# Responses to Reviewers Comments

**Reviewer #1**

After several revisions, the questions raised by the reviewer have been well addressed and improved, meeting the publication requirements of the journal.

**Thank you very much for the valuable feedback and suggestions.**

## Reviewer #2

The manuscript combined MODIS data and random forest machine learning algorithms to map long-term vegetation on the Qinghai-Tibet Plateau, and considered the CCDC algorithm to reduce uncertainty on the time scale. The results could present data basis for understanding the vegetation response mechanism under the background of climate change. However, the introduction and method description of the present version of the manuscript are not convincing, making it difficult to assess the uncertainty of the results. Therefore, I recommend to reject at its present state. I list my major concerns as follows:

***Q1:*** The abstract does not clearly specify the new method. Please include a brief description of the main aspects of the new method.

***Answer:*** Thank you for your suggestion. We have added a description of the key aspects of the new method in the abstract. Please see lines 15-17 in the revised manuscript.

***Q2:*** The term "independent classification method" is not commonly used in remote sensing image classification studies. Could you consider using a more widely recognized term?

***Answer:*** Thank you. We have revised "independent classification methods for each period's product" to "traditional classification methods for each period's product." Please refer to line 13 in the revised manuscript.

***Q3:*** Please distinguish the citation for Liu et al., 2021. There are two authors named Liu who published articles in 2021 in the reference list, and it is unclear which specific paper is being cited.

***Answer:*** Thank you. We have added "a" and "b" annotations to the two references by Liu et al., 2021 in the revised manuscript to distinguish between them. The specific changes can be found in lines 40 and 43 of the revised version.

***Q4:*** The climate data sources within and outside of China are not unified, with one having a resolution of 1km and the other 50km, resulting in a significant difference. Downscaling is required to unify the resolution. However, the author did not specify the subsequent processing steps for the climate data.

***Answer:*** Thank you for your suggestion. In this study, we adopted a mean resampling method based on Google Earth Engine for data processing. All climate data, including 1 km resolution data in China and 50 km resolution data outside China, were resampled to a 500 m resolution to ensure consistency with other datasets, such as remote sensing imagery.

***Q5:*** For each vegetation category, please provide descriptive information to help readers understand their characteristics. For instance, alpine scrub meadow (ASM), alpine meadow (AM), alpine grassland (AG), and alpine vegetation (AV) may be difficult to distinguish by name alone. A table with descriptions for each category and the number of sample points would enhance the article's readability.

***Answer:*** Thank you for your suggestion. In the revised manuscript, we have added Table 1, which includes the names, definitions, and the number of training and validation samples for each of the 16 vegetation types in this study. To further enhance clarity, the number of training and validation samples is also visually represented in a bar chart in Figure 1. Please refer to line 106 in the revised manuscript for these updates.

***Q6:*** When selecting training samples for the classification of the 2020 MODIS dataset, based on the 10-meter resolution QTP vegetation classification map, why was 70% purity chosen? Is there any basis for 70% in other studies?

***Answer:*** Thank you. In this study, a purity threshold of 70% was chosen as the criterion for training sample selection, primarily based on the characteristics of the study area and the quality requirements. In Table 2, we present the area proportions for different purity levels, with regions of greater than 70% purity covering approximately 62.34% of the area of the QTP (in China). Choosing a higher purity threshold would significantly reduce the available sampling area, which is not conducive to collect samples for smaller and more dispersed vegetation types. On the other hand, choosing a lower purity threshold would increase the proportion of mixed pixels, affecting the reliability of the samples. Taking these factors into account, we believe that a 70% purity threshold strikes a good balance between sample quality and the available sampling area in this study.

***Q7:*** "Each sample was independently interpreted regarding its vegetation type by three interpreters, using long-time series temperature and precipitation data as well as Landsat remote sensing images." Could you clarify how the long-term temperature and precipitation data were used to determine the sample class?

***Answer:*** Thank you for your question. The visual interpretation of vegetation types on the QTP primarily relies on long-term Landsat remote sensing imagery, with temperature and precipitation data serving as auxiliary information for sample quality control. Different vegetation types usually have specific climatic suitability ranges. For example, alpine meadows have a higher demand for precipitation and temperature, while alpine grasslands are adapted to drier and colder environments. By integrating long-term temperature and precipitation data, we can verify whether the climatic conditions of each sample are consistent with the characteristics of its corresponding vegetation type. This allows us to exclude samples that significantly deviate from the suitable climatic range, thereby enhancing sample quality and ensuring the scientific accuracy of the classification results.

***Q8:*** In Section 2.2.2, it might be helpful to summarize the main information and move the detailed methodology to supplementary information. This could improve the article's readability.

***Answer:*** Thank you for your suggestion. After careful consideration, this section mainly describes the process of obtaining validation samples, which is closely related to the main content and presented in a textual format. Moving it to the supplementary information might compromise the reader's understanding of the sample acquisition process. To improve readability, we have streamlined this section by removing redundant descriptions while retaining the key information.

***Q9:*** "This study utilized climate data which included annual precipitation (AP) and annual average temperature (AT) across the entire QTP from 2000 to 2022." Please clarify the specific role of the climate data to help readers understand its importance in the research.

***Answer:*** Thank you. We have added content in Section 2.2.4 to emphasize the importance of climate data in determining vegetation distribution on the QTP. Please see lines 177-179 in the revised manuscript.

***Q10:*** Please revise Equation 6 to avoid any misunderstanding that n can only go up to 3.

***Answer:*** Thank you for your suggestion. We have revised the formula and explanatory text to avoid the misunderstanding that the upper limit of $n$ can only be 3. In the updated version, $N$ has been introduced in the formula to represent the maximum order of harmonics, indicating that this value can be adjusted flexibly according to research needs rather than being fixed at 3. Please see lines 259-261 in the revised manuscript.

***Q11:*** The "Description" section of Table 2 requires more detail. Instead of abbreviations like MIR or SWIR1, please provide the full name and specify the wavelength details. Additionally, for the indices, adding a brief description of their characteristics, such as their physical significance, would be helpful.

***Answer:*** Thank you. We have revised Table 3 (formerly Table 2), supplemented the full name and wavelength ranges of the bands, as well as annotations explaining the physical significance of each index along with the corresponding references. Please see line 208 in the revised manuscript.

***Q12:*** "The 'breakpointBands' parameter specifies the bands for breakpoint detection, including Red, NIR, and SWIR 1, which correlate with chlorophyll content, leaf structure, and water content, respectively." Please ensure consistency with the abbreviations used earlier, particularly if SWIR 1 refers to S1 (Swir1).

***Answer:*** Thanks. We have carefully reviewed and ensured consistency between the abbreviations used in the text and those in Table 3. For example, R, N, and S1 represent the Red, Near-infrared, and Shortwave Infrared 1 bands, respectively. Please see lines 276-277 in the revised manuscript.

***Q13:*** "The vegetation map of the QTP includes 16 types (Fig. 4)." Please specify that this refers to the 2020 classification.

***Answer:*** Thanks. We have revised the text to: "The 2020 vegetation map of the QTP includes 16 types (Fig. 4)." to clarify that it refers to the classification results for 2020. Please see line 323 in the revised manuscript.

***Q14:*** In Section 4.1, it would be helpful to explain why the Red, NIR, and SWIR 1 bands were chosen for breakpoint detection in CCD. Could you discuss the relevance of these bands for breakpoint identification based on the characteristics of QTP vegetation?

***Answer:*** Thank you. In Section 4.1, we have added the reasons for selecting the R, N, and S1 bands for breakpoint detection in the CCD process. Specifically, the R band is related to vegetation chlorophyll content, the N band is associated with vegetation canopy structure, and the S1 band reflects vegetation water content. Additionally, these three bands are commonly used to construct vegetation indices such as NDVI and SAVI. Please see lines 427-428 in the revised manuscript.

***Q15:*** In the discussion, it would be useful to elaborate on why certain variables were more significant in the 2020 RF classification. Have these variables been found to be important in other studies as well? Is the QTP classification unique, making some variables more critical?

***Answer:*** Thank you for your suggestion. In previous study on the 10-meter vegetation map of the QTP, we have demonstrated the importance of elevation, annual average temperature (AT), annual precipitation (AP), slope, and aspect in the 2020 RF classification (Zhou et al., 2023). However, studies focusing on vegetation distribution at the 500-meter scale for this region are relatively scarce. At this scale, we found that elevation, AT, AP, and slope remain key variables, while the influence of aspect diminishes. Given the limited impact of human activities on the QTP (Chen et al., 2023), the selected variables in this study further highlight the unique geographical and climatic conditions that shape vegetation classification in this region.

***Q16:*** Lines 29-30: Among ESA's land cover data products, ESA-CCI is more representative because it has good temporal continuity and a spatial resolution of 300 m.

***Answer:*** Thank you for your suggestion. We have explicitly introduced the ESA-CCI land cover data product in the manuscript and highlighted its provision of excellent temporal continuity at a 300 m spatial resolution. Please see lines 30-31 in the revised manuscript.

***Q17:*** Lines 41-43: Why can't direct comparisons be made if there are significant differences? How do the authors rule out situations where these differences actually occur. As far as I know, the mainstream data products in the world are obtained by classifying single-period data after pre-training.

***Answer:*** Thank you for your question. The differences in data processing and classification methods between GlobCover 2005 and 2009 make these maps more suitable as independent land cover datasets rather than as a basis for change detection (Bontemps et al., 2010). Liu et al. (2021) pointed out that single-period products from different years often suffer from inconsistencies in spatial and temporal accuracy due to variations in classification algorithms or data processing, which can lead to misinterpretation of processing noise as actual changes. Even high-resolution (30 m) GLC products have significant classification errors in complex terrains, such as shrublands and grasslands, which limit their capability for interannual change analysis. In contrast, dynamic change detection methods, such as Continuous Change Detection and Classification (CCDC), enhance interannual stability through time-series analysis and differentiate between classification errors and true changes. For instance, the GLC_FCS30D product (Zhang et al., 2024b) used the CCDC method to generate a global 30-meter dynamic land cover dataset for 1985–2022, effectively improving temporal consistency. This demonstrates that global land cover monitoring has gradually shifted from single-period classifications to time-series analyses, which significantly improving monitoring accuracy and interannual stability.

***Q18:*** Lines 39-54: The background introduction of the current version is not convincing. Will the data products that take into account time continuity bring uncertainty to the mapping results of areas where vegetation mutations occur on the Qinghai-Tibet Plateau?

***Answer:*** Thank you. According to your suggestion, we have revised the background section to further emphasize the issues of spatial and temporal consistency in traditional long-term data products, and clarified the solutions based on post-processing methods and continuous change detection techniques. In particular, the CCDC method significantly enhances the stability of time-continuous data products, especially in areas with large changes. This method effectively identifies and reduces the temporal instability of time-series classification products. Please see lines 41-59 in the revised manuscript.

***Q19:*** Lines 55-60: Are these all the author's opinions? Why are there no references?

***Answer:*** Thank you for your comments. This section is based on conclusions supported by existing literature. In the revised manuscript, we have added the corresponding references to more accurately reflect the sources of this information. Please see lines 60-66 in the revised version.

***Q20:*** Lines 61-72: There is insufficient summary of vegetation mapping research at the scale of the Qinghai-Tibet Plateau, and there is a lack of summaries of some influential studies. For example, https://doi.org/10.1007/s11629-015-3485-y.

***Answer:*** Thanks. We have added a summary of vegetation mapping studies at the QTP, including the influential study you mentioned (DOI: 10.1007/s11629-015-3485-y). Additionally, we have referenced other relevant studies (DOI: 10.1016/j.ecolind.2022.108599; DOI: 10.1016/j.scib.2023.07.035) to provide a more comprehensive overview. Please see lines 71-76 in the revised manuscript for the specific changes.

***Q21:*** Lines 86-87: What is the "permanent glaciers"? Glaciers, snow cover and permafrost are not vegetation.

***Answer:*** Thank you. We have removed the sections on "permanent glaciers, snow cover, and permafrost," which are unrelated to vegetation, to maintain accuracy and relevance to vegetation distribution. Please see lines 94-96 in the revised manuscript.

***Q22:*** Lines 90-95: This classification strategy is also designed from the perspective of land cover. How did the authors start from the perspective of vegetation cover? In addition, what strategy did the authors use to distinguish "evergreen broad-leaved forest (EBF), evergreen coniferous forest (ECF), coniferous and broad-leaved mixed forest (CBMF), deciduous broad-leaved forest (DBF), and deciduous coniferous forest (DCF)" at a spatial resolution of 500 m? Are they clearly distinguishable at such a coarse spatial resolution? Has their spectral separability been evaluated? This is my main concern. In addition, how are "alpine vegetation (AV) and cultivated vegetation (CV)" defined, and how are they distinguished from other vegetation? Does the bare land type on the Qinghai-Tibet Plateau only include "alpine desert (AD)"?

***Answer:*** Thank you. The classification strategy in this study focuses on vegetation cover, integrating ground survey data and spectral validation to ensure that different vegetation types (e.g., EBF, ECF, CBMF, DBF, DCF) can be reasonably distinguished at a 500 m resolution. While the resolution is relatively coarse, extensive ground surveys and spectral analyses conducted by our team in the QTP indicate that these vegetation types have separability in spectral characteristics and ecological distributions, allowing effective differentiation using a random forest classifier. It is important to note that, unlike land cover products such as GlobeLand30 (Chen et al., 2015), which classify categories like forest and grassland, this study focuses on a more refined delineation of vegetation types, such as alpine meadow, alpine grassland, and alpine desert. To aid readers' understanding of the classification criteria, we have added definitions and characteristic descriptions of "alpine vegetation (AV) and cultivated vegetation (CV)" in Table 1. Regarding desert types, the "alpine Desert (AD)" in this study is defined based on the Editorial Board of the Vegetation Map of China, Chinese Academy of Sciences (2007), which is characterized by the Deserts composed of cold- and drought-tolerant cushion subshrubs.

***Q23:*** Lines 96-111: I have the same concerns as the first round of reviewers that the errors of the 10 m resolution data product will be introduced into the results of this study. In addition, the authors did not avoid the existence of mixed pixels during the upscaling process, which is another concern of mine, and will bring great uncertainty to the results. Homogeneous areas should be selected to form training data, and I am not sure whether 70% purity is sufficient.

***Answer:*** Thanks. While the 10 m resolution vegetation map serves as the reference data for this study, its influence on the results has been managed. We selected training samples using a 70% purity threshold and validated the results with independent third-party samples. Additionally, mixed pixels are indeed a challenge at the 500 m scale, but we have mitigated this issue by selecting training samples only from areas with a purity greater than 70%. This threshold ensures that the dominant vegetation type constitutes the majority of the pixel, enhancing the representativeness of the training data. A higher threshold, while potentially reducing uncertainties, would significantly reduce the number of samples, particularly for less common vegetation types. Conversely, a lower threshold would increase the proportion of mixed pixels, diminishing the quality of the training data. The choice of 70% purity represents a balance between sample quality and availability, as approximately 62.34% of the QTP (within China) consists of areas exceeding this purity level, ensuring sufficient high-quality samples for robust model training. In summary, this study has minimized the error propagation from the 10-meter vegetation map as much as possible. At the same time, the 70% purity threshold provides an effective balance between ensuring sample quality and maintaining sufficient sample coverage.

***Q24:*** Lines 105-107: Why is this method not used in China? Generally speaking, the sample data obtained by visual interpretation is more accurate. Is it sufficient to use only one year of sample data to generate classification results for such a long time series?

***Answer:*** Thank you for your question. We used the " Vegetation map of Qinghai Tibet Plateau in 2020 with 10 m spatial resolution" as the basis for training samples due to its high resolution and reliability. The vegetation map was generated at a 10-meter spatial resolution with an overall accuracy of 89.5%, constructed based on visual interpretation and multi-source data integration (terrain, climate, and remote sensing information) (Zhou et al., 2023). Such high-precision foundational data provides support for vegetation classification at the 500-meter scale. Additionally, as vegetation types on the QTP are primarily influenced by climate, with less human activity impact (Chen et al., 2023), it is reasonable to use 2020 sample data to generate long-term classification results. Our methodology not only ensures consistency of the classification system but also incorporates change detection techniques, enabling the capture of dynamic vegetation changes over time.

***Q25:*** Section 2.2.2: The selection method of validation samples is more standardized than that of training samples. The method of selecting validation samples is more standardized than that of training samples. Why don't we follow the standards when selecting training samples?

***Answer:*** Thank you. The selection methods for training and validation samples differ due to their distinct purposes: validation samples aim to strictly control quality to assess model accuracy, and thus a more rigorous filtering approach is adopted. Training samples focus on quantity and diversity to meet the model's learning requirements. The training samples were primarily derived from a high-resolution vegetation map with an overall accuracy of 89.5%. To ensure their representativeness and consistency, samples were filtered based on pixel purity (≥70%). Additionally, high-resolution imagery interpretation was integrated to ensure adequate spatial and type coverage. Although the validation sample standards were not fully adopted for training, the current approach achieves a balance between sample quantity and quality, effectively supporting model training.

***Q26:*** Section 2.2.3: The introduction of preprocessing is too brief. The pretreatment methods and standards used need to be introduced, and relevant literature should be cited.

***Answer:*** Thank you for your suggestion. In Section 2.2.3, we have added a detailed description of the preprocessing methods for MOD09A1 data, including its generation as a standardized NASA Level 3 data product and the additional processing steps we applied in this study, such as coordinate system transformation and spatial clipping. Relevant references have also been added. Please see lines 165-176 in the revised manuscript.

***Q27:*** Lines 176-178: How to draw this conclusion from this reference?

***Answer:*** Thank you for your valuable comments. The climate data used in this study were obtained from publicly available datasets provided by the National Tibetan Plateau Data Center, namely the "1-km Monthly Precipitation Dataset for China (1901–2023)" and the "1-km Monthly Mean Temperature Dataset for China (1901–2023)." These references are relevant literature explicitly requested by the data provider to be cited, aiming to acknowledge the source and generation method of the data and ensure its reliability and scientific validity. Therefore, these citations are included to comply with data usage specifications rather than directly supporting the conclusions of this study.

***Q28:*** Lines 185-188: Direct resampling is no different from using the original spatial resolution and may even reduce product accuracy, especially from 50000m to 500m.

***Answer:*** Thank you for your insightful comments. In the mapping process of this study, in addition to temperature and precipitation data, vegetation indices derived from MODIS data and topographic features played a significant role. Although meteorological data with a 50 km spatial resolution were resampled directly to 500 m, the inherent 500 m resolution of MODIS data and the 30 m resolution of topographic data helped mitigate potential impacts on product accuracy. Additionally, we chose two regions for validation. Cultivated vegetation shown in Fig. S1a is clearly represented in Fig. S1b, while water bodies, glaciers, and snow in Fig. S1c are accurately depicted in Fig. S1d. It is worth noting that the display areas in Fig. S1 are all within 50 km. Therefore, it is feasible to use 50 km resolution meteorological data for regions outside China, and high-accuracy 500 m classification results can be obtained.

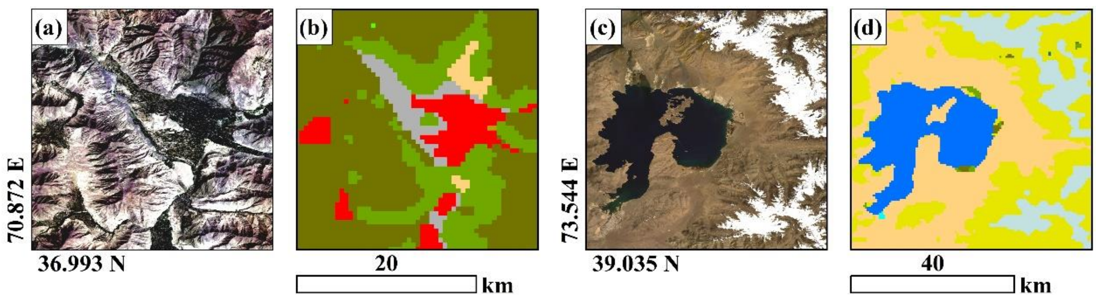


**Fig. S1 Comparison of 2020 Landsat imagery and classification results for regions outside China on the QTP**

***Q29:*** Section 2.3.2: Why were these features chosen?

***Answer:*** Thank you. We selected these features based on the following considerations: first, vegetation indices (e.g., NDVI, EVI, etc.) and spectral characteristics (e.g., red, near-infrared bands, etc.) are core indicators widely used in vegetation classification and monitoring in existing literature. They can effectively reflect the physiological condition and spectral properties of vegetation. Second, topographic features (e.g., elevation, slope, etc.) are critical in the QTP region, as vegetation distribution in this region is significantly related to elevation and terrain. Additionally, meteorological data (e.g., AT and AP) are key drivers of vegetation distribution. Therefore, the selection of these features is based on the theoretical support from previous research and the understanding of the environmental characteristics of the study area (Wang et al., 2022, Wang et al., 2023; Zhang et al., 2024a), which can effectively enhance the scientific validity and accuracy of the classification.

***Q30:*** Section 2.3.3: I could not understand from the current introduction and the cited reference the method adopted to evaluate feature importance, nor could I assess whether it could be used to rule out multicollinearity.

***Answer:*** Thank you. We have provided a detailed description of the feature importance evaluation method and the means of dealing with multicollinearity in the manuscript. Specifically, to address potential multicollinearity issues in optical features, we introduced the Variance Inflation Factor (VIF) method. This allowed us to quantitatively filter out features with severe collinearity, thereby reducing model redundancy and computational load. Subsequently, by combining the feature importance ranking with the VIF selection results, optimal feature combination was selected for vegetation classification on the QTP based on the minimal out-of-bag error. The methods employed in this study are widely used in relevant literature and have been verified for their reliability and applicability in experiments (Ngabire et al., 2022; Zhang et al., 2019).

***Q31:*** Section 2.4.1: The necessity and advantages of using this algorithm in this study should be mentioned.

***Answer:*** Thanks for your suggestion. In section 2.4.1, we have added an explanation of the necessity and advantages of using the CCDC algorithm in this study. Specifically, we describe that it improves the temporal consistency of the classification products by considering both temporal and spectral features to identify the "breakpoint" areas and time periods of vegetation on the QTP from 2000 to 2022. Please see the revised manuscript, lines 242-247.

***Q32:*** Section 2.4.3: References?

***Answer:*** Thank you for your suggestion! The method described in section 2.4.3 is an innovative approach we proposed specifically for the data characteristics and research needs of this study. The detailed operational process is clearly presented through formulas, and as such, this section does not reference any external literature.

***Q33:*** Lines 298-299: How do authors consider local-scale transient disturbances induced by human activities or extreme climate?

***Answer:*** Thank you for your question. Intense human activities and extreme climate events may indeed cause transient disturbances at the local scale on the Qinghai-Tibet Plateau. However, a study by Chen et al. (2023) points out that the impact of human activities on the plateau is relatively weak, and its growth rate has slowed since 2010. Furthermore, despite the fact that the warming rate on the QTP is twice the global average, the region has generally experienced a greening trend, with ecological recovery and overall good environmental quality (Chen et al., 2023). Additionally, considering that the CCDC algorithm used in this study has strong change detection capabilities (Pasquarella et al., 2022), it is able to effectively capture and detect any transient disturbances caused by extreme climate events or human activities on the plateau.

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