EXAMPLES OF APPLICATIONS OF SENSITIVITY ANALYSIS AND THE SAFE TOOLBOX

GSA to support calibration of large-scale simulation models: application to karst systems

Karst develops through the dissolution of carbonate rock and is a major source of groundwater contributing up to half of the total drinking water supply in some European countries. Previous approaches to model future water availability in Europe are either too-small scale or do not incorporate karst processes, i.e. preferential flow paths. This study presents the first simulations of groundwater recharge in all karst regions in Europe with a parsimonious karst hydrology model. The model is calibrated by means of a novel parameter confinement strategy, based on **Regional Sensitivity Analysis**, which combines a priori information with recharge-related observations (actual evapotranspiration and soil moisture) at locations across Europe while explicitly identifying uncertainty in the model parameters. Simulation results are consistent with independent observations of mean annual recharge and significantly better than other global hydrology models that do not consider karst processes (PCR-GLOBWB, WaterGAP) and systematically over-estimate actual evapotranspiration and surface runoff.

Reference: Hartmann, A., Gleeson, T., Rosolem, R., Pianosi, F., Wada, Y. and Wagener, T. (2015), A large-scale simulation model to assess karstic groundwater recharge over Europe and the Mediterranean. *Geoscientific Model Development*, 8, 1729-1746.

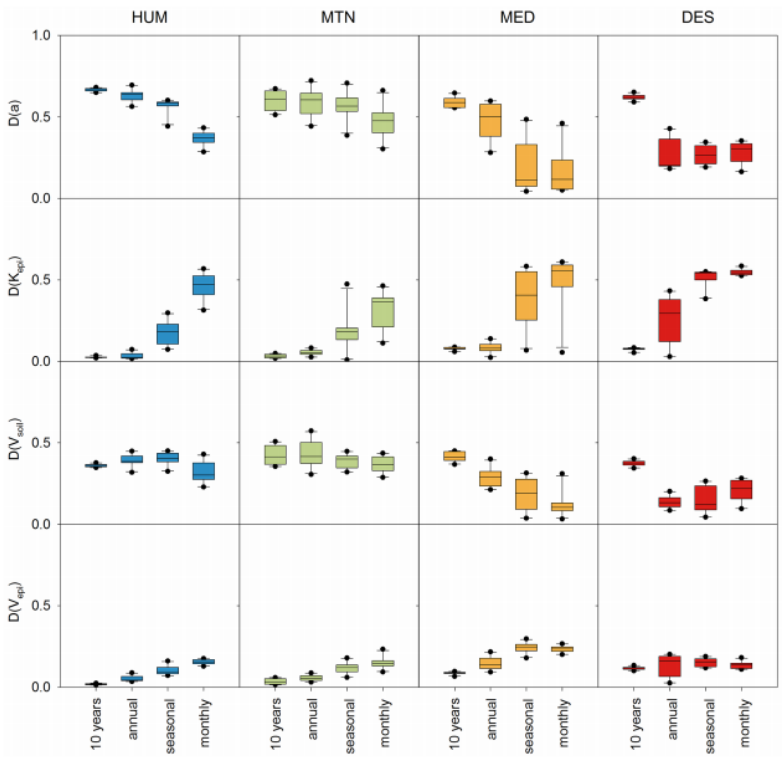

Figure 1: Sensitivity of simulated recharge to the model parameters at different timescales and in the different karst landscapes.

GSA for dominant controls analysis: application to mountain headwater sub-catchments

Ungauged headwater basins are an abundant part of the river network, but dominant influences on headwater hydrologic response remain difficult to predict. To address this gap, a physically based watershed model and **Global Sensitivity Analysis (method of Morris)** were used to investigate the influence of different processes on hydrological partitioning across five adjacent headwater subcatchments in Montana, US. The analysis reveals that, despite between-catchment differences in topography and vegetation, hydrologic partitioning across all sub-catchments was sensitive to a similar subset of snow, vegetation, and soil processes.

Reference: Kelleher, C. Wagener, T. and Mcglynn, B. (2015). Model-based analysis of the influence of catchment properties on hydrologic partitioning across five mountain headwater subcatchments. *Water Resources Research*, 51, doi:10.1002/2014WR016147.

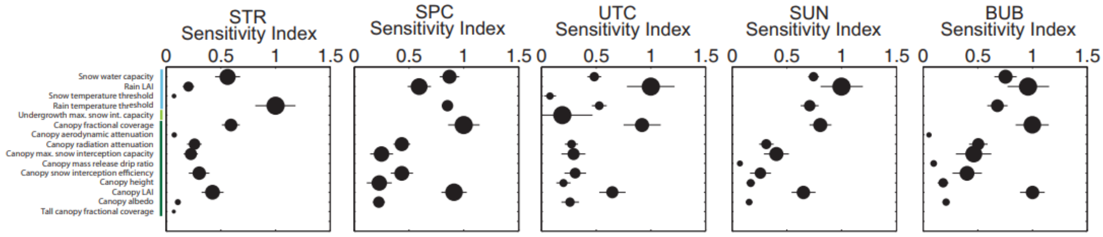

Figure 2: Controls on peak snow water equivalent for the 5 subcatchments: Stringer Creek (STR); Spring Park Creek (SPC); Upper Tenderfoot Creek (UTC); Sun Creek (SUN); and Bubbling Creek (BUB).

GSA to investigate the complexity-uncertainty tradeoffs in spatially distributed models: application to a flood inundation model

The trade-off between complexity and uncertainty is one that affects many modellers. This is particularly the case in flood inundation models where the increased availability of high-resolution LiDAR data and growing computing power allow models to be run at increased complexity. However, when used in real-time, running multiple models at such fine scale resolutions remains computationally expensive and a decision must be made on whether it is better to spend computational resource on resolving topography at finer resolutions or to run Monte Carlo simulations so to account for the many inherent model uncertainties. In this study **Variance-Based Sensitivity Analysis** was applied to explore how influential the spatial resolution and resampling of a fine scale Digital Elevation Model is in comparison to parametric and boundary condition uncertainty. It was found that spatial resolution and uncertainty introduced by resampling topographic data to coarser resolutions are much more important for water depth predictions rather than for flood extent, which are also sensitive to different input factors spatially and temporally. Therefore, the source of uncertainty that a decision maker should prioritise will differ depending on the model output that is required to make their decision and the location of interest across the domain.

Reference: Savage, J. T. S., F. Pianosi, P. Bates, J. Freer, and T. Wagener (2016), Quantifying the importance of spatial resolution and other factors through global sensitivity analysis of a flood inundation model, Water Resour. Res., 52, 9146–9163, doi:10.1002/2015WR018198.

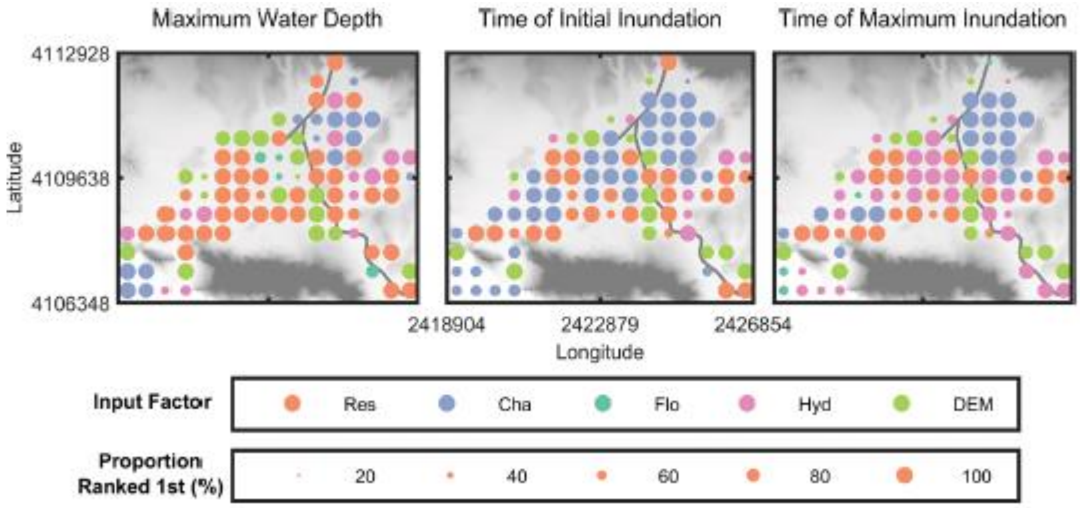

Figure 3: Nodal maps showing the spatial distribution of the most influential input factor (Res: Spatial Resolution; Cha: Channel Friction parameter; Flo: Floodplain Friction parameter; Hyd: Inflow Hydrograph; DEM: Digital Elevation Model) for the maximum water depth, time of initial inundation, and time of maximum inundation model outputs. The color of the dots represents the most influential factor and the size of the dots represents the proportion of bootstrap resamples where that factor was ranked most influential.

GSA to support model calibration and evaluation using different data products: application to a land surface model

In this work, **Variance-Based Sensitivity Analysis** and **Density-Based Sensitivity Analysis (PAWN)** were used to support the calibration and evaluation of the Joint UK Land Environment Simulator (JULES), a global land surface model developed and currently employed by the UK Met Office. Sensitivity estimates are used to narrow down uncertainty in parameter ranges; to identify a set of parameterisations that would enhance the model accuracy with respect to default parameterisation, and that might be used as starting point for a finer model calibration; and to assess the information content in soil moisture data from different sensor types, including the novel cosmic-ray neutron sensor technology.

Reference: Pianosi, F, Iwema, J, Rosolem, R & Wagener, T 2017, A Multimethod Global Sensitivity Analysis Approach to Support the Calibration and Evaluation of Land Surface Models. in G Petropoulos & PK Srivastava (eds), *Sensitivity Analysis in Earth Observation Modelling.* Amsterdam:Elsevier, pp. 125-144.

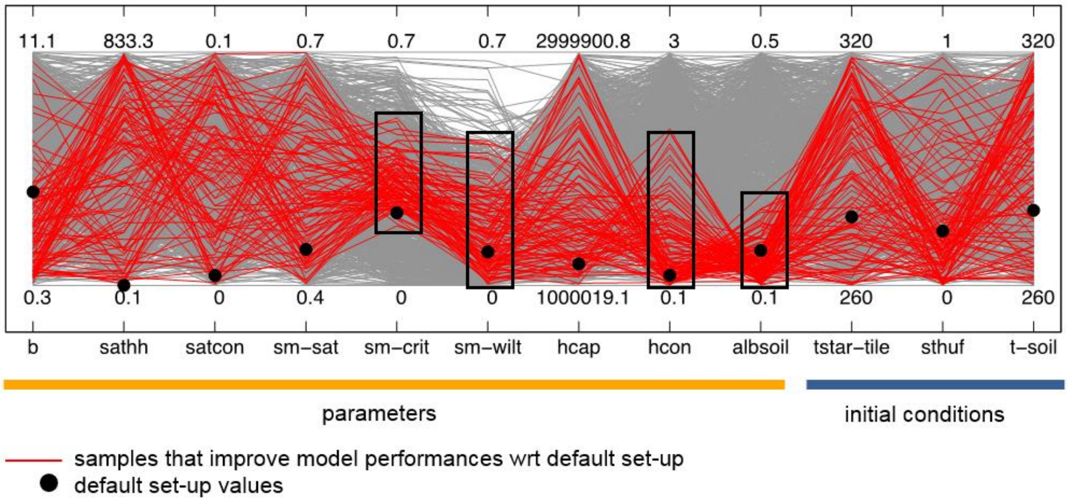

Figure 4: Parallel coordinate plot. Gray lines are nonbehavioural input combinations, red lines are behavioral ones, black dots are default inputs, and black boxes indicate influential parameters for which a reduction of their range of values is possible.

GSA to advance our understanding of epistemic uncertainty: application to a landslide model

In this work, **CART Classification and Regression Trees** was used to evaluate the impacts of uncertainty about slope physical properties and future climate change on predictions of landslide occurrence. The methodology was tested for a case study in the Caribbean. The key finding for the study region is that slope properties could be a more important driver of landslide occurrence than uncertain future climate change. This suggests that failure to account for both sources of uncertainty may lead to underestimation of landslide hazards and associated impacts on society. The methodology provides a valuable tool to identify the dominant drivers of slope instability, and the critical thresholds at which slope failure will occur. This information can help decisionmakers to target data acquisition to improve predictability of landslide occurrence, and also supports development of policy (e.g. improving slope drainage, restricting development in high risk areas) to reduce the occurrence and impacts of landslides.

Reference: Almeida, S., E. A. Holcombe, F. Pianosi, and T. Wagener (2017), Dealing with deep uncertainties in landslide modelling for disaster risk reduction under climate change, *Nat. Hazards Earth Syst. Sci.*, *17*(2), 225–241, doi:10.5194/nhess-17-225-2017.

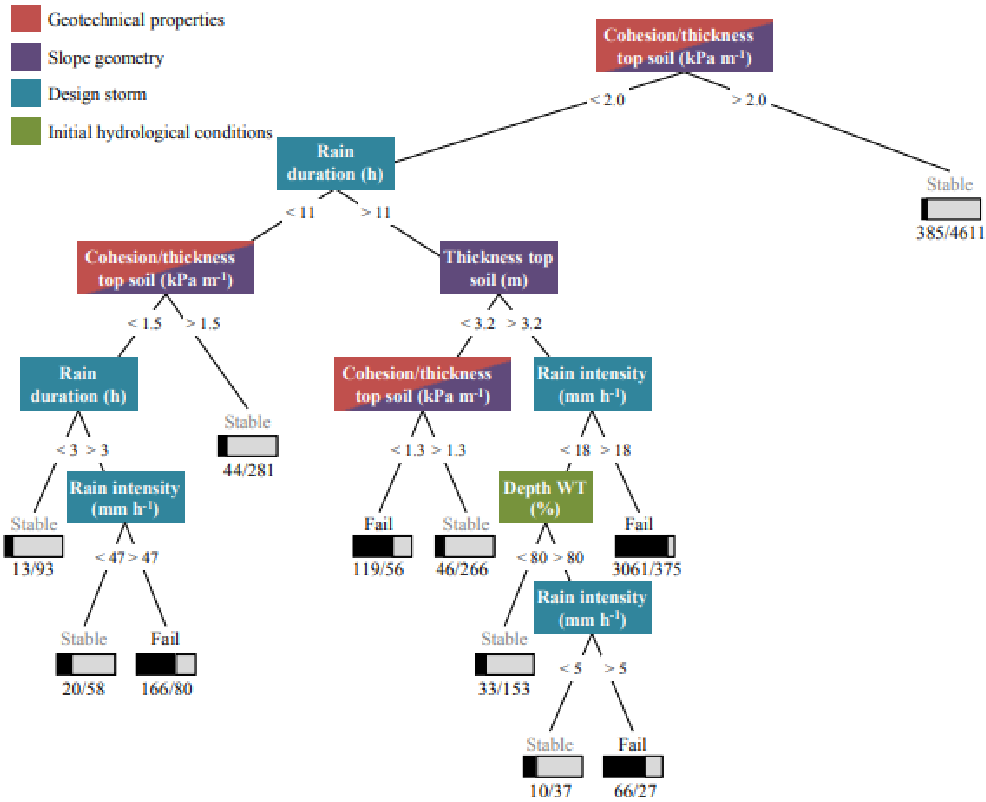

Figure 5: Classification tree of slope response. Each interior node corresponds to one of the analysed uncertain input factors (model parameters, boundary conditions and design storm properties). The bar under each leaf shows the proportion of simulations that resulted in slope failure (black) or stability (grey) for that leaf.