Reply to Comment by Anonymous Referee #2

S. Scherrer, G. De Lannoy, Z. Heyvaert, M. Bechtold, C. Albergel ,T. S. El-Madany, W. Dorigo

August 23, 2023

We thank the anonymous reviewer for the recommendations and adapted the manuscript accordingly.

In the following, review comments will be styled in *blue italics*, our responses in black normal text, and proposed changes in green.

1

Regarding the title, it might be useful to consider that some readers may not be familiar with the term "Noah-MP". To enhance clarity and avoid potential ambiguity, I recommend revising it to "Noah-MP Land Surface Model".

We agree, the revised title is Bias-blind and bias-aware assimilation of leaf area index into the Noah-MP land surface model over Europe.

2

While I commend the authors' approach to presenting the DA impact on LAI equilibrium and suggesting for multi-DA or parameter updates for reducing model instability, the rational for this analysis isn't immediately clear within section 2.6. To enhance understanding, it would be beneficial to 1) clarify the purpose of this analysis at the beginning; 2) defining LAI equilibrium and its relationship with soil moisture; 3) simplify and reduce the technical details of the approximation method (move it to appendix) or clearly states why it is used and how it defers from the model physics; and 4) perhaps add more context before bringing up equation 2 or move it to Appendix as well and provide with a simpler version here.

We agree that the motivation for this analysis was not clear immediately in the original version. We rephrased the first paragraph of section 2.6 as follows:

As will be seen later, each update step in the bias-blind DA is followed by a strong drift of the model LAI towards the earlier forecast values, i.e. the bias-blind DA system quickly "forgets" systematic corrections made in earlier steps. This indicates that there is a stable equilibrium LAI (i.e. a model-based 'attractor') whose value is not modified by the bias-blind LAI DA. To make full use of the information contained in the observations, a bias-blind DA system should also modify this equilibrium LAI value to have more persistent DA updates.

Additionally, we followed the recommendation to move the technical details, including the defining equation of the equilibrium LAI to the appendix, and only shortly summarise the results in section 2.6 as such:

An analysis of the Noah-MP leaf growth model (Appendix A) shows that the main factors influencing the equilibrium LAI value are (i) root zone soil moisture, represented via the soil moisture factor β, and (ii) leaf parameters, e.g. specific leaf area (SLA, leaf mass per area). Including β or SLA in the DA state vector could thus help to obtain more persistent updates.

We therefore analysed how sensitive the equilibrium LAI is to these variables using a climatological approximation of the Noah-MP leaf model (shown in Appendix B). The result of this analysis is presented in subsection 3.6 for two example sites with constrasting bias between Noah-MP and CGLS, (i) the Majadas site in Spain, where observed LAI is much lower than modelled LAI, and (ii) the Nile delta, where observed LAI is much higher than modelled LAI.

In the appendix, we added the following section that gives more details on how we found the climatological approximation for the model physics:

The equilibrium LAI value (model-based 'attractor') is the LAI value at which Equation A1 is zero. It is therefore an implicit function of all the terms and variables on the right hand side of Equation A1. However, some of the terms on the right hand side of this equation strongly depend on the meteorological forcings (e.g., GPP). Evaluating the equilibrium LAI as function of soil moisture and leaf parameters would therefore require running the complete Noah-MP model with a wide range of forcing conditions, which quickly becomes computationally intractable. Therefore, we use a climatological approximation of the term in Equation A1 to eliminate the explicit dependence on the meteorological forcings.

We obtain a climatological approximation of GPP as a function of LAI and β by assuming that GPP is proportional to LAI, β, and a factor that depends solely on the forcings F or constant parameters not including the leaf parameters:

$$GPP(LAI, \beta) \approx LAI \cdot \beta \cdot \alpha(F) \tag{1}$$

The linear dependence on β is part of the Noah-MP model physics, while the assumption of linear dependence on LAI is justified in case vegetation growth is not light limited. This is reasonable for the areas with a large bias in the southern part of the domain, where vegetation growth is mainly water limited. To find an approximation for α, we perform a least-squares fit of Equation 1 using daily mean model output for GPP, LAI, and β for each calendar month. This results in 12 separate approximations of $GPP(LAI, \beta)$, one for each calendar month. The fit for the month with the highest discrepancy between Noah-MP OL and CGLS are shown in Figure 1

For the other terms in [Equation A1 in the manuscript], we simply insert the mean forcing value if required. The resulting defining equation for the equilibrium LAI for the month m is then

$$\begin{aligned} 0 = &\beta_m \cdot (1 - \text{FRAGR}) \cdot [f_l(LAI_{eq,m}) \cdot \alpha_m \cdot LAI_{eq,m} - R_{m,w}(LAI_{eq,m}, T_{c,m})] \\ &- D_c(LAI_{eq,m}, T_{c,m}) - D_d(LAI_{eq,m}, \beta) - T_l(LAI_{eq,m}) \end{aligned} \tag{2}$$

where $T_{c,m}$ is the mean canopy temperature, β_m the mean plant available water, and α_m the GPP proportionality factor from Equation 1 for month m, respectively. The solution can be obtained numerically with common root-finding algorithms.

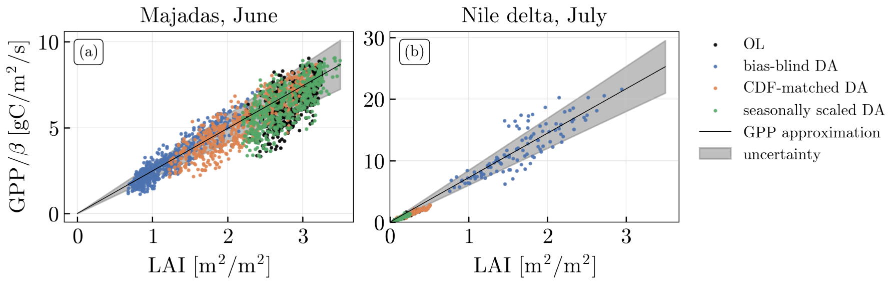

Figure 1: [Figure B1 in manuscript] Dependence of soil-moisture-normalized GPP (GPP/β) on LAI for the OL and DA runs, and linear approximation via least-squares fit for (a) Majadas in June and (b) the Nile delta in July.

3

Regarding section 3.3, if the decision is to not incorporate additional reference ET datasets for comparison, it would be beneficial for the authors to extend their discussion, specifically addressing the potential shortcomings or uncertainties of GLEAM ET datasets for specific regions, such as those under irrigation agriculture. Besides, I think providing references to literature that addresses ET uncertainties or comparisons within the study region could also strengthen this section. Given that the bias-blind DA has shown large impact (both positive and negative) on ET compared to bias-aware DA, it is crucial to provide a more comprehensive analysis or discussion surrounding these effects. This becomes especially necessary considering the current lack of consensus regarding a state-of-art reference ET product.

We rephrased section 2.5.3 and added a paragraph to highlight the shortcomings of GLEAM for strongly irrigated areas:

The Global Land Evaporation Amsterdam Model v3 (GLEAM; Martens et al., 2017; Miralles et al., 2011) ET dataset is a gridded ET product based on a land surface model and satellite observations. It has been evaluated against other products in various benchmarking activities (Greve et al., 2014; Martens et al., 2016, 2017, 2018), and it has been used for assessing DA systems (e.g., Albergel et al., 2019; Bonan et al., 2020; Kumar et al., 2019b; Rahman et al., 2022b, a). We used version 3.6b, as it provides data in our evaluation period (2003-2019) and does not rely on either reanalysis as forcing data or optical data for dynamic inputs. It is thus largely independent of the assimilated CGLS LAI and of the Noah-MP-modelled ET, but inevitably suffers from model assumptions and input errors.

GLEAM calculates ET as a combination of potential evaporation (based on the Priestley-Taylor equation), stress, and interception (based on the Gash model). Water stress is based on a soil moisture model included in GLEAM, and an additional scaling based on observations of vegetation optical depth, a proxy for vegetation water content.

Since the soil moisture model does not include irrigation explicitly, it will provide biased estimates over strongly irrigated areas (Chen et al., 2021; Shah et al., 2019). Evaluations of absolute values (e.g., via RMSD) over irrigated areas should therefore be analysed carefully, as they might show decreased performance stemming from an actually improved representation of irrigation (as for example in Thiery et al., 2017), even if satellite-based soil moisture anomalies were assimilated and might partly compensate for missed irrigation.

4

Regarding Figure 6, it appears that the bias-blind approach exhibits notable improvements in anomaly correction for SM2 compared to ISMN sites. Could this potentially indicate an enhancement of deeper zone soil moisture? Why this is the case? And how does the correlation look like instead of anomaly correlation? It would be helpful if the authors could elaborate on what the soil moisture climatology looks like for these sits where marked improvements in anomaly R are observed. Additionally, is there a specific reason not including the R analysis for soil moisture evaluation? This is necessary to provide insightful information about the impact of DA on soil moisture seasonality and provide more evidence for the statement made in the abstract.

We agree that there is some value in also providing the raw correlation values and we added them in Figure 6, along with a short description of the results. The revised figure is shown in Figure 2 (this document, Figure 6 in the manuscript).

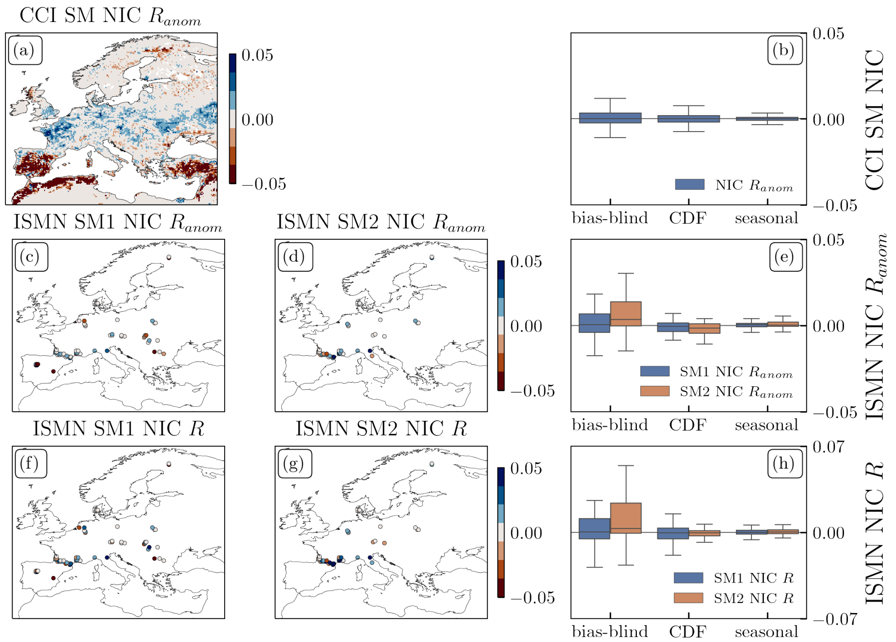

Figure 2: Top row: (a) Map of NIC R_{anom} with ESA CCI SM for the bias-blind DA and (b) box plots of NIC R_{anom} with ESA CCI SM for all three DA runs. Middle row: Maps of NIC R_{anom} with ISMN for the bias-blind DA for (c) SM1 (0-10 cm) R_{anom} and (d) SM2 (10-40 cm) R_{anom}, and (e) box plots of NIC R_{anom} with ISMN for SM1 and SM2 and all three DA runs. Bottom row: Maps of NIC R with ISMN for the the bias-blind DA for (f) SM1 (0-10 cm) R and (g) SM2 (10-40 cm) R, and (h) box plots of NIC R with ISMN for SM1 and SM2 and all three DA runs.

The raw correlations show a similar pattern of improvement as the anomaly correlations, and we indeed believe that this is due to improved subsurface soil moisture. However, as none of the ISMN stations are in the areas of strong bias, this finding is of limited value to discuss the influence of biased DA on the climatology of root zone soil moisture.

We added the following sentence in the discussion section 4.1:

The comparison to ISMN indicates improvements in deeper layer soil moisture, but none of the in situ sites considered are in the areas with large bias.

Additionally, we rephrased the sentence in the abstract concerning soil moisture climatology as follows:

While comparisons to in-situ soil moisture in areas with weak bias indicate an improvement of the representation of soil moisture climatology, bias-blind LAI DA can lead to unrealistic shifts in soil moisture climatology in areas with strong bias.