Revisions and Responses 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 and reviewers have graciously provided. These major revisions include:

1 Enhanced the introduction and discussion regarding the significance of this dataset.

2 Augmented experiments with more data for validation and comparison to prove the data reliability.

3 Conducted in-depth analysis and discussion on the validations and comparisons.

4 Adjusted the structure of the article.

5 Improved the expression of the article.

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.

Monthly vegetation and soil fractions products are important to understand the global landcover change and evaluate the impacts of climate change and human activities on the terrestrial ecosystem. The topic is interesting and the MESMA algorithm may be a practical method for decoupling the mixed pixels. I acknowledge the potential of the algorithm; however, I have some major concerns regarding the dataset itself, including its significance, validation methods, as well as the overall organization of the article. Given that the ESSD journal focuses more on the dataset, I am unable to provide a positive evaluation.

Thank you very much for your feedback on our manuscript. We understand your concerns regarding the significance and reliability of the vegetation and soil fractions products presented in our manuscript, possibly due to our insufficient description of advantages and validation. We believe our dataset holds certain advantages in terms of its significance and reliability. Our response primarily encompasses the following points:

[Significance] (1) Our dataset surpasses traditional vegetation index and fractional vegetation cover datasets by offering a comprehensive view of various surface elements including vegetation, photosynthetic vegetation, bare soil, dark material, ice and snow. This expanded coverage not only enhances our comprehension of heterogeneous surface dynamics but also presents distinct advantages for modeling Earth's biophysical processes. Both our team and researchers have validated these advantages[1]. Consequently, we firmly believe in the practical significance of our dataset. (2) Unlike high-resolution fractional vegetation cover data typically constrained by temporal resolution limits, our dataset presents a unique perspective on surface evolution across extended periods (>20 years) and at high frequencies. Meanwhile, Currently, the academic community extensively utilizes high temporal resolution images like MODIS and AVHRR to analyze global surface changes and biophysical processes [2], This suggests our 500-meter product stands out as exceptionally valuable globally. (3) Moreover, owing to the intrinsic significance of these surface endmembers, achieving high spatial and temporal resolution abundance data through spatiotemporal fusion[3] becomes notably easier compared to traditional spectral or spectral index approaches. This attribute underscores the dataset's ability to capture intricate surface dynamics with enhanced precision.

We have included a review about vegetation index and fractional vegetation cover in Section of Introduction (page 3, line 72-87) and discussed advantage of our product in Section 4.1 (page 24-25, line 455-469).

Section 1: "Continuous vegetation indexes (e.g., normalized difference vegetation index (NDVI), enhanced vegetation index (EVI)) provide limited information on

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[1] Sun, Q., Zhang, P., Jiao, X., Han, W., Sun, Y., Sun, D.: Identifying and understanding alternative states of dryland landscape: a hierarchical analysis of time series of fractional vegetation-soil nexuses in China's Hexi Corridor. Landscape and urban planning. 215,104225, https://doi.org/10.1016/j.landurbplan.2021.104225, 2021.
Franke, J., Roberts, D.A., Halligan, K., Menz, G.: Hierarchical Multiple Endmember Spectral Mixture Analysis (MESMA) of hyperspectral imagery for urban environments. Remote Sens. Environ., 113, 1712-1723, https://doi.org/10.1016/j.rse.2009.03.018, 2022.
Daldegan, G.A., Roberts, D.A., Ribeiro, F.: Spectral mixture analysis in Google Earth Engine to model and delineate fire scars over a large extent and a long time-series in a rainforest-savanna transition zone. Remote Sens. Environ., 232, 111340. https://doi.org/10.1016/j.rse.2019.111340, 2019
[2] Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R.: China and India lead in greening of the world through land-use management. Nature Sustainability, 2, 122-129, https://doi.org/10.1038/s41893-019-0220-7, 2019
Qin, Y., Xiao, X., Dong, J., Zhang, Y., Wu, X., Shimabukuro, Y., Arai, E., Biradar, C., Wang, J., Zou, Z.: Improved estimates of forest cover and loss in the Brazilian Amazon in 2000–2017. Nature Sustainability, 2, 764-772, https://doi.org/10.1038/s41893-019-0336-9, 2019.
[3] Small, C., Milesi, C.: Multi-scale standardized spectral mixture models. Remote Sens. Environ., 136, 442-454, https://doi.org/10.1016/j.rse.2013.05.024, 2013.
Zhang, Y., Foody, G. M., Ling, F., Li, X., Ge, Y., Du, Y., & Atkinson, P. M.: Spatial-temporal fraction map fusion with multi-scale remotely sensed images. Remote Sensing of Environment, 213, 162-181, 2018.

surface composition, which hinders our ability of understanding ecosystem's structurally and functionally multifaceted shifts (Smith et al. 2019; Sun 2015; Zeng et al., 2023). In recent years, there have been significant advancements in fractional vegetation cover within the fields of remote sensing and environmental science. This progress has led to the development of various products at multiple resolutions, such as long-term global land surface satellite (GLASS), GEOV Fcover, multi-source data synergized quantitative remote sensing production system (MuSyQ) fractional vegetation cover (Baret et al. 2013; Jia et al., 2015; Mu et al., 2017; Zhao et al., 2023). These products primarily integrate and utilize data from different spectral bands and sensors, employing methods including machine learning and radiative transfer model. However, these data primarily focus on green vegetation, posing significant limitations in capturing information regarding non-photosynthetic vegetation and bare soil. This constraint also restricts the applicability of this data in arid regions. Although some initiatives and products focused on multi-element fractions, such as MOD44B and the Global Vegetation Fractional Cover Product (DiMiceli et al., 2015; Guerschman et al., 2015). For instance, the Global Vegetation Fractional Cover Product primarily targets arid regions, particularly Australia, focusing on photosynthetic vegetation, non-photosynthetic vegetation, and bare soil. Meanwhile, MOD44B achieves global-scale acquisition of trees, non-trees, and non-vegetative cover. There is a lack of unified classification systems among these products across global scale"

Section 4.1: "Moreover, our product demonstrates good scalability in terms of time and endmember types. These monthly estimates of fractional vegetation-soil nexuses can be upgraded to multi-timescale (daily, yearly) products to serve different needs, and thus provide time series of multicomponent information on surface heterogeneous composition and interactive evolution. Besides, considering the meaningful physical interpretations of endmember fraction values, these endmembers can be conveniently integrated across different temporal and spatial scales using spatiotemporal fusion methods (Zhang et al. 2018). The temporal and spatial variability of endmembers has always been a significant constraint in obtaining global-scale vegetation and soil fractions from imagery (Wang et al. 2021). The spatio-temporally adaptive framework employed helps to increase the representativeness of endmember selection, and MESMA also considers the suitability of each combination of these endmembers within each pixel. However, considering the limitations of computational resources, our solution on hierarchical clusters of the endmember spectra can improve considerably cost-effective unmixing of long time-series satellite records over globe under the trade-offs of certain accuracy requirements (Fig. 3). With the assumption of increased computational power in the future, we believe that utilization of combination models from selected endmember spectra (35 GV spectra, 40 BS spectra, 25 NPV spectra, 16 DA spectra, and 15 IS spectra) or expanded endmember spectra may further improve the accuracy and stability of estimates of gradations of five surface vegetation and soil components at global scale."

[Reliability] Concerning data validation, we've improved endmember fraction validations through incorporating comprehensive global land cover and land use reference data, which were obtained from the Geo-Wiki crowdsourcing platform across four campaigns[4]. We conducted comparisons with four distinct pre-existing datasets: NDVI, MOD44B Vegetation Continuous Fields product, GLASS FVC dataset, and GEOV Fcover dataset.

(1) We have improved validation through incorporating comprehensive global land cover and land use reference data, which were obtained from the Geo-Wiki crowdsourcing platform across four campaigns (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 comparing the measured percent of land cover with the mean of endmember fractions within the corresponding 1×1km pixels."

(2) Moreover, we strengthened the comparisons between our generated data and four existing datasets: NDVI, MOD44B Vegetation Continuous Fields product, GLASS FVC dataset, and GEOV Fcover dataset (page 12-13, line 277-293).

"2.4 Comparisons and limitations analysis

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

[4] 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.

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."

(3) Furthermore, to validate the uncertainties of the hierarchical clustering, we select a spectral spectrum from selected endmember spectra that exhibit the largest mean squared error from the mean of cluster for each cluster. These selected spectral spectra were then used to reconstruct an extreme library of endmember spectra and used to estimate fractional vegetation and soil using MESMA. Methodologically, we've maximized our model optimizations within the constraints of current computational capabilities. This involved leveraging endmember curves from five distinct endmember types, totaling 15 subclasses. Through meticulous optimization, we obtained superior unmixed results from a pool of 692 models. Notably, the model's uncertainty has been thoroughly elucidated in Section 3.3. While our current computational resources set the boundaries, our aim is to further refine and amplify these models in the future. This includes expanding the spectrum of endmember types and increasing the count of endmember spectral curves using the provided code, provided that computational resources allow.

We thus discussed the reliability of our product in Section 4.1 Advances and limitations of estimates of global vegetation and soil fractions

1. For significance and usefulness, the product is derived using the MODIS data with a resolution of 500m. Actually, there are a lot of available global or regional higher-resolution land cover products and FVC products. As a user, why do I have to select your product for the analysis? I think using higher-resolution products can acquire more reasonable results. There is not enough evidence in the article that convince me of the indispensability of your dataset at this stage. More content indicating the importance should be included in the Introduction.

Thank you very much for your valuable suggestions. Although there are numerous high spatial resolution land cover and fractional vegetation cover products available, we believe our dataset holds certain advantages for conducting global-scale analyses. This is primarily showcased in the following aspects:

Unique Comprehensive Insights: We highlight the distinctiveness of the dataset in providing a comprehensive view that encompasses fractional multiple surface features (including vegetation, photosynthetic vegetation, bare soil, dark material, ice and snow) beyond traditional land cover or fractional vegetation cover products. This breadth of information can offer a holistic understanding of surface dynamics globally.

Analytical Advantages: Our data exhibits favorable advantages in extended periods and at high frequencies, which aids in discovering finer processes. Considering the physical significance of the endmembers, it contributes to our dataset's ability to conduct clear downscaling and upscaling at the spatiotemporal scale[5]. Moreover, the scalability of the MESMA assists us in expanding the dataset's accuracy in the future by broadening endmember types and spectral curves. This dataset can serve as a baseline or reference for enhancing our comprehension of heterogeneous surface dynamics and modeling Earth's biophysical processes in the future studies, its potential applications in various fields such as ecology, climate studies, or urban planning.

By incorporating these into the Introduction and Discussions, we can provide a more compelling argument for the indispensability and significance of our dataset, effectively addressing the concerns of potential users seeking higher-resolution products for analysis.

Introduction (page 3, line 75-87)

"In recent years, there have been significant advancements in fractional vegetation cover within the fields of remote sensing and environmental science. This progress has led to the development of various products at multiple resolutions, such as Long-term global land surface satellite (GLASS), GEOV Fcover, Multi-source data Synergized Quantitative remote sensing production system (MuSyQ) fractional vegetation cover (Baret et al. 2013; Jia et al., 2015; Mu et al., 2017; Zhao et al., 2023). These products primarily integrate and utilize data from different spectral bands and sensors, employing methods including machine learning and radiative transfer model. However, these data primarily focus on green vegetation, posing significant limitations in capturing information regarding non-photosynthetic vegetation and bare soil. This constraint also restricts the applicability of this data in arid regions."

[5] Small, C., Milesi, C.: Multi-scale standardized spectral mixture models. Remote Sens. Environ., 136, 442-454, https://doi.org/10.1016/j.rse.2013.05.024, 2013.
Zhang, Y., Foody, G. M., Ling, F., Li, X., Ge, Y., Du, Y., & Atkinson, P. M.: Spatial-temporal fraction map fusion with multi-scale remotely sensed images. Remote Sensing of Environment, 213, 162-181, 2018.

Discussions (page 24, line 443-454):

"Our product can overcome the problem of saturation of NDVI in the regions embodying high coverage vegetation. Such advance can be supported by previous regional comparison research (Rogan et al. 2002; Sun et al. 2019; Sun et al. 2020). Additionally, the diversity of information stands as one of the strengths of this dataset, encompassing the five primary components of the Earth's land surface globally. Moreover, it can be extended to encompass more types through different levels of clustering. For instance, the DA component has not been emphasized in many datasets, yet current scientific research underscores the need for increased attention to vegetation shadows (Zeng et al., 2023). Although our DA component represents various types across different land regions, such as water bodies, shadows, bare rocks, this dataset may effectively enhance our precise understanding of complex vegetation structures. The NPV component is a vital element in arid ecosystems and represents a crucial part of vegetation biomass. Our dataset, by finely characterizing NPV, not only aids in understanding the evolving features of vegetation structure under photosynthetic and non-photosynthetic interactions (Guerschman et al. 2015), but also contributes to a more accurate quantification of global biomass in arid land systems (Smith et al. 2019)."

2. The current classification system comprises only five types. While I understand that the algorithm proposed by the authors can effectively decompose mixed pixels, I am not sure if it is enough for the practical analysis only based on these categories.

We appreciate your concerns about the choice of five endmember types. A framework encompassing substrate, vegetation, dark, and ice/snow has been proposed and globally validated for both Landsat and MODIS. This framework ensures consistent comparison of estimated fractions across diverse climate patterns and land cover types[6]. To enrich the diversity of surface elements on a global scale, we also expanded the variety of endmember types based on endmember types commonly used in drylands[7]. Therefore, our selection of five endmembers is both feasible and necessary.

We added descriptions regarding the determination of endmember types (page 6, line 163-171).

"Recent studies have proposed various compositional endmember frameworks in different application contexts. For example, a framework including substrate, vegetation, dark and ice/snow was proposed and verified globally for both Landsat

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[6] Sousa, D., Small, C.: Globally standardized MODIS spectral mixture models. Remote Sens Lett, 10, 1018-1027, https://doi.org/10.1080/2150704X.2019.1634299, 2019

[7] Guerschman, J. P., Scarth, P. F., McVicar, T. R., Renzullo, L. J., Malthus, T. J., Stewart, J. B., Trevithick, R.: Assessing the effects of site heterogeneity and soil properties when unmixing photosynthetic vegetation, non-photosynthetic vegetation and bare soil fractions from Landsat and MODIS data. Remote Sens. Environ., 161, 12-26, https://doi.org/10.1016/j.rse.2015.01.021, 2015

and MODIS to allow estimated fractions, this framework ensures consistent comparison of estimated fractions across diverse climate patterns and land cover types (Small and Milesi 2013; Sousa and Small 2019). Another framework includes photosynthetic vegetation, non-photosynthetic vegetation, soil, and shade (Roberts et al. 1993), this framework was widely adopted for presentation surface structure worldwide, particularly in tropical rainforest and dryland ecosystems (Guerschman et al., 2015). These elements can characterize the fundamental composition of the Earth surface. Thus, we embody five endmembers to represent surface units, these five endmembers include photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), bare soil (BS), dark (DA), ice/snow (IS)"

We also discussed the expandability of endmember types of MESMA models (page 24-25, line 461-469).

"The spatio-temporally adaptive framework employed helps to increase the representativeness of endmember selection, and MESMA also considers the suitability of each combination of these endmembers within each pixel. However, considering the limitations of computational resources, our solution on hierarchical clusters of the endmember spectra can improve considerably cost-effective unmixing of long time-series satellite records over globe under the neglect of certain accuracy requirements (Fig. 3). With the assumption of increased computational power in the future, we believe that utilization of combination models from selected endmember spectra (35 GV spectra, 40 BS spectra, 25 NPV spectra, 16 DA spectra, and 15 IS spectra) or expanded endmember spectra may further improve the accuracy and stability of estimates of gradations of five surface vegetation and soil components at global scale."

3. The superiority of your dataset is only proved by the comparison with the NDVI and MOD44B product and I think is not adequate for the validation and drawing a reasonable conclusion that your model is more accurate.

We appreciate your concerns about comparison and validation. Although our dataset's comparison with NDVI and MOD44B products is informative, additional comparison and validation measures would indeed fortify the claim of superior accuracy. We thus explore further validation to bolster the credibility of our model.

First, 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 (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)[8], which were obtained

[8] 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,

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

1-8, https://doi.org/10.1038/sdata.2017.75, 2017.

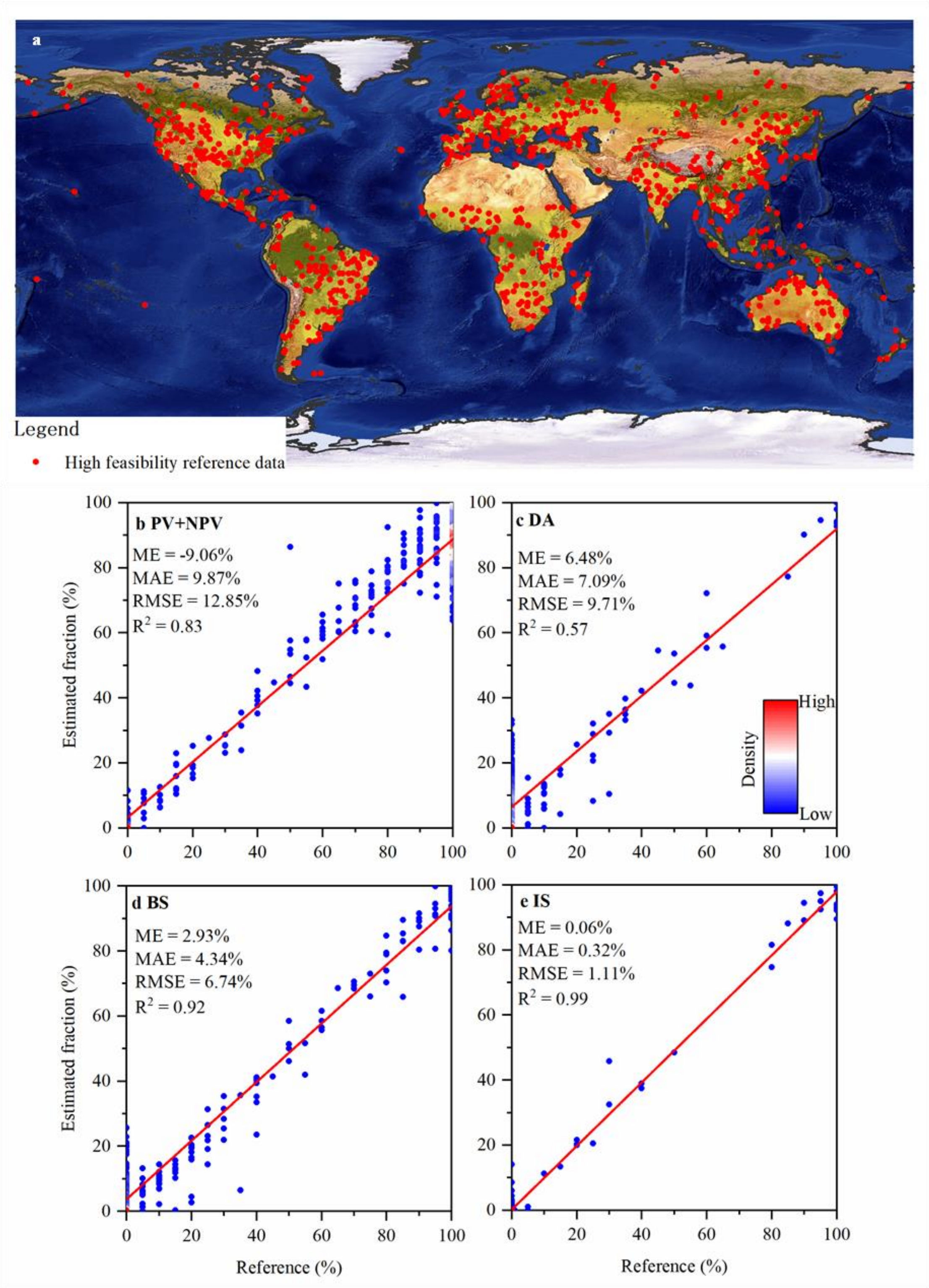

Fig. S5 Evaluation of global fractional endmember estimates based on land cover reference data. a, the location of high-feasibility land cover reference data. b-d, Scatter plots of PV+NPV, BS, DA, IS fractions against land cover reference data

Second, we present further comparison with other fractional vegetation cover dataset (page 12-13, line 277-293) using scatter plot (Fig. 4) and detailed images (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 FVC 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. 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."

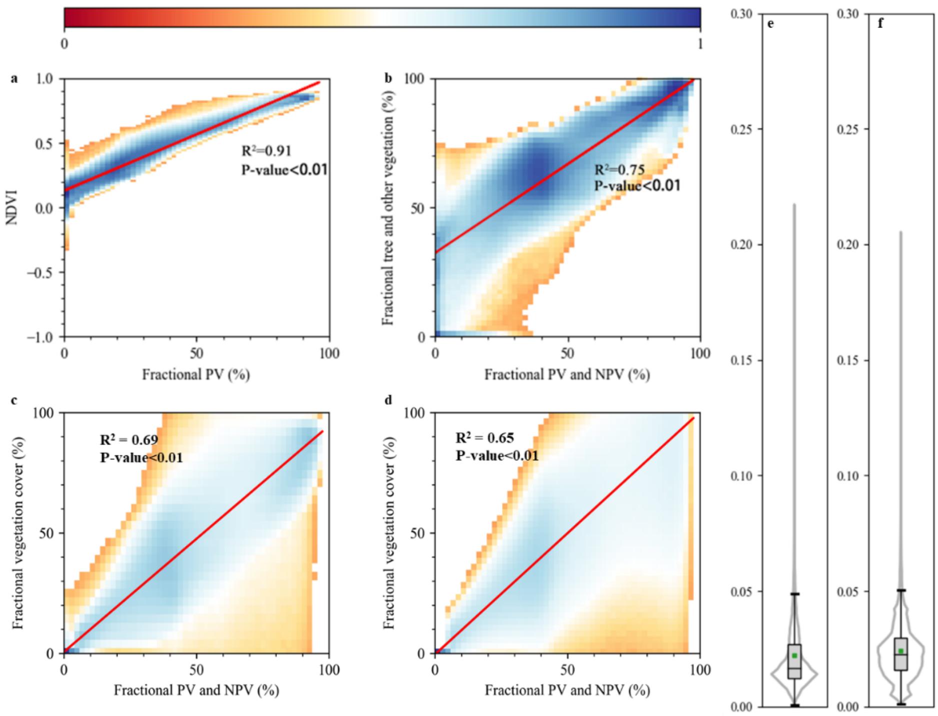

Figure 4: Comparisons with other datasets and traditional spectral mixture analysis models. a, b, c, d the bi-dimensional histogram of fractional endmembers

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).

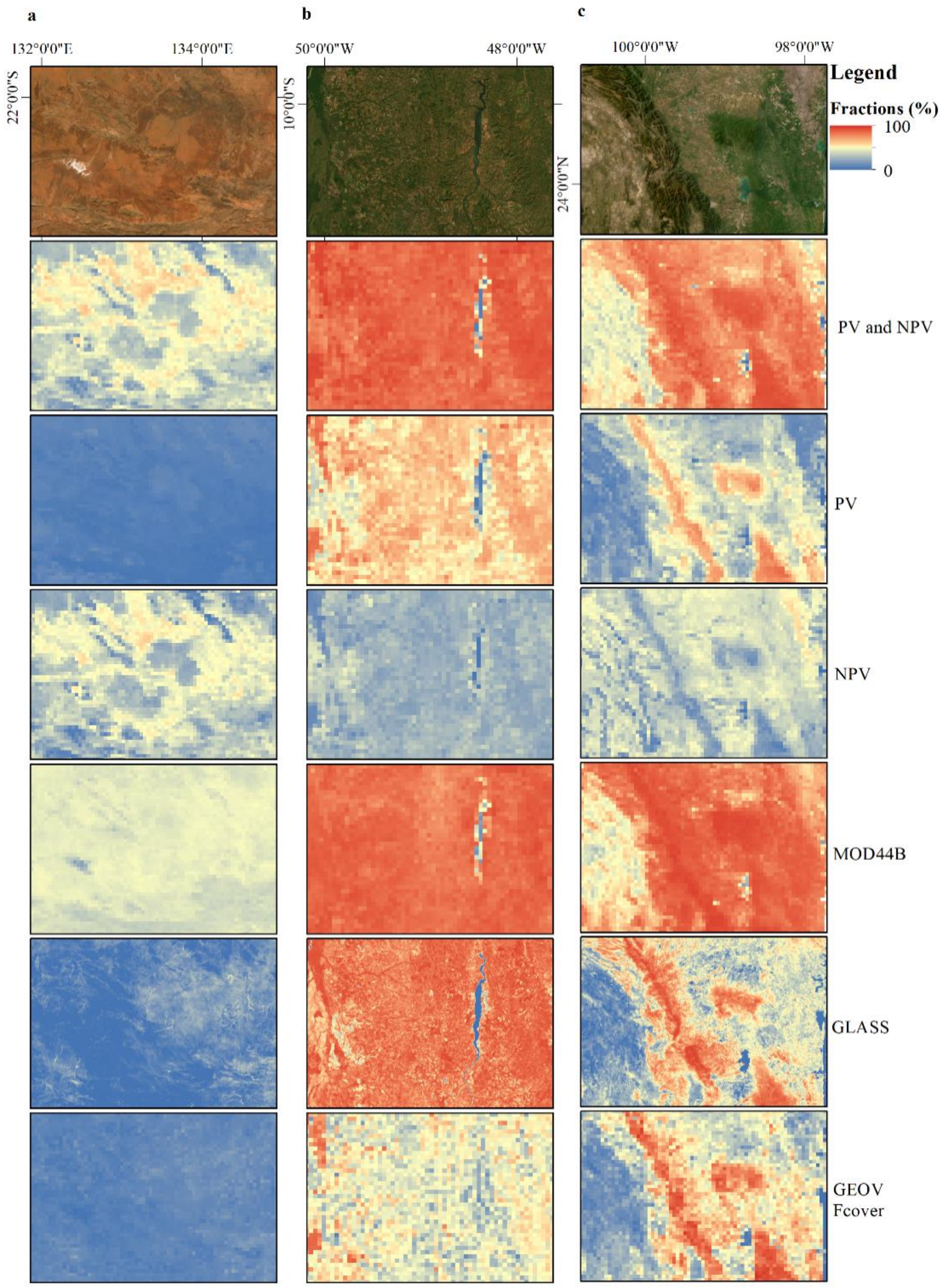

Fig. S6 The detailed graphs for comparing different datasets. a, b, and c represent comparisons of vegetation abundance products in different scenarios, specifically, regions with low vegetation cover in arid areas, high vegetation cover in tropical rainforests, and transitional zones from low to high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

4. I think the accuracy of the algorithm shown in Fig.3e-h is not promising. For the BS/DA/IS type, when the reference values are low, why does the algorithm show a pronounced overestimation? I think the authors should explain it in the Discussion. Comparison with other methods or products is necessary here to prove the superiority of your dataset. Additionally, high R-squared values for the IS type are likely attributable to the data being excessively scattered along the X-axis and more samples should be included for this type.

Your insights regarding the algorithm's accuracy in Fig. 3e-h are valuable. This is resulted from the fact that our estimated DA/BS less than 0.2 is presented as 0 in the reference data, because the interpreted reference dataset of high-spatial satellite observations ignored the shadows of the vegetation and bare soil within tree. In blocks with a DA/BS greater than 0.2, the estimated fractions and measured fractions present better consistency, in which the shadows and soil are well measured by GLCVRD.

We have revised that in the Discussions (page 25, line 470-474)

"However, due to the absence of corresponding reference data for validation, we solely rely on two high-quality land cover reference datasets for validation. Unfortunately, these datasets do not intricately characterize small-scale shadows and bare soil within complex vegetation structures. Consequently, this leads to a misconception in the validation, where our DA and BS are overestimated in low-value areas and vegetation is underestimated in high-value areas (Fig. 3, Fig.S5). Therefore, in the future, there is a need to further develop high-quality relevant reference data."

The IS sample count aligns with other endmembers. However, numerous samples lack snow cover, resulting in our predictions and measurements scattering around the (0,0) coordinate. This condition contributes to a higher R^2 for IS. To bolster the reliability of predictive accuracy for these endmember fractions, we've introduced an additional 1083 new samples from incorporating comprehensive global land cover and land use reference data, which were obtained from the Geo-Wiki crowdsourcing platform across four campaigns (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. High feasibility reference data is then selected through the confidence information of land cover estimates and the status of use of high spatial resolution imagery provided by the metadata. Similarly to the procedural description used for fractional vegetation-soil compared to GLCVRD, we reclassify 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 involve comparing the measured percent of land cover with the mean of endmember fractions within the corresponding 1×1km pixels."

5. The current analysis in the paper is predominantly focused on the Chinese region and its surroundings. Moreover, much of the work is centered around validating existing conclusions. Given that the authors have generated long-time-series global products, it is suggested to incorporate more globally relevant and newly discovered findings.

Thank you for your insightful suggestions. Expanding the scope beyond the Chinese region and its surroundings to encompass more globally relevant insights aligns with the long-time-series products. We have therefore strengthened our analysis of the remaining regions in the Results and Discussion section.

Incorporating newly discovered findings on a global scale would enrich the depth and breadth of our analysis, and provide a more comprehensive understanding of Earth's dynamics. On one hand, we demonstrate the reliability of our data in surface process analysis by leveraging existing discoveries. On the other hand, our exploration of surface processes highlights the strengths of our data, wherein the interaction between these end-members enables a more accurate analysis of surface evolution. For instance, the simultaneous increase of photosynthetic and non-photosynthetic vegetation signifies the greening of the Earth driven by afforestation. These new findings are discussed in Section 4.2 Implications of global and regional shifts from pairs of two endmembers. Moreover, we'll diligently consider this recommendation to enhance the global relevance of our work and include other novel discoveries in our future researches (page 26, line 512-517).

"This dataset can serve as a baseline for enhancing our comprehension of heterogeneous surface dynamics and modeling Earth's biophysical processes through a multi-endmember coupling perspective, may significantly advance future research by serving as a foundational reference for delving deeper into complex land systems. Anticipating its potential applications across diverse domains such as ecology, climate studies, and urban planning, this dataset emerges as a pivotal resource. Its multifaceted utility is expected to play a pivotal role in informing environmental management decisions, advancing studies on ecological shifts, predicting climate trends, and facilitating strategic landscape planning."

6. The organizational structure of the paper needs revision. Currently, the Method, Results, and Discussion sections are intermingled with contents from other sections. For example, Lines 150-153, should be moved to the Introduction; Lines 312-313, Line 318-320 explain the further reasons, moving them to the Discussion should be better; Section 4.1 just describes the intercomparison of different products or methods, instead of discuss the potential reasons, I think it should be described in the Results section.

Thank you for your detailed feedback regarding the organizational structure. We acknowledge the need for refinement and reorganization within the paper.

Wo have moved content describing the advantage of spectral mixture analysis model to the Introduction for better contextualization (page 4, line 94-96), and shifted the description of the comparison of different products or methods from Section 4.1 to the Section 3.2 to provide more clarity aligns with ensuring a logical flow within the paper.

We appreciate your input and will promptly address these structural adjustments to enhance the coherence and readability of our manuscript.

Some technical problems:

Thank you for your detailed feedback regarding the technical problems, we are sorry for these mistakes. we have corrected these errors and have also carefully examined and revised the manuscript to ensure the accuracy of the presentation.

Lines 44-45: The full name of PV and NPV should be presented for the first time.

- Full name of PV and NPV has been presented (page 2, line 38-39).

Line 72-73: indexes-->indices; leaf area index (LAI) should be a structural variable for the vegetation instead of vegetation index; The abbreviation for Normalized Difference Vegetation Index (NDVI) should be mentioned here.

- Continuous vegetation indexes (e.g., normalized difference vegetation index (NDVI), enhanced vegetation index (EVI)) provide limited information on surface composition, which hinders our ability of understanding ecosystem's structurally and functionally multifaceted shifts (page 3, line 72-74).

Line 80: human -->human activity?

- under the influence of a changing environment and human activity (page 4, line 93)

Lines 138-140: the introduction of the spectral mixture analysis model should be moved to the Introduction section.

- The introduction of the spectral mixture analysis model was blended into Introduction Section (page 4, line 94-96):

  Recent studies have proven that spectral mixture analysis model has the advantage of providing more accurate and physically based representation of fraction vegetation-soil continues field in the subpixel level without training samples (Daldegan et al. 2019; Smith et al. 2007).

Lines 153-155: You only mentioned the applicability of this classification system to tropical rainforests and drylands. Its suitability for global application is unclear.

- this framework was widely adopted for presentation surface structure worldwide, particularly in tropical rainforest and dryland ecosystems (page 6, line 167-168)

Figure 2: The wavelength of B1-B7 should be specified.

- B1-B7 represent MODIS spectral bands, including 459-479nm, 545-565nm, 620-670nm, 841-876nm, 1230-1250nm, 1628-1652nm, and 2105-2155nm (page 10, line 221-222).

Line 204: MESMA has already been declared in the Introduction, so it is not necessary to use its full name here.

- The MESMA has been used to estimate fractional vegetation-soil nexuses based on selected endmember spectra (page 10, line 224).

Line 137 and Line 231: RMSE is defined twice. Different subscripts should be used for distinction.

- We have defined root-mean-square-error of MESMA fitting as $RMSE_{sma}$ (page 6, line 152-153).

Lines 236-245: The introduction of the Mann-Kendall test should not be presented here, because the methods section should emphasize your own work. It is suggested to move it to the supporting information.

- We refined the descriptions of seasonal Mann-Kendall test (page 13-14, line 302-317).

Line 262: "reasonably satisfactory" is not an object expression. Only presenting the numbers is enough here.

- Specifically, the performance of PV+NPV, BS, and IS endmember estimates have MAE less than 0.118, RMSE less than 0.149, R^2 greater than 0.592. (page 14, line 325-326).

Lines 264-266 should be moved to the Discussion.

- We have move that to the Discussion.

Line 274-277: Where is Figure 3 i-k? The full name of LAI should be mentioned here.

- We are sorry for this error; we have deleted that.

Line 294: ×106 km2 -->×10^{6} km^{2}

- $\times 10^6$ km^2 (page 20, line 393)

Line 312: result from -->results from

- This outcome results from the forest loss induced soil exposure in Brazilian Amazon and Southeast Asia (page 20, line 411)

Line 378: RESE -->RMSE

- It can be found that 90% of the $RMSE_{sma}$'s differences are concentrated within 1%. (page 18, line 371)