Estimation of annual ~~discharge~~ runoff using supraglacial channel geometry derived from UAV surveys of Qiyi Glacier~~geometric parameters of the UAV-based supraglacial channel over the Qiyi Glacier~~, northern Tibetan Plateau

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Abstract. Due to difficulties in direct field observation and uncertainties in glacier runoff models, accurately estimating the glacier runoff remains one of the foremost challenges in cryospheric science. Using a digital elevation model (DEM) and orthophotos (both with a resolution of 5 cm) obtained from an unmanned aerial vehicle (UAV), this study developed a novel remote sensing ~~novel~~ method for estimating the annual discharge ~~volume~~ of the supraglacial channel over Qiyi Glacier in the northern Tibetan Plateau, which contributes to the majority of the ~~annual~~ glacier runoff. Our results showed that the catchment areas of the six main supraglacial channels covered 92.02% of the total glacier area and transported 89.43% of the annual surface meltwater yield (each ranging from 0.07×10^6 to 0.66×10^6 m^3). Some geometric parameters of the supraglacial channels (including lateral deviation, gradient, and width) were selected to predict the annual discharge using a stepwise regression model, which explained ~78.2% of the variance in the measurement-based glacier annual discharge, with the explained variance increasing to 81.8% after five-point moving filtering. In comparison, a nonlinear regression model incorporating only the lateral deviation and specific gradient, which were more easily obtained practically, performed somewhat less well, accounting for 66.2% of the discharge variation; however, the explained variance increased to 81.4% after five-point filtering. If satellite remote sensing data with meter-level spatial resolution are available for a specific glacier research area, our regression models, based solely on the UAV-derived supraglacial channel network, will be a promising solution for monitoring changes in annual glacier discharge. ~~Our regression models, based solely on the UAV-derived supraglacial channel network, will be a promising solution for monitoring changes in annual glacier discharge if satellite remote sensing data have centimeter-class spatial resolution.~~

1 Introduction

In the context of global warming, most mountain glaciers worldwide are suffering from accelerated retreat with substantial influences on the glacier-fed rivers, especially for the "water tower of Asia" (Tibetan Plateau), which seriously threatens the livelihoods of hundreds of millions of people downstream with rising risks to water resource safety (Bolch et al., 2012; Huss, 2011; Immerzeel et al., 2020; Nie et al., 2021; Wang et al., 2021; Yao et al., 2022; Zemp et al., 2019). Emergent remote sensing data from different types of spaceborne sensors have been widely used to study various aspects of the influence of climate change on glaciers (Paul et al., 2015; Xu et al., 2025), such as glacier area (Burns and Nolin, 2014), ice mass change (Curran et al., 2025; Kääb et al., 2012), equilibrium line altitude (ELA) (Rabatel et al., 2013), glacier surface velocity (Dehecq et al., 2019; Kraaijenbrink et al., 2016), and glacier surface temperature (Ren et al., 2024; Wu et al., 2019). However, there is still a lack of remote sensing retrieval methods for glacier runoff that link glacier changes directly to the water supply for downstream human communities, which has become a major obstacle for understanding the patterns of glacier runoff changes for practical water resource management and policy-making at the watershed or larger scale.

The supraglacial stream and channel network, one of the most common landscapes on the surfaces of continental ice sheets and mountain glaciers, is formed by the incision and erosion effects of glacial meltwater, which has been shown to have river morphology and processes similar to those of terrestrially based bedrock rivers (Knighton, 1981; Pitcher and Smith, 2019) with the discharge closely related to the channel geometry (e.g., width and depth) (Jarosch and Gudmundsson, 2012). However, compared with the relatively sophisticated methods for estimating terrestrial river runoff by retrieving the water level, river width, channel slope, and flow velocity from satellite remote sensing data (Bjerklie et al., 2018; Xu et al., 2024), the retrieval methods for meltwater runoff of mountain glaciers remain less developed, mainly for two reasons. First, most supraglacial rivers of mountain glaciers are very narrow (sub-meter or meter scale), making it difficult to be identified from the commonly used satellite images with meters or tens of meters pixel sizes, even though these satellite images have been widely used to extract the spatial distribution of relatively wider supraglacial rivers on the Greenland Ice Sheet (GrIS) and other large polar glaciers (e.g., Bell et al., 2017; Legleiter et al., 2014; Yang and Smith, 2016; Zhang et al., 2023). Second, it remains challenging to obtain continuous field measurements or estimations of supraglacial river discharge from those ice sheets or mountain glaciers under relatively harsh environmental and climatic conditions (Gleason et al., 2016). To date, estimates of meltwater runoff at basin or larger scales have often relied either on the limited field observations (Gleason et al., 2016; Smith et al., 2017, 2021) or on glacier runoff models driven by coarse-resolution climate data (Beamer et al., 2016; Hock, 2005; Sicart et al., 2008; Wang et al., 2024; Yang et al., 2025). Although in situ meteorological observations from weather stations are used in some glacier studies, such data are often unavailable or sparse for remote glacierized regions, leading to uncertainties in modeled runoff that hinder a robust quantitative analysis of its relationship with supraglacial channel geometry estimates of meltwater runoff at basin or larger scales have often relied either on the limited field observations (Gleason et al., 2016; Smith et al., 2017, 2021) or on glacier runoff models driven by coarse-resolution climate data (Beamer et al., 2016; Hock, 2005; Sicart et al., 2008; Wang et al., 2024; Yang et al., 2025), but the lack of in situ meteorological observations has made the

64 ~~accuracy of meltwater runoff estimation hardly adequate for quantitative analysis of its relationship with supraglacial river~~

65 ~~geometry~~ (Smith et al., 2017). Furthermore, during the ablation season, supraglacial channels can terminate in meltwater lakes,

66 moulins, and crevasses (Colgan et al., 2011; Smith et al., 2015; Yang and Smith, 2016), further complicating the estimation of

67 meltwater runoff of supraglacial rivers.

68 Currently, uncrewed~~unmanned~~ aerial vehicle (UAV) remote sensing has been widely used to monitor glacier changes by

69 combining its optical images and digital elevation model (DEM) data or airborne synthetic aperture radar (SAR) images, which

70 are performed at a centimeter-level spatial resolution (Bhardwaj et al., 2016; Dall'Asta et al., 2017; Hugenholtz et al., 2013;

71 Immerzeel et al., 2014; Kraaijenbrink and Immerzeel, 2025; Śledź et al., 2021; Wang et al., 2025). Although UAVs are

72 generally equipped with visible light cameras, which have limited ability to discriminate water bodies from the surrounding

73 narrow and deep supraglacial channels on mountain glaciers, UAV remote sensing data have great strengths in identifying

74 supraglacial channel networks and their cross-sectional geometry. According to studies based on UAV field observations,

75 channel migration and curvature adjustments occur annually in supraglacial rivers in polar glaciers (Bergstrom et al., 2021;

76 Rippin et al., 2015; St Germain and Moorman, 2019). Similarly, significant interannual variability in supraglacial rivers has

77 also been reported in the Ganglongjiama Glacier on the central Tibetan Plateau using a terrestrial laser scanner (TLS) data

78 (Xue et al., 2024). Our field observations at the Qiyi Glacier also revealed that supraglacial channel adjustment appears to be

79 positively related to the intensity of ice melting on an annual timescale: years of more intense melting are generally

80 characterized by stronger surface meltwater erosion with deeper and wider channels, and vice versa. This phenomenon inspired

81 us to investigate the relationship between the channel morphology and annual discharge ~~volume~~ of supraglacial rivers.

82 Therefore, in this study, using a DJI M300 series UAV, a 5 cm spatial resolution DEM and orthomosaic map over the Qiyi

83 Glacier were obtained to extract the channel geometric parameters at different elevations, which were used to explore their

84 relationships with meltwater discharge calculated by field observations rather than the glacier runoff model.

85 **2 Data and methods**

86 **2.1 Study area**

87 The Qiyi Glacier, located in the Qilian Mountains (39°14′13″N, 97°45′18″E), is a typical polythermal mountain glacier of the

88 Tibetan Plateau (Fig. 1). The elevation of the Qiyi Glacier ranges from 4,322 to 5,158 m.a.s.l., with a total area of approximately

89 2.69 km^2 and length of 2.9 km in 2023. Since 1975, the glacier area has shrunk by approximately 4.5%, with the terminus

90 continuously receding by 235 m. Mountain glaciers (including the Qiyi Glacier) offer important water resources to the

91 downstream arid regions over the Hexi Corridor, with glacier meltwater accounting for approximately 20% of the runoff of

92 the Beida River (Wang et al., 2017). According to our regular meteorological, hydrological, and mass balance observations

93 (June to August) starting in 2002, the Qiyi Glacier has suffered from an obviously increasing ice-melting trend since 2016

94 (Chen et al., 2024). Over the past decade, the acceleration of glacial melting has increased surface meltwater runoff, which has

95 contributed to the deepening and widening of supraglacial stream channels.
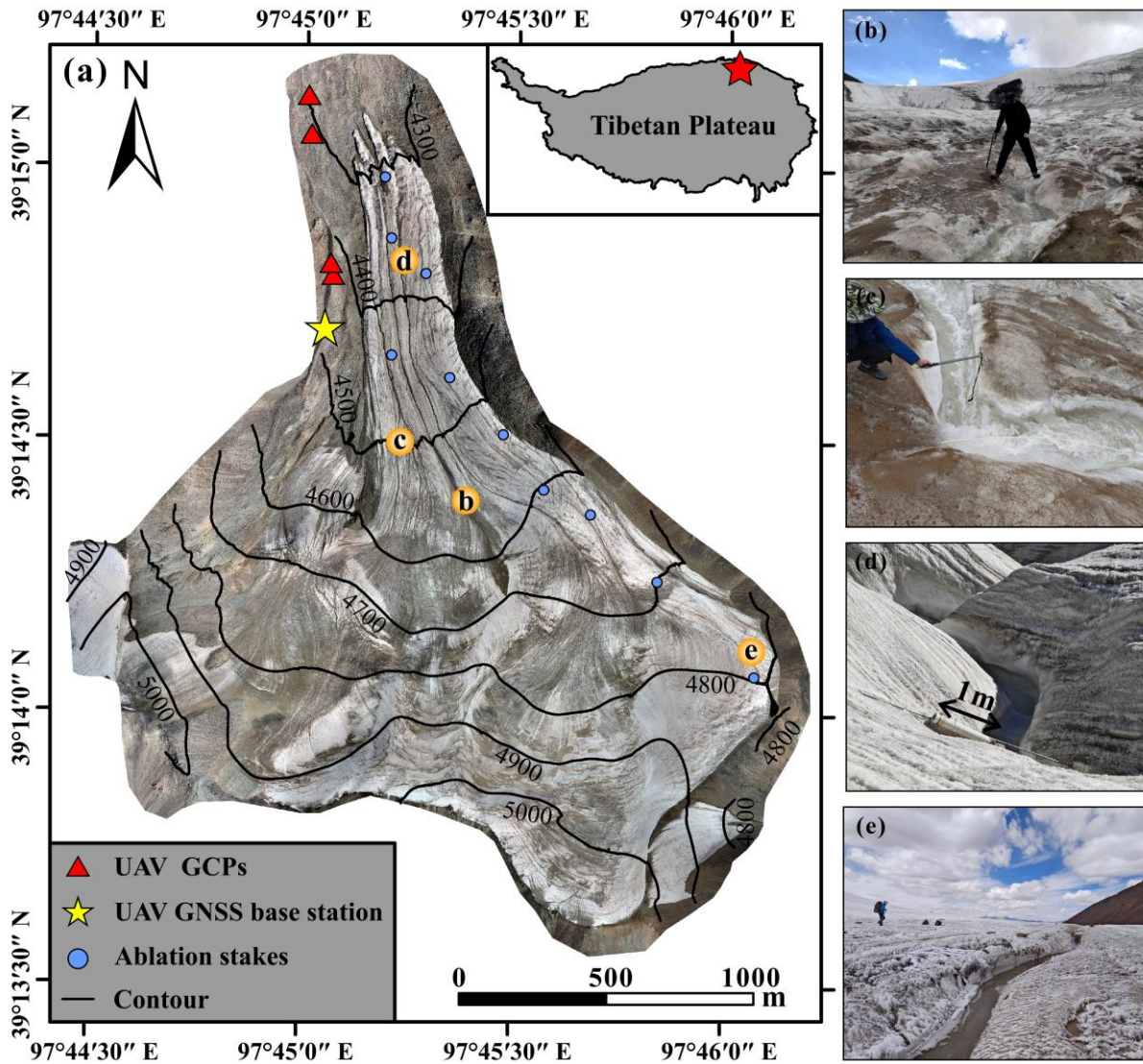
Figure 1. Location of the Qiyi Glacier and photos of its typical supraglacial stream channels. (a) Orthomosaic map of the Qiyi Glacier generated from UAV data (5 cm spatial resolution), with red triangles marking the locations of ground control points (GCPs) each with a fixed solution for UAV flights, yellow stars indicating the Global Navigation Satellite System (GNSS) base station of UAV, blue dots representing the locations of ablation stakes on the glacier, and orange circles showing the locations where photos (b)–(e) were taken.

2.2 UAV data acquisition and processing

A DJI Matrice300 real time kinematic (RTK) UAV was used to produce the DEM and orthophotos (both with a resolution of 5 cm) of the Qiyi Glacier. The UAV was equipped with a Zenmuse L1 lens integrating a visible-light camera and a light detection and ranging (LiDAR) sensor. From August 15 to August 20, 2023, 2,585 photographs and LiDAR data were collected

4

105   at a flight altitude of 100 m to cover the entire Qiyi Glacier. The geolocation accuracy requirements of the DEM and

106   orthomosaic map were ensured by ground control points (GCPs), and Hi-Target RTK was used to obtain fixed solutions for

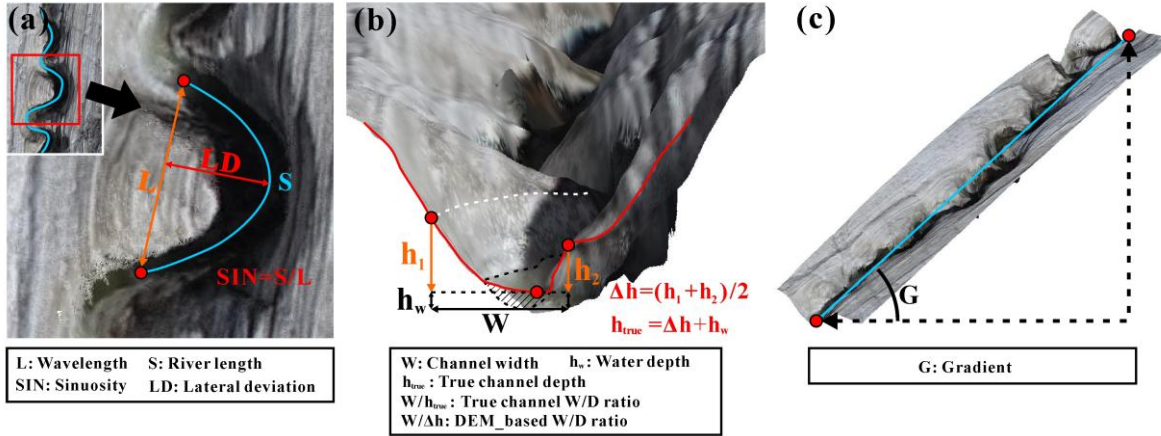107   high-precision geolocation information.

108   Pix4D Mapper 4.5.6 software was used to process the visible light images, including data preprocessing, aerial triangulation,

109   and point cloud encryption. The root mean square errors (RMSE) in x, y, and z directions for the positions of the GCPs were

110   0.24m, 0.09m, and 0.35m, respectively. The LiDAR data were processed using the CloudCompare and Lidar360 software,

111   including denoising, smoothing, thinning, and rasterizing the point cloud. It should be noted it is relatively difficult to

112   identify homologous image points on the snow surface of the upper glacier under visible light, and the density of the point

113   cloud data generated from visible light images is very low, while for the photons actively emitted by the lidar sensor, due to

114   their property of being easily absorbed by the liquid water, the density of the point cloud is very low in the region of the lower

115   glacier where the melting is strong. Therefore, these two types of point-cloud data have good spatial complementarity for

116   generating a complete high-precision point-cloud dataset for glacier surfaces. The iterative closest point (ICP) algorithm was

117   applied to register these two, and the merged point-cloud data were rasterized to the final DEM with a spatial resolution of

118   0.05 m.

119   **2.3 Extraction of morphological characteristics of supraglacial channels**

120   The supraglacial channel network was extracted from UAV-derived DEM data by using the hydrological analysis module of

121   the ArcGIS platform and Global Mapper software, from which we extracted several morphological characteristics, including

122   channel sinuosity (*SIN*), lateral deviation (*LD*), channel gradient (*G*), and cross-section geometry (width *W*, depth Δh, and

123   width/depth ratio) (Fig. 2). To ensure consistency in defining channel geometry, we applied a standardized approach to

124   determine channel width and depth. Since supraglacial channels are continuously eroded by rapid water flow, there are

125   relatively distinct inflection points in the slope of the cross-section. The two points on the cross-section with the steepest slope

126   gradients were designated as h_1 and h_2. Channel depth (Δh) was defined as the average vertical distance from these two points

127   to the lowest point of the channel, whereas channel width (*W*) was defined as the horizontal distance between h_1 and h_2. A

128   representative cross-section (channel A at 4350 m) has been included in the Supplement (Fig. S1) to illustrate the positions of

129   h_1 and h_2.

130   Supraglacial rivers can terminate in crevasses and moulins, potentially leading to the misidentification of channels. Although

131   crevasses also exist in the Qiyi Glacier, they are generally small in size and mainly distributed in the steep area of the upper

132   glacier as well as the edge area of the middle and lower parts; therefore, they have a minor influence on the process of river

133   confluence and continuity of the river channel (Fig. 1). After several comparative trials, a minimum drainage area of 0.02 km^2

134   was determined as the threshold for the automatic extraction method. The automated algorithm identified a total of 33 channel

135   segments, including not only the six main channels (labeled A–F in Fig. 4a) but also smaller, low-order tributaries. To ensure

136   the realism of the extracted channels, all automatically derived streams were carefully compared with the orthophotos, channels

137   that could not be clearly identified in the orthophotos were truncated, particularly small tributaries and river sections at the

5

138 upstream headwaters. Finally, six main supraglacial channels on the Qiyi Glacier were correctly identified and extracted, from

139 which the glacier was divided into six catchments (labeled A–F in Fig. 4a).

L: Wavelength   S: River length
SIN: Sinuosity   LD: Lateral deviation

W: Channel width h_w: Water depth
h_{true}: True channel depth
W/h_{true}: True channel W/D ratio
$W/\Delta h$: DEM_based W/D ratio

$\Delta h = (h_1 + h_2)/2$
$h_{true} = \Delta h + h_w$

G: Gradient

140

141 **Figure 2.** Diagrams showing the process of obtaining the channel geometric parameters: (a) sinuosity and lateral deviation of an individual

142 meander; (b) geometry of the channel profile (width, depth, and width/depth ratio); the white dashed line indicates the maximum slope, and

143 the black dashed line and shaded area indicate the water surface and underwater channel profile, respectively; (c) the channel gradient.

2.4 Calculation of the annual glacial discharge transported by supraglacial channels

145 Excluding the negligible glacier mass loss due to surface sublimation, the annual meltwater yield of a given pixel (5 cm × 5

146 cm) on the glacier can be estimated as follows:

147 $Q_a = (P_0 - MB + (H - 4310) \times 6.8/100) \times S,$ (1)

148 where P_0 is the precipitation at the glacier terminus based on field observations, MB and H represent the glacier mass balance

149 and the elevation of the pixel, mass balance is expressed in millimeters water equivalent (mm w.e.), with negative values

150 indicating mass loss. respectively, 4,310 (m) means the elevation of the glacier terminus, S denotes the area of the pixel, and

151 6.8 mm/(100m) is the precipitation gradient regressed from rain gauge networks on the Qiyi Glacier (Jiang et al., 2010).

152 From the nine ablation stakes across the glacier with long-term mass balance (MB) measurements, the MB of all pixels was

153 calculated using spatial extrapolation linear interpolation (Fig. 3a). The stakes were measured at annual intervals. Several new

154 ablation stakes were installed on July 20, 2022, and subsequently measured and maintained on August 24, 2023. Detailed

155 information for each stake data, including stake ID, position, elevation, and mass balance records, are provided in Supplement

156 (Table S2). The uncertainty of the mass balance based on the ablation stakes is discussed in detail in Section 4.2.

157 Because our rain gauge observations at the glacier terminus were not collected every year, precipitation data from a

158 neighboring weather station (Tuole Station, ~70 km from the Qiyi Glacier) were used to establish a relationship to reconstruct

159 the precipitation at the glacier terminus. Comparisons between two sets of precipitation data during the period 2006–2013 (Fig.

160 3b) showed a good linear relationship, with the coefficient of determination (R^2) value as high as 0.967; therefore, the annual

161   precipitation (P_0) of 2023 at the glacier terminus (4,310 m) can be inferred from the precipitation data at the Tuole station (P_t)

162   as follows:

163    $P_0 = 1.1267 \times P_t + 15.205.$ (2)

164   Equations 1 and 2 were used to calculate the meltwater yield for each pixel. From the upper to the lower glacier, the volume

165   of discharge transported by the ice channel at each 10 m elevation decrease can be determined from watershed analysis by

166   placing outlets at each elevation interval (10 m).
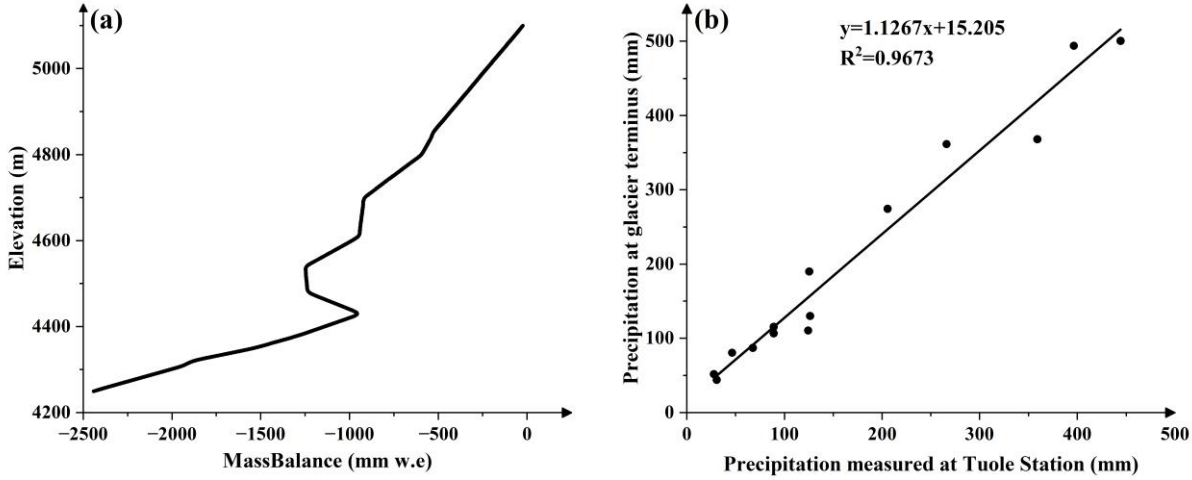
167

168   **Figure 3.** (a) Variations in mass balance of the Qiyi Glacier reconstructed from ablation stake measurements with elevation in 2023. (b)

169   Comparisons of monthly/annual precipitation between Tuole station records and rain gauge observations at the terminus of Qiyi Glacier

170   during 2006–2013.

171   **2.5 Statistical modeling methods**

172   Pearson's correlation (r) and Spearman's rank correlation (ρ) were used to analyze the correlation between the morphological

173   characteristics of the supraglacial channels and the annual meltwater discharge transported by these channels at different

174   elevations. Because previous studies found that the total energy of the flowing water (including pressure energy, gravitational

175   potential energy, and kinetic energy) is the initial driving force for the channel formation (Rodríguez–Iturbe et al., 1992) and

176   that discharge and slope are the most influential fluvial factors (St Germain and Moorman, 2019), here we took the product of

177   gradient G and annual discharge Q_a as the water potential energy factor GQ_a in the correlation analysis.

178   In addition to the water flow conditions (discharge and water potential energy), the morphology of supraglacial channels is

179   influenced by other factors, such as pre-existing ice structure (e.g. fractures and moulins), thermal differences (ice and water

180   temperatures and channel frictional heat), topographic relief (slope, roughness, and surface albedo), and ice velocity (Pitcher

181   and Smith, 2019). To eliminate the influence of discharge and water potential energy, Q_a and GQ_a were used as control

182   variables to conduct a partial correlation analysis for each pair of morphological characteristics.

7

183   The fitting model was developed using only morphological characteristics that showed a strong correlation with the discharge,
184   and the regression methods included simple linear regression, stepwise regression, and nonlinear least squares (NLS). The
185   coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and normalized root mean
186   square error (nRMSE) evaluated the performance of the fitting models. Specific details of the regression model and error
187   analysis can be found in Sections 3.4 and 4.2.

188   **3 Results**

189   **3.1 Supraglacial channel network and annual discharge**

190   The watersheds of the six main supraglacial channels covered 92.02% of the total area of the Qiyi Glacier (Fig. 4a) with an
191   annual discharge volume of about 2.4×10^6 m^3 (each ranging from 0.07–0.66×10^6 m^3), which contributed 89.43% to the total
192   meltwater of the glacier surface (2.68×10^6 m^3) during the hydrological year from August 2022 to August 2023. Approximately
193   63.21% of the channel discharge was transported to the glacial terminus (by channels A, B, C, and D). In particular, the
194   discharge in the lower reaches of channels A and C was significantly higher than that in the other channels (Fig. 4b), accounting
195   for approximately 45.30% of the total glacial discharge. Channel F was the only river that was newly formed during the
196   summer of 2023 because two separate smaller catchments merged into one larger catchment, reflecting how supraglacial rivers
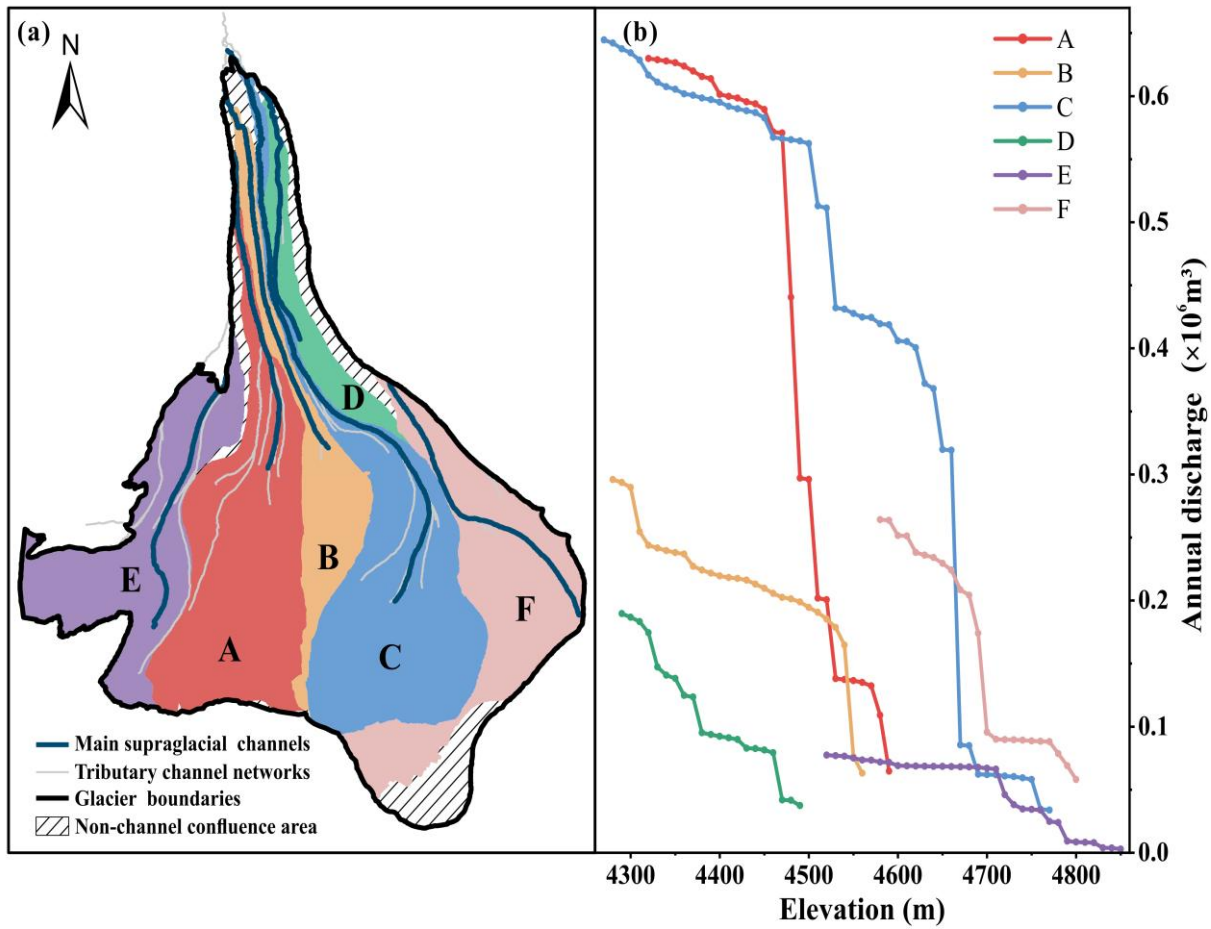197   reshape the surface topography in a short period as meltwater flow increases.

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Figure 4. (a) Supraglacial channel network over the Qiyi Glacier and (b) variations in the annual discharge of six main supraglacial channels with elevation changes at a 10 m elevation interval. The catchment areas of the main channels are filled with different colors.

201

3.2 Spatial variability of morphological characteristics of supraglacial channels

3.2.1 Variations in the sinuosity and lateral deviation

The mean sinuosity and mean lateral deviation integrated with a 10 m elevation interval show similar variation trends among the six main supraglacial channels, and both are lower in the upper reaches and higher in the lower reaches (Fig. 5a and 5b). The median of 10 m average sinuosity and lateral deviation ranges from 1.05 to 1.27 and 0.42 to 1.06, respectively. The maximum sinuosity and lateral deviation were observed near the outfalls of channels C (2.75) and D (4.41), respectively. In general, channels with relatively higher discharge (channels A and C) tended to have larger sinuosity and lateral deviation in both their median and ~~averages~~mean, while those with relatively lower discharge (e.g., channels D and E) had lower sinuosity

210 and lateral deviation (Fig. 5c), suggesting a possible positive correlation between the discharge and sinuosity/lateral deviation

211 of the supraglacial channel.

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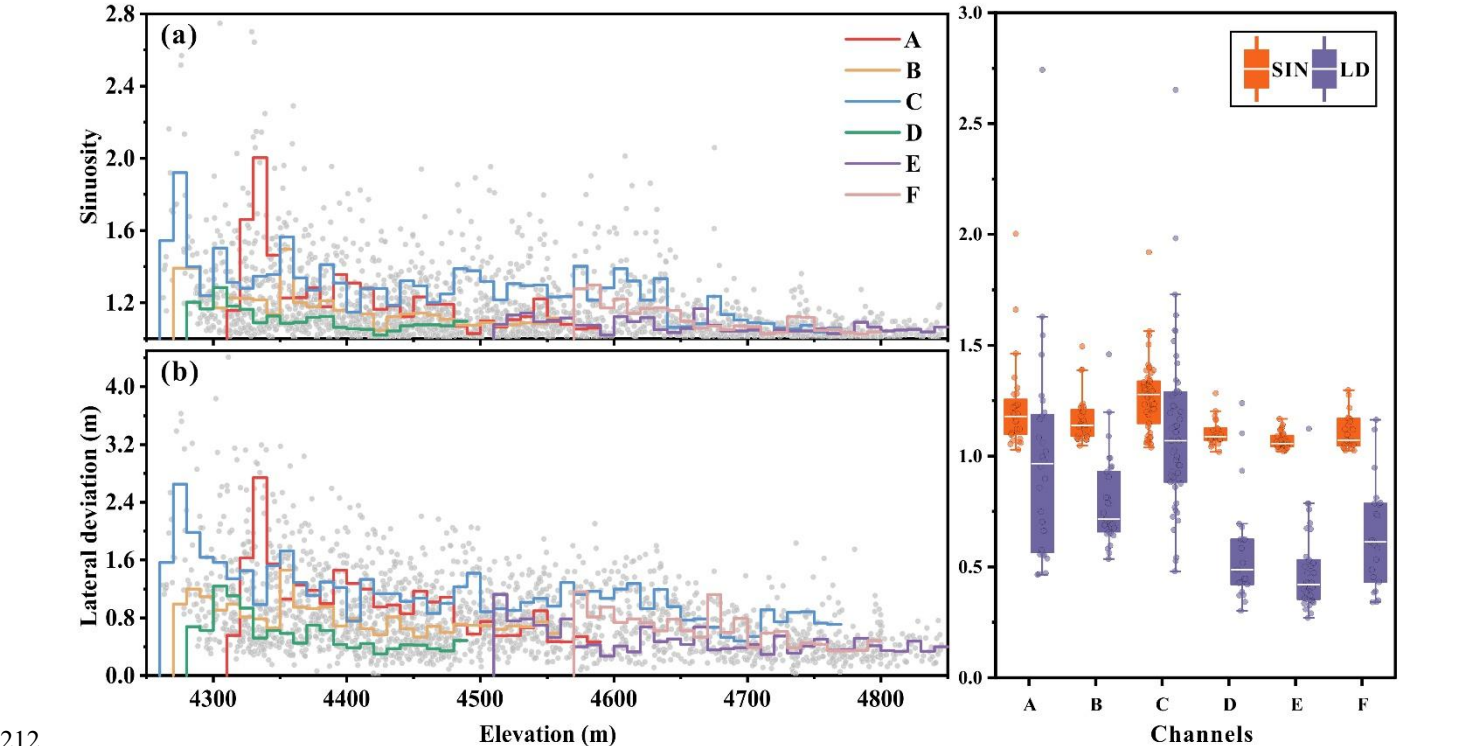
213 **Figure 5.** Variations in the (a) sinuosity and (b) lateral deviation of six supraglacial channels (gray dots indicate values at each meandering)

214 and their ~~averages~~ mean at a 10 m elevation interval (colored stairs); (c) box plot of 10 m average sinuosity and lateral deviation for six

215 supraglacial channels, where the box represents the interquartile range (IQR), the whiskers denote 1.5 times the IQR from both ends of the

216 box, and the white horizontal line shows the median; the labeling A to F corresponds to channels A to F as shown in Fig.4a.

217 **3.2.2 Variations in the channel gradient**

218 The incision depth (no more than 1 m) of supraglacial rivers is much shallower than the ice thickness of the Qiyi Glacier (tens

219 to hundreds of meters), which implies that their incision ability is relatively limited. Changes in the gradients of the six

220 supraglacial channels showed a relatively consistent pattern because they were influenced by the complex undulating

221 topography of the glacier surface (Fig. 6). The mean gradient of the six supraglacial channels ranges from 0.22 to 0.41, with

222 channel E having the steepest mean gradient. For a 10 m elevation interval, the maximum channel gradient (0.81) was observed

223 at an elevation of 4,640 m in channel E, while the minimum channel gradient (0.09) was found in channel F near the glacier-
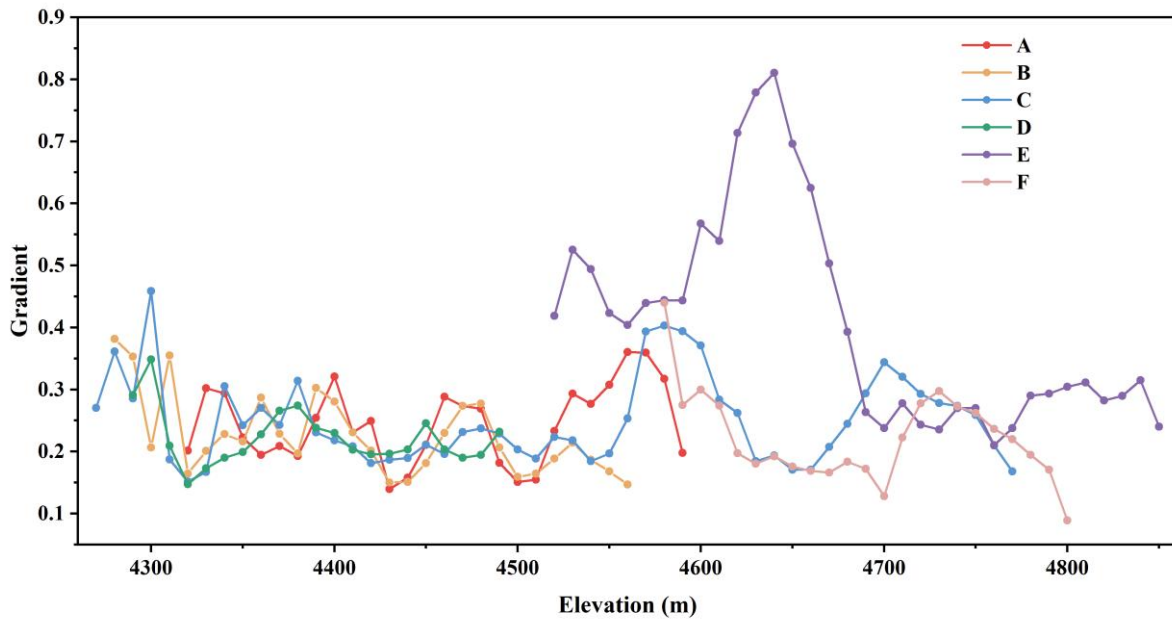
224 covered mountain pass.

Figure 6. Variations in the gradient of six supraglacial channels with elevation at a 10 m interval (the labeling A to F corresponds to channels A to F as shown in Fig. 4a).

3.2.3 Variations in the geometry of the channel cross section

Both channel width and depth of all six supraglacial channels generally show decreasing trends with increasing elevation (Fig. 7a and 7b), with the maximum channel width and depth (1.25 and 1.00 m, respectively) observed near the channel outfall at the glacier terminus. In general, for a given channel, its width increases with depth and vice versa; however, exceptions are found for the lower reaches of channel C, which does not have the widest channel near the outlet with the deepest channel. Another noteworthy point is that, instead of the outlet, channel F has the deepest and relatively wider channel at its headwater at 4,800 m.a.s.l., possibly because its headwater is a shallow supraglacial lake over a relatively flat mountain pass that provides warmer meltwater to the channel.

Assuming a constant ratio of water depth to channel depth (water depth + Δh), the ratio of width to Δh was calculated as a surrogate for the true channel width/depth (W/D) ratio. In general, the W/D ratio increased with elevation for all channels, except the upper reaches of channel F, which may have been influenced by the supraglacial lake at the headwater (Fig. 7c). The distribution pattern of the W/D ratio with elevation suggests that regions with a larger discharge in the lower part of the glacier may experience stronger downward erosion than lateral erosion.
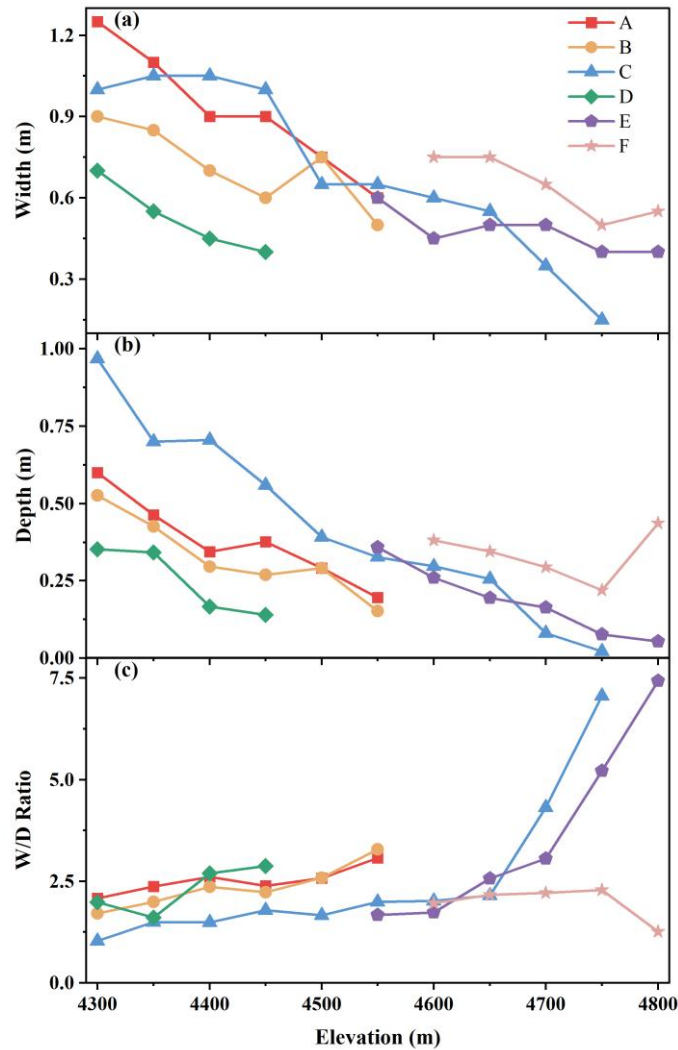
Figure 7. Variations in (a) width, (b) depth, and (c) *W/D* ratio of six supraglacial channels with elevation changes at a 50 m elevation interval.

3.3 Relationships between channel geometry and annual discharge

Both the Pearson and Spearman correlations showed that annual discharge (Q_a) was significantly positively correlated with sinuosity, lateral deviation, channel width and depth, but significantly negatively correlated with width to depth ratio(W/D) and gradient (Table 1). The water potential energy (GQ_a) showed a correlation pattern similar to that of discharge. Among all the geometric parameters, channel width showed the strongest correlation with discharge in both Pearson ($r = 0.82$) and Spearman ($\rho = 0.86$) correlation analyses, followed by lateral deviation ($r = 0.80$, $\rho = 0.82$), which was very similar to those of water potential energy despite of some slight differences. This suggests that both the channel profile and the meander of

250 supraglacial channels were closely correlated with the discharge and water potential energy, and thus could be considered as
251 indicators of changes in them.

252 Table 1. Pearson's (r) and Spearman's rank (ρ) coefficients of geometric parameters with discharge Q_a and water potential energy GQ_a, all
253 coefficients that are significant at a minimum level of 0.05, 0.01, and 0.001 are labeled with *, **, and ***, respectively.

	Sinuosity		Lateral deviation		Width		Depth		W/D		Gradient	
	r	ρ	r	ρ	r	ρ	r	ρ	r	ρ	r	ρ
Q_a	0.73***	0.80***	0.80***	0.82***	0.82***	0.86***	0.74***	0.76***	-0.44***	-0.51***	-0.20**	-0.21**
GQ_a	0.77***	0.82***	0.81***	0.79***	0.76***	0.82***	0.74***	0.74***	-0.43***	-0.53***	0.15*	0.10

254

255 Partial correlation analysis, after excluding the effects of discharge and water potential energy, further revealed an inherent
256 connection between the geometric parameters (Table 2). When discharge was considered the control variable, the highest
257 correlation coefficient was found between sinuosity and lateral deviation (0.75), followed by that between width and depth
258 (0.70). When water potential energy was used as the control variable, the highest correlation was observed between width and
259 depth (0.72), as well as between sinuosity and lateral deviation (0.72). Regardless of whether discharge or water potential
260 energy was used as the controlling factor, after removing their influence, strong correlations remained between sinuosity and
261 lateral deviation, width and depth, indicating that both channel meander and profile characteristics exhibited stable internal
262 variation patterns. Furthermore, the relatively weak correlation between channel meander characteristics and width or depth
263 showed that their variations may not be synergistic, and thus can be jointly used to estimate discharge. These findings provided
264 a crucial reference for the selection of independent variables in discharge regression models.

265 Table 2. The partial correlation coefficient between each two geometric parameters, with discharge Q_a and water potential energy GQ_a as
266 control variables. Significance levels of 0.05, 0.01, and 0.001 are denoted by *, **, and ***, respectively.

	Sinuosity		Lateral deviation		Width		Depth		W/D	
	Q_a	GQ_a	Q_a	GQ_a	Q_a	GQ_a	Q_a	GQ_a	Q_a	GQ_a
Lateral deviation	0.75***	0.72***								
Width	0.18*	0.20**	0.09	0.16*						
Depth	0.29***	0.24**	0.26***	0.24***	0.70***	0.72***				
W/D	-0.07	-0.05	0.04	0.05	-0.47***	-0.46***	-0.53***	-0.53***		
Gradient	0.20**	-0.14	0.13	-0.28***	0.13	-0.27***	0.29***	-0.08	-0.24**	-0.07

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3.4 Regression models of annual discharge of the supraglacial channels

As stated in Section 2.5, b~~B~~oth linear and nonlinear regression models were used to fit the annual discharge Q_a of the supraglacial channels using geometric parameters with significant correlations with Q_a. For the linear regression method, all variables were initially included to obtain an optimal fit of Q_a; then, a stepwise regression method was used to establish a more efficient linear fitting formula by excluding variables with minimal impact on the regression results. For the nonlinear regression method, the focus was on the robustness of the NLS model, which was fitted using a minimal number of parameters that are easier to obtain without significantly reducing the simulation results.

As illustrated in Fig. 8a, the linear regression model incorporating all variables (SIN, LD, G, W, D, β, and Elevation) showed a similar R^2 value to that of the stepwise regression model including only LD, G, and W (0.780 vs. 0.782), with RMSE of 0.096 and 0.097×10^6 m^3, MAE of 0.077 and 0.076×10^6 m^3, and nRMSE of 10.64% and 10.60%, respectively. This indicates that the inclusion of Elevation, D, and β in the linear regression model does not improve the explanation of the variation in the annual discharge. The stepwise regression model was expressed as follows:

$$Q_{step} = 0.230 \times LD - 0.232 \times G + 0.493 \times W - 0.181. \tag{3}$$

In contrast to the difficulty in obtaining width W in Eq. (3) from high-spatial-resolution satellite images, LD and SIN are the most easily and accurately extracted supraglacial channel characteristics from the digitized river network. According to the correlation analysis described in Section 3.3, the r values of LD and SIN with GQ_a were both improved compared with those of Q_a, particularly for LD, which showed the highest r value with GQ_a. Therefore, it may be more appropriate to develop a regression model using a nonlinear relationship. LD was selected as the independent variable using a simple linear regression model.

$$GQ_a = a \times LD + b, \tag{4}$$

where a and b are the regression coefficients. The nonlinear equation can be obtained by transforming Eq. (4) as follows:

$$Q_{NLS} = a \times \frac{LD}{G} + \frac{b}{G} + c, \tag{5}$$

where the regression coefficients are $a = 0.108$, $b = -0.061$, and $c = 0.137$ in our study area and Q_{NLS} is the annual discharge predicted using the nonlinear model. The R^2, RMSE, MAE, and nRMSE values in Eq. (5) are 0.662, 0.122×10^6 m^3, 0.091×10^6 m^3, and 12.87%, respectively.

When compared with the observed annual discharge, both the linear and nonlinear models exhibited large fluctuations. Therefore, the stepwise and NLS methods were smoothed using a five-point moving average, and the filtered results were more consistent than the original curves, with R^2 increasing to 0.818 and 0.814, respectively. Their RMSE, MAE, and nRMSE values were 0.091 and 0.099×10^6 m^3, 0.073 and 0.077×10^6 m^3, and 12.58% and 15.11%, respectively. The NLS model is more robust and can be more widely applied as its input parameters require only LD and the channel gradient G, which can be easily calculated from the DEM data.
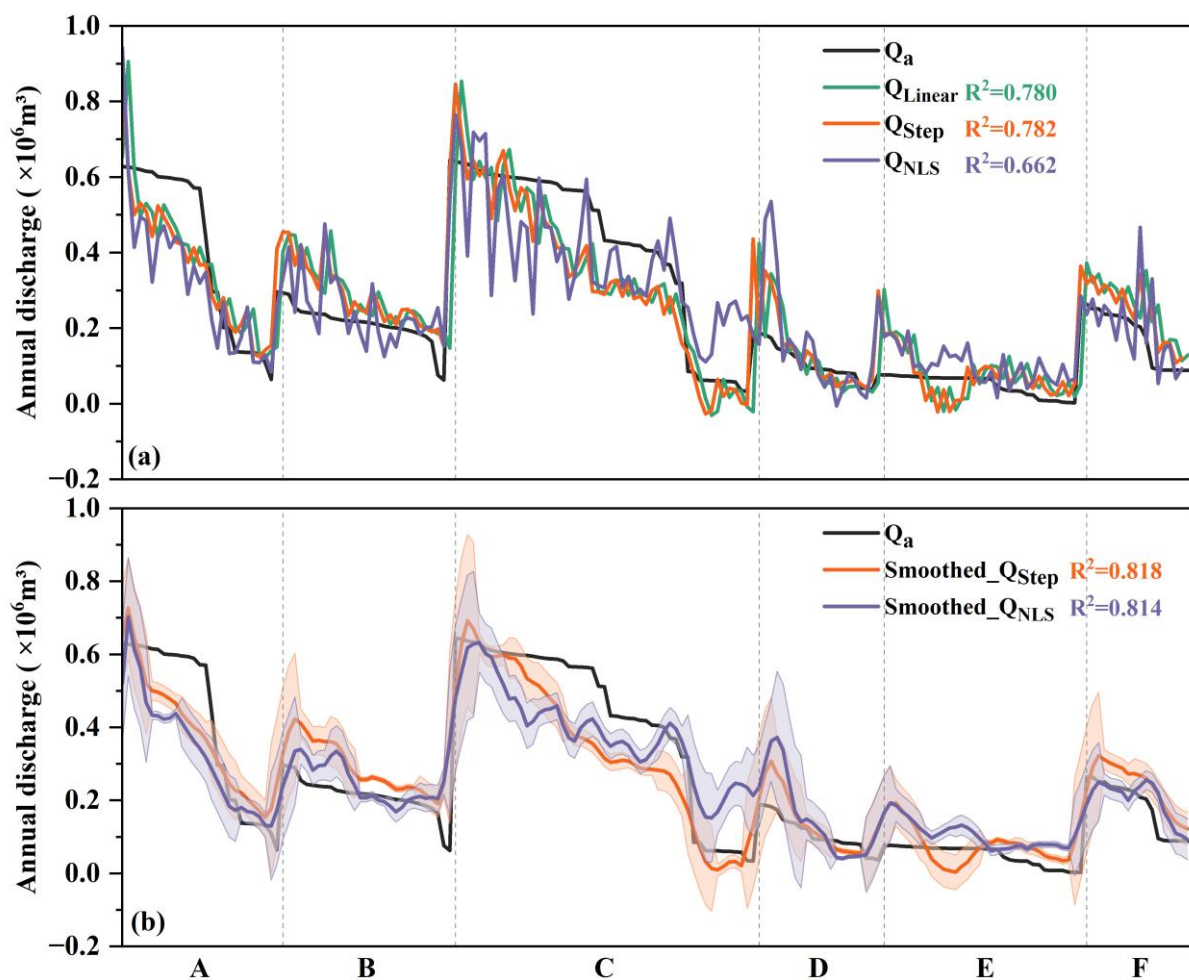
Figure 8. Comparison between observed annual discharge (Q_a) and (a) original results and (b) five-point moving average fitted results using linear, stepwise, and NLS regression models. The shaded error bands indicate twice the standard deviation range. The x axis is arranged at an order of increasing elevation for each channel meander, and each channel is divided by vertical gray dashed lines.

4 Discussion

Smith et al. (2015) highlighted that the processes of meltwater generation, storage and transport on the surface of the Greenland Ice Sheet "remain one of the least studied hydrological processes on Earth"~~, especially for mountain glaciers~~. This knowledge gap is also significant for mountain glaciers. The extreme lack of field observations and challenges associated with data collection have resulted in significant uncertainties in our understanding and estimation of meltwater discharge volume from mountain glaciers, particularly in the Tibetan Plateau region. Previous studies have primarily estimated supraglacial runoff through direct discharge observations or runoff models driven by meteorological data (Muthyala et al., 2022; Yang et al.,

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310 2019). Yang and Smith (2016) demonstrated that catchment area is a dominant control on runoff, with larger basins generally

311 producing greater discharge. However, when catchments originate from high elevation mountain glaciers, steep and complex

312 glacier surfaces may weaken the dominant relationship between catchment area and glacier runoff. The supraglacial channel

313 morphology is more strongly influenced by local topography, which is one of the reasons we retained gradient as a variable.

314 Building on established physical principles, In this study, given the significant correlations of Q_a and $\not GQ_a$ with the geometric

315 parameters of the supraglacial channels (Table 1, 2 and Fig. 8a, 8b), we innovatively used these geometric parameters to predict

316 the surface meltwater discharge in mountain glacier and establish quantitative relationship between supraglacial channel

317 geometry and annual glacier runoffs. Our results are of great importance for estimating meltwater discharge over mountain

318 glaciers with complex topography. In the following sections, we will further discuss the uncertainties of the supraglacial

319 channel parameters, limitations of the regression models, and the applicability of these models.

4.1 Uncertainties in supraglacial channel parameters

321 The sinuosity and lateral deviation of supraglacial channels can be derived from DEM data based on hydrological analysis or

322 digitization of the orthomosaic map (Fig. 2a). If the spatial resolution requirements of visible-light images are satisfied, the

323 sinuosity and lateral deviation are the easiest parameters to obtain. However, the identification of other parameters such as

324 river width, and depth and gradient requiresrequire DEM data with a higher spatial resolution (Fig. 2b). Although While the

325 width is discernible in certain regions from visible light images (e.g., the wider parts of the river at the lower reaches of the

326 glacier), discriminating the spectral character between the narrower channel and the adjacent bank over the upper and middle

327 parts of the glacier remains a challenge, making it difficult to extract complete width data across the entire glacier based on

328 the visible light image alone. Therefore, sinuosity and lateral deviation are currently the most promising and accurate

329 supraglacial channel parameters that can be obtained using commercial optical satellite imagery at a centimeter resolution.

330 In addition, during the glacial ablation season, part of the supraglacial river channel is often occupied by flowing water, making

331 it difficult to derive the true channel depth from UAV-based DEM data. Therefore, the UAV-based depth (Δh) represents the

332 channel depth by considering the water surface as the "bottom" of the glacier (Fig. 2b). This might exert a greater influence in

333 the shallower channel over the upper glacier but a relatively minor influence for the deeper channel over the lower parts. This

334 study assumes a constant ratio of true channel depth to depth above the water surface (i.e., Δh), although this assumption

335 inevitably introduces some error when compared to actual conditions. Furthermore, the channel depth was not included in the

336 stepwise regression model, but this does not necessarily mean that the true channel depth cannot improve the predictive ability

337 of the regression model. Nevertheless, the depth of the supraglacial channel depends on centimeter-level DEM data, which

338 remains a challenge given the current development trend of high-resolution commercial optical satellites.

339 The channel gradient must also be derived from DEM data. In regions without UAV data, channel gradient derived from lower-

340 resolution DEMs (e.g., 30 m GDEM, SRTM) still require further evaluation regarding their applicability. Therefore, sinuosity

341 and lateral deviation are currently the most promising and accurate supraglacial channel parameters that can be obtained using

342 commercial optical satellite imagery at a centimeter resolution.

4.2 Uncertainties in the calculation of glacier annual discharge and regression model

The reliability of glacier discharge calculations depends heavily on the accuracy of the observed glacier mass balance and precipitation data. The estimation of the distributed glacier mass balance is hampered by a lack of true validation values, which complicates the error assessment of spatial patterns in mass balance calculations based on single-point measurements of ablation stakes (Kaser et al., 2006; Xu et al., 2019). Specifically, the uncertainties of stake-based mass balance can be classified into three groups: (1) errors in field observations; (2) errors related to spatial extrapolation over the entire glacier; and (3) error due to unaccounted interannual changes in glacier area (Dyurgerov et al., 2002). Among these, (1) is very small (centimeter scale) and negligible at the annual scale, and (3) typically arises in multi-year studies. Since this study focuses solely on Qiyi Glacier's 2023 data, it is also excluded. The primary error is spatial extrapolation from ablation stakes, which typically requires higher resolution DEMs (e.g., obtained by TLS laser scanning (Xue et al., 2024)) for assessment, but such data were unavailable for Qiyi Glacier in 2022–2023 due to the absence of the UAV-derived high-resolution DEM in 2022. However, given the geographic proximity, similar glacier types, and comparable elevation range covered by stakes, we adopted the error assessment from Urumqi Glacier No.1 reported by Xu et al. (2019) as a reference, where the error of traditional stake-based mass balance was about ±0.12 m w.e., within 17%.

However, according to the assessment results from another subcontinental glacier in China, Urumqi No. 1 Glacier, the error in this traditional stake-based mass balance is about ±0.12 m w.e. (Xu et al., 2019). Regarding the error in the precipitation pattern over mountain glaciers, although the elevation effect of precipitation is obtained from in situ precipitation observations, the influence of wind and local topography also introduces some uncertainty in the precipitation distribution. To evaluate the combined effect of uncertainties errors in mass balance and precipitation on glacier discharge calculations, the meltwater volume of each pixel of the Qiyi Glacier was manually respectively changed by a range of ±5%, ±10%, and ±20% for both stepwise regression and NLS model results. Based on the reference from Xu et al. (2019), we set the maximum uncertainty range of our stake-based mass balance estimates at ±20%. The error distribution of the fitting results showed that the MAE approached zero under different error scenarios, RMSE fluctuated in the range of 0.077–$0.146 \times 10^6 \, \text{m}^3$, and nRMSE ranged from 17.06% to 19.68% (Fig. 9), suggesting reasonable robustness of two current regression methods. These results indicate that, although spatial extrapolation uncertainty is the dominant error source, it does not affect our finding that channel geometry can be used to estimate glacier runoff.
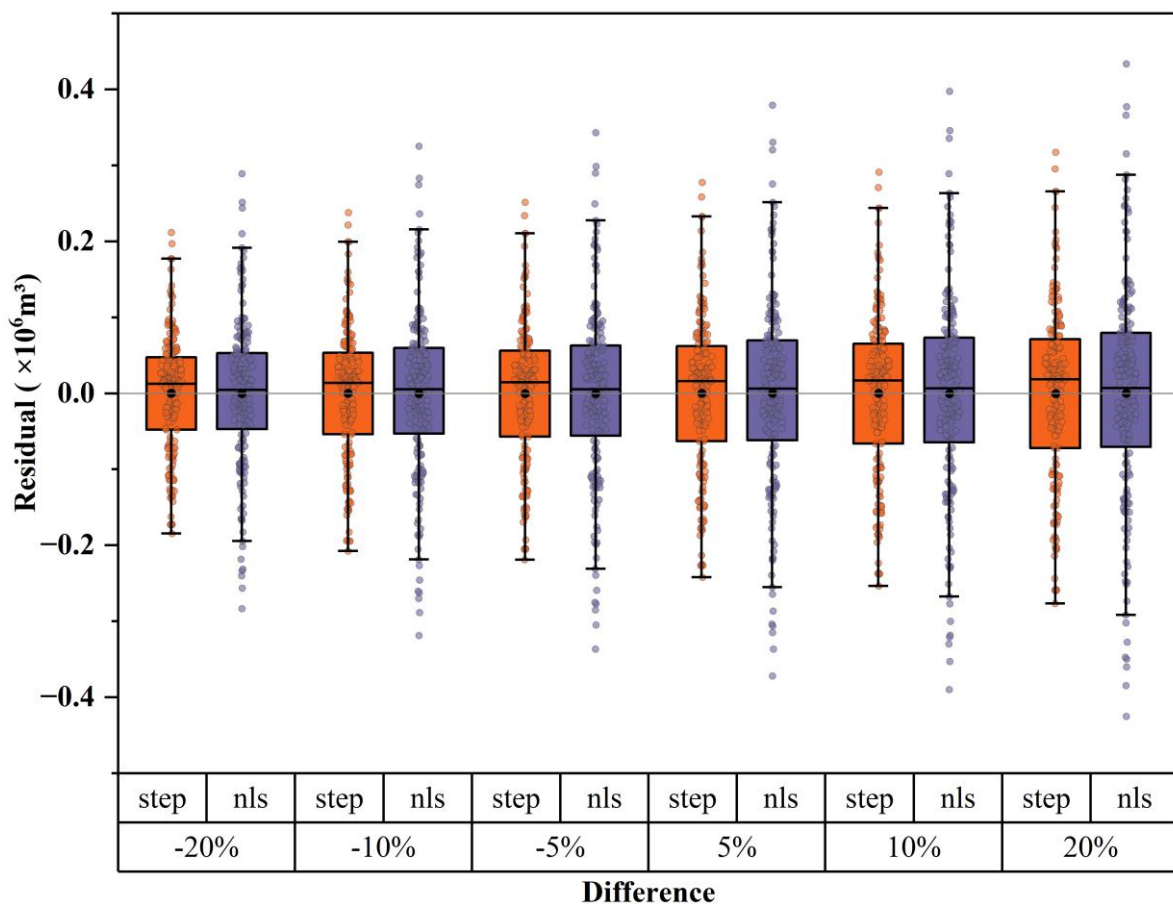
Figure 9. Residual distribution for two regression methods under three artificial error scenarios (±5%, ±10%, and ±20%). The black dots and black short lines of the box plots are the mean and median of the residuals, respectively; the whiskers denote 1.5 times the IQR from both ends of the box; the white horizontal line indicates the median.

4.3 Limitations of statistical regression methods

There is still a lack of studies on the physical theories of the formation of each morphological characteristic, which hinders us from proposing an ideal nonlinear statistical regression model framework, even after several attempts. For instance, we tried to consider the effect of ice temperature on erosion intensity by incorporating normalized elevation as well as more complex regression models from the physical symbolic optimization (PhySO) framework, but their performance did not improve evidently compared to our simple regression models. According to a theoretical model of channel meander formation (Karlstrom et al., 2013), for a given supraglacial channel with a fixed cross section, runoff, and ice temperature, a bender channel meander tends to produce more heat by flowing water, which favors ice melting and lateral migration at the vertex. This implies that, in addition to the influence of external forces, such as water discharge, the channel morphology itself has a complex self-feedback process. Although Pitcher and Smith (2019) emphasized the importance of integrating thermal forcing

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383 models (ice and water temperature), topography, and hydraulic parameters because they are helpful in understanding the

384 physical mechanism behind the formation of supraglacial river systems, the framework of physical-based models or more

385 appropriate forms of nonlinear models that can help improve the performance of predicted discharge using only the geometric

386 parameters of channels are still unavailable.

4.4 Applicability and perspective of ~~our~~ regression model

388 The Qiyi Glacier is a typical subcontinental glacier on the Tibetan Plateau with weak subglacial hydrological processes. As a

389 result, meltwater mainly originates from the glacier surface and flows across the surface, forming a relatively continuous

390 channel network. The model proposed in this study provides a valuable reference for quantifying the annual discharge of this

391 type of glacier.

392 However, the applicability of this approach is limited for some other glacier types. For example, on ~~for~~ maritime glaciers with

393 extensive crevasses and relatively stronger subglacial hydrological processes (e.g., in the southern Tibetan Plateau and the

394 Greenland Ice Sheet)~~over the southern Tibetan Plateau and the GrIS~~, some supraglacial rivers often terminate ~~at~~ in crevasses

395 or moulins, which makes our regression model less suitable for estimating glacier runoff. Similarly, temperate glaciers, debris-

396 covered glaciers, and glaciers with strong surface structures are likely too complex to be represented without substantial

397 modifications to the model. But the model~~may not be suitable for use in our regression model when estimating glacier surface~~

398 ~~discharge, but it~~ still has positive implications for supraglacial river segments between crevasses and moulins. The drainage

399 areas of supraglacial river segments can be obtained by watershed delineation, and the meltwater discharge of each drainage

400 area can be estimated from their geometry.

401 It should also be emphasized that, while channel geometric parameters can be derived from remote sensing data alone, the

402 establishment of this regression model require mass balance data for calibrating the coefficients in runoff estimation due to

403 scaling differences among glaciers. Therefore, the broader application of this method to other glaciers must be accompanied

404 by reliable mass balance data.

5 Conclusions

406 Accurate estimation of glacier meltwater runoff is of great importance for quantifying the effects of climate change on glacier

407 dynamics and evaluating the impacts of glacier changes on downstream water resource security. Based on high-precision UAV

408 orthophotos and LiDAR data, this study derived a comprehensive supraglacial channel network over the Qiyi Glacier for the

409 first time, from which a series of channel morphological characteristics were used to predict the meltwater discharge using

410 different regression methods. Compared with traditional methods based on field observations or glacier runoff models, our

411 study provides a novel perspective for accurately estimating annual glacier discharge for larger glaciated areas without

412 meteorological and hydrological observations. The stepwise regression model incorporating the parameters of lateral deviation,

413 channel gradient, and width of the supraglacial channel performed better, explaining approximately 78.2% of the variation in

the observed meltwater discharge. The regression accuracy improved to 81.8% after the five-point moving filtering. The NLS regression model using only the more readily available parameters of lateral deviation and channel gradient performed slightly less well, explaining 66.2% of the variation in meltwater discharge, whereas the explained variance was improved to 81.4% after applying a five-point moving average. In recent years, centimeter-scale multi-satellite constellations with predominantly onboard optical sensors, such as the WorldView Legion satellites, Pelican-2 satellite, and Gen-3 constellation, have become an important development trend. Our study indicated that although the skill of the stepwise regression model incorporating lateral deviation, channel gradient, and width was higher than that of the NLS regression model using only lateral deviation and channel gradient, their performances were nearly the same after five-point moving filtering. When using centimeter-resolution satellite remote sensing data to predict glacier meltwater yield over larger areas, it is recommended to use a nonlinear fitting model with a minimum amount of input data and higher reliability.

Author Contribution

Conceptualisation: YW. Methodology: LX, YW, AC. Investigation: LX, YW, AC. Project administration: NW, SZ. Resources: NW, SZ. Software: HS. Visualisation: LX, HS. Writing (original draft): LX. Writing (review and editing): YW.

Competing interests

The contact author has declared that none of the authors has any competing interests.

Data Availability Statement

The UAV-processed data (orthomosaic and DEM), supraglacial channel line vectors, and regression data (including geometric parameters and regression results) are available online (Xie and Wu, 2025).

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