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Brief Communication: AI-driven rapid landslides mapping following the 2024 Hualien City Earthquake in Taiwan

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Abstract.

On April 2nd, 2024, a Mw 7.4 earthquake struck Taiwan's eastern coast, triggering numerous landslides and severely impacting infrastructure. To create the preliminary inventory of earthquake-induced landslides in Eastern Taiwan (3,300 km^2) we deployed automated landslide detection methods by combining Earth Observation (EO) data with Artificial Intelligence (AI) models. The models allowed us to identify 7,090 landslide events covering >75 km^2, in about 3 hours after the acquisition of the EO imagery. This research underscores AI's role in enhancing landslide detection for disaster response and situational awareness, and the landslide inventory can improve the understanding of earthquake-landslide interactions to improve seismic hazard mitigation.

1 Introduction

Taiwan is a country that is prone to high landslide hazards due to frequent rainfall and earthquake events (Hung, 2000; Chuang et al., 2021; Shou and Chen, 2021). A significant portion of Taiwan's population and its infrastructure are vulnerable to these landslide hazards (Lee and Fei, 2015). On 2nd of April 2024, the island of Taiwan was hit by a Mw 7.4 earthquake (United States Geological Survey - USGS, 2024). The shaking resulted in a large number of landslides along transport routes with >1,100 people injured (https://disasterphilanthropy.org/disasters/2024-taiwan-earthquake/). Currently, no landslide inventory for the 2024 Hualien City earthquake has been released, even through international and authoritative entities such as the Copernicus Emergency Management Service and the Disaster Charter. A complete and up-to-date landslide inventory is important not only as a support during the emergency response but also for a better understanding of the spatio-temporal relationships between landslide occurrence and driving factors (Lombardo et al., 2020). Such information can redefine triggering thresholds for landslide early warnings and hazard zoning for land use planning.

Over the last decades, spaceborne Earth Observation (EO) has become a predominant source for mapping landslides, which are particularly useful to first responders (Amatya et al., 2023; Novellino et al., 2024). Mapping landslides using Earth Obser-

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vation (EO) data has become crucial for providing vital situational awareness to first responders during large-scale landslide events affecting regional or national scales. Recently, there's been significant advances in AI-based automated landslide detection and mapping (Novellino et al., 2024). These approaches include utilizing crowdsourced data (Catani, 2021) and Unmanned Aerial Vehicles (UAVs) (Dai et al., 2023), as well as analyzing LIDAR (Fang et al., 2022) and satellite optical imagery (Amatya et al., 2021; Bhuyan et al., 2023), and SAR (Nava et al., 2022).

Additionally, there is a growing trend toward training DL models capable of providing reliable predictions in new areas for rapid assessment of emerging MLEs. We find studies focusing on a single data source, such as Copernicus Sentinel-2 (Prakash et al., 2021) and PlanetScope (Meena et al., 2023), while others investigate the integration of multisource data (Fang et al., 2024; Xu et al., 2024) to enhance accuracy and improve transferability.

However, there remains a scarcity of real-world applications leveraging AI techniques and deriving actionable insights from them. Currently, to our best knowledge, Amatya et al. (2023) stand out as one of the few research where automatic landslides mapping methods were applied as part of disaster response activities following the 2021 earthquake in Haiti. However, as areas and methods change, more investigation of such applications as well as AI-based methods must be undertaken to speed up the trust and understanding of how such automated systems can efficiently improve hazard assessment. This underscores the pressing need for more such applications to fully harness the potential of AI in enhancing the efficiency and effectiveness of landslide mapping during emergencies.

In this Brief Communication, we test in practice state-of-the-art AI techniques on different EO satellite data for the automatic detection and mapping of landslides associated with the event. We further provide suggestions about how these tools can support future rapid landslide mapping efforts following major disasters worldwide. Lastly, we provide the preliminary co-seismic landslide inventory for updating landslide hazard models and supporting resilience to future events.

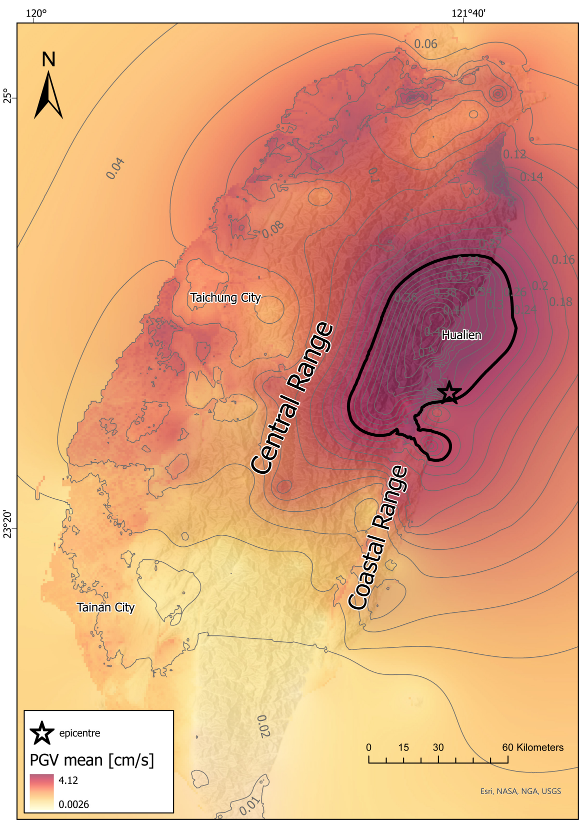

Figure 1. Peak Ground Velocity (PGV) values, Peak Ground Acceleration (PGA) contours and epicentre for the Hualien City earthquake (from USGS, 2024). The 0.2%g is in black bold and represents the area of study of this work. Sources: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community.

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2 Hualien City earthquake and study area

On the 2nd of April 2024 (23:58 UTC), a Mw 7.4 earthquake struck the eastern coast of Taiwan (USGS, 2024). The event was located at a depth of 40km with an epicentre near the town of Hualien (Figure 1) as a result of a reverse NE-SW fault near the boundary between the Eurasian and Philippine Sea plates. The main earthquake was followed by a Mw 6.5 aftershock 13 minutes later. Eastern Taiwan is not only tectonically active but is also relentlessly battered by hurricanes, making this location particularly prone to the rapid erosion of the mountain chains built by tectonics. Following information about the earthquake epicentre and effect (PGA) and reports on landslides from social media through the Global Landslide Detector (Pennington et al., 2022), we defined a 3,300 km^2 area of interest (AoI) for mapping landslides centred around the town of Hualien. The extent of the AoI is a trade-off between the extent of the shaking and the availability of cloud-free images in the aftermath of the event.

3 Automated Landslide Detection and Mapping

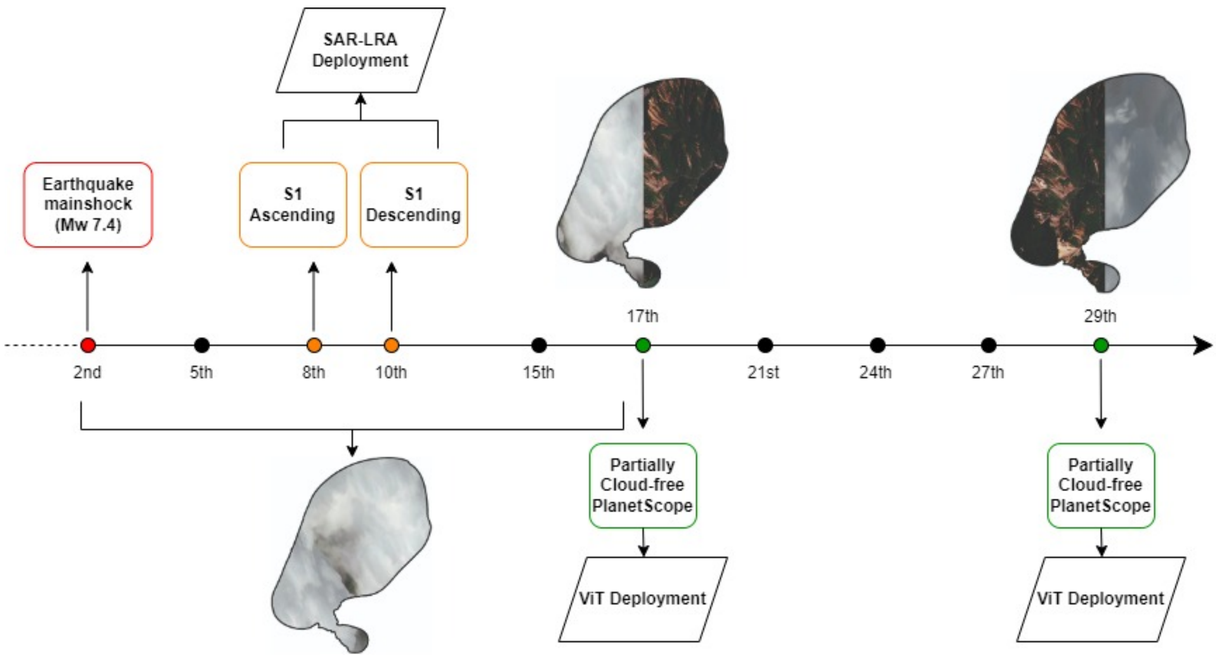

Figure 2. Timeline of satellite image acquisitions and models deployment in April 2024.

The landslide maps have been generated using the Synthetic Aperture Radar (SAR) Landslide Rapid Assessment (SAR-LRA) tool based on Convolutional Neural Networks (Nava et al., 2024) and a Vision Transformer (ViT) model (Tang et al., 2022; Fang et al., 2024).

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The SAR-LRA tool was trained and validated on 11 MLEs globally distributed and uses pre- and post-event SAR imagery in a change-detection-like approach to identify surface changes due to co-seismic slope failures. No transfer learning or fine-tuning was necessary; the model was directly deployed in the area. The tool is freely available at https://github.com/lorenzonava96/SAR-and-DL-for-Landslide-Rapid-Assessment. SAR-LRA was applied over five Sentinel-1 acquisitions at 10m resolution. This included one acquisition on April 8, 2024, for the ascending geometry (over two different tracks), five SAR acquisitions within 60 days preceding the event, and one acquisition on April 10, 2024, for the descending geometry. SAR data enabled landslide detection even under cloudy conditions, which prevented the use of optical Sentinel-2 data for several weeks post-earthquake (see Figure 2). Additionally, SAR-LRA led us to identify preliminary hotspots of changes on the ground, where higher resolution datasets could be considered, and to time such changes.

The ViT model was pre-trained and validated on a multi-source landslide segmentation dataset (Fang et al., 2024), the Globally Distributed Coseismic Landslide Dataset (GDCLD). GDCLD is a diverse and comprehensive collection of multi-source remote sensing images. This dataset includes imagery from PlanetScope, Gaofen-6, Map World, and Unmanned Aerial Vehicles, covering a wide range of geographical and geological contexts worldwide. The GDCLD is available at https://doi.org/10.5281/zenodo.11369484 (Fang et al., 2024). We fine-tune the model (Bhuyan et al., 2023) on 814 landslides manually mapped within the Taiwan study area. Satellite images from the Google Earth Pro archive have been used for the pre-event stage whose collection includes data from CNES and Airbus acquired up to September 2023. For the post-event stage, ViT has been applied on 33 composited PlanetScope images at 3m spatial resolution acquired on the 17th and 29th of April, 2024.

4 Results and Discussion

We retrieved a total of 7090 co-seismic landslides along with the 2,617 pre-seismic ones. SAR-LRA outputs 262 SAR-LRA bound8ing boxes: 63 in the ascending geometry and 199 in the descending geometry (Figure 3a). The co-seismic landslides encompass new failures and reactivation or enlargement of existing failures (Figures 3b-c). Most co-seismic failures occurred on slopes between 30 and 50 degrees on the SE slopes (Figure 3d). The total co-seismic landslide area resulting from the earthquake equals 75.3 km^2 with an individual polygon minimum size set to 250 m^2, due to the resolution of Planet images, up to a maximum of 2.9 km^2 (Figure 3e). We specifically targeted areas with the most severe ground-shaking conditions for our analysis. By meticulously examining daily pre- and post-event imagery, we achieved a precise understanding of when co-seismic landslides occurred, addressing a significant challenge often encountered in post-disaster landslide inventories. This comprehensive dataset is indispensable for emergency responders, providing critical insights that are essential for orchestrating swift and effective relief efforts on a large scale.

Our processing workflow demonstrated remarkable time efficiency: SAR-LRA yielded results in approximately 20 minutes, while ViT analysis, including both pre- and post-processing tasks, took about 2 hours. This quick turnaround allowed us to produce reliable findings within hours of satellite image acquisition. The SAR-LRA tool was fundamental in initially identifying landslide locations, even under persistent cloud cover. In areas partially obscured by clouds, this approach provided the location of landslides.

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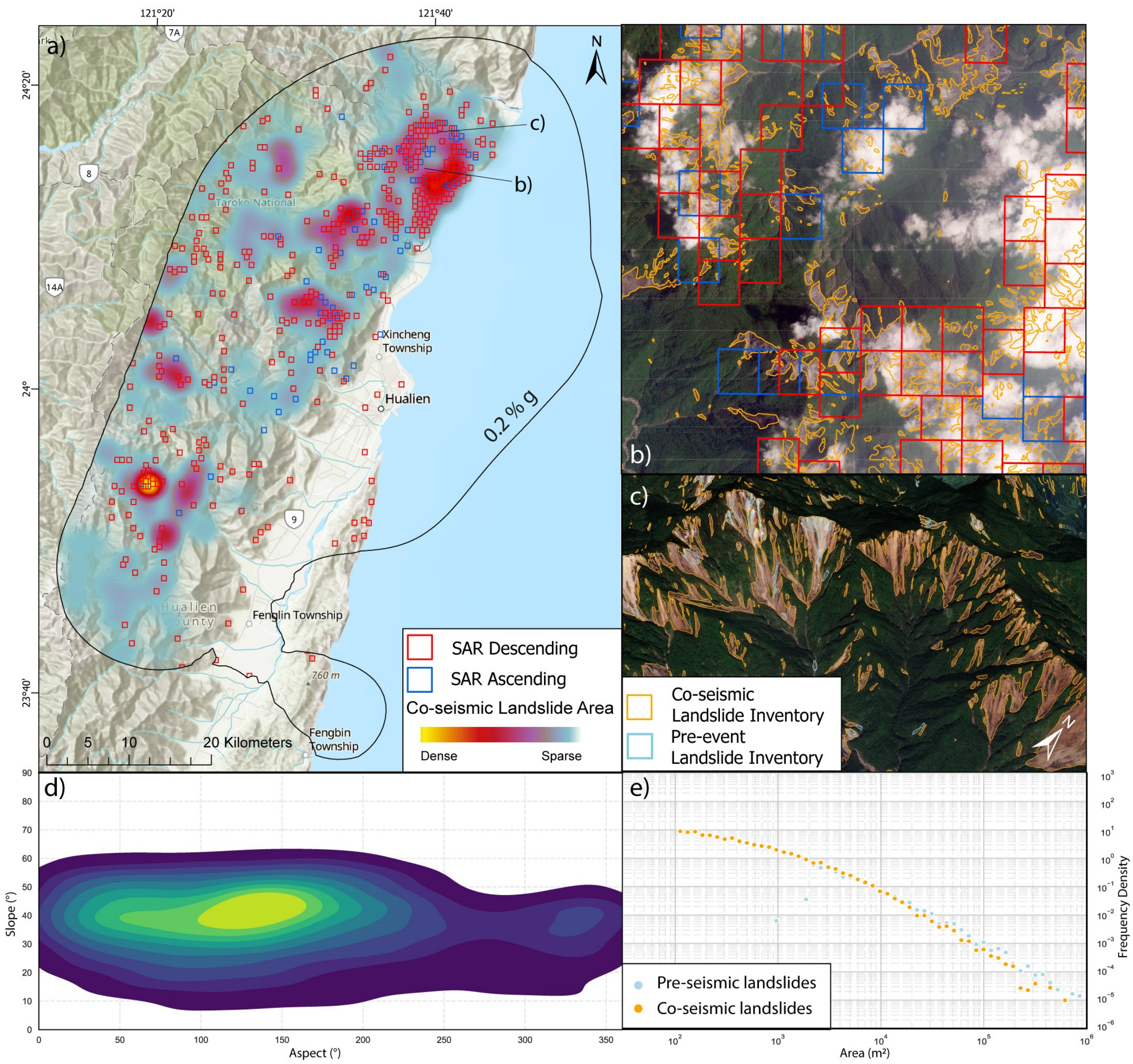

Figure 3. Overview of the landslide inventory (a). A zoom of the co-seismic landslides mapped with squares of SAR-LRA and the polygons of ViT (b-c). Density plot of slope vs aspect for the co-seismic landslides (d). Frequency area distribution of pre- and co-seismic landslides (e). Sources: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community. Map data ©2024 Google.

100 Reflecting on our methodology, initial reservations about the suitability of SAR imagery for steep slopes were mitigated by its successful validation once cloud-free areas became available. The initial skepticism likely stemmed from the unconventional

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appearance of SAR data, which makes it difficult for the human eye to confirm the presence of landslides. However, complete cloud coverage over an entire region is rare, highlighting the potential for a hybrid SAR-Optical AI approach. Advancements in this direction could enhance the reliability and trustworthiness of our rapid assessment models and significantly improve their performance under diverse and challenging weather conditions.

Regarding the optical-based predictions, after model fine-tuning, the results were reliable, with few false positives in flat areas that were easily masked out. Here a clear advantage is that we get the exact extent of the slope failures. However, since our approach relied solely on post-event imagery, we had to deploy the model also on pre-event imagery and subtract the two inventories to identify the co-seismic landslides. Reflecting on this, approaches that integrate change-detection mechanisms within the model are preferable and welcome.

5 Conclusions

Following the Hualien City earthquake event, we semi-automatically map 7,090 co-seismic landslides from satellite imagery at different resolutions and different data modalities using AI-based approaches. While there is a wealth of literature on the use of AI for landslide detection, there are few documented cases of its application for rapid mapping in the aftermath of major disasters. Our inventory provides key information for situational awareness and for supporting emergency responders in the aftermath of the event. Moreover, we provide the co-event landslide inventory, fundamental over the long term for updating landslide hazard models and supporting resilience to future events. The growing accessibility of satellite data alongside processing software and platforms is leading to an increase in new techniques with increasingly accurate results which has allowed us to collect and compare different outputs. In this case, SAR-LRA proved fundamental in identifying landslide locations despite persistent cloud cover over the area. In contrast, while optical data was more precise and interpretable, it was not available until much later. Given the proven effectiveness of the tested approaches and tools, we are confident that these methods can be successfully deployed in future large-scale earthquake-triggered landslide events. Integrating SAR and Optical AI approaches will further improve the reliability and performance of rapid assessment models, especially in challenging weather conditions. These advancements are crucial for enhancing disaster response capabilities and decision-making processes.

Code and data availability. The generated inventory is freely available on Zenodo at the link: https://zenodo.org/records/11519683. The code of SAR-LRA tool is available at https://github.com/lorenzonava96/SAR-and-DL-for-Landslide-Rapid-Assessment/tree/main. The Globally Distributed Coseismic Landslide Dataset (GDCLD) is available at https://doi.org/10.5281/zenodo.11369484. Planet imagery can be found at https://www.planet.com/. Sentinel-1 imagery can be found in the Copernicus Data Space Ecosystem at https://dataspace.copernicus.eu/.

Author contributions. LN and AN: conceptualization, data curation, analysis, visualization, and writing– original draft. CF and KB: data curation, analysis, writing– original draft, writing– review, and editing. KL, IGA, CD, SD, RC, EM, SRM, XF, and XT: writing– review, and editing. FC: writing– review, editing, and funding acquisition.

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Competing interests. At least one of the (co-)authors is a member of the editorial board of Natural Hazards and Earth System Sciences.

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