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Hydrology and Earth System Sciences Discussions

Interactive comment on "Assimilation of ASCAT near-surface soil moisture into the French SIM hydrological model" *by* C. Draper et al.

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article

We thank Dr Crow for his comments on the paper, which have helped us to greatly improve the manuscript. Dr Crow's comments are reproduced below, with our response to each comment provided as a bullet point.

This is a very well-written manuscript on a methodologically sound data assimilation analysis. It's examination of the added utility associated with assimilating ASCAT sur-

face soil moisture retrievals into an operational model represents a significant contribution to the hydrological data assimilation literature. However, I do have two (related) major concerns that should be addressed prior to publication.

Major 1) Page 5439 (lines 15-20). The primary focus of the manuscript is on the correction of bias in the SIM_NRT results (relative to the baseline SIM_DEL case). This focus is surprising given that the assimilated ASCAT have been pre-processed to be non- biased relative to SIM_NRT surface soil moisture predictions. As far as I can see - the only way the assimilation of a non-biased observation can invoke a biased response in analyzed model states is for there to be some type of non-linearity in the forecast model (i.e. some reason why the impact of positive filtering innovations are not simply canceled by negative filtering innovations in the long term...as they would be in any linear model). Consequently, I think the author's need to describe exactly what type of nonlinear mechanism is responsible for the non-mean-zero response they see to the assimilation of a mean-zero observation. Judging from Figure 8c it might have something to do with the nonlinear relationship between evaporation and soil moisture (soil moisture tends to accumulate because positive soil moisture perturbations do not impact ET due to energy-limited conditions but negative perturbations push the model into water-limited ET conditions which reduces ET...thus the net impact over time is to decrease ET which, in turn, produces a net increase in root-zone soil moisture?). The authors are obviously aware of this issue and address it directly on lines 20-25 of page 5439...but I had trouble following their exact reasoning there (e.g. "signal of the low-biased response to individual precipitation events"...not sure what that means) and it doesn't seem like a complete explanation is possible without invoking some type of model non-linearity.

2) A second (highly related) concern is that, if the non-mean-zero response of the SIM_NRT case is actually due to a model non-linearity, than the known cause of the bias problem appears to be detached from the proposed solution. The bias is explicitly caused by a bias in the NRT forcing data but then the analysis involves a bias solution

that requires a specific non-linearity in the model. So it seems like the authors are proposing an ad hoc solution that is detached from the true source of the problem. This raises the possibility of the (generally positive) results presented here being somewhat non-robust. For example, a purely-linear model would experience the same bias due to overly-dry NRT forcing but (after rescaling) ASCAT soil moisture data assimilation would have no discernible impact on this bias. Or, again for example, if SIM_NRT soil moisture was POSITIVELY biased, than the model non-linearity would actually cause ASCAT soil moisture data assimilation to exacerbate this positive bias. This might be an unfair perception...but the revised manuscript should address this concern.

- We agree with both aspects of this comment, and have changed the manuscript accordingly. Since submitting the original article, the reasons why the assimilation generated a net increase in w_2 (or a reduction of the dry bias) have been further investigated. As suggested by the reviewer this is due largely to nonlinear aspects of the model. Below, the reasons for this result are discussed, together with the implications of this, and an outline of the changes that have been made to the paper to address these issues.

  This study attempted to assimilate ASCAT near-surface soil moisture to correct for errors in SIM associated with the use of NRT forcing. The NRT forcing errors were dominated by a dry bias in the NRT precipitation fields, which resulted in the SIM_NRT w_1 and w_2 being biased dry. In ISBA, w_1 varies rapidly, and has a very short memory, so that the SIM_NRT and SIM_DEL w_1 timeseries only diverged briefly immediately following each rain event, and were in general well converged in between rain events. In contrast, w_2 has a much longer memory, and it slowly developed a larger bias due to the accumulation of biased precipitation events. In this instance a bias-aware assimilation will not be useful, since the principle variable that is being analysed (root-zone soil moisture) is not observed, and a bias aware assimilation of soil moisture cannot estimate the bias in layers for which no observations or knowledge of the truth is available (de Lannoy et al,

2006). Another option to address the SIM_NRT root-zone soil moisture biases (or at least increase the coupling between the w_1 and w_2 biases) would be to include parameter estimation in the DA scheme, however this would certainly result in decoupling the solution and cause of the NRT w_2 biases, and has not been pursued.

  Instead, in this work we proceeded with a bias-blind assimilation in the hope that the ASCAT observations, even after being corrected to the SIM_NRT climatology, are accurate enough to detect the errors in the SIM_NRT w_1 caused by the under-estimated precipitation, allowing the data assimilation to correct for the erroneous precipitation as it occurs. While in a linear model a bias-blind assimilation of unbiased observations would not be expected to affect the model biases, in practise land surface models are nonlinear, and it is common to see change in the mean soil moisture from assimilation of unbiased (relative to the model) observations (e.g., Muñoz Sabater et al (2009)). In fact, some temporal correlation in the analysis updates is desirable in any land surface assimilation: given the dissipative nature of the land surface, analysis updates that are purely white would have a very limited impact on model forecasts.

  The results of the assimilation experiment showed that despite the observations being unbiased relative to the model, the assimilation had a strong tendency to add moisture to w_2 (particularly in the summer), with a mean net positive increment of 0.1 mm day^{-1}, resulting in a net increase in the model root-zone soil moisture. While this result is consistent with the assimilation having correctly updated the model in response to the underestimated NRT precipitation, an investigation of the assimilation system and model physics indicated that there may also be other causes of the net addition of moisture.

  Firstly, scatterplots of the Kalman gain for updating w_2 ($\mathbf{K}_2$) vs. the observation departures show a very clear tendency for increased $\mathbf{K}_2$ when the observation departure becomes more positive. For example, averaged across the whole experiment, the mean $\mathbf{K}_2$ for positive observation departures was 0.063m^3m^{-3}, while for negative observation departures it was 0.030m^3m^{-3}. The main cause of this is the observation operator, which is a 24 hour integration of the forecast model (SIM), followed by conversion to the observation equivalent variable (w_1). That is, for $y^o = w_1$ and $x = [w_1, w_2]^T$, $H = [d(w_1)^{t+24}/d(w_1)^t, d(w_1)^{t+24}/d(w_2)^t]^T$. During periods of rain, $H_2 = d(w_1)^{t+24}/d(w_2)^t$ is reduced, since the signal in w_1 of w_2 is overridden by the precipitation. As a result, H_2 and consequently K_2 tends to be smaller when the model w_1 is wetter. An additional (although lesser) influence on $\mathbf{K}_2$ came from the observations errors used in R, which were estimated by calculating the sensitivity of the retrieval algorithm to noise in the ASCAT backscatter observations. Scatterplots of these error values values show a clear tendency to decrease as the ASCAT observation becomes wetter (at least within the range of most of the ASCAT data used here). This results in higher $\mathbf{K}_2$ for wetter ASCAT observations. In combination these two factors lead to tendency towards higher $\mathbf{K}_2$ when the observation departure (=ASCAT - w_1) was more positive, giving the assimilation a clear preference towards adding net moisture to the model.

It is difficult to determine how the above issues should be addressed within the EKF framework. The relationship between the ASCAT observation value and observation error could be eliminated by reverting to a constant $\mathbf{R}$, as is more often used in soil moisture assimilation. For the $\mathbf{H}_2$ term, since w_1 will not be influenced by w_2 during precipitation events, the tendency for $\mathbf{H}_2$ to decrease under these conditions is physically correct. However, the model error should also be larger during periods of rain, to reflect the large uncertainties in the precipitation observations used to force the model (recall that the timing of precipitation events is reasonable, while the volume is often incorrect), and this is not accounted for in the current Simplified EKF. Consequently, adopting an additive forecast error term ($\mathbf{Q}$) (not used here, but used in related studies with the full EKF) that is parametrised to depend on the model rainfall would help to offset the reductions

in $\mathbf{H}_2$ after rain, giving a more symmetric relationship between $\mathbf{K}_2$ and rainfall. Work is currently underway to incorporate a rainfall-dependent $\mathbf{Q}$ into the EKF (Mahfouf, 2010).

While the above behaviour of $\mathbf{K}$ will cause the assimilation to favour adding moisture to the model surface, this is partly offset by the non-linear response of the model to the applied updates. In particular, when the ISBA model soil moisture is perturbed away from the model's preferred trajectory, the rate at which it will converge back to its preferred (typically incorrect) trajectory depends on the soil moisture state. Specifically, the model will return to its preferred climatology more rapidly in wetter conditions, than in drier conditions. This is evident in Table 1 of Thirel at al (2010) - see the second and eighth lines of data, showing the impact on the model forecast stream flow ("no assim") of applying positive and negative 10% perturbations to the model soil moisture. The positive perturbation resulted in a larger initial change in the forecast stream-flow than the negative perturbation, because the stream-flow is more sensitive to soil moisture for wetter soils. However, the influence of the positive perturbation on the stream-flow forecasts reduced much more rapidly than that of the negative perturbations, so that after 21 days the impact on the stream-flow was less for the positive perturbation than for the negative perturbation. Consequently it will be more difficult for an assimilation to correct a dry bias in the model, since the positive increments will be more quickly lost, than for a wet bias.

In summary the SEKF assimilation was biased, with a tendency to make larger increments when the observation departure was positive. This was then offset by a tendency for the positive increments to be forgotten by the model more rapidly than negative increments. While the influence of these two phenomena on the model bias will have offset each other to some extent, it is impossible to determine by how much, and what their net combined effect on the model bias is. Hence, the finding that the assimilation reduced the biases in the ISBA model cannot be assumed to imply that this was due to the ASCAT data correctly detecting errors in the NRT w_1. In response to this the paper has now been substantially rewritten to include much of the above discussion. While the basic experiments presented are unchanged, the presentation of the results and the conclusions drawn from these results have been updated. Specifically, any implication that the results of these experiments necessarily reflect positively on the skill of the ASCAT data has been removed, and a discussion has been added of the consequences of the above issues for assimilating near-surface soil moisture data into ISBA with the SEKF, as well as the steps that could be taken to better address these issues in the future.

1) p.5434 (lines 22-25). I had problems getting a grasp on the author's definition of the observation operator here. In (3), H is defined as a diagnostic operator (mapping between states and observations at the same time) so why is a dynamic model integration with a 24-hr forecast window required to define it? This makes it sound like the observation operator is mapping between two quantities at different times. . .which is inconsistent with the definition of H in (3). This is probably just my ignorance...but it should be clarified.

- In the SEKF used here H consists of a 24-hour integration of the forecast model (taking the state vector forward in time), followed by a conversion to the observation equivalent variable (the diagnostic operator). Accordingly, the observations are 24-hours later than the analysis time. This has now been explained more explicitly in the paper, and the t index has been removed from equation 3 to reduce the implication that the ith observation and ith analysis update occur at the same time.

2) p.5437 (lines 10-20). Equation 1 has be inverted in order to output VSM and perform the mapping discussed here (ASCAT SDS to VSM in the SIM_NRT range)...right? If

so, that should be clarified here.

- Yes, equation 1 was inverted. This sentence has been updated to state this explicitly.

3) p.5434 (lines 12). In the SEKF, does P evolve during the forecast step? The text here seems to suggest that it does but then doesn't describe how it evolves.

- Yes, since a 24 hour forecast is included in the observation operator, applying H to B carries B_0 forward in time, so that HB_0H^T represents the model error in the observed variables (w_1) at the end of the 24-hour forecast. In line with comment 1, the temporal evolution of B_0 through the assimilation cycle has now been explicitly described.

4) p.5437 (lines 20-25). Isn't the fact that the transferred soil moisture are unbiased (despite having the same max/min bounds) just due to non-equal skewness in the two soil moisture distributions? I don't know if you need any exotic explanation for this...maybe just say that it's well-known that modeled and remotely-sensed soil moisture almost never demonstrate the same pdf (i.e. the same 1st, 2nd AND 3rd order statistical moments)?

- Yes. This was the exact point we were attempting to make: even though the ASCAT data have been re-scaled in such a way that they match range of the ISBA model, there are still differences between the PDFs, which was expected given the fundamental differences between the two variables. These sentences have been changed as suggested above.

5) Figure 4 – explicitly define what is meant by "improvement in RMSE" in the caption. At first glance, I wrongly interpreted positive values to indicated degradation.

- The caption has been changed to "reduction in RMSE".

6) p.5444 – define “discharge ratio”

- "(discharge ratio=forecast discharge / observed discharge)" has been added at first reference to the discharge ration.

7) The data assimilation evaluation strategy applied here is very similar to the “data denial” approach applied in Bolten et al. (2010) (i.e. use good retrospective forcing to create a baseline, degrade using realistic real-time data and evaluation data assimilation based on its ability to recover the baseline). A citation using be useful to establish that this is an appropriate and accepted methodology for evaluating a land data assimilation system.

Bolten, J.D., W.T. Crow, T.J. Jackson, X. Zhan and C.A. Reynolds,"Evaluating the utility of remotely-sensed soil moisture retrievals for operational agricultural drought monitoring," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 3, 57-66, 10.1109/JSTARS.2009.2037163, 2010.

- This paper has now been referenced in the introduction. Additionally, the contrast in the results obtained by Bolten et al (2010) (as well as Crow et al 2010) has also been mentioned in the discussion. Those two papers use TRMM precipitation as their degraded forcing, which is of much lower quality that the NRT SAFRAN forcing used here. Hence the evaluation criteria used in this paper was far more ambitious (and the results were less conclusive).

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