Dear Editor:

Thank you very much for the extensive effort you have made in handling our manuscript and identifying reviewers. We have revised our manuscript according to the insightful comments from the reviewers. All the comments (in black) are addressed with point-by-point responses (blue). The sentences copied from the manuscript are in italic format.

1. Line 23 and 294: with link: https://data.tpdc.ac.cn/zh-hans/disallow/50de2d4f-75e1-4bad-b316-6fb91d915a1a/. This link looks like a temporary link. Please change to a formal form.

Response: Thank you for the advice. We have changed the link to the formal form.

2. Please modify the article as the referee's suggestions:

(1)Line 40: please change "get 875 thaw slumps" to "map 875 thaw slumps"

(2)Line 391: please change " on north-facing slopes with gentle degrees" to " on gentle north-facing slopes"

Response: We have revised the manuscript accordingly.

3. Since you have put the data at the National Tibetan Plateau/Third Pole Environment Data Center, you are welcome to cite the relevant introduction papers into the articles as: https://doi.org/10.1175/BAMS-D-21-0004.1 and https://doi.org/10.1175/BAMS-D-19-0280.1

Response: We have added the citations in the Data available section. The revised sentence is:

" The Chinese version is in the National Tibetan Plateau/Third Pole Environment Data Center (Pan et al., 2021; Li et al., 2020), with link DOI:10.11888/Cryos.tpdc.272672."

4. Please modify the article according to the comments from the referees as shown in the attached file.

Response: We have revised the article accordingly.

5. Since the research is related to permafrost, it is suggested that the author may reference relevant articles in the special issue， such as https://doi.org/10.5194/essd-13-4207-2021, and https://doi.org/10.5194/essd-14-865-2022

Response: We added the citations in our manuscript, as follows:

"Because the underlying permafrost on the plateau is characterized by shallow thickness and relatively high temperature (Ran et al., 2022; Wu and Zhang, 2008; Wu et al., 2010; Zhao et al., 2021; Zhou et al., 2000), it is vulnerable to degradation under climate warming and disturbance due to human activities."

Best Regards,

Zhuoxuan XIA and co-authors

Responses to reviewers

1. The trained DeeplabV3+ model used pre-trained weights using the ImageNet dataset. It is sometimes questioned that ImageNet dataset's context/scene is very different from remote sensing images and therefore difficult for transfer learning. And the model performance is highly dependent on how the fine-tuning is done. So, maybe it's helpful to reveal some details on how the ImageNet pre-trained model is fine-tuned, and the accuracy on the test set. Although this manuscript is a data description paper rather than a methodology paper, but as part of the data is auto-generated, it is crucial for the readers to fully understand the data generation process. Also, there's a limitation for ImageNet pre-trained model that it was trained on RGB channels, which makes its adaption to multi-bands satellite image data very difficult. In the future maybe consider the use of BigEarthNet to pre-train the model.

Response: We agree that the data in ImageNet dataset are distinct from remote sensing images, so we fine-tuned all layers of the pre-trained model using our dataset. To reveal the details of how we fine-tuned the model, we have revised the sentences as :*"The DeepLabv3+ model (http://download.tensorflow.org/models/deeplabv3_xception_2018_01_04.tar.gz) we used was pre-trained using the ImageNet dataset (Russakovsky et al., 2015), making the model parameters effective in extracting general image features. To make the model feasible for identifying RTSs, we copied the architecture and parameters of the pre-trained model and fine-tuned all the parameters using corresponding PlanetScope images and labels as training data."*

The accuracy on the test dataset is important in assessing the model performance, but was not provided in our manuscript for several reasons. Firstly, we didn't have the ground truths of RTSs in this region, so there was not a direct way to calculate the test accuracy. Secondly, our iterative mapping strategy utilized the power of deep learning to generate RTS boundaries. During our mapping iterations, RTSs missed in a previous mapping exercise could be identified in the later iterations, indicating that the test accuracies vary with iterations. Thirdly, we didn't divide the data or the study area into subsets of training, validation, and test. Still, we chose an area outside the study area (Figure R1) and conducted the accuracy assessment for the last trained model of the iterative mapping. The recall rate is 0.79, the precision is 0.95, and F1 score is 0.86. We decided not to include some test results in the manuscript for the sake of conciseness and focusing on the generated inventory.

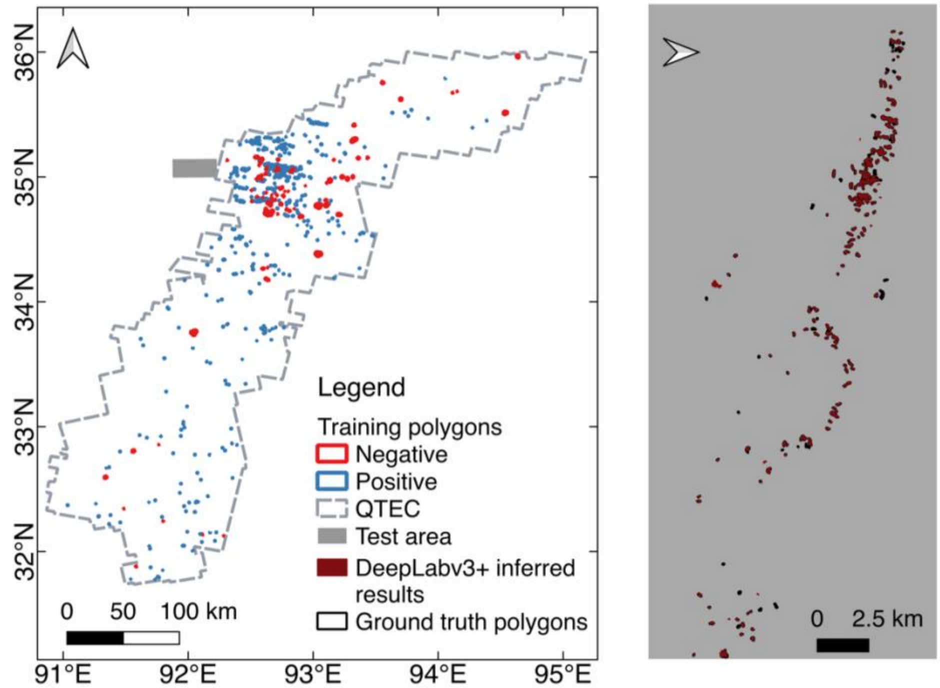

Figure R1. Location of the test area and the inferred results by our DeepLabv3+ model trained in the final iteration.

The data generation contains pre-process and post-processing. We illustrated the post-processing in the manuscript but didn't focus on the pre-processing. As our pre-processing is the same as Huang et al. (2018), we decided only to cite the paper and not repeat the technical details of pre-/post-processing steps.

Thanks for suggesting BigEarthNet for our future work, and we will use it in our deep learning work of mapping permafrost disturbance in Tibet, which potentially can overcome the limitation of RGB channels in ImageNet and be adaptable to other multi-band remote sensing imagery.

2. It will be helpful to have a figure of a/some successfully predicted RTS by the model, and the same RTS polygon that finally delineated from the prediction. This can help the readers to understand the manual inspect process.

Response: Following the suggestion, we have added a figure in the supplementary material showing the example of pixel-based classification result, DeepLabv3+ inferred polygons, and manually modified polygons. The figure is referred in the main text (Line 159) and copied as below.

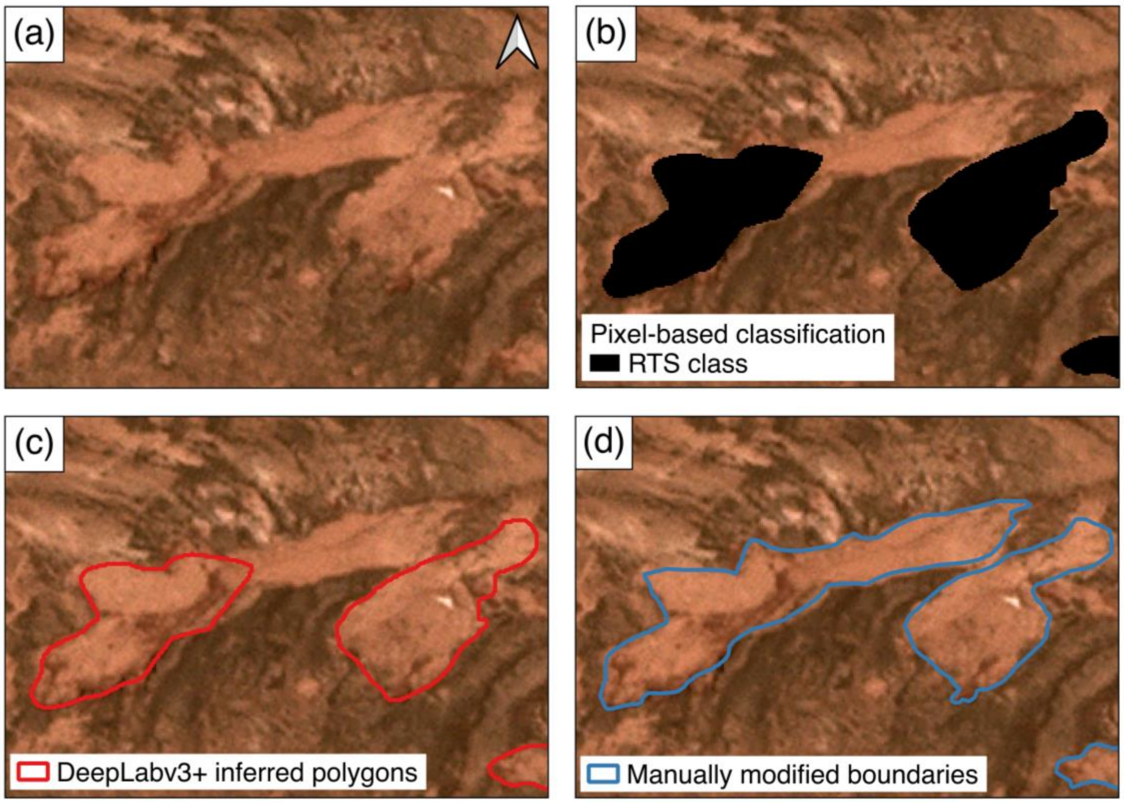

Figure S1. Examples of DeepLabv3+ outputs and manually modified RTS boundaries. (a) Planet images. (b) Pixel-based classification results. (c) DeepLabv3+ predicted RTS polygons. (d) Manually modified RTS boundaries. The location is 92.76° E, 35.09° N.

3. For the probability assessment, it will be helpful to have a table/figure to show the percentage/number of each category, i.e. high/medium/low. To give an overview of the quality of the dataset.

Response: We briefly summarize the numbers of each category in our manuscript. The sentence is:

"The numbers of the RTSs with high, medium or low probability are 810 (92%), 33 (4%), and 32 (4%), respectively."

Minor points

1. Line 182 complied – compiled?

Response: Revised.