Responses to Reviewers Comments

Editor

Q: Given the significant concerns raised by the reviewer regarding the originality, it is essential that you thoroughly address all their feedback and make the required revisions to your manuscript. Once you have finalized the revisions, kindly resubmit your manuscript for further evaluation.

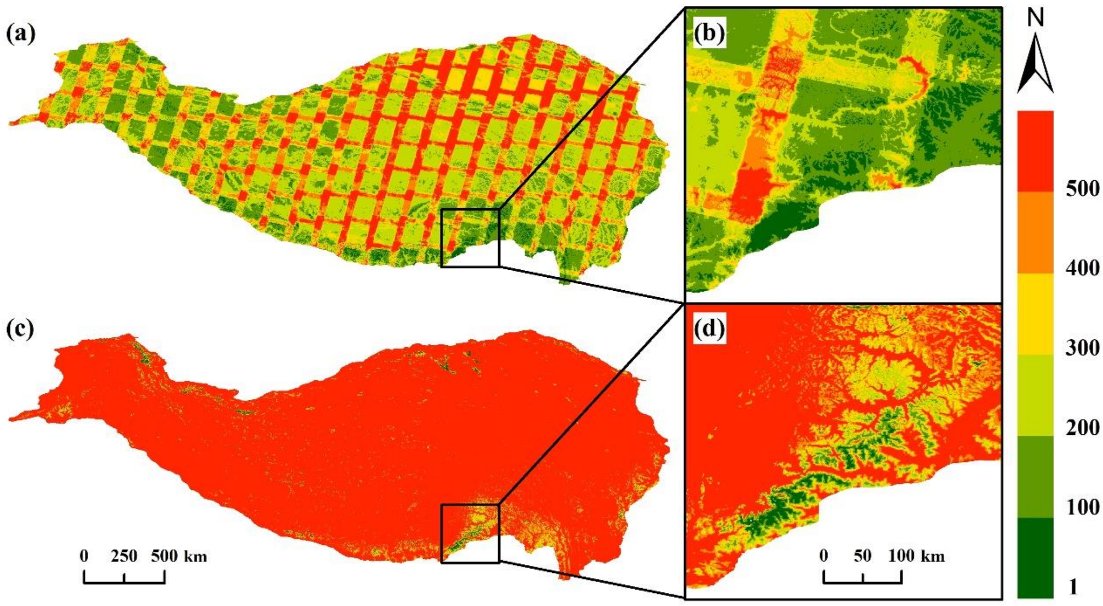
Specifically the reviewer has the following comment: "During my review, I found a similar paper on vegetation type mapping in the region, published by the same author team in Scientific Data (https://www.nature.com/articles/s41597-024-03649-7). There appears to be some overlap in the methods and data between the two studies. I am unclear on the rationale for generating annual 500-m vegetation maps in this paper, given that 30-m time series data already exist for the region." Please address this concern.

Answer: Liu et al. (2021) pointed out that although existing land cover products meet performance requirements, they fall short in ensuring interannual stability. This is because these products are typically generated independently for each year, which limits their utility for studying land cover changes over time. To address this issue, our team has developed two approaches aimed at improving the stability of annual land cover products.

First, we use visually interpreted and stable samples, which are consistent across multiple years, to generate long-term vegetation maps. This method employs an independent annual generation process but ensures consistency by focusing on stable samples. We applied this approach in our study published in *Scientific Data* (https://www.nature.com/articles/s41597-024-03649-7), where we produced 30 m resolution vegetation maps at ten-year intervals (Ren et al., 2024). While this method uses stable samples to establish classification models, it is still limited by the classifier's inherent misclassification errors, which tend to accumulate spatially over time. In ten-year interval maps, these errors are minimal, but when applied to annual products, the errors compound over 23 years, leading to potentially unpredictable errors.

To overcome this limitation, we propose a second method: a dynamic vegetation mapping approach based on the Continuous Change Detection (CCD) model. First, a reference vegetation map of the QTP for 2020 was produced using terrain-climate-remote sensing data. The CCD model was then applied to detect potential change areas, identifying the temporal and spatial positions of breakpoints. The RF model was used only for pixel-based classification in these breakpoint regions, while non-breakpoint areas were not reclassified. Finally, a spatio-temporal consistency approach was implemented to reduce misclassified pixels, enhancing interannual stability. The key innovation of this method lies in dynamically updating the map each year, rather than classifying the entire study area annually. By reducing the number of pixels requiring classification, we minimize the risk of misclassification that could accumulate over the 23-year period.

However, the Qinghai Tibet Plateau (QTP) presents unique challenges, particularly in the southeastern forested areas, which are frequently cloud-covered. Landsat observations in these regions are sparse, with fewer than 100 usable images over the 23-year period (R2 Fig. 1a, R2 Fig. 1b). This scarcity is insufficient for CCD, which relies on dense, high-quality time series data. In contrast, MODIS data offer a higher temporal resolution with daily global coverage. Its MOD09A1 product provides 8-day composites, offering a much higher observation frequency compared to Landsat's 16-day revisit cycle (R2 Fig. 1b-d). Despite CCD being originally developed for Landsat, we opted for MODIS data due to its higher temporal coverage, which better suited the mapping objectives for the QTP. Although MODIS's spatial resolution (500 m) is lower, it was the most practical solution for producing consistent annual vegetation maps in this region.



R2 Figure 1: Frequency of Cloud-Free Pixels from Landsat (a, b) and MOD09A1 (c, d) over the QTP (2000-2022)

References

Liu, L., Zhang, X., Gao, Y., Chen, X., Shuai, X., and Mi, J.: FinerResolution Mapping of Global Land Cover: Recent Developments, Consistency Analysis, and Prospects, J. Remote Sens., 2021, 5289697, https://doi.org/10.34133/2021/5289697, 2021.

Ren, H., Wu, F., and Zhou, G.: The 30 m vegetation maps of the Tibetan Plateau (1990-2020), TPDC [dataset], https://doi.org/10.11888/Terre.tpdc.301126, 2024.

Thank you very much for the valuable feedback and suggestions.

Reviewer #1

This study presents a novel approach for continuous annual vegetation mapping on the Qinghai-Tibet Plateau (QTP), and achieved good validation accuracy. Detailed vegetation classification data is crucial for ecological management and geographical modeling. According to the previous reviewers' comments, the manuscript has been significantly improved. Here are some issues that need to be addressed.

Q1: Line 37 What are the "independent classification methods"? The introduction is too brief, especially lacking a description of other representative methods, which makes it difficult to highlight the advantages of the method used in this study.

Answer: Thanks. We have expanded the explanation of the "independent classification method" by detailing its use in products like GlobCover and MOD12Q1. These examples illustrate the limitations of independently generated land cover maps, particularly in terms of interannual stability. This additional context highlights the advantages of our method in addressing these limitations. The revised content is included in lines 39-53 of the revised manuscript.

Q2: Line 8 There is an extra quotation mark in "Third Pole" of the Earth".

Answer: Thank you for pointing this out. We have removed the extra quotation mark from "Third Pole of the Earth" in line 8 of the revised manuscript.

Q3: Line 42 Is it "LCSV" or "LUSV"? Please check through the text.

Answer: Thank you. We have reviewed the text and corrected it to "LCSV" (land cover and surface vegetation) in lines 67 and 69 of the revised manuscript.

Q4: Several abbreviations are missing their full forms the first time they appear, such as "CLCD".

Answer: Thank you. We have added the full forms of abbreviations like CLCD, GLC_FCS30, GLC_FCS30D, and NASA upon their first mention in lines 30-36 of the revised manuscript.

Q5: Line 85 Why was the "Vegetation map of Qinghai Tibet Plateau in 2020 with 10 m spatial resolution" chosen as the source of training samples? There is a lack of description regarding its production method and product accuracy.

Answer: Thank you for your suggestion. The "Vegetation map of Qinghai Tibet Plateau in 2020 with 10 m spatial resolution" was selected because of its overall accuracy of 89.5%, achieved using a regional vegetation mapping method that integrates terrain, climate, and remote sensing data. Its classification system is consistent with the one used in this study, with the exception of glacial snow and ice. We have added a detailed explanation for selecting this product, along with descriptions of its production method and accuracy, in lines 96-99 of the revised manuscript.

Q6: Line 91 How was the 70% threshold determined?

Answer: Thank you for your question. In Table 1, we provide the area proportions for different purity classes after resampling. Areas with purity levels above 70% cover approximately 62.34% of the QTP (within China). A higher threshold would reduce the available sampling area, making it challenging to sample discrete and smaller vegetation types like shrubs. Conversely, a lower threshold would increase the presence of mixed pixels, affecting the quality of training samples. After careful consideration, we determined that 70% strikes the best balance.

Q7: CCD can detect significant changes, such as the conversion from grassland to water bodies. However, how should more subtle changes between similar vegetation types, such as the transition between alpine meadows and alpine steppes, be managed?

Answer: Thank you for your question. The CCD method can indeed detect significant changes, such as the transition from grassland to water bodies, as shown in Fig. 7 and Fig. 13. In addition, the CCD method can detect transitions between similar vegetation types, such as the shift from alpine meadows to alpine grasslands, by distinguishing subtle differences in their spectral-temporal characteristics. Fig. 14 demonstrates the gradual transition from grassland to meadow in the sample area from 2001 to 2021, primarily occurring in transitional zones between vegetation types. Finally, for areas flagged by CCD as having potential changes, we used a Random Forest (RF) model incorporating terrain, climate, and remote sensing data to verify the changes and classify the vegetation types before and after the transitions.

Q8: Line 44, The sentence is missing a preposition.

Answer: Thanks. We have added the preposition "for" after "critical," and the revised sentence now reads: "The QTP, known as the 'Roof of the World' and the 'Water Tower of Asia', is critical for global climate regulation and regional socio-economic development." This change is reflected in line 54 of the revised manuscript.

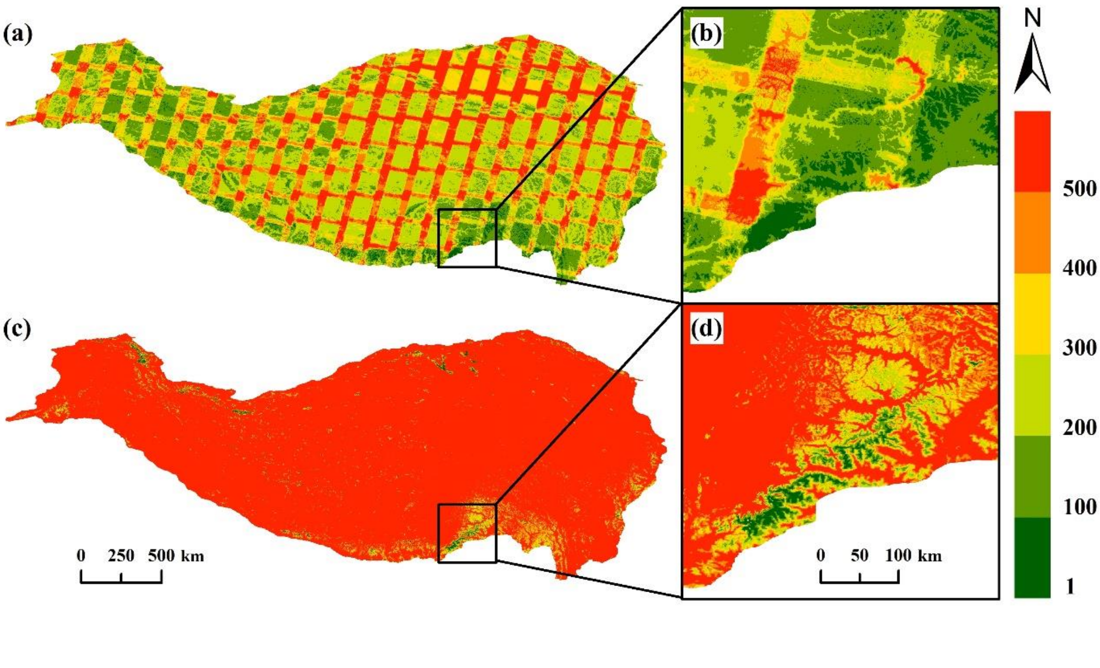
Thank the reviewer very much for these constructive comments and suggestions.

Reviewer #2

This study produced annual 500-m vegetation maps for the Qinghai-Tibet Plateau from 2000 to 2020 by integrating MODIS data, random forest and CCDC algorithms. While this dataset has the potential to support climate regulation and ecosystem conservation efforts in the region, I have significant concerns regarding the data quality, validation process, and methodological innovation after reviewing the manuscript.

Q1: ESSD is a journal that emphasizes the publication of original, high-quality datasets. It is unclear why vegetation types were mapped at a relatively coarse 500-m resolution and why the MOD09A1 product was chosen over higher-resolution data like Landsat, particularly considering CCDC was originally developed for Landsat time series.

Answer: The objective of this study is to develop annual vegetation maps for the Qinghai-Tibet Plateau (QTP). However, certain areas, such as the southeastern forests, are frequently cloud-covered. In these regions, Landsat provides fewer than 100 usable images over the 23-year period (R2 Fig. 1a, R2 Fig. 1b), which is insufficient for the CCD algorithm's requirement for dense time series data. In contrast, MODIS, with its daily global coverage and 8-day composite MOD09A1 product, offers a much higher observation frequency compared to Landsat's 16-day revisit cycle (R2 Fig. 1b-d). Although CCD was initially designed for Landsat data, MODIS's higher temporal resolution made it the more suitable choice for the mapping objectives of this study. Despite its lower spatial resolution (500 m), MODIS was the most practical solution for consistently generating annual vegetation maps of the QTP from 2000 to 2022.



R2 Figure 1: Frequency of Cloud-Free Pixels from Landsat (a, b) and MOD09A1 (c, d) over the QTP (2000-2022)

Q2: High-resolution vegetation maps have already been produced at 10-m levels (Zhou et al., 2022), and these were used as a baseline to generate samples in this study. This means the samples were extracted from vegetation maps resampled from 10 m to 500 m. For a 500 m × 500 m pixel, significant mixing of different vegetation types is likely. The authors performed random sampling in areas where purity exceeded 70%, but this raises the question: why exclude mixed areas? What were the classification results in these mixed areas?

Answer: Thank you for your valuable suggestion. The presence of mixed pixels at the 500-meter scale is indeed a common issue in vegetation classification. In such cases, the vegetation type of a mixed pixel is typically determined by the dominant vegetation type at the sub-pixel level. To account for this, we set a threshold of 70% purity to select samples, ensuring that the dominant vegetation type occupies a significant portion of the pixel.

In addition, we conducted a correlation test to examine the impact of pixel purity on classification accuracy. Pixels with a purity greater than 70% were defined as high-purity, while those below 70% were considered low-purity. The results showed that models built from high-purity samples provide reliable guidance for classifying low-purity pixels. Specifically, when low-purity pixels were used as validation samples, the model's classifications aligned with the dominant vegetation type of those pixels. However, models built from low-purity samples tended to misclassify high-purity pixels. resulting in lower accuracy compared to models built from high-purity samples and validated with high-purity pixels.

In Table 1, we present the distribution of different purity classes and their area proportions after resampling. Approximately 62.34% of the QTP (within China) consists of areas with purity levels above 70%. We chose 70% as a threshold because setting it too high would reduce the area available for sampling, especially for discrete and smaller vegetation types like shrubs. Conversely, a lower threshold would increase the proportion of mixed pixels, which would negatively affect the quality of training samples.

In summary, the vegetation type of mixed pixels depends on the dominant vegetation type at the sub-pixel scale, and models built from high-purity samples can provide guidance for classifying low-purity areas, while models built from low-purity samples tend to mislead the classification of high-purity areas.

Q3: Regarding data validation, I find the process insufficiently rigorous, which is a crucial element for a data-focused paper. The samples, spanning 2000–2020, were derived from the literature, but the description of this process is vague. How were the samples defined and extracted? How was their quality assessed? What was their spatial coverage?

Answer: Thank you for your suggestion. The quality of validation samples is indeed crucial for the accuracy assessment of our product. Based on your suggestion, we have updated the validation sample dataset and included a more detailed description of the quality control measures implemented.

We collected third-party samples from several sources, including the First All-season Sample Set produced by Li et al. (2017), the Global Land Cover Validation Samples collected by Zhang et al. (2021), and additional validation samples gathered through literature review. To ensure the quality of these samples, we applied the quality control method outlined by Feng et al. (2012).

Specifically, at the spatial scale, we analyzed the homogeneity of validation samples using a 3×3 grid of nine 500 m resolution pixels. The maximum and minimum values for several spectral bands (blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2) were used to calculate the difference, which served as an indicator of homogeneity. The thresholds for homogeneity were 0.03 for the blue, green, red, and shortwave infrared bands, and 0.06 for the near-infrared band. If the range for all bands within a 3×3 grid fell below these thresholds, the area was considered homogeneous. This ensures that at most one representative sample is present within a 500 m spatial extent for the third-party validation samples, and that this sample lies within a 1.5 km×1.5 km homogeneous region.

After implementing these quality control measures, we finalized a set of 1,014 third-party validation samples, consisting of 327 from the Global All-season Sample Library, 499 from the Global Validation Sample Set, and 188 from literature search.

Q4: Additionally, these samples were used to validate static maps, not the change maps. In the Discussion, the authors claim that CCDC detects higher frequencies of vegetation type changes (e.g., 5 times), but they also argue that the maps generated in this study are more accurate due to fewer detected changes. How can this claim be substantiated when the accuracy of the change maps was not assessed?

Answer: Thank you for your suggestion. The validation samples used in this study can only assess the accuracy of static vegetation maps, and therefore cannot be applied to evaluate change maps. The term "more accurate" in the text refers specifically to a reduction in false positive errors compared to the potential change areas detected by the CCD algorithm. While the CCD algorithm may detect a breakpoint, it does not always correspond to an actual change in vegetation type.

To support this conclusion, we provide an example from Fig. 12. The CCD algorithm detected a breakpoint in this area; however, based on our mapping method and visual interpretation of remote sensing imagery, the area remains classified as cultivated vegetation. As a result, the vegetation changes detected in this study exhibit a smaller spatial extent and fewer occurrences than the potential changes identified by the CCD method (Fig. 5). This suggests that our maps are more accurate when compared to the CCD detection results, as they avoid false detections of vegetation change.

Q5: Moreover, methodological innovation is a key issue for publication in ESSD. As another reviewer noted, the "RF+CCDC+Spatial-temporal Consistency" framework is a common mapping approach in the existing literature, which limits the method novelty of this study.

Answer: Thank you for your comment. As Liu et al. (2021) noted, while existing land cover products generally meet user requirements in terms of performance, they often fail to ensure interannual stability because they are generated independently for each year. The "RF+CCDC+Spatial-temporal Consistency" framework is an effective approach to address this issue. The CCD model segments long time series remote sensing data at 'breakpoints', creating sub-sequences with different coefficients. In the study by Xian et al. (2021), CCD output parameters and auxiliary data were used as variables in a classification model, which uniformly classified the entire study area to generate annual land cover products.

However, this manuscript proposes a dynamic mapping method that updates annually, offering a novel approach to enhancing interannual stability. First, a reference vegetation map of the QTP for 2020 was produced using terrain-climate-remote sensing data. The CCD model was then applied to detect potential change areas, identifying the temporal and spatial positions of breakpoints. The RF model was used only for pixel-based classification in these breakpoint regions, while non-breakpoint areas were not reclassified. Finally, a spatio-temporal consistency approach was implemented to reduce misclassified pixels, enhancing interannual stability.

The key innovation of this study lies in dynamically updating the mapping annually, rather than classifying the entire study area each year. By reducing the number of pixels subject to classification, we minimize the risk of misclassification. Specifically, for non-breakpoint areas, labels were derived directly from the nearest neighbor vegetation map from the preceding year. For example, the non-breakpoint areas in 2019 were assigned labels based on the 2020 map. This approach significantly differs from the "RF+CCDC+Spatial-temporal Consistency" framework of Xian et al. (2021), as our method focuses on reducing the classification area and employing dynamic updates to ensure interannual consistency.

In summary, the methodological innovation of this study lies in its dynamic, annually updated mapping approach, which aims to address the challenge of interannual stability in land cover products.

Q6: Finally, the language issues. There are many subjective and vague descriptions lacking proper citations in the manuscript. For instance, Section 2.3.2: "Additionally, 6 percentiles: 5%, 30%, 45%, 60%, 75%, and 90%, were calculated for the 7 reflectance bands and the 14 indices. " How were these percentiles selected?

Answer: Thank you for your suggestion. We apologize for the error, and we have corrected "5%" to "15%" in the revised manuscript (see line 197). Additionally, we have included relevant explanations and citations to clarify the selection of these percentiles (see lines 198-202). In this study, six percentiles (15%, 30%, 45%, 60%, 75%, and 90%) were calculated from intra-annual observations of time series remote sensing imagery to create a vegetation mapping feature set. The 15% and 90% percentiles were chosen as substitutes for the minimum and maximum values to mitigate the influence of extreme values in the time series data (Zhang et al., 2021). Meanwhile, the intermediate percentiles (30%, 45%, 60%, and 75%) were selected to capture temporal trends evenly across the time series, ensuring uniformity without creating feature redundancy (Sulla-Menashe et al., 2019; Zhang et al., 2024).

Q7: Section 2.2.3: "For the QTP within China, climate data at 1,000 m was obtained from the National Tibetan Plateau Data Center. " What specific climate data was used?

Answer: Climate data for the QTP within China were obtained from the National Qinghai-Tibet Plateau Data Center, specifically the "1-km monthly precipitation dataset for China (1901-2023)" and the "1-km monthly mean temperature dataset for China (1901-2023)." To derive the precipitation and temperature features used in this study, the monthly precipitation data were summed to calculate annual totals, and the monthly mean temperature data were averaged to obtain annual mean temperatures. For relevant details on the climate data and their citation, please see the revised manuscript, lines 178-181.

Q8: The Discussion also repeatedly uses subjective phrases such as, "Fortunately, our annual vegetation map also reflected this characteristic, " and "Our long-time annual vegetation maps also reflected this characteristic, " which undermines the objectivity of the writing.

Answer: Thank you for your suggestion. We have revised the subjective language in the manuscript. For instance, we changed "Fortunately, our annual vegetation map also reflected this characteristic" to "The annual vegetation maps accurately captured this transition" and "Our long-time annual vegetation maps also reflected this characteristic" to "The long-time annual vegetation maps consistently reflected this characteristic." In addition, we reviewed the Discussion section and removed other subjective phrases to maintain objectivity. Please refer to Sections 4.1 and 4.2 of the revised manuscript.

References

Feng, M., Huang, C., Channan, S., Vermote, E. F., Masek, J. G., and Townshend, J. R.: Quality assessment of Landsat surface reflectance products using MODIS data, Comput. Geosci., 38, 9–22, https://doi.org/10.1016/j.cageo.2011.04.011, 2012.

Li, C., Peng, G., Wang, J., Zhu, Z., Biging, G. S., Yuan, C., Hu, T., Zhang, H., Wang, Q., and Li, X.: The first all-season sample set for mapping global land cover with Landsat-8 data, Sci. Bull., 62, 508–515, https://doi.org/10.1016/j.scib.2017.03.011, 2017.

Liu, L., Zhang, X., Gao, Y., Chen, X., Shuai, X., and Mi, J.: FinerResolution Mapping of Global Land Cover: Recent Developments, Consistency Analysis, and Prospects, J. Remote Sens., 2021, 5289697, https://doi.org/10.34133/2021/5289697, 2021.

Sulla-Menashe, D., Gray, J. M., Abercrombie, S. P., and Friedl, M. A.: Hierarchical mapping of annual global land cover 2001 to present: The MODIS Collection 6 Land Cover product, Remote Sens. Environ., 222, 183-194, https://doi.org/10.1016/j.rse.2018.12.013, 2019.

Xian, G. Z., Smith, K., Wellington, D., Horton, J., Zhou, Q., Li, C., Auch, R., Brown, J. F., Zhu, Z., and Reker, R. R.: Implementation of the CCDC algorithm to produce the LCMAP Collection 1.0 annual land surface change product, Earth Syst. Sci. Data, 14, 143–162, https://doi.org/10.5194/essd-14-143-2022, 2022.

Zhang, X., Liu, L., Chen, X., Gao, Y., Xie, S., and Mi, J.: GLC_FCS30: global land-cover product with fine classification system at 30m using time-series Landsat imagery, Earth Syst. Sci. Data, 13, 2753–2776, https://doi.org/10.5194/essd-13-27532021, 2021.

Zhang, X., Zhao, T., Xu, H., Liu, W., Wang, J., Chen, X., and Liu, L.: GLC_FCS30D: the first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method, Earth Syst. Sci. Data, 16, 1353–1381, https://doi.org/10.5194/essd-16-1353-2024, 2024.

Thanks to the reviewer for these valuable feedback and valuable suggestions.