EGU General Assembly 2023

HS3.1 Hydroinformatics: data analytics, machine learning, hybrid modelling, optimisation

A hybrid method to tackle conditional systematic errors of hydrological models

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What is a hydrological model

- Definition 1: A mathematical formula $O(t)= f(x_1(t), x_2(t), \ldots)$, where O the dependent (discharge), and x_1, x_2, … the independent (the stresses) time-varying variables.
- Definition 2: A stochastic function $\underline{O}= f(\underline{x}_1, \underline{x}_2, \ldots)$, where $\underline{O}$, $\underline{x}_1$, $\underline{x}_2$ … stochastic variables.
- Definition 3: A mutual information function $I[\{\underline{x}_1, \underline{x}_2, \ldots\}, \underline{O}]$.

Uncertainty

- Aleatory – lack of knowledge (unknown errors in measurements, unknown physical processes, …)
- Epistemic – insufficient model (simplistic structure, poor calibration, …)

Note: this is not the most common definition.

Modelling uncertainty

AR1 Residual Error

- Definition 1: $O(t) = f(x_1(t), x_2(t), \ldots) + \rho\,\delta(t-1) + \varepsilon(t)$

  epistemic aleatory

  (Schaefli et al., 2007).

- Definition 2: → …

- Definition 3: epistemic $I[\{\underline{x}_1, \underline{x}_2, \ldots\}, \underline{O}] - I[\underline{O}, \underline{\hat{O}}]$

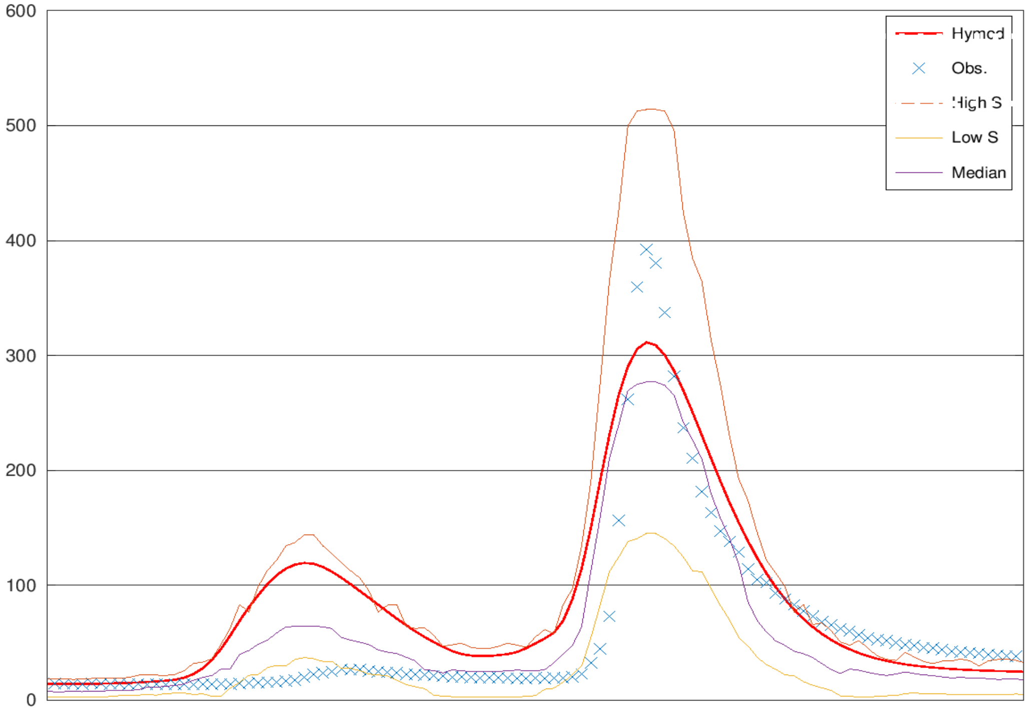
  aleatory $\Phi[\underline{O} \mid \{\underline{x}_1, \underline{x}_2, \ldots\}]$

  (Findanis and Loukas, 2022).

Modelling uncertainty – stochastic approach

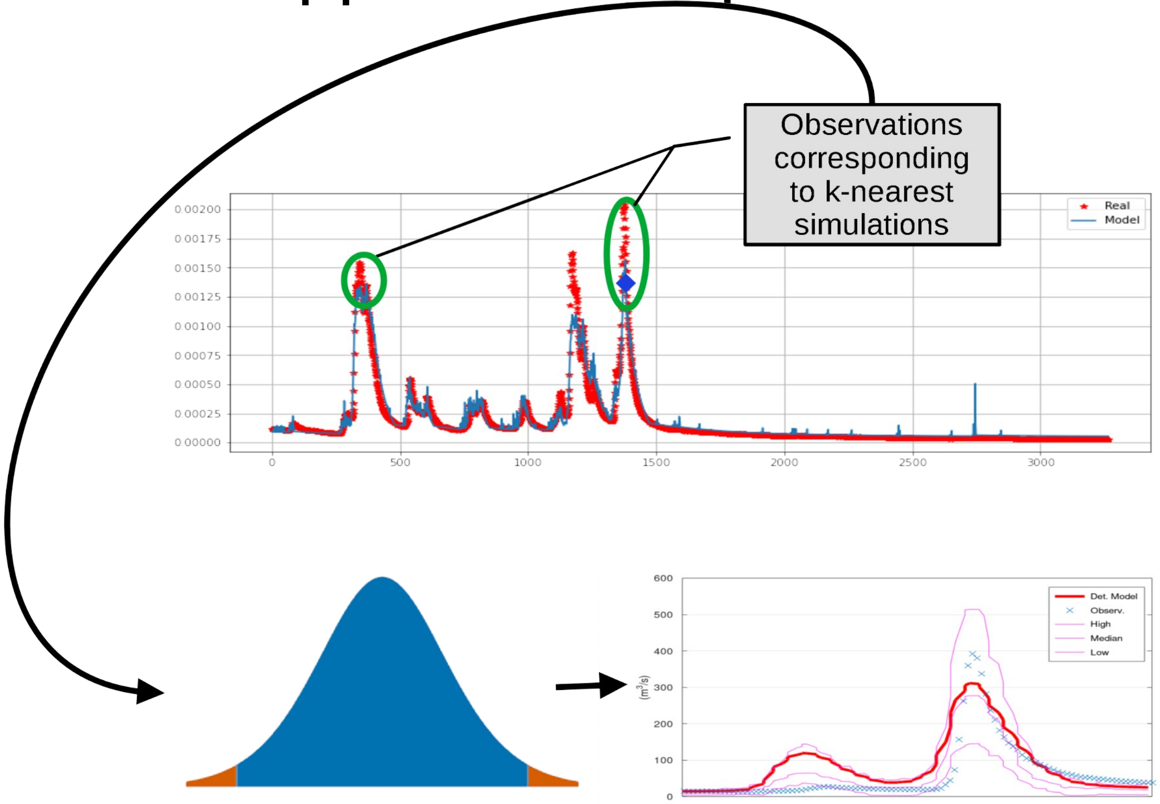
- $F_{\underline{O}|\hat{O}}(O|\hat{O}) \approx P\{\, \underline{O} \le O \,|\hat{O} - \Delta\hat{O}_1 \le \hat{O} \le \hat{O} + \Delta\hat{O}_2 \,\}$

epistemic
+
aleatory



See BlueCat (Koutsoyiannis and Montanari, 2022)

Stochastic approach – implementation



This is actually KNN, see Rozos et al., (2022)

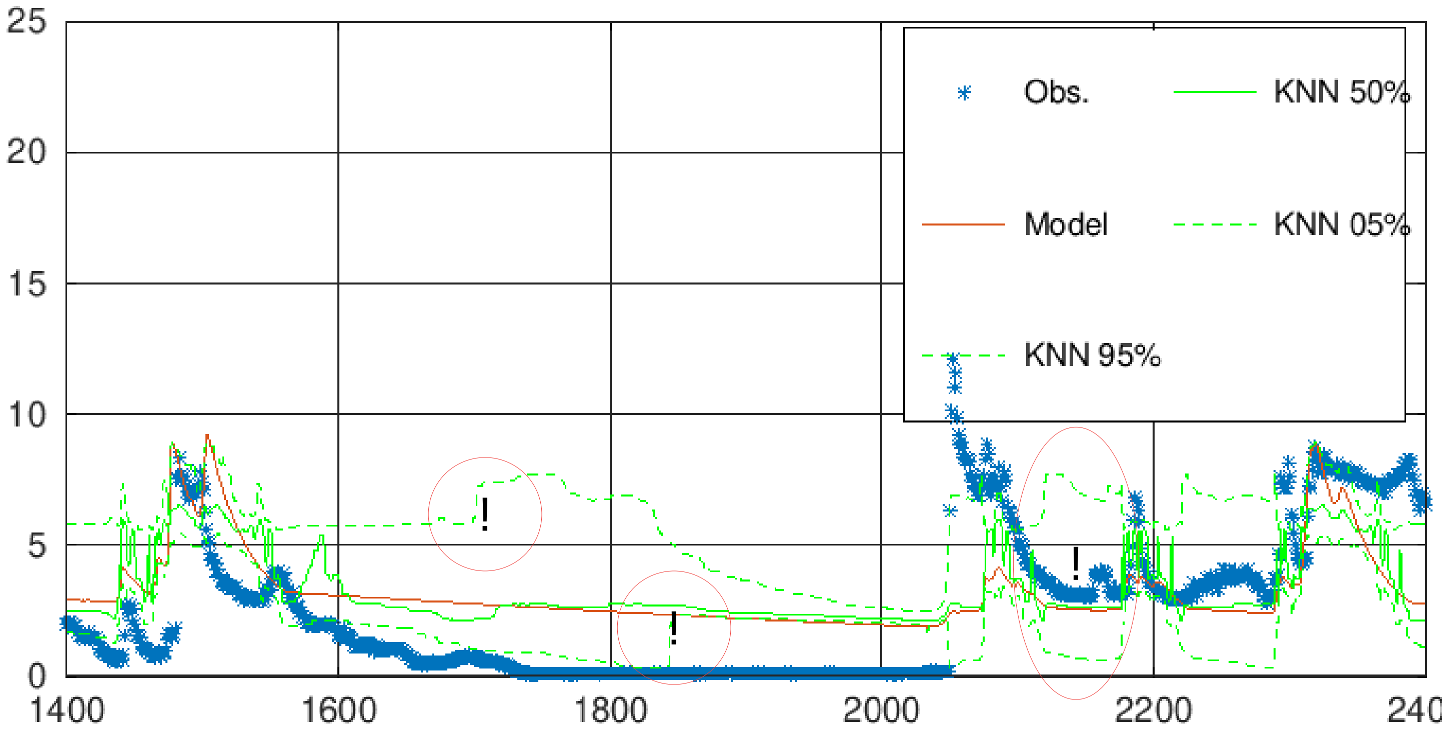
Case studies

How do the different types of errors manifest?

Where to get the tools:

- KNN C code for MATLAB or command prompt from **hydronoa.gr** (software → … uncertainty with KNN).
- BlueCat R code from Alberto Montanari’s github (just search for **hymodbluecat**).

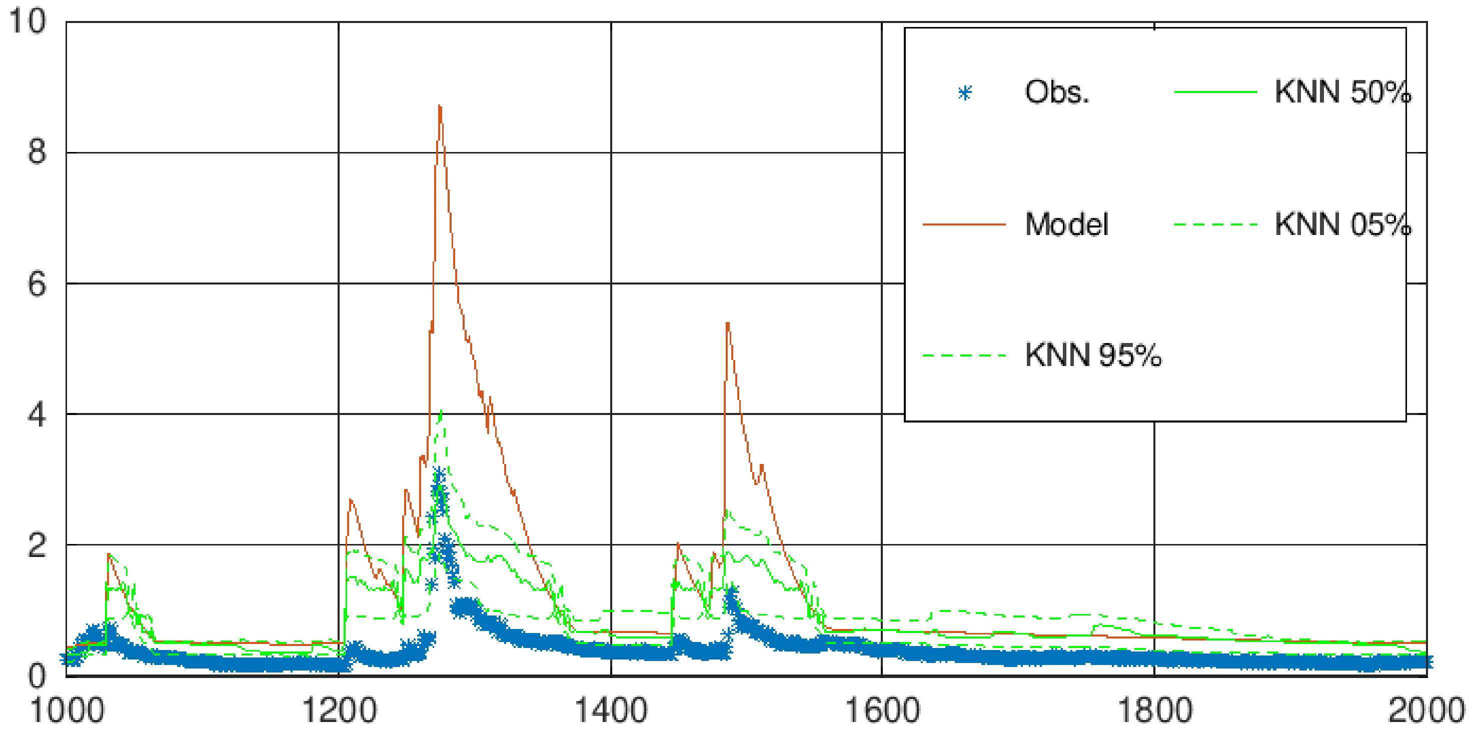
Case studies – Aleatory uncertainty



Unknown physical process

(Rozos, 2023)

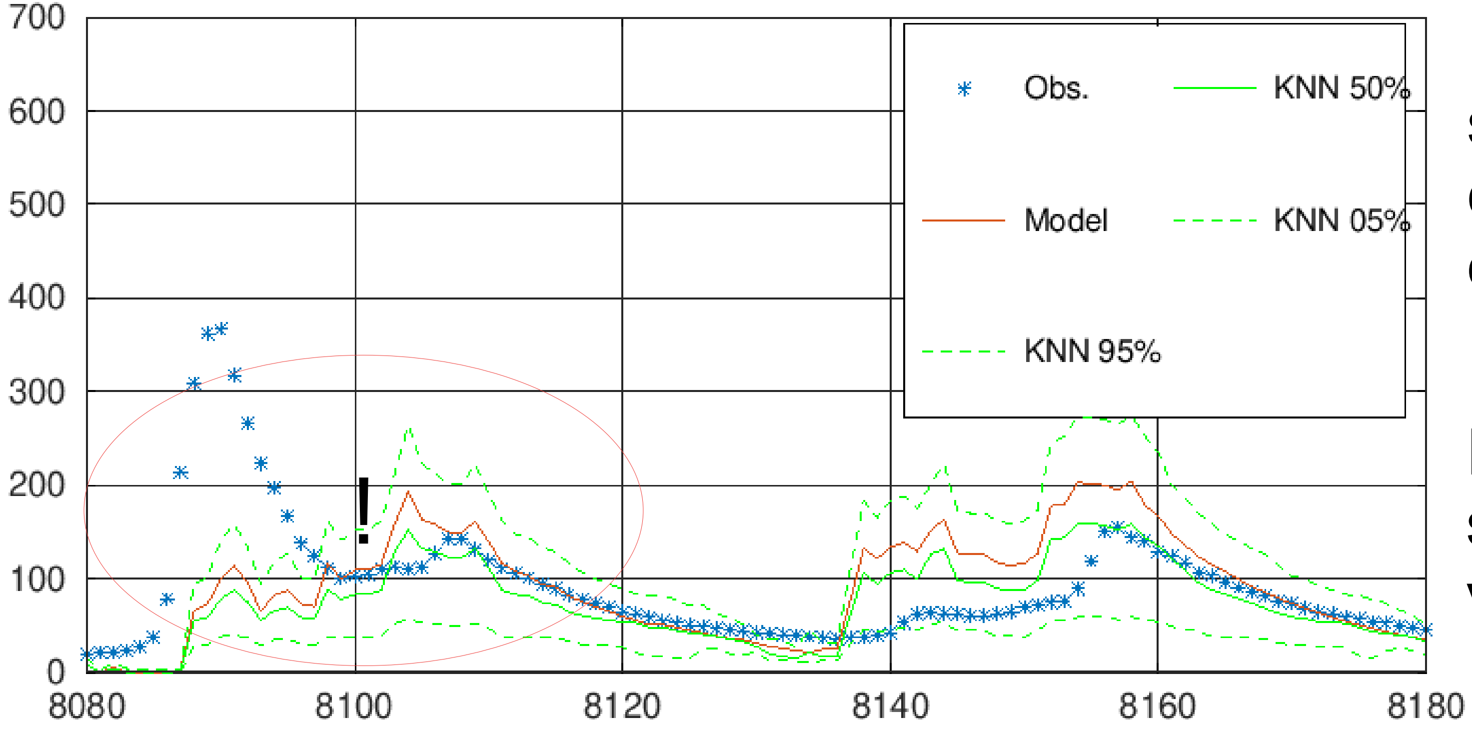
Case studies – Epistemic uncertainty



Poorly calibrated model, systematic error

(Rozos, 2023)

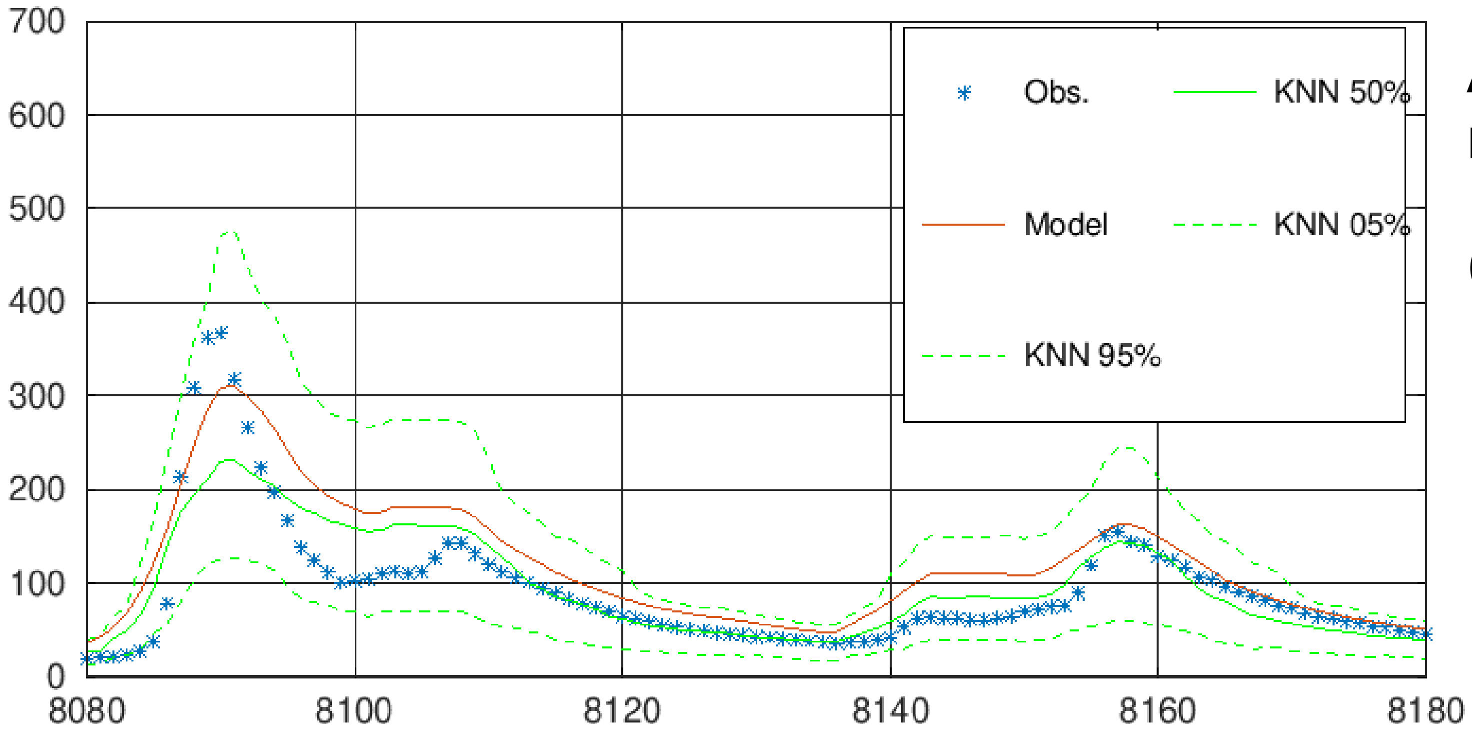
Case studies – Epistemic uncertainty



Insufficient structure, conditional errors

It may not show in verification!

Case studies – Epistemic uncertainty



Another model

(Rozos, 2023)

How to cope with aleatory uncertainty

- Get more information
- Evaluate the reliability of the available data
- More independent variables
- Monte Carlo simulations

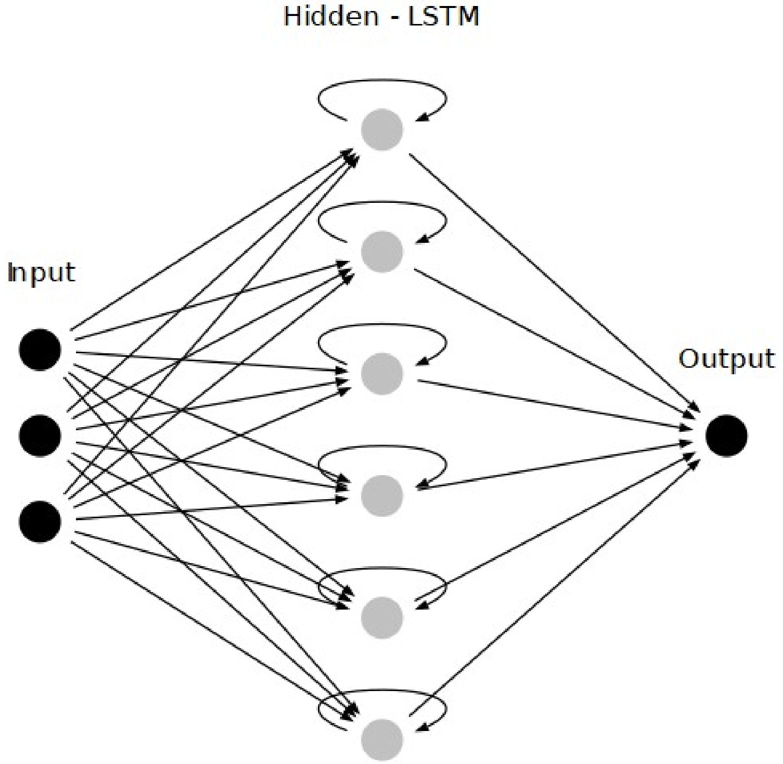
How to cope with epistemic uncertainty

- Recalibrate the model
- Try another model (latent conditional errors)
- Model ensembles

Here a hybrid approach is suggested that combines a feedforward neural network with model ensembles.

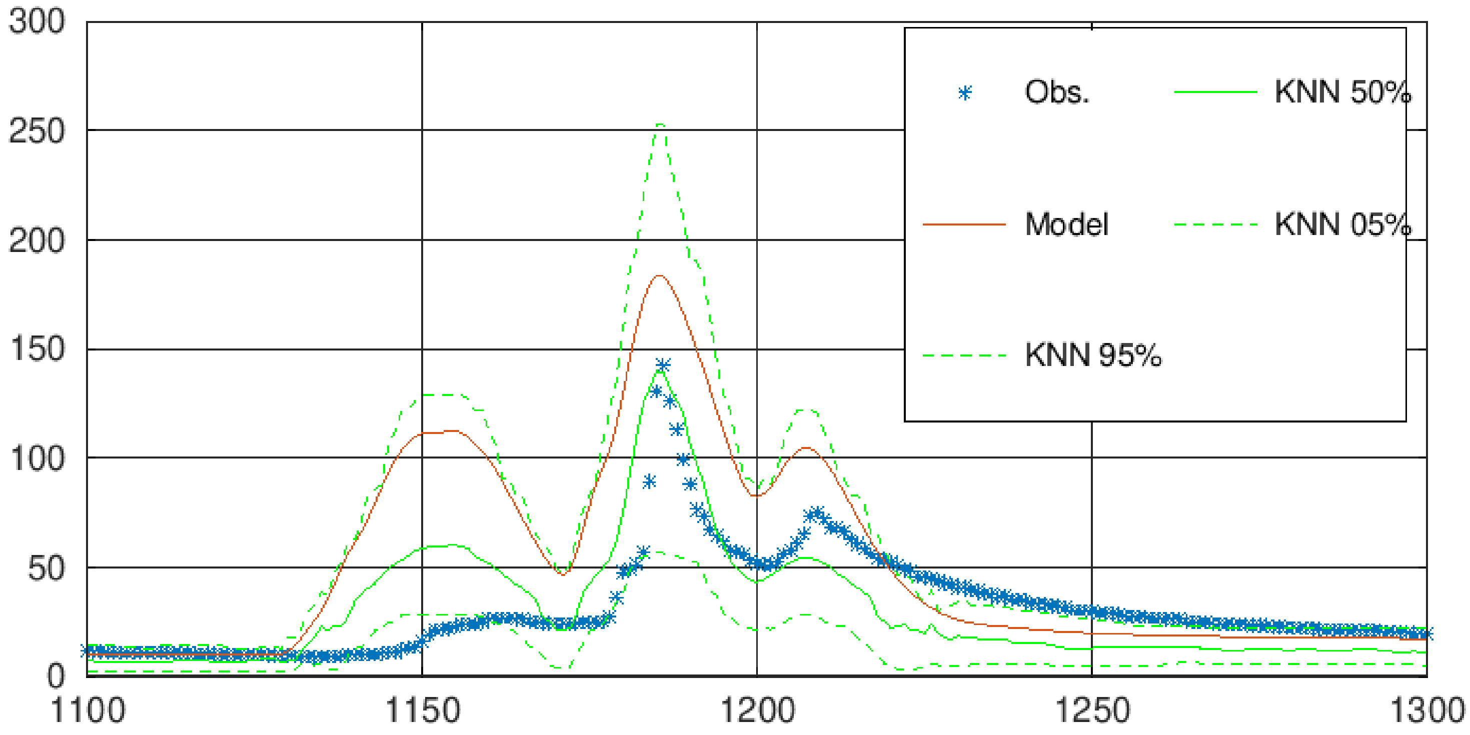
Hybrid approach

Stresses and model**s** outputs



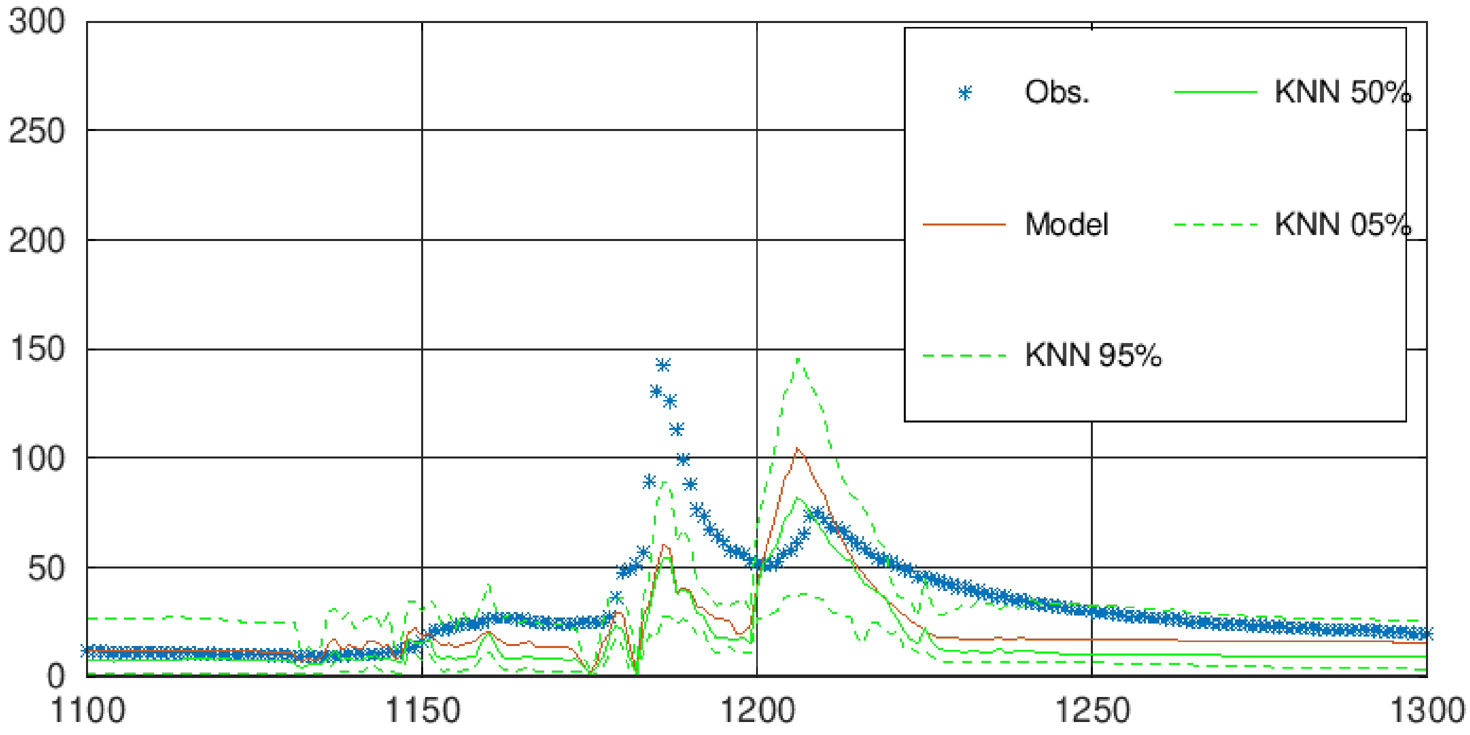
Simulated time series

Results: Model A



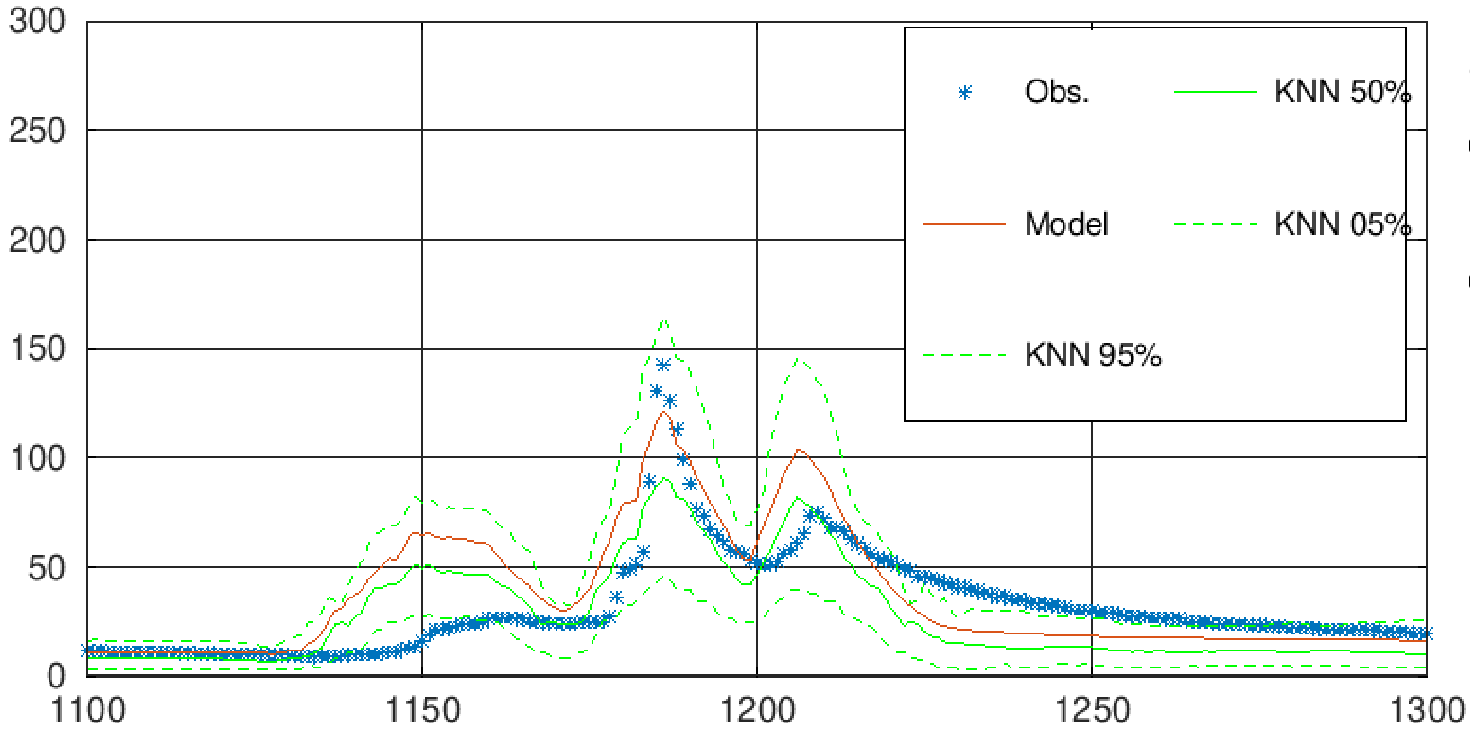
Model A systematic overestimati on of flows

Results: Model B



Model B conditional error

Results: model A + model B → FNN



Conditional error eliminated, over-estimation minimized

Conclusions

- A stochastic approach can be employed to analyze both aleatory and epistemic uncertainties in hydrological models.
- Aleatory and epistemic uncertainties manifest as characteristic patterns in the plot of the confidence intervals; however, conditional errors may remain hidden.
- A hybrid approach, combining multi-model ensembles with FNN, can be employed to cope with epistemic uncertainties, especially in addressing latent conditional errors.

End of presentation

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