#Referee 1

Assimilation of vegetation optical depth retrievals from passive microwave radiometry
Kumar et al., 2020

This manuscript shows the impact of microwave-based VOD and/or soil moisture data assimilation into the Noah-MP as part of LIS. The results are extensively evaluated using a wide set of independent estimates of various variables (incl. evapotranspiration, GPP, soil moisture, discharge). Overall, this is a great paper, worthy of publication after some clarifications and corrections.

We really appreciate your thoughtful comments and have made significant changes to the manuscript in response to your suggestions. Please see below for our responses to your specific questions.

Methodology:

- Why is VOD rescaled to MODIS LAI (GLASS) instead of rescaling it to the model LAI? There may be a large bias between the MODIS LAI and model LAI, which would violate the Kalman filter assumptions. Perhaps show the spatial map of RMSD between the model LAI and the VOD after transformation to LAI (via GLASS)?

Thanks for the comment. The reviewer is correct if there are large and systematic biases between the model LAI and the MODIS LAI, the rescaling approach used here would be problematic. The approach was employed here based on the findings from the previous study assimilating GLASS LAI (Kumar et al., JHM 2019), which showed that the overall bias between the model and the observation was small (Figure 2 of that paper). Further, Kumar et al. 2019 study showed that the major improvements from assimilation are primarily from the correction of seasonality of vegetation, rather than from bias improvements (See Figures 1, 5, 6, and 7 in particular). Similar impacts are seen with the results in the current manuscript. For example, the time series at location A (Figure 7) shows the phase shift in ET introduced by VOD-DA, which results in an improvement in ET and GPP (Figure 3,4). The transformation of VOD into the LAI space, therefore, provides a quick way to enable the assimilation of VOD. To acknowledge this issue further, we have modified the description as follows on page 7:

"Note that the rescaling strategy used here also relies on the fact that the systematic errors between the GLASS LAI data and the NoahMP LAI are small, as demonstrated in Kumar et al. (2019b). In this prior study when GLASS LAI retrievals were assimilated within NoahMP, the demonstrated improvements were primarily from the adjustment of vegetation/crop seasonality, rather than from the correction of systematic errors. In addition, the positive impacts from the use of this strategy shown in the following sections, further confirm that this rescaling approach is reasonable."

Another main concern with GLASS is that this product is filled with climatological values. Optical data do not have the same good coverage as microwave data (see also comment below). By now mapping VOD to GLASS, we basically undermine a key advantage of microwave data, i.e. we destroy the VOD information by mapping it to climatological LAI where insufficient LAI data are available.

The spatial gap-filling in the GLASS product is enabled by a general regression neural network (Xiao et al. 2014) (and not climatology) and prior studies have shown that the improved spatiotemporal coverage of the GLASS product has greater utility over that of the standard MODIS LAI product (Liang et al. 2014). The validation of the GLASS data and comparison against LAI products have also demonstrated the high quality of this product (Liao et al. (2012), Fang et al. (2013), Xiao et al. (2016)). Further, the previous study Kumar et al. (2019) demonstrated that the assimilation of GLASS LAI lead to significant improvements in the simulation of vegetation seasonality, water and carbon budget terms. The improvements in the simulation of vegetation seasonality over human managed agricultural areas were an important outcome of this study. The results in Kumar et al. (2019) confirm that the improvements from assimilation are not simply because of climatological improvements. The time series comparisons in this paper show that the variability in the VOD time series is preserved even after rescaling (Figure 7).

- Why is VOD rescaled instead of installing an observation operator (H) that maps the model LAI to VOD? The latter would have the advantage that the Kalman gain would be able to capture more of the dynamic errors.

Thank you for raising this point. The use of an observation operator (forward model) that maps LAI to VOD is another possible approach to assimilating VOD and we agree that it would enable capturing the dynamic errors. Note that we have already acknowledged this as a natural extension of this study on page 19 as:

"As noted in the description of the data assimilation methodology, the VOD retrievals are assimilated by rescaling them to the GLASS MODIS LAI climatology. This approach was employed as the prior study Kumar et al. (2019b) demonstrated significant positive impacts from the assimilation of the GLASS LAI data. Such an approach is needed also because the LSM does not have a prognostic representation of VOD. Though the beneficial impacts observed in the results indicate that this is a reasonable strategy, the rescaling essentially ignores the information on vertical heterogeneity in the canopy from these sensors. For example, the X-band data is documented to be more sensitive to the vegetation, whereas the L-band data is more representative of the lower canopy. A more direct use of the VOD data is likely to help in resolving these sensitivities within modeling. Extensions to this study that either uses a prognostic representation of VOD or a forward model that simulates VOD will enable such approaches. The current study serves as a useful benchmark for such future efforts."

- Why is VOD (after rescaling) not bias-corrected, whereas soil moisture is?

There are a number of reasons for employing bias-correction (and essentially assimilating anomalies only) for soil moisture DA, whereas the VOD is assimilated directly after rescaling to LAI. Direct assimilation of soil moisture retrievals is difficult because there are significant differences between the model estimates and satellite retrievals, in terms of their geophysical definitions and horizontal and vertical representativeness. Since the modeled soil moisture is essentially and index of wetness, a highly model-dependent quantity (Koster et al. 2009, Journal of Climate), it is generally inconsistent with satellite soil moisture retrievals and cannot be directly assimilated. As noted in our response about the rescaling of VOD, we use this approach based on success of directly assimilating LAI, as reported in Kumar et al. (2019). The text on page 8 clarifies these issues:

"Soil moisture in the LSMs is a model-specific quantify, an index of the moisture state (Koster et al. (2009)). As a result, there are significant differences in soil moisture estimates from different LSMs, even when forced with the same meteorology and land surface parameters (Dirmeyer et al. (2006)). Similarly, remote sensing based estimates of soil moisture are also indirect measurements generated through a retrieval model from direct measurements of the microwave emission of the land surface. Therefore, direct assimilation of soil moisture without resolving these inconsistencies is meaningless. Here we apply the commonly used strategy of CDF-matching (Reichle and Koster (2004)) to address the relative differences between the remote sensing and LSM-based soil moisture by rescaling the soil moisture retrievals into the LSM climatology before assimilation."

- Isn't the SMAP VOD simply pre-calculated before retrieving soil moisture? The ATBD says that SMAP VOD is based on optical data (NDVI & stem index) and then used as an ancillary input to the soil moisture retrieval. It is then not surprising at all that the SMAP VOD corresponds more to optical LAI estimates (L. 222).

The SMAP VOD used in this study is not the pre-flight VOD discussed in the ATBD. The VOD product used here is the SPL2SMP_E and its retrievals based on using both polarizations (V and H pol) to estimate soil moisture and VOD. We modified the description in section 2.1 as:

"The SMAP satellite launched in January 2015 is a mission dedicated to measuring soil moisture and freeze/thaw states, employing a passive microwave radiometer to collect measurements of vertical and horizontal polarizations of L-band brightness temperature data at an incident angle of 40°. The retrievals from SMAP are also developed using the τ-ω model. The soil moisture retrievals are made using a single channel algorithm using the vertical polarizations (Chan et al. (2018)) whereas the VOD retrievals employ both polarized brightness temperature observations (Chaubell et al. (2020)). Though the sampling resolution of the SMAP radiometer is approximately 36 km, 150 oversampling of the antenna overpasses is used to enhance the spatial resolution to 9 km. This 9km, level 2 SMAP dataset (SPL2SMP−E) is used in this study. "

- Regardless of how SMAP VOD is pre-calculated or retrieved, the SMAP VOD and soil moisture estimates will have strongly correlated observation errors. Are these accounted for? If not, at least the individual errors should be increased to compensate for this lack or error correlations.

When SMAP VOD and soil moisture estimates are assimilated jointly, note that we simply combine two separate sequential assimilation instances (the observation vector does not consist of both VOD and soil moisture). In addition, the state vector used in these sequential assimilation instances are different. The soil moisture assimilation employs model soil moisture states whereas LAI is updated in the VOD assimilation instances. We have clarified this detail in the manuscript on page 17 as:

"As the results in the previous section indicate that assimilation of soil moisture and VOD can provide mutually exclusive information, an assimilation configuration that employs these retrievals simultaneously is developed. Note that in this joint configuration, rather than augmenting the observation vector to encompass both VOD and soil moisture retrievals, we simply combine the two separate sequential univariate assimilation instances within a single integration. Similar to the univariate configurations, in this multivariate configuration, soil moisture retrievals are used to update the surface soil moisture state, whereas VOD retrievals are used to update the prognostic LAI variable within the LSM."

- The microwave retrievals are not at the same resolution as the model 1/8ˆo resolution. How does the 1-dimensional filter then work? There has to be some down- or upscaling.

The 1d filter employs interpolated observations (using nearest neighbor approach) within the assimilation. This detail has been clarified in the text on page 7 as:

"In this study, the innovation calculations employ observations interpolated to the model grid using a nearest neighbor approach."

- Data assimilation update vector: can you explicitly state the content of the update vector and does it change between VOD and SM assimilation experiments? (I do not think the vector should change with the experiment, but in between the lines of the text, I had the impression that it was changed; if done right, the update will naturally go where it needs to go).

The state vector is not the same for VOD and SM experiments. In the VOD experiment, we update LAI and leaf biomass whereas in the SM experiment, we update the top soil moisture layer. These details are specified in the text on page 9 as:

"For VOD DA, additive perturbations with a standard deviation of 0.01 are applied to the model LAI fields (Kumar et al. (2019b)), every 3 hours. The updated LAI from DA is divided by the specific leaf area to revise the leaf biomass variable within Noah-MP. The state vector used in the soil moisture DA consists of the top soil moisture layer of Noah-MP, which is perturbed with an additive noise of 0.02 m^3/m^3, applied every 3 hours.

The perturbations also include time series correlations employed through a first order autoregressive (AR(1)) model with timescales of 24 and 3 hours, for the forcing and model state variables, respectively."

- Are the perturbations for all DA and OL experiments exactly the same?

There are no perturbations applied to the OL. In the DA experiments, the same exact perturbations are applied to the forcing variables. Similarly, the same set of model state perturbations are applied in all VOD DA configurations. Since the state vector used in the soil moisture DA is different, the state perturbations differ (as explained on page 9).

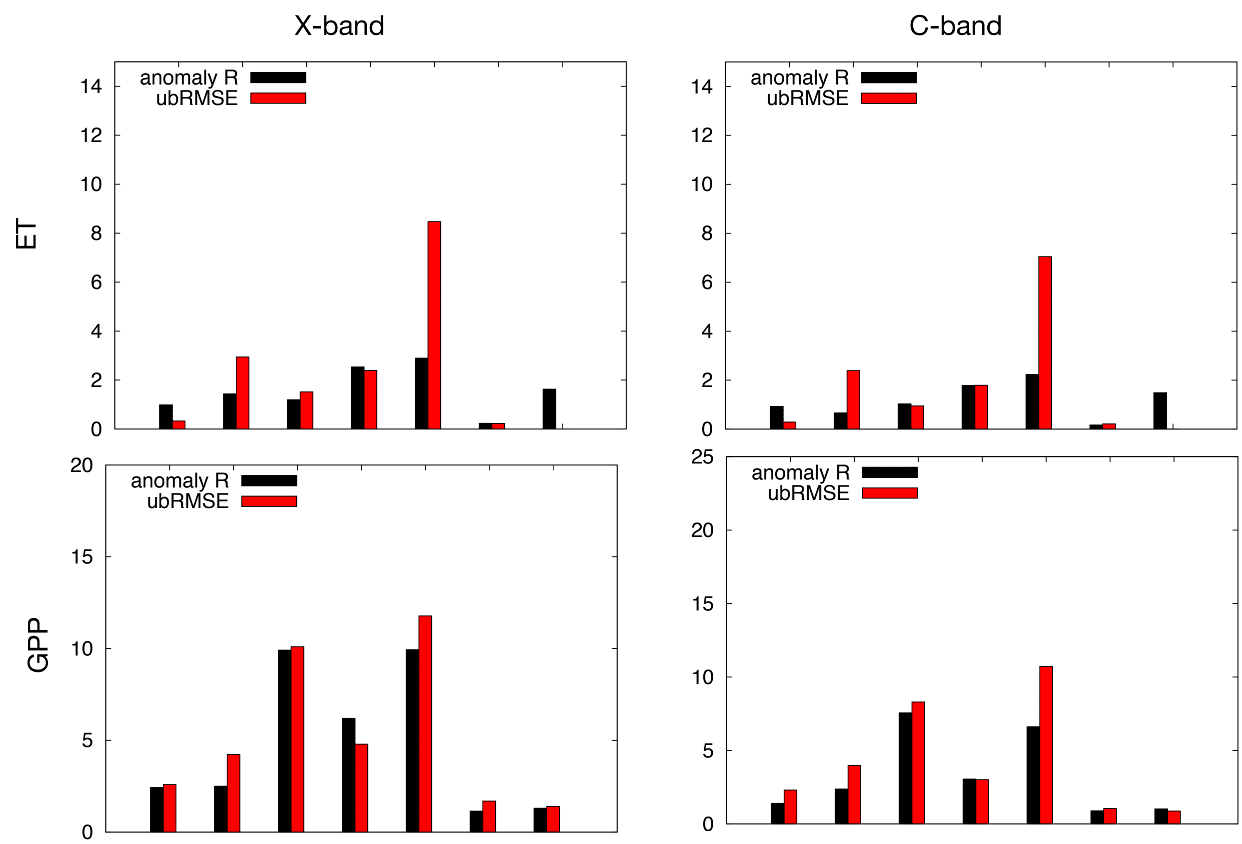
- Soil moisture is rescaled via CDF-matching on a monthly basis. Is this monthly using multi-year information, or year by year?

This is done monthly using a multi-year information. We have added this clarification on page 7 as:

"Monthly CDFs using multi-year information are computed for both the VOD and LAI datasets using all available data, at every model grid point."

Results:
- Fig 5: how is the change in unbiased RMSE or anomaly correlation for ET and GPP?

Based on your query, we computed the changes in the unbiased RMSE and anomaly R for ET (using ALEXI as the reference) and GPP (using FLUXCOM as the reference). The figure below shows the % improvements from X-band and C-band DA. The results are similar to Figure 5, except that the level of improvements are smaller for anomaly oriented metrics. Improvements are also larger for moderate vegetation, similar to Figure 5. In the interest of not overwhelming the reader with additional metrics, we have not included these comparisons in the article.



– L. 345: monthly mean? Year by year or multi-year means?

The anomaly R values are computed based on multi-year monthly means. We have updated the text on page 11 to say:

"The anomaly R value at each grid point is computed based on daily soil moisture anomalies (of model and in-situ observations) calculated by subtracting the multi-year monthly mean values from the daily averages."

- L. 428: "seasonality in the anomalies and not the mean signal is the key factor in the CDF-matching"? But the CDF matching exactly tries to harmonize the mean signal of the observations and simulations. Rephrase?

We have rephrased this statement on page 14 as:

"Compared to location A, over the grassland location B, there are small climatological differences in the VOD retrievals from X- and L-band. These amplitudinal differences are reduced by the CDF matching, as the rescaled X- and L-band VOD estimates are similar to each other."

- Around L. 510: one of the key results of the paper is in this paragraph and only supported by 2 time series at single points. It would be nice to have a more robust or convincing figure. For example, the correlation between RMSD(DA-OL) vs long- term mean soil moisture and vegetation for various DA experiments for all pixels, or something else that is spatially covering?

Thanks for the comment. We respectfully disagree that contrasting the relative impacts from soil moisture and VOD DA are only supported by 2 time series at single points. Figure 8 essentially presents a spatially distributed comparison of long-term soil moisture, similar to the suggestion of the reviewer. Direct evaluations of soil moisture and vegetation is difficult as those sources are assimilated in our integrations. Figure 11 is supposed to supplement the spatially distributed evaluations of Figures 8-10, by drawing the contrast on the influence on the ET components. Reference datasets of the ET components (much less spatially distributed) are difficult to obtain. Therefore, we believe the current set of evaluations are sufficient to convey the key findings of the paper.

Textual issues:
- L. 70: typo guaranteed

Corrected
- L. 177: write “1d”

Corrected
- L. 292: pattern (without s; verb is singular)

Corrected
- L. 340: indicate earlier on that the results are not shown.

Though figures are not shown, the results of these evaluations are summarized in the text. We believe it is appropriate to provide the caveats of Figures not being shown for each comparison.

- L. 365-368, Table 1: text and caption are cumbersome, consider rewriting to be more precise. Table 1 and caption are not clear. Caption first line “*for* DA configuration*s*”? These are percentage improvements *relative to the OL*? What are the 2 numbers in the evaluation against ALEXI? What is the purpose of the units here? The values are all percentages, no?

The caption now reads:

“Comparison of the percentage improvements in domain averaged skill metrics (relative to the model OL) for DA configurations that assimilates MODIS LAI (from Kumar et al. (2019b)), and those that employ X- and C-band VOD retrievals, for different variables. “

The table has also been updated after removing the units. The evaluation against ALEXI shows the percentage improvements in RMSE and R. The table row has been updated to reflect this detail.

- (!) Fig 6: panels or caption are not correct (RMSE-R).

Corrected

- (!) Fig 9: caption is not correct.

Corrected

- L. 498: switch the sentence to start with location C and then location D. Confusing now.

Assuming that the reviewer is talking about line 488, the updated text on page 18 now reads:

“Location C is in the arid western U.S. with moderate vegetation, whereas location D is in the eastern U.S., representing a wet region with thick vegetation.”

- Fig 11: LAI for location B: this is troublesome. The model LAI shows a clear interannual difference. With the DA, this interannual difference is removed. I am afraid that here, the VOD values are possibly rescaled to a multi-year average GLASS climatology, which inherently would not hold any interannual variability.

We assume that the reviewer is talking about Figure 7 instead of 11. In the figure, the reviewer is correct that the OL LAI shows an interannual difference unlike the DA time series. However, this is not due to the influence of GLASS climatology. Note that the rescaling of VOD is done to the GLASS data to generate LAI inputs for DA. Therefore, the model OL has no influence in the rescaling process. The time series of VOD (shown in the top panel) does not show a big interannual difference, which is why the rescaling does not show large interannual differences in LAI.

- L. 568: capitalize Kalman

Corrected

- L.577-583: do something else than starting with “Though” in 3 subsequent sentences.

The sentence on page 18 has been changed to say:

“The impacts on soil moisture, terrestrial water storage, and streamflow from VOD DA are found to be marginal.”