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Uncertainty quantification and global sensitivity analysis with dependent inputs: Application to the 2D hydraulic model of the Loire River

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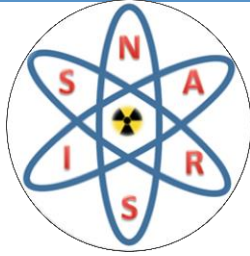
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 **EGU** General
Assembly 2020

Online | 4–8 May 2020



Session NH1.1



The NARSIS project

- Contribution to the **NARSIS** (New Approach to Reactor Safety Improvements) European project initiated in 2017
- Objectives of the NARSIS project:
 - Bring contributions to the safety assessment methodologies
 - Improve the Probabilistic Safety Assessment (PSA)
- Our objectives:
 - Propose a methodology to evaluate uncertainties in 2D hydraulic models by taking into account the dependencies between inputs
 - Apply this methodology to a 2D operational model

Context of the study

- External hazards (*i.e.* flooding) assessed through numerical modelling
- Numerous uncertainties in the hydraulic models related to:
 - the chosen numerical model (Telemac-2D, HEC-RAS, *etc.*)
 - the lack of knowledge of the physical parameters describing the system
 - the model numerical parameters:
 - river geometry, roughness coefficients
 - levee physical characteristics and levee breach parameters
 - flood hydrograph, *etc.*
- Use of Uncertainty Quantification (UQ) and Global Sensitivity Analysis (GSA) to better understand these uncertainties
- Consideration of the dependence between model inputs (usually, inputs are considered to be independent in uncertainty quantification studies)

Case study: why the Loire River?

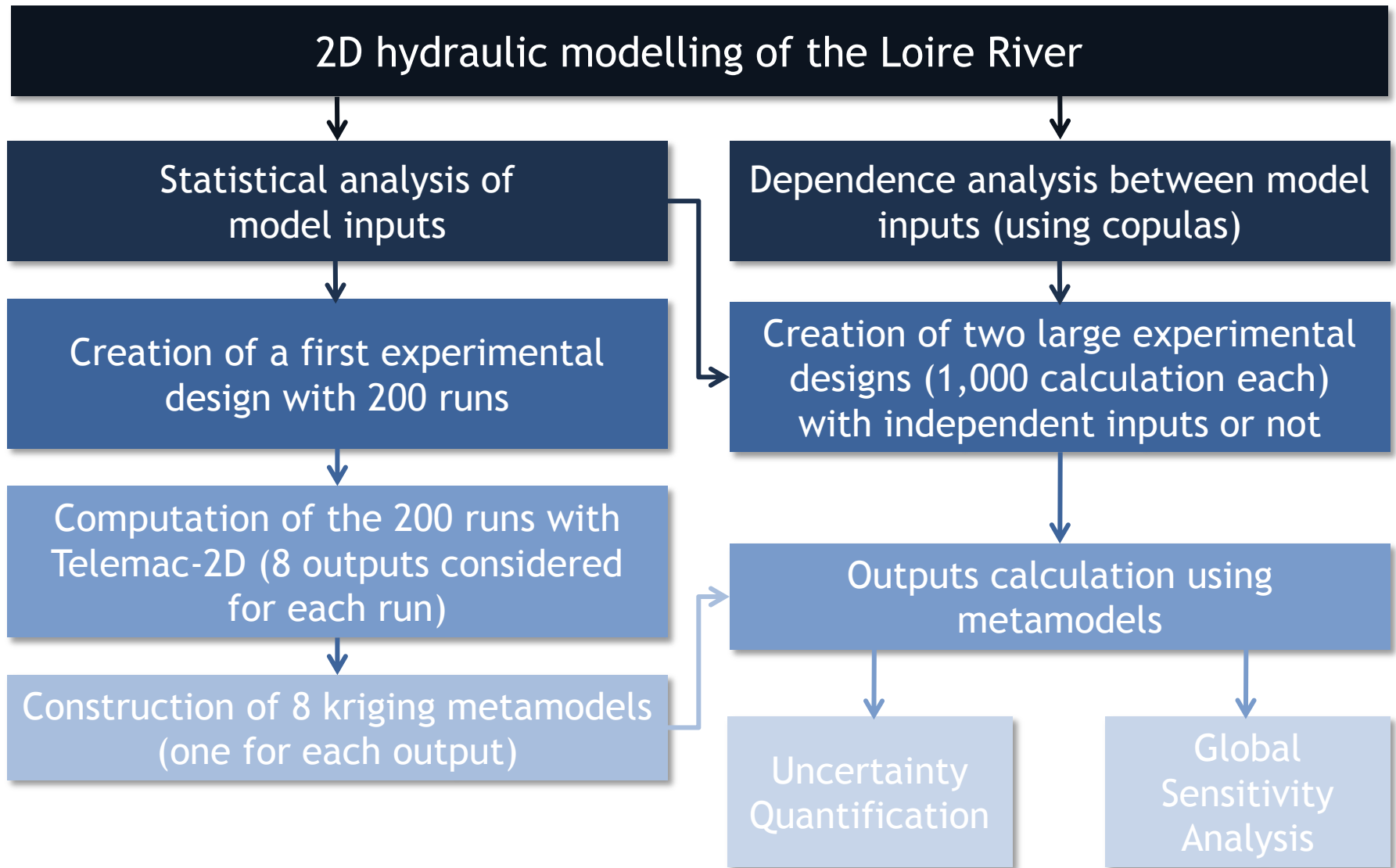
- Several historical major floods identified (1846, 1856, 1866, 1917)
- Historical sites, industrial facilities and large cities along the Loire River → **Risk of human and material damages**
- Numerous open data available



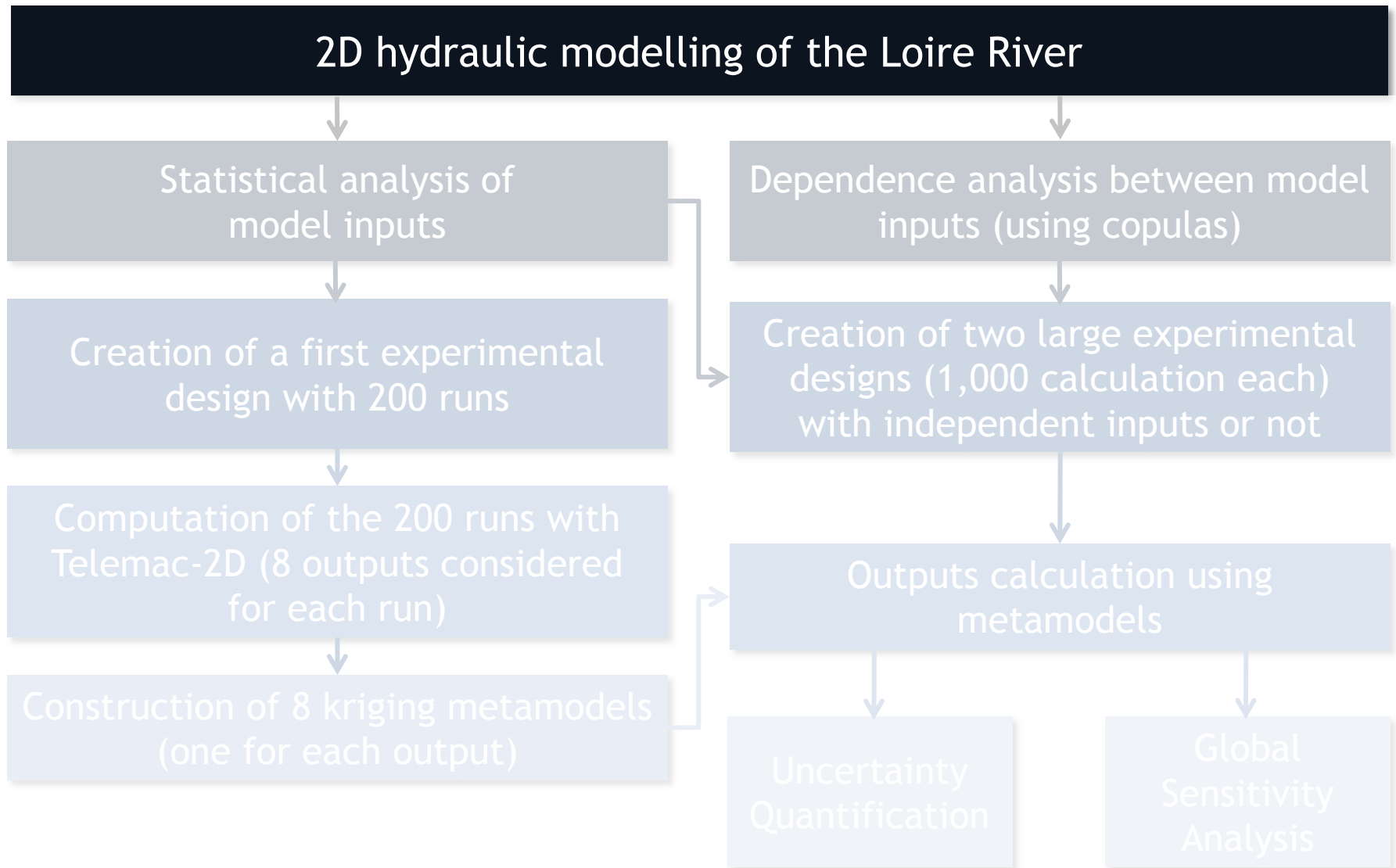
Floods in 2016 in the Centre-Val de Loire Region © France3



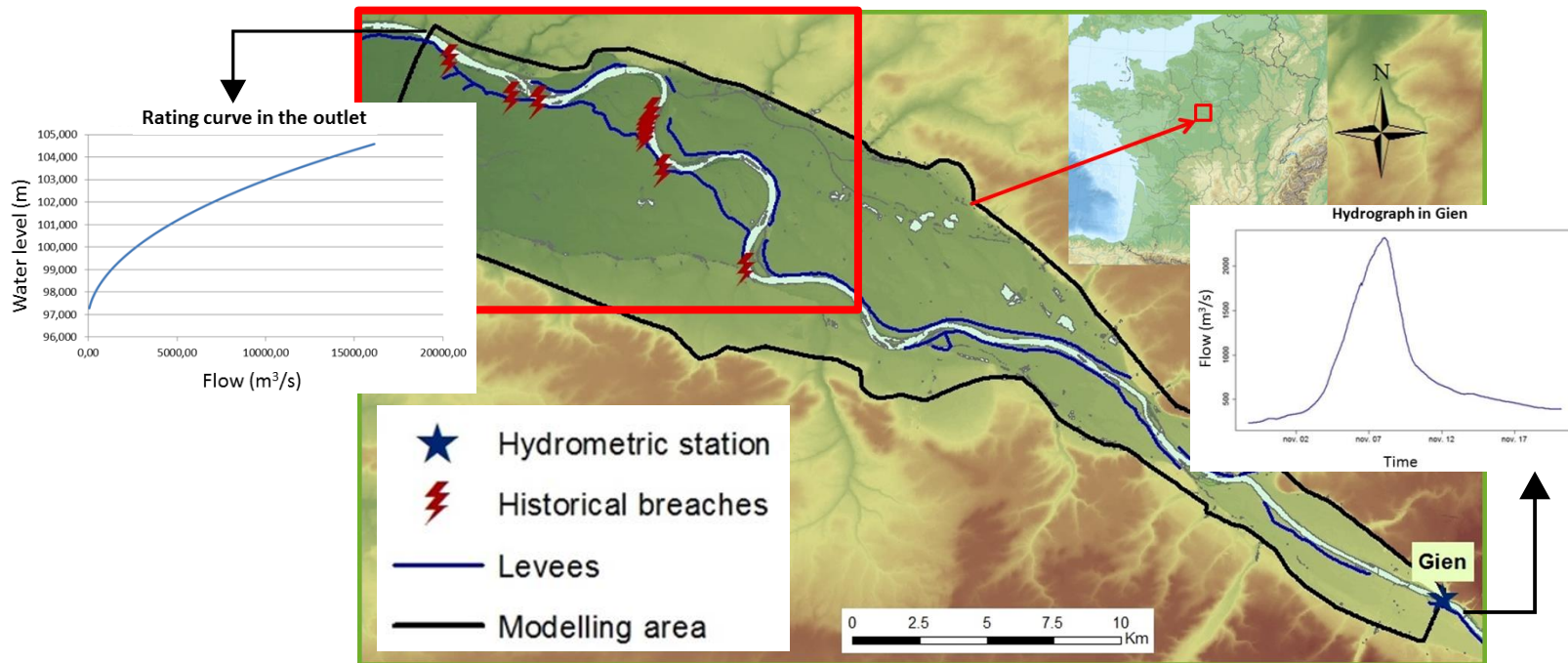
Methodology



Methodology



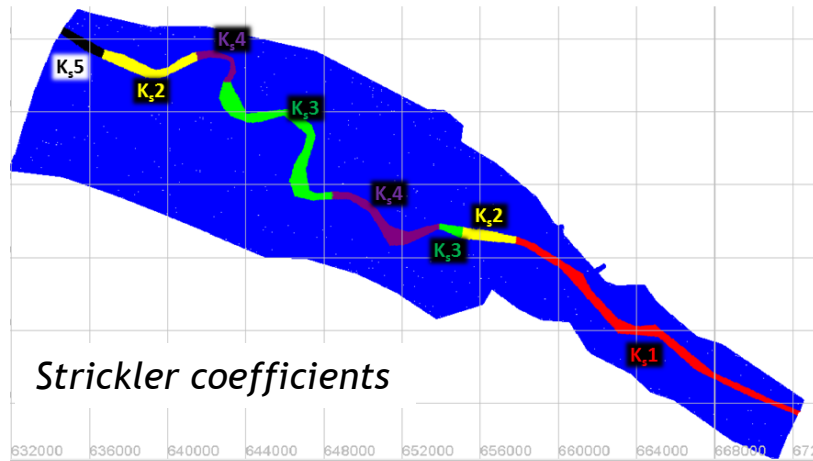
2D hydraulic modelling of the Loire River



- 50 km-long reach modelling between Gien and Orléans
- 2D modelling with **Telemac-2D**
- **262,800** meshes
- Computation time: **1h30** in average, depending on the flood duration
- Limit conditions: **hydrograph** in Gien and **rating curve** in the outlet
- Focus on the lower part of the model (red square)

2D hydraulic modelling of the Loire River

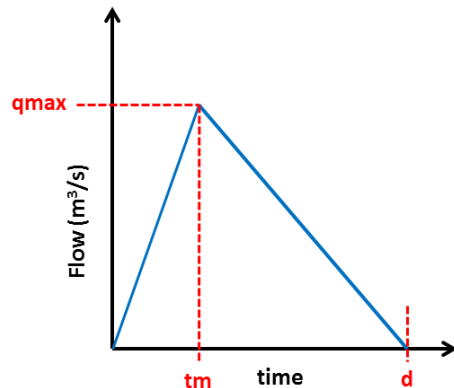
Uncertain inputs and outputs investigated



8 Inputs:

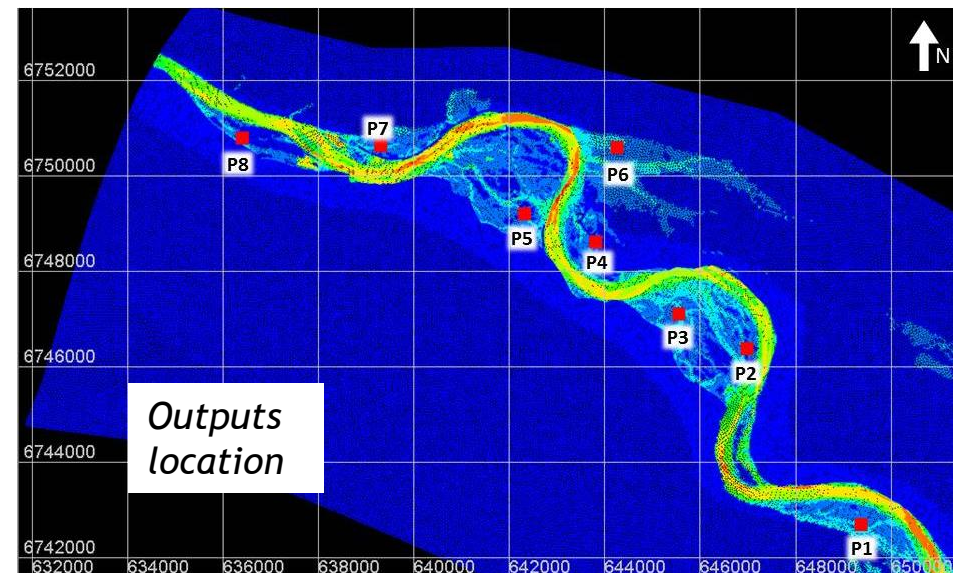
- 5 different Strickler coefficients (K_s1 to K_s5)
- 3 inputs linked to the hydrograph:
 - maximum flow (q_{max})
 - total duration of the flood (d)
 - rise time (t_m)

Inputs linked to the triangular hydrograph

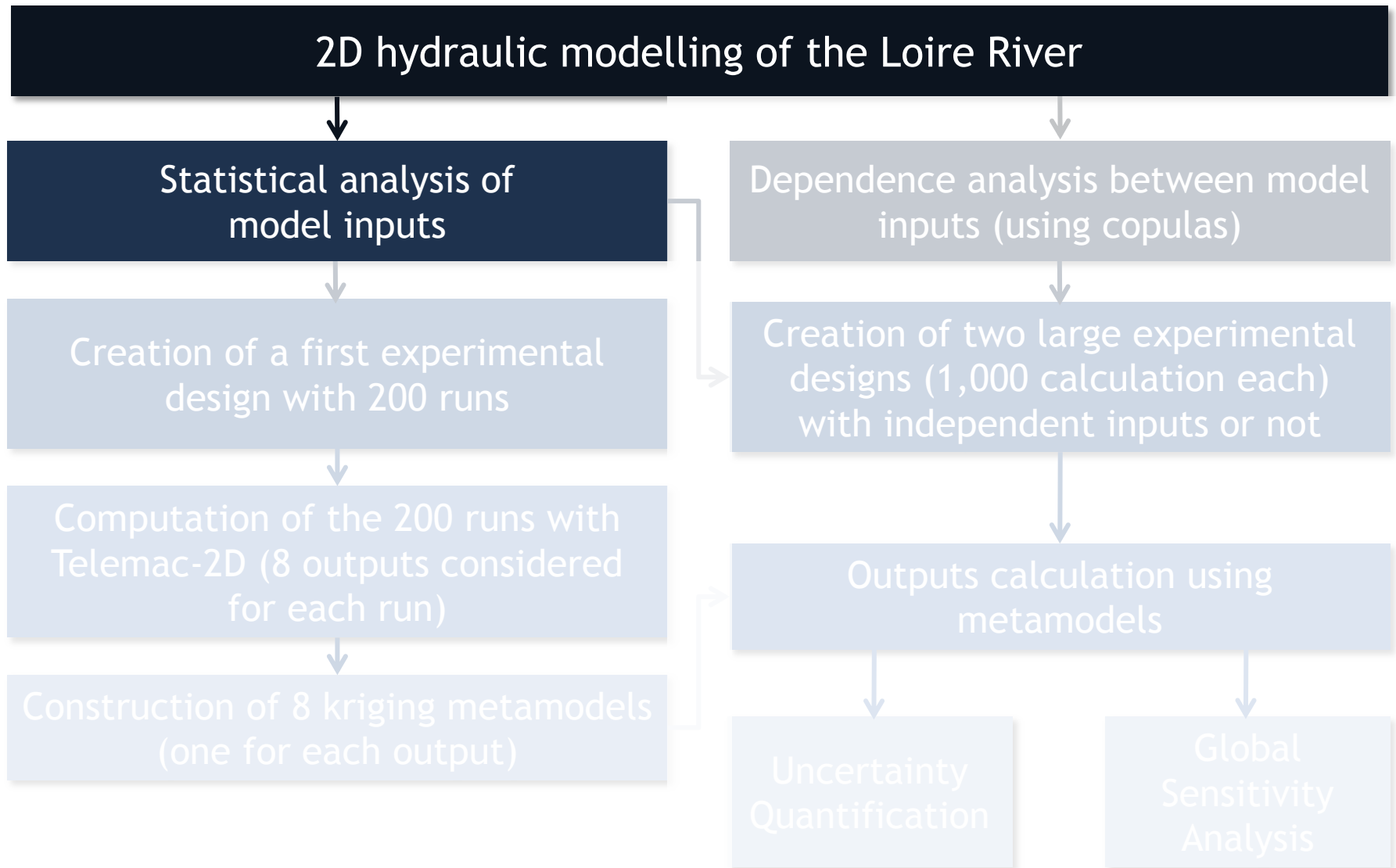


8 outputs (P1 to P8)

- Extraction of the maximum water level

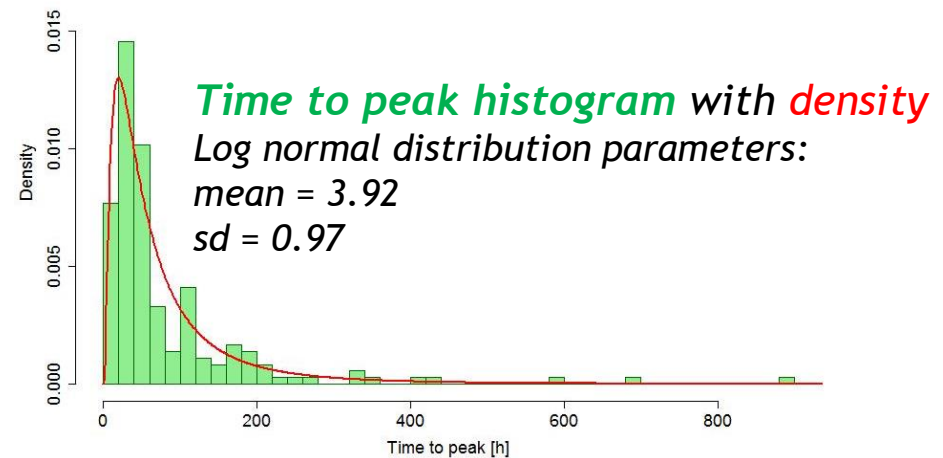
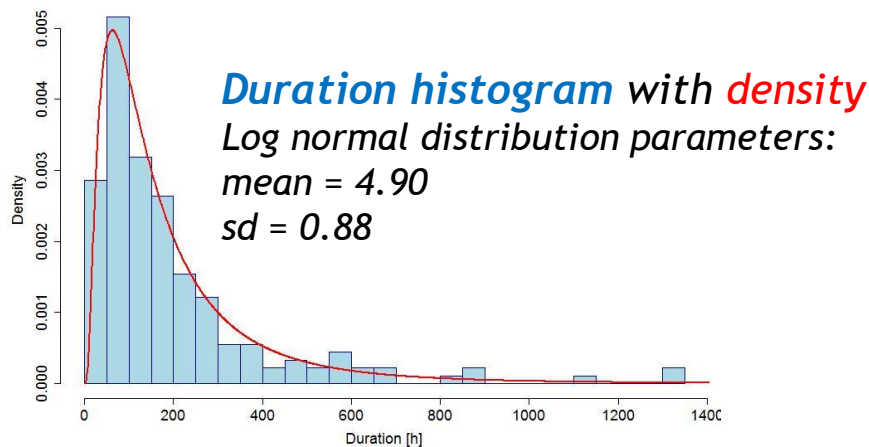


Methodology



Statistical analysis of model inputs (hydrograph parameters)

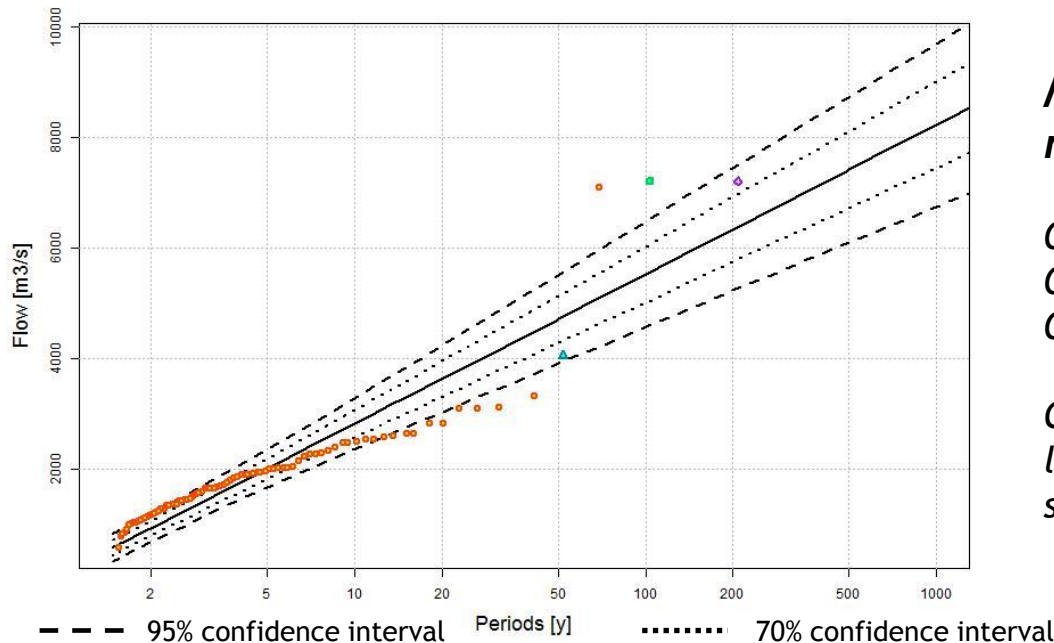
- Objective: define the probability distribution of each input
- For the **duration (d)** and the **time to peak (tm)**:
 - Extraction of the major floods between 1953 and 2019 (flood considered when flow > 600 m³/s, duration > 24h and time between two floods > 24h)
 - 182 floods selected
 - For each flood, extraction of the total duration, time to peak and maximum flow
 - Research of the most accurate probability distributions for d and tm → **Log normal distributions**



Statistical analysis of model inputs (hydrograph parameters)

For the maximum flow → extreme value analysis

- From the maximum annual discharges since 1936 + 4 historical floods (1846, 1856, 1866, 1917)
- Adjustment of the maximum annual discharges with a **Gumbel distribution function** (R-package *Renext*)



Maximum annual discharges return levels

$$Q_{10} = 2,637 \text{ m}^3/\text{s}$$

$$Q_{100} = 5,301 \text{ m}^3/\text{s}$$

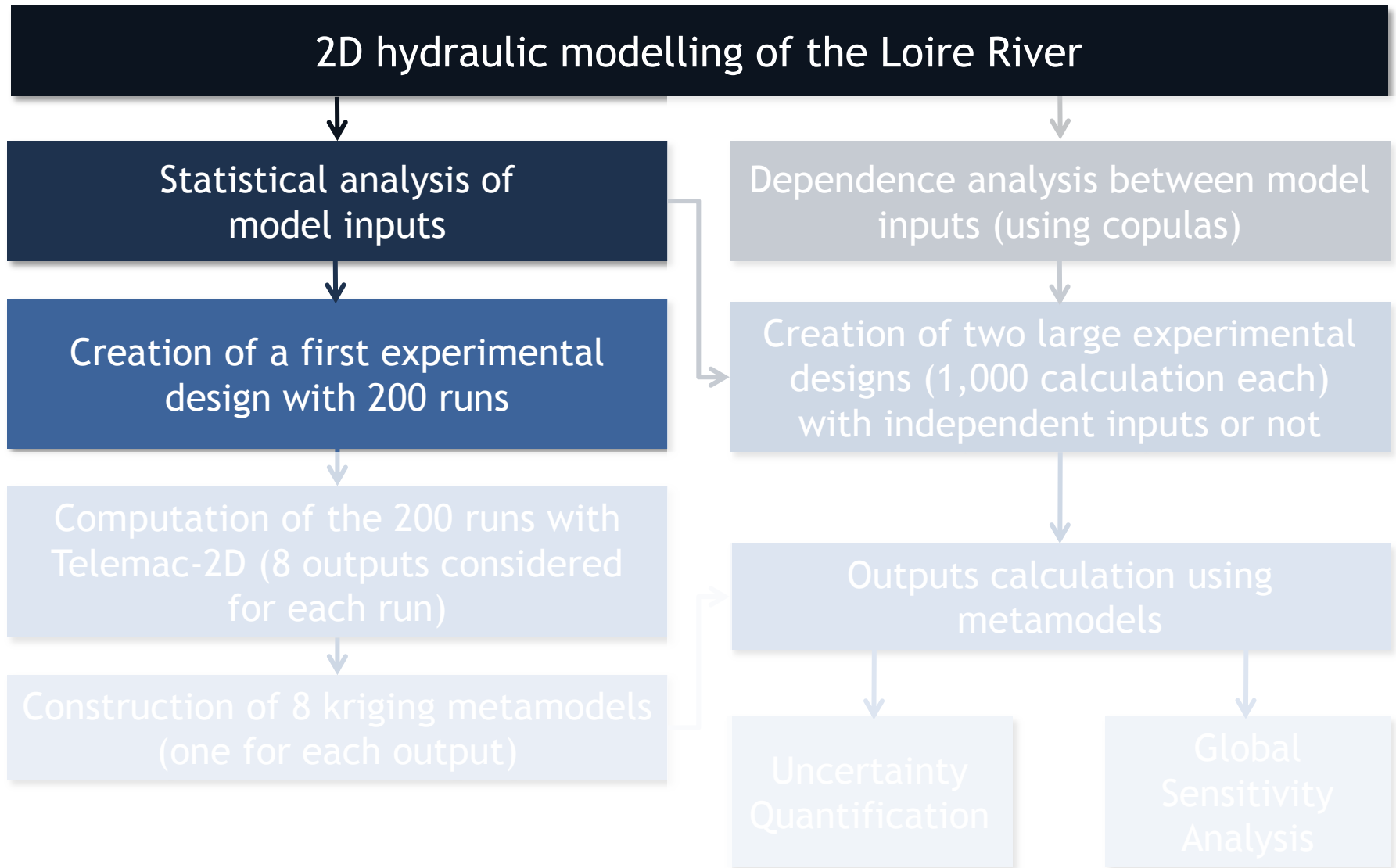
$$Q_{1000} = 7,916 \text{ m}^3/\text{s}$$

Gumbel distribution parameters:

$$\text{location} = 116.65$$

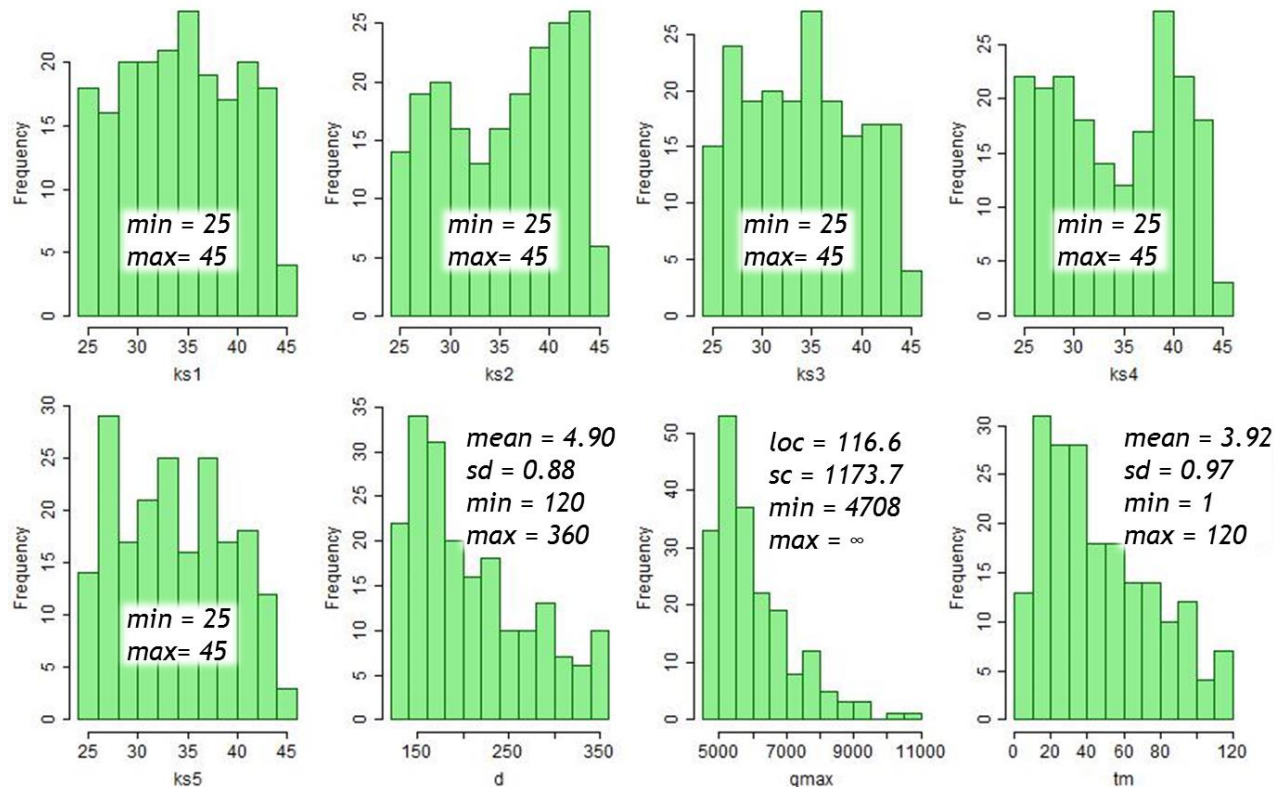
$$\text{scale} = 1173.74$$

Methodology



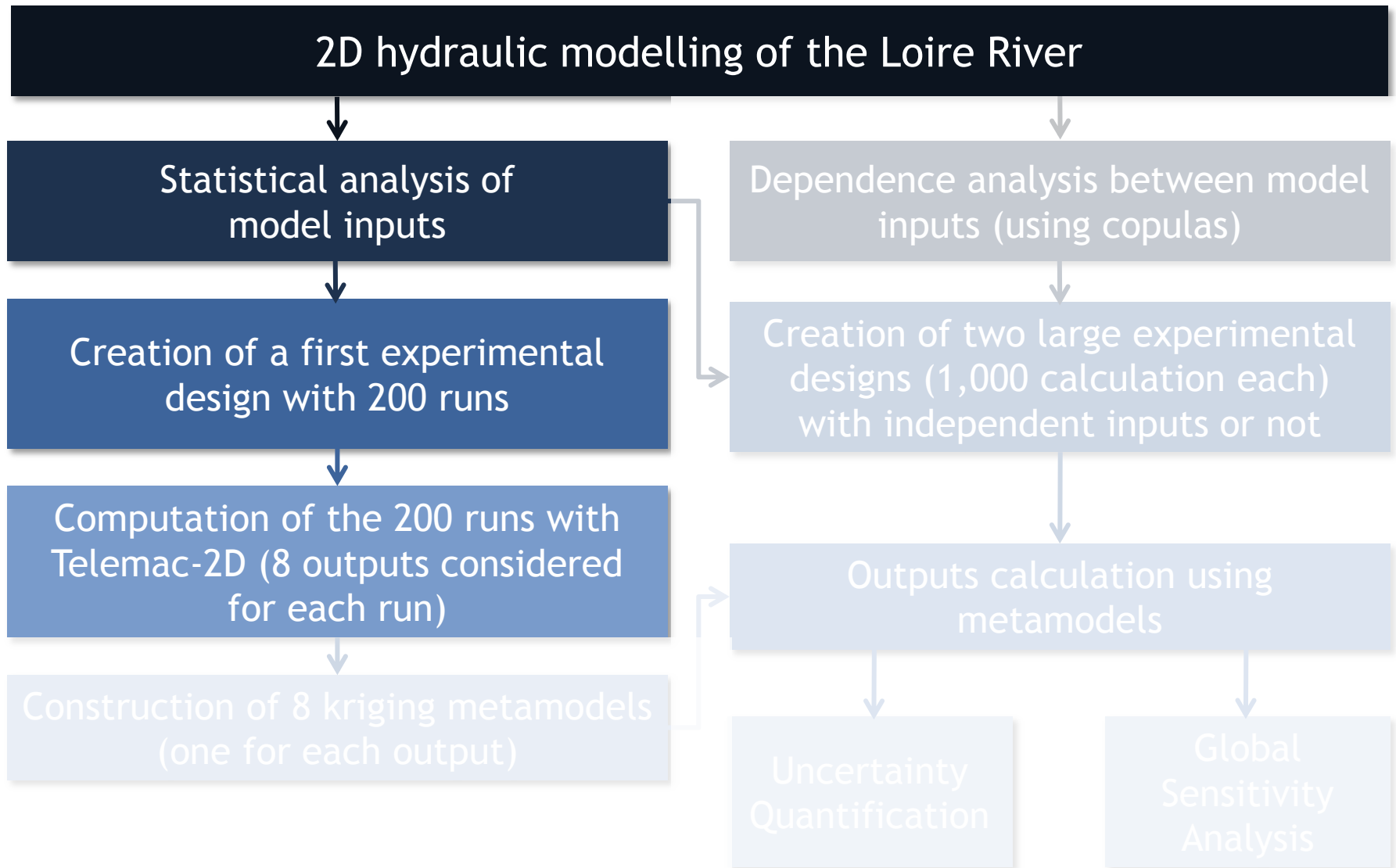
Creation of an experimental design

- Objective: create an input parameter table of **200** runs with Telemac-2D
 - Strickler parameters (K_{s1} to K_{s5}) sampled inside uniform distributions
 - Hydrograph parameters sampled inside the distributions previously defined (here truncated distributions are used):



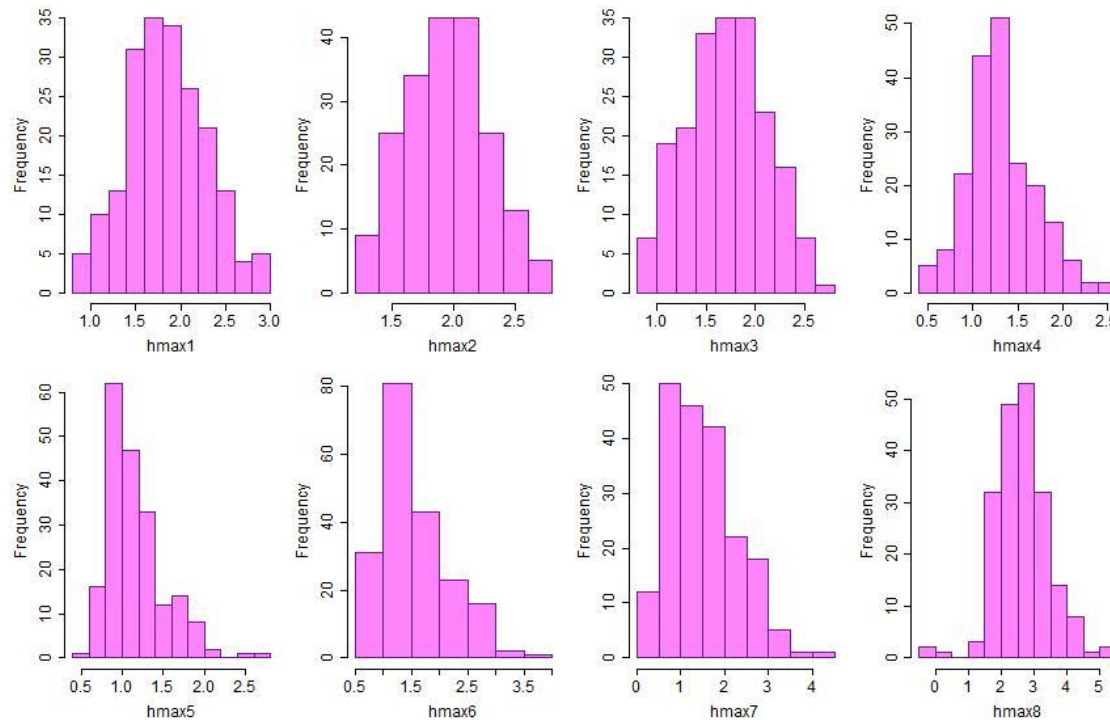
Distribution histograms of sampled inputs & value of parameters for the associated probability distributions

Methodology



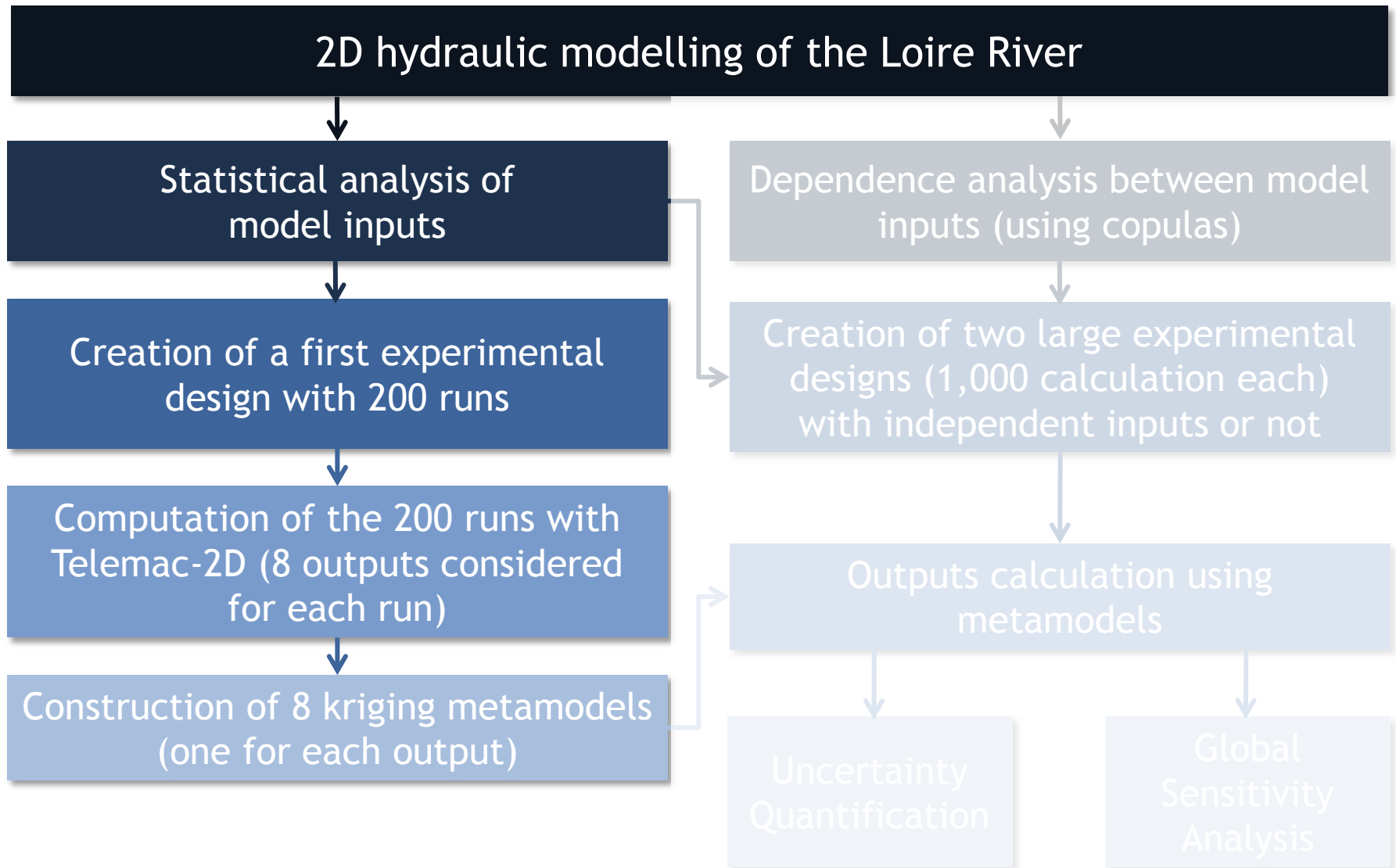
200 runs with Telemac 2D

- Use of the parametric computing environment developed in IRSN: Funz (<https://github.com/Funz>)
- Coupling between Funz and Telemac-2D to run the 200 calculations successively
- Computation time: between 36 min and 2h30 for one run (mean = 1h20)
- In total = 260 hours (~11 days) with 38 parallel processors)



Distribution histograms of outputs

Methodology



Construction of kriging metamodels

Generalities

What is it?

- Mathematical tool used to replace the original model with a function
- Function constructed using statistical criteria (*e.g.* maximum likelihood) in order to fit the “experimental” computation of the original model

Objective of the metamodel: reduce the computation time

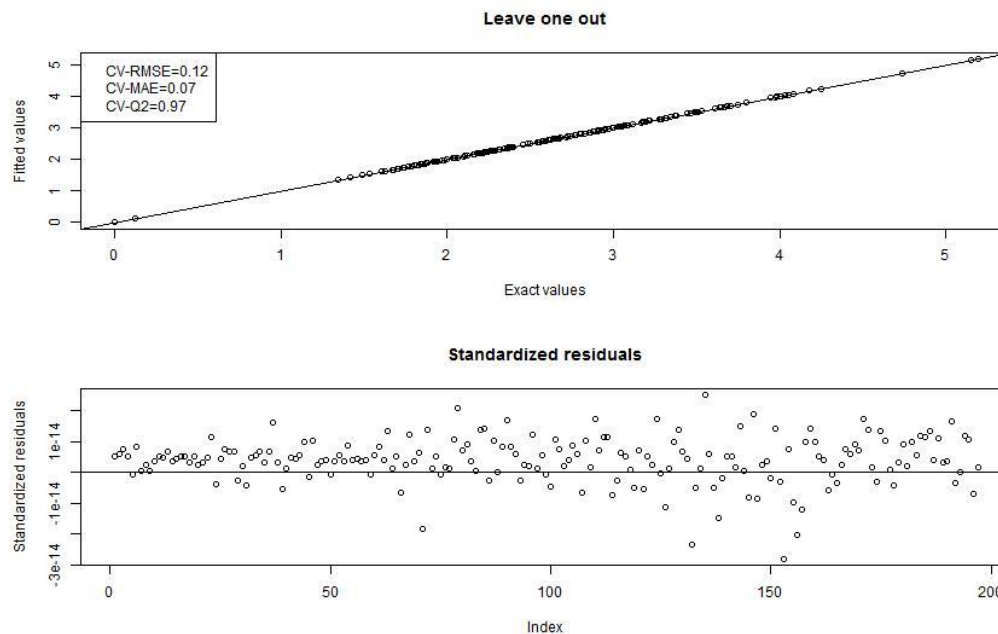
Three main steps to construct a metamodel:

1. **Design:** creation of an “experimental” dataset used as learning basis for the metamodel
2. **Construction:** it depends on the chosen function (*e.g.* kriging, random forest)
3. **Validation** of the metamodel through statistical tests (*e.g.* leave-one-out & K-fold cross validation)

Construction of the kriging metamodels

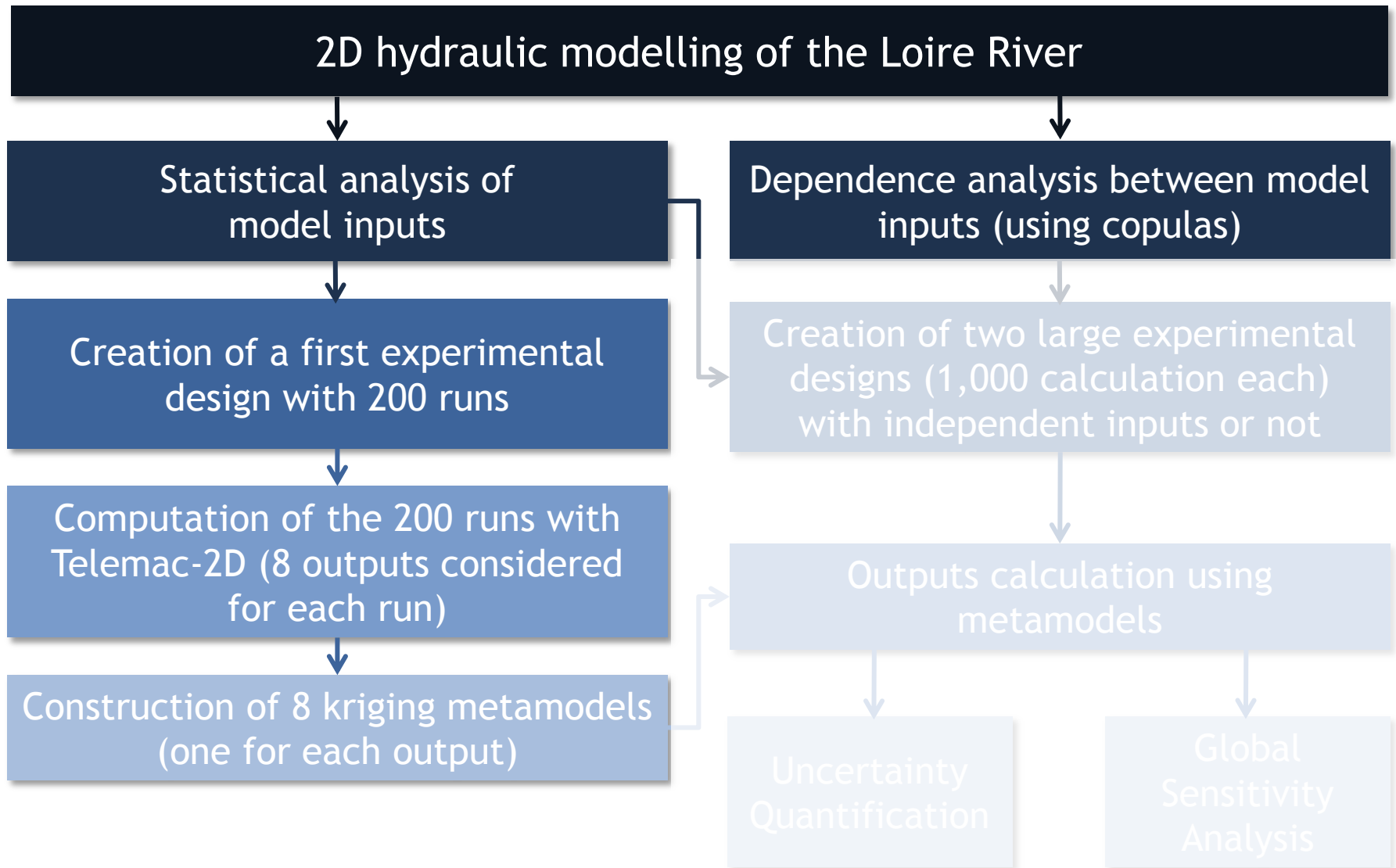
Metamodels of the Loire River model

- Construction of 8 metamodels (one for each output) with the R-package *DiceEval*
- Validation: cross validation & leave one out validation
 → $R^2 > 0.97$ for the 8 metamodels



Example of metamodel validation for the output $n^{\circ}8$

Methodology



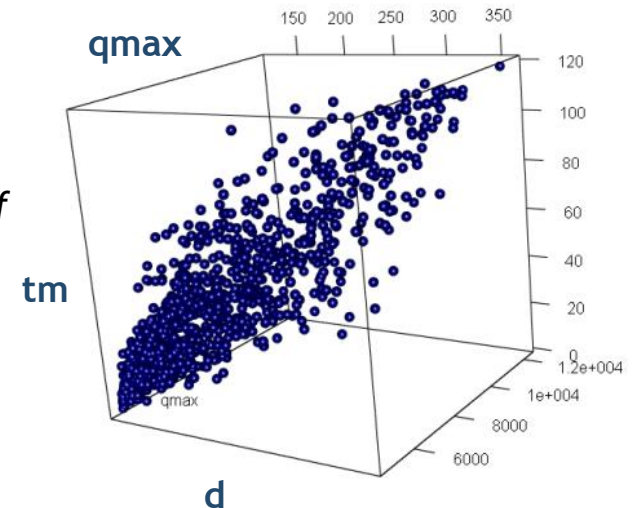
Dependence analysis between inputs

- Use of the 182 floods extracted from the flow data between 1953 to 2019
- Extraction of the 3 parameters: maximum discharge (qmax), time to peak (tm) and duration (d)

Correlation matrix between inputs (pearson coefficients)

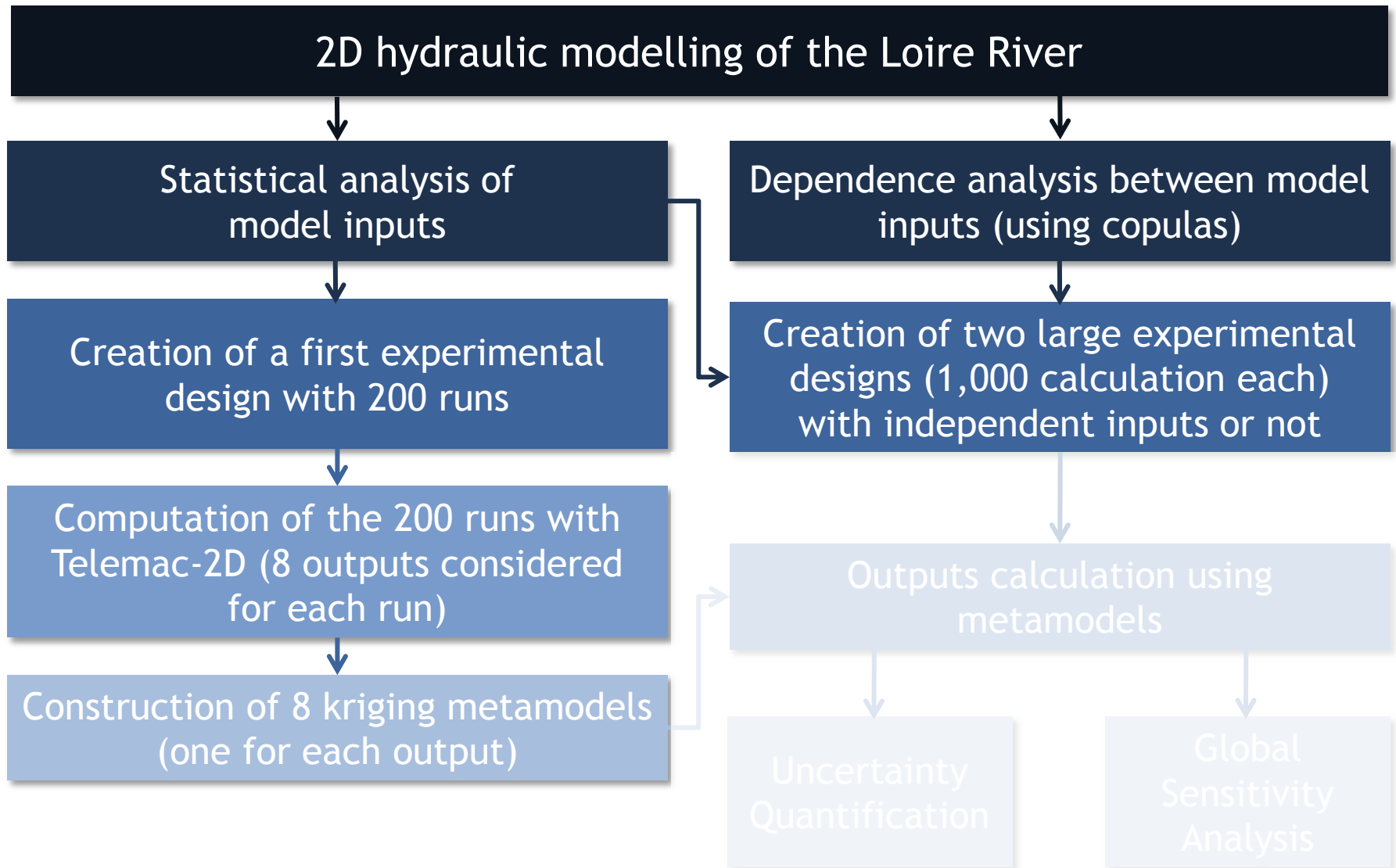
| | d | qmax | Tm |
|------|---|------|------|
| d | 1 | 0.68 | 0.77 |
| qmax | - | 1 | 0.57 |
| tm | - | - | 1 |

Representation of the dependence between the 3 inputs



- Research of the best copula to represent the dependence between inputs (R-package *Copula*)
 - Goodness of fit tests to select the best copula and the most adapted parameters (Cramer von Mises tests)
 - Selection of a normal copula with 3 parameters (class of meta-elliptical copula)

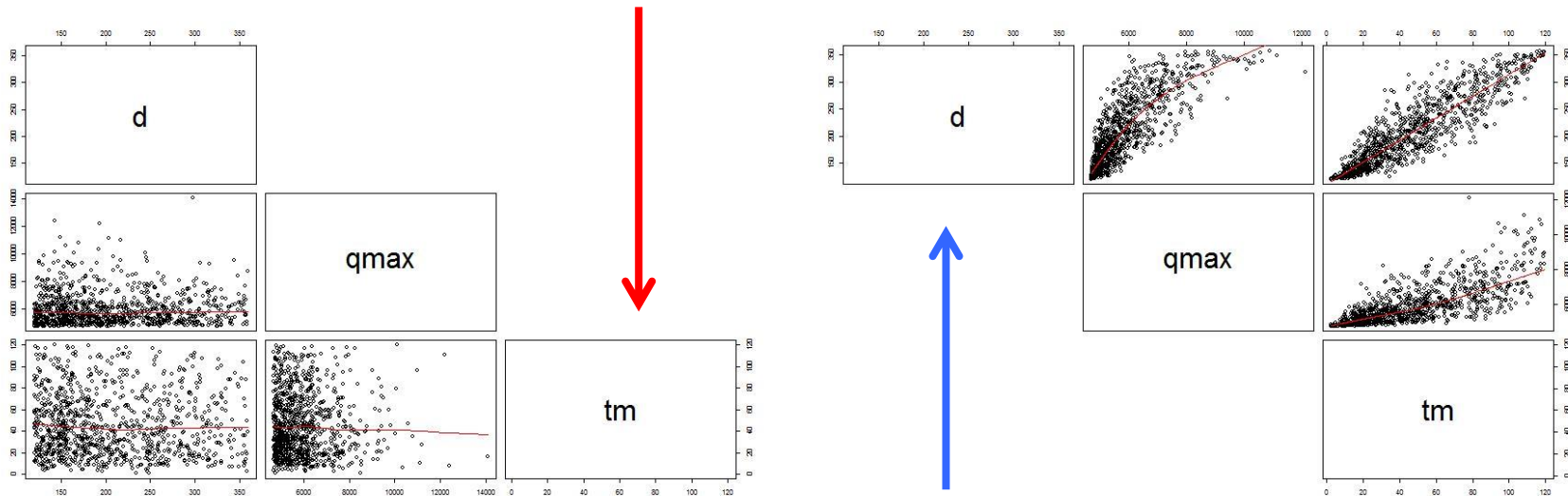
Methodology



Creation of new experimental designs

First design considering **independent inputs**:

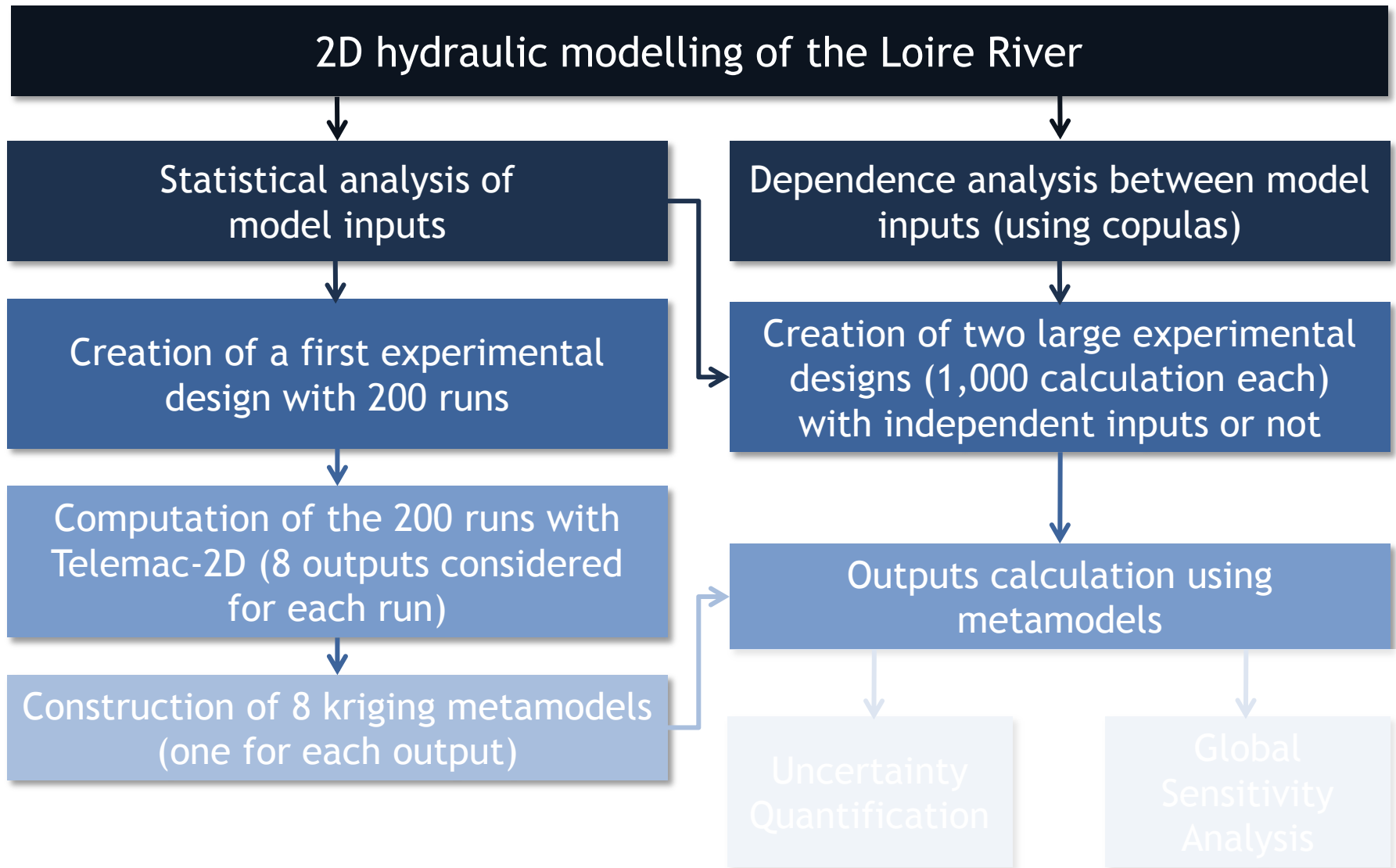
- For each of the 8 inputs: random sampling of 1,000 values inside their own probability distributions



Second design considering some **dependent inputs**:

- For each independent input (5 Strickler coefficients, K_{s1} to K_{s5}): random sampling of 1000 values inside their own probability distributions
- For each dependent input: random sampling of 1,000 values inside a multivariate distribution defined by the combination between the normal copula previously defined and the probability distribution of each input

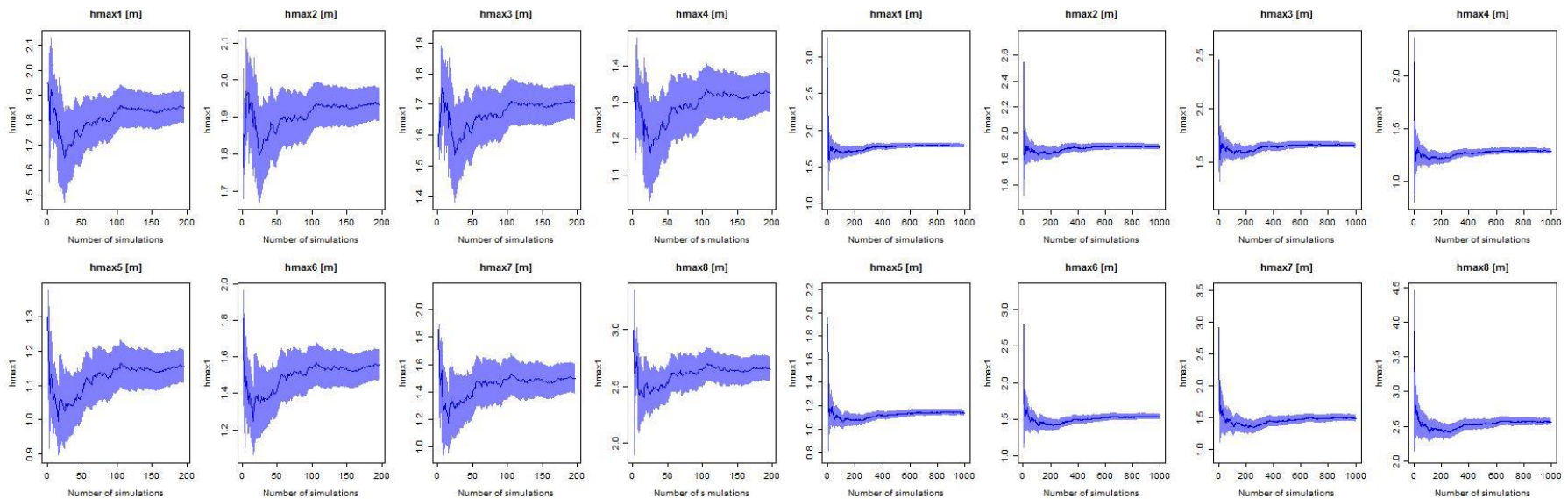
Methodology



Outputs calculation using metamodels

- Calculation of the 8 outputs for the 1,000 runs of each experimental design (using the 8 kriging metamodels)
- Computation time: **less than 10 seconds !** (instead of 2,600 hours with the hydraulic model)

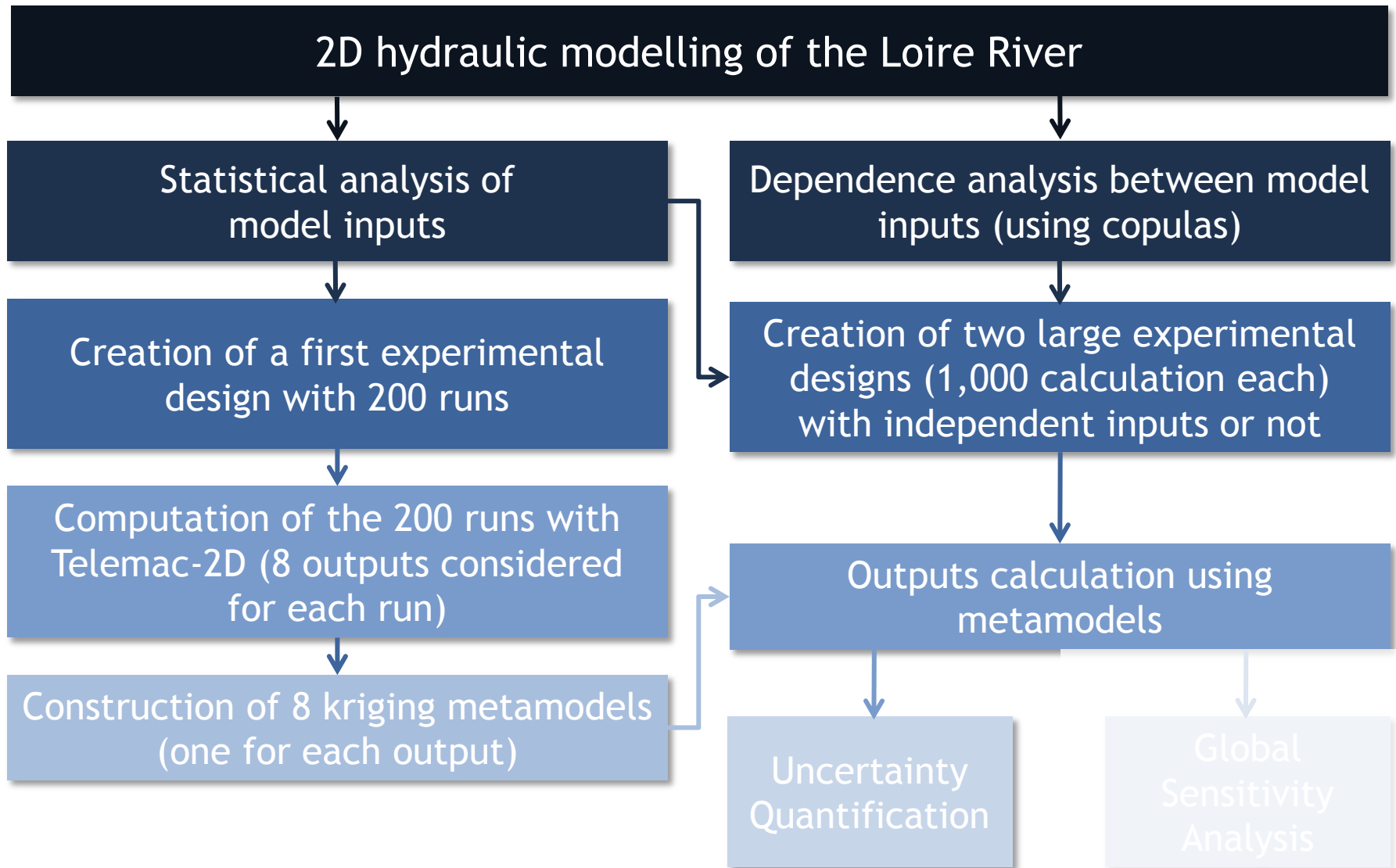
Mean convergence plots for the 8 outputs



200 runs from the Telemac-2D model

*1,000 runs from the metamodels
(considering independent inputs)*

Methodology



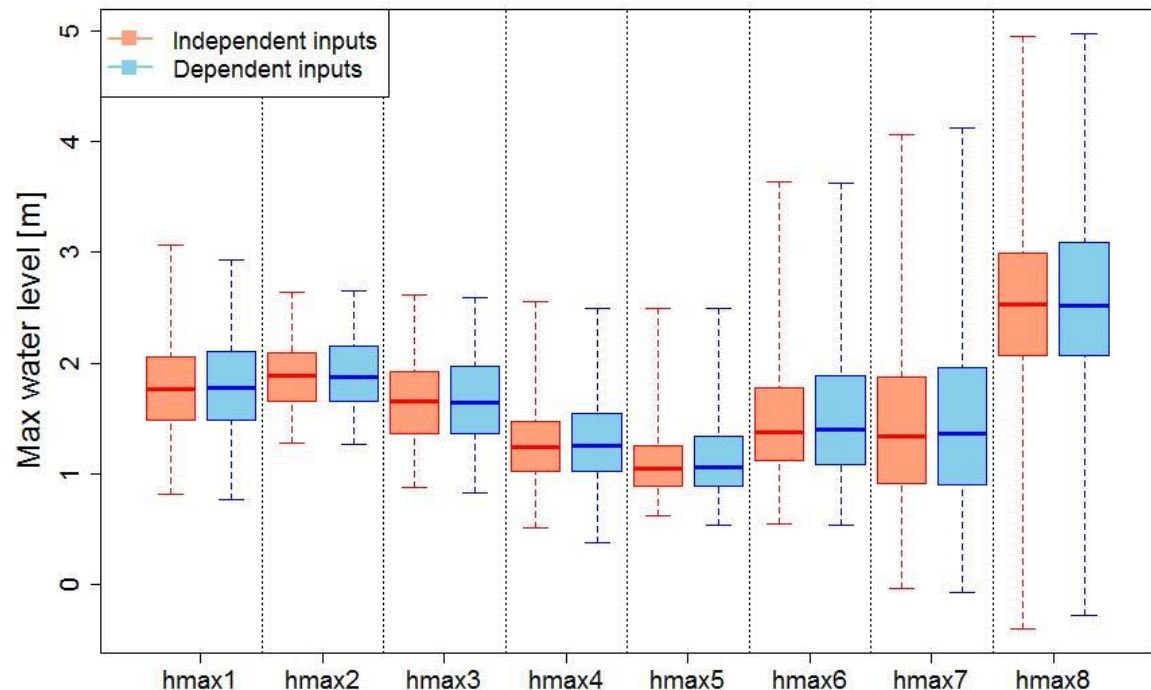
Uncertainty Quantification (1)

Generalities:

- Used to describe every possible outputs considering the input system which are not perfectly known
- Conducted with a random sampling (*e.g.* Monte-Carlo sampling) of the input parameters to obtain the distributions of the resulting outputs
- Description of the range of outputs using basic statistics (*e.g.* mean, sd), histograms, boxplots, *etc.*

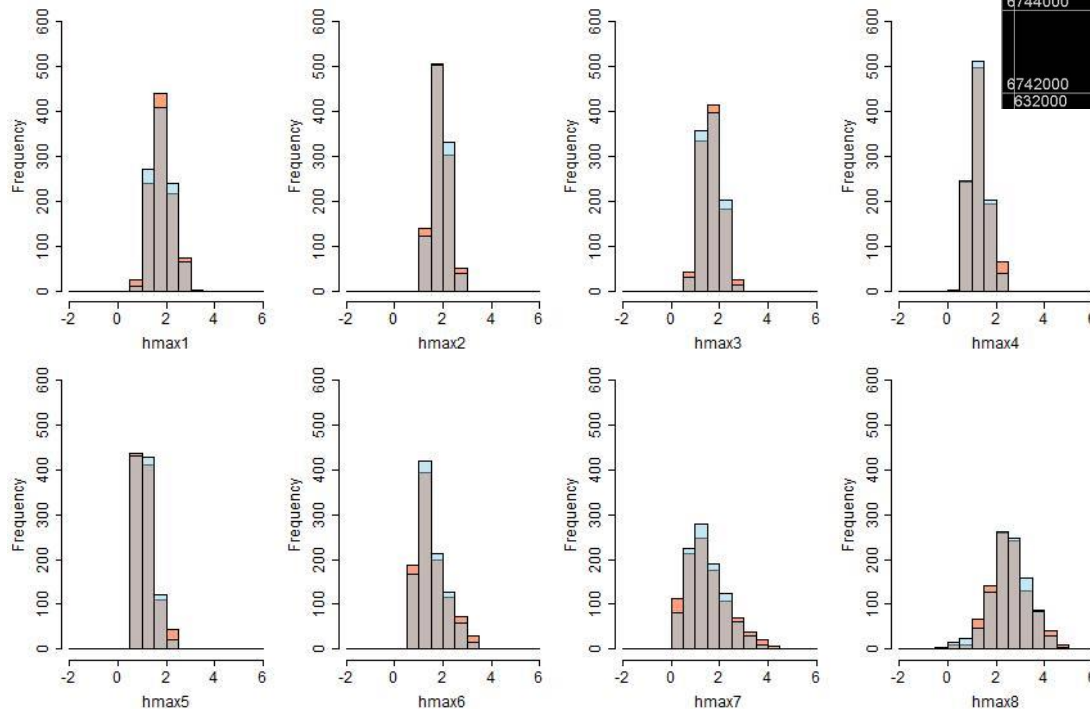
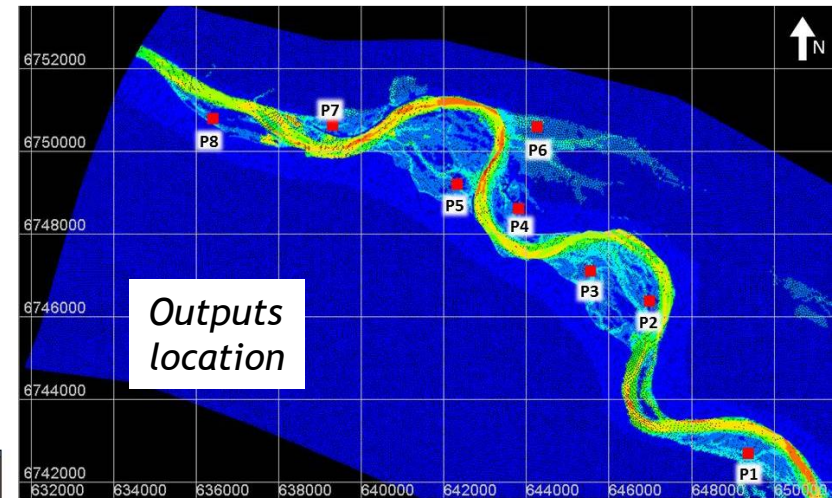
Boxplots of the outputs considering dependent or independent inputs

→ Almost no differences between the 2 cases



Uncertainty Quantification (2)

Histograms of the 8 outputs considering **dependent** or **independent** inputs

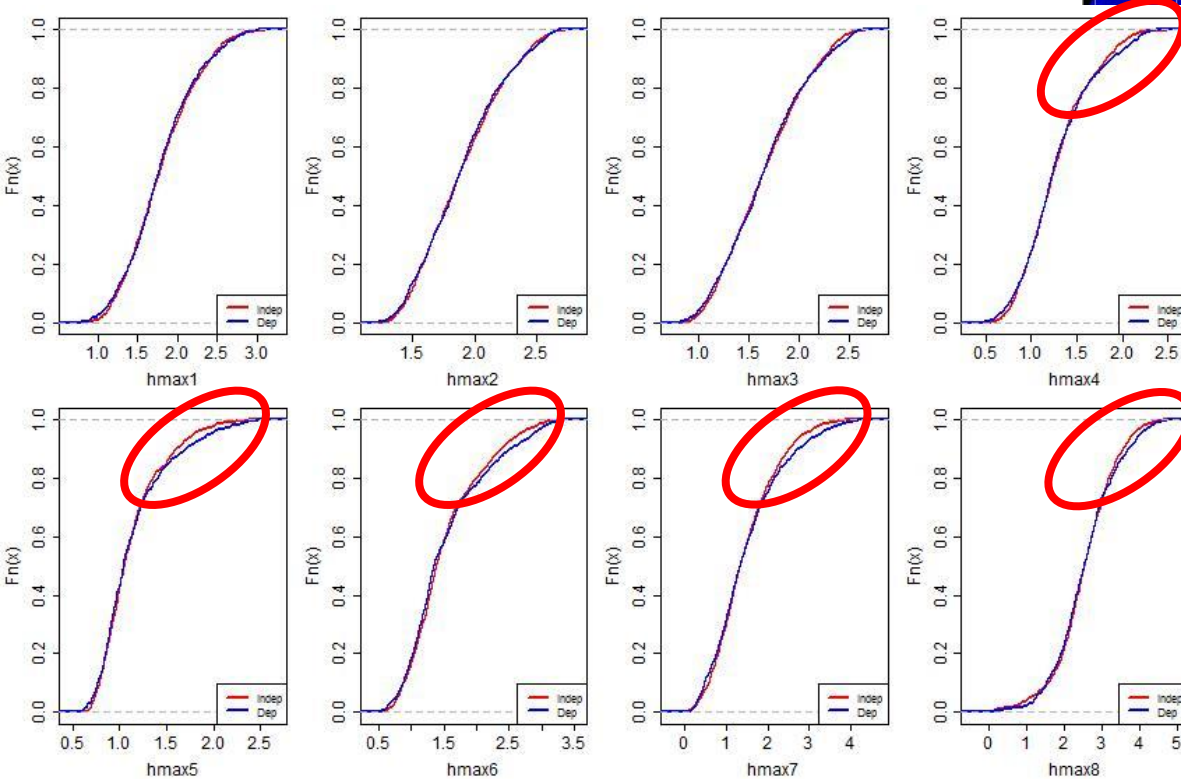
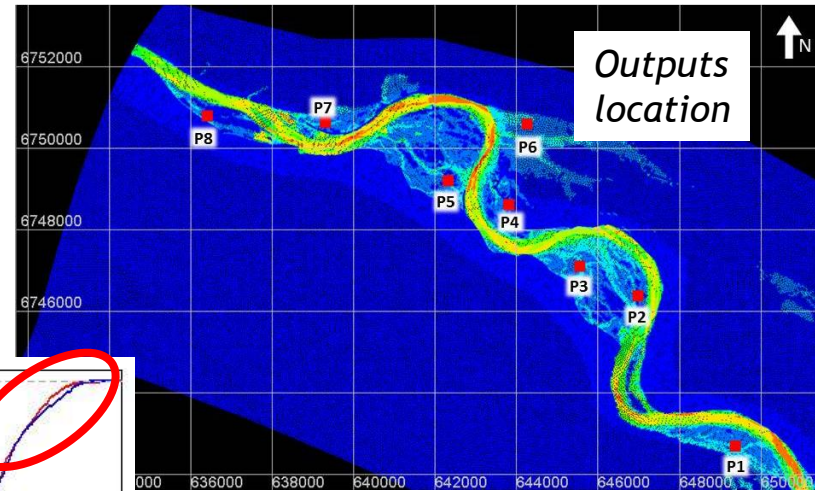


- Considering independent inputs
- Considering dependent inputs
- Histograms overlap

→ A few differences between both cases are observed but without any trend

Uncertainty Quantification (3)

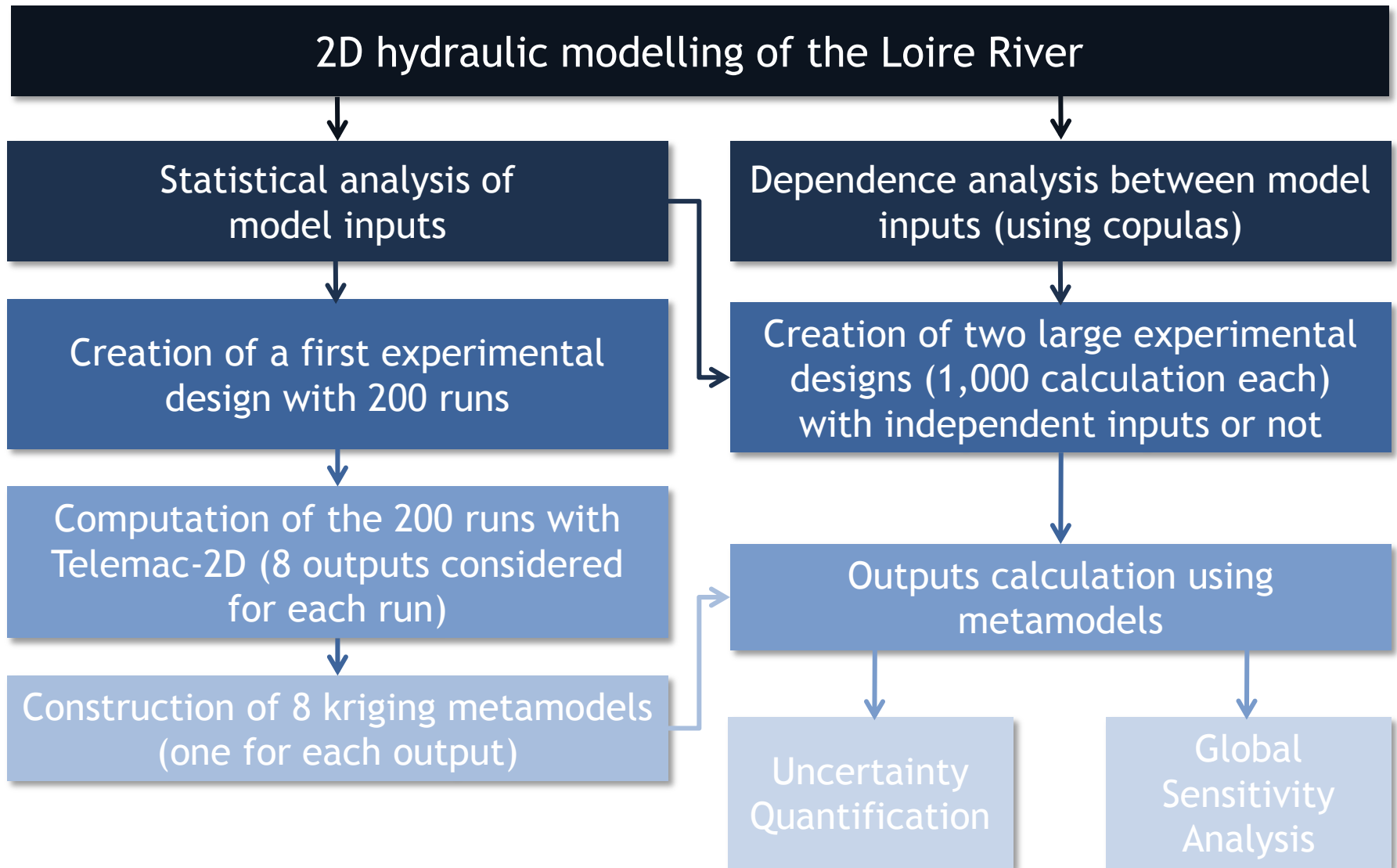
Empirical Cumulative Density Functions (eCDF) of the 8 outputs considering **dependent** or **independent** inputs



— Considering independent inputs
 — Considering dependent inputs

→ Different behavior of the tail distribution for the downstream outputs

Methodology



Global Sensitivity Analysis (1)

Generalities:

- Used to analyze the impact of the variability of inputs parameters on the variability of the outputs
- Useful to determine the most contributing variables, the non-influential ones and to rank parameters
- Use of sensitivity indices (SI) (*e.g.* Sobol' Indices) for this kind of analysis
- Indicators between 0 and 1 measuring the main effect (1st order SI) or the total effect (total order SI) of the considered input on the output

Problem:

- The SI computation is different if we consider dependent inputs or not → **traditional methods of GSA cannot be used with dependent inputs**

Use of 3 new methods to compute sensitivity indices with dependent inputs:

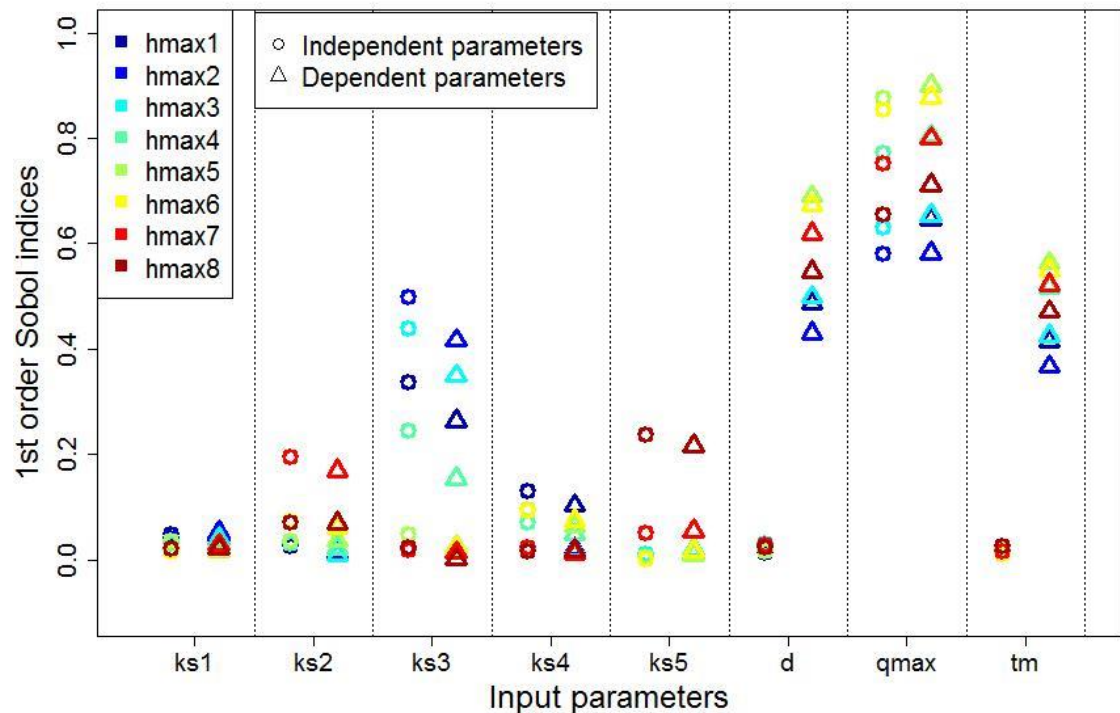
- **Li and Mahadevan, 2016**: method to directly estimate the 1st order Sobol' SI
- **McKay, 1995**: method using Latin Hypercube Sampling to compute the 1st order Sobol' SI
- **Iooss and Prieur, 2018**: method to compute Shapley effects and Sobol' SI (1st and total order) with the R-package *sensitivity*

Global Sensitivity Analysis (2)

Computation of the 1st order Sobol' SI (Li method) for all outputs:

- Depending the location of an output, the influence of each K_s coefficients differs
- For all the inputs except d and tm , the indices are almost equal considering inputs dependency or not
- For d and tm , the indices considering certain dependent inputs are much higher than considering only independent inputs → **the parameter ranking changes**

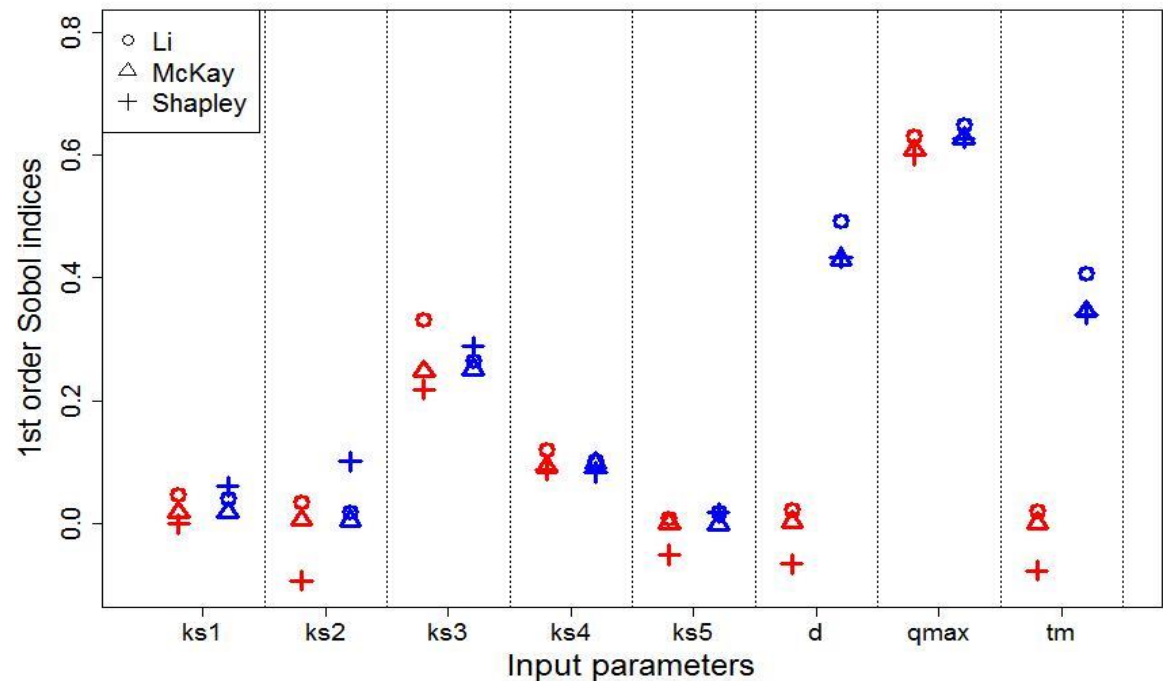
- *The Strickler coefficients (K_s1 to K_s5) are always considered to be independent*
- *d , $qmax$ and tm are considered to be dependent in the analysis: “ Δ Dependent inputs”*



Global Sensitivity Analysis (3)

- Comparison between the 3 methods previously cited for the output P1 (upstream)
 - Few differences between the 3 methods
 - The Li method is the fastest
 - With the looss and Prieur method ("Shapley") it is also possible to compute total order SI which are slightly higher than the 1st order SI

■ *Considering independent inputs*
■ *Considering dependent inputs*



Conclusion and perspectives

- Strong dependence between the hydrograph parameters (d , q_{\max} , t_m) → use of copula to model the dependencies
- Metamodel very useful for uncertainty analysis studies (almost all done during the containment with limited computation resources)
- Limited impact of inputs dependency in uncertainty quantification in this study
- The duration and time to peak inputs have strong influence on the outputs → **The hydrograph shape should not be ignored in hydraulic studies**
- Further work: study the influence of other hydraulic parameters dependencies (*i.e.* breach levee parameters)

Thank you for your attention



*INONDATION DE LA LOIRE (21 Octobre 1907).
ORLEANS. — En Bateau dans la Rue des Charreliers.*

Orleans archives

References

- I. M. Sobol, « *Sensitivity Estimates for Nonlinear Mathematical Models* », *MMCE*, vol. 1, n° 4, p. 8, 1993.
- M. D. McKay, « *Evaluating prediction uncertainty* », *Nuclear Regulatory Commission*, 1995.
- C. Li et S. Mahadevan, « *An efficient modularized sample-based method to estimate the first-order Sobol' index* », *Reliability Engineering & System Safety*, vol. 153, p. 110-121, sept. 2016.
- B. Iooss et C. Prieur, « *Shapley effects for sensitivity analysis with dependent inputs: comparisons with Sobol' indices, numerical estimation and applications* », p. 39, 2018.