Global Sensitivity Analysis for the calibration of a fully-distributed hydrological model

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1) Motivation

- LISFLOOD [1] is a fully-distributed hydrological model used for flood forecasting at Pan-European scale within the **E**uropean **F**lood **A**wareness **S**ystem (**EFAS**, www.efas.eu), and for Climate Change studies in Europe.
- Model parameters are estimated through calibration [2]-[3], in order to constrain simulated discharges to the corresponding observed values.
- So far, **nine (9) parameters** of the model have been selected as sensitive, mostly through expert knowledge accumulated over years in the research group. However, for highly non-linear models that approach may not result in a proper identification of the most sensitive parameters for model calibration.

2) Aims

- To use **G**lobal **S**ensitivity **A**nalysis (**GSA**) as a formal method to identify relevant parameters that contribute significantly to model performance.
- To elucidate if the model performance obtained by calibrating sensitive parameters identified by GSA is higher than the model performance obtained by calibrating parameters identified by prior expert knowledge.

3) Case Studies

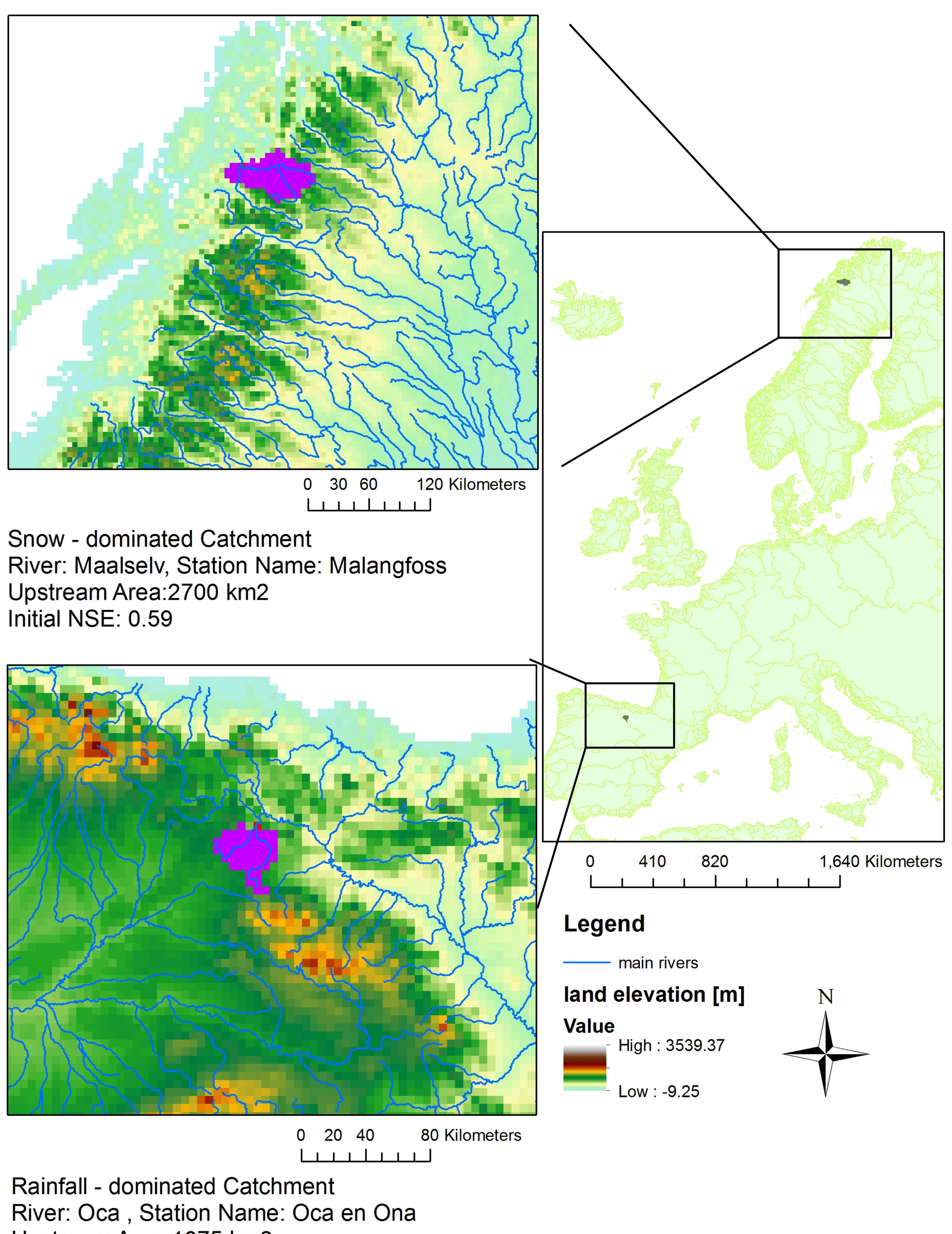

Fig 1. Location of the two case studies used in this work. In the snow-dominated catchment (Sweeden) snow-related model parameters are expected to be found the most sensitive. In the rainfall-dominated catchment, model parameters related to infiltration and flow routing are expected to be found the most sensitive.

4) Hydrological model

- The LISFLOOD model [1] has many parameters that may be calibrated.
- Based on prior expert knowledge on the research group, 26 parameters have been selected for sensitivity analysis. Remaining parameters were mostly GIS-related, so they were assumed to have already their best possible value.
- A single model run takes ~ 1 or 2 minutes → makes computationally unfeasible to run a large number of model runs.
- Model outputs (daily time series) were transformed into a real value by using the Nash-Sutcliffe efficiency as a measure of model performance:

$$NSE = 1 - \frac{\sum_{i=1}^{N} (O_i - M_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2}$$

O_i: observed values, [m^3/s]

M_i: simulated values, [m^3/s]

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5) Methodology

Parameters Definition	26 uncertain parameters U[min, max]
Screening	**Morris' method:** k = 26 (parameters), p = 8 (levels), r = 20 (out of 200)
Global Sensitivity Analysis	**Sobol's method:** k = 15 (parameters), N = 150 (sample size)
Global Optimisation	**Standard Particle Swarm Optimisation 2011:** k = 7 (parameters), npart = 20 (number of particles), maxit = 55 (number of iterations)

5.a) Screening (Morris' GSA)

- The screening method of Morris [8] aims to identify sensitivity parameters with a small number of sample points (model runs), i.e., with a **low computational cost**. The recommended number of simulations is $C = r\,(k + 1)$, where k is the number of parameters (input factors) and r is a user-defined number of *elementary effects* (usually r=10).
- The method results in two sensitivity measures for each parameter:
  - **μ*** : a high value indicates a parameter with an important overall effect on model output.
  - **σ** : a high value indicates that either the parameter is interacting with other parameters or the parameter has non-linear effects on model output.

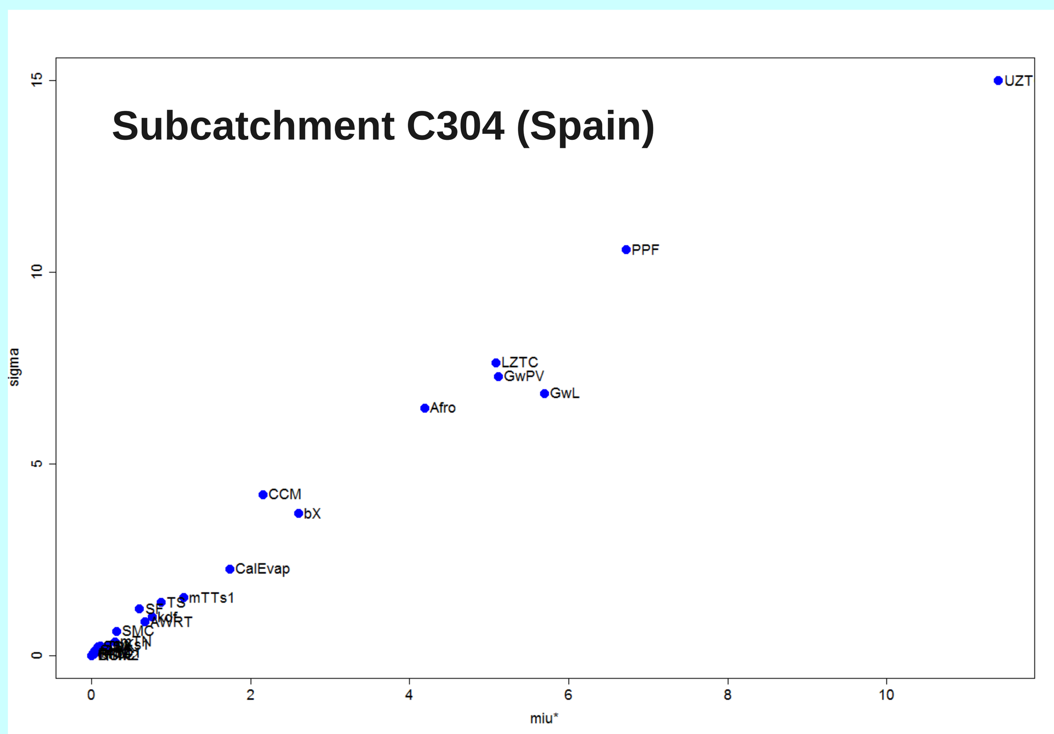
5.b) GSA (Sobol's method)

- The variance-based method of Sobol [9] quantifies the amount of variance that each parameter contributes with on the unconditional variance of the model output.
- The total cost of of the Sobol analysis proposed in [10] is: $C = N\,(k + 2)$, where k is the number of parameters (input factors) and N is a user-defined large number (usually $N \geq 500$, if computationally feasible).
- The method results in two sensitivity measures:
  - $\mathbf{S_i}$: fraction of the total model variance explained by each parameter. $S_i = V_i / V$, where: V_i is the variance due to parameter i, and V is the total variance.
  - $\mathbf{St_i}$: total effect of parameter i (including interactions).
- The difference $\mathbf{St_i}$ - $\mathbf{S_i}$ is a measure of interactions of parameter i.

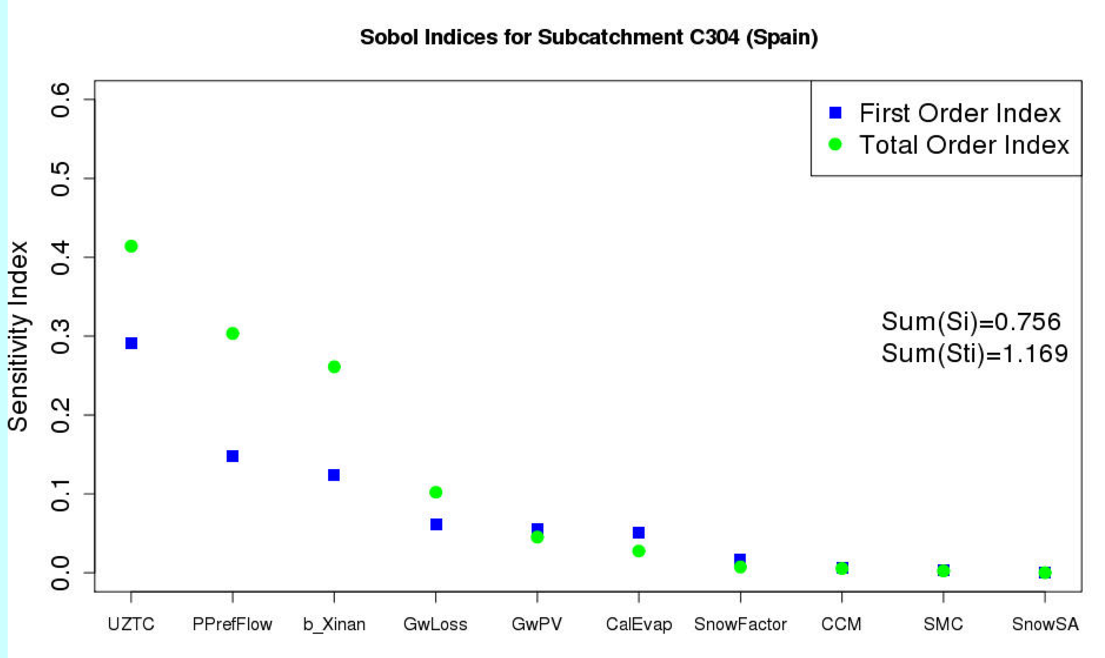
5.c) Global Optimisation (SPSO-2011)

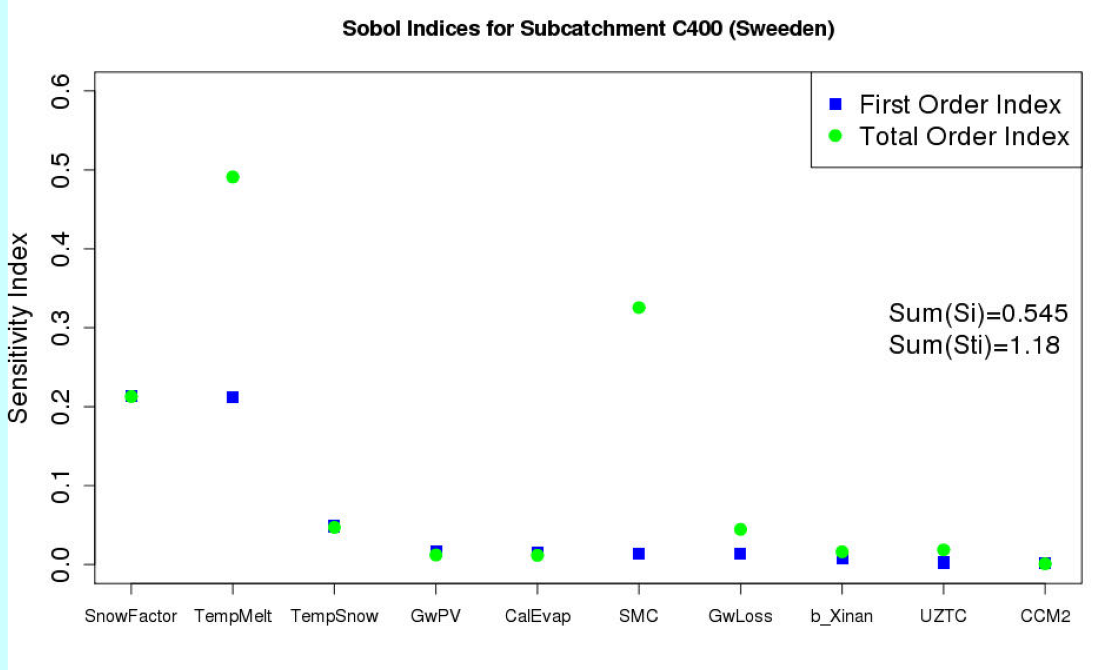
- The Standard Particle Swarm Optimisation 2011 (SPSO-2011) [2-3] was used as global optimisation algorithm for calibrating the LISFLOOD model. SPSO is a recent population-based stochastic evolutionary algorithm inspired by the social behavior of a bird flock looking for food [4]. It has been benchmarked against state-of-the-art global optimisation algorithms [3], where proved to be both efficient and effective. More details: [2-4].
- The LISFLOOD model was calibrated in each catchment using a daily time step, during the period 1995-2003, using the first year as a warming up period.

6.a) Results (Screening with Morris' method)



6.b) Results (GSA with Sobol's method)





8) Conclusions

- Sensitive parameters identified by GSA corresponded to the **dominant hydrological processes** in each catchment → LISFLOOD works as expected by the modellers.
- Qualitative ranking provided by the screening method of **Morris** were in general **agreement** with those provided by the more computationally-intensive **Sobol's** method.
- In the ranfall-dominated catchment (C304), the 4 most sensitive parameters were related to **groundwater** and **infiltration** processes. Those 4 sensitive parameters presented **large interactions** among themselves.
- Sensitive parameters for C304 were a **subset** of the original set defined by prior expert knowledge. New calibration results were slightly **worse** (NSE=0.45) than those of the original calibration (NSE=0.47).
- In the snow-dominated catchment (C400), the 3 most sensitive parameters were related to **snowfall** and **snowmelt** processes. Those 3 sensitive parameters presented very small interactions among themselves.
- Sensitive parameters for C400 were **different** from those identified by prior expert knowledge. New calibration results were much **better** (NSE=0.72) than those of the original calibration (NSE=0.59).
- Initial uncertainty ranges defined for threshold-like parameters proved to have a large influence in the identification of sensitive parameters (both Morris' and Sobol's method) (not shown here).
- Sensitivity indices may change when a different goodness-of-fit measure is used for assessing model's performance.

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