Response to Reviewer Comments

A global daily seamless 9-km Vegetation Optical Depth (VOD) product from 2010 to 2021

Die Hu [a], Yuan Wang [b], Han Jing [a], Linwei Yue [c], Qiang Zhang [d], Lei Fan [e*], Qiangqiang Yuan [a, f, g, †], Huanfeng Shen [h], and Liangpei Zhang [i]

[a] School of Geodesy and Geomatics, Wuhan University, Wuhan, China.

[b] School of Atmospheric Physics, Nanjing University of Information Science and Technology, Nanjing, China.

[c] School of Geography and Information Engineering, China University of Geosciences, Wuhan, China.

[d] Center of Hyperspectral Imaging in Remote Sensing (CHIRS), Information Science and Technology College, Dalian Maritime University, Dalian, China.

[e] Chongqing Jinfo Mountain Karst Ecosystem National Observation and Research Station, School of Geographical Sciences, Southwest University, Chongqing,China.

[f] Key Laboratory of Geospace Environment and Geodesy, Ministry of Education, Wuhan University, Wuhan, China.

[g] Key Laboratory of PolarEnvironment Monitoring and Public Governance, Ministry of Education, Wuhan University, Wuhan, China.

[h] School of Resource and Environmental Science, Wuhan University, Wuhan, China.

[i] State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing, Wuhan University, Wuhan, China.

* Corresponding authors. E-mail address: leifan33@swu.edu.cn

† Corresponding authors. E-mail address: qqyuan@sgg.whu.edu.cn

Response to Comments of Reviewer #2:

Response to General comments:

Q: 1) A more detailed discussion of the results would strengthen the manuscript. In particular, further analysis of the performance of the new product across different land cover types would be beneficial. Additionally, evaluating VOD against vegetation-related parameters, such as aboveground biomass (AGB), NDVI, and LAI, would enhance clarity.

Response: Thanks for the comment. Regarding the first point about a more detailed discussion of the results, especially the performance of the new product across different land cover types, we have already conducted relevant analyses. As shown in Figure 7 of our paper, we present the temporal variation results for four selected land cover types: forest, shrubland, cropland, and grassland. This analysis allows us to understand how the new product behaves differently under various land cover conditions, providing a solid basis for discussing its performance in different environments.

For the second point about evaluating VOD against vegetation - related parameters, we add a related experiment in which we compare VOD_st with NDVI. The monthly average comparison results are shown in the Figure 1. We can observe that the seasonal trends of VOD_st and NDVI are highly consistent, showing obvious periodic characteristics. During the summer months corresponding to the period of maximum vegetation growth and leaf production, the values of these parameters increase significantly, and they decline as the vegetation ages. This consistency indicates that VOD_st can effectively capture the changes in vegetation growth, similar to traditional optical - based indices like NDVI. Notably, VOD_st exhibits a slight lag in its seasonal changes compared to NDVI, but this lag is not due to the quality of VOD_st. Our findings are in line with previous studies by Lawrence et al. [1] and Xiaojun Li et al. [2], which also reported that VOD data has a slight lag when compared with optical vegetation indices.

The reasons for this lag are related to their distinct biophysical meanings. Firstly, NDVI is highly sensitive to rapid changes in leaf - level characteristics such as chlorophyll content and leaf area as it is based on the reflection and absorption of visible and near - infrared light by the vegetation canopy. In contrast, VOD_st, relying on microwave - vegetation interactions, reflects more comprehensive and large - scale vegetation structural information and responds more to gradual changes in the overall vegetation structure over a longer time frame. Secondly, NDVI is mainly influenced by the optical properties of vegetation and is less directly affected by moisture in the short - term, while VOD_st is highly sensitive to changes in vegetation moisture content and the scattering and absorption properties of the medium. The time it takes for moisture - related changes to impact VOD_st compared to the relatively instantaneous optical changes captured by NDVI contributes to the lag. Thirdly, differences in temporal resolution and data processing between the two parameters can also lead to the non - alignment of their peaks and troughs.

Overall, this comparison between VOD_st and NDVI provides valuable insights into the relationship between microwave - based VOD and optical - based NDVI, helping to better understand the characteristics and performance of the VOD product.

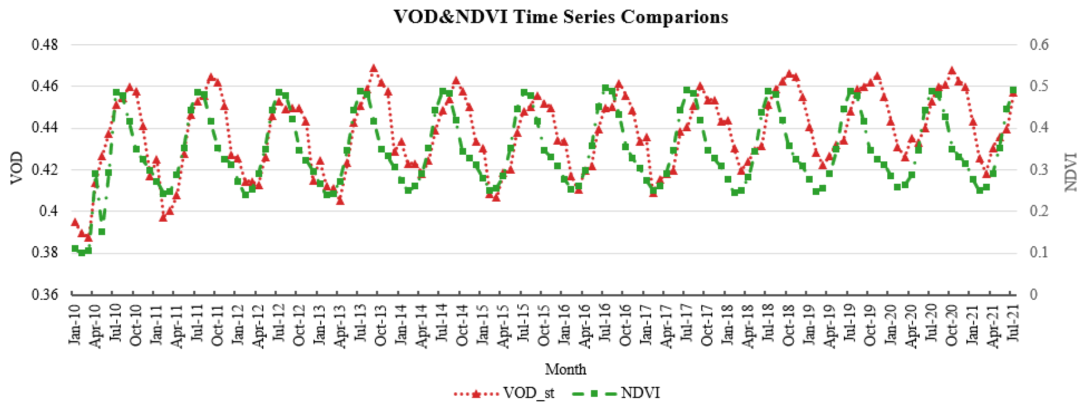

Fig. 1. Long - term monthly average trend comparison between VOD and NDVI.

References:

[1] Lawrence H, Wigneron J, Richaume P, et al. Comparison between SMOS Vegetation Optical Depth products and MODIS vegetation indices over crop zones of the USA[J]. Remote Sensing of Environment. 2014, 140: 396-406.

[2] Li X, Wigneron J, Frappart F, et al. Global-scale assessment and inter-comparison of recently developed/reprocessed microwave satellite vegetation optical depth products[J]. Remote Sensing of Environment. 2021, 253: 112208.

Q: 2) It may be helpful to consider measures to reduce the bias between SMOS VOD and SMAP VOD, as this discrepancy could impact the accuracy of the fused product. A more detailed analysis of this uncertainty would be valuable.

Response: Thank you for highlighting the importance of uncertainty analysis for our fused product. First I would like to illustrate how bias between SMOS and SMAP VOD affect the results. SMOS and SMAP sensors have different observational capabilities, and the differences in instrumentation result in different ways of sensing and measuring VOD. In addition, the two have different VOD retrieval algorithms, which can also cause bias. The bias between SMOS and SMAP VOD products may introduce errors during the data fusion process, thereby affecting the accuracy and reliability of the fused product [1].

In the context of our study, we focus on the overall temporal and spatial trends of VOD rather than eliminating the bias between the two sensors' products. This is based on an assumption that within the same spectral band, high - resolution and low - resolution data obtained from different sensors have similar temporal changes.

We believe that these similar temporal variations can still provide valuable information for our research objectives. For instance, when analyzing the long - term trends of vegetation dynamics or the response of vegetation to environmental changes, the common temporal patterns in SMOS and SMAP VOD data can be used to draw meaningful conclusions. In addition, our study is more concerned with the general performance and usability of the fused product. We believe that the bias does not significantly distort the overall patterns and relationships.

We understand the importance of the bias issue and acknowledge that it may be necessary to further explore ways to mitigate bias in future studies for more accurate and refined results. However, in the scope of this current study, our approach based on the assumption of similar temporal variations is a valid strategy.

This bias can also lead to uncertainty in the final product. We can identify the following sources of uncertainty for the fused VOD product:

1. *The errors of original SMOS VOD and SMAP VOD products*. Our fused VOD product is generated based on the original SMOS VOD and SMAP VOD products.

These original datasets inherently contain errors, due to the satellite sensor's performance and the difference of VOD retrieval algorithms. These errors from the original data sources are propagated into our fused product, affecting its accuracy. In addition, we perform a gap-filling process on the original data, which also introduces uncertainty and increases the error in the final fused product.

2. *The meteorological factors.* Meteorological factors can affect vegetation phenology. Vegetation phenology plays a crucial role. For instance, rapid changes in vegetation growth stages, such as the sudden onset of leaf senescence or new growth, can cause significant variations in VOD values. If our fusion method does not fully account for these rapid changes, it can lead to inaccuracies in the fused product. Moreover, the presence of clouds and aerosols can interfere with the satellite measurements of VOD which can introduce uncertainties into the final product.
3. *The generalization limitations of the fusion model*. Our spatiotemporal fusion model is trained using a specific set of data. However, there are differences between the training data and the actual data used for testing and generating the final product. For example, the land cover types in the testing data might have different spatial distributions or compositions compared to those in the training data. Different land cover types have distinct VOD responses, and if the model is not well - generalized to these variations, it can lead to uncertainties in the fused product. Additionally, the temporal coverage of the training data might not fully capture all the possible seasonal and interannual variations in VOD, which can limit the model's ability to accurately fuse data in different scenarios and contribute to the overall uncertainty of the final product.

References:

[1] Li X, Wigneron J P, Frappart F, et al. The first global soil moisture and vegetation optical depth product retrieved from fused SMOS and SMAP L-band observations[J]. Remote Sensing of Environment, 2022, 282: 113272.

Q: 3) The overall readability of the manuscript could be improved, particularly in

terms of phrasing, organization, and paragraph structure. The authors may wish to have the manuscript reviewed by a native English speaker to refine grammar, style, and syntax.

Response: Thank you for your feedback regarding the language presentation in our manuscript. We sincerely appreciate your careful reading and constructive comments.

We completely understand your concerns about the English fluency and readability. Please allow us to explain that we have already undergone multiple rounds of language editing, including:

1. Professional proofreading by colleagues fluent in academic English;
2. Grammar checking using advanced language tools (Grammarly and Hemingway Editor);
3. Several iterations of meticulous self-editing to improve clarity.

While we acknowledge that perfecting academic language remains challenging for non-native speakers, we have made our best effort to ensure the technical content is presented with precision and clarity. The current version represents what we believe to be the optimal balance between scientific accuracy and linguistic quality given our capabilities.

However, we fully respect your expert opinion. Should the manuscript be accepted pending minor revisions, we would be happy to collaborate with professional editing services to make final language improvements at the production stage.

Response to Specific Comments:

Q: 1) Page 4, line 191. Define "IGBP, UMD and LAI" before their first use.

Response: Thank you for your careful review and the valuable comment. We have taken your suggestion into consideration and have made the necessary corrections. On page 4, line 191, before the first use of "IGBP", "UMD", and "LAI", we have added definitions. Detailed explanations are provided below:

-IGBP (International Geosphere-Biosphere Programme) [1] refers to a global research initiative that developed a widely used classification scheme for land cover types based on satellite data.

-UMD (University of Maryland) [2] refers to the land cover classification system developed by the University of Maryland, which is based on multi-temporal satellite data and has been widely applied in various environmental studies.

-LAI (Leaf Area Index) [3] is a key parameter in vegetation studies, representing the total leaf area per unit of ground area, which is important for understanding vegetation structure and function.

References:

[1] Loveland T R, Zhu Z, Ohlen D O, et al. An analysis of the IGBP global land-cover characterization process[J]. Photogrammetric engineering and remote sensing, 1999, 65: 1021-1032.

[2] Hansen M C, DeFries R S, Townshend J R G, et al. Global land cover classification at 1 km spatial resolution using a classification tree approach[J]. International journal of remote sensing, 2000, 21(6-7): 1331-1364.

[3] Chen J M, Black T A. Defining leaf area index for non‐flat leaves[J]. Plant, Cell & Environment, 1992, 15(4): 421-429.

Q: 2) Page 5, line 220. Define "DCT-PLS" before its first use.

Response: Thanks for the suggestion to improve our paper. In response to the reviewer's comment regarding "DCT-PLS" on page 5, line 220, we have added the definition before its initial use. Detailed explanations are provided below:

DCT-PLS stands for Discrete Cosine Transform - Partial Least Squares. Discrete Cosine Transform (DCT) is a mathematical transformation that converts a signal from the spatial domain to the frequency domain. It is often used for data compression and feature extraction as it can represent the data in terms of its frequency components.

Partial Least Squares (PLS) is a statistical method that is used for dimensionality reduction and regression modeling. In the context of our research, PLS is employed to establish a relationship between different variables in the VOD data to fill gaps. It combines the advantages of DCT in extracting relevant features from the data and PLS in finding the optimal relationship between variables, aiming to reconstruct missing or incomplete data in a more accurate and efficient manner.

Q: 3) Page 7, line 288. The bias between SMOS and SMAP products should be considered (e.g., 10.1016/j.rse.2022.113272). This addition is relevant and could significantly broaden the manuscript's appeal.

Response: Thank you for your suggestion regarding the consideration of the bias between SMOS and SMAP products. This question has already been discussed in comment 2 in General comments. The addition you suggested has been added to the Discussion part in our study.

SMOS and SMAP sensors have different observational capabilities, and the differences in instrumentation result in different ways of sensing and measuring VOD. In addition, the two have different VOD retrieval algorithms, which can also cause bias. The bias between SMOS and SMAP VOD products may introduce errors during the data fusion process, thereby affecting the accuracy and reliability of the fused product [1].

In the context of our study, we focus on the overall temporal and spatial trends of VOD rather than eliminating the bias between the two sensors' products. This is based on an assumption that within the same spectral band, high - resolution and low - resolution data obtained from different sensors have similar temporal changes.

We believe that these similar temporal variations can still provide valuable information for our research objectives. For instance, when analyzing the long - term trends of vegetation dynamics or the response of vegetation to environmental changes, the common temporal patterns in SMOS and SMAP VOD data can be used to draw meaningful conclusions. In addition, our study is more concerned with the general performance and usability of the fused product. We believe that the bias does not significantly distort the overall patterns and relationships.

References:

[1] Li X, Wigneron J P, Frappart F, et al. The first global soil moisture and vegetation optical depth product retrieved from fused SMOS and SMAP L-band observations[J].

Remote Sensing of Environment, 2022, 282: 113272.

Q: 4) Page 7, Line 313. Please consider adding a more detailed description of the spatiotemporal fusion experiment. This should include the relationship between the reconstructed SMOS VOD and reconstructed SMAP VOD, the division of time segments, and the relationship between the fusion product and the reconstructed SMOS VOD and SMAP VOD.

Response: Thank you for your valuable comment regarding the need for a more detailed description of the spatiotemporal fusion experiment.

The reconstructed SMOS VOD and SMAP VOD play distinct yet complementary roles in our spatiotemporal fusion approach. On the one hand, the reconstruction results offer long - term SMOS VOD products from 2010 to 2015, filling the temporal gap before the SMAP mission’s start. This data provides a continuous record of VOD trends over a relatively long period, allowing us to capture the seasonal and inter - annual variations in vegetation properties. On the other hand, the reconstructed SMAP VOD provides high - resolution data (9 km). This spatial information enables us to resolve local - scale details in vegetation distribution and structure.

We would like to emphasize that the time segment division in our spatiotemporal fusion experiment is clearly presented in Fig.1 of our paper (Figure 2 in this response). The division is based on the launch dates of the SMOS and SMAP satellites. The SMOS VOD data has been available since January 1, 2010, while the SMAP VOD data is accessible from April 1, 2015, to July 31, 2021. To fill the temporal blank in 9-km spatial resolution L-VOD products before the launch of the SMAP satellite, we select April 1, 2015, the initial date when the SMAP VOD products become available, as the time node. We define the prediction period of the fused product VOD_st as T1, which spans from January 1, 2010, to March 31, 2015. To construct the baseline data required for the spatiotemporal fusion model and consider the temporal correlation, we extend the fusion input period by one year. The T2 period is defined from April 1, 2015, to April 1, 2016. For the purpose of validating the quality of the fused product VOD_st, we define the remaining period from April 2, 2016, to December 31, 2017, as the T3 period. By comparing the fused product with the actual data during this period, we can effectively evaluate the performance and reliability of the spatiotemporal fusion method.

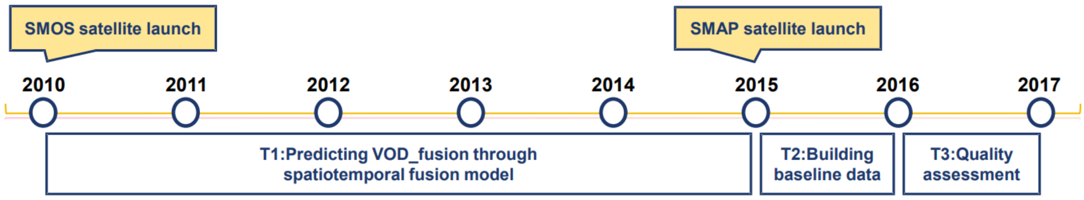

Fig. 2. Temporal division of spatiotemporal fusion experiment.

Both the reconstructed SMOS VOD and SMAP VOD serve as the input data for our spatiotemporal fusion model. They are used to construct the baseline data for the model, which is a key step in learning the transformation relationships between high - resolution and low - resolution data across different time periods. By analyzing the co - variations between the SMOS and SMAP VOD data at different scales and time intervals, the model can identify patterns that are characteristic of the relationship between the two datasets. This learned relationship is then applied to predict the high - resolution VOD_st at the target time. As shown in Fig.3, we input daily low-resolution VOD_resmos for each corresponding month into the model. Once the model learns from the SMOS and SMAP VOD data during the training phase, it is able to predict the daily high-resolution fusion product VOD_st. Thus, the fusion product VOD_st combines the spatial and temporal complementarities of the reconstructed SMOS VOD and SMAP VOD.

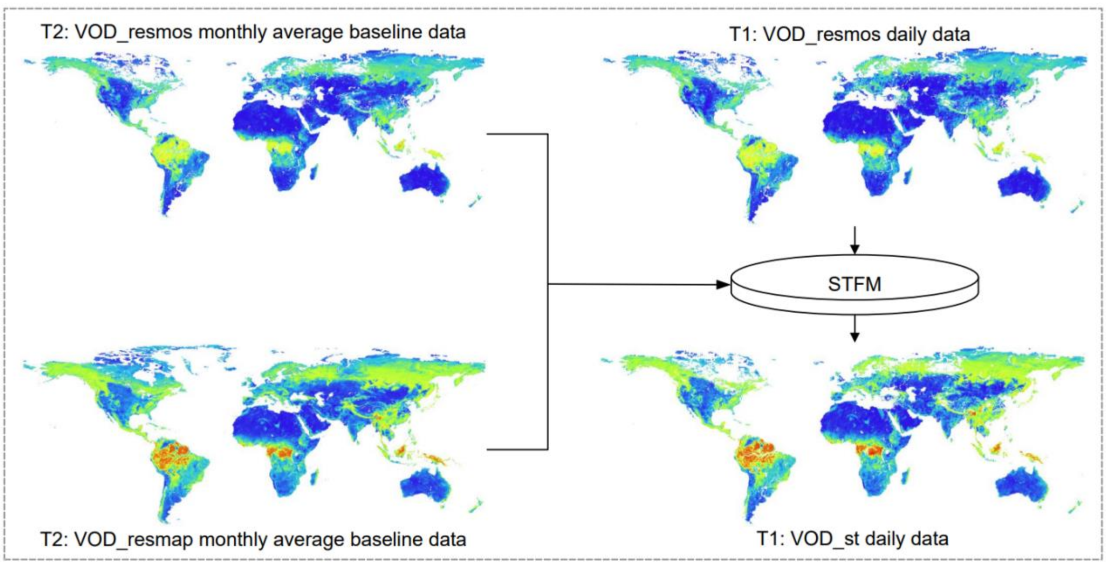

Fig. 3. Spatiotemporal fusion Process.

Q: 5) Page 12, Fig. 7. The text in this figure is too small.

Response: Thanks for the comment. In response to your comment, we have carefully adjusted the proportion of Fig. 7 within the manuscript. By enlarging the figure, we have ensured that the text within it is now in a more harmonious size relative to the overall graphic. This adjustment has been made to optimize the visual presentation of the data and information in the figure, making it easier for readers to interpret and understand the content.

Q: 6) Page 13, Fig. 9. Please explain why the reconstructed products were more blurred than the original product.

Response: Thanks for the comment. After analyzing the data and the reconstruction process, we find several factors that may have contributed to the blurring of the results.

Firstly, the reconstruction algorithm itself might introduce a certain level of smoothing. The reconstruction method involves complex mathematical operations such as interpolation. These operations can average out the details in the original data, resulting in a blurred appearance.

Secondly, the quality of the input data plays a crucial role. The original products generally capture the true characteristics of the target phenomenon with high fidelity. In contrast, the reconstructed product depends on the quality and quantity of the available data for reconstruction. If there are limitations in the data, such as missing values or noisy measurements, the reconstruction algorithm may not be able to fully replicate the details of the original. In our case, although we have taken measures to pre - process and filter out outliers, there may still be some uncertainties and inaccuracies that affect the clarity of the reconstructed product.

In addition to the factors we previously mentioned, there is another significant aspect contributing to the difference in the blurred effect between the reconstructed and original products. We stitch and store the daily raster data for a month as a 3D data (2-D spatial + time), which is subsequently fed into the reconstruction model for learning and training. Monthly averages of VOD are the basis for learning these time-series features, but extreme values tend to be ignored when calculating monthly averages.

This smoothing effect can make the reconstructed products appear more blurred compared to the original product, which retains all the fine - grained details, including those extreme values.

We understand that this is an important consideration, and we are exploring ways to better incorporate extreme value information into our reconstruction process to improve the representativeness of the reconstructed products.

Q: 7) Page 19, Fig. 16. Discuss the reseason of white pixels over land in VOD_st winter.

Response: Thanks for the comment. Maybe the "reseason" in your question is "reason"? We appreciate your concern and have carefully considered the possible reasons, with a focus on the aspect of original data loss.

Regarding VOD data retrieval, Radio Frequency Interference (RFI) is likely to be a critical factor. In winter, RFI may intensify in certain regions for various reasons. For example, the increased use of electronic heating devices or the operation of communication systems in the same frequency bands as the sensors can render the VOD values unreliable. As a result, these values are removed during data retrieval.

Secondly, the snow and ice cover in winter can distort or attenuate the microwave signals used for VOD measurement. This distortion or attenuation can prevent the sensors from accurately detecting the underlying vegetation, leading to data loss.

Furthermore, low temperatures and other harsh winter weather conditions can impact the calibration of the sensors. Inaccurate calibration can produce unreliable measurement results, which are then discarded, contributing to the loss of data.