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Hydrology and Earth System Sciences Discussions

# *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.**

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Herein we provide answers to the comments raised by the Anonymous Referee #1 to facilitate further interaction on the critical points listed in his/her review. During the final phase we will be providing a more extensive response and will revise the manuscript to address the reviewer's comments.

- We would like to clarify the GLUE application in this study. For a known set of the Catchment model parameters (provided by previous applications of the specific model), which represent what the reviewer can call a calibrated parameter set, we determine model performance sensitivities to variations of two of its sensitive parameters. Specif-



ically, we determine the Efficiency score metric between model integrations using the calibrated parameter set versus a range of parameter variations. We then set a goodness of fit threshold (Efficiency score of 0.8) to define the range of parameter values that represent 'equifinality' (namely, the model performance differences are not distinguishable within a tolerance). This is different than the typical GLUE approach where model performances are determined against independent observations. Therefore, and to avoid confusion, we will rename the framework to GLUE-based model parameter uncertainty approach. We agree with the reviewer regarding the arbitrariness of the threshold value for the goodness of fit. We understand this is a limitation, first and foremost, of GLUE, and, as a result, of our methodology, which is built on the GLUE approach. However, in any calibration/validation process it is necessary to define a performance criterion of acceptance. We believe it is fair to define an acceptance criterion, as long as it is set in advance, and there is objectivity in the process that follows.

- About adding noise to model prognostics, in this study we adopted the method that is currently used in the NASA-GMAO Land Data Assimilation System (LDAS) to perturb model variables of the Catchment model. Specifically, we applied normally distributed additive perturbations to the model prognostics, constraining ensemble means to zero, and imposing time series correlations via a first-order autoregressive model. The perturbation parameter values are taken from the literature (Reichle et al. 2007, Liu et al. 2011), and are the ones that are actually used in the NASA-GMAO-LDAS. We will provide more information about the calibration of these parameters in the revised manuscript. As far as ensemble verification, this would require independent observations of soil moisture, which is not typically available in large scale applications. In fact, this study should be seen from the data assimilation application perspective. We investigate how errors introduced through regionally defined model and rainfall forcing uncertainty impact the characterization of soil moisture prediction uncertainty, and, consequentially (in a future study) the assimilation of satellite soil moisture observations in a land data assimilation framework.

- In our paper, we do demonstrate that by adding rainfall uncertainty to model parameter uncertainty we obtain larger ensemble members, but we also show that these ensembles are NOT overestimated (UR close to 1) and better encapsulate the 'reference' simulation (smaller values of ER) when compared to the rainfall uncertainty only experiment. In addition, we prove that using the prognostic perturbations contributes a modest increase in the soil moisture prediction uncertainty, but, still underestimates the uncertainty in the soil moisture output (UR smaller than 1). These observations highlight the value of using model parameter uncertainty as described in our paper combined with a stochastic model of satellite rainfall error for global land surface modeling applications. 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.

- We agree with the reviewer that two parameters are not enough to fully characterize the model sensitivity. In order to pick the two parameters presented in this study, we performed a few analyses on different model parameters. We are attaching here in Figure 3a just an example for another parameter (matric potential at saturation), to which the model was found to be non-sensitive. This was typically the case for other parameters in the model. As data assimilation runs are computationally expensive, we find it very promising to be able to describe adequately uncertainty in soil moisture by perturbing rainfall and a small sub-set of the model parameters. Further studies could look at different parameters and investigate how results would differ from our findings. Our conclusions may be different across varying hydroclimatic regimes, which is a point we need to clearly make in the revised version of this paper.

- Fourteen probably represents the minimum acceptable number of ensemble members if we deal with long time series and large regions. In this study we are considering a very long time series (3 years at 3-hr time scale), and a large domain (220 pixels). These ensemble time series represent a significant sample size of independent data



to ensure statistical significance.

- Anomaly correlation coefficients are chosen as a performance metrics due to our focus on data assimilation applications. In fact, traditional metrics, such as bias and RMSE, would be inadequate to evaluate the performance of the model estimates in a land data assimilation experiment, because of the underlying assumptions of unbiased forcings, unbiased model errors, and unbiased observation errors. The ACC metric captures the correspondence in phase between model estimates and ground observations, and it emphasizes relative soil moisture variations at daily to weekly time scales while disregarding any bias in the absolute values of the mean soil moisture or its variability (Entekhabi et al. 2010, Liu et al. 2011).

- Exceedance and uncertainty ratios have been demonstrated to be viable metrics to evaluate ensemble prediction performance in several studies (i.e., Hossain et al. 2004, Hossain and Anagnostou 2005, Borga et al. 2006, Moradkhani et al. 2006). The combination of these two statistics is very powerful as two contrasting issues are considered: if the uncertainty limits are too narrow (that is, ER is high), then the comparison with the reference fields suggests that the model errors are underestimated; on the other hand, if the limits are too wide (that is, UR is high), the model may not have an adequate predictive capability (Hossain et al. 2004). However, the authors are willing to add some more traditional ensemble verification in the revised manuscript (such as the first few moments of the soil moisture ensemble pdfs).

- We'll fix the references in the revised manuscript.

- We agree with the reviewer regarding the fact the parameters were perturbed following a systematic procedure (and not by adding random noise). The approach we are using here deviates from the standard GLUE technique, from which we borrow, though, the 'equifinality' concept and the scheme to split the total sample of simulations into behavioral and non-behavioral parameter sets, based on a cutoff threshold. As stated earlier, to avoid confusion, we will rename the framework to GLUE-based model parameter uncertainty approach, instead of defining it as the GLUE approach.

- We'll fix the caption of Figure 1 in the revised manuscript.

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Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 9, 2283, 2012.



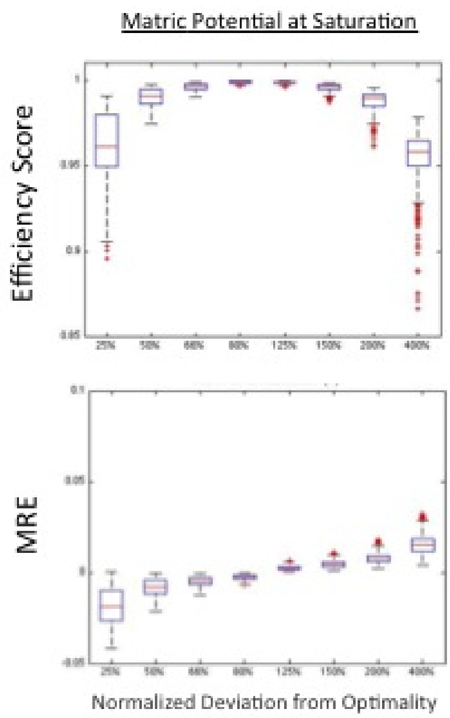


**Fig. 1.** Figure 3a Efficiency score and relative bias as a function of model parameter value deviations (presented in %) for the matric potential at saturation.