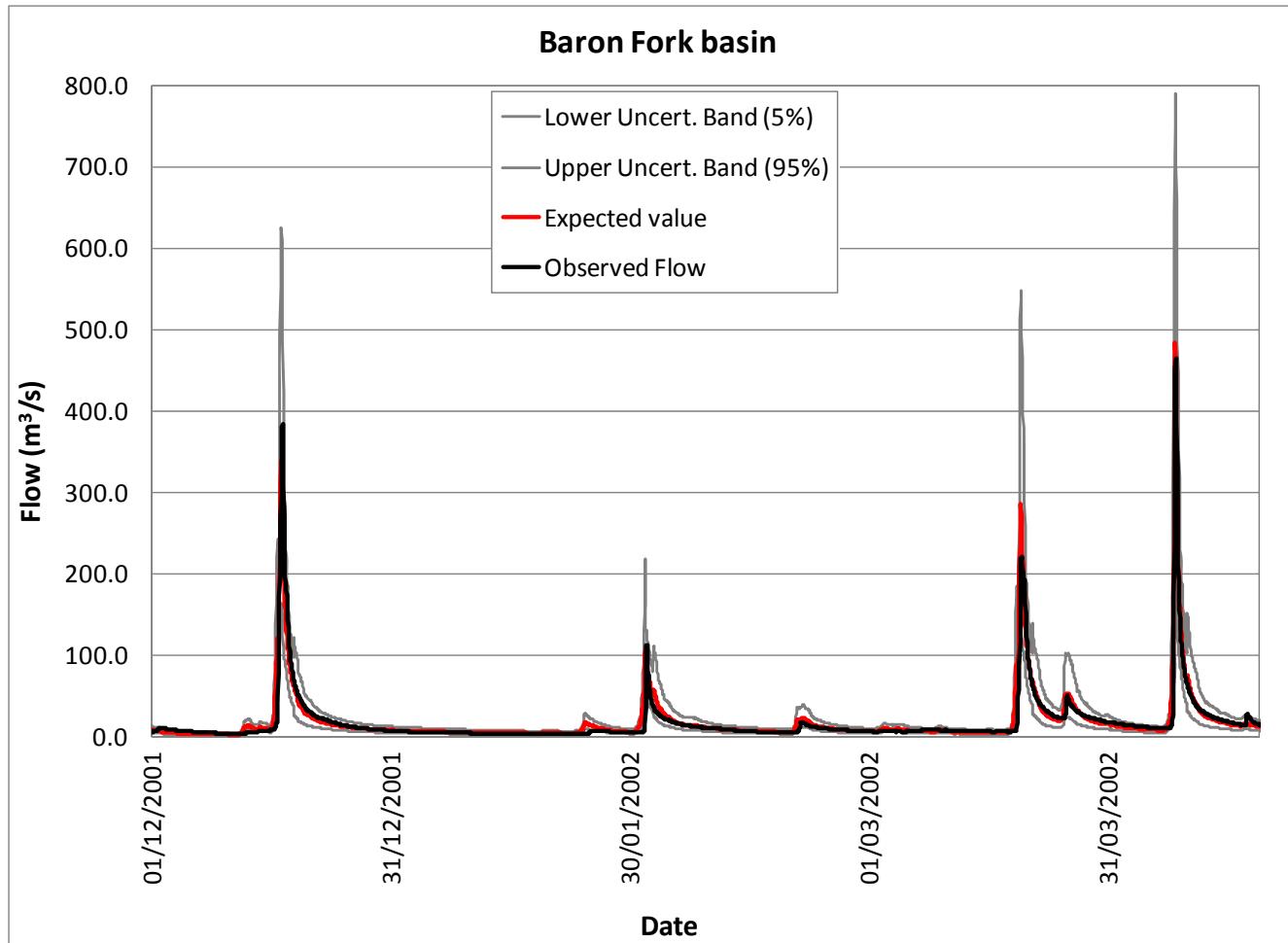
Results at gauged sites

- Single models at the outlet point: calibration period



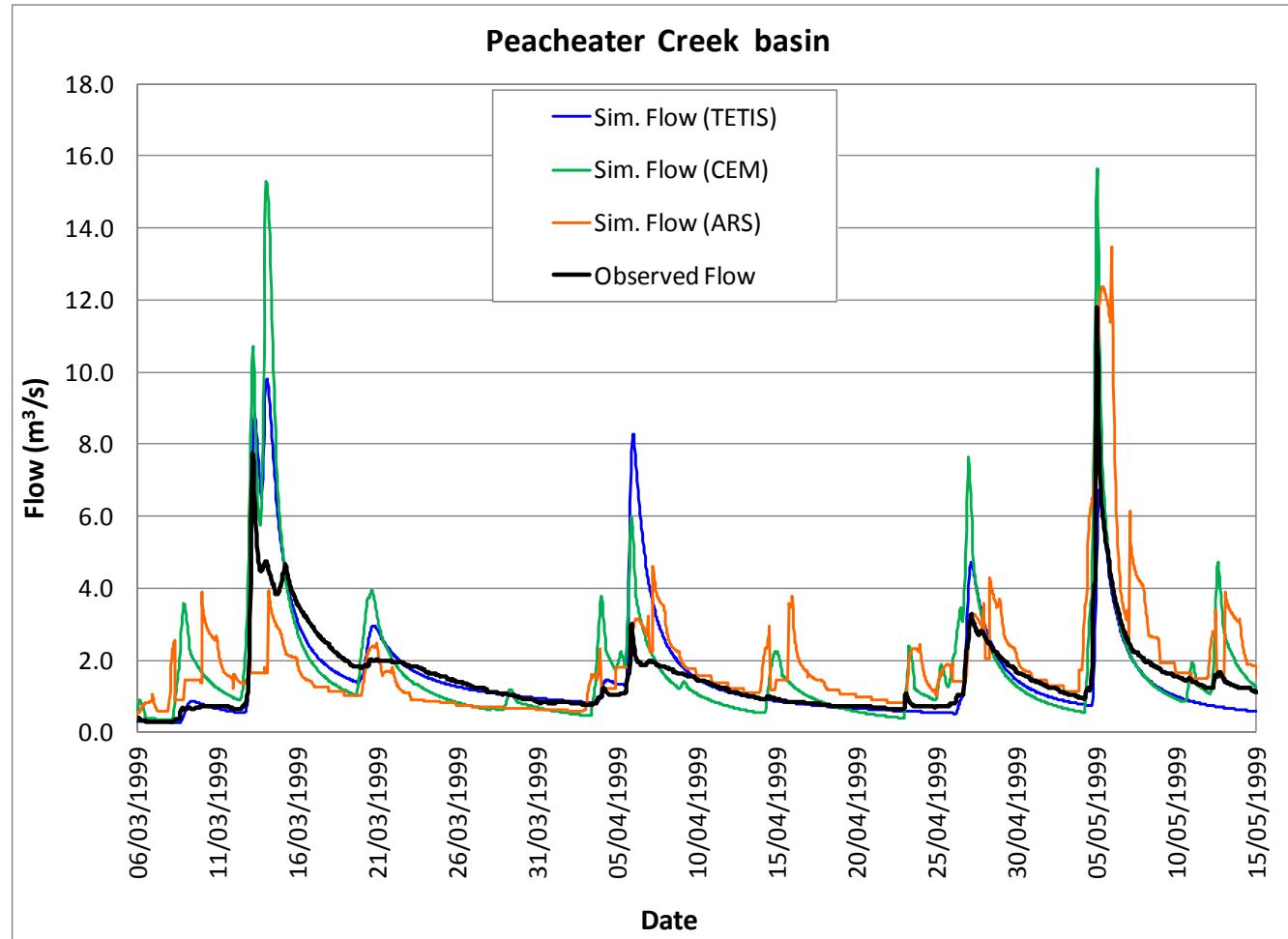
Results at gauged sites

- Predictive Uncertainty Band (90 %) for the combination of 4 models



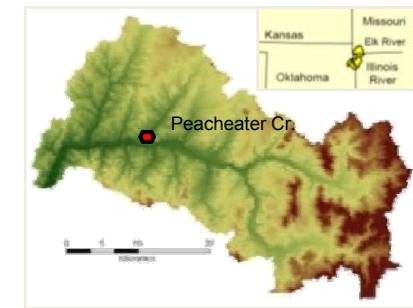
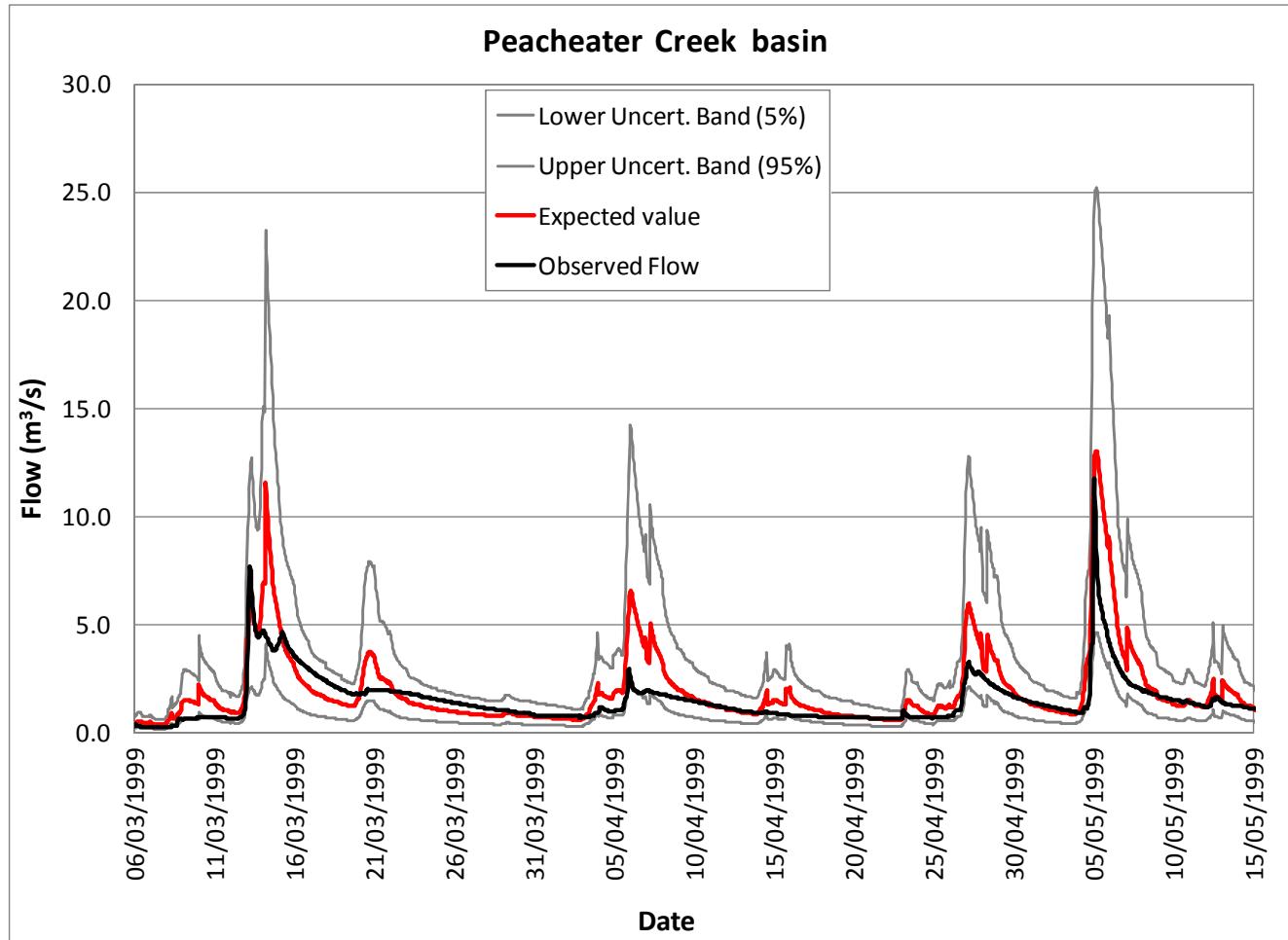
Results at gauged sites

- Model predictions (interior point): spatial and temporal validation



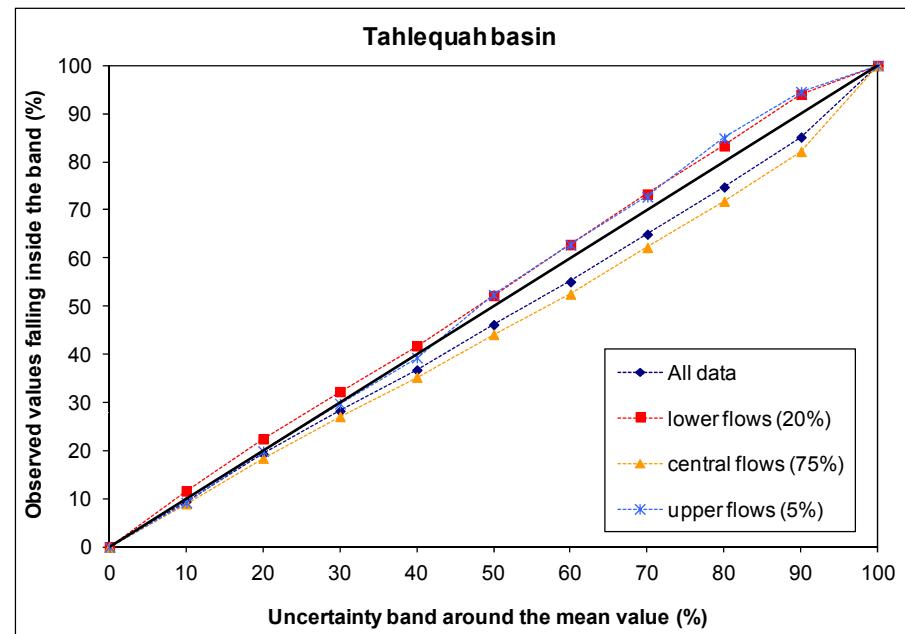
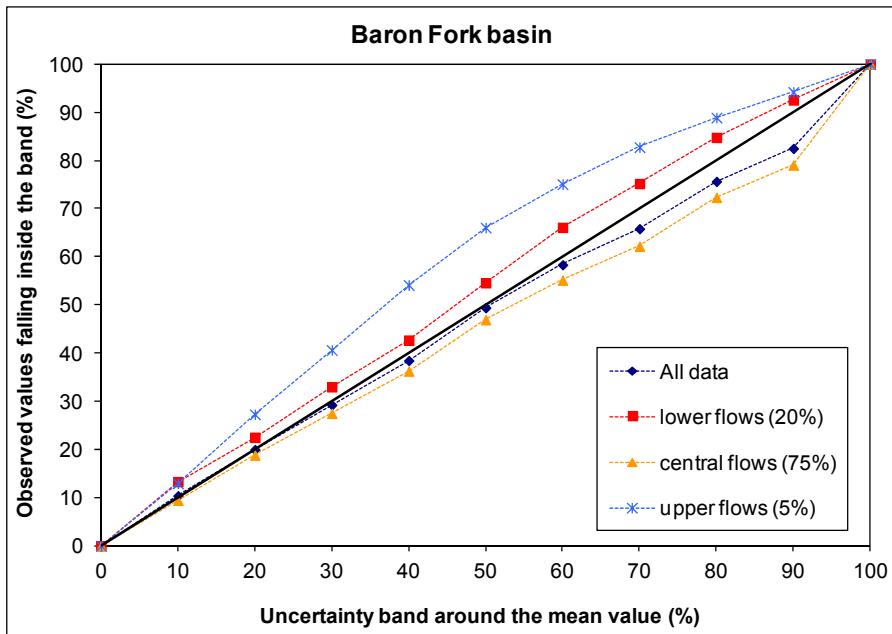
Results at gauged sites

- Predictive Uncertainty Band (90 %) with the combination of 3 models



PU band reliability assessment

- Percentage of observed data that fall inside the uncertainty band at different probability levels. Combination of 4 models.



Extension for PUB

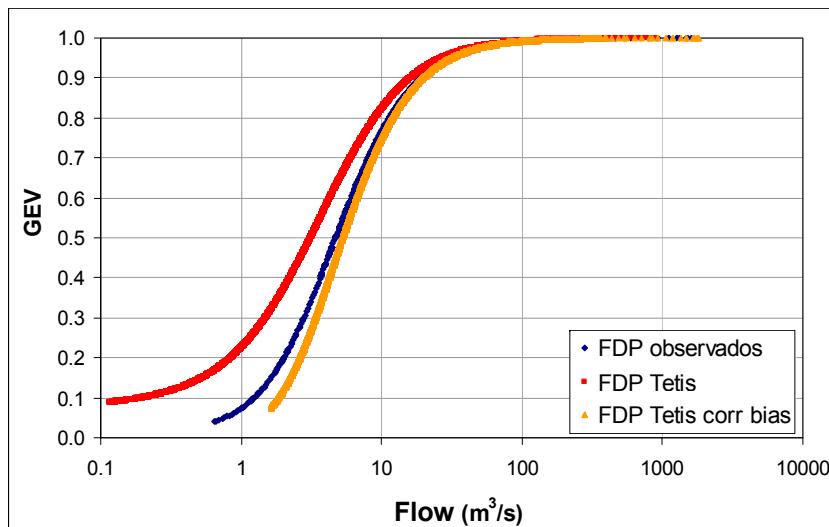
- Reduce uncertainty by models combination using MCP approach
- Regionalization to extend the MCP approach to **ungauged sites**:
 - Use of an analytical CDF instead of the empirical Weibull Plotting Position
 - Parameter estimation by L-moments (Hosking, 1990; Hosking and Wallis, 1995)
 - L-moments estimation at ungauged sites by regression with simulated L-moments and basin descriptors
 - Regression of “correlation coefficients” (ρ) in the Gaussian space vs “drainage area”

Analytical NQT transformation

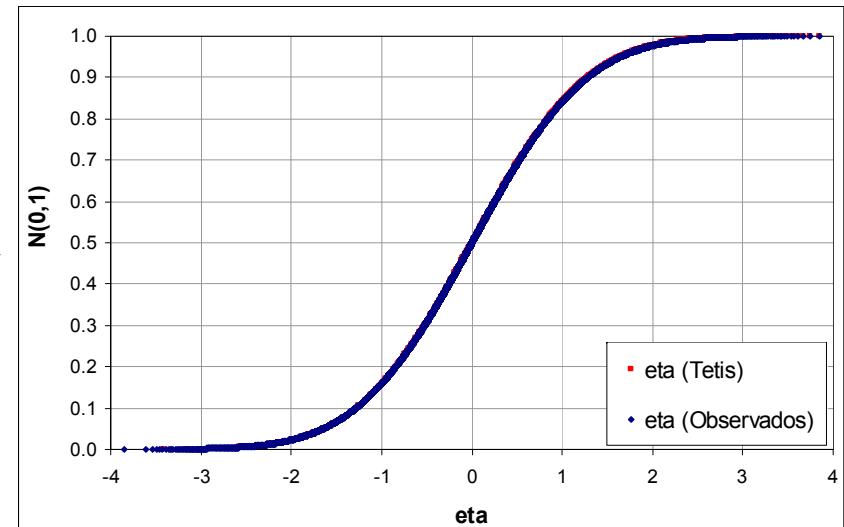
- Chosen CDF: General Extreme Value (GEV):

$$F = \exp \left[-\left\{ 1 - k(x - \xi) / \alpha \right\}^{1/k} \right]$$

$$x = \xi + \frac{\alpha \left\{ 1 - (-\log F)^k \right\}}{k}$$

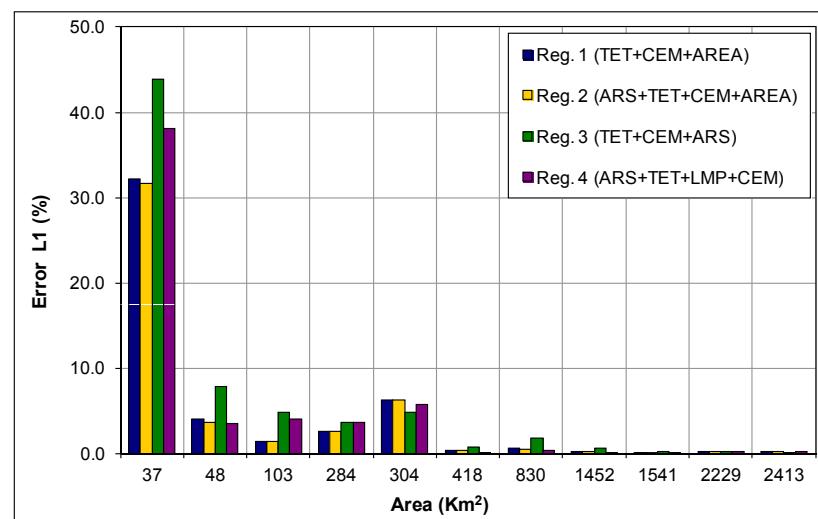
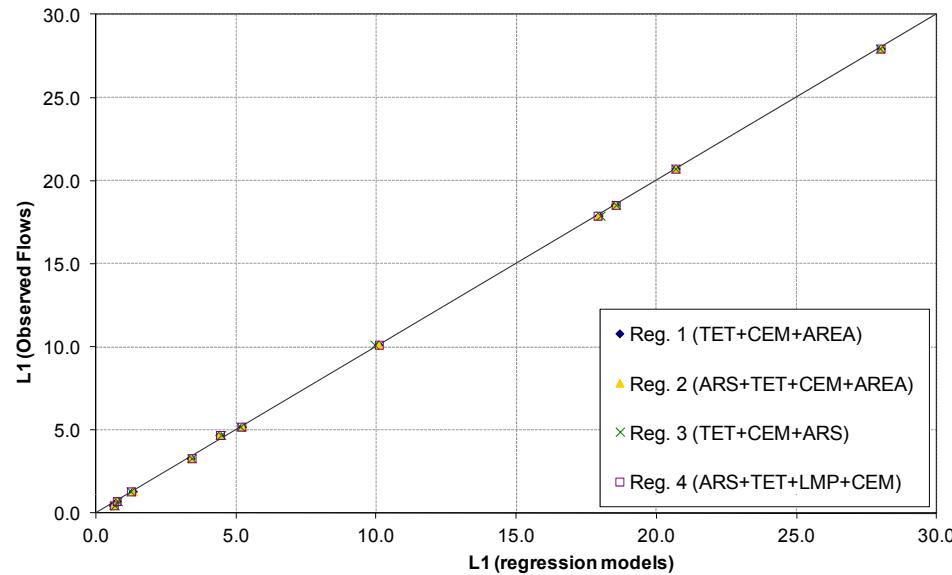


NQT



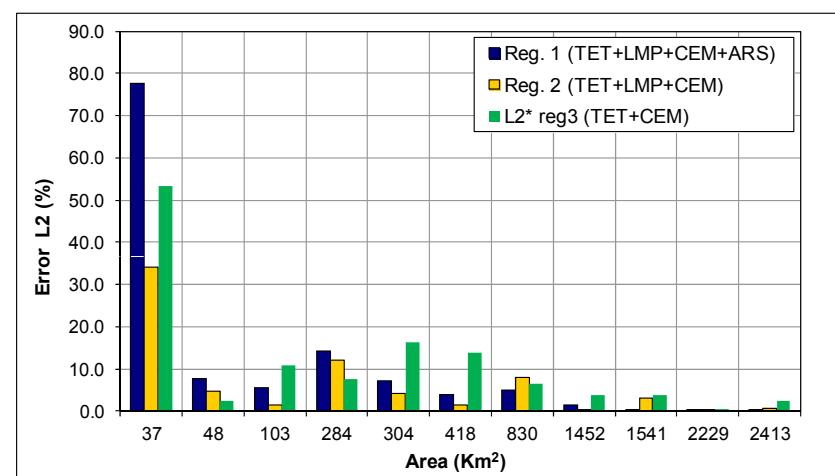
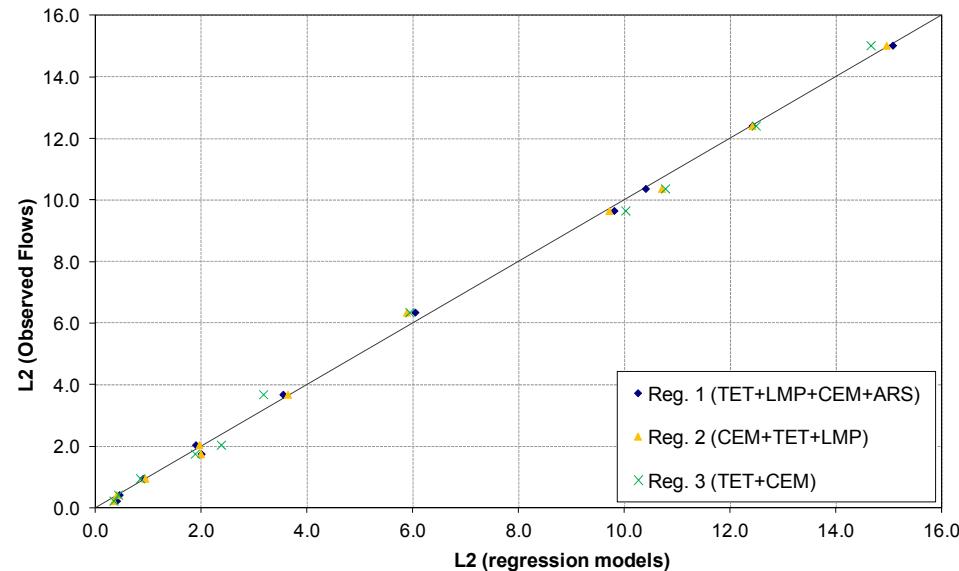
L-moments regression

- First L-moment (L1)



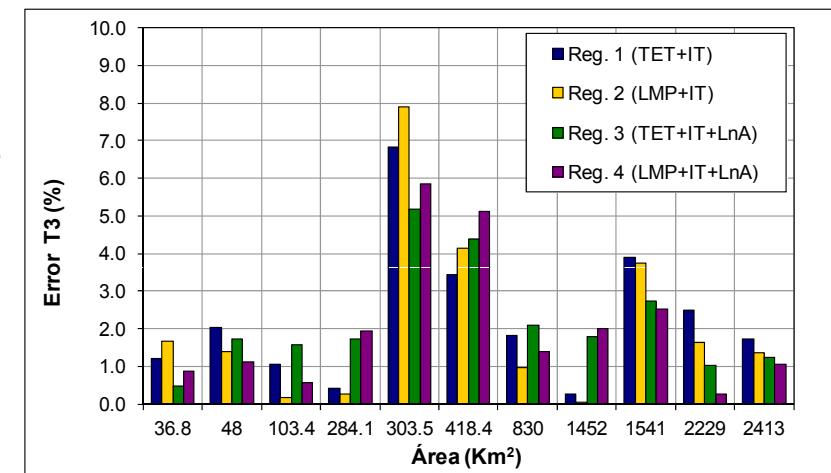
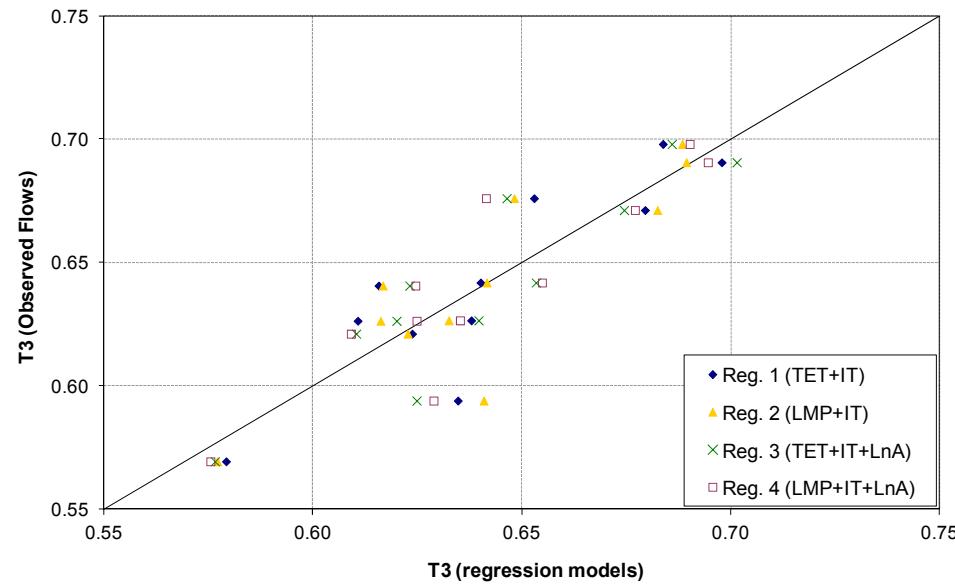
L-moments regression

- Second L-moment (L2)



L-moments regression

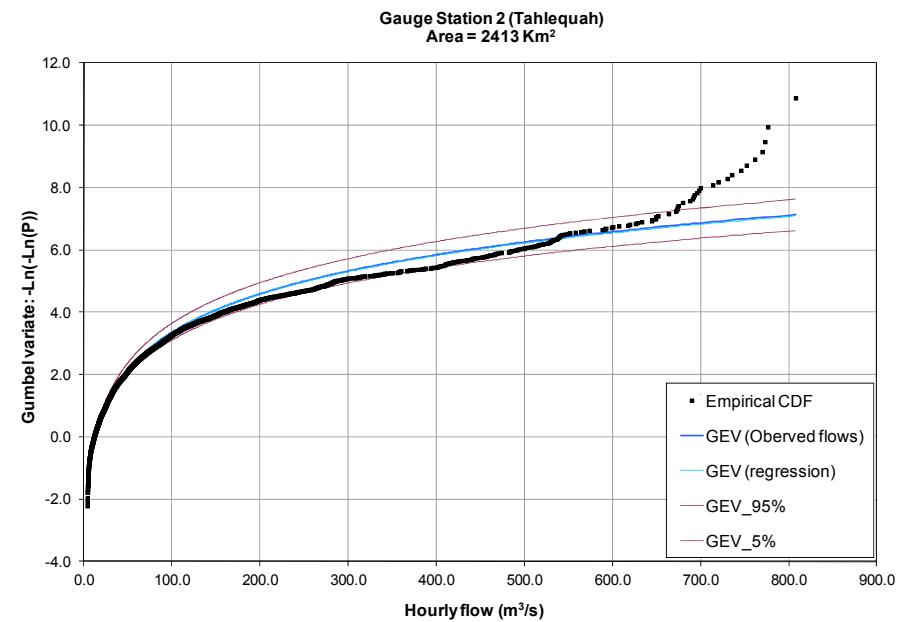
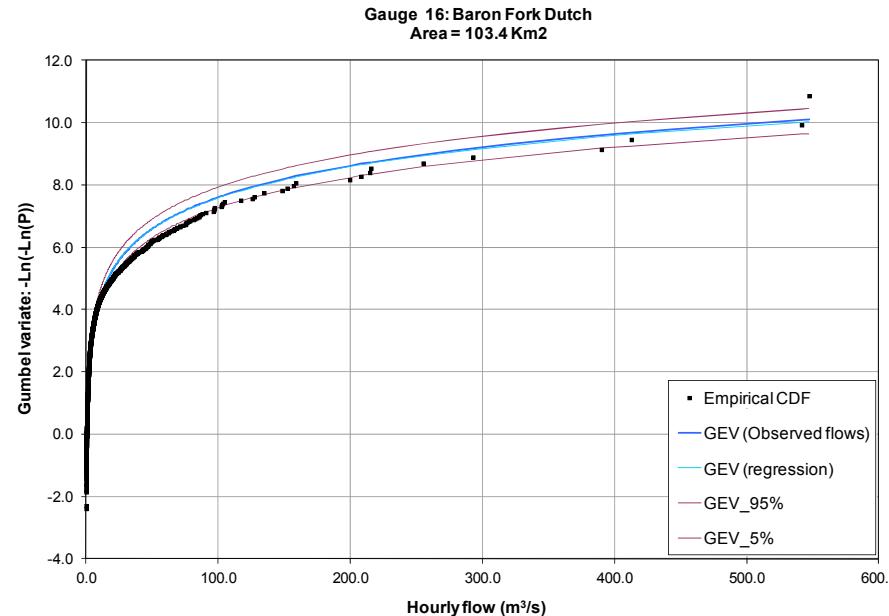
□ L-Skewness (T3)



CDF estimation by regressions

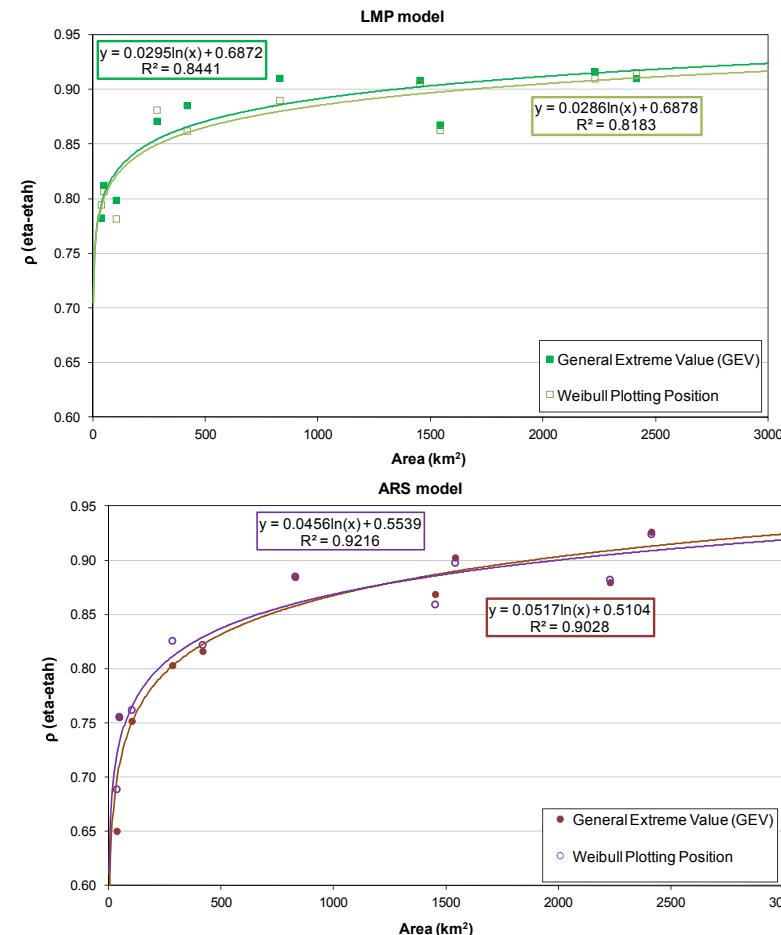
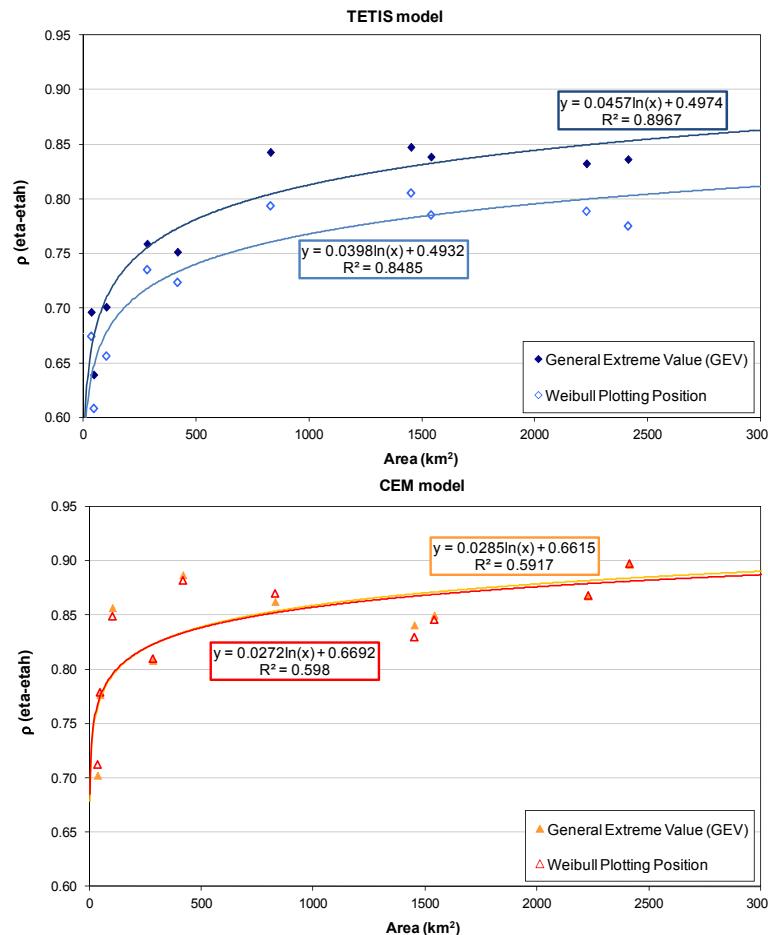
- Empirical, adjusted and estimated (L-moments statistical regression) CDF of hourly flows.

General Extreme Value Function (GEV)



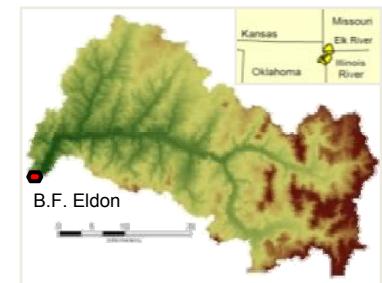
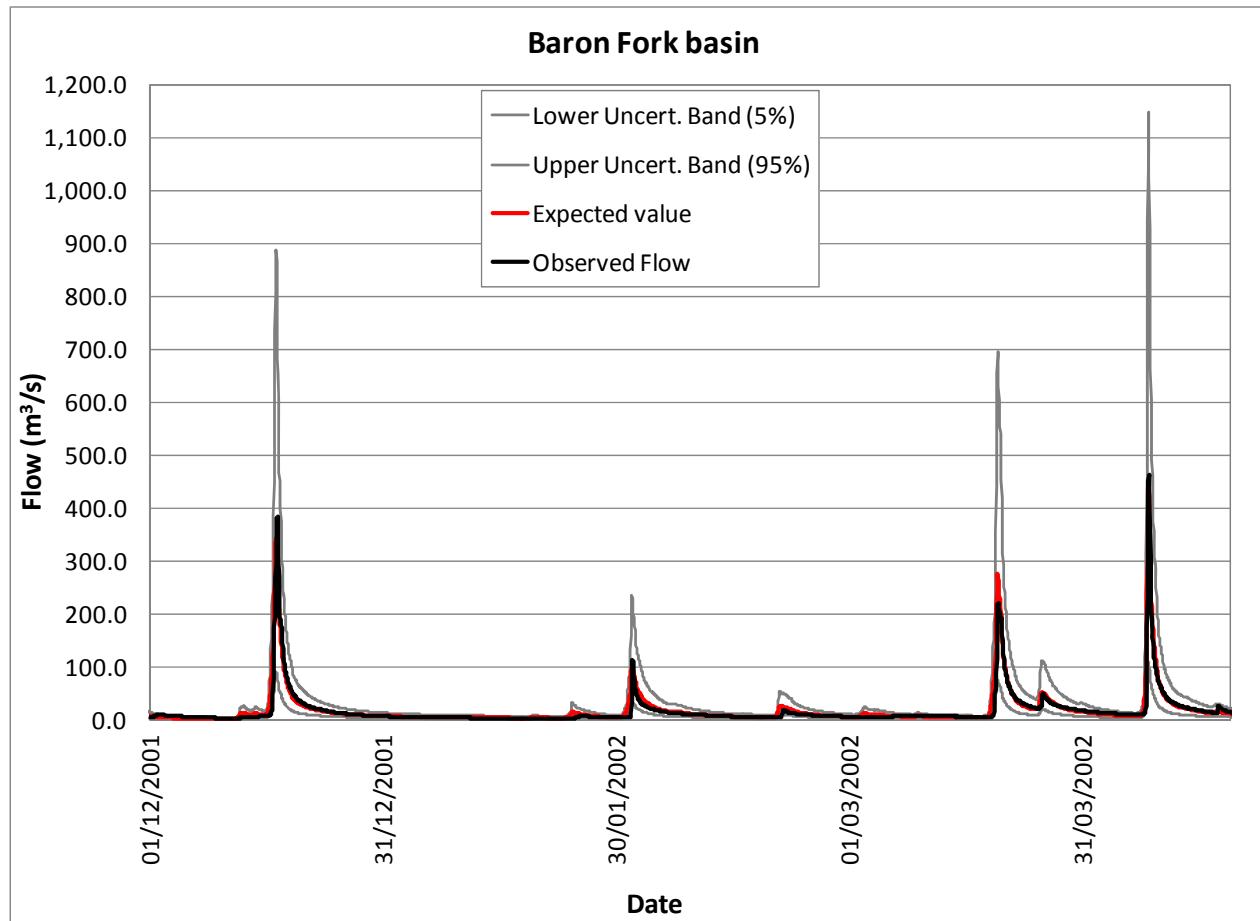
Correlation coefficients regressions

- Regression of “correlation coefficient” (ρ) between observed and simulated flows in the Gaussian field vs “drainage area”



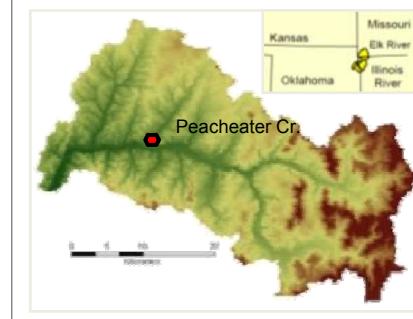
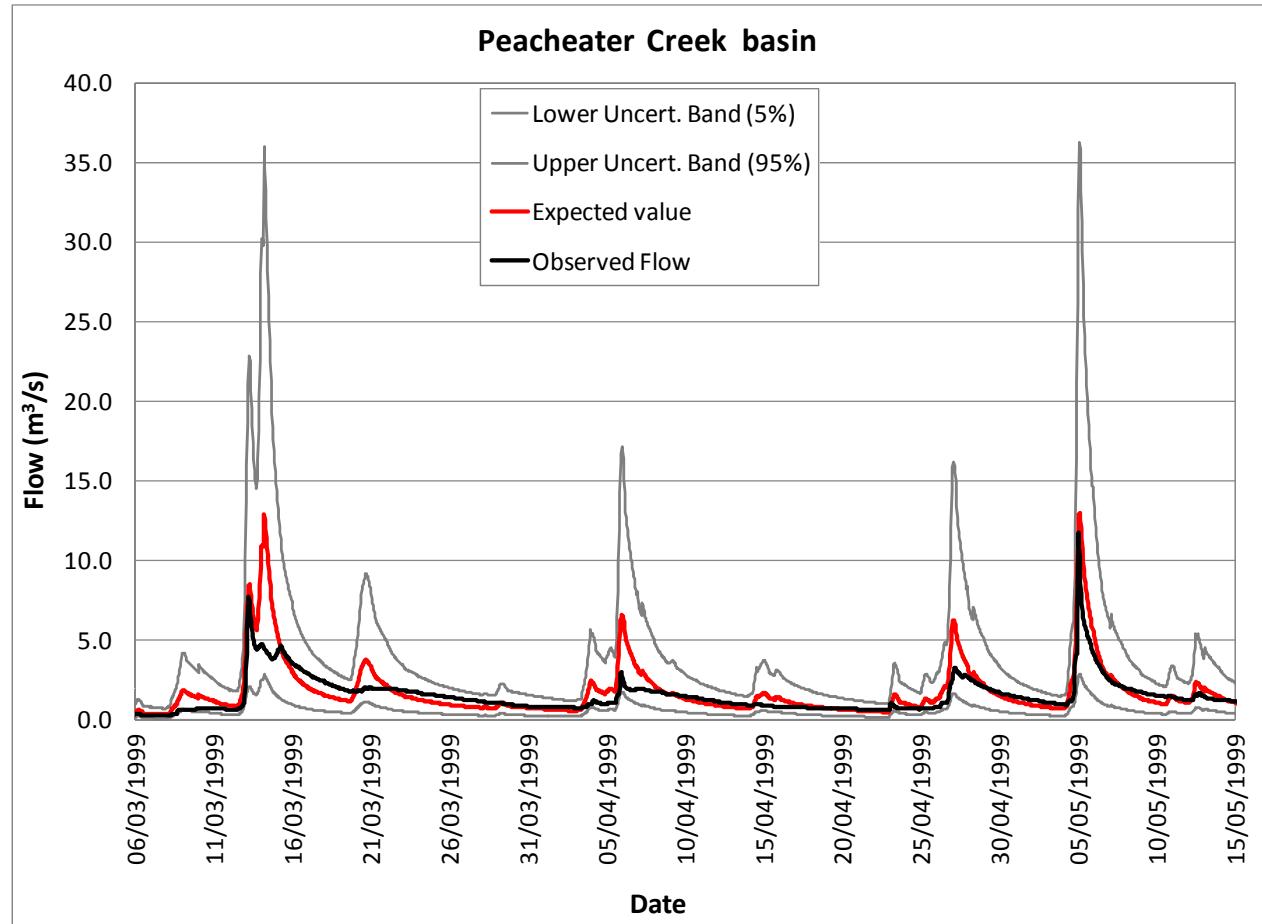
Multi-model combination

- PU band (90 %). Regression approach, combination of 4 models at Baron Fork => using regressions at a gauge site



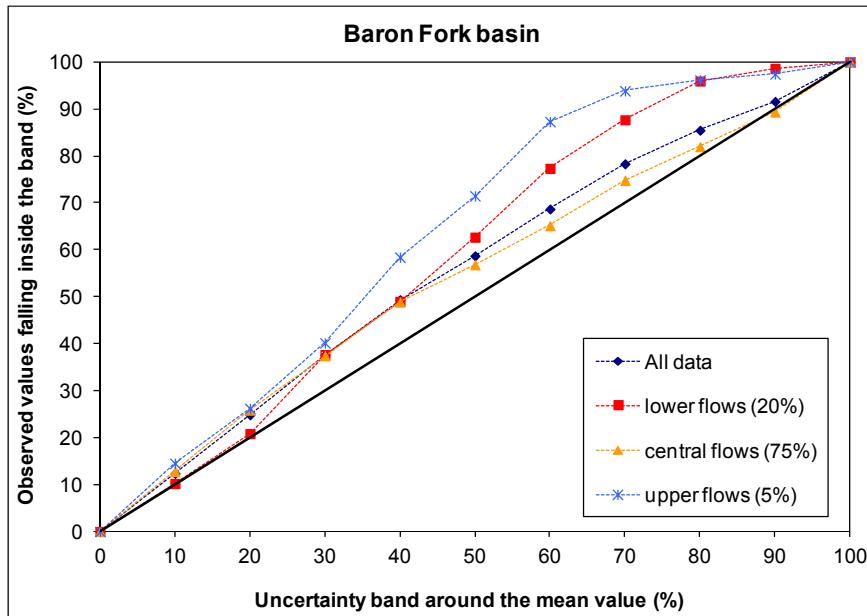
Multi-model combination

- PU band (90 %). Regression approach, combination of 3 models at Peacheater => using regressions at an ungauged site



PU band reliability assessment

- Percentage of observed data that fall inside the uncertainty band at different probability levels.

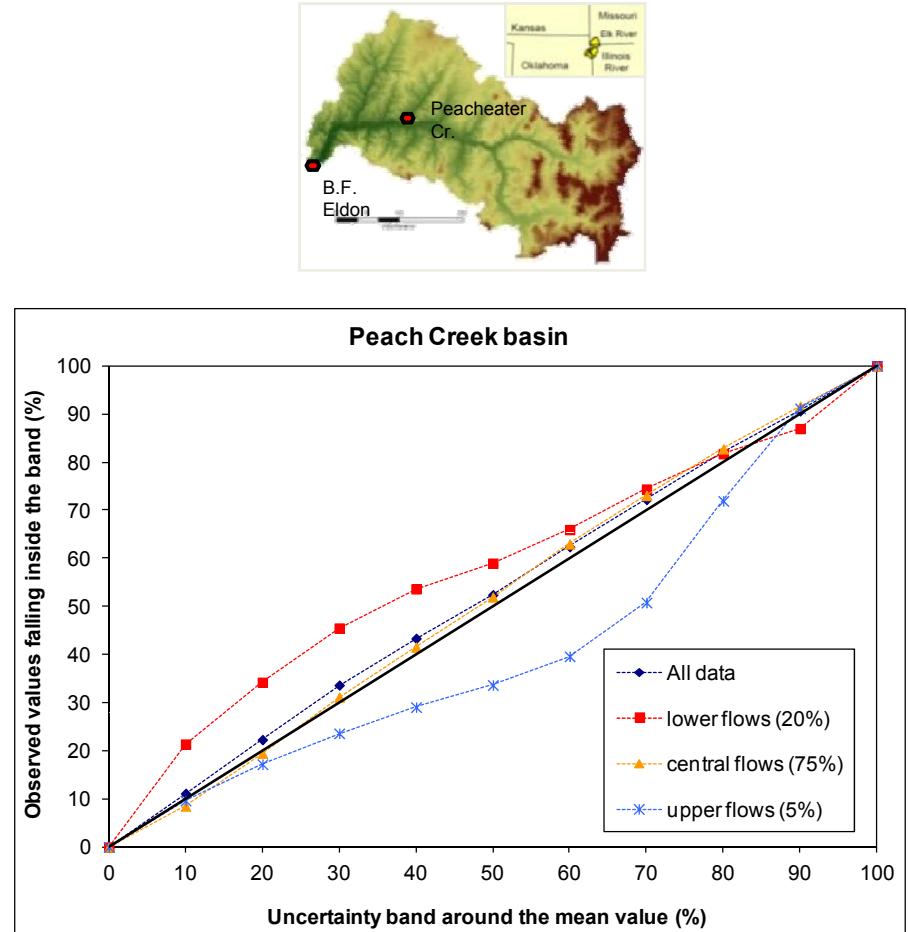


Baron Fork: combination of 4 models.

Overestimation of PU for all flows.

Peachester Creek: combination of 3 models.

Underestimation of PU for high flows and overestimation for low flows.



Conclusions

- **Models combination** reduces Predictive Uncertainty at gauged and ungauged sites.

- It has been proposed to estimate the PU at ungauged sites: models combination using the **bayesian MCP post-processor** with L-moments and correlation **regionalization by regressions**.

- The reliability of the estimated PU at gauged and ungauged sites was verified through a “PU band assessment” for probabilities 10 (10) 90%, with **satisfactory results**.



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Thanks for your attention!

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