

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

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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 km² 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 (Erhardter 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 km² (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 measure-

ments and permafrost was warming at an average rate of $0.11^{\circ}\text{C}/10\text{ yr}$ 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).

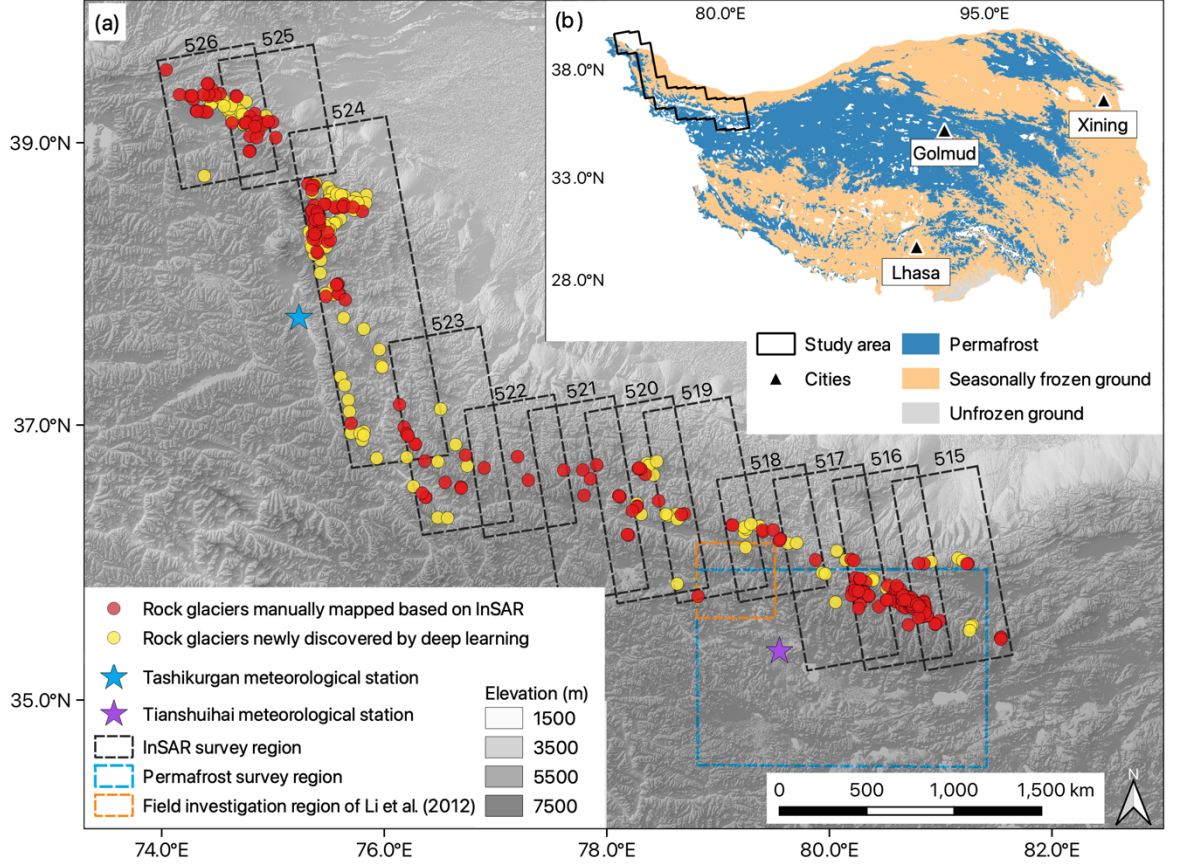


Figure 1. (a) Distribution of the mapped rock glaciers in the West Kunlun. The red dots are manually mapped rock glaciers (290 in total), and the yellow dots represent newly identified rock glaciers by our deep learning method but were missed in the InSAR-based sub-dataset (123 in total). The background 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

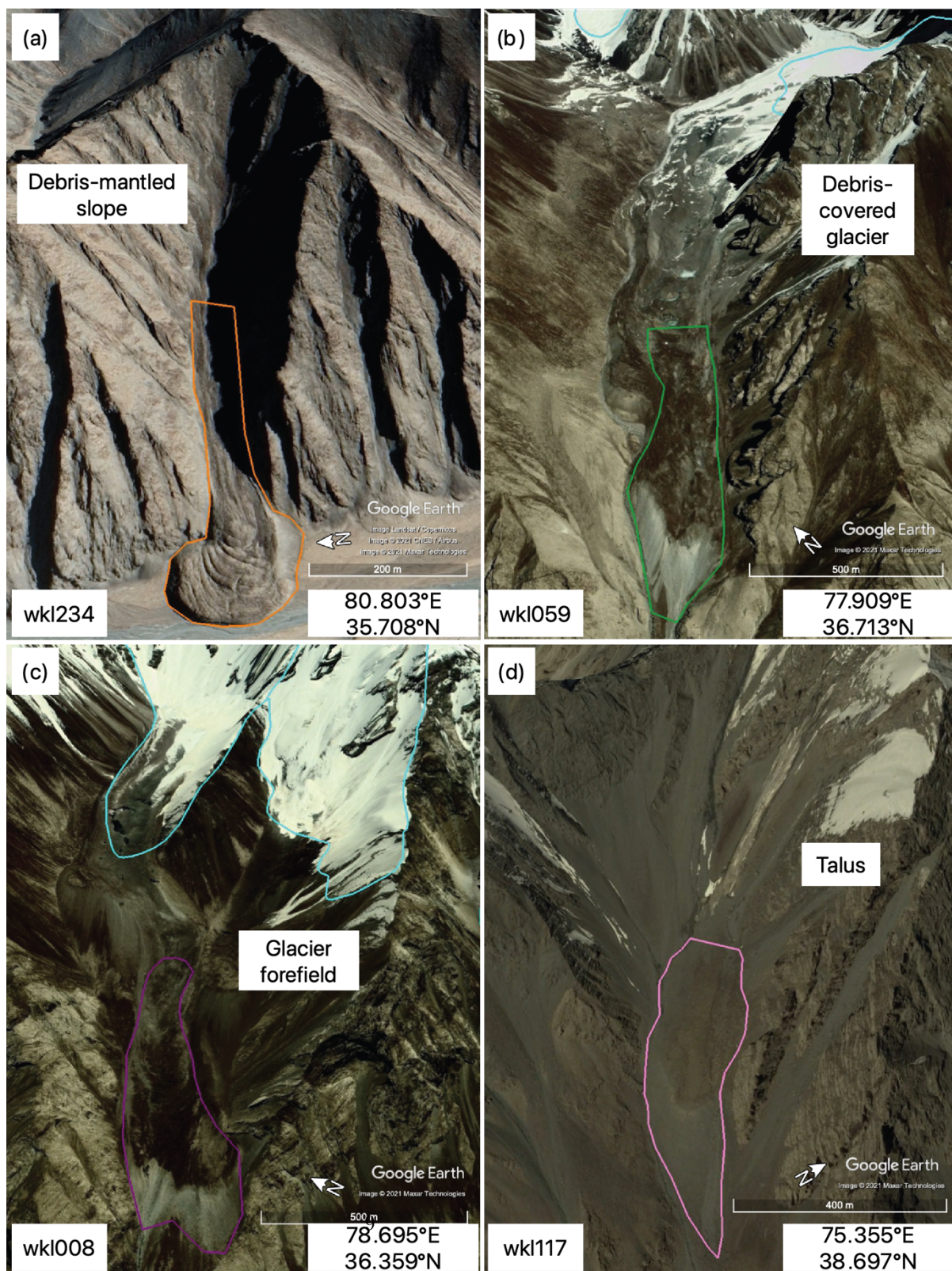
In total, twenty-two interferograms generated from ALOS-1 PALSAR images covering the West Kunlun Mountains were used for ground movement detection between 2007–2008 (Table 1). To maintain high interferometric coherence and reduce topographic error, we selected image pairs with temporal spans of 46 days 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: wk1234). (b) focuses on a glacier-connected rock glacier (G-RG) in green (ID: wk1059). 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: wk1008). 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: wk1117), from which the upslope talus can be observed.

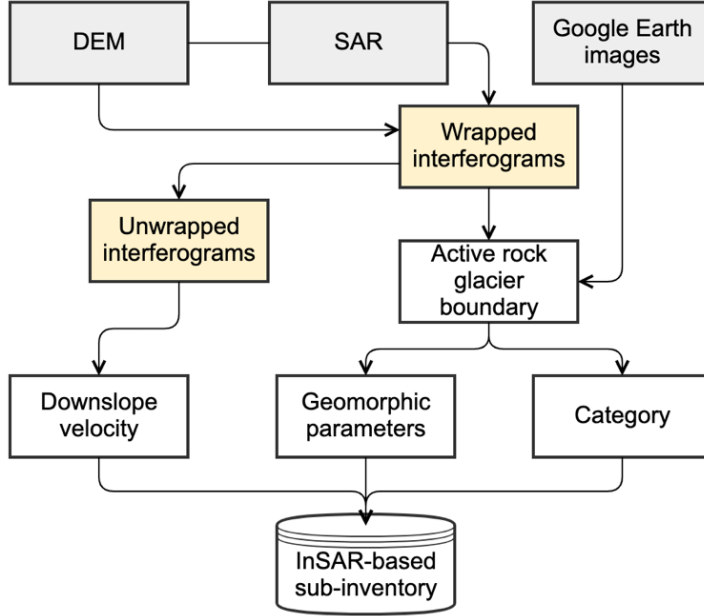


Figure 3. Diagram of the workflow to manually map active rock glaciers based on InSAR and Google Earth images.

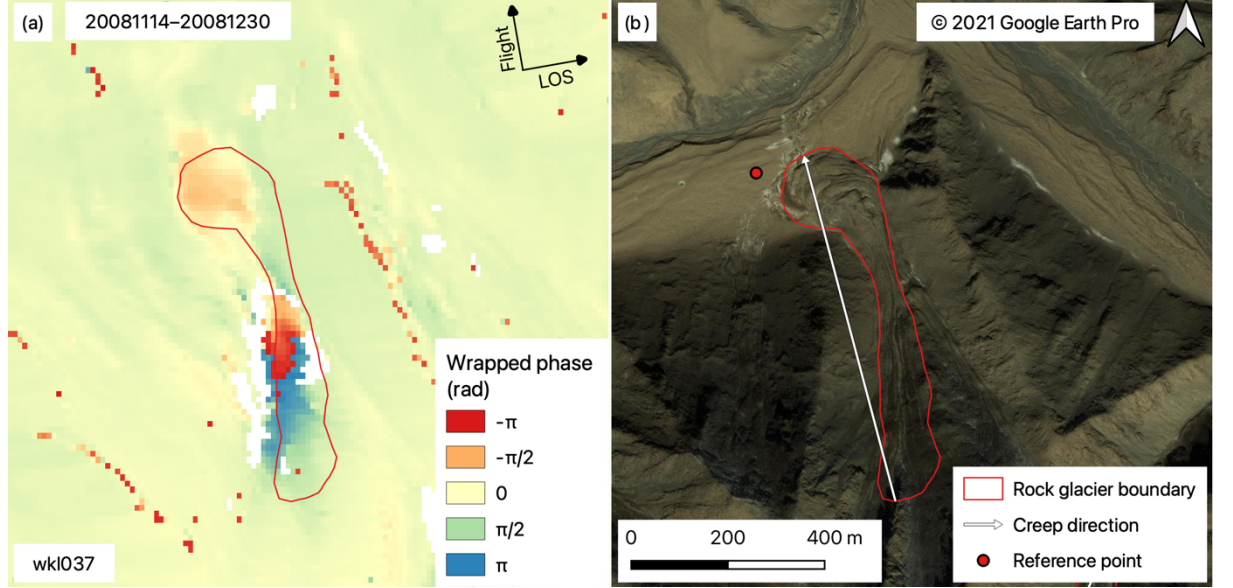


Figure 4. An example of identified active rock glacier (ID: wkl037). (a) shows the contrasting wrapped phases between the landform and surrounding background. The ALOS-1 PALSAR image pair generating the interferogram were acquired on 14/11/2008 and 30/12/2008. (b) is the corresponding Google Earth image 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. Mercer (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. Erharder 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 iter-

ations) 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:

$$\text{IoU} = \text{TP} / (\text{TP} + \text{FP} + \text{FN})$$

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.

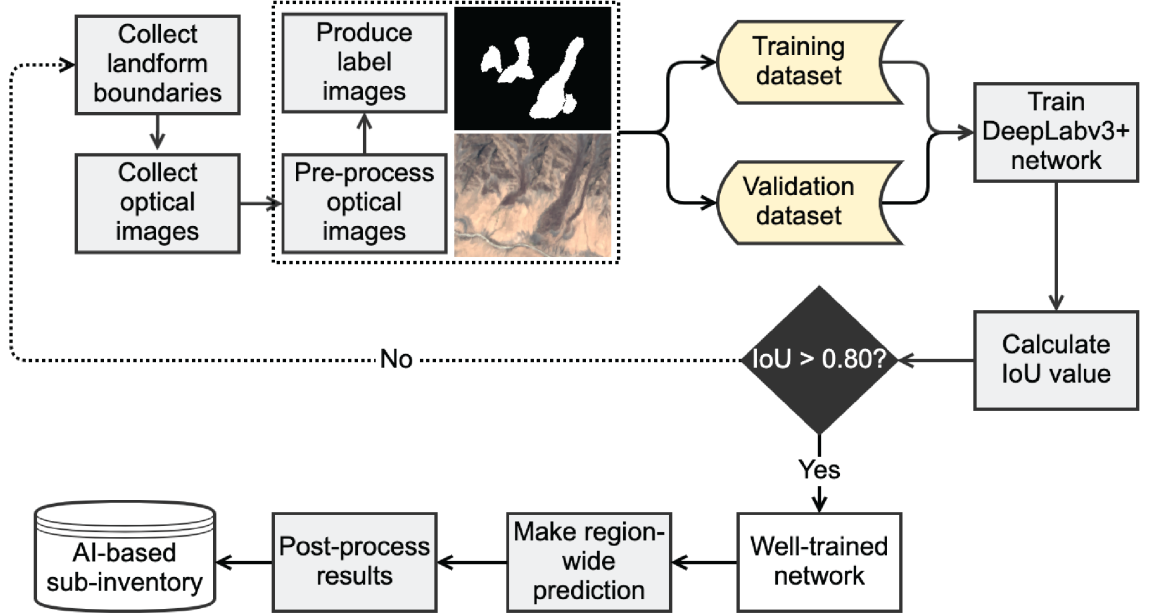


Figure 5. Diagram of the workflow to automatically map rock glaciers using DeepLabv3+ network. AI stands for artificial intelligence.

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 $\text{IoU} = 0.801$ 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).

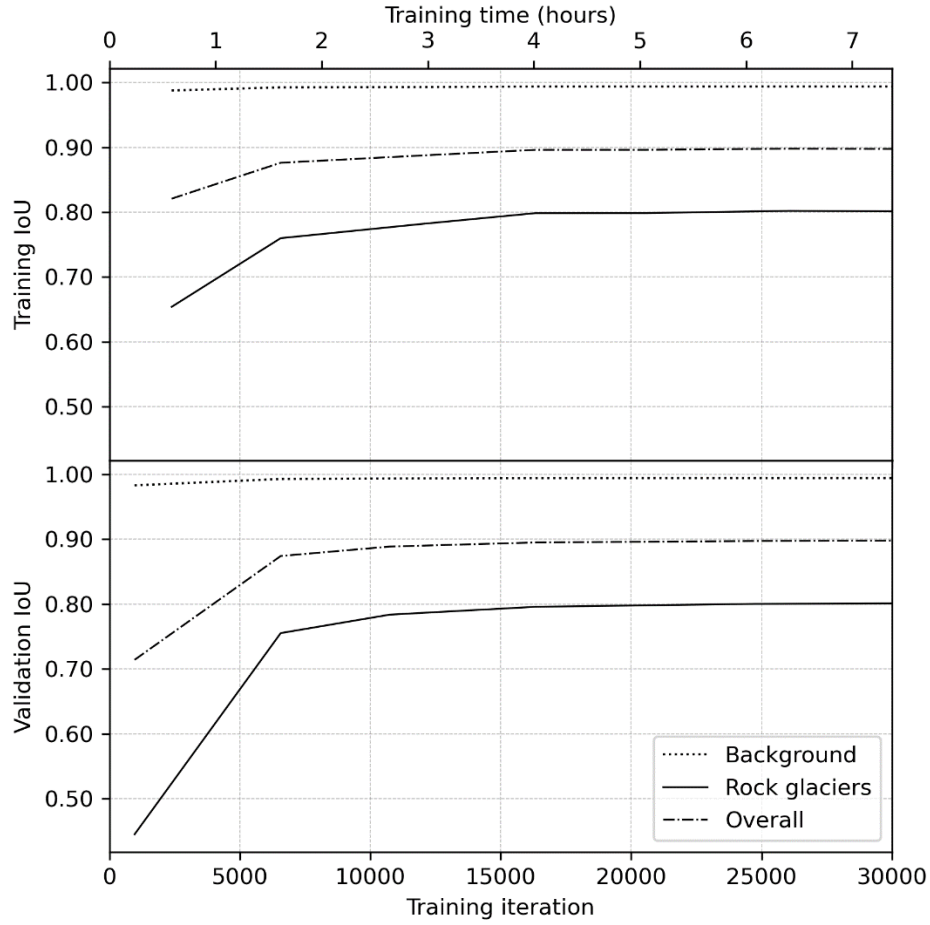


Figure 6. Performance of the deep learning model for recognizing rock glaciers from background on the training and validation datasets, respectively.

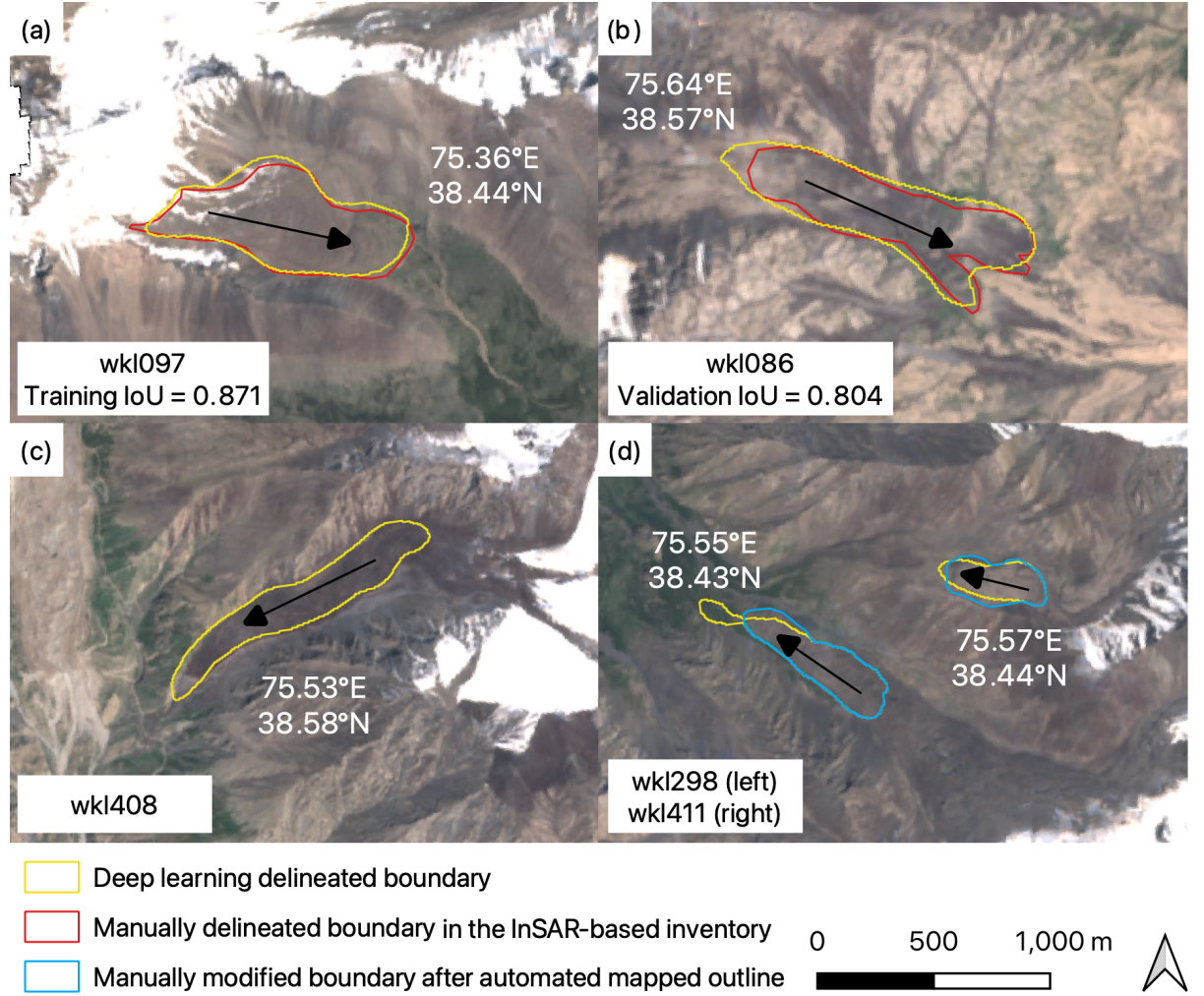


Figure 7. (a) Comparison of the deep learning mapped rock glacier boundary (in yellow) with the manually delineated polygon (in red) in the training dataset. The IoU between the two is 0.871. The black arrow indicates the flow direction. (b) Similar visual comparison between the automatically outlined 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 km² for individual landforms, followed by GF-RGs with a mean area of 0.38 km². Both are much (~50%) larger than the mean area (0.26 km²) of all RGs. The DMS-RGs are the smallest (0.05 km²), covering ~7% of the total area occupied by all RGs in the study region. The mean surface slope of all RGs is 17°, which is similar to the mean slope (18°) of the T-RGs. The G-RGs and GF-RGs have relatively flat surfaces with mean slope angles of 14° and 15°, respectively, whereas the DMS-RGs develop a steeper average slope angle of 23°. Most (64%) of the mapped RGs occur on east-facing (0°–180°) 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°–90°) slopes (Figure 9c, d), whereas the DMS-RGs and T-RGs mostly move towards southeastern directions (90°–180°) (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 (°)	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

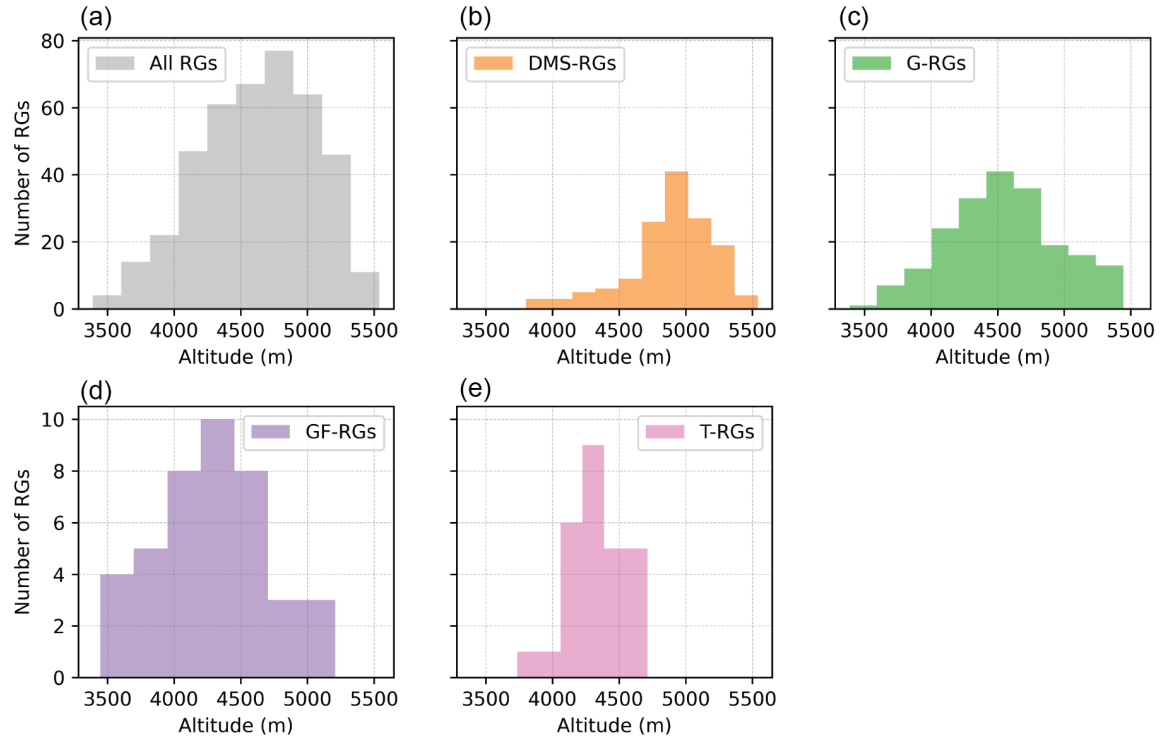


Figure 8. Histograms of the average altitudes for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively. The altitudes are calculated from the SRTM DEM data.

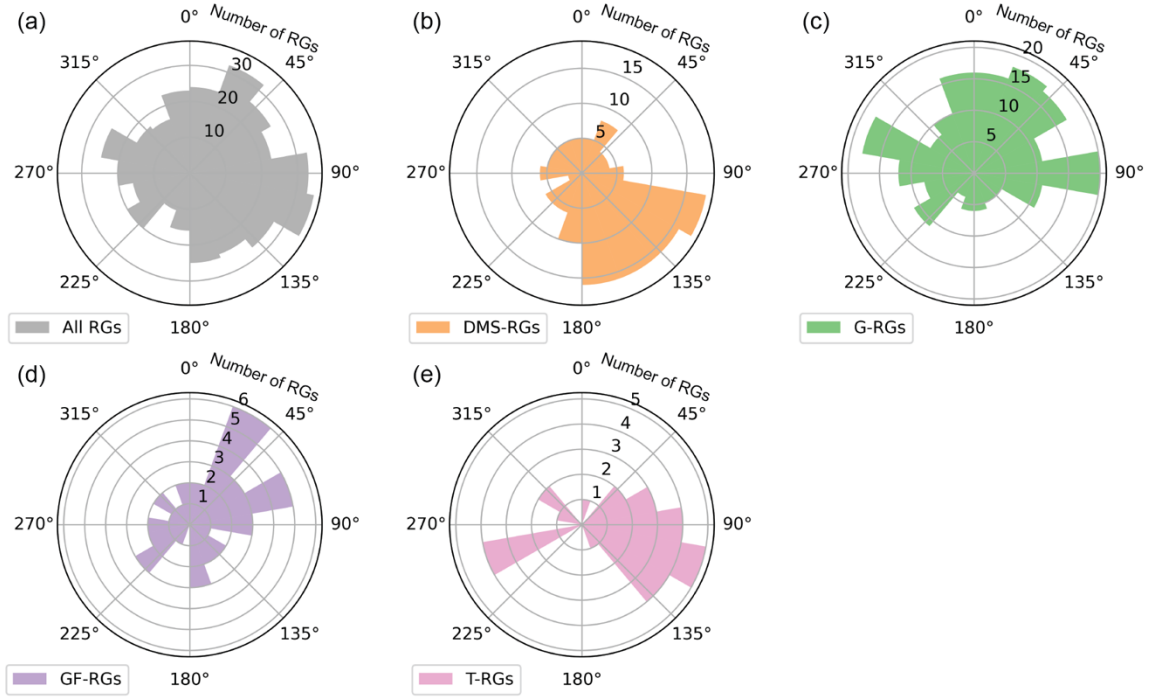


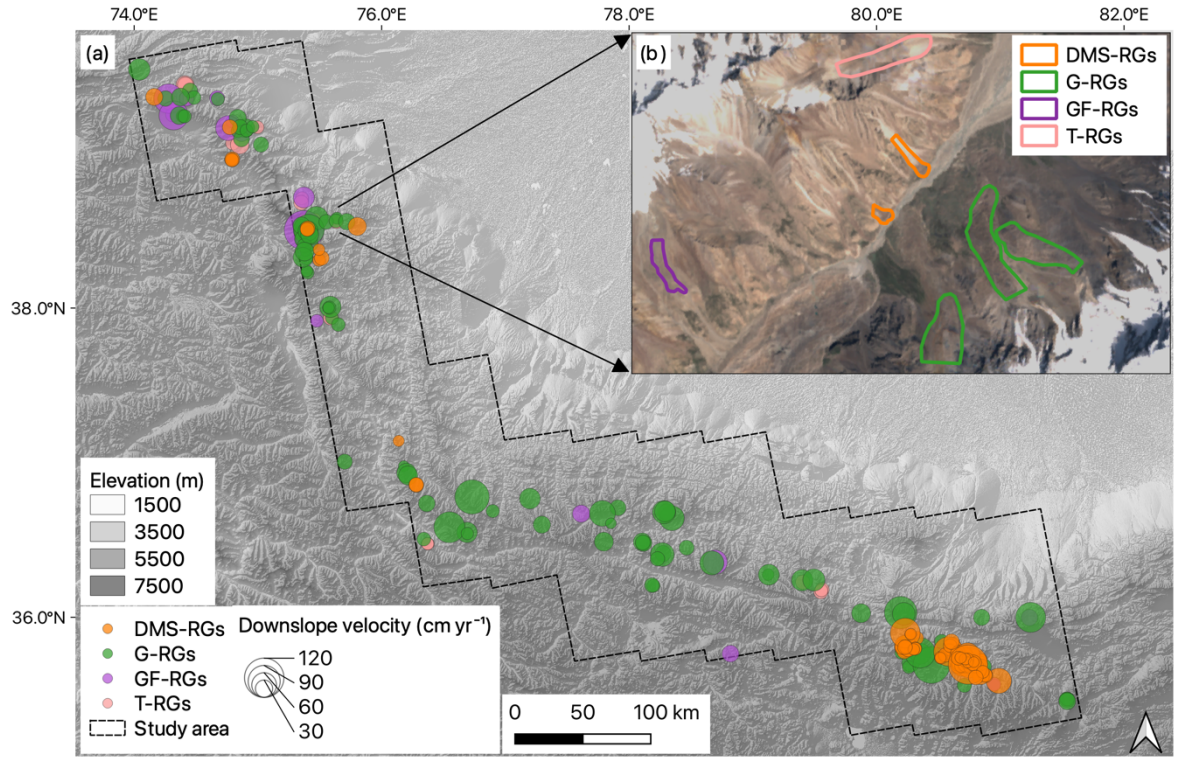
Figure 9. Histograms of the landform aspects for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs.

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 $79 \pm 6 \text{ cm yr}^{-1}$ (Figure 11a), $44 \pm 1 \text{ cm yr}^{-1}$ (Figure 11b), $32 \pm 1 \text{ cm yr}^{-1}$ (Figure 11c), and $24 \pm 1 \text{ cm yr}^{-1}$ (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 $127 \pm 7 \text{ cm yr}^{-1}$.



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

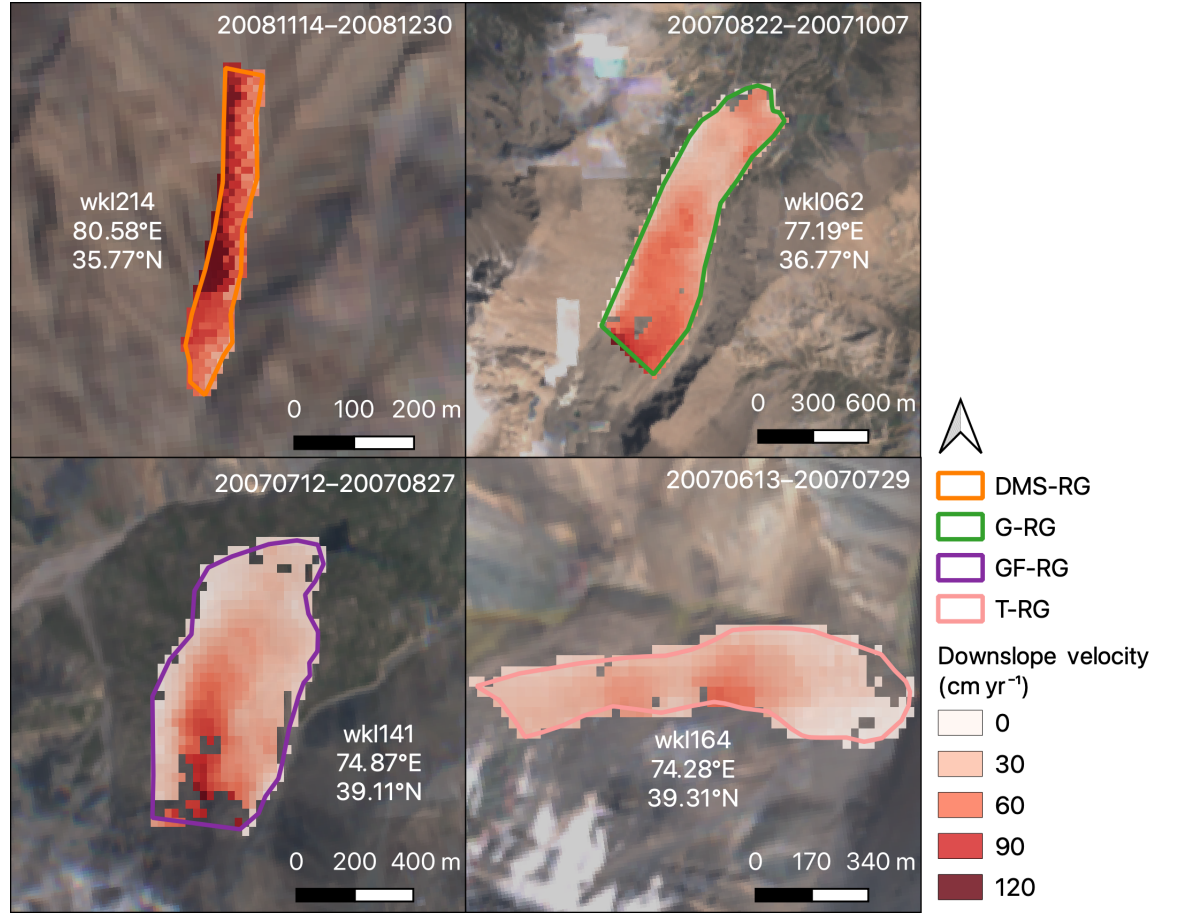


Figure 11. Velocity field maps show the downslope movement rates of rock glaciers of different categories including a DMS-RG outlined in orange (ID: wkl214), a G-RG in green (ID: wkl062) a GF-RG in purple (ID: wkl141), and a T-RG in pink (ID: wkl164). Their IDs and coordinates of central locations are 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

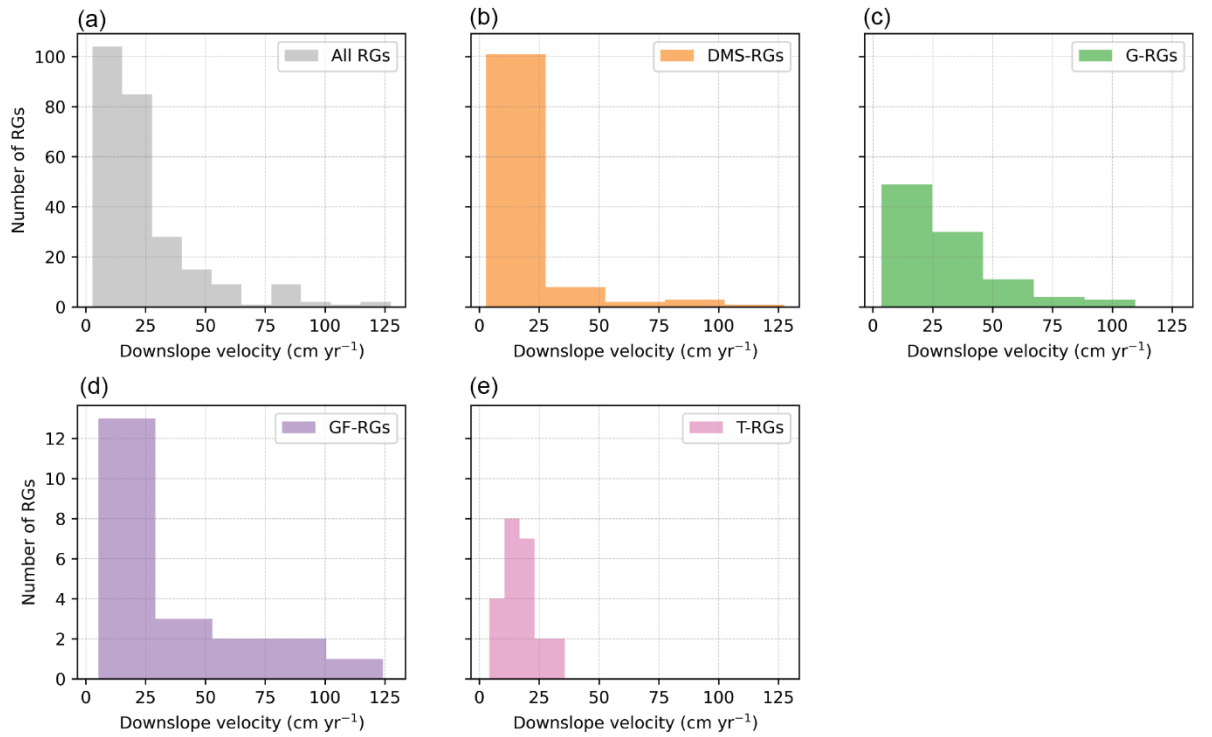


Figure 12. Histograms of the downslope velocities for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively.

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 evolutionary 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 $30,000 \text{ m}^2$, 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 evolutionary 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 evolutionary 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 km²) 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 evolutionary 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 evolutionary 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 km² vs. 0.26 km²), 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 (wk1019 and wk1020) 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 $\sim 108 \text{ km}^2$ 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 Availability 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).

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