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Assessment of the total predictive uncertainty of a real-time hydro-meteorological flood forecasting system using bivariate meta-gaussian density.

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Context

Floods : one of the most important natural hazards

A tool for flood risk management : hydro-meteorological modelling

Medium range rainfall forecasts as a means for extending lead-times of prediction

Research issues :

From rainfall to discharge real-time forecasts

* Set up a reliable hydro-meteorological forecasting chain,

* Assess the total predictive uncertainty.

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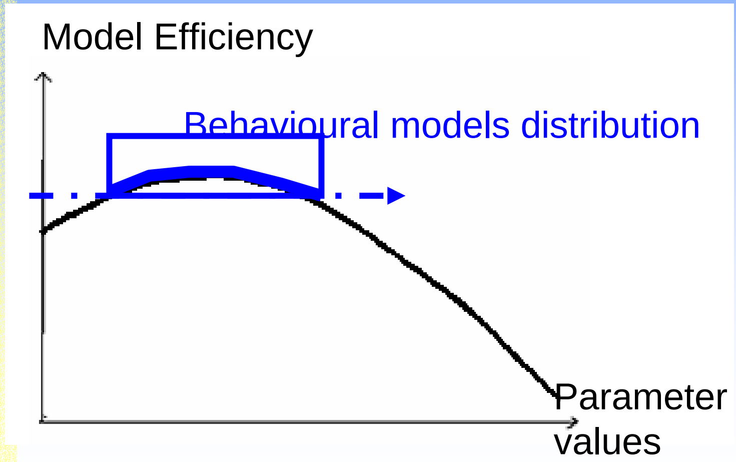
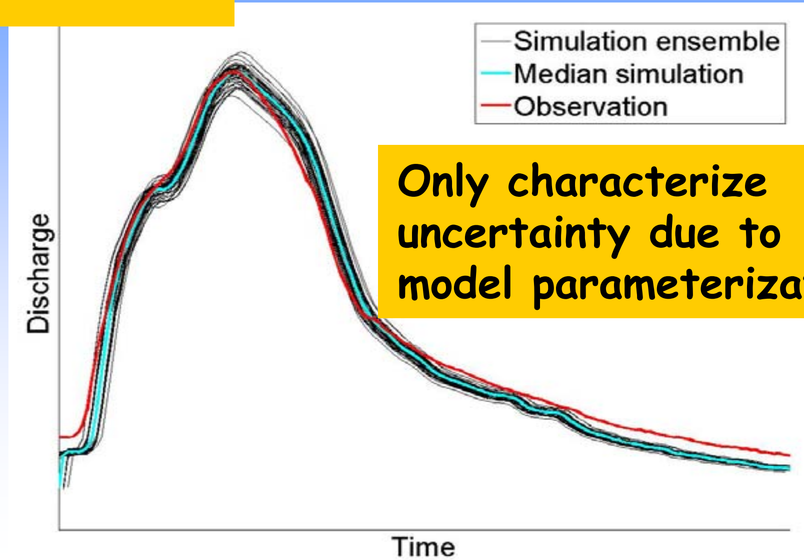
Scientific context : quantification of uncertainty

INTRODUCTION

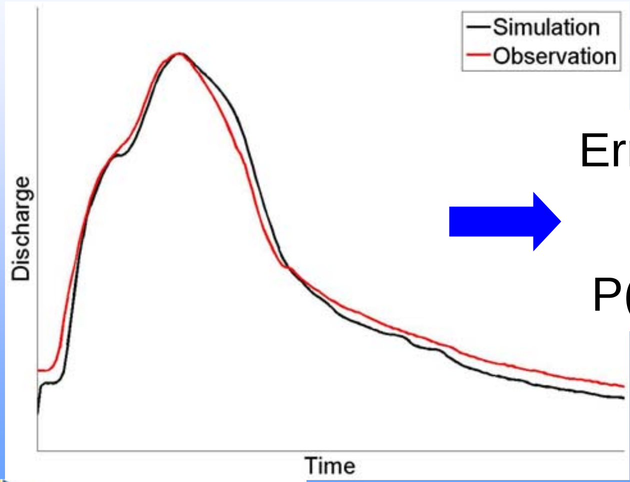
GLUE approach (Beven and Binley, 1992)





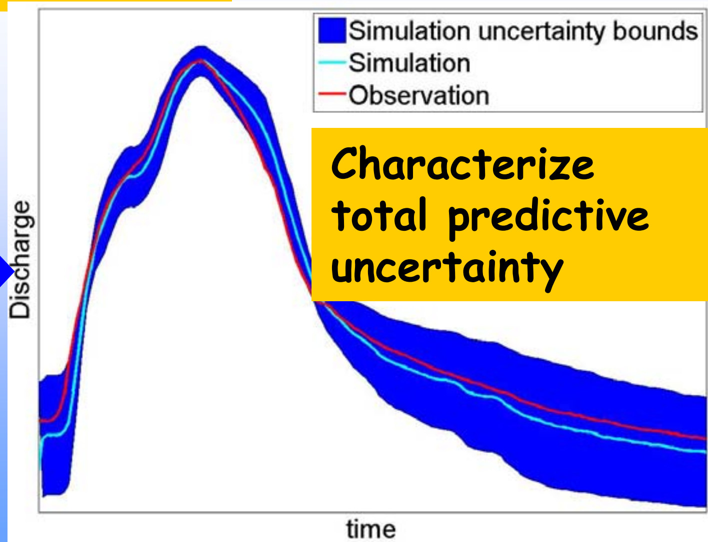
Only characterize uncertainty due to model parameterization

Stochastic approach e.g.: (Kelly and Krzysztofowicz, 1997; Montanari and Brath 1994)



Error conditional probability:

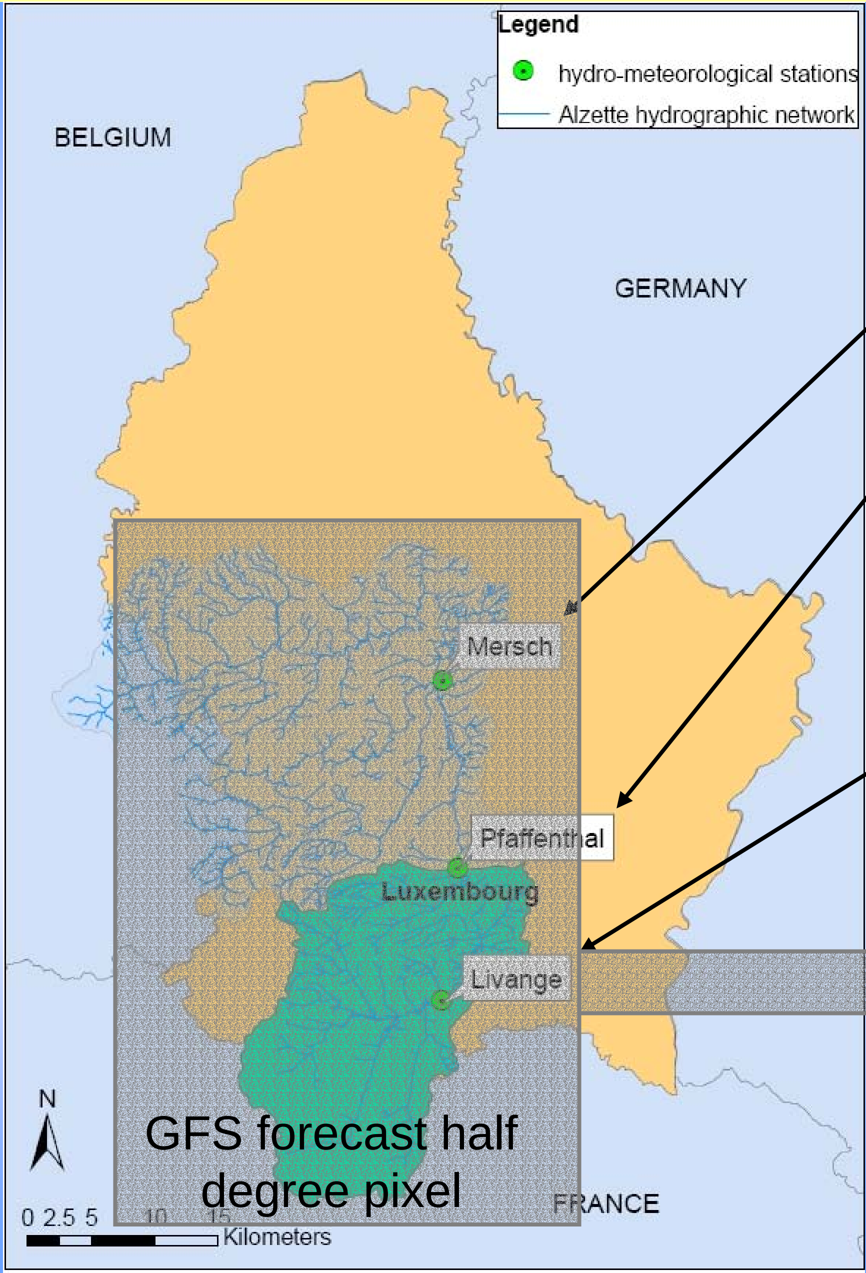
P(e<e(t)/sim(t))



Characterize total predictive uncertainty

Alzette study area

INTRODUCTION



Temperature obs. (hourly)

2000-2008

Water stage➔Discharge obs. (hourly)

2000-2008

Rainfall obs. (hourly)

2000-2008

4 forecast/day
(0-6-12-18h UTC):

➔3 hours cumulated rainfall forecasts

2006-2009

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Aim and approach

Aim :

Set up a reliable hydro-meteorological forecasting chain

Proposed approach :

1. Calibrate the hydrologic FLEX model
2. Reduce model error using an AR error model

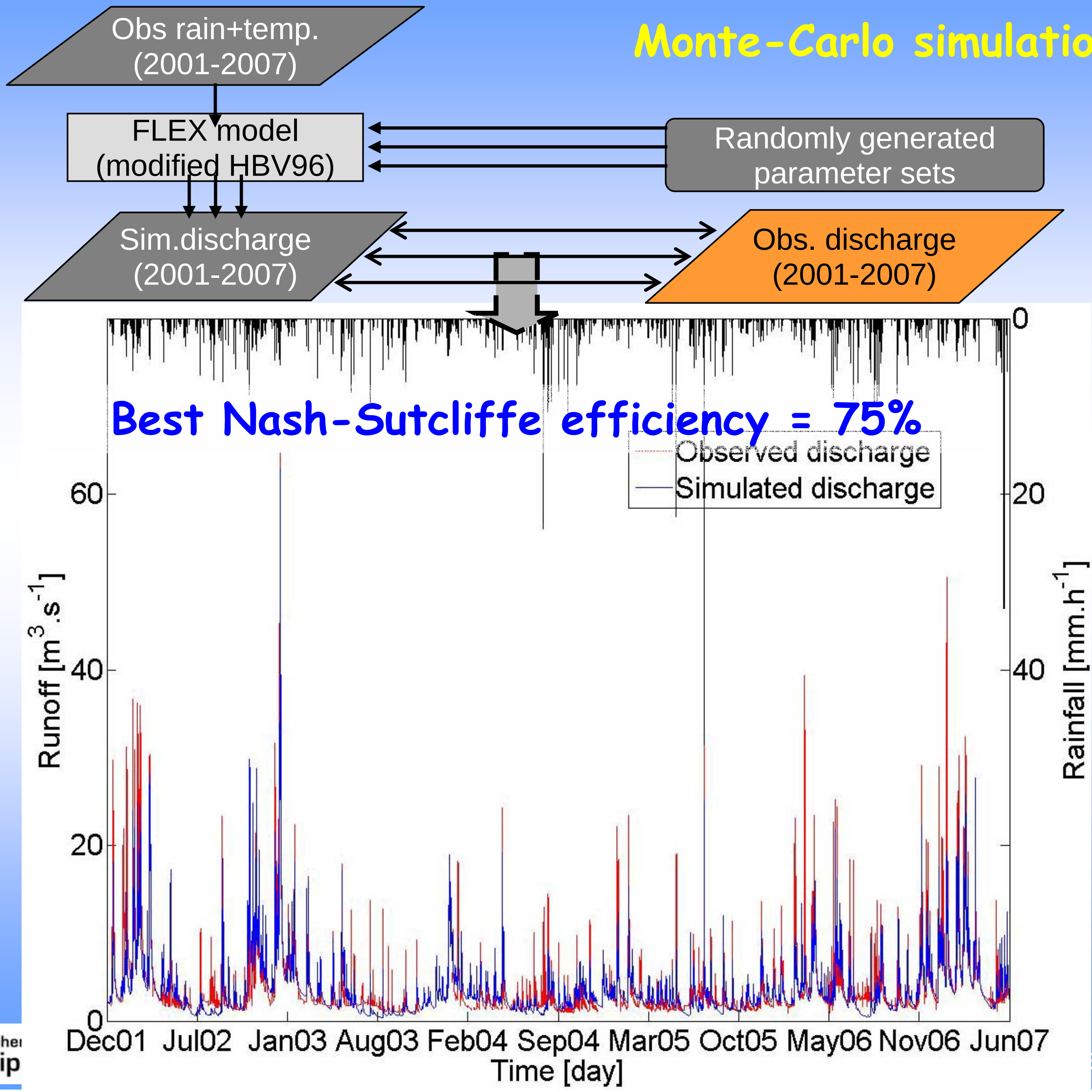
Input Data:

Hydro-meteorological measurements

1. Hydrologic FLEX model: calibration

I. FORECASTING CHAIN

Monte-Carlo simulations



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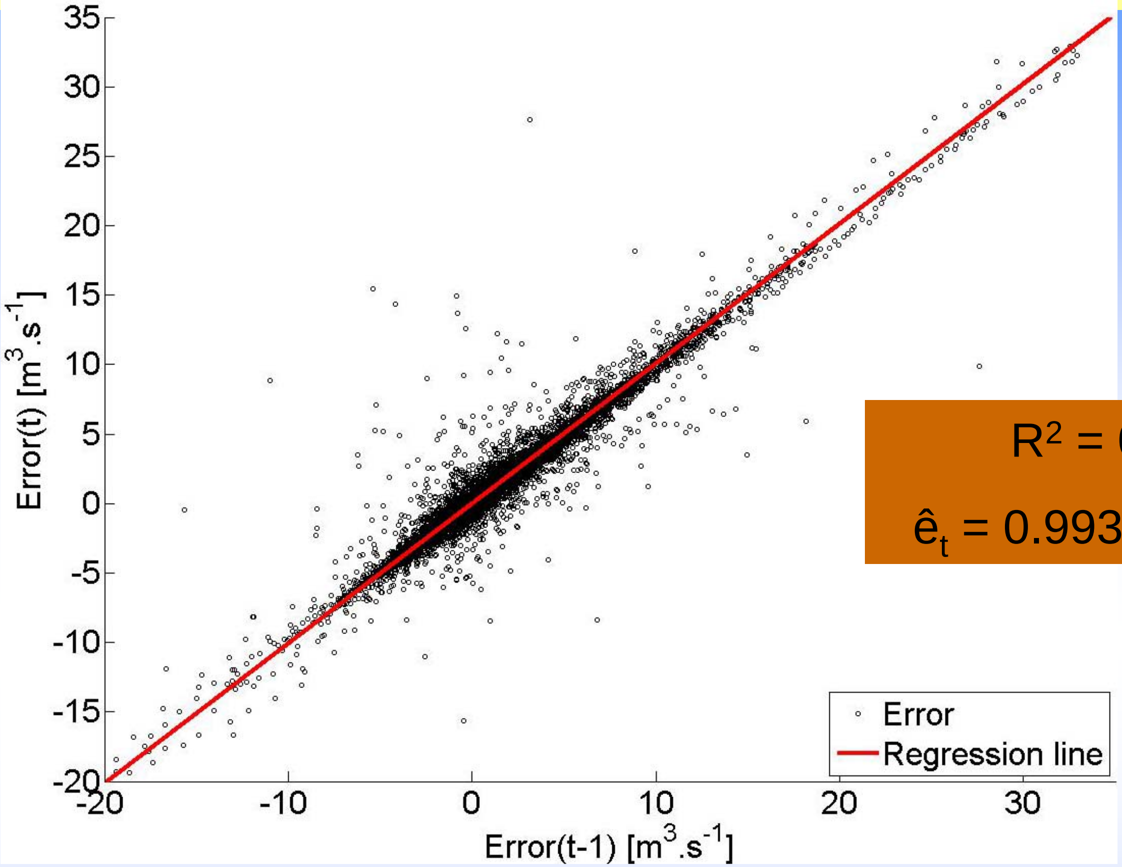
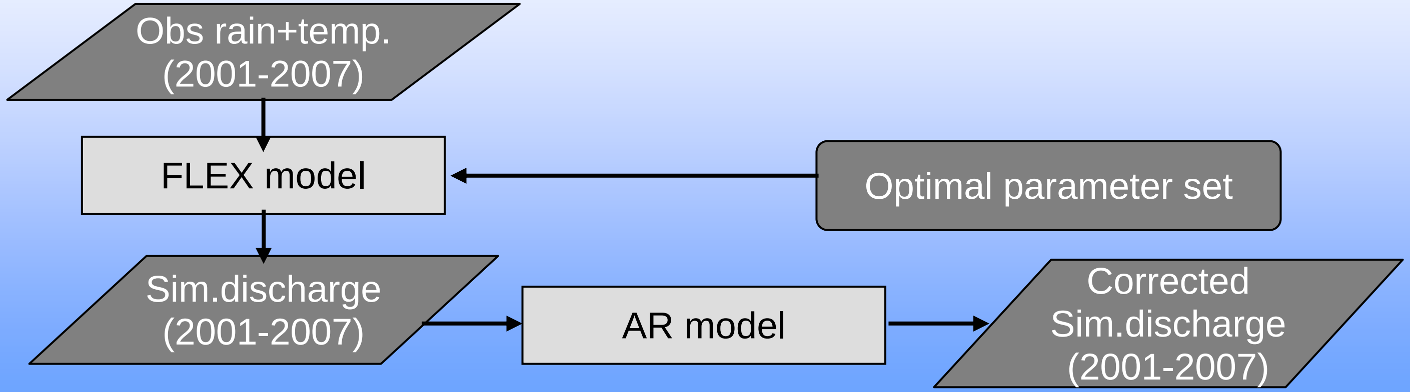
2. AR error model



$R^2 = 0.9443$

$\hat{e}_t = 0.993 * e_{t-1} + 6E\text{-}5$



2. AR error correction efficiency in forecasting mode

I. FORECASTING CHAIN

Known at time t:

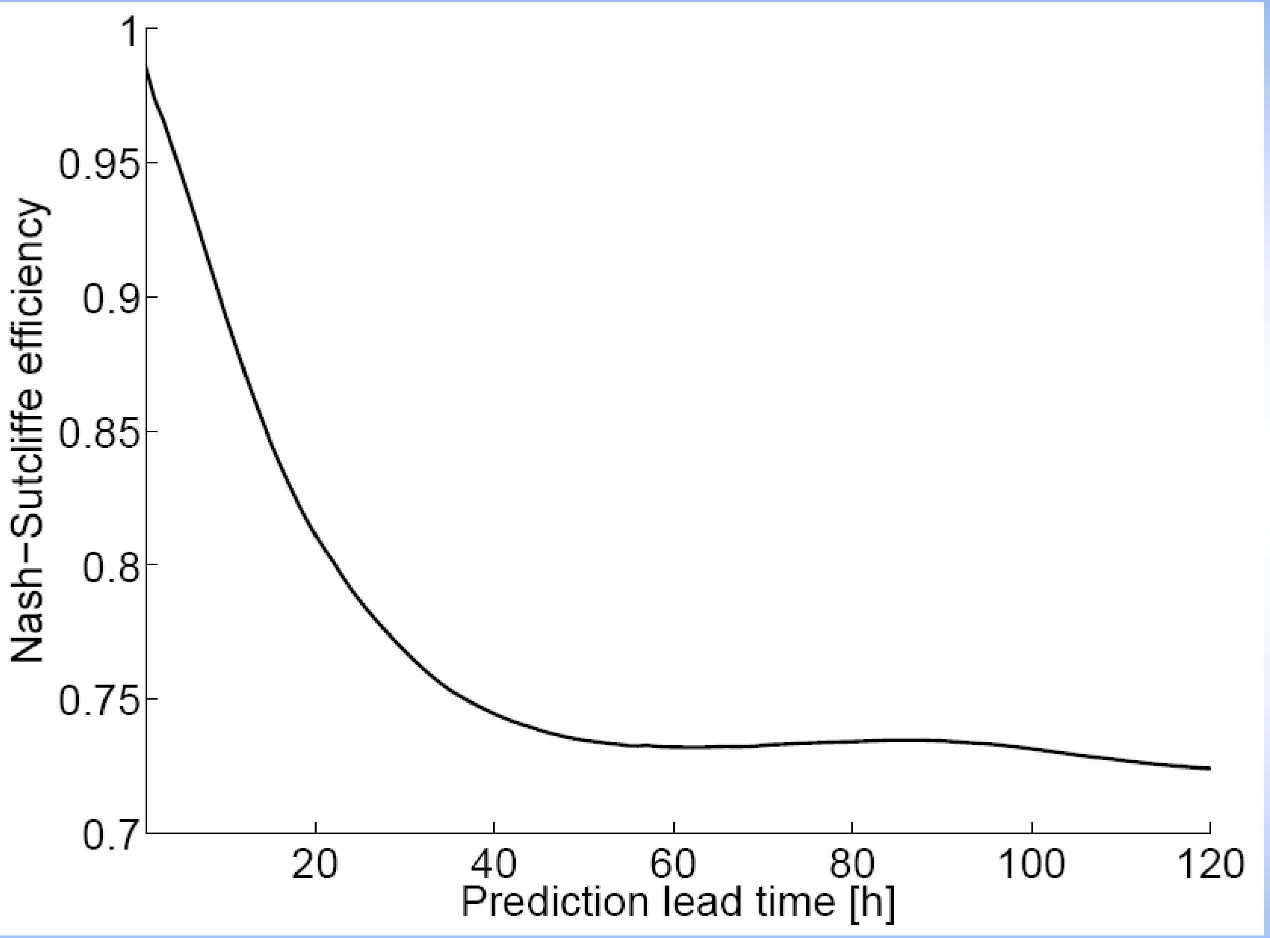
1. Qs(t)
2. Qo(t)

$e(t) = Qs(t) - Qo(t)$

$\hat{e}(t+1) = a * e(t) + b$

$\hat{e}(t+2) = a * \hat{e}(t+1) + b$

...



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Aim and approach

II. UNCERTAINTY ASSESSMENT

Aim :

Assess the total predictive uncertainty

Approach :

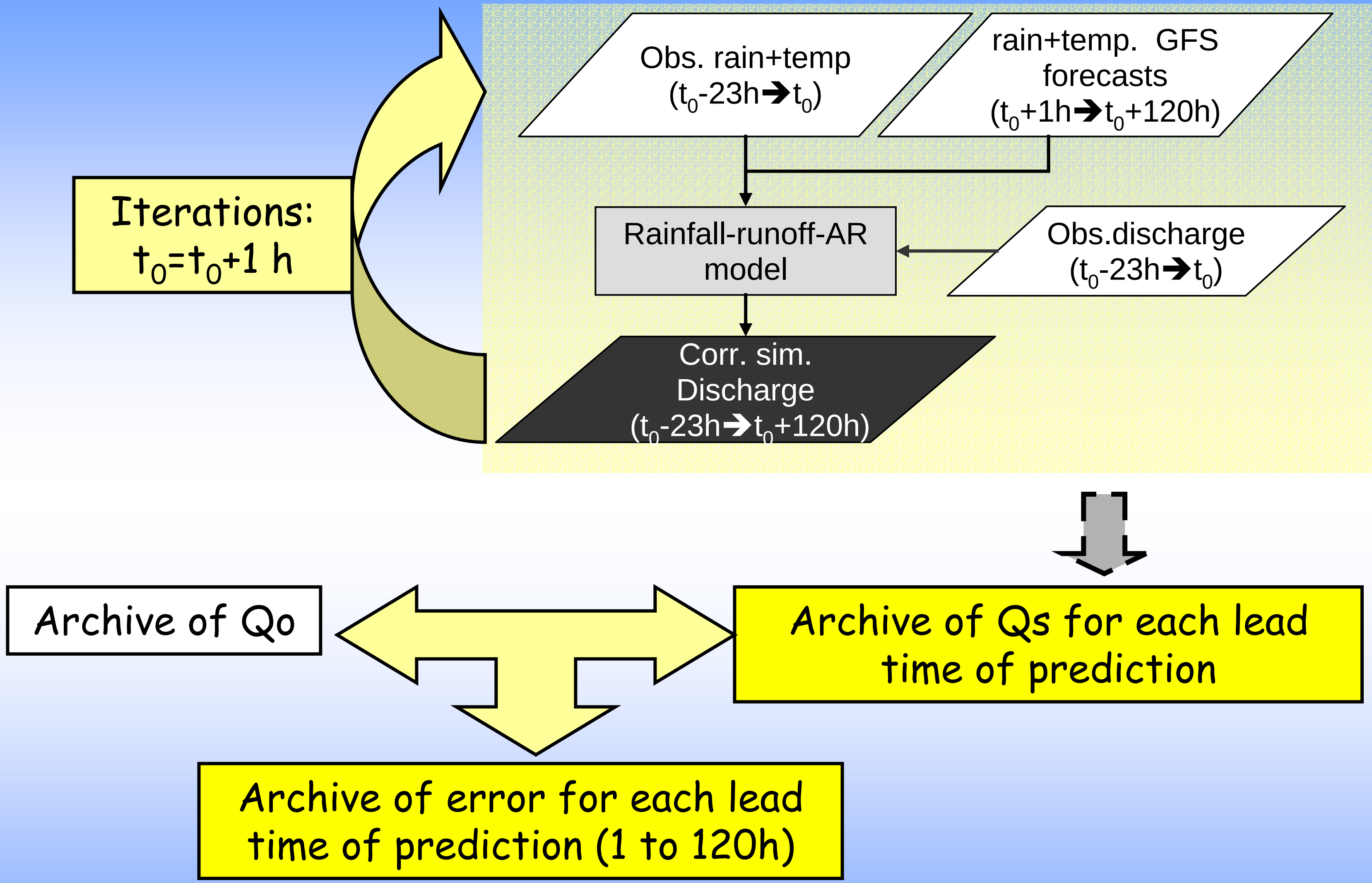
1. Build an archive of model error for each lead time of prediction
2. Estimate meta-gaussian bivariate densities -P(e>e(t)/Q(t))
3. Compute confidence intervals of model forecasts

Input data :

GFS rainfall and temperature forecasts

Time series of Discharge measurements

1. Coupling GFS forecasts/flex-AR model ➔ error archive computation



2. Meta-gaussian bivariate densities computation: general outline

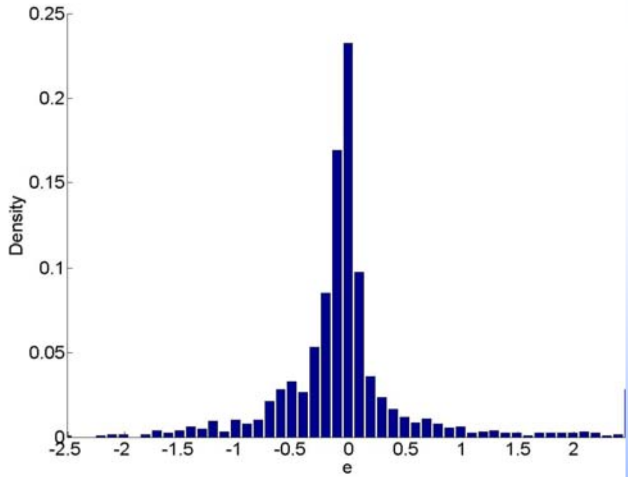
Aim: estimate confidence intervals of discharge forecasts

Means: by estimating conditional probability of error, knowing discharge forecast P(e<e(t)/Q(t))

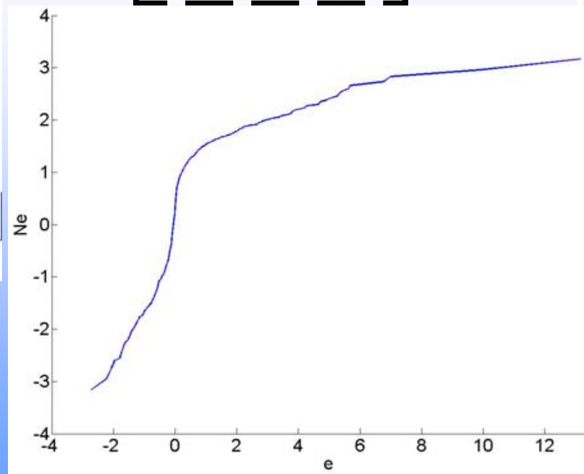
Drawback: analytical error distribution unknown *a priori*

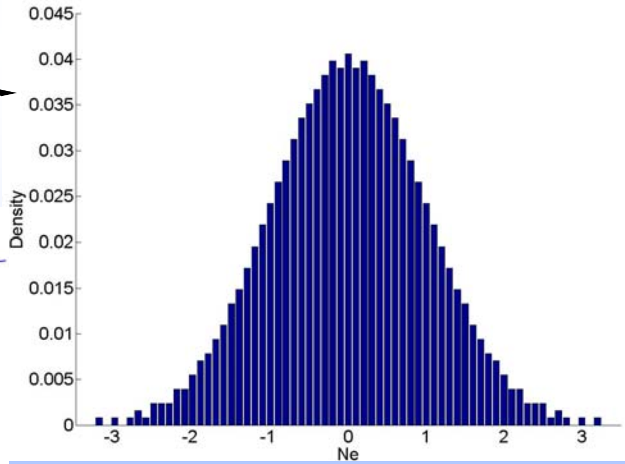
Proposed solution: use of the Normal Quantile Transform

➔ make e & Q distribution gaussian (Montanari and Brath, 2004)



NQT

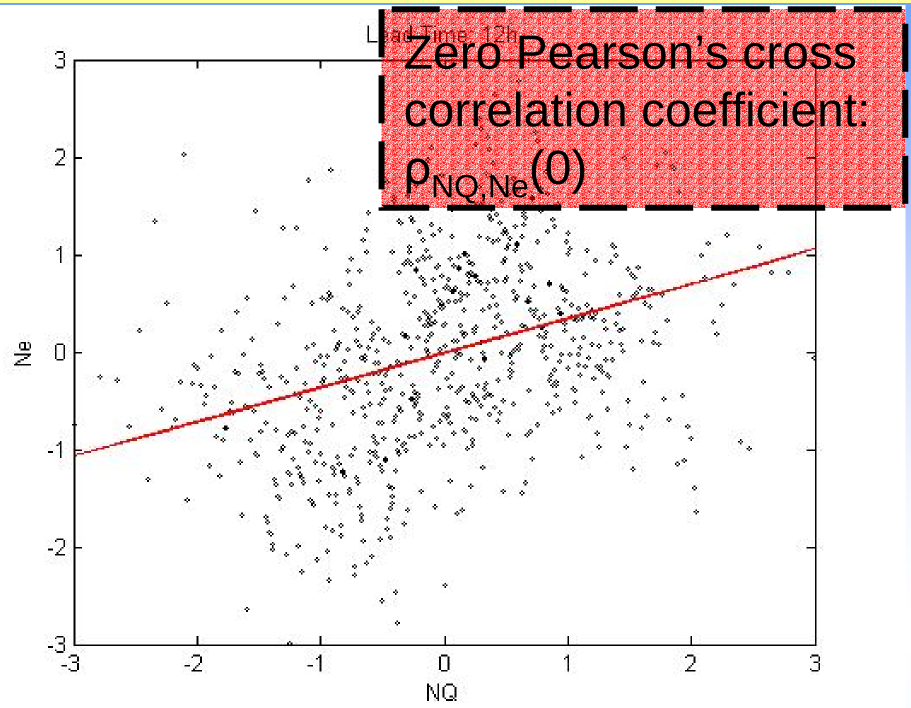




Normal Quantile Transform: NQTe=(e,Ne)

Idem for Qs NQT(Qs,NQs)

3. Confidence intervals of model forecasts computation



Zero Pearson's cross correlation coefficient: $\rho_{NQ,Ne}(0)$

Hypothesis:

$$Ne = \rho_{NQ,Ne}(0).NQ + N\varepsilon$$

With $N\varepsilon$:

1. indep. of NQ, & homoscedastic
2. Normally distributed
   ➔ $Mean(N\varepsilon)=0$
   ➔ $Var(N\varepsilon)= 1-(\rho_{NQ,Ne}(0))^2$

90% confidence intervals:

$$Ne^{\pm}=\rho_{NQ,Ne}(0).NQ \pm 1.655(1-(\rho_{NQ,Ne}(0))^2)^{0.5}$$

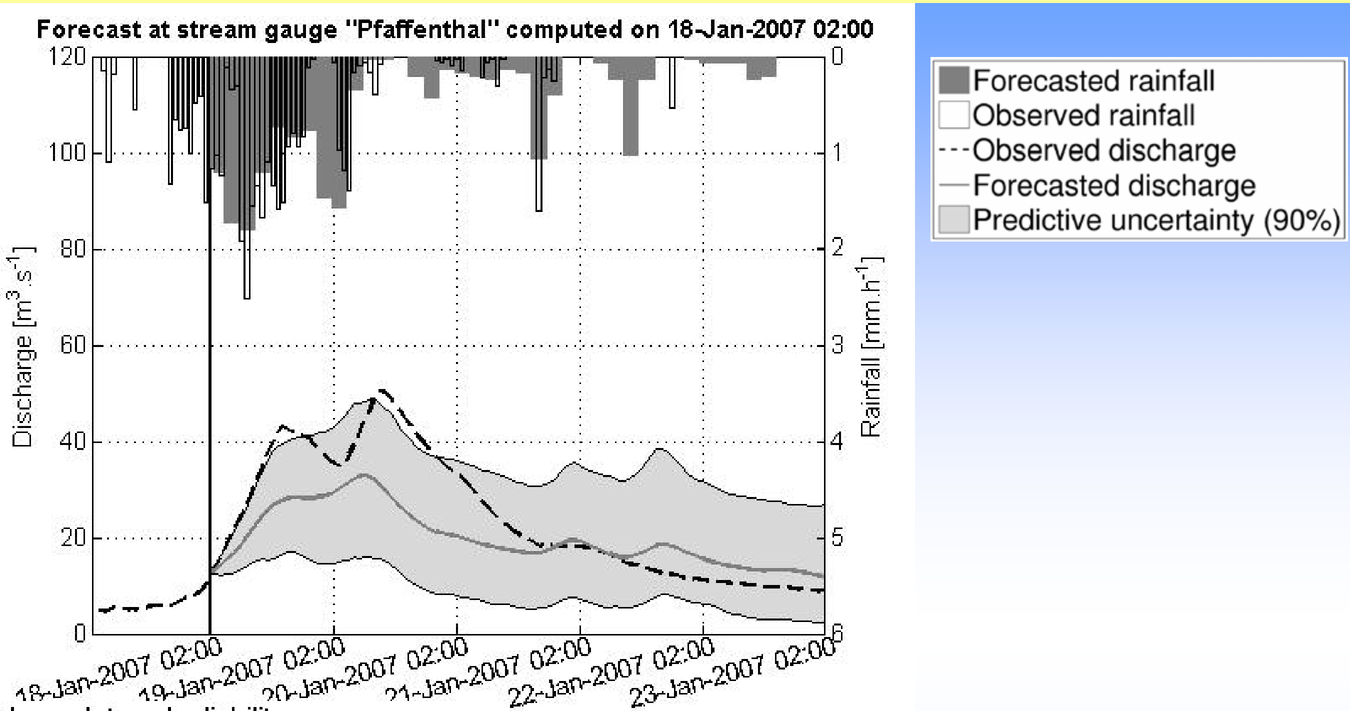
$$Q^{\pm} = Q + NQT_e^{-1}(Ne^{\pm})$$

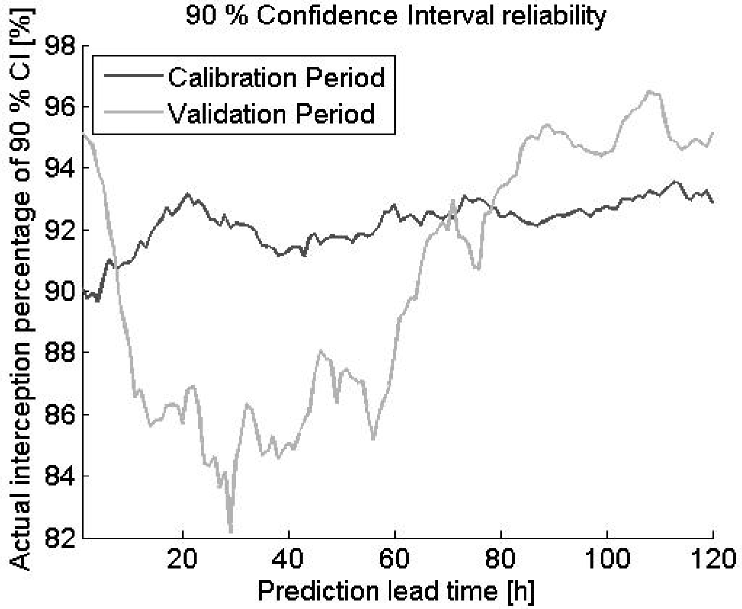
Rk:

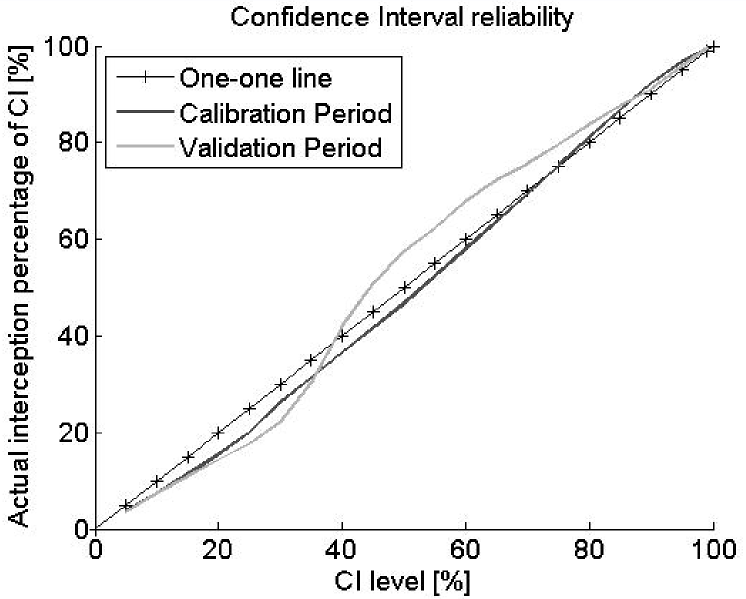
1. Separation positive/negative errors
2. Only $Q \geq 6.5 m3/s$

3. Confidence intervals of model forecasts computation

II. UNCERTAINTY ASSESSMENT







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Innovative approach for:

- setting-up a flood forecasting system,
- assessing the total predictive uncertainty of coupled atmospheric-hydrologic-autoregressive models.

Use of meta-gaussian model:

Allow to assess total predictive uncertainty and not only parameterization uncertainty

Provide suitable confidence intervals of discharge forecasts:

→ Confidence intervals of discharge forecasts encompass the measured discharge with probability close to those they are supposed to do (~82% compared to 90 % CI in the worst case)

Requirements: archive of model errors

This study has been done in the framework of the MAPRISK project, funded by the National Research Fund (FNR) of Luxembourg through the VIVRE program (FNR/VIVRE/06/36/04)

Thank you for your attention

Questions ?

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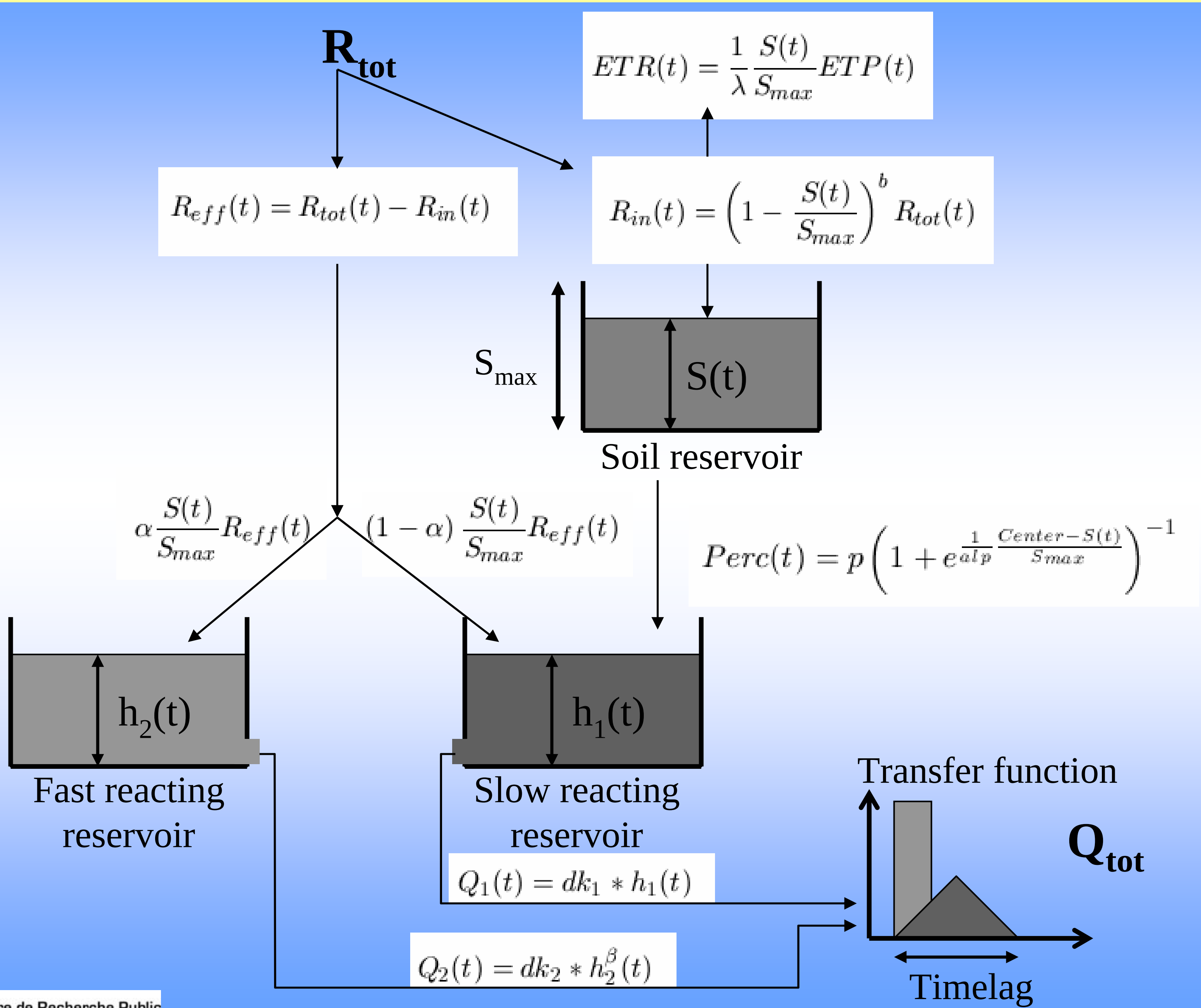
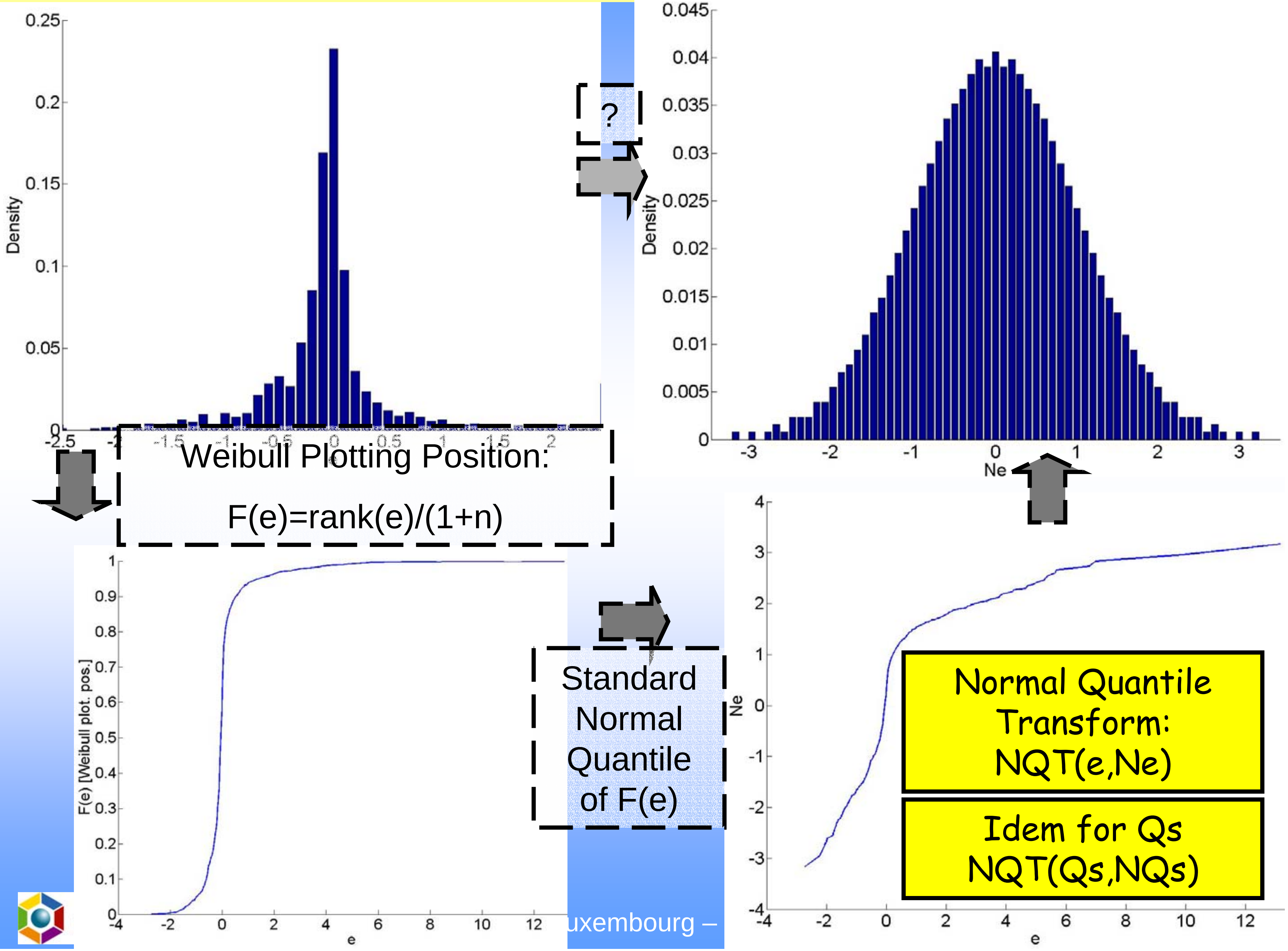
Hydrologic FLEX model: model structure

APPENDIX 1



2. Meta-gaussian bivariate densities computation



Use of various atmospheric model inputs

e.g.: ECMWF-EPS

Coupling the presented model with hydrodynamic computation

Provide flood extent forecasts in real time with confidence intervals.