Mapping and Characterizing Rock Glaciers in the Arid Western Kunlun Mountains Supported by InSAR and Deep Learning

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

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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. There is a complete lack of knowledge about rock glaciers in the Western Kunlun Mountains, one of the driest mountain ranges in Asia, where extensive 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 Western Kunlun Mountains: 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 3,390 m and 5,540 m with an average size of 0.26 km2 and a mean slope angle of 17°. The median and maximum surface downslope velocities of the active ones are 17±1 cm yr-1 and 127±6 cm yr-1, respectively. Characteristics of the inventoried rock glaciers provided insights into permafrost distribution in the Western Kunlun Mountains.

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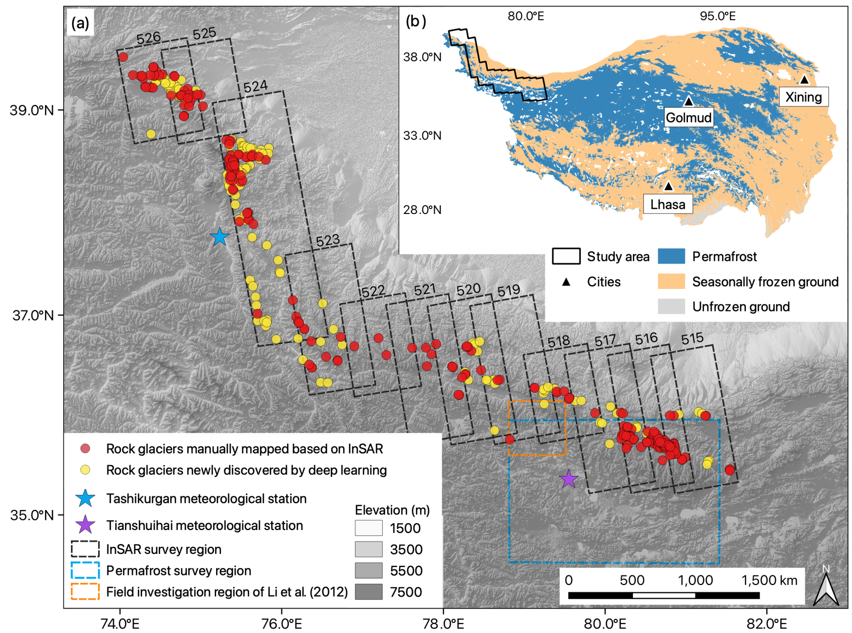
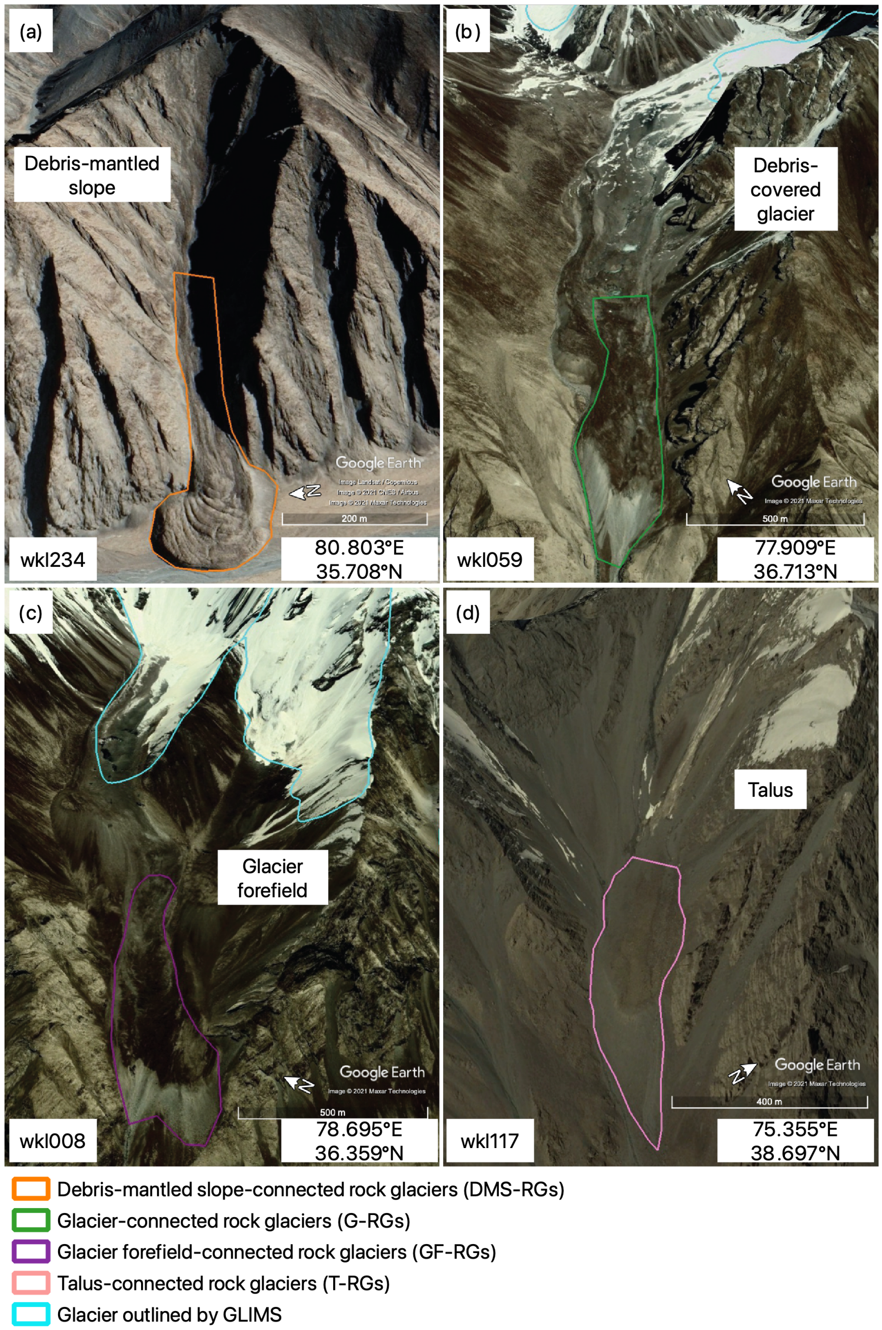
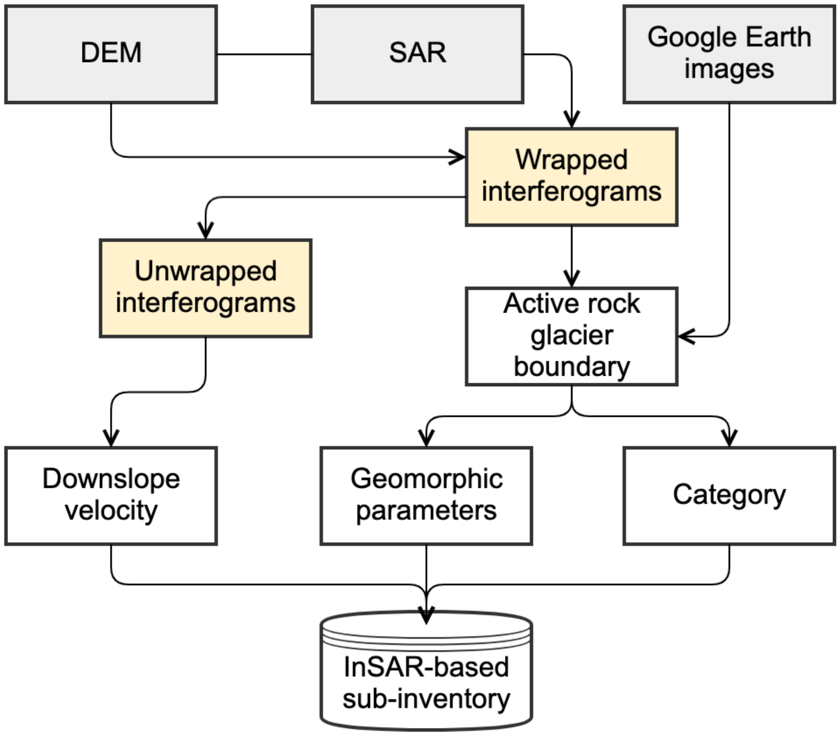
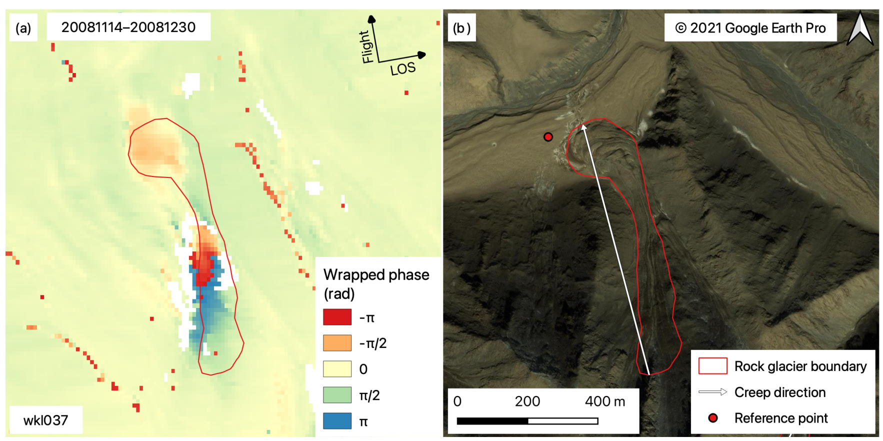


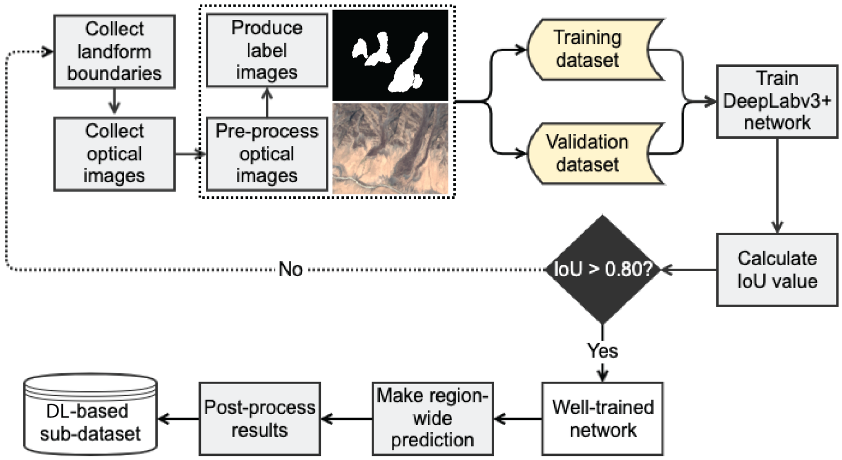
(a)
(b)
526
525
524
523
522
521
520
519
518
517
516
515
39.0°N
37.0°N
35.0°N
74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
80.0°E
95.0°E
38.0°N
33.0°N
28.0°N
Xining
Golmud
Lhasa
Study area
Cities
Permafrost
Seasonally frozen ground
Unfrozen ground
Rock glaciers manually mapped based on InSAR
Rock glaciers newly discovered by deep learning
Tashikurgan meteorological station
Tianshuihai meteorological station
InSAR survey region
Permafrost survey region
Field investigation region of Li et al. (2012)
Elevation (m)
1500
3500
5500
7500
0
500
1,000
1,500 km
N

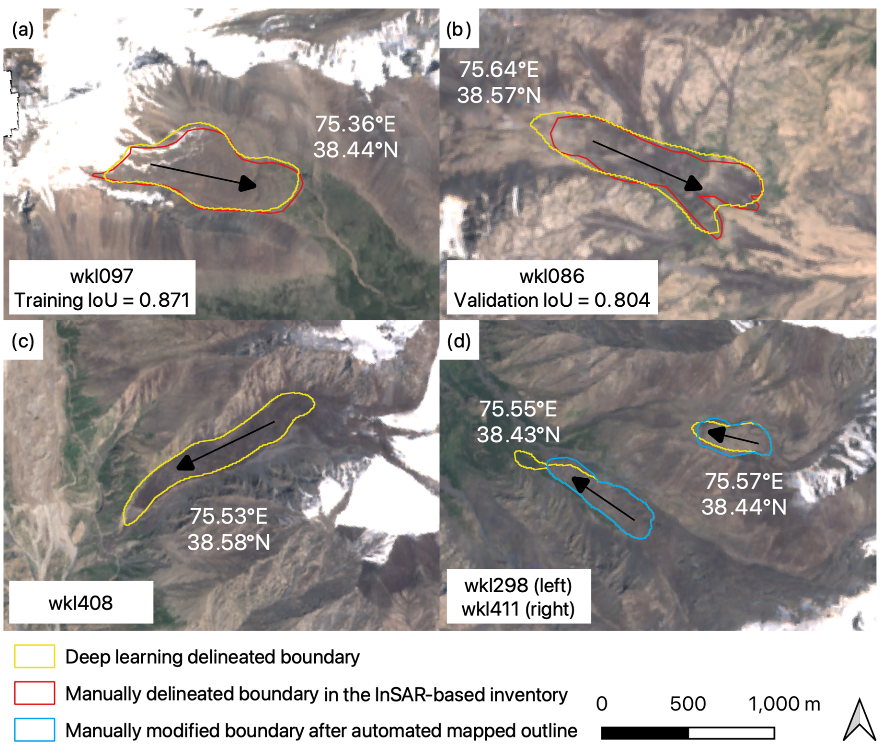


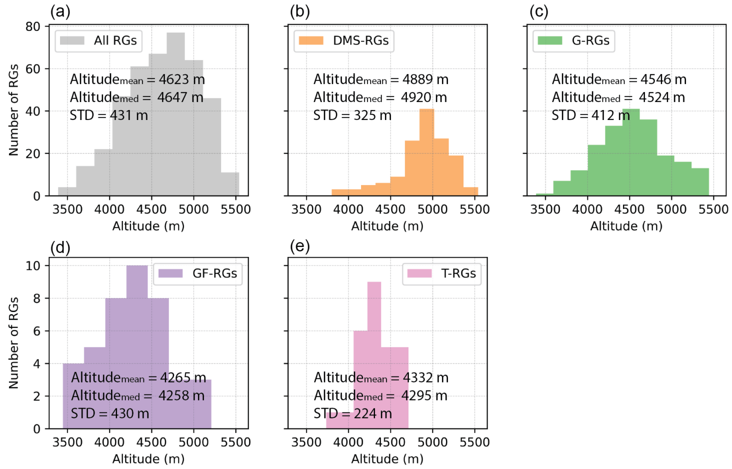
(a)
Debris-mantled slope
wkl234
80.803°E
35.708°N
200 m
Google Earth
(b)
Debris-covered glacier
wkl059
77.909°E
36.713°N
500 m
Google Earth
(c)
Glacier forefield
wkl008
78.695°E
36.359°N
500 m
Google Earth
(d)
Talus
wkl117
75.355°E
38.697°N
400 m
Google Earth
Debris-mantled slope-connected rock glaciers (DMS-RGs)
Glacier-connected rock glaciers (G-RGs)
Glacier forefield-connected rock glaciers (GF-RGs)
Talus-connected rock glaciers (T-RGs)
Glacier outlined by GLIMS

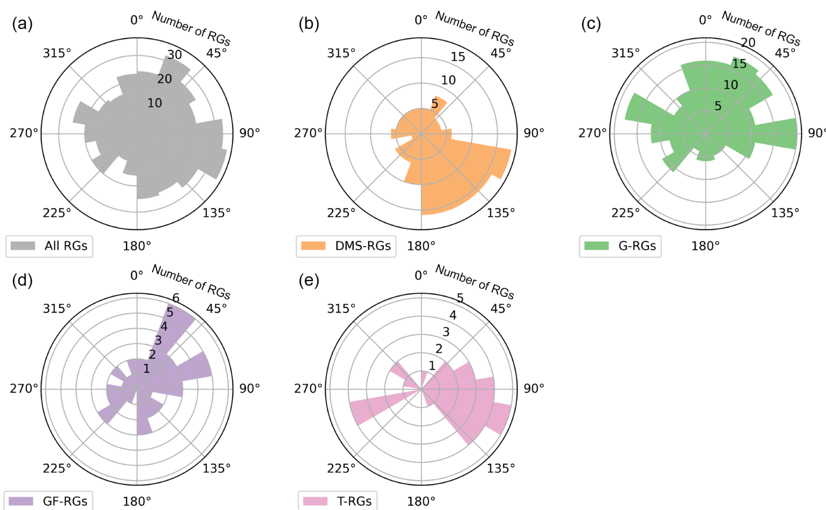

DEM
SAR
Google Earth images
Wrapped interferograms
Unwrapped interferograms
Active rock glacier boundary
Downslope velocity
Geomorphic parameters
Category
InSAR-based sub-inventory

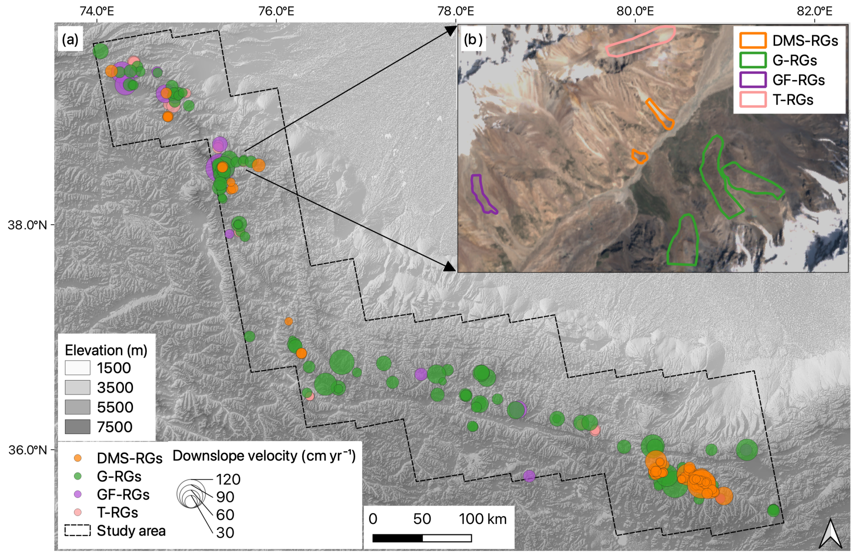

(a)
20081114–20081230
Flight
LOS
Wrapped phase (rad)
-π
-π/2
0
π/2
π
wkl037
(b)
© 2021 Google Earth Pro
Rock glacier boundary
Creep direction
Reference point
0
200
400 m

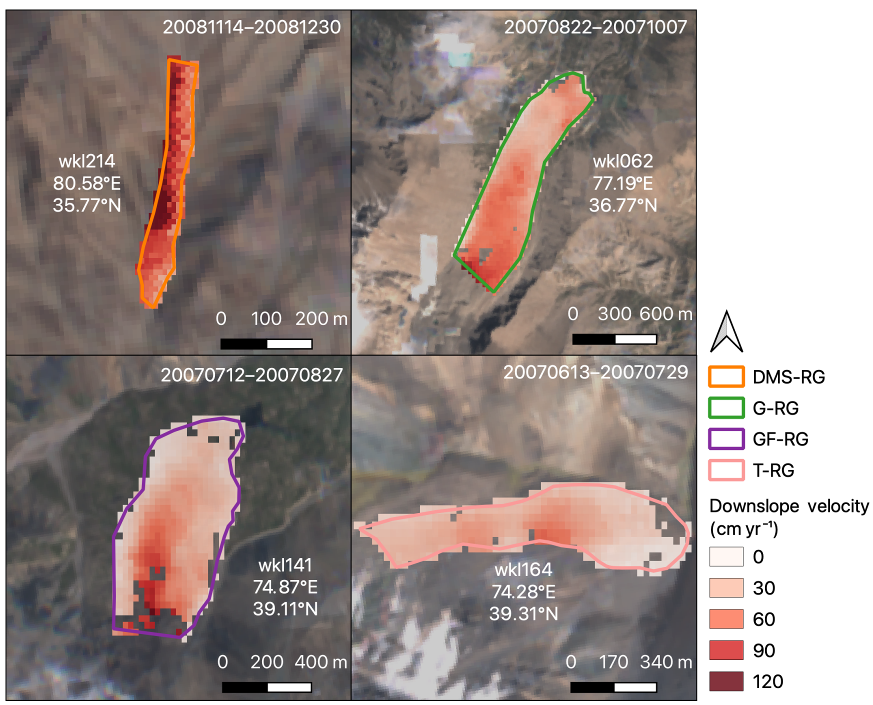

Collect landform boundaries
Collect optical images
Pre-process optical images
Produce label images
Training dataset
Validation dataset
Train DeepLabv3+ network
Calculate IoU value
IoU > 0.80?
No
Yes
Well-trained network
Make region-wide prediction
Post-process results
DL-based sub-dataset

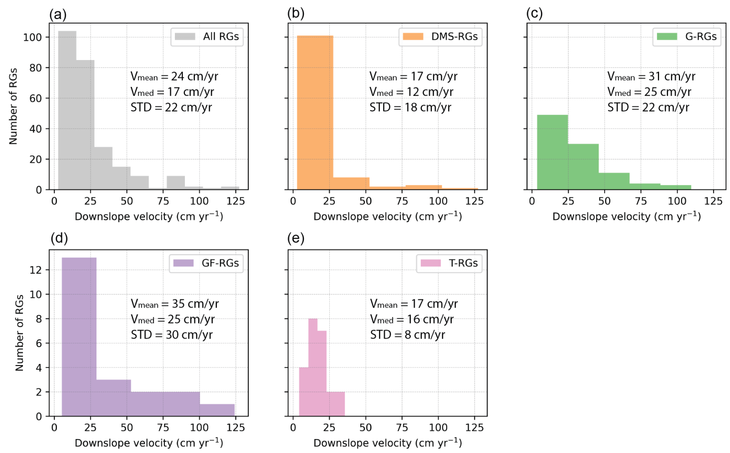

(a)
75.36°E
38.44°N
wkl097
Training IoU = 0.871
(b)
75.64°E
38.57°N
wkl086
Validation IoU = 0.804
(c)
75.53°E
38.58°N
wkl408
(d)
75.55°E
38.43°N
75.57°E
38.44°N
wkl298 (left)
wkl411 (right)
Deep learning delineated boundary
Manually delineated boundary in the InSAR-based inventory
Manually modified boundary after automated mapped outline
0
500
1,000 m

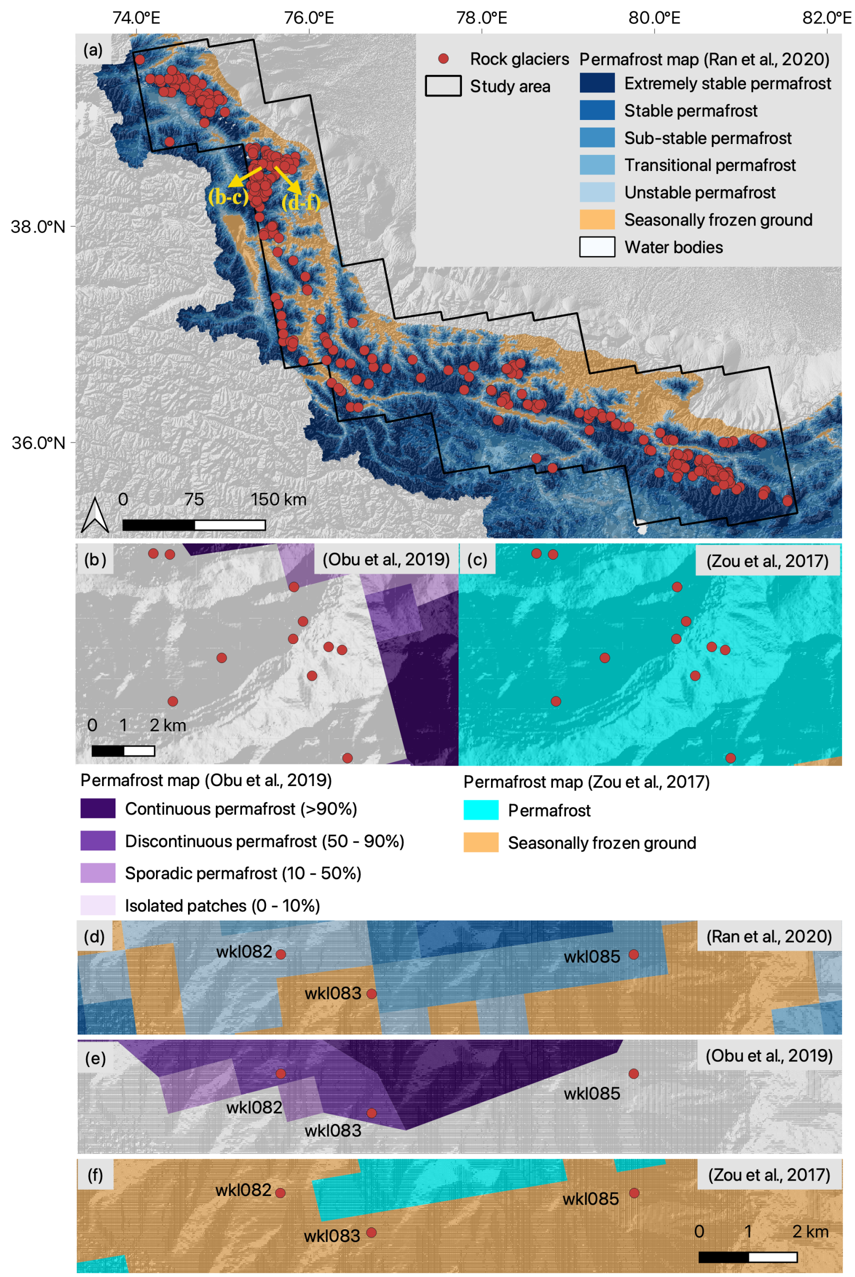

(a)
All RGs
Altitude$_{mean}$ = 4623 m
Altitude$_{med}$ = 4647 m
STD = 431 m
(b)
DMS-RGs
Altitude$_{mean}$ = 4889 m
Altitude$_{med}$ = 4920 m
STD = 325 m
(c)
G-RGs
Altitude$_{mean}$ = 4546 m
Altitude$_{med}$ = 4524 m
STD = 412 m
(d)
GF-RGs
Altitude$_{mean}$ = 4265 m
Altitude$_{med}$ = 4258 m
STD = 430 m
(e)
T-RGs
Altitude$_{mean}$ = 4332 m
Altitude$_{med}$ = 4295 m
STD = 224 m
Number of RGs
Altitude (m)


(a)
(b)
(c)
(d)
(e)
Number of RGs
All RGs
DMS-RGs
G-RGs
GF-RGs
T-RGs


74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
38.0°N
36.0°N
(a)
(b)
DMS-RGs
G-RGs
GF-RGs
T-RGs
Elevation (m)
1500
3500
5500
7500
Downslope velocity (cm yr⁻¹)
120
90
60
30
Study area
0 50 100 km


20081114–20081230
wkl214
80.58°E
35.77°N
0 100 200 m
20070822–20071007
wkl062
77.19°E
36.77°N
0 300 600 m
20070712–20070827
wkl141
74.87°E
39.11°N
0 200 400 m
20070613–20070729
wkl164
74.28°E
39.31°N
0 170 340 m
DMS-RG
G-RG
GF-RG
T-RG
Downslope velocity
(cm yr⁻¹)
0
30
60
90
120


(a)
All RGs
Vmean = 24 cm/yr
Vmed = 17 cm/yr
STD = 22 cm/yr
Number of RGs
Downslope velocity (cm yr−1)
(b)
DMS-RGs
Vmean = 17 cm/yr
Vmed = 12 cm/yr
STD = 18 cm/yr
Downslope velocity (cm yr−1)
(c)
G-RGs
Vmean = 31 cm/yr
Vmed = 25 cm/yr
STD = 22 cm/yr
Downslope velocity (cm yr−1)
(d)
GF-RGs
Vmean = 35 cm/yr
Vmed = 25 cm/yr
STD = 30 cm/yr
Number of RGs
Downslope velocity (cm yr−1)
(e)
T-RGs
Vmean = 17 cm/yr
Vmed = 16 cm/yr
STD = 8 cm/yr
Downslope velocity (cm yr−1)



74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
38.0°N
36.0°N
(a)
Rock glaciers
Study area
Permafrost map (Ran et al., 2020)
Extremely stable permafrost
Stable permafrost
Sub-stable permafrost
Transitional permafrost
Unstable permafrost
Seasonally frozen ground
Water bodies
(b-c)
(d-f)
0 75 150 km
(b)
(Obu et al., 2019)
(c)
(Zou et al., 2017)
0 1 2 km
Permafrost map (Obu et al., 2019)
Continuous permafrost (>90%)
Discontinuous permafrost (50 - 90%)
Sporadic permafrost (10 - 50%)
Isolated patches (0 - 10%)
Permafrost map (Zou et al., 2017)
Permafrost
Seasonally frozen ground
(d)
(Ran et al., 2020)
wkl082
wkl083
wkl085
(e)
(Obu et al., 2019)
wkl082
wkl083
wkl085
(f)
(Zou et al., 2017)
wkl082
wkl083
wkl085
0 1 2 km

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[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 over optical images and InSAR automates mapping rock glaciers at the regional scale
- We compile the first rock glacier inventory in the Western Kunlun Mountains with kinematic and geomorphic information documented
- Geomorphologic characteristics of rock glaciers provide insights on the glacial and periglacial processes and interactions in the Western Kunlun Mountains

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. There is a complete lack of knowledge about rock glaciers in the Western Kunlun Mountains, one of the driest mountain ranges in Asia, where extensive 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 Western Kunlun Mountains: 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 3,390 m and 5,540 m with an average size of 0.26 km^2 and a mean slope angle of 17°. The median and maximum surface downslope velocities of the active ones are 17±1 cm yr^{-1} and 127±6 cm yr^{-1}, respectively. Characteristics of the inventoried rock glaciers provided insights into permafrost distribution in the Western Kunlun Mountains.

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 Western Kunlun Mountains 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 characteristics provide insights into the permafrost distribution in the arid mountains.

1 Introduction

Rock glaciers are debris-ice landforms widely distributed in areas of mountain permafrost globally (Ballantyne 2018; Jones et al. 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 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 (Jones et al. 2018 and 2021). 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). Rock glacier inventories are therefore valuable datasets for setting up monitoring systems of rock glacier kinematics, which indicate permafrost changes under climate influence and can be quantified continuously and remotely. Moreover, intact rock glaciers contain ground ice and contribute to the local 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).

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 the application of using rock glaciers to indicate permafrost distribution. 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., Western 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 in some previous research 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, 2022a, 2022b).

Deep learning is the computer algorithm based on neural networks that are capable of learning representations of data and determining functions to project 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); and it 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) developed 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 was not 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.

Here we combine the InSAR technique and a deep learning model (DeepLabv3+Xception71) to map rock glaciers across the Western Kunlun Mountains of China where 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, 2022a, 2022b). 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, such as the coherence loss and the insensitivity to the movement perpendicular to the line-of-sight (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 Western 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 Western Kunlun Mountains is usually considered as part of the Eastern Pamir in previous research (e.g., Bolch et al. 2019a). It is 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 (Figure S1), 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 Western 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 Western Kunlun Mountains. 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/decade 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 Western Kunlun Mountains (Li et al. 2012).

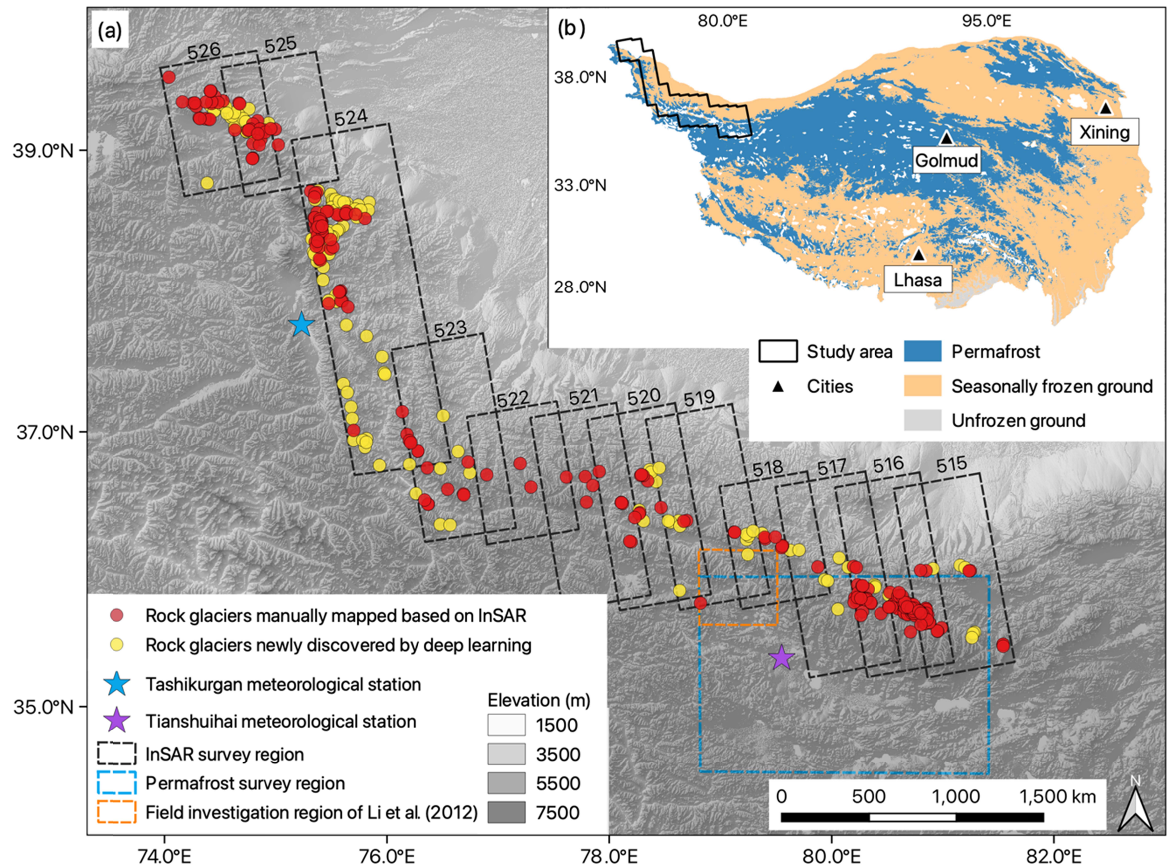

Figure 1. (a) Distribution of the mapped rock glaciers in the Western Kunlun Mountains. The red dots are manually mapped rock glaciers (290 in total), and the yellow dots represent newly identified rock glaciers by our deep learning method but were missed in the InSAR-based sub-dataset (123 in total). 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 Manual method: 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: wrapped interferograms and Google Earth images (Figure 3). 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 (2022a, 2022b) including the frontal and lateral margin morphology, and the surface ridge-and-furrow topography as an optional indicator. As much of our study area is occupied by glaciers at present (Kääb et al. 2015), one challenge is to distinguish rock glaciers from debris-covered glaciers. We used the updated GAMDAM glacier inventory to help recognize the surrounding glacier units (Sakai, 2019), then we referred to the indicative features such as the occurrence of ice cliffs, the presence of supraglacial channels, and the flow field coherence, as detailed in RGIK (2022b), for identifying the landforms as rock glaciers or debris-covered glaciers. 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 Western Kunlun Mountains were used for ground movement detection between 2007–2009 (Table 1). The SAR images are in an ascending orbit. To maintain high interferometric coherence and reduce topographic error, we selected image pairs with a fixed 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. 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). For each rock glacier, we calculated the velocities of all the pixels within the detected moving area(s), then we used the mean velocity of all the moving pixels to represent the overall kinematic status of the rock glacier unit, if the data 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, 2022a, 2022b). 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. 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 features such as the occurrence of exposed ice and thermokarst ponds. As suggested by RGIK (2022b), a straight line was drawn for delimiting the upper boundary of the rock glacier when it is infeasible to discern the boundary based on geomorphological and textural characteristics with high confidence. In addition, as we used the outlines for training the deep learning model to map rock glaciers from optical images (detailed in Sect. 3.2), a conservative strategy for determining the upper boundary was adopted given the relatively low resolution of the Sentinel-2 images. Finally, we created the InSAR-based sub-dataset. The entire workflow is illustrated in Figure 3 with one example shown in Figure 4.

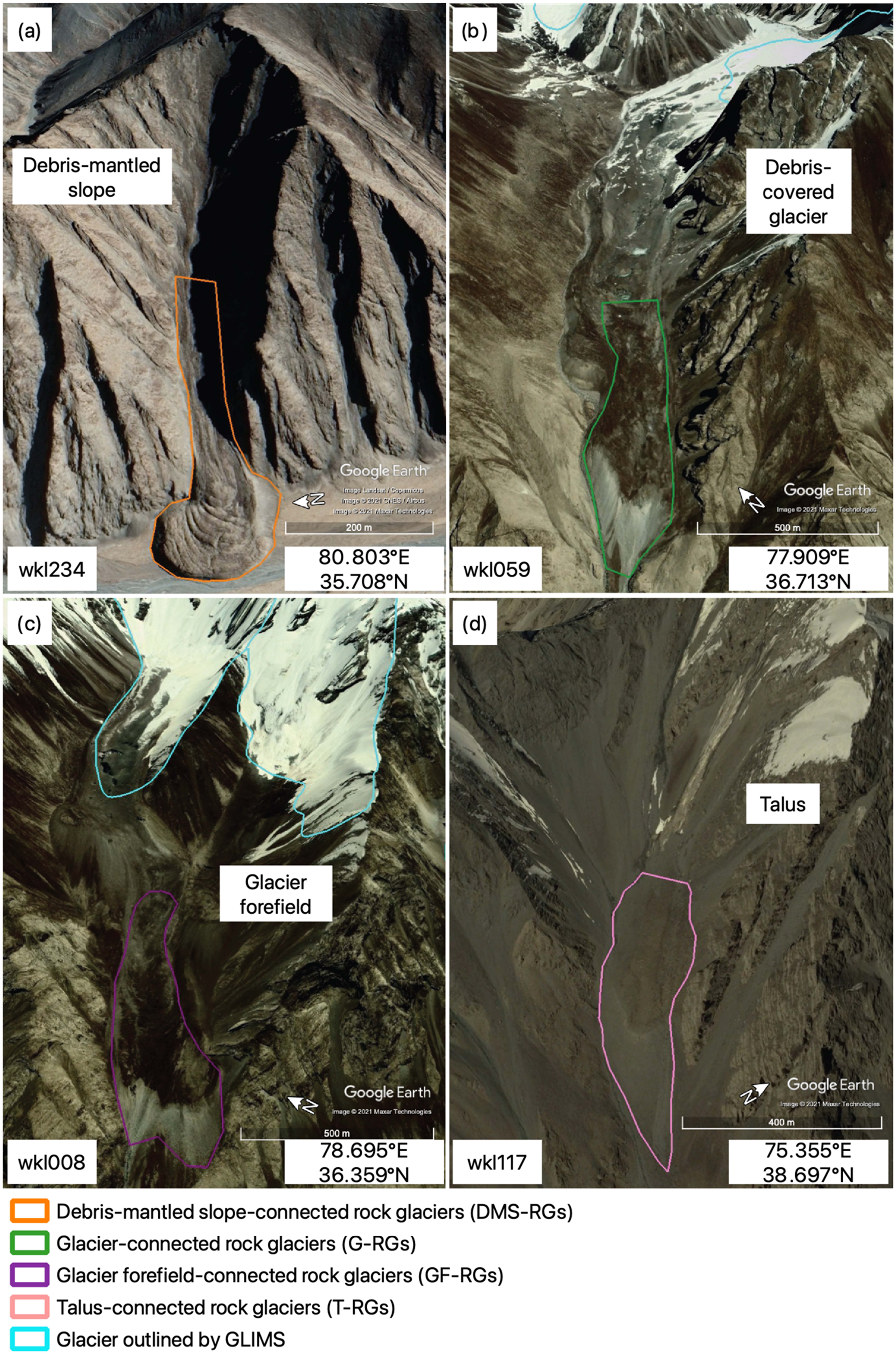
(a)
Debris-mantled slope
Google Earth
200 m
wkl234
80.803°E 35.708°N
(b)
Debris-covered glacier
Google Earth
Image © 2021 Maxar Technologies
500 m
wkl059
77.909°E 36.713°N
(c)
Glacier forefield
Google Earth
Image © 2021 Maxar Technologies
500 m
wkl008
78.695°E 36.359°N
(d)
Talus
Google Earth
Image © 2021 Maxar Technologies
400 m
wkl117
75.355°E 38.697°N
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)
Glacier outlined by GLIMS

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 GAMDAM 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.

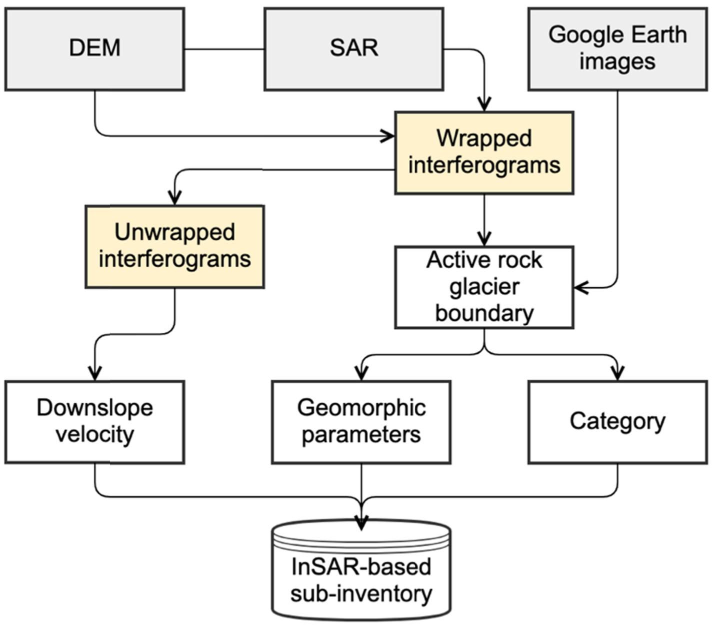

Figure 3. Diagram of the workflow to manually map active rock glaciers based on InSAR and Google Earth images.

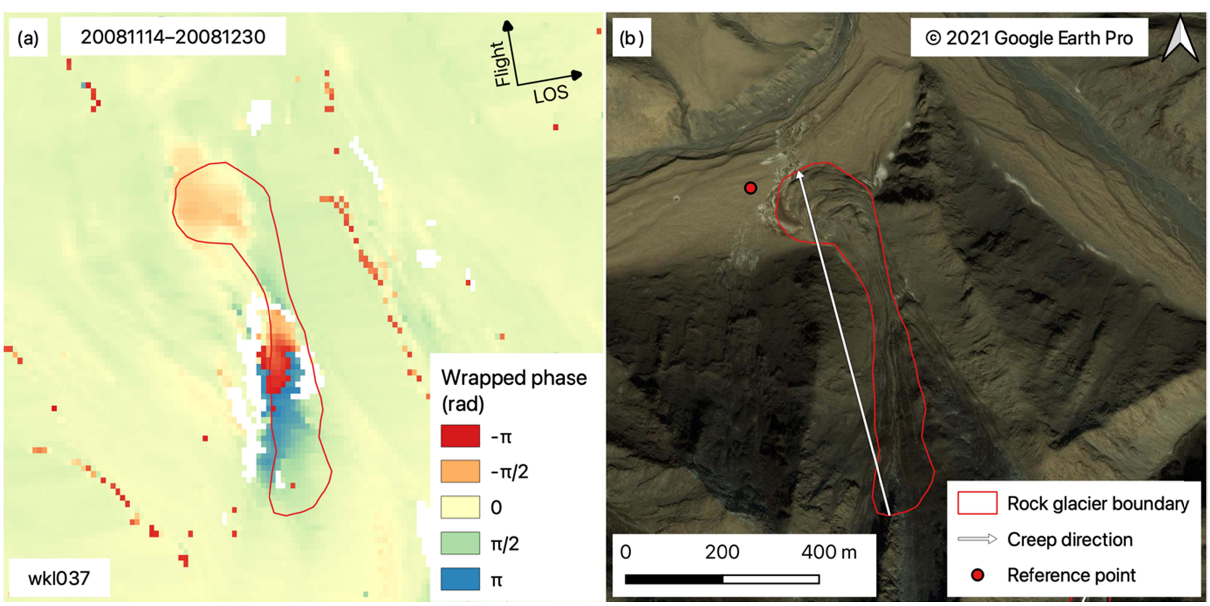

Figure 4. An example of identified active rock glacier (ID: wkl037). (a) shows the contrasting wrapped phases between the landform and surrounding background. The ALOS-1 PALSAR image pair generating the interferogram were acquired on 14/11/2008 and 30/12/2008. (b) is the corresponding Google Earth image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

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-based method 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, i.e., binary rasters that have pixel values as 0 or 1, with 1 indicating rock glaciers and 0 indicating the background, 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 Western Kunlun region acquired during July and August of 2019 (Table S2). 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, we used the manually identified rock glaciers in the format of ESRI Shapefiles created in the InSAR-based mapping process to label the Sentinel-2 images. We removed 118 rock glacier samples from the manually outlined rock glaciers 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 GAMDAM 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 (Huang et al. 2018 and 2020). 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 model we adopted was pre-trained using the ImageNet dataset and fine-tuned during our training and validation processes. 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 (Huang et al., 2020). IoU evaluates the degree of overlap between the ground truth polygons and the predicted polygons. 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 Western Kunlun Mountains. The input data occupied ~ 0.6% of the total mapping area. To refine the inference results, we excluded the predicted polygons smaller than 30000 m^2 (~300 pixels) due to the limited spatial resolution of the Sentinel-2 images and the usual areal extent of rock glaciers (>0.01 km^2). Then we inspected each automatically delineated landform and modified the boundaries when necessary. Examples are given in Sect. 4.1. 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.

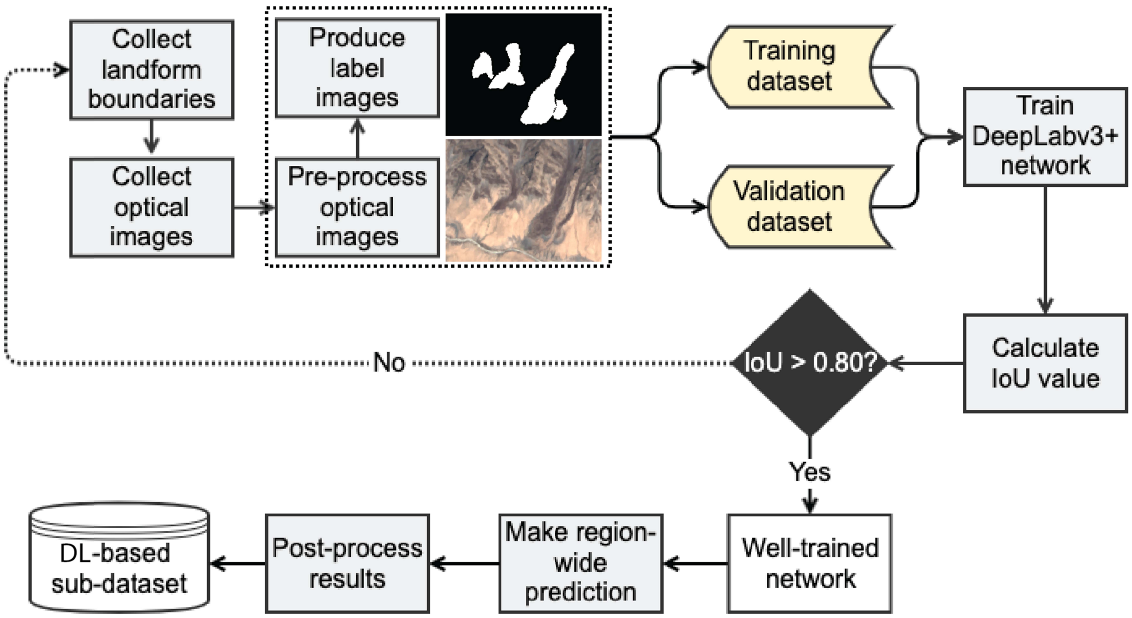

Figure 5. Diagram of the workflow to automatically map rock glaciers using DeepLabv3+ network. DL stands for deep learning.

4 Results

We produced an inventory consisting of 413 rock glaciers across the Western 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 S2).

Over the entire Western 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. Figures 6a and b present the accuracy of automated delineation by comparing the deep learning mapped rock glaciers with the manually mapped boundaries in the training and validation datasets, respectively. Specifically, Figure 6b presents an example of just passing the IoU threshold. The delineation accuracy was also acceptable for the newly discovered rock glaciers in general, as shown in Figure 6c. However, we still conducted modifications to 100 out of the 123 landforms to ensure the quality of the mapping results after manual inspection (Figure 6d). The modification was made based on the Sentinel-2 optical images according to the geomorphic criteria presented in the IPA guideline (RGIK, 2022a, 2022b). The supplementary modifications were much less labour-intensive and time-consuming than manually identifying and delineating rock glaciers from scratch.

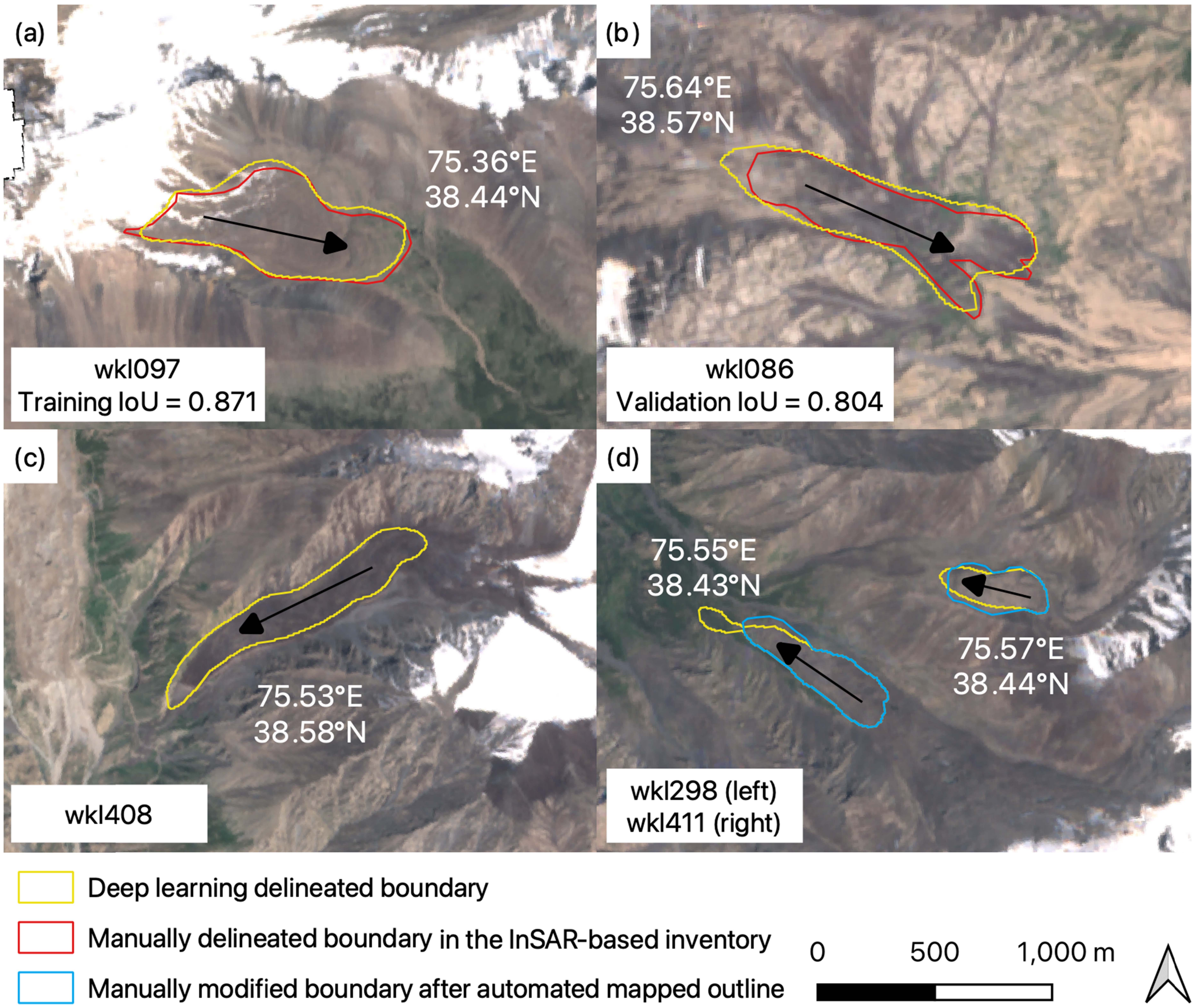

Figure 6. (a) Comparison of the deep learning mapped rock glacier boundary (in yellow) with the manually delineated polygon (in red) in the training dataset. The IoU between the two is 0.871. The black arrow indicates the flow direction. (b) Similar visual comparison between the automatically outlined 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, 2019.

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 mean altitudes between 3,390 m and 5,540 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 7a, c). The DMS-RGs generally occur at a higher altitude (Figure 7b), 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 7d, 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. Uncertainty and variability of rock glacier boundaries can occur in inventorying practice (Brardinoni et al. 2019). In our results, as each boundary was manually examined according to the IPA guidelines, we estimated the range of uncertainty of rock glacier area within 10%. 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 8a) as the movement towards eastern direction is sensitive to the InSAR detection, though the AI-based sub-dataset may suffer less from this problem. Among different categories, the G-RGs and GF-RGs are more frequently located on northeastern-facing (0º–90º) slopes (Figure 8c, d), whereas the DMS-RGs and T-RGs mostly move towards southeastern directions (90º–180º) (Figure 8b, e). Finally, we briefly compared the attributes of rock glaciers between our inventory and other research focusing on the Qinghai-Tibet Plateau (Ran and Liu, 2018; Hassan et al. 2021; Reinosch et al. 2021; Zhang et al. 2022) and found similar characteristics among the existing studies (Table S3).

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 followed 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

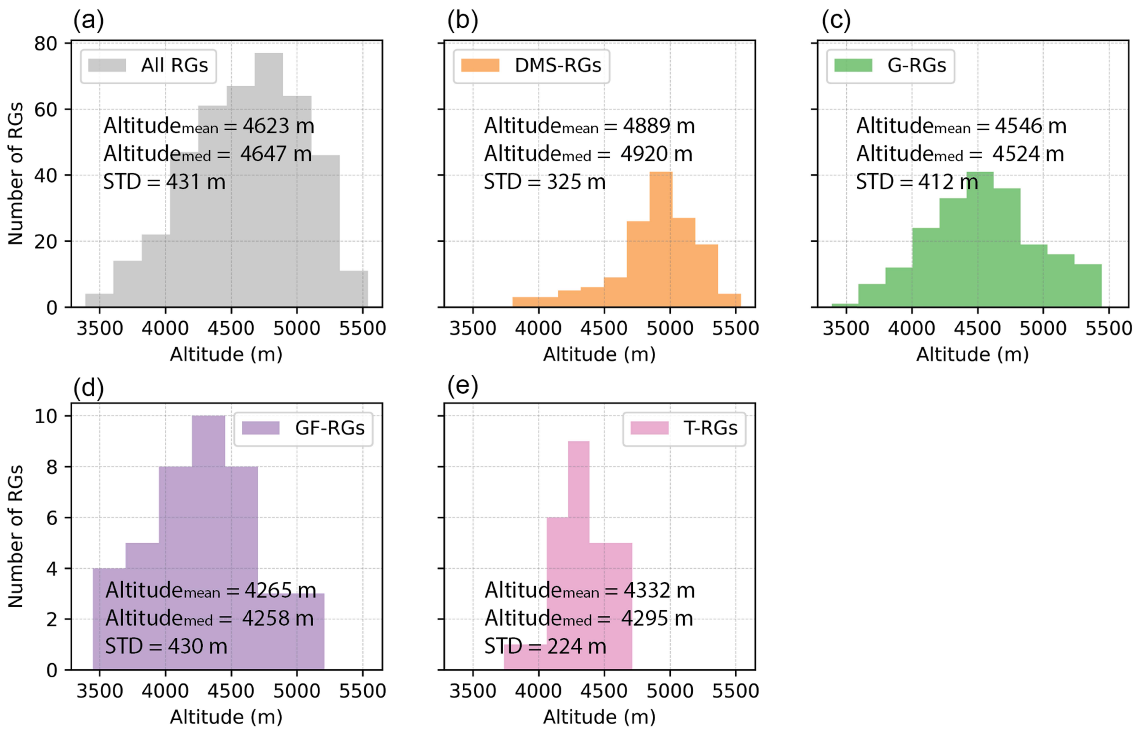

Figure 7. Histograms of the average altitudes for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively. The altitudes are calculated from the SRTM DEM data.

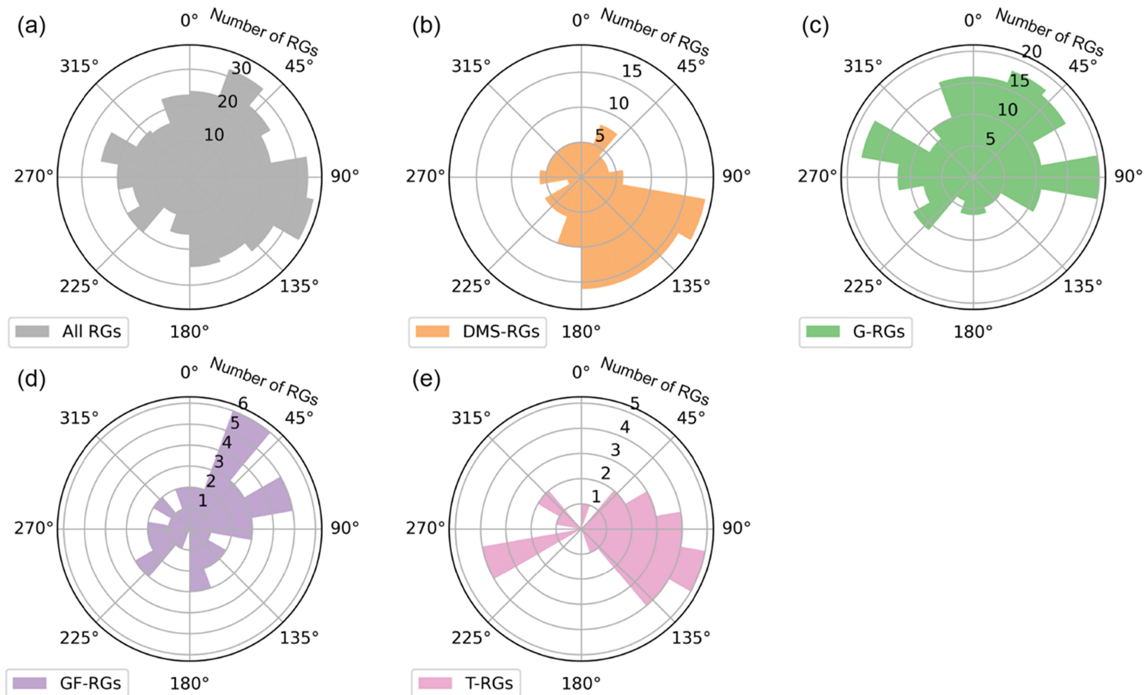

Figure 8. Histograms of the landform aspects for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs.

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 9). 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 10 gives examples of the velocity distributions of the four categories of rock glaciers. The spatial average velocities of the four categories are 79±6 cm yr^{-1} (Figure 10a), 44±1 cm yr^{-1} (Figure 10b), 32±1 cm yr^{-1} (Figure 10c), and 24±1 cm yr^{-1} (Figure 10d), 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 the kinematic data displayed a positively skewed distribution, as shown in Figure 11. Among all the mapped rock glaciers, a DMS-RG has the largest mean velocity of 127±7 cm yr^{-1}.

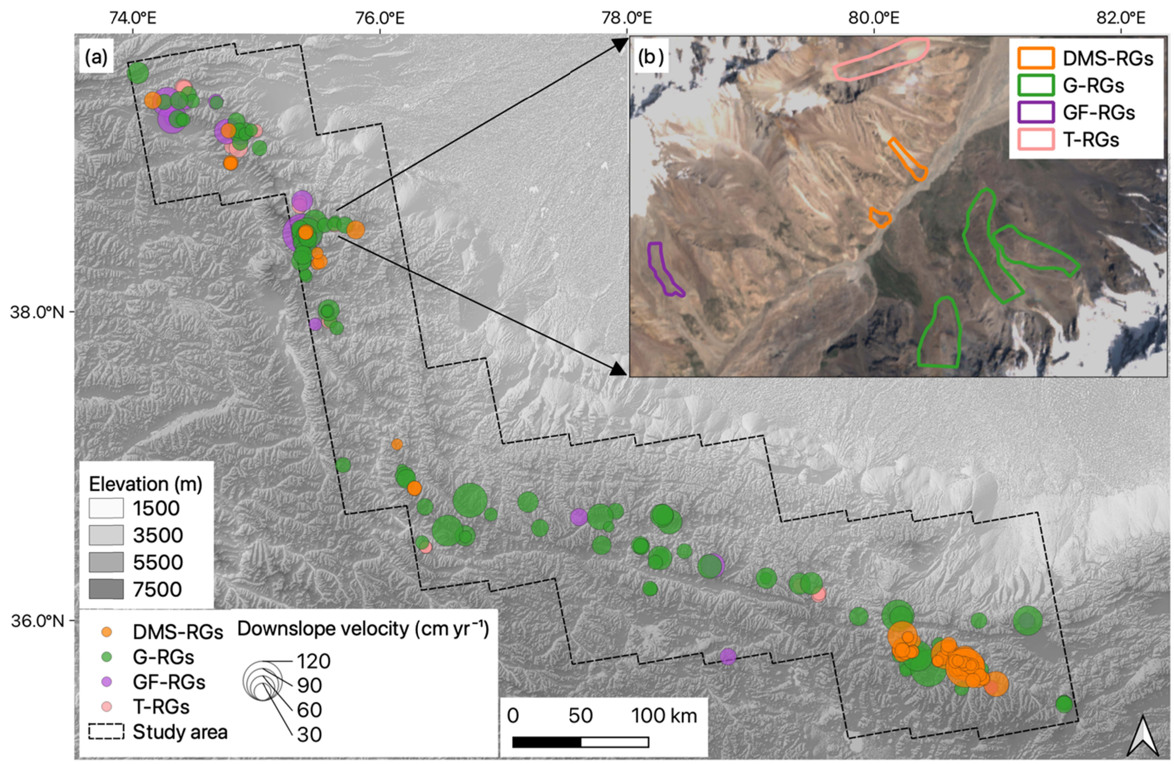

Figure 9. (a) Distribution of the mapped active rock glaciers in the study area. The four categories of rock glaciers are marked by different colours: orange for DMS-RGs, green for G-RGs, purple for GF-RGs, and pink for T-RGs. The size of the dots indicates the mean downslope velocity of each landform. The topography is mapped based on SRTM DEM. (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, 2019.

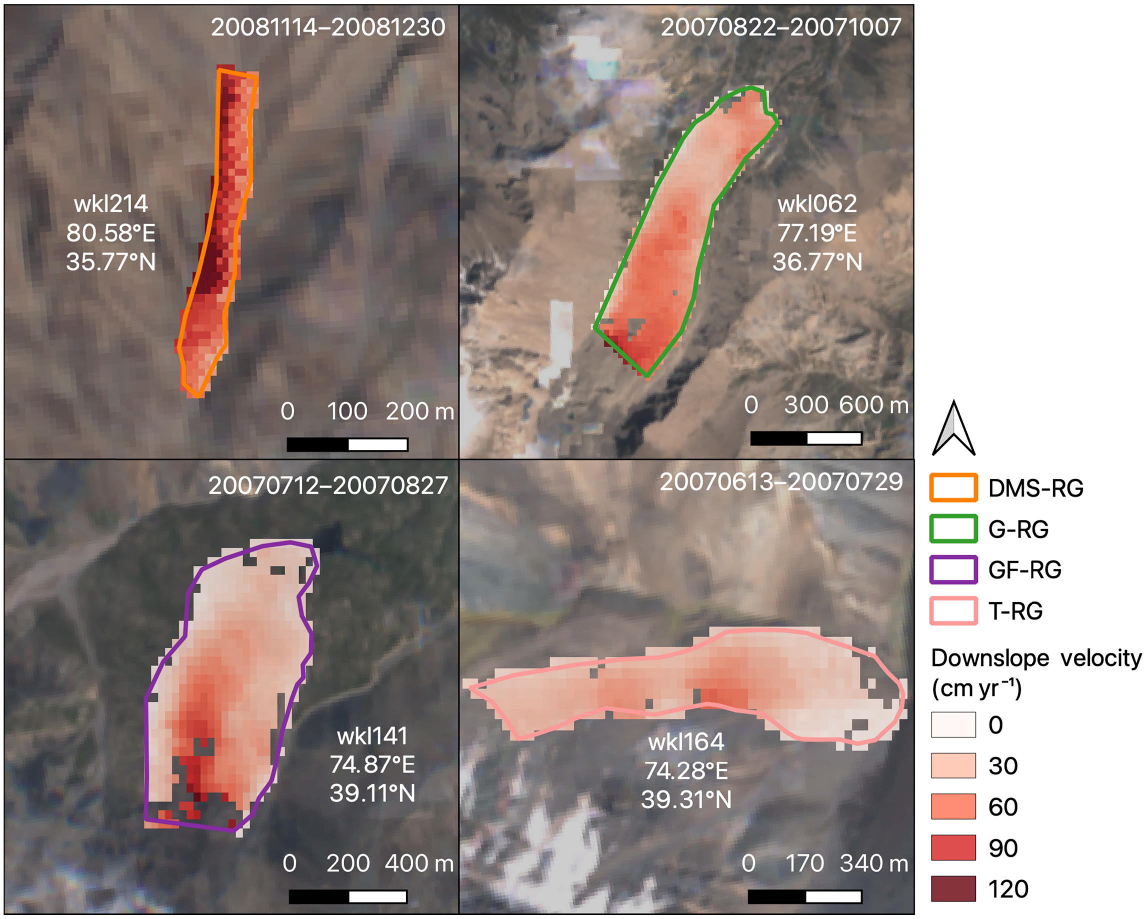

Figure 10. Velocity field maps show the downslope movement rates of rock glaciers of different categories including a DMS-RG outlined in orange (ID: wkl214), a G-RG in green (ID: wkl062) a GF-RG in purple (ID: wkl141), and a T-RG in pink (ID: wkl164). Their IDs and coordinates of central locations are 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 2019.

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

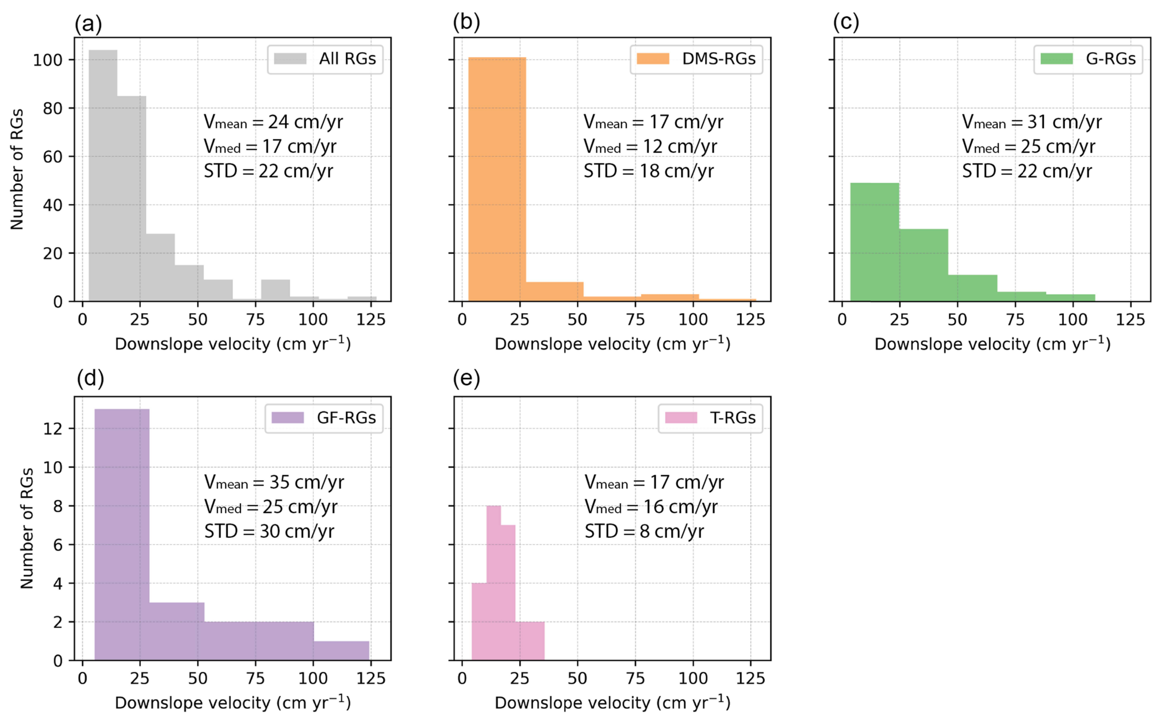

Figure 11. Histograms of the downslope velocities for (a) all RGs, (b) DMS-RGs, (c) G-RGs, (d) GF-RGs, and (e) T-RGs, respectively.

5 Discussion

In this section, we first summarize the potential and limitations of using the combined methodology for mapping rock glaciers (Sect. 5.1). Then we discuss the insights gained from the compiled inventory about the permafrost distribution across the Western Kunlun Mountains (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 Western 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, 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). By combining with 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, 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 (Figure 5). Quality of the input images is 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 (area < 30,000 m^2), from these optical images and possibly leading to inaccuracy in the output. Therefore, manual inspection is needed to build an inventory due to the false positives and a few inaccurate boundaries output by DL-based mapping method. Previous study used Sentinel-2 imagery to map rock glaciers with deep learning, but this is limited to a small region (Robson et al., 2020). Finally, the Google Earth images (2009–2020) and ALOS PALSAR data (2007–2009) we referred to while creating the InSAR-based sub-dataset are unsynchronized with the Sentinel-2 images (Jul–Aug of 2019) 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 (Bodin et al. 2017; Marcer et al. 2021).

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 (2022a, 2022b). 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.

5.2 Insights into permafrost distribution in the Western Kunlun Mountains

By comparing the locations of rock glaciers in our inventory against three permafrost maps across the study area, we observed general consistency between the rock glacier and permafrost distribution inferred in the existing maps (Figure 12a). Moreover, we gained new insights into the different permafrost maps based on our rock glacier inventory, which can be used as an indicator of permafrost distribution (Barsch, 1996).

First, in the map generated by Obu et al. (2019), a cluster of rock glaciers (10 out of 413 inventoried landforms, ~2%) are situated in the non-permafrost zone which is consistently categorized as permafrost region in the two other maps created by Zou et al. (2017) and Ran et al. (2020) (Figure 12a–c).

Second, two rock glaciers (wkl083 and wkl085) are in a region where two out of the three maps identified as seasonally frozen ground (Figure 12d–f). However, both landforms are located close to the permafrost boundary (Zou et al., 2017) or in the transitional permafrost zone (Ran et al., 2020).

Third, besides the above examples, there are rock glaciers (12 out of 413 inventoried landforms, ~3%) occasionally situating in the area classified as seasonally frozen ground by Zou et al., (2017) but as permafrost by the other two (Obu et al., 2019; Ran et al., 2020). These rock glaciers also occur near the permafrost boundaries. Figure 12f gives an example (wkl082).

In the first case, we consider that permafrost is very likely to develop in the sub-area. In the latter two cases, however, it is challenging to determine the presence or absence of permafrost from the isolated occurrence of rock glaciers near the permafrost boundaries. As the surface debris of rock glaciers usually acts as an insulating layer (Haeberli et al., 2006), the presence of rock glaciers indicates an environment where permafrost can develop under favourable conditions. Therefore, we consider these rock glaciers to represent the occurrence of permafrost within the local extent of the landforms, but we are cautious about drawing conclusions at the regional scale.

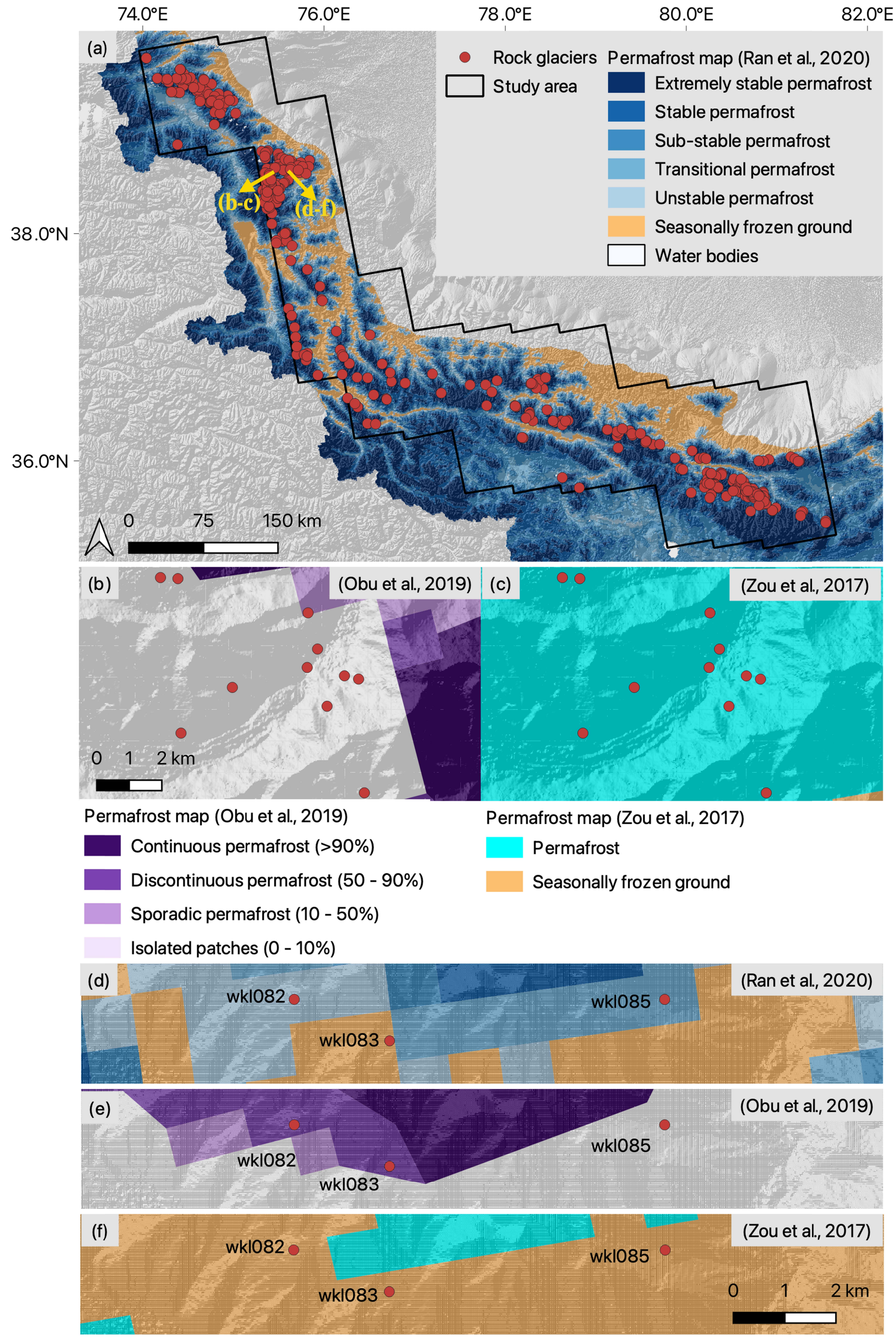

Figure 12. Comparisons between the inventoried rock glaciers and existing permafrost maps. (a) shows locations of the rock glaciers and permafrost map generated by Ran et al. (2020). (b) and (c) show the distribution of rock glaciers and permafrost over the same sub-region where different maps made contrasting predictions. (d), (e), and (f) show another sub-region where rock glaciers are situated near the permafrost boundaries identified by different maps.

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 deep learning method helped improve efficiency and overcome the limitations of InSAR-based mapping method. The combined method was applied to map rock glaciers across the Western 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 3390 m and 5540 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) 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±1 cm yr^{-1} and 127±6 cm yr^{-1}, respectively.

(5) 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 optical imagery to manually map active rock glaciers proves to be an effective way to quantify rock glacier kinematics consistently in remote areas. 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., Haberkorn et al. 2021; Thibert and Bodin, 2022).

Several improvements can be implemented to optimize the deep learning method: (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. With the utilization of improved 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.

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Open Research

Data Availability Statement

The ALOS-1 PALSAR data were copyrighted and provided by the Japan Aerospace Exploration Agency through the EO-RA2 project ER2A2N081. The TanDEM-X DEM data were copyrighted and provided by the German Aerospace Centre through project DEM_GLAC1408. The Sentinel-2 (ESA) image courtesy of the U.S. Geological Survey. Figures were made with Matplotlib version 3.4.1 (Caswell et al., 2021; Hunter, 2007), available under the Matplotlib license at https://matplotlib.org/. Maps were plotted by using QGIS (QGIS Development Team, 2009), available at http://qgis.osgeo.org. SAR interferograms were generated using ISCE version 2.2.0 (ISCE, 2021), available at https://github.com/isce-framework/isce2. 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 Zenodo (https://doi.org/10.5281/zenodo.7824698).

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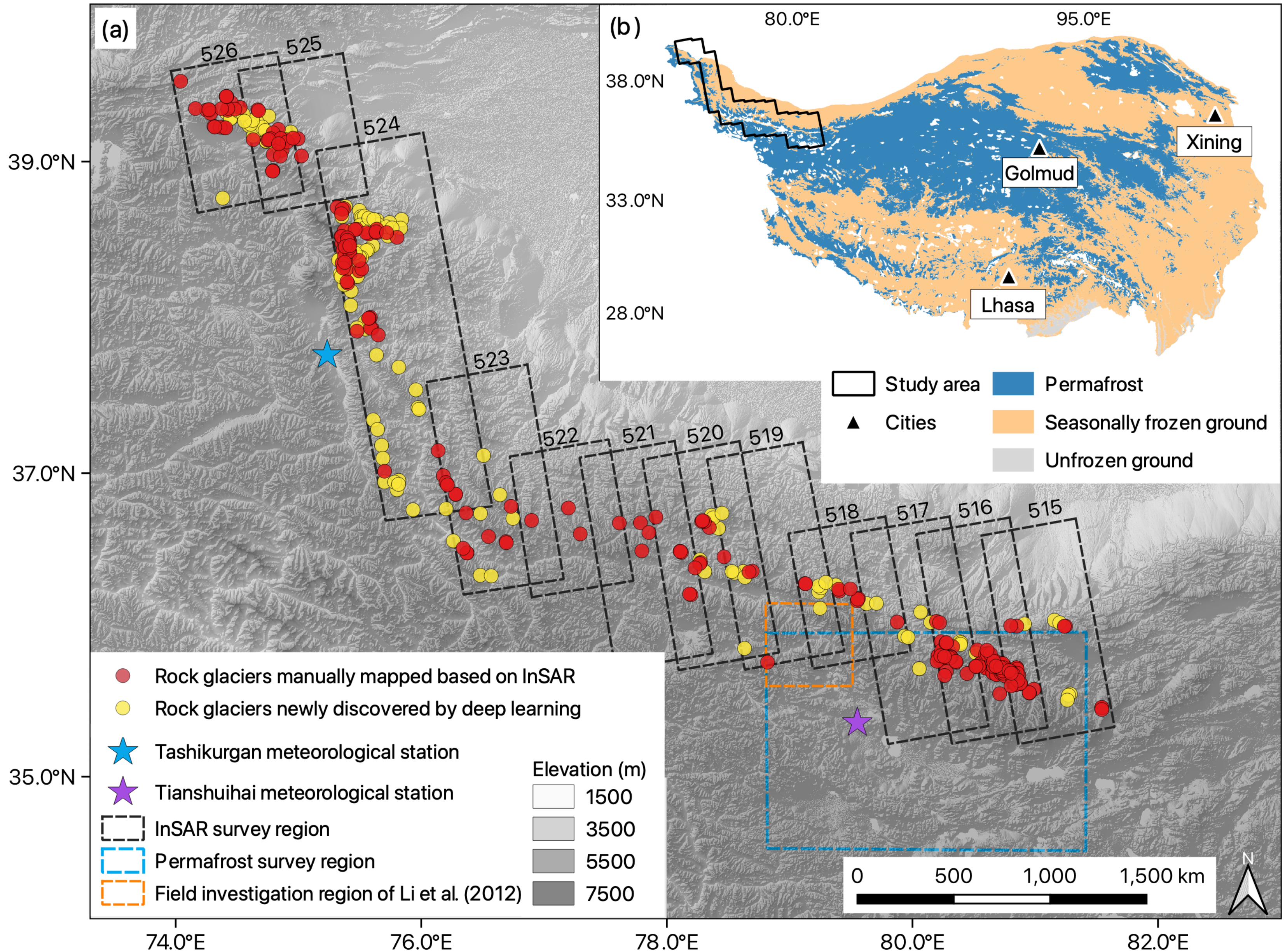
Figure 1.



(a)
(b)
526
525
524
523
522
521
520
519
518
517
516
515
39.0°N
37.0°N
35.0°N
74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
80.0°E
95.0°E
38.0°N
33.0°N
28.0°N
Golmud
Xining
Lhasa
Study area
Cities
Permafrost
Seasonally frozen ground
Unfrozen ground
Rock glaciers manually mapped based on InSAR
Rock glaciers newly discovered by deep learning
Tashikurgan meteorological station
Tianshuihai meteorological station
InSAR survey region
Permafrost survey region
Field investigation region of Li et al. (2012)
Elevation (m)
1500
3500
5500
7500
0
500
1,000
1,500 km
N

Figure 2.

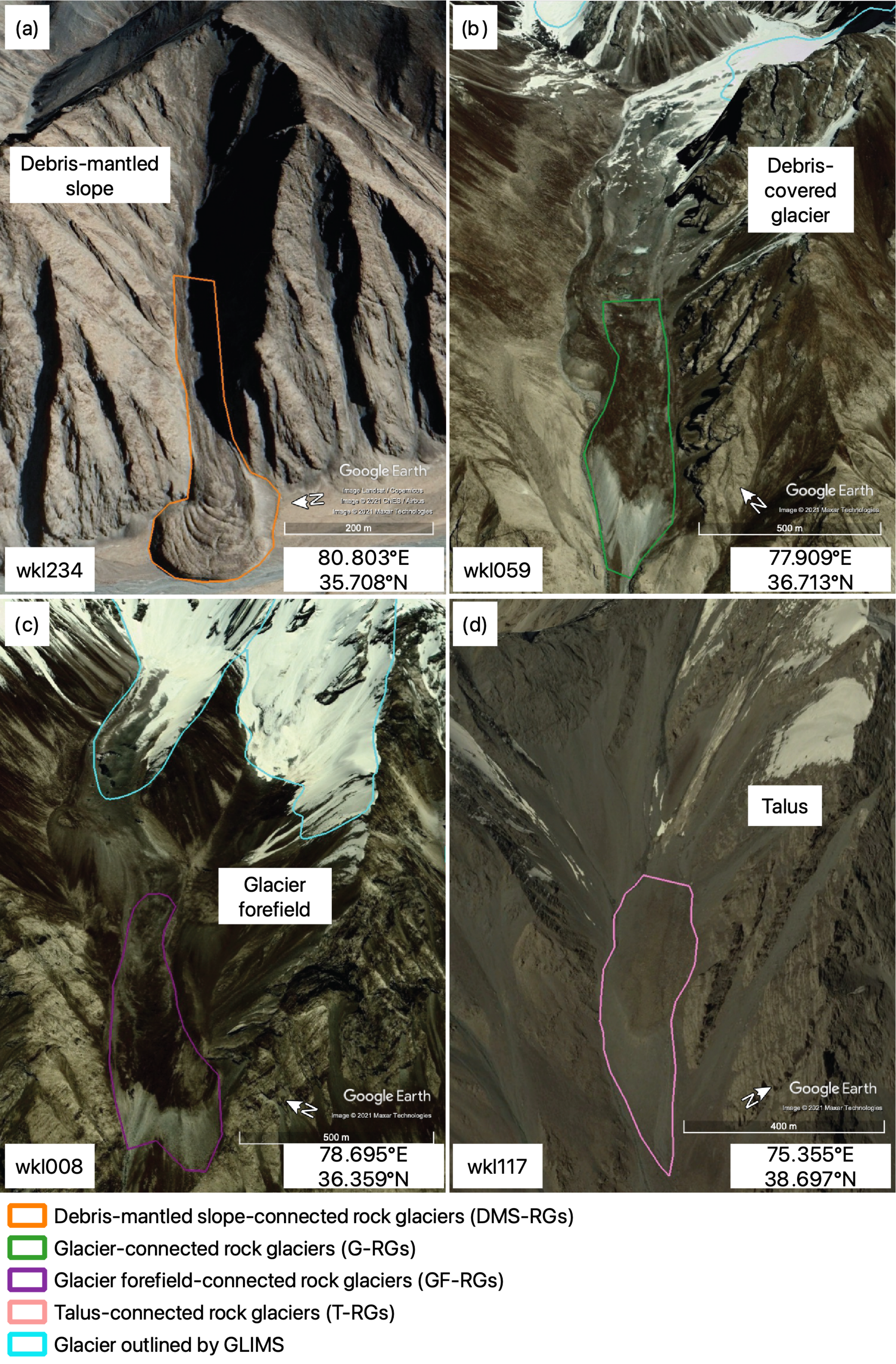

(a)
Debris-mantled slope
Google Earth
Image Landsat / Copernicus
Image © 2021 CNES / Airbus
Image © 2021 Maxar Technologies
N
200 m
wkl234
80.803°E
35.708°N
(b)
Debris-covered glacier
Google Earth
Image © 2021 Maxar Technologies
N
500 m
wkl059
77.909°E
36.713°N
(c)
Glacier forefield
Google Earth
Image © 2021 Maxar Technologies
N
500 m
wkl008
78.695°E
36.359°N
(d)
Talus
Google Earth
Image © 2021 Maxar Technologies
N
400 m
wkl117
75.355°E
38.697°N
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)
Glacier outlined by GLIMS

Figure 3.

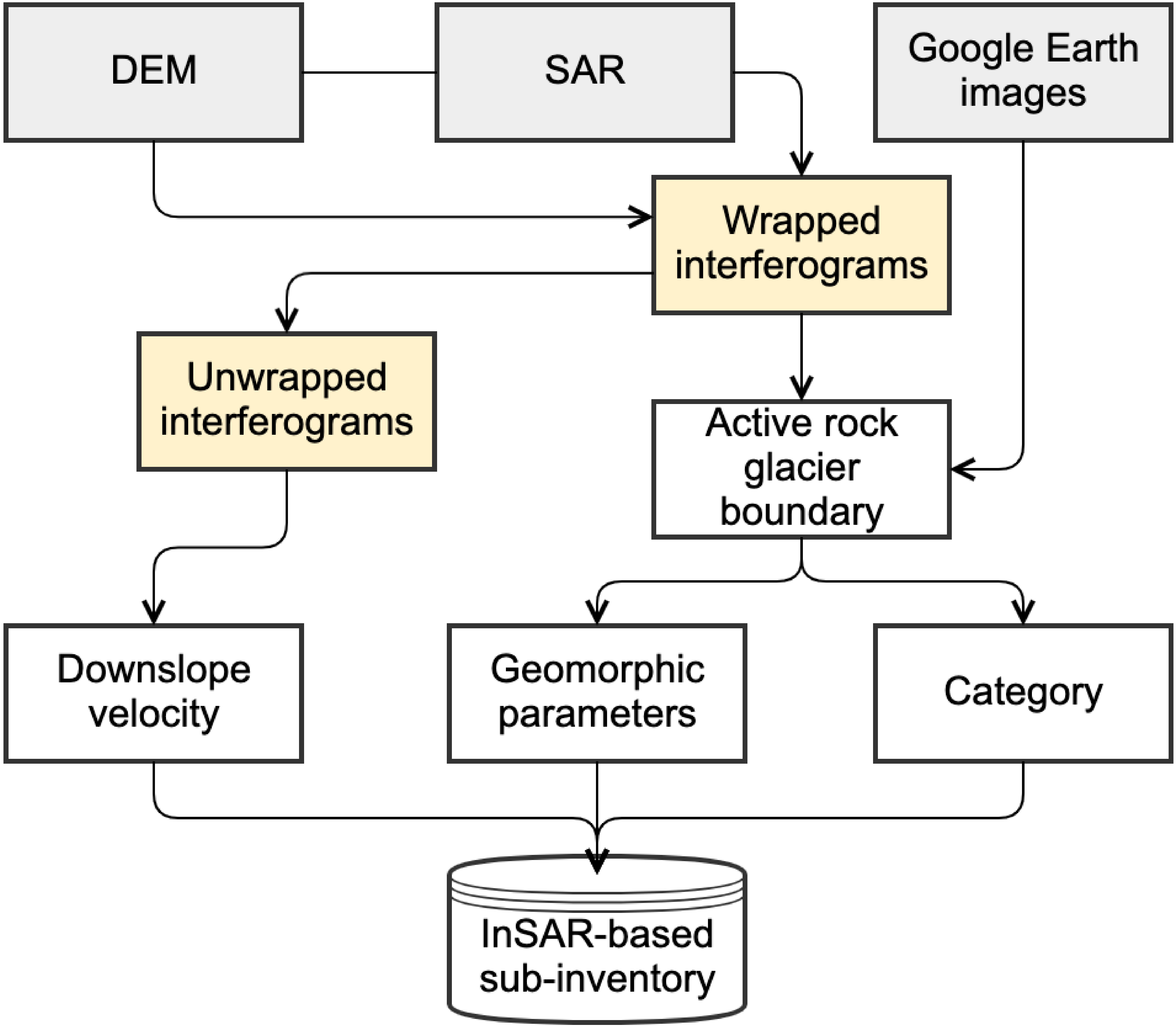

DEM
SAR
Google Earth images
Wrapped interferograms
Unwrapped interferograms
Active rock glacier boundary
Downslope velocity
Geomorphic parameters
Category
InSAR-based sub-inventory

Figure 4.

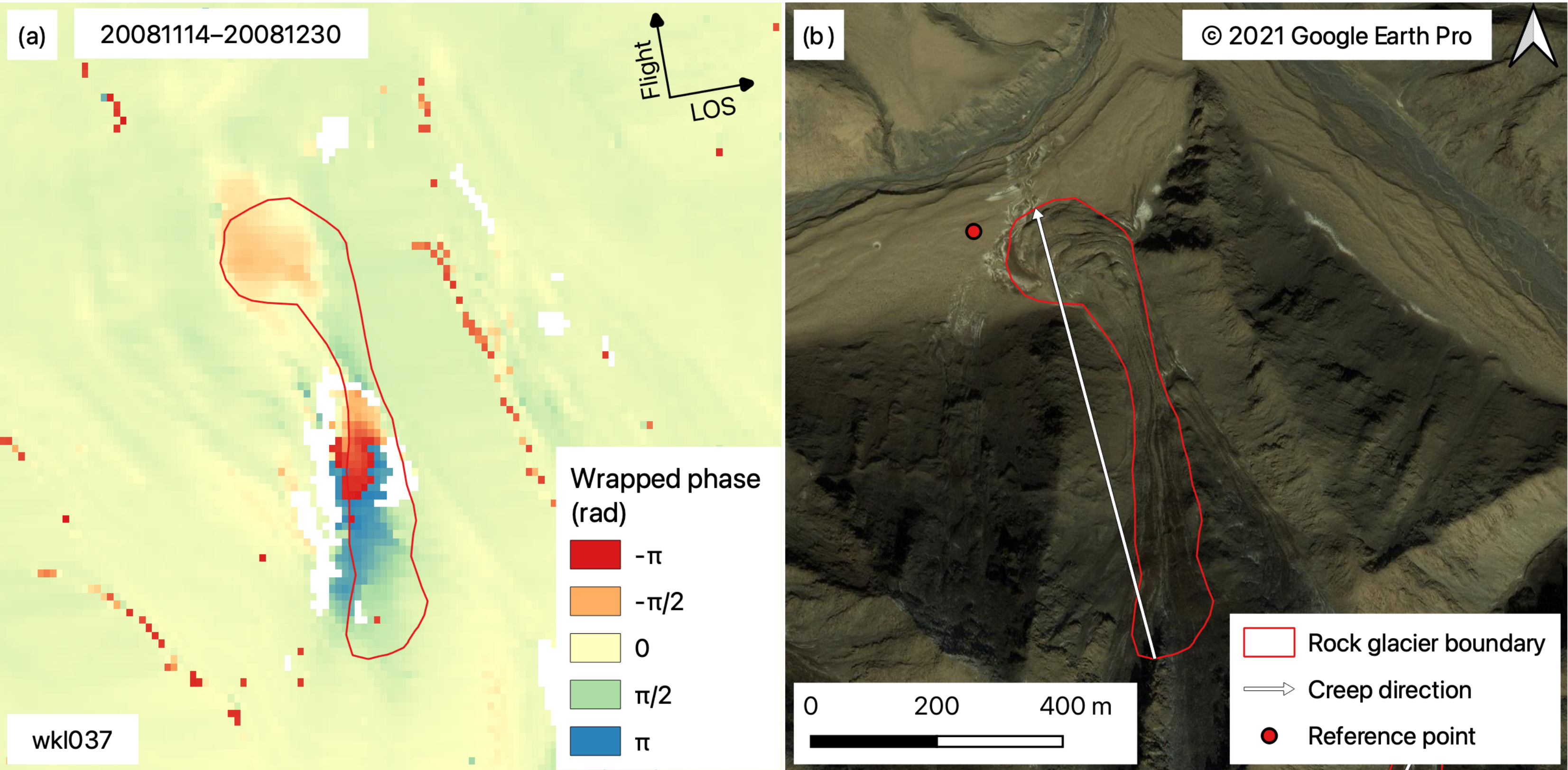

(a)
20081114–20081230
Flight
LOS
Wrapped phase (rad)
-π
-π/2
0
π/2
π
wkl037
(b)
© 2021 Google Earth Pro
0
200
400 m
Rock glacier boundary
Creep direction
Reference point

Figure 5.

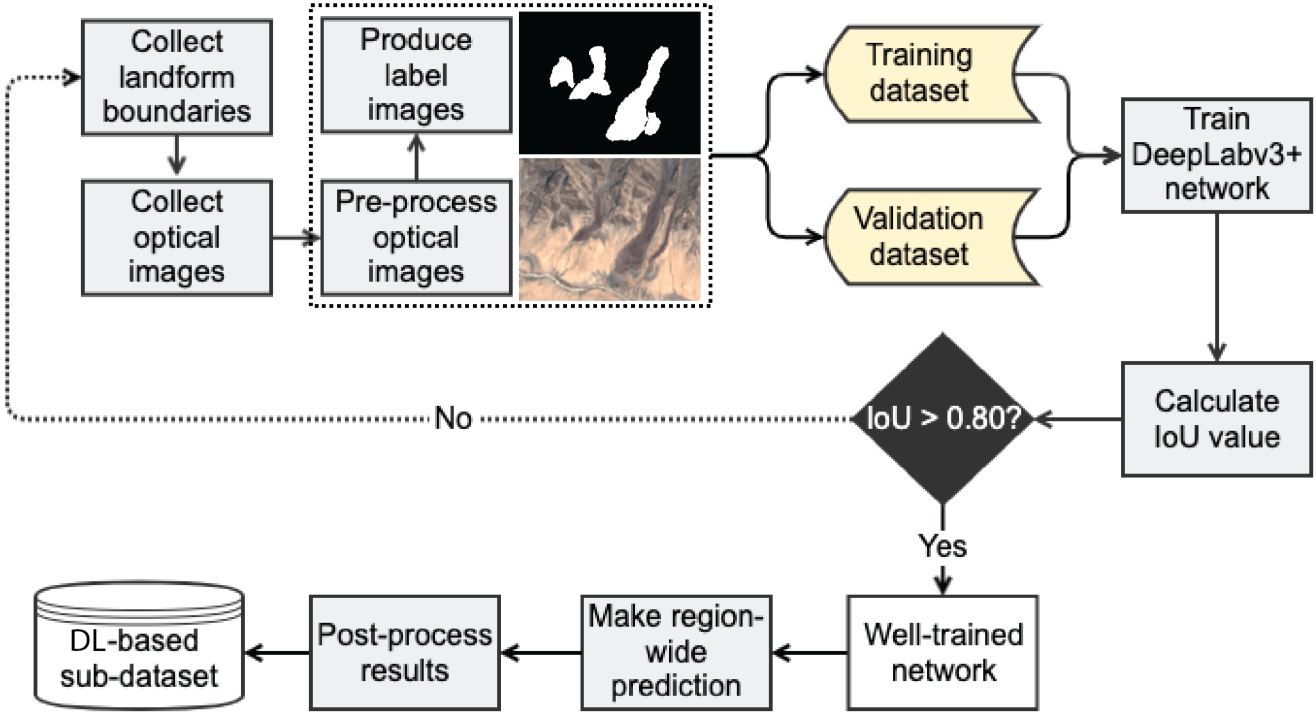

Collect landform boundaries
Collect optical images
Produce label images
Pre-process optical images
Training dataset
Validation dataset
Train DeepLabv3+ network
Calculate IoU value
IoU > 0.80?
No
Yes
Well-trained network
Make region-wide prediction
Post-process results
DL-based sub-dataset

Figure 6.

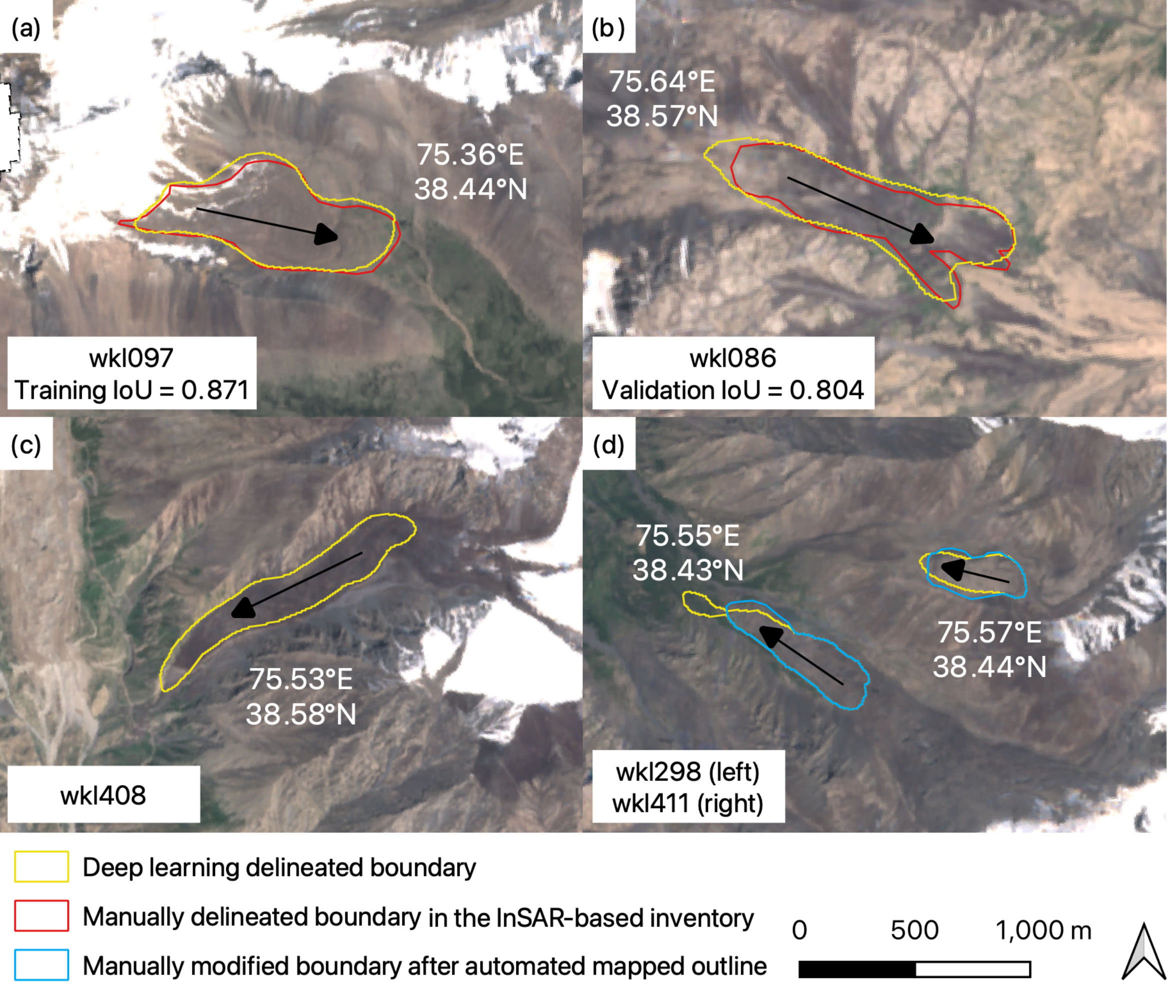
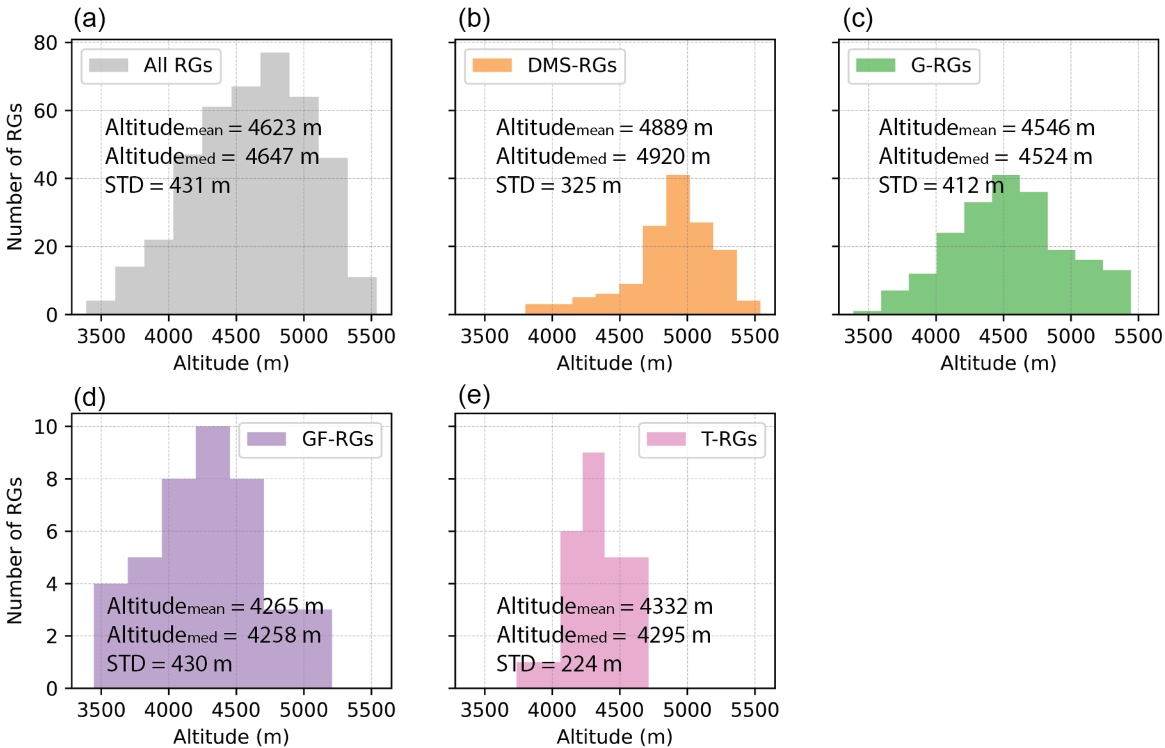
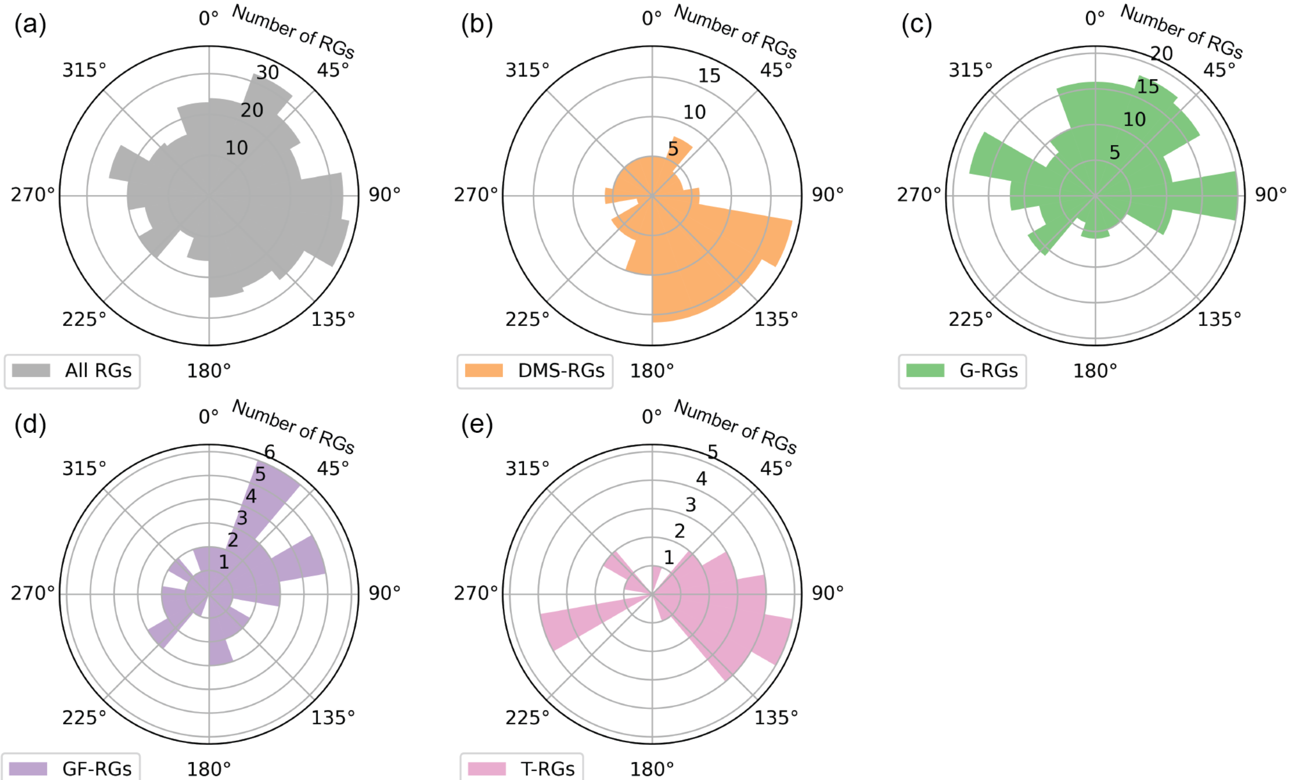

(a)
75.36°E
38.44°N
wkl097
Training IoU = 0.871
(b)
75.64°E
38.57°N
wkl086
Validation IoU = 0.804
(c)
75.53°E
38.58°N
wkl408
(d)
75.55°E
38.43°N
75.57°E
38.44°N
wkl298 (left)
wkl411 (right)
Deep learning delineated boundary
Manually delineated boundary in the InSAR-based inventory
Manually modified boundary after automated mapped outline
0
500
1,000 m

Figure 7.



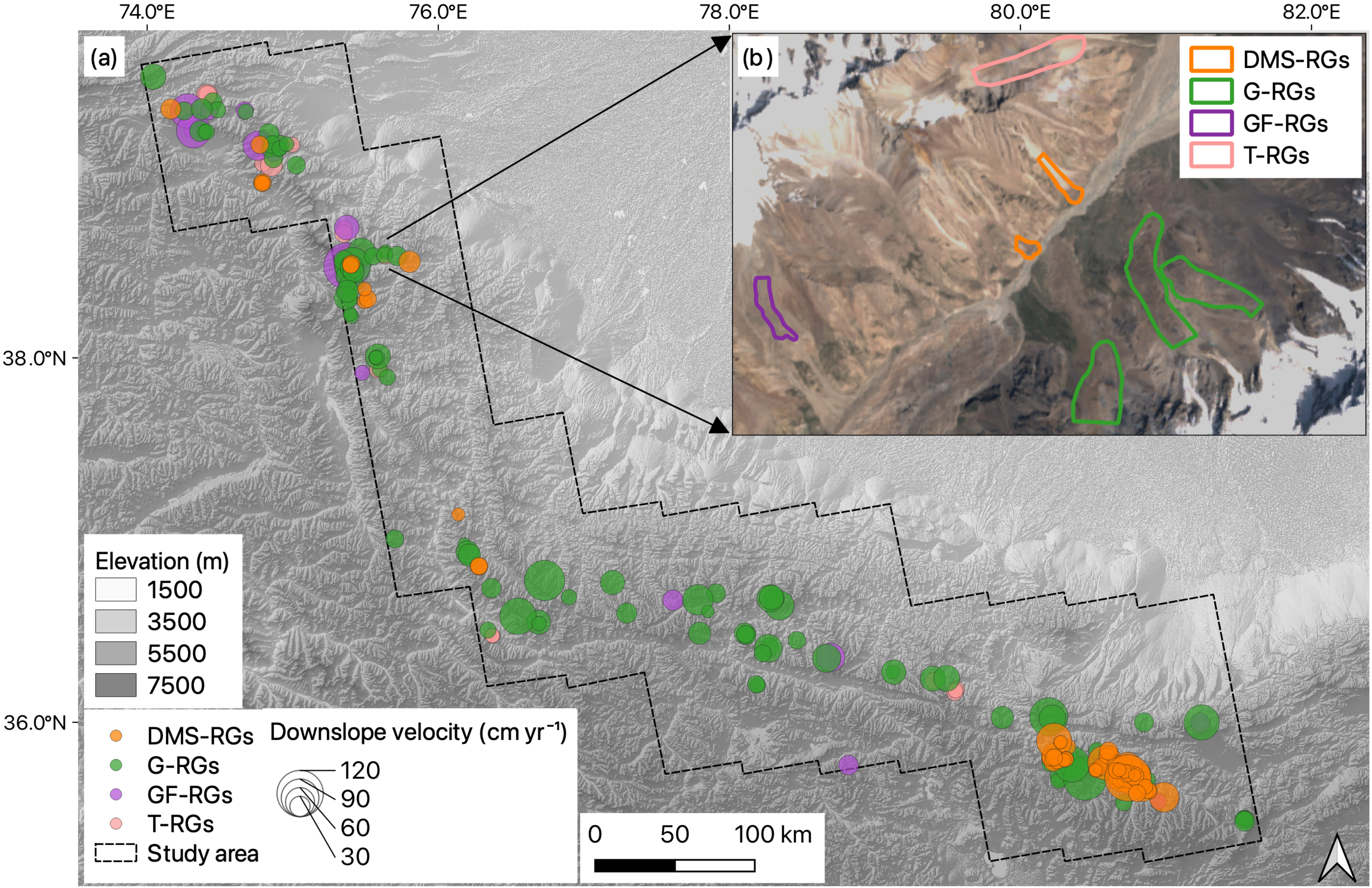
(a)
All RGs
Altitude_mean = 4623 m
Altitude_med = 4647 m
STD = 431 m
(b)
DMS-RGs
Altitude_mean = 4889 m
Altitude_med = 4920 m
STD = 325 m
(c)
G-RGs
Altitude_mean = 4546 m
Altitude_med = 4524 m
STD = 412 m
(d)
GF-RGs
Altitude_mean = 4265 m
Altitude_med = 4258 m
STD = 430 m
(e)
T-RGs
Altitude_mean = 4332 m
Altitude_med = 4295 m
STD = 224 m
Number of RGs
Altitude (m)
0
20
40
60
80
2
4
6
8
10
3500
4000
4500
5000
5500

Figure 8.



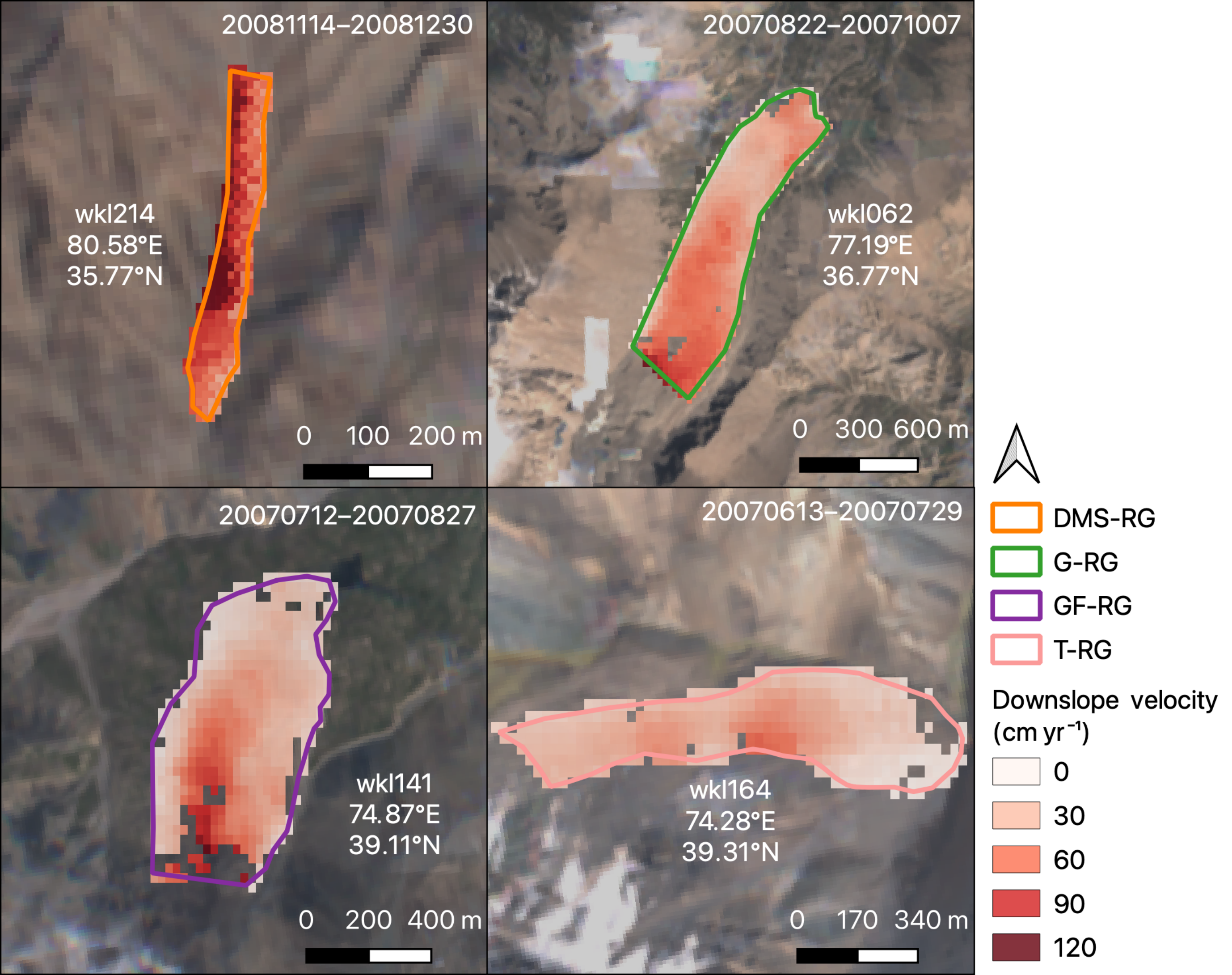
(a)
0°
Number of RGs
10
20
30
45°
90°
135°
180°
225°
270°
315°
All RGs
(b)
Number of RGs
5
10
15
DMS-RGs
(c)
Number of RGs
5
10
15
20
G-RGs
(d)
Number of RGs
1
2
3
4
5
6
GF-RGs
(e)
Number of RGs
1
2
3
4
5
T-RGs

Figure 9.



74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
38.0°N
36.0°N
(a)
(b)
DMS-RGs
G-RGs
GF-RGs
T-RGs
Elevation (m)
1500
3500
5500
7500
DMS-RGs
G-RGs
GF-RGs
T-RGs
Study area
Downslope velocity (cm yr⁻¹)
120
90
60
30
0 50 100 km

Figure 10.



20081114–20081230
wkl214
80.58°E
35.77°N
0 100 200 m
20070822–20071007
wkl062
77.19°E
36.77°N
0 300 600 m
20070712–20070827
wkl141
74.87°E
39.11°N
0 200 400 m
20070613–20070729
wkl164
74.28°E
39.31°N
0 170 340 m
DMS-RG
G-RG
GF-RG
T-RG
Downslope velocity
(cm yr⁻¹)
0
30
60
90
120

Figure 11.

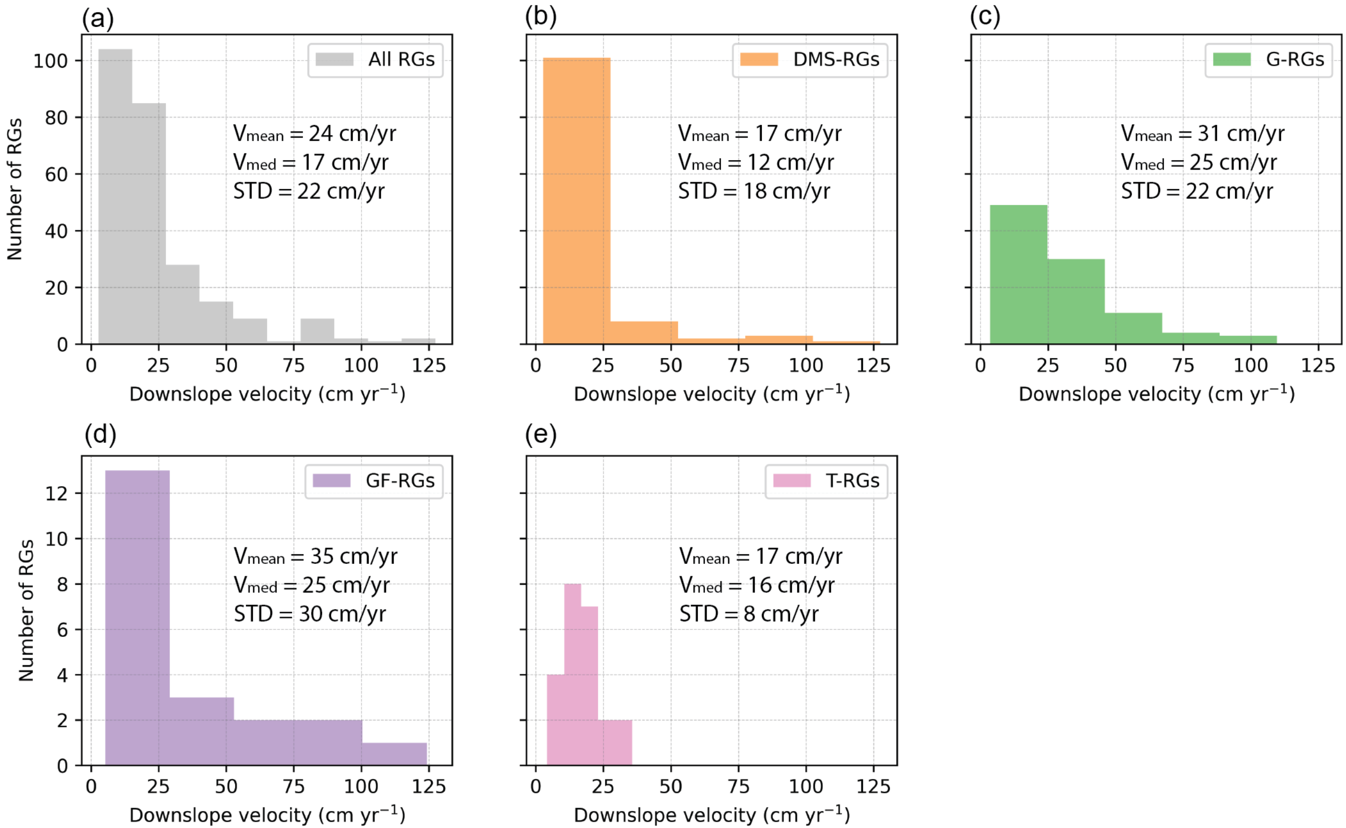
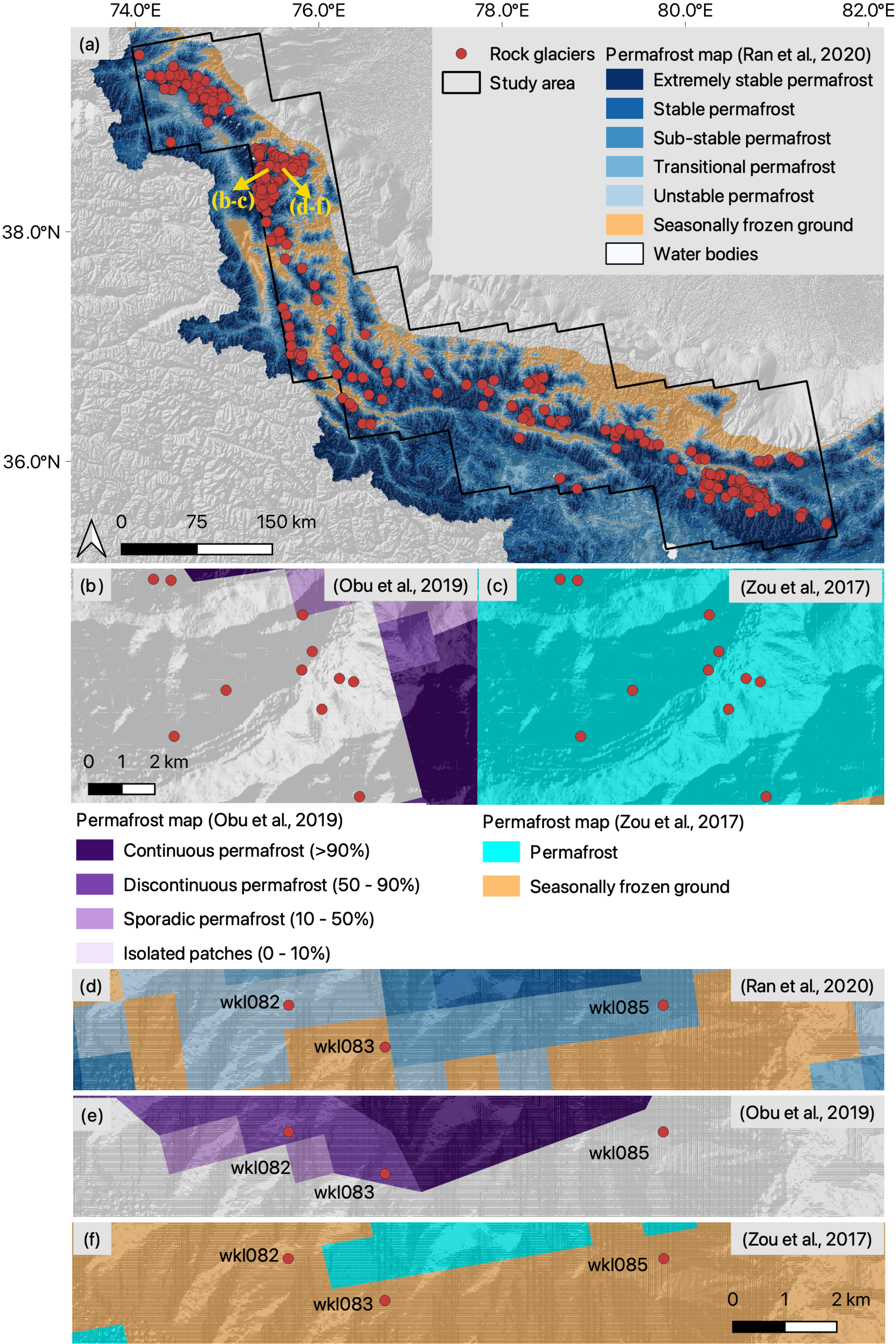

(a)
All RGs
Vmean = 24 cm/yr
Vmed = 17 cm/yr
STD = 22 cm/yr
Number of RGs
Downslope velocity (cm yr⁻¹)
(b)
DMS-RGs
Vmean = 17 cm/yr
Vmed = 12 cm/yr
STD = 18 cm/yr
(c)
G-RGs
Vmean = 31 cm/yr
Vmed = 25 cm/yr
STD = 22 cm/yr
(d)
GF-RGs
Vmean = 35 cm/yr
Vmed = 25 cm/yr
STD = 30 cm/yr
(e)
T-RGs
Vmean = 17 cm/yr
Vmed = 16 cm/yr
STD = 8 cm/yr

Figure 12.



74.0°E
76.0°E
78.0°E
80.0°E
82.0°E
38.0°N
36.0°N
(a)
Rock glaciers
Study area
Permafrost map (Ran et al., 2020)
Extremely stable permafrost
Stable permafrost
Sub-stable permafrost
Transitional permafrost
Unstable permafrost
Seasonally frozen ground
Water bodies
(b-c)
(d-f)
0 75 150 km
(b)
(Obu et al., 2019)
0 1 2 km
(c)
(Zou et al., 2017)
Permafrost map (Obu et al., 2019)
Continuous permafrost (>90%)
Discontinuous permafrost (50 - 90%)
Sporadic permafrost (10 - 50%)
Isolated patches (0 - 10%)
Permafrost map (Zou et al., 2017)
Permafrost
Seasonally frozen ground
(d)
(Ran et al., 2020)
wkl082
wkl083
wkl085
(e)
(Obu et al., 2019)
wkl082
wkl083
wkl085
(f)
(Zou et al., 2017)
wkl082
wkl083
wkl085
0 1 2 km