The manuscript presents different data assimilation methods for a joint estimation of soil moisture states and model parameters for the VIC hydraulic model and the Community Land Model. The models were tuned and evaluated at a single site and the main objectives include the advantages of the joint state and parameter estimation incorporating real data from the field, performance of the DA methods as well as the different land surface schemes.

The topic is interesting for the scientific community and the paper is clearly structured and well written. I agree for the most part with referee #1, who emphasizes shortcomings with respect to the presentation and discussion of the given objectives, to which I will add only a few more comments.

Reply: We thank the reviewer for pointing out the contribution of our work. We will revise the manuscript taking into account the comments.

Furthermore, I have a comment regarding the usefulness of the presented data assimilation techniques for land surface modeller. In my opinion, the merits of a joint state and parameter estimation should not only be discussed with respect to DA schemes updating states only, but also with respect to alternative methods like conventional Bayesian interference, e.g. (Yang et al., 2008), as well as the issue of optimizing time-invariant parameter vs. time-variant parameter, which has been intensely studied in the group of the authors (Vrugt et al., 2005, 2013). Therefore a discussion of the following (which might be too obvious for the authors to mention) can help to increase the significance for a broader community: What are the advantages of the joint parameter estimation versus optimizing time-invariant parameter? There seem to be shortcomings as time-variant parameter may be highly dependent on the end of the training sequence, especially when it ended shortly after a large precipitation event, like in this study. Will the parameter converge in the given training data set of 5 months? Vrugt et al. (2013) show that time-variant parameter can exhibit considerable non-stationarity, which is caused by changing sensitivity of the target variable on the parameters. Is there a difference/advantage of the joint estimation with time-variant parameter in terms of equifinality/identifiability of the parameter?

Reply: Yes, we agree that there are other relevant methods for parameter estimation/calibration of hydrologic models, for example Bayesian recursive estimation [Thiemann et al., 2001], particle swarm optimization [Scheerlinck et al., 2009] and differential evolution adaptive metropolis [Vrugt and Ter Braak, 2011]. However these methods require in general a large number of model evolutions, which is often prohibitive for large scale land surface models. We refer therefore in the revised version of the manuscript shortly to alternative methods and point to the limitations of those methods.

Generally, parameters are time variant when jointly estimated with state variables as they are updated at each assimilation time step. It is true that time-variant parameters may be dependent on the end of the training sequence, especially for the parameters which are very sensitive to model forcings. The fact that we replace heterogeneous soil properties and soil moisture content for a given area by spatially homogeneous values, also introduces temporal variability in the effective parameters that are estimated in this study. In this context, it can be expected that estimated parameters show temporal evolution. Uncertainties and errors in model forcings and model structural errors will introduce additional temporal fluctuation of estimated parameter values. In a batch calibration approach, these temporal parameter variations will be averaged out and parameters are estimated which on average perform better over the period of consideration. The advantage of sequential data assimilation is that parameter estimation is faster whereas temporal parameter variations in some cases are meaningful. Kurtz et al. (2012) were successful in estimating a temporal variable parameter with EnKF, but concluded that the algorithm needs time to adjust to new parameter values. Vrugt et al. (2013) found considerable temporal non-stationarity in parameters estimated by McMC-PF.

This will be discussed in the revised version of the manuscript. We will point to both limitations and advantages of estimating temporally variable parameters, which depend on the data assimilation algorithm used, and also on different types of errors being involved. It is important

to notice that especially for EnKF, parameters converged towards more stable values at the end of the assimilation period. .

P.10, ll.28ff: For me there seems to be no need to show the spin-up time series (Figure 2). Precipitation and temperature of the assimilation and verification period seem to be enough.

Reply: We will revise this part in our revised manuscript.

P.11: What is the reason of choosing July 31 as the date to switch from assimilation to verification period? This choice seems to be critical for me, as the parameters of the final time step are chosen for the verification period. What would be the impact, if e.g. July 20 would have been chosen, as Figure 5 suggests, that some parameter for the MCMCPF method were significantly different?

Reply: For 2013, there are issues with a large number of sensors in the area and the mean soil moisture content would have to be estimated from fewer (and different) sensors. We started the assimilation in March 2012 as in the winter before soil moisture content readings were affected by soil freezing and therefore unreliable (at least in February). We will test the impact of the choice of the last assimilation day on the parameter estimation with the MCMCPF method and discuss this issue in the revised manuscript.

P.11: state updating only: How does the model then learn for the verification period? How are the parameter chosen in this case? Please describe this more clearly.

Reply: when only the state is updated in the assimilation period, the model gets more accurate initial state conditions in the verification period. We would indeed expect that an improved characterization of initial states has some positive impact during the first weeks, but vanishes over time. We will address this point more clearly in the revised manuscript.

P.11, ll.34ff, Table 1: soil moisture observation errors and parameter perturbations are given by normal and uniform distributions and corresponding ranges, means and standard deviations are given with numbers without further reasoning. As a comprehensive set of soil moisture measurements and soil core data is available, I would assume, the range of perturbation is related to the measured distributions, but I did not see a hint in the text. Referee #1 already addressed this issue related to measurement uncertainty and spatial heterogeneity, and the authors gave detailed reply, but I still miss, how the prior distributions and measurement uncertainties are related to the measured pdfs. It is surprising for me, that the uncertainty of the soil moisture measurements related to spatial heterogeneity is smaller than the given instrument uncertainty of 0.02m^3/m^3.

Reply: For the CLM model parameters, the parameter perturbations are taken from Han et al. (2014), and for the model parameter perturbations for VIC, we refer to Demaria et al. (2007) and Troy et al. (2008). Also measurements were available at the Rollesbroich site to estimate parameter uncertainty. In particular, soil texture measurements are available. If we calculate the uncertainty of the mean soil texture based on those data, we get very small uncertainties. The range of parameter perturbations should be large enough to have enough spread among the state ensemble members, which helps for better assimilation performance. In this case, the uncertainty has to be increased in order to fit the data. This is related to the fact that ultimately soil hydraulic parameters, and not soil texture, are important for calculating water and energy fluxes in the soil. The pedotransfer functions which are used to relate soil texture and soil hydraulic parameters are also subject to uncertainty. We therefore did not use directly the uncertainty of the soil texture estimated from the measurements, but increased it. In the revised version of the manuscript we will give details on this important point.

Qu et al. (2014) calculated the root mean square error (RMSE) associated with soil water content estimation, which is 0.026 m^3/m^3, after the two-step calibration procedure for this catchment. The uncertainty of the mean soil moisture content, assuming a Gaussian distribution, from 41 measurements in this catchment was $\frac{0.026}{\sqrt{41}}$ m^3/m^3. However, in our study we used

$0.02 m^3/m^3$ as observation error, because a larger observation error elevates problems with filter inbreeding. We found also in this case that the small measurement error estimated from the data was too small for our purposes and we will add discussion in the revised version of the manuscript to discuss this.

P 13. ll3-5: You state: "Even although the soil moisture time series for the state augmentation and dual estimation method are very similar, the temporal evolution of their parameter values are different". This hints at the issue of equifinality and identifiability of the parameters with respect to the time series to be predicted. Please discuss this problem.

Reply: Equifinality is handled by both methods because not a single best solution is calculated but an ensemble of different solutions, which are all compatible with the measurement data. The ensemble mean values are plotted. The updating of the parameters follows for both methods the same general tendency. However, as the reviewer stresses, the ensemble mean values also differ for the two assimilation methods. We believe that in this case differences are related to the assimilation methods. The land surface model is ran twice in EnKF in case of dual estimation but only once for the augmentation approach. Model structure errors and biases "contribute" to different extents to parameter updating by these two data assimilation methods. Therefore the temporal evolution of parameter values is different. Discussion will be added in the paper.

Figures 3,7,9,12: Legend: "OBS" were coded with 2 dots. Please make use of different line types for a better discrimination between the displayed series. Especially red and green will be indistinguishable for many readers

Reply: We will revise this in the revised manuscript.

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