# Mapping and Characterizing Rock Glaciers in the Arid West Kunlun of China

Yan Hu[1], Lin Liu[1], Lingcao Huang[2], Lin Zhao[3], Tonghua Wu[4], Xiaowen Wang[5], and Jiaxin Cai[5]

[1]The Chinese University of Hong Kong
[2]University of Colorado Boulder
[3]Nanjing University of Information Science and Technology
[4]Northwest Institute of Eco-environment and Resources, Chinese Academy of Sciences
[5]Southwest Jiaotong University

January 20, 2023

## Abstract

Rock glaciers manifest the creep of mountain permafrost occurring in the past or at present. Their presence and dynamics are indicators of permafrost distribution and changes in response to climate forcing. Knowledge of rock glaciers is completely lacking in the West Kunlun, one of the driest mountain ranges in Asia, where widespread permafrost is rapidly warming. In this study, we first mapped and quantified the kinematics of active rock glaciers based on satellite Interferometric Synthetic Aperture Radar (InSAR) and Google Earth images. Then we trained DeepLabv3+, a deep learning network for semantic image segmentation, to automate the mapping task. The well-trained model was applied for a region-wide, extensive delineation of rock glaciers from Sentinel-2 images to map the landforms that were previously missed due to the limitations of the InSAR-based identification. Finally, we mapped 413 rock glaciers across the West Kunlun: 290 of them were active rock glaciers mapped manually based on InSAR and 123 of them were newly identified and outlined by deep learning. The rock glaciers are categorized by their spatial connection to the upslope geomorphic units. All the rock glaciers are located at altitudes between 3,389 m and 5,541 m with an average size of 0.26 $km^2$ and a mean slope angle of 17°. The mean and maximum surface downslope velocities of the active ones are 24 cm $yr^{-1}$ and 127 cm $yr^{-1}$, respectively. Characteristics of the rock glaciers of different categories hold implications on the interactions between glacial and periglacial processes in the West Kunlun.

**Mapping and Characterizing Rock Glaciers in the Arid West Kunlun of China**

Yan Hu[1,2], Lin Liu[1,2], Lingcao Huang[3], Lin Zhao[4,5], Tonghua Wu[4], Xiaowen Wang[6,7] and Jiaxin Cai[6]

[1]Institute of Environment, Energy and Sustainability, The Chinese University of Hong Kong, Hong Kong SAR, China.

[2]Earth and Environmental Sciences Programme, Faculty of Science, The Chinese University of Hong Kong, Hong Kong SAR, China.

[3]Earth Science and Observation Center, Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, CO, USA.

[4]Cryosphere Research Station on the Qinghai-Tibet Plateau, State Key Laboratory of Cryospheric Science, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou, China.

[5]School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing, China.

[6]Faculty of Geosciences and Environmental Engineering, Southwest Jiaotong University, Chengdu, China.

[7]State-Province Joint Engineering Laboratory of Spatial Information Technology of High-Speed Rail Safety, Chengdu, China.

Corresponding author: Yan Hu (huyan@link.cuhk.edu.hk)

Key Points:

- A combined use of deep learning and InSAR automates mapping rock glaciers at the regional scale
- We compile the first rock glacier inventory in West Kunlun with kinematic and geomorphic information documented
- Geomorphologic characteristics of rock glaciers provide insights on the glacial and periglacial processes and interactions in West Kunlun

Abstract

Rock glaciers manifest the creep of mountain permafrost occurring in the past or at present. Their presence and dynamics are indicators of permafrost distribution and changes in response to climate forcing. Knowledge of rock glaciers is completely lacking in the West Kunlun, one of the driest mountain ranges in Asia, where widespread permafrost is rapidly warming. In this study, we first mapped and quantified the kinematics of active rock glaciers based on satellite Interferometric Synthetic Aperture Radar (InSAR) and Google Earth images. Then we trained DeepLabv3+, a deep learning network for semantic image segmentation, to automate the mapping task. The well-trained model was applied for a region-wide, extensive delineation of rock glaciers from Sentinel-2 images to map the landforms that were previously missed due to the limitations of the InSAR-based identification. Finally, we mapped 413 rock glaciers across the West Kunlun: 290 of them were active rock glaciers mapped manually based on InSAR and 123 of them were newly identified and outlined by deep learning. The rock glaciers are categorized by their spatial connection to the upslope geomorphic units. All the rock glaciers are located at altitudes between 3,389 m and 5,541 m with an average size of 0.26 $km^2$ and a mean slope angle of 17°. The mean and maximum surface downslope velocities of the active ones are 24 cm $yr^{-1}$ and 127 cm $yr^{-1}$, respectively. Characteristics of the rock glaciers of different categories hold implications on the interactions between glacial and periglacial processes in the West Kunlun.

## Plain Language Summary

Rock glaciers are debris-ice landforms and indicators of the status of perennially frozen ground, as known as permafrost, which is warming and thawing under climate change. The West Kunlun is among the driest mountain ranges in Asia where permafrost has been changing over the past decades and the information of rock glaciers is completely lacking. In this paper, we developed an effective workflow for mapping rock glaciers in a semi-automated manner and characterized their geomorphology and kinematics. The compiled dataset allows further investigation on rock glaciers for multiple scientific motivations such as geohazard management, water resource assessment, and permafrost change monitoring. The documented geomorphic characteristics provide insights into the genesis and evolution of rock glaciers in the arid mountains.

## 1 Introduction

Rock glaciers are debris-ice landforms widely distributed in areas of mountain permafrost globally (Ballantyne 2018). Rock glaciers have drawn a lot of research interest since their first identification at the beginning of the 20th century (Capps 1910), because they serve as visible indicators for alpine permafrost which is defined by its underground temperature and has been warming and undergoing degradation (Barsch 1996; Biskaborn et al. 2019). Inventorying rock glaciers is therefore motivated by producing baseline knowledge for addressing various scientific questions associated with alpine permafrost, such as indicating permafrost occurrence through the rock glacier distribution, characterizing permafrost changes in the warming climate, and assessing the future hydrological significance of rock glaciers. Several studies have revealed that multi-annual acceleration of rock glaciers is synchronous with the rise of air and ground temperatures (Haeberli et al. 2006; Delaloye et al. 2010; Delaloye et al. 2013; Sorg et al. 2015; Marcer et al. 2021), and their short-term velocity variations are sensitive to the pore pressure in the shear horizon which is adjusted by the precipitation and snow melt conditions (Ikeda et al. 2008; Müller et al. 2016; Wirz et al. 2016; Cicoira et al. 2019a; Cicoira et al. 2019b; Kenner et al. 2019). Hence rock glacier inventories are valuable databases for studying how climatic factors cause permafrost changes manifesting in landform kinematics which can be quantified continuously and remotely. Moreover, rock glaciers can contain massive amounts of ground ice and contribute significantly to hydrological systems in some catchments, such as the Andes, Himalayas, and Sierra Nevada (Azócar and Brenning 2010; Millar et al. 2013; Geiger et al. 2014; Jones et al. 2018; Schaffer et al. 2019; Jones et al. 2021). A comprehensive inventory of rock glaciers lays the foundation for estimating the potential water storage and evaluating their future role in maintaining water supplies.

Numerous efforts have been put into inventorying rock glaciers in various mountain ranges worldwide in the past several decades, such as in Central Europe (Chueca 1992; Roer and Nyenhuis 2007; Scotti et al. 2013; Onaca et al. 2017), South America (Brenning 2005; Falaschi et al. 2014; Rangecroft et al. 2014; Villarroel et al. 2018), and North America (Ellis and Calkin 1979; Janke 2007; Millar and Westfall 2008; Liu et al. 2013). Rock glaciers are abundant in mountainous western China where a vast area of alpine permafrost is underlying and undergoing accelerated degradation in response to the warming climate (Yang et al. 2010; Cheng et al. 2019; Yang et al. 2019; Yao et al. 2019; Zhao and Sheng 2019; Ni et al. 2020; Zhao et al. 2020; IPCC 2021). However, few regional-scale inventories of rock glaciers have been compiled until recently (Schmid et al. 2015; Wang et al. 2017; Ran and Liu 2018), which hinders rock glaciers functioning as a permafrost indicator. Such lack of knowledge is attributed to the following reasons: (1) rock glaciers in western China are mostly situated in remote and harsh environment where early in situ investigations are scarce and limited to case studies or small catchment-scale research (e.g., Cui 1985; Cui and Zhu 1988; Zhu et al. 1996; Harris et al. 1998); (2) mapping rock glaciers conventionally relies on manually detecting and outlining the landforms from optical images (Schmid et al. 2015), which is labor-intensive to apply to large permafrost region (e.g., West Kunlun Mountains) following an exhaustive strategy; (3) contentious opinions of identifying rock glaciers exist due to the complexity of the landforms (Harris et al. 1998; Berthling 2011; Hu et al. 2021), which obscures the definition of rock glaciers and makes it challenging to recognize the landforms.

To address these problems, recent research progress in compiling rock glacier inventories includes (1) integrating InSAR techniques to facilitate active rock glacier identification and kinematics quantification (e.g., Liu et al. 2013; Barboux et al. 2014; Wang et al. 2017; Cai et al. 2021; Reinosch et al. 2021; Zhang et al. 2021); (2) implementing Convolutional Neural Networks (CNN) to demonstrate the feasibility of automating rock glacier delineation (Robson et al. 2020) or to improve the consistency of existing rock glacier inventories (Erharter et al. 2022); and (3) establishing widely accepted inventorying guidelines by the international rock glacier research community (RGIK, 2021).

Here we combine the InSAR technique and a state-of-the-art deep learning network, namely DeepLabv3+ (Chen et al. 2018), to map rock glaciers across the West Kunlun Mountains of China where widespread permafrost is warming (Li 1986; Cheng et al. 2019), and knowledge of rock glaciers is completely lacking. Manual delineation of rock glaciers based on InSAR and high-resolution optical imagery in this study is guided by the baseline concepts proposed by the International Permafrost Association (IPA) Action Group on rock glaciers to ensure a standard high-quality dataset utilized to train the deep learning network, and thus, the final mapping results (RGIK, 2021). We adopted the deep learning method to improve the mapping efficiency by automating the identification and delineation tasks, and more importantly, to generate a more comprehensive geodatabase by overcoming the limitations of InSAR-based method (Cai et al., 2021).

This study aims to develop an automated approach to map rock glaciers on a regional scale in western China, i.e., the West Kunlun Mountains. By producing the first automatically mapped inventory at the mountain-range scale, we demonstrate the effectiveness of using a deep-learning-based method to delineate rock glaciers in a consistent manner across the vast study area. We provide essential attributes to the mapped landforms according to the inventorying guidelines. We also conduct statistical analyses to summarize the spatial distribution and geomorphologic characteristics of the mapped rock glaciers. The compiled inventory will provide baseline knowledge for conducting long-term studies of rock glaciers and permafrost in a changing climate.

## 2 Study area

The West Kunlun is a major mountain range situated in the northwest of Tibetan Plateau, extending ~800 km from the eastern margin of Pamir Plateau to the Keriya Pass of Kunlun Mountains, with a total study area of ~124,000 km$^2$(74–81.5°E, 35–39.5°N) (Figure 1). The elevation of the study region ranges between 3,000 m and 7,500 m.

Across the vast study area, a cold desert climate (Köppen climate classification BWk) is dominant (Peel et al. 2007). Climatic conditions of the western part are revealed by the record of the nearest meteorological station in Tashikurgan (75.23°E, 37.77°N; 3090 m a.s.l.) during 1957–2017: the mean annual air temperature (MAAT) and mean annual accumulated precipitation are 4.2°C and 51 mm, respectively (data source: China Meteorological Administration,*http://data.cma.cn/* ). The study area has been warming at a rate of ~0.033°C/yr during the past six decades, similar to the average warming rate (0.031°C/yr) across the entire plateau (Zhang et al. 2020). In the eastern part, the MAAT is -6 °C and the annual precipitation is 103.3 mm, as reported by the Tianshuihai meteorological station (79.55°E, 35.36°N; 4844 m a.s.l) from 2015 to 2018 (Zhao et al. 2021).

The easternmost part of the study region is overlapped with the West Kunlun permafrost survey area (78.8–81.4°E, 34.5–36.0°N; 4,200–6,100 m a.s.l.) established by the Cryosphere Research Station (CRS) on the Qinghai-Tibet Plateau, Chinese Academy of Sciences, where in situ observations are available to represent the state of permafrost in the West Kunlun. Ice-rich permafrost is widely distributed in the survey area (Zhao and Sheng, 2019). The mean annual ground temperature (MAGT) is higher than -2.7°C as revealed by borehole measurements and permafrost was warming at an average rate of 0.11°C/10 yr from 2010 to 2017 (Cheng et al. 2019; Zhao and Sheng, 2019). The lowest altitudinal limit of permafrost occurrence is between 4,650 m and 4,800 m depending on different slope aspects according to previous field surveys focusing on a subregion of the West Kunlun (Li et al. 2012).

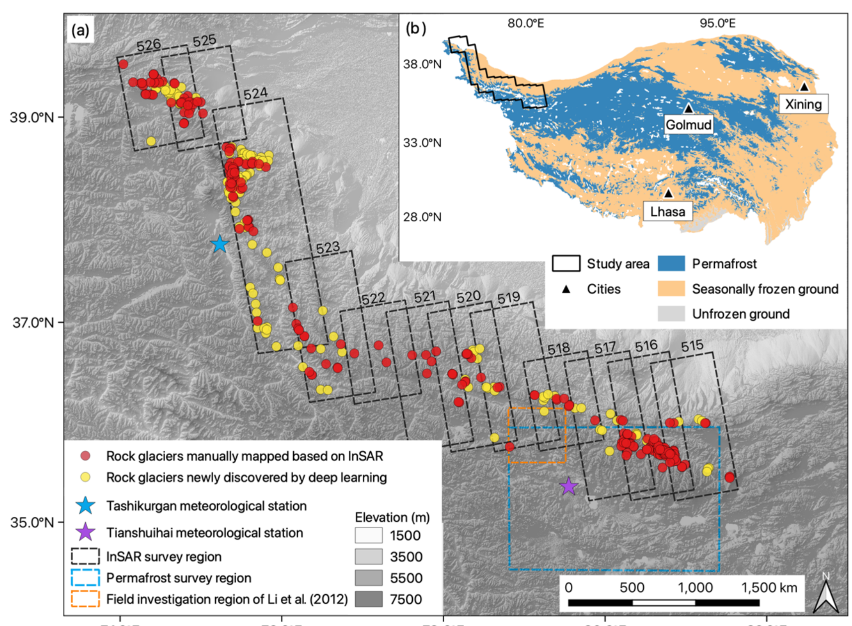


**Figure 1** . (a) Distribution of the mapped rock glaciers in the West Kunlun. The red dots are manually mapped rock glaciers (290 in total), and the yellow dots represent newly identified rock glaciers by our deep learning method but were missed in the InSAR-based sub-dataset (123 in total). The background is a topographical map showing the ground coverage of ALOS-1 PALSAR data used in this study (dashed black box), with the path number of each ground track labelled aside. The dashed blue and orange boxes show the extents of the CRS permafrost survey region (Zhao and Sheng 2019), and the previous in situ investigation area (Li et al. 2012), respectively. The blue and purple stars denote the location of the Tashikurgan and Tianshuihai meteorological stations, respectively. The topography is plotted based on the 1-arcsec SRTM DEM (spatial resolution ~30 m). (b) Permafrost distribution (Zou et al. 2017) and the location of the study area on the Qinghai-Tibet Plateau.

**Table 1**

*List of Interferograms Generated from ALOS-1 PALSAR Data*

| Path/frame | Start-end dates | Perpendicular baseline (m) |
|---|---|---|
| 515/700 | 20081213–20090128 | 300 |
| 515/710 | 20081213–20090128 | 307 |
| 516/700 | 20081114–20081230 | -38 |
| 516/710 | 20081114–20081230 | -31 |
| 517/700 | 20070829–20071014 | 364 |
| 517/710 | 20070829–20071014 | 370 |
| 518/710 | 20080317–20080502 | 652 |
| 519/710 | 20080102–20080217 | 972 |
| 519/720 | 20080102–20080217 | 337 |
| 520/710 | 20080119–20080305 | 581 |
| 520/720 | 20080119–20080305 | 587 |
| 521/710 | 20080205–20080322 | 62 |
| 521/720 | 20080205–20080322 | 71 |
| 522/720 | 20070822–20071007 | 212 |
| 523/720 | 20070608–20070724 | 288 |
| 523/730 | 20070608–20070724 | 289 |
| 524/730 | 20080210–20080327 | 115 |
| 524/740 | 20070810–20070925 | 108 |
| 524/750 | 20080210–20080327 | 130 |
| 524/760 | 20080210–20080327 | 137 |
| 525/770 | 20070712–20070827 | 292 |
| 526/770 | 20070613–20070729 | 471 |

## 3 Methodology

The method we adopted consists of two parts and is detailed below. First, we mapped active rock glaciers manually from interferograms and Google Earth images. Second, we used the manually labelled images to train a deep learning network, i.e., DeepLabv3+, for mapping rock glaciers automatically from Sentinel-2 optical images.

### 3.1 Mapping active rock glaciers from interferograms and Google Earth images

In this subsection, we first describe the strategy of delineating rock glaciers. Then we present the method for quantifying rock glacier kinematics by InSAR. Finally, we introduce how to determine the geomorphic attributes of the mapped landforms.

#### 3.1.1 Manual identification and delineation of rock glaciers

We mapped active rock glaciers by combining two imagery sources: interferograms and Google Earth images. The displacement maps generated by InSAR allow us to easily recognize moving parts of the ground surface, meanwhile the high-resolution and multi-temporal Google Earth images provide geomorphic information to distinguish rock glaciers from the other active surface units, such as debris-covered glaciers, solifluction lobes, and slow-moving landslides. Visual identification was conducted based on the geomorphological criteria proposed by RGIK (2021) including the frontal and lateral margin morphology, and the surface ridge-and-furrow topography as an optional indicator. We then outlined the recognized landforms along their extended geomorphological footprints, i.e., the frontal and lateral margins are included within the boundaries. We followed the IPA guidelines because it provides practical and standardized baseline concepts for identifying and outlining rock glaciers from remote sensing images and readily applicable to producing consistent inventories over wide-extent regions.

3.1.2 Kinematic quantification by InSAR

In total, twenty-two interferograms generated from ALOS-1 PALSAR images covering the West Kunlun Mountains were used for ground movement detection between 2007–2008 (Table 1). To maintain high interferometric coherence and reduce topographic error, we selected image pairs with temporal spans of 46 days and perpendicular baselines smaller than 1,000 m. The topographic phase were estimated and removed by using a digital elevation model (DEM) produced by the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of ~30 m over most of the study region. A tile of TanDEM-X DEM (spatial resolution ~12 m) was adopted for correcting topographic phases for one interferogram overlapping with the permafrost survey region. Multi-looking operation and adaptive Goldstein filter (8×8 pixels) were applied in the interferometric processing, which was implemented by the open-source software InSAR Scientific Computing Environment (ISCE) version 2.2.0 (available at*https://github.com/isce-framework/isce2* ). We then unwrapped the interferograms with the SNAPHU (Chen and Zebker 2002) and selected one point located at the flat and stable ground close to each rock glacier to re-reference the unwrapped phases measured within the boundary of each landform. By doing so, we managed to remove the long-wavelength orbital errors and the atmospheric artefacts including the water vapor delay and ionospheric effects, all of which can be assumed identical within the extent of a rock glacier (Hanssen 2001).

We determined the surface downslope velocities of rock glaciers as their kinematic attributes. The surface velocities along the SAR satellite line-of-sight (LOS) direction were derived from the unwrapped interferograms and then projected to the downslope direction of each landform (Hu et al. 2021). Associated uncertainties including the InSAR measurements and geometric parameters were quantified through error propagation (Hu et al. 2021). We used the spatial mean velocity within a rock glacier to represent its overall kinematic status. Then we refined the results by selecting data that fulfilled the following criteria: (1) after masking out the pixels with low coherence ($< 0.3$) (Wang et al. 2017), the remaining pixels account for more than 40% of the entire landform extent; (2) the relative errors of the spatial mean velocities are lower than 20%.

### 3.1.3 Determination of geomorphic attributes

Essential geomorphic attributes such as the elevation range, mean slope angle, and landform aspect were quantified using the SRTM DEM. Qualitative attributes including the spatial connection of the rock glacier to the upslope unit and the activity category were described and assigned to the dataset following the IPA guideline (RGIK, 2021). We primarily classified the mapped rock glaciers according to their spatial connection to the upslope unit because it could provide implications regarding the landform genesis (Sect. 5.2). We used the Global Land Ice Measurements from Space (GLIMS) dataset to help recognize the surrounding glacier units (GLIMS and NSIDC, 2005). Figure 2 presents examples of rock glaciers that were classified by their upslope units into four categories. For instance, Figure 2b shows a glacier-connected rock glacier, the frontal and lateral margins of which are discernible from the Google Earth image, though the rooting zone is ambiguous. We separated the rock glacier from the upslope unit from surface structure in this case. Finally, we created the InSAR-based sub-dataset. The entire workflow is illustrated in Figure 3 with one example shown in Figure 4.

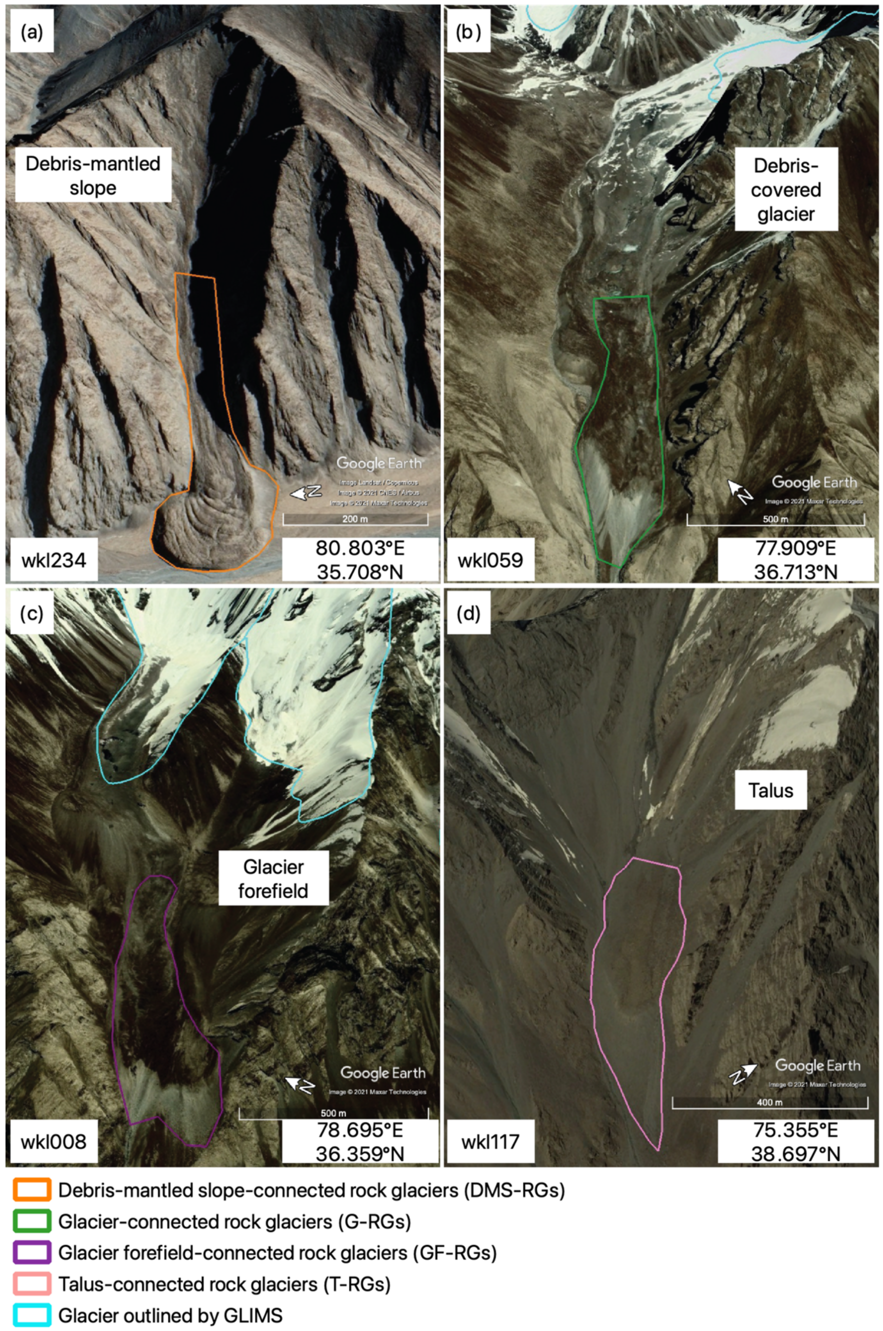



**Figure 2** . Google Earth images showing rock glaciers of four different types and their spatial connections to the upslope units. (a) shows a debris-mantled slope-connected rock glacier (DMS-RG) in orange (ID: wkl234). (b) focuses on a glacier-connected rock glacier (G-RG) in green (ID: wkl059). The cyan polygons are glaciers outlined by the GLIMS dataset and the feature in between is recognized as a debris-covered glacier. (c) presents a glacier forefield-connected rock glacier (GF-RG) in purple (ID: wkl008). Note that the GF-RG disconnects from the upslope glacier in cyan, whereas the G-RG in (b) is in continuation of the upslope debris-covered glacier. (d) displays a talus-connected rock glacier in pink (ID: wkl117), from which the upslope talus can be observed.

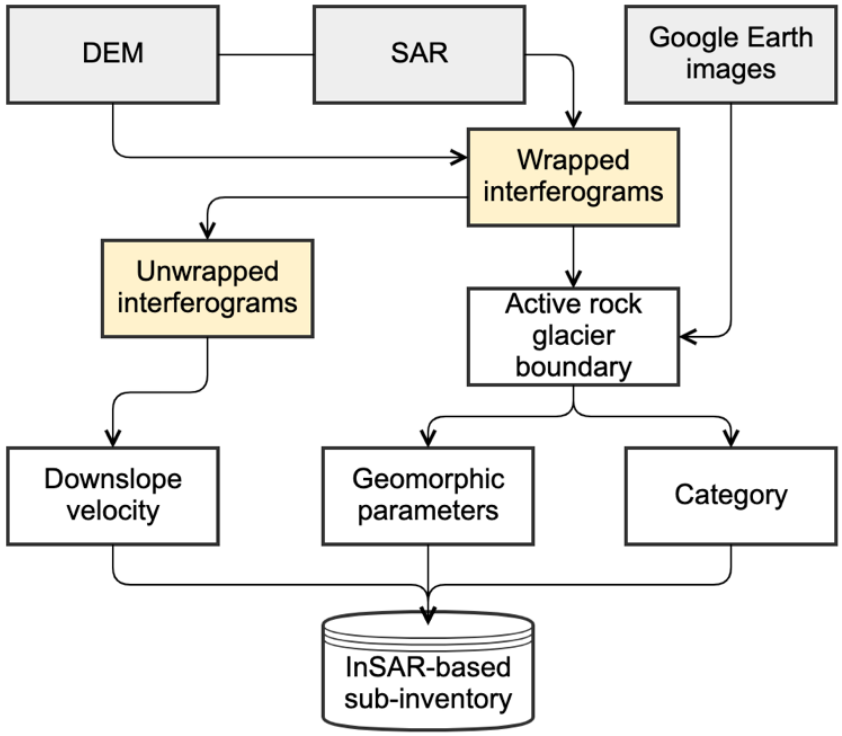



**Figure 3** . Diagram of the workflow to manually map active rock glaciers based on InSAR and Google Earth images.

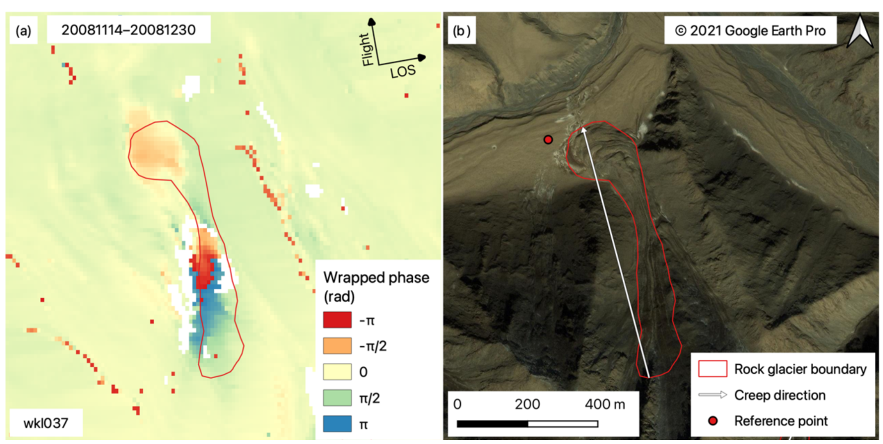



**Figure 4** . An example of identified active rock glacier (ID: wkl037). (a) shows the contrasting wrapped phases between the landform and surrounding background. The ALOS-1 PALSAR image pair generating the interferogram were acquired on 14/11/2008 and 30/12/2008. (b) is the corresponding Google Earth image presenting the geomorphic characteristics of the mapped active rock glacier. The white arrow indicates the direction of the movement, and the red dot marks the location of reference point used for phase correction. This rock glacier is debris-mantled slope-connected.

## 3.2 Automated mapping of rock glaciers using deep learning

Deep learning is the computer algorithm based on neural networks that are capable of determining functions to map from inputs to output (LeCun et al. 2015). It has proved powerful in semantic segmentation by using a convolutional neural network to progressively extract visual features at different levels from input images (Mottaghi et al. 2014), which is suitable for handling difficult mapping tasks as in the case of delineating rock glaciers. Marcer (2020) first proposed a convolutional neural network to detect rock glaciers from orthoimages and suggested further development of this methodology. Robson et al. (2020) has validated a new methodology to detect rock glaciers semi-automatically by advanced image processing techniques including deep learning and object-based image analysis, yet their method has not been used to compile new inventories. Erharter et al. (2022) developed a framework based on U-Net architecture to support the refinement of existing rock glacier inventories. Among the open-source deep learning architectures designed for semantic segmentation, we adopted the DeepLabv3+ with the backbone of Xception71 (termed as DeepLabv3+Xception71 hereafter) as the framework for us to develop the automatic mapping method (Chen et al. 2018) because of its outstanding performance demonstrated in the past PASCAL VOC tests (the benchmark dataset for assessing performance of semantic segmentation models, as detailed in Everingham et al. 2015) and recent research applications to cryospheric remote sensing (Huang et al. 2020; Huang et al. 2021; Zhang et al. 2021a).

Development of the deep learning model for delineating rock glaciers can be divided into three major steps: (1) preparing input data, (2) training and validating deep learning network, and (3) inferring and post-processing results, as detailed below. Figure 5 illustrates the workflow and full details are provided below.

### 3.2.1 Preparing input data

The data preparation step aimed to produce a dataset of optical images and corresponding rock glacier label images to feed into the convolutional neural network. The input optical images were cloud-free (cloud cover $< 5\%$) Sentinel-2 Level-2A products (spatial resolution ~10 m) covering the West Kunlun region acquired during July and August of 2018. We pre-processed the images by extracting the visible red, green, and blue bands and converting to 8-bit, so that the satellite images were in the same format as the training datasets used for pre-training the DeepLabv3+ network we adopted (Chen et al. 2018). To generate the label images, i.e., binary rasters that have pixel values as 0 or 1, with 1 indicating rock glaciers and 0 indicating the background, we used the ESRI Shapefiles of the manually identified rock glaciers created in the InSAR-based mapping process to label the Sentinel-2 images. We removed 118 rock glacier samples from the training dataset because they are unrecognizable due to cloud cover or relatively low resolution (10 m) of the Sentinel-2 images. In addition, we delineated 145 negative polygons, which are similar-looking landforms such as debris-covered glaciers identified by GLIMS and solifluction slopes based on our image interpretation, and environments where no rock glaciers occur, e.g., water bodies and villages. These negative polygons were used to produce negative label images which constitute the input dataset along with the positive ones. More negative samples were included during the iterative training and validating process by adding the incorrectly inferred examples to the negative training dataset for the next experiment. We extracted the positive polygons with their surrounding background (a buffer size of 1,500 m) from the optical images to provide environmental information and cropped these sub-images into image patches of sizes no larger than 480x480 pixels. Finally, we split the whole dataset of input image patches by randomly selecting 90% of the data as the training set (2,007 image patches) and the remaining 10% as the validation set (223 image patches).

### 3.2.2 Training and validating deep learning network

Then we trained the DeepLabv3+Xception71 network with the initial hyper-parameters (e.g., learning rate, learning rate decay, batch size, number of iterations) suggested by Chen et al. (2018) and evaluated the model performance on the training and validation datasets. The evaluation was conducted throughout the training process by monitoring the Intersection over Union (IoU) value, which is defined as:

IoU=TP/(TP+FP+FN)

where TP (true positive), FP (false positive), and FN (false negative) are pixel-based. The mean IoU, which is calculated by averaging the IoU of each class, is commonly adopted to indicate the accuracy of semantic segmentation models. Our network classified each pixel of the optical images into two classes, namely the rock glacier and the background. As the amounts of pixels in the two classes are imbalanced (the rock glacier class only occupies a small portion (~10%) of the image patches), we only used the IoU value of the rock glacier class to represent the model performance. We set 0.80 as the threshold: when the IoU value of a trained model was lower than it, we increased the size and diversity of the training dataset by performing image augmentation (e.g., blurring, rotation, flip) on the positive samples and including incorrectly inferred examples to the negative samples and conducted a new experiment until obtaining a model with target IoU value on the validation dataset and regarded the deep learning network had been well trained. The IoU threshold 0.80 was selected considering the validation mIoU (79.55%) of DeepLabV3+Xception71 on the Cityscapes validation dataset, as detailed in Chen et al. (2018).

### 3.2.3 Inferring and post-processing results

We applied the trained model to map rock glaciers from Sentinel-2 images covering the West Kunlun. The input data occupied ~ 0.6% of the total mapping area. To refine the inference results, we excluded the predicted polygons smaller than 0.03 km2 due to the limited spatial resolution of the Sentinel-2 images and the usual areal extent of rock glaciers. Then we inspected each automatically delineated landform and modified the boundaries when necessary. Finally, we determined the same set of landform attributes as the InSAR-based sub-dataset (Sect 3.1) and compiled the outputs produced by the two methods into one inventory.

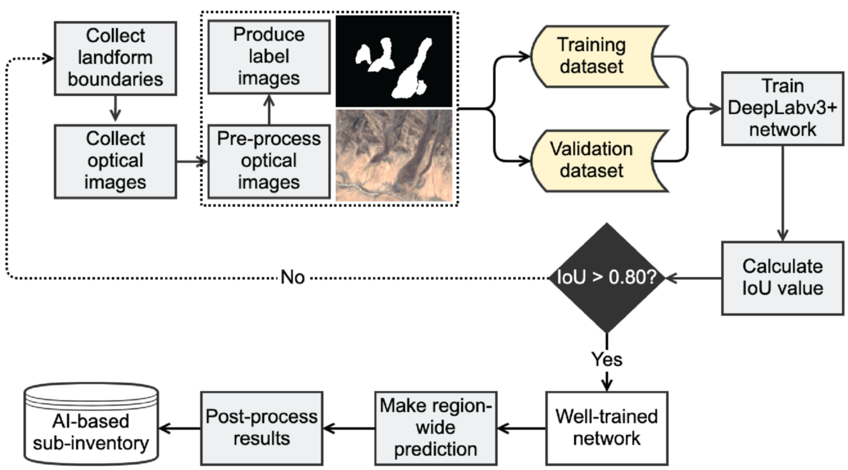



**Figure 5** . Diagram of the workflow to automatically map rock glaciers using DeepLabv3+ network. AI stands for artificial intelligence.

4 Results

We compiled an inventory consisting of 413 rock glaciers across the West Kunlun Mountains: 290 of them were mapped by the conventional method based on interferograms and Google Earth images, the other 123 landforms were identified by deep learning network with supplementary modifications to the automatically delineated boundaries (Figure 1).

In this section, we first present the accuracy of the automated mapping method. Then we analyze the features of all the mapped rock glaciers from the geomorphological perspective. Finally, we summarize the kinematic characteristics of the active rock glaciers measured by InSAR.

4.1 Performance of the automated mapping approach

After iteratively training and improving the model (Sect. 3.2), we trained a model attaining a performance of IoU = 0.801 on both the training and validation datasets (Figure 6).

Over the entire West Kunlun region, our trained model automatically identified and delineated 337 landforms as rock glaciers, among which 123 rock glaciers were newly discovered, 49 predicted polygons were false positives, the rest (165) were true positives but already present in the InSAR-based sub-dataset. Figure 7a and b present the satisfactory accuracy of automated delineation by comparing the deep learning mapped rock glaciers with the manually mapped boundaries in the training and validation datasets, respectively. And Figure 7b is an example just passing the IoU threshold. The delineation accuracy was also acceptable for the newly discovered rock glaciers in general, as shown in Figure 7c. However, we still conducted modifications to 100 out of the 123 landforms to ensure the quality of the mapping results after manual inspection (Figure 7d). The modification was made based on the Sentinel-2 optical images according to the geomorphic criteria presented in the IPA guideline (RGIK, 2021).

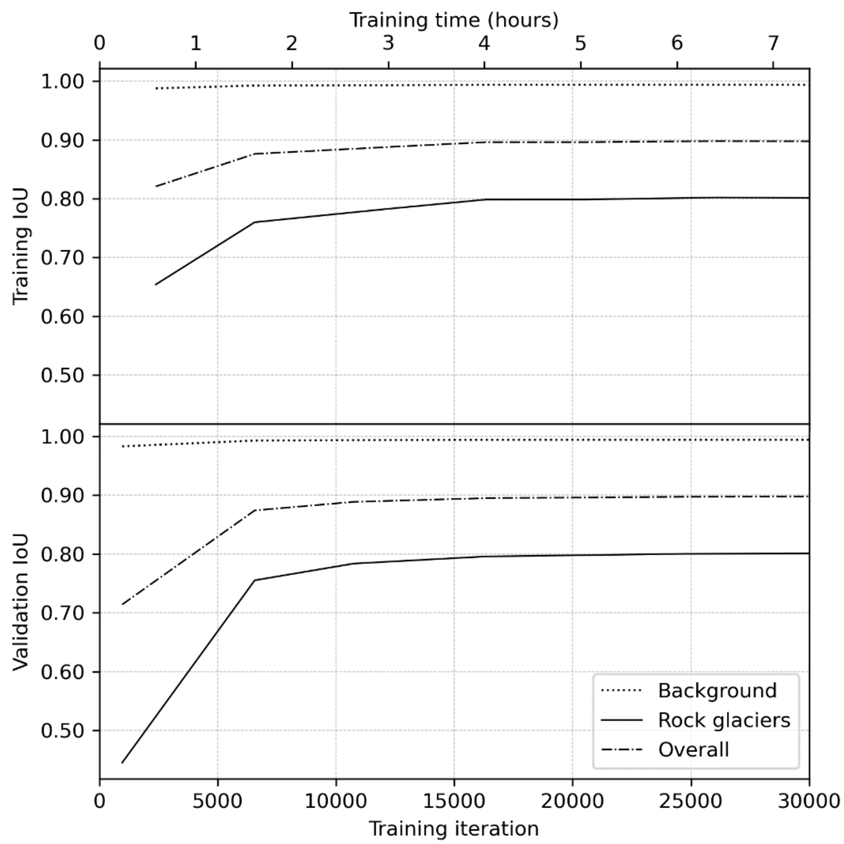



Figure 6. Performance of the deep learning model for recognizing rock glaciers from background on the training and validation datasets, respectively.

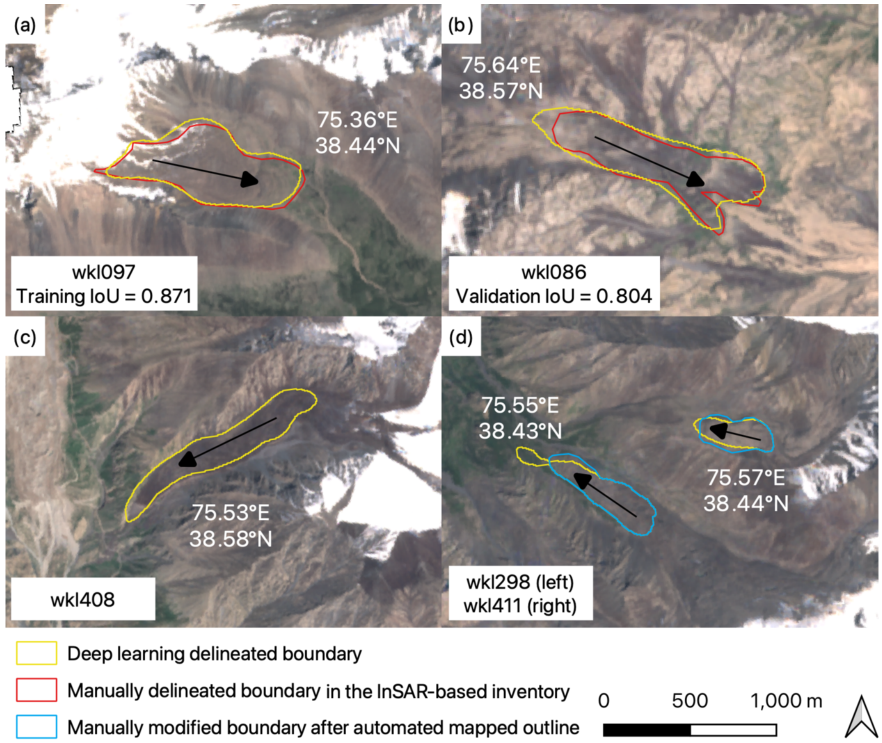



Figure 7. (a) Comparison of the deep learning mapped rock glacier boundary (in yellow) with the manually delineated polygon (in red) in the training dataset. The IoU between the two is 0.871. The black arrow indicates the flow direction. (b) Similar visual comparison between the automatically outlined boundary (in yellow) and the manually mapped one (in red) in the validation dataset, with an IoU of 0.804. (c) Example of a rock glacier newly discovered by deep learning with good delineation accuracy. (d) Examples of two automatically identified and outlined rock glaciers (in yellow) that need manual modifications (in blue). The landform IDs of these examples are labelled on the figures. The background is a Sentinel-2 image acquired on July 12th, 2018.

## 4.2 Geomorphic characteristics of the mapped rock glaciers

Table 2 presents the overall geomorphic information of the mapped rock glaciers. Among the 413 rock glaciers (RGs), almost half of them (202 in total) are spatially connected to glaciers or debris-covered glaciers (G-RGs), and the debris-mantled slope-connected rock glaciers (DMS-RGs) are the second largest category, accounting for ~35% (143 in total) of the mapped landforms. There are 41 rock glaciers occurring at the glacier forefield (GF-RGs) and 27 developing at the terminus of talus (T-RGs), taking up ~10% and ~7% of the total amount, respectively.

All RGs are located at altitudes between 3,389 m and 5,541 m, with an average of 4,623 m. The G-RGs have a similar mean altitude of 4,546 m. Both groups (namely all RGs and the G-RGs) of landforms show a norm distribution in altitude (Figure 8a, c). The DMS-RGs generally occur at a higher altitude (Figure 8b), the average of which is up to 4,889 m, whereas the GF-RGs and T-RGs are distributed at a lower elevation band (Figure 8d, e), whose average altitudes are 4,265 m and 4,332 m, respectively.

The G-RGs are the largest with an average area of 0.40 km$^2$ for individual landforms, followed by GF-RGs with a mean area of 0.38 km$^2$. Both are much (~50%) larger than the mean area (0.26 km$^2$) of all RGs. The DMS-RGs are the smallest (0.05 km$^2$), covering ~7% of the total area occupied by all RGs in the study region. The mean surface slope of all RGs is 17$^{o}$, which is similar to the mean slope (18$^{o}$) of the T-RGs.

The G-RGs and GF-RGs have relatively flat surfaces with mean slope angles of $14^{\circ}$ and $15^{\circ}$, respectively, whereas the DMS-RGs develop a steeper average slope angle of $23^{\circ}$. Most (64%) of the mapped RGs occur on east-facing ($0^{\circ}$–$180^{\circ}$) slopes (Figure 9a) as the movement towards eastern direction is sensitive to the InSAR detection, though the AI-based sub-dataset does not suffer from this problem. Among different categories, the G-RGs and GF-RGs are more frequently located on northeastern-facing ($0^{\circ}$–$90^{\circ}$) slopes (Figure 9c, d), whereas the DMS-RGs and T-RGs mostly move towards southeastern directions ($90^{\circ}$–$180^{\circ}$) (Figure 9b, e).

**Table 2**

*Statistical Summary of the Geomorphic Parameters of the Mapped Rock Glaciers (All RGs), the Debris-mantled Slope-connected Rock Glaciers (DMS-RGs), the Glacier-connected Rock Glaciers (G-RGs), the Glacier forefield-connected Rock Glaciers (GF-RGs), and the Talus-connected Rock Glaciers (T-RGs). Each Column Presents the Mean Values of the Geomorphic Parameter Following by the Corresponding Standard Deviations in the Brackets.*

| | Number | Mean altitude (m) | Slope ($^{\circ}$) | Area ($km^2$) | Total area ($km^2$) |
|---|---|---|---|---|---|
| All RGs | 413 | 4623 (431) | 17 (6) | 0.26 (0.28) | 108.27 |
| DMS-RGs | 143 | 4889 (325) | 23 (5) | 0.05 (0.04) | 7.44 |
| G-RGs | 202 | 4546 (412) | 14 (4) | 0.40 (0.29) | 79.79 |
| GF-RGs | 41 | 4265 (430) | 15 (5) | 0.38 (0.32) | 15.51 |
| T-RGs | 27 | 4332 (224) | 18 (5) | 0.20 (0.13) | 5.53 |

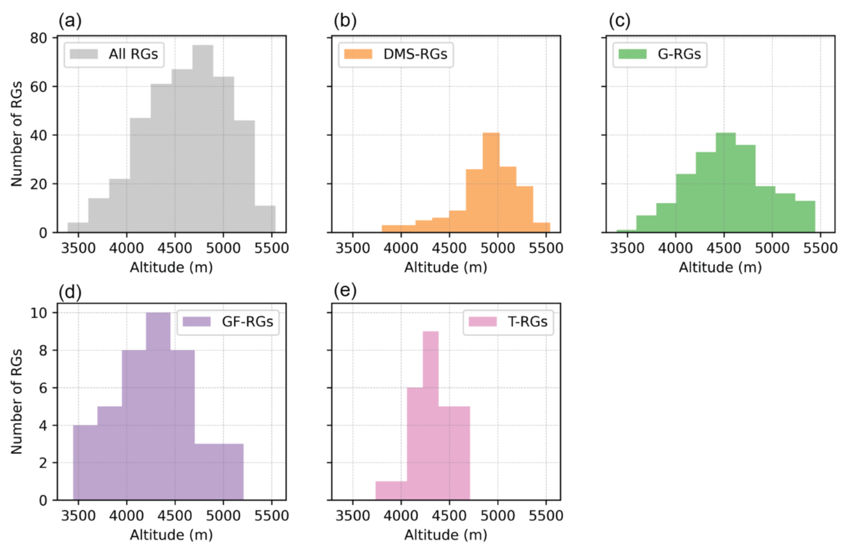



Figure 8. Histograms of the average altitudes for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively. The altitudes are calculated from the SRTM DEM data.

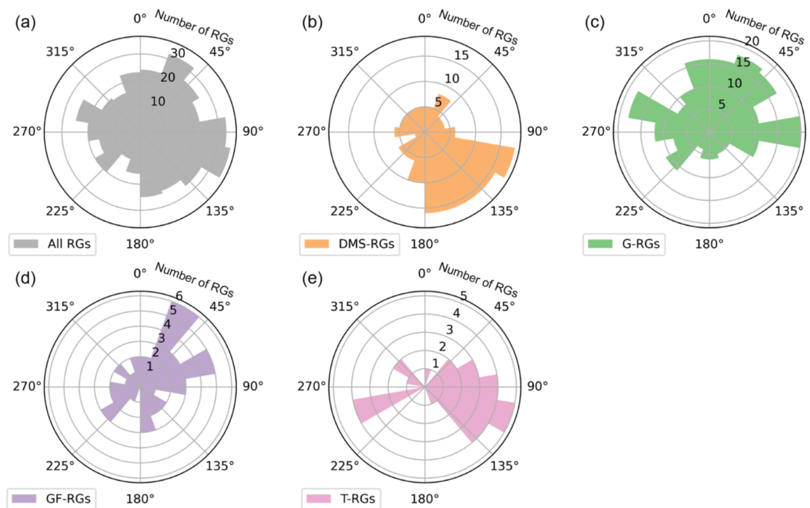



Figure 9. Histograms of the landform aspects for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs.

4.3 Surface kinematics of the mapped active rock glaciers

Among the 290 active rock glaciers mapped based on InSAR, we obtained the surface velocities of 256 rock glaciers in total, including 115 DMS-RGs, 97 G-RGs, 21 GF-RGs, and 23 T-RGs (Figure 10). We lacked high-quality InSAR data over the rest of the mapped rock glaciers. Each velocity result was presented in the format of apparent annual velocity (unit: cm $yr^{-1}$) while the observation period was labelled in the dataset. Figure 11 gives examples of the velocity distributions of the four categories of rock glaciers. The spatial average velocities of the four rock glaciers are 79±6 cm $yr^{-1}$ (Figure 11a), 44±1 cm $yr^{-1}$(Figure 11b), 32±1 cm $yr^{-1}$ (Figure 11c), and 24±1 cm $yr^{-1}$ (Figure 11d), respectively. The movement rates usually decrease towards the terminus with the highest values occurring in the upper and middle parts of the landforms.

Table 3 presents the general statistics of the documented rock glacier velocities. Most (90%) RGs move towards the downslope direction at a rate lower than 50 cm $yr^{-1}$, with a mean velocity of 24 cm $yr^{-1}$. The G-RGs and GF-RGs have faster mean velocities of 31 cm $yr^{-1}$ and 35 cm $yr^{-1}$, respectively, whereas the DMS-RGs and T-RGs creep at a relatively lower rate of 17 cm $yr^{-1}$. The median velocities of the mapped rock glaciers are all smaller than the corresponding mean velocities, indicating most of the kinematic data are distributed near the lower end, as shown in Figure 12. Among all the mapped rock glaciers, a DMS-RG has the largest mean velocity of 127±7 cm $yr^{-1}$.

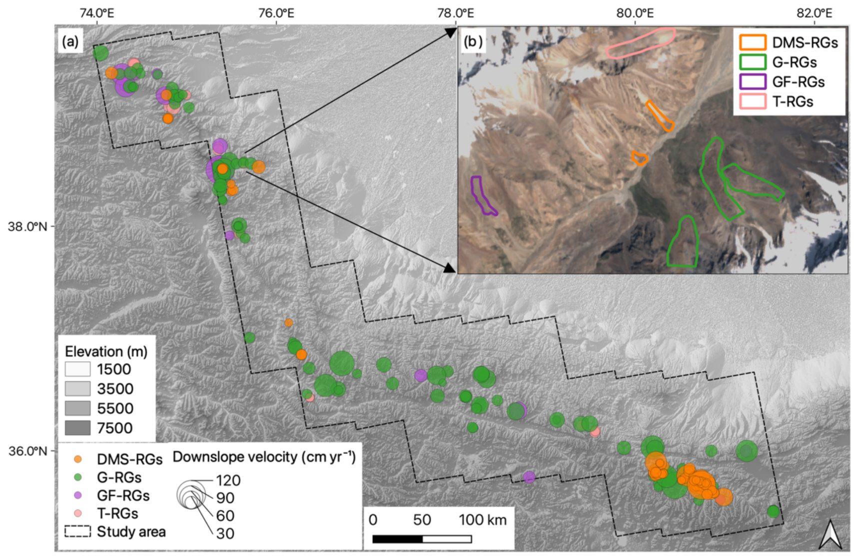



Figure 10. (a) Distribution of the mapped active rock glaciers in the study area. The four categories of rock glaciers are marked by different colours: orange for DMS-RGs, green for G-RGs, purple for GF-RGs, and pink for T-RGs. The size of the dots indicates the mean downslope velocity of each landform. (b) shows the distribution of rock glaciers in a sub-region as indicated by the black arrows. The background is a Sentinel-2 image acquired on July 12, 2018.

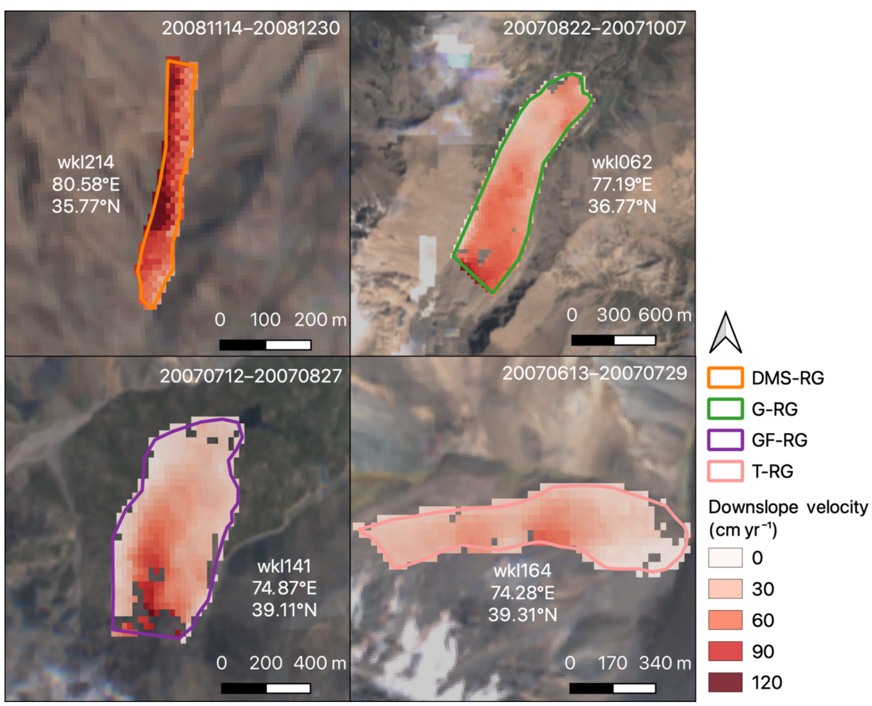



Figure 11. Velocity field maps show the downslope movement rates of rock glaciers of different categories

including a DMS-RG outlined in orange (ID: wkl214), a G-RG in green (ID: wkl062) a GF-RG in purple (ID: wkl141), and a T-RG in pink (ID: wkl164). Their IDs and coordinates of central locations are labelled beside the landforms. The dates on the upper-left corners show the time spans of the velocity measurements. The background maps are Sentinel-2 images acquired in July of 2018.

**Table 3**

*Statistical Summary of the Kinematic Features of the Mapped Rock Glaciers. The Mean Velocity Column Gives the Mean Value of the Rock Glacier Movement Rate for Each Category and the Standard Deviations in the Brackets. The Median and Maximum Velocity Columns Present the Median and Largest Landform Creep Velocity in Each Category with Their Associated Uncertainties, Respectively.*

| | Number | Mean velocity (cm yr$^{-1}$) | Median velocity (cm yr$^{-1}$) | Maximum velocity (cm yr$^{-1}$) |
|---|---|---|---|---|
| All RGs | 256 | 24 (22) | 17±1 | 127±7 |
| DMS-RGs | 115 | 17 (18) | 12±1 | 127±7 |
| G-RGs | 97 | 31 (22) | 25±1 | 110±1 |
| GF-RGs | 21 | 35 (30) | 25±1 | 124±4 |
| T-RGs | 23 | 17 (8) | 16±1 | 36±1 |

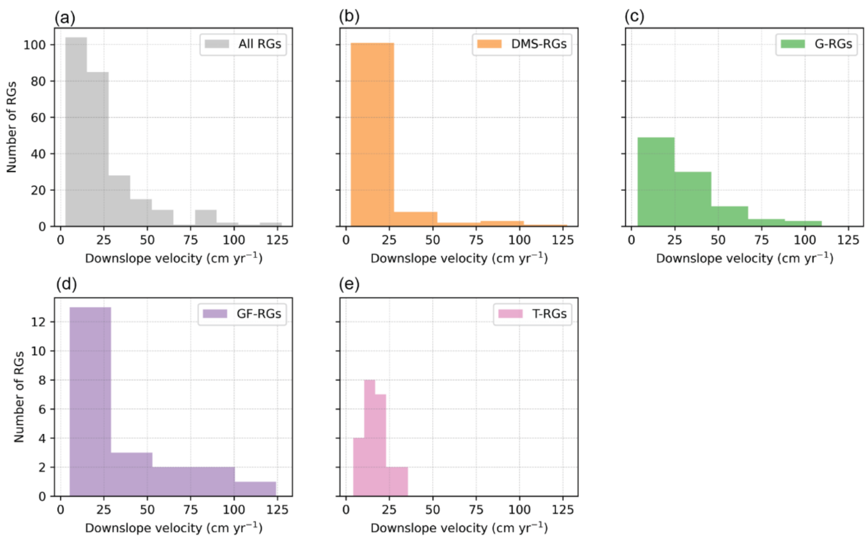



Figure 12. Histograms of the downslope velocities for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively.

5 Discussion

In this section, we firstly summarize the potential and limitations of using the combined methodology for mapping rock glaciers (Sect. 5.1). Then we discuss the genetic and evolutional implications carried by the geomorphic characteristics of the mapped rock glaciers (Sect. 5.2).

5.1 Potential and limitations of the InSAR-Deep learning combined method for mapping rock glaciers

We used an InSAR-Deep learning combined approach to map rock glaciers across the West Kunlun Mountains. The advantage of the combined methodology is twofold: the InSAR-based mapping approach provides essential information on surface kinematics and accurate manual delineation for training the deep learning model; whereas the automated method improves mapping efficiency and more importantly, overcomes the conservativeness of the former approach and expands the InSAR-based sub-dataset. More specifically, some rock glaciers cannot be detected by InSAR due to coherence loss in interferogram, geometric distortions, their topographic orientations insensitive to InSAR line-of-sight measurements, or simply their inactive kinematic status (Wang et al. 2017; Robson et al. 2020). As we used the conventional Differential InSAR method, the smaller amount of interferograms adopted for identifying rock glaciers could lead to more serious omission in the dataset compared with using multi-temporal data (Cai et al., 2021; Zhang et al., 2021; Bertone et al., 2022). By combining the deep learning method, we can map the landforms that had been omitted due to coherence loss in the limited number of interferograms. In addition, rock glaciers moving parallel to the satellite direction, or along a steep slope, or at a very fast or slow pace, can be mapped as well.

However, our deep learning approach has a limited level of automation: the results produced by this methodology still requires manual inspections and modifications to increase the accuracy. Among the factors controlling the deep learning performance, the amount and quality of training and validation samples is one primary factor that affects the mapping accuracy. In this study, the training and validation datasets consist of the boundaries of active rock glaciers in the InSAR-based sub-dataset overlying the Sentinel-2 optical images (examples as shown in Figure 5). The amount of rock glaciers (172) as training and validation samples is in the same order of magnitude as the landform amount (338) used by Robson et al. (2020) for training their deep learning network; yet the training data size can be improved to fully achieve the potential of the state-of-the-art network (DeepLabv3+Xception71) we adopted. Quality of the input images is also moderate, as the Sentinel-2 images have a medium spatial resolution of ~10 m, making it challenging to characterize some rock glaciers, especially small ones with areas smaller than 30,000 $m^2$, from these optical images and possibly leading to inaccuracy in the output. Therefore, manual inspection is required in the post-processing to improve the accuracy of the automatically delineated boundaries. Additionally, the cloud cover of the images hinders the compilation of a complete inventory across the large area. Finally, the Google Earth images (2009–2020) we referred to while creating the InSAR-based sub-dataset are unsynchronized with the Sentinel-2 images (Jul–Aug of 2018) used for producing the training data and for predicting rock glaciers by the trained model. Accordingly, we conducted additional manual inspections while preparing the input data and recognized few differences requiring corrections to the training data because the rock glacier activity is relatively low in the study area (Sect. 4.3), yet this asynchronization may lead to errors in areas where rock glaciers have been moving fast in recent decades.

Furthermore, as we evaluated the effectiveness of the deep learning-based method by applying the trained model to a test area outside the original study area and the validation IoU, which reached a value of ~0.8 comparable with the previous milestone research (Chen et al., 2018), the imperfect metric we achieved (i.e., validation IoU $< 1$) reveals the possibility that some rock glaciers may still be missed in our inventory. We estimated the magnitude of landform underestimation by calculating an index from the validation IoU and a test experiment in a new region (methodology detailed in Text S1); yet it is challenging to provide a precise estimate given that no ground truth data is available over the study region.

In addition, our combined approach is limited to mapping intact landforms, i.e., active and transitional rock glaciers according to the updated categorization scheme of rock glacier activity proposed by RGIK (2021). The InSAR-based sub-inventory contains active rock glaciers, the surface of which display coherent downslope motion as revealed by the interferograms. The transitional rock glaciers, on the other hand, show little movement over the surface, yet their geomorphologic characteristics are less distinguishable from the active landforms. Our deep learning model essentially learned the visual features of active rock glaciers through the optical images in the training dataset, and thus the model is likely to identify and delineate transitional rock glaciers as well. In contrast, relict rock glaciers usually develop distinct geomorphologic features such as subdued topography and vegetation cover, which cannot be mapped by the deep-learning model.

Considering the above limitations, several improvements can be implemented in our future research: (1) to increase the amount and diversity of training samples by including rock glacier boundaries from other regions; (2) to adopt higher-resolution and more cloud-free optical images for producing input dataset; and (3) to use generative adversarial network for translating optical images (for landform inference) to the domain of training data and include them during training. Nevertheless, the developed model will be useful for regions where data gap exists, such as many mountain ranges on the Tibetan Plateau. The inventory produced by this work will serve as an important database for scientific investigations such as managing geohazards (e.g., Kummert and Delaloye, 2018), assessing sediment budget (e.g., Kofler et al., 2022), and monitoring permafrost changes (e.g., Thibert and Bodin, 2022).

### 5.2 Genetic and evolutional implications from the geomorphic characteristics of rock glaciers

We classified the mapped rock glaciers into glacier-connected (G-RGs), glacier-forefield-connected (GF-RGs), debris-mantled slope-connected (DMS-RGs), and talus-connected rock glaciers (T-RGs). This classification scheme was adopted firstly for a practical reason: spatial connection of the rock glacier to its upslope unit is mostly well discernible from the optical images (as illustrated in Figure 2). Moreover, we take the distinction as an indication of the evolution of rock glaciers in terms of their ice origin, sediment source, and debris transfer process. In this subsection, we interpret the genetic and evolutional implications held by the characteristics of rock glaciers in the regional geomorphologic context.

Nearly half (˜49%) of the mapped rock glaciers are spatially connected to glaciers. The amount appears to be reasonable because much of the West Kunlun Mountains (˜12,500 $km^2$) is occupied by modern glaciers (Kääb et al. 2015), constituting one of the most prominent glacierization centers on the Tibetan Plateau (Shi 2006). G-RGs occurring at the immediate downslope of the modern glaciers are likely to have the ice core embedded within the landforms, representing the transitional process from glacier (or debris-covered glacier) to rock glacier (Potter 1972; Whalley and Azizi 1994). However, we postulate that such transition is not actively ongoing given that glaciers in the West Kunlun are in mass balance or even slightly gaining mass in recent decades (Bao et al. 2015; Kääb et al. 2015; Wang et al. 2018; Zhou et al. 2018). The G-RGs are likely to gradually evolve from glaciers since the last cold period, i.e., the Little Ice Age (LIA, 200–600 aBP), and this transitional process tends to slow down in the past several decades (Shi 2006).

Although the landform transition is currently not active in our study area, we propose that the glacier-to-rock glacier continuum, as one classical theory about rock glacier genesis (Berthling 2011), can be adopted to interpret the evolution of the GF-RGs in our inventory. The GF-RGs are spatially disconnected from the upslope modern glaciers (Figure 2c), occurring at the lowest altitudes among all the categories in the study area (Sect. 4.2). Interactions between the GF-RGs and the glacier units are likely to take place during the glacier advance phases in geologic history. Anderson et al. (2018) modelled the glacier – debris-covered glacier – rock glacier evolutional process by simulating the rise of environmental equilibrium line altitude in response to climate warming: a pure glacier melts and separates from the emerging debris-covered terminus, which preserves its ice core due to insulation effect produced by the surface sediment and finally transforms into a rock glacier. Accordingly, we postulate that the GF-RGs in our study area once were part of the upslope glaciers during the Neoglaciation (3000–4000 aBP), when glaciers extended to altitudes hundreds of meters lower than the present glacier termini in the West Kunlun (Li and Shi 1992; Shi 2006).

Interactions between glaciers and rock glaciers are highlighted in the West Kunlun Mountains by the occurrence of abundant surge-type glaciers, whose flow velocities peaking at 0.2–1 km $yr^{-1}$ during their active phases (Quincey et al. 2015; Yasuda and Furuya 2015). Excess materials consisting of ice and debris are carried downslope to areas far beyond the normal termini of the surge-type glaciers and may deliver sediments to the nearby glaciers (or debris-covered glaciers), whereby the surge events tend to contribute to the glacier-to-rock glacier transition provided that glaciers in the West Kunlun will retreat in the future as the glaciers in other alpine regions worldwide nowadays. A comparable case is the ongoing glacier-to-rock glacier transition in the Himalayas: based on field observation and sedimentologic analysis, Jones et al. (2019) elaborated that debris supply from the environmental sediment sources (in addition to the sediment derived from glaciation of the transitional landform per se) drives the evolution as an important factor. Moreover, the ice-debris body transferred and deposited at the far end of a surge-type glacier may gradually evolve into a rock glacier under favorable climatic and topographic conditions. Figure 13 presents an example of the potential evolutional process: the terminus of a surge-type glacier is covered by debris (Chudley and

Willis, 2019) and many thermokarst lakes develop on the surface of the ice-debris mixture, which is likely to transform into a rock glacier in a warming climate. Two rock glaciers (wkl019 and wkl020) are situated in the surroundings and may receive debris and ice input during the surge events.

The genesis of two categories of rock glaciers, namely the T-RGs and the DMS-RGs, are related to periglacial processes. The T-RGs are conventionally considered as features originated in the periglacial domain: the rock glaciers contain interstitial ice developed by various processes such as burial of surface snow that typically occur in the formation of frozen ground (Humlum 1988; Haeberli 2000; Berthling 2011). The DMS-RGs are seldomly reported in the literature (Hu et al. 2021), yet display unique geomorphologic characteristics and constitute the second largest category (~35%) in the study area. In the absence of an upslope glacial system, we suggest that the DMS-RGs also represent the periglacial processes controlling the landform genesis. In comparison with the other three categories, the DMS-RGs occupy the highest and steepest slopes, where mechanical weathering dominates and produces sufficient sediments transferred and accumulated to the base of the slopes. During the glacial period, interstitial ice is formed within the deposits. The ice-debris mixture gradually develops and at one point overcomes the friction and starts to creep as an active rock glacier. Considering the lack of a headwall and the very small dimension (~one fifth of the average size of all mapped landforms, 0.05 $km^2$ vs. 0.26 $km^2$), it is likely that the DMS-RGs began to emerge during the Little Ice Age and are still at their embryonic stage.

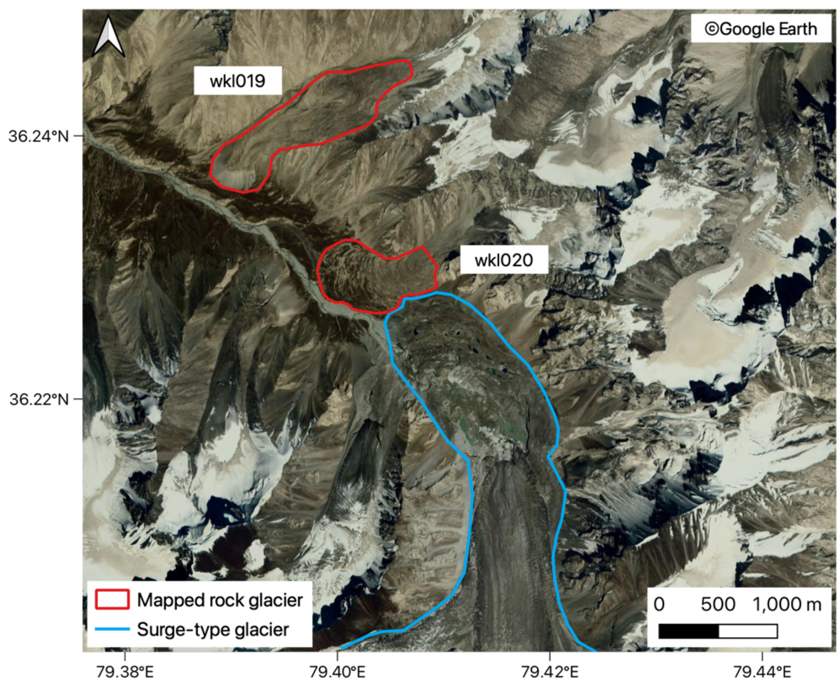



Figure 13. The blue line delineates the boundary of a surge-type glacier (Chudley and Willis 2019). Two rock glaciers (wkl019 and wkl020) in our inventory are situated in the surroundings.

## 6 Conclusions

We mapped rock glaciers at a regional scale and quantified their surface kinematics by combining InSAR and image semantic segmentation powered by deep learning. The combined method was applied to map rock glaciers across the West Kunlun Mountains, where the extremely dry climate represents one characteristic environmental setting on the Tibetan Plateau. We draw the main conclusions as follows:

(1) The DeepLabv3+ network trained by manually labelled data based on InSAR and Google Earth images can successfully identify and delineate rock glaciers from Sentinel-2 images, attaining an IoU value of 0.801 for both training and validation datasets. The well-trained model newly mapped 123 rock glaciers to supplement the non-exhaustive InSAR-based sub-inventory of 290 active rock glaciers.

(2) There are 413 rock glaciers mapped over the study area, including 202 glacier-connected rock glaciers (G-RGs), 143 debris-mantled slope-connected rock glaciers (DMS-RGs), 41 glacier forefield-connected rock glaciers (GF-RGs), and 27 talus-connected rock glaciers (T-RGs). The mapped rock glaciers occupy a total area of ~ 108 $km^2$ and are located at altitudes between 3389 m and 5541 m. The average slope angle is 17° and the dominating landform aspect is towards the east.

(3) Among the mapped rock glaciers, the G-RGs and GF-RGs are larger (average areas: 0.40 $km^2$ and 0.38 $km^2$) and occur on gentler slopes (14° and 15°) predominantly facing northeast, whereas the DMS-RGs are the smallest (0.05 $km^2$) and occupy steep (23°) southeastern-facing slopes at the highest altitudes (4889 m). The T-RGs display a medium size (0.20 $km^2$) and slope angle (18°) and mostly occur on southeastern-facing slopes at lower altitudes (4332 m). The GF-RGs have the lowest average altitude (4265 m).

(4) Considering the geomorphologic context, we postulated that the glacier – debris-covered glacier – rock glacier transition is currently inactive due to the abnormal mass gain of glaciers in the West Kunlun: the mapped G-RGs and GF-RGs evolved from glacier to rock glacier during the past Holocene glacial periods, e.g., the Little Ice Age and the Neoglaciation. Surge events of glaciers may provide material supply and promote the glacier-to-rock glacier transition in the future.

(5) Based on the geomorphic characteristics of mapped rock glaciers, we suggest that the genesis of T-RGs and DMS-RGs are controlled by periglacial processes. The DMS-RGs, as a distinct type of rock glaciers in our study area, represent embryonic rock glaciers derived from prevalent mechanical erosion of the slopes and interstitial ice formation during the Little Ice Age. Note that the hypothesis on landform genesis formulated here needs further validation based on measured evidence.

(6) We adopted the spatial average velocity of all pixels within the boundary of each rock glacier to represent the landform surface kinematics. In total, 256 rock glaciers have valid kinematic quantifications. Nearly 90% of the rock glaciers move slower than 50 cm $yr^{-1}$. The mean downslope velocity is 24 cm $yr^{-1}$, and the standard deviation is 22 cm $yr^{-1}$. The median and maximum velocities are 17 cm $yr^{-1}$ and 127 cm $yr^{-1}$, respectively.

(7) Among the active rock glaciers, the G-RGs and GF-RGs move faster at mean velocities of 31 cm $yr^{-1}$ and 35 cm $yr^{-1}$, respectively. The DMS-RGs and T-RGs creep at a slower average velocity of 17 cm $yr^{-1}$.

In summary, combining InSAR and high-resolution optical imagery to manually map active rock glaciers proves to be an effective way to quantify rock glacier kinematics consistently in remote areas. With the utilization of deep learning techniques, it is promising to compile rock glacier inventories efficiently over a significant extent of permafrost areas, e.g., the Tibetan Plateau, which provides a baseline dataset and allows the monitoring of rock glaciers as indicators of permafrost degradation and potential water sources in a changing climate.

## Data Availablity Statement

The rock glacier inventory produced by this work will be available on PANGAEA (https://doi.org/10.1594/PANGAEA.938686, the link will become accessible once the related paper is published). The training data will be provided by Y. Hu upon request. Codes are available on GitHub (https://github.com/cryoyan/Landuse_DL).

## Acknowledgments

The authors declare that they have no known competing interest that could have appeared to influence the work presented in this paper. This work was supported by the Hong Kong Research Grants Council [grant numbers CUHK14303417, CUHK14303119, and HKPFS PF16-03859]; the National Natural Science Foundations of China [grant number 41690142 and 42071410]; the CUHK Direct Grant for Research [grant number 4053282 and 4053426]; and the CAS "Light of West China" Program. The ALOS-1 PALSAR data are copyrighted and provided by the Japan Aerospace Exploration Agency through the EO-RA2 project ER2A2N081. The TanDEM-X DEM data are copyrighted and provided by the German Aerospace Centre through project DEM_GLAC1408.

## References

Anderson, R. S., Anderson, L. S., Armstrong, W. H., Rossi, M. W., & Crump, S. E. (2018). Glaciation of alpine valleys: The glacier – debris-covered glacier – rock glacier continuum. *Geomorphology* , *311* , 127–142. https://doi.org/10.1016/j.geomorph.2018.03.015

Azócar, G. F., & Brenning, A. (2010). Hydrological and geomorphological significance of rock glaciers in the dry Andes, Chile (27°–33°S). *Permafrost and Periglacial Processes* , *21* (1), 42–53 . https://doi.org/10.1002/ppp.669

Ballantyne, C. K. (2018). *Periglacial geomorphology* . Oxford UK: John Wiley & Sons.

Bao, W., Liu, S., Wei, J., & Guo, W. (2015). Glacier changes during the past 40 years in the West Kunlun Shan. *Journal of Mountain Science* , *12* (2), 344–357 . https://doi.org/10.1007/s11629-014-3220-0

Barboux, C., Delaloye, R., & Lambiel, C. (2014). Inventorying slope movements in an Alpine environment using DInSAR. *Earth Surface Processes and Landforms* , *39* (15), 2087–2099. https://doi.org/10.1002/esp.3603

Barsch, D. (1996). *Rockglaciers: indicators for the present and former geoecology in high mountain environments* (Vol. 16). Springer Science & Business Media.

Berthling, I. (2011). Beyond confusion: Rock glaciers as cryo-conditioned landforms. Geomorphology, *131* (3–4), 98–106. https://doi.org/10.1016/j.geomorph.2011.05.002

Bertone, A., Barboux, C., Bodin, X., Bolch, T., Brardinoni, F., Caduff, R., et al. (2022). Incorporating InSAR kinematics into rock glacier inventories: insights from 11 regions worldwide. *Cryosphere* , *16* (7 ), 2769–2792. https://doi.org/10.5194/tc-16-2769-2022

Biskaborn, B. K., Smith, S. L., Noetzli, J., Matthes, H., Vieira, G., Streletskiy, D. A., et al. (2019). Permafrost is warming at a global scale. *Nature Communications* , *10* (1), 264. https://doi.org/10.1038/s41467-018-08240-4

Brenning, A. (2005). Geomorphological, hydrological and climatic significance of rock glaciers in the Andes of Central Chile (33 –35°S). Permafrost and Periglacial Processes, 16(3),231–240. https://doi.org/10.1002/ppp.528

Cai, J., Wang, X., Liu, G., & Yu, B. (2021). A comparative study of active rock glaciers mapped from geomorphic-and kinematic-based approaches in daxue shan, southeast tibetan plateau. *Remote Sensing* , *13* (23), 4931. https://doi.org/10.3390/rs13234931

Capps, S. R. (1910). Rock Glaciers in Alaska. *The Journal of Geology* , *18* (4), 359–375. https://doi.org/10.1086/621746

Chen, C. W., & Zebker, H. A. (2002). Phase Unwrapping for Large Sar Interferograms: Statistical Segmentation and Generalized Network Models. *IEEE Transactions on Geoscience and Remote Sensing* , *40* (8), 1709. https://doi.org/10.1109/tgrs.2002.802453

Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. *ArXiv* .

Cheng, G., Zhao, L., Li, R., Wu, X., Sheng, Y., Hu, G., et al. (2019). Characteristic, changes and impacts of permafrost on Qinghai-Tibet Plateau. *Chinese Science Bulletin* , *64* (27), 2783–2795. https://doi.org/10.1360/tb-2019-0191

Chudley, T. R., & Willis, I. C. (2019). Glacier surges in the north-west West Kunlun Shan inferred from 1972 to 2017 Landsat imagery.*Journal of Glaciology* , *65* (249), 1–12. https://doi.org/10.1017/jog.2018.94

Chueca, J. (1992). A statistical analysis of the spatial distribution of rock glaciers, Spanish Central Pyrenees. Permafrost and Periglacial Processes, 3(3), 261–265. https://doi.org/10.1002/ppp.3430030316

Cicoira, A., Beutel, J., Faillettaz, J., Gärtner-Roer, I., & Vieli, A. (2019). Resolving the influence of temperature forcing through heat conduction on rock glacier dynamics: A numerical modelling approach. Cryosphere, 13(3), 927–942. https://doi.org/10.5194/tc-13-927-2019

Cicoira, A., Beutel, J., Faillettaz, J., & Vieli, A. (2019). Water controls the seasonal rhythm of rock glacier flow. *Earth and Planetary Science Letters* , *528* , 115844. https://doi.org/10.1016/j.epsl.2019.115844

Cui, Z. (1985). Discovery of Kunlunshan-type rock glaciers and the classification of rock glaciers. *Kexue Tongbao* , *30* (3), 365–369. https://doi.org/10.1360/sb1985-30-3-365

Cui, Z., & Cheng, Z. (1988). Rock glaciers in the source region of Urumqi River, middle Tian Shan, China (pp. 724–727). Presented at the 5th International Conference on Permafrost.

Delaloye, R., Lambiel, C., & Gärtner-Roer, I. (2010). Overview of rock glacier kinematics research in the Swiss Alps: Seasonal rhythm, interannual variations and trends over several decades.*Geographica Helvetica* , *65* (2), 135–145. https://doi.org/10.5194/gh-65-135-2010

Delaloye, R., Morard, S., Barboux, C., Abbet, D., Gruber, V., Riedo, M., & Gachet, S. (2013). Rapidly moving rock glaciers in Mattertal. Geographica Helvetica, 21–31.

Ellis, J. M., & Calkin, P. E. (1979). Nature and Distribution of Glaciers, Neoglacial Moraines, and Rock Glaciers, East-Central Brooks Range, Alaska. *Arctic and Alpine Research* , *11* (4), 403–420. https://doi.org/10.1080/00040851.1979.12004149

Everingham, M., Eslami, S. M. A., Gool, L. V., Williams, C. K. I., Winn, J., & Zisserman, A. (2015). The Pascal Visual Object Classes Challenge: A Retrospective. *International Journal of Computer Vision* ,*111* (1), 98–136. https://doi.org/10.1007/s11263-014-0733-5

Falaschi, D., Castro, M., Masiokas, M., Tadono, T., & Ahumada, A. L. (2014). Rock Glacier Inventory of the Valles Calchaquíes Region (˜ *25* °S), Salta, Argentina, Derived from ALOS Data. Permafrost and Periglacial Processes, 25(1), 69–75. https://doi.org/10.1002/ppp.1801

Geiger, S. T., Daniels, J. M., Miller, S. N., & Nicholas, J. W. (2014). Influence of Rock Glaciers on Stream Hydrology in the La Sal Mountains, Utah. *Arctic, Antarctic, and Alpine Research* , *46* (3),*64* 5–658. https://doi.org/10.1657/1938-4246-46.3.645

Haeberli, W., Hallet, B., Arenson, L., Elconin, R., Humlum, O., Kääb, A., et al. (2006). Permafrost creep and rock glacier dynamics. Permafrost and Periglacial Processes, 17(3), 189–214. https://doi.org/10.1002/ppp.561

Haeberli, Wilfried. (2000). Modern Research Perspectives Relating to Permafrost Creep and Rock Glaciers: A Discussion. Permafrost and Periglacial Processes, 11(4), 290–*293* . https://doi.org/10.1002/1099-1530(200012)11:4<290::aid-ppp372>3.0.co;2-0

Hanssen, R. F. (2001). *Radar interferometry : data interpretation and error analysis* . Dordrecht Boston: Kluwer Academic.

Harris, S. A., Zhijiu, C., & Guodong, C. (1998). Origin of a bouldery diamiction, Kunlun pass, Qinghai-Xizang Plateau, People's Republic of China: gelifluction deposit or rock glacier? Earth Surface Processes and Landforms, 23(10), 943–952. https://doi.org/10.1002/(sici)1096-9837(199810)23:10<943::aid-esp913>3.0.co;2-7

Hu, Y., Liu, L., Wang, X., Zhao, L., Wu, T., Cai, J., et al. (2021). Quantification of permafrost creep provides kinematic evidence for classifying a puzzling periglacial landform. Earth Surface Processes and Landforms, 46(2), 465–477. https://doi.org/10.1002/esp.5039

Huang, L., Luo, J., Lin, Z., Niu, F., & Liu, L. (2020). Using deep learning to map retrogressive thaw slumps in the Beiluhe region (Tibetan Plateau) from CubeSat images. *Remote Sensing of Environment* ,*237* , 111534. https://doi.org/10.1016/j.rse.2019.111534

Huang, L., Liu, L., Luo, J., Lin, Z., & Niu, F. (2021). Automatically quantifying evolution of retrogressive thaw slumps in Beiluhe (Tibetan Plateau) from multi-temporal CubeSat images. *International Journal of Applied Earth Observation and Geoinformation* , *102* , 102399. https://doi.org/10.1016/j.jag.2021.102399

Humlum, O. (2000). The geomorphic significance of rock glaciers: estimates of rock glacier debris volumes and headwall recession rates in West Greenland. Geomorphology, 35(1–2), 41–67. https://doi.org/10.1016/s0169-555x(00)00022-2

Ikeda, A., Matsuoka, N., & Kaab, A. (2008). Fast deformation of perennially frozen debris in a warm rock glacier in the Swiss Alps: An effect of liquid water. *Journal of Geophysical Research: Earth Surface* , *113* (1). https://doi.org/10.1029/2007jf000859

IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change In V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Pean, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekci, R. Yu, and B. Zhou (Ed.)

Janke, J. R. (2007). Colorado Front Range rock glaciers: distribution and topographic characteristics. Arctic, Antarctic, and Alpine Research, 39(1), 74–83.

Jones, D. B., Harrison, S., Anderson, K., & Betts, R. A. (2018). Mountain rock glaciers contain globally significant water stores.*Scientific Reports* , *8* (1), 2834. https://doi.org/10.1038/s41598-018-21244-w

Jones, D. B., Harrison, S., & Anderson, K. (2019). Mountain glacier-to-rock glacier transition. *Global and Planetary Change* ,*181* , 102999. https://doi.org/10.1016/j.gloplacha.2019.102999

Jones, D. B., Harrison, S., Anderson, K., Shannon, S., & Betts, R. A. (2021). Rock glaciers represent hidden water stores in the Himalaya.*Science of The Total Environment* , *793* , 145368. https://doi.org/10.1016/j.scitotenv.2021.145368

Potter Jr., N. (1972). Ice-cored rock glacier, Galena Creek, northern Absaroka Mountains, Wyoming. *Bulletin of the Geological Society of America* , *83* (10), 3025–3058. https://doi.org/10.1130/0016-7606(1972)83[3025:irggcn]2.0.co;2

Kaab, A., Treichler, D., Nuth, C., & Berthier, E. (2015). Brief Communication: Contending estimates of 2003–2008 glacier mass balance over the Pamir–Karakoram–Himalaya. *The Cryosphere* , *9* (2), 557–564. https://doi.org/10.5194/tc-9-557-2015

Kenner, R., Pruessner, L., Beutel, J., Limpach, P., & Phillips, M. (2020). How rock glacier hydrology, deformation velocities and ground temperatures interact: Examples from the Swiss Alps. Permafrost and Periglacial Processes, 31(1), 3–14. https://doi.org/10.1002/ppp.2023

Kofler, C., Mair, V., Comiti, F., Zebisch, M., Schneiderbauer, S., & Steger, S. (2022). Towards a sediment transfer capacity index of rock glaciers: Examples from two catchments in South Tyrol, (Eastern Italian Alps). *Catena* , *216* , 106329. https://doi.org/10.1016/j.catena.2022.106329

Kummert, M., & Delaloye, R. (2018). Mapping and quantifying sediment transfer between the front of rapidly moving rock glaciers and torrential gullies. Geomorphology, *309* , 60–76. https://doi.org/10.1016/j.geomorph.2018.02.021

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature,*521* (7553), 436–444. https://doi.org/10.1038/nature14539

Li, J. (1986). *Tibetan glaciers* . Beijing: Science Press.

Li, K., Chen, J., Zhao, L., Zhang, X., Pang, Q., Fang, H., & Liu, G. (20*12* ). Permafrost distribution in typical area of West Kunlun Mountains derived from a comprehensive survey. *Journal of Glaciology and Geocryology* , *34* (2), 447–454.

Li, S., & Shi, Y. (1992). Glacial and lake fluctuations in the area of the west Kunlun mountains during the last 45000 years. *Annals of Glaciology* , *16* , 79–84.

Liu, L., Millar, C. I., Westfall, R. D., & Zebker, H. A. (2013). Surface motion of active rock glaciers in the Sierra Nevada, California, USA: Inventory and a case study using InSAR. Cryosphere, 7(4),*11* 09–1119. https://doi.org/10.5194/tc-7-1109-2013

Marcer, M., Cicoira, A., Cusicanqui, D., Bodin, X., Echelard, T., Obregon, R., & Schoeneich, P. (2021). Rock glaciers throughout the French Alps accelerated and destabilised since 1990 as air temperatures increased. *Communications Earth and Environment* , *2* (1), 81. https://doi.org/10.1038/s43247-021-00150-6

Marcer, Marco. (2020). Rock glaciers automatic mapping using optical imagery and convolutional neural networks. Permafrost and Periglacial Processes, 31(4), 561–566. https://doi.org/10.1002/ppp.2076

Millar, C.I., & Westfall, R. D. (2008). Rock glaciers and related periglacial landforms in the Sierra Nevada, CA, USA; inventory, distribution and climatic relationships. *Quaternary International* , *188* (1), 90–104. https://doi.org/10.1016/j.quaint.2007.06.004

Millar, Constance I., Westfall, R. D., & Delany, D. L. (2013). Thermal and hydrologic attributes of rock glaciers and periglacial talus landforms: Sierra Nevada, California, USA. Quaternary International,*310* , 169–180. https://doi.org/10.1016/j.quaint.2012.07.019

Mottaghi, R., Chen, X., Liu, X., Cho, N.-G., Lee, S.-W., Fidler, S., et al. (2014). The role of context for object detection and semantic segmentation in the wild. In *Computer Vision and Pattern Recognition* (pp. 891–898). Columbus, OH.

Muller, J., Vieli, A., & Gartner-Roer, I. (2016). Rock glaciers on the run - Understanding rock glacier landform evolution and recent changes from numerical flow modeling. Cryosphere, 10(6), 2865–2886. https://doi.org/10.5194/tc-10-2865-2016

Ni, J., Wu, T., Zhu, X., Hu, G., Zou, D., Wu, X., et al. (2021). Simulation of the Present and Future Projection of Permafrost on the Qinghai-Tibet Plateau with Statistical and Machine Learning Models.*Journal of Geophysical Research: Atmospheres* , *126* (2). https://doi.org/10.1029/2020jd033402

Onaca, A., Ardelean, F., Urdea, P., & Magori, B. (2017). Southern Carpathian rock glaciers: Inventory, distribution and environmental controlling factors. Geomorphology, 293, 391–404. https://doi.org/10.1016/j.geomorph.2016.03.032

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Koppen-Geiger climate classification. *Hydrology and Earth System Sciences* , *11* (5), 1633–1644. https://doi.org/10.5194/hess-11-1633-2007

Quincey, D. J., Glasser, N. F., Cook, S. J., & Luckman, A. (2015). Heterogeneity in Karakoram glacier surges. Journal of Geophysical Research: Earth Surface, *120* (7), 1288–1300. https://doi.org/10.1002/2015jf003515

Ran, Z., & Liu, G. (2018). Rock glaciers in Daxue Shan, south-eastern Tibetan Plateau: an inventory, their distribution, and their environmental controls. The Cryosphere, 12(7), 2327–2340. https://doi.org/10.5194/tc-12-2327-2018

Rangecroft, S., Harrison, S., Anderson, K., Magrath, J., Castel, A. P., & Pacheco, P. (2014). A First Rock Glacier Inventory for the Bolivian Andes. Permafrost and Periglacial Processes, 25(4), 333–343. https://doi.org/10.1002/ppp.1816

Reinosch, E., Gerke, M., Riedel, B., Schwalb, A., Ye, Q., & Buckel, J. (2021). Rock glacier inventory of the western Nyainqentanglha Range, Tibetan Plateau, supported by InSAR time series and automated classification. Permafrost and Periglacial Processes, 32(4), 657–672. https://doi.org/10.1002/ppp.2117

RGIK. (2022). *Towards standard guidelines for inventorying rock glaciers: baseline concepts (Version 4.2.2)* (p. 13).

Robson, B. A., Bolch, T., MacDonell, S., Holbling, D., Rastner, P., & Schaffer, N. (2020). Automated detection of rock glaciers using deep learning and object-based image analysis. Remote Sensing of Environment,*250* , 112033. https://doi.org/10.1016/j.rse.2020.112033

Roer, I., & Nyenhuis, M. (2007). Rockglacier activity studies on a regional scale: comparison of geomorphological mapping and photogrammetric monitoring. Earth Surface Processes and Landforms, 32(12), 1747–1758. https://doi.org/10.1002/esp.1496

Schaffer, N., MacDonell, S., Reveillet, M., Yanez, E., & Valois, R. (2019). Rock glaciers as a water resource in a changing climate in the semiarid Chilean Andes. *Regional Environmental Change* ,*19* (5), 1263–1279. https://doi.org/10.1007/s10113-018-01459-3

Schmid, M.-O., Baral, P., Gruber, S., Shahi, S., Shrestha, T., Stumm, D., & Wester, P. (2015). Assessment of permafrost distribution maps in the Hindu Kush Himalayan region using rock glaciers mapped in Google Earth. The Cryosphere, 9(6), 2089–2099. https://doi.org/10.5194/tc-9-2089-2015

Scotti, R., Brardinoni, F., Alberti, S., Frattini, P., & Crosta, G. B. (2013). A regional inventory of rock glaciers and protalus ramparts in the central Italian Alps. Geomorphology, *186* , 136–149. https://doi.org/10.1016/j.geomorph.2012.12.028

Shi, Y. (2006). *The quaternary glaciations and environmental variations in China* . Shijiazhuang: Hebei Science & Technology Press.

Sorg, A., Kaab, A., Roesch, A., Bigler, C., & Stoffel, M. (2015). Contrasting responses of Central Asian rock glaciers to global warming. Scientific Reports, 5(1), 8228. https://doi.org/10.1038/srep08228

Thibert, E., & Bodin, X. (2022). Changes in surface velocities over four decades on the Laurichard rock glacier (French Alps). Permafrost and Periglacial Processes, 33(3), 323–335. https://doi.org/10.1002/ppp.2159

Villarroel, C. D., Beliveau, G. T., Forte, A. P., Monserrat, O., & Morvillo, M. (2018). DInSAR for a regional inventory of active rock glaciers in the Dry Andes Mountains of Argentina and Chile with sentinel-1 data. Remote Sensing, 10(10), 1588. https://doi.org/10.3390/rs10101588

Wang, X., Liu, L., Zhao, L., Wu, T., Li, Z., & Liu, G. (2017). Mapping and inventorying active rock glaciers in the northern Tien Shan of China using satellite SAR interferometry. Cryosphere, 11(2), 997–1014. https://doi.org/10.5194/tc-11-997-2017

Wang, Y., Hou, S., Huai, B., An, W., Pang, H., & Liu, Y. (2018). Glacier anomaly over the western Kunlun Mountains, Northwestern Tibetan Plateau, since the 1970s. Journal of Glaciology, 64(246), 624–636. https://doi.org/10.1017/jog.2018.53

Whalley, W. B., & Azizi, F. (1994). Rheological models of active rock glaciers: Evaluation, critique and a possible test. Permafrost and Periglacial Processes, 5(1), 37–51. https://doi.org/10.1002/ppp.3430050105

Wirz, V., Gruber, S., Purves, R. S., Beutel, J., Gartner-Roer, I., Gubler, S., & Vieli, A. (2016). Short-term velocity variations at three rock glaciers and their relationship with meteorological conditions.*Earth Surface Dynamics* , *4* (1), 103–123. https://doi.org/10.5194/esurf-4-103-2016

Yang, M., Nelson, F. E., Shiklomanov, N. I., Guo, D., & Wan, G. (2010). Permafrost degradation and its environmental effects on the Tibetan Plateau: A review of recent research. *Earth-Science Reviews* ,*103* (1–2), 31–44. https://doi.org/10.1016/j.earscirev.2010.07.002

Yang, M., Wang, X., Pang, G., Wan, G., & Liu, Z. (2019). The Tibetan Plateau cryosphere: Observations and model simulations for current status and recent changes. Earth-Science Reviews, *190* , 353–369. https://doi.org/10.1016/j.earscirev.2018.12.018

Yao, T., Xue, Y., Chen, D., Chen, F., Thompson, L., Cui, P., et al. (2018). Recent Third Pole's rapid warming accompanies cryospheric melt and water cycle intensification and interactions between monsoon and environment: multi-disciplinary approach with observation, modeling and analysis Recent Third Pole's rapid warming accompanies cryospheric melt and water cycle intensification and interactions between monsoon and environment: multi-disciplinary approach with observation, modeling and analysis. *Bulletin of the American Meteorological Society* ,*100* (3), 423–444. https://doi.org/10.1175/bams-d-17-0057.1

Yasuda, T., & Furuya, M. (2015). Dynamics of surge-type glaciers in West Kunlun Shan, Northwestern Tibet. Journal of Geophysical Research: Earth Surface, 120(11), 2393–2405. https://doi.org/10.1002/2015jf003511

Zhang, E., Liu, L., Huang, L., & Ng, K. S. (2021). An automated, generalized, deep-learning-based method for delineating the calving fronts of Greenland glaciers from multi-sensor remote sensing imagery. Remote Sensing of Environment, *254* , 112265. https://doi.org/10.1016/j.rse.2020.112265

Zhang, G., Yao, T., Xie, H., Yang, K., Zhu, L., Shum, C. K., et al. (2020). Response of Tibetan Plateau lakes to climate change: Trends, patterns, and mechanisms. Earth-Science Reviews, *208* , 103269. https://doi.org/10.1016/j.earscirev.2020.103269

Zhang, X., Feng, M., Zhang, H., Wang, C., Tang, Y., Xu, J., et al. (2021). Detecting rock glacier displacement in the central himalayas using multi-temporal insar. Remote Sensing, 13(23), 4738. https://doi.org/10.3390/rs13234738

Zhao, L., & Sheng, Y. (2019). *Permafrost in the Qinghai-Tibet plateau and its changes* . Beijing: Science Press.

Zhao, L., Zou, D., Hu, G., Du, E., Pang, Q., Xiao, Y., et al. (2020). Changing climate and the permafrost environment on the Qinghai–Tibet (Xizang) plateau. Permafrost and Periglacial Processes, 31(3), 396–405. https://doi.org/10.1002/ppp.2056

Zhao, L., Zou, D., Hu, G., Wu, T., Du, E., Liu, G., et al. (2021). A synthesis dataset of permafrost thermal state for the Qinghai–Tibet (Xizang) Plateau, China. *Earth System Science Data* , *13* (8), 4207–4218. https://doi.org/10.5194/essd-13-4207-2021

Zhou, Y., Li, Z., Li, J., Zhao, R., & Ding, X. (2018). Glacier mass balance in the Qinghai–Tibet Plateau and its surroundings from the mid-1970s to 2000 based on Hexagon KH-9 and SRTM DEMs. Remote Sensing of Environment, *210* , 96–112. https://doi.org/10.1016/j.rse.2018.03.020

Zhu, C., Zhang, J., & Cheng, P. (1996). Rock glaciers in the Central Tianshan Mountains, China. Permafrost and Periglacial Processes, 7(1), 69–78. https://doi.org/10.1002/(sici)1099-1530(199601)7:1<69::aid-ppp210>3.0.co;2-b

Zou, D., Zhao, L., Sheng, Y., Chen, J., Hu, G., Wu, T., et al. (2017). A new map of permafrost distribution on the Tibetan Plateau. The Cryosphere, 11(6), 2527–2542. https://doi.org/10.5194/tc-11-2527-2017

**Mapping and Characterizing Rock Glaciers in the Arid West Kunlun of China**

Yan Hu[1,2], Lin Liu[1,2], Lingcao Huang[3], Lin Zhao[4,5], Tonghua Wu[4], Xiaowen Wang[6,7] and Jiaxin Cai[6]

[1]Institute of Environment, Energy and Sustainability, The Chinese University of Hong Kong, Hong Kong SAR, China.

[2]Earth and Environmental Sciences Programme, Faculty of Science, The Chinese University of Hong Kong, Hong Kong SAR, China.

[3]Earth Science and Observation Center, Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, CO, USA.

[4]Cryosphere Research Station on the Qinghai-Tibet Plateau, State Key Laboratory of Cryospheric Science, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou, China.

[5]School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing, China.

[6]Faculty of Geosciences and Environmental Engineering, Southwest Jiaotong University, Chengdu, China.

[7]State-Province Joint Engineering Laboratory of Spatial Information Technology of High-Speed Rail Safety, Chengdu, China.

Corresponding author: Yan Hu (huyan@link.cuhk.edu.hk)

Key Points:

- A combined use of deep learning and InSAR automates mapping rock glaciers at the regional scale
- We compile the first rock glacier inventory in West Kunlun with kinematic and geomorphic information documented
- Geomorphologic characteristics of rock glaciers provide insights on the glacial and periglacial processes and interactions in West Kunlun

Abstract

Rock glaciers manifest the creep of mountain permafrost occurring in the past or at present. Their presence and dynamics are indicators of permafrost distribution and changes in response to climate forcing. Knowledge of rock glaciers is completely lacking in the West Kunlun, one of the driest mountain ranges in Asia, where widespread permafrost is rapidly warming. In this study, we first mapped and quantified the kinematics of active rock glaciers based on satellite Interferometric Synthetic Aperture Radar (InSAR) and Google Earth images. Then we trained DeepLabv3+, a deep learning network for semantic image segmentation, to automate the mapping task. The well-trained model was applied for a region-wide, extensive delineation of rock glaciers from Sentinel-2 images to map the landforms that were previously missed due to the limitations of the InSAR-based identification. Finally, we mapped 413 rock glaciers across the West Kunlun: 290 of them were active rock glaciers mapped manually based on InSAR and 123 of them were newly identified and outlined by deep learning. The rock glaciers are categorized by their spatial connection to the upslope geomorphic units. All the rock glaciers are located at altitudes between 3,389 m and 5,541 m with an average size of 0.26 $km^2$ and a mean slope angle of 17°. The mean and maximum surface downslope velocities of the active ones are 24 cm $yr^{-1}$ and 127 cm $yr^{-1}$, respectively. Characteristics of the rock glaciers of different categories hold implications on the interactions between glacial and periglacial processes in the West Kunlun.

**Plain Language Summary**

Rock glaciers are debris-ice landforms and indicators of the status of perennially frozen ground, as known as permafrost, which is warming and thawing under climate change. The West Kunlun is among the driest mountain ranges in Asia where permafrost has been changing over the past decades and the information of rock glaciers is completely lacking. In this paper, we developed an effective workflow for mapping rock glaciers in a semi-automated manner and characterized their geomorphology and kinematics. The compiled dataset allows further investigation on rock glaciers for multiple scientific motivations such as geohazard management, water resource assessment, and permafrost change monitoring. The documented geomorphic characteristics provide insights into the genesis and evolution of rock glaciers in the arid mountains.

## 1 Introduction

Rock glaciers are debris-ice landforms widely distributed in areas of mountain permafrost globally (Ballantyne 2018). Rock glaciers have drawn a lot of research interest since their first identification at the beginning of the 20th century (Capps 1910), because they serve as visible indicators for alpine permafrost which is defined by its underground temperature and has been warming and undergoing degradation (Barsch 1996; Biskaborn et al. 2019). Inventorying rock glaciers is therefore motivated by producing baseline knowledge for addressing various scientific questions associated with alpine permafrost, such as indicating permafrost occurrence through the rock glacier distribution, characterizing permafrost changes in the warming climate, and assessing the future hydrological significance of rock glaciers. Several studies have revealed that multi-annual acceleration of rock glaciers is synchronous with the rise of air and ground temperatures (Haeberli et al. 2006; Delaloye et al. 2010; Delaloye et al. 2013; Sorg et al. 2015; Marcer et al. 2021), and their short-term velocity variations are sensitive to the pore pressure in the shear horizon which is adjusted by the precipitation and snow melt conditions (Ikeda et al. 2008; Müller et al. 2016; Wirz et al. 2016; Cicoira et al. 2019a; Cicoira et al. 2019b; Kenner et al. 2019). Hence rock glacier inventories are valuable databases for studying how climatic factors cause permafrost changes manifesting in landform kinematics which can be quantified continuously and remotely. Moreover, rock glaciers can contain massive amounts of ground ice and contribute significantly to hydrological systems in some catchments, such as the Andes, Himalayas, and Sierra Nevada (Azócar and Brenning 2010; Millar et al. 2013; Geiger et al. 2014; Jones et al. 2018; Schaffer et al. 2019; Jones et al. 2021). A comprehensive inventory of rock glaciers lays the foundation for estimating the potential water storage and evaluating their future role in maintaining water supplies.

Numerous efforts have been put into inventorying rock glaciers in various mountain ranges worldwide in the past several decades, such as in Central Europe (Chueca 1992; Roer and Nyenhuis 2007; Scotti et al. 2013; Onaca et al. 2017), South America (Brenning 2005; Falaschi et al. 2014; Rangecroft et al. 2014; Villarroel et al. 2018), and North America (Ellis and Calkin 1979; Janke 2007; Millar and Westfall 2008; Liu et al. 2013). Rock glaciers are abundant in mountainous western China where a vast area of alpine permafrost is underlying and undergoing accelerated degradation in response to the warming climate (Yang et al. 2010; Cheng et al. 2019; Yang et al. 2019; Yao et al. 2019; Zhao and Sheng 2019; Ni et al. 2020; Zhao et al. 2020; IPCC 2021). However, few regional-scale inventories of rock glaciers have been compiled until recently (Schmid et al. 2015; Wang et al. 2017; Ran and Liu 2018), which hinders rock glaciers functioning as a permafrost indicator. Such lack of knowledge is attributed to the following reasons: (1) rock glaciers in western China are mostly situated in remote and harsh environment where early in situ investigations are scarce and limited to case studies or small catchment-scale research (e.g., Cui 1985; Cui and Zhu 1988; Zhu et al. 1996; Harris et al. 1998); (2) mapping rock glaciers conventionally relies on manually detecting and outlining the landforms from optical images (Schmid et al. 2015), which is labor-intensive to apply to large permafrost region (e.g., West Kunlun Mountains) following an exhaustive strategy; (3) contentious opinions of identifying rock glaciers exist due to the complexity of the landforms (Harris et al. 1998; Berthling 2011; Hu et al. 2021), which obscures the definition of rock glaciers and makes it challenging to recognize the landforms.

To address these problems, recent research progress in compiling rock glacier inventories includes (1) integrating InSAR techniques to facilitate active rock glacier identification and kinematics quantification (e.g., Liu et al. 2013; Barboux et al. 2014; Wang et al. 2017; Cai et al. 2021; Reinosch et al. 2021; Zhang et al. 2021); (2) implementing Convolutional Neural Networks (CNN) to demonstrate the feasibility of automating rock glacier delineation (Robson et al. 2020) or to improve the consistency of existing rock glacier inventories (Erharter et al. 2022); and (3) establishing widely accepted inventorying guidelines by the international rock glacier research community (RGIK, 2021).

Here we combine the InSAR technique and a state-of-the-art deep learning network, namely DeepLabv3+ (Chen et al. 2018), to map rock glaciers across the West Kunlun Mountains of China where widespread permafrost is warming (Li 1986; Cheng et al. 2019), and knowledge of rock glaciers is completely lacking. Manual delineation of rock glaciers based on InSAR and high-resolution optical imagery in this study is guided by the baseline concepts proposed by the International Permafrost Association (IPA) Action Group on rock glaciers to ensure a standard high-quality dataset utilized to train the deep learning network, and thus, the final mapping results (RGIK, 2021). We adopted the deep learning method to improve the mapping efficiency by automating the identification and delineation tasks, and more importantly, to generate a more comprehensive geodatabase by overcoming the limitations of InSAR-based method (Cai et al., 2021).

This study aims to develop an automated approach to map rock glaciers on a regional scale in western China, i.e., the West Kunlun Mountains. By producing the first automatically mapped inventory at the mountain-range scale, we demonstrate the effectiveness of using a deep-learning-based method to delineate rock glaciers in a consistent manner across the vast study area. We provide essential attributes to the mapped landforms according to the inventorying guidelines. We also conduct statistical analyses to summarize the spatial distribution and geomorphologic characteristics of the mapped rock glaciers. The compiled inventory will provide baseline knowledge for conducting long-term studies of rock glaciers and permafrost in a changing climate.

2 Study area

The West Kunlun is a major mountain range situated in the northwest of Tibetan Plateau, extending ~800 km from the eastern margin of Pamir Plateau to the Keriya Pass of Kunlun Mountains, with a total study area of ~124,000 km$^2$ (74–81.5°E, 35–39.5°N) (Figure 1). The elevation of the study region ranges between 3,000 m and 7,500 m.

Across the vast study area, a cold desert climate (Köppen climate classification BWk) is dominant (Peel et al. 2007). Climatic conditions of the western part are revealed by the record of the nearest meteorological station in Tashikurgan (75.23°E, 37.77°N; 3090 m a.s.l.) during 1957–2017: the mean annual air temperature (MAAT) and mean annual accumulated precipitation are 4.2°C and 51 mm, respectively (data source: China Meteorological Administration, http://data.cma.cn/). The study area has been warming at a rate of ~0.033°C/yr during the past six decades, similar to the average warming rate (0.031°C/yr) across the entire plateau (Zhang et al. 2020). In the eastern part, the MAAT is -6 °C and the annual precipitation is 103.3 mm, as reported by the Tianshuihai meteorological station (79.55°E, 35.36°N; 4844 m a.s.l) from 2015 to 2018 (Zhao et al. 2021).

The easternmost part of the study region is overlapped with the West Kunlun permafrost survey area (78.8–81.4°E, 34.5–36.0°N; 4,200–6,100 m a.s.l.) established by the Cryosphere Research Station (CRS) on the Qinghai-Tibet Plateau, Chinese Academy of Sciences, where in situ observations are available to represent the state of permafrost in the West Kunlun. Ice-rich permafrost is widely distributed in the survey area (Zhao and Sheng, 2019). The mean annual ground temperature (MAGT) is higher than -2.7°C as revealed by borehole measurements and permafrost was warming at an average rate of 0.11°C/10 yr from 2010 to 2017 (Cheng et al. 2019; Zhao and Sheng, 2019). The lowest altitudinal limit of permafrost occurrence is between 4,650 m and 4,800 m depending on different slope aspects according to previous field surveys focusing on a subregion of the West Kunlun (Li et al. 2012).

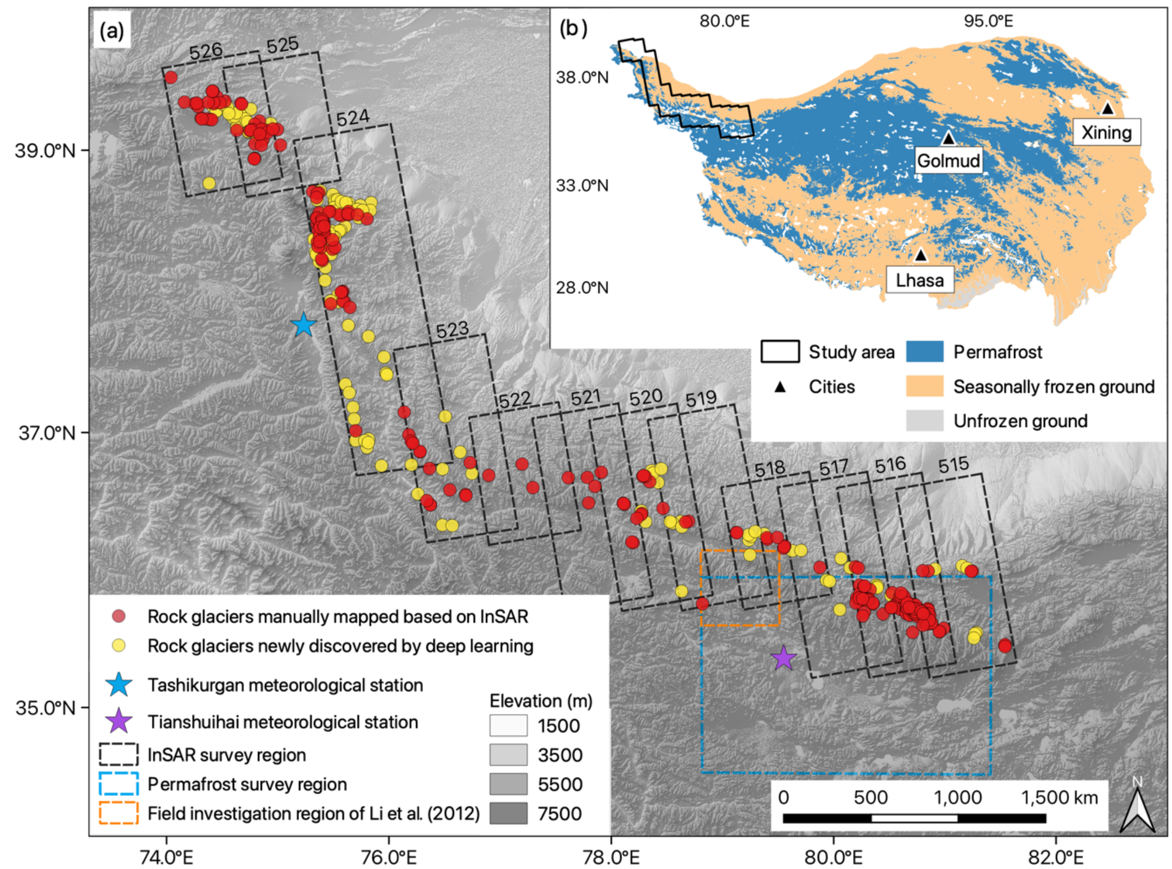



**Figure 1**. (a) Distribution of the mapped rock glaciers in the West Kunlun. The red dots are manually mapped rock glaciers (290 in total), and the yellow dots represent newly identified rock glaciers by our deep learning method but were missed in the InSAR-based sub-dataset (123 in total). The background is a topographical map showing the ground coverage of ALOS-1 PALSAR data used in this study (dashed black box), with the path number of each ground track labelled aside. The dashed blue and orange boxes show the extents of the CRS permafrost survey region (Zhao and Sheng 2019), and the previous in situ investigation area (Li et al. 2012), respectively. The blue and purple

stars denote the location of the Tashikurgan and Tianshuihai meteorological stations, respectively. The topography is plotted based on the 1-arcsec SRTM DEM (spatial resolution ~30 m). (b) Permafrost distribution (Zou et al. 2017) and the location of the study area on the Qinghai-Tibet Plateau.

**Table 1**

*List of Interferograms Generated from ALOS-1 PALSAR Data*

| Path/frame | Start-end dates | Perpendicular baseline (m) |
|---|---|---|
| 515/700 | 20081213–20090128 | 300 |
| 515/710 | 20081213–20090128 | 307 |
| 516/700 | 20081114–20081230 | -38 |
| 516/710 | 20081114–20081230 | -31 |
| 517/700 | 20070829–20071014 | 364 |
| 517/710 | 20070829–20071014 | 370 |
| 518/710 | 20080317–20080502 | 652 |
| 519/710 | 20080102–20080217 | 972 |
| 519/720 | 20080102–20080217 | 337 |
| 520/710 | 20080119–20080305 | 581 |
| 520/720 | 20080119–20080305 | 587 |
| 521/710 | 20080205–20080322 | 62 |
| 521/720 | 20080205–20080322 | 71 |
| 522/720 | 20070822–20071007 | 212 |
| 523/720 | 20070608–20070724 | 288 |
| 523/730 | 20070608–20070724 | 289 |
| 524/730 | 20080210–20080327 | 115 |
| 524/740 | 20070810–20070925 | 108 |
| 524/750 | 20080210–20080327 | 130 |
| 524/760 | 20080210–20080327 | 137 |
| 525/770 | 20070712–20070827 | 292 |
| 526/770 | 20070613–20070729 | 471 |

## 3 Methodology

The method we adopted consists of two parts and is detailed below. First, we mapped active rock glaciers manually from interferograms and Google Earth images. Second, we used the manually labelled images to train a deep learning network, i.e., DeepLabv3+, for mapping rock glaciers automatically from Sentinel-2 optical images.

### 3.1 Mapping active rock glaciers from interferograms and Google Earth images

In this subsection, we first describe the strategy of delineating rock glaciers. Then we present the method for quantifying rock glacier kinematics by InSAR. Finally, we introduce how to determine the geomorphic attributes of the mapped landforms.

### 3.1.1 Manual identification and delineation of rock glaciers

We mapped active rock glaciers by combining two imagery sources: interferograms and Google Earth images. The displacement maps generated by InSAR allow us to easily recognize moving parts of the ground surface, meanwhile the high-resolution and multi-temporal Google Earth images provide geomorphic information to distinguish rock glaciers from the other active surface units, such as debris-covered glaciers, solifluction lobes, and slow-moving landslides. Visual identification was conducted based on the geomorphological criteria proposed by RGIK (2021) including the frontal and lateral margin morphology, and the surface ridge-and-furrow topography as an optional indicator. We then outlined the recognized landforms along their extended geomorphological footprints, i.e., the frontal and lateral margins are included within the boundaries. We followed the IPA guidelines because it provides practical and standardized baseline concepts for identifying and outlining rock glaciers from remote sensing images and readily applicable to producing consistent inventories over wide-extent regions.

### 3.1.2 Kinematic quantification by InSAR

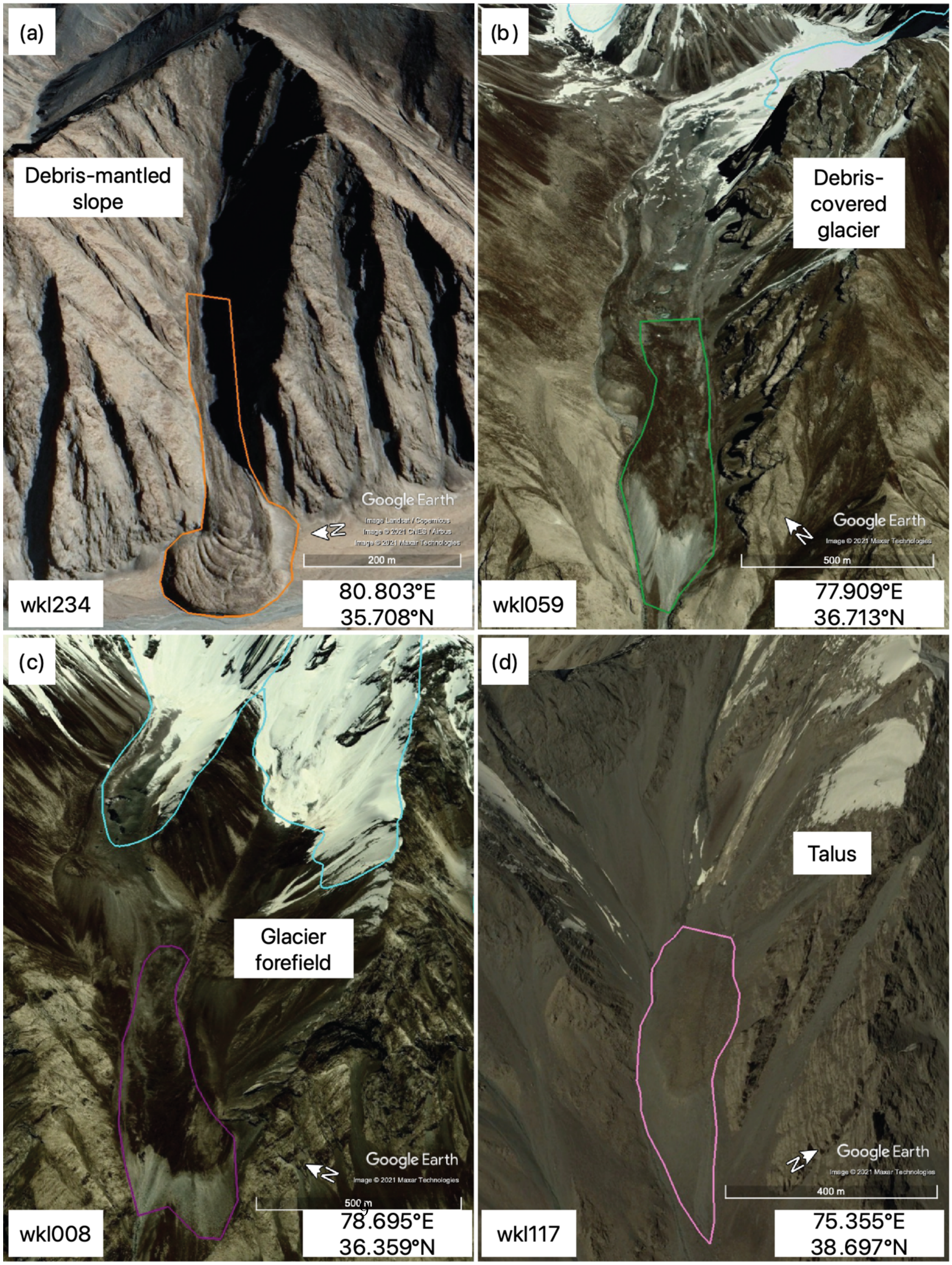
In total, twenty-two interferograms generated from ALOS-1 PALSAR images covering the West Kunlun Mountains were used for ground movement detection between 2007–2008 (Table 1). To maintain high interferometric coherence and reduce topographic error, we selected image pairs with temporal spans of 46 days and perpendicular baselines smaller than 1,000 m. The topographic phase were estimated and removed by using a digital elevation model (DEM) produced by the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of ~30 m over most of the study region. A tile of TanDEM-X DEM (spatial resolution ~12 m) was adopted for correcting topographic phases for one interferogram overlapping with the permafrost survey region. Multi-looking operation and adaptive Goldstein filter (8×8 pixels) were applied in the interferometric processing, which was implemented by the open-source software InSAR Scientific Computing Environment (ISCE) version 2.2.0 (available at https://github.com/isce-framework/isce2). We then unwrapped the interferograms with the SNAPHU (Chen and Zebker 2002) and selected one point located at the flat and stable ground close to each rock glacier to re-reference the unwrapped phases measured within the boundary of each landform. By doing so, we managed to remove the long-wavelength orbital errors and the atmospheric artefacts including the water vapor delay and ionospheric effects, all of which can be assumed identical within the extent of a rock glacier (Hanssen 2001).

We determined the surface downslope velocities of rock glaciers as their kinematic attributes. The surface velocities along the SAR satellite line-of-sight (LOS) direction were derived from the unwrapped interferograms and then projected to the downslope direction of each landform (Hu et al. 2021). Associated uncertainties including the InSAR measurements and geometric parameters were quantified through error propagation (Hu et al. 2021). We used the spatial mean velocity within a rock glacier to represent its overall kinematic status.

Then we refined the results by selecting data that fulfilled the following criteria: (1) after masking out the pixels with low coherence (< 0.3) (Wang et al. 2017), the remaining pixels account for more than 40% of the entire landform extent; (2) the relative errors of the spatial mean velocities are lower than 20%.

#### 3.1.3 Determination of geomorphic attributes

Essential geomorphic attributes such as the elevation range, mean slope angle, and landform aspect were quantified using the SRTM DEM. Qualitative attributes including the spatial connection of the rock glacier to the upslope unit and the activity category were described and assigned to the dataset following the IPA guideline (RGIK, 2021). We primarily classified the mapped rock glaciers according to their spatial connection to the upslope unit because it could provide implications regarding the landform genesis (Sect. 5.2). We used the Global Land Ice Measurements from Space (GLIMS) dataset to help recognize the surrounding glacier units (GLIMS and NSIDC, 2005). Figure 2 presents examples of rock glaciers that were classified by their upslope units into four categories. For instance, Figure 2b shows a glacier-connected rock glacier, the frontal and lateral margins of which are discernible from the Google Earth image, though the rooting zone is ambiguous. We separated the rock glacier from the upslope unit from surface structure in this case. Finally, we created the InSAR-based sub-dataset. The entire workflow is illustrated in Figure 3 with one example shown in Figure 4.




Debris-mantled slope-connected rock glaciers (DMS-RGs)

Glacier-connected rock glaciers (G-RGs)

Glacier forefield-connected rock glaciers (GF-RGs)

Talus-connected rock glaciers (T-RGs)

**Figure 2**. Google Earth images showing rock glaciers of four different types and their spatial connections to the upslope units. (a) shows a debris-mantled slope-connected rock glacier (DMS-RG) in orange (ID: wkl234). (b) focuses on a glacier-connected rock glacier (G-RG) in green (ID: wkl059). The cyan polygons are glaciers outlined by the GLIMS dataset and the feature in between is recognized as a debris-covered glacier. (c) presents a glacier forefield-connected rock glacier (GF-RG) in purple (ID: wkl008). Note that the GF-RG disconnects from the upslope glacier in cyan, whereas the G-RG in (b) is in continuation of the upslope debris-covered glacier. (d) displays a talus-connected rock glacier in pink (ID: wkl117), from which the upslope talus can be observed.

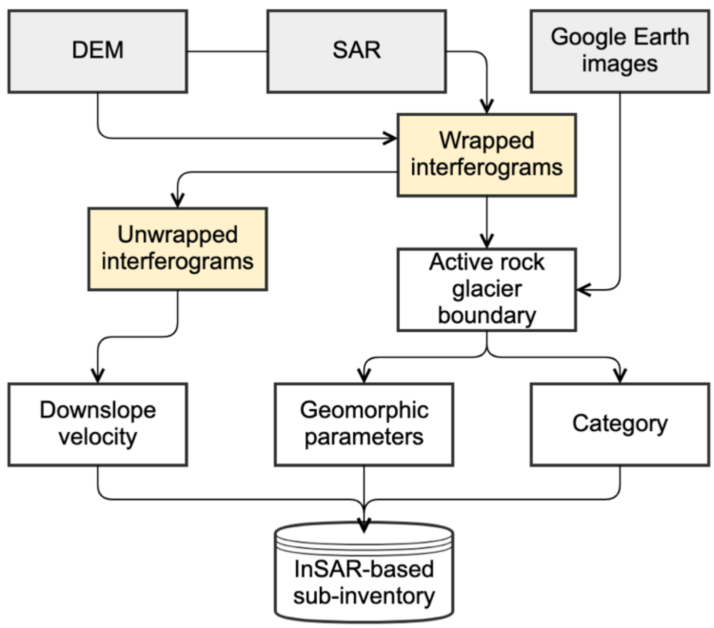



**Figure 3**. Diagram of the workflow to manually map active rock glaciers based on InSAR and Google Earth images.

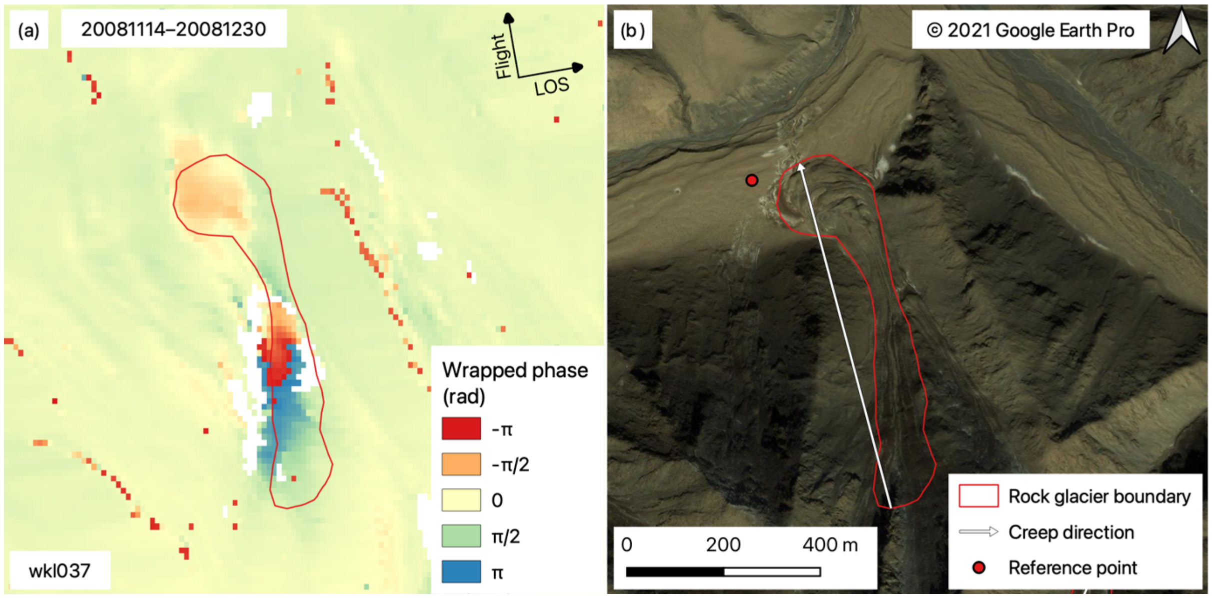



**Figure 4**. An example of identified active rock glacier (ID: wkl037). (a) shows the contrasting wrapped phases between the landform and surrounding background. The ALOS-1 PALSAR image pair generating the interferogram were acquired on 14/11/2008 and 30/12/2008. (b) is the corresponding Google Earth image presenting the geomorphic characteristics of the mapped active rock glacier. The white arrow indicates the direction of the movement, and the red dot marks the location of reference point used for phase correction. This rock glacier is debris-mantled slope-connected.

## 3.2 Automated mapping of rock glaciers using deep learning

Deep learning is the computer algorithm based on neural networks that are capable of determining functions to map from inputs to output (LeCun et al. 2015). It has proved powerful in semantic segmentation by using a convolutional neural network to progressively extract visual features at different levels from input images (Mottaghi et al. 2014), which is suitable for handling difficult mapping tasks as in the case of delineating rock glaciers. Marcer (2020) first proposed a convolutional neural network to detect rock glaciers from orthoimages and suggested further development of this methodology. Robson et al. (2020) has validated a new methodology to detect rock glaciers semi-automatically by advanced image processing techniques including deep learning and object-based image analysis, yet their method has not been used to compile new inventories. Erharter et al. (2022) developed a framework based on U-Net architecture to support the refinement of existing rock glacier inventories. Among the open-source deep learning architectures designed for semantic segmentation, we adopted the DeepLabv3+ with the backbone of Xception71 (termed as DeepLabv3+Xception71 hereafter) as the framework for us to develop the automatic mapping method (Chen et al. 2018) because of its outstanding performance demonstrated in the past PASCAL VOC tests (the benchmark dataset for assessing performance of semantic segmentation models, as detailed in Everingham et al. 2015) and recent research applications to cryospheric remote sensing (Huang et al. 2020; Huang et al. 2021; Zhang et al. 2021a).

Development of the deep learning model for delineating rock glaciers can be divided into three major steps: (1) preparing input data, (2) training and validating deep learning network, and (3) inferring and post-processing results, as detailed below. Figure 5 illustrates the workflow and full details are provided below.

### 3.2.1 Preparing input data

The data preparation step aimed to produce a dataset of optical images and corresponding rock glacier label images to feed into the convolutional neural network. The input optical images were cloud-free (cloud cover $< 5\%$) Sentinel-2 Level-2A products (spatial resolution ~10 m) covering the West Kunlun region acquired during July and August of 2018. We pre-processed the images by extracting the visible red, green, and blue bands and converting to 8-bit, so that the satellite images were in the same format as the training datasets used for pre-training the DeepLabv3+ network we adopted (Chen et al. 2018). To generate the label images, i.e., binary rasters that have pixel values as 0 or 1, with 1 indicating rock glaciers and 0 indicating the background, we used the ESRI Shapefiles of the manually identified rock glaciers created in the InSAR-based mapping process to label the Sentinel-2 images. We removed 118 rock glacier samples from the training dataset because they are unrecognizable due to cloud cover or relatively low resolution (10 m) of the Sentinel-2 images. In addition, we delineated 145 negative polygons, which are similar-looking landforms such as debris-covered glaciers identified by GLIMS and solifluction slopes based on our image interpretation, and environments where no rock glaciers occur, e.g., water bodies and villages. These negative polygons were used to produce negative label images which constitute the input dataset along with the positive ones. More negative samples were included during the iterative training and validating process by adding the incorrectly inferred examples to the negative training dataset for the next experiment. We extracted the positive polygons with their surrounding background (a buffer size of 1,500 m) from the optical images to provide environmental information and cropped these sub-images into image patches of sizes no larger than 480x480 pixels. Finally, we split the whole dataset of input image patches by randomly selecting 90% of the data as the training set (2,007 image patches) and the remaining 10% as the validation set (223 image patches).

### 3.2.2 Training and validating deep learning network

Then we trained the DeepLabv3+Xception71 network with the initial hyper-parameters (e.g., learning rate, learning rate decay, batch size, number of iterations) suggested by Chen et al. (2018) and evaluated the model performance on the training and validation datasets. The evaluation was conducted throughout the training process by monitoring the Intersection over Union (IoU) value, which is defined as:

IoU=TP/(TP+FP+FN)

where TP (true positive), FP (false positive), and FN (false negative) are pixel-based. The mean IoU, which is calculated by averaging the IoU of each class, is commonly adopted to indicate the accuracy of semantic segmentation models. Our network classified each pixel of the optical images into two classes, namely the rock glacier and the background. As the amounts of pixels in the two classes are imbalanced (the rock glacier class only occupies a small portion (~10%) of the image patches), we only used the IoU value of the rock glacier class to represent the model performance. We set 0.80 as the threshold: when the IoU value of a trained model was lower than it, we increased the size and diversity of the training dataset by performing image augmentation (e.g., blurring, rotation, flip) on the positive samples and including incorrectly inferred examples to the negative samples and conducted a new experiment until obtaining a model with target IoU value on the validation dataset and regarded the deep learning network had been well trained. The IoU threshold 0.80 was selected considering the validation mIoU (79.55%) of DeepLabV3+Xception71 on the Cityscapes validation dataset, as detailed in Chen et al. (2018).

### 3.2.3 Inferring and post-processing results

We applied the trained model to map rock glaciers from Sentinel-2 images covering the West Kunlun. The input data occupied ~ 0.6% of the total mapping area. To refine the inference results, we excluded the predicted polygons smaller than 0.03 km2 due to the limited spatial resolution of the Sentinel-2 images and the usual areal extent of rock glaciers. Then we inspected each automatically delineated landform and modified the boundaries when necessary. Finally, we determined the same set of landform attributes as the InSAR-based sub-dataset (Sect 3.1) and compiled the outputs produced by the two methods into one inventory.

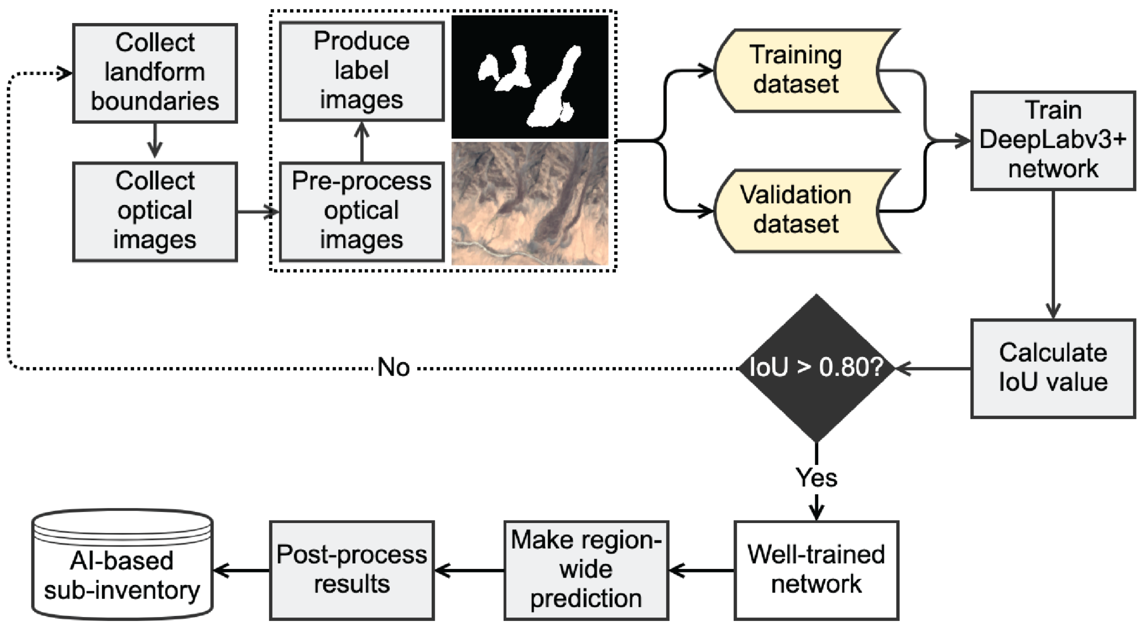



**Figure 5**. Diagram of the workflow to automatically map rock glaciers using DeepLabv3+ network. AI stands for artificial intelligence.

4 Results

We compiled an inventory consisting of 413 rock glaciers across the West Kunlun Mountains: 290 of them were mapped by the conventional method based on interferograms and Google Earth images, the other 123 landforms were identified by deep learning network with supplementary modifications to the automatically delineated boundaries (Figure 1).

In this section, we first present the accuracy of the automated mapping method. Then we analyze the features of all the mapped rock glaciers from the geomorphological perspective. Finally, we summarize the kinematic characteristics of the active rock glaciers measured by InSAR.

4.1 Performance of the automated mapping approach

After iteratively training and improving the model (Sect. 3.2), we trained a model attaining a performance of IoU = 0.801 on both the training and validation datasets (Figure 6).

Over the entire West Kunlun region, our trained model automatically identified and delineated 337 landforms as rock glaciers, among which 123 rock glaciers were newly discovered, 49 predicted polygons were false positives, the rest (165) were true positives but already present in the InSAR-based sub-dataset. Figure 7a and b present the satisfactory accuracy of automated delineation by comparing the deep learning mapped rock glaciers with the manually mapped boundaries in the training and validation datasets, respectively. And Figure 7b is an example just passing the IoU threshold. The delineation accuracy was also acceptable for the newly discovered rock glaciers in general, as shown in Figure 7c. However, we still conducted modifications to 100 out of the 123 landforms to ensure the quality of the mapping results after manual inspection (Figure 7d). The modification was made based on the Sentinel-2 optical images according to the geomorphic criteria presented in the IPA guideline (RGIK, 2021).

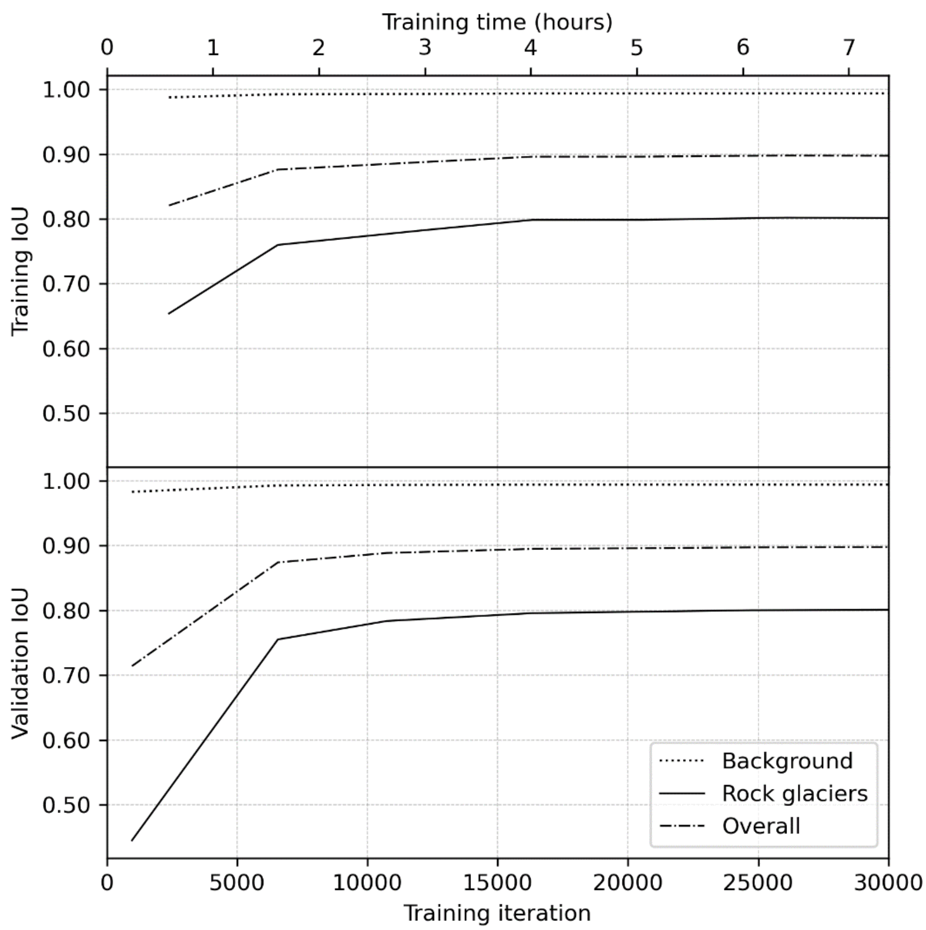



Figure 6. Performance of the deep learning model for recognizing rock glaciers from background on the training and validation datasets, respectively.

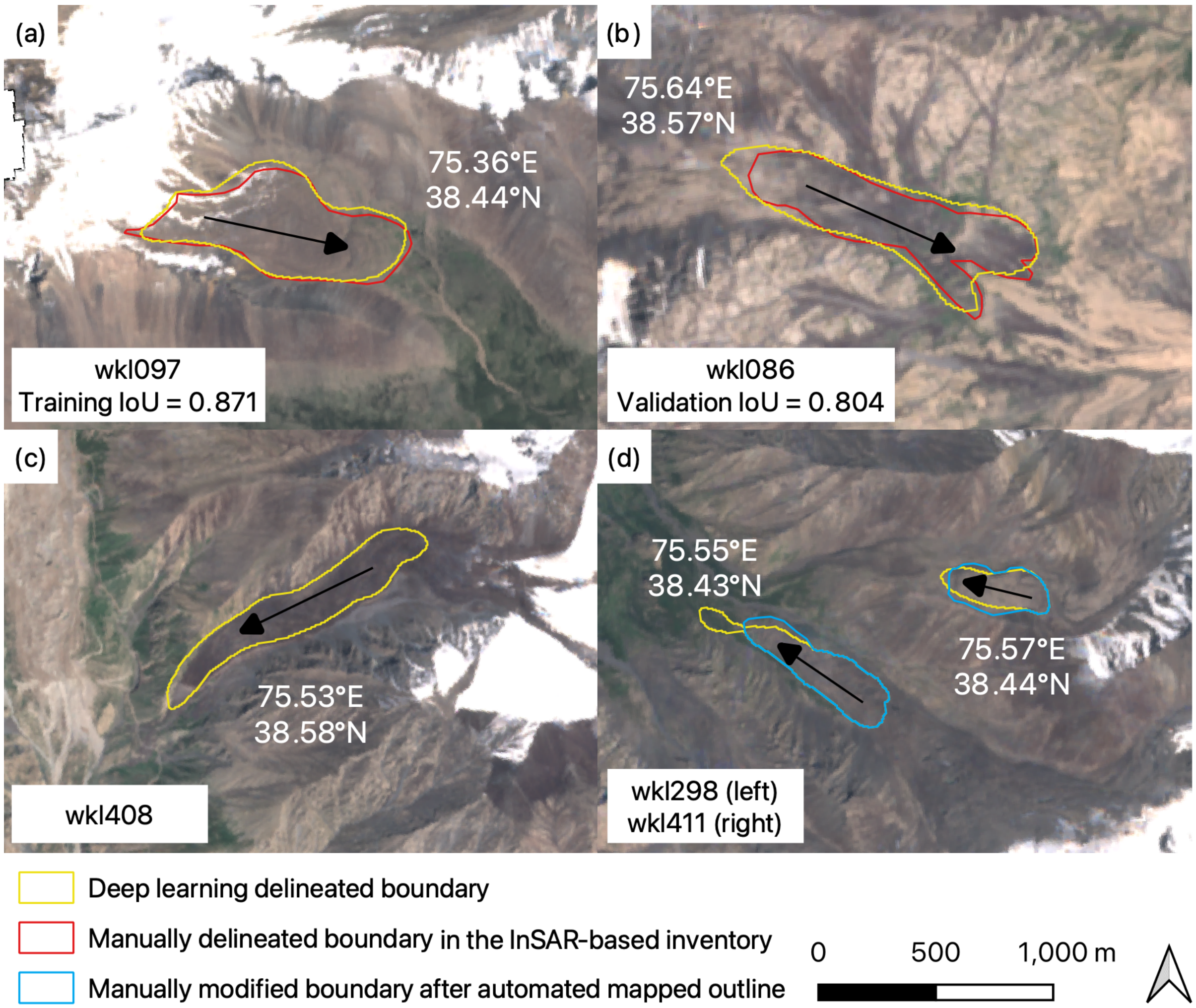



Figure 7. (a) Comparison of the deep learning mapped rock glacier boundary (in yellow) with the manually delineated polygon (in red) in the training dataset. The IoU between the two is 0.871. The black arrow indicates the flow direction. (b) Similar visual comparison between the automatically outlined boundary (in yellow) and the manually mapped one (in red) in the validation dataset, with an IoU of 0.804. (c) Example of a rock glacier newly discovered by deep learning with good delineation accuracy. (d) Examples of two automatically identified and outlined rock glaciers (in yellow) that need manual modifications (in blue). The landform IDs of these examples are labelled on the figures. The background is a Sentinel-2 image acquired on July 12th, 2018.

4.2 Geomorphic characteristics of the mapped rock glaciers

Table 2 presents the overall geomorphic information of the mapped rock glaciers.

Among the 413 rock glaciers (RGs), almost half of them (202 in total) are spatially connected to glaciers or debris-covered glaciers (G-RGs), and the debris-mantled slope-connected rock glaciers (DMS-RGs) are the second largest category, accounting for ~35% (143 in total) of the mapped landforms. There are 41 rock glaciers occurring at the glacier forefield (GF-RGs) and 27 developing at the terminus of talus (T-RGs), taking up ~10% and ~7% of the total amount, respectively.

All RGs are located at altitudes between 3,389 m and 5,541 m, with an average of 4,623 m. The G-RGs have a similar mean altitude of 4,546 m. Both groups (namely all RGs and the G-RGs) of landforms show a norm distribution in altitude (Figure 8a, c). The DMS-RGs generally occur at a higher altitude (Figure 8b), the average of which is up to 4,889 m, whereas the GF-RGs and T-RGs are distributed at a lower elevation band (Figure 8d, e), whose average altitudes are 4,265 m and 4,332 m, respectively.

The G-RGs are the largest with an average area of 0.40 $km^2$ for individual landforms, followed by GF-RGs with a mean area of 0.38 $km^2$. Both are much (~50%) larger than the mean area (0.26 $km^2$) of all RGs. The DMS-RGs are the smallest (0.05 $km^2$), covering ~7% of the total area occupied by all RGs in the study region. The mean surface slope of all RGs is 17º, which is similar to the mean slope (18º) of the T-RGs. The G-RGs and GF-RGs have relatively flat surfaces with mean slope angles of 14º and 15º, respectively, whereas the DMS-RGs develop a steeper average slope angle of 23º. Most (64%) of the mapped RGs occur on east-facing (0º–180º) slopes (Figure 9a) as the movement towards eastern direction is sensitive to the InSAR detection, though the AI-based sub-dataset does not suffer from this problem. Among different categories, the G-RGs and GF-RGs are more frequently located on northeastern-facing (0º–90º) slopes (Figure 9c, d), whereas the DMS-RGs and T-RGs mostly move towards southeastern directions (90º–180º) (Figure 9b, e).

**Table 2**

*Statistical Summary of the Geomorphic Parameters of the Mapped Rock Glaciers (All RGs), the Debris-mantled Slope-connected Rock Glaciers (DMS-RGs), the Glacier-connected Rock Glaciers (G-RGs), the Glacier forefield-connected Rock Glaciers (GF-RGs), and the Talus-connected Rock Glaciers (T-RGs). Each Column Presents the Mean Values of the Geomorphic Parameter Following by the Corresponding Standard Deviations in the Brackets.*

| | Number | Mean altitude (m) | Slope (º) | Area ($km^2$) | Total area ($km^2$) |
|---|---|---|---|---|---|
| All RGs | 413 | 4623 (431) | 17 (6) | 0.26 (0.28) | 108.27 |
| DMS-RGs | 143 | 4889 (325) | 23 (5) | 0.05 (0.04) | 7.44 |
| G-RGs | 202 | 4546 (412) | 14 (4) | 0.40 (0.29) | 79.79 |
| GF-RGs | 41 | 4265 (430) | 15 (5) | 0.38 (0.32) | 15.51 |
| T-RGs | 27 | 4332 (224) | 18 (5) | 0.20 (0.13) | 5.53 |

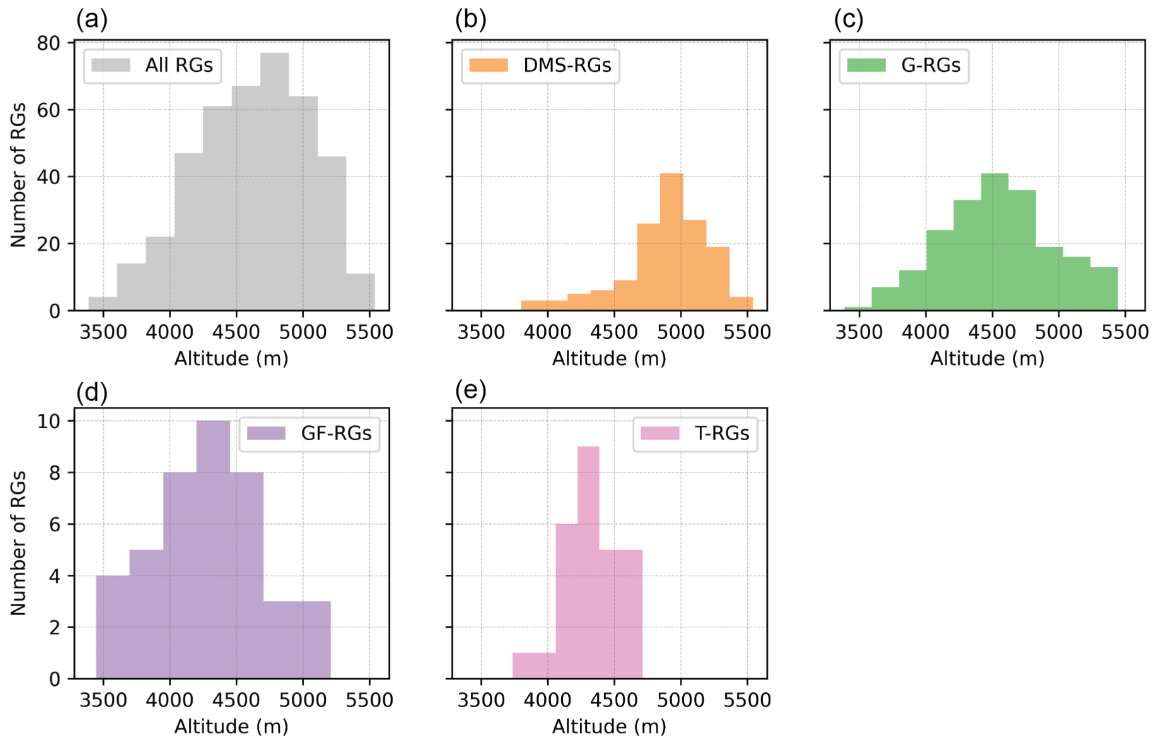



Figure 8. Histograms of the average altitudes for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively. The altitudes are calculated from the SRTM DEM data.

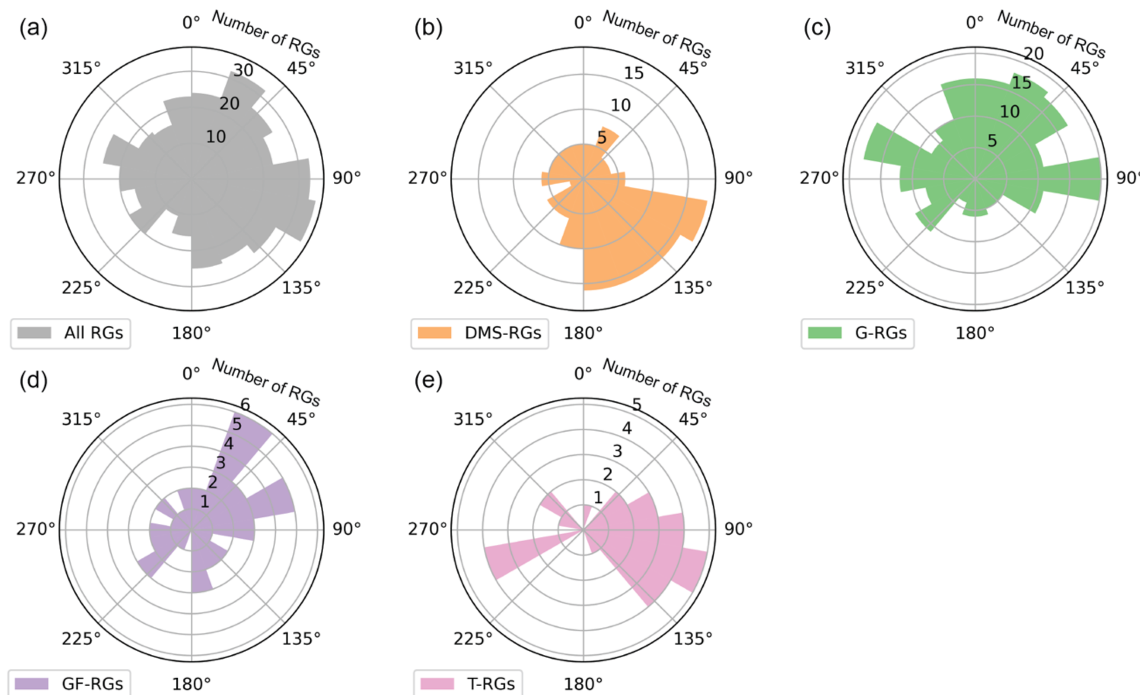



Figure 9. Histograms of the landform aspects for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs.

4.3 Surface kinematics of the mapped active rock glaciers

Among the 290 active rock glaciers mapped based on InSAR, we obtained the surface velocities of 256 rock glaciers in total, including 115 DMS-RGs, 97 G-RGs, 21 GF-RGs, and 23 T-RGs (Figure 10). We lacked high-quality InSAR data over the rest of the mapped rock glaciers. Each velocity result was presented in the format of apparent annual velocity (unit: cm $yr^{-1}$) while the observation period was labelled in the dataset. Figure 11 gives examples of the velocity distributions of the four categories of rock glaciers. The spatial average velocities of the four rock glaciers are 79±6 cm $yr^{-1}$ (Figure 11a), 44±1 cm $yr^{-1}$ (Figure 11b), 32±1 cm $yr^{-1}$ (Figure 11c), and 24±1 cm $yr^{-1}$ (Figure 11d), respectively. The movement rates usually decrease towards the terminus with the highest values occurring in the upper and middle parts of the landforms.

Table 3 presents the general statistics of the documented rock glacier velocities. Most (90%) RGs move towards the downslope direction at a rate lower than 50 cm $yr^{-1}$, with a mean velocity of 24 cm $yr^{-1}$. The G-RGs and GF-RGs have faster mean velocities of 31 cm $yr^{-1}$ and 35 cm $yr^{-1}$, respectively, whereas the DMS-RGs and T-RGs creep at a relatively lower rate of 17 cm $yr^{-1}$. The median velocities of the mapped rock glaciers are all smaller than the corresponding mean velocities, indicating most of the kinematic data are distributed near the lower end, as shown in Figure 12. Among all the mapped rock glaciers, a DMS-RG has the largest mean velocity of 127±7 cm yr$^{-1}$.

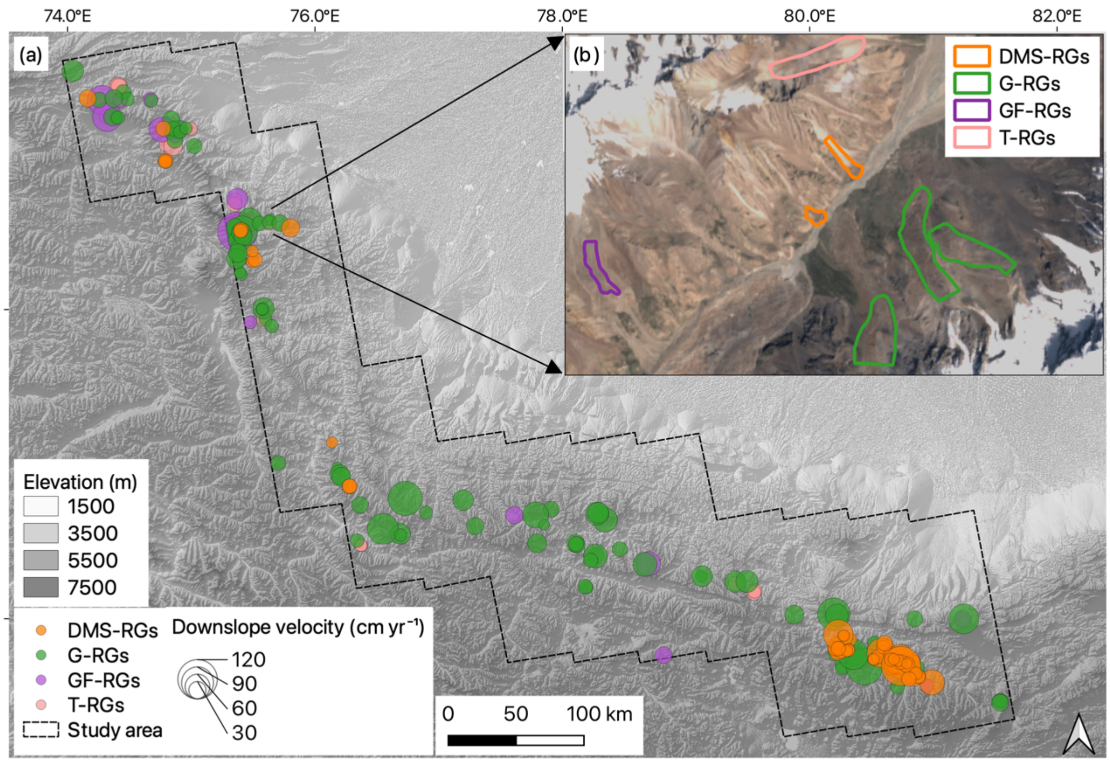



Figure 10. (a) Distribution of the mapped active rock glaciers in the study area. The four categories of rock glaciers are marked by different colours: orange for DMS-RGs, green for G-RGs, purple for GF-RGs, and pink for T-RGs. The size of the dots indicates the mean downslope velocity of each landform. (b) shows the distribution of rock glaciers in a sub-region as indicated by the black arrows. The background is a Sentinel-2 image acquired on July 12, 2018.

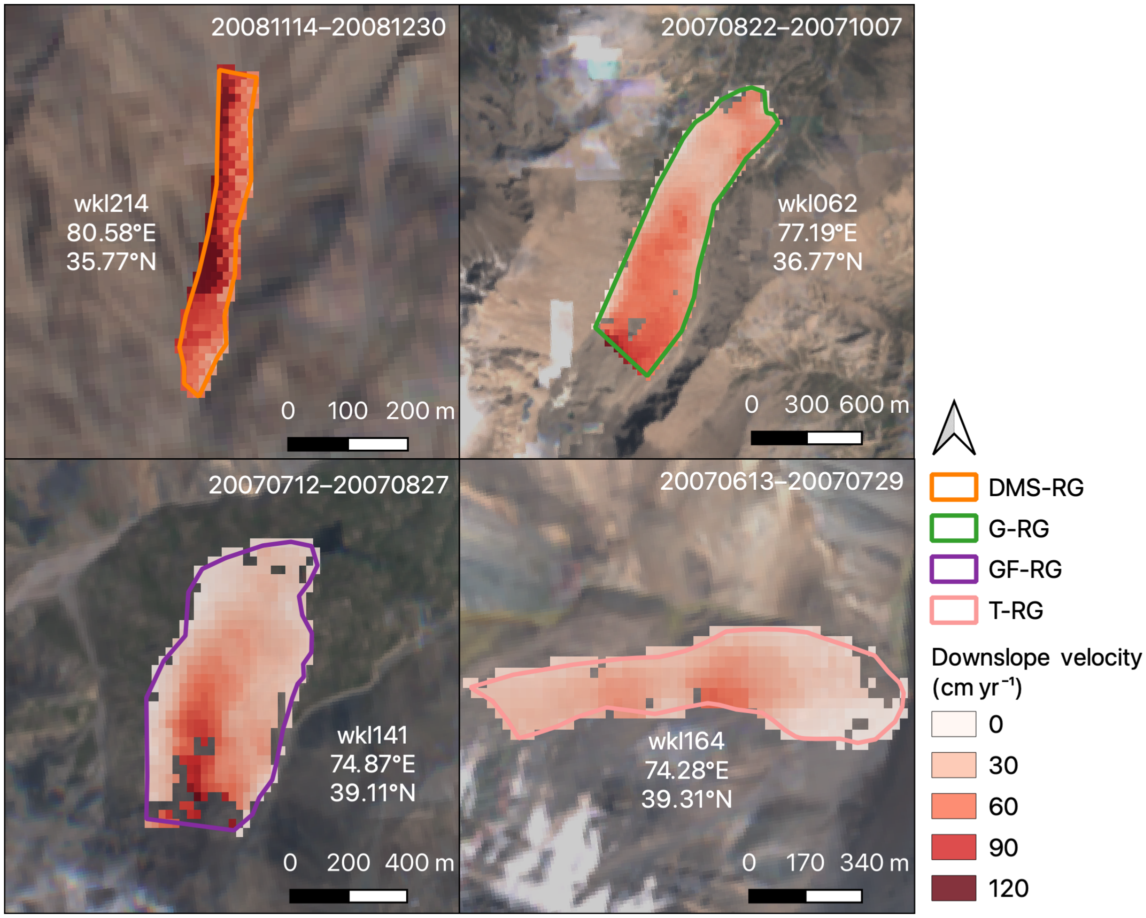



Figure 11. Velocity field maps show the downslope movement rates of rock glaciers of different categories including a DMS-RG outlined in orange (ID: wkl214), a G-RG in green (ID: wkl062) a GF-RG in purple (ID: wkl141), and a T-RG in pink (ID: wkl164). Their IDs and coordinates of central locations are labelled beside the landforms. The dates on the upper-left corners show the time spans of the velocity measurements. The background maps are Sentinel-2 images acquired in July of 2018.

**Table 3**

*Statistical Summary of the Kinematic Features of the Mapped Rock Glaciers. The Mean Velocity Column Gives the Mean Value of the Rock Glacier Movement Rate for Each Category and the Standard Deviations in the Brackets. The Median and Maximum Velocity Columns Present the Median and Largest Landform Creep Velocity in Each Category with Their Associated Uncertainties, Respectively.*

Number Mean velocity (cm yr-1) Median velocity (cm yr-1) Maximum velocity (cm yr-1)

| | Number | Mean velocity (cm yr$^{-1}$) | Median velocity (cm yr$^{-1}$) | Maximum velocity (cm yr$^{-1}$) |
|---|---|---|---|---|
| All RGs | 256 | 24 (22) | 17±1 | 127±7 |
| DMS-RGs | 115 | 17 (18) | 12±1 | 127±7 |
| G-RGs | 97 | 31 (22) | 25±1 | 110±1 |
| GF-RGs | 21 | 35 (30) | 25±1 | 124±4 |
| T-RGs | 23 | 17 (8) | 16±1 | 36±1 |

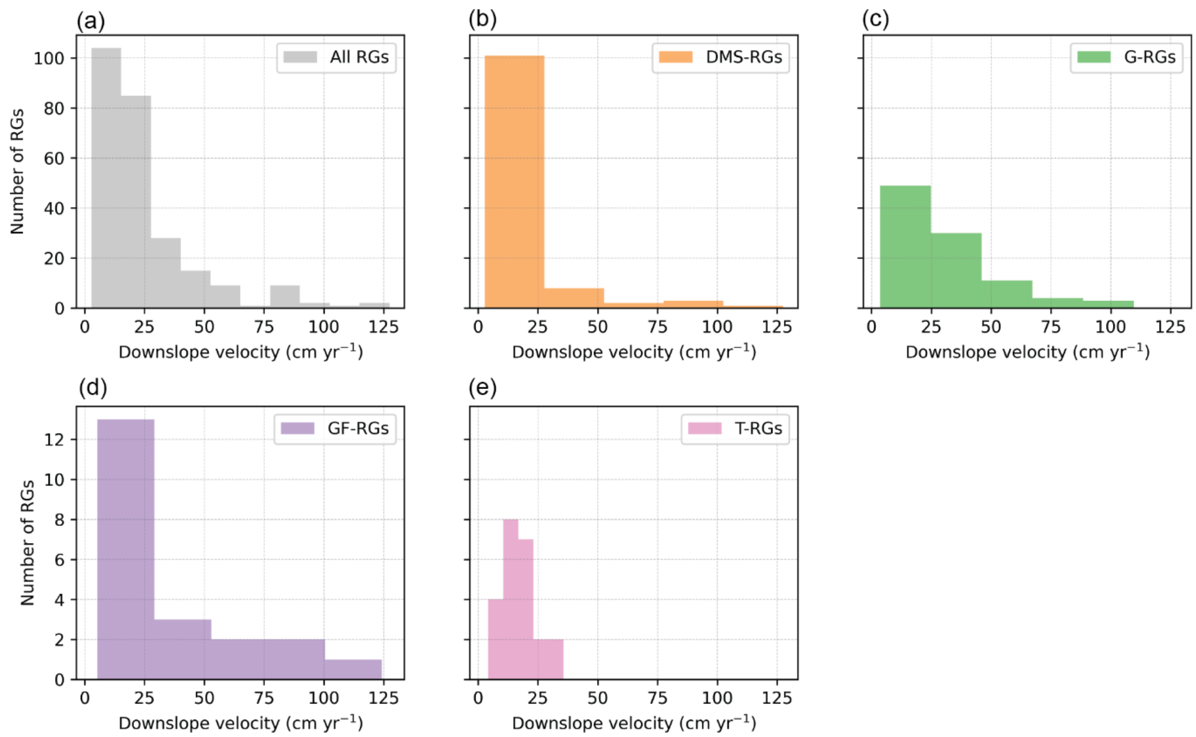



Figure 12. Histograms of the downslope velocities for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively.

## 5 Discussion

In this section, we firstly summarize the potential and limitations of using the combined methodology for mapping rock glaciers (Sect. 5.1). Then we discuss the genetic and evolutional implications carried by the geomorphic characteristics of the mapped rock glaciers (Sect. 5.2).

### 5.1 Potential and limitations of the InSAR-Deep learning combined method for mapping rock glaciers

We used an InSAR-Deep learning combined approach to map rock glaciers across the West Kunlun Mountains. The advantage of the combined methodology is twofold: the InSAR-based mapping approach provides essential information on surface kinematics and accurate manual delineation for training the deep learning model; whereas the automated method improves mapping efficiency and more importantly, overcomes the conservativeness of the former approach and expands the InSAR-based sub-dataset. More specifically, some rock glaciers cannot be detected by InSAR due to coherence loss in interferogram, geometric distortions, their topographic orientations insensitive to InSAR line-of-sight measurements, or simply their inactive kinematic status (Wang et al. 2017; Robson et al. 2020). As we used the conventional Differential InSAR method, the smaller amount of interferograms adopted for identifying rock glaciers could lead to more serious omission in the dataset compared with using multi-temporal data (Cai et al., 2021; Zhang et al., 2021; Bertone et al., 2022). By combining the deep learning method, we can map the landforms that had been omitted due to coherence loss in the limited number of interferograms. In addition, rock glaciers moving parallel to the satellite direction, or along a steep slope, or at a very fast or slow pace, can be mapped as well.

However, our deep learning approach has a limited level of automation: the results produced by this methodology still requires manual inspections and modifications to increase the accuracy. Among the factors controlling the deep learning performance, the amount and quality of training and validation samples is one primary factor that affects the mapping accuracy. In this study, the training and validation datasets consist of the boundaries of active rock glaciers in the InSAR-based sub-dataset overlying the Sentinel-2 optical images (examples as shown in Figure 5). The amount of rock glaciers (172) as training and validation samples is in the same order of magnitude as the landform amount (338) used by Robson et al. (2020) for training their deep learning network; yet the training data size can be improved to fully achieve the potential of the state-of-the-art network (DeepLabv3+Xception71) we adopted. Quality of the input images is also moderate, as the Sentinel-2 images have a medium spatial resolution of ~10 m, making it challenging to characterize some rock glaciers, especially small ones with areas smaller than 30,000 $m^2$, from these optical images and possibly leading to inaccuracy in the output. Therefore, manual inspection is required in the post-processing to improve the accuracy of the automatically delineated boundaries. Additionally, the cloud cover of the images hinders the compilation of a complete inventory across the large area. Finally, the Google Earth images (2009–2020) we referred to while creating the InSAR-based sub-dataset are unsynchronized with the Sentinel-2 images (Jul–Aug of 2018) used for producing the training data and for predicting rock glaciers by the trained model. Accordingly, we conducted additional manual inspections while preparing the input data and recognized few differences requiring corrections to the training data because the rock glacier activity is relatively low in the study area (Sect. 4.3), yet this asynchronization may lead to errors in areas where rock glaciers have been moving fast in recent decades.

Furthermore, as we evaluated the effectiveness of the deep learning-based method by applying the trained model to a test area outside the original study area and the validation IoU, which reached a value of ~0.8 comparable with the previous milestone research (Chen et al., 2018), the imperfect metric we achieved (i.e., validation IoU $< 1$) reveals the possibility that some rock glaciers may still be missed in our inventory. We estimated the magnitude of landform underestimation by calculating an index from the validation IoU and a test experiment in a new region (methodology detailed in Text S1); yet it is challenging to provide a precise estimate given that no ground truth data is available over the study region.

In addition, our combined approach is limited to mapping intact landforms, i.e., active and transitional rock glaciers according to the updated categorization scheme of rock glacier activity proposed by RGIK (2021). The InSAR-based sub-inventory contains active rock glaciers, the surface of which display coherent downslope motion as revealed by the interferograms. The transitional rock glaciers, on the other hand, show little movement over the surface, yet their geomorphologic characteristics are less distinguishable from the active landforms. Our deep learning model essentially learned the visual features of active rock glaciers through the optical images in the training dataset, and thus the model is likely to identify and delineate transitional rock glaciers as well. In contrast, relict rock glaciers usually develop distinct geomorphologic features such as subdued topography and vegetation cover, which cannot be mapped by the deep-learning model.

Considering the above limitations, several improvements can be implemented in our future research: (1) to increase the amount and diversity of training samples by including rock glacier boundaries from other regions; (2) to adopt higher-resolution and more cloud-free optical images for producing input dataset; and (3) to use generative adversarial network for translating optical images (for landform inference) to the domain of training data and include them during training. Nevertheless, the developed model will be useful for regions where data gap exists, such as many mountain ranges on the Tibetan Plateau. The inventory produced by this work will serve as an important database for scientific investigations such as managing geohazards (e.g., Kummert and Delaloye, 2018), assessing sediment budget (e.g., Kofler et al., 2022), and monitoring permafrost changes (e.g., Thibert and Bodin, 2022).

### 5.2 Genetic and evolutional implications from the geomorphic characteristics of rock glaciers

We classified the mapped rock glaciers into glacier-connected (G-RGs), glacier-forefield-connected (GF-RGs), debris-mantled slope-connected (DMS-RGs), and talus-connected rock glaciers (T-RGs). This classification scheme was adopted firstly for a practical reason: spatial connection of the rock glacier to its upslope unit is mostly well discernible from the optical images (as illustrated in Figure 2). Moreover, we take the distinction as an indication of the evolution of rock glaciers in terms of their ice origin, sediment source, and debris transfer process.

In this subsection, we interpret the genetic and evolutional implications held by the characteristics of rock glaciers in the regional geomorphologic context.

Nearly half (~49%) of the mapped rock glaciers are spatially connected to glaciers. The amount appears to be reasonable because much of the West Kunlun Mountains (~12,500 $km^2$) is occupied by modern glaciers (Kääb et al. 2015), constituting one of the most prominent glacierization centers on the Tibetan Plateau (Shi 2006). G-RGs occurring at the immediate downslope of the modern glaciers are likely to have the ice core embedded within the landforms, representing the transitional process from glacier (or debris-covered glacier) to rock glacier (Potter 1972; Whalley and Azizi 1994). However, we postulate that such transition is not actively ongoing given that glaciers in the West Kunlun are in mass balance or even slightly gaining mass in recent decades (Bao et al. 2015; Kääb et al. 2015; Wang et al. 2018; Zhou et al. 2018). The G-RGs are likely to gradually evolve from glaciers since the last cold period, i.e., the Little Ice Age (LIA, 200–600 aBP), and this transitional process tends to slow down in the past several decades (Shi 2006).

Although the landform transition is currently not active in our study area, we propose that the glacier-to-rock glacier continuum, as one classical theory about rock glacier genesis (Berthling 2011), can be adopted to interpret the evolution of the GF-RGs in our inventory. The GF-RGs are spatially disconnected from the upslope modern glaciers (Figure 2c), occurring at the lowest altitudes among all the categories in the study area (Sect. 4.2). Interactions between the GF-RGs and the glacier units are likely to take place during the glacier advance phases in geologic history. Anderson et al. (2018) modelled the glacier – debris-covered glacier – rock glacier evolutional process by simulating the rise of environmental equilibrium line altitude in response to climate warming: a pure glacier melts and separates from the emerging debris-covered terminus, which preserves its ice core due to insulation effect produced by the surface sediment and finally transforms into a rock glacier. Accordingly, we postulate that the GF-RGs in our study area once were part of the upslope glaciers during the Neoglaciation (3000–4000 aBP), when glaciers extended to altitudes hundreds of meters lower than the present glacier termini in the West Kunlun (Li and Shi 1992; Shi 2006).

Interactions between glaciers and rock glaciers are highlighted in the West Kunlun Mountains by the occurrence of abundant surge-type glaciers, whose flow velocities peaking at 0.2–1 km $yr^{-1}$ during their active phases (Quincey et al. 2015; Yasuda and Furuya 2015). Excess materials consisting of ice and debris are carried downslope to areas far beyond the normal termini of the surge-type glaciers and may deliver sediments to the nearby glaciers (or debris-covered glaciers), whereby the surge events tend to contribute to the glacier-to-rock glacier transition provided that glaciers in the West Kunlun will retreat in the future as the glaciers in other alpine regions worldwide nowadays. A comparable case is the ongoing glacier-to-rock glacier transition in the Himalayas: based on field observation and sedimentologic analysis, Jones et al. (2019) elaborated that debris supply from the environmental sediment sources (in addition to the sediment derived from glaciation of the transitional landform per se) drives the evolution as an important factor. Moreover, the ice-debris body transferred and deposited at the far end of a surge-type glacier may gradually evolve into a rock glacier under favorable climatic and topographic conditions. Figure 13 presents an example of the potential evolutional process: the terminus of a surge-type glacier is covered by debris (Chudley and Willis, 2019) and many thermokarst lakes develop on the surface of the ice-debris mixture, which is likely to transform into a rock glacier in a warming climate. Two rock glaciers (wkl019 and wkl020) are situated in the surroundings and may receive debris and ice input during the surge events.

The genesis of two categories of rock glaciers, namely the T-RGs and the DMS-RGs, are related to periglacial processes. The T-RGs are conventionally considered as features originated in the periglacial domain: the rock glaciers contain interstitial ice developed by various processes such as burial of surface snow that typically occur in the formation of frozen ground (Humlum 1988; Haeberli 2000; Berthling 2011). The DMS-RGs are seldomly reported in the literature (Hu et al. 2021), yet display unique geomorphologic characteristics and constitute the second largest category (~35%) in the study area. In the absence of an upslope glacial system, we suggest that the DMS-RGs also represent the periglacial processes controlling the landform genesis. In comparison with the other three categories, the DMS-RGs occupy the highest and steepest slopes, where mechanical weathering dominates and produces sufficient sediments transferred and accumulated to the base of the slopes. During the glacial period, interstitial ice is formed within the deposits. The ice-debris mixture gradually develops and at one point overcomes the friction and starts to creep as an active rock glacier. Considering the lack of a headwall and the very small dimension (~one fifth of the average size of all mapped landforms, 0.05 $km^2$ vs. 0.26 $km^2$), it is likely that the DMS-RGs began to emerge during the Little Ice Age and are still at their embryonic stage.

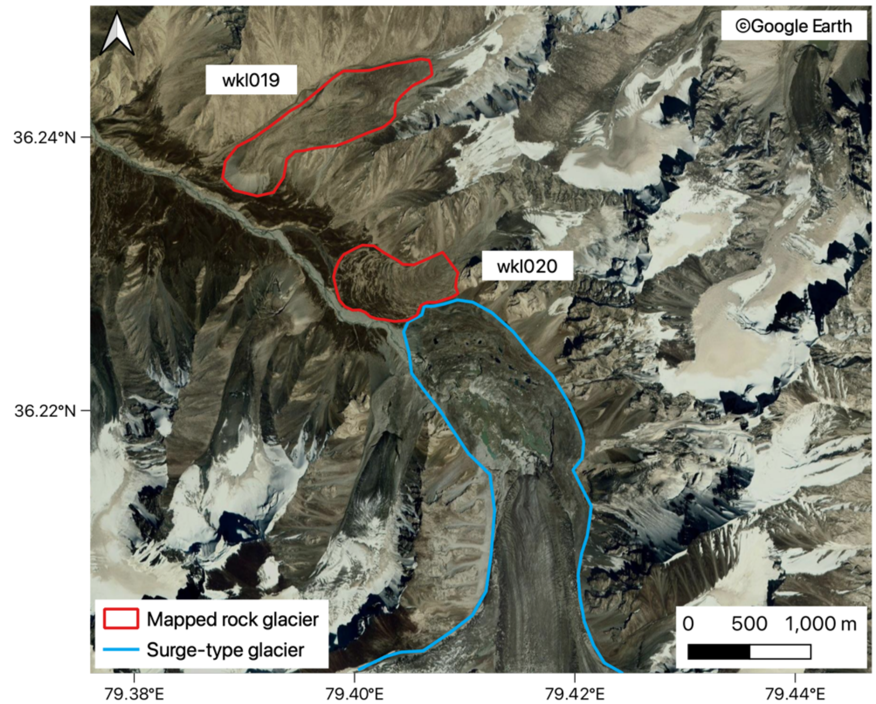



Figure 13. The blue line delineates the boundary of a surge-type glacier (Chudley and Willis 2019). Two rock glaciers (wkl019 and wkl020) in our inventory are situated in the surroundings.

## 6 Conclusions

We mapped rock glaciers at a regional scale and quantified their surface kinematics by combining InSAR and image semantic segmentation powered by deep learning. The combined method was applied to map rock glaciers across the West Kunlun Mountains, where the extremely dry climate represents one characteristic environmental setting on the Tibetan Plateau. We draw the main conclusions as follows:

(1) The DeepLabv3+ network trained by manually labelled data based on InSAR and Google Earth images can successfully identify and delineate rock glaciers from Sentinel-2 images, attaining an IoU value of 0.801 for both training and validation datasets. The well-trained model newly mapped 123 rock glaciers to supplement the non-exhaustive InSAR-based sub-inventory of 290 active rock glaciers.

(2) There are 413 rock glaciers mapped over the study area, including 202 glacier-connected rock glaciers (G-RGs), 143 debris-mantled slope-connected

rock glaciers (DMS-RGs), 41 glacier forefield-connected rock glaciers (GF-RGs), and 27 talus-connected rock glaciers (T-RGs). The mapped rock glaciers occupy a total area of ~ 108 $km^2$ and are located at altitudes between 3389 m and 5541 m. The average slope angle is 17° and the dominating landform aspect is towards the east.

(3) Among the mapped rock glaciers, the G-RGs and GF-RGs are larger (average areas: 0.40 $km^2$ and 0.38 $km^2$) and occur on gentler slopes (14° and 15°) predominantly facing northeast, whereas the DMS-RGs are the smallest (0.05 $km^2$) and occupy steep (23°) southeastern-facing slopes at the highest altitudes (4889 m). The T-RGs display a medium size (0.20 $km^2$) and slope angle (18°) and mostly occur on southeastern-facing slopes at lower altitudes (4332 m). The GF-RGs have the lowest average altitude (4265 m).

(4) Considering the geomorphologic context, we postulated that the glacier – debris-covered glacier – rock glacier transition is currently inactive due to the abnormal mass gain of glaciers in the West Kunlun: the mapped G-RGs and GF-RGs evolved from glacier to rock glacier during the past Holocene glacial periods, e.g., the Little Ice Age and the Neoglaciation. Surge events of glaciers may provide material supply and promote the glacier-to-rock glacier transition in the future.

(5) Based on the geomorphic characteristics of mapped rock glaciers, we suggest that the genesis of T-RGs and DMS-RGs are controlled by periglacial processes. The DMS-RGs, as a distinct type of rock glaciers in our study area, represent embryonic rock glaciers derived from prevalent mechanical erosion of the slopes and interstitial ice formation during the Little Ice Age. Note that the hypothesis on landform genesis formulated here needs further validation based on measured evidence.

(6) We adopted the spatial average velocity of all pixels within the boundary of each rock glacier to represent the landform surface kinematics. In total, 256 rock glaciers have valid kinematic quantifications. Nearly 90% of the rock glaciers move slower than 50 cm $yr^{-1}$. The mean downslope velocity is 24 cm $yr^{-1}$, and the standard deviation is 22 cm $yr^{-1}$. The median and maximum velocities are 17 cm $yr^{-1}$ and 127 cm $yr^{-1}$, respectively.

(7) Among the active rock glaciers, the G-RGs and GF-RGs move faster at mean velocities of 31 cm $yr^{-1}$ and 35 cm $yr^{-1}$, respectively. The DMS-RGs and T-RGs creep at a slower average velocity of 17 cm $yr^{-1}$.

In summary, combining InSAR and high-resolution optical imagery to manually map active rock glaciers proves to be an effective way to quantify rock glacier kinematics consistently in remote areas. With the utilization of deep learning techniques, it is promising to compile rock glacier inventories efficiently over a significant extent of permafrost areas, e.g., the Tibetan Plateau, which provides a baseline dataset and allows the monitoring of rock glaciers as indicators of permafrost degradation and potential water sources in a changing climate.

## Data Availablity Statement

The rock glacier inventory produced by this work will be available on PANGAEA (https://doi.org/10.1594/PANGAEA.938686, the link will become accessible once the related paper is published). The training data will be provided by Y. Hu upon request. Codes are available on GitHub (https://github.com/cryoyan/Landuse_DL).

## Acknowledgments

The authors declare that they have no known competing interest that could have appeared to influence the work presented in this paper. This work was supported by the Hong Kong Research Grants Council [grant numbers CUHK14303417, CUHK14303119, and HKPFS PF16-03859]; the National Natural Science Foundations of China [grant number 41690142 and 42071410]; the CUHK Direct Grant for Research [grant number 4053282 and 4053426]; and the CAS "Light of West China" Program. The ALOS-1 PALSAR data are copyrighted and provided by the Japan Aerospace Exploration Agency through the EO-RA2 project ER2A2N081. The TanDEM-X DEM data are copyrighted and provided by the German Aerospace Centre through project DEM_GLAC1408.

## References

Anderson, R. S., Anderson, L. S., Armstrong, W. H., Rossi, M. W., & Crump, S. E. (2018). Glaciation of alpine valleys: The glacier – debris-covered glacier – rock glacier continuum. *Geomorphology*, *311*, 127–142. https://doi.org/10.1016/j.geomorph.2018.03.015

Azócar, G. F., & Brenning, A. (2010). Hydrological and geomorphological significance of rock glaciers in the dry Andes, Chile (27°–33°S). *Permafrost and Periglacial Processes*, *21*(1), 42–*53*. https://doi.org/10.1002/ppp.669

Ballantyne, C. K. (2018). *Periglacial geomorphology.* Oxford UK: John Wiley & Sons.

Bao, W., Liu, S., Wei, J., & Guo, W. (2015). Glacier changes during the past 40 years in the West Kunlun Shan. *Journal of Mountain Science*, *12*(2), 344–*357*. https://doi.org/10.1007/s*116*29-014-*32*20-0

Barboux, C., Delaloye, R., & Lambiel, C. (2014). Inventorying slope movements in an Alpine environment using DInSAR. *Earth Surface Processes and Landforms*, *39*(15), 2087–2099. https://doi.org/10.1002/esp.3603

Barsch, D. (1996). *Rockglaciers: indicators for the present and former geoecology in high mountain environments* (Vol. 16). Springer Science & Business Media.

Berthling, I. (2011). Beyond confusion: Rock glaciers as cryo-conditioned landforms. Geomorphology, *131*(3–4), 98–106. https://doi.org/10.1016/j.geomorph.2011.05.002

Bertone, A., Barboux, C., Bodin, X., Bolch, T., Brardinoni, F., Caduff, R., et al. (2022). Incorporating InSAR kinematics into rock glacier inventories: insights from 11 regions worldwide. *Cryosphere*, *16*(*7*), 2769–2792. https://doi.org/*10*.5194/tc-16-2769-2022

Biskaborn, B. K., Smith, S. L., Noetzli, J., Matthes, H., Vieira, G., Streletskiy, D. A., et al. (2019). Permafrost is warming at a global scale. *Nature Communications*, *10*(1), 264. https://doi.org/10.1038/s41*46*7-018-08240-4

Brenning, A. (2005). Geomorphological, hydrological and climatic significance of rock glaciers in the Andes of Central Chile (*33*–35°S). Permafrost and Periglacial Processes, 16(3), *23*1–240. https://doi.org/10.1002/ppp.528

Cai, J., Wang, X., Liu, G., & Yu, B. (2021). A comparative study of active rock glaciers mapped from geomorphic-and kinematic-based approaches in daxue shan, southeast tibetan plateau. *Remote Sensing*, *13*(23), 4931. https://doi.org/*10*.3390/rs1*32*34931

Capps, S. R. (1910). Rock Glaciers in Alaska. *The Journal of Geology*, *18*(4), 359–375. https://doi.org/10.1086/62*17*46

Chen, C. W., & Zebker, H. A. (2002). Phase Unwrapping for Large Sar Interferograms: Statistical Segmentation and Generalized Network Models. *IEEE Transactions on Geoscience and Remote Sensing*, *40*(8), 1709. https://doi.org/10.*11*09/tgrs.2002.802453

Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. *ArXiv*.

Cheng, G., Zhao, L., Li, R., Wu, X., Sheng, Y., Hu, G., et al. (2019). Characteristic, changes and impacts of permafrost on Qinghai-Tibet Plateau. *Chinese Science Bulletin*, *64*(27), 2783–2795. https://doi.org/10.1360/tb-2019-0191

Chudley, T. R., & Willis, I. C. (2019). Glacier surges in the north-west West Kunlun Shan inferred from 1972 to 2017 Landsat imagery. *Journal of Glaciology*, *65*(249), 1–12. https://doi.org/10.1017/jog.2018.94

Chueca, J. (1992). A statistical analysis of the spatial distribution of rock glaciers, Spanish Central Pyrenees. Permafrost and Periglacial Processes, 3(3), 261–265. https://doi.org/10.1002/ppp.3430030316

Cicoira, A., Beutel, J., Faillettaz, J., Gärtner-Roer, I., & Vieli, A. (2019). Resolving the influence of temperature forcing through heat conduction on rock glacier dynamics: A numerical modelling approach. Cryosphere, 13(3), 927–942. https://doi.org/10.5194/tc-13-927-2019

Cicoira, A., Beutel, J., Faillettaz, J., & Vieli, A. (2019). Water controls the seasonal rhythm of rock glacier flow. *Earth and Planetary Science Letters*, *528*, 115844. https://doi.org/10.1016/j.epsl.2019.115844

Cui, Z. (1985). Discovery of Kunlunshan-type rock glaciers and the classification of rock glaciers. *Kexue Tongbao*, *30*(3), 365–369. https://doi.org/10.1360/sb1985-30-3-365

Cui, Z., & Cheng, Z. (1988). Rock glaciers in the source region of Urumqi River, middle Tian Shan, China (pp. 724–727). Presented at the 5th International Conference on Permafrost.

Delaloye, R., Lambiel, C., & Gärtner-Roer, I. (2010). Overview of rock glacier kinematics research in the Swiss Alps: Seasonal rhythm, interannual variations and trends over several decades. *Geographica Helvetica*, *65*(2), 135–145. https://doi.org/10.5194/gh-65-135-2010

Delaloye, R., Morard, S., Barboux, C., Abbet, D., Gruber, V., Riedo, M., & Gachet, S. (2013). Rapidly moving rock glaciers in Mattertal. Geographica Helvetica, 21–31.

Ellis, J. M., & Calkin, P. E. (1979). Nature and Distribution of Glaciers, Neoglacial Moraines, and Rock Glaciers, East-Central Brooks Range, Alaska. *Arctic and Alpine Research*, *11*(4), 403–420. https://doi.org/10.1080/00040851.1979.12004149

Everingham, M., Eslami, S. M. A., Gool, L. V., Williams, C. K. I., Winn, J., & Zisserman, A. (2015). The Pascal Visual Object Classes Challenge: A Retrospective. *International Journal of Computer Vision*, *111*(1), 98–136. https://doi.org/10.1007/s11263-014-0733-5

Falaschi, D., Castro, M., Masiokas, M., Tadono, T., & Ahumada, A. L. (2014). Rock Glacier Inventory of the Valles Calchaquíes Region (~ *25*°S), Salta, Argentina, Derived from ALOS Data. Permafrost and Periglacial Processes, 25(1), 69–75. https://doi.org/10.1002/ppp.1801

Geiger, S. T., Daniels, J. M., Miller, S. N., & Nicholas, J. W. (2014). Influence of Rock Glaciers on Stream Hydrology in the La Sal Mountains, Utah. *Arctic, Antarctic, and Alpine Research*, *46*(3), *64*5–658. https://doi.org/10.1657/1938-4246-46.3.645

Haeberli, W., Hallet, B., Arenson, L., Elconin, R., Humlum, O., Kääb, A., et al. (2006). Permafrost creep and rock glacier dynamics. Permafrost and Periglacial Processes, 17(3), 189–214. https://doi.org/10.1002/ppp.561

Haeberli, Wilfried. (2000). Modern Research Perspectives Relating to Permafrost Creep and Rock Glaciers: A Discussion. Permafrost and Periglacial Processes, 11(4), 290–*293*. https://doi.org/10.1002/1099-1530(200012)11:4%3c290::aid-ppp372%3e3.0.co;2-0

Hanssen, R. F. (2001). *Radar interferometry: data interpretation and error analysis*. Dordrecht Boston: Kluwer Academic.

Harris, S. A., Zhijiu, C., & Guodong, C. (1998). Origin of a bouldery diamiction, Kunlun pass, Qinghai-Xizang Plateau, People's Republic of China: gelifluction deposit or rock glacier? Earth Surface Processes and Landforms, 23(10), 943–952. https://doi.org/10.1002/(sici)1096-9837(199810)23:10%3c943::aid-esp913%3e3.0.co;2-7

Hu, Y., Liu, L., Wang, X., Zhao, L., Wu, T., Cai, J., et al. (2021). Quantification of permafrost creep provides kinematic evidence for classifying a puzzling periglacial landform. Earth Surface Processes and Landforms, 46(2), 465–477. https://doi.org/10.1002/esp.5039

Huang, L., Luo, J., Lin, Z., Niu, F., & Liu, L. (2020). Using deep learning to map retrogressive thaw slumps in the Beiluhe region (Tibetan Plateau) from CubeSat images. *Remote Sensing of Environment*, *237*, 111534. https://doi.org/10.1016/j.rse.2019.111534

Huang, L., Liu, L., Luo, J., Lin, Z., & Niu, F. (2021). Automatically quantifying evolution of retrogressive thaw slumps in Beiluhe (Tibetan Plateau) from multi-temporal CubeSat images. *International Journal of Applied Earth Observation and Geoinformation*, *102*, 102399. https://doi.org/10.1016/j.jag.2021.102399

Humlum, O. (2000). The geomorphic significance of rock glaciers: estimates of rock glacier debris volumes and headwall recession rates in West Greenland. Geomorphology, 35(1–2), 41–67. https://doi.org/10.1016/s0169-555x(00)00022-2

Ikeda, A., Matsuoka, N., & Kääb, A. (2008). Fast deformation of perennially frozen debris in a warm rock glacier in the Swiss Alps: An effect of liquid water. *Journal of Geophysical Research: Earth Surface*, *113*(1). https://doi.org/10.1029/2007jf000859

IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change In V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (Ed.)

Janke, J. R. (2007). Colorado Front Range rock glaciers: distribution and topographic characteristics. Arctic, Antarctic, and Alpine Research, 39(1), 74–83.

Jones, D. B., Harrison, S., Anderson, K., & Betts, R. A. (2018). Mountain rock glaciers contain globally significant water stores. *Scientific Reports*, *8*(1), 2834. https://doi.org/10.1038/s41598-018-21244-w

Jones, D. B., Harrison, S., & Anderson, K. (2019). Mountain glacier-to-rock glacier transition. *Global and Planetary Change*, *181*, 102999. https://doi.org/10.1016/j.gloplacha.2019.102999

Jones, D. B., Harrison, S., Anderson, K., Shannon, S., & Betts, R. A. (2021). Rock glaciers represent hidden water stores in the Himalaya. *Science of The Total Environment*, *793*, 145368. https://doi.org/10.1016/j.scitotenv.2021.145368

Potter Jr., N. (1972). Ice-cored rock glacier, Galena Creek, northern Absaroka Mountains, Wyoming. *Bulletin of the Geological Society of America*, *83*(10), 3025–3058. https://doi.org/10.1130/0016-7606(1972)83%5b3025:irggcn%5d2.0.co;2

Kääb, A., Treichler, D., Nuth, C., & Berthier, E. (2015). Brief Communication: Contending estimates of 2003–2008 glacier mass balance over the Pamir–Karakoram–Himalaya. *The Cryosphere*, *9*(2), 557–564. https://doi.org/10.5194/tc-9-557-2015

Kenner, R., Pruessner, L., Beutel, J., Limpach, P., & Phillips, M. (2020). How rock glacier hydrology, deformation velocities and ground temperatures interact: Examples from the Swiss Alps. Permafrost and Periglacial Processes, 31(1), 3–14. https://doi.org/10.1002/ppp.2023

Kofler, C., Mair, V., Comiti, F., Zebisch, M., Schneiderbauer, S., & Steger, S. (2022). Towards a sediment transfer capacity index of rock glaciers: Examples from two catchments in South Tyrol, (Eastern Italian Alps). *Catena*, *216*, 106329. https://doi.org/10.1016/j.catena.2022.106329

Kummert, M., & Delaloye, R. (2018). Mapping and quantifying sediment transfer between the front of rapidly moving rock glaciers and torrential gullies. Geomorphology, *309*, 60–76. https://doi.org/10.1016/j.geomorph.2018.02.021

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Li, J. (1986). *Tibetan glaciers.* Beijing: Science Press.

Li, K., Chen, J., Zhao, L., Zhang, X., Pang, Q., Fang, H., & Liu, G. (20*12*). Permafrost distribution in typical area of West Kunlun Mountains derived from a comprehensive survey. *Journal of Glaciology and Geocryology*, *34*(2), 447–454.

Li, S., & Shi, Y. (1992). Glacial and lake fluctuations in the area of the west Kunlun mountains during the last 45000 years. *Annals of Glaciology*, *16*, 79–84.

Liu, L., Millar, C. I., Westfall, R. D., & Zebker, H. A. (2013). Surface motion of active rock glaciers in the Sierra Nevada, California, USA: Inventory and a case study using InSAR. Cryosphere, 7(4), *11*09–1119. https://doi.org/10.5194/tc-7-1109-2013

Marcer, M., Cicoira, A., Cusicanqui, D., Bodin, X., Echelard, T., Obregon, R., & Schoeneich, P. (2021). Rock glaciers throughout the French Alps accelerated and destabilised since 1990 as air temperatures increased. *Communications Earth and Environment*, *2*(1), 81. https://doi.org/10.1038/s43247-021-00150-6

Marcer, Marco. (2020). Rock glaciers automatic mapping using optical imagery and convolutional neural networks. Permafrost and Periglacial Processes, 31(4), 561–566. https://doi.org/10.1002/ppp.2076

Millar, C.I., & Westfall, R. D. (2008). Rock glaciers and related periglacial landforms in the Sierra Nevada, CA, USA; inventory, distribution and climatic relationships. *Quaternary International*, *188*(1), 90–104. https://doi.org/10.1016/j.quaint.2007.06.004

Millar, Constance I., Westfall, R. D., & Delany, D. L. (2013). Thermal and hydrologic attributes of rock glaciers and periglacial talus landforms: Sierra Nevada, California, USA. Quaternary International, *310*, 169–180. https://doi.org/10.1016/j.quaint.2012.07.019

Mottaghi, R., Chen, X., Liu, X., Cho, N.-G., Lee, S.-W., Fidler, S., et al. (2014). The role of context for object detection and semantic segmentation in the wild. In *Computer Vision and Pattern Recognition* (pp. 891–898). Columbus, OH.

Müller, J., Vieli, A., & Gärtner-Roer, I. (2016). Rock glaciers on the run - Understanding rock glacier landform evolution and recent changes from numerical flow modeling. Cryosphere, 10(6), 2865–2886. https://doi.org/10.5194/tc-10-2865-2016

Ni, J., Wu, T., Zhu, X., Hu, G., Zou, D., Wu, X., et al. (2021). Simulation of the Present and Future Projection of Permafrost on the Qinghai-Tibet Plateau with Statistical and Machine Learning Models. *Journal of Geophysical Research: Atmospheres*, *126*(2). https://doi.org/10.1029/2020jd033402

Onaca, A., Ardelean, F., Urdea, P., & Magori, B. (2017). Southern Carpathian rock glaciers: Inventory, distribution and environmental controlling factors. Geomorphology, 293, 391–404. https://doi.org/10.1016/j.geomorph.2016.03.032

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences*, *11*(5), 1633–1644. https://doi.org/10.5194/hess-11-1633-2007

Quincey, D. J., Glasser, N. F., Cook, S. J., & Luckman, A. (2015). Heterogeneity in Karakoram glacier surges. Journal of Geophysical Research: Earth Surface, *120*(7), 1288–1300. https://doi.org/10.1002/2015jf003515

Ran, Z., & Liu, G. (2018). Rock glaciers in Daxue Shan, south-eastern Tibetan Plateau: an inventory, their distribution, and their environmental controls. The Cryosphere, 12(7), 2327–2340. https://doi.org/10.5194/tc-12-2327-2018

Rangecroft, S., Harrison, S., Anderson, K., Magrath, J., Castel, A. P., & Pacheco, P. (2014). A First Rock Glacier Inventory for the Bolivian Andes. Permafrost and Periglacial Processes, 25(4), 333–343. https://doi.org/10.1002/ppp.1816

Reinosch, E., Gerke, M., Riedel, B., Schwalb, A., Ye, Q., & Buckel, J. (2021). Rock glacier inventory of the western Nyainqêntanglha Range, Tibetan Plateau, supported by InSAR time series and automated classification. Permafrost and Periglacial Processes, 32(4), 657–672. https://doi.org/10.1002/ppp.2117

RGIK. (2022). *Towards standard guidelines for inventorying rock glaciers: baseline concepts (Version 4.2.2)* (p. 13).

Robson, B. A., Bolch, T., MacDonell, S., Hölbling, D., Rastner, P., & Schaffer, N. (2020). Automated detection of rock glaciers using deep learning and object-based image analysis. Remote Sensing of Environment, *250*, 112033. https:

//doi.org/10.1016/j.rse.2020.112033

Roer, I., & Nyenhuis, M. (2007). Rockglacier activity studies on a regional scale: comparison of geomorphological mapping and photogrammetric monitoring. Earth Surface Processes and Landforms, 32(12), 1747–1758. https://doi.org/10.1002/esp.1496

Schaffer, N., MacDonell, S., Réveillet, M., Yáñez, E., & Valois, R. (2019). Rock glaciers as a water resource in a changing climate in the semiarid Chilean Andes. *Regional Environmental Change*, *19*(5), 1263–1279. https://doi.org/10.1007/s10113-018-01459-3

Schmid, M.-O., Baral, P., Gruber, S., Shahi, S., Shrestha, T., Stumm, D., & Wester, P. (2015). Assessment of permafrost distribution maps in the Hindu Kush Himalayan region using rock glaciers mapped in Google Earth. The Cryosphere, 9(6), 2089–2099. https://doi.org/10.5194/tc-9-2089-2015

Scotti, R., Brardinoni, F., Alberti, S., Frattini, P., & Crosta, G. B. (2013). A regional inventory of rock glaciers and protalus ramparts in the central Italian Alps. Geomorphology, *186*, 136–149. https://doi.org/10.1016/j.geomorph.2012.12.028

Shi, Y. (2006). *The quaternary glaciations and environmental variations in China*. Shijiazhuang: Hebei Science & Technology Press.

Sorg, A., Kääb, A., Roesch, A., Bigler, C., & Stoffel, M. (2015). Contrasting responses of Central Asian rock glaciers to global warming. Scientific Reports, 5(1), 8228. https://doi.org/10.1038/srep08228

Thibert, E., & Bodin, X. (2022). Changes in surface velocities over four decades on the Laurichard rock glacier (French Alps). Permafrost and Periglacial Processes, 33(3), 323–335. https://doi.org/10.1002/ppp.2159

Villarroel, C. D., Beliveau, G. T., Forte, A. P., Monserrat, O., & Morvillo, M. (2018). DInSAR for a regional inventory of active rock glaciers in the Dry Andes Mountains of Argentina and Chile with sentinel-1 data. Remote Sensing, 10(10), 1588. https://doi.org/10.3390/rs10101588

Wang, X., Liu, L., Zhao, L., Wu, T., Li, Z., & Liu, G. (2017). Mapping and inventorying active rock glaciers in the northern Tien Shan of China using satellite SAR interferometry. Cryosphere, 11(2), 997–1014. https://doi.org/10.5194/tc-11-997-2017

Wang, Y., Hou, S., Huai, B., An, W., Pang, H., & Liu, Y. (2018). Glacier anomaly over the western Kunlun Mountains, Northwestern Tibetan Plateau, since the 1970s. Journal of Glaciology, 64(246), 624–636. https://doi.org/10.1017/jog.2018.53

Whalley, W. B., & Azizi, F. (1994). Rheological models of active rock glaciers: Evaluation, critique and a possible test. Permafrost and Periglacial Processes, 5(1), 37–51. https://doi.org/10.1002/ppp.3430050105

Wirz, V., Gruber, S., Purves, R. S., Beutel, J., Gärtner-Roer, I., Gubler, S., & Vieli, A. (2016). Short-term velocity variations at three rock glaciers and their relationship with meteorological conditions. *Earth Surface Dynamics*, *4*(1), 103–123. https://doi.org/10.5194/esurf-4-103-2016

Yang, M., Nelson, F. E., Shiklomanov, N. I., Guo, D., & Wan, G. (2010). Permafrost degradation and its environmental effects on the Tibetan Plateau: A review of recent research. *Earth-Science Reviews*, *103*(1–2), 31–44. https://doi.org/10.1016/j.earscirev.2010.07.002

Yang, M., Wang, X., Pang, G., Wan, G., & Liu, Z. (2019). The Tibetan Plateau cryosphere: Observations and model simulations for current status and recent changes. Earth-Science Reviews, *190*, 353–369. https://doi.org/10.1016/j.earscirev.2018.12.018

Yao, T., Xue, Y., Chen, D., Chen, F., Thompson, L., Cui, P., et al. (2018). Recent Third Pole's rapid warming accompanies cryospheric melt and water cycle intensification and interactions between monsoon and environment: multidisciplinary approach with observation, modeling and analysis Recent Third Pole's rapid warming accompanies cryospheric melt and water cycle intensification and interactions between monsoon and environment: multi-disciplinary approach with observation, modeling and analysis. *Bulletin of the American Meteorological Society*, *100*(3), 423–444. https://doi.org/10.1175/bams-d-17-0057.1

Yasuda, T., & Furuya, M. (2015). Dynamics of surge-type glaciers in West Kunlun Shan, Northwestern Tibet. Journal of Geophysical Research: Earth Surface, 120(11), 2393–2405. https://doi.org/10.1002/2015jf003511

Zhang, E., Liu, L., Huang, L., & Ng, K. S. (2021). An automated, generalized, deep-learning-based method for delineating the calving fronts of Greenland glaciers from multi-sensor remote sensing imagery. Remote Sensing of Environment, *254*, 112265. https://doi.org/10.1016/j.rse.2020.112265

Zhang, G., Yao, T., Xie, H., Yang, K., Zhu, L., Shum, C. K., et al. (2020). Response of Tibetan Plateau lakes to climate change: Trends, patterns, and mechanisms. Earth-Science Reviews, *208*, 103269. https://doi.org/10.1016/j.earscirev.2020.103269

Zhang, X., Feng, M., Zhang, H., Wang, C., Tang, Y., Xu, J., et al. (2021). Detecting rock glacier displacement in the central himalayas using multi-temporal insar. Remote Sensing, 13(23), 4738. https://doi.org/10.3390/rs13234738

Zhao, L., & Sheng, Y. (2019). *Permafrost in the Qinghai-Tibet plateau and its changes*. Beijing: Science Press.

Zhao, L., Zou, D., Hu, G., Du, E., Pang, Q., Xiao, Y., et al. (2020). Changing climate and the permafrost environment on the Qinghai–Tibet (Xizang) plateau. Permafrost and Periglacial Processes, 31(3), 396–405. https://doi.org/10.1002/ppp.2056

Zhao, L., Zou, D., Hu, G., Wu, T., Du, E., Liu, G., et al. (2021). A synthesis dataset of permafrost thermal state for the Qinghai–Tibet (Xizang) Plateau, China. *Earth System Science Data*, *13*(8), 4207–4218. https://doi.org/10.5194/essd-13-4207-2021

Zhou, Y., Li, Z., Li, J., Zhao, R., & Ding, X. (2018). Glacier mass balance in the Qinghai–Tibet Plateau and its surroundings from the mid-1970s to 2000 based on Hexagon KH-9 and SRTM DEMs. Remote Sensing of Environment, *210*, 96–112. https://doi.org/10.1016/j.rse.2018.03.020

Zhu, C., Zhang, J., & Cheng, P. (1996). Rock glaciers in the Central Tianshan Mountains, China. Permafrost and Periglacial Processes, 7(1), 69–78. https://doi.org/10.1002/(sici)1099-1530(199601)7:1%3c69::aid-ppp210%3e3.0.co;2-b

Zou, D., Zhao, L., Sheng, Y., Chen, J., Hu, G., Wu, T., et al. (2017). A new map of permafrost distribution on the Tibetan Plateau. The Cryosphere, 11(6), 2527–2542. https://doi.org/10.5194/tc-11-2527-2017