Responses and Revisions to Comments

Dear reviewer

Thanks for your reviewing and valuable comments of our manuscript entitled "***A global estimate of monthly vegetation and soil fractions from spatio-temporally adaptive spectral mixture analysis during 2001–2022***". We also appreciate you for providing insightful feedback and comments to strengthen our manuscript.

We have revised our manuscript with considering each detailed suggestion that you have graciously provided. These major revisions include:

1 More comprehensive description of the validation and comparison processes.

2 Additional land cover and land use reference data and fractional vegetation cover data for validation and comparison.

3 A more accurate representation.

Besides these revisions, all authors checked the manuscript carefully and several minor revisions have been done to finalize the manuscript.

The following is a point-by-point response to the questions and comments delivered in your letter. For your convenience, revisions made by the authors have been highlighted in red color in the both response and revised manuscript, which could be easily checked. We hope that our revisions and responses can satisfactorily address all the issues and concerns.

Spatially-explicit monitoring of vegetation and soil fractions is critical for understanding terrestrial ecological processes. There are thus many global vegetation fractional cover products including ENVISAT, CYCLOPES, GEOV, MuSyQ, GLASS, and CGLS. The authors provided a unified monthly fractional vegetation-soil nexuses product during 2001-2022 with MESMA. As a user, we would like to rely on more precise satellite-derived fraction data. Therefore, I pay more attention to the credibility of the new fraction products presented in this paper. This paper merely presented the evaluation of the estimates of vegetation and soil fractions datasets in Section 3.1 and Section 4.1, respectively. However, this validation is inadequate. It's difficult to persuade me that the presented product is superior to existing fraction products. Thus, further validations are required.

We value your thoughtful recommendations regarding the validation of vegetation and soil fractions. Acknowledging the crucial role of data reliability in accurately depicting land surface processes, our manuscript incorporates CLCVRD data along with other land cover and land use reference data for validating the estimated vegetation and soil fractions in Sections 3.1, and provides additional fractional vegetation cover data for comparison in Section 3.2.

First, to enhance the validation process for the showcased product, we have enhanced the procedural description for estimating fractional vegetation-soil compared to GLCVRD, ensuring product reliability (page 11, line 236-251).

"Moreover, due to challenges in conducting fraction estimation validation through field surveys, we employ reference data obtained from high spatial resolution images as validation set. We thus select for two sets of reference data that their land cover classification systems are closely related to our five endmembers.

...

Firstly, we filter the estimated fractions based on the corresponding year and month obtained from the reference data. Simultaneously, aligning the interpretations of land cover types with our endmembers, we pair them accordingly, that is, tree and other vegetation represent PV and NPV, barren stands for BS, water and shadow correspond to DA, and ice & snow denote IS. Subsequently, we reclassify these paired land cover types and calculated their percentage within 5×5 km blocks, in which we exclude cloud coverage (named no data). Additionally, utilizing these cloud-free pixels in each block, we compute the mean of fractional values for each endmember, and then compare these estimated fractions with the measured percentage of paired the reclassified land cover types to validate the reliability of our product (Fig. S4)."

We further authenticate our product through incorporating comprehensive global land cover and land use reference data, which were obtained from the Geo-Wiki crowdsourcing platform across four campaigns[1] (page 12, line 265-276).

"Besides, we also authenticate our product through incorporating comprehensive global land cover and land use reference data (Fritz et al. 2017), which were obtained from the Geo-Wiki crowdsourcing platform across four campaigns: Human impact, wilderness, reference and disagreement. Over 150000 samples of land cover and land use were acquired in this reference data. To effectively validate our product, we need to filter the reference data, considering aspects such as data acquisition time, measurement methods, and credibility. We select first three campaigns, which have a good match with MODIS pixels (size 1×1km) and were observed during 2001 to 2022, and then select 1038 high feasibility reference data through the confidence information of land cover estimates and the status of use of high spatial resolution imagery provided by the metadata. Finally, Similarly to the procedural description used for fractional vegetation-soil compared to GLCVRD, we reclassified ten classes of this dataset into our four groups of endmembers, including (1) tree cover, shrub cover, herbaceous vegetation/grassland, cultivated and managed, and mosaic of cultivated and managed/natural vegetation to PV and NPV; (2) flooded/wetland and open water to DA; (3) urban and barren to BS; (4) snow and ice to IS. This involved

[1] Fritz, S., See, L., Perger, C., McCallum, I., Schill, C., Schepaschenko, D., Duerauer, M., Karner, M., Dresel, C.,r Laso-Bayas, J. C., Lesiv, M., Moorthy, I., Salk, C. F., Danylo, O., Sturn, T., Albrecht, F., You, L., Kraxner F., Obersteiner, M.: A global dataset of crowdsourced land cover and land use reference data. Scientific data, 4, 1-8, https://doi.org/10.1038/sdata.2017.75, 2017.

comparing the measured percent of land cover with the mean of endmember fractions within the corresponding 1x1km pixels."

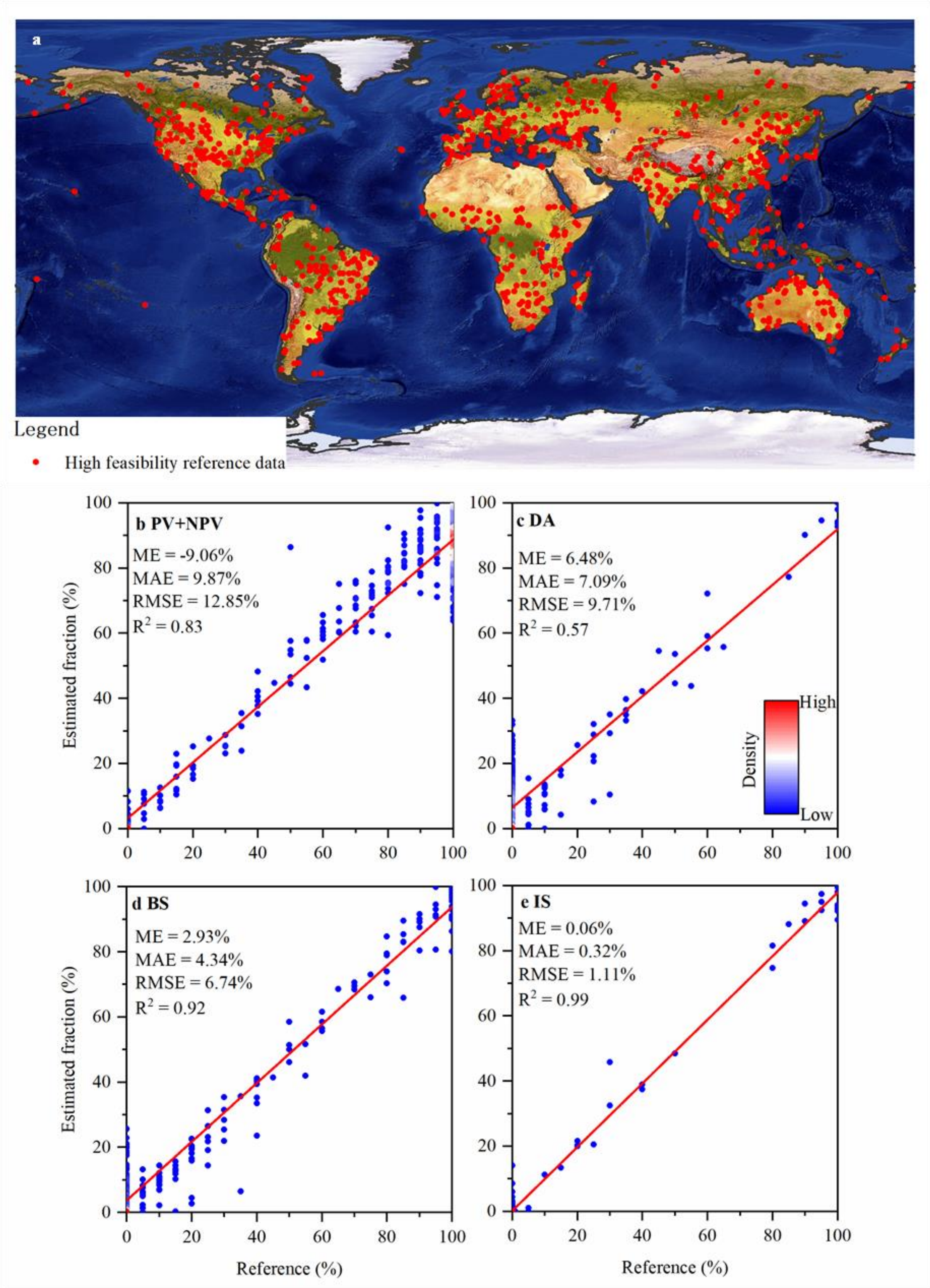

Fig. S5 Evaluation of global fractional endmember estimates based on land cover reference data. a, the location of high-feasibility land cover reference data. b-d, Scatter plots of PV+NPV, BS, DA, IS fractions against land cover reference data

Moreover, in addition to the original two datasets, we included two additional datasets recommended by you for conducting relevant comparisons. Finally, we strengthened the comparisons between our generated data and four existing datasets: NDVI, MOD44B Vegetation Continuous Fields product, GLASS fractional vegetation cover dataset, and GEOV Fcover dataset in Section 2.4 Comparisons and uncertainties analysis (page 12-13, line 278-293), and present results in Section 3.2 Compared with other datasets and traditional spectral mixture analysis model. Such comparisons include bi-dimensional histogram of fractional endmembers and other dataset (Fig. 4) and detailed figures (Fig. S6).

"To verify the consistency and merits of our dataset against existing ones, we conducted comparisons with four distinct pre-existing datasets: NDVI, MOD44B Vegetation Continuous Fields product, GLASS fractional vegetation cover dataset, and GEOV Fcover dataset. NDVI is derived from monthly synthesized MCD43A4 images. Both mean values of NDVI and our estimated fractional PV across all years and months are considered for comparison. The MOD44B Vegetation Continuous Fields product provides annual information about the percent tree cover, percent non-tree cover, and percent non-vegetated within each 250-meter pixel globally (DiMiceli et al., 2015). Consequently, we compare vegetation cover proportions—sum of percent tree cover and percent non-tree cover—to the sum of fractional PV and NPV. To align spatial and temporal resolutions, we aggregated the sum of percent tree cover and percent non-tree cover to a 500-meter scale. Simultaneously, we computed monthly Fractional PV and NPV as annual averages. The GLASS fractional vegetation cover dataset, offering an 8-day temporal frequency and dual spatial resolutions of 0.05° and 500 meters, was generated using a machine learning approach correlating MODIS reflectance with fractional vegetation cover (Jia et al., 2015). In our study, the 500-meter GLASS data was utilized to validate our estimated fractions. We computed annual averages from all the CLASS fractional vegetation cover data within a year and compared it with the annual averages of Fractional PV and NPV. GEOV FCover is a 10-day product estimated through the neural network using visible, near-infrared and shortwave infrared at 1km resolution (Baret et al. 2013). We aggregate our product to a 1km spatial resolution, and compare their annual averages with the annual averages of GEOV FCover."

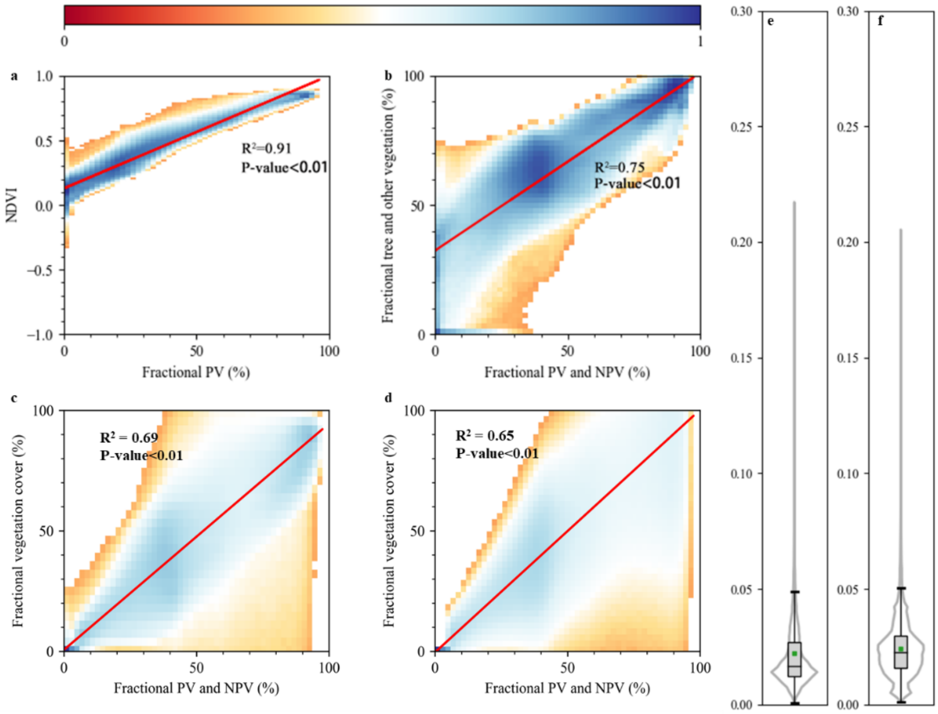

Figure 4: Comparisons with other datasets and traditional spectral mixture analysis models. a, b, **c**, **d** the bi-dimensional histogram of fractional endmembers and other dataset with bin size of 2%, including fractional PV against NDVI (a), fractional PV and NPV against fractional tree and non-tree vegetation of MOD44B vegetation continuous fields product (b), fractional PV and NPV against GLASS fractional vegetation cover product (c), fractional PV and NPV against fractional vegetation cover of GEOV Fcover product; **e**, **f**, the boxplot and violin plot for average of monthly $RMSE_{sma}$ for two fixed endmember spectral curves using fully constrained linear spectral mixture models, including (e) average of all spectral spectra for each endmember and (f) existing spectral spectra from Small and Sousa (2019).

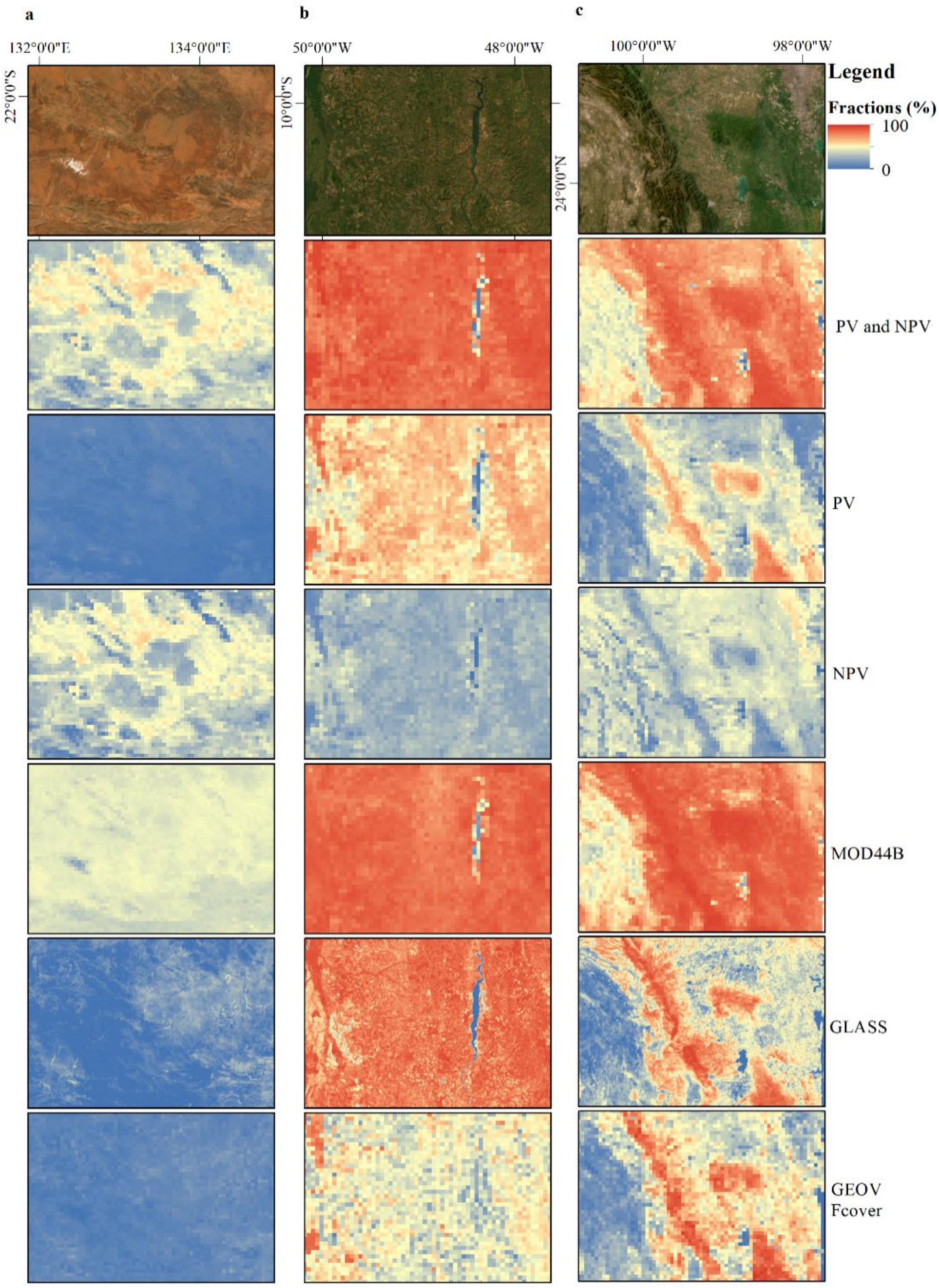

Fig. S6 The detailed graphs for comparing different datasets. a, b, and c represent comparisons of vegetation abundance products in different scenarios, specifically, regions with low vegetation cover in arid areas, high vegetation cover in tropical rainforests, and transitional zones from low to high values. The compared products include our produced PV and NPV, MOD44B, GLASS, and GEOV.

MESMA needs a large library of endmembers representative of each ground component. In Section 2.2.1, the paper depicted the selection of endmembers. I suggest that supplement some RGB images of these selected pure pixels.

Thank you very much for your valuable suggestions, we've chosen several typical images representing selected pure pixel of each endmember. These images have been used as part of the supporting material (supplement) to underpin the reliability of the data.

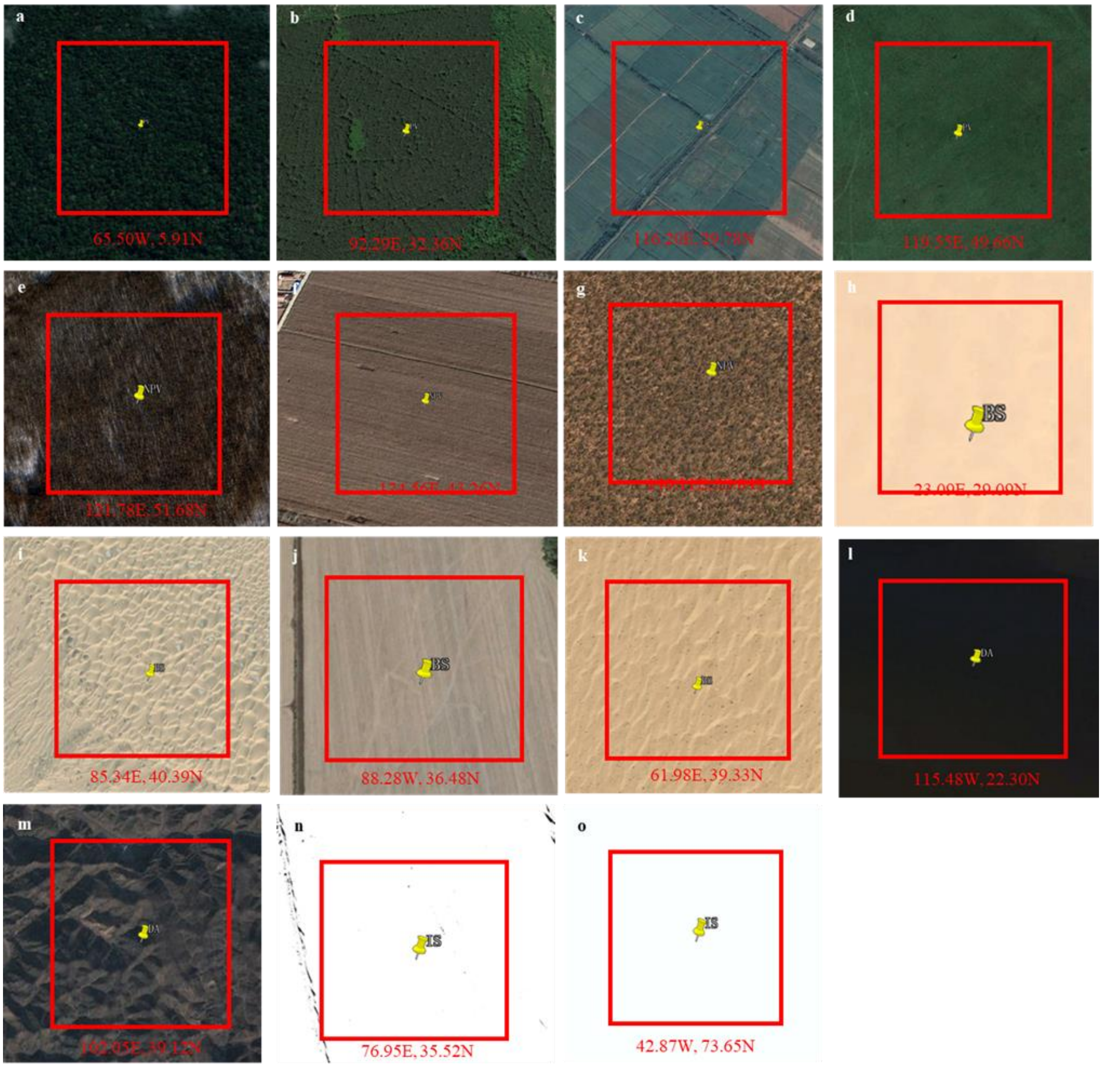

Figure S2: Typical images representing selected pure pixel of each endmember. a-o are tropical rainforest, temperate forest, cropland, grasslands, temperate deciduous forest in winter, crop residues, shrubs in dryland, moving sands, sand dunes, bare ground, moving sands. waters, bare rock, polar glaciers, and alpine glaciers.

Please clarify the reason that the mean error and mean absolute error were used as accuracy metrics.

The mean error (ME) and mean absolute error (MAE) are commonly used accuracy metrics in various fields, especially in statistics and machine learning, for assessing the performance of predictive models.

Mean Error (ME): ME measures the average of all errors in a dataset where errors are the differences between predicted and actual values. ME helps in understanding the overall bias of the model. Mean Absolute Error (MAE): MAE is the average of the absolute differences between predicted and actual values. It measures the average magnitude of errors without considering their direction. It's easier to interpret as it provides a straightforward understanding of the average prediction error.

Both ME and MAE are useful metrics to evaluate the accuracy of predictive models, the use of ME and MAE depends on the specific context of the problem and what kind of error measurement is more important for the analysis[2].

We thus improve the descriptions of these four accuracy metrics (page 11, line 253-258).

"ME measures the average of all errors in the dataset where errors are the differences between predicted and actual values, MAE calculates the average of the absolute differences between predicted and actual values, RMSE provides a measure of prediction error, whereas R^2 offers insight into the amount of variability in the dependent variable that the model explains. These metrics provide a more comprehensive assessment of the model's accuracy, helping to understand different facets of its performance, such as bias, variability, and overall predictive power (James et al., 2013)."

Please provide additional information on the source of GLCVRD, such as GLCVRD (Bruce Pengra et al., 2015).

Thanks for your valuable suggestions, we have provided additional information on the source of GLCVRD (Olofsson et al. 2012; Pengra et al. 2015; Stehman et al. 2012)[3]. (page 11, line 240)

"Global Land Cover Validation Reference Dataset (GLCVRD) is provided with a 2m reference dataset from very high resolution commercial remote sensing data within 5 × 5 km blocks from 2003 to 2012 (Olofsson et al. 2012; Pengra et al. 2015; Stehman et al. 2012)"

Could you please provide an explanation for the red dot appearing at the top of Figure 3?

The overlaid red dots in Figure 3a were spatial distribution of the 5 × 5 km validation blocks of GLCVRD reference dataset.

We have included this explanation in page 15, line 338-339:

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[2] James, G., Witten, D., Hastie, T., Tibshirani, R.: An introduction to statistical learning. New York: springer, https://doi.org/10.1007/978-1-0716-1418-1. 2013

[3] Olofsson, P., Stehman, S.V., Woodcock, C.E., Sulla-Menashe, D., Sibley, A.M., Newell, J.D., Friedl, M.A., Herold, M.: A global land-cover validation data set, part I: Fundamental design principles. Int. J. Remote Sens., 33, 5768-5788, https://doi.org/10.1080/01431161.2012.674230,2012.

Pengra, B., Long, J., Dahal, D., Stehman, S.V., Loveland, T.R.: A global reference database from very high resolution commercial satellite data and methodology for application to Landsat derived 30 m continuous field tree cover data. Remote Sens. Environ., 165, 234-248, https://doi.org/10.1016/j.rse.2015.01.018, 2015.

Stehman, S.V., Olofsson, P., Woodcock, C.E., Herold, M., Friedl, M.A.: A global land-cover validation data set, II: Augmenting a stratified sampling design to estimate accuracy by region and land-cover class. Int. J. Remote Sens., 33, 6975-6993, https://doi.org/10.1080/01431161.2012.695092, 2012.

"The overlaid red dots were spatial distribution of the 5 × 5 km validation blocks of GLCVRD reference dataset (n=500)"

Could you please provide a detailed procedure for fractional vegetation-soil estimates compared to GLCVRD?

Thanks for your valuable suggestions, to enhance the validation process for the showcased product, we have enhanced the procedural description for estimating fractional vegetation-soil compared to GLCVRD through detailed textual descriptions and supporting figures (page 11, line 244-251).

"Firstly, we filtered the estimated fractions based on the corresponding year and month obtained from the reference data. Simultaneously, aligning the interpretations of land cover types with our endmembers, we paired them accordingly, that is, tree and other vegetation represent PV and NPV, barren stands for BS, water and shadow correspond to DA, and ice & snow denote IS. Subsequently, we reclassified these paired land cover types and calculated their percentage within 5×5 km blocks, in which we excluded cloud coverage (named no data). Additionally, utilizing these cloud-free pixels in each block, we computed the mean of fractional values for each endmember, and then compared these estimated fractions with the measured percentage of paired the reclassified land cover types to validate the reliability of our product (Fig. S4)."

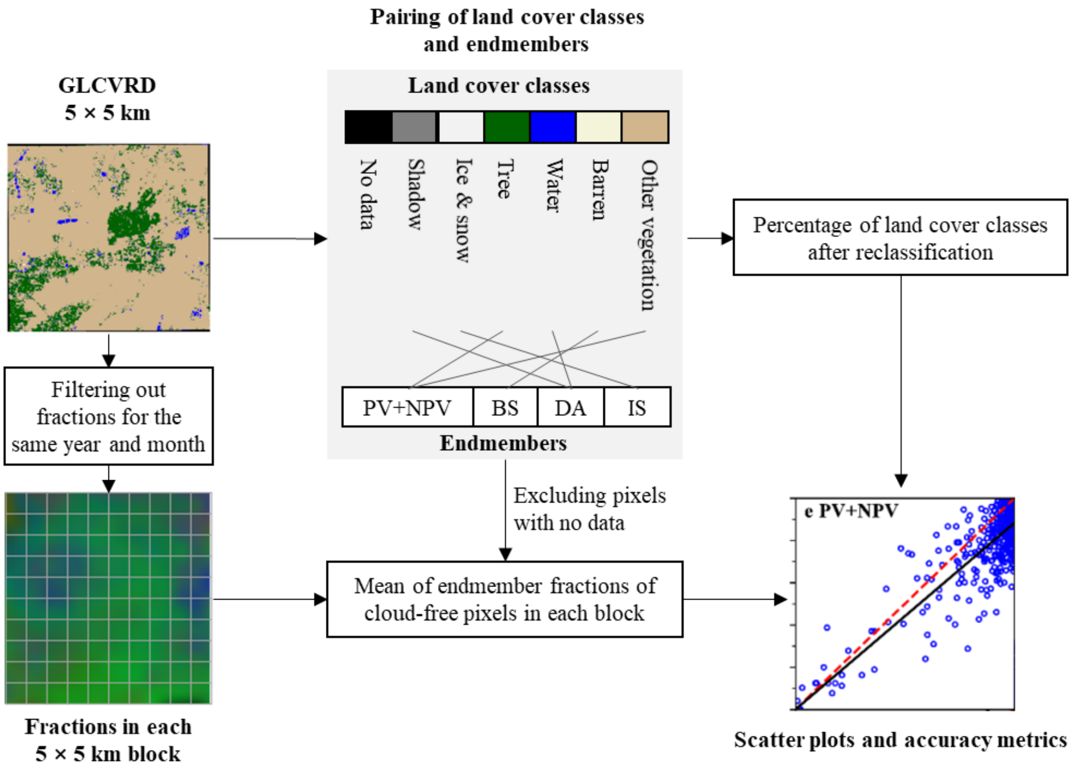

Figure S4: Procedural description for estimating fractional vegetation-soil compared to GLCVRD.

Line 332 "estimates vegetation and soil fractions": estimates of vegetation and soil fractions

Thank you very much for your careful review of our manuscript, we have corrected these errors and have also carefully examined and revised the manuscript to ensure the accuracy of the presentation.