“Probabilistic inference of ecohydrological parameters using observations from point to satellite scales” by Maoya Bassiouni et al.

Response to Xue Feng (Referee #4)

The manuscript titled “Probabilistic inference of ecohydrological parameters using observations from point to satellite scales” by Bassiouni et al. adopts a Bayesian inference approach to estimate parameters from a parsimonious soil moisture model based on readily available data (soil texture, rainfall, soil moisture) at the point, footprint, and satellite scales. This is a worthwhile exercise and paves the way for the evaluation of the utility of soil moisture data from satellite products. I recommend its publication contingent on clarification on a few issues.

Thank you for your thorough review and constructive suggestions. We have provided responses and preliminary corrections below.

1. A key assumption embedded in the use of this approach requires that the time series of soil moisture capture the whole range of realizable values. This is required to disentangle cases where soil moisture values cannot be observed due to physical constraints (e.g., imposed by saturation thresholds – the point of this study) versus heuristic constraints (e.g., we simply have not measured it under sufficiently wet or dry conditions). Please include this caveat and discuss practical considerations in overcoming this issue.

We agree. This is an important assumption that should be described more explicitly and addressed in the discussion.

We will revise the Introduction and add a sentence before presenting the study hypothesis.

We assume that if a sufficient range of soil moisture values are observed at a site, then the shape of the empirical soil saturation pdf, derived from these observations is constrained by the ecohydrological factors driving soil moisture dynamics. We hypothesize that key information required to determine these ecohydrological factors is encoded in empirical soil saturation pdfs, and that this information can be extracted by calculating the inverse of the commonly used stochastic soil water balance.

We will also rephrase the introduction of the key questions addressed in this paper.

What is the minimum amount of data necessary to determine empirical soil saturation pdfs, which are complete and robust enough for estimating ecohydrological parameters through a Bayesian inversion?

In the Methods, this assumption will be mentioned in section 2.2.2 “Climate, soil and vegetation parameter characterization”

A key assumption in this analysis is that the whole range of realizable soil moistures values is captured by the selected time series and the empirical soil moisture pdf determined from these observations is not truncated by missing data. In these conditions, the shape of the empirical soil saturation pdf is constrained by the ecohydrological factors driving soil moisture dynamics and the parameters of the analytical pdf can be determined with certainty. In addition, the predetermined value for s_h, based on soil texture, is lower than the observed soil saturation observation. This extends the parameter space for s_w in areas that may not be observed in dry enough conditions. It is possible to estimate a value for s_w that is between the minimum observed soil saturation value and s_h and not be observed in the time series. The minimum and maximum observed soil saturation values during the April to September 2012 period are reported in Table 1 to indicate the range of observed soil saturation values used to estimate ecohydrological parameters. We expect that estimated soil saturation thresholds (s_w and s^*) will have greater certainty if the empirical soil saturation pdf is most defined around those values and greater uncertainty if there are relatively fewer soil saturations values observed around the thresholds. Thus s_w may be more certain for drier sites and s^* may be more certain at wet sites. If the range of observed values is not representative of the soil moisture pdf because it is truncated by missing observations or affected by noise in the data, parameter estimates may have biases.

We will also amend the results and discussion section to better evaluate the validity of assumption and relate it to the uncertainty of the parameter estimates and the model inversion convergences. In particular, results from the sub-sampling sensitivity test will be used to discuss this point and describe practical considerations to overcome this issue in future analyses.

2. Relatedly, the study concludes that “model inference at wetter sites… is more successful than at dry sites” because known rainfall parameters have been used to constrain the model at wetter sites, where it is hypothesized to play a stronger role in determining the soil moisture pdf. I think this is true, but does not capture the whole story. The “drier” sites used in this study (Tonzi Ranch and Metolius) are also located in Mediterranean climates where substantial seasonal variations in soil *moisture can occur between early summer (April/May) and late summer (Sept), which span the period of study. This is apparent from inspection of Figure 1, where soil moisture undergoes an initial rapid decay in Tonzi and Metolius.*

As such, I suspect that this assumption of steady state may impact the following statement which I found very interesting (Page 11, line 15): "sw was more important in the analytical equation for soil saturation pdfs and soil water loss equations than s." If the time series span a transient period that eventually converge toward a dry state, then the shape of the soil moisture pdf would be less defined around s* because there would be relatively fewer soil moisture values near s* than near sw. In that case, sw would naturally become a more important parameter because the shape of the soil moisture pdf would be more defined around sw, but this would be purely an artifact of the relative data availability around sw and s*. To test this issue, I think it might be useful to divide the time series into more distinct periods of "wet," "transition," or "dry" and use those periods to explicitly estimate the relevant parameters sfc, s*, and sw.*

We agree with your interpretation and will amend the results and discussion sections to explain that the assumption of steady state impacts the ability to fit the ecohydrological parameters to data taken during a transitional-dry period at the Tonzi and Metolius sites. We acknowledge that the date range selected may not be optimal for stationary behaviour at each site. A steady state period could have been better selected for each individual site. For simplicity/consistency we selected a single concurrent period for all sites and scales. Results therefore revealed which sites had poorer goodness of fit statistics and for which the steady-state solution for the analytical soil saturation pdf may not have been most appropriate.

We will amend the study goals, methods and discussion to include an additional sensitivity aimed at addressing the issues associated with the steady-state assumption. We will use data from the 2012 record periods and compare the goodness of fit of empirical and analytical pdfs using the full year of observations, and dry and wet periods selected specifically for records at each site/scale.

And a tangential note on Page 6, line 22 "this framework was derived under the assumption of steady state, wherein parameters are constant for a given period of time."

Constant parameter values are not sufficient criteria for achieving steady state – as it can also result in a transient period based on initial conditions. Please be careful with this terminology.

We now clarify that the theoretical pdf equation is the steady state solution of the stochastic soil water balance but it does not necessarily imply that the data indicates a steady state.

3. The role of rooting depth. While the model-data fit was not greatly affected by different rooting depths, the resulting values for Emax certainly was. Thus, the authors were able to demonstrate equifinality of results by using Emax to compensate for changes in Z. If the goal is to ultimately estimate meaningful values of vegetation and hydrological thresholds from data, is model-data fit a sufficient metric for evaluation of this approach? My own take away from this part of the study was that rooting depth can in fact be a very sensitive parameter due to the large amount of change in Emax required to achieve similar fit with data. Perhaps a more useful way of tacking this question would be to include Z as another model parameter and evaluate the site and climate conditions under which its impacts would be limited.

Z was not included as a parameter to be estimated because it is most appropriate for Z to be equal to the measurement depth associated with each measurement. Our analysis shows that estimates of sw and s* are not very sensitive to the depth Z assumed in the model inversion while E_{max} scales as expected with Z. This is important if the sensing depth is not precisely known or is variable in time and space, which is the case for the cosmos and satellite measurements. The model inversion convergence, and the coefficient of variation of posteriori parameter estimates are more important metrics to detect equifinality than goodness of fit. We have previously tested the model inversion including Z as a parameter to be estimated. We found in this case, a decreased the number of MH-MCMC runs that converge without significantly increasing goodness of fit because there is equifinality between pairs of Z and E_{max}.

In the revised manuscript we will only consider Z equal to the sensing depth. We will remove the sensitivity teste related to soil depth because it is not useful to determine whether estimates of sw and s* derived from surface soil moisture measurements are relevant to deeper soil depths. In the results comparing model complexity alternatives, the figure will be revised to visualize model inversion convergence, and the coefficient of variation of posteriori parameter estimates in addition to goodness of fit. This will clarify the arguments for the choice of models and the explanation related to equifinality.

4. A few definitions:

Page 1, line 14: "parameter uncertainties" – how are these defined?

The term "parameter uncertainties" will be changed. The sentence will read: the coefficient of variation of posteriori parameter distributions were on average under 10 %.

Page 11, line 9: "the most successful parameter estimations were obtained. . . with 97, 94, 85 percent converging results" – how are these percentages defined (via GR diagnostics?) and what is the significance of the different levels of convergence? I couldn't find a reference in the text.

We defined in the methods section that the GR diagnostic determines that the algorithm reaches convergence when the within-run variability (σ_w) is roughly equal to the between-run variability (σ_b), i.e. σ_w/σ_b approaches 1. We repeated the optimizations 10 time (with 5 run samples each) for each sensitivity test and the percentage of converging results indicates the percentage of the repeats that had a GR diagnostics for each parameters inferior to 1.1. We considered that a model inversion had appropriately converged if the GR diagnostics was lower than 1.1 for each estimated parameter.

Minor point: section 4 (results and discussion) should actually be section 3.

The numbering will be corrected.