REVIEWER 1

General comments: This study proposes observation operators to enable the assimilation of SMAP 1.4 GHz vertically polarized signals and AMSR2 10.65 GHz vertically polarized signals, with the objective of improving LAI and soil moisture retrievals within LDAS-Monde. The analysis focuses on cropland areas at the global scale. To facilitate the direct assimilation of passive microwave brightness temperatures (TB), the authors develop an observation operator based on neural networks, linking geophysical and static predictors to the observed TB. The implementation of these forward operators within LDAS demonstrates improvements in the departures, particularly for SMAP observations, likely due to the higher variability of TB at L-band compared to X-band. Regarding LAI, the results indicate a positive impact at the global scale. However, at regional scales, the results appear more mixed and depend on the evaluation metric, with improvements mainly observed in terms of bias. I fully agree with the authors on the importance of such studies aiming at the direct assimilation of observations, and I support the general methodology presented here. I also recognize the amount of work from designing the observation operator to experiments within an assimilation system. However, I have two major concerns: 1) I find it limiting that only vertical polarization is exploited, while horizontal polarization is also available and contains valuable information. Although I understand the challenges associated with developing observation operators for H-polarization, it would have been beneficial to include results for this polarization, even if their performance is inferior to that of V-polarization. Presenting such results, at least for observation operator, would provide a more complete picture. Scientific progress also relies on documenting difficulties and limitations, which can guide future developments toward assimilating a broader range of observations; 2) The manuscript is sometimes difficult to follow. Certain information appears to be missing or is introduced only later in the text, which affects the overall clarity and understanding especially for reader which is not exactly in the field. More detailed comments are provided in the specific remarks below. I tried to separate them between major and minor even though some might in the middle.

RESPONSE 1.0:

Thank you for the review and all your suggestions. Regarding your concern (1) we included our training results for H polarisation to show that is has no benefit on the performance of the observation operator. For concern (2), we addressed all the remarks from both reviews in order to make the text easier to follow.

COMMENT 1.1: Title and abstract: It is not very clear for the reader that the study focuses only on cropland areas, despite being conducted at the global scale. This should be explicitly stated in both the title and the abstract to avoid potential misunderstanding.

RESPONSE 1.1:

We agree, we propose "A neural-network based forward operator for the assimilation of microwave satellite observations with LDAS-Monde on global croplands for improving land-surface variables" for the title. We will add this specification in the abstract (L. 3-4) as well:

[…], we assimilate the observations of the satellite microwave sensors SMAP and AMSR2 with our land-data assimilation system (LDAS) on global croplands."

COMMENT 1.2: Section 4.1: From my point view, important information regarding the NN configuration is missing. While the outputs are the brightness temperatures (TBs), it is unclear whether a single NN is used to predict both AMSR2 and SMAP TBs, or whether separate networks are trained for each instrument. This information only appears later in Section 5.1, from which I infer that different NNs are used. This point should be clarified earlier in the manuscript, within the methodological description of the observation operator.

RESPONSE 1.2:

Yes, we trained one NN for each sensor separately indeed. We propose to add this information in Section 4.1:

Our strategy is to train a NN on the Tb observations of each sensor separately in a first step, and subsequently applying the resulting weights as a forward operator to the model variables during the assimilation cycle. In this cycle, each sensor observation is assimilated separately. Training and assimilation of both sensors simultaneously is possible. However, a separate treatment is required at this stage of research to understand the behaviour of the system.

COMMENT 1.3: Section 4.1: The study focuses only on vertical polarization. In Corchia et al. (2023), this choice is justified because they rely on ASCAT active instrument, which only provides vertical polarization. However, in the present study, both passive instruments SMAP and AMSR2 provide horizontal polarization, which contains important information, particularly regarding vegetation. Several studies (e.g., [1–6]) demonstrate the added value of combining both V- and H-polarizations for vegetation-related applications. The omission of H-polarization therefore requires stronger justification or, ideally, complementary analysis.

RESPONSE 1.3:

We actually studied H polarisation as an output parameter for the NN as well. The improvement of using both H and V polarisation compared to only V polarisation turned out to be negligible for both instruments. For simplicity but also to be comparable with the previous studies by Corchia (2024), we decided to use V polarisation only.
We propose to adapt the paragraph in question but also add corresponding Taylor plots in the appendix/supplements (Figs. R1.1, R1.2) to demonstrate the (lack of) impact:

We trained on Tb of both H- and V-polarisations originally. In accordance to the findings of Corchia (2024), we found that the addition of H polarisation is not able to improve the skill metrics of the NN significantly compared to training on V-polarisation only. Additionally, H polarisation yields significantly higher RMSE values than the V polarisation. This is probably due to the generally higher variability of emissivity in the H polarisation (see De Gélis et al. 2025), which seems to be difficult for the NN to match. In general, this suggests that changes in surface water have a smaller impact on emissivity than changes in surface temperature, the latter of which is more effectively traced by V polarisation (Owe et al. 2001).

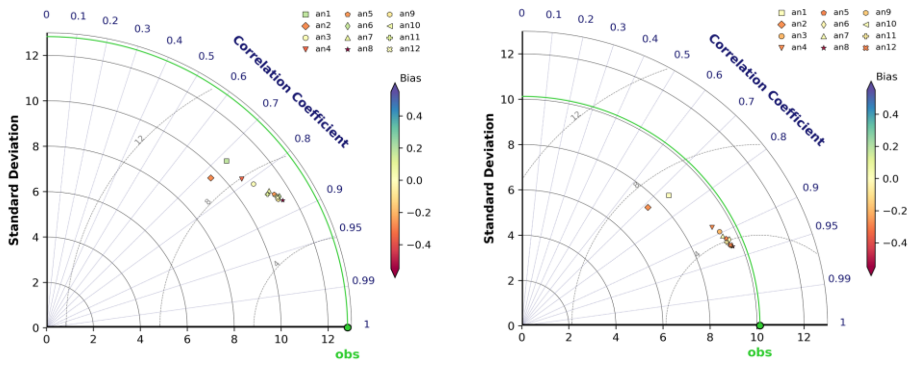

Figure R1.1: Taylor diagrams (adapted from Rochford 2016) of AMSR2 training experiments using only H (left) or V polarisation (right). The standard deviation is shown on the x- and y-axes, the correlation coefficient corresponds to the polar angle, the RMSE is marked by the distance from the observations (green point), and the bias is indicated by the colour of the respective point.

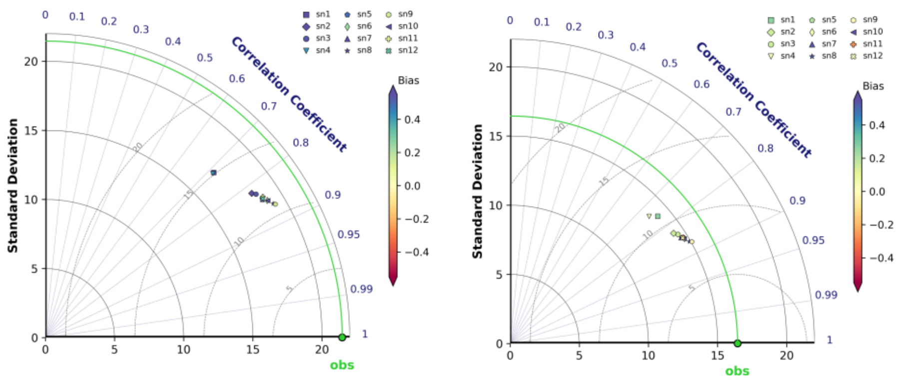

Figure R1.2: As in Fig. R1.1, except for the SMAP training experiments.

COMMENT 1.4: Section 4.1: The statement "likely due to lower emissivity" is somewhat misleading. While it is true that emissivity at H-polarization is generally lower than at V-polarization, the main difficulty in reproducing H-polarized signals arises from their higher variability compared to V-polarization. Moreover, the cited reference attributes the difference in performance to the "lower emissivity variability observed at V polarization," rather than lower emissivity at H-polarization. Thus, H-polarized signals are more challenging to model because of their strong variability under varying surface conditions (e.g., vegetation, soil moisture, surface water presence, terrain roughness). This point should be clarified or corrected to avoid misinterpretation.

RESPONSE 1.4:

We agree, we included changes in the paragraph above to clarify (see Response 1.3).

COMMENT 1.5: Section 4.1 and Table 1: A clearer and more detailed description of the potential input parameters is needed. Some variables may not be easily understood by readers unfamiliar with the ISBA model or ECOCLIMAP-SG. For example, the choice of using soil water index and soil temperature from layer 2 (and not another layer) is not explained until Section 4.2. Or for example what do you expect the long/short wave

radiation brings to observed signal. More generally, it would be beneficial to briefly describe the expected relationships between the presented input parameters and the observed TB. This could be included in Section 3 to better motivate the selection of predictors.

RESPONSE 1.5:

The selection of input parameters was not only motivated by potentially correlated variables but also by what is easily accessible for the training/testing period. We tested variables of deeper soil layers as well in the beginning but since they did not seem to have an impact, we omitted them for the systematic tests. We will elaborate on this.
We propose the following addition:

For the input fields, we employ observed LAI (Sect. 2.3) as well as different static (e.g., coordinates, physiographic data) and variable model fields as predictors and analyse their contribution to the final training performance. Since the ISBA LAI is known to be biased, we expect more accurate information from observed LAI.
As model fields, we select soil moisture and temperature of the soil layer (0.01-0.04 m), which corresponds to the second layer in the ISBA model. Deeper layers can be used as well in principle, but tests did not show any benefits, which is likely due to the strong cross-correlation of the different layers, i.e. no additional information is brought into the system. The top most layer (0-0.01 m) is subject to rapid changes determined by atmospheric forcing and therefore, generally considered challenging in the context of assimilation (Draper et al. 2009, Vural et al. 2021). Unlike X-band measurements, such as those taken by AMSR2, which have a shallower penetration depth, observations at longer wavelengths, such as the L-band (SMAP), are more sensitive to the subsurface soil layer (Escorihuela et al. 2010; Enthekabi et al. 2010, Yee at al. 2017). Passive observations are highly dependent on surface altitude and surface roughness at different scales (Mätzler and Standley 2000, Njoku et al. 2006, Monerris et al. 2008). Consequently, terrain altitude and topographic complexity are expected to be important factors in the accurate simulation of Tb.
Depending on the wavelength, microwave observations are more or less affected by the atmosphere. Thus, atmospheric effects cannot be completely neglected when retrieving surface variables from microwave emissions, especially at the X band. To account for this, we also examine the effect of using relevant atmospheric forcing variables (see Sect. 3.1) as predictors, such as air temperature and humidity (Tair, Qair), long-wave downwelling radiation (LWdown) and shortwave downwelling direct and scattered radiation (SWdir, SWsca). We are aware that other variables might contribute as well to the Tb. At one point, too many predictors might increase the probability of overfitting though. As a consequence, we try to keep the number of predictors small and, additionally, test the systematic omission of static predictors.

COMMENT 1.6: Fig 3: The results obtained with AMSR2 appear to exhibit a negative bias. Could the authors provide insight into the possible reasons for this behaviour, particularly if separate neural networks are trained for each instrument (as suggested in Section 5.1)?

RESPONSE 1.6:

Yes, separate neural networks were trained for both instruments. We added this information in the answer to Section 4.1 (see above).
Part of the paragraph about the Taylor diagram should actually be moved to the beginning of the performance section (4.2) and can then be complemented with the second part of the

following:

The Taylor diagram (Fig. 3) and Table 1 suggest that most of the experiments are actually quite similar. There is a clear trend towards better matching of STD, RMSE and correlation, as well as poor performance by experiments that do not use enough surface variables as predictors. Both, Fig. 3 and Table 1 show that biases in both directions can remain. This is an indication that the NN is either lacking information, as in e.g. sn10 and an12, that keeps the simulated data close to the observations on average but also too many predictors as in an8 seem to result in an unbalanced system.

Additionally, we propose to add this after the paragraph starting in line 197:

The 2D histogram in Fig. 5 (right) for AMSR2 suggests that the negative bias is primarily caused by the tail of the distribution. This means that low values are overestimated, whereas fewer high values are underestimated. The behaviour traced by Fig. 3 indicates that attempting to match the variability of the data more closely is compensated for by an overly strong correction to the mean. In contrast, the SMAP model equivalent (Fig. 5, left) is driven by large scatter at the lower end, which seems to offset the bias for large observation values.

COMMENT 1.7: Additionally, the readability of the figure could be improved. The ordering of the experiment numbers seems shuffled, making it even more difficult to relate each case to its corresponding input parameters. As a minor suggestion, inverting the color scale (e.g., blue for lower values) could improve interpretability.

RESPONSE 1.7:

The ordering of the experiment numbers was improved (see Taylor diagrams above), the colour map seems to be a personal taste though, red is frequently used for negative values.

COMMENT 1.8: Data Assimilation: From what I understood, the assimilation tests are made separately for each sensor, which is important to understand what each observation is bringing. Did you also tried to assimilate both instruments to see if the information may be complementary?

RESPONSE 1.8:

Indeed, we did not assimilate both instruments together, in order to understand each sensor's behaviour well enough before combining them. We propose to start Section 5.1. like this:

We implemented the observation operators described in Sect. 4 into our assimilation system (see Sect. 3). Note that both sensors are treated separately, both during the training phase and during assimilation. In other words, the process flow sketched in Fig. 2 is applied to each sensor individually. While a joint assimilation of both SMAP and AMSR2 observations is technically possible, at this stage of the research we consider the system too immature to progress to the next, more complex stage of joint assimilation.

COMMENT 1.9: Conclusion (L. 367): The conclusion states that SMAP outperforms AMSR2, which seems inconsistent with statements made in the abstract and Section 5. This discrepancy should be clarified to ensure consistency throughout the manuscript.

RESPONSE 1.9:

SMAP *can* indeed outperform AMSR2 on some specific regions (e.g., India) but in total, AMSR2 exhibits better performance. We will rephrase this to clarify:

Compared to the SMAP assimilation experiments, the AMSR2 experiments better match the temporal evolution of LAI on a global scale. However, SMAP outperforms AMSR2 in some regions prone to drought when considering total metrics. For example, in INDI and ENRT, SMAP has a lower RMSE of LAI and a higher SWI anomaly correlation in MUDA.

COMMENT 1.10: Conclusion: This point is linked to point 3. The conclusion should explicitly recall that the experiments are conducted using only vertical polarization, and for AMSR2 only at X-band. Given the known sensitivity of horizontal polarization to vegetation, it would be important to acknowledge this limitation and at least briefly discuss its implications.

RESPONSE 1.10:

We agree, we propose to address this as follows in the beginning of the section:

In this study, we investigated the advantages of using a neural network as an observation operator in LDAS-Monde for assimilating vertically polarised microwave brightness temperatures. The optimal NN configurations were determined for SMAP L-band and AMSR2 X-band observations using static predictors, LAI observations, as well as forcing and model variables.

COMMENT 1.11: Abstract: It would be helpful to briefly specify what is meant by "unsolved issues," as this term can be quite broad. Additionally, the reference to "the model" is somewhat ambiguous, as it could refer either to the land surface model or to the neural networks used for the observation operator.

RESPONSE 1.11:

We agree, we propose:

Nevertheless, the seasonal and sub-seasonal variability is still not well represented though due to systematic errors in our land surface model.

(see Rojas-Munoz et al. 2026)

COMMENT 1.12: Introduction (l.23): The expression "providing gridded data" when referring to passive microwave instruments is somewhat misleading. Given the acquisition geometry of these instruments, the data are not inherently gridded but are typically resampled on grid.

RESPONSE 1.12:

We agree, we propose the following:

For LSVs in particular, the availability of microwave-satellite instruments that observe in near-real time and provide data resampled on a grid covering the entire globe offers the opportunity to improve the state of the model variables.

COMMENT 1.13: AMSR2 observation: Only the 10.65 GHz channel is used in this study. It would have been interesting to include additional frequencies, as their sensitivity to vegetation has been demonstrated in several studies (e.g., 6 GHz [3], 18 GHz [4], 36 GHz [1], or multi-frequency approaches [6]). I list this as a minor comment, as extending the analysis to other frequencies would likely require substantial additional work, but it would be worth mentioning in the discussion or perspectives.

RESPONSE 1.13:

This is a very good point, we will add the following after the first sentence of 2.2:

As this study employs a novel approach to gain a more detailed understanding of the assimilation system's behaviour, we utilise the channel most sensitive to vegetation, with low to moderate sensitivity to atmospheric effects. More AMSR2 channels could also be employed, since these can contribute to the estimation of vegetation variables (Prigent et al., 2026).

COMMENT 1.14: A temporal resolution of 3 hours is mentioned, whereas both SMAP and AMSR2 provide only two overpasses per day. This is somewhat confusing, and the distinction between model time step and observation availability should be clarified.

RESPONSE 1.14:

Indeed, we propose to adapt the concerned paragraphs to the following:

2.1. SMAP brightness temperatures
We combine several SMAP swathes by averaging spatially overlapping points from one day, in order to achieve maximum spatial coverage in a single day. Full global coverage is achieved within 2-3 days. Setting up the assimilation system requires partitioning the observations from one full day into bins, as only the assimilation of observations close to the assimilation hour is sensible for the variables under investigation. To strike a balance between maximum temporal resolution and the capabilities of our computing resources, we bin the observations into 3-hour bins for NN training.

2.2. AMSR2 brightness temperatures
Full global coverage is achieved by AMSR2 after approximately two days. As for SMAP, global coverage is obtained by averaging spatially overlapping points from one day.

COMMENT 1.15: (L. 135): For readers unfamiliar with ISBA, the terms C3 and C4 are not meaning-full and should be defined.

RESPONSE 1.15:

We agree, we propose to add:

The terms C3 and C4 refer to two different types of carbon fixation in plants, mainly differing by their efficiency of photosynthesis, which depends on their specific photorespiration rate (Slack & Hatch 1967).

COMMENT 1.16: Fig 1: To facilitate the reading, it would be helpful to include the tile names directly on the map.

RESPONSE 1.16:

We propose the following revised version of Fig. 1:

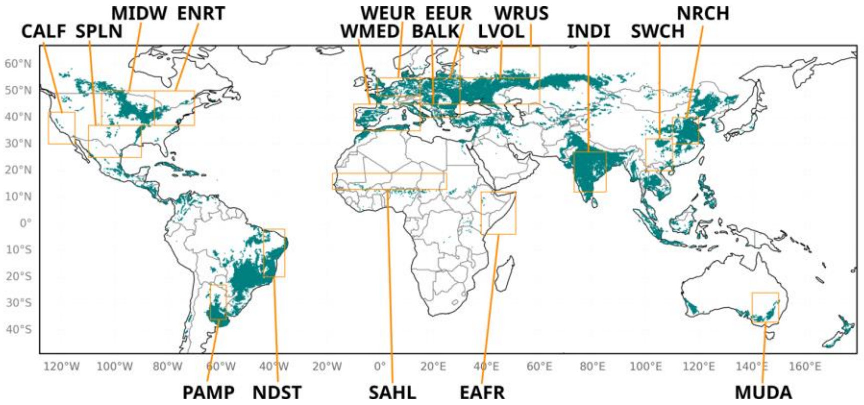

Figure R1.3: Map of the model domain, where the teal points display the croplands as used in the ISBA model. Orange rectangles denote areas that are especially prone to droughts and heatwaves as identified by Albergel et al. (2020). The regions are named in agreement with the notation of these authors.

COMMENT 1.17: Fig 4: For readability, it would be preferable to use full parameter names instead of acronyms.

RESPONSE 1.17:

Thank you for this suggestion. We tried using full parameter names in Fig. 4 by reducing the font size, but unfortunately this made the graphic more difficult to read than the original. As an alternative, we propose the solution shown in Fig. R1.4, in which the acronyms are listed outside the graph and expanded in the figure caption.

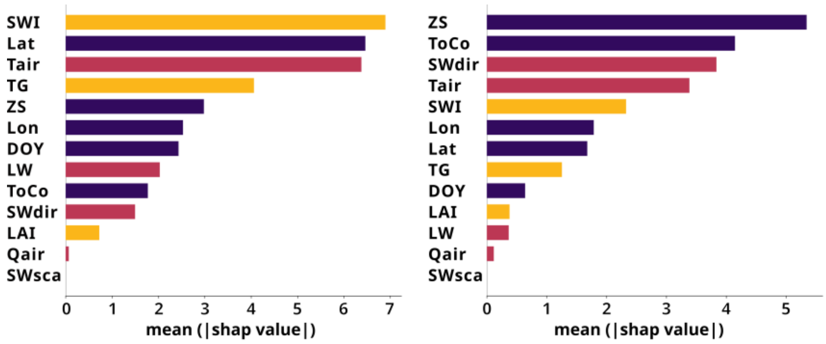

Figure R1.4: Feature importance using Shapley values of training experiments using all tested predictors for SMAP (left) and AMSR2 (right). Metadata predictors are indicated in dark violet, forcing variables in red, and surface variables in orange. The displayed variables are the longitude (Lon), latitude (Lat), day of the year (DOY), LAI, soil water index at level 2 (SWI), soil temperature at level 2 (TG), altitude (ZS), topographic complexity (ToCo), air temperature (Tair), air humidity (Qair), long wave radiation (LW), direct short wave radiation (SWdir), and scattered short wave radiation (SWsca).

COMMENT 1.18: Paragraph 4.2: The neural network is trained to predict brightness temperatures (TB). Given the radiative transfer equation, it is expected that temperature-related variables play a major role. Did the authors analyse intercorrelations between the input parameters? This could help better interpret the model behaviour.

RESPONSE 1.18:

This type of evaluation can be helpful when little prior knowledge exists. We had a good initial idea of the input parameters based on the previous work carried out by Corchia in 2024. In addition, it can be challenging to spot correlations between combined parameter sets. Therefore, we opted to let the NN 'decide'. We hope that the explanations provided in answer R1.5 will clarify our choice of input parameters.

COMMENT 1.19: L 180 181: “This indicates that AMSR2 brightness temperatures are more sensitive to short-range diurnal variations.” Considering that AMSR2 overpass times (≈1:30 AM/PM) differ significantly from those of SMAP (≈6 AM/PM), could this apparent sensitivity be related to observation timing rather than intrinsic sensor characteristics? This comment also relates to the need for a clearer description of input parameters and their physical links to the observations (see major comment above).

RESPONSE 1.19:

Good point. We propose to add the following:

Furthermore, measuring brightness temperatures during the transition phase between day at night like for SMAP, which has overpass times at 6am and 6pm, could make the training more difficult since the state of the atmosphere is changing more rapidly and variations of the variables might be more difficult to learn by the NN compared to a time of the day with more constant solar irradiation. Since we observe that L-band Tb are more variable than X-band Tb, we do not assume that this is the dominant effect though.

COMMENT 1.20: L203-206: This behaviour is expected when latitude, longitude, and day-of-year are used as predictors. If certain regions or seasons are underrepresented in the training dataset, the model may struggle to generalize to those conditions.

RESPONSE 1.20:

We agree, we propose to include this as follows:

In these areas, the NN may struggle to describe underrepresented conditions, which could then be simulated using values closer to the temporal average due to the use of static predictors.

COMMENT 1.21: L230: Should the same observation error be used for both SMOS and

SMAP, given that, although they operate at similar frequencies, the instruments have different characteristics?

RESPONSE 1.21:

Each instrument have their own observation error. We propose to clarify this as follows:

This study did not use SMOS data. Many authors (e.g. Muñoz-Sabater et al., 2018) have shown that the theoretical observation error for SMOS is too small in a data assimilation context. In our data assimilation experiments, the theoretical value for SMAP that we used (8 K, derived using the Desroziers method) also did not produce the best results. In this case, a smaller value is better.

COMMENT 1.22: Fig 8: The comparison is performed at the global scale. However, it might be more rigorous to analyse results separately by hemisphere, as seasonal cycles differ and could impact vegetation-related signals. Given that most croplands are located in the Northern Hemisphere, the figure likely reflects primarily Northern Hemisphere seasonality. Additionally, the legend size could be increased for better readability.

RESPONSE 1.22:

Good point, indeed the larger changes in the SH get lost with the averaging. We propose replacing Fig. 8 by Fig. R1.5, thus separating northern and southern hemispheres.

We propose adding the following to the revised manuscript:

"To account for the different seasonal cycles, we divided the dataset into northern (NH) and southern (SH) hemispheres when evaluating the temporal evolution. For both the SMAP and AMSR2 instruments, we obtained improved temporal LAI evolution compared to the OL run for almost all experiments on both the NH and the SH (see Fig. 8), with a more pronounced impact on the latter."

In Section 5.5., we would adapt the paragraph after L.291 to:

As for LAI, the impact on GPP is more pronounced on the SH than for the NH (see Fig. 8). The experiments do not differ greatly from each other, and in most cases the assimilation moves the analyses further away from GPP observations. Only s3 and a3 have a slightly positive impact over the entire assimilation period. Nevertheless [...]

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and in section 5.6, the paragraph after L. 303 to:

The impact on SWI anomalies is mostly negligible in the NH (see Fig. 8, right). The strongest impact is seen in a3 in the SH, resulting in degradation. The extreme mismatch in the OL time series is difficult to correct. The initial improvement in a3 cannot be maintained over the summer in the SH, as negative increments are added throughout the year.
The different direction of impact between s1 and a1 suggests that the system exploits the information provided by the inclusion of atmospheric forcing in training in a different way here.

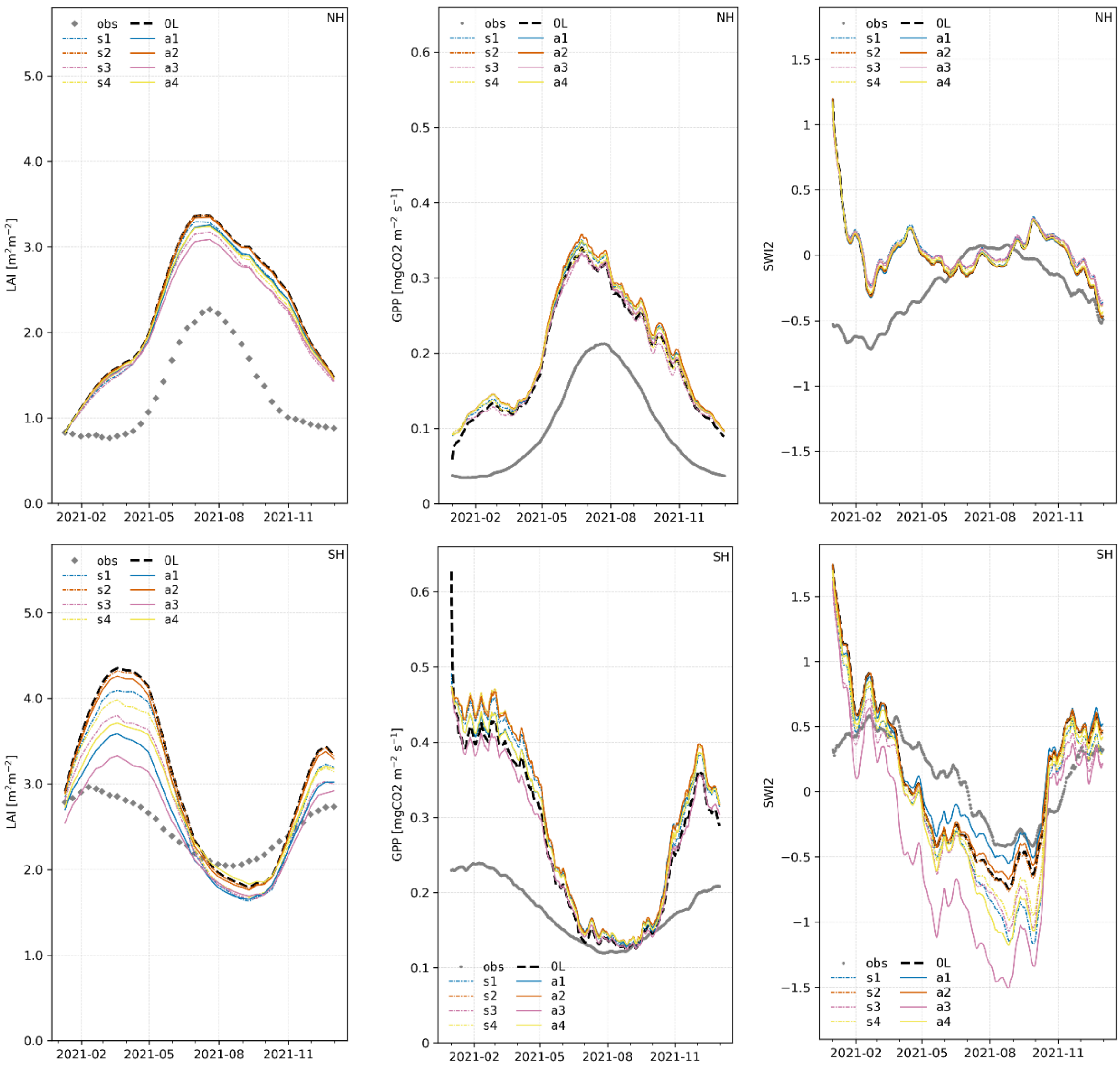

Figure R1.5: Comparison of (from left to right) time series of LAI, GPP, and scaled SWI anomalies averaged over global croplands for northern (NH; top row) and southern hemisphere (SH; bottom row). Observations (grey points), OL (black dashed line), and DA experiments (SMAP: dash-dotted lines, AMSR2: solid lines) are shown in comparison.

COMMENT 1.23: Fig 10: It is not clear over which period these maps are computed. Additionally, the legend title is too small and difficult to read.

RESPONSE 1.23:

The font size of the label of the colour bar will be increased. We propose to improve the figure caption as follows:

Verification against observed LAI. Difference between the RMSE of the LAI of the DA experiment and the OL for experiments s3 (top) and a3 (bottom) over the whole assimilation period (2021).

COMMENT 1.24: Paragraph 5.6: Given that L-band is generally more sensitive to soil moisture than X-band, the reported sensitivity seems somewhat counterintuitive and would benefit from further explanation.

RESPONSE 1.24:

Indeed, this is something that is difficult to understand. We think that the observation operator might neglect physical connections as indicated towards the end of the discussion. To elaborate more on this to emphasise this unexpected behaviour, we propose to add this:

Since L-band observations are generally more sensitive to soil moisture than X-band observations, these results are rather unexpected. We suspect that the observation operator may have neglected physical connections, resulting in unrealistic increments being added to the model background. These increments are ultimately ignored by the subsequent model computations.

COMMENT 1.25: Discussion (l.366-369). The term “unremarkable” is unclear in this context and should be clarified. The analysis presented here is in fact interesting.

RESPONSE 1.25:

You are referring to L. 336-339. We propose to rephrase this sentence to clarify:

Since the model equivalents (Fig. 2) do not exhibit any characteristics that could explain this behaviour, we suspect that the added LAI at the beginning of the year leads to increased soil water depletion and, consequently, an overestimation of the decrease in LAI during the dry season, provided that the physical connections between the variables are not properly mapped by the observation operator.

COMMENT 1.26: (l. 43) GPP acronym appears in the introduction but is only defined in section 2.4.

RESPONSE 1.26:

We will add the definition at the first occurrence.

COMMENT 1.27: (l 77) ‘within one the time interval of 3 hours’: the formulation seems strange; I would have use: within a 3-hour time interval

RESPONSE 1.27:

We propose to rephrase:

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several swaths are combined within a 3-hour time interval.

COMMENT 1.28: Paragraph between lines 182-185: Sentences are very long.

RESPONSE 1.28:

We propose the following:

Some predictors show only minor feature importance (see Fig. 4). We therefore tested whether some of them, especially the static predictors, had become redundant. We found that omitting any of them degraded the performance (Table 1, Fig. 3). We suspect that the marked improvement observed upon adding the forcing variables is primarily due to the inclusion of diurnal cycle information not present in TG2. This is supported by the fact that omitting one of the variables exhibiting a diurnal cycle slightly degrades performance again.

References:

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[4] Jones, M. O., Jones, L. A., Kimball, J. S., & McDonald, K. C. (2011). Satellite passive microwave remote sensing for monitoring global land surface phenology. Remote Sensing of Environment, 115(4), 1102-1114.

[5] Munchak, S. J., Ringerud, S., Brucker, L., You, Y., De Gelis, I., & Prigent, C. (2020). An active–passive microwave land surface database from GPM. IEEE Transactions on Geoscience and Remote Sensing, 58(9), 6224-6242.

[6] Prigent, C., Jimenez, C., Santoro, M., Cartus, O., & Favrichon, S. (2026). Assessing the combination of passive and active microwave satellite observations (1.4 to 36 GHz) to estimate above ground biomass (AGB) globally. Science of Remote Sensing, 100386.
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