Response to comments by Anonymous Referee #2

Received and published: 12 May 2018

General:

The submitted manuscript of Naz et al. (2018) evaluates the effect of soil moisture assimilation (namely ESA-CCI product) into the CLM 3.5 over Europe during 2000-2006. The Ensemble Kalman Filter is used for the model analysis, the observations are sampled using 100 randomly located points across the entire domain, while the remaining locations are used for independent evaluation. The CLM model operates at 3km spatial resolution, while the assimilation product is available at coarser, approx. 25km (0.25degree) resolution. Additionally, the gridded (monthly) runoff product available at 0.5 degree is used for evaluation of the model runs. Results are presented for the open loop (OL) and data assimilation (DA) runs. Results are presented in terms of the RMSE and relative bias per nine PRUDENCE regions. I find this topic relevant for HESS, however, according to my opinion, the manuscript is not suitable for publication in the present form:

We would like to thank the anonymous reviewer for his/her comments and constructive suggestions, which we believe have led to an improved manuscript.

1. As correctly stated in Section 3.3, before applying any DA methods, the modeler should better parameterize and constrain the model parameters, reduce systematic biases etc. I am afraid you cannot apply DA after seeing those strong biases in the open loop estimates (Figures 6 or 10) at all. I encourage authors to pay attention to proper model calibration before DA analysis.

RESPONSE: Hydrologic states and fluxes simulated by Land Surface Models (LSM) are often biased due to, e.g., systematic biases in input forcings, uncertainty of input parameters, the use of parameterizations and uncertainty related to the (bio)physical processes representation in the models (e.g Yin et al., 2014; Han et al., 2014). Traditionally, the calibration of model parameters is performed using in situ data to resolve these biases. However, such in situ data – soil moisture in particular – are often unavailable at a large scale. In this study, we have utilized the remotely sensed soil moisture for evaluating the performance of DA in reducing the model biases as previous studies have shown (e.g. Moradkhani et al., 2005; Liu and Gupta, 2007; Kumar et al., 2008; Nie et al., 2011; Chen et al., 2013; Lievens et al., 2016; Lannoy and Reichle, 2016). Another motivation of this study is not only to improve the soil moisture through data assimilation approach, but also to evaluate the assimilations impacts on other land surface variables such as runoff. Model calibration prior to assimilation, e.g., with the runoff data set of Gudmundsson and Seneviratne (2016) would violate the independency criterion of calibration and validation data for the impact assessment of the data assimilation procedure.

Furthermore, in land surface modeling systematic differences between the model climatology and the observation data climatology are traditionally corrected before assimilation, to ensure that data assimilation is applied under conditions of no systematic bias. However, different procedures to correct bias are used, like the estimation of a single constant bias value, seasonal dependent bias or CDF-matching (e.g. Reichle and Koster, 2004 and Drusch et al., 2005). The procedure has some important limitations: (i) the bias is only partially corrected or over-corrected; (ii) the bias in the DA-procedure is not assigned to the model or measurement data, but after the assimilation it is implicitly assumed that the systematic bias is related to the bias in the measurements (model states are not corrected for a systematic bias). We did therefore not perform any bias correction of the soil moisture observation by rescaling of the observations to model climatology. A further argument for not following this approach was that spatial patterns could be altered and thereby some of the independent information provided by the satellite may be removed; it is desirable to retain as much of the independent satellite information as possible.

The alternative procedure we followed here was to neglect systematic biases, but assimilate with a sufficient ensemble spread so that observations allow correcting model predictions. This approach results in a stronger corrective effect of measurement data. A further alternative is to attribute systematic biases to erroneous model parameter values, which is one of the main sources of error and uncertainty in land surface model predictions. We explore this option now in the revised version of the manuscript using a joint state-parameter estimation approach. Although this approach has also important limitations, related to the fact that we do not know well enough the relative importance of systematic model errors and systematic errors in the measurement data, an advantage is that we correct for possible systematic model bias by modifying soil texture parameters.

Therefore, we evaluated now the impact of soil texture properties like the percentages of clay and sand on the CLM model performance and jointly estimated model states and parameters in the data assimilation experiment. We plotted the results as mean monthly soil moisture for the 2000 – 2006 time period for CLM-OL, CLM-DA (only state update) and CLM-DA (joint state and parameter updates) as shown in Fig. R1. We see that in both cases (state updating alone, joint state-parameter updating) the DA-runs are quite close to the observed values. However, parameter updating is supposed to have corrected part of the systematic model bias and other fluxes like evapotranspiration and also discharge can show larger modifications as response to the different parameters.

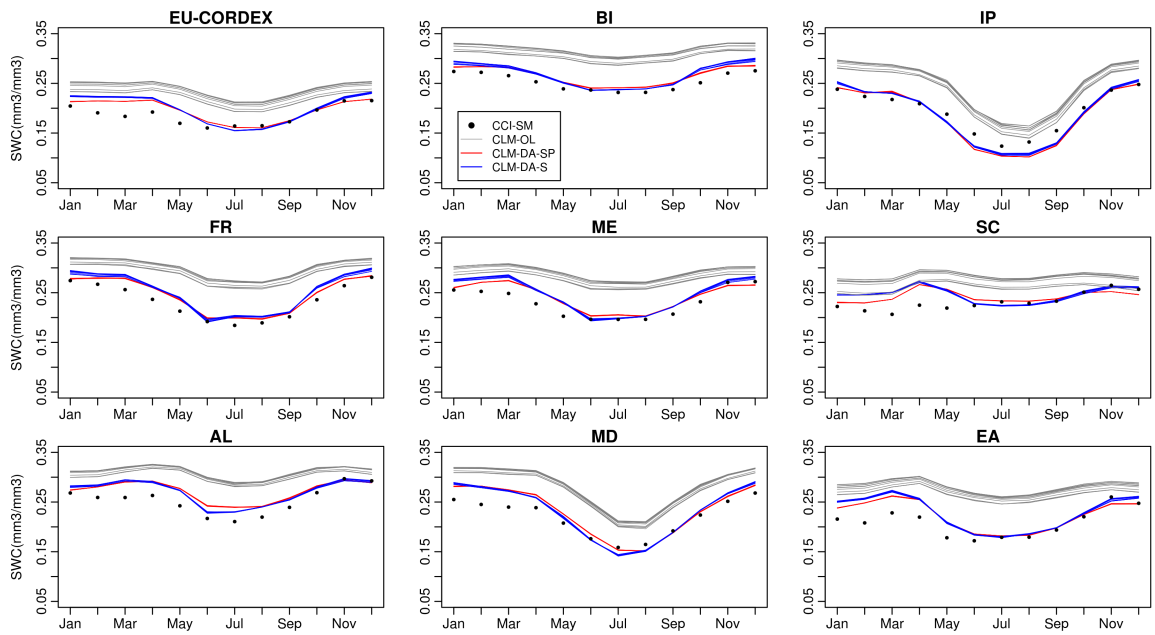

Figure R1: Multi-ensemble spatially averaged mean monthly soil water content (2000 – 2006) simulated with CLM-OL (no assimilation; gray colour) and CLM-DA (with data assimilation) and compared with CCI-SM data over the PRUDENCE regions. The blue colour indicates CLM-DA-S (state updates only) and red colour indicates CLM-DA-SP (joint state-parameter update).

We have now discussed above points in the revised version of the paper and also include information from additional experiments for joint state-parameter updating in the revised manuscript.

2. This is not much of surprise when soil moisture gets assimilated into a model that model simulations at the analysis step get more close to the "observation- based" product, as much as the prescribed observation errors allow (given there exists spatial correlation between the 100 assimilated locations and remaining "withheld" observations). By assimilating the ESA-CCI product, the authors claim to improve the initial conditions of the model. That's all . . . I would welcome then the added value/implications of the improved initial model (wetness) conditions (e.g. with respect to some longer lead-times): OL vs. DA.

RESPONSE: Most land data assimilation studies only aim at improving the model initial conditions. These improved model initial conditions would impact other modeled fluxes like discharge (which is a focus of this paper), but also latent and sensible heat fluxes between the land and atmosphere, which could potentially improve weather predictions. The added value of our study is to apply a data assimilation modeling framework over Europe along the complete simulation time span to derive a longer-term and high spatial resolution land surface data assimilation product in order to increase monitoring accuracy for land surface moisture and water states and fluxes.

Beyond that, a continuous DA approach allows to monitor long-term changes of the terrestrial water cycle and enhance our understanding of the role of land surface processes on, e.g. atmospheric boundary layer dynamics. Therefore, high quality soil moisture product is needed. Since point scale measurements from in situ sensors are only available at a limited number of locations, remotely sensed soil moisture products are promising for a more large scale improvement of soil moisture variations. However, sparse data coverage in satellite observations still limits their ability to provide spatially and temporally consistent time series of water balance estimates. To overcome this limitation, in our study, we used data assimilation to merge coarse resolution satellite observations with a land surface model to generate higher horizontal resolution i.e. downscaled estimates of the full soil moisture profile with complete spatio-temporal coverage.

We now discussed the added value of our data assimilation experiment in the introduction and conclusions section of the revised manuscript.

3. Additionally, using EnKF the authors modify the internal model states and thus introduce some numerical instability (against internal physical constraints for the model), which was not discussed at all. How do you handle this issue after the analysis step?

RESPONSE: In the DA scheme we ensure that updated states (soil moisture) are kept in reasonable physical ranges (between residual soil moisture and porosity) to yield physically consistent estimates of fluxes and maintained the water budget. Additionally, numerical stability is not significant compared to, e.g., groundwater models/ atmospheric models where PDE's are solved with iterative methods. In CLM (and generally in land surface models) the equations/algorithms for deriving mass/energy budgets/transfer are simpler and more robust (numerically) than for full PDE-based systems.

We have now discussed these points in the revised manuscript.

4. Hardly any discussion for (OL and DA) results is done with respect to other SM data assimilation/modeling studies over Europe ... which could be used as a benchmark(?)

RESPONSE: We appreciate the suggestion. We added several references of other assimilation/modeling studies over Europe in the introduction section of the revised manuscript. For instance, many studies have explored the role of soil moisture assimilation in different modeling frameworks over Europe (e.g. Albergel et al., 2017; de Rosnay et al., 2013; Brocca et al., 2010; Draper et al., 2009; Ni-Meister et al., 2006). Albergel et al. (2017) applied a global land data assimilation system at 0.5° over the Europe and Mediterranean domain to sequentially assimilate ESA CCI satellite-derived soil moisture data and leaf-area index product into the ISBA (Interactions between Soil, Biosphere and Atmosphere) land surface model. They found more improvements in the surface soil moisture and particularly in the summer and autumn than in the winter and spring but found little improvements to the discharge when compared to the open loop (i.e. no assimilation) simulations.

Applying CLM over EU is indeed challenging, but there are other models already able to simulate SM and the choice of CLM is not well described either.

(Below is the same response to Reviewer 1, comment 1)

RESPONSE: We selected CLM because it is one of the most complete land surface model at the moment and part of a large community effort (Community Earth System Model; http://www.cesm.ucar.edu/). It has been widely applied at continental and global scales to understand how land processes and anthropogenic impact on land states affect climate (e.g. Bonan et al., 2002; Dickinson et al., 2006). The CLM model parameterizes most of the land surface processes (such as infiltration, evaporation, surface runoff, subsurface drainage, canopy and snow processes) using the water and energy balance equations. In addition, CLM was designed for coupling with climate models and is also part of the fully coupled Terrestrial Systems Model Platform (TerrSysMP; Shrestha et al., 2014) that simulates the full terrestrial hydrologic cycle including feedbacks between atmosphere, land-surface and subsurface compartments of the water cycle. For upcoming studies, it is planned to use TerrSysMP including the parallel data assimilation framework (PDAF) to assess the impacts of satellite soil moisture assimilation on other water cycle variables across the soil-vegetation-atmosphere system and its effects on the accuracy of model simulations at the continental scale can be explored. Moreover, the CLM model can efficiently run for large model domains and at high spatial resolution. Since we performed our simulations at high spatial resolution at continental scale, we selected the TerrSysMP -PDAF modeling framework which can be run on high performance computational infrastructure and can efficiently cope with the high computational burden of ensemble-based data assimilation framework.

The authors have "high-resolution" in their title. I strongly encourage them to eliminate this from the title, especially if they use such coarse scale data to as-similate.

RESPONSE: As discussed in the response to comment 2, in this study we used data assimilation approach to highlight the added value of merging coarse resolution satellite observations with a land surface model to generate higher spatial resolution, downscaled estimates of the surface soil moisture profile with complete spatio-temporal coverage and with a higher accuracy than that of the open loop model estimates. Many applications (such as drought, flood, irrigation management) require observations of the complete soil moisture profile and with finer spatial and temporal resolutions than those of remotely sensed products. To the best of our knowledge, this is the first study of its kind to provide a downscaled daily soil moisture product at 3km resolution over Europe. In order to accommodate the reviewer comment, we replaced "high resolution" in the title with "3km".

5. Why the authors did not use "high-resolution" discharge data for independent model evaluation? There are thousands of gauges with daily time step over Europe, if the routing would be enabled. I am afraid that using monthly gridded runoff is not sufficient for a "high-resolution" study.

RESPONSE: We agree that discharge data from many gauging stations are available and can be used for independent evaluation. However, in the current version of the CLM model, the routing scheme is based on simple linear storage outflow relationships, in which a prescribed channel velocity field without temporal variability is used. This simplified assumption can lead to an offset even in the monthly peak streamflow in large catchments (Li et al., 2011). In addition, in the CLM 3.5, the river routing module is implemented at 0.5° where the discretization of river routing elements is based on a grid method in which the grid for river routing is independent of the grid for runoff simulation. Therefore, a coarse spatial resolution, such as 0.5° can lead to unrealistic flow accumulation paths and cannot be used to evaluate discharge at small catchments. Due to the aforementioned points, adequate validation of the results is therefore not possible.

In this study, we instead used the E-RUN runoff product which combines observed river flow with gridded estimates of precipitation and temperature using machine learning. Therefore, this gridded runoff dataset is solely derived from observations and does not rely on any modeling assumptions. We believe that using an observation-based non-routed gridded runoff product has distinct advantage to evaluate the impact of soil moisture assimilation on runoff at every grid cell within a spatial domain. Using gridded runoff is also useful to evaluate model structure errors in representation of runoff generation in the model. In the land surface models such as CLM, the representation of runoff is often simplistic and conceptual and many previous studies have shown that performance of the CLM model in simulating hydrological processes varies based on regions. This might be attributed to the fact that assumptions to estimate surface and subsurface runoff in the model might be valid in some regions but not in other regions (e.g. humid vs. dry regions). We also noted similar behavior of CLM in our study where the assimilation of soil moisture helps to improve runoff in some regions but degraded in other regions.

In the CLM 3.5 runoff scheme, runoff is partitioned into surface flow and subsurface flow and basic simulation element of runoff is the grid cell. In the revised version of the manuscript, the performances of the surface flow and base flow are evaluated separately in order to identify the dominant factor in total runoff generation as a result of soil moisture assimilation.

6. The authors could have easily run their model at the resolution of the data and save their larger efforts in computer resources.

RESPONSE: The goal and added value of the study was to produce a high-resolution, downscaled land surface hydrology over Europe. It is true that (a large number of) 1D soil moisture DA-experiments could have been conducted at the measurement locations (where we assimilated ESA CCI soil moisture in this experiment), but an essential component of this work is that we updated soil moisture contents at other locations (at the European scale), based on spatial correlations, and investigated whether soil moisture characterization between measurement locations could also be improved, and if this improves also runoff characterization at the European scale. As a conclusion, we respectfully disagree with this point of the reviewer.

It should also be noted that we made an extensive effort to collect and organize high resolution land surface data and atmospheric forcing datasets to implement the CLM model at 3-km resolution over Europe. Particularly, the COSMO-REA6 is available at a high 6 km spatial resolution. The organization of COSMO-REA6 hourly record for the entire Europe is not a trivial task. The applicability of COSMO-REA6 for a land surface model simulation over the EURO-CORDEX domain has never been shown previously.

In addition to forcings, this study also uses high-resolution land surface information in order to better represent the effects of land surface heterogeneity and provide climate information at the scales needed for impact assessment. In the current version of the CLM model, the officially released land surface datasets are provided at 0.5° by 0.5° or coarser resolutions. For example, in our study, PFTs fractional cover data were derived using high resolution MODIS data. Such a data-intensive effort is unprecedented in the previous studies, and hence the new resource will be valuable because it will prompt future hydro-climate studies.

7. Another limitation of this study is the limited ensemble size. 12 members are way too low (this number is stated on p. 7, l. 23). Also, the ad-hoc construction of the perturbations needs better reasoning and clarifications!

RESPONSE: While we agree with this comment, the number of ensemble member, however, was set to 12 members in our study, due to the large number of grid cells and required computational resources. From previous literatures (e.g., Kumar et al., 2008; Pan and Wood, 2010; De Lannoy et al., 2012; Yin et al., 2015), it is clear that the performance of EnKF relies on the ensemble size. For example, (Kumar et al., 2008; Yin et al., 2015) indicated that when the ensemble size is close to 12, it may lead to efficient DA updating process, while (Pan and Wood, 2010; De Lannoy et al., 2012) suggested 20 ensemble members.

We now evaluated the impact of the number of ensembles numbers on the performance of EnKF by increasing the ensemble size to 20 and run the model for one test year (i.e. 2006). We plotted the results as an ensemble mean of spatially averaged daily soil moisture for the year 2006 for CLM-DA (12 vs. 20 ensemble members) and compared with the daily ESA CCI soil moisture values over PRUDENCE regions as shown in Fig. R2.

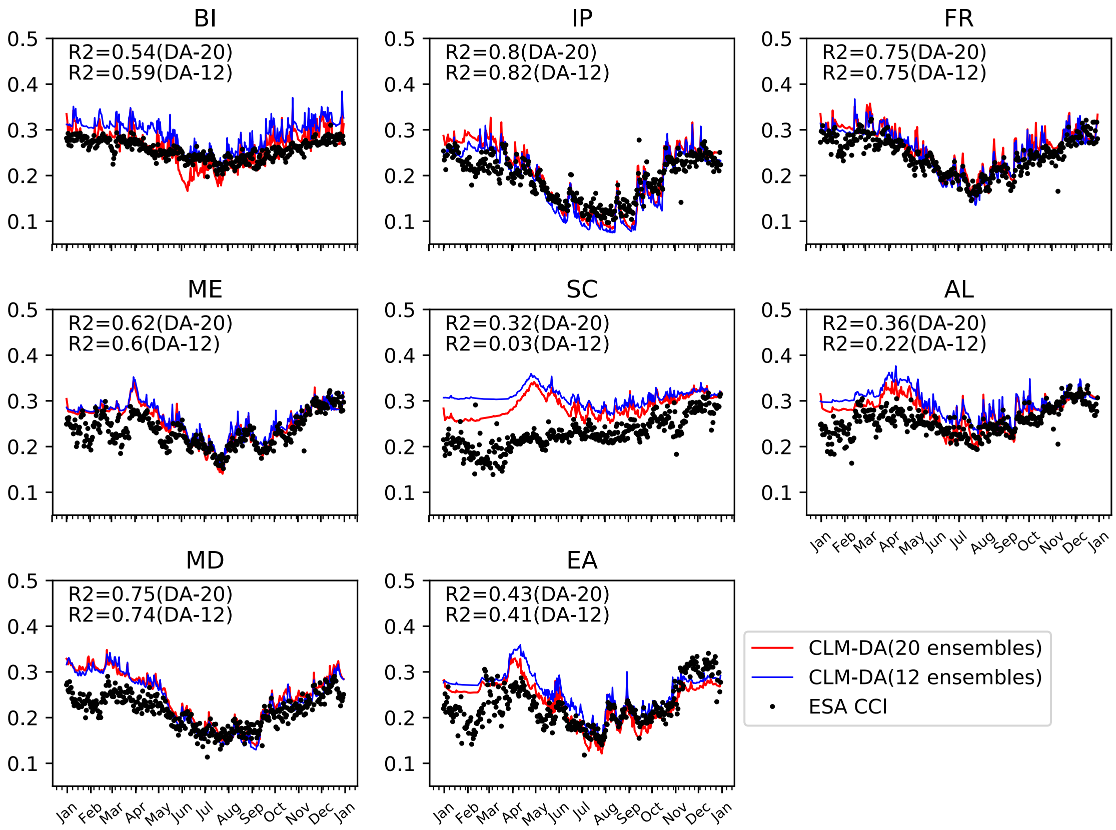

Figure R2: Spatially averaged ensemble daily soil water content (SWC) simulated with CLM-DA (ensemble mean of 12 and 20 ensemble members) and compared with CCI-SM data for year 2006 over the PRUDENCE regions. The R2 values in each panel are r-squared calculated for both CLM-DA with 12 and 20 ensemble members.

While, we see some improvements in the simulated soil moisture as results of using 20 ensemble members, particularly in the winter season and in some regions such as, SC, Al and EA when compared to observations, in both cases the simulated soil moisture from the DA-runs with 12 and 20 ensemble members are quite close to the observed values. We will now include this sensitivity analysis in the discussion section of revised manuscript.

In addition, please note that using an increased number of ensemble members is a big challenge for large-scale high-resolution model because of needed computation memory and storage, and to a lesser degree also because of the computational burden. One year of model run with 20 ensemble members requires 680GB of computer storage per output variable (i.e. equivalent to 5TB of storage for 7 years of simulations per variable at daily time scale) and has resulted in the use of 76,800 CPU core-hours (compare to 46,000 core-hours with 12 ensemble members).

We clearly noted the limitations of our study in the manuscript. In future, with improved availability of computing resources, larger ensemble sizes will be possible.

8. The uncertainty in the time series figures is for the 12 ensemble members?

Correct. We included this information in the figure captions.

9. Numerous papers mentioned in the text are not included in the reference list!!!

Thanks you for pointing this out. We added missing references in the reference list.

Technical:

Spell-out ESA-CCI in the abstract.

This modification has been made

p.1,line 14: remove "and the . . . due to"

This modification has been made

p.5, line 28: remove "In their study"

This modification has been made.

p. 6: "this product" => which product you refer to here?

We referred to gridded runoff product E-RUN version 1.1 (Gudmundsson and Seneviratne, 2016). We modified text for clarity.

p. 6, line 19: missing space after parenthesis

We removed the space after parenthesis.

p.10, l. 13: "UK" => "BI"

This modification has been made

p.12, line 9: runoff => "monthly runoff"

This modification has been made.

Figs. 5 and 9, caption: "a,c" => "a,b"

The figure caption has been modified for clarity.

References:

Albergel, C., Munier, S., Leroux, D. J., Dewaele, H., Fairbairn, D., Barbu, A. L., Gelati, E., Dorigo, W., Faroux, S., Meurey, C., Le Moigne, P., Decharme, B., Mahfouf, J.-F., and Calvet, J.-C.: Sequential assimilation of satellite-derived vegetation and soil moisture products using SURFEX_v8.0: LDAS-Monde assessment over the Euro-Mediterranean area, Geosci. Model Dev., 10, 3889-3912, https://doi.org/10.5194/gmd-10-3889-2017, 2017.

Bonan, Gordon B., Keith W. Oleson, Mariana Vertenstein, Samuel Levis, Xubin Zeng, Yongjiu Dai, Robert E. Dickinson, and Zong-Liang Yang. "The land surface climatology of the Community Land Model coupled to the NCAR Community Climate Model." Journal of climate 15, no. 22 (2002): 3123-3149.

Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., and Hasenauer, S.: Improving runoff prediction through the assimilation of the ASCAT soil moisture product, Hydrol. Earth Syst. Sci., 14, 1881-1893, https://doi.org/10.5194/hess-14-1881-2010, 2010.

Chen, Y., Yang, K., Qin, J., Zhao, L., Tang, W. and Han, M., 2013. Evaluation of AMSR‐E retrievals and GLDAS simulations against observations of a soil moisture network on the central Tibetan Plateau. Journal of Geophysical Research: Atmospheres, 118(10), pp.4466-4475.

De Lannoy, G.J. and Reichle, R.H., 2016. Global assimilation of multiangle and multipolarization SMOS brightness temperature observations into the GEOS-5 catchment land surface model for soil moisture estimation. Journal of Hydrometeorology, 17(2), pp.669-691.

De Lannoy, G.J., Reichle, R.H., Arsenault, K.R., Houser, P.R., Kumar, S., Verhoest, N.E. and Pauwels, V., 2012. Multiscale assimilation of Advanced Microwave Scanning Radiometer–EOS snow water equivalent and Moderate Resolution Imaging Spectroradiometer snow cover fraction observations in northern Colorado. Water Resources Research, 48(1).

de Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C., and Isaksen, L.: A Simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF, Q. J. Roy. Meteorol. Soc., 139, 1199–1213, doi:10.1002/qj.2023, 2013.

Dickinson, R.E., Oleson, K.W., Bonan, G., Hoffman, F., Thornton, P., Vertenstein, M., Yang, Z.L. and Zeng, X., 2006. The Community Land Model and its climate statistics as a component of the Community Climate System Model. Journal of Climate, 19(11), pp.2302-2324.

Draper, C. S., J.-F. Mahfouf, and J. P. Walker (2009), An EKF assimilation of AMSR-E soil moisture into the ISBA landsurface scheme, J. Geophys. Res., 114, D20104, doi:10.1029/2008JD011650.

Drusch, M., Wood, E.F. and Gao, H., 2005. Observation operators for the direct assimilation of TRMM microwave imager retrieved soil moisture. Geophysical Research Letters, 32(15).

Gudmundsson, L. and Seneviratne, S.I., 2016. Observational gridded runoff estimates for Europe (E-RUN version 1.0). Earth System Science Data, 2016, pp.1-1.

Han, X., Franssen, H.J.H., Montzka, C. and Vereecken, H., 2014. Soil moisture and soil properties estimation in the Community Land Model with synthetic brightness temperature observations. Water resources research, 50(7), pp.6081-6105.

Kumar, S.V., Reichle, R.H., Peters-Lidard, C.D., Koster, R.D., Zhan, X., Crow, W.T., Eylander, J.B. and Houser, P.R., 2008. A land surface data assimilation framework using the land information system: Description and applications. Advances in Water Resources, 31(11), pp.1419-1432.

Lievens, H., Tomer, S.K., Al Bitar, A., De Lannoy, G.J.M., Drusch, M., Dumedah, G., Franssen, H.J.H., Kerr, Y.H., Martens, B., Pan, M. and Roundy, J.K., 2015. SMOS soil moisture assimilation for improved hydrologic simulation in the Murray Darling Basin, Australia. Remote Sensing of Environment, 168, pp.146-162.

Li, H., Huang, M., Wigmosta, M.S., Ke, Y., Coleman, A.M., Leung, L.R., Wang, A. and Ricciuto, D.M., 2011. Evaluating runoff simulations from the Community Land Model 4.0 using observations from flux towers and a mountainous watershed. Journal of Geophysical Research: Atmospheres, 116(D24).

Liu, Y. and Gupta, H.V., 2007. Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework. Water Resources Research, 43(7).

Moradkhani, H., Hsu, K.L., Gupta, H. and Sorooshian, S., 2005. Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter. Water resources research, 41(5).

Nie, S., Zhu, J. and Luo, Y., 2011. Simultaneous estimation of land surface scheme states and parameters using the ensemble Kalman filter: identical twin experiments. Hydrology and Earth System Sciences, 15(8), pp.2437-2457.

Pan, M. and Wood, E.F., 2010. Impact of accuracy, spatial availability, and revisit time of satellite-derived surface soil moisture in a multiscale ensemble data assimilation system. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 3(1), pp.49-56.

Ni-Meister, W., P. R. Houser, and J. P. Walker (2006), Soil moisture initialization for climate prediction: Assimilation of scanning multifrequency microwave radiometer soil moisture data into a land surface model, J. Geophys. Res., 111, D20102, doi:10.1029/2006JD007190.

Reichle, R.H. and Koster, R.D., 2004. Bias reduction in short records of satellite soil moisture. Geophysical Research Letters, 31(19).

Shrestha, P., Sulis, M., Masbou, M., Kollet, S. and Simmer, C., 2014. A scale-consistent terrestrial systems modeling platform based on COSMO, CLM, and ParFlow. Monthly weather review, 142(9), pp.3466-3483.

Yin, J., Zhan, X., Zheng, Y., Hain, C.R., Liu, J. and Fang, L., 2015. Optimal ensemble size of ensemble Kalman filter in sequential soil moisture data assimilation. Geophysical Research Letters, 42(16), pp.6710-6715.

Yin, J., Zhan, X., Zheng, Y., Liu, J., Hain, C.R. and Fang, L., 2014. Impact of quality control of satellite soil moisture data on their assimilation into land surface model. Geophysical Research Letters, 41(20), pp.7159-7166.