

Quantifying geomorphically effective floods using satellite observations of river mobility

Anya S Leenman¹, Louise J. Slater¹, Simon J Dadson¹, Michel Wortmann¹, and Richard Boothroyd²

¹University of Oxford

²University of Glasgow

April 20, 2023

Abstract

Geomorphologists have long debated the relative importance of disturbance magnitude, duration and frequency in shaping landscapes. For river-channel adjustment during floods, some argue that cumulative flood ‘power’, rather than magnitude or duration, matters most. However, studies of flood-induced river-channel change often draw upon small datasets. Here, we combine Sentinel-2 imagery with flow data from laterally-active rivers to address this question using a larger dataset. We apply automated algorithms in Google Earth Engine to map rivers and detect their lateral shifting; we generate a large dataset to quantify channel change during 160 floods across New Zealand, Russia, and South America. Widening during these floods is best explained by their duration and cumulative hydrograph. We use a random forest regression model to predict flood-induced channel widening, with potential applications for hazard management. Ultimately, better global data on sediment supply and caliber would help us to understand flood-driven change to river planforms.

1 **Quantifying geomorphically effective floods using**
2 **satellite observations of river mobility**

3 **A. S. Leenman¹, L. J. Slater¹, S. J. Dadson^{1,2}, M. Wortmann^{1,3} and R.**
4 **Boothroyd⁴**

5 ¹School of Geography and the Environment, University of Oxford

6 ²UK Centre for Ecology and Hydrology

7 ³European Centre for Medium-Range Weather Forecasts

8 ⁴School of Geographical and Earth Sciences, University of Glasgow

9 **Key Points:**

- 10 • We develop a method to quantify river planform change during flood events, us-
11 ing Google Earth Engine
- 12 • We do so for a dataset of 160 floods that exceeded the 80th percentile stage, at
13 41 flow gauging sites on laterally active rivers
- 14 • Erosion during these high-flow events was most correlated with the event dura-
15 tion and summed hydrograph

Corresponding author: Anya Leenman, anya.leenman@chch.ox.ac.uk

Abstract

Geomorphologists have long debated the relative importance of disturbance magnitude, duration and frequency in shaping landscapes. For river-channel adjustment during floods, some argue that cumulative flood ‘power’, rather than magnitude or duration, matters most. However, studies of flood-induced river-channel change often draw upon small datasets. Here, we combine Sentinel-2 imagery with flow data from laterally-active rivers to address this question using a larger dataset. We apply automated algorithms in Google Earth Engine to map rivers and detect their lateral shifting; we generate a large dataset to quantify channel change during 160 floods across New Zealand, Russia, and South America. Widening during these floods is best explained by their duration and cumulative hydrograph. We use a random forest regression model to predict flood-induced channel widening, with potential applications for hazard management. Ultimately, better global data on sediment supply and caliber would help us to understand flood-driven change to river planforms.

Plain Language Summary

Some rivers change their shape over time. In this paper, we explore how high-flow events drive these river channels to reshape themselves. We use Google Earth Engine to automatically map the shapes of rivers in satellite images. We apply this method to pairs of satellite images before and after high-flow events, to understand how the river shape is changed by the event. We compare the amount of channel-widening measured to aspects of the high-flow event, including its peak, duration and total flow. We do so for 160 high-flow events, and find that the duration and total flow are most important for explaining how much a channel widens during the event. Finally, we build a statistical model to predict the average amount of channel widening for a given high-flow event. This method has potential applications for hazard management in rivers that are known to change their shape.

1 Introduction

The relative importance of disturbance magnitude, duration and frequency for shaping landscapes is a crucial question in geomorphology. Many studies have considered the effects of high-magnitude versus high-frequency events: for cumulative sediment transport (Wolman & Miller, 1960; Webb & Walling, 1982), for generating and reworking landforms (Wolman & Gerson, 1978; Kale, 2002, 2003; Surian et al., 2015), and for the resulting sedimentology (Magilligan et al., 1998; Marren, 2005). Others have considered the duration and total energy expenditure of individual disturbances and how this relates to their ability to transport sediment and reshape river channels (Costa & O’Connor, 1995; Magilligan et al., 2015). In rivers, understanding which disturbances perform the most geomorphic work — both instantaneously, and cumulatively over time — has important implications for sediment budgeting, flood conveyance, depositional records, and natural hazard management.

In rivers, the major disturbances are flood events, which have the power to reshape the channels that convey them. Such reshaping ranges from bar deposition and bank erosion (Bryndal et al., 2017) or aggradation (Morche et al., 2007; Hooke, 2016) through to widening (Fuller, 2008; Yousefi et al., 2018), reoccupation of abandoned channels (Arnaud-Fassetta et al., 2005) and large-scale reworking of floodplains (Miller, 1990). The latter can have severe impacts for society, including erosion of agricultural or residential land (Yousefi et al., 2018) or the destruction of transport and river management infrastructure (Arnaud-Fassetta et al., 2005). Conversely, aggradation during floods can raise riverbeds by several meters (Morche et al., 2007; Tunnicliffe et al., 2018), reducing a channel’s conveyance capacity and the freeboard below bridges (Johnson et al., 2001). Quantitative

65 methods are needed to understand, model, and predict how river channels can be reshaped
66 by individual flood events.

67 The geomorphic effectiveness of a flood is thought to be a function of its duration
68 and magnitude. Here, we define geomorphic effectiveness as the extent to which a flood
69 alters the channel form by eroding or depositing sediment. We use the term 'flood' to
70 mean any temporary rise in the water level (in our analysis, one that exceeds the 80th
71 percentile of the water surface elevation measurements). Previous studies have suggested
72 that the cumulative stream power (defined by Bagnold (1966) as the product of water
73 density, acceleration due to gravity, discharge and slope) beneath a flood hydrograph must
74 be high for the event to be geomorphically effective; the implication is that high-magnitude
75 but brief floods, and low-magnitude but long floods, are not likely to be effective (Costa
76 & O'Connor, 1995). However, others have suggested that additional factors (not just the
77 cumulative power) make a flood geomorphically effective. For instance, Middleton et al.
78 (2019) demonstrated that flood magnitude does influence geomorphic effectiveness: in
79 the proglacial braided river they studied, planform change during floods increased with
80 their peak discharges. Others propose that a flood's geomorphic effectiveness is not deter-
81 mined by the hydrograph alone, but also by the sediment supply (Church, 2014; Hooke,
82 2016; Bennett et al., 2017; Pfeiffer et al., 2019) or the time since the previous flood, which
83 can influence both sediment availability and the looseness of the riverbed (Gintz et al.,
84 1996; Hooke, 2015). These studies have advanced our understanding of geomorphic ef-
85 fectiveness, but almost all were small-sample case studies of 1-10 flood events or river
86 reaches, often in similar regional or climatic contexts. Larger samples of flood events from
87 a more geomorphically and geographically diverse set of rivers are required to produce
88 a robust empirical assessment of what makes a geomorphically effective flood.

89 Google Earth Engine (GEE) has recently emerged as a key tool facilitating large-
90 sample analyses of landscape characteristics — through both its computational platform
91 and archive of quality controlled satellite data. The 'large-sample' approach, which ad-
92 dresses environmental questions using data from tens to thousands of sites, is popular
93 in hydrology (Addor et al., 2017; Klingler et al., 2021) and has begun to be applied in
94 geomorphology (Slater et al., 2015; Slater, 2016; Pfeiffer et al., 2019; Sylvester et al., 2019;
95 Valenza et al., 2020; Ahrendt et al., 2022; Brooke et al., 2022; Clubb et al., 2022; Ed-
96 monds et al., 2022). A large-sample approach to studying planimetric river adjustments
97 can be readily deployed in GEE, drawing on automated methods to map river planform
98 (Allen & Pavelsky, 2015; Pekel et al., 2016; Zou et al., 2018; Isikdogan et al., 2019; Pick-
99 ens et al., 2020; Boothroyd et al., 2021) and to track planform deformation (Wickert et
100 al., 2013; Rowland et al., 2016; Schwenk et al., 2017; Jarriel et al., 2021; Chadwick et
101 al., 2022; Langhorst & Pavelsky, 2022). By automating river planform tracking in GEE,
102 the geomorphic effectiveness of a large sample of flood events can be assessed.

103 In this paper, we investigate the streamflow drivers of geomorphically effective floods
104 using Sentinel-2 satellite imagery in GEE. We pursue two research questions:

- 105 1. Which hydrograph metrics best explain a flood's 2D geomorphic effectiveness?
- 106 2. How well can a flood's 2D geomorphic effectiveness be predicted from hydrologic
107 and environmental variables?

108 We measure geomorphic effectiveness as the reach-averaged channel widening during a
109 flood. We compute this planimetric erosion in GEE for flood events in Brazil, Colom-
110 bia, New Zealand and Russia. We use 160 flood events at 41 flow gauging sites on lat-
111 erally active rivers to evaluate our research questions (see Figure S1, Supplementary Ma-
112 terial (SM), for gauge locations). We ascertain the influence of hydrograph shape on ge-
113 omorphic effectiveness in our dataset. Finally, we develop an empirical model to predict
114 flood-induced erosion. When coupled with streamflow forecasts, the model may be use-
115 ful for hazard management in sites that are known to be laterally active.

116 **2 Methods**

117 Our method can be summarized as follows. First, we identified sites with historical
 118 daily stage (water level) measurements and a laterally active channel. For those rivers,
 119 we identified peaks in the stage records. Second, for each flood peak we extracted the
 120 pre- and post-flood channel planform from Sentinel-2 data in GEE, and conducted a change
 121 detection between the two planforms to quantify erosion during the flood hydrograph. Ultimately,
 122 we compared the lateral erosion detected to parameters of the flood hydrograph. Figure 1
 123 illustrates these steps with an example of one flood in Colombia. Our code is available
 124 at <https://github.com/a-leenman/2dFloodsPublic>; GEE processing was per-
 125 formed via the ‘rgee’ r package (Aybar, 2022).

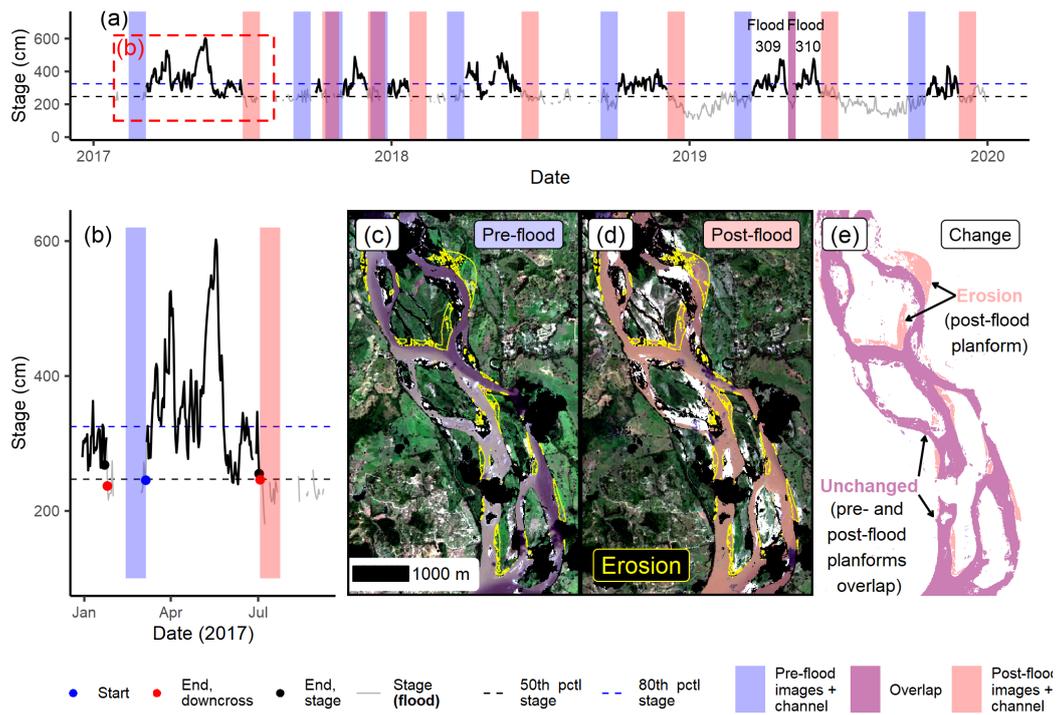


Figure 1. Methods used to define floods and detect planform change. (a) The pre-flood (blue) and post-flood (red) search windows for a sequence of floods (bold lines), showing how the windows can overlap (purple). (b) Example flood from Colombian gauge 23097040, with the flood start date (blue circle), two options for flood end date (black and red circles; the ‘downcross’ (red circle) method was most appropriate) and the pre- and post-flood search windows. (c) Pre-flood channel morphology, mosaicked from all cloud-free pixels in the six satellite images covering part of the AOI within the pre-flood search window. Erosion during the following flood is outlined in yellow. Black patches have no data due to cloud. (d) Corresponding post-flood mosaic (10 source images within the time and space filter). (e) The pre- and post-flood channel planforms are overlaid, highlighting the erosion (red) detected.

126 **2.1 Site selection and area of interest**

127 Hydrologic records are crucial to our analysis, providing flood occurrence and hydro-
 128 graph shape data. We obtained publicly available stage records and gauging locations

129 for Brazil, Colombia, New Zealand and Russia. These countries were chosen for their lat-
 130 laterally active rivers and availability of recent daily stage records.

131 Other authors used discharge or stream power records to pursue this problem. How-
 132 ever, we chose to use stage data so that differences in stage could provide a proxy for
 133 depth fluctuations when estimating the time series of shear stress. Ultimately, we aimed
 134 to approximate the sediment transport capacity of each hydrograph.

135 We filtered the stage records to include only those gauges that:

- 136 1. Were located on a river with a mean annual discharge above $100 \text{ cm}^3 \text{ s}^{-1}$ (data from
 137 Grill et al. (2019)), to ensure these rivers were large enough to be visible in our
 138 10 m satellite imagery.
- 139 2. Were located on a laterally active river whose dynamics could be measured from
 140 satellite data. Laterally active rivers were identified by filtering the ‘water per-
 141 manence’ layer from Pekel et al. (2016). After computing planform change dur-
 142 ing floods, a site was removed if the eroded area never exceeded 1% of the water
 143 surface area or if the flood-induced widening never exceeded 3 m. These thresh-
 144 olds enabled the largest possible dataset while excluding channels that were not
 145 laterally active.
- 146 3. Were not adjacent to large lakes or dams.
- 147 4. Overlapped with the Sentinel-2 record (June 2015 - present) by at least one year.

148 This filtering isolated a sample of 41 gauges. River widths ranged from 60 to 1000
 149 m; their gradients ranged from 0.00001 to 0.002. Their mean long-term discharge ranged
 150 from 100 to $7000 \text{ cm}^3 \text{ s}^{-1}$, and upstream catchment area ranged from 3800 to 430000 km^2 .
 151 Values of the Richards-Baker index (Baker et al., 2004) ranged from 0.005 (very seasonal)
 152 to 0.33 (moderately flashy). Gauge altitudes ranged from 3 to 500 m. Forest cover at
 153 the gauges ranged from 0 to 100%, and mean annual rainfall from 440 to 4100 mm. The
 154 range of rivers (including braided, wandering and meandering forms) encompassed by
 155 these values highlights the geographic and geomorphic diversity of the rivers we incor-
 156 porate.

157 For each gauge, we defined an ‘Area of Interest’ (AOI) in which we extract the river
 158 planform and monitor its deformation. The ‘HydroSHEDS Free Flowing Rivers’ vector
 159 network (Lehner et al., 2008; Grill et al., 2019) was used to select all river segments within
 160 40 km of each gauge. We kept only the segments on the same branch as the gauge, and
 161 also removed segments that were past a jump in average discharge of $>20\%$, implying
 162 that a ‘major’ tributary had been passed; we computed such jumps using the average
 163 discharge data for each segment in Grill et al. (2019). If two gauges were nearby on the
 164 same river, we divided the intervening segments between them. This left a remaining ‘linked
 165 reach’ (comprising one or more HydroSHEDS segments) assigned to each gauge. We ex-
 166 tracted water masks along each reach from Allen and Pavelsky (2018a, 2018b), as a first
 167 approximation of the channel area. However, these masks do not always encompass the
 168 entire channel in our study reaches (which are extremely laterally mobile: some shift by
 169 more than 30 m in a single flood) and so we buffered these masks by 500 m to create the
 170 AOI. Finally, lakes in the HydroLAKES (Messenger et al., 2016) dataset were subtracted
 171 from the AOI, to avoid spurious change detection from varying lake levels. We thus as-
 172 signed to each gauge a unique AOI within which we extracted the river planform before
 173 and after each flood.

174 2.2 Flood delineation and search window definition

175 We delineated floods temporally based on the daily stage record for each gauge.
 176 Although higher frequency records were available for some countries, we resampled them
 177 by taking the daily mean stage. While this process smoothed some maxima and min-

178 ima, it gave all records the same frequency. We defined a flood as any period exceeding
 179 the 80th percentile of the stage record during the Sentinel-2 record (June 2015 onwards;
 180 Figure 1a, b). Floods were extracted from the daily stage records using the hydroEvents
 181 R package (Wasko & Guo, 2022). To ensure we captured the rising and falling limbs, we
 182 defined the flood start date as the first measurement before the peak which was also be-
 183 low the 50th percentile of stage (Figure 1a, blue points). We defined the flood end date
 184 in two ways: either as

- 185 1. the first measurement following the peak which also fell below the 50th percentile
 186 of stage (Figure 1a, red points), or
- 187 2. the first measurement following the peak which was within 30 cm of the stage at
 188 the start of the flood (Figure 1a, black points). Occasionally, missing data meant
 189 that the first method created flood end dates that were unreasonably far after the
 190 end of the flood, necessitating the second method.

191 For each flood, we chose the flood end date with the stage measurement that was clos-
 192 est to the stage on the start date. Following the discussion in Slater et al. (2021), floods
 193 separated by less than seven days were counted as one event, and floods lasting more than
 194 5 months were discounted as these were mostly anomalies from missing data. While this
 195 approach of using the 50th percentile to give the start and end dates assigns a longer length
 196 to floods than some standard approaches, it allows us to capture the geomorphic effects
 197 of the rising and falling limbs, and recognizes that geomorphic change and sediment en-
 198 trainment likely start before the 80th percentile stage is exceeded.

199 Directly before and after each flood, we defined pre- and post-flood time windows
 200 of up to three weeks (Figure 1a, b). We truncated a time window if floods were less than
 201 three weeks apart; for example, flood 309 (Figure 1a) finished nine days before the fol-
 202 lowing event, and so its post-flood window was truncated. If sequential events were less
 203 than six weeks apart, their pre- and post-flood windows were allowed to overlap; the post-
 204 flood window for one flood could even overlap entirely with the pre-flood window of the
 205 following event, as with floods 309 and 310 (Figure 1a; this would mean that the post-
 206 flood channel mask of flood 309 was reused as the pre-flood mask of flood 310). We used
 207 these pre- and post-flood time windows to search the Sentinel-2 archive (Level 1C, har-
 208 monized).

209 **2.3 Planform extraction and change detection**

210 Within each pre- and post-flood time window, we extracted the river planform from
 211 Sentinel-2 (S2) imagery. First, we mosaicked all cloud-free S2 pixels within the time win-
 212 dow and AOI, taking the minimum reflectance in each band if multiple copies of one pixel
 213 were available. Figure 1c and d are examples of these mosaics. We proceeded with an
 214 event if at least 50% of its AOI was cloud-free; only pixels that were cloud-free in both
 215 mosaics were used. For sites in New Zealand and Russia, we also mapped snow using the
 216 normalized difference snow index, following Hofmeister et al. (2022). For snow-free scenes
 217 that met our cloud threshold, we mapped channel planform from a combination of spec-
 218 tral indices, following Zou et al. (2018) and Boothroyd et al. (2021); these were the nor-
 219 malized difference vegetation index (Rousel et al., 1973), modified normalized difference
 220 water index (Xu, 2006), and enhanced vegetation index (Huete et al., 2002). Following
 221 Boothroyd et al. (2021), we counted both water and exposed sediment (i.e. non-vegetated
 222 bars) as part of the channel, given that a lack of vegetation indicates bars are frequently
 223 inundated. While this mapping method is simple, it is generalizable to rivers with dif-
 224 ferent lighting conditions and suspended sediment concentrations.

225 We conducted change detection between the pre- and post-flood planforms to es-
 226 timate each flood's geomorphic impact. To isolate areas that were permanently (as op-
 227 posed to transiently) changed during a flood, we tracked the state (wet or dry) of each

228 pixel at monthly intervals for the following 24 months, loosely following the pixel-by-pixel
 229 trend analysis of Nagel et al. (2022). We only considered a pixel to be eroded if it switched
 230 from dry-to-wet in the flood and then continued to be wet for the subsequent two years.
 231 If cloud cover meant there were <18 months of these after-flood observations for an event,
 232 we discounted it; we chose this threshold by checking the change detection for bias due
 233 to stage fluctuations. This pixel-tracking method allowed us to eliminate spurious change
 234 detection resulting from transient stage fluctuations.

235 We measured a flood’s geomorphic effectiveness as the area that was permanently
 236 eroded (i.e. changed from ‘dry’ to ‘wet’) during the event. We normalized this eroded
 237 area by the reach length to give the reach-averaged channel widening. Because we counted
 238 non-vegetated bars as part of the channel, it was difficult to measure deposition follow-
 239 ing the flood; newly deposited sediment was typically registered as ‘channel’ by our map-
 240 ping algorithm. This is why we consider post-flood erosion to be the most appropriate
 241 metric of geomorphic change in our data.

242 Our procedures for gauge selection, cloud- and snow-filtering isolated a dataset of
 243 160 events for which we measured geomorphic effectiveness. Because there were less than
 244 11 floods in some countries, we pooled all floods for our subsequent analyses.

245 2.4 Regression and prediction

246 Our first research question considers the influence of hydrograph shape on geomor-
 247 phic effectiveness. There are numerous metrics to characterize hydrographs, including
 248 measures of height, duration, integrated power, volume or transport capacity, and asym-
 249 metry (Brunner et al., 2021; Slater et al., 2021). Because these rivers feature a range of
 250 hydrographs (for instance, flashy versus seasonal), we use three simple metrics that al-
 251 low comparison with previous studies. The first is the flood peak height, relative to the
 252 mean daily stage. The second is the cumulative value of all daily stage measurements
 253 during the flood, measured relative to mean daily stage. This cumulative water level met-
 254 ric is akin to the ‘volume’ of a hydrograph when using discharge records (e.g. Brunner
 255 et al. (2021), Figure 3). Because we use stage records, the metric accounts for the com-
 256 bined influence of changes in flow depth during the flood (exerting stress on the river banks/bed)
 257 and of flood duration; we refer to it as the ‘summed hydrograph’. The third metric is
 258 the flood duration.

259 As well as exploring how hydrograph metrics correlated with erosion, we built a
 260 random forest regression model to rank the predictors’ importance (by estimating how
 261 much they decreased the model’s mean square error, MSE). In addition to these hydro-
 262 graph metrics, we incorporated the pre-flood channel width, as channel size can positively
 263 influence channel mobility (Constantine et al., 2014; Nanson & Hickin, 1986; Langhorst
 264 & Pavelsky, 2022). Although sediment supply also increases channel mobility (e.g. Constantine
 265 et al. (2014); Ahmed et al. (2019); Donovan et al. (2021)), we do not have sediment sup-
 266 ply time-series for our gauging sites. Instead, we used stream gradients and stage records
 267 to estimate the sediment transport capacity for each flood (see Section S1, SM for de-
 268 tails), and added these estimates to the random forest model. We built the model us-
 269 ing the randomForest r package (Liaw & Wiener, 2002) with 500 trees and two variables
 270 randomly sampled at each split. We used the model to predict each flood’s reach-averaged
 271 erosion using leave-one-out cross-validation (LOOCV).

272 3 Results

273 In the laterally active rivers we study, floods and their geomorphic impacts vary
 274 by orders of magnitude. Peak heights vary from 30 to 700 cm above mean daily stage.
 275 The summed hydrographs vary from 40 to 30000 cm above mean daily stage, and flood
 276 durations from 1 to 152 days. The geomorphic effects of these floods are diverse, with

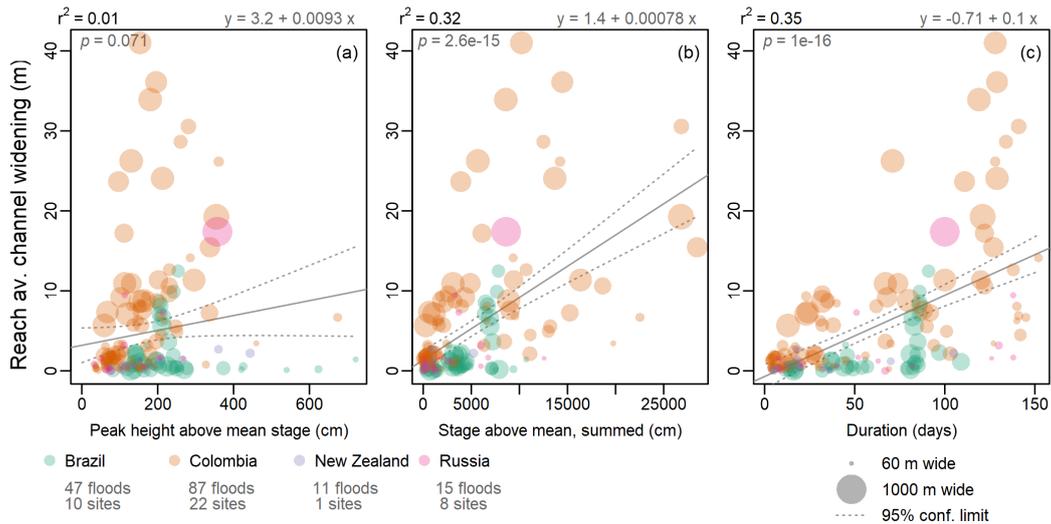


Figure 2. Flood metrics and their relationship to reach-averaged channel widening (i.e. plan-view erosion normalized by reach length) during each flood. (a) Flood peak height above the mean daily stage. (b) Cumulative stage exceeding mean daily stage (‘summed hydrograph’). (c) Flood duration. Each point represents one event; colors indicate the four countries; point size is proportional to pre-flood channel width. The solid gray line shows a linear regression and dotted lines show 95% confidence limits; the regression equation is at the top-right. r^2 and p -values are at the top left. r^2 values for individual countries are in Table S1, SM.

277 reach-averaged widening as low as 0.005 m and as high as 41 m. The least geomorphi-
 278 cally active country is New Zealand, with an average flood-induced widening of 0.9 m,
 279 while the most active is Colombia, with an average widening of 7 m across all floods.

280 Our first research question considers the erosional response of river channels to flood
 281 hydrographs. Figure 2 demonstrates how reach-averaged erosion varies with three hy-
 282 drograph metrics in the 160 floods we study. Each point represents one event, with the
 283 reach-averaged erosion compared to the flood’s peak height (a), summed hydrograph (b),
 284 and flood duration (c). Figure 2 therefore shows how hydrograph metrics influence ge-
 285 omorphic effectiveness for 160 floods at 41 sites across Brazil, Colombia, New Zealand
 286 and Russia between 2015 and 2021.

287 Our results indicate that reach-averaged channel widening is only weakly related
 288 to flood height in our dataset (Figure 2a). A linear regression of reach-averaged erosion
 289 during each flood against the peak height had an r^2 of just 0.01. Erosion scaled more
 290 strongly with the summed hydrograph (Figure 2b), with an r^2 of 0.32, and most strongly
 291 with flood duration (Figure 2c), with an r^2 of 0.35. See Table S1 (SM) for country-specific
 292 relationships. These coefficients of determination are surprisingly high, considering that
 293 they represent observations from real systems and are thus confounded by other natu-
 294 ral variables in each location. Some of the relationships in Figure 2 appear non-linear
 295 (especially panel (c)), but we lack sufficient data to fit non-linear models and so we use
 296 linear regression to make a first-order comparison. These metrics are correlated among
 297 themselves (see Figure S2, SM); longer floods often had higher peaks, so that the r^2 val-
 298 ues shown here indicate *relative* importance and we cannot say that the increase in ero-
 299 sion with flood duration was independent of the concurrent increase in height for many
 300 floods. Nevertheless, panels a-c indicate that, at least for our sample of laterally active

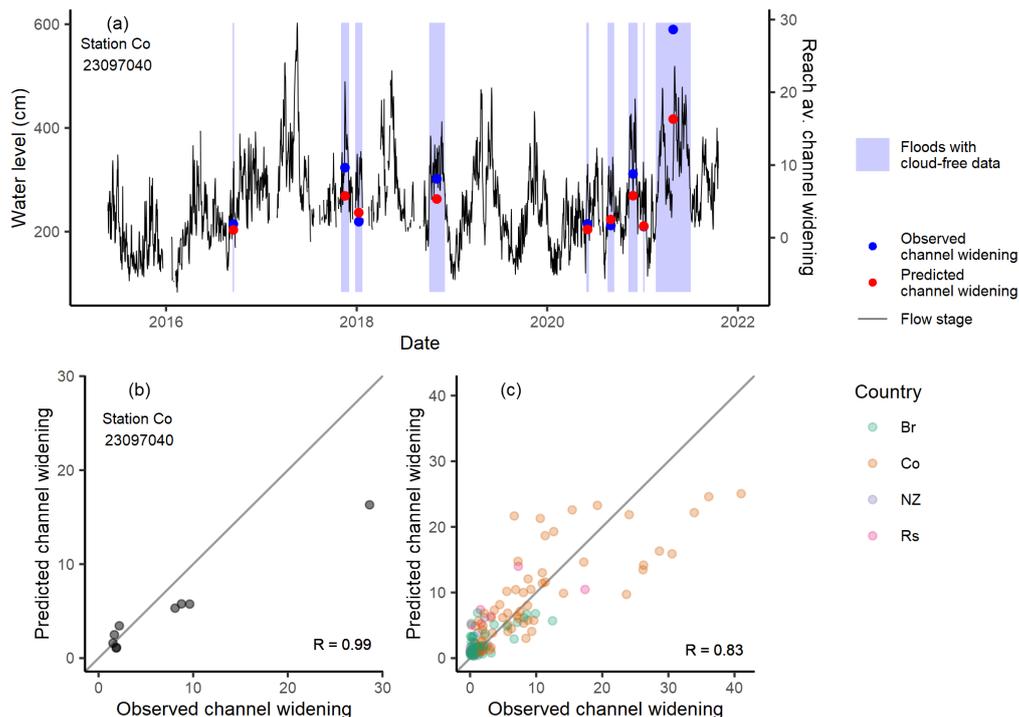


Figure 3. Predictions from our random forest regression model. (a) The stage record for Colombian gauge 23097040; flood events with sufficient cloud-free satellite data are highlighted. The observed and predicted reach-averaged erosion (channel widening) during each flood are overlain and scale with the secondary y-axis. (b) A comparison of observed and predicted channel-widening at this gauge; each point is one flood. (c) A comparison of observed and predicted channel-widening for all floods in our dataset. Grey lines in (b) and (c) show a 1:1 relation.

301 rivers, flood duration was the most important variable for explaining flood-driven erosion of the vegetated channel boundary.
302

303 We built a random forest regression model to rank the importance of the hydro-
304 graph metrics, channel width, and estimated sediment transport for explaining flood ero-
305 sion. The random forest model ranked these variables in the following order: estimated
306 transport, channel width, flood duration, summed hydrograph and peak height; the rank-
307 ings reflect how much each variable reduced the model’s MSE. This ranking is similar
308 to the r^2 values in Figure 2 and Figures S3-S4 (SM). Because the summed hydrograph
309 and flood duration were correlated ($R = 0.79$), we ran two additional model versions,
310 omitting either summed hydrograph or flood duration. Although these omissions altered
311 the variables’ MSE reductions, neither altered the remaining variable rankings, imply-
312 ing that the rankings are not affected by this co-linearity in the predictors.

313 We predicted erosion for all floods in our dataset using the random forest model
314 with LOOCV. We were able to predict erosion with at least 60% accuracy ($R = 0.83$;
315 Figure 3c) using the pooled dataset. The model performed best for sites in Colombia with
316 numerous floods, such as site 23097040 (Figure 3a,b). For Colombian sites with data for
317 > 7 floods, R values were 0.78–0.99. The model tended to under-predict the highest val-
318 ues of reach-averaged erosion.

4 Discussion

Although there is no firm consensus, previous literature has laid the case for a hydrograph's cumulative power as the best explainer of a flood's geomorphic effectiveness. For instance, based on 10 events in Arkansas, California, Colorado, Idaho, Oregon and Washington, Costa and O'Connor (1995) suggested that a flood's geomorphic effectiveness reflected the cumulative unit stream power exceeding the threshold for alluvial erosion. Rose et al. (2020) likewise found that the most geomorphically effective floods in a sample of seven had a high energy expenditure, high peak and long duration. Kale and Hire (2007) observed that sediment transport (a proxy for geomorphic effectiveness) during monsoons rose exponentially with their cumulative stream power. Magilligan et al. (2015) attributed the limited widening during an extreme flood to its low cumulative power, resulting from a high peak but short duration. Our data partly support this hypothesis; the summed hydrograph was positively correlated with erosion during the floods we studied. However, in our dataset flood duration was a slightly better predictor of erosion of the vegetated channel boundary. This result was consistent when we raised the flood definition threshold to the 90th percentile of stage, and the summed hydrograph and flood duration had equal effects when we lowered the threshold to the 70th percentile (Figures S5 and S6, SM).

One reason for the weaker influence of the summed hydrograph in our data may be that these previous studies used the unit stream power hydrograph, whereas we used the stage hydrograph. We used stage so that changes could be used as a proxy for depth fluctuations when estimating shear stress and each hydrograph's sediment transport capacity. Although the unit transport capacity was a weaker predictor than the summed hydrograph or duration, transport became a stronger predictor when multiplied by channel width (see section S1 and Figure S3 (SM) for more detail).

The importance of flood duration in our dataset implies that, once these floods exceed the entrainment threshold, further stage increases have a smaller effect than the duration above the threshold. That is, shear stress exposure duration has a greater effect than the peak stress. This result suggests that the threshold for entrainment was low in the rivers we studied, so that full mobility of all sediment sizes was attained frequently. The regional breakdown of Figure 2 (Table S1, SM) supports this notion, as the influence of duration is strongest for Colombia where some studies have reported sand beds (e.g. Smith (1986); Martínez Silva and Nanny (2020)).

Other studies have used flood peak height, rather than cumulative power, to explain geomorphic effectiveness. For instance, Middleton et al. (2019) mapped planimetric change during floods in a proglacial river and showed that, once an annually-reset threshold discharge had been exceeded, planimetric change increased with peak discharge. Miller (1990) found that, in alluvial rivers wider than 200 m, peak unit stream power during floods was correlated with geomorphic effectiveness. In alluvial fan experiments featuring different hydrographs of the same volume, surface reworking increased with the peak discharge (Leenman et al., 2022). Nevertheless, in our dataset flood height was only weakly related to geomorphic change. It is possible that a threshold above which peak height becomes important can only be extracted by analyzing numerous floods at one location. Such an analysis is difficult in the remote sensing of real rivers, either due to seasonal floods or to persistent cloud cover, both of which limit the number of events that can be assessed.

Our results, and particularly the importance of flood duration, highlight some complexities of investigating flood impacts with a large-sample remote-sensing analysis. First, while we measured the flood-induced erosion of the vegetated channel boundaries, others simply categorized flood-driven change (e.g. (Costa & O'Connor, 1995)) or quantified sedimentological impacts (Magilligan et al., 2015). The importance of duration here is relevant to vegetated channel boundaries, but results may differ if measuring a differ-

371 ent aspect of channel morphology — for instance, Magilligan et al. (2015) highlight how
372 a flood event can have large sedimentological effects but a smaller impact on channel shape.
373 Second, our large-sample analysis highlights the difficulty of finding a single parameter
374 explaining flood effectiveness in all rivers. Flood duration was the most important driver
375 of erosion in some rivers in our dataset, but not all; Table S1 shows that peak height was
376 more important in Russia. Third, the relationship between a flood hydrograph and the
377 erosion caused can be compounded by other variables, including the presence and char-
378 acter of vegetation, the caliber and structure of bed and bank sediment, the sediment
379 supplied from upstream, and the time elapsed since the previous flood. In this paper,
380 we make a first attempt at a large-sample analysis of geomorphically effective floods, and
381 our work highlights the need for global datasets on these additional variables in order
382 to fully address this problem.

383 Others have suggested that the causal relationship between a flood and its geomor-
384 phic effectiveness is moderated by sediment supply. For instance, in comparing two events
385 on the Peace River (Canada), Church (2014, Chapter 10) found that their geomorphic
386 effects were best explained by differences in the sediment influx. Pfeiffer et al. (2019) found
387 that bed-level changes in Washington State were not related to high-flow events, but to
388 sediment supply from glaciers upstream. Dean and Schmidt (2013) observed that geo-
389 morphic change during a flood in the Rio Grande was highest downstream of sediment-
390 rich tributaries. For longer-term channel mobility, sediment supply positively influences
391 channel migration (Constantine et al., 2014), and some rivers in our dataset (e.g. the
392 Magdalena) have very high sediment loads (Restrepo et al., 2006; Higgins et al., 2016;
393 Dethier et al., 2022). This question is an interesting and important one, and further work
394 to measure sediment transport alongside flow during floods is crucial for understanding
395 how sediment availability modulates a hydrograph’s geomorphic effectiveness.

396 Our methods have some limitations which provide avenues for further research. The
397 first is the suitability of using planform measurements to quantify three-dimensional chan-
398 nel adjustment. For landslides, erosional area scales with volume (Guzzetti et al., 2009;
399 Larsen et al., 2010), but in rivers a 2D for 3D substitution would not be appropriate where
400 channels are laterally confined. We have side-stepped this problem by using only later-
401 ally mobile rivers, which are therefore the rivers where a 2D for 3D substitution is most
402 appropriate. Middleton et al. (2019) demonstrated experimentally that sediment trans-
403 port scaled linearly with planimetric change, providing further justification for 2D change
404 detection. However, further work on the suitability of measuring geomorphic change in
405 planview would be valuable.

406 Further potential limitations include that of data resolution; the Sentinel-2 imagery
407 we use has a 10 m resolution. Because erosion may occupy a smaller footprint than de-
408 position of the same volume (Lindsay & Ashmore, 2002), finer-scale imagery may bet-
409 ter capture erosion and would facilitate equal monitoring of both processes. An inves-
410 tigation of improvements with higher-resolution imagery would be worthwhile. In ad-
411 dition, our method computes change in the vegetated channel boundaries, so that non-
412 vegetated bars moving through these rivers are not counted. Work comparing different
413 algorithms to quantify river dynamics would be a useful contribution. Finally, similar-
414 ity between the spectral signatures of snow and water in the mNDWI (Huang et al., 2018)
415 meant we had to discard snowy scenes. We thus compromised slightly on our goal of a
416 geomorphically diverse set of rivers. As the S2 record approaches a decade, the main lim-
417 itation on this work is the availability of flow records, which constrains the range of sites
418 that can be used. Methods to measure or model flow in ungauged basins could extend
419 this work to an even more geographically diverse range of rivers.

420 **5 Conclusions**

421 We used Google Earth Engine and the Sentinel-2 satellite archive to map planform
422 geomorphic change in laterally-mobile rivers during 160 flood events. By tracking each
423 pixel for two years, we were able to separate permanent planform change from transient
424 water extent fluctuations arising from stage variability. We measured each flood's geo-
425 morphic effectiveness as the reach-averaged erosion during the flood, and compared this
426 to the flood hydrograph.

427 In the 41 laterally active rivers studied, we found that the flood peak height was
428 only weakly correlated with erosion. The summed hydrograph was a better predictor,
429 but erosion was most closely correlated with flood duration in our dataset of events ex-
430 ceeding the 80th percentile of stage.

431 We built a random forest regression model to predict geomorphic change for each
432 flood, using hydrograph metrics, estimated sediment transport and channel size. The model
433 had a prediction accuracy above 60%, which is promising for the predictability of river-
434 bank erosion in mobile reaches.

435 Our work highlights the need for high-frequency flow monitoring in the world's lat-
436 erally active rivers, to better understand how a flood's hydrograph controls its erosional
437 impact. Moreover, better data on land cover, bank strength, and sediment caliber at stream
438 gauging sites would elucidate how these characteristics modulate flood-driven erosion.
439 Finally, monitoring sediment transport alongside river flows would help us to understand
440 how sediment availability influences a flood's geomorphic effectiveness.

References

- 441 Addor, N., Newman, A. J., Mizukami, N., & Clark, M. P. (2017). The CAMELS
442 data set: catchment attributes and meteorology for large-sample studies. *Hy-*
443 *drology and Earth System Sciences*, *21*(10), 5293–5313.
- 444 Ahmed, J., Constantine, J. A., & Dunne, T. (2019). The role of sediment supply in
445 the adjustment of channel sinuosity across the Amazon Basin. *Geology*, *47*(9),
446 807–810.
- 447 Ahrendt, S., Horner-Devine, A. R., Collins, B. D., Morgan, J. A., & Istanbuluoglu,
448 E. (2022). Channel Conveyance Variability can Influence Flood Risk as Much
449 as Streamflow Variability in Western Washington State. *Water Resources*
450 *Research*, *58*(6), e2021WR031890.
- 451 Allen, G. H., & Pavelsky, T. M. (2015). Patterns of river width and surface area re-
452 vealed by the satellite-derived North American River Width data set. *Geophys-*
453 *ical Research Letters*, *42*(2), 395–402.
- 454 Allen, G. H., & Pavelsky, T. M. (2018a). Global extent of rivers and streams. *Sci-*
455 *ence*, *361*(6402), 585–588.
- 456 Allen, G. H., & Pavelsky, T. M. (2018b). *Global River Widths from Landsat*
457 *(GRWL) Database*. Zenodo. Retrieved from [https://gee-community-](https://gee-community-catalog.org/projects/grwl/)
458 [catalog.org/projects/grwl/](https://gee-community-catalog.org/projects/grwl/) (Accessed through Google Earth Engine)
459 doi: 10.5281/ZENODO.1297434
- 460 Arnaud-Fassetta, G., Cossart, E., & Fort, M. (2005). Hydro-geomorphic hazards and
461 impact of man-made structures during the catastrophic flood of June 2000 in
462 the Upper Guil catchment (Queyras, Southern French Alps). *Geomorphology*,
463 *66*(1-4), 41–67.
- 464 Aybar, C. (2022). rgee: R Bindings for Calling the 'Earth Engine' API [Com-
465 puter software manual]. (<https://github.com/r-spatial/rgee/>, [https://r-](https://r-spatial.github.io/rgee/)
466 [spatial.github.io/rgee/](https://r-spatial.github.io/rgee/), <https://github.com/google/earthengine-api/>)
- 467 Bagnold, R. A. (1966). *An approach to the sediment transport problem from gen-*
468 *eral physics* (Report No. 422I). Retrieved from [http://pubs.er.usgs.gov/](http://pubs.er.usgs.gov/publication/pp422I)
469 [publication/pp422I](http://pubs.er.usgs.gov/publication/pp422I) doi: 10.3133/pp422I
- 470 Baker, D. B., Richards, R. P., Loftus, T. T., & Kramer, J. W. (2004). A new flash-
471 ness index: Characteristics and applications to midwestern rivers and streams.
472 *JAWRA Journal of the American Water Resources Association*, *40*(2), 503–
473 522.
- 474 Bennett, G., Kean, J., Rengers, F., Ryan, S., & Rathburn, S. (2017). Landslide-
475 channel feedbacks amplify flood response and channel erosion. In *EGU General*
476 *Assembly Conference Abstracts* (p. 14326).
- 477 Boothroyd, R. J., Williams, R. D., Hoey, T. B., Barrett, B., & Prasojo, O. A.
478 (2021). Applications of Google Earth Engine in fluvial geomorphology for
479 detecting river channel change. *Wiley Interdisciplinary Reviews: Water*, *8*(1),
480 e21496.
- 481 Brooke, S., Chadwick, A. J., Silvestre, J., Lamb, M. P., Edmonds, D. A., & Ganti,
482 V. (2022). Where rivers jump course. *Science*, *376*(6596), 987–990.
- 483 Brunner, M. I., Slater, L., Tallaksen, L. M., & Clark, M. (2021). Challenges in
484 modeling and predicting floods and droughts: A review. *WIREs Water*, *8*(3),
485 e1520. doi: <https://doi.org/10.1002/wat2.1520>
- 486 Bryndal, T., Franczak, P., Krocak, R., Cabaj, W., & Kołodziej, A. (2017). The im-
487 pact of extreme rainfall and flash floods on the flood risk management process
488 and geomorphological changes in small Carpathian catchments: a case study of
489 the Kasiniczanka river (Outer Carpathians, Poland). *Natural Hazards*, *88*(1),
490 95–120.
- 491 Chadwick, A., Steel, E., Williams-Schaetzel, R., Passalacqua, P., & Paola, C. (2022).
492 Channel migration in experimental river networks mapped by particle im-
493 age velocimetry. *Journal of Geophysical Research: Earth Surface*, *127*(1),
494 e2021JF006300.
- 495

- 496 Church, M. (2014). *The Regulation of Peace River: A Case Study for River Manage-*
 497 *ment*. Hoboken, UK: John Wiley & Sons.
- 498 Clubb, F. J., Weir, E. F., & Mudd, S. M. (2022). Continuous measurements of valley
 499 floor width in mountainous landscapes. *Earth Surface Dynamics*, 10(3), 437–
 500 456.
- 501 Constantine, J. A., Dunne, T., Ahmed, J., Legleiter, C., & Lazarus, E. D. (2014).
 502 Sediment supply as a driver of river meandering and floodplain evolution in
 503 the Amazon Basin. *Nature Geoscience*, 7(12), 899–903.
- 504 Copernicus. (n.d.). *Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-1C*.
 505 Retrieved from [https://developers.google.com/earth-engine/datasets/](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_HARMONIZED#description)
 506 [catalog/COPERNICUS_S2_HARMONIZED#description](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_HARMONIZED#description) (Accessed through
 507 Google Earth Engine)
- 508 Costa, J. E., & O'Connor, J. E. (1995). Geomorphically Effective Floods. *Natural*
 509 *and Anthropogenic Influences in Fluvial Geomorphology: AGU Geophysical*
 510 *Monograph*, 89, 45–56.
- 511 Dean, D. J., & Schmidt, J. C. (2013). The geomorphic effectiveness of a large flood
 512 on the Rio Grande in the Big Bend region: Insights on geomorphic controls
 513 and post-flood geomorphic response. *Geomorphology*, 201, 183–198.
- 514 Dethier, E. N., Renshaw, C. E., & Magilligan, F. J. (2022). Rapid changes to global
 515 river suspended sediment flux by humans. *Science*, 376(6600), 1447–1452.
- 516 Donovan, M., Belmont, P., & Sylvester, Z. (2021). Evaluating the relationship be-
 517 tween meander-bend curvature, sediment supply, and migration rates. *Journal*
 518 *of Geophysical Research: Earth Surface*, 126(3), e2020JF006058.
- 519 Edmonds, D. A., Martin, H. K., Valenza, J. M., Henson, R., Weissmann, G. S.,
 520 Miltenberger, K., ... Hajek, E. A. (2022, Jan). Rivers in reverse: Upstream-
 521 migrating dechannelization and flooding cause avulsions on fluvial fans. *Geol-*
 522 *ogy*, 50(1), 37–41. doi: 10.1130/G49318.1
- 523 Fuller, I. C. (2008). Geomorphic impacts of a 100-year flood: Kiwitea Stream, Man-
 524 awatu catchment, New Zealand. *Geomorphology*, 98(1-2), 84–95.
- 525 Gintz, D., Hassan, M. A., & Schmidt, K.-H. (1996). Frequency and magnitude
 526 of bedload transport in a mountain river. *Earth Surface Processes and Land-*
 527 *forms*, 21(5), 433–445.
- 528 Grill, G., Lehner, B., Thieme, M., Geenen, B., Tickner, D., Antonelli, F., ... Zarfl,
 529 C. (2019). Mapping the world's free-flowing rivers. *Nature*, 569(7755),
 530 215–221. Retrieved from [https://developers.google.com/earth-engine/](https://developers.google.com/earth-engine/datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description)
 531 [datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description](https://developers.google.com/earth-engine/datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description)
 532 (Data accessed via Google Earth Engine)
- 533 Guzzetti, F., Ardizzone, F., Cardinali, M., Rossi, M., & Valigi, D. (2009). Land-
 534 slide volumes and landslide mobilization rates in Umbria, central Italy. *Earth*
 535 *and Planetary Science Letters*, 279(3-4), 222–229.
- 536 Higgins, A., Restrepo, J. C., Ortiz, J. C., Pierini, J., & Otero, L. (2016). Suspended
 537 sediment transport in the Magdalena River (Colombia, South America): Hy-
 538 drologic regime, rating parameters and effective discharge variability. *Internat-*
 539 *ional Journal of Sediment Research*, 31(1), 25–35.
- 540 Hofmeister, F., Arias-Rodriguez, L. F., Premier, V., Marin, C., Notarnicola, C.,
 541 Disse, M., & Chiogna, G. (2022). Intercomparison of Sentinel-2 and modelled
 542 snow cover maps in a high-elevation Alpine catchment. *Journal of Hydrology*
 543 *X*, 15, 100123.
- 544 Hooke, J. (2015). Variations in flood magnitude–effect relations and the implications
 545 for flood risk assessment and river management. *Geomorphology*, 251, 91–107.
- 546 Hooke, J. (2016). Geomorphological impacts of an extreme flood in SE Spain. *Geo-*
 547 *morphology*, 263, 19–38.
- 548 Huang, C., Chen, Y., Zhang, S., & Wu, J. (2018). Detecting, extracting, and mon-
 549 itoring surface water from space using optical sensors: A review. *Reviews of*
 550 *Geophysics*, 56(2), 333–360.

- 551 Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002).
 552 Overview of the radiometric and biophysical performance of the MODIS vege-
 553 tation indices. *Remote sensing of environment*, *83*(1-2), 195–213.
- 554 Isikdogan, L. F., Bovik, A., & Passalacqua, P. (2019). Seeing through the clouds
 555 with deepwatermap. *IEEE Geoscience and Remote Sensing Letters*, *17*(10),
 556 1662–1666.
- 557 Jarriel, T., Swartz, J., & Passalacqua, P. (2021). Global rates and patterns of chan-
 558 nel migration in river deltas. *Proceedings of the National Academy of Sciences*,
 559 *118*(46), e2103178118.
- 560 Johnson, P. A., Hey, R. D., Horst, M. W., & Hess, A. J. (2001, February). Aggrada-
 561 tion at bridges. *Journal of Hydraulic Engineering*, *127*(2), 154–157. Retrieved
 562 from [https://doi.org/10.1061/\(asce\)0733-9429\(2001\)127:2\(154\)](https://doi.org/10.1061/(asce)0733-9429(2001)127:2(154)) doi:
 563 10.1061/(asce)0733-9429(2001)127:2(154)
- 564 Kale, V. S. (2002). Fluvial geomorphology of Indian rivers: an overview. *Progress in*
 565 *physical geography*, *26*(3), 400–433.
- 566 Kale, V. S. (2003). Geomorphic Effects of Monsoon Floods on Indian Rivers.
 567 In M. M. Q. Mirza, A. Dixit, & A. Nishat (Eds.), *Flood Problem and Man-*
 568 *agement in South Asia* (p. 65–84). Dordrecht: Springer Netherlands. doi:
 569 10.1007/978-94-017-0137-2_3
- 570 Kale, V. S., & Hire, P. S. (2007). Temporal variations in the specific stream power
 571 and total energy expenditure of a monsoonal river: The Tapi River, India. *Ge-*
 572 *omorphology*, *92*(3-4), 134–146.
- 573 Klingler, C., Schulz, K., & Herrnegger, M. (2021). LamaH-CE: LARge-SaMple DAta
 574 for hydrology and environmental sciences for central Europe. *Earth System*
 575 *Science Data*, *13*(9), 4529–4565.
- 576 Langhorst, T., & Pavelsky, T. (2022). Global Observations of Riverbank Erosion and
 577 Accretion from Landsat Imagery. *Journal of Geophysical Research: Earth Sur-*
 578 *face*, e2022JF006774.
- 579 Larsen, I. J., Montgomery, D. R., & Korup, O. (2010). Landslide erosion controlled
 580 by hillslope material. *Nature Geoscience*, *3*(4), 247–251.
- 581 Leenman, A., Eaton, B., & MacKenzie, L. G. (2022). Floods on alluvial fans: impli-
 582 cations for reworking rates, morphology and fan hazards. *Journal of Geophysi-*
 583 *cal Research: Earth Surface*, *127*(2), e2021JF006367.
- 584 Lehner, B., Verdin, K., & Jarvis, A. (2008). New global hydrography derived from
 585 spaceborne elevation data. *Eos, Transactions American Geophysical Union*,
 586 *89*(10), 93–94.
- 587 Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest.
 588 *R News*, *2*(3), 18–22. Retrieved from [https://CRAN.R-project.org/doc/](https://CRAN.R-project.org/doc/Rnews/)
 589 [Rnews/](https://CRAN.R-project.org/doc/Rnews/)
- 590 Lindsay, J. B., & Ashmore, P. E. (2002). The effects of survey frequency on es-
 591 timates of scour and fill in a braided river model. *Earth Surface Processes*
 592 *and Landforms: The Journal of the British Geomorphological Research Group*,
 593 *27*(1), 27–43.
- 594 Magilligan, F. J., Buraas, E., & Renshaw, C. (2015). The efficacy of stream power
 595 and flow duration on geomorphic responses to catastrophic flooding. *Geomor-*
 596 *phology*, *228*, 175–188.
- 597 Magilligan, F. J., Phillips, J. D., James, L. A., & Gomez, B. (1998). Geomorphic
 598 and sedimentological controls on the effectiveness of an extreme flood. *The*
 599 *Journal of geology*, *106*(1), 87–96.
- 600 Marren, P. M. (2005). Magnitude and frequency in proglacial rivers: a geomorpho-
 601 logical and sedimentological perspective. *Earth-Science Reviews*, *70*(3-4), 203–
 602 251.
- 603 Martínez Silva, P., & Nanny, M. A. (2020). Impact of microplastic fibers from
 604 the degradation of nonwoven synthetic textiles to the Magdalena River water
 605 column and river sediments by the City of Neiva, Huila (Colombia). *Water*,

- 12(4), 1210.
- 606 Messenger, M. L., Lehner, B., Grill, G., Nedeva, I., & Schmitt, O. (2016). Es-
 607 timating the volume and age of water stored in global lakes using a geo-
 608 statistical approach. *Nature communications*, 7(1), 1–11. Retrieved from
 609 <https://gee-community-catalog.org/projects/hydrolakes/> (Accessed
 610 via Google Earth Engine)
- 612 Middleton, L., Ashmore, P., Leduc, P., & Sjogren, D. (2019). Rates of planimet-
 613 ric change in a proglacial gravel-bed braided river: Field measurement and
 614 physical modelling. *Earth Surface Processes and Landforms*, 44(3), 752–765.
- 615 Miller, A. J. (1990). Flood hydrology and geomorphic effectiveness in the central
 616 Appalachians. *Earth Surface Processes and Landforms*, 15(2), 119–134.
- 617 Morche, D., Schmidt, K.-h., Heckmann, T., & Haas, F. (2007). Hydrology and ge-
 618 omorphic effects of a high-magnitude flood in an alpine river. *Geografiska An-
 619 naler: Series A, Physical Geography*, 89(1), 5–19.
- 620 Nagel, G. W., de Moraes Novo, E. M. L., Martins, V. S., Campos-Silva, J. V., Bar-
 621 bosa, C. C. F., & Bonnet, M. P. (2022). Impacts of meander migration on the
 622 Amazon riverine communities using Landsat time series and cloud computing.
 623 *Science of The Total Environment*, 806, 150449.
- 624 Nanson, G. C., & Hickin, E. J. (1986). A statistical analysis of bank erosion and
 625 channel migration in western Canada. *Geological Society of America Bulletin*,
 626 97(4), 497–504.
- 627 Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution
 628 mapping of global surface water and its long-term changes. *Nature*, 540(7633),
 629 418–422.
- 630 Pfeiffer, A. M., Collins, B. D., Anderson, S. W., Montgomery, D. R., & Istanbul-
 631 luoglu, E. (2019). River bed elevation variability reflects sediment supply,
 632 rather than peak flows, in the uplands of Washington State. *Water Resources
 633 Research*, 55(8), 6795–6810.
- 634 Pickens, A. H., Hansen, M. C., Hancher, M., Stehman, S. V., Tyukavina, A.,
 635 Potapov, P., ... Sherani, Z. (2020). Mapping and sampling to characterize
 636 global inland water dynamics from 1999 to 2018 with full Landsat time-series.
 637 *Remote Sensing of Environment*, 243, 111792.
- 638 Restrepo, J. D., Kjerfve, B., Hermelin, M., & Restrepo, J. C. (2006). Factors
 639 controlling sediment yield in a major South American drainage basin: the
 640 Magdalena River, Colombia. *Journal of Hydrology*, 316(1-4), 213–232.
- 641 Rose, T., Erskine, W., & Miners, B. (2020). A customised approach to determining
 642 the geomorphic effectiveness of small flood events in a regulated river. *River
 643 Research and Applications*, 36(4), 580–594.
- 644 Rousel, J., Haas, R., Schell, J., & Deering, D. (1973). Monitoring vegetation systems
 645 in the Great Plains with ERTS. In *Proceedings of the Third Earth Resources
 646 Technology Satellite—1 Symposium; NASA SP-351* (pp. 309–317).
- 647 Rowland, J. C., Shelef, E., Pope, P. A., Muss, J., Gangodagamage, C., Brumby,
 648 S. P., & Wilson, C. J. (2016). A morphology independent methodology for
 649 quantifying planview river change and characteristics from remotely sensed
 650 imagery. *Remote Sensing of Environment*, 184, 212–228.
- 651 Schwenk, J., Khandelwal, A., Fratkin, M., Kumar, V., & Foufoula-Georgiou, E.
 652 (2017). High spatiotemporal resolution of river planform dynamics from Land-
 653 sat: The RivMAP toolbox and results from the Ucayali River. *Earth and Space
 654 Science*, 4(2), 46–75.
- 655 Slater, L. J. (2016). To what extent have changes in channel capacity contributed to
 656 flood hazard trends in England and Wales? *Earth Surface Processes and Land-
 657 forms*, 41(8), 1115–1128.
- 658 Slater, L. J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., ...
 659 Wilby, R. L. (2021). Nonstationary weather and water extremes: a review
 660 of methods for their detection, attribution, and management. *Hydrology and*

- 661 *Earth System Sciences*, 25(7), 3897–3935. doi: 10.5194/hess-25-3897-2021
- 662 Slater, L. J., Singer, M. B., & Kirchner, J. W. (2015). Hydrologic versus geomorphic
- 663 drivers of trends in flood hazard. *Geophysical Research Letters*, 42(2), 370–376.
- 664 doi: <https://doi.org/10.1002/2014GL062482>
- 665 Smith, D. G. (1986). Anastomosing river deposits, sedimentation rates and basin
- 666 subsidence, Magdalena River, northwestern Colombia, South America. *Sedi-*
- 667 *mentary Geology*, 46(3-4), 177–196.
- 668 Surian, N., Barban, M., Ziliani, L., Monegato, G., Bertoldi, W., & Comiti, F.
- 669 (2015). Vegetation turnover in a braided river: frequency and effectiveness
- 670 of floods of different magnitude. *Earth Surface Processes and Landforms*,
- 671 40(4), 542–558.
- 672 Sylvester, Z., Durkin, P., & Covault, J. A. (2019). High curvatures drive river mean-
- 673 dering. *Geology*, 47(3), 263–266.
- 674 Tunncliffe, J., Brierley, G., Fuller, I. C., Leenman, A., Marden, M., & Peacock, D.
- 675 (2018). Reaction and relaxation in a coarse-grained fluvial system following
- 676 catchment-wide disturbance. *Geomorphology*, 307, 50–64.
- 677 Valenza, J., Edmonds, D., Hwang, T., & Roy, S. (2020). Downstream changes in
- 678 river avulsion style are related to channel morphology. *Nature communications*,
- 679 11(1), 1–8.
- 680 Wasko, C., & Guo, D. (2022). Understanding event runoff coefficient variability
- 681 across Australia using the hydroEvents R package. *Hydrological Processes*,
- 682 36(4), e14563.
- 683 Webb, B., & Walling, D. (1982). The magnitude and frequency characteristics
- 684 of fluvial transport in a Devon drainage basin and some geomorphological
- 685 implications. *Catena*, 9(1-2), 9–23.
- 686 Wickert, A. D., Martin, J. M., Tal, M., Kim, W., Sheets, B., & Paola, C. (2013).
- 687 River channel lateral mobility: Metrics, time scales, and controls. *Journal of*
- 688 *Geophysical Research: Earth Surface*, 118(2), 396–412.
- 689 Wolman, M. G., & Gerson, R. (1978). Relative scales of time and effectiveness of cli-
- 690 mate in watershed geomorphology. *Earth surface processes*, 3(2), 189–208.
- 691 Wolman, M. G., & Miller, J. P. (1960). Magnitude and frequency of forces in geo-
- 692 morphic processes. *The Journal of Geology*, 68(1), 54–74.
- 693 Xu, H. (2006). Modification of normalised difference water index (NDWI) to en-
- 694 hance open water features in remotely sensed imagery. *International journal of*
- 695 *remote sensing*, 27(14), 3025–3033.
- 696 Yousefi, S., Mirzaee, S., Keesstra, S., Surian, N., Pourghasemi, H. R., Zakizadeh,
- 697 H. R., & Tabibian, S. (2018). Effects of an extreme flood on river morphology
- 698 (case study: Karoon River, Iran). *Geomorphology*, 304, 30–39.
- 699 Zou, Z., Xiao, X., Dong, J., Qin, Y., Doughty, R. B., Menarguez, M. A., ... Wang,
- 700 J. (2018). Divergent trends of open-surface water body area in the contigu-
- 701 ous United States from 1984 to 2016. *Proceedings of the National Academy of*
- 702 *Sciences*, 115(15), 3810–3815.

1 **Quantifying geomorphically effective floods using**
2 **satellite observations of river mobility**

3 **A. S. Leenman¹, L. J. Slater¹, S. J. Dadson^{1,2}, M. Wortmann^{1,3} and R.**
4 **Boothroyd⁴**

5 ¹School of Geography and the Environment, University of Oxford

6 ²UK Centre for Ecology and Hydrology

7 ³European Centre for Medium-Range Weather Forecasts

8 ⁴School of Geographical and Earth Sciences, University of Glasgow

9 **Key Points:**

- 10 • We develop a method to quantify river planform change during flood events, us-
11 ing Google Earth Engine
- 12 • We do so for a dataset of 160 floods that exceeded the 80th percentile stage, at
13 41 flow gauging sites on laterally active rivers
- 14 • Erosion during these high-flow events was most correlated with the event dura-
15 tion and summed hydrograph

Corresponding author: Anya Leenman, anya.leenman@chch.ox.ac.uk

Abstract

Geomorphologists have long debated the relative importance of disturbance magnitude, duration and frequency in shaping landscapes. For river-channel adjustment during floods, some argue that cumulative flood ‘power’, rather than magnitude or duration, matters most. However, studies of flood-induced river-channel change often draw upon small datasets. Here, we combine Sentinel-2 imagery with flow data from laterally-active rivers to address this question using a larger dataset. We apply automated algorithms in Google Earth Engine to map rivers and detect their lateral shifting; we generate a large dataset to quantify channel change during 160 floods across New Zealand, Russia, and South America. Widening during these floods is best explained by their duration and cumulative hydrograph. We use a random forest regression model to predict flood-induced channel widening, with potential applications for hazard management. Ultimately, better global data on sediment supply and caliber would help us to understand flood-driven change to river planforms.

Plain Language Summary

Some rivers change their shape over time. In this paper, we explore how high-flow events drive these river channels to reshape themselves. We use Google Earth Engine to automatically map the shapes of rivers in satellite images. We apply this method to pairs of satellite images before and after high-flow events, to understand how the river shape is changed by the event. We compare the amount of channel-widening measured to aspects of the high-flow event, including its peak, duration and total flow. We do so for 160 high-flow events, and find that the duration and total flow are most important for explaining how much a channel widens during the event. Finally, we build a statistical model to predict the average amount of channel widening for a given high-flow event. This method has potential applications for hazard management in rivers that are known to change their shape.

1 Introduction

The relative importance of disturbance magnitude, duration and frequency for shaping landscapes is a crucial question in geomorphology. Many studies have considered the effects of high-magnitude versus high-frequency events: for cumulative sediment transport (Wolman & Miller, 1960; Webb & Walling, 1982), for generating and reworking landforms (Wolman & Gerson, 1978; Kale, 2002, 2003; Surian et al., 2015), and for the resulting sedimentology (Magilligan et al., 1998; Marren, 2005). Others have considered the duration and total energy expenditure of individual disturbances and how this relates to their ability to transport sediment and reshape river channels (Costa & O’Connor, 1995; Magilligan et al., 2015). In rivers, understanding which disturbances perform the most geomorphic work — both instantaneously, and cumulatively over time — has important implications for sediment budgeting, flood conveyance, depositional records, and natural hazard management.

In rivers, the major disturbances are flood events, which have the power to reshape the channels that convey them. Such reshaping ranges from bar deposition and bank erosion (Bryndal et al., 2017) or aggradation (Morche et al., 2007; Hooke, 2016) through to widening (Fuller, 2008; Yousefi et al., 2018), reoccupation of abandoned channels (Arnaud-Fassetta et al., 2005) and large-scale reworking of floodplains (Miller, 1990). The latter can have severe impacts for society, including erosion of agricultural or residential land (Yousefi et al., 2018) or the destruction of transport and river management infrastructure (Arnaud-Fassetta et al., 2005). Conversely, aggradation during floods can raise riverbeds by several meters (Morche et al., 2007; Tunnicliffe et al., 2018), reducing a channel’s conveyance capacity and the freeboard below bridges (Johnson et al., 2001). Quantitative

65 methods are needed to understand, model, and predict how river channels can be reshaped
66 by individual flood events.

67 The geomorphic effectiveness of a flood is thought to be a function of its duration
68 and magnitude. Here, we define geomorphic effectiveness as the extent to which a flood
69 alters the channel form by eroding or depositing sediment. We use the term 'flood' to
70 mean any temporary rise in the water level (in our analysis, one that exceeds the 80th
71 percentile of the water surface elevation measurements). Previous studies have suggested
72 that the cumulative stream power (defined by Bagnold (1966) as the product of water
73 density, acceleration due to gravity, discharge and slope) beneath a flood hydrograph must
74 be high for the event to be geomorphically effective; the implication is that high-magnitude
75 but brief floods, and low-magnitude but long floods, are not likely to be effective (Costa
76 & O'Connor, 1995). However, others have suggested that additional factors (not just the
77 cumulative power) make a flood geomorphically effective. For instance, Middleton et al.
78 (2019) demonstrated that flood magnitude does influence geomorphic effectiveness: in
79 the proglacial braided river they studied, planform change during floods increased with
80 their peak discharges. Others propose that a flood's geomorphic effectiveness is not deter-
81 mined by the hydrograph alone, but also by the sediment supply (Church, 2014; Hooke,
82 2016; Bennett et al., 2017; Pfeiffer et al., 2019) or the time since the previous flood, which
83 can influence both sediment availability and the looseness of the riverbed (Gintz et al.,
84 1996; Hooke, 2015). These studies have advanced our understanding of geomorphic ef-
85 fectiveness, but almost all were small-sample case studies of 1-10 flood events or river
86 reaches, often in similar regional or climatic contexts. Larger samples of flood events from
87 a more geomorphically and geographically diverse set of rivers are required to produce
88 a robust empirical assessment of what makes a geomorphically effective flood.

89 Google Earth Engine (GEE) has recently emerged as a key tool facilitating large-
90 sample analyses of landscape characteristics — through both its computational platform
91 and archive of quality controlled satellite data. The 'large-sample' approach, which ad-
92 dresses environmental questions using data from tens to thousands of sites, is popular
93 in hydrology (Addor et al., 2017; Klingler et al., 2021) and has begun to be applied in
94 geomorphology (Slater et al., 2015; Slater, 2016; Pfeiffer et al., 2019; Sylvester et al., 2019;
95 Valenza et al., 2020; Ahrendt et al., 2022; Brooke et al., 2022; Clubb et al., 2022; Ed-
96 monds et al., 2022). A large-sample approach to studying planimetric river adjustments
97 can be readily deployed in GEE, drawing on automated methods to map river planform
98 (Allen & Pavelsky, 2015; Pekel et al., 2016; Zou et al., 2018; Isikdogan et al., 2019; Pick-
99 ens et al., 2020; Boothroyd et al., 2021) and to track planform deformation (Wickert et
100 al., 2013; Rowland et al., 2016; Schwenk et al., 2017; Jarriel et al., 2021; Chadwick et
101 al., 2022; Langhorst & Pavelsky, 2022). By automating river planform tracking in GEE,
102 the geomorphic effectiveness of a large sample of flood events can be assessed.

103 In this paper, we investigate the streamflow drivers of geomorphically effective floods
104 using Sentinel-2 satellite imagery in GEE. We pursue two research questions:

- 105 1. Which hydrograph metrics best explain a flood's 2D geomorphic effectiveness?
- 106 2. How well can a flood's 2D geomorphic effectiveness be predicted from hydrologic
107 and environmental variables?

108 We measure geomorphic effectiveness as the reach-averaged channel widening during a
109 flood. We compute this planimetric erosion in GEE for flood events in Brazil, Colom-
110 bia, New Zealand and Russia. We use 160 flood events at 41 flow gauging sites on lat-
111 erally active rivers to evaluate our research questions (see Figure S1, Supplementary Ma-
112 terial (SM), for gauge locations). We ascertain the influence of hydrograph shape on ge-
113 omorphic effectiveness in our dataset. Finally, we develop an empirical model to predict
114 flood-induced erosion. When coupled with streamflow forecasts, the model may be use-
115 ful for hazard management in sites that are known to be laterally active.

116 **2 Methods**

117 Our method can be summarized as follows. First, we identified sites with historical
 118 daily stage (water level) measurements and a laterally active channel. For those rivers,
 119 we identified peaks in the stage records. Second, for each flood peak we extracted the
 120 pre- and post-flood channel planform from Sentinel-2 data in GEE, and conducted a change
 121 detection between the two planforms to quantify erosion during the flood hydrograph. Ultimately,
 122 we compared the lateral erosion detected to parameters of the flood hydrograph. Figure 1
 123 illustrates these steps with an example of one flood in Colombia. Our code is available
 124 at <https://github.com/a-leenman/2dFloodsPublic>; GEE processing was per-
 125 formed via the ‘rgee’ r package (Aybar, 2022).

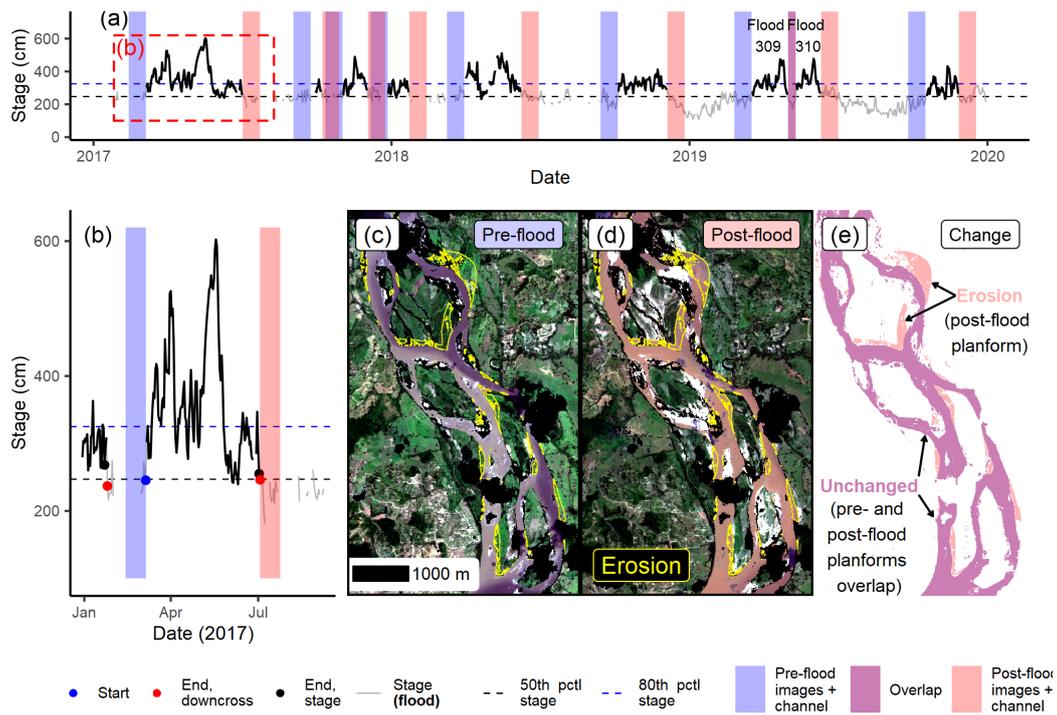


Figure 1. Methods used to define floods and detect planform change. (a) The pre-flood (blue) and post-flood (red) search windows for a sequence of floods (bold lines), showing how the windows can overlap (purple). (b) Example flood from Colombian gauge 23097040, with the flood start date (blue circle), two options for flood end date (black and red circles; the ‘downcross’ (red circle) method was most appropriate) and the pre- and post-flood search windows. (c) Pre-flood channel morphology, mosaicked from all cloud-free pixels in the six satellite images covering part of the AOI within the pre-flood search window. Erosion during the following flood is outlined in yellow. Black patches have no data due to cloud. (d) Corresponding post-flood mosaic (10 source images within the time and space filter). (e) The pre- and post-flood channel planforms are overlaid, highlighting the erosion (red) detected.

126 **2.1 Site selection and area of interest**

127 Hydrologic records are crucial to our analysis, providing flood occurrence and hydro-
 128 graph shape data. We obtained publicly available stage records and gauging locations

for Brazil, Colombia, New Zealand and Russia. These countries were chosen for their laterally active rivers and availability of recent daily stage records.

Other authors used discharge or stream power records to pursue this problem. However, we chose to use stage data so that differences in stage could provide a proxy for depth fluctuations when estimating the time series of shear stress. Ultimately, we aimed to approximate the sediment transport capacity of each hydrograph.

We filtered the stage records to include only those gauges that:

1. Were located on a river with a mean annual discharge above $100 \text{ cm}^3 \text{ s}^{-1}$ (data from Grill et al. (2019)), to ensure these rivers were large enough to be visible in our 10 m satellite imagery.
2. Were located on a laterally active river whose dynamics could be measured from satellite data. Laterally active rivers were identified by filtering the ‘water permanence’ layer from Pekel et al. (2016). After computing planform change during floods, a site was removed if the eroded area never exceeded 1% of the water surface area or if the flood-induced widening never exceeded 3 m. These thresholds enabled the largest possible dataset while excluding channels that were not laterally active.
3. Were not adjacent to large lakes or dams.
4. Overlapped with the Sentinel-2 record (June 2015 - present) by at least one year.

This filtering isolated a sample of 41 gauges. River widths ranged from 60 to 1000 m; their gradients ranged from 0.00001 to 0.002. Their mean long-term discharge ranged from 100 to $7000 \text{ cm}^3 \text{ s}^{-1}$, and upstream catchment area ranged from 3800 to 430000 km^2 . Values of the Richards-Baker index (Baker et al., 2004) ranged from 0.005 (very seasonal) to 0.33 (moderately flashy). Gauge altitudes ranged from 3 to 500 m. Forest cover at the gauges ranged from 0 to 100%, and mean annual rainfall from 440 to 4100 mm. The range of rivers (including braided, wandering and meandering forms) encompassed by these values highlights the geographic and geomorphic diversity of the rivers we incorporate.

For each gauge, we defined an ‘Area of Interest’ (AOI) in which we extract the river planform and monitor its deformation. The ‘HydroSHEDS Free Flowing Rivers’ vector network (Lehner et al., 2008; Grill et al., 2019) was used to select all river segments within 40 km of each gauge. We kept only the segments on the same branch as the gauge, and also removed segments that were past a jump in average discharge of $>20\%$, implying that a ‘major’ tributary had been passed; we computed such jumps using the average discharge data for each segment in Grill et al. (2019). If two gauges were nearby on the same river, we divided the intervening segments between them. This left a remaining ‘linked reach’ (comprising one or more HydroSHEDS segments) assigned to each gauge. We extracted water masks along each reach from Allen and Pavelsky (2018a, 2018b), as a first approximation of the channel area. However, these masks do not always encompass the entire channel in our study reaches (which are extremely laterally mobile: some shift by more than 30 m in a single flood) and so we buffered these masks by 500 m to create the AOI. Finally, lakes in the HydroLAKES (Messenger et al., 2016) dataset were subtracted from the AOI, to avoid spurious change detection from varying lake levels. We thus assigned to each gauge a unique AOI within which we extracted the river planform before and after each flood.

2.2 Flood delineation and search window definition

We delineated floods temporally based on the daily stage record for each gauge. Although higher frequency records were available for some countries, we resampled them by taking the daily mean stage. While this process smoothed some maxima and min-

178 ima, it gave all records the same frequency. We defined a flood as any period exceeding
 179 the 80th percentile of the stage record during the Sentinel-2 record (June 2015 onwards;
 180 Figure 1a, b). Floods were extracted from the daily stage records using the hydroEvents
 181 R package (Wasko & Guo, 2022). To ensure we captured the rising and falling limbs, we
 182 defined the flood start date as the first measurement before the peak which was also be-
 183 low the 50th percentile of stage (Figure 1a, blue points). We defined the flood end date
 184 in two ways: either as

- 185 1. the first measurement following the peak which also fell below the 50th percentile
 186 of stage (Figure 1a, red points), or
- 187 2. the first measurement following the peak which was within 30 cm of the stage at
 188 the start of the flood (Figure 1a, black points). Occasionally, missing data meant
 189 that the first method created flood end dates that were unreasonably far after the
 190 end of the flood, necessitating the second method.

191 For each flood, we chose the flood end date with the stage measurement that was clos-
 192 est to the stage on the start date. Following the discussion in Slater et al. (2021), floods
 193 separated by less than seven days were counted as one event, and floods lasting more than
 194 5 months were discounted as these were mostly anomalies from missing data. While this
 195 approach of using the 50th percentile to give the start and end dates assigns a longer length
 196 to floods than some standard approaches, it allows us to capture the geomorphic effects
 197 of the rising and falling limbs, and recognizes that geomorphic change and sediment en-
 198 trainment likely start before the 80th percentile stage is exceeded.

199 Directly before and after each flood, we defined pre- and post-flood time windows
 200 of up to three weeks (Figure 1a, b). We truncated a time window if floods were less than
 201 three weeks apart; for example, flood 309 (Figure 1a) finished nine days before the fol-
 202 lowing event, and so its post-flood window was truncated. If sequential events were less
 203 than six weeks apart, their pre- and post-flood windows were allowed to overlap; the post-
 204 flood window for one flood could even overlap entirely with the pre-flood window of the
 205 following event, as with floods 309 and 310 (Figure 1a; this would mean that the post-
 206 flood channel mask of flood 309 was reused as the pre-flood mask of flood 310). We used
 207 these pre- and post-flood time windows to search the Sentinel-2 archive (Level 1C, har-
 208 monized).

209 **2.3 Planform extraction and change detection**

210 Within each pre- and post-flood time window, we extracted the river planform from
 211 Sentinel-2 (S2) imagery. First, we mosaicked all cloud-free S2 pixels within the time win-
 212 dows and AOI, taking the minimum reflectance in each band if multiple copies of one pixel
 213 were available. Figure 1c and d are examples of these mosaics. We proceeded with an
 214 event if at least 50% of its AOI was cloud-free; only pixels that were cloud-free in both
 215 mosaics were used. For sites in New Zealand and Russia, we also mapped snow using the
 216 normalized difference snow index, following Hofmeister et al. (2022). For snow-free scenes
 217 that met our cloud threshold, we mapped channel planform from a combination of spec-
 218 tral indices, following Zou et al. (2018) and Boothroyd et al. (2021); these were the nor-
 219 malized difference vegetation index (Rousel et al., 1973), modified normalized difference
 220 water index (Xu, 2006), and enhanced vegetation index (Huete et al., 2002). Following
 221 Boothroyd et al. (2021), we counted both water and exposed sediment (i.e. non-vegetated
 222 bars) as part of the channel, given that a lack of vegetation indicates bars are frequently
 223 inundated. While this mapping method is simple, it is generalizable to rivers with dif-
 224 ferent lighting conditions and suspended sediment concentrations.

225 We conducted change detection between the pre- and post-flood planforms to es-
 226 timate each flood's geomorphic impact. To isolate areas that were permanently (as op-
 227 posed to transiently) changed during a flood, we tracked the state (wet or dry) of each

228 pixel at monthly intervals for the following 24 months, loosely following the pixel-by-pixel
229 trend analysis of Nagel et al. (2022). We only considered a pixel to be eroded if it switched
230 from dry-to-wet in the flood and then continued to be wet for the subsequent two years.
231 If cloud cover meant there were <18 months of these after-flood observations for an event,
232 we discounted it; we chose this threshold by checking the change detection for bias due
233 to stage fluctuations. This pixel-tracking method allowed us to eliminate spurious change
234 detection resulting from transient stage fluctuations.

235 We measured a flood's geomorphic effectiveness as the area that was permanently
236 eroded (i.e. changed from 'dry' to 'wet') during the event. We normalized this eroded
237 area by the reach length to give the reach-averaged channel widening. Because we counted
238 non-vegetated bars as part of the channel, it was difficult to measure deposition follow-
239 ing the flood; newly deposited sediment was typically registered as 'channel' by our map-
240 ping algorithm. This is why we consider post-flood erosion to be the most appropriate
241 metric of geomorphic change in our data.

242 Our procedures for gauge selection, cloud- and snow-filtering isolated a dataset of
243 160 events for which we measured geomorphic effectiveness. Because there were less than
244 11 floods in some countries, we pooled all floods for our subsequent analyses.

245 2.4 Regression and prediction

246 Our first research question considers the influence of hydrograph shape on geomor-
247 phic effectiveness. There are numerous metrics to characterize hydrographs, including
248 measures of height, duration, integrated power, volume or transport capacity, and asym-
249 metry (Brunner et al., 2021; Slater et al., 2021). Because these rivers feature a range of
250 hydrographs (for instance, flashy versus seasonal), we use three simple metrics that al-
251 low comparison with previous studies. The first is the flood peak height, relative to the
252 mean daily stage. The second is the cumulative value of all daily stage measurements
253 during the flood, measured relative to mean daily stage. This cumulative water level met-
254 ric is akin to the 'volume' of a hydrograph when using discharge records (e.g. Brunner
255 et al. (2021), Figure 3). Because we use stage records, the metric accounts for the com-
256 bined influence of changes in flow depth during the flood (exerting stress on the river banks/bed)
257 and of flood duration; we refer to it as the 'summed hydrograph'. The third metric is
258 the flood duration.

259 As well as exploring how hydrograph metrics correlated with erosion, we built a
260 random forest regression model to rank the predictors' importance (by estimating how
261 much they decreased the model's mean square error, MSE). In addition to these hydro-
262 graph metrics, we incorporated the pre-flood channel width, as channel size can positively
263 influence channel mobility (Constantine et al., 2014; Nanson & Hickin, 1986; Langhorst
264 & Pavelsky, 2022). Although sediment supply also increases channel mobility (e.g. Constantine
265 et al. (2014); Ahmed et al. (2019); Donovan et al. (2021)), we do not have sediment sup-
266 ply time-series for our gauging sites. Instead, we used stream gradients and stage records
267 to estimate the sediment transport capacity for each flood (see Section S1, SM for de-
268 tails), and added these estimates to the random forest model. We built the model us-
269 ing the randomForest r package (Liaw & Wiener, 2002) with 500 trees and two variables
270 randomly sampled at each split. We used the model to predict each flood's reach-averaged
271 erosion using leave-one-out cross-validation (LOOCV).

272 3 Results

273 In the laterally active rivers we study, floods and their geomorphic impacts vary
274 by orders of magnitude. Peak heights vary from 30 to 700 cm above mean daily stage.
275 The summed hydrographs vary from 40 to 30000 cm above mean daily stage, and flood
276 durations from 1 to 152 days. The geomorphic effects of these floods are diverse, with

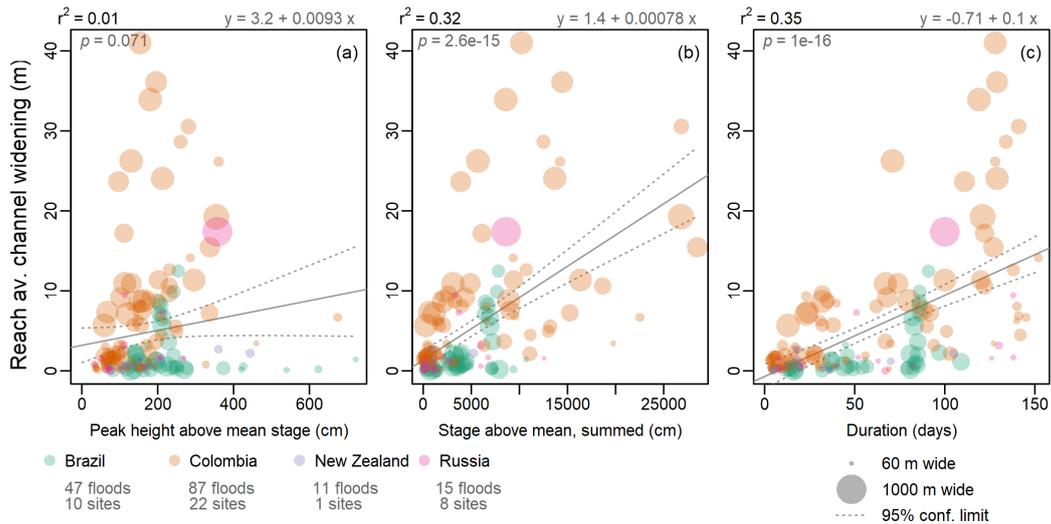


Figure 2. Flood metrics and their relationship to reach-averaged channel widening (i.e. plan-view erosion normalized by reach length) during each flood. (a) Flood peak height above the mean daily stage. (b) Cumulative stage exceeding mean daily stage (‘summed hydrograph’). (c) Flood duration. Each point represents one event; colors indicate the four countries; point size is proportional to pre-flood channel width. The solid gray line shows a linear regression and dotted lines show 95% confidence limits; the regression equation is at the top-right. r^2 and p -values are at the top left. r^2 values for individual countries are in Table S1, SM.

277 reach-averaged widening as low as 0.005 m and as high as 41 m. The least geomorphi-
 278 cally active country is New Zealand, with an average flood-induced widening of 0.9 m,
 279 while the most active is Colombia, with an average widening of 7 m across all floods.

280 Our first research question considers the erosional response of river channels to flood
 281 hydrographs. Figure 2 demonstrates how reach-averaged erosion varies with three hy-
 282 drograph metrics in the 160 floods we study. Each point represents one event, with the
 283 reach-averaged erosion compared to the flood’s peak height (a), summed hydrograph (b),
 284 and flood duration (c). Figure 2 therefore shows how hydrograph metrics influence ge-
 285 oomorphic effectiveness for 160 floods at 41 sites across Brazil, Colombia, New Zealand
 286 and Russia between 2015 and 2021.

287 Our results indicate that reach-averaged channel widening is only weakly related
 288 to flood height in our dataset (Figure 2a). A linear regression of reach-averaged erosion
 289 during each flood against the peak height had an r^2 of just 0.01. Erosion scaled more
 290 strongly with the summed hydrograph (Figure 2b), with an r^2 of 0.32, and most strongly
 291 with flood duration (Figure 2c), with an r^2 of 0.35. See Table S1 (SM) for country-specific
 292 relationships. These coefficients of determination are surprisingly high, considering that
 293 they represent observations from real systems and are thus confounded by other natu-
 294 ral variables in each location. Some of the relationships in Figure 2 appear non-linear
 295 (especially panel (c)), but we lack sufficient data to fit non-linear models and so we use
 296 linear regression to make a first-order comparison. These metrics are correlated among
 297 themselves (see Figure S2, SM); longer floods often had higher peaks, so that the r^2 val-
 298 ues shown here indicate *relative* importance and we cannot say that the increase in ero-
 299 sion with flood duration was independent of the concurrent increase in height for many
 300 floods. Nevertheless, panels a-c indicate that, at least for our sample of laterally active

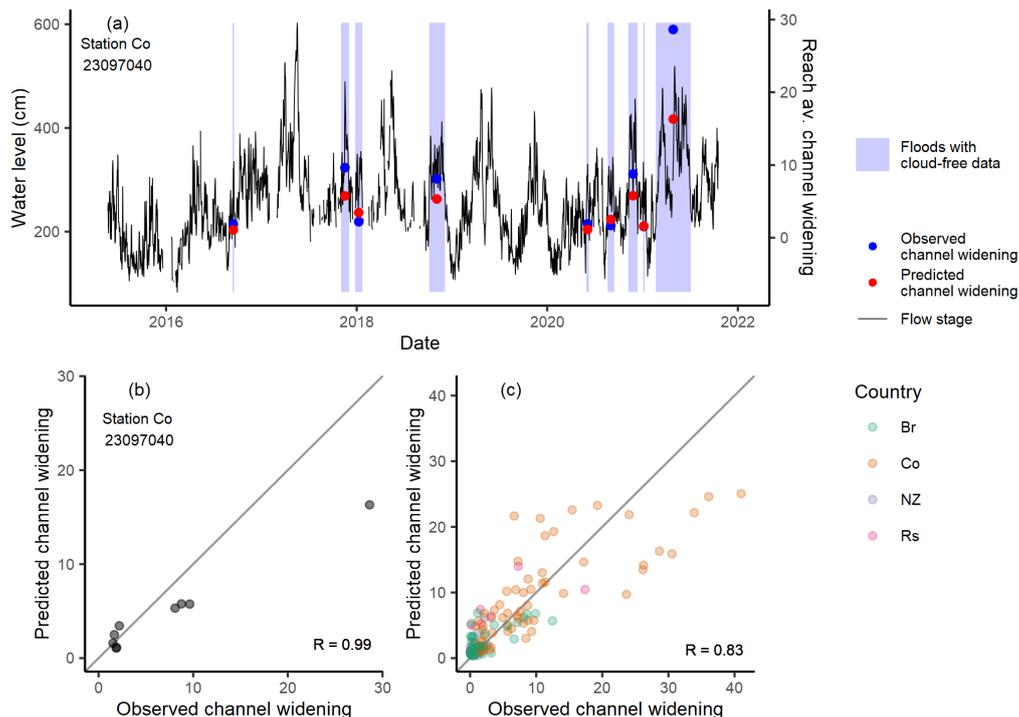


Figure 3. Predictions from our random forest regression model. (a) The stage record for Colombian gauge 23097040; flood events with sufficient cloud-free satellite data are highlighted. The observed and predicted reach-averaged erosion (channel widening) during each flood are overlain and scale with the secondary y-axis. (b) A comparison of observed and predicted channel-widening at this gauge; each point is one flood. (c) A comparison of observed and predicted channel-widening for all floods in our dataset. Grey lines in (b) and (c) show a 1:1 relation.

301 rivers, flood duration was the most important variable for explaining flood-driven erosion of the vegetated channel boundary.
302

303 We built a random forest regression model to rank the importance of the hydro-
304 graph metrics, channel width, and estimated sediment transport for explaining flood ero-
305 sion. The random forest model ranked these variables in the following order: estimated
306 transport, channel width, flood duration, summed hydrograph and peak height; the rank-
307 ings reflect how much each variable reduced the model’s MSE. This ranking is similar
308 to the r^2 values in Figure 2 and Figures S3-S4 (SM). Because the summed hydrograph
309 and flood duration were correlated ($R = 0.79$), we ran two additional model versions,
310 omitting either summed hydrograph or flood duration. Although these omissions altered
311 the variables’ MSE reductions, neither altered the remaining variable rankings, imply-
312 ing that the rankings are not affected by this co-linearity in the predictors.

313 We predicted erosion for all floods in our dataset using the random forest model
314 with LOOCV. We were able to predict erosion with at least 60% accuracy ($R = 0.83$;
315 Figure 3c) using the pooled dataset. The model performed best for sites in Colombia with
316 numerous floods, such as site 23097040 (Figure 3a,b). For Colombian sites with data for
317 > 7 floods, R values were 0.78–0.99. The model tended to under-predict the highest val-
318 ues of reach-averaged erosion.

4 Discussion

Although there is no firm consensus, previous literature has laid the case for a hydrograph's cumulative power as the best explainer of a flood's geomorphic effectiveness. For instance, based on 10 events in Arkansas, California, Colorado, Idaho, Oregon and Washington, Costa and O'Connor (1995) suggested that a flood's geomorphic effectiveness reflected the cumulative unit stream power exceeding the threshold for alluvial erosion. Rose et al. (2020) likewise found that the most geomorphically effective floods in a sample of seven had a high energy expenditure, high peak and long duration. Kale and Hire (2007) observed that sediment transport (a proxy for geomorphic effectiveness) during monsoons rose exponentially with their cumulative stream power. Magilligan et al. (2015) attributed the limited widening during an extreme flood to its low cumulative power, resulting from a high peak but short duration. Our data partly support this hypothesis; the summed hydrograph was positively correlated with erosion during the floods we studied. However, in our dataset flood duration was a slightly better predictor of erosion of the vegetated channel boundary. This result was consistent when we raised the flood definition threshold to the 90th percentile of stage, and the summed hydrograph and flood duration had equal effects when we lowered the threshold to the 70th percentile (Figures S5 and S6, SM).

One reason for the weaker influence of the summed hydrograph in our data may be that these previous studies used the unit stream power hydrograph, whereas we used the stage hydrograph. We used stage so that changes could be used as a proxy for depth fluctuations when estimating shear stress and each hydrograph's sediment transport capacity. Although the unit transport capacity was a weaker predictor than the summed hydrograph or duration, transport became a stronger predictor when multiplied by channel width (see section S1 and Figure S3 (SM) for more detail).

The importance of flood duration in our dataset implies that, once these floods exceed the entrainment threshold, further stage increases have a smaller effect than the duration above the threshold. That is, shear stress exposure duration has a greater effect than the peak stress. This result suggests that the threshold for entrainment was low in the rivers we studied, so that full mobility of all sediment sizes was attained frequently. The regional breakdown of Figure 2 (Table S1, SM) supports this notion, as the influence of duration is strongest for Colombia where some studies have reported sand beds (e.g. Smith (1986); Martínez Silva and Nanny (2020)).

Other studies have used flood peak height, rather than cumulative power, to explain geomorphic effectiveness. For instance, Middleton et al. (2019) mapped planimetric change during floods in a proglacial river and showed that, once an annually-reset threshold discharge had been exceeded, planimetric change increased with peak discharge. Miller (1990) found that, in alluvial rivers wider than 200 m, peak unit stream power during floods was correlated with geomorphic effectiveness. In alluvial fan experiments featuring different hydrographs of the same volume, surface reworking increased with the peak discharge (Leenman et al., 2022). Nevertheless, in our dataset flood height was only weakly related to geomorphic change. It is possible that a threshold above which peak height becomes important can only be extracted by analyzing numerous floods at one location. Such an analysis is difficult in the remote sensing of real rivers, either due to seasonal floods or to persistent cloud cover, both of which limit the number of events that can be assessed.

Our results, and particularly the importance of flood duration, highlight some complexities of investigating flood impacts with a large-sample remote-sensing analysis. First, while we measured the flood-induced erosion of the vegetated channel boundaries, others simply categorized flood-driven change (e.g. (Costa & O'Connor, 1995)) or quantified sedimentological impacts (Magilligan et al., 2015). The importance of duration here is relevant to vegetated channel boundaries, but results may differ if measuring a differ-

371 ent aspect of channel morphology — for instance, Magilligan et al. (2015) highlight how
372 a flood event can have large sedimentological effects but a smaller impact on channel shape.
373 Second, our large-sample analysis highlights the difficulty of finding a single parameter
374 explaining flood effectiveness in all rivers. Flood duration was the most important driver
375 of erosion in some rivers in our dataset, but not all; Table S1 shows that peak height was
376 more important in Russia. Third, the relationship between a flood hydrograph and the
377 erosion caused can be compounded by other variables, including the presence and char-
378 acter of vegetation, the caliber and structure of bed and bank sediment, the sediment
379 supplied from upstream, and the time elapsed since the previous flood. In this paper,
380 we make a first attempt at a large-sample analysis of geomorphically effective floods, and
381 our work highlights the need for global datasets on these additional variables in order
382 to fully address this problem.

383 Others have suggested that the causal relationship between a flood and its geomor-
384 phic effectiveness is moderated by sediment supply. For instance, in comparing two events
385 on the Peace River (Canada), Church (2014, Chapter 10) found that their geomorphic
386 effects were best explained by differences in the sediment influx. Pfeiffer et al. (2019) found
387 that bed-level changes in Washington State were not related to high-flow events, but to
388 sediment supply from glaciers upstream. Dean and Schmidt (2013) observed that geo-
389 morphic change during a flood in the Rio Grande was highest downstream of sediment-
390 rich tributaries. For longer-term channel mobility, sediment supply positively influences
391 channel migration (Constantine et al., 2014), and some rivers in our dataset (e.g. the
392 Magdalena) have very high sediment loads (Restrepo et al., 2006; Higgins et al., 2016;
393 Dethier et al., 2022). This question is an interesting and important one, and further work
394 to measure sediment transport alongside flow during floods is crucial for understanding
395 how sediment availability modulates a hydrograph’s geomorphic effectiveness.

396 Our methods have some limitations which provide avenues for further research. The
397 first is the suitability of using planform measurements to quantify three-dimensional chan-
398 nel adjustment. For landslides, erosional area scales with volume (Guzzetti et al., 2009;
399 Larsen et al., 2010), but in rivers a 2D for 3D substitution would not be appropriate where
400 channels are laterally confined. We have side-stepped this problem by using only later-
401 ally mobile rivers, which are therefore the rivers where a 2D for 3D substitution is most
402 appropriate. Middleton et al. (2019) demonstrated experimentally that sediment trans-
403 port scaled linearly with planimetric change, providing further justification for 2D change
404 detection. However, further work on the suitability of measuring geomorphic change in
405 planview would be valuable.

406 Further potential limitations include that of data resolution; the Sentinel-2 imagery
407 we use has a 10 m resolution. Because erosion may occupy a smaller footprint than de-
408 position of the same volume (Lindsay & Ashmore, 2002), finer-scale imagery may bet-
409 ter capture erosion and would facilitate equal monitoring of both processes. An inves-
410 tigation of improvements with higher-resolution imagery would be worthwhile. In ad-
411 dition, our method computes change in the vegetated channel boundaries, so that non-
412 vegetated bars moving through these rivers are not counted. Work comparing different
413 algorithms to quantify river dynamics would be a useful contribution. Finally, similar-
414 ity between the spectral signatures of snow and water in the mNDWI (Huang et al., 2018)
415 meant we had to discard snowy scenes. We thus compromised slightly on our goal of a
416 geomorphically diverse set of rivers. As the S2 record approaches a decade, the main lim-
417 itation on this work is the availability of flow records, which constrains the range of sites
418 that can be used. Methods to measure or model flow in ungauged basins could extend
419 this work to an even more geographically diverse range of rivers.

420 **5 Conclusions**

421 We used Google Earth Engine and the Sentinel-2 satellite archive to map planform
422 geomorphic change in laterally-mobile rivers during 160 flood events. By tracking each
423 pixel for two years, we were able to separate permanent planform change from transient
424 water extent fluctuations arising from stage variability. We measured each flood's geo-
425 morphic effectiveness as the reach-averaged erosion during the flood, and compared this
426 to the flood hydrograph.

427 In the 41 laterally active rivers studied, we found that the flood peak height was
428 only weakly correlated with erosion. The summed hydrograph was a better predictor,
429 but erosion was most closely correlated with flood duration in our dataset of events ex-
430 ceeding the 80th percentile of stage.

431 We built a random forest regression model to predict geomorphic change for each
432 flood, using hydrograph metrics, estimated sediment transport and channel size. The model
433 had a prediction accuracy above 60%, which is promising for the predictability of river-
434 bank erosion in mobile reaches.

435 Our work highlights the need for high-frequency flow monitoring in the world's lat-
436 erally active rivers, to better understand how a flood's hydrograph controls its erosional
437 impact. Moreover, better data on land cover, bank strength, and sediment caliber at stream
438 gauging sites would elucidate how these characteristics modulate flood-driven erosion.
439 Finally, monitoring sediment transport alongside river flows would help us to understand
440 how sediment availability influences a flood's geomorphic effectiveness.

References

- 441 Addor, N., Newman, A. J., Mizukami, N., & Clark, M. P. (2017). The CAMELS
442 data set: catchment attributes and meteorology for large-sample studies. *Hy-*
443 *drology and Earth System Sciences*, *21*(10), 5293–5313.
- 444 Ahmed, J., Constantine, J. A., & Dunne, T. (2019). The role of sediment supply in
445 the adjustment of channel sinuosity across the Amazon Basin. *Geology*, *47*(9),
446 807–810.
- 447 Ahrendt, S., Horner-Devine, A. R., Collins, B. D., Morgan, J. A., & Istanbuluoglu,
448 E. (2022). Channel Conveyance Variability can Influence Flood Risk as Much
449 as Streamflow Variability in Western Washington State. *Water Resources*
450 *Research*, *58*(6), e2021WR031890.
- 451 Allen, G. H., & Pavelsky, T. M. (2015). Patterns of river width and surface area re-
452 vealed by the satellite-derived North American River Width data set. *Geophys-*
453 *ical Research Letters*, *42*(2), 395–402.
- 454 Allen, G. H., & Pavelsky, T. M. (2018a). Global extent of rivers and streams. *Sci-*
455 *ence*, *361*(6402), 585–588.
- 456 Allen, G. H., & Pavelsky, T. M. (2018b). *Global River Widths from Landsat*
457 *(GRWL) Database*. Zenodo. Retrieved from [https://gee-community-](https://gee-community-catalog.org/projects/grwl/)
458 [catalog.org/projects/grwl/](https://gee-community-catalog.org/projects/grwl/) (Accessed through Google Earth Engine)
459 doi: 10.5281/ZENODO.1297434
- 460 Arnaud-Fassetta, G., Cossart, E., & Fort, M. (2005). Hydro-geomorphic hazards and
461 impact of man-made structures during the catastrophic flood of June 2000 in
462 the Upper Guil catchment (Queyras, Southern French Alps). *Geomorphology*,
463 *66*(1-4), 41–67.
- 464 Aybar, C. (2022). rgee: R Bindings for Calling the 'Earth Engine' API [Com-
465 puter software manual]. (<https://github.com/r-spatial/rgee/>, [https://r-](https://r-spatial.github.io/rgee/)
466 [spatial.github.io/rgee/](https://r-spatial.github.io/rgee/), <https://github.com/google/earthengine-api/>)
- 467 Bagnold, R. A. (1966). *An approach to the sediment transport problem from gen-*
468 *eral physics* (Report No. 422I). Retrieved from [http://pubs.er.usgs.gov/](http://pubs.er.usgs.gov/publication/pp422I)
469 [publication/pp422I](http://pubs.er.usgs.gov/publication/pp422I) doi: 10.3133/pp422I
- 470 Baker, D. B., Richards, R. P., Loftus, T. T., & Kramer, J. W. (2004). A new flash-
471 ness index: Characteristics and applications to midwestern rivers and streams.
472 *JAWRA Journal of the American Water Resources Association*, *40*(2), 503–
473 522.
- 474 Bennett, G., Kean, J., Rengers, F., Ryan, S., & Rathburn, S. (2017). Landslide-
475 channel feedbacks amplify flood response and channel erosion. In *EGU General*
476 *Assembly Conference Abstracts* (p. 14326).
- 477 Boothroyd, R. J., Williams, R. D., Hoey, T. B., Barrett, B., & Prasojo, O. A.
478 (2021). Applications of Google Earth Engine in fluvial geomorphology for
479 detecting river channel change. *Wiley Interdisciplinary Reviews: Water*, *8*(1),
480 e21496.
- 481 Brooke, S., Chadwick, A. J., Silvestre, J., Lamb, M. P., Edmonds, D. A., & Ganti,
482 V. (2022). Where rivers jump course. *Science*, *376*(6596), 987–990.
- 483 Brunner, M. I., Slater, L., Tallaksen, L. M., & Clark, M. (2021). Challenges in
484 modeling and predicting floods and droughts: A review. *WIREs Water*, *8*(3),
485 e1520. doi: <https://doi.org/10.1002/wat2.1520>
- 486 Bryndal, T., Franczak, P., Krocak, R., Cabaj, W., & Kołodziej, A. (2017). The im-
487 pact of extreme rainfall and flash floods on the flood risk management process
488 and geomorphological changes in small Carpathian catchments: a case study of
489 the Kasiniczanka river (Outer Carpathians, Poland). *Natural Hazards*, *88*(1),
490 95–120.
- 491 Chadwick, A., Steel, E., Williams-Schaetzel, R., Passalacqua, P., & Paola, C. (2022).
492 Channel migration in experimental river networks mapped by particle im-
493 age velocimetry. *Journal of Geophysical Research: Earth Surface*, *127*(1),
494 e2021JF006300.
- 495

- 496 Church, M. (2014). *The Regulation of Peace River: A Case Study for River Manage-*
 497 *ment*. Hoboken, UK: John Wiley & Sons.
- 498 Clubb, F. J., Weir, E. F., & Mudd, S. M. (2022). Continuous measurements of valley
 499 floor width in mountainous landscapes. *Earth Surface Dynamics*, 10(3), 437–
 500 456.
- 501 Constantine, J. A., Dunne, T., Ahmed, J., Legleiter, C., & Lazarus, E. D. (2014).
 502 Sediment supply as a driver of river meandering and floodplain evolution in
 503 the Amazon Basin. *Nature Geoscience*, 7(12), 899–903.
- 504 Copernicus. (n.d.). *Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-1C*.
 505 Retrieved from [https://developers.google.com/earth-engine/datasets/](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_HARMONIZED#description)
 506 [catalog/COPERNICUS_S2_HARMONIZED#description](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_HARMONIZED#description) (Accessed through
 507 Google Earth Engine)
- 508 Costa, J. E., & O'Connor, J. E. (1995). Geomorphically Effective Floods. *Natural*
 509 *and Anthropogenic Influences in Fluvial Geomorphology: AGU Geophysical*
 510 *Monograph*, 89, 45–56.
- 511 Dean, D. J., & Schmidt, J. C. (2013). The geomorphic effectiveness of a large flood
 512 on the Rio Grande in the Big Bend region: Insights on geomorphic controls
 513 and post-flood geomorphic response. *Geomorphology*, 201, 183–198.
- 514 Dethier, E. N., Renshaw, C. E., & Magilligan, F. J. (2022). Rapid changes to global
 515 river suspended sediment flux by humans. *Science*, 376(6600), 1447–1452.
- 516 Donovan, M., Belmont, P., & Sylvester, Z. (2021). Evaluating the relationship be-
 517 tween meander-bend curvature, sediment supply, and migration rates. *Journal*
 518 *of Geophysical Research: Earth Surface*, 126(3), e2020JF006058.
- 519 Edmonds, D. A., Martin, H. K., Valenza, J. M., Henson, R., Weissmann, G. S.,
 520 Miltenberger, K., ... Hajek, E. A. (2022, Jan). Rivers in reverse: Upstream-
 521 migrating dechannelization and flooding cause avulsions on fluvial fans. *Geol-*
 522 *ogy*, 50(1), 37–41. doi: 10.1130/G49318.1
- 523 Fuller, I. C. (2008). Geomorphic impacts of a 100-year flood: Kiwitea Stream, Man-
 524 awatu catchment, New Zealand. *Geomorphology*, 98(1-2), 84–95.
- 525 Gintz, D., Hassan, M. A., & Schmidt, K.-H. (1996). Frequency and magnitude
 526 of bedload transport in a mountain river. *Earth Surface Processes and Land-*
 527 *forms*, 21(5), 433–445.
- 528 Grill, G., Lehner, B., Thieme, M., Geenen, B., Tickner, D., Antonelli, F., ... Zarfl,
 529 C. (2019). Mapping the world's free-flowing rivers. *Nature*, 569(7755),
 530 215–221. Retrieved from [https://developers.google.com/earth-engine/](https://developers.google.com/earth-engine/datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description)
 531 [datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description](https://developers.google.com/earth-engine/datasets/catalog/WWF_HydroSHEDS_v1_FreeFlowingRivers#description)
 532 (Data accessed via Google Earth Engine)
- 533 Guzzetti, F., Ardizzone, F., Cardinali, M., Rossi, M., & Valigi, D. (2009). Land-
 534 slide volumes and landslide mobilization rates in Umbria, central Italy. *Earth*
 535 *and Planetary Science Letters*, 279(3-4), 222–229.
- 536 Higgins, A., Restrepo, J. C., Ortiz, J. C., Pierini, J., & Otero, L. (2016). Suspended
 537 sediment transport in the Magdalena River (Colombia, South America): Hy-
 538 drologic regime, rating parameters and effective discharge variability. *Internat-*
 539 *ional Journal of Sediment Research*, 31(1), 25–35.
- 540 Hofmeister, F., Arias-Rodriguez, L. F., Premier, V., Marin, C., Notarnicola, C.,
 541 Disse, M., & Chiogna, G. (2022). Intercomparison of Sentinel-2 and modelled
 542 snow cover maps in a high-elevation Alpine catchment. *Journal of Hydrology*
 543 *X*, 15, 100123.
- 544 Hooke, J. (2015). Variations in flood magnitude–effect relations and the implications
 545 for flood risk assessment and river management. *Geomorphology*, 251, 91–107.
- 546 Hooke, J. (2016). Geomorphological impacts of an extreme flood in SE Spain. *Geo-*
 547 *morphology*, 263, 19–38.
- 548 Huang, C., Chen, Y., Zhang, S., & Wu, J. (2018). Detecting, extracting, and mon-
 549 itoring surface water from space using optical sensors: A review. *Reviews of*
 550 *Geophysics*, 56(2), 333–360.

- 551 Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002).
 552 Overview of the radiometric and biophysical performance of the MODIS vege-
 553 tation indices. *Remote sensing of environment*, *83*(1-2), 195–213.
- 554 Isikdogan, L. F., Bovik, A., & Passalacqua, P. (2019). Seeing through the clouds
 555 with deepwatermap. *IEEE Geoscience and Remote Sensing Letters*, *17*(10),
 556 1662–1666.
- 557 Jarriel, T., Swartz, J., & Passalacqua, P. (2021). Global rates and patterns of chan-
 558 nel migration in river deltas. *Proceedings of the National Academy of Sciences*,
 559 *118*(46), e2103178118.
- 560 Johnson, P. A., Hey, R. D., Horst, M. W., & Hess, A. J. (2001, February). Aggrada-
 561 tion at bridges. *Journal of Hydraulic Engineering*, *127*(2), 154–157. Retrieved
 562 from [https://doi.org/10.1061/\(asce\)0733-9429\(2001\)127:2\(154\)](https://doi.org/10.1061/(asce)0733-9429(2001)127:2(154)) doi:
 563 10.1061/(asce)0733-9429(2001)127:2(154)
- 564 Kale, V. S. (2002). Fluvial geomorphology of Indian rivers: an overview. *Progress in*
 565 *physical geography*, *26*(3), 400–433.
- 566 Kale, V. S. (2003). Geomorphic Effects of Monsoon Floods on Indian Rivers.
 567 In M. M. Q. Mirza, A. Dixit, & A. Nishat (Eds.), *Flood Problem and Man-*
 568 *agement in South Asia* (p. 65–84). Dordrecht: Springer Netherlands. doi:
 569 10.1007/978-94-017-0137-2_3
- 570 Kale, V. S., & Hire, P. S. (2007). Temporal variations in the specific stream power
 571 and total energy expenditure of a monsoonal river: The Tapi River, India. *Ge-*
 572 *omorphology*, *92*(3-4), 134–146.
- 573 Klingler, C., Schulz, K., & Herrnegger, M. (2021). LamaH-CE: LARge-SaMple DAta
 574 for hydrology and environmental sciences for central Europe. *Earth System*
 575 *Science Data*, *13*(9), 4529–4565.
- 576 Langhorst, T., & Pavelsky, T. (2022). Global Observations of Riverbank Erosion and
 577 Accretion from Landsat Imagery. *Journal of Geophysical Research: Earth Sur-*
 578 *face*, e2022JF006774.
- 579 Larsen, I. J., Montgomery, D. R., & Korup, O. (2010). Landslide erosion controlled
 580 by hillslope material. *Nature Geoscience*, *3*(4), 247–251.
- 581 Leenman, A., Eaton, B., & MacKenzie, L. G. (2022). Floods on alluvial fans: impli-
 582 cations for reworking rates, morphology and fan hazards. *Journal of Geophysi-*
 583 *cal Research: Earth Surface*, *127*(2), e2021JF006367.
- 584 Lehner, B., Verdin, K., & Jarvis, A. (2008). New global hydrography derived from
 585 spaceborne elevation data. *Eos, Transactions American Geophysical Union*,
 586 *89*(10), 93–94.
- 587 Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest.
 588 *R News*, *2*(3), 18–22. Retrieved from [https://CRAN.R-project.org/doc/](https://CRAN.R-project.org/doc/Rnews/)
 589 [Rnews/](https://CRAN.R-project.org/doc/Rnews/)
- 590 Lindsay, J. B., & Ashmore, P. E. (2002). The effects of survey frequency on es-
 591 timates of scour and fill in a braided river model. *Earth Surface Processes*
 592 *and Landforms: The Journal of the British Geomorphological Research Group*,
 593 *27*(1), 27–43.
- 594 Magilligan, F. J., Buraas, E., & Renshaw, C. (2015). The efficacy of stream power
 595 and flow duration on geomorphic responses to catastrophic flooding. *Geomor-*
 596 *phology*, *228*, 175–188.
- 597 Magilligan, F. J., Phillips, J. D., James, L. A., & Gomez, B. (1998). Geomorphic
 598 and sedimentological controls on the effectiveness of an extreme flood. *The*
 599 *Journal of geology*, *106*(1), 87–96.
- 600 Marren, P. M. (2005). Magnitude and frequency in proglacial rivers: a geomorpho-
 601 logical and sedimentological perspective. *Earth-Science Reviews*, *70*(3-4), 203–
 602 251.
- 603 Martínez Silva, P., & Nanny, M. A. (2020). Impact of microplastic fibers from
 604 the degradation of nonwoven synthetic textiles to the Magdalena River water
 605 column and river sediments by the City of Neiva, Huila (Colombia). *Water*,

- 12(4), 1210.
- 606 Messenger, M. L., Lehner, B., Grill, G., Nedeva, I., & Schmitt, O. (2016). Es-
 607 timating the volume and age of water stored in global lakes using a geo-
 608 statistical approach. *Nature communications*, 7(1), 1–11. Retrieved from
 609 <https://gee-community-catalog.org/projects/hydrolakes/> (Accessed
 610 via Google Earth Engine)
- 612 Middleton, L., Ashmore, P., Leduc, P., & Sjogren, D. (2019). Rates of planimet-
 613 ric change in a proglacial gravel-bed braided river: Field measurement and
 614 physical modelling. *Earth Surface Processes and Landforms*, 44(3), 752–765.
- 615 Miller, A. J. (1990). Flood hydrology and geomorphic effectiveness in the central
 616 Appalachians. *Earth Surface Processes and Landforms*, 15(2), 119–134.
- 617 Morche, D., Schmidt, K.-h., Heckmann, T., & Haas, F. (2007). Hydrology and ge-
 618 omorphic effects of a high-magnitude flood in an alpine river. *Geografiska An-
 619 naler: Series A, Physical Geography*, 89(1), 5–19.
- 620 Nagel, G. W., de Moraes Novo, E. M. L., Martins, V. S., Campos-Silva, J. V., Bar-
 621 bosa, C. C. F., & Bonnet, M. P. (2022). Impacts of meander migration on the
 622 Amazon riverine communities using Landsat time series and cloud computing.
 623 *Science of The Total Environment*, 806, 150449.
- 624 Nanson, G. C., & Hickin, E. J. (1986). A statistical analysis of bank erosion and
 625 channel migration in western Canada. *Geological Society of America Bulletin*,
 626 97(4), 497–504.
- 627 Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution
 628 mapping of global surface water and its long-term changes. *Nature*, 540(7633),
 629 418–422.
- 630 Pfeiffer, A. M., Collins, B. D., Anderson, S. W., Montgomery, D. R., & Istanbul-
 631 luoglu, E. (2019). River bed elevation variability reflects sediment supply,
 632 rather than peak flows, in the uplands of Washington State. *Water Resources
 633 Research*, 55(8), 6795–6810.
- 634 Pickens, A. H., Hansen, M. C., Hancher, M., Stehman, S. V., Tyukavina, A.,
 635 Potapov, P., ... Sherani, Z. (2020). Mapping and sampling to characterize
 636 global inland water dynamics from 1999 to 2018 with full Landsat time-series.
 637 *Remote Sensing of Environment*, 243, 111792.
- 638 Restrepo, J. D., Kjerfve, B., Hermelin, M., & Restrepo, J. C. (2006). Factors
 639 controlling sediment yield in a major South American drainage basin: the
 640 Magdalena River, Colombia. *Journal of Hydrology*, 316(1-4), 213–232.
- 641 Rose, T., Erskine, W., & Miners, B. (2020). A customised approach to determining
 642 the geomorphic effectiveness of small flood events in a regulated river. *River
 643 Research and Applications*, 36(4), 580–594.
- 644 Rousel, J., Haas, R., Schell, J., & Deering, D. (1973). Monitoring vegetation systems
 645 in the Great Plains with ERTS. In *Proceedings of the Third Earth Resources
 646 Technology Satellite—1 Symposium; NASA SP-351* (pp. 309–317).
- 647 Rowland, J. C., Shelef, E., Pope, P. A., Muss, J., Gangodagamage, C., Brumby,
 648 S. P., & Wilson, C. J. (2016). A morphology independent methodology for
 649 quantifying planview river change and characteristics from remotely sensed
 650 imagery. *Remote Sensing of Environment*, 184, 212–228.
- 651 Schwenk, J., Khandelwal, A., Fratkin, M., Kumar, V., & Foufoula-Georgiou, E.
 652 (2017). High spatiotemporal resolution of river planform dynamics from Land-
 653 sat: The RivMAP toolbox and results from the Ucayali River. *Earth and Space
 654 Science*, 4(2), 46–75.
- 655 Slater, L. J. (2016). To what extent have changes in channel capacity contributed to
 656 flood hazard trends in England and Wales? *Earth Surface Processes and Land-
 657 forms*, 41(8), 1115–1128.
- 658 Slater, L. J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., ...
 659 Wilby, R. L. (2021). Nonstationary weather and water extremes: a review
 660 of methods for their detection, attribution, and management. *Hydrology and*

- 661 *Earth System Sciences*, 25(7), 3897–3935. doi: 10.5194/hess-25-3897-2021
- 662 Slater, L. J., Singer, M. B., & Kirchner, J. W. (2015). Hydrologic versus geomorphic
- 663 drivers of trends in flood hazard. *Geophysical Research Letters*, 42(2), 370–376.
- 664 doi: <https://doi.org/10.1002/2014GL062482>
- 665 Smith, D. G. (1986). Anastomosing river deposits, sedimentation rates and basin
- 666 subsidence, Magdalena River, northwestern Colombia, South America. *Sedi-*
- 667 *mentary Geology*, 46(3-4), 177–196.
- 668 Surian, N., Barban, M., Ziliani, L., Monegato, G., Bertoldi, W., & Comiti, F.
- 669 (2015). Vegetation turnover in a braided river: frequency and effectiveness
- 670 of floods of different magnitude. *Earth Surface Processes and Landforms*,
- 671 40(4), 542–558.
- 672 Sylvester, Z., Durkin, P., & Covault, J. A. (2019). High curvatures drive river mean-
- 673 dering. *Geology*, 47(3), 263–266.
- 674 Tunncliffe, J., Brierley, G., Fuller, I. C., Leenman, A., Marden, M., & Peacock, D.
- 675 (2018). Reaction and relaxation in a coarse-grained fluvial system following
- 676 catchment-wide disturbance. *Geomorphology*, 307, 50–64.
- 677 Valenza, J., Edmonds, D., Hwang, T., & Roy, S. (2020). Downstream changes in
- 678 river avulsion style are related to channel morphology. *Nature communications*,
- 679 11(1), 1–8.
- 680 Wasko, C., & Guo, D. (2022). Understanding event runoff coefficient variability
- 681 across Australia using the hydroEvents R package. *Hydrological Processes*,
- 682 36(4), e14563.
- 683 Webb, B., & Walling, D. (1982). The magnitude and frequency characteristics
- 684 of fluvial transport in a Devon drainage basin and some geomorphological
- 685 implications. *Catena*, 9(1-2), 9–23.
- 686 Wickert, A. D., Martin, J. M., Tal, M., Kim, W., Sheets, B., & Paola, C. (2013).
- 687 River channel lateral mobility: Metrics, time scales, and controls. *Journal of*
- 688 *Geophysical Research: Earth Surface*, 118(2), 396–412.
- 689 Wolman, M. G., & Gerson, R. (1978). Relative scales of time and effectiveness of cli-
- 690 mate in watershed geomorphology. *Earth surface processes*, 3(2), 189–208.
- 691 Wolman, M. G., & Miller, J. P. (1960). Magnitude and frequency of forces in geo-
- 692 morphic processes. *The Journal of Geology*, 68(1), 54–74.
- 693 Xu, H. (2006). Modification of normalised difference water index (NDWI) to en-
- 694 hance open water features in remotely sensed imagery. *International journal of*
- 695 *remote sensing*, 27(14), 3025–3033.
- 696 Yousefi, S., Mirzaee, S., Keesstra, S., Surian, N., Pourghasemi, H. R., Zakizadeh,
- 697 H. R., & Tabibian, S. (2018). Effects of an extreme flood on river morphology
- 698 (case study: Karoon River, Iran). *Geomorphology*, 304, 30–39.
- 699 Zou, Z., Xiao, X., Dong, J., Qin, Y., Doughty, R. B., Menarguez, M. A., ... Wang,
- 700 J. (2018). Divergent trends of open-surface water body area in the contigu-
- 701 ous United States from 1984 to 2016. *Proceedings of the National Academy of*
- 702 *Sciences*, 115(15), 3810–3815.

1 **Supplementary Material: Quantifying geomorphically**
2 **effective floods using satellite observations of river**
3 **mobility**

4 **A. S. Leenman¹, L. J. Slater¹, S. J. Dadson^{1,2}, M. Wortmann^{1,3} and R.**
5 **Boothroyd⁴**

6 ¹School of Geography and the Environment, University of Oxford, UK

7 ²UK Centre for Ecology and Hydrology

8 ³European Centre for Medium-Range Weather Forecasts

9 ⁴School of Geographical and Earth Sciences, University of Glasgow

Corresponding author: Anya Leenman, anya.leenman@chch.ox.ac.uk

Table 1. The r^2 values for the relationships in Figure 2 (main manuscript), for each individual country. ‘Av. mag.’ is the mean peak height in cm (measured above the gauge’s mean daily stage) across all flood events in that country. ‘Av. total’ is the mean (across all floods in a country) of the total water level (in cm) exceeding mean stage. ‘Av. dur.’ is the mean flood duration (in days) in that country. ‘Av. widening’ is the mean reach-averaged widening (in m) across all floods and sites in that country.

Country	r^2 , Peak height above mean stage (cm)	r^2 , Stage above mean, summed (cm)	r^2 , Duration (days)	N. floods	N. gauge sites	Av. mag.	Av. total	Av. dur.	Av. widening
Brazil	-0.018	0.219	0.293	47	10	230	4100	53	1.90
Colombia	0.110	0.321	0.442	87	22	160	5300	57	7.30
New Zealand	0.796	0.278	0.171	11	1	190	1100	29	0.92
Russia	0.348	0.082	0.081	15	8	150	3700	71	3.20

Table 2. The variables used in the random forest model. Column 1 shows how each variable contributed to reducing MSE. The final column shows the rank assigned to each variable by the random forest regression.

% Decr. in MSE	Variables	Rank
22.18	Estimated sediment transport	1
16.77	Channel width	2
15.65	Duration	3
8.54	Total stage exceeding mean	4
7.61	Peak height above mean daily stage	5

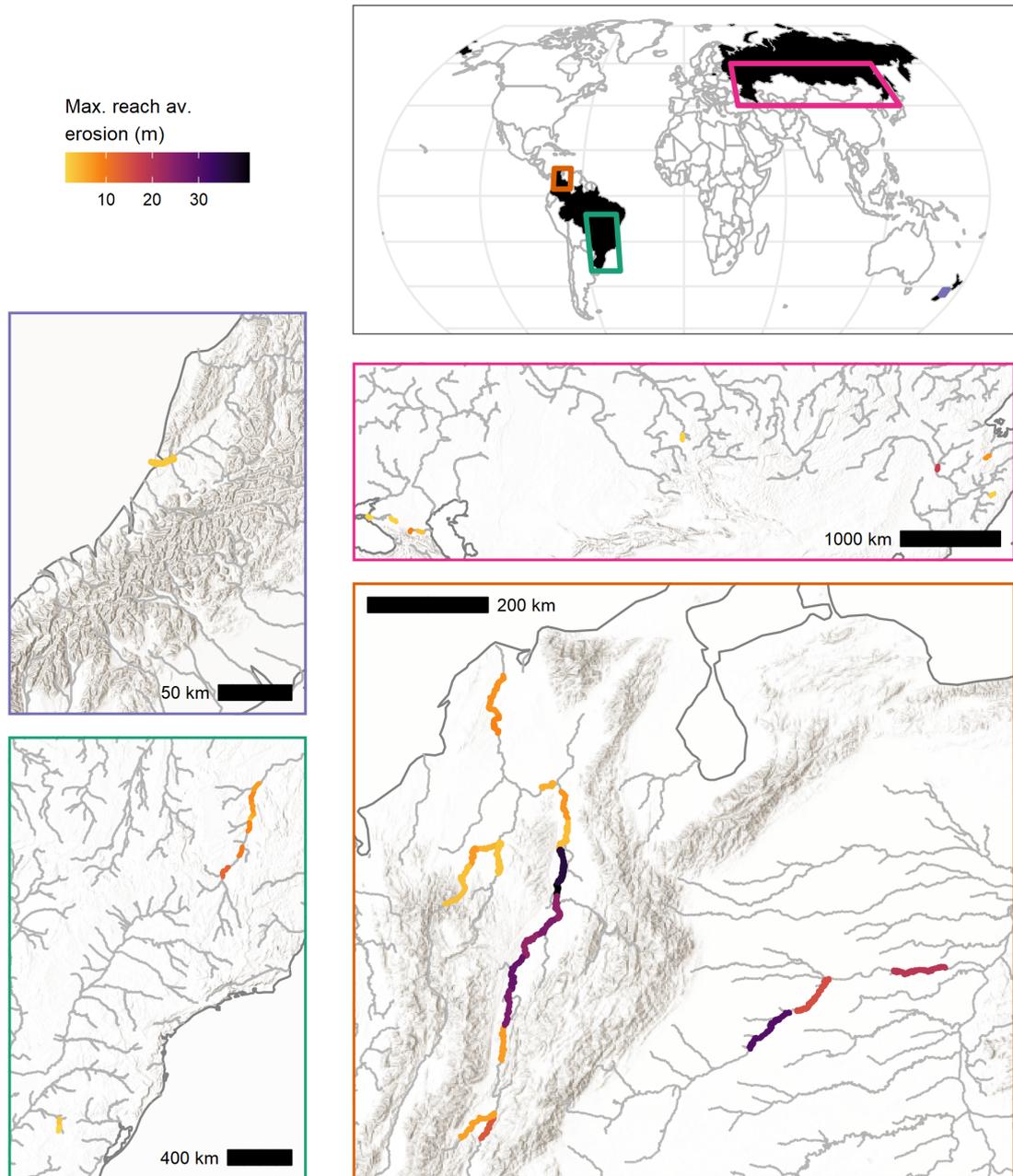


Figure 1. Map showing the areas of interest (AOIs) associated with each gauge. Colors show the magnitude of reach-averaged widening (in metres) during the most effective flood at each site.

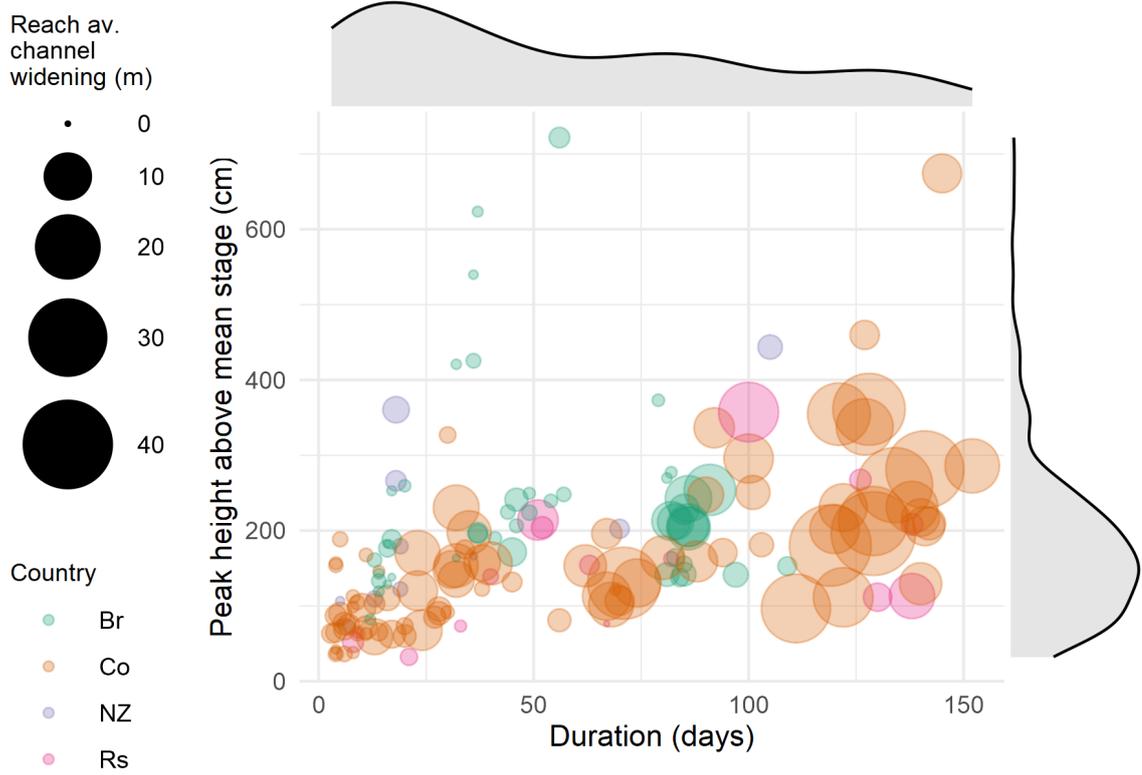


Figure 2. Duration, magnitude (peak height) and geomorphic effectiveness (reach-averaged erosion) for each flood event in our dataset. Each point is one flood event; colours correspond to countries and size corresponds to geomorphic effectiveness of each flood.

1 Sediment transport capacity

We estimated sediment transport capacity based on the stage and slope data available to us. Sediment transport equations often predict transport as the $\frac{3}{2}$ power of some flow property — often that which exceeds a threshold value at which sediment of a given size can be entrained (Church, 2010). Often that flow property is the dimensionless shear stress τ_* , but we have no data on grain size with which to calculate this. Instead, we approximate the dimensional boundary shear stress τ , which scales with the depth-slope product dS . We have no data on flow depth and approximate it with flow stage h instead; our estimates of channel slope S are calculated along the area of interest polygon for each gauging site using elevation data from the MERIT DEM (Yamazaki et al., 2017).

We therefore estimate unit sediment transport q_s as a function of stage and slope. We do not have data on the threshold for motion in our study sites, so we assume that the threshold is 25% of the difference between minimum and maximum stage in each gauge record, during the ~7 year period for which we have satellite data. While arbitrary, this value of 25% is based on a literature search for reported values of the onset of transport as a percentage of peak discharge, and it also performed better than other thresholds we tried.

We thus estimate a flood’s cumulative transport as a function of changes in stage:

$$q_s = \sum_1^n ((h - h_{r25})S)^{\frac{3}{2}} \quad (1)$$

where n is the total number of days in the flood, h is the stage value for each day, $r25$ is the stage that is 25% of the difference between the minimum and maximum stage during the satellite record, and S refers to the channel slope. We performed this calculation for each day in a flood and summed across the entire event.

Finally, we multiply q_s by channel width to estimate the channel-integrated (total) sediment transport Q_s . While q_s did not scale with erosion as well as the flood duration or summed hydrograph did, the estimated Q_s scaled rather closely ($r^2 = 0.63$) with each flood’s geomorphic effectiveness (Figure S3). It is Q_s that we used in our random forest model.

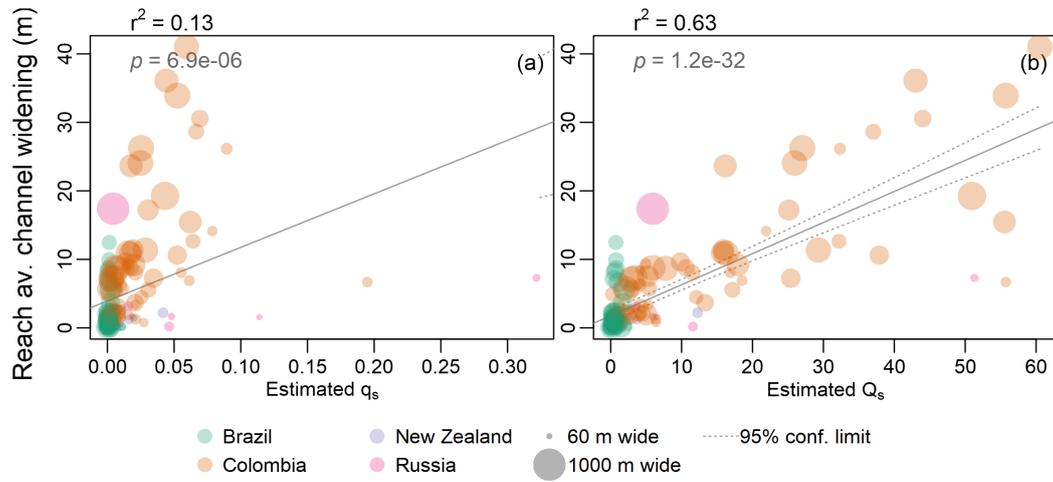


Figure 3. Linear regression of flood-driven erosion (reach-averaged) against our estimates of the cumulative sediment transport capacity of each hydrograph: (a) unit transport q_s (b) integrated (total) transport Q_s .

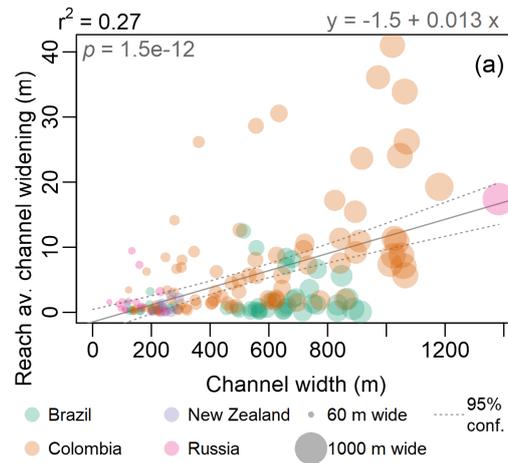


Figure 4. Linear regression of flood-driven erosion (reach-averaged) against mean channel width prior to each flood.

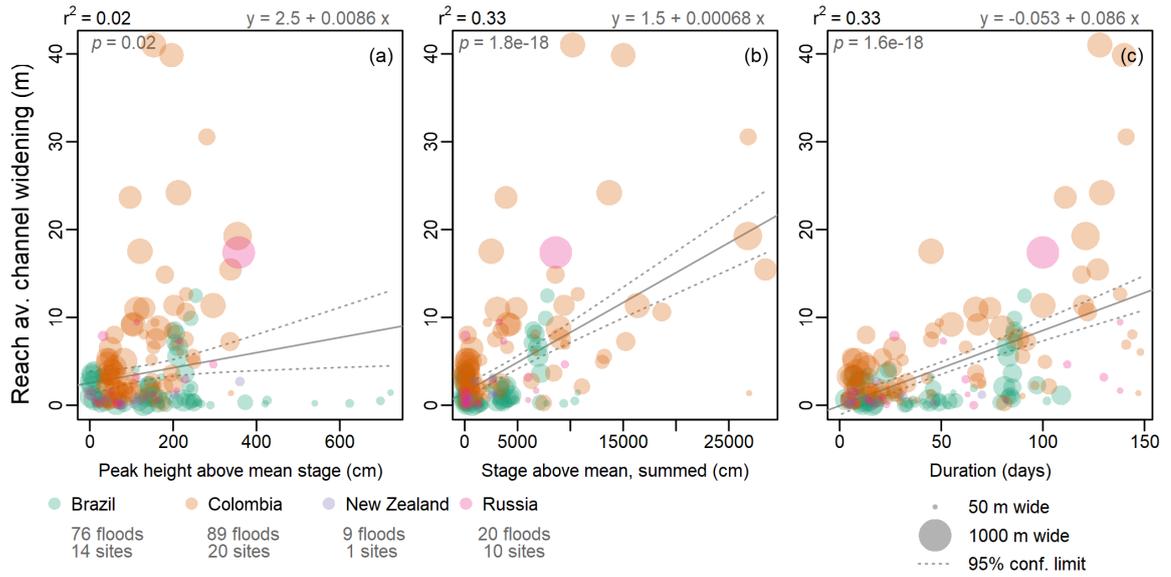


Figure 5. The results in Figure 2 (main manuscript) when the flood-delineation threshold is lowered to the 70th percentile of stage.

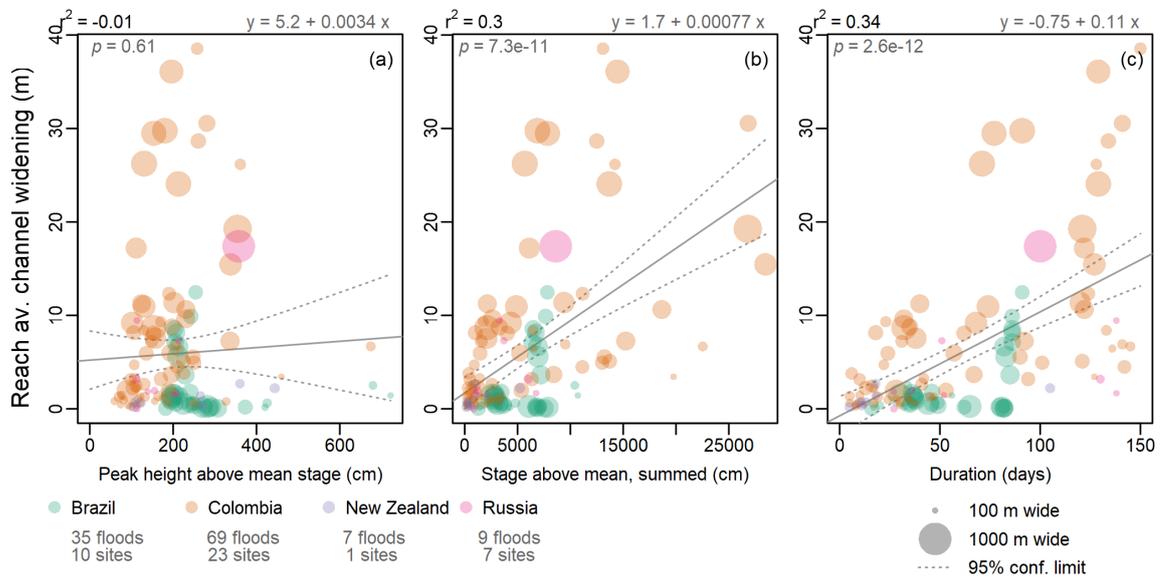


Figure 6. The results in Figure 2 (main manuscript) when the flood-delineation threshold is raised to the 90th percentile of stage.

37 **References**

- 38 Church, M. (2010). Gravel-Bed Rivers. In T. Burt & R. Allison (Eds.), *Sediment*
39 *Cascades: An Integrated Approach* (p. 241-269). Chichester: Wiley-Blackwell.
- 40 Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O'Loughlin, F., Neal,
41 J. C., ... Bates, P. D. (2017). A high-accuracy map of global terrain ele-
42 vations. *Geophysical Research Letters*, *44*(11), 5844–5853. Retrieved from
43 [https://developers.google.com/earth-engine/datasets/catalog/](https://developers.google.com/earth-engine/datasets/catalog/MERIT_DEM_v1_0_3#description)
44 [MERIT_DEM_v1_0_3#description](https://developers.google.com/earth-engine/datasets/catalog/MERIT_DEM_v1_0_3#description) (Data accessed via Google Earth Engine)