1 Low variability runoff inhibits coupling of climate, tectonics, and topography in
2 the Greater Caucasus
3

4 Adam M. Forte[1], Joel S. Leonard[2], Matthew W. Rossi[3], Kelin X. Whipple[2], Arjun M.
5 Heimsath[2], Lasha Sukhishvili[4], Tea Godoladze[4], Fakhraddin Kadirov[5]
6
7 [1]Department of Geology & Geophysics, Louisiana State University, Baton Rouge, LA,
8 USA
9 [2]School of Earth and Space Exploration, Arizona State University, Tempe, AZ, USA
10 [3]Earth Lab, Cooperative Institute for Research in Environmental Sciences (CIRES),
11 University of Colorado, Boulder, CO, USA
12 [4]Institute of Earth Sciences and National Seismic Monitoring Center, Ilia State
13 University, Tbilisi, Georgia
14 [5]Institute of Geology and Geophysics of Azerbaijan National Academy of Sciences,
15 Baku, Azerbaijan
16
17 Corresponding Author: Adam M. Forte (aforte8@lsu.edu)
18

19 Highlights
20 • Large, new cosmogenic dataset from the Greater Caucasus
21 • Channel steepness index sublinearly varies with erosion rates
22 • Stochastic-threshold incision model explains erosion-steepness relationship
23 • Nonlinearity interpreted to reflect orographic controls on snowmelt runoff
24 • Precipitation phase may modulate degree of climate-tectonic coupling possible
25

26 Abstract
27

28 Hypothesized feedbacks between climate and tectonics are mediated by the

29 relationship between topography and long-term erosion rates. While many studies show

30 monotonic relationships between channel steepness and erosion rates, the degree of

31 nonlinearity in this relationship varies by landscape. Mechanistically explaining controls

32 on this relationship in natural settings is critical because highly nonlinear relationships

33 imply low sensitivity between climate and tectonics. To this end, we present a

34 coordinated analysis of cosmogenic [10]Be concentrations in river sands paired with

35 topographic, hydroclimatic, and tectonic data for the Greater Caucasus Mountains

36 where topography is invariant along-strike despite large gradients in modern

37 precipitation and convergence rates. We show that spatial patterns in erosion rates

38 largely reflect regional tectonics with little sensitivity to mean precipitation or runoff. The

39 nonlinearity in the erosion rate – steepness relationship may arise from very low runoff

40 variability, which we attribute to the large contribution from snowmelt. Transitioning from

41 rainfall- to snowmelt-driven runoff as mean elevation increases is common to many mid-

42 latitude mountain ranges. The associated decrease in runoff variability may represent

43 important, unrecognized dynamics inhibiting the sensitivity of tectonics to climate more

44 broadly.

45

46 **1. Motivation**

47   The potential for dynamic coupling between climate and tectonics has driven

48 decades of research. However, empirical data are equivocal with results both

49 supporting and rejecting two-way coupling (Whipple, 2009). The extent to which climate

50 can influence tectonics in fluvial landscapes depends on how climate influences erosion

51 rates which, in turn, drives the tectonic response to the redistribution of mass in the

52 lithosphere (Willett, 1999). If the response of topography to increasing uplift and erosion

53 rates is sublinear, then large changes in rates can only drive slight changes in fluvial

54 relief and the potential for two-way coupling is low (Whipple and Meade, 2004). In this

55 study, we focus on daily runoff variability, which when paired with a threshold to

56 incision, strongly influences the form of the topography-erosion rate relationship (e.g.,

57 DiBiase and Whipple, 2011; Lague, 2014; Lague et al., 2005). Under this view, regions

58 with extremely low runoff variability should exhibit a highly nonlinear topography-erosion

59 rate relationship. We examine this expectation in the Greater Caucasus (GC), where

60 prior work demonstrates a lack of simple climatic or tectonic influences on topography

61 despite substantial along-strike gradients in both (Forte et al., 2016). We present a

62 large, new suite of basin-averaged ^{10}Be erosion rates along with detailed analyses of

63 topography, tectonics, and hydroclimate to evaluate whether very low runoff variability in

64 the GC attributed to snowmelt hydrology can explain the apparent disconnect between

65 climate, tectonics, and topography. We then consider results in the broader context of

66 how the relative contributions from snowmelt versus rainfall runoff are expected to

67 change as mountain ranges grow.

68

69 **2. Background**

70 **2.1 Fluvial Incision Modeling**

2

The rate of bedrock erosion by rivers, E [L/t], is often estimated using the stream power incision model (Lague, 2014) (SPIM):

$$E = KA^m S^n \qquad (1)$$

where K [L^{1-2m}/t] is a constant encapsulating climate and substrate properties, A [L^2] is drainage area as a proxy for discharge, S [L/L] is local river slope, and m and n are dimensionless constants related to erosional process, friction relationship, and width scaling (Lague, 2014). Within this framework, it is useful to consider a normalized metric of channel steepness that accounts for the expected co-variation of drainage area and slope. Normalized channel steepness index (k_{sn} [L$^{2m/n}$]) is an empirical relationship (e.g., Kirby and Whipple, 2012) of the form:

$$k_{sn} = A^{\theta_{ref}} S \qquad (2)$$

where θ_{ref} is a dimensionless index describing the concavity of a channel. In the context of SPIM, θ_{ref} is equivalent to m/n at steady state. Substituting eq. 2 into eq. 1 generates a direct, if simple, prediction relating long term erosion rates, E, to the topography of a landscape as described by k_{sn} (Kirby and Whipple, 2012; Lague, 2014):

$$k_{sn} = K^{-1/n} E^{1/n} \qquad (3)$$

At steady state, n governs the sensitivity of topography to changes in tectonics or climate whereby high values imply weaker coupling (e.g., Whipple and Meade, 2004). Globally, E-k_{sn} relationships vary widely and range from linear to highly sublinear (Harel et al., 2016; Kirby and Whipple, 2012; Lague, 2014), necessitating consideration of this relationship at the landscape scale when evaluating potential climate-tectonic coupling.

While predictions from SPIM explain a variety of observations (Kirby and Whipple, 2012), its simplicity impedes interpretation of the shape of E-k_{sn} relationships. One promising alternative are models that incorporate event-scale runoff variability with erosion thresholds, i.e. stochastic threshold incision models (STIM) (Campforts et al.,

102 2020; Deal et al., 2018; DiBiase and Whipple, 2011; Lague et al., 2005; Scherler et al.,

103 2017; Tucker, 2004) where the instantaneous incision rate I is expressed as:

104

105
$$I = K\bar{R}^m Q^{*\gamma} S^n - \Psi_c \tag{4}$$

106

107 $\bar{R}$ [L/t] is mean discharge ($\bar{Q}$ [L^3/t]) divided by drainage area, Q^* is daily discharge divided

108 by mean daily discharge, γ is the local discharge exponent, and Ψ_c is a threshold

109 parameter that scales with the critical shear stress for incision (τ_c [LM^{-1}T^{-2}]) and

110 substrate erodibility (k_e [L$^{2.5}$T^{2}M$^{-1.5}$]). Eq. 4 reduces to eq. 1 for a constant runoff ($Q^* = $

111 1) and zero threshold (Ψ_c=0). Under STIM, the long-term erosion rate, E, is the

112 integration of eq. 4 over a distribution of discharges:

113

114
$$E = \int_{Q_c(k_s)}^{Q_m} I(Q, k_s) pdf(Q) dQ \tag{5}$$

115

116 where Q_c is the minimum discharge that exceeds τ_c, Q_m is the maximum discharge

117 considered, and the $pdf(Q)$ is the probability distribution of discharge. While a variety of

118 probability distributions have been used (e.g., Lague et al., 2005; Tucker, 2004)(e.g.,

119 Tucker, 2004; Lague et al., 2005), we use here a two parameter Weibull distribution:

120

121
$$pdf(Q^*; Q_0, c) = \frac{c}{Q_0}\left(\frac{Q^*}{Q_0}\right)^{c-1} e^{-(Q^*/Q_0)^c} \tag{6}$$

122

123 where c is a variability parameter describing the shape of the distribution and Q_0 is a

124 scale parameter related to the mean of the distribution. Weibull distributions have been

125 shown to describe a wide array of observed daily discharge distributions (Rossi et al.,

126 2016) and better characterize observations in the GC than the more commonly used

127 inverse gamma distribution (Lague, 2014). Application and derivation of the general

128 form of STIM is well documented and thus we refer interested readers to prior studies

129 (e.g., Campforts et al., 2020; Deal et al., 2018; DiBiase and Whipple, 2011; Lague,

130 2014; Lague et al., 2005; Scherler et al., 2017; Tucker, 2004).

131   The conceptual framing for STIM (Lague et al., 2005; Tucker, 2004) was built

132   around rainfall events that trigger runoff over the span of hours to days. Stochastic

133   descriptions of streamflow can be similarly built for snowmelt processes, which are

134   potentially important in our study area, as long as they account for the transient

135   accumulation and release of snow water (Schaefli et al., 2013). While there have been

136   efforts to integrate snowmelt hydrology into the STIM framework (Deal et al., 2018), we

137   fully recognize that the complex dynamics of long duration, snowmelt hydrographs on

138   sediment entrainment, deposition, and bedrock erosion (e.g., Johnson et al., 2010) is

139   not well represented by the probability distribution of flows alone. Nevertheless,

140   accounting of the probability distribution of flows is a necessary, if not sufficient, step

141   towards building an erosion law that can account for both rainfall and snowmelt runoff.

142   By using STIM as a unifying framework, the degree of nonlinearity of the E-k_{sn}

143   relationship is directly related to watershed hydrology via the variability parameter (Deal

144   et al., 2018). Settings with lower discharge variability and thus higher values of c will

145   exhibit more nonlinear E-k_{sn} relationships, all other things being equal.

146

147   **2.2 Regional Setting**

148   The Greater Caucasus Mountains (GC) represent the northernmost extent of

149   deformation caused by the Arabia-Eurasia collision. In the central portion of this

150   collision, the GC are the main locus of shortening since plate reorganization at ~5 Ma

151   (Allen et al., 2004). While the timing of reorganization coincides with rapid exhumation

152   throughout the GC (e.g., Avdeev and Niemi, 2011; Vincent et al., 2020), large

153   uncertainties remain as to the location, rates, and nature of major structures within the

154   GC (e.g., Cowgill et al., 2016). Since ~1-2 Ma, active shortening largely stepped out

155   from the range and localized on a series of foreland fold-thrust belts along its northern

156   and southern flanks. However, uplift is kinematically linked to active shortening via the

157   geometry of active faults at depth within the main range (e.g., Forte et al., 2014, 2013;

158   Mosar et al., 2010; Trexler et al., 2020). Modern convergence (Reilinger et al., 2006)

159   and precipitation (Forte et al., 2016) rates vary by an order-of-magnitude along strike,

160   with shortening increasing and precipitation decreasing eastward (Fig. 1). While along-

161   strike patterns in convergence are complex (Fig. S1), we focus on the component

5

162 accommodated along the southern range front where we collected new samples (Fig.

163 1). Whether modern geodetic velocities represent long-term convergence rates is

164 unclear (Forte et al., 2016), though geodetic rates of shortening are at least consistent

165 with average rates of shortening from the last 1-2 Ma estimated from balanced cross-

166 sections (Forte et al., 2013; Trexler et al., 2020).

167   Theory suggests that along-strike variations in precipitation and convergence

168 rates should lead to an eastward increase in mean elevation, local relief, and width

169 (Whipple and Meade, 2004). This is not observed in the GC and is not explained by

170 potential confounding factors like glaciation and lithological heterogeneity (Forte et al.,

171 2016). Instead, despite similar orogenic widths, topography is relatively invariant along-

172 strike with an across-strike pattern of lower relief flanks and a higher relief core (Forte et

173 al., 2016) (Fig. 1). Prior studies attributed the across-strike gradient in topography to a

174 northward increase in uplift rates along the southern flank of the GC with local maxima

175 near drainage divides (Forte et al., 2015). Forte et al. (2016) also evaluated whether

176 trends in mean precipitation were masking other important climate gradients (e.g.,

177 streamflow variability) that might better explain topographic patterns, to no avail. They

178 concluded that invariant topography along-strike was either due to a: (1) disconnect

179 between modern tectonics and climate with the longer-term forcing, or (2) complex, co-

180 varying relationships between the two. However, interpreting topography alone is

181 fraught, and testing such hypotheses requires careful sampling of erosion rate data

182 (e.g., DiBiase et al., 2010; Scherler et al., 2014), a key motivation for this study.

183   Prior estimates of exhumation and erosion rates in the GC largely come from

184 low-temperature thermochronology (e.g., Avdeev and Niemi, 2011; Vincent et al., 2020,

185 2011) and modern sediment yields and provenance (e.g., Vezzoli et al., 2020).

186 Thermochronology data, mostly concentrated west of 44°E, suggests older cooling ages

187 along the lower relief flanks than the higher relief core, patterns that are broadly

188 reflected in the topography (Forte et al., 2016). Exhumation rates are representative of

189 the last ~5-10 Ma and suggest rates of ~1000 m Myr^{-1} in the core that decrease to <250

190 m Myr^{-1} towards the flanks (Avdeev and Niemi, 2011; Vincent et al., 2020). Over the

191 modern era, erosion rates inferred from sediment yields and heavy mineral provenance

192 imply similar average rates and spatial patterns, but with erosion rates near the range

193 core >2000-3000 m Myr^{-1} locally (Vezzoli et al., 2020). At the millennial scale, there is

194 only one published basin-averaged, ^{10}Be erosion rate from the Inguri river in the

195 western GC. The 1100 m Myr^{-1} rate (Vincent et al., 2011) is comparable to the long-term

196 and short-term rates, though it averages across significant variations in steepness and

197 major knickpoints, and is thus hard to relate to topography. Our new dataset seeks to fill

198 this knowledge gap by reporting a large, new, millennial-scale, ^{10}Be erosion rate dataset

199 that systematically samples across gradients in topographic relief and hydroclimate in

200 the GC.

201

202 **3. Methods**

203 To understand how well topography reflects erosion rates, we sampled and

204 measured cosmogenic ^{10}Be in quartz river sands (e.g., Bierman and Nichols, 2004)

205 from 34 carefully selected, locally equilibrated, unglaciated basins (Fig. 1). Sampling

206 was coordinated with analyses of modern tectonics, topography, and hydrology of rivers

207 to better assess predictions of SPIM and STIM fluvial erosion laws. Below, we

208 summarize these methods. Where appropriate, we provide additional detail in the

209 Supplement, and raw data and algorithms are archived in a GitHub repository.

210

211 **3.1. Characterizing climate, tectonics, and topography**

212 *3.1.1 Modern Precipitation and Streamflow*

213 We use rainfall data from the Tropical Rainfall Measuring Mission (TRMM) 3B42

214 product (Huffman et al., 2007), and we use basin-averaged standard deviation of mean

215 monthly snow cover calculated from MODIS MOD10C2 (Hall et al., 2006). The latter

216 dataset is used as a proxy for snowmelt, whereby high values imply significant variation

217 in snow cover through the year (i.e., large amount of snowmelt) and low values imply

218 small variations in snow cover through the year. Data processing of both are described

219 elsewhere (Forte et al., 2016). Daily records of discharge (converted to runoff by

220 dividing by drainage area) for the Caucasus region comes from the Global Runoff Data

221 Centre (GRDC) and was also originally presented elsewhere (Forte et al., 2016). We

222 reprocess runoff data here to remove basins whose variability may be artificially low due

223   to dams and fit the distribution of discharge more carefully, the procedure for which we

224   describe in detail below.

225   To better understand patterns in daily runoff variability, we sought to partition

226   daily flows into annual, seasonal, and event components (Table S1). Baseflow

227   separation techniques have received much attention (see review by Eckhardt, 2008),

228   and our methods are akin to the widely used 'sliding interval' baseflow separation

229   method of Sloto & Crouse (1996). However, baseflow separation efforts typically focus

230   on binary separation of the overland flow component of the hydrograph. Given our

231   somewhat different objectives, we instead seek to decompose hydrographs into three

232   components: (1) an event component that includes event-scale overland flow and

233   subsurface contributions, (2) a seasonal component that includes the lagged release of

234   snowmelt runoff and autocorrelated series of rainstorms, and (3) slower inter-annual

235   changes to the water table. To this end, we quantify the inter-annual component using

236   the 365-day moving minima and the seasonal component using a 31-day moving

237   minima minus the annual component. The event-driven component is inferred from the

238   daily flows minus both the seasonal and annual components, thus satisfying the

239   condition that the three components sum to the total streamflow (Fig. S2). While

240   drainage area differences will influence the temporal lag of runoff responses to rainfall

241   or snowmelt inputs, our analysis focuses only on the regularity of flows under uniform

242   intervals. In much the same way that our estimates of mean runoff and runoff variability

243   implicitly subsume the role of drainage area, so does our partitioning of the time series

244   of streamflow. To develop a climatology of daily flows, we also calculated mean daily

245   runoff as a function of day of year and apply a 31-day moving mean to smooth over the

246   influence of individual, large events. Similar analyses on mean daily rainfall from TRMM

247   are only used to determine the timing and magnitude of peak rainfall in the main text,

248   though full time series are shown in Fig. S3.

249

250   *3.1.2 Modern convergence rates*

251   To compare erosion rates to modern convergence rates, we follow prior efforts

252   which divided GPS velocities into either a Greater Caucasus or Lesser Caucasus

253   domain (Avdeev and Niemi, 2011; Forte et al., 2014) and calculated average velocities

254 along-strike using a sliding 50-km moving window (Fig. S1). Convergence between the

255 Lesser and Greater Caucasus is the difference between these velocities along-strike.

256 Our results are similar to prior estimates (Forte et al., 2014), but incorporate updated

257 GPS velocities (Sokhadze et al., 2018).

258

259 *3.1.3 Topographic metrics*

260   Topographic analyses of individual basins used TopoToolbox (Schwanghart and

261 Scherler, 2014) and TAK for TopoToolbox (Forte and Whipple, 2019). Specifically, we

262 relied on 'ProcessRiverBasins' and related tools within TAK to calculate basin-averaged

263 statistics of topography and climatology. For basin-averaged topographic metrics, we

264 use the SRTM 30-m DEM and calculated k_{sn} using a reference concavity of 0.5. While

265 this reference concavity is appropriate for the GC (e.g., Forte et al., 2016), we tested

266 whether the observed shape of the relationship between k_{sn} and ^{10}Be erosion rate was

267 sensitive to the choice of reference concavity and found no measurable differences

268 across a range of concavities from 0.3-0.6 (Fig. S4).

269

270 **3.2. Cosmogenic Erosion Rates from Alluvial ^{10}Be Inventories**

271   Prior to field sampling, we vetted basins that appear to be in local topographic

272 steady-state (i.e., lacking major knickpoints; outside the influence of LGM glaciation) so

273 that basin-averaged, ^{10}Be erosion rates can be reliably related to k_{sn} (Fig. S5). This

274 motivated the sampling of 76 basins across the southern range front of the Greater

275 Caucasus. A subset of 47 were processed for erosion rates (Table S2). Low abundance

276 of quartz and difficulty in processing due to lithology (see discussion in Supplement)

277 resulted in usable amounts of quartz for 34 samples. For each sample, we selected the

278 0.25-1 mm size fraction and used a combination of traditional HF and HNO_3 leaches

279 and the 'hot phosphoric acid' technique (Mifsud et al., 2013) to isolate and purify quartz.

280 Samples were spiked with either commercial or custom low-background ^{9}Be carrier, Be

281 was extracted through liquid chromatography, and BeO was analyzed by accelerator

282 mass spectrometry at PRIME Lab, Purdue University. To convert blank-corrected, ^{10}Be

283 concentrations into erosion rates, we calculated effective latitude and elevations to

284 determine basin-averaged ^{10}Be production rates (Portenga and Bierman, 2011) and

285 calculated erosion rates in v3.0 of the online calculator formerly known as the CRONUS

286 calculator (Balco et al., 2008). Erosion rates are reported for a time independent scaling

287 scheme (Stone, 2000). Additional details on site selection, sample processing, and

288 erosion rate calculations are provided in the Supplement. All relevant parameters

289 needed to reproduce erosion rates are provided in Table S3.

290   Due to low quartz yields, we also examined the bedrock geology for each basin

291 (Forte, 2021) to assess the influence of variable quartz sourcing. By recalculating

292 topographic metrics and erosion rates after removing portions of basins with lithologies

293 unlikely to provide quartz, we found no meaningful difference in the E-k_{sn} patterns (Fig.

294 S6, Table S3). As another test on the potential sensitivity to non-uniform quartz yields,

295 we also considered the end-member scenarios where we assume that quartz is entirely

296 sourced from the upper or lower 50% of each basin and recalculated topographic

297 metrics and erosion rates (Fig. S6, Tables S3). We found negligible differences in E-k_{sn}

298 patterns - the central conclusions of this work are insensitive to this complication. For all

299 three cases, recalculated E generally lies within the uncertainty bounds of E calculated

300 assuming equal sourcing from the entire catchment. This suggests that analytical

301 uncertainty on erosion rates encompasses uncertainty in quartz sourcing in this setting.

302

303 **3.3 Numerical Modeling of River Incision**

304 *3.3.1 Parameterization of SPIM*

305   To assess which SPIM parameters best characterize the relationship between

306 channel steepness and [10]Be erosion rates, we fit eq. 3 to measured E and k_{sn} data. To

307 do this, we linearize eq. 3 using a log-transform and fit the data using the orthogonal

308 distance regression (ODR) algorithm in SciPy. To estimate ranges of acceptable fits, we

309 tested both a Monte Carlo (similar to Adams et al., 2020) and a bootstrap method. While

310 results are comparable, the bootstrap approach produced wider estimates of

311 uncertainty. As such, we report fits and uncertainties using the bootstrap method as

312 more conservative estimates. In fitting the data, we excluded data from one basin

313 whose uncertainty exceeds its mean value (Fig. S7). We also tested the sensitivity of

314 fits to the two highest erosion rates. While removal of these two rates suggest a lower n,

315 the range of uncertainties inclusive and exclusive of these data substantially overlap

316   (Fig. S7). Given the lack of any meaningful reason to exclude these data, the reported

317   fits include these two high erosion rate basins.

318

319   *3.3.2 Parameterization of STIM*

320   STIM is a more complex model than SPIM and requires calibration of a larger

321   number of parameters. Prior studies provide more detailed discussion of the derivation

322   of STIM and reasonable parameter values (Campforts et al., 2020; Deal et al., 2018;

323   DiBiase and Whipple, 2011; Lague et al., 2005; Scherler et al., 2017). For this work,

324   parameter values are summarized in the Supplement and many (k_t, ω_a, ω_s, α, β, a) are

325   set to previously used values (e.g., DiBiase and Whipple, 2011). The six parameters we

326   vary and/or explicitly test in our analysis are; $\bar{R}$, c, Q_0, k_w, τ_c, and k_e, each of which are

327   described and justified below.

328   Because none of the [10]Be basins are gauged, we generalize runoff parameters in

329   gauged GRDC basins for attribution. To estimate $\bar{R}$ in sampled basins, we needed to

330   relate $\bar{R}$ (known for gauged basins) with mean precipitation as measured by TRMM

331   ($\bar{P}_{TRMM}$) (known for all basins). To do this, we fit a power law relationship between $\bar{P}_{TRMM}$

332   and $\bar{R}$ in gauged basins (Fig. 2A) and used this relationship to interpolate $\bar{R}$ for [10]Be

333   basins (Fig. 2B). It is important to note that this regression implies runoff ratios > 1 for

334   basins with high runoff. We suspect that runoff ratios > 1 are due to the well-known

335   underestimation of snowfall from TRMM (Wulf et al., 2016). Increased snow fraction is

336   generally expected to increase average runoff ratios (e.g., Berghuijs et al., 2014), and

337   the high runoff ratios for basins with high mean runoff are suggestive of an increasing

338   contribution from snowmelt. However, we cannot quantitatively assess how snow

339   fraction may covary with mean precipitation given the uncertainty on $\bar{P}_{TRMM}$.

340   Runoff distributions for gauged basins are characterized using the shape (c) and

341   scale (Q_0) parameters of the Weibull distribution (eq. 6). In detail, runoff distributions

342   within the Caucasus are complex and likely represent distinct seasonal components

343   described by different probability distributions as observed in the Himalaya (e.g.,

344   Scherler et al., 2017). However, unlike prior attempts to account for this using hybrid

345   distributions, the seasonality of the Caucasus is more variable spatially and temporally

346   than monsoonal settings (e.g., Sutcliffe et al., 2008) and thus systematic separation of

347   just two components is untenable. As such, we instead fit a single distribution to each

348   individual gauged record that minimizes the misfit between: (1) the observed $\bar{R}$ and

349   implied $\bar{R}$ of the distribution fit and (2) the shape of the tail of the observed and fit

350   distribution. To do this, we first fit exceedance probability distributions on the natural log

351   linearized right tail of the distribution above a given threshold (Wilson and Toumi, 2005).

352   By varying this threshold from 1% (rare) to 60% (frequent) daily exceedances, we found

353   the threshold that minimizes an objective function that weights a normalized sum of the

354   mean square of the error on the right tail fit and a normalized difference between the

355   observed and implied $\bar{R}$ (Fig. S8). We found the best results when we weighted the

356   difference between the implied and observed mean by 1.5x. Comparing the observed

357   and implied mean $\bar{R}$ (Fig. 3C) and the observed and implied runoff for a flow with a 2-

358   year return interval (as a proxy for how well the tail of the distribution is honored; Fig.

359   3D) suggests this method is providing a decent description of both mean and tail

360   statistics.

361   The scaling between channel width and discharge (k_w) is an important, and hard

362   to constrain, hydraulic geometry relationship that strongly influences the shape of the *E-*

363   *k_{sn}* relationship predicted by STIM (Lague, 2014). Channel width (w) is typically related

364   to discharge (Q) using the function:

365

366      $$w = k_w Q^{\omega_a} \tag{7}$$

367

368   where ω_a is a constant we set to 0.5. Following DiBiase and Whipple (2011), we set the

369   value of k_w to 15 but test its importance by comparing observed channel widths to

370   predicted widths for both the mean and 2-year flows (Figs. 4, S10). We measure

371   channel widths for 26 of the 34 sampled basins using satellite imagery and ChanGeom

372   (Fisher et al., 2013). We were unable to measure channel widths for all basins because

373   of poor imagery and/or density of tree cover. This analysis suggests that a k_w of 15

374   largely encompasses observations and effectively represents a minimum value for k_w.

375   Higher values of k_w imply increasingly nonlinear *E-k_{sn}* relationships. As such, setting

376   this parameter to 15 for all basins ensures that we are not overestimating the degree of

377   nonlinearity based on potential variations in k_w (Fig. 4).

378   Both the erosional efficiency (k_e) and threshold shear stress (τ_c) control the

379   magnitude of the threshold parameter (Ψ_c) in STIM (eq. 5), neither of which is well

380   constrained for our setting. Given the need to fix one parameter to calibrate the other,

381   our goal is to find a single, best-fit value of k_e that can be used as representative of the

382   entire erosion rate dataset. As an initial step, we first seek to find meaningful divisions

383   within the estimated runoff distributions using k-means clustering on the values of c and

384    $\bar{R}$ from the gauged basins (Figure 5A). Clustering results suggest there are 4 semi-

385   distinct hydroclimatic populations within the gauged basins (Fig. 5A, S11). For each

386   population, we characterize the aggregate $\bar{R}$, c, and Q_0 in two different ways, either by

387   arithmetic means or by creating composite discharge records within each cluster and

388   refitting the composite distribution (for c and Q_0 only). The results of both are similar and

389   we use the refit composite values of c and Q_0 for subsequent components. We then

390   assess which runoff cluster ungauged basins belong to based on estimated $\bar{R}$, the

391   maximum elevation of the catchments (which is correlated with the shape and scale

392   parameters, e.g., Fig. 5C), and geographic proximity to gauged basins (Fig. 5D-E).

393   Within a given cluster, we then fix the distribution parameters c and Q_0 to the aggregate

394   values for that cluster, use the estimated $\bar{R}$ for individual ungauged basins, fix τ_c at 45

395   Pa, and use STIM to find the k_e for each basin that most closely reproduces measured E

396   using the known value of k_{sn} (Fig. 6A). To account for uncertainty in both k_{sn} and E for

397   each basin, we generate a synthetic distribution of 500 k_{sn} and E values using the mean

398   and uncertainties of individual basin values of k_{sn} and E. We then find a population of k_e

399   values for each basin such that individual random k_{sn} values drawn from the synthetic

400   k_{sn} distribution minimize the misfit between individual random E values drawn from the

401   synthetic E distribution. This produces a distribution of k_e values for each [10]Be basin.

402   We use the median k_e as our best estimate of k_e for a particular basin and the statistics

403   of this distribution (i.e., interquartile range) as an estimate for uncertainty on this value.

404   To represent populations of basins (whole dataset and clusters), we report medians of

405   best fit k_e values (Fig. 6A). We also do a similar exercise where we fix k_e to the median

406   value from above and estimating τ_c values for individual [10]Be basins (Fig. 6B).

407   The approach we take to estimate k_e (or τ_c) assumes limited influence of

408   lithology on k_e or τ_c, which is consistent with prior results from the GC (Forte et al.,

409   2016, 2014) and reinforced by the lack of correlation between the optimized k_e values

410   and lithology (Fig. S12). While some studies applying STIM to cosmogenic erosion rates

411   use grain size measurement to constrain τ_c (DiBiase and Whipple, 2011), the challenge

412   of obtaining such data prompts many studies like ours to assume a reasonable grain

413   size and corresponding τ_c (Campforts et al., 2020; Scherler et al., 2017), as we do here.

414

415   **4. Results**

416   **4.1 Relating Erosion Rates to Topography**

417   Erosion rates, E, vary from 33-5610 m Myr^{-1} (Figs. 7). Rates do not simply vary

418   with along-strike position (Fig. S13), but increase monotonically with LC-GC

419   convergence rates (Forte et al., 2014; Kadirov et al., 2012; Reilinger et al., 2006;

420   Sokhadze et al., 2018) (Fig. 7). Across-strike E systematically increases from the

421   southern flanks of the range towards the core, reaching a peak south of the topographic

422   crest (Fig. 7C). Despite the wide range of E, all data lie on a single, highly nonlinear

423   relationship between k_{sn} and E (Fig. 8A). Similar relationships exist between E and

424   mean basin slope due to the quasi-linear relationship between k_{sn} and slope in this

425   setting (Fig. 8C). Remarkably, over erosion rates from ~300 to >5000 m Myr^{-1}, channel

426   steepness is essentially invariant, ranging between ~300-500 m (Fig. 8). While there is

427   substantial scatter in these high E and k_{sn} basins, this is not unusual for these kinds of

428   datasets and reflects both geologic and analytical uncertainty in the erosion rate

429   estimates and the merging of two distinct ksn-E relationships associated with

430   catchments in clusters 2 and 3 (30 of 34 data points, Fig. 8A). Moreover, detailed

431   interrogation of potential confounding factors reveals no meaningful way to subdivide

432   these data into different physically interpretable populations (Fig. S14).

433

434   **4.2 River Incision Modeling**

435   Fitting data with the SPIM (eq. 3) suggests an n of 3.1 to 4 with a median value

436   of 3.5 (Fig. 8, Fig. S7). This is in the range of n found elsewhere, but well above the

437   global mean value of ~2.5 (Harel et al., 2016; Lague, 2014). E does not systemically

438   vary with $\bar{P}_{TRMM}$ (Fig. 8B) or $\bar{R}$ (Fig. 8A). Similarly, while channel narrowing in response

439   to increasing uplift rates can produce a nonlinearity in E-k_{sn} relationships during

440 transients (e.g., Gallen and Fernández Blanco, 2021), in the GC there is not a clear

441 relationship between the wideness of channels and k_{sn}, suggesting this is not a

442 significant contributor (Fig. 4C) and consistent with observations in equilibrium

443 landscapes across a range of uplift rates elsewhere (e.g., Whipple et al., 2022). Given

444 this outcome, we turn to STIM which explicitly accounts for daily runoff variability, to see

445 how well it explains the strong nonlinearity in the empirical E-k_{sn} relationship.

446   Figure 6 shows that optimized k_e varies over six orders of magnitude, though

447 most data lies within 1 order of magnitude of the median k_e (Fig. 6). There is an

448 apparent relation between position within the range and/or erosion rate (which are

449 correlated, e.g., Fig. 7C) and k_e or τ_c (Fig. 6). We further consider possible implications

450 of spatial variations in k_e or τ_c implied from our optimization in the discussion.

451   Within a given cluster, application of STIM using the whole population k_e and τ_c

452 parameters and either the aggregate or individual gauged basins values of c and Q_0

453 produces moderate correspondence with the observed E-k_{sn} relationship within that

454 cluster (Fig. 9, S15). Ultimately, while the single SPIM relationship provides a suitable fit

455 to the entire dataset (Fig. 8, S15), the application of the STIM within clusters highlights

456 that the degree of scatter in the observed E-k_{sn} may reflect the detailed hydroclimatic

457 variations within the Caucasus region, facilitating a data-driven interpretation to the

458 nonlinear relationships observed. In detail, the appearance of a pseudo-maximum k_{sn},

459 appears to largely result from the mixing of primarily two different, but both sublinear E-

460 k_{sn} relationships (i.e., cluster 2 & 3, Fig. 8A).

461

462 **5. Discussion**

463 **5.1 Tectonic Implications for the Greater Caucasus**

464   Our new cosmogenic erosion rates in the GC are broadly consistent with prior

465 million-year and decadal rates. All suggest systematic increases in E toward the core of

466 the range, with maximum E greater than 1000-2000 m Myr^{-1} (Avdeev and Niemi, 2011;

467 Vezzoli et al., 2020; Vincent et al., 2020, 2011), though our maximum rates of ~5000 m

468 Myr^{-1} exceed most estimates from thermochronology or sediment yields. The broad

469 agreement between E and GC-LC convergence rates suggest that millennial scale E

470 faithfully records modern tectonic forcing (Fig. 7), which likely reflect average geologic

471 rates of shortening over the last 1-2 Ma (Forte et al., 2013; Trexler et al., 2020). Spatial

472 patterns in cosmogenic E are consistent with the expected vertical components of GC-

473 LC shortening rates applied to north-dipping structures with reasonable dips (Fig. 7D),

474 though we emphasize that the geometry of structures in the interior of the GC are not

475 well constrained (e.g., Cowgill et al., 2016; Forte et al., 2014). The across-strike pattern

476 of increasing E toward the topographic crest, is consistent with prior suggestions of a

477 thrust ramp beneath the southeastern range-front (e.g., Forte et al., 2015), but does not

478 require this geometry. While there is substantial scatter in these spatial relationships,

479 likely due to local structural complexity, this result strongly contrasts with the poor

480 correlation between E and mean rainfall or estimated runoff (Fig. 8). From this, we reject

481 a simple climatic control on E in this setting, and the rest of our discussion focuses on

482 what more careful consideration of hydroclimate reveals.

483

484 **5.2 Application of STIM to the Greater Caucasus**

485   The ability of STIM to reproduce observed E-k_{sn} relationships (Fig. 9) suggests

486 that the shape of this relationship in the GC is aided by considering the systematic

487 decrease in runoff variability with elevation (e.g., Fig. 5C). STIM unpacks the bulk

488 treatment of climate in SPIM by characterizing hydroclimate using a simplified model of

489 runoff generation ($Q = R * A$) and an assumed probability distribution of daily runoff

490 (Weibull parameters c and Q_0, which are genetically related to the empirical mean). The

491 k-means cluster analysis suggests at least four distinct hydroclimatic regimes in the

492 Caucasus (Fig. 5, S11). Specifically, we find clusters generally correspond to high runoff

493 and higher variability (Cluster 1: $\bar{R} > 4$, $c < 1$), high runoff and lower variability (Cluster

494 1: $\bar{R} > 4$, $c > 1$), low runoff and higher variability (Cluster 2: $\bar{R} < 4$, $c < 0.9$), and low

495 runoff and lower variability (Cluster 3: $\bar{R} < 4$, $c > 0.9$). These clusters also have clear

496 spatial relationships, with a general trend of basins with higher maximum elevations

497 corresponding to lower daily runoff variability (Fig. 5C).

498   Cluster analysis allows us to evaluate model performance in terms of broad

499 variations in hydroclimate. In general, model parameters derived from gauged basins

500 improves E-k_{sn} predictions for ungauged basins (Fig. 9). This is especially true for

501 Cluster 2, which includes the bulk of the erosion rate basins, but also performs

16

502 acceptably for Cluster 3, despite the apparent mismatch between the imposed k_e and

503 the ranges of k_e for Cluster 3 basins (Fig. 6). The high runoff clusters 1 and 4 do not

504 perform as well with only 1 of the 4 basins being well explained by the model. Given that

505 none of the other 3 basins are clear outliers in the overall E-k_{sn} relationship (Fig. 8A) or

506 relationships between E and convergence velocity (Fig. 7D), we interpret the mismatch

507 to be due to anomalously high k_{sn} in these basins. Lithological differences do not

508 explain these anomalously steep basins (e.g., Fig. S16) indicating that other model

509 parameters must differ for these basins and/or vary systematically with runoff. It is

510 important to note here that the boundaries between clusters appear gradational (Fig.

511 5C). Thus, the extent to which individual basins are not well explained by predicted E-

512 k_{sn} relationships could in part reflect either (1) incorrect cluster membership or (2) that

513 the true range of discharge distributions are not represented by the admittedly small

514 number of gauged basins.

515   The observed mismatches within clusters could also reflect real variability in k_e,

516 which we impose as a constant. Optimization of k_e results suggest that rock erodibility

517 increases (or incision thresholds decrease) towards the center of the range (Fig. 6). If

518 real, it could imply a systematic weakening of rocks (or decrease in mean grain sizes)

519 toward the core of the orogen. This could be indicative of more fractured rocks due to

520 periglacial processes or accumulated tectonic damage. There also exists a weak

521 positive correlation between optimized k_e and erosion rate (Fig. 6), which is cross

522 correlated with distance from the center of the range (Fig. 7C). Systematic variations of

523 incision thresholds with increasing erosion rate have been suggested (Shobe et al.,

524 2018), but are thought to operate in the opposite direction whereby more rapid uplift

525 leads to coarser material and less erodible channels. However, the apparent variability

526 within k_e may also be an artifact of discrete clustering of data that reflect a continuum

527 of behavior. For example, clusters 2 and 3 overlap. Use of cluster 2 parameters for

528 cluster 3 largely erases cross-correlations among optimized k_e, erosion rate, and

529 proximity to the core of the range, begging caution in interpreting these findings.

530 Interpretation of these patterns requires detailed observations of rock properties and

531 grain size distribution to provide an additional constraint. Regardless of the challenge of

532 determining which set of parameters are 'most representative,' the utility of the cluster

17

533   analysis is that it highlights that the range of scatter observed in the E-k_{sn} relationship

534   should be expected for the range of hydroclimatic variability observed in this setting.

535   Furthermore, sub-dividing by these hydroclimatic domains reveal that (1) runoff

536   distributions are all strongly sublinear and (2) the sublinear nature of the observed E-k_{sn}

537   relationship in aggregate reflects mixing of a suite of different sublinear relationships,

538   which is dominated by contributions from cluster 2 and 3 (Fig. 8A, 9).

539   To further probe the E-k_{sn} relationship, we attempt to relate the clusters to their

540   underlying hydroclimatology. Figure 10A shows smoothed mean daily runoffs as a

541   function of time of year. In general, we interpret the strong seasonal signals in the GC

542   as indicative of a dominant component of snowmelt runoff, especially when maxima

543   occur in the spring or summer, though this could reflect other sources (e.g., where

544   seasonal rainfall is correlated with seasonal streamflow). This is consistent with prior

545   observations in the GC highlighting the importance of spring and summer snowmelt in

546   the hydrology of the range (e.g., Kuchment et al., 2010; Rets et al., 2018; Verdiev,

547   2009). Snowmelt contributions contribute up to 50% of the runoff during the summer

548   months in high elevation catchments (e.g., Vasil'chuk et al., 2016). For high mean

549   runoffs, both cluster 1 and 4 basins show a strong seasonal signal that is systematically

550   offset from peak precipitation. While cluster 4 generally has a single high runoff mode in

551   the GC, cluster 1 appears more complex with multi-modal seasonality. At lower mean

552   runoff, cluster 2 basins exhibit muted to non-existent seasonality in runoff and less

553   systematic relations to the timing of peak rainfall. Cluster 3 basins show clear

554   seasonality with a dominant peak in runoff in the late spring and early summer. This

555   peak in runoff occurs shortly after a peak in rainfall, also in the late spring, but there is a

556   noticeable peak in the late fall with no corresponding runoff peak which we attribute to

557   the building of a snowpack (Fig. S3). Regardless of cluster, higher elevation basins

558   typically show summer seasonality, reinforcing our interpretation that snowmelt is the

559   dominant driver of seasonal flows throughout the Caucasus region (Fig. 10A).

560   Figure 10A does not fully characterize the regularity of flows because data were

561   smoothed to develop a seasonal climatology. To probe whether and how well

562   streamflow seasonality explains the runoff variability parameter, c, we also partitioned

563   time series data into three components: event, seasonal, and annual fractions which

564 together sum to the total water flux. For gauged basins, the seasonal component shows

565 a positive correlation with runoff variability (shape), especially for basins in the GC (Fig.

566 10B). Similarly, the shape and scale parameters exhibit a strong negative correlation

567 with the event component (Fig. S17). Given that we attribute the seasonal component to

568 spring/summer snowmelt with modest contributions from seasonal rainfall in some

569 basins, we interpret patterns in runoff variability to be principally driven by the

570 contribution of snowmelt to runoff. This is reinforced with the observed positive

571 relationship between daily runoff variability (shape) and basin-averaged standard

572 deviation of mean monthly snow cover, a metric used by Forte et al., (2016) as a proxy

573 for snowmelt (Fig. 10C). We thus interpret our STIM results to at least partially account

574 for orographic patterns in runoff variability that embed the long hydrologic response

575 times associated with snowmelt runoff (Deal et al., 2018).

576

577 **5.3 Implications for Interactions Among Climate, Tectonics, and Topography**

578   The nonlinearity of the E-k_{sn} relationship in the GC explains why prior work (Forte

579 et al., 2016) failed to recognize the influence of either precipitation or convergence

580 gradients in the topography of the range (e.g., Fig. 1). Such a relationship predicts

581 relatively invariant k_{sn} at high erosion rates. Millennial scale erosion patterns are also

582 concordant with convergence rates and proximity to the core of the range (Fig. 7).

583 Higher rates near the core of the range are similar to patterns observed in both

584 sediment flux estimates (Vezzoli et al., 2020, 2014) and bedrock thermochronology

585 (Avdeev and Niemi, 2011; Vincent et al., 2020), suggesting this reflects a fundamental

586 detail of the orogen's architecture. The similar width of the range along-strike (Forte et

587 al., 2014) (Fig. 1) and the low sensitivity of channel steepness to E exceeding 300-500

588 m Myr^{-1} (Fig. 8A) explains why topography (e.g., mean elevation and local relief) is

589 relatively invariant along-strike. STIM helps reconcile apparently large contrasts in mean

590 annual precipitation and runoff between basins (Fig. 8B) by only considering the role of

591 flows above the incision threshold. While we recognize that the simplistic representation

592 of events in STIM does not fully capture seasonal dynamics in the GC (e.g., Fig. 9,10,

593 S3,S9), the general result that low variability runoff leads to highly nonlinear E-k_{sn}

594 relationships (DiBiase and Whipple, 2011; Lague, 2014; Lague et al., 2005) coupled

19

595   with the mixing of primarily two different, but both sublinear E-k_{sn} relationships provides

596   a satisfying explanation for the pseudo-threshold-k_{sn} behavior (e.g., Fig. 8, 9) and the

597   lack of a clear climate signal in the topography.

598   While significant uncertainties remain, we consider the most likely explanation to

599   be one where the orographic patterns in variability and the nonlinearity of the E-k_{sn}

600   relationship relate to the importance of snowmelt. This is consistent with previous work

601   probing seasonal patterns of runoff in the GC (e.g., Kuchment et al., 2010; Rets et al.,

602   2018; Vasil'chuk et al., 2016; Verdiev, 2009) and the more general observation that

603   mountain regions with a large snow fraction tend to have lower event-scale runoff

604   variability (e.g., Rossi et al., 2016) as the dominant flood generating mechanism

605   changes from rainfall to snowmelt runoff (e.g., Berghuijs et al., 2016). If correct, our

606   hypothesized link between the nonlinearity in the E-k_{sn} relation and low variability

607   snowmelt runoff has interesting implications. Under modern climate, only tributary

608   basins on the low elevation and low erosion rate flanks of the range should be

609   topographically sensitive to either climatic or tectonic changes. These areas: (1) have

610   higher runoff variability due to a lesser influence of snowmelt (Fig. 5, 10), and (2) are in

611   the quasi-linear portion of the E-k_{sn} relationship (Fig. 8). Conventional approaches

612   toward accounting for orographic precipitation in landscape evolution have focused on

613   elevation-dependent mean annual rainfall (Bookhagen and Burbank, 2006) or snowfall

614   (Anders et al., 2008). This work highlights the critical role of the transition from rainfall-

615   to snowmelt- driven hydrology in mediating runoff variability itself (Rossi et al., 2020), an

616   important complexity rarely considered in landscape evolution studies. Transitioning

617   from rainfall- to snowmelt- driven hydrology is dictated by the elevation distribution

618   within a mountain range and presents a possible direct relation between climate and

619   erosion rates in orogenic systems, albeit not in the traditional sense where there is a

620   positive correlation between erosion and precipitation or runoff rates (Ferrier et al.,

621   2013) . Importantly, a snowmelt control on runoff variability may be relevant to many

622   mountain ranges where the growth of topographic relief has undermined the erosive

623   ability of higher mean annual precipitation by distributing flows over longer duration

624   snowmelt events.

625

6. Conclusions

We present a large suite of new basin-averaged [10]Be erosion rates from the Greater Caucasus that are consistent with longer term exhumation and shorter-term decadal scale rates. Erosion systematically varies with convergence rates between the Greater Caucasus and Lesser Caucasus and is uncorrelated to mean annual rainfall, favoring a tectonic control on erosion rates. The relationship between erosion and channel steepness is extremely nonlinear in this setting. However, consideration of regional hydro-climatology incorporated into a stochastic threshold incision model of river incision suggests that low variability, snowmelt runoff may drive this nonlinearity, thus explaining why prior efforts failed to recognize a clear climatic imprint on topography in the mountain range.

Our results also highlight the importance of both: (1) considering regionally constrained relationships between topography and erosion when assessing potential climate-tectonic interactions, and (2) endeavoring to understand the underlying mechanism(s) setting that form. In the Greater Caucasus, significant climate-tectonic interactions are precluded because topography becomes insensitive to changes in forcing at uplift rates exceeding 300-500 m Myr^{-1}. This contrasts with settings where relationships between erosion and topography may be more linear. We emphasize that the observed nonlinearity between erosion rates and channel steepness in the GC is not a global solution to an apparent lack of coupling between climate and tectonics. Rather, the wide range of such relationships around the world likely reflects important landscape specific, hydro-climatic details that must be considered when applying erosion models. Our results also show that spatial and temporal patterns in precipitation phase that alter flood frequency may be an underappreciated governor on the degree of climate-tectonic coupling possible in mid-latitude mountain ranges not heavily influenced by glacial erosion.

665

666   **Data Availability**

667   The authors certify that all data necessary to reproduce the key findings of this paper

668   are presented in the manuscript or its supplement. We additionally provide the majority

669   of the data tables as plain text, shapefiles of the [10]Be basins, the GRDC basins, some

670   select rasters that are generally not easily available, and many of the analysis scripts in

671   a GitHub repository (https://github.com/amforte/Caucasus_Erosion; DOI:

672   10.5281/zenodo.6353857). The lithologic compilations are provided as a separate open

673   access permanent repository (Forte, 2021: https://doi.org/10.5281/zenodo.5752511).

Figure Captions

Fig 1. (A) Regional map with location of alluvial cosmogenic [10]Be samples (white symbols) within the Greater and Lesser Caucasus (LC). Line A-A' and corresponding box outline 50-km wide swath referenced in other figures and is centered on the topographic crest of the range. Dotted rectangle is outline of Fig 7A. KFTB – Kura Fold Thrust Belt, KB – Kura Basin, RB – Rioni Basin. (B) TRMM 3B42 mean daily rainfall (Forte et al., 2016). (C) Blue shaded region is maximum and minimum rainfall within the swath in panel B (line is mean value). Blue symbols are mean rainfall in sampled basins. Red shaded region is estimated convergence rates between the Greater and Lesser Caucasus along the southern margin of the Greater Caucasus, and is largely similar to that calculated by Forte et al., (2014). It was recalculated to include more recent GPS data (see Supplement and Fig. S1). (D) Swath of topography. Symbols are mean elevation within sampled basins. (E) Swath of local relief using a 5-km radius circular moving window. Symbols are mean relief within sampled basins.

Fig 2. (A) Relationship between mean TRMM rainfall within gauged GRDC basins and mean runoff used to estimate runoff in ungauged basins from mean TRMM rainfall. (B) Comparison between mean TRMM rainfall and implied runoff ratio for both the gauged basins and the ungauged basins. Note that both in the gauged and ungauged basins, runoff ratios exceed 1 at high rainfall (runoff) rates. This likely implies an underestimation of TRMM rainfall, e.g., from missing snowfall (Wulf et al., 2016), as opposed to a real runoff ratio which exceeds 1.

Fig 3. (A) Exceedance frequency versus daily runoff for each GRDC basin and colored by mean rainfall estimated from TRMM 3B42. Runoff calculations assume a linear scaling with drainage area, see 3B. (B) Mean discharge versus drainage area colored by mean rainfall for each GRDC basin. The quasi-linear relationship between discharge and drainage area, after parsing by mean rainfall, is consistent with a linear scaling of runoff ($\bar{Q} = \bar{R}A$). Lines represent constant mean runoff assuming this linear scaling. (C) Comparison of observed mean runoff and that implied by the fitting of the individual gauged basin discharge distributions with a Weibull (stretched exponential) distribution, see text for details. (D) Comparison of observed and implied 2-year return flood runoff magnitudes from the fitting of the distributions (E) Comparison of shape and scale parameters resultant from the fits. Dots are scaled by the threshold (i.e., average number of events per year that define the tail of the distribution) that yielded the best fit for individual basins. Fig. S8 provides an example of the fitting technique we use and Fig. S9 compares the results of our preferred fitting technique and a fit of the whole distribution via the method of moments.

Fig 4. (A) Example of channel width as measured on satellite imagery from Google Earth using ChanGeom (Fisher et al., 2013). (B) Measured widths (dots colored by estimated runoff of each basin) and predicted widths using k_w = 15 and either the mean discharge or the 2-year flood (black symbols) as a function of drainage area. Additional comparisons between width and drainage area scaling are provided in Fig. S10. (C)

720   Comparison of mean wideness (k_{wn}) to mean k_{sn} within 1 km segments, colored by the
721   maximum drainage area of the same segments. Wideness is calculated as discussed in
722   Lague (2014), i.e., $k_{wn} = wA^{-0.5}$.

723

724   **Fig 5.** Hydroclimate cluster analysis. (A) Comparison of shape and mean runoff. These
725   two parameters were the input to the k-means cluster analysis. Squares indicate the
726   single value of shape and mean runoff used for the cluster as a whole in subsequent
727   analysis, see main text. An elbow plot for choosing the number of clusters is provided in
728   Fig. S11. Note that dashed line boundaries are meant to aid visualization and do not
729   define known edges of the clusters (B) Comparison of scale and mean runoff, colored
730   by cluster membership. Squares indicate the single value of shape and mean runoff
731   used for the cluster as a whole in subsequent analysis. (C) Comparison of shape and
732   maximum elevation within the catchment for gauged (GRDC) basins. (D) Comparison of
733   mean runoff and maximum elevation for the gauged and ungauged basins. Colors
734   represent cluster membership. For the gauged basins, these are outcomes of the k-
735   means clustering described in the text. For the ungauged basins, they were assigned
736   cluster membership by breaking this space into four quadrants (shown with the light
737   gray lines). For the boundary between cluster 2-3, this was tuned such that a basin
738   which lies within a cluster 3 gauged basin was assigned to cluster 3. (E) Spatial
739   distribution of clusters for both the gauged basins used to define the clusters and
740   ungauged basins assigned to clusters.

741

742   **Fig. 6** Results of optimization of k_e (A) and τ_c (B) compared to distance from center of
743   the range (x axis) and erosion rate (scale of dots). Horizontal dotted lines represent
744   median by cluster and for the entire population. Shaded region indicates interquartile
745   range for the whole population estimates. Points are colored by cluster membership
746   (see Fig. 5). Comparison of the optimized values of k_e and τ_c and lithology are
747   presented in Fig. S12.

748

749   **Fig 7.** (A) Cosmogenic [10]Be erosion rates for sampled basins. Black basins indicate
750   unsuccessful samples (insufficient quartz yield; see Supplemental Methods for
751   additional discussion). White shading represents extent of LGM glaciation (Gobejishvili
752   et al., 2011) and black dashed line marks center of swath shown in Fig. 1. (B) Estimated
753   N25°E convergence between the GC and LC along the southern margin of the GC,
754   identical to the red curve in Fig 1B. (C) Cosmogenic [10]Be erosion rates vs distance
755   from the center of the swath (colored by mean elevation of sampled basins – Fig. S14
756   presents a direct relationship between erosion rate and mean elevation). Pearson's
757   correlation coefficient (r) is shown comparing erosion rates and distance from the swath
758   center, along with respective p value. (D) Cosmogenic [10]Be erosion rates vs
759   convergence velocity (7B, colored by distance from the swath center). Contours
760   represent the vertical component of rock uplift if convergence was accommodated along
761   a thrust of a specified dip, these are for reference only and do not imply known
762   structural geometries. Correlation coefficient between E and GC-LC convergence (Fig
763   1C) is shown. Average time is calculated as the amount of time required to erode 60
764   cm. A plot of erosion rate as a function of along-strike distance is provided in Fig. S13.

765

766   **Fig. 8** (A) ^{10}Be erosion rate vs basin-averaged normalized channel steepness (k_{sn}).
767   Individual basins are colored by cluster membership (see Fig. 5D) and the size of the
768   circles are scaled by estimated mean runoff. Curve is the best-fit power law function.
769   Vertical dashed lines highlight the range of E above which k_{sn} becomes largely
770   invariant. Inset shows same data on a linear scale. Details of the power law fit are
771   provided in Fig. S7. Also shown are the composite STIM relationships (Fig. 9) for
772   clusters 2 and 3, which represent the bulk of the data. A more direct comparison of the
773   degree of correspondence between the observed data and both STIM and SPIM
774   relationships are provided in the supplement (Fig. S15). (B) ^{10}Be erosion rate vs mean
775   rainfall in each basin colored by k_{sn}. Pearson's correlation coefficient (r) between
776   erosion rate and rainfall along with p-value is shown, note that this suggests non-
777   statistically significant correlation between these variables. (C) Mean basin k_{sn}
778   compared to mean hillslope gradient, colored by E. Note that the linear relationship
779   between k_{sn} and gradient reflects that both k_{sn} and gradient become insensitive to
780   increases in erosion rate at ~500 m Myr^{-1} (Fig. S4).
781
782   **Fig. 9** Details of runoff distributions and erosion rates for cluster 1 (A), cluster 2 (B),
783   cluster 3 (C), and cluster 4 (D). For all plots, the top panels display the individual runoff
784   distributions (gray dots) and the fits to those distributions (thin lines). Also displayed are
785   the implied distribution using the mean shape, scale, and runoff from each population
786   (thick dashed lines). Black dots represent binned composite of runoff with interquartile
787   range of runoff within each bin. Thick solid line is the fit to the composite distribution.
788   Bottom panels display implied E-k_{sn} relationships using either the individual mean
789   runoff, shape, and scale parameters for gauged basins (thin lines), using the population
790   mean (thick dashed lines), and using the fit to the composite distribution (thick solid
791   lines). All individual relationships use the median k_e (1.55e-11, e.g., Fig. 6), but shaded
792   region shows range of possible relationships using the interquartile range of k_e and the
793   composite distribution values. The mean runoff and composite shape and scale
794   parameters are reported for each cluster.
795
796   **Fig 10.** (A) Daily GRDC runoff, averaged over the full length of each dataset and after
797   applying a 31-day moving average. Dots are day of peak rainfall from TRMM processed
798   in the same way for the basin of interest (see Fig. S3 for rainfall time series and
799   difference between rainfall and runoff). Almost all basins show a peak in runoff in either
800   the spring or summer consistent with derivation from snowmelt. (B) Seasonal fraction of
801   runoff versus shape parameter for the distribution. Symbol size is scaled by maximum
802   elevation, shapes indicate the season of maximum mean runoff, and colors indicate
803   cluster membership. GC basins (solid symbols) show a more consistent relationship
804   than those further afield (open symbols) between seasonal fraction and shape. (C)
805   Standard deviation in mean seasonal snow cover vs shape. Symbols are the same as in
806   10B. Additional comparisons between fractions and both the shape and scale
807   parameters are provided in Fig. S17.
808
809
810   **References**

811 Allen, M.B., Jackson, J., Walker, R., 2004. Late Cenozoic reorganization of the Arabia-Eurasia
812   collision and the comparison of short-term and long-term deformation rates. Tectonics
813   23, doi:10.1029/2003TC001530-doi:10.1029/2003TC001530.
814 Anders, A.M., Roe, G.H., Montgomery, D.R., Hallet, B., 2008. Influence of precipitation phase on
815   the form of mountain ranges. Geology 36, 479. https://doi.org/10.1130/G24821A.1
816 Avdeev, B., Niemi, N.A., 2011. Rapid Pliocene exhumation of the central Greater Caucasus
817   constrained by low-temperature thermochronometry. Tectonics 30.
818   https://doi.org/10.1029/2010TC002808
819 Balco, G., Stone, J., Lifton, N.A., Dunai, T., 2008. A complete and easily accessible means of
820   calculating surface exposure ages or erosion rates from 10Be and 26Al measurements.
821   Quat. Geochronol. 3, 174–195. https://doi.org/10.1016/j.quageo.2007.12.001
822 Berghuijs, W.R., Woods, R.A., Hrachowitz, M., 2014. A precipitation shift from snow towards
823   rain leads to a decrease in streamflow. Nat. Clim. Change 4, 583–586.
824   https://doi.org/10.1038/nclimate2246
825 Berghuijs, W.R., Woods, R.A., Hutton, C.J., Sivapalan, M., 2016. Dominant flood generating
826   mechanisms across the United States: Flood Mechanisms Across the U.S. Geophys. Res.
827   Lett. 43, 4382–4390. https://doi.org/10.1002/2016GL068070
828 Bierman, P.R., Nichols, K.K., 2004. Rock to sediment - slope to sea with 10Be - rates of
829   landscape change. Annu. Rev. Earth Planet. Sci. 32, 215–235.
830 Bookhagen, B., Burbank, D., 2006. Topography, relief, and TRMM-derived rainfall variations
831   along the Himalaya. Geophys. Res. Lett. 33, L08405–L08405.
832   https://doi.org/10.1029/2006GL026037
833 Campforts, B., Vanacker, V., Herman, F., Vanmaercke, M., Schwanghart, W., Tenorio, G.E.,
834   Willems, P., Govers, G., 2020. Parameterization of river incision models requires
835   accounting for environmental heterogeneity: insights from the tropical Andes. Earth
836   Surf. Dyn. 8, 447–470. https://doi.org/10.5194/esurf-8-447-2020
837 Cowgill, E., Forte, A.M., Niemi, N.A., Avdeev, B., Tye, A.R., Trexler, C.C., Javakishvirli, Z., Elashvili,
838   M., Godoladze, T., 2016. Relict basin closure and crustal shortening budgets during
839   continental collision: An example from Caucasus sediment provenance. Tectonics 35,
840   2918–2947. https://doi.org/10.1002/2016TC004295
841 Deal, E., Braun, J., Botter, G., 2018. Understanding the Role of Rainfall and Hydrology in
842   Determining Fluvial Erosion Efficiency. J. Geophys. Res. Earth Surf. 123, 744–778.
843   https://doi.org/10.1002/2017JF004393
844 DiBiase, R.A., Whipple, K.X., 2011. The influence of erosion thresholds and runoff variability on
845   the relationships among topography, climate, and erosion rate. J. Geophys. Res. 116.
846   https://doi.org/10.1029/2011JF002095
847 DiBiase, R.A., Whipple, K.X., Heimsath, A.M., Ouimet, W.B., 2010. Landscape form and
848   millennial erosion rates in the San Gabriel Mountains, CA. Earth Planet. Sci. Lett. 289,
849   134–144.
850 Eckhardt, K., 2008. A comparison of baseflow indices, which were calculated with seven
851   different baseflow separation methods. J. Hydrol. 352, 168–173.
852   https://doi.org/10.1016/j.jhydrol.2008.01.005
853 Ferrier, K.L., Huppert, K.L., Perron, J.T., 2013. Climatic control of bedrock river incision. Nature
854   496, 206–209. https://doi.org/10.1038/nature11982

855 Fisher, G.B., Bookhagen, B., Amos, C.B., 2013. Channel planform geometry and slopes from
856   freely available high-spatial resolution imagery and DEM fusion: Implications for channel
857   width scalings, erosion proxies, and fluvial signatures in tectonically active landscapes.
858   Geomorphology 194, 46–56. https://doi.org/10.1016/j.geomorph.2013.04.011
859 Forte, A.M., 2021. Lithologic compilation of basins sampled for cosmogenic 10BE in the Greater
860   Caucasus Mountains.
861 Forte, A.M., Cowgill, E., Murtuzayev, I., Kangarli, T., Stoica, M., 2013. Structual geometries and
862   magnitude of shortening in the eastern Kura fold-thrust belt, Azerbaijan: Implications
863   for the development of the Greater Caucasus Mountains. Tectonics 32.
864   https://doi.org/10.1002/tect.20032
865 Forte, A.M., Cowgill, E., Whipple, K.X., 2014. Transition from a singly vergent to doubly vergent
866   wedge in a young orogen: The Greater Caucasus. Tectonics 33, 2077–2101.
867   https://doi.org/10.1002/2014TC003651
868 Forte, A.M., Whipple, K.X., 2019. Short communication : The Topographic Analysis Kit (TAK) for
869   TopoToolbox. Earth Surf. Dyn. 7, 87–95. https://doi.org/10.5194/esurf-7-87-2019
870 Forte, A.M., Whipple, K.X., Bookhagen, B., Rossi, M.W., 2016. Decoupling of modern shortening
871   rates, climate, and topography in the Caucasus. Earth Planet. Sci. Lett. 449, 282–294.
872   https://doi.org/10.1016/j.epsl.2016.06.013
873 Forte, A.M., Whipple, K.X., Cowgill, E., 2015. Drainage network reveals patterns and history of
874   active deformation in the eastern Greater Caucasus. Geosphere 11.
875   https://doi.org/10.1130/GES01121.1
876 Gallen, S.F., Fernández-Blanco, D., 2021. A New Data-driven Bayesian Inversion of Fluvial
877   Topography Clarifies the Tectonic History of the Corinth Rift and Reveals a Channel
878   Steepness Threshold. J. Geophys. Res. Earth Surf.
879   https://doi.org/10.1029/2020JF005651
880 Gobejishvili, R., Lomidze, N., Tielidze, L., van der Meer, J.J.M., 2011. Late Pleistocene (Würmian)
881   Glaciations of the Caucasus, in: Ehlers, J., Gibbard, P.L., Hughes, P.D. (Eds.), Quaternary
882   Glaciations - Extent and Chronology. Elsevier, Amsterdam, pp. 141–147.
883 Hall, D.K., Riggs, G.A., Salomonson, V.V., 2006. MODIS/Terra Snow Cover 5-Min L2 Swath 500m.
884   Version 5. NASA National Snow and Ice Data Center Distributed Archive Center, Boulder,
885   CO.
886 Harel, M.A., Mudd, S.M., Attal, M., 2016. Global analysis of the stream power law parameters
887   based on worldwide 10Be denudation rates. Geomorphology 268, 184–196.
888   https://doi.org/10.1016/j.geomorph.2016.05.035
889 Huffman, G.J., Adler, R.F., Bolvin, D.T., Gu, G., Nelkin, E.J., Bowman, K.P., Hong, Y., Stockler, E.F.,
890   Wolff, D.B., 2007. The TRMM multisatellite precipitation analysis (TMPA): Quasi-global,
891   multiyear, combined-sensor precipitation estimate at fine scales. J. Hydrometeorol. 8,
892   38–55. https://doi.org/10.1175/JHM560.1
893 Johnson, J.P.L., Whipple, K.X., Sklar, L., 2010. Contrasting bedrock incision rates from snowmelt
894   and flash floods in the Henry Mountains, Utah. Geol. Soc. Am. Bull. 122, 1600–1615.
895 Kadirov, F., Floyd, M., Alizadeh, A., Guliev, I., Reilinger, R., Kuleli, S., King, R., Toksoz, M.N., 2012.
896   Kinematics of the eastern Caucasus near Baku, Azerbaijan. Nat. Hazards 63, 997–1006.
897 Kirby, E., Whipple, K.X., 2012. Expression of active tectonics in erosional landscapes. J. Struct.
898   Geol. 44, 54–75.

899   Kuchment, L.S., Gelfan, A.N., Demidov, V.N., 2010. A spatial model of snowmelt-rainfall runoff
900   formation of the mountain river (by the example of the Upper Kuban River). Russ.
901   Meteorol. Hydrol. 35, 842–850. https://doi.org/10.3103/S1068373910120083
902   Lague, D., 2014. The stream power river incision model: evidence, theory and beyond. Earth
903   Surf. Process. Landf. 39, 38–61. https://doi.org/10.1002/esp.3462
904   Lague, D., Hovius, N., Davy, P., 2005. Discharge, discharge variability, and the bedrock channel
905   profile. J. Geophys. Res. 110, F04006–F04006. https://doi.org/10.1029/2004JF000259
906   Mifsud, C., Fujioka, T., Fink, D., 2013. Extraction and purification of quartz in rock using hot
907   phosphoric acid for in situ cosmogenic exposure dating. Nucl. Instrum. Methods Phys.
908   Res. B 294, 203–207. https://doi.org/10.1016/j.nimb.2012.08.037
909   Mosar, J., Kangarli, T., Bochud, M., Glasmacher, U.A., Rast, A., Brunet, M.-F., Sosson, M., 2010.
910   Cenozoic-Recent tectonics and uplift in the Greater Caucasus: a perspective from
911   Azerbaijan, in: Sosson, M., Kaymakci, N., Stephenson, R.A., Bergerat, F., Starostenko, V.I.
912   (Eds.), Sedimentary Basin Tectonics from the Black Sea and Caucasus to the Arabian
913   Platform. Geological Society, London, pp. 261–280.
914   Portenga, E.W., Bierman, P.R., 2011. Understanding Earth's eroding surface with 10Be. GSA
915   Today 21, 4–10. https://doi.org/10.1130/G111A.1
916   Reilinger, R., McClusky, S., Vernant, P., Lawrence, S., Ergintav, S., Cakmak, R., Ozener, H.,
917   Kadirov, F., Guliev, I., Stepanyan, R., Nadariya, M., Hahubia, G., Mahmoud, S., Sakr, K.,
918   ArRajehi, A., Paradissis, D., Al-Aydrus, A., Prilepin, M., Guseva, T., Evren, E., Dmitrotsa,
919   A., Filikov, S.V., Gomez, F., Al-Ghazzi, R., Karam, G., 2006. GPS constraints on continental
920   deformation in the Africa-Arabia-Eurasia continental collision zone and implications for
921   the dynamics of plate interactions. J. Geophys. Res. 111, doi:10.1029/2005JB004051-
922   doi:10.1029/2005JB004051.
923   Rets, E.P., Dzhamalov, R.G., Kireeva, M.B., Frolova, N.L., Durmanov, I.N., Telegina, A.A.,
924   Telegina, E.A., Grigoriev, V.Yu., 2018. RECENT TRENDS Of RIVER RUNOff IN THE NORTH
925   CAUCASUS. Geogr. Environ. Sustain. 11, 61–70. https://doi.org/10.24057/2071-9388-
926   2018-11-3-61-70
927   Rossi, M.W., Anderson, R.S., Anderson, S.P., Tucker, G.E., 2020. Orographic Controls on Subdaily
928   Rainfall Statistics and Flood Frequency in the Colorado Front Range, USA. Geophys. Res.
929   Lett. 47. https://doi.org/10.1029/2019GL085086
930   Rossi, M.W., Whipple, K.X., Vivoni, E.R., 2016. Precipitation and evapotranspiration controls on
931   event-scale runoff variability in the contiguous United States and Puerto Rico. J.
932   Geophys. Res. 121. https://doi.org/10.1002/2015JF003446
933   Schaefli, B., Rinaldo, A., Botter, G., 2013. Analytic probability distributions for snow-dominated
934   streamflow: Snow-Dominated Streamflow Pdfs. Water Resour. Res. 49, 2701–2713.
935   https://doi.org/10.1002/wrcr.20234
936   Scherler, D., Bookhagen, B., Strecker, M.R., 2014. Tectonic control on 10 Be-derived erosion
937   rates in the Garhwal. J. Geophys. Res. Earth Surf. 119, 83–105.
938   https://doi.org/10.1002/2013JF002955
939   Scherler, D., DiBiase, R.A., Fisher, G.B., Avouac, J.-P., 2017. Testing monsoonal controls on
940   bedrock river incision in the Himalaya and Eastern Tibet with a stochastic-threshold
941   stream power model. J. Geophys. Res. Earth Surf. 122, 1389–1429.
942   https://doi.org/10.1002/2016JF004011

943 Schwanghart, W., Scherler, D., 2014. Short Communication: TopoToolbox 2 - MATLAB based
944   software for topographic analysis and modeling in Earth surface sciences. Earth Surf.
945   Dyn. 2, 1–7. https://doi.org/10.5194/esurf-2-1-2014
946 Shobe, C.M., Tucker, G.E., Rossi, M.W., 2018. Variable-Threshold Behavior in Rivers Arising
947   From Hillslope-Derived Blocks. J. Geophys. Res. Earth Surf. 123, 1931–1957.
948   https://doi.org/10.1029/2017JF004575
949 Sloto, R.A., Crouse, M.Y., 1996. HYSEP: A Computer Program for Streamflow Hydrograph
950   Separation and Analysis. https://doi.org/10.3133/wri964040
951 Sokhadze, G., Floyd, M., Godoladze, T., King, R., Cowgill, E.S., Javakhishvili, Z., Hahubia, G.,
952   Reilinger, R., 2018. Active convergence between the Lesser and Greater Caucasus in
953   Georgia: Constraints on the tectonic evolution of the Lesser–Greater Caucasus
954   continental collision. Earth Planet. Sci. Lett. 481, 154–161.
955   https://doi.org/10.1016/j.epsl.2017.10.007
956 Stone, J.O., 2000. Air pressure and cosmogenic isotope production. J. Geophys. Res. Solid Earth
957   105, 23753–23759. https://doi.org/10.1029/2000JB900181
958 Sutcliffe, J.V., Farquharson, F.A.K., Tate, E.L., Folwell, S.S., 2008. Flood regimes in the Southern
959   Caucasus: the influence of precipitation on mean annual floods and frequency curves.
960   Hydrol. Res. 39, 385–401. https://doi.org/10.2166/nh.2008.025
961 Trexler, C.C., Cowgill, E., Spencer, J.Q.G., Godoladze, T., 2020. Rate of active shortening across
962   the southern thrust front of the Greater Caucasus in western Georgia from kinematic
963   modeling of folded river terraces above a listric thrust. Earth Planet. Sci. Lett. 544,
964   116362. https://doi.org/10.1016/j.epsl.2020.116362
965 Tucker, G.E., 2004. Drainage basin sensitivity to tectonic and climatic forcing: Implications of a
966   stochastic model for the role of entrainment and erosion thresholds. Earth Surf. Process.
967   Landf. 29, 185–204. https://doi.org/10.1002/esp.1020
968 Vasil'chuk, Yu.K., Rets, E.P., Chizhova, Ju.N., Tokarev, I.V., Frolova, N.L., Budantseva, N.A.,
969   Kireeva, M.B., Loshakova, N.A., 2016. Hydrograph separation of the Dzhankuat River,
970   North Caucasus, with the use of isotope methods. Water Resour. 43, 847–861.
971   https://doi.org/10.1134/S0097807816060087
972 Verdiev, R.G., 2009. Computation and prediction of the flood runoff of the Eastern Caucasus
973   Rivers. Russ. Meteorol. Hydrol. 34, 46–50.
974 Vezzoli, G., Garzanti, E., Limonta, M., Radeff, G., 2020. Focused erosion at the core of the
975   Greater Caucasus: Sediment generation and dispersal from Mt. Elbrus to the Caspian
976   Sea. Earth-Sci. Rev. 200, 102987. https://doi.org/10.1016/j.earscirev.2019.102987
977 Vezzoli, G., Garzanti, E., Vincent, S.J., Ando, S., Carter, A., Resentini, A., 2014. Tracking sediment
978   provenance and erosional evolution of the western Greater Caucasus. Earth Surf.
979   Process. Landf. https://doi.org/10.1002/esp.3567
980 Vincent, S.J., Carter, A., Lavrishchev, A., Rice, S.P., Barabadze, T.G., Hovius, N., 2011. The
981   exhumation of the western Greater Caucasus: a thermochronometric study. Geol. Mag.
982   148, 1–21. https://doi.org/10.1017/S0016756810000257
983 Vincent, S.J., Somin, M.L., Carter, A., Vezzoli, G., Fox, M., Vautravers, B., 2020. Testing Models
984   of Cenozoic Exhumation in the Western Greater Caucasus. Tectonics 39.
985   https://doi.org/10.1029/2018TC005451

986   Whipple, K.X., 2009. The influence of climate on the tectonic evolution of mountain belts. Nat.
987   Geosci. 2, 97–104.

988   Whipple, K.X., DiBiase, R.A., Crosby, B., Johnson, J.P.L., 2022. Bedrock Rivers, in: Shroder, J.
989   (Jack) F. (Ed.), Treatise on Geomorphology (Second Edition). Academic Press, Oxford, pp.
990   865–903. https://doi.org/10.1016/B978-0-12-818234-5.00101-2

991   Whipple, K.X., Meade, B., 2004. Controls on the strength of coupling among climate, erosion,
992   and deformation in two-sided, frictional orogenic wedges at steady state. J. Geophys.
993   Res. 109, F01011–F01011. https://doi.org/10.1029/2003JF000019

994   Willett, S.D., 1999. Orogeny and orography: The effects of erosion on the structure of mountain
995   belts. J. Geophys. Res. 104, 28,928-957,981.

996   Wilson, P.S., Toumi, R., 2005. A fundamental probability distribution for heavy rainfall.
997   Geophys. Res. Lett. 32, n/a-n/a. https://doi.org/10.1029/2005GL022465

998   Wulf, H., Bookhagen, B., Scherler, D., 2016. Differentiating between rain, snow, and glacier
999   contributions to river discharge in the western Himalaya using remote-sensing data and
1000   distributed hydrologic modeling. Adv. Water Resour. 88, 152–169.
1001   https://doi.org/10.1016/j.advwatres.2015.12.004

1002

A — Elevation (km) map with color scale 0 1 2 3 4. ¹⁰Be Basins: □ Northern GC, ○ Southern GC, △ LC. Labels: Black Sea, Caspian Sea, Greater Caucasus, Lesser Caucasus, RB, KFTB, KB. Scale bar 100 km.

B — TRMM 3B42 Mean Rainfall, scales 0 1 2 m/yr and 0 2 4 6 mm/day. Scale bar 100 km.

C — TRMM Mean Daily Rainfall (blue), GC-LC Convergence (red). Left axis: N25°E Velocity [mm/yr] 0 4 8 12 16. Right axis: Rainfall [mm/day] 0 2 4 6. A to A'.

D — Topography. Elevation [km] 0 2 4 6 (both axes).

E — 5km Local Relief. Relief [km] 0 2 4.

X-axis: Distance Along Swath [km] 0 100 200 300 400 500 600 700 800 900 1000 1100.

A. Plot of Mean Runoff [mm/day] versus Mean TRMM Rainfall [mm/day] with fit $y = 0.0023x^{5.07} + 0.6$, RMSE $= 1.47$.

B. Plot of Runoff / Rainfall versus Mean TRMM Rainfall [mm/day] for Gauged Basins and Estimated Ungauged.

A

B

Estimated Runoff [mm/day]

△ Width for Q$_{2yr}$
■ Width for Mean Q

Width [m]

Drainage Area [km^2]

C

Drainage Area [km^2]

Binned k$_{wn}$ [m/m]

Binned k$_{sn}$ [m]

A — Map showing ¹⁰Be Erosion Rate [m/Myr] with color-coded basins over elevation [km] topography. Legend: 3000-5600, 2500-3000, 1000-2500 (red to orange); 500-1000, 400-500, 250-400 (orange to yellow); 150-250, 100-150, 50-100, 25-50 (green to blue).

B — GC-LC N25°E Convergence [mm/yr] plotted against Distance Along Swath [km].

C — ¹⁰Be Erosion Rate [m/Myr] versus Distance From Swath Center [km], colored by Mean Elevation [km] and Averaging Time [kyr]. Symbols: Northern GC (square), LC (triangle), Southern GC (circle). r=-0.45 (p=0.0081). S to N.

D — ¹⁰Be Erosion Rate [m/Myr] versus GC-LC N25°E Convergence [mm/yr], colored by Distance from Swath Center [km]. Dashed lines for 2.5°, 5°, 15°, 25°, 45°. All Basins r=0.48 (p=0.0043); Southern GC r=0.53 (p=0.0029).

Top row panels (A–D):

A — Runoff [mm/day]; Exceedance Frequency
Cluster 1
- - - Mean of Cluster
—— Fit to Composite
— Individual Fits

B — Runoff [mm/day]
Cluster 2
- - - Mean of Cluster
—— Fit to Composite
— Individual Fits

C — Runoff [mm/day]
Cluster 3
- - - Mean of Cluster
—— Fit to Composite
— Individual Fits

D — Runoff [mm/day]
Cluster 4
- - - Mean of Cluster
—— Fit to Composite
— Individual Fits

Bottom row panels:

A — k_{sn} [m] vs Erosion Rate [m/Myr]
$\overline{R}$: 5.27 mm/day
c: 0.75
Q_0: 0.70
k_e Interquartile Range

B —
$\overline{R}$: 0.98 mm/day
c: 0.52
Q_0: 0.49
k_e Interquartile Range

C —
$\overline{R}$: 1.58 mm/day
c: 1.22
Q_0: 1.16
k_e Interquartile Range

D —
$\overline{R}$: 5.1 mm/day
c: 1.2
Q_0: 0.99
k_e Interquartile Range