A globally distributed dataset of coseismic landslide mapping via multi-source high-resolution remote sensing images

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Abstract

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.

1. Introduction

Landslides triggered by extreme events such as earthquakes and heavy precipitation are responsible for most of the damage to mountainous settlements (Huang and Fan, 2013). In some cases, landslides can be even more disastrous than the triggering events themselves, as they can render emergency responses ineffective by cutting off roads and other transportation lifelines (Cigna et al., 2012; Huang et al., 2012; Valagussa et al., 2019; Chau et al., 2004). Therefore, the rapid and accurate identification of landslides after extreme events is crucial for timely and quantitative assessment of disasters. This is especially important for emergency rescue operations and subsequent risk management in mountainous areas with complex environments and possibly inconvenient transportation routes. (Cigna et al., 2018; Chau et al., 2004; Gorum et al., 2011).

Conventional landslide mapping efforts rely on traditional surveying methods such as topographic total stations, field observations to collect essential data on slope stability and terrain morphology (Brardinoni et al., 2003; Coe et al., 2003; Zhong et al., 2020). These methods may not capture the full extent of terrain dynamics due to their static nature (Metternicht et al., 2005). Consequently, these methods are not effective for detailed landslide mapping, especially when traversing the affected and unstable regions for field surveys is not possible. This was particularly true for the Wenchuan co-seismic landslides, which mobilized large amounts of material that obstructed roads, complicating disaster response efforts as well as surveying and mapping activities (Gorum et al., 2011). With the development of remote sensing technology in the past decades, landslide investigation has been supported by digital mapping, which reduces time and labor costs (Fiorucci et al., 2011; Fiorucci et al., 2019; Gao and Maro, 2010; Guzzetti et al., 2012). This mapping has also been enhanced by various modalities of sensors, such as synthetic aperture radar (Mondini et al., 2021; Nava et al., 2021), multi-spectral (Udin et al., 2019), and hyper-spectral (Ye et al., 2019). However, visual identification is highly subjective due to operator experience, and the interpretation of events involving numerous landslides is still time-consuming. Therefore, this subjectivity and the time-

62 consuming nature of interpretation hinder the reliability and efficiency of landslide mapping, for

63 example, after major events such as the Wenchuan, China (2008), and Gorkha, Nepal (2015)

64 earthquakes.

65   Generally, the ideal solution is to develop automated models or tools that can save time

66 and costs while ensuring an objective protocol in the mapping process (Casagli et al., 2023).

67 While some researchers have endeavored to employ machine learning or deep learning in

68 constructing these models, most of them lack the generalization capability for application across

69 diverse environmental backgrounds and remote sensing images (Burrows et al., 2019; Bhuyan

70 et al., 2023; Li et al., 2016; Liu et al., 2022; Lu et al., 2019; Luppino et al., 2022; Meena et al.,

71 2021; Soares et al., 2022; Yang et al., 2022a; Mohan et al., 2021; Ss and Shaji, 2022; Li et al.,

72 2024). To improve such models, more abundant data that consider the diverse

73 geomorphological and climatic settings where landslides occur are essential. The Bijie landslide

74 dataset, based on Map World image, presents a small-scale dataset of mountainous landslides,

75 filling the gap in landslide detection tasks for the first time (Ji et al., 2020). Landslide4sense,

76 based on Sentinel-2 image, introduces a multispectral landslide dataset, pioneering semantic-

77 level annotation of landslides (Ghorbanzadeh et al., 2022). The HRGLDD and GVLM datasets,

78 based on PlanetScope and Google Earth image respectively, propose global-scale high-

79 resolution landslide datasets (Meena et al., 2022; Zhang et al., 2023). However, these datasets

80 are limited by their reliance on single remote sensing data sources, restricting the applicability

81 of models across different sensors and resolutions. The CAS dataset introduces a mountain

82 landslide dataset containing various remote sensing data sources (Xu et al., 2024). However,

83 due to its limited annotated landslide quantity, high image overlap, and lack of negative samples

84 (background/non-landslide), it is still insufficient to effectively generalize to landslide automatic

85 mapping tasks in various complex environments especially where signatures of landslides often

86 resemble nearby terrain.

87   Therefore, there is an urgent need to develop a carefully curated and diverse dataset. Such

88 a dataset would facilitate the rapid and accurate mapping of landslides using available prior

89 knowledge. Hence, we present a comprehensive landslide dataset derived from nine

earthquake-triggered landslide events, encompassing multi-sensor images from 3m-PlanetScope, 2m-Gaofen-6, 0.5m-Map World, and 0.2m-UAV. This work addresses the shortcomings of existing datasets in terms of accuracy and generalization for training large and complex deep-learning models. It is of great significance for accurate, rapid, and automatic mapping of landslides occurring anywhere in the world, providing strong support for efficient geohazard emergency response and investigation.

The paper is structured as follows: Section 2 reviews existing high-quality landslide datasets to provide an overview of the current state of research. Section 3 introduces the data collection and preparation process to showcase the extensive research events and scientific methodology behind our data production. Section 4 describes the semantic segmentation algorithms, loss functions, and parameter settings used in this study, and shows their rationality. Section 5 presents the results, including the training, validation, and testing outcomes of the dataset, as well as the generalization ability of the GDCLD trained model in independent regions. Section 6 discusses the innovation and effectiveness of GDCLD, illustrating its effective application in several landslide events.

2. Related work

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).

The Bijie landslide dataset comprises high-resolution satellite images captured in landslide-prone areas of Guizhou province, China. The dataset includes 770 landslide samples and 2,003 non-landslide samples. The positive samples consist of rockfalls, rockslides, and a small number of debris avalanches, while the negative samples include mountains, villages, roads, rivers, and farmland, among others. The image resolutions vary from 61×61 pixels to

117 1,239×1,197 pixels, with RGB channels. There is a total of $7.23×10^6$ pixels assigned for

118 landslide within the dataset (Ji et al., 2020).

119 The landslide4sense dataset consists of multispectral satellite images captured across four

120 distinct regions. This dataset comprises 3,799 images, each with dimensions of 64×64 pixels

121 and a spatial resolution of 10 meters. Each image contains 14 bands, including 12 bands from

122 the Sentinel-2 satellite and 2 bands from Digital Elevation Model (DEM) data. The dataset

123 includes negative background samples such as bare soil, rivers, and buildings. There is a total

124 of $1.76×10^6$ pixels assigned for landslide within the dataset (Ghorbanzadeh et al., 2022).

125 The HR-GLDD spans 10 distinct geographic regions, capturing landslide instances across

126 various geographical environments in South Asia, Southeast Asia, East Asia, South America,

127 and Central America. HR-GLDD comprises a total of 1,756 image patches, each standardized

128 to a size of 128×128 pixels with a spatial resolution of up to 3 meters. The dataset is sourced

129 from four spectral bands of the PlanetScope satellite. It includes a variety of negative samples,

130 such as non-landslide terrain features, buildings, and roads, ensuring a comprehensive

131 representation for model training. There is a total of $2.96×10^6$ pixels assigned for landslide

132 within the dataset (Meena et al., 2022).

133 The GVLM dataset spans across six continents and 17 different landslide sites, GVLM

134 covers a diverse range of geological and climatic conditions, from the lush landscapes of Asia

135 to the rugged terrain of South America. Comprising 17 pairs of dual-temporal VHR images,

136 each image pair boasts a spatial resolution of 0.59 meters, ensuring detailed capture of

137 landslide features and their surrounding environments. GVLM incorporates various negative

138 samples, including non-landslide landforms, infrastructure such as buildings, and transportation

139 networks, providing a holistic training ground for models. Image sizes within the GVLM dataset

140 range from 1,861×1,749 pixels to 10,828×7,424 pixels. There is a total of $3.24×10^7$ pixels

141 assigned for landslide within the dataset (Zhang et al., 2023).

142 The CAS Landslide Dataset covers nine different geographic regions spanning South Asia,

143 Southeast Asia, East Asia, South America, and Central America. Comprising 20,865 image

144 patches, each standardized to a size of 512×512 pixels, the dataset offers a spatial resolution

145 ranging from 0.2 to 5 meters. During the cropping process, an overlap setting parameter of 0.5

146 was used. These images are sourced from unmanned aerial vehicles (UAVs) and satellite

147 platforms, integrating data from the PlanetScope satellite and other sources. The dataset

148 removes background images that do not contain landslide pixels and therefore lacks sufficient

149 background noise as negative samples to enhance the robustness of the model. There is a total

150 of 1.95×10^8 pixels assigned for landslide within the dataset (Xu et al., 2024).
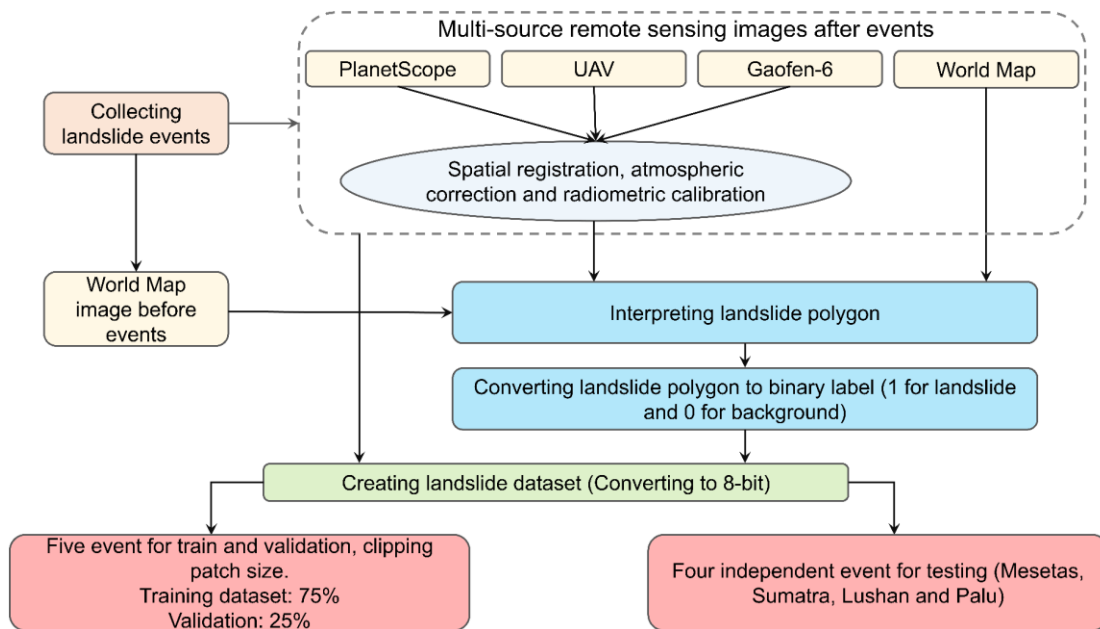
151 In summary, comparing with other remote sensing detection tasks such as land cover/use,

152 the currently available landslide datasets are exceedingly scarce, predominantly comprising

153 single remote sensing images with low spatial resolutions. Overall, the available landslide

154 datasets are exceedingly limited, primarily comprising single remote sensing images with low

155 spatial resolution. Most crucially, these datasets lack sufficient annotations of landslide

156 instances, exhibit high overlap, and suffer from a dearth of diverse negative samples. As a

157 result, they are ill-equipped to tackle the challenges of mapping landslides in large-scale areas

158 with complex background objects, especially those sharing spectral and textural characteristics

159 with landslide surfaces, such as bare soil and rocks. Furthermore, they fail to provide adequate

160 data sources for effectively training large-scale neural network baseline models.

161

Table.1 Existing landslide dataset statistics

Dataset	Bands	events	Tiles	Landslides number	Labeling pixels
Bijie landslide	3	1	2773	770	7.23×10^6
Landslide4sense	14	4	3799	>30000	1.76×10^6
HR-GLDD	4	13	1756	7193	2.96×10^6
GVLM	3	17	17	-	3.24×10^7
CAS Landslide	3	9	20865	-	1.95×10^8

3. Globally Distributed Coseismic Landslide Dataset (GDCLD)

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 triggered by earthquakes worldwide over the past seven years and obtained the corresponding remote sensing image. 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

## 3.1 Data collection

Our dataset encompasses a catalog of landslides triggered by nine seismic occurrences, delineated across the Himalayan seismic belt and the Circum-Pacific belt, as depicted in Figure.2. These regions have witnessed actively seismic events with magnitudes over 5.9, triggering numerous landslides (Table.2). We obtained data of these locations from various remote sensing sources. This section delineates the particulars of the seismic events and the provenance of the remote sensing data.

Table.2 Summary table of landslide event information in GDCLD

Events	Mw	time	Geographic coordinates	Landslide number	Total landslide area (km^2)
Jiuzhaigou	6.5	2017	(102.82°E, 33.20°N)	2498	14.5
Mainling	6.4	2017	(95.02°E, 29.75°N)	1448	33.6
Hokkaido	6.6	2018	(142.01°E, 42.69°N)	7962	23.8
Palu	7.5	2018	(119.84°E, 0.18°S)	15700	43.0
Mesetas	6.0	2019	(76.19°W, 3.45°N)	804	8.5
Nippes	7.2	2021	(73.45°W, 18.35°N)	4893	45.6
Sumatra	6.1	2022	(100.10°E, 0.22°N)	602	10.6
Lushan	5.9	2022	(102.94°E, 30.37°N)	1063	7.2
Luding	6.8	2022	(102.08°E, 29.59°N)	15163	28.53
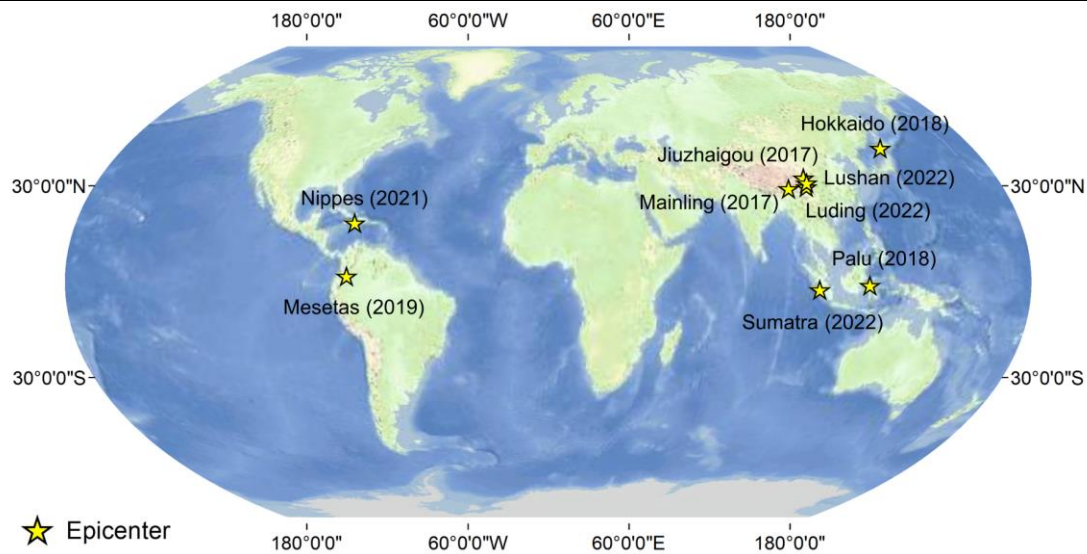
Figure.2 Distribution of earthquake-triggerred landslide events

3.1.1 The 2017 Jiuzhaigou earthquake-triggered landslides

On August 8, 2017, a Mw 6.5 earthquake struck Jiuzhaigou County in Sichuan Province, China (102.82°E, 33.20°N), triggering 2,498 landslides, predominantly shallow surface slides and collapses. The largest landslide covered approximately $2.3 \times 10^5 m^2$ (Fan et al., 2018). Jiuzhaigou, situated on the northeastern margin of the Qinghai-Tibet Plateau within the tectonically active zone north of the Longmenshan fault, is part of the Mediterranean Himalayan seismic belt (Fan et al., 2018). The region's average elevation exceeds 3,000m with a maximum

189 relief of 2,228m and a vegetation cover surpassing 70% (Yi et al., 2020; Chen et al., 2019).

190 Exposed geological formations include various gray-white sandstones and dolomites from the

191 Devonian, Carboniferous, Permian, Triassic, and Tertiary periods (Fang et al., 2022). Post-

192 earthquake, we acquired multiple remote sensing images: 0.2m-resolution UAV image (Phase

193 One IXU1000) on September 22, 2017, 3m-resolution PlanetScope image on October 13, 2017,

194 and 0.5m-resolution from Map World (Figure.S1).

195 **3.1.2 The 2017 Mainling earthquake-triggered landslides**

196   On November 18, 2017, a magnitude 6.4 earthquake struck Mainling County (95.02°E,

197 29.75°N), resulting in three injuries and affecting 12,000 individuals. The earthquake triggered

198 over 1,000 landslides, obstructing numerous watercourses and covering a total area of

199 33.61km², with the largest landslide spanning 4.9km² (Hu et al., 2019). Mainling County, located

200 on the southeastern margin of the Qinghai-Tibet Plateau within the Yarlung Zangbo Grand

201 Canyon, is part of the Mediterranean Himalayan seismic zone. This region, with altitudes

202 ranging from 800 to 7,782m and an average elevation of 2,500m, features a maximum elevation

203 differential of 2,000m and a robust vegetation coverage of 60% (Gao et al., 2023; Chen et al.,

204 2019). The monsoonal climate here brings annual rainfall between 1,500 and 2,000mm (Huang

205 et al., 2021). Following the earthquake, we acquired 3m-resolution PlanetScope images on

206 December 17, 2017, and April 08, 2018, to interpret the landslides (Figure.S2).

207 **3.1.3 The 2018 Hokkaido earthquake**

208   On September 6, 2018, a Mw 6.6 earthquake struck Hokkaido, Japan (142.01°E, 42.69°N),

209 resulting in 44 fatalities and over 660 injuries. Approximately 80% of the casualties were due to

210 coseismic landslides. The earthquake triggered over 7,800 landslides, causing extensive

211 damage to infrastructure. The total area affected by landslides was 23.77 km², with the largest

212 individual landslide covering 0.5km² (Wang et al., 2019). The region, which receives an annual

213 precipitation of 1,200–1,800mm—relatively low compared to other parts of Japan (Yamagishi

214 and Yamazaki, 2018)—is characterized by sandstone, mudstone, siltstone, and shale

215 formations, overlain by substantial volcanic sediments (Wang et al., 2019). Following the

216 Hokkaido earthquake, we acquired PlanetScope image with a 3m resolution on December 12,

217   2018, and Map World image with a 0.5m resolution (Figure.S3).

218   **3.1.4 The 2018 Palu earthquake**

219   On September 28, 2018, the Palu region of Sulawesi, Indonesia, was struck by a Mw 7.5

220   earthquake with a focal depth of 10 km (0.18°S, 119.84°E). A detailed analysis by Shao et al.

221   (2023) identified approximately 15,700 co-seismic landslides across a 14,600km² area, with a

222   combined landslide area of about 43.0km². These landslides were predominantly concentrated

223   in the mountainous canyon regions south of the epicenter. This study provides a semantic-level

224   interpretation of these landslides, which were mainly shallow disruptions (Shao et al., 2023).

225   However, some larger-scale flow slides, rockfalls, and debris flows were also observed. High-

226   resolution Map World image (1m) was utilized to support this analysis (Figure.S4).

227   earthquake

228   **3.1.5 The 2019 Mesetas earthquake**

229   The research site is located in the eastern foothills of the Colombian Eastern Cordillera.

230   On December 24, 2019, the Mesetas Earthquake, with a magnitude of 6.0, struck this region,

231   as documented by Poveda et al. (2022). The earthquake's epicenter was located at 76.19°W,

232   3.45°N, triggering approximately 800 co-seismic landslides. The distribution and predominant

233   orientation of these landslides were influenced by the shear zone confined within the Guapecito

234   Fault, a subsidiary offshoot of the Algeciras Fault (Poveda et al., 2022). High-resolution

235   PlanetScope images (3m) was acquired on January 5 and February 12, 2020, to analyze these

236   phenomena (Figure.S5).

237   **3.1.6 The 2021 Nippes earthquake**

238   On August 14, 2021, a Mw 7.2 earthquake struck the Nippes Mountains in Haiti (73.45°W,

239   18.35°N). This seismic event, compounded by heavy rainfall from Tropical Storm Grace on

240   August 16-17, triggered numerous secondary geological hazards across the Tiburon Peninsula.

241   The disaster resulted in at least 2,246 fatalities and injured over 12,763 individuals (Calais et

242   al., 2022). The earthquake-induced landslides totaled 4,893, covering an estimated 45.6km²,

243   with the largest individual landslide spanning $3.1×10^5$ m² (Zhao et al., 2022b). The affected area,

244   with elevations up to 2,300 m (Alpert, 1942), consists mainly of volcanic rocks, such as basalts,

and sedimentary formations, particularly limestones (Harp et al., 2016). Post-earthquake, we utilized 3m-resolution PlanetScope image (August 29, 2022) and 0.5m-resolution Map World image to assess the damage (Supplementary Figure 6).

On August 14, 2021, a seismic event registering Mw 7.2 hit in the Nippes Mountains of Haiti (73.45°W, 18.35°N). This seismic activity, coupled with substantial rainfall from Tropical Storm Grace between August 16 and 17, precipitated a significant number of secondary geological hazards in the Tiburon Peninsula. The calamity resulted in a tragic loss of at least 2,246 lives and inflicted injuries upon more than 12,763 individuals (Calais et al., 2022). The earthquake triggered a total of 4,893 landslides, covering an estimated area of 45.6km^2, with the maximum individual area reaching $3.1×10^5$m^2 (Zhao et al., 2022b). The study area, characterized by elevations reaching up to 2,300 m above sea level (Alpert, 1942). Comprised predominantly of volcanic rocks, such as basalts, and sedimentary formations, notably limestones (Harp et al., 2016). In addition to obtaining 3m-resolution PlanetScope image after the Nippes earthquake, we also acquired 0.5m-resolution Map World image (Figure.S6).

3.1.7 The 2022 Sumatra earthquake

On February 25, 2022, a Mw 6.1 earthquake struck West Sumatra, Indonesia, at a shallow depth of 4.9 km. The epicenter was located approximately 20 km from Mount Talakmau (100.10°E, 0.22°N), a compound volcano rising to about 3,000m. Mount Talakmau, active during the Holocene, consists of andesite and basalt from the Pleistocene-Holocene epoch (Basofi et al., 2016). The earthquake induced extensive landslides over a 6km² area on the volcano's eastern and northeastern flanks. High-resolution PlanetScope image (3m) from March 5 and April 24, 2022, captured these landslides (Figure.S7).

3.1.8 The 2022 Lushan earthquake

On June 1, 2022, an Mw 5.9 earthquake (102.94°E, 30.37°N) struck Lushan County, China, resulting in 4 fatalities and 42 injuries, affecting 14,427 individuals. The seismic event triggered 1,063 landslides over a total area of 7.2km², with the largest landslide covering 0.3km² (Zhao et al., 2022a). This region, located on the southeast margin of the Qinghai-Tibet Plateau, features an average elevation exceeding 2,000m, with altitudes ranging from 557 to 4,115m

273 (Tang et al., 2023). It is characterized by lush vegetation covering 80% of the area and

274 experiences a subtropical monsoon climate with annual rainfall between 1,100 and 1,300mm

275 (Chen et al., 2019). The geological composition predominantly consists of exposed sandstones

276 and mudstones (Zhao et al., 2022a). High-resolution imagery, including 3 m-resolution

277 PlanetScope images, 0.5m-resolution Map World image, and 0.2m-resolution UAV images

278 acquired on June 13, 2022, using a Sony ILCE-5100, was collected for the affected region

279 (Figure.S8).

280 **3.1.9 The 2022 Luding earthquake**

281 On September 5, 2022, an Mw 6.8 earthquake struck Luding County, China (102.08°E,

282 29.59°N), resulting in 93 fatalities. The seismic event triggered approximately 15,000 landslides

283 over an area of 28.53km², with the largest individual landslide covering 2.4×10^5m² (Dai et al.,

284 2023). This region lies on the southeastern margin of the Qinghai-Tibet Plateau within the "Y"-

285 shaped Xianshuihe Fault Zone (Yang et al., 2022b). The geological composition predominantly

286 includes limestone, sandstone, dolomite, and some intrusive rocks (Dai et al., 2023). In the

287 aftermath of the earthquake, rapid rescue operations and data collection were undertaken,

288 utilizing 0.2m-resolution UAV image (acquired on October 7, 2022, via Phase One IXU1000),

289 3m-PlanetScope image (acquired on September 25, 2022), Map World image (0.5m), and

290 Gaofen-6 (2m) (Figure.S9).

3.2 Preprocessing of landslide dataset

292 In the aforementioned nine events, the available public data primarily focuses on geological

293 analysis rather than tasks related to semantic segmentation. After performing multi-source data

294 spatial registration, atmospheric correction and radiometric calibration on remote sensing

295 images, we used QGIS for landslide interpretation. These labels were delineated with reference

296 to pre-earthquake remote sensing imagery and post-earthquake multi-source remote sensing

297 image. By comparing spectral disparities and analyzing morphological attributes between bi-

298 temporal images, we mapped the semantic landslide labels. (Figure.3). The mapping of

299 landslide polygons for these nine events was primarily conducted by a team of five researchers,
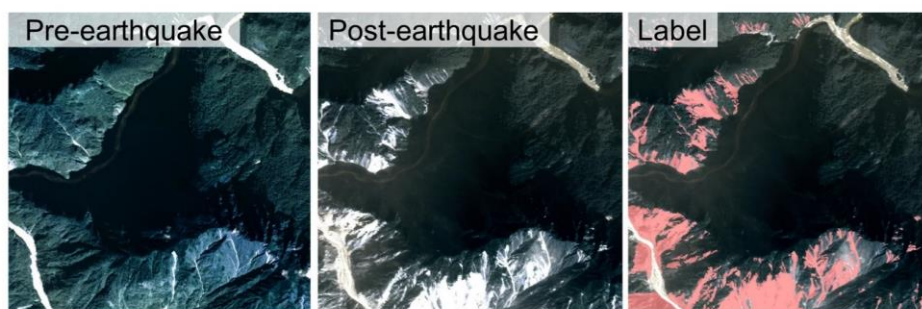
302
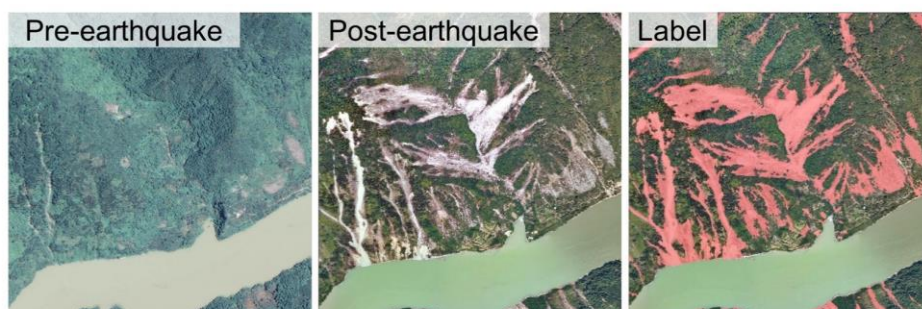
Luding earthquake region (UAV image)
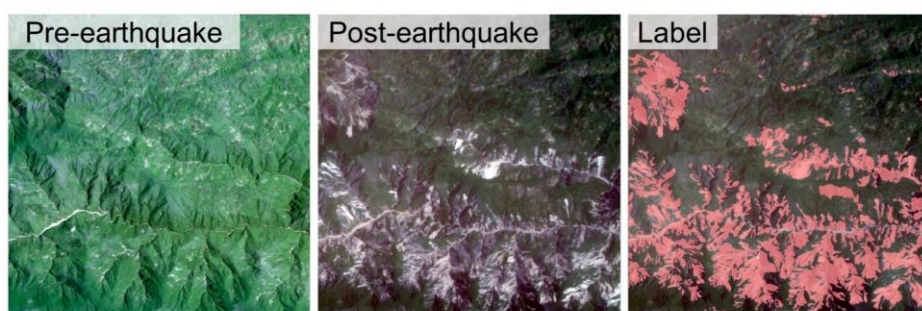
Haiti earthquake region (PlanetScope image)

Mainling earthquake region (PlanetScope image)

303 **Figure.3** Remote sensing images before and after the earthquake and landslide interpretation

304 results (landslides marked in red).

305 Moreover, we actively participated in emergency response and field investigation after

306 these major earthquakes in China. This further improved the reliability of the landslide

307 inventories. Figure.4 showcases photographs captured on-site after the Jiuzhaigou earthquake,

308 Lushan earthquake, and Luding earthquake. Specifically, Figure.4 (A_1) and 4 (B_1) were taken

309 in Luding, Sichuan, depicting the extensive devastation caused by concentrated coseismic

310 landslides, impacting Wandonghe Village and resulting in severe destruction of local

14

infrastructure. Corresponding aerial photos with a resolution of 0.2m, Figure.4 (A_2) and 4 (B_2),

offer a comprehensive perspective of the affected area. Figure.4 (C_1), taken in Lushan, Sichuan,

captures the consequences of the earthquake-triggered large landslide dam, which obstructed

the river channel. The corresponding PlanetScope image, Figure.4 (C_2), provides an overhead

view of the altered landscape. Furthermore, Figure.4 (D_1), taken in the Jiuzhaigou Panda Sea,

illustrates a significant volume of landslide deposits reaching the sea, with the accompanying

UAV image at a resolution of 0.2m, Figure.4 (D_2), offering detailed insights. Lastly, Figure.4 (E)

presents a field work photo involved in these surveys. These field investigations serve to

enhance comprehension and subsequent calibration on our remote sensing interpretation.
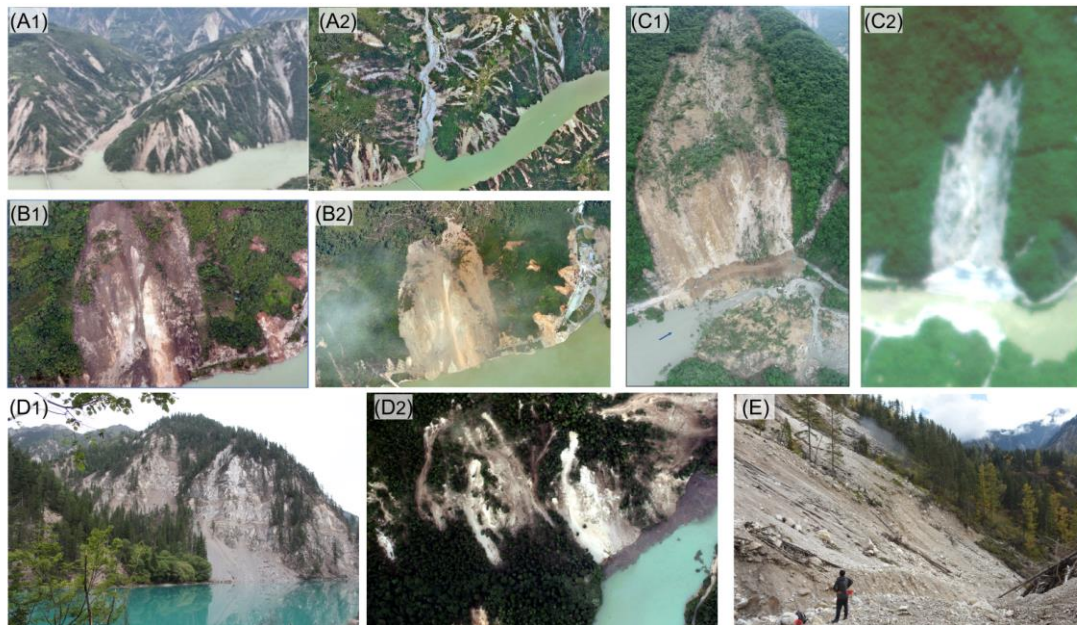
Figure.4 Comparison of field survey photos and remote sensing images: A_1 and A_2 are the

Wandong landslides induced by the 2022 Luding earthquake; B_1 and B_2 are the Dadu River

Bridge landslide induced by the 2022 Luding earthquake; C_1 and C_2 are the Baoxing landslides

induce by the 2022 Lushan earthquake; D_1 and D_2 are the Panda sea landslides induced by

the 2017 Jiuzhaigou earthquake; E is a photo of field work at Jiuzhaigou.

To obtain semantic-level annotations for landslide labels, all remote sensing images were

converted into RGB images (8-bit). the preprocessing stage was conducted through three steps:

binary mask generation, data sampling, and image patching. First, utilizing the Rasterio library

in Python, landslide vector labels for each selected region were transformed into binary masks,

where 1 denoted landslide and 0 represented background. Subsequently, regions densely populated with landslides were sampled, and both remote sensing images and masks were patched and cropped into regular grids, yielding patches of 1,024×1,024 pixels. To mitigate interference among patches, overlap parameter was set as 0. Given the obvious imbalance between non-landslide and landslide areas, we manually removed most of the images without any landslide pixel annotations. The ratios of positive landslide samples and negative non-landslide samples were 8.01% and 91.99%, respectively. Table.3 presents detailed information regarding different remote sensing data sources for each study case.

Table.3 Detailed information of each event in GDCLD

Events	Data sources	Resolution	Number of tiles
Jiuzhaigou 2017 (Mw 6.5)	UAV	0.2m	2,288
	PlanetScope	3m	176
Mainling 2017 (Mw 6.4)	PlanetScope	3m	118
Hokkaido 2018 (Mw 6.6)	Map World	0.5m	796
	PlanetScope	3m	123
Palu 2018 (Mw 7.5)	Map World	1m	335
Mesetas 2019 (Mw 6.0)	PlanetScope	3m	144
Haiti 2021 (Mw 7.2)	PlanetScope	3m	238
	Map World	0.5m	404
Sumatra 2022 (Mw 6.1)	PlanetScope	3m	110
Lushan 2022 (Mw 5.9)	UAV	0.2m	210
	Map World	0.5m	182
	PlanetScope	3m	110
Luding 2022	UAV	0.2m	9,252

(Mw 6.6)	Map World	0.5m	1,540
	GF-6	2m	496
	PlanetScope	3m	190
Sum	-	-	16712

339   Additionally, to enhance the robustness and generalization capability of deep learning

340   models, a subset of background noise elements such as clouds, roads, buildings, bare land,

341   and rocks were manually selected as negative non-landslide samples. The negative samples

342   can be outlined as follows: diverse roads (Figure.5: (e), (k), (m), (n), (p), (s)), river channels

343   (Figure.5: (e), (k), (n), (s), (t)), clouds (Figure.5: (o), (r)), barren land (Figure.5: (c), (h), (q)).

344   Additionally, human-engineered structures and buildings are also considered (Figure.5: (e), (k)).
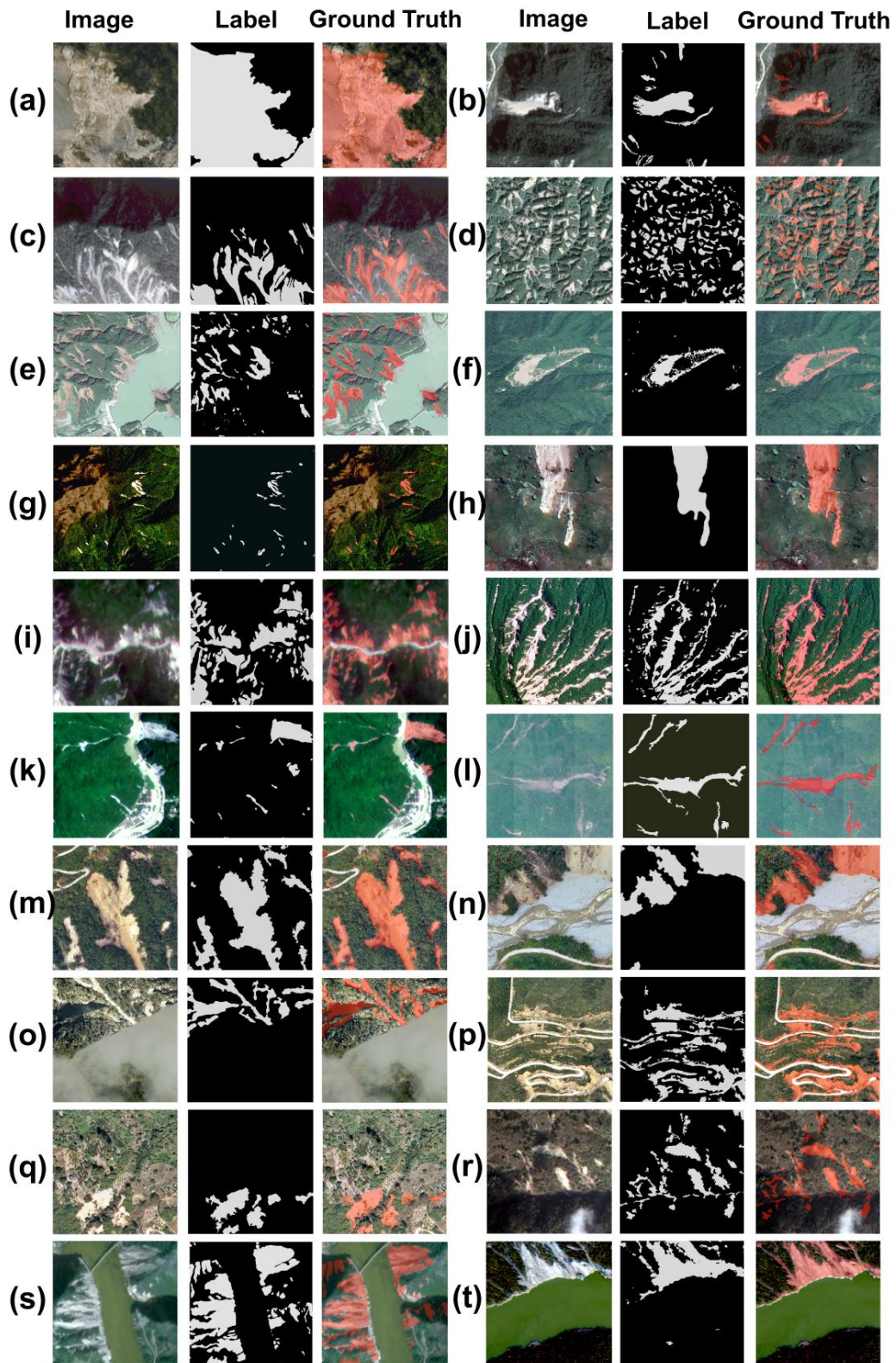
Figure.5 Display of landslide sample data from different study areas and different remote sensing data sources: Jiuzhaigou UAV (a), Jiuzhaigou PlanetScope (b), Mainling PlanetScope (c), Hokkaido PlanetScope(d), Hokkaido Map World (e), Palu Map World (f), Mesetas

PlanetScope (g), Haiti Map World (h), Haiti PlanetScope (i), Sumatra PlanetScope (j), Lushan

PlanetScope (k), Lushan UAV (l), Luding UAV(m~q), Luding Map World (r), Luding PlanetScope

(s), and Luding Gaofen-6 (t). The "label" refers to the binary landslide mask, whereas the "Ground Truth" illustrates the concordance between the annotated and actual landslide in images.

4. Experimental setup

After the completion of dataset construction, the experimental phase follows. In this section, we will introduce several semantic segmentation algorithms used for validating the dataset, the loss functions and accuracy evaluation metrics employed in the experiments, as well as various hyperparameter settings utilized during the experiments.

4.1 Segmentation algorithms

In this section, we have selected seven of the most popular semantic segmentation networks, including four models based on the CNN architecture and three based on the Transformer architecture. These seven algorithms have medium to large-scale parameter sizes and computational complexities, and show excellent performance in a variety of remote sensing semantic scenarios, making them suitable for Precision comparison and validation of novel datasets.

(1) UNet: As one of the earliest and most renowned semantic segmentation models, UNet is distinguished by its unique U-shaped architecture (Ronneberger et al., 2015). This design facilitates efficient learning and precise localization by combining high-resolution features from the contracting path with up-sampled outputs from the expanding path. Both the encoder and decoder in UNet are composed purely of CNN structures (O'shea and Nash, 2015). This simplicity, along with a relatively small number of parameters, allows UNet to achieve exceptional accuracy and rapid inference on small datasets. Consequently, it is widely utilized in applications such as small-scale object classification, change detection, and medical imaging.

(2) ResUNet: ResUNet is an advanced variant of the UNet model, incorporating residual

375   connections to enhance its performance and learning efficiency (Diakogiannis et al., 2020). The

376   key innovation in ResUNet is the integration of residual blocks within both the encoder and

377   decoder paths, which address the vanishing gradient problem and enable the training of deeper

378   networks (He et al., 2016). These residual blocks allow the network to learn identity mappings,

379   facilitating gradient flow through the network and improving convergence rates. Similar to UNet,

380   ResUNet maintains a U-shaped architecture that combines high-resolution features from the

381   contracting path with up-sampled outputs from the expanding path, ensuring precise

382   localization and context capture. The combination of residual connections improves feature

383   reuse and learning efficiency, enabling ResUNet to effectively improve Recall and small target

384   detection capabilities in semantic segmentation tasks.

385   (3) DeepLabV3: DeepLabV3, is a semantic segmentation model known for its

386   sophisticated use of atrous convolution, or dilated convolution (Chen et al. 2018). This

387   technique allows the network to capture multi-scale contextual information without losing spatial

388   resolution, addressing the limitations of traditional convolutional networks in dense prediction

389   tasks. DeepLabV3 incorporates atrous spatial pyramid pooling to robustly segment objects at

390   multiple scales by applying atrous convolution with different rates in parallel. This model also

391   integrates features from both the encoder and decoder paths, enhancing the Precision of

392   boundary delineation. In addition, the architecture of DeepLabV3 utilizes batch normalization

393   and depth-separable convolution. This design can effectively reduce the complexity and

394   computational cost of the model, while enabling the model to have stronger feature extraction

395   capabilities and generalization than simple networks such as UNet.

396   (4) HRNet: High-Resolution Network (HRNet) is noted for its innovative approach to

397   maintaining high-resolution representations throughout the network (Wang et al., 2020). Unlike

398   traditional models that gradually down-sample the input to extract features, HRNet preserves

399   high-resolution features by maintaining parallel high-to-low resolution subnetworks. This design

400   allows HRNet to integrate multi-scale information effectively, ensuring precise localization and

401   robust feature representation. The network continuously exchanges information across

402   different resolutions, resulting in superior accuracy and detailed segmentation results. Due to

403   its ability to retain fine-grained spatial information and adapt to various scales, HRNet excels in

404   complex tasks such as fine-grained terrain classification, semantic segmentation in urban

405   scenes, and fine-grained visual detection.

406   (5) UperNet: UperNet employs a pyramid feature extraction method, integrating multi-scale

407   information to capture contextual details across different resolutions (Xiao et al., 2018; Liu et

408   al., 2022). It utilizes a Feature Pyramid Network (FPN) backbone for hierarchical feature

409   extraction, enhanced by a global context integration module to enrich overall scene

410   understanding. Additionally, UperNet incorporates lateral connections for efficient

411   communication between feature pyramid levels, ensuring seamless information flow and

412   accurate segmentation. This sophisticated architecture enables UperNet to achieve superior

413   segmentation performance, particularly in challenging scenarios with complex scenes and

414   diverse object scales.

415   (6) SwinUNet: Built upon the Swin Transformer architecture, SwinUNet blends self-

416   attention mechanisms with UNet for exceptional performance (Cao et al., 2022). It inherits Swin

417   Transformer's hierarchical feature extraction for capturing both local and global contextual

418   information efficiently (Liu et al., 2021). The self-attention mechanism enables capturing

419   nuanced relationships in data. SwinUNet integrates UNet's contracting and expanding paths in

420   decoding, emphasizing spatial detail preservation. This combination empowers SwinUNet to

421   excel in tasks requiring precise localization and robust contextual understanding. (7)

422   SegFormer: SegFormer, represents a significant advancement in semantic segmentation by

423   leveraging a transformer-based architecture (Xie et al., 2021). Unlike traditional CNN

424   approaches, SegFormer employs a hierarchical transformer encoder to capture multi-scale

425   contextual information effectively, without relying on complex designs such as positional

426   encodings or large pre-training datasets. The decoder in SegFormer integrates features from

427   different scales using lightweight multi-layer perceptron, ensuring efficient and precise

428   segmentation. This innovative design enables SegFormer to achieve excellent segmentation

429   results with medium-sized parameters and fast inference speed in high-resolution complex

430   scenes.

4.2 Loss function and accuracy evaluation

Since the landslide detection is a two-class semantic segmentation task, we choose the Binary Cross-Entropy (De Boer et al., 2005) as the loss function for model training, whose mathematical expression is shown as follow:

$$L(y,\hat{y})=-\frac{1}{N}\sum_{i=1}^{N}[y_i\log(\hat{y}_i)+(1-y_i)\log(1-\hat{y}_i)] \tag{1}$$

where L is the loss function, N is the number of samples, y_i is the true label (0 or 1) of the i-th sample, and $\hat{y}_i$ is the predicted probability of the i-th sample.

For accuracy evaluation, the following accuracy indicators are calculated through confusion matrices (Townsend, 1971): Precision, Recall, F1 score (Chicco and Jurman, 2020) and mean intersection over union (mIoU) (Rezatofighi et al., 2019). Their calculation formulas are as follows:

$$Precision=\frac{TP}{TP+FP} \tag{2}$$

$$Recall=\frac{TP}{TP+FN} \tag{3}$$

$$F1=\frac{2\times Precision\times Recall}{Precision+Recall} \tag{4}$$

$$mIoU=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i+FP_i+FN_i} \tag{5}$$

where the TP is the True Positive, FP is the False Positive, TN is the True Negative and FN is the False Negative.

4.3 Equipment and Parameter

The deep learning framework employed in this study is conducted based on PaddlePaddle 2.3.2 (Ma et al., 2019), with the environment configured for Python 3.8, CUDA 11.2, and CuDNN 8.3.0. The experimental setup encompasses Intel Xeon CPU, W2255, 3.7GHz, equipped with 256GB of system memory. The GPU infrastructure consists of Tesla V100, with 32GB of video memory. The operating system employed is Ubuntu 20.04. The model's optimizer is selected as AdamW (Loshchilov and Hutter, 2017), with an initial learning rate of 0.0006, beta1 set to 0.9, beta2 to 0.999, weight decay to 0.01 and epoch to 100.

5. Results

To validate the accuracy of the GDCLD dataset, this study selected four types of remote sensing images (UAV, PlanetScope, Map World image, and Gaofen-6) from five seismic events (Luding, Jiuzhaigou, Hokkaido, Mainling, and Nippes) as training and validation datasets for model construction and accuracy evaluation. The ratio of training dataset to validation dataset is 3:1. To further assess the generalization ability of this dataset, we chose three types of remote sensing images (UAV, PlanetScope, and Map World image) from four independent seismic events (Lushan, Mestas, Sumatra, and Palu) as the test dataset. Considering the geographical distribution, these four regions, located on different continents and characterized by distinct tectonic settings and climatic conditions, ensure complete independence from the training dataset. From the perspective of data sources, the four study areas represent three major types of remote sensing imagery: PlanetScope, UAV, and Map World. Additionally, the UAV sensor used in the Lushan area is different from those used in other regions. This data partitioning strategy is designed to rigorously evaluate the generalization capability of the GDCLD-trained model.

We conducted evaluations on our dataset utilizing the aforementioned seven semantic segmentation algorithms. After each model is trained for 100 epochs, we meticulously examined the performance of the GDCLD dataset in landslide identification. we present the performance of the seven algorithms on the validation dataset in Table.4.
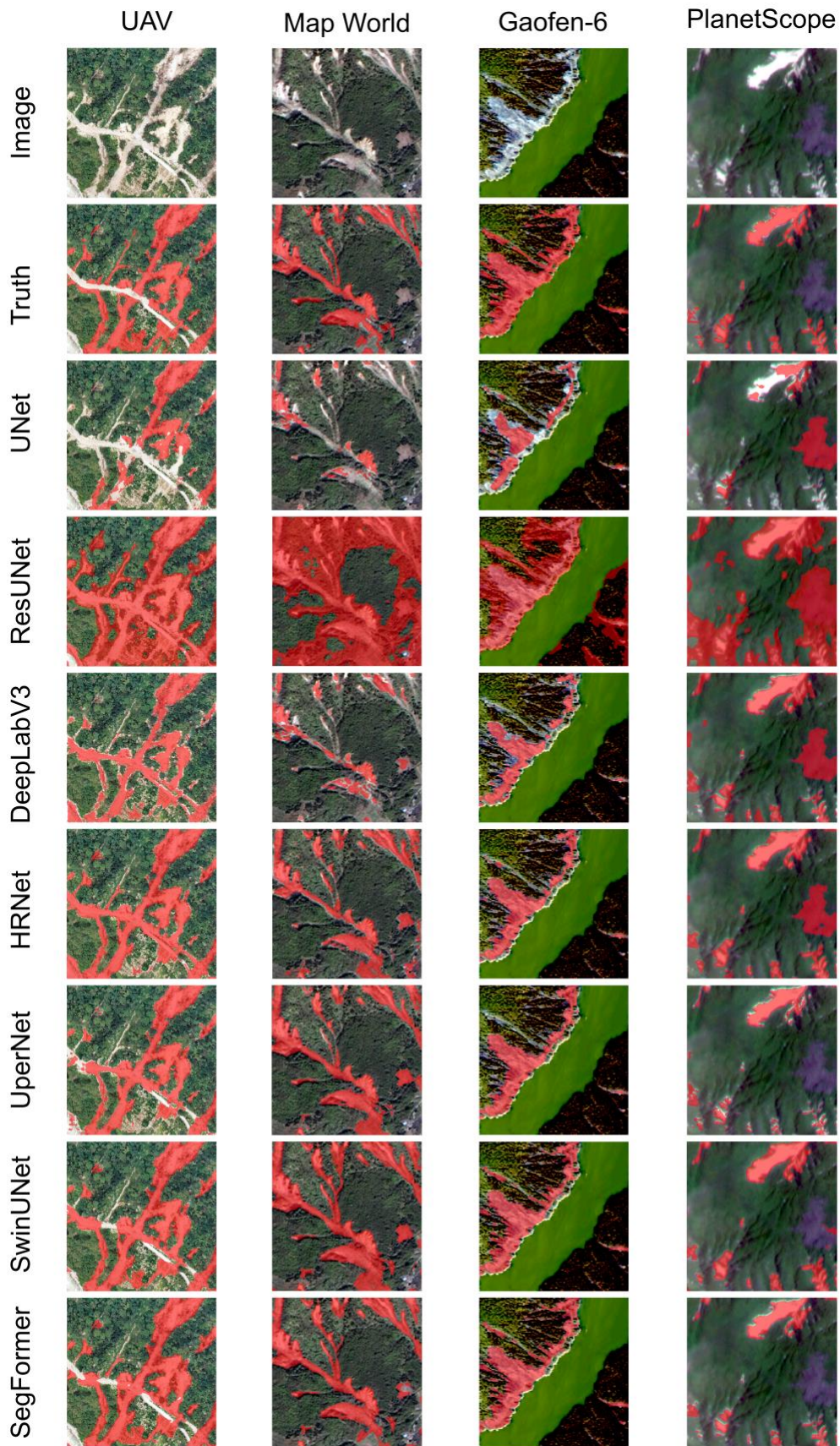
Among these seven algorithms, UNet, ResUNet, DeepLabV3, and HRNet serve as neural network models with convolutional structures, whereas UperNet, SwinUNet, and SegFormer are based on transformer-based neural network architectures. From Table.4, it is evident that Transformer-based semantic segmentation models exhibit superior performance compared to models based on convolutional structures. Overall, the mIoU of the seven algorithms on GDCLD validation set spans from 71.07% to 85.06%. Notably, UNet demonstrates the least detection with the mIoU and F1 score of 71.07% and 79.54%. In contrast, SegFormer yields the best performance with the accuracy of 91.35%, Recall of 91.70%, F1 score of 91.52%, and

23

483　mIoU of 85.06%. Figure.6 illustrates the detection results of different models across various

484　remote sensing data sources. it can be seen that transformer-based semantic segmentation

485　models achieve superior segmentation outcomes.

486　**Table.4** Comparison of result on GDCLD validation dataset

Method	Backbone	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
UNet	-	77.05	82.01	79.54	71.07
ResUNet	ResNet-50	78.17	86.48	82.11	71.94
DeepLabV3	ResNet-50	81.27	86.96	84.02	74.61
HRNet	HRNet-48	81.88	87.21	84.46	75.19
UperNet	ViT-B16	88.18	90.64	89.39	81.97
SwinUNet	-	89.78	**92.01**	90.72	83.68
SegFormer	MiT-B4	**91.35**	91.70	**91.52**	**85.06**

Columns: UAV, Map World, Gaofen-6, PlanetScope

Rows: Image, Truth, UNet, ResUNet, DeepLabV3, HRNet, UperNet, SwinUNet, SegFormer

487

488 **Figure.6** Comparative results of different algorithms on validation dataset

25

489　　　　To demonstrate the robustness and generalization capability of the dataset-trained models

490　　in other environment, we conducted testing by using four independent events, as illustrated in

491　　Table.5. Overall, the mIoU performance of the algorithms trained on GDCLD ranges from 56.09%

492　　to 72.84%. SegFormer exhibits the best performance, achieving Precision of 77.09%, Recall of

493　　87.09%, F1 score of 81.88%, and mIoU of 72.84%. we present detailed results of six types of

494　　remote sensing images in these four events in Table.6. The overall mIoU ranges from 69.01%

495　　to 82.31%, while the F1 ranges from 80.63% to 89.30%. Furthermore, we noticed a remarkable

496　　imbalance between Recall and Precision in the predicted results. The Recall is always higher

497　　than the Precision, as it is crucial to not miss any important landslides for disaster assessment

498　　and rescue operations. From the perspective of remote sensing sensors, except for the

499　　Sumatra incident, higher resolution was directly related to better landslide detection

500　　performance.

501　　　　　　　　　　　　　　**Table.5** Comparison of result on test dataset

Method	Backbone	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
UNet	-	61.69	61.22	61.45	56.09
ResUNet	ResNet-50	66.56	64.46	65.49	57.06
DeepLabV3	ResNet-50	65.26	67.75	66.48	59.73
HRNet	HRNet-48	65.52	72.03	68.62	61.79
UperNet	ViT-B16	69.96	78.08	73.80	65.42
SwinUNet	-	71.56	82.26	76.54	67.18
SegFormer	MiT-B4	**77.09**	**87.09**	**81.88**	**72.84**

502　　　　　　　　　　　　**Table.6** Detection results of SegFormer in different events

Events	Image type	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
	UAV	74.72	90.35	81.80	72.96
Lushan	Map World	76.18	87.35	81.38	71.92
	PlanetScope	81.50	82.28	81.78	69.05
Palu	Map World	73.48	91.24	81.40	71.12
Mesetas	PlanetScope	80.26	80.97	80.63	69.01
Sumatra	PlanetScope	83.57	97.45	89.30	82.31

503　　　　Figures.7 to 10 respectively illustrate the detection results for Mesetas (PlanetScope),

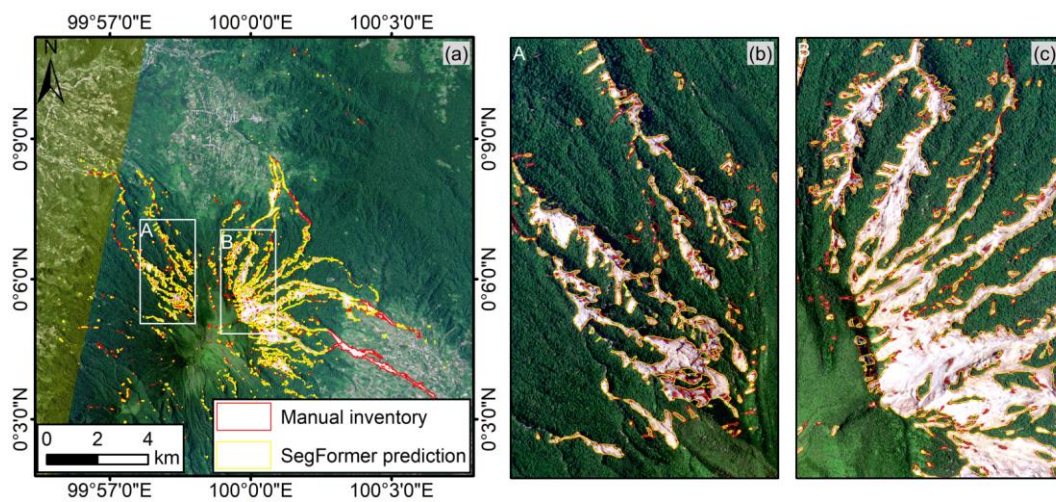504   Sumatra (PlanetScope), Palu (Map World image), and Lushan (UAV). The F1 score of the

505   Mesetas event model is 80.63%, with Recall and Precision exhibiting relative balance. As

506   observed in Figure.7, our model demonstrates strong capabilities in detecting and segmenting

507   the majority of landslides, particularly in regions of mountainous slopes (Figure.7 (d)). In areas

508   affected by mountain shadows (Figure.7 (b, c, e)), as expected, since, pixel signatures of

509   shadows are very different than those of landslides. The model effectively identifies most large

510   landslides but exhibits some omissions in detecting small landslides. In the Sumatra event, we

511   attained remarkably excellent detection results, with F1 score of 89.30%, Recall of 97.45%, and

512   Precision of 83.57%, Recall is 13.88% higher than Precision. As illustrated in Figure.8, the

513   model effectively identifies nearly all landslides (Figure.8 (b, c)). However, there are instances

514   of missed landslide detection in the lower-right corner of Figure.8 (a). This is due to the apparent

515   confusion between the landslide accumulation area and river channels, resulting in sub-optimal

516   detection. In the Palu event, our F1 score yielded a result of 81.40%, with Recall reaching 91.24%

517   and Precision by 73.48%, Recall is 17.76% higher than Precision. As depicted in Figure.9, the

518   detection outcomes effectively discriminate between numerous cloud obscuration, bare lands,

519   and buildings, underscoring the positive efficacy of augmenting negative samples in our dataset

520   to improve the model's detection capabilities. Similarly, for the Lushan event captured by UAV,

521   we achieved the F1 score of 81.80%, with Recall and Precision of 90.35% and 74.72%, Recall

522   exceeding Precision by 15.63%. As shown in Figure.10, in the UAV data, the model

523   demonstrates exceptional segmentation capabilities for large-scale landslides (Figure.10 (b, c,

524   d)), while its detection performance for some small-scale disasters is less satisfactory. Overall,

525   the model trained based on GDCLD demonstrated excellent generalization capabilities across

526   four independent test datasets. It successfully detected all major landslides and effectively

527   segmented landslide boundaries. More importantly, the model effectively excluded background

528   noise from river channels, bare ground in residential areas, and cloud region, showcasing its

529   remarkable robustness.

530
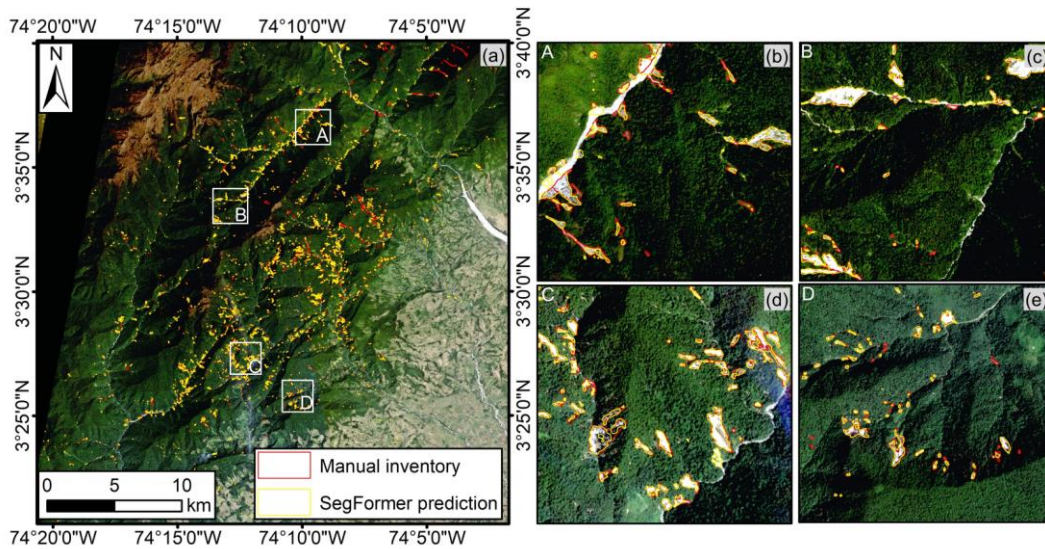
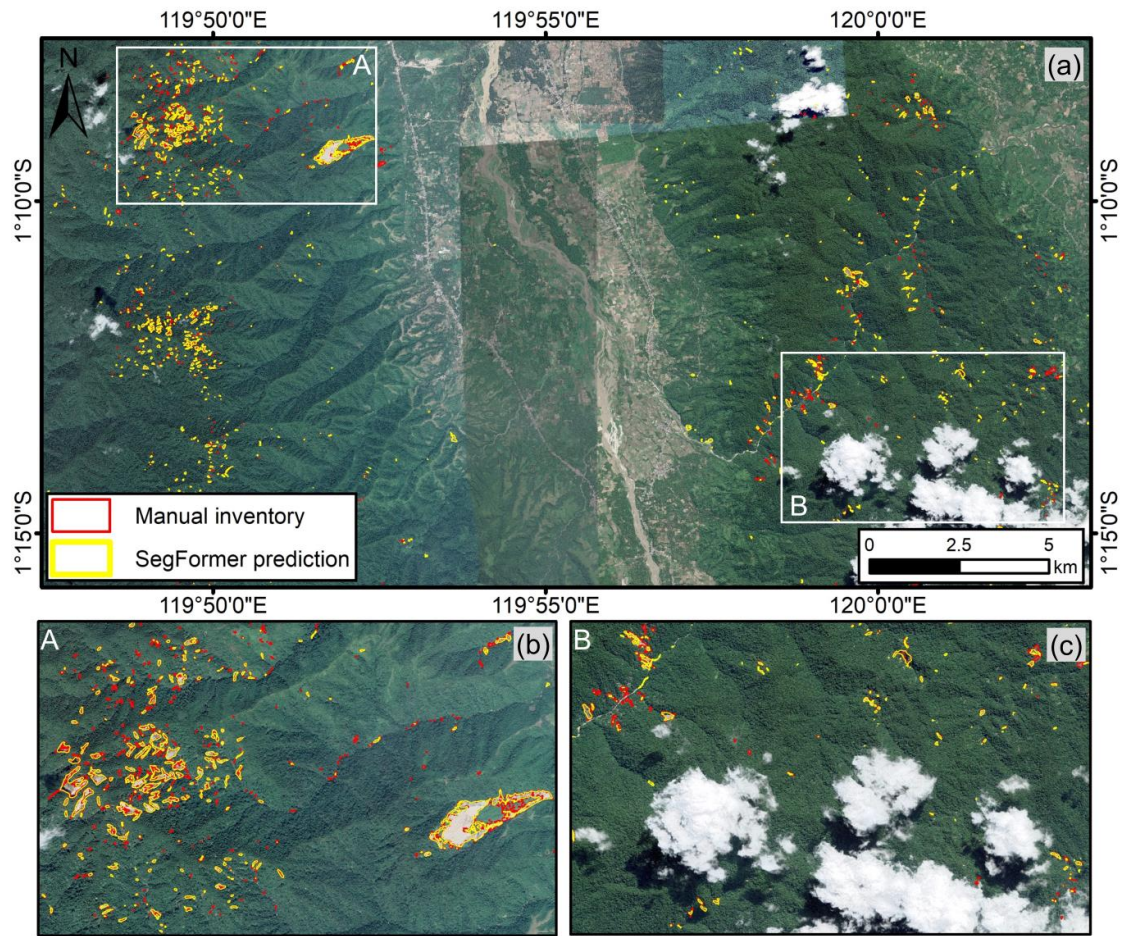**Figure.7** Mesetas PlanetScope dataset. (a) Regional aerial view. (b-e) Detection results of four

magnified areas.

533

Figure.8 Sumatra PlanetScope dataset. (a) Regional aerial view. (b-c) Detection results of two
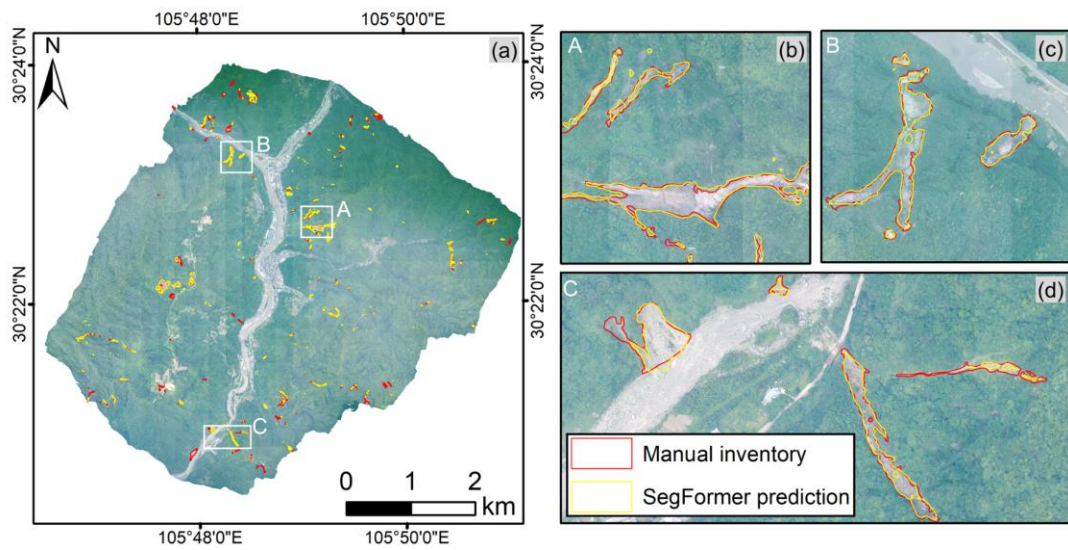
magnified areas.

536

537　**Figure.9** Palu Map World dataset. (a) Regional aerial view. (b-c) Detection results of two

538　magnified areas.

539

540

541　**Figure.10** Lushan UAV dataset. (a) Regional aerial view. (b-d) Detection results of three

542　magnified areas.

6. Discussion

6.1 Sample richness of GDCLD

The GDCLD dataset stands out as the most extensive and comprehensive repository of landslide data currently available, encompassing landslide data from various geographic environments and multiple remote sensing sources. the annotated landslide labels within this dataset tally up to approximately 1.39×10^9 pixels, roughly six times as many annotations as all the other publicly accessible landslide datasets (Figure.11). Additionally, this dataset includes a variety of negative samples with optical characteristics similar to landslides which can significantly enhance the model's generalization capability. In contrast to other datasets, which are limited to training small-scale semantic segmentation models like UNet and DeepLabV3 (Xu et al., 2024; Meena et al., 2022; Ghorbanzadeh et al., 2022), the GDCLD dataset can effectively train large-scale semantic segmentation models such as Transformers. Moreover, unlike Sentinel-2 and Landsat satellite image, where moderate spatial resolutions can limit the accurate delineation of landslide boundaries, GDCLD provides remarkably high spatial resolutions (0.2m~3m) and diverse spectral characteristics. This dataset not only performs well in landslide mapping across diverse geographical settings, but also serves as a baseline dataset for transfer learning in landslide detection.
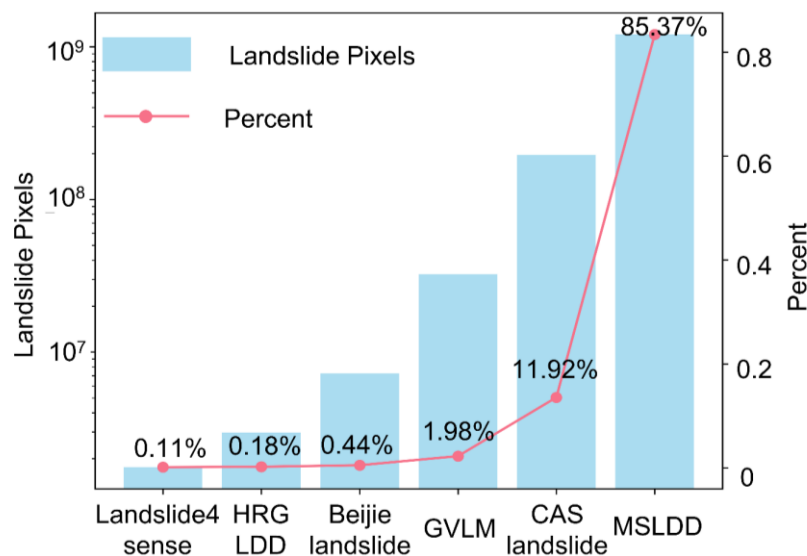
Figure.11 Statistical comparison of landslide pixels in different landslide datasets.

6.2 Enhancement in model generalization

In the GDCLD dataset, a general selection of remote sensing data from multiple sources enhances the overall generalization capability of the landslide identification model. To substantiate this assertion, we conduct a comparative analysis between models trained by single- and multi-source datasets. The datasets from different sensors are segregated, and the SegFormer, which is an advanced and widely used transformer-based algorithm, is applied to train the landslide models. Their performance was verified by their respective test dataset as well as an independent event of Lushan earthquake.

The accuracy metrics for the validation dataset are presented in Table.7. Across four remote sensing sources—PlanetScope, Gaofen-6, Map World, and UAV—models trained on single-source datasets consistently demonstrate higher performance on test samples, with mIoU indices surpassing those of multi-source datasets by 2.26%, 1.63%, 0.64%, and 0.13%, respectively. However, a noteworthy observation emerges when models are transferred to the independent Lushan earthquake case (Table.8). The model trained on the multi-source dataset achieves significantly enhanced performance compared to the model derived from single-source counterpart. The mIoU of UAV-, Map World- and PlanetScope based datasets are improved by 8.16%, 7.95% and 0.09%. As depicted in Figure.12, the models trained by multi-source images exhibit higher recalls, accurate landslide boundaries, and robust resistance to interference. The yellow circle highlights the enhancements of models trained by multi-source images compared to single-source images. From the perspective of data sources, Map World contains different types of images (such as Gaofen and Jilin), encompassing multitude of spectral responses across these sensors. the UAV image in the Lushan event utilize the sensor different from those in the Luding and Jiuzhaigou event, resulting in noticeable spectrum differences in images. Consequently, compared to a single remote sensing source, the generalization capability of the models trained by multi-source images demonstrate a more pronounced improvement. In contrast, the PlanetScope image, obtaining from the same satellite sensors, exhibits smaller spectral variations in various images. As a result, the model trained on both single and multi-source datasets achieve similar performance. This highlights

31

590   the importance of datasets with diverse images sources for enhanced model performance in

591   landslide mapping. This indicate that the utilization of multi-source remote sensing datasets

592   enables the model to learn the spectral characteristics of the images from diverse sensors.

593   Hence, the model trained by GDCLD possesses enhanced generalization ability and

594   robustness, enabling it to effectively perform landslide mapping in independent cases without

595   prior knowledge.

596   **Table.7** GDCLD performances on validation dataset through single- and multi-source dataset

Data source	Data type	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
Single source	UAV	**92.20**	**92.90**	**92.54**	**87.07**
	PlanetScope	**87.98**	**87.81**	**87.89**	**80.11**
	Map World	**86.49**	**90.01**	**88.21**	**80.66**
	Gaofen-6	**91.25**	**88.04**	**89.62**	**83.61**
Multiple source	UAV	91.91	92.64	92.27	86.94
	PlanetScope	85.01	87.79	86.37	77.85
	Map World	86.42	89.12	87.74	80.02
	Gaofen-6	90.49	85.20	87.77	81.98

597   **Table.8** GDCLD performances on unseen dataset through single- and multi-source dataset

Data source	Data type	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
Single source	UAV	64.92	**90.68**	75.67	64.80
	PlanetScope	81.25	**82.29**	81.75	68.96
	Map World	68.39	80.16	73.81	63.97
Multiple source	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**

Legend ▭ Landslide labels ■ Landslide predictions
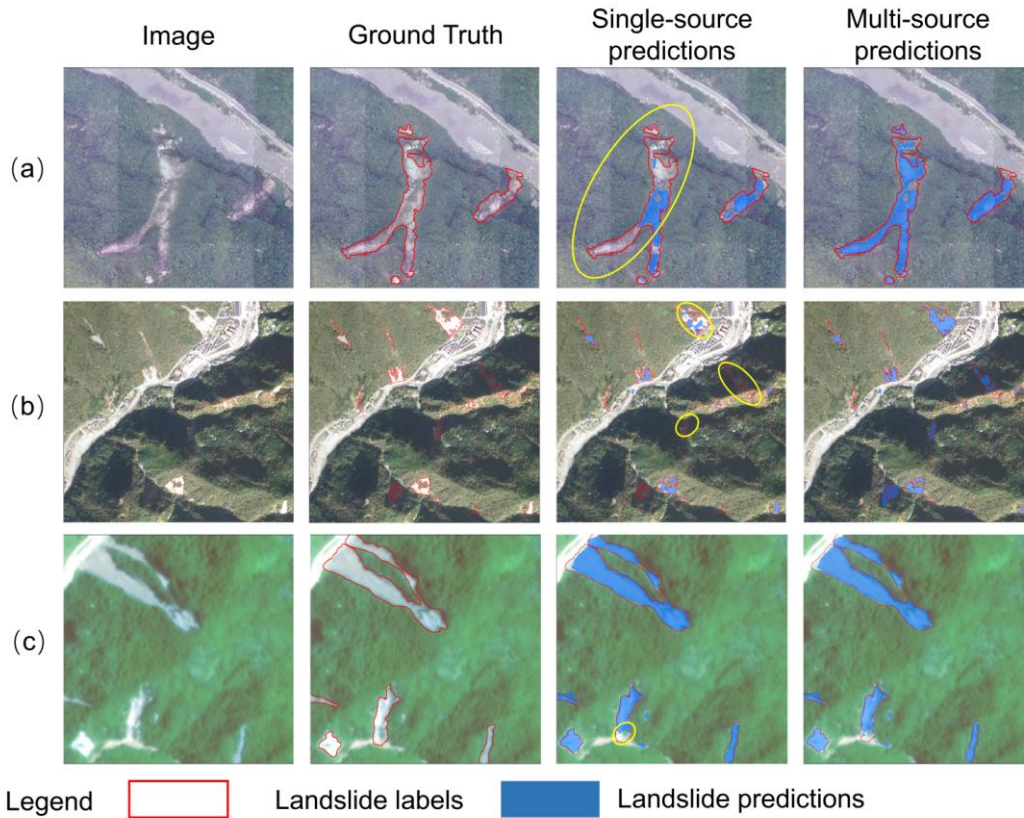
Figure.12 Comparative results of ablation experiments between multi- and single-source (a). UAV, (b). Map World, (c). PlanetScope

6.3 Comparison with existing landslide datasets and models

To assess the robustness and generalization capabilities of the GDCLD dataset, we employ SegFormer trained on the GDCLD dataset (GDCLD-S model) to identify landslides within three distinct datasets: HR-GLDD, GVLM, and CAS. Initially, we standardize the data from these three datasets into 1024×1024 remote sensing tiles. Subsequently, utilizing the GDCLD-S model, we conduct landslide identification across all these datasets. Table.9 demonstrates favorable performance of the model across these diverse datasets. For instance, in the HR-GLDD dataset, which shares similarities with the PlanetScope image in GDCLD, the model achieves an mIoU of 76.97%, indicating a balance between Precision and Recall metrics. Similarly, when applied to the GVLM dataset, leveraging Map World image, our dataset exhibits robust predictive outcomes, resulting in a comprehensive mIoU of 70.07%. Likewise, for the CAS dataset, GDCLD demonstrates strong generalization capabilities, yielding an outstanding

33

613   comprehensive metric with mIoU = 76.91%, alongside balanced Recall and Precision metrics.

614   Although all landslide samples contained in GDCLD are induced by seismic activity, our

615   model demonstrates good detection capabilities for rainfall-induced landslides. These two

616   categories exhibit distinct spectral characteristics from their surrounding environments.

617   Consequently, models trained on GDCLD exhibit proficient detection capabilities for rainfall-

618   induced landslides. We present the identification performance of GDCLD-based model for

619   rainfall-induced landslides from the GVLM dataset in Table.9 and Figure.13. Figure.13

620   underscores the excellent detection performance of the GDCLD-S model on rainfall-induced

621   landslides in the GVLM dataset. Despite occasional misclassifications of small-size targets, the

622   model effectively delineates the majority of rain-induced landslides. the Precision metrics in

623   Table.8 affirm this observation with an mIoU reaching 78.22% and both Recall and Precision

624   exceeding 85%. This highlights the robust generalization capability of the model trained by our

625   dataset, enabling effective identification of rainfall-induced landslides.

626   <div align="center">**Table.9** Validation results of other public datasets</div>

Dataset	Precision (%)	Recall (%)	F1 (%)	mIoU (%)
HR-GLDD	84.88	86.81	85.84	76.97
GVLM	72.83	87.54	80.68	70.07
CAS	82.95	86.35	84.62	76.91
GVLM-rainfall	85.88	86.71	86.29	78.22
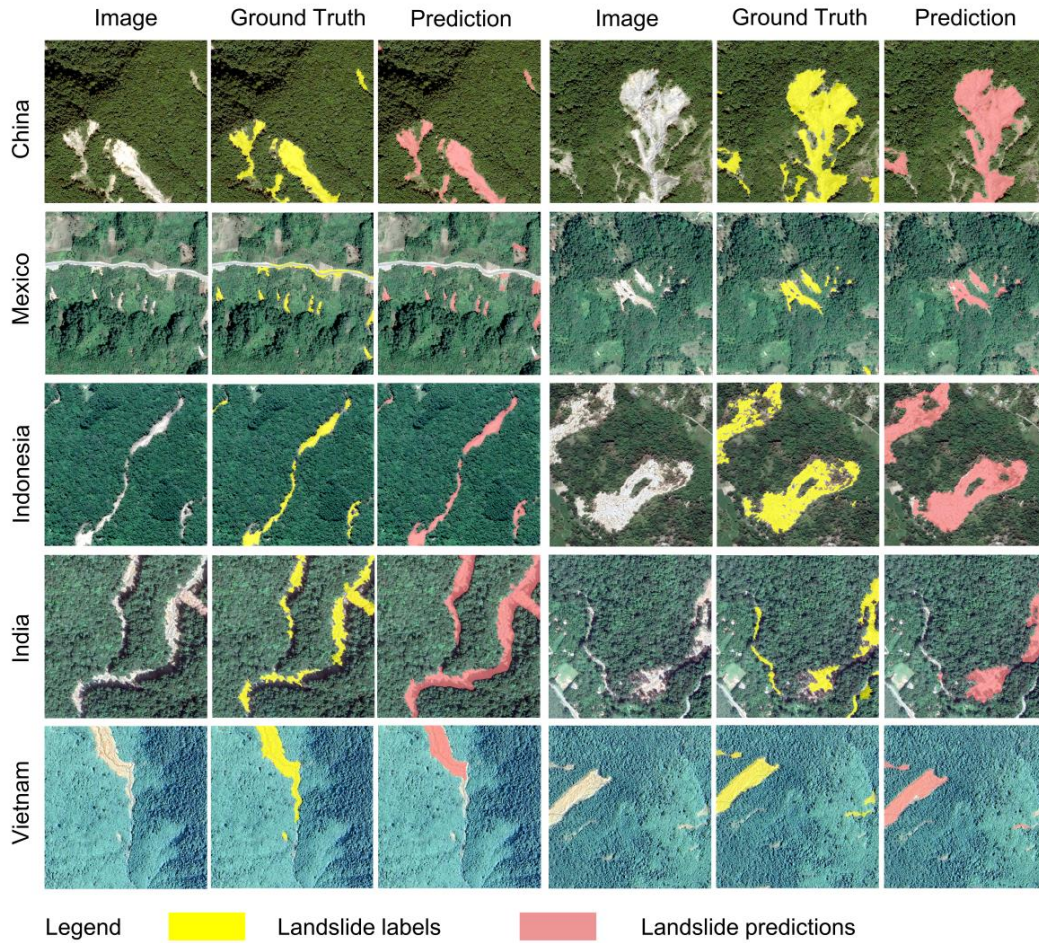
Figure.13 Detection results of rainfall landslides by GDCLD-S model. Map credits: GVLM.

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,

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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.

Table.10 Performance comparison of GDCLD-S, GVLM-S, CAS-S, CAS-D on the Lushan

dataset

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**

6.4 Practical Applications of GDCLD

To evaluate the practical applicability of the CDCLD, we selected two significant landslide-

triggering events that occurred in April 2024 for rapid landslide identification. These events

include landslides induced by a heavy rainfall in Meizhou, China and landslides triggered by an

earthquake in Hualien, China. In both cases, PlanetScope image was employed for

656   experimentation. For the Meizhou case, we obtained the image on May 14, 2024, and applied

657   SegFormer model trained on GDCLD data to identify landslides triggered by the heavy rainfall.

658   The results, shown in Figure.14, demonstrate that the GDCLD-trained model effectively

659   mapped newly-induced landslides with a total area of 8.49 km^2. The model exhibited excellent

660   accuracy in avoiding false positives such as buildings, roads, and rivers. In terms of the Hualien

661   event, we acquired post-event images from April 17 to 29, 2024. The rapid identification results,

662   displayed in Figure.15, indicate that the GDCLD-trained model effectively eliminates false

663   positives, such as roads, buildings, bare ground, and rivers, with the identified landslide area

664   of 90.9 km^2. The original PlanetScope images and landslide recognitions of the two events are

665   available at https://doi.org/10.5281/zenodo.13612636 (Fang et al., 2024)
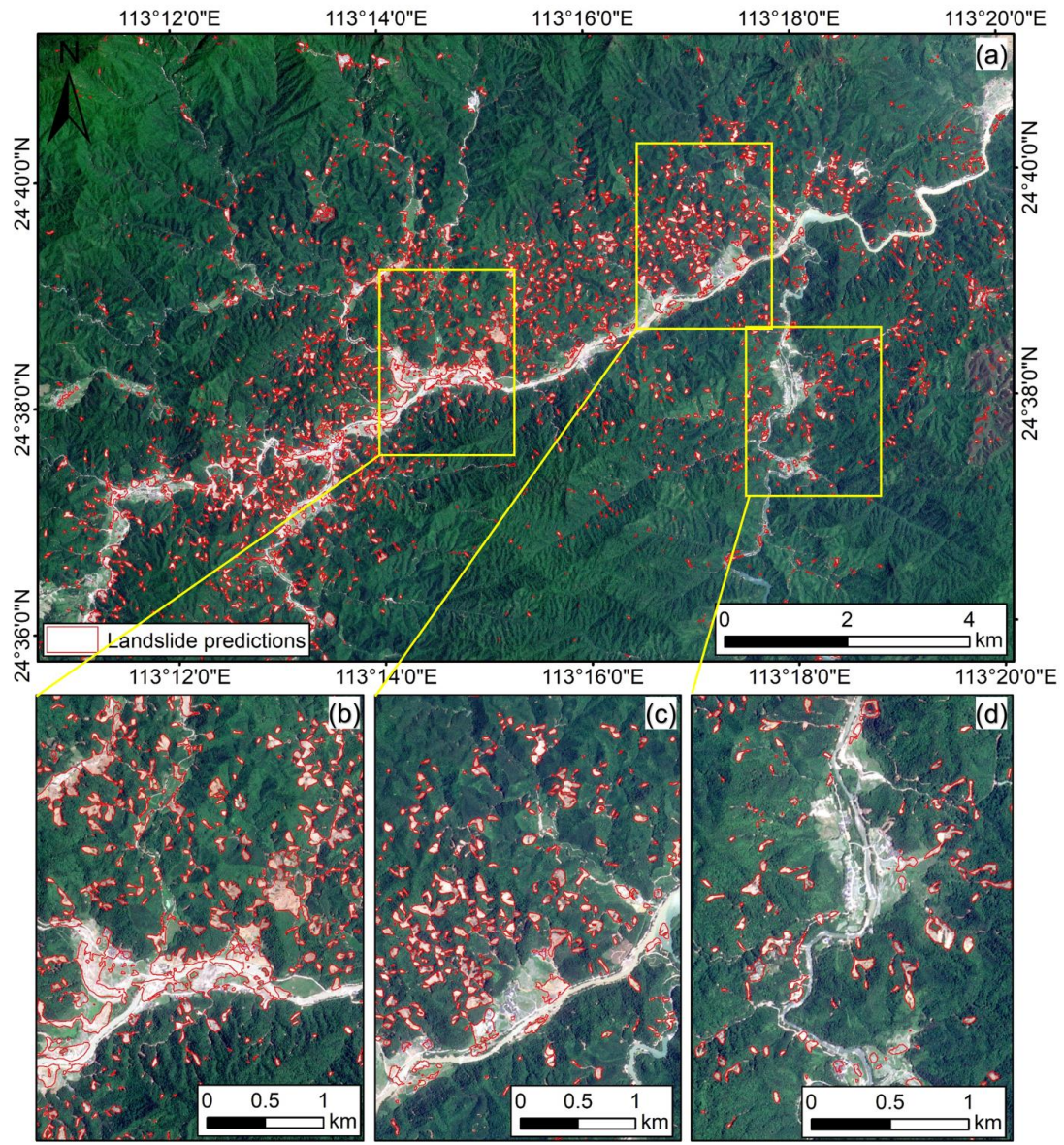
Figure.14 Detection results of rainfall-induced landslides for Meizhou, China. (a) is the aerial view of the whole area, (b), (c) and (d) is the partial details. Map credits: PlanetScope.
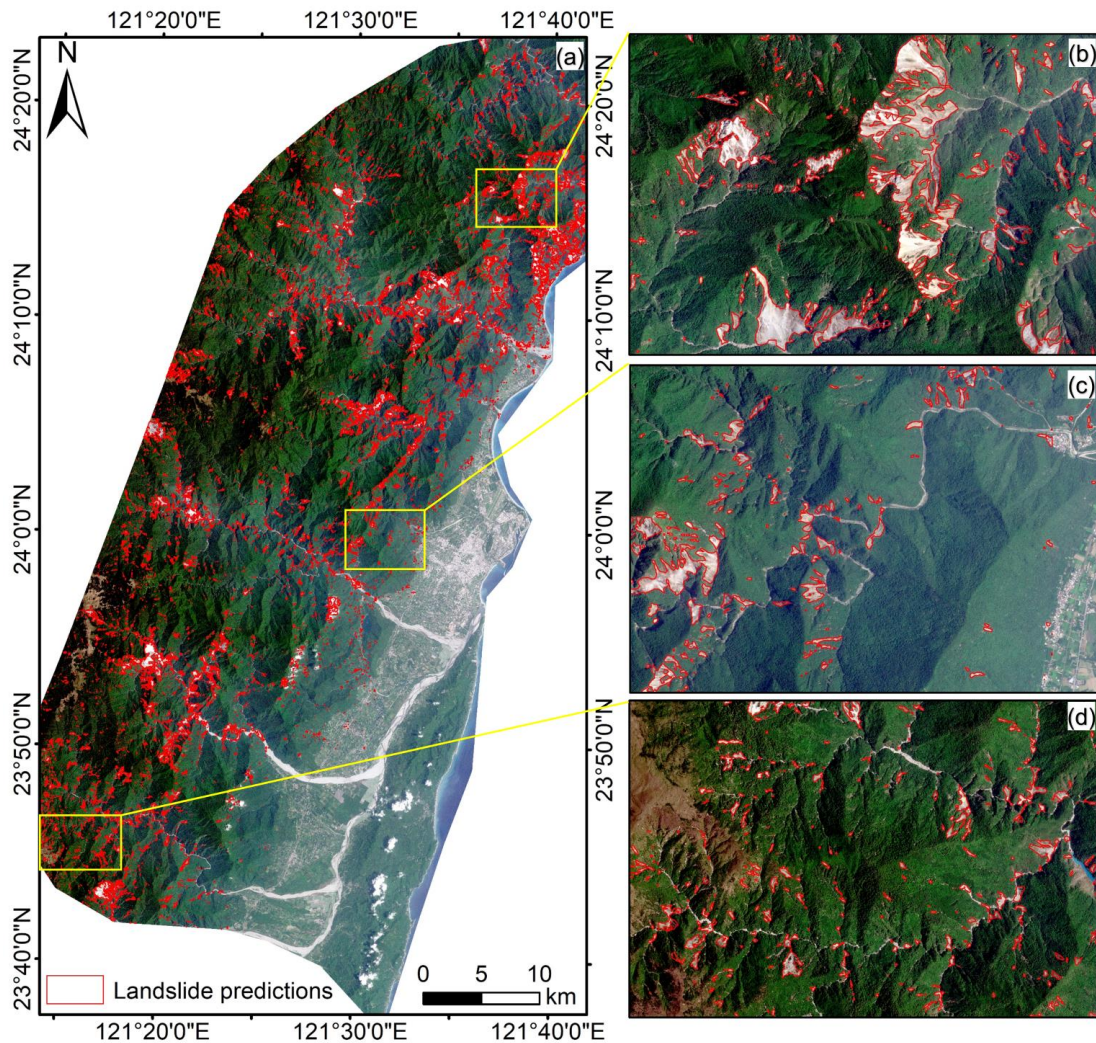
Figure.15 Detection results of earthquake-triggered landslides for Hualien, China. (a) is the aerial view of the whole area, (b), (c) and (d) is the partial details. Map credits: PlanetScope.

7. Future research directions

The current GDCLD primarily comprises landslide samples from regions with significant vegetation coverage, with limited representation from areas with low vegetation cover, such as loess landslides. To address this, we have updated the database with high-resolution UAV data (0.1m resolution) of loess landslides triggered by the M_w 6.2 earthquake in Jishishan, Gansu, China, in December 2023. Incorporating these loess landslide samples would enhance the dataset's diversity and improve the generalization capability of landslide detection models. Ongoing efforts to track and integrate data from landslides triggered by future extreme events

702 8. Code and data availability

703   The data is freely available at https://doi.org/10.5281/zenodo.13612636 (Fang et al., 2024).

704 There are compressed folders, namely train_dataset.zip, val_dataset.zip and test_dataset.zip.

705 The train_dataset.zip file contains 11,162 TIFF-format RGB images and their corresponding

706 binary label data, with each image having dimensions of 1024×1024 pixels. The val_dataset.zip

file comprises 4,459 TIFF-format RGB images and binary label data, with each image also sized at 1024×1024 pixels. The test_data.zip file includes seven original remote sensing images from four landslide events, with images in TIFF-format RGB and labels in TIFF-format binary data, though the image dimensions vary. The Future work folder contains some remote sensing data that will be added later. For each label, "0" indicates the background, while "1" denotes the landslide. 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. You can get original imageries at https://www.planet.com/ (Planet Team, 2019). And the code used to produce data described in this paper, as well as to create figures and tables, can be accessed at https://github.com/PaddlePaddle/PaddleSeg.

9. Conclusion

Landslide mapping across extensive geographic areas using remote sensing proves to be a significant challenge. Although previous attempts have produced landslide datasets and advanced automation and intelligence, they have not been able to overcome limitations of specific events and data sources. In this research, we proposed the Globally Distributed Coseismic Landslide Dataset (GDCLD), an innovative resource crafted to autonomously and precisely tackle the intricacies of landslide mapping. We made three significant contributions in this word. Firstly, we meticulously interpreted multi-source remote sensing data to create a comprehensive dataset for landslide detection. This dataset contains $1.39×10^{9}$ annotated landslide pixels and remote sensing image at four different resolutions, spanning nine global regions. It successfully addresses the crucial lack of large-scale datasets in current landslide identification research. Secondly, we utilized GDCLD -trained model to showcase its robustness and generalization in landslide identification across diverse geographical contexts. Our proposed dataset shows a great potential in rapid response and emergency management of

geological hazards. Although the landslide samples are obtained from seismic events, the trained model enable to capture and learn the characteristic differences between landslides and the surroundings, making them suitable for landslide mapping beyond seismic-triggered events, such as those caused by rainfall. The comparative analyses with existing datasets highlight its effectiveness as the data base of deep learning model in mapping landslides across various global regions. Finally, we demonstrate the superiority of the Transformer architecture over conventional CNN architecture in the task of landslide identification using multi-source remote sensing image. The GDCLD-S model further highlights the enhanced generalization capabilities of multi-source data compared to single-source data. This work has great practical implications for prevention and mitigation of geological hazard worldwide.

Supplement

The supplement related to this article is available online at: XXXX

Author contributions

All the authors contributed equally to the preparation of the paper, from data curation to the review of the final paper.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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