

## Response to Reviewer:

(Retype your comments in *italic font* and then present our responses to the comments)

*The submitted manuscript presents HiQ-LAI, a reprocessed leaf area index (LAI) dataset based on the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product that attempts to improve spatiotemporal consistency. There is a need to reduce spatiotemporal noise in global LAI products, and the HiQ-LAI dataset appears to offer improvements in this respect, so there is obvious potential for it to be useful to the community. I was able to access the 5 km dataset on Zenodo (though files appeared to be in .tif format, rather than HDF as claimed on L449), as well as the 500 m collection in Google Earth Engine without issue. Although the dataset appears useful, I do have several concerns and requests for clarification.*

Response: Special thanks for your positive comments and very detailed suggestions to make the paper better. HDF format data has not been stored in GEE at present, and corresponding modifications have been made in the paper. Following the Reviewers' comments, we have carefully revised our manuscript, and adequately addressed all the questions and concerns that the referees have raised. Hope this revised manuscript has solved all your concerns.

*Main concerns:*

*1. Too little detail is provided about the Spatio-Temporal Information Compositing Algorithm (STICA) used to derive the dataset. Whilst I appreciate that STICA is described in a previous publication (<https://doi.org/10.1109/TGRS.2023.3264280>), a brief overview of how it actually works is still needed. The current description is very superficial, outlining only the names of each step, rather than how each step is actually achieved. For example, it is not clear what the Multiple Quality Assessment (MQA) information is. Does it relate to the 'FparLai\_QC' and 'FparExtra\_QC' quality indicators? Likewise, how is the MQA information actually used to weight different observations in the 'fusion strategy'?*

Response: Thanks for your suggestions, and we added a detailed description of the STICA in Sect 3.1: "Satellite remote sensing observations are often subject to uncertainties arising from climatic factors, sensor malfunctions, and other sources, resulting in varying levels of uncertainty for individual pixels. To address this issue, this approach employed multiple indicators to evaluate the uncertainty for each pixel (referred to as MQA hereafter). These indicators encompass the algorithm path, STD LAI, and Relative Time-series Stability (TSS). The algorithm path (AP) is a crucial quality index, distinguishing between the main and backup algorithms. The main algorithm offers superior quality and precision retrieval, and the weight ratio of the main algorithm and backup algorithm is determined as 6:4 in the previous study (Wang et al., 2023). STD LAI reflects the retrieval uncertainty. The AP and STD LAI are derived from the FparLai\_QC and LaiStdDev layers of the original MODIS data. The third indicator, Relative TSS (RE-TSS), indicates the fluctuation of a time series (Zou et al., 2022). Following the principle of assigning a higher weight to smaller values, STD LAI and RE-TSS are incorporated into the retrieval with the main algorithm, resulting in the generation of a new quality classification indicator, MQA. Subsequently, the Inverse Distance Weighting (IDW) method is utilized on the spatial scale to calculate the weighted average of all eligible pixels (belonging to the same land cover type) within a certain spatial range of the target pixel. In this algorithm, the contribution of a pixel is determined not only by its spatial distance but also by its MQA value. In a word, pixels with closer proximity and higher MQA value make a more significant contribution to the target pixel. On the temporal scale, the Simple Exponential Smoothing (SES) method is employed to calculate the weighted average of all eligible pixels within a specific period. Pixels that are closer in time to the

target pixel and possess higher MQA values are assigned greater weights. Utilizing spatial/temporal correlation is based on spatial and temporal autocorrelation, i.e., everything is related to everything else, but near things are more related than distant things. The final step of the algorithm is to take a weighted average of the original MODIS LAI and the LAI calculated using spatial/temporal correlation, with their respective weights quantified using an indicator (TSS) that represents the temporal fluctuation of the time series (Zou et al., 2022). All processes of the method are implemented using the GEE cloud computing platform. The reprocessed LAI dataset, namely the HiQ-LAI product, has been generated with the help of the powerful cloud computing capability of GEE, covering the period from 2000 to 2022.”

*2. Related to point 1, the authors should make clear what the difference is between the validation results they are presenting here and the validation results from the previous publication (<https://doi.org/10.1109/TGRS.2023.3264280>), which seem quite similar (e.g. Figure 6 of the previous publication vs. Figure 2 in this paper). How is the present study building on the previous work? Was the previous study limited in time and space, whereas this one is more comprehensive? It needs to be made clear to the reader.*

Response: Considering the Reviewer’s suggestion, we added a detailed description of the difference between the new results presented here and the validation results from the previous publication.

“In this study, we utilized the GBOV LAI measurements from a total of 29 sites spanning from 2013 to 2021 as our ground reference LAI (Bai et al., 2019; Brown et al., 2020). A 3 km × 3 km square centered on the site location was selected as the study area (Fig. 1) so that the corresponding LAI product of each site was 36 (6 × 6) pixels. To enhance the credibility of the ground truth LAI, we filtered the ground LAI reference of these 29 sites based on the criterion that the "effective pixel" exceeded 90% and the input and output of land product value in the data aggregation process were within the specified range. This filtering process yielded a total of 818 reliable verification data points. Contrary to previous studies (Wang et al., 2023) that utilized only 2018 data from the GBOV site as a reference, this study expanded the timeline from 2013 to 2021, increased the number of sites from 24 to 29, and raised the criterion for effective pixels from 80% to 90%. These modifications were aimed at enhancing the reliability of the ground LAI data. Additionally, previous research focused on proposing and testing algorithms mainly at the tile scale, but this study migrated the algorithm to GEE for generating global long-term data series. Furthermore, the scope of analysis was also broadened to a global spatial scale and long-term time series.”

*3. Clarification is required regarding the choice of nearest neighbour resampling to go from 500 m to 5 km, which appears unsuitable. Surely some form of aggregation (e.g. mean value downsampling) needs to be carried out first? Otherwise, a 5 km pixel is being assigned the value of the single 500 m pixel that is closest to its centroid. That single 500 m pixel could be surrounded by pixels with very different LAI values, unless you are in an environment that is homogeneous at 5 km (which I would suggest is unheard of in terrestrial landscapes). This could be a major source of error, and I would strongly suggest the authors revisit this aspect. A proper aggregation should be easy to implement in Google Earth Engine using the ‘reduceResolution’ method (<https://developers.google.com/earth-engine/guides/resample>).*

Response: Yep, we carefully considered the Reviewer’s suggestion, and we generated the 5km data using bicubic interpolation on the Google Earth Engine (GEE). This process involves considering information beyond just the nearest pixel and incorporating additional data from surrounding pixels to calculate new pixel values. The resulting 5km dataset has been successfully stored in GEE (includes

one LAI layer) and is accessible via the following link [https://code.earthengine.google.com/?asset=projects/verselab-398313/assets/HiQ\\_LAI/wgs\\_5km\\_8d\\_Bicubic](https://code.earthengine.google.com/?asset=projects/verselab-398313/assets/HiQ_LAI/wgs_5km_8d_Bicubic).

4. The term 'uncertainty' is used too loosely throughout the manuscript. For example, it's stated on L177-178 that 'the approach employed multiple indicators to evaluate the uncertainty for each pixel (referred to as MQA hereafter)'. If the MQA information is indeed based on categorical quality indicators, then it does not represent 'uncertainty'. According to the International Standards Organisation's Guide to the Expression of Uncertainty in Measurement, uncertainty 'characterizes the dispersion of the values that could reasonably be attributed to the measurand' (<https://www.iso.org/sites/JCGM/GUM/JCGM100/C045315e-html/C045315e.html?csnumber=50461>). Later in the manuscript, it's suggested that according to validation with ground data, the HiQ-LAI dataset 'reduces uncertainties of the raw LAI retrievals' (L310). Again, this is improper use of the term 'uncertainty' – here the appropriate term is 'error' or 'apparent error' (which represents the difference between the reference value and the retrieval, see <https://doi.org/10.1016/j.envsci.2015.03.018> for more details).

Response: Thanks for your comments and we had overwritten this sentence as follows:

"It reduces apparent error of the raw LAI retrievals and generates smoother time series LAI profiles that align better with expected phenological patterns."

5. In the comparison with GBOV data, it's stated that 'GBOV LAI measurements' are used, but it's unclear whether a correction for woody material was undertaken to go from PAI to LAI. Note that the values provided by GBOV represent PAI, not LAI (<https://doi.org/10.1016/j.isprsjprs.2021.02.020>). If no correction was carried out, the 'GBOV LAI' should really be relabelled 'GBOV PAI', and this difference should then be considered in the discussion of the results. Related to the GBOV data, it's also not clear whether upscaled maps or individual in situ reference measurements were used – this should be clarified.

Response: Yep, we carefully read the «Ground-Based Observations for Validation (GBOV) of Copernicus Global Land Products -Algorithm Theoretical Basis Document - Vegetation Products LP3 (LAI), LP4 (FAPAR) and LP5 (FCOVER)», which mentions that "For simplicity, the terms LAI and LAIe are used interchangeably with PAI and PAIe when referring to LP3". We have added the relevant instructions in Sect 5: "Note that since in-situ measurements may be sensitive to all elements of the canopy, the resulting estimate should technically be called the term plant area index (Brown et al., 2021). Insufficient ground observation data in these regions further hinders accurate uncertainty assessments."

In addition, we added a description of the use of the data in Sect 2.3.1 "The Copernicus Ground-Based Observations for Validation (GBOV) service, which is part of the Copernicus Global Land Service (CGLS), is dedicated to the development and distribution of robust in situ datasets from various ground monitoring sites for the systematic and quantitative validation of land products (Bai et al., 2019; Brown et al., 2020). A comprehensive GBOV reference measurement database has been established through quality control and raw measurements reprocessing obtained from existing in situ sites. This database includes canopy reflectance, surface albedo, LAI, FPAR, cover area, 5 cm soil moisture, and surface temperature. Currently, 29 available sites provide LAI references from 2013 to 2022. The data from this database are freely accessible to the scientific community through the GBOV portal (<https://gbov.acri.fr>). In this study, we used the Land Products 3- leaf area index (LP3) as reference LAI."

6. The current ground-based validation is rather simple, and more information on the improvement of the HiQ-LAI dataset could be provided by reporting the validation statistics over all sites, but split by LAI magnitude, season, and biome, so we could clearly see when and where the improvements are. This would help back up the existing discussion.

Response: Thanks for your comments and considering the Reviewer's suggestion, we added two figures (Figure 3 and Figure 4) to explore the accuracy comparison between two products and GBOV LAI under different vegetation types, Scatter plot distribution comparison MODIS LAI (green) and HiQ-LAI (black) with GBOV LAI reference under different seasons in this study.

Comparing the LAI difference distribution among various vegetation types (Fig. 3) revealed that HiQ-LAI exhibited a tighter concentration around the zero value, resulting in decreased RMSE across most categories, except for the third biome type (Grasses & Shrubs). Mixed savannas and forests emerged as the vegetation types with the widest MODIS LAI difference range. The enhanced HiQ-LAI notably narrowed this distribution range, although the median and mean deviated further from zero. Notably, the two biome types exhibiting the most conspicuous changes in difference distribution were pure forest and mixed crops and savannas. The verification analysis (Fig. 4), comparing both products against GBOV LAI references across different seasons, demonstrated that HiQ-LAI had superior performance over MODIS LAI throughout all four seasons and exhibited outperformance with the ground references. Analyzing the LAI density distribution revealed that MODIS LAI (green) skewed towards higher values on the right side compared to HiQ-LAI (black). This indicated that MODIS LAI predominantly occupied high-value areas. Furthermore, the RMSE and RRMSE of HiQ-LAI are always smaller than that of MODIS LAI.

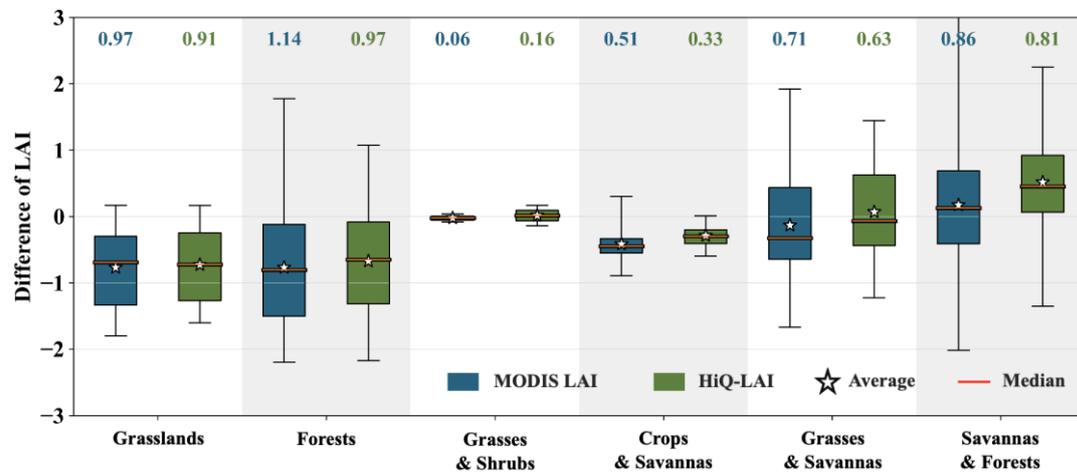
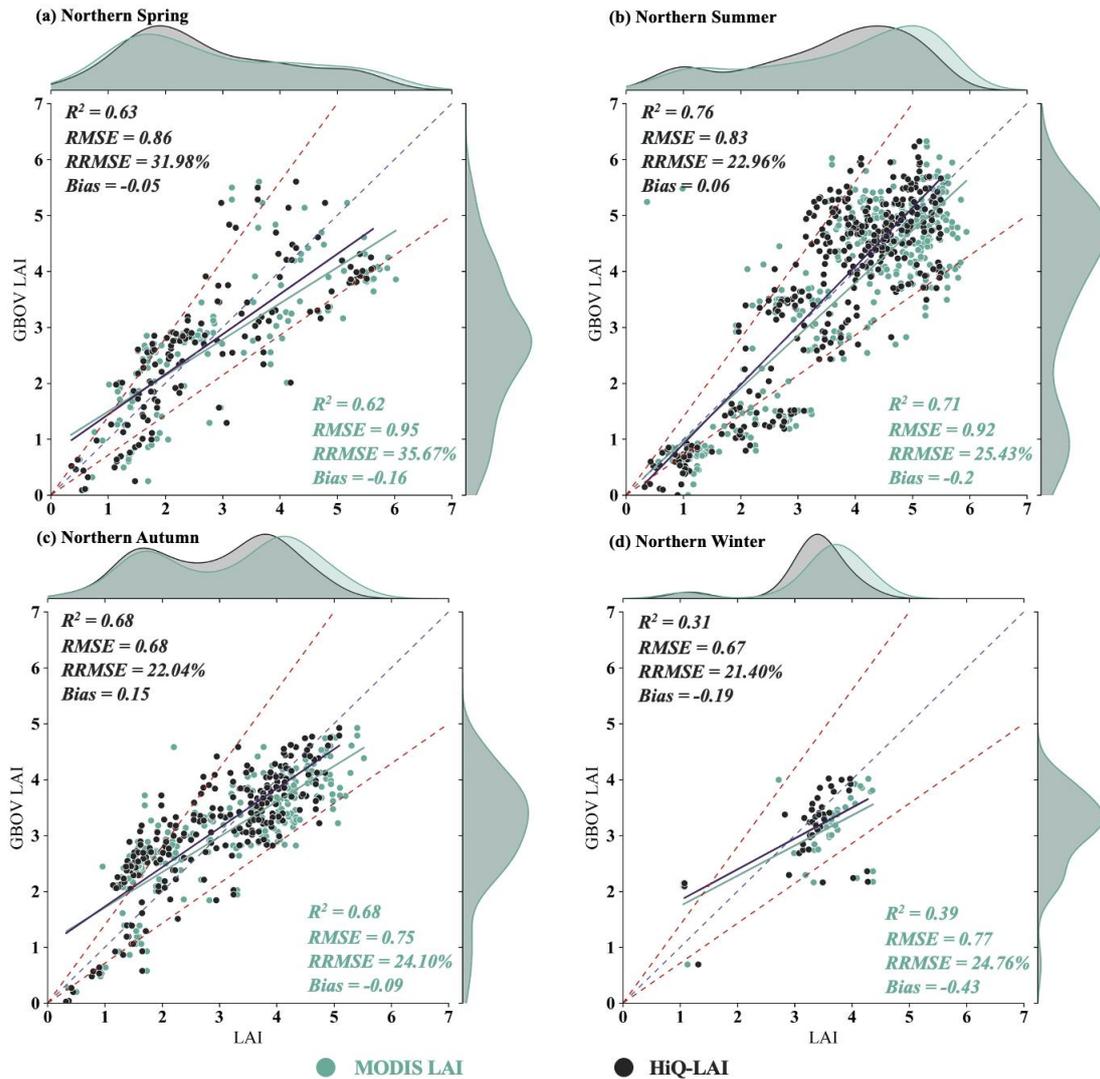


Figure 3. Accuracy comparison between two products and GBOV LAI under different vegetation types. The numbers at the top represent the RMSE between the two products and the GBOV LAI reference, respectively.



**Figure 4. Scatter plot distribution comparison MODIS LAI (green) and HiQ-LAI (black) with GBOV LAI reference under different seasons.**

7. In the introduction, the need for the HiQ-LAI dataset could be presented more clearly. Whilst I agree that the MODIS LAI product can be subject to noise, the claim needs to be backed up with specific examples and references to previous studies that have demonstrated this (for example <https://doi.org/10.3390/rs12061017> and <https://doi.org/10.1016/j.rse.2020.111935> demonstrate noisier temporal profiles from MODIS LAI when compared to the Copernicus Global Land Service LAI product from PROBA-V). Likewise, it's suggested that the noise in the MODIS LAI product leads to 'limitations on its practical applications' – again some specific examples and references are needed here.

Response: Thanks for your suggestions, and we added the references and specific examples as suggested.

“Specifically, atmospheric conditions (e.g., cloud cover, snow, and aerosol pollution), sensor malfunctions, and the inherent uncertainties of the retrieval algorithm all introduce challenges, resulting in poor spatiotemporal consistency and high noise in MODIS LAI products (Brown et al., 2020; Fuster et al., 2020; Yan et al., 2021). Consequently, inconsistency and excessive noise impose limitations on its practical applications in research involving yield estimation, crop-growth monitoring, terrestrial carbon monitoring, and global ecosystem dynamic simulation (Li et al., 2017;

Xiao et al., 2009; Chen et al., 2020).”

8. It's stated several times that 'MODIS LAI retrievals are calculated independently for each pixel and daily' (e.g. L67-068, L341-342), which may be true on an internal basis. However, I understood that the C6.1 MODIS LAI products available to external users (i.e. MOD15A2H, MYD15A2H and MCD15A2H) are only available as 4-day and 8-day composites. So, some clarification (and careful wording) is needed here to avoid confusion.

Response: Thank you for pointing this out, and we reorganized this sentence.

“The best retrievals are then selected using the temporal compositing method, and the 4-day or 8-day product is generated from the daily retrievals. Therefore, MODIS LAI retrievals are calculated independently for each pixel and daily. Differences in adjacent observation conditions lead to significant uncertainty in the LAI time series.”

9. The distinction between the results and discussion seemed somewhat arbitrary, since new results were shown in the discussion. In this case, a combined results & discussion section might make more sense. It was also a bit strange to have sections starting with figures.

Response: Thanks for your suggestions, we combined the Results and Discussion section and adjusted the order of paragraphs and figures.

#### **Other comments:**

#### **Abstract**

L19: 'reliable validation results' -> 'extensive validation results'?

Response: Thanks for your suggestion. We have replaced the 'reliable validation results' with 'extensive validation results'.

L35: It would be better to avoid the term 'significantly' unless statistical significance has been tested for – 'substantially' would be more appropriate. There are similar occurrences throughout the manuscript.

Response: Thank you for pointing this out. We checked all the 'significantly' in this paper and corrected the incorrect ones with 'substantially.'

#### **1. Introduction**

L48: The meaning of 'irreplaceable characteristics' is unclear.

Response: Thanks for your comments, and we reorganized this sentence as follows:

“Among the various time-series LAI products with global coverage, Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product was among the most extensively utilized LAI datasets.”

L64 and L66: What is the 'specified threshold'?

Response: The yellow ellipse is the uncertainty range of the  $\chi^2$  distribution determined according to the error level set in the red and near-infrared bands, and the average of all the inversion values corresponding to the ellipse is taken as the output (rather than only the red dot in the **Figure** as the output). When the uncertainty of the input BRFs falls within a point on the red-NIR plane and an area, all canopy or soil patterns are considered as the candidate solutions, and the mean LAI values of these solutions are used as the output values of the main algorithm.

In order to avoid the reader's misunderstanding, we have revised this sentence:

“When the uncertainty of the input BRFs falls within a point on the red-NIR plane and an area, all canopy or soil patterns are considered as the candidate solutions, and the mean LAI values of these solutions are used as the output values of the main algorithm.”

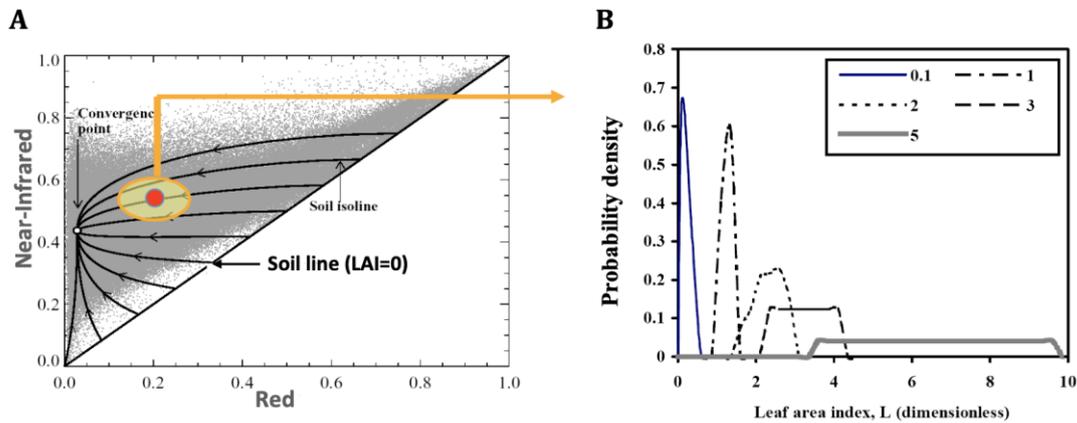


Figure. Schematic illustration of the main algorithm (Myneni, 2020). Panel A: Distribution of vegetated pixels with respect to their reflectances at red and near-infrared (NIR) spectral bands from Terra MODIS tile h12v04. A point on the red-NIR plane and an area about it (yellow ellipse defined by a  $\chi^2$  distribution) are treated as the measured BRF at a given sun- sensor geometry and its uncertainty. Each combination of canopy/soil parameters and corresponding FPAR values for which modeled reflectances belong to the ellipse is an acceptable solution. Panel B: Density distribution function of acceptable solutions. Shown is solution density distribution function of LAI for five different pixels. The mean LAI and its dispersion (STD LAI) are taken as the LAI retrieval and its uncertainty. This technique is used to estimate mean FPAR and its dispersions (STD FPAR).

L98: 'data value-added' -> 'value-added data' (here and throughout)?

Response: Thanks for your comments, and we have replaced all phrases of 'data value-added' in this paper with 'value-added data'.

L102: A reference for Google Earth Engine might be needed here (<https://doi.org/10.1016/j.rse.2017.06.031>).

Response: Thanks for your comments and we added the references as suggested.

“We implemented the entire algorithm process using the Google Earth Engine (GEE) cloud computing platform (Gorelick et al., 2017) to reprocess MODIS C6.1 LAI”

## 2. Materials

L145: Perhaps the paragraph on BELMANIP V2.1 belongs in its own section, since it's related to product intercomparison rather than validation with ground reference data.

Response: Thanks for your suggestion. We reorganized the chapter structure to include BELMANIP V2.1 as a separate Section 2.4.

L162: The CEOS WGCV LPV LAI good practice document should be referenced here (<https://doi.org/10.5067/doc/ceoswgcv/lpv/lai.002>).

Response: Thanks for your comments and we added the references as suggested.

“By the CEOS WGCV LPV LAI good practices (Fernandes et al., 2014), the ground data were upscaled using an empirical "transfer function" between high spatial resolution radiation data and biophysical



	<b>ONAQ</b>	0.31	0.29	0.06	0.04	95.57	90.81	-0.20	-0.19
	<b>SRER</b>	0.21	0.21	0.84	0.86	45.16	44.94	-0.11	-0.05
	<b>STER</b>	---	---	---	---	---	---	---	---
	<b>WOOD</b>	1.29	1.19	0.55	0.66	110.19	102.07	-1.24	-1.15
<b>Forests</b>	<b>HARV</b>	0.82	0.53	0.72	0.83	19.37	12.41	-0.24	-0.15
	<b>TALL</b>	1.29	1.14	0.77	0.81	38.72	34.10	-1.08	-0.96
	<b>TUMB</b>	1.33	1.31	0.94	0.95	77.58	76.23	-1.19	-1.19
<b>Grasses</b>	<b>JORN</b>	0.06	0.16	1.00	1.00	14.95	35.91	-0.03	0.01
<b>&amp; Shrubs</b>	<b>VASN</b>	---	---	---	---	---	---	---	---
<b>Crops</b>	<b>BLAN</b>	0.53	0.34	0.41	0.71	36.72	23.76	-0.44	-0.31
<b>&amp; Savannas</b>	<b>LAJA</b>	0.32	0.17	0.99	0.20	25.31	13.42	-0.24	-0.13
<b>Grasses</b> <b>&amp; Savannas</b>	<b>GUAN</b>	0.72	0.49	0.36	0.43	22.23	15.13	-0.59	-0.33
	<b>JERC</b>	0.72	0.80	0.70	0.81	24.69	27.42	0.61	0.76
	<b>LITC</b>	0.85	0.68	0.58	0.66	149.71	120.21	-0.83	-0.66
	<b>NIWO</b>	0.49	0.31	0.68	0.64	66.89	42.19	-0.47	-0.30
<b>Savannas</b> <b>&amp; Forests</b>	<b>BART</b>	0.75	0.46	0.80	0.89	19.60	11.87	-0.14	0.06
	<b>DELA</b>	1.16	1.10	0.05	0.03	26.67	25.17	0.42	0.91
	<b>DSNY</b>	0.76	0.89	0.75	0.86	30.34	35.54	0.75	0.89
	<b>HAIN</b>	1.11	0.45	0.50	0.88	24.83	10.16	0.16	0.21
	<b>ORNL</b>	0.73	0.68	0.44	0.55	18.50	17.05	-0.02	0.39
	<b>OSBS</b>	0.45	0.42	0.85	0.74	18.44	17.24	0.20	0.30
	<b>SCBI</b>	1.05	0.81	0.52	0.78	23.00	17.67	0.41	0.54
	<b>SERC</b>	0.84	1.38	0.83	0.80	18.85	30.92	0.75	1.31
	<b>STEI</b>	0.75	0.65	0.54	0.67	18.17	15.81	-0.20	0.42
	<b>UNDE</b>	0.42	0.28	0.03	0.47	9.50	6.40	0.07	0.14
	<b>WOMB</b>	---	---	---	---	---	---	---	---

*L264-266: References needed here?*

Response: Thanks for your comments and we added the references as suggested.

“These regions are affected by the long-term influence of large cloud cover, high concentration of aerosol and saturation of Red-NIR, resulting in limited availability of high-quality observation data

and poor accuracy in LAI retrieval (Xu et al., 2018; Yan et al., 2016).”

## 5. Discussion

*L305: ‘unusually high noise’ – unusual compared to what?*

Response: Thanks for your comments, and we have revised it as follows:

“When affected by atmospheric conditions, sensor malfunctions, and retrieval algorithm uncertainties, MODIS LAI experiences poor spatiotemporal consistency and accompanies increased noise level.”

*L325: Rather than being about ‘the dense vegetation period of summer’, I suspect this is more related to your next point – the high LAI is mostly found in tropical regions where there is greater cloud cover and aerosol load.*

Response: Thanks for your comments, and we have revised it as follows:

“Ground verification also reveals a consistent pattern between low MQA values and high LAI retrievals. Regions with high LAI values are mainly observed in tropical regions where there is greater cloud cover and aerosol load, which is prone to signal saturation.”

*L326: Whilst I know what is meant by ‘pixel quality is assessed based on the algorithm path’ (i.e. main vs. back-up algorithm), it might not be clear to readers who are less familiar with the ins and outs of MODIS LAI. It would also be helpful to explain how this is assessed (I am assuming you are assigning a higher quality to the main algorithm and a lower one to the backup algorithm, but this is not explicitly mentioned).*

Response: Thank you for pointing this out, and we added the detail description in Sect 3.1.

“To address this issue, this approach employed multiple indicators to evaluate the uncertainty for each pixel (referred to as MQA hereafter). These indicators encompass the algorithm path, STD LAI, and Relative Time-series Stability (TSS). The algorithm path (AP) is a crucial quality index, distinguishing between the main and backup algorithms. The main algorithm offers superior quality and precision retrieval, and the weight ratio of the main algorithm and backup algorithm is determined as 6:4 in the previous study (Wang et al., 2023). STD LAI reflects the retrieval uncertainty. The AP and STD LAI are derived from the FparLai\_QC and LaiStdDev layers of the original MODIS data. The third indicator, Relative TSS (RE-TSS), indicates the fluctuation of a time series (Zou et al., 2022). Following the principle of assigning a higher weight to smaller values, STD LAI and RE-TSS are incorporated into the retrieval with the main algorithm, resulting in the generation of a new quality classification indicator, MQA.”

*L336: ‘Equator’ -> ‘Equatorial’ (here and throughout)?*

Response: Thanks for your comments, and we have replaced word of ‘Equator’ in this paper with ‘Equatorial’.

## References:

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