Response to Reviewer 3 are structured as follow: (1) 3.X: comments from Reviewer 3, (2) Response to 3.X: author's response and author's changes in manuscript when any. For sake of clarity, line and page numbering from the revised version are used.

Reviewer#3

[...] Overall, the LDAS-Monde system is great, but the paper needs a thorough revision [...]

Dear Reviewer#3 many thanks for reviewing the manuscript and for highlighting its relevance and interest. Your comments and suggestions led to an improved version of the manuscript. Below is a point by point answer to your specific comments, all your editorial and technical comments were accounted for in the revised version of the manuscript.

3.1 [Are the perturbations chosen to get an optimal data assimilation system? Please discuss]

Response to 3.1

Yes, several studies have investigated the size of the perturbations within the ISBA LSM. In particular Draper et al., 2009, for soil moisture, Rüdiger et al., 2010, for LAI. The following sentence has been added to the revised version of the manuscript (as well as the new reference to Draper et al., 2009):

<u>Section 2.1.3 on data assimilation</u>

P.7, Lines 202-204:"Several studies (e.g. Draper et al., 2009; Rüdiger et al., 2010) have demonstrated that small perturbations lead to a good approximation of this linear behaviour, provided that computational round-off error is not significant."

References:

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

Rüdiger, C., Albergel, C., Mahfouf, J.-F., Calvet, J.-C., and Walker, J. P.: Evaluation of Jacobians for Leaf Area Index data assimilation with an extended Kalman filter, J. Geophys. Res., 115, D09111, https://doi.org/10.1029/2009JD012912, 2010.

3.2 [How are the cross correlations between the errors in the various soil layers defined, and the error correlations between LAI and soil moisture?]

Response to 3.2

In the SEKF, no covariance is directly prescribed between LAI and soil moisture or soil moisture between the various soil layers. The sensitivity of model variables to observations is entirely driven by the Jacobian of the observation operator, which is defined as the product of the model state evolution from t to t + 24h and the conversion of the model state into the observation equivalent (see paragraph 2.3.1 and supplementary material of Bonan et al. (2020)). The value of Jacobian has been heavily studied in previous publications such as Albergel et al. (2017) or Tall et al. (2019).

Within LDAS-Monde, cross correlations between the errors in the various variables (soil moisture of the different layers and LAI) will be investigated in a near future based on the Ensemble Square Root Filter (EnSRF) proposed by Bonan et al., 2020.

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, B., Albergel, C., Zheng, Y., Barbu, A. L., Fairbairn, D., Munier, S., and Calvet, J.-C.: An Ensemble Square Root Filter for the joint assimilation of surface soil moiture and leaf area index within LDAS-Monde: application over the Euro-Mediterranean region, Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-391, accepted, 2020.
Tall, M.; Albergel, C.; Bonan, B.; Zheng, Y.; Guichard, F.; Dramé, M.S.; Gaye, A.T.; Sintondji, L.O.; Hountondji, F.C.C.; Nikiema, P.M.; Calvet, J.-C. Towards a Long-Term Reanalysis of Land Surface Variables over Western Africa: LDAS-Monde Applied over Burkina Faso from 2001 to 2018. *Remote Sens.*, *11*, 735, 2019

3.3 [ASCAT has an approximate resolution of 25 km. How are these coarse data assimilated/downscaled into the 0.1ˆo model simulations?]

Response to 3.3

The assimilated SWI product is provided by the Copernicus Global Land Service directly on a global 0.1° regular grid. Informations on how the SWI product is derived from ASCAT data at 25-km resolutions can be found in the Product User Manual (https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_PUM_SWIV3-SWI10-SWI-TS_I2.60.pdf).

3.4 [CDF matching ‘ refers to rescaling of the entire CDF, and is not a correct terminology when only rescaling the mean and variance.]

Response to 3.4

We use in this paper a seasonal linear rescaling. Linear rescaling was introduced by Scipal et al. (2008) and has been shown giving results that are very similar to an exact CDF matching. Nevertheless, to avoid any confusion, we have rewritten the sentence as follows (P.9-10, Lines 299-301): “This is done through a linear rescaling as proposed by Scipal et al. (2007), where the mean and variance of observations are matched to the mean and variance of the modelled soil moisture from the second layer of soil (1-4 cm depth). This rescaling gives in practice very similar results to CDF (cumulative distribution function) matching. The linear rescaling is performed on a seasonal basis (with a 3-month moving window) as suggested by Draper et al., (2011), Barbu et al., (2014).” Further mentions of CDF matching in the manuscript have been replaced by “seasonal linear rescaling”.

3.5 [How exactly are the LAI data ‘interpolated’ from 1 km to 0.25 degree? Do you mean interpolation to bridge cloudy pixels and then aggregation (upscaling)?]

Response to 3.5

Thanks for this suggestion. As in previous studies (e.g, Barbu et al., 2014, Albergel et al., 2019), observations are aggregated using an arithmetic average to the model grid points (0.25° or 0.10° in this study), if at least 50 % of the model grid points are observed (i.e. half the maximum amount).

Future work will focus on looking at the impact of cloud cover on the LAI upscaling process. Instead of 50%, a possibility could be to use an arithmetic average to the model grid point if at least

70% of the model grid point are observed. Then during the assimilation/evaluation ERA5 (or HRES IFS) total cloud cover field (tcc) could be use to mask out grid point if tcc is greater than 30%. This is already used when evaluating e.g. satellite land surface temperature to model data (e.g. Johannsen et al., 2019).

Reference:

Johannsen, F.; Ermida, S.; Martins, J.P.A.; Trigo, I.F.; Nogueira, M.; Dutra, E. Cold Bias of ERA5 Summertime Daily Maximum Land Surface Temperature over Iberian Peninsula. *Remote Sens., 11*, 2570, 2019.

3.6 [Is the LAI also 'converted from the observation space to the model space' as is done for soil moisture? Please describe how? If there is no such rescaling, then the results may be trivial, i.e there will be more impact of a non-rescaled LAI assimilation than when doing a gentle nudging with rescaled soil moisture. However, since you use a KF variant, there probably is some rescaling for both (otherwise the KF assumptions would be violated).]

Response to 3.5

Soil moisture is a very model-specific variable, precipitation, evapotranspiration, soil texture, topography, vegetation, and land use could either enhance or reduce the spatial variability of soil moisture depending on how it is distributed and combined with other factors (Famiglietti et al. 2008). In particular, differences in soil properties between the model grid points and reality could imply important variations in the mean and variance of soil moisture. Furthermore, vegetation effects are not completely corrected when going from the satellite measurement (e.g. radar backscatter in the case of ASCAT) to SSM, leading to potential seasonal biases (e.g. Shamambo et al., 2019). That is why we apply the linear rescaling to the ASCAT SWI. It also acts as an observation operator to go from the observational space (SWI, an index 0 and 1) to the model space (SSM in m^3m^{-3}).

For LAI, biases between the model and the observations are linked to the way processes are represented in the model as well as uncertainties on the atmospheric forcing (cumulated effect on modelled LAI). The assimilation sequentially removes bias in the modelled LAI (with respect to the observed LAI). This technical difference between SSM and LAI assimilation, combined with the longer memory of LAI compared to SSM contributes to the results presented in this study. See also response to comment 3.14.

References:

Famiglietti, J. S., D. Ryu, A. A. Berg, M. Rodell, and T. J. Jackson, 2008: Field observations of soil moisture variability across scales. *Water Resour. Res.*, 44, W01423, doi:10.1029/2006WR005804.
Shamambo, D.C.; Bonan, B.; Calvet, J.-C.; Albergel, C.; Hahn, S. Interpretation of ASCAT Radar Scatterometer Observations Over Land: A Case Study Over Southwestern France. *Remote Sens.* **2019**, *11*, 2842.

3.6 [How exactly is the 'climatology' defined? Is it seasonally varying, how much smoothing is applied, etc?]

Response to 3.6

The following sentence "This 9-yr global reanalysis was then used to provide a climatology for estimating anomalies of the land surface conditions." has been reformulated and is now (P.10, Lines 317-320) "This 9-yr global reanalysis was then used to provide a monthly climatology for estimating anomalies of the land surface conditions. For each month (and variable considered) of 2018 we have removed the monthly mean and scaled by the monthly standard deviation of the 2010-2018 period"

3.7 [The spinup period for the 0.1ˆo simulation seems unrealistically short. How was it initialized? Could you cycle over the short April-December period multiple times?

Response to 3.7

Nine months can be perceived as a too short period to spin up the system. Unfortunately, HRES atmospheric forcing is only available from April 2016 and the LDAS-HRES experiment ends in December 2018. We have considered this 9 months period for the spin up in order to have the longest possible time series for land surface variables, thus giving more strength to statistics. We could have considered a longer period for spin up (April 2016 to December 2017) and studied only 2018. This gives very similar results on surface soil moisture and LAI (not shown). While not being fully spun-up, results obtained with LDAS-HRES can be considered as representative of the system response to data assimilation. Note that most initial values of the LDAS-HRES run are taken from the ECOCLIMAP-II database. For instance, initial LAI is set from a 1999-2005 climatology derived from MODIS

Another possibility to initialise LDAS-HRES could have been to downscale the state of LDAS-ERA5 run in April 2016 to 0.10°x0.10° spatial resolution. LDAS-ERA5 runs have been set to an equilibrium spinning up 20 times the first year (2010).

The following sentence: "The period 2017-2018 is presented, HRES is available at this spatial resolution from April 2016, only, and the time period from April to December 2016 is used as a short spinup." has been modified and is now (P.10, L.327-332): "HRES is available at a 0.1° x 0.1° resolution only from April 2016. April to December 2016 is used as a short period for spinup and results are presented for the period 2017-2018. Although a 9-month spinup period can be seen as rather short, evaluating LDAS-HRES on either 2017-2018 or 2018 (using instead a 21-month spinup) leads to similar results on surface soil moisture and LAI (not shown). While the system is not fully spun-up, it can be considered as representative of the system response to data assimilation."

3.8 [Table II: An observation operator is a function, not a variable; also explain what you mean by control variable (updated variables) for readers who are new to the field. In fact, the control vector enters the observation operator, which in turn selects a subset of relevant variables to produce the observation prediction.]

Response to 3.8

Agreed, in Table II "Observations operators" has been replaced by "Model equivalents" and the following sentences have been added to the revised version of the manuscript (section 2.1.3 on data assimilation, P.6, Lines 200-202): "The eight control variables are directly updated using their sensitivity to observed variables (i.e. defined by the Jacobians). Other variables are indirectly modified through biophysical processes and feedbacks from the model"

3.9 [Why is there no skill evaluation in terms of anomalies? Would be interesting.]

Response to 3.9

Thank your for your highly relevant comment. Following it and similar comments from the other Reviewers, it has been decided to revisit the soil moisture evaluation part of the study:
(1) we have added an evaluation of soil moisture from LDAS-Monde fourth layer of soil (10 to 20 cm) against in situ measurements of soil moisture at 20 cm depth when available (10 networks and 685 stations),
(2) for surface soil moisture (SSM), correlation values (R) were calculated for both absolute and anomaly time-series in order to remove the strong impact from the SSM seasonal cycle on this specific metric,
(3) a 95% Confidence Interval (CI) has been added to R values.
(4) we have added the number of stations for which correlations differences are significant (significant improvement or degradation from the analysis) as well as a map over North America for illustration.

It involves several changes in the revised version of the manuscript, they are listed below.

Methodology section, 2.5 Evaluation datasets and metrics

P.11, Lines 358-365:"In situ measurements of surface soil moisture from 19 networks across 14 countries available from the ISMN are also used to evaluate the performance of the soil moisture analysis. They represent 782 stations with at least 2 years of daily data over 2010-2018. Sensors at 5 cm depth (SSM) are compared with soil moisture from LDAS_ERA5 third layer of soil (4-10 cm), sensors at 20 cm depth with the fourth layer of soil (10-20 cm, 685 stations from 10 networks). Beside 11 stations located in 4 countries of Western Africa (Benin, Mali, Sénégal and Niger) and 21 stations in Australia, most stations are located in North America and Europe, see Table S3."

P.12, Lines 374-377: "For global estimates, Normalized RMSD (NRMSD, Eq.(2)) was used, also. Finally, for surface soil moisture, R was calculated for both absolute and anomaly time-series in order to remove the strong impact from the SSM seasonal cycle on this specific metric (see e.g. Albergel et al., 2018a, 2018b)."

Result section, 3..1.2 Ground-based datasets

P.17-18, Lines 548-582: "The statistical scores for soil moisture from LDAS_ERA5 open-loop and analysis (third and fourth layers of soil, 4-10 cm depth, 10-20 cm depth, respectively) over 2010-2018 when compared with ground measurements from the ISMN (5 cm depth and 20 cm depth) are presented in Table S2 for each individual network. Averaged statistical metrics (ubRMSD, R,$R_{anomaly}$ and bias) are similar for both LDAS_ERA5 analysis and open-loop even if local differences exist. For the analysis, averaged R ($R_{anomaly}$) values along with its 95% Confidence Interval (CI) using in situ measurements at 5 cm (782 stations from 19 networks) are 0.68±0.03 (0.53±0.04) (0.67±0.03(0.53±0.04) for the open-loop) with averaged-network values going up to 0.88±0.01 (0.58±0.04) for the analysis (SOILSCAPE network, 49 stations in the USA) and always higher than 0.55 except for one network, ARM (10 stations in the USA) presenting an averaged R value of 0.29±0.05. Averaged ubRMSD and bias (LDAS_ERA5 minus in situ) are 0.060 m^3m^{-3} and 0.077 m^3m^{-3} for the analysis, 0.060 m^3m^{-3} and 0.076 m^3m^{-3} for the open-loop, respectively. NIC (Eq.1) has also been applied to R values, 65% of the pool of stations present a neutral impact from the analysis (511 stations at NIC ranging between -3 and +3), 12% present a negative impact (91 stations at NIC < -3) and 23% present a positive impact at (180 stations at NIC > +3).
The number of stations where R differences between the analysis and the openloop are significant (i.e. their 95% CI are not overlapping) is 186 out of 782 (about 26%). There is an improvement from the analysis w.r.t. the openloop for 128 stations (out of 186, i.e. about 69%) and a degradation for 58 stations (about 31%). Figure 7 illustrates R differences between the analysis and the openloop runs. When differences (analysis minus openloop) are not significant stations are

represented by a small dot. When they are significant, large circles have been used, blue for positive differences (an improvement from the analsysis) and red for negative differences (a degradation from the analysis). For most of the stations where a significant difference is obtained, it represent an improvement from the analysis.

Averaged analysis R (95%CI), bias and ubRMSD for the fourth layer of soil (685 stations from 10 networks) are 0.65±0.03, 0.049 m^3m^{-3} and 0.055 m^3m^{-3}, respectively. For the open-loop, they are 0.064±0.03, 0.048 m^3m^{-3} and 0.056 m^3m^{-3}, respectively. For soil moisture at that depth, about 60% of the stations present a neutral impact from the analysis (410 stations at NIC ranging between -3 and +3), 28% a positive impact (189 stations at NIC > +3) and 12% a negative impact (86 stations at NIC < -3). Although differences between the openloop run and the analysis are rather small, these results underline the added value of the analysis with respect to the model run. Figure S6 represents the distribution of the scores values for LDAS_ERA5 open-loop and analysis using boxplots centred on the median value. They look very similar and from this figure, it is difficult to see either improvement or degradation from the analysis."

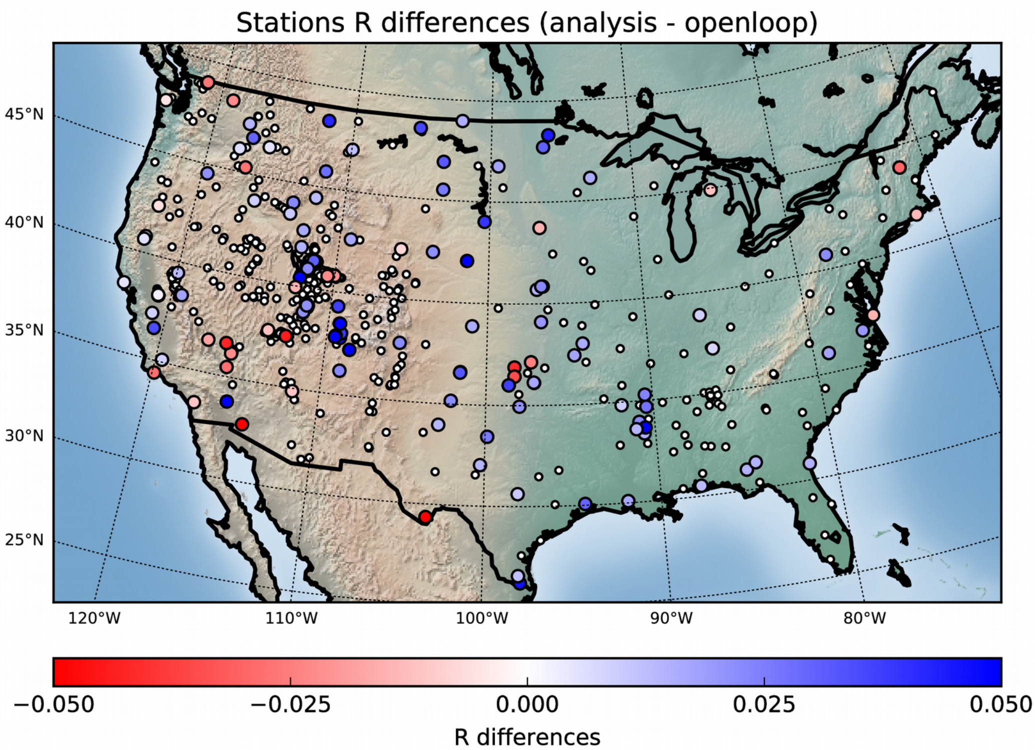

Figure 7: Map of correlations (R) differences (analysis minus openloop) for stations available over North America. Small dots represent stations where R differences are not significant (i.e. 95% confidence intervals are overlapping), large circles where differences are significant.

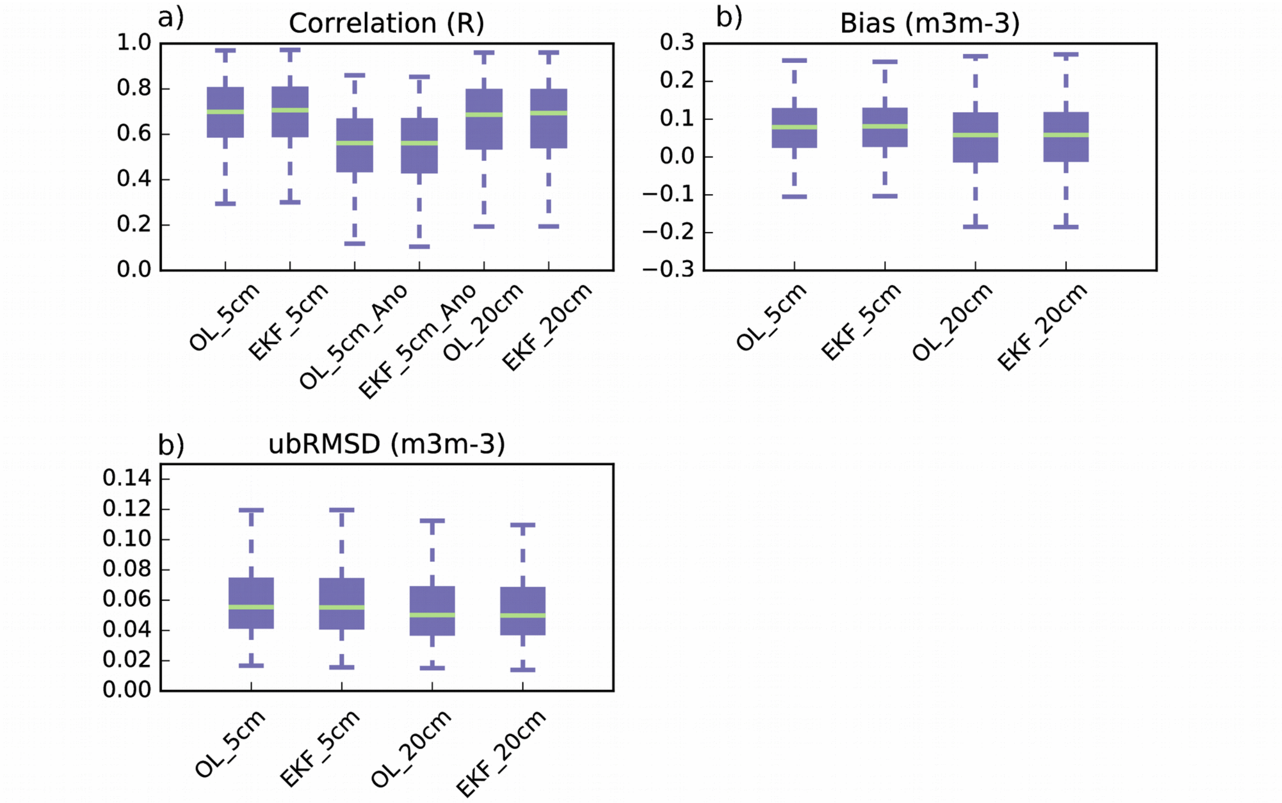

Figure S6: a) Boxplots representing the distribution of the correlation values on absolute time-series and anomaly time-series ("Ano") between the stations with in situ measurements of soil moisture either 5cm depth or 20 cm depth and soil moisture from LDAS_ERA5 openloop and analysis over 2010-2018 (third and forth layer of soil, respectively). Correlation values are presented for surface soil moisture (5 cm depth measurements against third layer of soil), only. Distribution are centred on the median values. b) Distribution of the Bias values between the stations with in situ measurements of soil moisture either 5cm depth or 20 cm depth and soil moisture from LDAS_ERA5 openloop and analysis over 2010-2018 (third and forth layer of soil, respectively).c) Same as b) for ubRMSD.

The following text has been added to the revised version of the manuscript: "Figure S6 represents the distribution of the scores values for LDAS_ERA5 open-loop and analysis using boxplots centred on the median value. They look very similar and from this figure, it is difficult to see either improvement or degradation from the analysis."

3.10 [Which variable in LDAS-Monde output is related to SIF and how?]

Response to 3.10

In ISBA, the fluorescence is not simulated directly, but the photosynthesis activity is simulated through the calculation of the GPP, which is driven by plant growth and mortality in the model. Sun et al. (2017) demonstrated that SIF and GPP were driven by the same environmental and biological factors and found that SIF observations from OCO-2 and GPP products from FLUXCOM were highly consistent in time and space. The modelled GPP values are expressed in $g(C)\cdot m^{-2}\cdot day^{-1}$, whereas SIF is an energy flux emitted by the vegetation in units of $mW\cdot m^{-2}\cdot sr^{-1}\cdot nm^{-1}$. Thus, GPP and SIF cannot be directly compared as they do not represent the same physical quantities. However, several studies (including Zhang et al., 2016, Sun et al., 2017, Leroux et al., 2018) have found that their time dynamics and their spatial distributions can be investigated.

The following paragraph has been added to the revised version of the manuscript (Section 2.5 on evaluation datasets and metrics, P.13, Lines 400-406): “As for SIF, in ISBA the fluorescence is not simulated directly, however photosynthesis activity is simulated through the calculation of the GPP, which is driven by plant growth and mortality in the model. Modelled GPP values are expressed in $g(C)\cdot m^{-2}\cdot day^{-1}$, while SIF is an energy flux emitted by the vegetation ($mW\cdot m^{-2}\cdot sr^{-1}\cdot nm^{-1}$). Hence, GPP and SIF cannot be directly compared as they do not represent the same physical quantities. However, several studies (e.g, Zhang et al., 2016, Sun et al., 2017, Leroux et al., 2018) have found that their time dynamics investigated, highlighting the potential of SIF products to be used as a validation support for GPP models.”

References:

Leroux, D.J.; Calvet, J.-C.; Munier, S.; Albergel, C. Using Satellite-Derived Vegetation Products to Evaluate LDAS-Monde over the Euro-Mediterranean Area. *Remote Sens.* **2018**, *10*, 1199.
Sun, Y.; Frankenberg, C.; Wood, J.D.; Schimel, D.S.; Jung, M.; Guanter, L.; Drewry, D.T.; Verma, M.; Porcar-Castell, A.; Griffis, T.J.; et al. OCO-2 advances photosynthesis observation from space via solar-induced chlorophyll fluorescence. Science **2017**, 358, 189.
Zhang, Y.; Xiao, X.; Jin, C.; Dong, J.; Zhou, S.; Wagle, P.; Joiner, J.; Guanter, L.; Zhang, Y.; Zhang, G.; et al. Consistency between sun-induced chlorophyll fluorescence and gross primary production of vegetation in North America. Remote Sens. Environ. **2016**, 183, 154–169.

3.11 [Overall, it is a bit disconcerting that trivial design results are shown repeatedly. Assimilate a variable, and sure, the model will get closer the assimilated observations. The results need to be thoroughly revised (both text and figures) to eliminate the trivial results. They can be mentioned once, but then the focus needs to be on the independent evaluation. It is also not correct to say that results “improve” if they simply get closer to the assimilated observations (e.g. L. 375, L. 516,...). This holds both for the global assessment and for the case studies, e.g. all of L. 505-512 is ‘trivial’ and can be removed.]

Response to 3.11

Verifying that the assimilation system works as intended is an important task. This is why several figures have been included for “sanity check”. We have emphasized in the manuscript that several presented evaluations are carried out to check if the assimilation system is working properly.

Also, using SSM and LAI as an independent source of information to evaluate the forecast has been further discussed and added in the revised version of the manuscript. While LAI remains an independent source of information for the forecast evaluation (although constrained by the assimilation), ASCAT SWI has been rescaled to match the model climatology. The seasonal rescaling impacts both bias and correlation. In an attempt to have a more independent evaluation, an additional figure has been put in the revised version of the manuscript. It displays maps of correlations between modelled soil moisture (1-4 cm) from the four experiments (LDAS-HRES openloop, analysis, LDAS_fc4 and LDAS_fc8) and ASCAT SWI (i.e. ASCAT data prior rescaling) for the WEUR domain. Correlations are applied to both absolute values and to anomalies (to assess the short term variability of soil moisture).

End of section 3.2.2

P.22, Lines 703-724: “Similarly to Figures 13(a, b, c, d), panels of Figure 15 illustrate the impact of the analysis on SSM using correlations., To that end, ASCAT SWI (i.e. no rescaling) has been used. Figure 14 (top panels) shows map of R values based on absolute values while Figure 14 (bottom panels) shows R values on anomalies (short term variability) as defined in Albergel et al., 2018a. Figure 15 (a) and (e) represents R values and anomaly R values for LDAS_HRES, respectively. As expected R values are higher than anomaly R values. Maps of differences (panels b and f) of Figure

15 suggest that after assimilation, both scores are improved rather equally. While the 4 day and 8-day forecast still show an improvement from the initial condition on R values (panels c and d of Figure 15 dominated by positive differences, analysis minus openloop), maps of anomaly R values forecast don't show any negative or positive impact (panels g and h of Figure 15)."

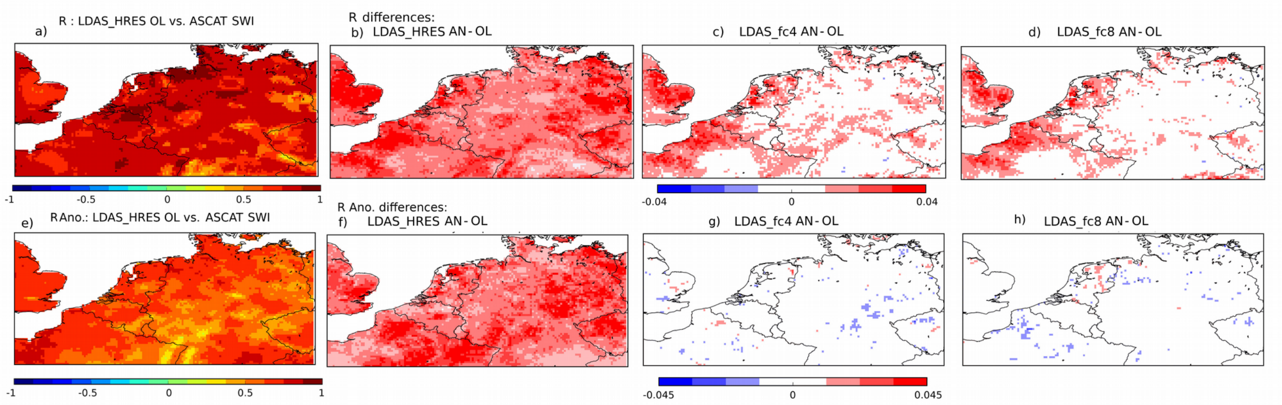

Figure 15: Top row, (a) R values between LDAS_HRES open-loop and ASCAT SWI estimates from the Copernicus Global Land Service (CGLS) over 2017-2018 for the WEUR domain, (b) R differences between LDAS_HRES analysis (open-loop) and ASCAT SWI. (c) and (d) same as (b) between LDAS_fc4 initialised by the analysis (open-loop) and LDAS_fc8. Bottom row, same as top row for R values based on anomaly time-series.

Discussion and conclusion sections

P.23, Lines 749-754: "For SSM, the assimilation is done after a rescaling to the model climatology (see section 2.3), which removes bias. For LAI, however it is not the case and the assimilation process removes bias in the modelled LAI (w.r.t. to the observation). This technical difference between SSM and LAI assimilation, combined with the longer memory of LAI compared to SSM, contributes to the results presented in this section"

3.12 [The snow cover results (Fig 7-8) can be removed. It is too trivial that there would be no impact on snow cover by assimilating soil moisture or LAI. Or else, explain in detail how either variable would affect the snow cover.]

Response to 3.12

Agreed, both figures have been moved to the supplementary document (Figures S1 and S2) and it has been further emphasized that there is no snow data assimilation yet. Those results are presented to highlight areas of improvements in LDAS-Monde:

P.15, Lines 487-492: "As expected, the analysis has an almost neutral impact on snow as both SSM and LAI observations are filtered out from frozen/snow condition and as there is no snow data assimilation in LDAS_ERA5 (Figure S2 and panels (j), (k) and (l) of Figure S1). This clearly shows however an area of potential improvement of data assimilation within LDAS-Monde using satellite data such as the IMS one (as in e.g. de Rosnay et al., 2014)."

3.13 [The independent validation (e.g against in situ SSM) shows no substantial improvement in any of the metrics due to data assimilation. Have the in situ data been thoroughly filtered to remove bad points? Why exactly do the authors see an advantage of LDAS_ERA5 for these variables relative to the open loop (L. 458)? There is some added value, but there is also significant degradation, i.e. I would say it is an equal game here.]

Response to 3.13

Agreed, last paragraph of section 3.1.2 on ground based dataset has been modified and is now (P.18, Lines 582-587): "For evapotranspiration, river discharge and surface soil moisture, there is a slight advantage for LDAS_ERA5 analysis with respect to its open-loop counterpart. Even if the distribution of the averaged statistical metrics can be rather similar for both (particularly true for surface soil moisture evaluation), there are significant differences for some sites, which shows the added value of the analysis with respect to the openloop. Note that for fewer sites, a negative impact from the analysis can also be observed."

We have also revisited the soil moisture evaluation part of the manuscript, see response to comment 3.9.

3.14 [L. 535 & L. 545: 'more sensitive to' is perhaps not the correct wording? Sensitivity would be quantified by something like the Jacobian. There is simply a larger update in LAI than in SSM by design, and this propagates in time differently due to the difference in memory for both variables (at this point in the paper, I am actually suspecting that LAI is assimilated with a bias, see comment above).]

Response to 3.14

Agreed, "more sensitive" has been replaced by "relies more". We also agree on the larger updates allowed when assimilating LAI, and it has been stressed out by adding the following paragraph to the discussions and conclusion stection (see also response to 3.5)

P.23, Lines 749-754: "For SSM, the assimilation is done after a rescaling to the model climatology (see section 2.3), which removes bias. For LAI, however it is not the case and the assimilation process removes bias in the modelled LAI (w.r.t. the observation). This technical difference between SSM and LAI assimilation, combined with the longer memory of LAI compared to SSM, contributes to the results presented in this section."

3.15 [Could you evaluate the impact of LAI and SSM assimilation in terms of runoff for the high-resolution simulation?]

Response to 3.15

Thank you for this suggestion, we have added a figure to show the impact of the assimilation (together with the impact of the initialisation on 4-day and 8-day forecasts) on drainage and runoff over the WEUR domain.

The following paragraph and figure have been added to the revised version of the manuscript (section 3.2.2 on Case studies for assessing LDAS-Monde high resolutions (0.1° x 0.1°) experiments, P.22; Lines 713-724): "Top panels of Figure 16 illustrate the impact of the analysis on drainage monitoring and forecast over WEUR. Fig. 16 a) represents drainage from LDAS_HRES openloop varying between 0 and 1 $kg.m^{-2}.day^{-1}$, as seen in Fig.16 b) (drainage difference between LDAS_HRES analysis and openloop) the analysis impact is rather small, about ±3% and more pronounced in areas where the analysis has affected LAI more (see panels f), g) and h) of Figure 16). As seen on panels c) and d), there is also an impact from the initialisation in areas were the analysis was more effectively correcting LAI. Bottom panels of Figure 16 illustrate similar impact on runoff. As for drainage, this variable is affected by the analysis. Initial conditions have an impact on its forecast, also. Although we did not present a quality assessment of those two variables, our findings on river discharge analysis impact, but also those from Albergel et al., 2017, 2018a, suggest a neutral to positive impact, propagated from the analysis of SSM and LAI to river discharge through variables such as drainage and runoff."

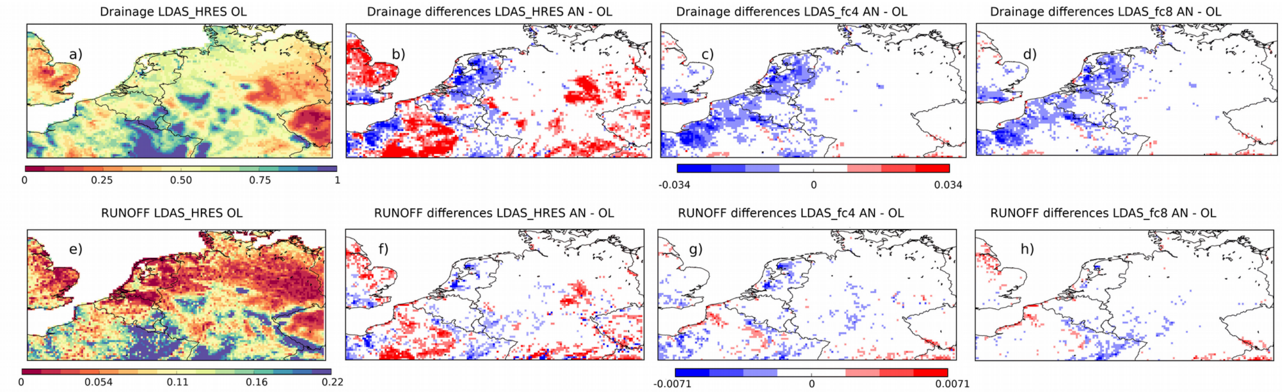

Figure 15: Top row, (a) drainage values for LDAS_HRES open-loop over 2017-2018 for the WEUR domain, (b) drainage differences between LDAS_HRES analysis and open-loop. (c), (d), same as (b) between LDAS_fc4 initialised by the analysis and LDAS_fc4 initialised by the open-loop, between LDAS_fc8 initialised by the analysis and LDAS_fc8 initialised by the open-loop. Bottom row, same as top row for runoff. Units are kg.m^{-2}.day^{-1}

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