

## ***Interactive comment on “The impact of land model structural, parameter, and forcing errors on the characterization of soil moisture uncertainty” by V. Maggioni et al.***

**V. Maggioni et al.**

viviana@engr.uconn.edu

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We would like to thank Anonymous Referee #2 for his/her helpful comments and suggestions. Herein we provide answers to his/her comments to facilitate further interaction on the points listed in the review. During the final phase we will be providing a more extensive response and will revise the manuscript to address the reviewer's comments.

1. In this study, we refer to ‘model uncertainty’ to describe model structural errors, model calibration errors and parametric errors (i.e., uncertainties related to the model itself). On the other hand, we define ‘prediction uncertainty’, or ‘modeling uncertainty’, as the combination of ‘model uncertainty’ and ‘input forcing data uncertainty’. We use

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the so-called GLUE approach to characterize the parametric error component of the ‘model uncertainty’. In fact, as the reviewer highlighted, the GLUE methodology does not separate out different error sources – all uncertainty is represented as parameter uncertainty. On the other hand, we tested another approach to characterize ‘model uncertainty’, which is adding randomly generated noise to the model prognostic variables. This approach is more comprehensive as it addresses statistically both structural and parametric uncertainties (Reichle et al. 2007). We would also like to clarify that GLUE is not used in its typical application to identify the model parameter values that give indistinguishable error metric results evaluated on the basis of independent data. In fact, we assume that the existing parameter set for the Catchment model (defined in previous studies) is the most appropriate, and then use the ‘equifinality’ concept of GLUE to determine the range of parameter variations around that parameter set that give model performances (relative to model simulations using the optimal parameter set) within a threshold error metric value (i.e. Efficiency Score=0.8 for surface soil moisture and 0.7 for root zone soil moisture).

2. We agree with the reviewer on the fact that the sensitivity methodology adopted in this study is local. However, this sensitivity analysis is only intended to identify parameters to which the model is sensitive. Our aim is to limit those parameters to a small subset that would allow computational efficiency. The two parameters that exhibited major model sensitivity were then combined to determine parameter sets that give model performances above the error metric threshold value used to define ‘equifinality’.

3. We agree with the reviewer regarding the subjectivity of the threshold value for the goodness of fit and the choice of the likelihood function. We understand this is a limitation of GLUE, and, as a result, of our methodology, which is built up on the GLUE approach. We will revise the text to address this point in our revised manuscript. However, we would like to point out that our approach is different than the typical GLUE technique. As a matter of fact, our methodology is closer to a model sensitivity anal-

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ysis. For this reason, we will avoid the term 'GLUE' in our revised manuscript and rename what we called the GLUE-approach with a more precise terminology in order to avoid any confusion. The parametric uncertainty in this paper defines deviations from a previously defined parameter set that provide similar model performances in terms of simulated soil moisture. We are not determining model performances using independent observations (as the typical GLUE approach), instead, we use a 'benchmark' model run as reference (i.e., unperturbed radar-rainfall forced Catchment model simulation with original calibrated parameters). From the GLUE approach we borrow the concept of 'equifinality', which recognizes the acceptability of different parameter sets that are similarly good in producing model predictions. We show that even with a small subset of those parameters (two parameter combinations) combined with rainfall forcing uncertainty we can encapsulate the 'benchmark' prediction, showing small ER values, and reproduce the total 'reference' uncertainty (i.e., 'modeling' uncertainty), showing UR values close to unity. In summary, our method differs from the Blasone et al. (2008) as we do not sample randomly the prior parameter space to find 'posterior' parameter estimates. Instead, we start from a priori known best set of parameters and perturb a subset of them - to which the model is mostly sensitive - to find parameter combination to provide indistinguishable model uncertainty in the simulated soil moisture.

4. We agree with the reviewer. We will make sure to add this discussion in the methodology limitations and simplify the language used regarding our parameter sensitivity. Again we plan to rephrase the statement used for GLUE.

5. We used two different approaches to study 'model uncertainty': the first one that only accounts parameter uncertainty and a second one that addresses both structural and parameter uncertainties. The first one was chosen to investigate uncertainty in the parameters only, and study how parameter perturbations, that will still meet the hypothesis of equifinality, would impact the output soil moisture uncertainty. We used the second one to take into account errors in the structure of the model as well. The

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prognostic-perturbation method was chosen because this is the method that is currently used in the NASA-GMAO Land Data Assimilation System (LDAS) to perturb model variables of the Catchment model.

6. This work is done with a data assimilation perspective, which is the reason why we are interested in adopting the method that is currently used in the NASA-GMAO Land Data Assimilation System (LDAS) to perturb model variables of the Catchment model. Our findings highlight the incapability of this approach, even when combined with rainfall model perturbations, to completely describe the 'modeling' (or prediction) uncertainty. On the other hand, by adding some model parameter perturbations (defined by the 'equifinality' concept) to rainfall forcing perturbations, we were able to better characterize the 'modeling' uncertainty in soil moisture simulations. These conclusions extensively contribute to the development of the NASA-GMAO land data assimilation system, giving valuable insights about the interaction between rainfall forcing and model uncertainties in case of satellite rainfall application in land data assimilation.

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