Responses to Reviewers Comments

Dear Reviewer #1:

This study developed a new approach to long-time continuous annual vegetation mapping from remote sensing imagery. The new approach is very important and effective for the use of remote sensing data to mapping long-term continuous annual vegetation. Using the new method, this study mapped the vegetation of Qinghai Tibet Plateau（QTP） from 2000 to 2022 at a 500 m spatial resolution through the MOD09A1 product. The valuable dataset facilitates the understanding of the spatial and temporal variations of vegetation in the QTP under the background of global warming. Therefore, I recommend accepting this manuscript. However, there are some minor issues that need to be addressed:

Q1.L39-40 Modify "Over time, the trend of increasing misclassified pixels and their positional uncertainties ultimately reduces the reliability of remote sensing interpretation for LCSV types." to "Over time, there is a trend of increasing misclassified pixels and their positional uncertainties, which ultimately reduces the reliability of remote sensing interpretation for LCSV types."

Answer: The sentence is modified based on the comment in the revised manuscript. Please see Lines 40-42 in the revised manuscript.

Q2.L104-106 Sentence structure is incomplete. The suggestion is as follows: "The MOD09A1 dataset provides surface reflectance in seven spectral bands (Red, Blue, Green, NIR, MIR, SWIR 1, and SWIR 2) with 500 m spatial resolution, and all cloud-contaminated pixels are removed."

Answer: The sentence structure is modified based on the suggestion in the revised manuscript. Please see Lines 122-123 in the revised manuscript.

Q3.L114 Use "were" instead of "was" to match the plural noun "data": "For the QTP within China, climate data at 1,000 m were obtained from..."

Answer: It is modified in the revised manuscript in the Line 131. Also, "climate data for areas of the QTP outside China was derived...." was modified by using "were" instead of "was" in the Line 132.

Q4.L301 The verb "confirms" should be corrected to "confirm" to match the plural subject.

Answer: The verb “confirm” is used in the revised manuscript. Please see Line 383.

Q5.(5) In the Figure 4, legend text is too small, please revise the font size.

Answer: In the revised manuscript, the Figure 4 is deleted based on the comments from Reviewer #2.

Thanks very much for these constructive comments and suggestions.

Dear Reviewer #2:

This manuscript combined the continuous change detection classification (CCDC), random forest (RF) classification models, and "Spatial-temporal Consistency" algorithm to develop the annual vegetation maps in QTP during 2000-2022 using time-series MODIS imagery. The results seem good with an overall accuracy of 86.5% and a kappa of 0.85. However, there are some serious concerns in the current manuscript:

Q1: The proposed method lacks of the novelty, the "CCDC+RF+ Spatial-temporal Consistency" has been applied in some previous works, such as: Xian et al. (2022) and Friedl et al. (2022). All of them used this strategy to generate the time-series global/national land-cover change maps at 30 m from Landsat imagery.

Answer: Thank you very much for the constructive comments and suggestions. While the method proposed in this study is based on "CCDC+RF+ Spatial-temporal Consistency", it differs from the approaches used by Xian et al. (2022) and Friedl et al. (2022). Firstly, the CCDC algorithm comprises two parts: "Continuous Change Detection (CCD)" and "Classification (C)"(Awty-Carroll et al., 2019; Zhu and Woodcock, 2014). Previous works often used the full CCDC, utilizing coefficients (spectral-temporal features) of each sub-series marked by CCD for classification through an RF model to determine vegetation types. However, our results showed that climate and terrain factors significantly influence vegetation distribution on the QTP. Therefore, we use only the "Break" points marked by the CCD to identify potential change (PC) areas on the QTP. The actual category labels are determined by the RF model, which is based on climate, terrain, and remote sensing data, rather than the sub-series model coefficients used in previous studies.

At present, the land-cover change maps in the QTP from other scientists primarily targets land use types and lacks detailed vegetation categorization. Our study designed a vegetation classification system tailored to the unique vegetation types of the QTP. For instance, we have refined the classification for the Tibetan Plateau by dividing grassland into three distinct categories: alpine meadow, alpine grassland, and alpine desert. Additionally, we provided a detailed classification of forest into five categories: evergreen broad-leaved forest, evergreen coniferous forest, coniferous and broad-leaved mixed forest, deciduous broad-leaved forest, and deciduous coniferous forest.

Q2: The descriptions about the CCDC algorithm should be strengthen. The CCDC can take advantage of continuous satellite observations and achieve higher robustness for capturing land-cover changes, however, it was a parameter-sensitive model, please refer the works of Zhu et al. (2019). So you should emphasize how to determine these parameters in your manuscript.

Answer: Thanks very much for the constructive comments and suggestions. We have strengthened the description of the CCDC in the revised manuscript; please refer to pages 9-10, lines 183-214. The CCDC is a parameter-sensitive model. Zhu et al. (2019) provided a set of well-performing parameters for the CCDC, which have been adopted as default parameters in GEE. These include "chiSquareProbability=0.99", "minObservations=6", "lambda=20", and several others. We modified the "breakpointBands" and "dateFormat", while the others remain at default settings. The "breakpointBands" parameter specifies the bands used for breakpoint detection, including Red, NIR, and SWIR 1, which correlate with chlorophyll content, leaf structure, and water content, respectively. The "dateFormat" parameter is set to 2, indicating that all breakpoint times are represented as Unix timestamps.

Q3: The applicability of the CCDC algorithm in the study area is questionable. The work of Pasquarella et al. (2022) clearly stated that the CCDC was suitable for the stationary time-series and is actually designed for forest disturbances. The Figure 6a in this manuscript obviously showed that the CCDC model suffered the under-fitting problems.

Answer: Thank you very much for the constructive comments and suggestions. Previous studies have shown that the CCDC algorithm was originally designed to detect land cover and land use changes that usually result in a large change magnitude. However, its accuracy is relatively lower when identifying forest disturbances with subtle spectral changes, particularly when the forest cover type remains unchanged after the disturbance (Cohen et al., 2017; Pasquarella et al; 2022; Zhu et al., 2019). Although Fig. 6a in the original manuscript (Fig. 11a in the revised manuscript) shows under-fitting issues with the CCDC, this problem did not occur in the NIR and SWIR bands. Furthermore, this study aims to identify transitions between different vegetation types, which typically involve more significant changes. Minor forest disturbances, which are challenging for the CCDC to detect, remain classified as forest types before and after the disturbance and thus do not affect our study results. Finally, the under-fitting of the CCD mainly manifests as the inability of the fitting coefficients (spectral-temporal features) to accurately represent the corresponding vegetation types. However, this study only uses the “break” (potential changes) detected by the CCD, and these potential changes significantly decrease after classification using our RF model, which is based on climate, terrain, and remote sensing data.

Q4: The validation section also cannot convince me. The validation points came from their 10m vegetation maps only using the purity index, I think the classification errors in the 10m product would transfer to the validation points. Then, since the training and validation samples came from the same sample pool, the final validation accuracy is also high, which is unconvincing.

Answer: Thank you for pointing out the issues in the validation section. Validation samples from the same pool as the training samples can result in overly optimistic validation results. To address this, we removed all the validation samples used in the origin manuscript. Instead, we gathered new validation samples through field surveys, literature reviews, and visual interpretation. For details, please refer to page 4, lines 97-110 in the revised manuscript. For the reference year (2020), we collected 1,382 samples, and for other years, we gathered between 1,100 and 1,200 samples. The validation results show an accuracy of 83.43% for the 2020 vegetation map, with an average accuracy of 81.82% for the annual vegetation maps from 2000 to 2022.

Q5: The descriptions about section 3.2 should be greatly revised. The Figure 4 is meaningless because there is no way to know where changes have occurred throughout the study area. I strongly suggest the authors can refer the works of Xian et al. (2022) to reorganize this content, and pay more attention to the analysis of land-cover changed areas.

Answer: Thank you for your insightful suggestion. Section 3.2, which covers the annual vegetation mapping results, was minimally detailed in the original manuscript and lacked details on vegetation changes. We reorganized this section by referring to the works of Xian et al. (2022). The revised content is on pages 13-18, lines 271-328. We first analyze vegetation changes across the entire QTP, then examine two sample areas in detail, using remote sensing images and vegetation maps to show vegetation distribution changes from 2000 to 2022.

Q6: At present, there are time-series 30 m global land-cover change products, thus, what are the strengths of this data, which need to be emphasized. I also suggest that the manuscript can add the comparisons between their results and some previous datasets such as: CLCD.

Answer: Thank you for your suggestion. We have reorganized Section 4.2 to include comparisons with MCD12Q1, CLCD, and GLC-FCS30D, highlighting the strengths of our dataset. We selected four regions with distinct dominant land cover types: water, glaciers and snow, grasslands, and forests. Please refer to pages 24-26 and lines 395-430 in the revised manuscript. Grasslands cover about 57% of the QTP, including AM, AG, ASM, and AD (Zhou et al., 2023). Previous products, such as MCD12Q1, CLCD, and GLC-FCS30D, do not differentiate between these types. Our dataset, however, accurately distinguishes between alpine meadows and alpine grasslands and identifies the unique alpine vegetation, which accounts for about 15% of the QTP.

References

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