The Response to Comments from Review 3

Comment 1
However, a significant concern with this work, as with any automated landslide mapping, is the potential clustering of multiple landslides in one location, leading to the incorrect identification of several landslides as a single event. For instance, in the Hokkaido landslide area, several crowns have merged, resulting in a unified depositional landscape. Was any attempt made to address this issue by separating the multiple landslides? If not, this should be discussed in the limitations section and considered for future work.
Response 1
Thank you for giving this comment. We strongly agree with your opinion that the current available landslide datasets are all facing such challenge. Currently, most publicly available landslide datasets are designed for semantic segmentation tasks rather than instance segmentation. Unlike other computer vision tasks, landslides are complex geological phenomena, and distinguishing multiple landslides that overlap or blend together is challenging when relying solely on optical imagery. Effective separation often requires additional data, such as digital elevation models (DEMs) and derived geomorphological features. We have addressed this issue in Section 7 and plan to develop a dedicated landslide instance segmentation dataset in future work. **"***Note that GDCLD is generally more applicable to semantic segmentation rather than instance segmentation for landslide identification task. Unlike other instance segmentation tasks, landslide segmentation presents unique challenges due to the frequent mixing of the "deposit" areas of adjacent landslide bodies (Hungr et al., 2014). In most cases, we can only intuitively identify the "source" area of a landslide. This phenomenon is commonly observed in events such as the landslides triggered by the 2022 Luding earthquake in China (Figure.S10). Under these circumstances, it is often not feasible to separate individual landslides directly from 2D optical images. Instead, it is necessary to consider the movement characteristics of each object from a 3D perspective (Bhuyan et al., 2024; Marc and Hovius, 2015) and combine this with topographic data to create accurate landslide labels for instance segmentation. However, generating such datasets requires high-resolution digital elevation models (DEM) and UAV or direct use of point cloud data. Given the global limitations in publicly available DEM (30m), achieving such fine distinctions is challenging. Therefore, our current study primarily focuses on semantic segmentation tasks. In future research, we plan to prepare landslide labels for instance segmentation based on LiDAR observation, and to develop specialized algorithms to address this complex issue. (**P40L686~701**)*

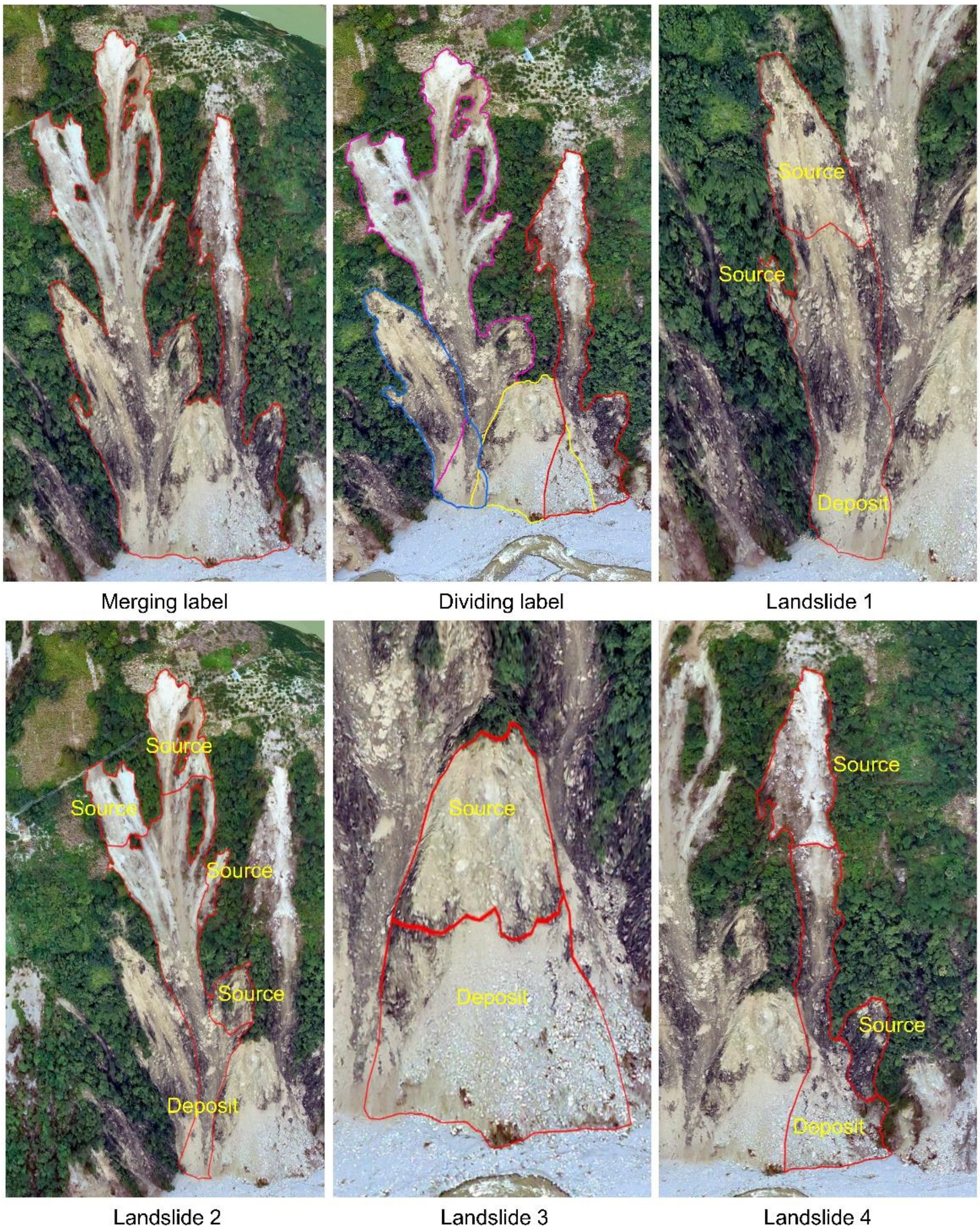

Figure.S10 Example of instance landslide label (2022 Luding earthquake-triggered landslides)
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Comment 2 and Comment 3

1. In the abstract, specify the number of events or case areas represented by this global ML-based inventory.
2. On line 27, mention the best-fit model used.

Response 2 and Response 3

Thanks for your insightful advices.

We have completely rewritten the summary and added content based on your suggestions.

"Rapid and accurate mapping of landslides triggered by extreme events is essential for

effective emergency response, hazard mitigation, and disaster management. However, the development of generalized machine learning models for landslide detection has been hindered by the absence of a high-resolution, globally distributed, event-based dataset. To address this gap, we introduce the Globally Distributed Coseismic Landslide Dataset (GDCLD), a comprehensive dataset that integrates multi-source remote sensing images, including PlanetScope, Gaofen-6, Map World, and Unmanned Aerial Vehicle data, with varying geographical and geological background for nine events across the globe. In this study, we evaluated the effectiveness of GDCLD by comparing the mapping performance of seven state-of-the-art semantic segmentation algorithms. These models were further tested by three different types of remote sensing images in four independent regions, while the GDCLD-SegFormer model get the best performance. Additionally, we extended the evaluation to a rainfall-induced landslide dataset, where the models demonstrated excellent performance as well, highlighting the dataset's applicability to landslide segmentation triggered by other factors. Our results confirm the superiority of GDCLD in remote sensing landslide detection modeling, offering a comprehensive data base for rapid landslide assessment following future unexpected events worldwide.” ***(P2L 16~32)***
Comment 4 On line 69, where it is stated that most models lack generalization capability across diverse environmental backgrounds and remote sensing images, please elaborate on what the authors mean by "generalization."
Response 4 Thank you for giving this comment. In this point, the term "generalization ability" refers to the capacity of machine learning or deep learning algorithms to adapt to new and unseen samples. This aims to illustrate that most models trained on existing datasets experience a significant decline in landslide detection performance when confronted with different geographic regions and remote sensing data sources. In the revised Section 6.3, we have included experiments to substantiate this observation. Specifically, we evaluated the ability of models trained on three datasets—CAS, GVLM, and GDCLD—to detect landslides in previously unseen areas. “*In addition to the aforementioned analyses, we compare the performance of GDCLD with other two datasets, GVLM and CAS. Specifically, we train landslide detection models using the SegFormer algorithm on the GVLM and CAS datasets, denoted as GVLM-S and CAS-S, respectively, with identical training parameters as previously described. Furthermore, we also use the DeepLabV3 to train the CAS-D model based on the CAS dataset and use it for comparison of landslide detection (Xu et al., 2024). Subsequently, the GDCLD-S, CAS-S, CAS-D and GVLM-S models were applied to identify landslides in the Lushan area using three distinct remote sensing data sources: UAV, PlanetScope, and Map World. The results of this comparison are presented in Table 10. From Table 10, it is evident that the GDCLD-S model outperformed CAS-S, CAS-D and GVLM-S across all three remote sensing datasets, achieving mIoU of 72.96%, 69.05%, and 71.92% on UAV, PlanetScope, and Map World. In contrast, CAS-S records mIoU values of 62.03%, 56.86%, and 60.35% for the same*

datasets, respectively, which is better than the CAS-D model trained with DeepLabV3, and also illustrates the advantages of the transformer architecture over the CNN architecture. Notably, GDCLD-S exhibited a significantly higher Recall than the other two models and also demonstrated an advantage in Precision. Overall, GDCLD-S, along with CAS-S, exhibited superior performance compared to the single-source data model GVLM-S, particularly in handling multisource remote sensing images. The extensive landslide data and negative samples included in GDCLD-S further contributed to its enhanced robustness against noise and improved Recall in landslide detection. ***(P35~36L629~648)***

Table.10 Performance of the GDCLD-S, GVLM-S, CAS-S, and CAS-D models on the 2022 Lushan case

Model	Data type	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
CAS-D	*UAV*	*72.73*	*55.34*	*62.88*	*57.91*
	PlanetScope	*52.07*	*56.05*	*53.93*	*52.86*
	Map World	*61.79*	*70.50*	*64.9*	*58.11*
GVLM-S	*UAV*	*73.03*	*54.84*	*57.67*	*53.41*
	PlanetScope	*60.13*	*53.40*	*54.82*	*51.52*
	Map World	***77.71***	*66.40*	*71.56*	*63.97*
CAS-S	*UAV*	*74.08*	*67.05*	*69.95*	*62.03*
	PlanetScope	*58.56*	*76.57*	*66.40*	*56.86*
	Map World	*75.02*	*64.65*	*68.37*	*60.35*
GDCLD-S	*UAV*	***74.72***	***90.35***	***81.80***	***72.96***
	PlanetScope	***81.50***	***82.28***	***81.78***	***69.05***
	Map World	*76.18*	***87.35***	***81.38***	***71.92***

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Comment 5

On line 74, consider starting the sentence with "For instance" or "For example.""

Response 5

Thanks for your careful comment.

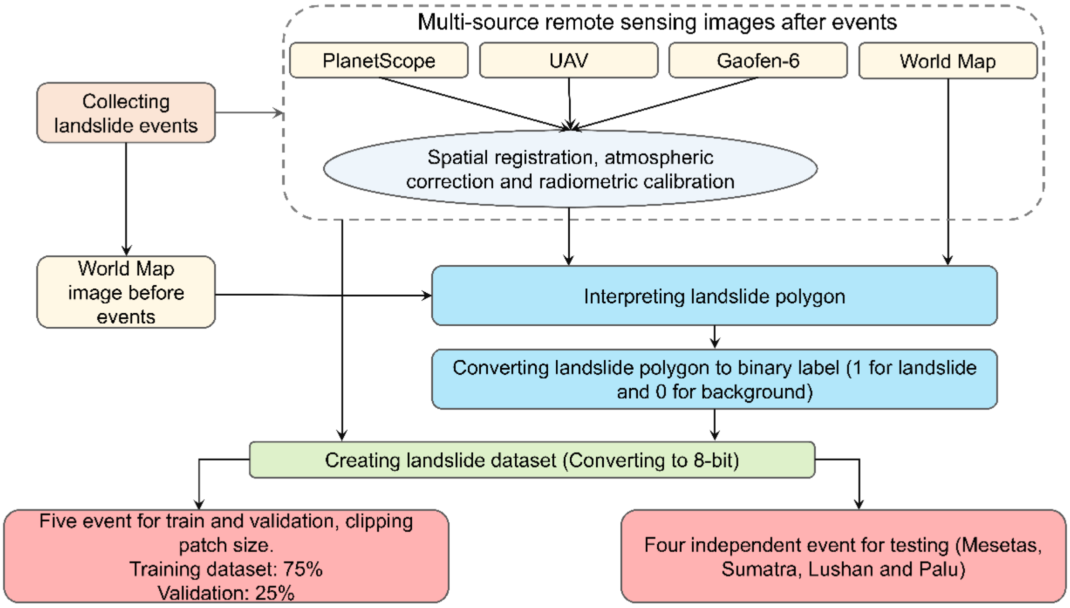
We have modified this word. "*for example, after major events such as the Wenchuan, China (2008), and Gorkha, Nepal (2015) earthquakes.*" ***(P4L62~64)***

Comment 6

It is advisable to use the full forms of abbreviations like CAS, HRGLDD, and GVLM at their first occurrence in the manuscript.

Response 6

Thanks for your careful comment.

We have reviewed the article and revised the content.
Comment 7 A flowchart detailing the method would be helpful for readers.
Response 7 Thanks for your insightful advices, which will improve our work a lot. We have drawn a flowchart of the dataset preprocessing and added it ***Section 3 (Figure.1)***. ***(P8L164~171)*** *"The creation of the GDCLD dataset can be broadly divided into two main components: landslide data collection and remote sensing data processing. In the first part, we compiled recent landslide events triggerred by earthquakes worldwide over the past seven years and obtained the corresponding remote sensing imagery. The second part details the process of annotating landslide labels and the methodology used to create the standard dataset. The workflow is illustrated in Figure.1.*  *Figure.1 The workflow of producing GDCLD"*
Comment 8 On line 96, consider changing the heading to "Related Work" or "Past Research.".
Response 8 Thanks for your comment. We have modified *"Relate Work"* to *"Related Work"*. ***(P5L105)***
Comment 9 On line 97, the intended meaning is unclear and needs clarification.
Response 9 Thanks for your careful comment. We have modified *this word*. *"The most effective approach for landslide mapping currently involves image segmentation, and computer vision segmentation tasks depend heavily on high-quality data to build accurate models. However, landslide segmentation tasks have developed relatively recently compared to other computer vision applications, resulting in only a limited number of studies that have constructed datasets for various landslide events. In*

this section, we review some of these landslide segmentation datasets and provide detailed information on each (Table.1).” ***(P5L106~111)***
Comment 10 On line 198, change the reference to "Hokkaido earthquake."
Response 10 Thanks for your careful comment. We have modified *this word*. “*Following the Hokkaido earthquake, we acquired PlanetScope image with a 3m resolution on December 12, 2018, and Map World image with a 0.5m resolution (Figure.S3).*” ***(P10~11L215~217)***
Comment 11 The source for the World Map image, as well as other data sources, such as the download link or web portal, should be mentioned for the readers.
Response 11 We thank the reviewer for raising these points. In section 8, we modified the content of Data availability and introduced the source of the dataset. “*In addition, the other original data of UAV, Map World and Gaofen-6 are non-public data. Both the Map World and GF-6 datasets were accessed under an image license acquired by our team. The UAV data are under the usage rights of the laboratory affiliated with our team. If you need to use them, please contact the corresponding author. The original PlanetScope data were obtained through the Planet Education and Research Program, which can be accessed at https://www.planet.com/ (Planet Team, 2019).*” ***(P41L713~718)***
Comment 12 Lines 274-275 and several other instances contain unclear grammar. It would be beneficial to revise these with the assistance of a native speaker.
Response 12 We thank the reviewer for raising these points. We have modified this line. “*In the aforementioned nine events, the available public data primarily focuses on geological analysis rather than tasks related to semantic segmentation.*” ***(P13L292~293)*** In addition, we also corrected other grammatical errors in the manuscript.
Comment 13 Additionally, validating the results with data from the recent Taiwan earthquake is suggested.
Response 13 Thank you for the suggestion. In the revised manuscript, we have added a new Section 6.4, which details the application of the GDCLD-SegFormer model to the two recent events in 2024: rainfall-induced landslides in Meizhou, and earthquake-induced landslides in Hualien. “*6.4 Practical Applications of GDCLD* *To evaluate the practical applicability of the CDCLD, we selected two significant landslide events that occurred in April 2024 for rapid identification. These events include landslides induced by a heavy rainfall in Meizhou, China and landslides triggered by an earthquake in Hualien, China. PlanetScope image was employed in both cases for*

experimentation. For the Meizhou case, we obtained the image on May 14, 2024, and applied SegFormer model trained on GDCLD to identify landslides triggered by the heavy rainfall. The results, shown in Figure.14, demonstrate that the GDCLD-trained model effectively mapped newly-induced landslides with a total area of 8.49 km^2. The model exhibited excellent accuracy in avoiding false positives such as buildings, roads, and rivers. In terms of the Hualien event, we acquired post-event images from April 17 to 29, 2024. The rapid identification results, displayed in Figure.15, indicate that. the GDCLD-trained model effectively eliminates false positives, such as roads, buildings, bare land, and rivers, with an identified landslide area of 90.9 km^2. The original PlanetScope images and landslide recognitions of the two events are available at https://doi.org/10.5281/zenodo.13612636 (Fang et al., 2024) ***(P36~39L651~671)***

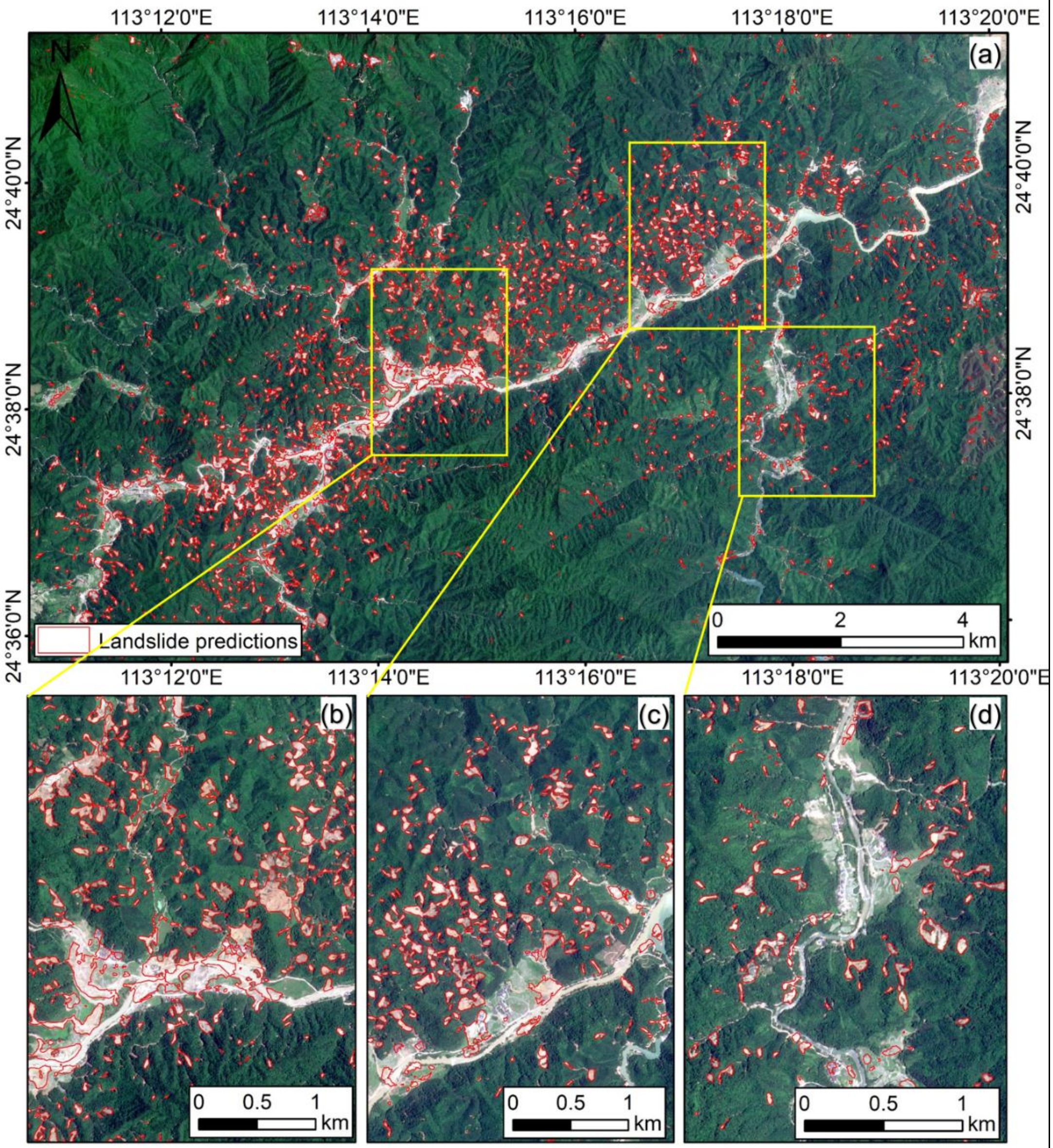


Figure.14 Detection results of rainfall-induced landslides for Meizhou, China. (a) is the aerial view of the whole area; (b), (c) and, (d) are the partial details.

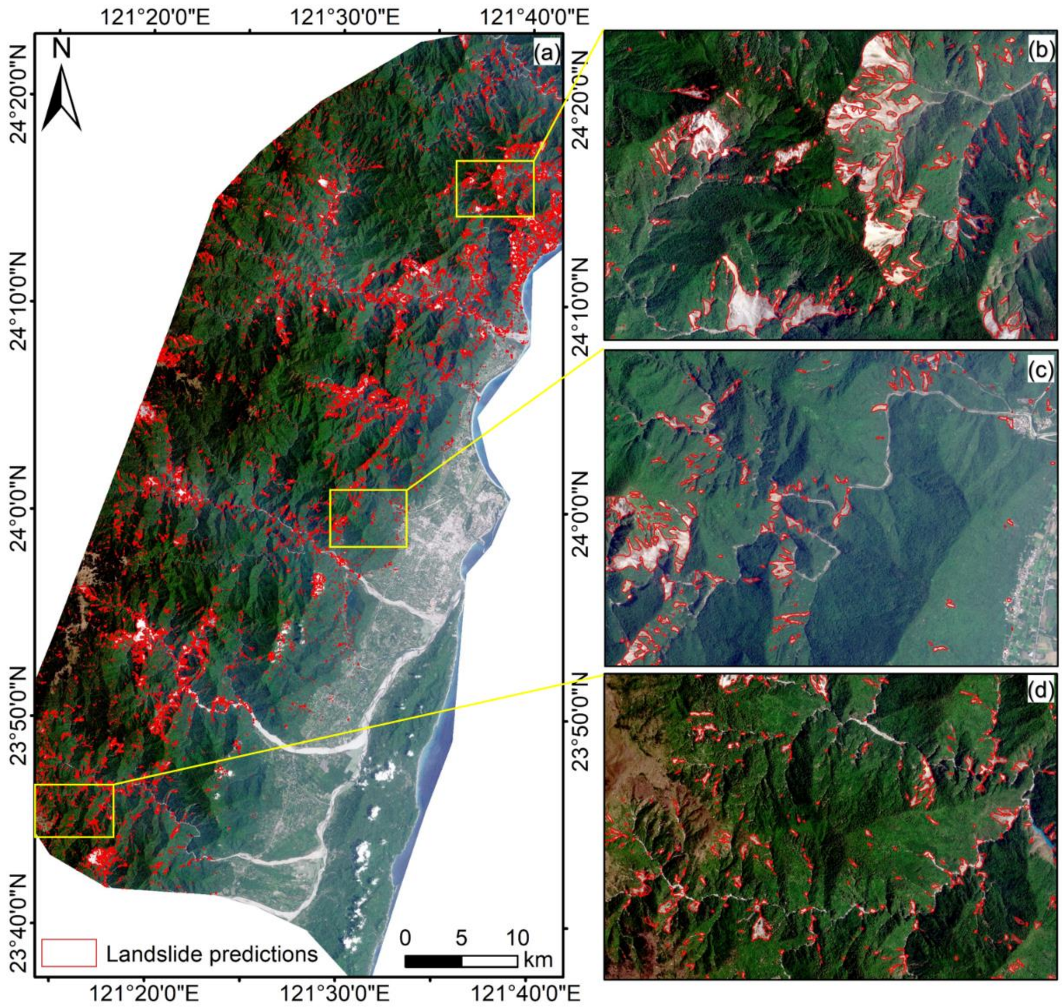


Figure.15 Detection results of earthquake-triggered landslides for Hualien, China. (a) is the aerial view of the whole area; (b), (c,) and (d) are the partial details.“

Reference

Bhuyan, K., Rana, K., Ferrer, J. V., Cotton, F., Ozturk, U., Catani, F., and Malik, N.: Landslide topology uncovers failure movements, Nature Communications, 15, 2633, 2024.

Marc, O. and Hovius, N.: Amalgamation in landslide maps: effects and automatic detection, Natural Hazards and Earth System Science, 15, 723-733, 2015

Hungr, O., Leroueil, S., and Picarelli, L.: The Varnes classification of landslide types, an update, Landslides, 11, 167-194, 2014.

Xu, Y., Ouyang, C., Xu, Q., Wang, D., Zhao, B., and Luo, Y.: CAS Landslide Dataset: A Large-Scale and Multisensor Dataset for Deep Learning-Based Landslide Detection, Sci Data, 11, 12, 10.1038/s41597-023-02847-z, 2024.