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A General Probabilistic Framework (GPF) for process-based models: blind validation, total error decomposition and uncertainty reduction.

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Process-based models are useful tools supporting research, policy analysis, and decision making. Ideally, they would only include input data and parameters having physical meaning and they could be applied in various conditions and scenario analysis. However, applicability of these models can be limited because they are affected by many sources of uncertainty, from scale issues to lack of knowledge.

To overcome this limitation, a General Probabilistic Framework (GPF) for the application of process-based models is proposed. A first assessment of the performance of the model is conducted in a blind validation, assuming all the possible sources of uncertainty. The Sobol/Saltelli global sensitivity analysis is used to decompose the total uncertainty of the model output. Based on the results of the sensitivity analysis, improvements of the model application are considered in a goal-oriented approach, in which monitoring and modeling are related in a continuous learning process.

This presentation describes the GPF and its application to two hydrological models. Firstly, the GPF is applied at field scale using a 1D physical-based hydrological model (SWAP). Secondly, the framework is applied at small catchment scale in combination with a spatially distributed hydrological model (SHETRAN). The models are evaluated considering different components of the water balance.

The framework is conceptually simple, relatively easy to implement and it requires no modifications to existing source codes of simulation models. It can take into account all the various sources of uncertainty i.e. input data, parameters, model structures and observations. It can be extended to a wide variety of modelling applications, also when direct measurements of model output are not available. Further research will focus on the methods to account for correlation between the different sources of uncertainty.