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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Technical note: Method of Morris effectively reduces the computational demands of global sensitivity analysis for distributed watershed models" *by* J. D. Herman et al.

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HESSD Technical Note: Summary of Key Revisions

This document contains a summary of the revisions undertaken in response to key points from the two reviewers. Minor comments are also addressed in our revision but are omitted here for brevity; please refer to the prior author comments for discussions of minor points. We again would like to thank the reviewers for their time and

consideration. Revisions will be shown in italicized font below. 1. Both reviewers have requested clarification regarding the sampling strategy used for the method of Morris. We utilize the sampling strategy originally proposed by Morris (1991), but we would also like to point readers to recent advances in methods to obtain better coverage of the parameter space, namely Campolongo et al. (2007, 2011) and Ruano et al. (2012). Thus, we have revised the end of Section 3.2 as follows:

[...] For this reason, the method of Morris (1991) performs the OAT method over N trajectories through the parameter space. *This study employs the sampling approach originally proposed by Morris (1991) in which trajectories through the parameter space are generated by randomly perturbing one factor at a time. Recent advances in this area by Campolongo et al. (2007, 2011) and Ruano et al. (2012) provide trajectories which maximize coverage of the parameter space, ensuring that the sampled elementary effects yield accurate estimates of global sensitivity. These improvements suggest promising directions for future investigation. Once trajectories are sampled*, the resulting set of elementary effects is then averaged to give μ [...]

2. In response to requests from both reviewers, we have added a supplementary figure showing the first-order Sobol indices, as well as the Morris standard deviation values (σ). These can be compared to the total-order Sobol indices and the Morris μ^* values, respectively, to determine the extent to which parameter interactions are present. In this study, we aim to compare the primary measures of sensitivity as shown in Figure 4 of the manuscript; however, these additional measures can also be used to obtain diagnostic insight, and will be a helpful addition to our supplemental material.

3. We have addressed several issues raised by both reviewers regarding the statistical comparison of results in Figure 5. First, we have rescaled the μ^* values from the method of Morris to the range $[0, 1]$ to maintain consistency with the values shown in

Figure 4. Second, we have moved the legend boxes to the bottom-right corner of all plots to avoid partially obscuring data points. Finally, we have added a discussion of the outliers in Figure 5 in response to thoughtful comments from Reviewer 2, in the fifth paragraph of Section 5:

The bottom row of Fig. 5 shows that the sensitivity rankings given by the method of Morris are well-correlated with those given by the Sobol method with $N = 6000$. Again, a sample size of $N = 20$ for the method of Morris appears sufficient to achieve a good correlation, and little is gained by increasing the sample size further. Of particular interest are the clusters of highly correlated parameters ranked near the most and least sensitive (ranks 1 and 1092, respectively). This indicates that the method of Morris can isolate the most and least sensitive parameters with high reliability, reinforcing its utility as a screening method. *The outliers in the bottom row of Fig. 5 reinforce the difficulty for the method of Morris to distinguish between sensitive parameters; it correctly identifies them as sensitive, but struggles to rank them quantitatively. The largest outliers occur in the upper-left of each plot, where the method of Morris attributes erroneously high rankings to certain parameters. These outliers correspond to parameters of average rank, whose low (but non-zero) sensitivity values are extremely difficult to differentiate from one another. Thus, these points highlight the limitations of the method of Morris for this model, but they do not detract from the success of the approach in correctly classifying the parameters with the highest and lowest sensitivity values.*

4. Reviewer 2 offered a number of helpful suggestions in the introduction section, namely, to identify common applications of sensitivity analysis and clearly state the goals of this investigation. These revisions are shown below. Additionally, we have followed the reviewer's advice to properly distinguish between "input factors" and "parameters", and add a brief introduction to the difference between local and global

methods:

Sensitivity analysis has long been used to derive diagnostic insight from hydrologic models by identifying the key *input factors* controlling model performance [citations omitted]. *The most common applications of sensitivity analysis include factor fixing, in which insensitive inputs are assigned fixed values to simplify further analysis; factor prioritization, in which the most sensitive inputs are identified; and factor mapping, which identifies the regions of the input space in which a particular input is most sensitive (Saltelli et al. 2008). A number of input factors can be explored in sensitivity analysis, including forcing variables, but in diagnostic applications it is common to analyze model parameters directly. In this study, we aim to analyze the ranking of sensitive model parameters (i.e., both those that are sensitive and insensitive) as well as to compare their quantitative measures of sensitivity.*

Sensitivity methods can be broadly divided into local methods and global methods. Local methods provide measures of importance around a single point in the parameter space. Global methods aim to reflect the importance of a parameter throughout the full multivariate space of a model. Relatively few studies have performed global sensitivity analysis for spatially distributed models [. . .]

5. Reviewer 2 has identified several points of confusion regarding the definition of the Sobol sample size, N. First, the sample matrices A and B should be defined to each have size N. The following revision in Section 3.1 addresses this issue:

The variance contributions D_i and $D_{\sim i}$ are calculated according to Sobol (2001) and Saltelli et al. (2008). *First, two matrices A and B are each assigned N sampled parameter sets.* The sample set A is used to calculate the total variance [. . .]

Additionally, the total number of samples required for the Sobol method should be $N(p+2)$ according to this definition of N. This is corrected in Section 3.1 as follows:

The sample set is denoted by the superscript A or B; the parameters taken from that set are denoted either by i (the i-th parameter) or $\sim i$ (all parameters except i). This scheme allows the estimation of first and total order sensitivity indices with a total of $N(p+2)$ model evaluations, where p is the number of parameters for which indices are to be calculated. [...]

Finally, the sample size values in Table 1 have been revised to match the above definitions. For the sample size $N = 1000$, $1\,094\,000$ model evaluations are required. For the sample size $N = 6000$, $6\,564\,000$ model evaluations are required. We thank the reviewer for pointing out this correction.

6. We have revised the description of the method of Morris in response to Reviewer 2's observation that the μ statistic is an estimate of total order sensitivity rather than first order:

These improvements suggest promising directions for future investigation. Once trajectories are sampled, the resulting set of elementary effects is then averaged to give μ, *which serves as an estimate of total-order effects*. Similarly, the standard deviation of the set of elementary effects σ describes the variability throughout the parameter space [...]

7. We have revised the end of Section 2.1 to underscore the importance of choosing appropriate parameter ranges for sampling in order to achieve representative model performance. Additionally, we have moved the total number of model parameters

forward to this section as recommended by the second reviewer.

This study performs sensitivity analysis on 14 parameters of the SAC-SMA model within each cell of the HRAP grid as shown in Fig. 1c. *Since the model contains* 78 *grid cells, a total of* $78 \times 14 = 1092$ *parameters are required to perform sensitivity analysis without spatial aggregation. The sampling ranges for these parameters are derived from prior work (Van Werkhoven et al. 2008) and in consultation with the National Weather Service. Note that the correct choice of sampling ranges is critical in sensitivity analyses that must ensure representative model performance (Sobol, 2001; Nossent and Bauwens, 2012a).*

8. In Section 4 (Computational Experiment), we have clarified the convergence of confidence intervals as suggested by Reviewer 2:

Confidence intervals for the sensitivity indices derived from the bootstrap method (Efron and Tibshirani, 1994; Archer et al., 1997) were monitored to ensure convergence of the Sobol′ method at the $N = 6000$ level. *Convergence was considered acceptable if the* 95% *confidence interval represented less than* 10% *of the sensitivity index value for the most sensitive parameters.* [...]

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 10, 4275, 2013.