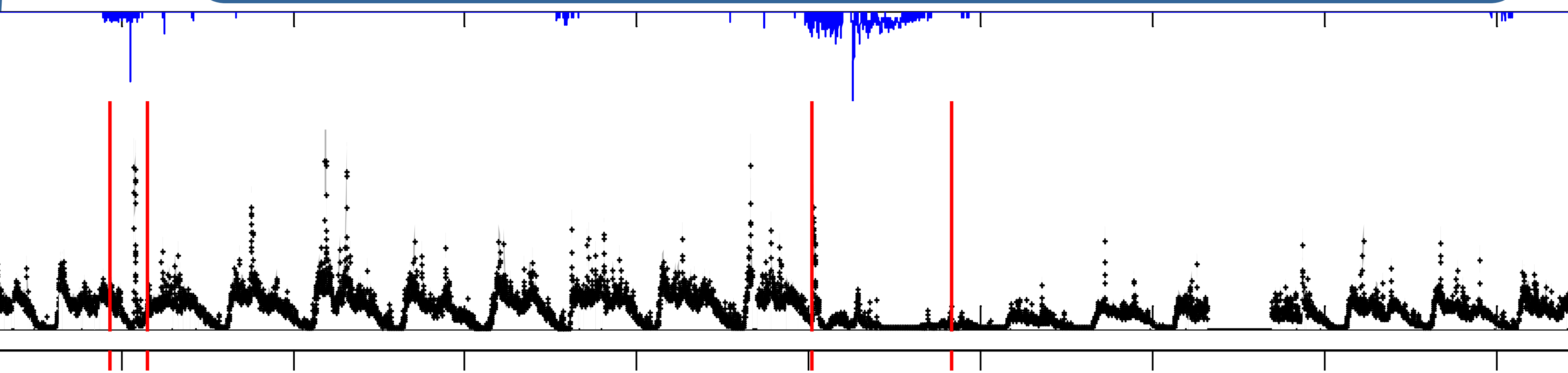
9th UDSM, Belgrade,
3-7 September 2012

Interest of Bayesian learning principle for stormwater quality modelling based on turbidity time series



INSA LYON
LGCIE LABORATOIRE DE GÉNIE CIVIL & INGÉNIERIE ENVIRONNEMENTALE
SAFEGE Ingénieurs Conseils

Marjolaine Métadier
(2007-2011)

Context

Rich data sets: - Continuous

Turbidity - Long time

↓

Formal Bayesian inference method

↓

Water quality models TSS

Representative models or poor structures?

What adapted or new approaches?

What perspectives for operational use?

Methodology

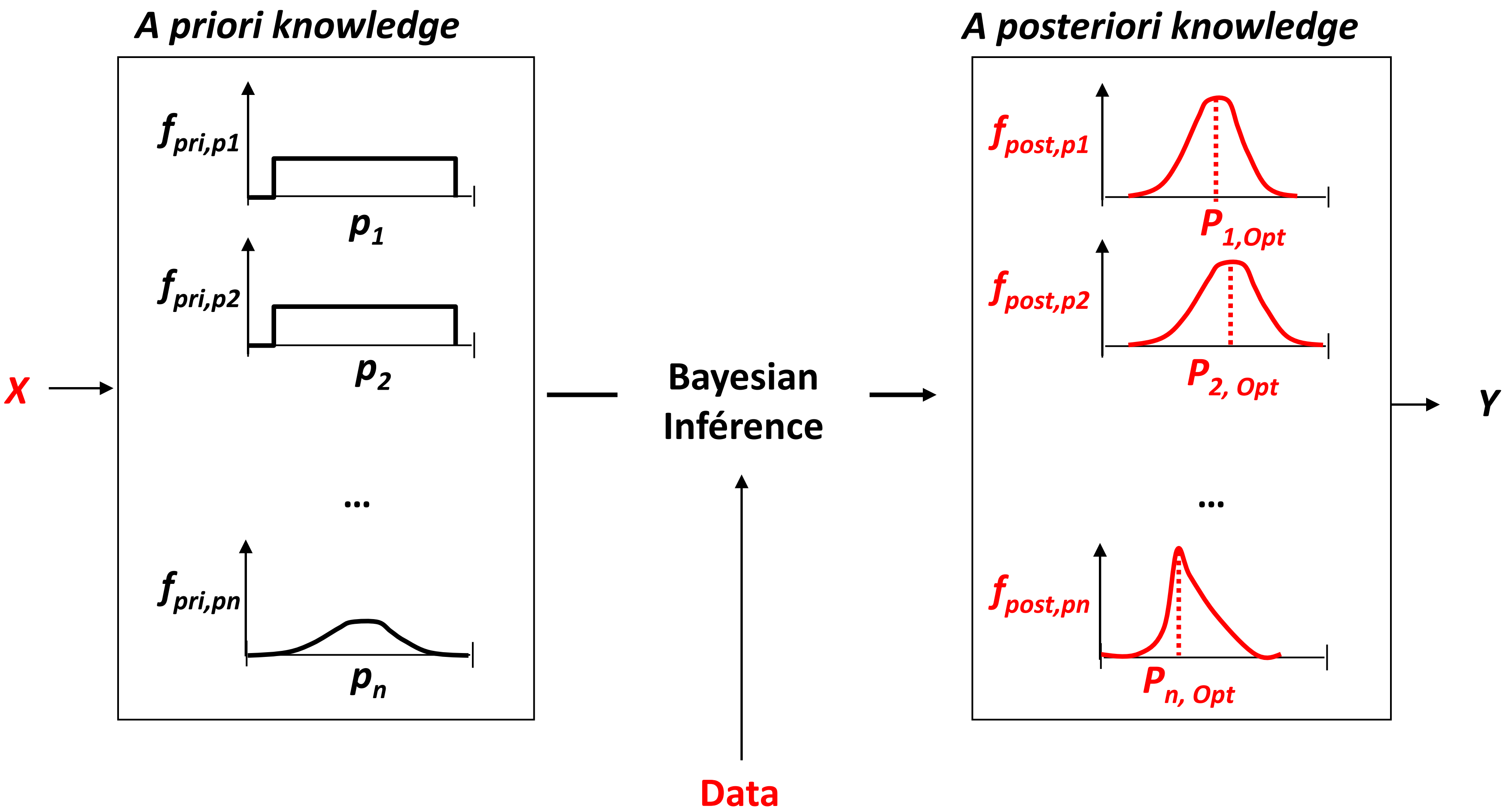
- **Formal Bayesian inference - Attention to:**
  - ✓ The right parametrization of the method
  - ✓ Application of learning principle

- **Pilot site: Chassieu (185 ha, industrial), France**
  - ✓ Flow and turbidity database, 2004-2008, 263 storm events

- **HYPOCRAS: simple conceptual approach**
  - ✓ Bertrand-Krajewski, 1992
  - ✓ With adaptations
  - ✓ 6 (hydraulic) & 8 parameters (quality)

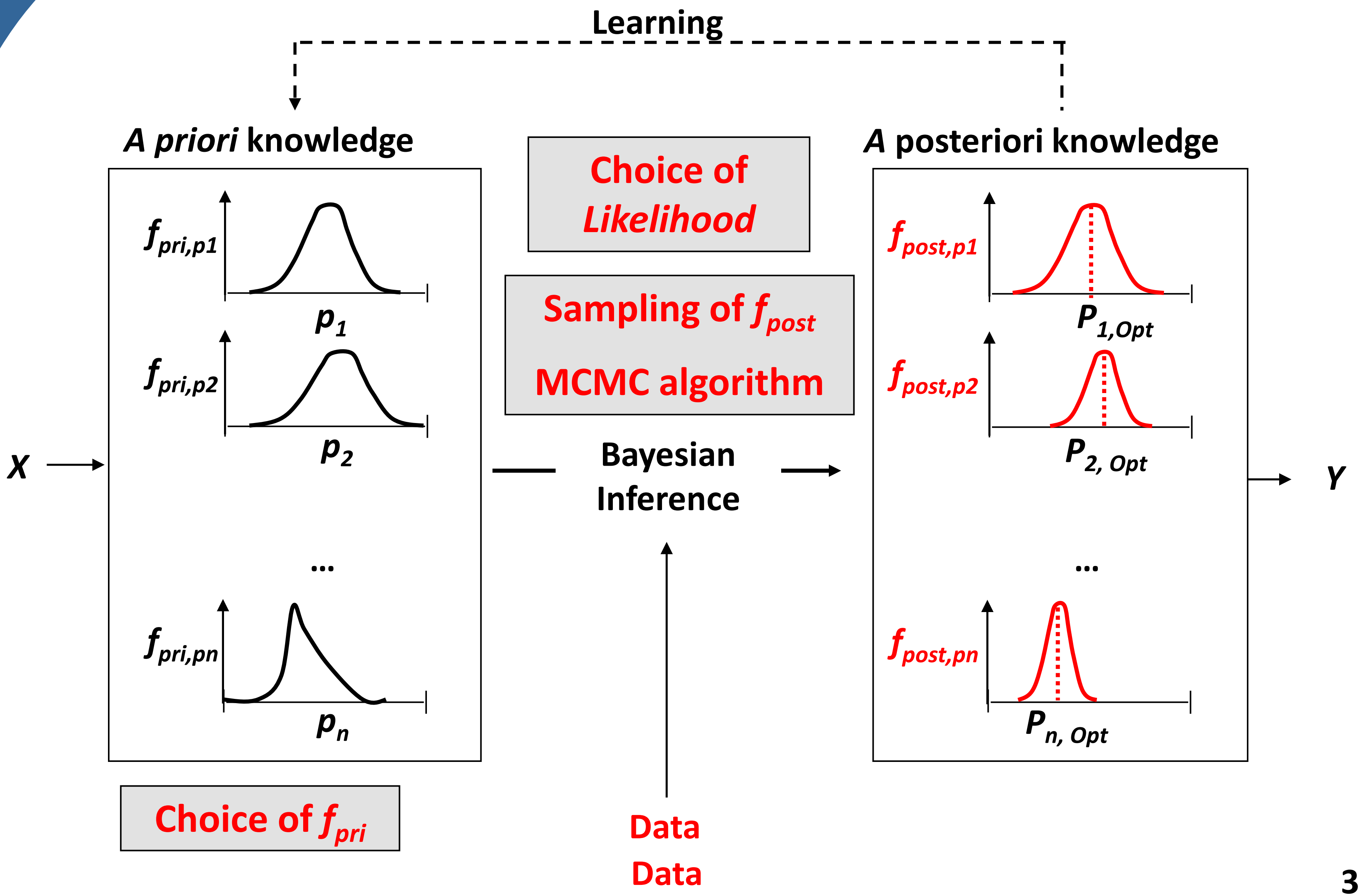
- **Tuning of the method with the hydraulic model**
  - ✓ 6 parameters model: Kh1, Kh2, to, PI, PCP, S

Bayesian inference



Data

Bayesian inference



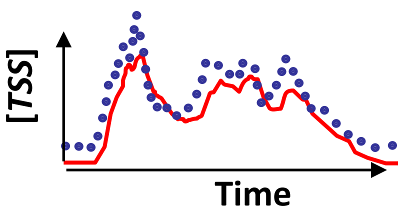
$$f_{post} \propto \boxed{Likelihood} \cdot \boxed{f_{pri}}$$

Choice of f_{pri}

1st run: uniform distribution

Choice of *Likelihood*

GLF: Global Likelihood function (Schoups & Vrugt, 2010):



5 + *p* adjustment parameters

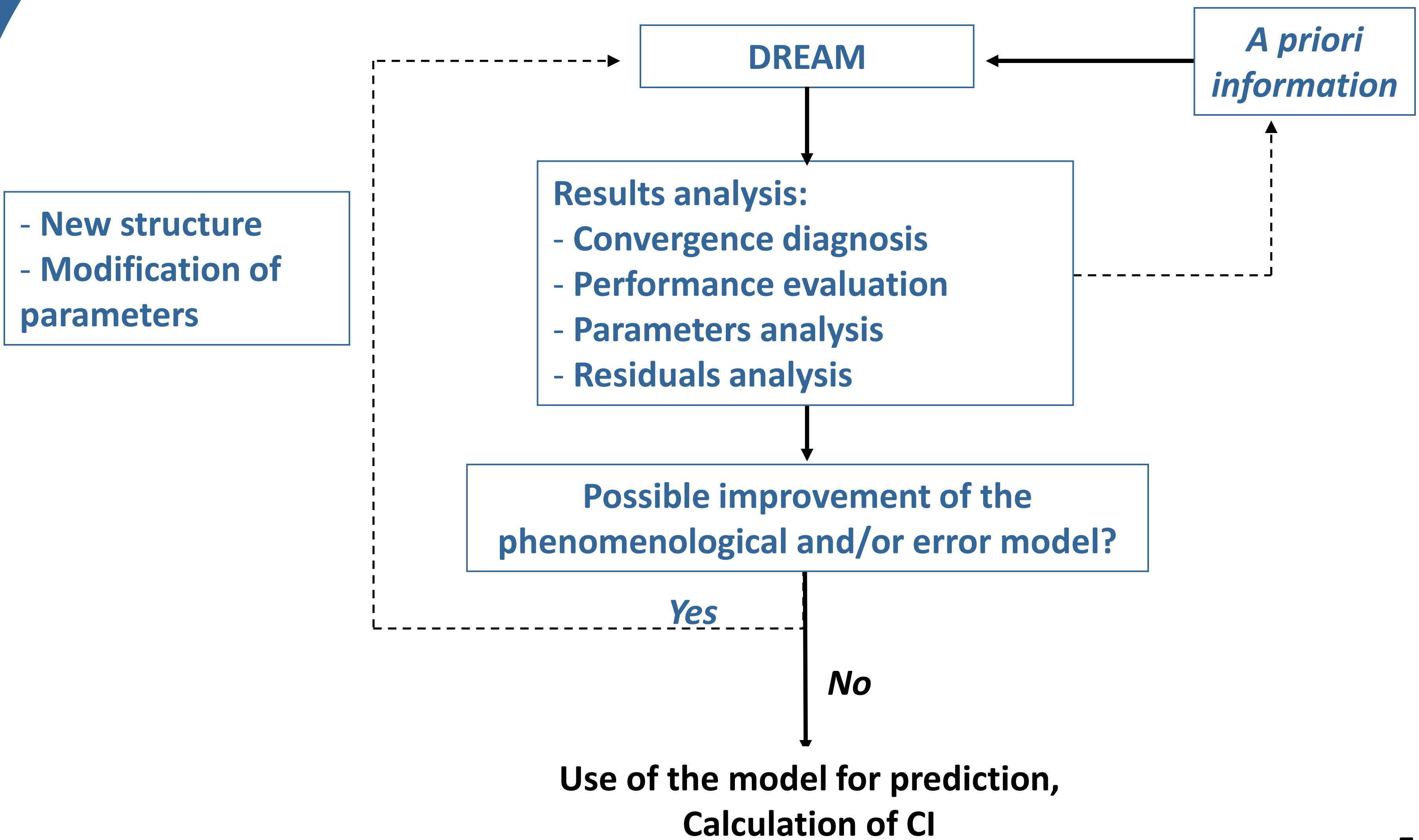
- Kurtosis parameter, β
- assymmetric effect, ξ
- Non homoscedasticity, σ_0, σ_1
- Bias effect, μ_h
- Auto-correlation, $\phi_{1,} \phi_{2,} \ldots \phi_p$

Sampling of f_{post}

MCMC algorithm

DREAM algorithm (Vrugt et al, 2009)

Iterative tests



A 2 step procedure

Initial error model: Normal and homoscedastic σ_0

1. Reduced chronic:

- 15 events Cal
- 60%-40% Cal-Eval
- Spring period

Iterative tests

If no more possible improvement

Results as new *a priori* information

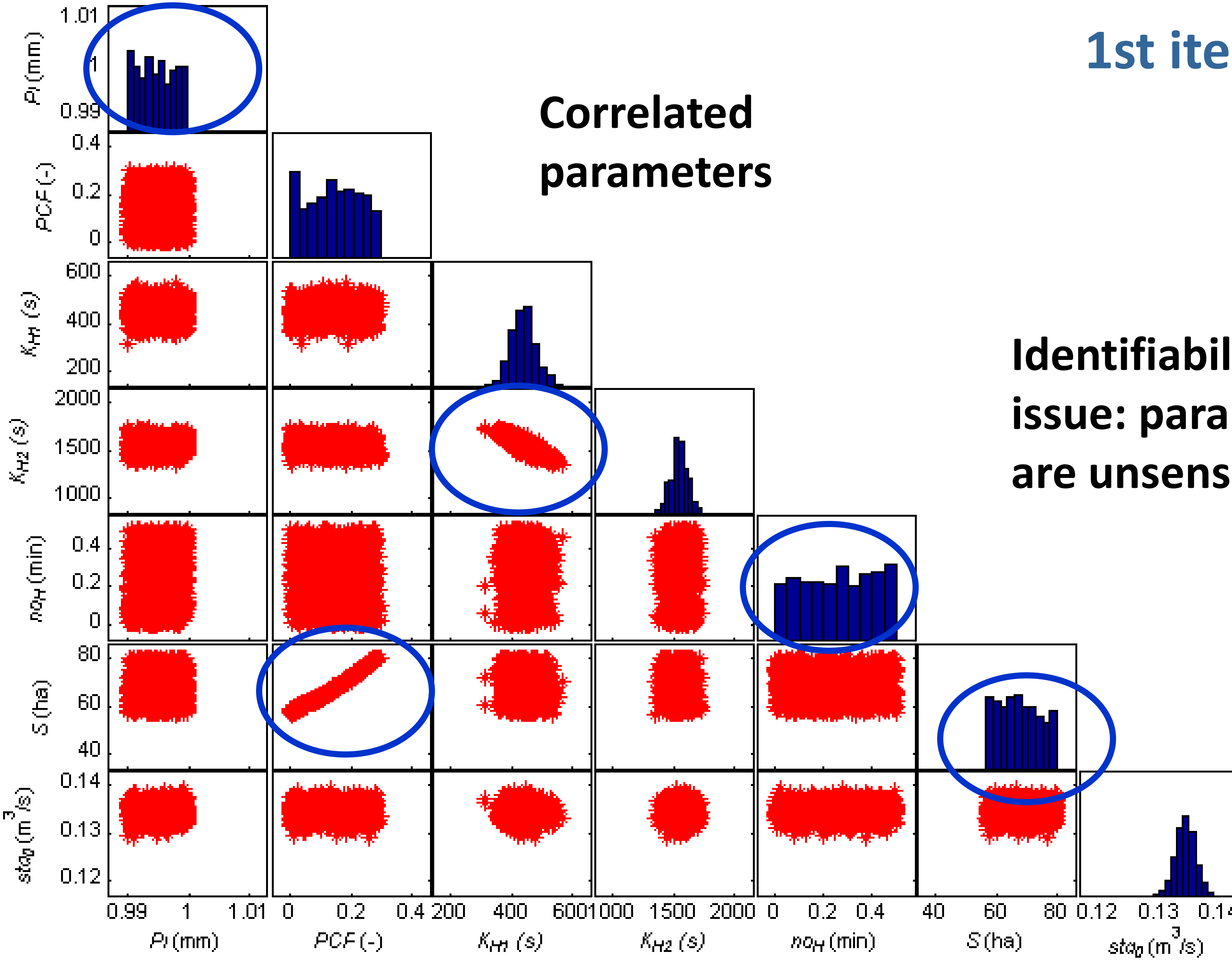
2. Total chronic:

- 95 events Cal
- 60%-40% Cal-Eval
- 2007-2008

Iterative tests

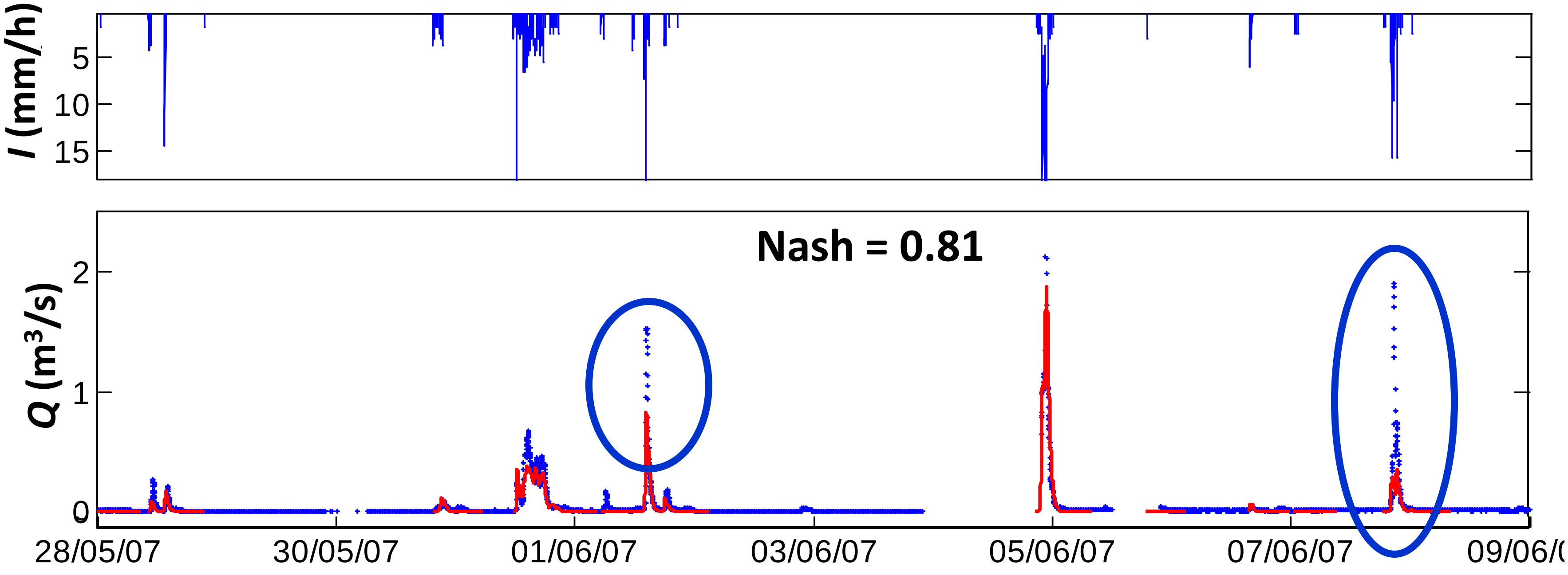
- 4 iterations: From 6 to 4 parameters

Hydraulic model – reduced chronic 1st iteration



Hydraulic model – reduced chronic
4th iteration

4 parameters model:
Kh1, Kh2, PI, PCP



Main results – hydraulic model

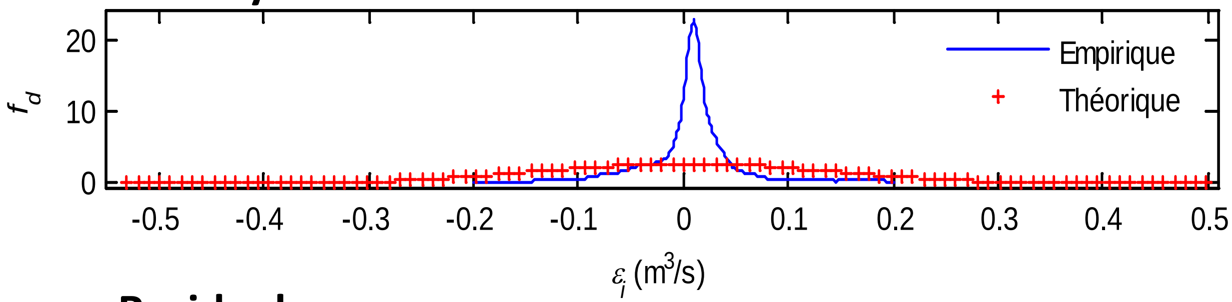
- 4 iterations: From 6 to 4 parameters
- Impossible to find a good error model

Results

OLS assumption – reduced chronic 1st iteration

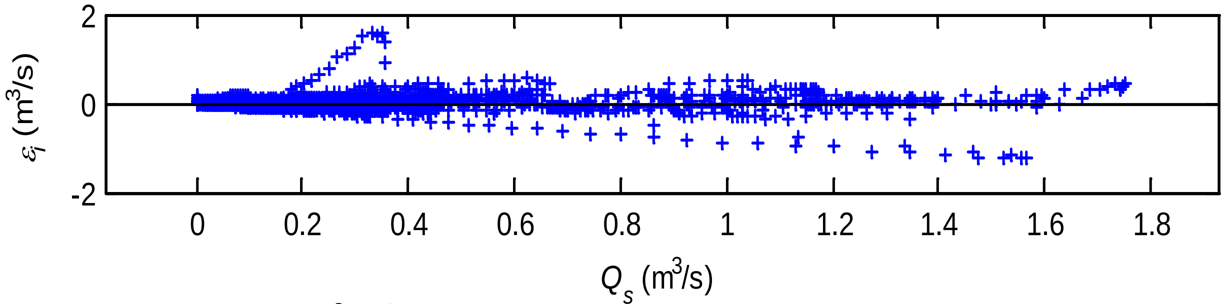
$$\sigma_0 = 0.13 m^3/s$$

Density function



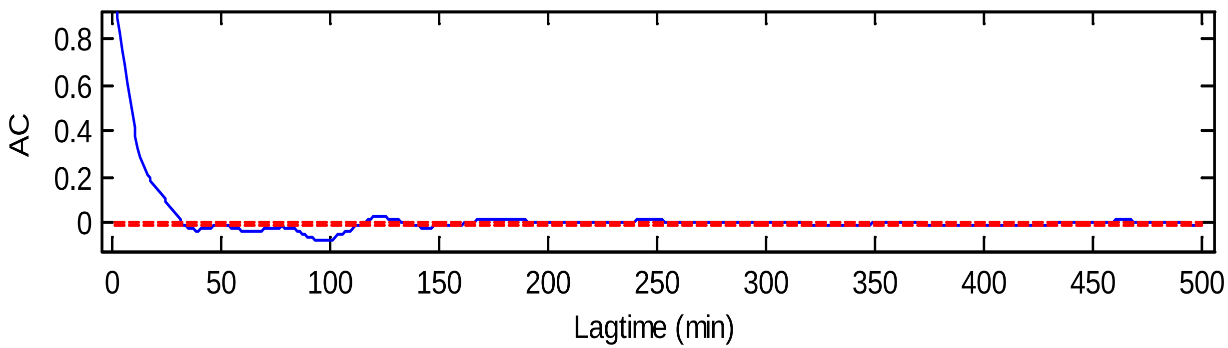
Non normality

Residuals



Non homoscedasticity

Auto-correlation

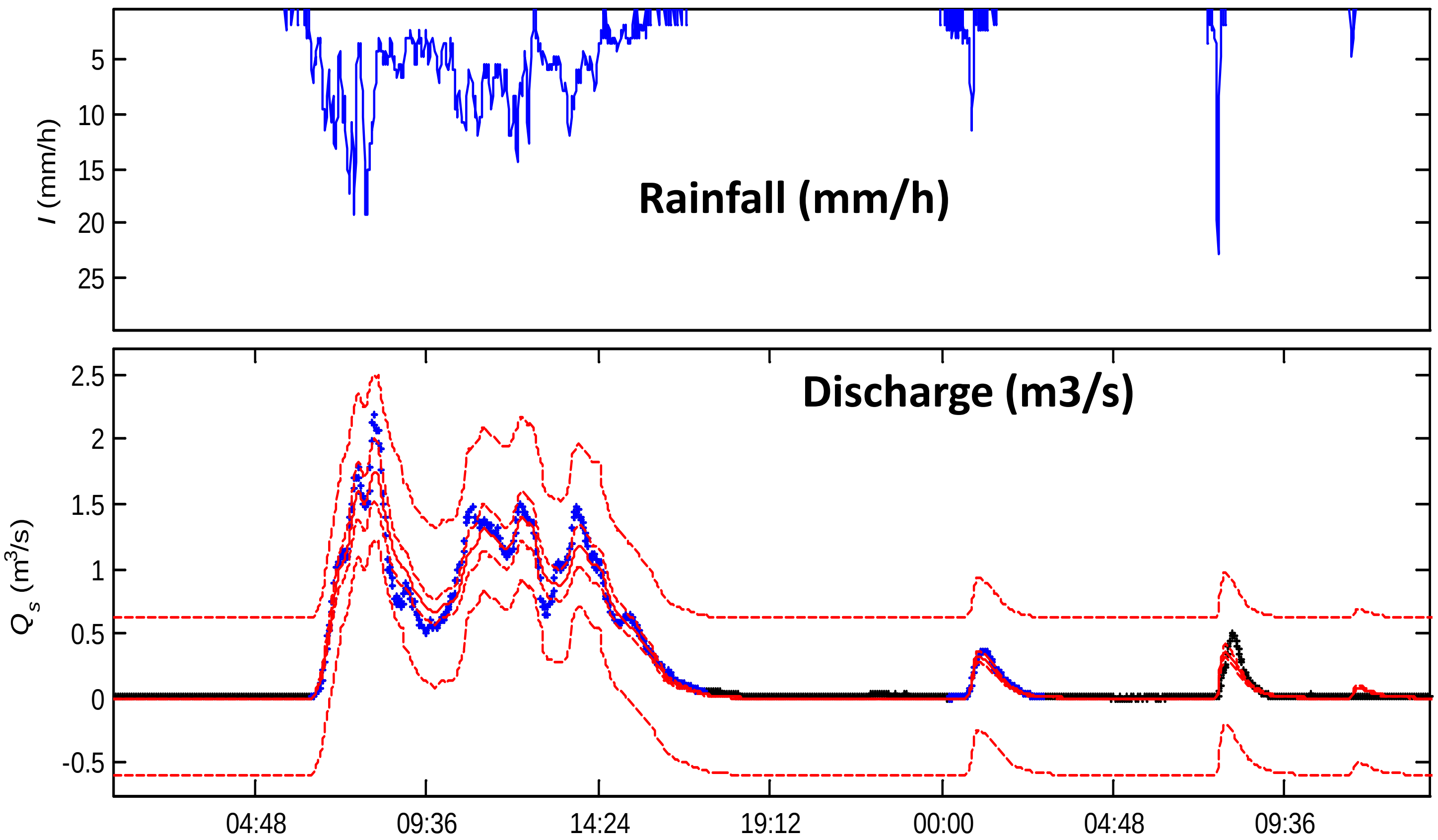


Residuals are auto-correlated

Results

OLS assumption – reduced chronic 1st iteration

$$\sigma_0 = 0.13 m^3 / s$$



Unrealistic CI

14 – 15 th May 2007

Results

OLS assumption – reduced chronic 2nd iteration

$$\sigma_0 = 2.14\,\mathrm{e}-3\ \mathrm{m}^3/\mathrm{s}$$

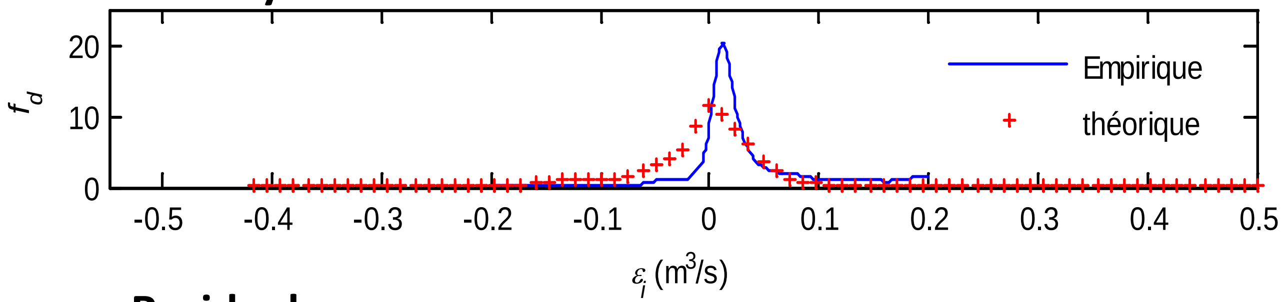
$$\sigma_1 = 0.12$$

$$\beta = 0.99$$

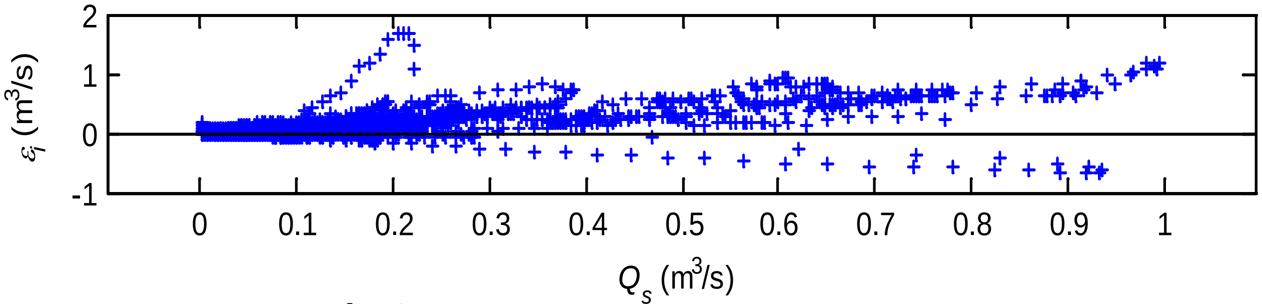
$$\boxed{\phi_1 = 0.97}$$

Not adapted for fast urban flow dynamic

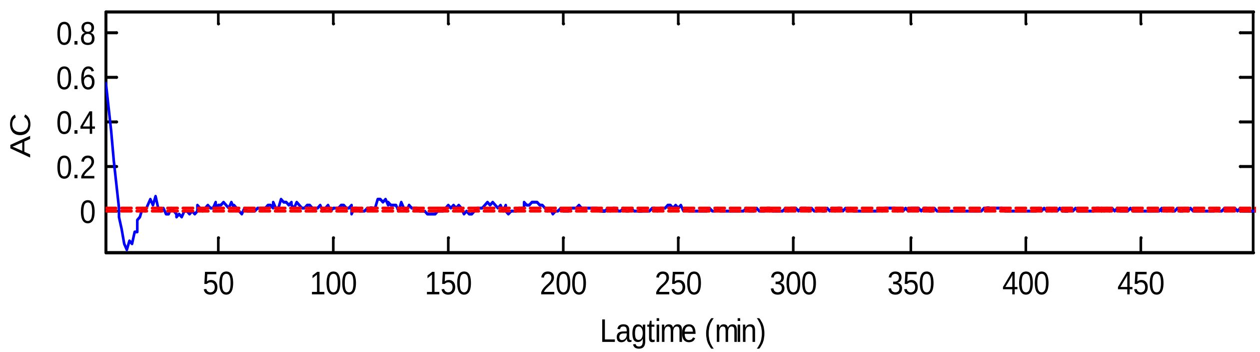
Density function



Residuals

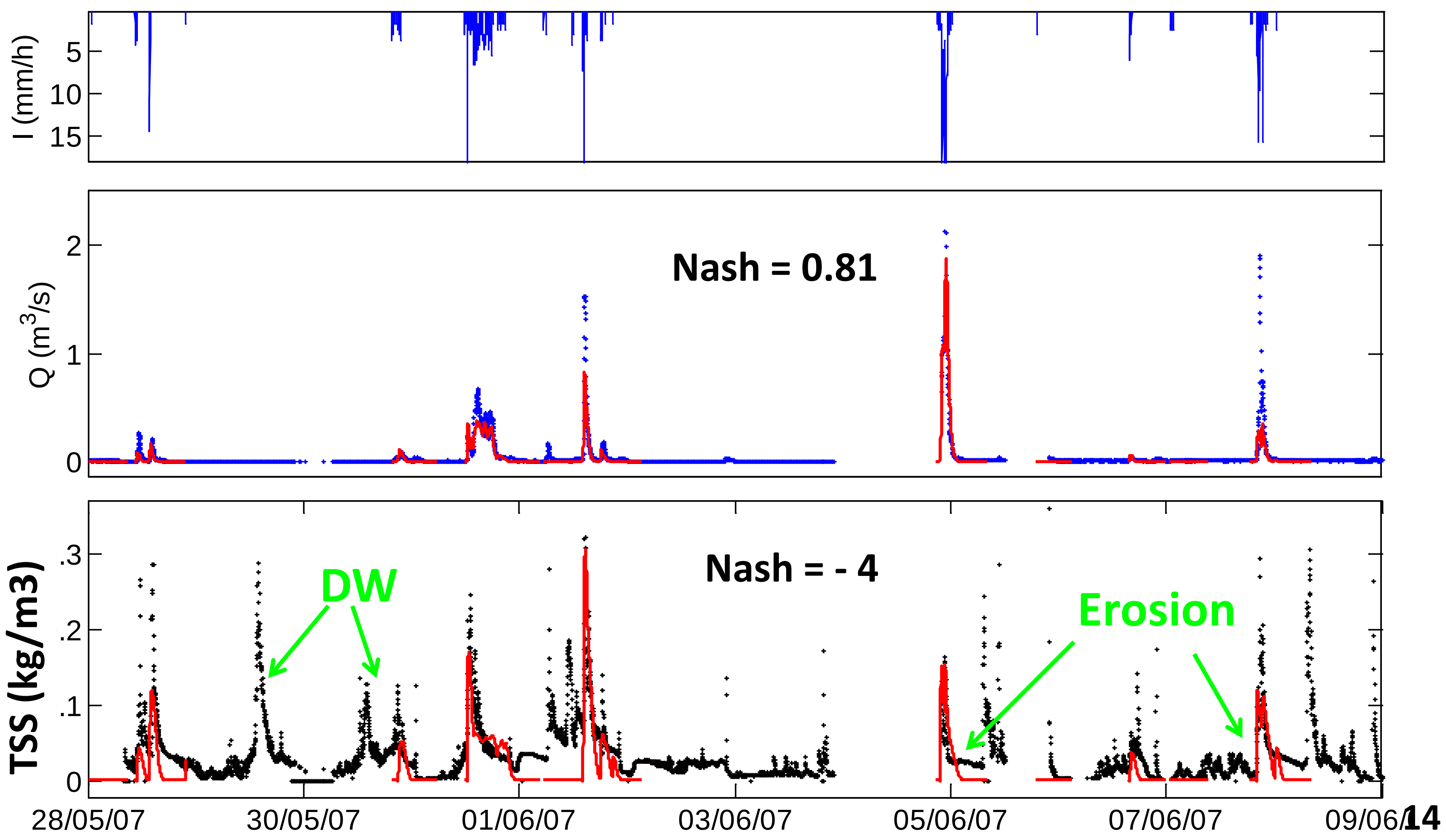


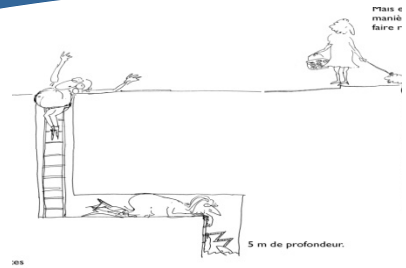
Auto-correlation



Main results – Quality model

- 7 iterations: From 8 to 5 parameters
- First results are not satisfactory
- Model should be improved: DW, Erosion model, radar data





Conclusions

- **Learning principle applied at several levels:**
  - ✓ **Phenological model: parameters & structure**
  - ✓ **Error model: parameters & structure**
  - ✓ ***A priori* parameters distribution**
  - ✓ **Calibration data sets: reduced & total**
- **Towards operational applications?**
  - ✓ **Limit of model structures**
  - ✓ **Calculation time – rather simple models**
  - ✓ **Availability of data and sensors – Willingness to pay**