Global methods for a global model - applying the Morris sensitivity analysis on the global gradient-based groundwater model G^3M

Reinecke R., Goethe University, Frankfurt,
Foglia L. , University of California, Davis,
Mehl, S., California State University, Chico,
Döll, P., Goethe University, Frankfurt

Key words: Global Groundwater, Sensitivity Analysis, Morris

Abstract

To represent groundwater-surface water interactions, lateral flows as well as human water use impacts on head dynamics and the impact of capillary rise on evapotranspiration it is necessary to simulate the location and temporal variation of the groundwater table. Global-scale hydrological models (GHMs) have recently moved to include these processes even though data is difficult to obtain. We present an application of the well-established Morris method on a newly developed **G**lobal **G**radient-based **G**roundwater **M**odel G^3M to assess the sensitivity of model inputs.

Introduction

Global groundwater dynamics have significantly changed due to human impacts and will further advance until the end of the 21st century due to climate change. Groundwater withdrawals have led to lowered water tables, decreased base flows, and groundwater depletion around the globe. To represent groundwater-surface water interactions, lateral and vertical flows as well as human water use impacts on head dynamics and the impact of capillary rise on evapotranspiration it is necessary to simulate the location and temporal variation of the groundwater table. Global-scale hydrological models (GHMs) have recently moved to include these processes by implementing a gradient-based groundwater model approach even though data is difficult to obtain [2].

Sensitivity analysis provides a powerful tool to assess how variability in model inputs affects the model outcome, and can provide insights about how the interactions between parameters influence the cost function. Especially global methods provide the capability to explore the full design space whereas local methods (e.g., One Factor At a Time - OAT) do not explore the full design space.. On the other hand, global methods require a large number of model evaluations in comparison to simple OAT methods. Increasing computational resources enable us to apply these methods even for complex models.

We present an application of the well-established Morris method [4] with the newly developed **G**lobal **G**radient-based **G**roundwater **M**odel G^3M coupled to the global hydraulic model WGHM [3] to assess the sensitivity of model inputs (e.g. groundwater recharge and other model parameters like the riverbed conductance) to simulated outputs of hydraulic head.

Furthermore, we present an outlook on possible applications of other methods like Sobol and their computational requirements.

Applying the method of Morris to G^3M

G^3M is a newly global developed gradient-based groundwater model for WGHM. To assess the sensitivity of highly uncertain parameters like the riverbed conductance, we apply the method of Morris. Morris provides a compromise between accuracy and a relatively low number of required model evaluations in comparison to other Monte-Carlo like methods [1]. Each model execution represents an individually randomized OAT experiment. Based on these runs Morris calculates elementary effects d for a given value of $\mathbf{X}$ for the ith model input, Δ is a multiple of $\frac{1}{p-1}$ where p is defined by the region of experimentation with k model inputs, which is a k-dimensional p-level grid [4].

$$d_i(\mathbf{X}) = \left(\frac{y(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - y(\mathbf{X})}{\Delta} \right) \tag{1}$$

To keep the complexity relatively low we apply global multipliers that vary specific model inputs over the whole globe (Table 1). To get a spatial representation, the calculated mean of elementary effects is evaluated at each model node and used to rank the model inputs. The resulting map shows a spatial representation of what model input multiplier has the highest impact on the calculated hydraulic head in a steady-state simulation (Figure 1).

Parameter	Abb.	Range of multiplier
Hydraulic conductivity of the first layer	K	0.1 - 100
Conductance of the lake bottom of local and global lakes	C_{Lake}	0.1 - 100
Conductance of the local wetland bottom	$C_{Wetland}$	0.1 - 100
Conductance of the global wetland bottom	$C_{Gl.Wetland}$	0.1 - 100
Groundwater recharge input from WaterGAP	Recharge	0.5 - 2
Riverbed conductance as described in section	C_{River}	0.1 - 100
Riverbed conductance for small streams	C_{Drain}	0.1 - 100
Thickness of the first layer	AqThick	0.1 - 10

Table 1: Model input multipliers used in the sensitivity analysis.

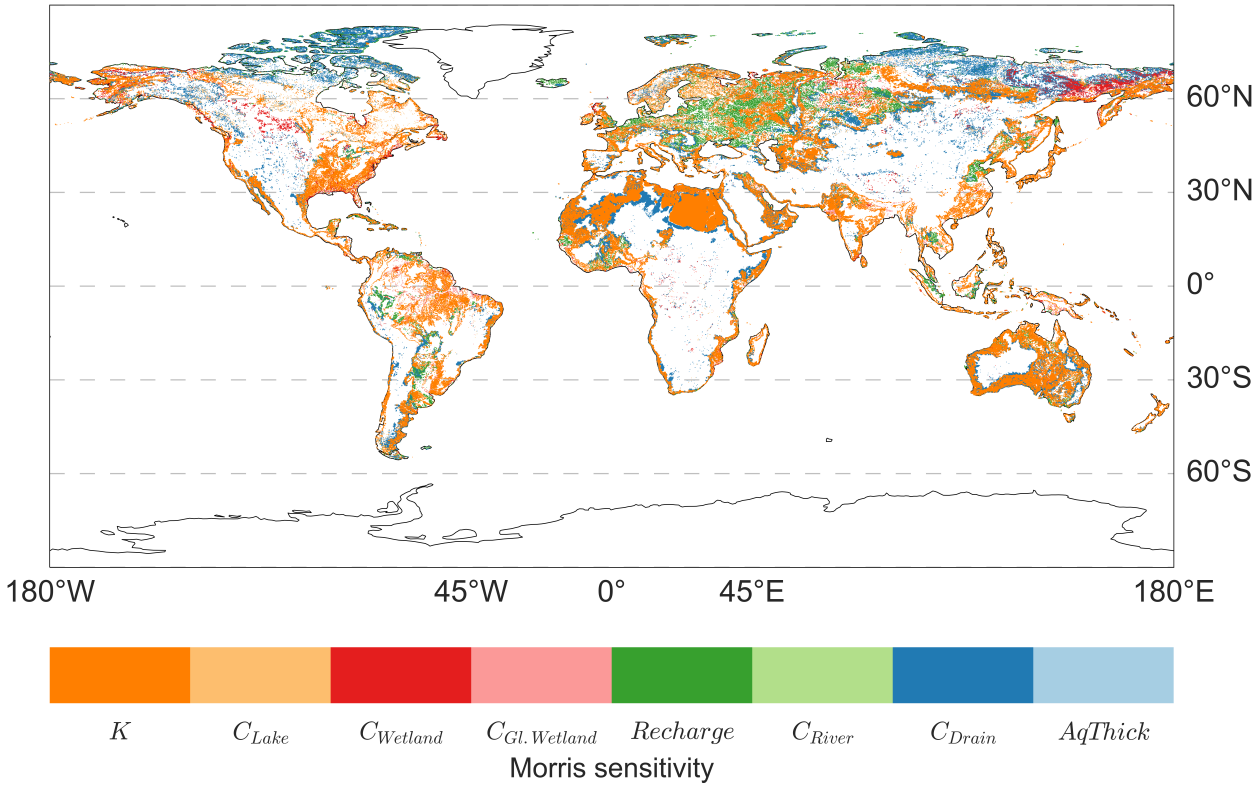

Figure 1: Parameter multipliers with the largest sensitivity as defined in Table 1.

Conclusions

Uncertainties in model input are an inherent problem to global-scale models. By applying a global sensitivity method to a newly developed global gradient-based groundwater model we show the general feasibility of applying global sensitivity methods on large scales. Conclusions can be drawn especially for parameters that affect the convergence time to move to even more complex methods like Sobol [5] (e.g. overall hydraulic conductivity is the most sensitive, whereas aquifer thickness is only sensitive in a very few regions). We further present how we can extend this assessment in future research.

References

[1] Francesca Campolongo, Jessica Cariboni, and Andrea Saltelli. An effective screening design for sensitivity analysis of large models. *Environmental modelling & software*, 22(10):1509–1518, 2007.

[2] IEM De Graaf, EH Sutanudjaja, LPH Van Beek, and MFP Bierkens. A high-resolution global-scale groundwater model. *Hydrology and Earth System Sciences*, 19(2):823–837, 2015.

[3] Petra Doell, Hannes Mueller Schmied, Carina Schuh, Felix T Portmann, and Annette Eicker. Global-scale assessment of groundwater depletion and related groundwater abstractions: Combining hydrological modeling with information from well observations and grace satellites. *Water Resources Research*, 50(7):5698–5720, 2014.

[4] Max D Morris. Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33(2):161–174, 1991.

[5] Ilya M Sobol. Sensitivity estimates for nonlinear mathematical models. *Mathematical Modelling and Computational Experiments*, 1(4):407–414, 1993.