Smartrock Transport in a Mountain Stream: Bedload Hysteresis and Changing Thresholds of Motion

Kealie L. G. Pretzlav1,2, Joel P. L. Johnson1, and D. Nathan Bradley3

1Department of Geological Sciences, The University of Texas at Austin, Austin, TX, USA, 2Now at Balance Hydrologics, Berkeley, CA, USA, 3U.S. Bureau of Reclamation, Denver, CO, USA

Abstract

Bedload movement is fundamentally probabilistic. Our quantitative understanding of gravel transport is particularly limited when flow conditions just exceed thresholds of motion, in part because of difficulties in measuring transport statistics during natural floods. We used accelerometer-embedded tracer clasts to precisely measure the timing of grain motions and rests during snowmelt floods in Halfmoon Creek, a gravel-bed mountain stream in Colorado, USA. These new data let us explore how probabilities of tracer movement varied as functions of discharge and time. Bedload hysteresis occurred over both daily and seasonal timescales and included clockwise, counterclockwise, and figure-eight patterns. We empirically explain the hysteresis by modifying a bedload transport model to have an evolving threshold of motion parameter. We calculate how the thresholds of motion progressively evolved through time over 22 days during the 2015 snowmelt flood. Our results quantitatively show that thresholds of motion are functions of both (a) cumulative shear stress and (b) temporal changes in shear stress during floods.

Plain Language Summary

Predicting the effects of floods on mountain river channels remains difficult but is important because floods affect people, communities, and ecosystems. Our research shows that the amount and timing of gravel transported downstream depends not only on how much water is flowing in the channel but also on the “history” of flow and sediment movement that has occurred previously during the flood or previous recent floods. We developed “smartrocks” that each hold sensors and batteries to measure the exact timing of movement of these artificial tracer gravels. We collected field data during a month-long flood in a stream in the Rocky Mountains near Leadville, Colorado, USA. By measuring exactly when rocks move during floods, we can better understand how to predict when channels will be stable or will change during future floods of different sizes and how much change is likely to occur.

1. Introduction

Predicting bedload transport and corresponding erosion and deposition during floods of different sizes is important for the effective management of natural and engineered river systems. Changes in sediment transport can also affect ecosystem health. Supplies of water and sediment to river channels are perturbed by human land use, flow diversions, check dams and reservoirs, and also by climate-related changes in flood frequency and magnitude. Bedload transport in gravel-bed rivers is controlled not only by spatial and temporal variations in flow but also by “thresholds” for grain motion (e.g., Buffington & Montgomery, 1997; Bunte et al., 2013; Church et al., 1998; Yager et al., 2018). Many of the simplest yet arguably most widely used bedload transport models have a typical form of \( q_s \propto (\tau - \tau_{cr})^{1/2} \), empirically assuming that transport rate \( q_s \) is a power-law function of just two variables: shear stress \( \tau \) (a function of discharge) and a threshold parameter \( \tau_{cr} \) (e.g., Meyer-Peter & Müller, 1948; Wong & Parker, 2006).

In practice, \( \tau_{cr} \) is commonly a model-dependent fitting parameter back-calculated from constraints on \( q_s, \tau \), and grain size rather than an absolute threshold (e.g., Paintal, 1971; Wilcock & Crowe, 2003; Wong & Parker, 2006). In transport models, \( \tau_{cr} \) affects \( q_s \) even when flow exceeds threshold conditions. Different bedload transport models result in different best-fit \( \tau_{cr} \) when applied to the same transport data set (e.g., Rickenmann, 2018). A second approach to quantifying thresholds of motion is to directly measure when grains of a given size first begin to move downstream (e.g., Paphitis & Collins, 2005; Yalin, 1972). This approach provides a threshold measure that is independent of particular bedload models but also less accurate for transport rate predictions using equations and can be challenging to objectively apply in practice (e.g., Buffington & Montgomery, 1997).
Even at a given discharge, gravel transport rates in individual rivers can span orders of magnitude (e.g., Lenzi et al., 2004; Rickenmann, 2001, 2018; Turowski et al., 2011). Compilations of \( \tau_c \) measurements similarly exhibit a great deal of scatter for the same general conditions (e.g., Buffington & Montgomery, 1997; Lamb et al., 2008). While bedload transport models have traditionally assumed that thresholds are temporally constant, factors related to grain interactions such as clast clustering, sheltering and protrusion, overlapping and interlocking, packing density, surface roughness, force chain development, sand and gravel supply, and local erosion and deposition have been shown to influence thresholds of motion and can also evolve through time in response to flow history (e.g., Hassan et al., 2020; Kirchner et al., 1990; Marquis & Roy, 2012; Masteller & Finnegan, 2017; Ockelford & Haynes, 2013; Recking, 2012; Rickenmann, 2018; Sanguinito & Johnson, 2012; Wilcock & Crowe, 2003; Yager et al., 2012). Using field data, Turowski et al. (2011) found systematic differences in the discharges at which bedload transport started and ended and started again from one flood to the next, suggesting systematic changes in thresholds. Building on these results, Masteller et al. (2019) demonstrated that \( \tau_c \) tended to progressively increase over seasonal timescales in response to small to intermediate high flow events. In contrast, the largest floods caused thresholds to decrease. Johnson (2016) developed equations to describe the temporal evolution of \( \tau_c \) as a function of sediment supply and local erosion and deposition and compared them to laboratory experiments. Yager et al. (2018) combined field, laboratory, and numerical model constraints to argue that friction between grains is a key control on thresholds of motion.

Bedload hysteresis is a specific example of discharge-dependent transport variability that is almost always observed in both field and laboratory settings (e.g., Alexandrov et al., 2007; Mao et al., 2014; Meirowich et al., 1998; Moog & Whiting, 1998; Olinde & Johnson, 2015). Current bedload transport models have difficulty predicting hysteresis. Clockwise hysteresis (higher transport rates on rising limbs of hydrographs) is sometimes attributed to gradual decreases in sediment availability or to progressive increases in bed surface stability through the evolution of structures such as coarse grains clustering or the degree of surface armor (e.g., Mao, 2012; Roth et al., 2014). Counterclockwise hysteresis (higher transport rates on falling limbs) can be caused by temporal lags as bedforms adjust to changing discharge (Bombard et al., 2011; Martin & Jerolmack, 2013) or to the destabilization of surface structures during hydrograph rising limbs (Kühne, 1992). Many of these mechanisms proposed to explain hysteresis have also been shown to cause changes in thresholds of motion. Bedload equations such as \( q_s \propto (\tau - \tau_c)^{1/2} \); could predict transport hysteresis if \( \tau_c \) evolved systematically through time.

The overall goal of the present research is to better understand how and why bedload transport probabilities and corresponding thresholds of motion change in response to river discharge during floods. Over what timescales do thresholds evolve? How well (or poorly) can we predict timeseries of threshold changes from timeseries of discharge? What physical mechanisms for threshold evolution are consistent with our smartrocks-based constraints on transport probabilities?

Instrumented tracer particles offer great potential for improving our statistical understanding of coarse particle transport in Earth surface processes, but their use also poses many challenges (e.g., Ergenzinger & Jupner, 1992; Gimbert et al., 2019; Gronz et al., 2016; Habersack, 2001; Maniatis et al., 2017; McNamara & Borden, 2004). Ergenzinger and Jupner (1992) developed a tracer cobble instrumented with pressure transducers to calculate relative drag and lift forces acting on grains. Habersack (2001) and McNamara and Borden (2004) used different tracer technologies to constrain hop lengths and hop and rest durations. Olinde and Johnson (2015) used concrete-encased accelerometer tracers to measure the timing of bedload motion during snowmelt floods in Reynolds Creek, Idaho, USA. They used Onset HOBO Pendant G data loggers which have ample battery life but limited data storage. Sensors were sampled once every 10 min, which allowed them to determine if a given particle had moved in the last 10 min. However, the duration and number of particle hops were unknown over shorter timescales. Because one of the goals of this work has been to improve the design of instrumented tracer “smartrocks,” we next describe our sensors, their new housings, and equipment limitations. Methods developed for data analysis include an algorithm to infer rest and hop durations from our time series of particle acceleration, validated using flume experiments. We then use our field data to calculate how transport probabilities changed through time.
2. Methods

2.1. Tracer Design and Motion Sensor Technology

The “smartrock” tracers we developed for this study sample nearly 4 orders of magnitude faster than those of Olinde and Johnson (2015), letting us measure the precise timing and duration of motions and rests. We chose an off-the-shelf motion sensor from Gulf Coast Data Concepts which used an InvenSense 9150 9-axis inertial measurement unit (IMU). This MEMS (Micro-Electro-Mechanical) microchip-based device contains a 3-axis accelerometer that can measure various ranges up to ±16 g, a 3-axis gyroscope that can measure up to ±2000°/s, and, a compass with a 3-axis ±1,200 μT magnetometer (Figure 1). We were unable to customize these overall manufacturer specifications, although we measured accelerations at a higher resolution of ±2 g in order to more precisely measure particle orientation with respect to gravity (described further in section 2.4). Neither this acceleration range nor the sampling rate were close to sufficient to measure impact accelerations or forces (e.g., Gimbert et al., 2019). The IMU can sample at up to 100 Hz, but because faster sampling consumes more power, a slower rate of 10 Hz was chosen to balance duration of data collection with data resolution. Each sensor was powered using three 3.6 V, 2.6 Ah nonrechargeable lithium batteries connected in parallel, which together powered the devices for a median duration of 40 days. These batteries had the same dimensions as common 1.5 V AA batteries. Each sensor recorded data on a micro SD card. Battery life, rather than data storage, limited data collection. Each tracer also held a backup HOBO Pendant G logger, which sampled three orthogonal axes of acceleration once every 10 min. These allowed data to be logged for approximately 5 months, ensuring that we would have some constraint on motions that occurred after batteries failed in the other sensors.

Each motion sensor was enclosed in a custom manufactured case which we designed (Figure 1). We chose an ellipsoid-like shape for the case with major, intermediate, and minor axis diameters of 12.0, 7.2, and 6.4 cm, respectively, representing a small cobble. These dimensions were chosen to make the tracers as small as possible (enabling transport in a broader range of flow conditions) while being able to fit the motion sensors, batteries, and a circular 30 mm RFID tag inside. Accounting for void space, batteries, and sensor components, the bulk tracer density was 2.65 g/cm³. Two identical halves were held together in four places with bolts and nuts resistant to loosening. An O-ring helped prevent water from entering the cavity (Figure 1).

![Figure 1. Tracer high-density plastic case with HOBO, IMU, and battery pack (left, mostly covered in black electrical tape) visible. The tape measure is in centimeter. Major, intermediate, and minor axis diameters are 12.0, 7.2, and 6.4 cm, respectively. X, Y, and Z axes for the IMU are indicated.](Image)
The cases were made of high density plastic (nylon embedded with copper powder). Although preliminary testing suggested that RFID tags would be readable through this plastic, after production, we found that the dispersed copper powder, batteries, and sensors were unfortunately sufficient to block the RFID signals (proximity to metal interferes with radio frequencies). Therefore, passive RFID tags were used for identification purposes when cases were open, but tracers were found visually on the stream bed and by using a metal detector when buried.

2.2. Study Site: Halfmoon Creek, Colorado, USA

Previous bedload transport studies conducted in Halfmoon Creek, a gravel-bed stream that drains Mount Elbert and Mount Massive in Colorado, USA (Figure 2a), include Torizzo and Pitlick (2004), Mueller and Pitlick (2005), Bunte and Swingle (2005), Bradley and Tucker (2012), and Bradley (2017). The drainage area at the study site is approximately 61.5 km², and the elevation is approximately 3,015 m. There are no
significant tributaries between our study site and USGS gage 07083000 located 1.5 km downstream. The gage has operated continuously since August 1946. Discharge is dominated by spring snowmelt and produces a seasonal flood that typically lasts from mid-May to mid-July, with daily discharge peaks. For simplicity, we refer to the daily high-flow events as daily “floods” regardless of whether they exceeded bankfull. The seasonal 2015 flood peaked at 11.5 m³/s on 17 June (Figure 2b). Based on a 69-year record, this discharge had a 10-year recurrence interval.

The study reach is alluvial, with bed-surface grain sizes ranging from fine gravel to meter-scale boulders. Using a ruler, we measured median surface grain sizes ($D_{50}$) of 6.4 and 12.9 cm based on Wolman-type pebble counts ($N = 400$) in two short reaches (Figure 2a,c). $D_{50}$ for both locations was about 29 cm. Our 7.2 cm intermediate axis tracers correspond to the 51st and 40th percentiles of surface grain sizes in the upstream and downstream locations, respectively. Bradley and Tucker (2012) reported $D_{50} = 5.5$ cm measured over a somewhat longer reach which includes our study area. Mueller and Pitlick (2005) report surface $D_{50}$ between 5.0 and 7.2 cm for six reaches within ~2 km upstream and downstream of the gaging station. Considering the reach-scale variability in grain sizes, we estimate that our tracer with intermediate axis of 7.2 cm is a reasonable approximation of the reach-averaged $D_{50}$.

In this reach, the thalweg of the channel is approximately 1 m below the banks, the channel is $≈7$ m wide, and the slope is 0.005. While the reach channel cross-section is relatively rectangular, there is a well-defined thalweg between several low-angle alternating bars. There is a large bar on the inside of a sharp channel bend approximately 200 m downstream of the deployment location (Figure 2a). The longer study reach from Bradley and Tucker (2012) is $≈10$ m wide with a slope of $≈1\%$. Mueller and Pitlick (2005) report slopes over similar longer reaches of 0.0084–0.0086. Bunte et al. (2008) report $S = 0.014$ and bankfull width 8.6 m for a reach $~2.5$ km downstream of ours.

This field site was chosen for several reasons. First, the timing of snowmelt floods is predictable, usually peaking in late May or early June. Due to limited battery life, predictability in the timing of flood above transport thresholds was important. Second, Bradley and Tucker (2012) conducted a multi-year passive tracer campaign in this reach which provides important context for this study. Finally, the stream is wadeable at low flow, allowing tracer recovery necessary to retrieve the motion data.

2.3. Field Methods

We deployed 33 motion tracers on 13 May 2015 in Halfmoon Creek, Colorado, in a similar location to the RFID-embedded tracers deployed by Bradley and Tucker (2012) (Figure 2a). Tracers were positioned across the width of the portion of the channel that was subaqueous at the time of deployment. Following the methodology of Bradley and Tucker (2012), tracers were placed on the streambed inside the pocket made by gently removing a similarly sized grain, with the goal of minimizing enhanced mobility during the first few motions. Deployment occurred when channel discharge was approximately 0.8 m³/s, well below the threshold of motion for the tracers. Pressure transducers (HOBO depth loggers) were installed in two locations in our study reach near the channel bank and recorded the water depth at each location once every 5 min (Figure 2a).

Tracers were recovered in October 2015, when the stream discharge was approximately 0.3 m³/s and easily wadeable. We were able to recover 27 of the 33 deployed tracers, an 82% recovery rate. Search efforts extended approximately 400 m downstream beyond the farthest recovered tracer; 23 of the 27 recovered tracers were on the bed surface and were found by eye. Four recovered tracers were buried below the surface and were located with a metal detector. Because the remaining six unrecovered tracers were likely buried, our data may have a bias toward surface grains. Deployment positions were surveyed using a total station with sub-centimeter resolution. Recovery positions were measured with a Trimble XT GPS giving ±1 m accuracy after post-processing. Of the 27 recovered, five tracer housings leaked due to subtle unrecognized warping of the housings during manufacture, and those IMUs did not record any motions before logging failed. One IMU logger malfunctioned despite remaining dry. The following analysis uses data recorded by the remaining 21 tracers. Total logging times ranged from 24 to 51 days, with 50% of recovered tracers lasting 40 days. The HOBOs recorded data once every 10 min until recovery in October, although some stopped logging prematurely.
2.4. Algorithm to Identify Motions and Rests

The accelerometer and gyroscope record the near-instantaneous acceleration and rate of rotation along three axes (x, y, and z) at 10 Hz. We use these data to detect the timing of particle entrainment and disentrainment. In practice, raw sensor data are noisy, and the motion sensors record all grain movements including wobbling of grains in place. We therefore developed a simple empirical algorithm using acceleration, rotation, and duration thresholds to identify motions which likely correspond to downstream translation of the particle. Controlled laboratory experiments were used to validate the algorithm and calibrate its parameters.

When a particle is at rest, the gyroscope records a rotation rate of zero for all three axes. When at rest, the accelerometer feels gravity and should record a vector sum of acceleration of \( \sqrt{A_x^2 + A_y^2 + A_z^2} \) equal to 1 g (where g is gravitational acceleration, 9.81 m/s\(^2\), and \( A_x, A_y, \) and \( A_z \) are accelerations measured along each axis). In practice, noise on the accelerometers produces a vector sum of 1 ± 0.1 g at rest. Changes in acceleration on different axes as well as nonzero gyroscope readings should indicate particle motion. To remove acceleration noise during rests while preserving acceleration changes indicating motion, we applied a 2-s moving window median filter to accelerations along all three axes. Cobble motion is generally initiated as a grain rotation out of a bed pocket. Significant acceleration changes may not be detected on all three axes because the change in acceleration of a given axis can vary from 0 to 1 g depending on the particle orientation relative to the axis of rotation. Therefore, entrainment was detected when the value of the filtered accelerometer data of at least one axis changed by 0.1 g/s. We found that the gyroscope data were most effective at determining when a particle movement ended. A tracer particle was considered at rest when the gyroscope reading falls below an empirically derived threshold (0.3 rad/s) for any of the three axes. Motions and rests are only detected if they persist for two or more samples (0.2 s).

Flume experiments were used to evaluate and calibrate the algorithm and suggest that it accurately identifies movements >0.5 s in duration. We video-recorded a sample tracer in a 0.5 m wide laboratory flume with a mobile gravel bed, and compared manually detected motions from the video to the motion detection algorithm (Figure 3). To make sure the timing of entrainments and disentrainments was clearly observable in the video, we set the flume discharge to be large enough to maintain motion if the particle was already in motion, but not too large so that the particle would instantly begin moving once placed on the bed. Throughout the test, the particle was placed on the bed surface in the upstream portion of the video.
frame and then pushed slightly by hand to initiate motion. Once the particle reached the edge of the video frame and stopped moving, we repositioned the tracer to the upstream portion of the video frame. The threshold values (0.1 g/s, 0.3 rad/s) were determined in order to allow all observed displacements to be identified correctly. Two instances of particle wobble (that occurred at 500 and 740 s on the timeline in Figure 3) and three impacts by another larger cobble (at 540, 550, and 690 s) were correctly not identified as motions.

While the algorithm reasonably identifies particle entrainment and disentrainment, the flume test revealed two limitations. First, in two instances, a single motion was incorrectly identified as two motions separated by a brief 0.2 s rest when the particle stopped rotating and momentarily slid across the pea gravel surface. The algorithm only detects particle rotations as a motion indicating displacement downstream and not pure sliding with no rotation. However, the coarse and rough bed surface in Halfmoon Creek means that our ellipsoid-like tracer particles are not likely to be able to slide across the bed surface without rotation very often. Second, two brief motions were identified when the particle was not actually displaced, approximately 580 and 810 s into the test. In both cases, the particle was artificially jostled by a hand resulting in a permanent rotation but not displacing it downstream (arrows in Figure 3). This would most likely occur in the field when a particle partially rotates up from the bed but does not fully exit its pocket. The results suggest that identified motions briefer than about 0.5 s may be less reliably detected than longer-duration motions. We assume that these uncertainties in detecting movements are acceptable for our analyses. Overall, the algorithm identified 15,578 motions in our dataset, with 6.7% shorter than 0.5 s.

2.5. Hydraulic Forcing and Bedload Transport Probabilities

To frame results in terms of hydraulic forcing, we calculate bed shear stress \( \tau \) using the depth-slope product, \( \tau = \rho ghS \), where \( \rho \) is water density (1,000 kg/m\(^3\)) and \( h \) is water depth. For reach slope \( S \), we use the average water surface slope between the two pressure transducers, 0.5%. Unfortunately, temporal changes in water surface slope were not resolved with sufficient accuracy relative to noise in the pressure transducer data, and so for simplicity, we assume that the water surface slope remained at 0.5% during both rising and falling limbs of the floods. We also confirmed that the reach bed slope was 0.5% using the surveyed recovery positions of the tracers. To determine water depths from the pressure transducer records (Figure 2a) we surveyed the average vertical distance between the pressure transducers and the channel thalweg. The two depth records were averaged so the time series of shear stress best represented reach-averaged conditions. We used depths averaged along the thalweg because previous work suggests that lateral transport down side slopes causes bedload to preferentially move along topographic lows (i.e., the thalweg) where shear stresses tend to be highest (e.g., Johnson & Whipple, 2010; Segura & Pitlick, 2015; Sekine & Parker, 1992). Consistent with this, smartrocks were preferentially recovered along the thalweg, which followed the outer banks of study reach channel bends (Figure 2a). Finally, we calculate dimensionless shear stress (Shields stress) as

\[
\tau^* = \frac{\tau}{(\rho_s - \rho)gD},
\]

where \( \rho_s \) is sediment density (2,650 kg/m\(^3\)) and \( D \) is intermediate tracer diameter (0.072 m).

From the time series of tracer motions and rests, we calculate the probability of transport, \( P_q \), as follows:

\[
P_q = \frac{n_m}{n_s},
\]

where \( n_m \) is the number of measurements that indicate a particle is in motion and \( n_s \) is the total number of measurements in that sampling interval, calculated for all of the tracers recording data over a given time interval. For temporal calculations of \( n_s \), we used 10 min intervals. For example, 10 tracers recording data over 10 min at a sampling frequency of 10 Hz would correspond to 60,000 total records, so \( n_s = 60,000 \). If, during the same interval and for the same tracers, we detected that 120 of these measurements (0.1 s each sample) indicated motion, then \( n_m = 120 \) and \( P_q = 120/60,000 \).

3. Results

Beginning 3 June 2015 (21 days after deployment), there were 28 consecutive days with some tracer transport. The following analysis of hysteresis and thresholds of motion is limited to the first 22 diurnal flood
events because subsequent days had too few movements to meaningfully calculate hysteresis and thresholds (Figure 4a). Discharge increased over the first 15 days and then decreased (Figure 4a). Superimposed diurnal floods are defined from the flow minimum of 1 day to the next. We began with a population of 21 functional tracers. Different sensors stopped working at different times (Figure 4b), and our calculations of $P_q$ account for decreasing numbers of functional tracers. Olinde and Johnson (2015) calculated $P_q$ in the same way, but since their motion sensors sampled once every 10 min, values of $n_s$ represent fewer samples collected in a period of time. As a result, our $P_q$ values are much lower than those presented in Olinde and Johnson (2015).

We first explore how transport probabilities varied with Shields stress (Figure 5). Rather than binning in time, samples ($n_s$) and motions ($n_m$) were binned into $\tau^*$ increments of 0.0004. $P_q$ was calculated for each bin using Equation 2. From these data, we visually observe an overall threshold of motion of $\tau^*_c = 0.0387$ (Figure 5). The corresponding threshold depth (along the thalweg) and discharge are 0.92 m and 3.5 m$^3$/s, respectively. This independently measured threshold discharge matches that reported by Bradley and Tucker (2012). Several short-duration motions less than half a second were identified during lower flows but with exceedingly small transport probabilities. We note that this $\tau^*_c = 0.0387$ estimate includes Event 1 when tracers were particularly mobile and is independent of any particular bedload transport model.

A logistic function fits the relationship between $P_q$ and $\tau^*$ well (Figure 5; $R^2 = 0.96$):

$$P_q = \frac{1}{1 + e^{-429.5(\tau^* - 0.0625)}} \text{ for } \tau^* \geq 0.0387.$$  

A power law can also be fit with $R^2 = 0.95$:

$$P_q = 10^{24.2 \tau^*^{20.4}} \text{ for } \tau^* \geq 0.0387.$$  

We use the logistic function for most of our analyses below because it asymptotes toward the physical limit of $P_q = 1$ for higher $\tau^*$. For
example, Equation 3 predicts $P_q \approx 0.97$ for $\tau^* = 0.071$. In contrast, the power-law fit predicts mathematically possible but unphysical transport probabilities of $P_q > 1$ for $\tau^* \geq 0.065$. Nonetheless, neither equation is expected to be accurate outside of the range of the fitted data ($0.0387 < \tau^* < 0.05$; Figure 5).

### 3.1. Bedload Hysteresis

The Shields stress-averaged analysis in Figure 5 effectively treats transport hysteresis as noise, which it is not. Figure 6 compares temporal relationships between transport probability $P_q$ and hydraulic forcing characterized by $\tau^*$. Over the 22 days of snowmelt flood used in our analysis, average discharge increased over 15 days and then decreased, with superimposed diurnal floods (Figure 4a). Figure 6a plots $P_q$ and $\tau^*$ calculated every hour, but averaged over a 24-hr moving window to smooth away the diurnal fluctuations. We find overall clockwise hysteresis with significantly higher transport probabilities on the rising limb (Events 1–15) compared with the falling limb. A decrease in discharge corresponding to Events 10–12 (Figure 4a) produced the smaller clockwise loop superimposed in the rising limb (Figure 6a).

A similar procedure is applied to each of the 22 diurnal flood events, but with $P_q$ calculated over 15 min intervals and data smoothed over 2 hr to reduce variability. Figures 6b–6f show Events 8, 9, 13, 14, and
15; all 22 events are plotted in the supporting information. Over the 22 diurnal flood events, hysteretic patterns are variable. For convenience, we categorize them into four groups: Clockwise hysteresis (Events 7, 8, 12, 13, 15, 16, and 18), counterclockwise hysteresis (Events 1 and 14), figure-eight hysteresis with higher transport at different times on both rising and falling limbs (Events 9, 10, 17, and 19–22), and “low-transport” with both minimal hysteresis and low transport rates throughout (Events 2–6 and 11). Some events could be classified in two ways. For example, Event 9 has figure-eight hysteresis but also higher average transport probabilities on the falling limb indicating net counterclockwise hysteresis (Figure 6c). Bunte and Swingle (2005) found evidence for qualitatively similar daily bedload transport hysteresis in Halfmoon Creek.

### 3.2. Thresholds of Motion

We notate thresholds of motion that are a function of time as \( \tau_{cr}(t) \) and determine how \( \tau_{cr}(t) \) would have to change to explain the observed transport hysteresis. The flow-based \( \tau^* \) timeseries (Figure 4a) and population-averaged \( \tau_{cr} = 0.0387 \) are used to calculate what the dimensionless transport rate (\( q^* \)) would be following the modified Meyer-Peter and Müller (1948) bedload formulation of Wong and Parker (2006):

\[
q^* = 4.93 (\tau^* - \tau_{cr}^*)^{1.6}.
\]  

We also calculate a transport rate based instead on transport probability (\( P_q \)). To do this, we first rearrange Equation 3 and change notation by substituting \( \tau_{P_q} \) for \( \tau^* \):

\[
\tau_{P_q}^* = -\frac{1}{429.5} \ln \left( \frac{1}{P_q} - 1 \right) + 0.0625.
\]  

\( \tau_{P_q}^* \) represents a time-dependent Shields stress, calculated from the time-dependent probability of transport. Next, we modify Equation 5 in two ways, by first setting \( \tau_{cr} = 0.0387 \) and second substituting in \( \tau_{P_q}^* \) for \( \tau^* \) using Equation 6, to develop an equation for \( q_{P_q}^* \), a nondimensional transport rate estimate based on \( P_q \):

\[
q_{P_q}^* = 4.93 \left[ -\frac{1}{429.5} \ln \left( \frac{1}{P_q} - 1 \right) + 0.0625 - 0.0387 \right]^{1.6}.
\]

We then assume that \( q^* = q_{P_q}^* \), and that temporal discrepancies between shear stress-based \( q^* \) and motion tracer-based \( q_{P_q}^* \) are caused by temporal changes in \( \tau_{cr} \). We equate Equations 5 and 7 and solve for time-dependent \( \tau_{cr}(t) \) to give

\[
\tau_{cr}(t) = \tau^* + \frac{1}{429.5} \ln \left( \frac{1}{P_q} - 1 \right) - 0.0238,
\]

where \( \tau_{cr}(t) \), \( \tau^* \), and \( P_q \) all vary through time.

Figure 7a shows the evolution of \( \tau_{cr}(t) \) calculated from our data, both averaged over each diurnal flood event and also averaged separately over each falling and rising hydrograph limb. Lower thresholds on rising limbs than falling limbs correspond to clockwise hysteresis and vice versa (Figures 5 and S1). Averaging \( \tau_{cr}(t) \) over Events 1–22 gives \( \tau_{cr} = 0.040 \); this value (rather than 0.0387) represents our best model-dependent average threshold (ignoring temporal variability). \( \tau_{cr} = 0.04 \) corresponds to a Halfmoon discharge of 4.0 m³/s.

The diurnal-averaged \( \tau_{cr}(t) \) gradually increases during the 22 days of flood. At the same time, \( \tau_{cr}(t) \) tends to decrease when discharge increases from 1 day to the next. To quantitatively evaluate correlations between diurnal flood-averaged thresholds of motion and flow, we conducted an ordinary least squares multi-parameter linear regression analysis (MLR) using five hydraulic variables: (a) flood-averaged Shields stress (\( \tau^* \)), (b) peak Shields stress (\( \tau^* \)), (c) difference between average rising and average falling Shields stress within each diurnal flood (\( \tau_{P_q} \)), (d) cumulative flood-averaged Shields stress summed over Events 1–22 (\( \tau^*_+ \)), and (e) the change in flood-averaged Shields stress from 1 day to the next (\( \Delta \tau^* \)).
Positive values of $\Delta \tau^*$ indicate an increase in Shields stress from one diurnal flood event to the next. For example, $\Delta \tau^*$ for Flood Event 2 is equal to $\tau^*$ for Flood Event 2 minus $\tau^*$ for Flood Event 1. Flood Event 1 is used to calculate $\Delta \tau^*$ and $\tau^*$ but is excluded from the regressions because its low critical Shields stress indicates that these motions were likely influenced by the initial placement of the tracers on the channel bed.

Table 1 shows regression analysis results for each variable individually and considered together. Figures 7b–7d show correlations between select variables. Single variable linear regressions indicate that $\Delta \tau^*$ is best correlated with $\tau^*$ ($R^2 = 0.496$), while $\tau^*$ is only slightly lower ($R^2 = 0.453$). Inclusion of all variables in the MLR resulted in $R^2 = 0.77$, but with coefficient-specific $t$ test $p$ values $>0.05$ for all variables except $\Delta \tau^*$. Because these variables have some degree of interdependency, various groupings were calculated using MLR to infer the most relevant variables without overfitting the data. Every MLR that did not include $\Delta \tau^*$ had a considerably lower $R^2$ (Table 1). No combination of three parameters produced a MLR in which all parameters had statistically significant $t$ test $p$ values for the slope coefficient. In a two-parameter MLR, use of $\Delta \tau^*$ with either $\tau^*$ or $\tau^*$ resulted in statistically significant coefficients and with $R^2$ ranging from 0.726 to 0.748. The MLR using $\tau^*$ and $\Delta \tau^*$ predicts $\tau^*_c(t)$ with $R^2 = 0.726$ (Figure 7d):

$$\tau^*_c(t) = 0.002\tau^* + 0.897\Delta \tau^* + 0.0389. \tag{9}$$

Equation 9 shows that, in our data, thresholds of motion tend to (a) increase with cumulative discharge and (b) decrease when discharge increases from one diurnal flood to the next. Although both of the other two-parameter MLR produce similar results, we selected $\tau^*$ as the second parameter as it explains a higher proportion of the data variability alone than the other two variable choices (i.e., $R^2 = 0.453$).
## Table 1

**Regression Results**

| Parameter | $R^2$ | $p$ value | Equation |
|-----------|-------|-----------|----------|
| $\tau_+^*$ | 0.453 | 0.0008   | $\tau_+^*(t) = 0.003\tau_+^* + 0.0383$ |
| $\Delta\tau^*$ | 0.496 | 0.0004   | $\tau_+^*(t) = -1.151\Delta\tau^* + 0.0401$ |
| $\bar{\tau}$ | 0.265 | 0.0170   | $\tau_+^*(t) = 0.314\bar{\tau}^* + 0.0260$ |
| $\bar{\tau}^*$ | 0.248 | 0.0217   | $\tau_+^*(t) = 0.272\bar{\tau}^* + 0.0027$ |
| $\tau_{rf}$ | 0.107 | 0.1475   | $\tau_+^*(t) = -0.321\tau_{rf}^* + 0.0396$ |

| Parameter | $R^2$ | $p$ value | Equation |
|-----------|-------|-----------|----------|
| $\Delta\tau^* + \bar{\tau}$ | 0.726 | <0.0001  | $\tau_+^*(t) = 0.002\tau_+^* - 0.897\Delta\tau^* + 0.0389$ (Equation 9) |
| $\Delta\tau^*, \bar{\tau}$ | 0.747 | <0.0001  | $\tau_+^*(t) = 0.305\bar{\tau}^* - 1.135\Delta\tau^* + 0.0275$ |
| $\Delta\tau^*, \bar{\tau}^*$ | 0.748 | <0.0001  | $\tau_+^*(t) = 0.271\bar{\tau}^* - 1.156\Delta\tau^* + 0.0266$ |

| Parameter | $R^2$ | $p$ value | Equation |
|-----------|-------|-----------|----------|
| All included | 0.770 | 0.0002 | $\tau_+^*(t) = 0.0008\tau_+^* - 1.061\Delta\tau^* + 0.244\bar{\tau}^* + 0.393\bar{\tau}^* - 0.144\tau_{rf}^* + 0.0323$ |
| Omitted | R² without parameter | Paired t test $p$ value of coefficient |
| $\tau_+^*$ | 0.766 | 0.5368 |
| $\Delta\tau^*$ | 0.490 | 0.0006 |
| $\bar{\tau}$ | 0.770 | 0.7493 |
| $\bar{\tau}^*$ | 0.767 | 0.5638 |
| $\tau_{rf}$ | 0.755 | 0.3071 |

### 4. Discussion

Because smartrock-based transport probabilities are a relatively novel but untested method for quantifying bedload transport variables, we first demonstrate that our calculated transport capacities ($\tau_+^*/\tau_{cr}^*$) are reasonable for most gravel-bed rivers. Similarly, the logistic and power-law fits to our temporally averaged transport data (Equations 3 and 4; Figure 5) provide new insights while being consistent with previous work. We then interpret that the evolution of grain interlocking is probably the most plausible mechanism to explain transport hysteresis and how motion thresholds changed quickly in our data, although coarse grain clustering may also adjust rapidly.

#### 4.1. Threshold Channels

Threshold compilations suggest that $\tau_{cr}^*$ can easily vary between perhaps 0.02 and 0.1 for gravel-bed rivers with slopes comparable to Halfmoon Creek (e.g., Buffington & Montgomery, 1997; Bunte et al., 2013; Lamb et al., 2008; Mueller et al., 2005; Schneider et al., 2015). Mueller and Pitlick (2005) present a relation suggesting $\tau_{cr}^* \approx 0.039$ for a Halfmoon Creek reach near ours (their Equation 6 for their reach 3), comparable to the average $\tau_{cr}^* = 0.04$ we found. For a Halfmoon reach ~2.5 km downstream with somewhat smaller sediment ($D_{50} = 4.9$ cm, $D_{95} = 11.9$ cm) and a slope nearly three times steeper ($S = 0.014$), Bunte et al. (2013) report $\tau_{cr}^* = 0.082$ and 0.068 for $D_{50}$ (and $\tau_{cr}^* = 0.041$ and 0.032 for $D_{95}$) for a riffle and bar surface, respectively. The difference between our average threshold (0.04) and those of Bunte et al. (2013) may reflect differences in grain size distributions, reach slope, and/or local morphology. Empirical regressions to steep mountain stream data from Bunte et al. (2013) ($\tau_{cr}^* = 0.98S^{0.67}$ for $0.01 < S < 0.05$) and Schneider et al. (2015) ($\tau_{cr}^* = 0.48S^{0.45}$ or $\tau_{cr}^* = 1.82S^{0.75}$) suggest that local slope could explain much of the $\tau_{cr}^*$ difference between reaches. Whether slope-controlled or not, bed mobility apparently varies spatially along the channel.
While transport thresholds vary systematically in our data, the range of \( \tau^*/\tau^*_{cr} \) is small, from \( \approx 0.038 \) to 0.043 when thresholds are averaged over each diurnal hydrograph (Figure 7). However, threshold values only control transport in relation to shear stresses. The range of daily-averaged Shields stress during the 22 days of monitored flooding is \( \approx 0.040-0.048 \) (e.g., Figure 6a). Thus, even though \( \tau^*/\tau^*_{cr} \) only varied over a small range of values (\( \approx 0.005 \)), they span over half of the range of Shields stresses (\( \approx 0.008 \)) that occurred while flow was above threshold conditions during this 10-year flood.

In addition, the average transport capacity for this flood was \( \tau^*/\tau^*_{cr} \approx 0.044/0.04 \approx 1.1 \). Previous empirical and theoretical work suggests that bedload transport during bankfull floods usually occurs close to thresholds of motion for many gravel-bed rivers (e.g., Mueller et al., 2005; Parker, 1978; Phillips & Jerolmack, 2016, 2019), although sediment supply may also influence \( \tau^*/\tau^*_{cr} \) at bankfull (Pfeiffer et al., 2017). Other factors including bedrock exposure in a channel bed or flow depth to grain size ratios may also influence bankfull transport capacity and the importance of thresholds (e.g., Bunte et al., 2013; Hodge et al., 2011; Johnson, 2014). Quantitatively, our \( \tau^*/\tau^*_{cr} \approx 1.1 \) value is similar to the “closure” condition of \( \tau^*/\tau^*_{cr} \approx 1.2 \) for the middle of channels proposed by Parker (1978) for bedload flow in many gravel-bed rivers. Dunne and Jerolmack (2018) suggest that alluvial river banks adjust (through widening or narrowing) to have \( \tau^*/\tau^*_{cr} \approx 1 \). Thus, \( \tau^*/\tau^*_{cr} \approx 1.1 \) is expected for threshold channels such as the study reach, suggesting that our probability-based smartrock threshold calculations are reasonable. Statistics calculated from the relatively small number of smartrocks that successfully recorded data (Figure 4b) appear to be sufficient for calculating bulk transport characteristics for gravels, probably because each tracer recorded large numbers of individual movements and rests.

### 4.2. Power Law Logistics

We found that transport probabilities scale as \( \tau^{20.4} \) for Shields stresses between 0.0387 and 0.05 (Equation 4), consistent with previous work showing that bedload transport rates are strongly nonlinear at low Shields stresses. For Halfmoon Creek, Bunte et al. (2008) reported that bedload transport rate scaled with discharge as \( Q^{1.5} \). If \( h \propto Q^{0.1} \) (Leopold & Maddock, 1953), then \( q^* \propto \tau^{19.5} \). Using field data at relatively low transport capacities from multiple streams (including Halfmoon), Schneider et al. (2015) find that a different measure of nondimensional transport rate scales as \( \tau^{17.9} \pm 7.3 \) (mean \( \pm 1 \) standard deviation). Parker (1990) suggested that gravel movement should scale with \( \tau^{1.57} \) for “very low sediment transport rates.” Paintal (1971) empirically found that transport rates scaled as \( q^* \propto \tau^{16} \) for 0.01 < \( \tau^* < 0.05 \) and then transitioned to much less nonlinear transport with \( q^* \propto \tau^{2.5} \) for \( \tau^* > 0.05 \). While our best-fit exponent is 20.4, Figure 5 shows that imposing a \( \tau^* \) exponent of 16 and regressing to find the scaling factor alone also gives a strong fit of \( P_q = 10^{18.4} \tau^{16} \), with \( R^2 = 0.93, p < 0.0001 \).

Equation 4 predicts that transport probability \( P_q = 1 \) at \( \tau^*/\tau^*_{cr} \approx 0.065/0.0387 \approx 1.8 \). This transport capacity of 1.8 is high but not unphysical for gravel-bed rivers during floods. Experiments and field data clearly demonstrate that gravel transport rates do not saturate near these flow conditions (e.g., Powell et al., 2001; Wilcock & Crowe, 2003). Therefore, \( P_q \) must be much less than 1 at \( \tau^*/\tau^*_{cr} \approx 1.8 \). The nonlinear \( \tau^{20.4} \) or \( \tau^{16} \) scaling exponents must decrease systematically at Shields stresses higher than the range of our data (Figure 5). In contrast to power laws, the benefit of the logistic function (Equation 3) is that it asymptotes to the physical transport limit of \( P_q = 1 \). However, our particular empirical fit asymptotes to \( P_q \approx 1 \) at a transport capacity of \( \approx 2 \), which is undoubtedly too low. Equation 3 describes a symmetric sigmoid. An asymmetric logistic function, with additional fitting parameters, would likely be required to also fit higher \( \tau^*/\tau^*_{cr} \) data.

### 4.3. Threshold Evolution and Correlations With Flow

The pervasiveness of near-threshold conditions (\( \tau^*/\tau^*_{cr} \approx 1.1 \)) in many gravel-bed channels during floods highlights the importance of understanding subtle changes in \( \tau^*_o(t) \) in order to accurately predict bedload transport rates. In our data, temporal changes in thresholds (\( \tau^*_o(t) \)) are well predicted by changes in diurnal Shields stress (\( \Delta \tau^* \)) and cumulative above-threshold Shields stress (\( \tau^*_{cr} \)) together (Figure 7d; Equation 9; Table 1). Furthermore, \( \Delta \tau^* \) and \( \tau^*_{cr} \) are not significantly correlated in our data (\( R^2 = 0.096, p = 0.073 \)), suggesting that these hydraulic measures are sufficiently independent to influence \( \tau^*_o(t) \) evolution in different ways. When shear stress increases from one event to the next (\( \Delta \tau^* > 0 \)), the threshold of
motion tends to decrease (Figure 7b). This is most noticeable for Events 4, 7, 13, and 14, which have relatively large increases in stress compared to the other events (Figure 7a). Much smaller increases in the diurnal flood event peak stress do not seem to produce the same decrease in $\tau^*_{cr}(t)$ (Events 6, 9, and 18). This is consistent with Equation 9, because cumulative shear stress also increases with each event. Small $\tau^*_{cr}(t)$ decreases predicted by the $\Delta \tau^*$ term in Equation 9 may be offset by small $\tau^*_{cr}(t)$ increases predicted from the cumulative $\tau^*$ term.

Rickenmann (2018) also found that temporal changes in daily thresholds of motion ($\tau^*_{cr}(t)$) were driven by daily mean hydraulic forcing. Using an exponential form of the Meyer-Peter and Müller equation (Cheng, 2002) for back-calculating $\tau^*_{cr}(t)$, Rickenmann (2018) found correlations between thresholds and daily-averaged Shields stress ($\tau^*_{cr}(t) = 1.14 e^{-0.99 t}$ and $\tau^*_{cr}(t) = 3.6 e^{-1.33 t}$ for two similar mountain streams). In our data, we only find weak correlations between $\tau^*_{cr}(t)$ and daily-averaged ($\tau^*$) or daily peak ($\hat{\tau}$) Shields stress (Table 1). Nonetheless, we note that $\tau^*$ is significantly correlated with both $\tau^*$ ($R^2 = 0.7$) and $\hat{\tau}$ ($R^2 = 0.69$). The interrelated nature of these variables is why two-parameter regressions including $\Delta \tau^*$ and $\tau^*$ or $\hat{\tau}$ can predict $\tau^*_{cr}(t)$ well (Table 1), suggesting that our results may not be inconsistent with Rickenmann (2018). We emphasize that threshold parameter values would be different when back-calculated using different bedload transport models, although no transport models that we are aware of could capture both increasing and decreasing thresholds with cumulative and changing shear stresses. Systematically exploring how threshold evolution differs among models is an opportunity for future work.

### 4.4. Possible Mechanisms for Hysteresis and Threshold Evolution Over Short Timescales

Our analysis builds on the observed seasonal hysteresis (Figure 6a) to calculate best-fit daily thresholds of motion that evolve as functions of cumulative and changing shear stress (Figure 7; Table 1). However, we do not have simultaneous observations of bed surface changes, tracer interactions with other grains, or upstream sediment supply that could prove which flow-dependent mechanisms caused hysteresis and threshold evolution. In the absence of independent constraints, we highlight mechanisms that previous work suggests might cause rapid (e.g., daily to seasonal) threshold evolution. We then hypothesize which mechanisms may best explain our data.

Hysteresis in bedload transport can likely be caused by a variety of mechanisms which are not mutually exclusive. Mao et al. (2014) observed day-to-day changes between clockwise and counterclockwise hysteresis and suggested that a combination of migrating sediment waves and seasonal sediment supply changes from melting banks might explain daily to seasonal hysteresis trends. Roth et al. (2014) observed bedload hysteresis using near-stream seismic signals in a channel with high gravel sediment supply and discussed plausible mechanisms for gravel-bed systems including time lags between discharge and bedform adjustment or surface roughness changes (Mao, 2012; Martin & Jerolmack, 2013), bedload wave migration, and surface sorting/grain size changes (Humphries et al., 2012).

Water surface slope changes, which are not included in our data, may also cause apparent bedload transport hysteresis (Meirovich et al., 1998). Higher water surface slopes when discharge increases would lead to higher shear stresses during hydrograph rising limbs and lower shear stresses during hydrograph falling limbs, compared to our assumption of steady uniform flow. Not accounting for this effect could give the appearance of clockwise bedload transport hysteresis (Meirovich et al., 1998). While a majority of our daily hydrographs did exhibit rather complex clockwise hysteresis, this phenomena cannot easily explain counterclockwise hysteresis in our data (e.g., Event 14; Figure 6c), or more complex “figure eight” patterns we also observe. Following Paola and Mohrig (1996), timescales over which steady flow can be assumed (i.e., unsteady flow effects are relatively unimportant) can be roughly estimated using $U/TgS \ll 1$, where $T$ is a timescale, $U$ is depth-averaged velocity, $g$ is gravitational acceleration ($9.81 \text{ m/s}^2$), and $S$ is reach slope. Our approximate conditions ($S = 0.005$, $U \approx 1 \text{ m/s}$) suggest that $T > 20 \text{ s}$ should be sufficient to assume steady flow. Both the daily and seasonal hydrograph durations meet this criteria for assuming quasi-steady flow.

Many other interrelated mechanisms can directly influence thresholds of motion. Biological factors, including algae biofilms, caddisfly larvae silk nets, and crayfish and fish bed surface modifications, influence thresholds of gravel motion (e.g., Johnson et al., 2009, 2011; Segura et al., 2010). We have no direct
constraints on biota during our study, although we interpret that similar biological effects would be minor in this channel during spring floods. Through modeling and experiments, Albertson et al. (2014) found that caddisfly silk could increase thresholds of motion for gravels up to ~45 mm over ~4 days but observed minimal effects on coarser gravels.

Changes in sediment supply from upstream can influence local bed mobility and thresholds of motion through grain size distribution changes, grain impacts, and other possible mechanisms (e.g., Johnson, 2016; Pfeiffer et al., 2017; Recking, 2012). For example, grains smaller than the bed surface average (including sand sizes) can preferentially fill topographic lows and smooth the bed, in turn influencing near-bed shear stresses (e.g., Venditti et al., 2010; Wilcock & Crowe, 2003).

Sorting during transport can spatially organize surface grains into coarse grain clusters and other stabilizing structures, which in turn influence drag and bedload transport. Most although not all studies have found that increased clustering tends to enhance the overall stability of the bed surface, decreasing transport rates (e.g., Church et al., 1998; Hassan & Church, 2000; Hassan & Reid, 1990; Johnson, 2017; Piedra et al., 2012; Strom et al., 2004). Using flume experiments, Hassan et al. (2020) showed that clusters can dynamically expand, contract, and change through particle exchange between the cluster and transported grains and interpret that clusters may buffer the bed and enhance stability by rapidly changing in response to short-term supply perturbations.

Cumulative discharge both somewhat below and somewhat above “threshold” flow conditions tends to increase bed stabilization through a variety of recognized mechanisms including bed compaction, changes in bed surface roughness, and decreasing protrusion (e.g., Marquis & Roy, 2012; Masteller & Finnegan, 2017; Ockelford & Haynes, 2013; Paphitis & Collins, 2005). These strengthening effects may also be strongly influenced by interlocking, intergranular friction, and overlapping between surrounding grains. In this granular physics view, force chains and particle contacts can evolve over short timescales and dictate mobility, though are difficult to measure directly. Yager et al. (2018) combined field measurements of lodgment forces with discrete element modeling of interacting spheres to support their model in which interparticle friction and grain protrusion relative to the surrounding bed are key variables controlling grain threshold distributions. In their model and data, forces needed to overcome friction between grains can be three to 10 times larger than mobilization forces expected based on grain weight, for particles with low protrusion. Earlier work has explored related factors that enhance thresholds of motion such as friction angles due to pocket geometry and resisting forces from grain overlap (e.g., Kirchner et al., 1990; Sanguinito & Johnson, 2012). Intergranular friction is a distinct mechanism from coarse grain clustering in that it does not require grains moving past other grains to become spatially reorganized by size.

Overall, we hypothesize that the mechanisms described by Yager et al. (2018)—intergranular friction, protrusion, and overlap—are the primary drivers of hysteresis and \( \tau_\text{cr}^* (t) \) evolution in our dataset. These factors can evolve quickly, explaining the observed transport hysteresis in our data, and describing \( \tau_\text{cr}^* (t) \) changes over timescales significantly shorter than individual floods. The first hydrograph had an anomalously low \( \tau_\text{cr}^* (t) \), which we associate with initial tracer positions being less stable (Figure 7) because the grains were not interlocked with surrounding grains. However, it appears that grains had attained more stable positions by Event 2. When hydrograph-averaged shear stress was stable or slightly decreasing from 1 day’s hydrograph to the next, \( \tau_\text{cr}^* (t) \) tended to gradually increase. We interpret that this was caused by grains being gradually jostled in place (building force chains and increasing intergranular friction while also compacting the bed over time) and/or transported to adjacent positions that were more stable (Masteller & Finnegan, 2017).

Statistically, some grains will be transported to less stable positions as well, but it is less probable that those grains remain there, as continued flow and turbulence will progressively move grains until they find more stable and interlocked positions. Thus, cumulative flow slightly above threshold conditions tends to increase thresholds of motion.

In general, given constant or perhaps very gradual increases in discharge, we interpret that intergranular friction remains constant and/or increases to balance the applied shear stress. When discharge drops and \( \tau^* \) subsequently decreases, the higher intergranular friction remains, resulting in modest increases in \( \tau_\text{cr}^* (t) \) that depend on the previous level of \( \tau^* \) (e.g., Events 10, 11, and 16). A grain will tend to be stable at shear stresses less than or equal to the stress that initially transported the grain to a given position. However,
we interpret that moderate increases in shear stress from 1 day’s hydrograph to the next (i.e., the $\Delta \tau^*$ term in Equation 9) can break up force chains and overwhelm the intergranular friction developed at lower $\tau^*$, “releasing” grains. This transport may further disrupt the bed through particle impacts or changes in local bed geometry, further increasing transport rates and decreasing thresholds of motion.

It is also possible that our data reflect coarse grain clusters or other surface structures that evolved over short timescales, enhancing stability as they expanded by adding grains and enhancing transport by releasing sediment when they shrunk or disintegrated (Hassan et al., 2020). Strom et al. (2004) found, using experiments with spherical grains over an immobile bed, that clustering generally increased over a range of $\tau^*/\tau_{cr}^* \approx 1.25$ to 2, acting as a net sink for moving grains. Clusters broke up and then decreased due to increasingly energetic transport for $\tau^*/\tau_{cr}^* > 2.25$, acting as a net source. However, our stresses are much lower than these values. This may suggest that intergranular friction/grain interlocking are more important than cluster changes in our data, assuming that these transport capacity ranges are appropriate for natural grains and mobile beds.

We cannot discount the possibility that the overall trend of increasing $\tau_{cr}^*(t)$ with time and cumulative shear stress primarily reflects tracers being progressively worked into the bed or scour and fill effects (e.g., Haschenburger, 2011) and that the gradual threshold increase is an artifact of initial conditions. However, 23 out of 27 smartrocks were found on the bed surface, which suggests that progressive burial or scour and fill effects are unlikely to explain the $\tau_{cr}^*(t)$ trend. In addition, previous work shows that thresholds increase with cumulative flow without relying on tracer data (e.g., Paphitis & Collins, 2005). Using 19 years of monitoring data from the Erlenbach Torrent, Switzerland, Masteller et al. (2019) found that gravel thresholds tended to progressively increase due to the cumulative effects of small floods and below-threshold flows between floods but that larger floods caused thresholds to decrease. Earlier monitoring work showed similar trends over multiple years of floods (Lenzi et al., 2004). Masteller et al. (2019) interpret that intense sediment transport in sufficiently large events disrupts bed surface grains enough to reset the “memory” of past flow conditions that led to shear stress increases. While these researchers found increasing and decreasing transport thresholds from before and after relatively large floods over multi-year timescales, our results expand the parameter space of our understanding by documenting systematic threshold evolution over shorter seasonal to daily timescales and with smaller changes in discharge. We interpret that threshold changes need not reflect complete surface destabilization or a significant reduction in the availability of mobile sediment but can also reflect subtle changes in grain interlocking.

Figure 2a suggests that the final deposition locations of tracers were influenced by channel morphology, because seven of the tracers that successfully collected data were found in the thalweg of the downstream meander bend. Channel morphology has been argued to influence tracer transport over long timescales (e.g., Hassan & Bradley, 2017). Without positional information during transport, we cannot be certain whether the timing of tracers reaching this bend influenced transport probabilities and therefore our calculated thresholds. Nonetheless, we interpret that the effect of the channel bend on transport statistics is probably minor. The final movements for tracers found in the meander bend occurred during daily hydrographs 13 through 23 (mean of hydrograph 17). Omitting two tracers that stopped sampling prematurely (with last recorded movements before Event 1 and during Event 2), the final movements of tracers not in the meander bend occurred between Events 7 through 28, with a mean of hydrograph 17. This suggests that the decrease in transport probabilities after Event 15 is not primarily caused by tracers stopping in the meander bend at that time.

We also cannot discount the possibility that the threshold evolution we observed was caused by changes in surface grain size. Perhaps thresholds increased because the bed progressively coarsened overall over the 22 day period, while sand or finer gravel pulses also moved through the reach during times of highest discharge, temporarily decreasing thresholds, but were then transported out of the reach. While we did not did repeat surface GSD measurements directly before or during the data collection period, the point counts done after smartrock recovery (fall 2015) are consistent with previous measurements in Halfmoon Creek (Bradley & Tucker, 2012). We thus feel like it is unlikely that overall surface coarsening with punctuating fining within our 22-day study period are responsible for observed trends. Masteller et al. (2019) similarly see no evidence that their threshold trends were controlled by systematic seasonal coarsening.
4.5. Implications and Applications

Our results may help improve predictions of bedload transport and bed stability, particularly in managed rivers where transport thresholds are important. Mobile bedload traps placed on the bed only sample a fraction of the channel width for relatively limited period of times (e.g., Bunte et al., 2008), although can measure most or all of the transported bedload GSD. Methodologically, our smartrock tracer methods sample much longer total durations, 24 hr per day, over much shorter time intervals. Smartrocks move laterally to be transported in “natural” positions across the channel width and so may result in data more representative of natural cross-section-averaged transport. Limitations of our smartrock methods include costs of devices (including not finding some tracers during recovery), time to find the devices after transporting events, restriction to channel sizes that are wadeable, and a minimum tracer size required to hold the instrumentation.

Gravel-bed reaches downstream of large dams tend to develop static and tightly interlocked armor layers, due to reduced sediment supply and decreased transport capacity from reservoir-attenuated flood peaks (e.g., Viparelli et al., 2011). An increasing number of dam managers are considering downstream impacts to habitat (e.g., salmonid spawning), such as including “naturalized” flow hydrographs sufficient to mobilize the bed surface. Understanding how larger controlled floods might decrease thresholds could improve estimates and uncertainties of bed mobilization as well as guide monitoring plans that could be implemented during managed floods and used for real-time decision making and hydrograph adjustment. For example, knowing when beds first destabilize during floods could be used to minimize water volumes released while still attaining bed mobilization goals. Conversely, overly mobile transport could potentially destabilize salmonid redds or impact other aquatic habitat.

In gravel-bed rivers, thresholds of motion are critical for predicting stability, transport, and changes across the full range of flood magnitudes, as climate change and human land use change impact the natural environment. Increases in the frequency and magnitude of floods are expected in many locations for decades or centuries to come (e.g., Milly et al., 2002), combined with climatic changes to hillslope hydrology and vegetation that will influence sediment supply to river networks. Our data suggest that how mountain channels respond to these environmental perturbations may be influenced by history-dependent thresholds of motion. Nonetheless, the extent to which thresholds of motion evolve in gravel-bed rivers remains an open question. Future work could (a) explore how rates of hydrograph rise and fall influence bed mobilization, (b) compare calculations of evolving thresholds using additional transport models, and (c) look for threshold evolution over a broad range of gravel-bed river slopes, grain sizes, and channel morphologies.

5. Conclusion

In 2015, we measured accelerations of smartrock tracer particles in Halfmoon Creek, Colorado, during a seasonal snowmelt flood with a 10-year recurrence interval. Transport data were collected during 22 daily hydrographs which had flow above threshold transport conditions. We used tracer particle accelerations to infer the precise timing of motions and rests using an empirical algorithm, which was tested and calibrated in a controlled laboratory setting.

Our results suggest that the critical thresholds of motion for populations of particles evolved systematically over time with changes in discharge. In particular, increases in average shear stress from 1 day to the next correlate with decreases in thresholds of motion. Conversely, thresholds of motion increase as cumulative shear stress increases over the duration of the entire flood. Together, these two factors can explain ≈73% of the variability we observe in transport thresholds (Figure 7b; Equation 9). Mechanistically, a variety of processes that influence bed stability could potentially explain our results, including changes in surface armor, grain size changes, sediment supply pulses, clustering, and interlocking of grains. Given that we observe rapid changes in thresholds of motion between rising and falling limbs of daily hydrographs, we interpret that changes in intergranular friction and evolving force chains between grains are the most likely explanation, as these mechanisms could evolve rapidly and sensitively in response to local shear stresses.

Evolving thresholds of motion are also illustrated by hysteresis in transport rates, which occurs in clockwise, counterclockwise, and figure eight patterns. Progressive stabilization of grains and increasing thresholds of motion are supported by overall clockwise hysteresis over the 22-day above-threshold measurement period.
and increasing entrainment thresholds after successive diurnal flood events with similar Shields stress. Counterclockwise hysteresis after increases in Shields stress from one daily flood to the next suggests that thresholds decrease, potentially due to changes in grain interlocking or clustering. Our data provide a unique look into the dynamics of coarse sediment transport in the field under rapidly changing hydraulic forcing.

Data Availability Statement

Data available at https://dataverse.tdl.org/dataverse/wr2020_smartrocks (with Johnson, 2020, https://doi.org/10.18738/T8/UVOFTH).

References

Albertson, L. K., Sklar, L. S., Pontau, P., Dow, M., & Cardinale, B. J. (2014). A mechanistic model linking insect (Hydropsychidae) silk nets to incipient sediment motion in gravel-bedded streams. *Journal of Geophysical Research: Earth Surface*, 119, 1833–1852. https://doi.org/10.1002/2013JF003024

Alexandrov, Y., Laromne, J. B., & Reid, I. (2007). Intra-event and inter-seasonal behaviour of suspended sediment in flash floods of the semi-arid northern Negev, Israel. *Geomorphology*, 85(1–2), 85–97. https://doi.org/10.1016/j.geomorph.2006.03.013

Bombar, G., Elçi, Ş., Tayfur, G., Güney, M., & Bor, A. (2011). Experimental and numerical investigation of bed-load transport under unsteady flows. *Journal of Hydraulic Engineering*, 137, 1276–1282. https://doi.org/10.1061/(ASCE)HY.1943-7900.0000412

Bradley, D. N. (2017). Direct observation of heavy tail behaviour in field test of the stochastic theory of bed load transport proposed by Einstein. *Hydrological Processes*, 31(3), 377–391. https://doi.org/10.1002/hyp.11974

Bradley, D. N., & Tucker, G. E. (2012). Measuring gravel transport and dispersion in a mountain river using passive radio tracers. *Earth Surface Processes and Landforms*, 37(10), 1034–1045. https://doi.org/10.1002/esp.3223

Buffington, J. M., & Montgomery, D. R. (1997). A systematic analysis of eight decades of incipient motion studies, with special reference to gravel-bedded rivers. *Water Resources Research*, 33(8), 1993–2029. https://doi.org/10.1029/96WR03190

Bunte, K., Abt, S. R., Potyondy, J. P., & Swingle, K. W. (2008). A comparison of coarse bedload transport measured with bedload traps and Helley Smith samplers. *Geodinamica Acta*, 21(2–3), 65–66. https://doi.org/10.3166/ga.21.43-66

Bunte, K., Abt, S. R., Swingle, K. W., Cenderecli, D. A., & Schneider, J. M. (2013). Critical Shields values in coarse-bedded steep streams. *Water Resources Research*, 49, 7427–7447. https://doi.org/10.1002/2012WR013662

Bunte, K., & Swingle, K. W. (2005). Using bedload traps at Halfmoon Creek, 2004: Transport rates, spatial variability of gravel transport, and long nets. Report submitted to the Stream Systems Technology Center, USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO. 116 pp.

Cheng, N.-S. (2002). Exponential formula for bedload transport. *Journal of Hydraulic Engineering*, 128(10), 942–946. https://doi.org/10.1061/(ASCE)0733-9429(2002)128:10(942)

Church, M., Hassan, M. a., & Wolcott, J. F. (1998). Stabilizing self-organized structures in gravel-bed stream channels: Field and experimental observations. *Water Resources Research*, 34(11), 3169–3179. https://doi.org/10.1029/98WR00484

Dunne, K. B. J., & Jerolmack, D. J. (2018). Evidence of, and a proposed explanation for, bimodal transport states in alluvial rivers. *Earth Surface Dynamics*, 6, 583–594. https://doi.org/10.5194/esurf-6-583-2018

Ergenzinger, P., & Jupner, R. (1992). Using COSSY (Cobble Satellite System) for measuring the effects of lift and drag forces. In D. Tsutsumi, & J. B. Laronne (Eds.), *Gravel Bed Rivers 8: Processes and disasters* (Vol. 210, pp. 41–49). United Kingdom: IAHS.

Gilbert, F., Fuller, B. M., Lamb, M. P., Tsai, V. C., & Johnson, J. P. L. (2019). Particle transport mechanics and induced seismic noise in fast flume experiments with accelerator-embedded tracers. *Earth Surface Processes and Landforms*, 44(1), 219–241. https://doi.org/10.1002/esp.4495

Gronz, O., Hiller, P. H., Wirtz, S., Becker, K., Iserloh, T., Seeger, M., et al. (2016). Smartstones: A small axis sensor implanted in stones to track their movements. *Catena*, 142, 245–251. https://doi.org/10.1016/j.catena.2016.03.030

Habersack, H. M. (2001). Radio-tracking gravel particles in a large braided river in New Zealand: A field test of the stochastic theory of bed load transport proposed by Einstein. *Hydrological Processes*, 15(3), 377–391. https://doi.org/10.1002/hyp.147

Haschenburger, J. K. (2011). The rate of fluvial gravel dispersion. *Geophysical Research Letters*, 38, L24403. https://doi.org/10.1029/2011GL049928

Hassan, M. A., & Bradley, D. N. (2017). Geomorphic controls on tracer particle dispersion in gravel-bedded rivers. In D. Tsutsumi, & J. B. Laromne (Eds.), *Gravel-Bed Rivers 8: Processes and disasters* (1st ed.). Hoboken, NJ: John Wiley & Sons Ltd. https://doi.org/10.1002/978111971437.ch6

Hassan, M. A., & Church, M. (2000). Experiments on surface structure and partial sediment transport on a gravel bed. *Water Resources Research*, 36(7), 1885. https://doi.org/10.1029/2000WR900055

Hassan, M. a., & Reid, I. (1990). The influence of microform bed roughness elements on flow and sediment transport in gravel bed rivers. *Earth Surface Processes and Landforms*, 15(8), 739–750. https://doi.org/10.1002/esp.3290190807

Hassan, M. A., Saletti, M., Zhang, C., Ferrer-Boix, C., Johnson, J. P. L., Müller, T., & von Flotow, C. (2020). Co-evolution of coarse grain structure and bed roughness in response to episodic sediment supply in an experimental aging channel. *Earth Surface Processes and Landforms*, 45, 948–961. https://doi.org/10.1002/esp.4788

Hodge, R. A., Hoey, T. B., & Sklar, L. S. (2011). Bed load transport in bedrock rivers: The role of sediment cover in grain entrainment, translation, and deposition. *Journal of Geophysical Research*, 116, F04028. https://doi.org/10.1029/2011JF002032

Humphries, R., Venditti, J. G., Sklar, L. S., & Wooster, J. K. (2012). Experimental evidence for the effect of hydrographs on sediment pulse dynamics in gravel-bedded rivers. *Water Resources Research*, 48, W01533. https://doi.org/10.1029/2011WR010419

Johnson, J. (2020). Replication Data For: Pretzlav KLG, JPL Johnson, DN Bradley (2020), Smartrock transport in a mountain stream: Bedload hysteresis and Changing Thresholds of Motion, Water Resources Research [Excel spreadsheet of smartrock and hydraulic monitoring data]. https://doi.org/10.18738/T8/UVOFTH

Acknowledgments

The work was funded by the National Science Foundation (EAR 1053508 to JPLJ) and by The University of Texas at Austin Jackson School of Geosciences. All authors contributed to project design and to field work. KLGP developed the methodologies used and conducted most of the data analysis. KLGP and JPLJ wrote the manuscript, with input from DNB. We thank Lindsay Ollide for informative discussions and Kristin Bunte, two anonymous reviewers, and the associate editor for thoughtful comments.
Johnson, J. P. L. (2014). A surface roughness model for predicting alluvial cover and bed load transport rate in bedrock channels. *Journal of Geophysical Research: Earth Surface*, 119, 2147–2173. https://doi.org/10.1002/2013JF003000

Johnson, J. P. L. (2016). Gravel threshold of motion: A state function of sediment transport disequilibrium? *Earth Surface Dynamics*, 4(3), 685–703. https://doi.org/10.5194/esurf-4-685-2016

Johnson, J. P. L. (2017). Clustering statistics, roughness feedbacks, and randomness in experimental step-pool morphodynamics. *Geophysical Research Letters*, 44, 3653–3662. https://doi.org/10.1002/2016GL072246

Johnson, J. P. L., & Whipple, K. X. (2010). Evaluating the controls of shear stress, sediment supply, alluvial cover, and channel morphology on experimental bedrock incision rate. *Journal of Geophysical Research*, 115, F02018. https://doi.org/10.1029/2009JF001335

Johnson, M. F., Reid, I., Rice, S. P., & Wood, P. J. (2009). Stabilization of fine gravels by net-spinning caddisfly larvae. *Earth Surface Processes and Landforms*, 34, 413–423. https://doi.org/10.1002/esp.1750

Johnson, M. F., Rice, S. P., & Reid, I. (2011). Increase in coarse sediment transport associated with disturbance of gravel river beds by signal crayfish (*Pacifastacus leniusculus*). *Earth Surface Processes and Landforms*, 36, 1680–1692. https://doi.org/10.1002/esp.2192

Kirchner, J. W., Dietrich, W. E., Isyä, F., & Ikeda, H. (1990). The variability of critical shear stress, friction angle, and grain protrusion in water-worked sediments. *Sedimentology*, 37(4), 647.

Kuhnle, R. A. (1992). Bed load transport during rising and falling stages on two small streams. *Earth Surface Processes and Landforms*, 17(2), 191–197. https://doi.org/10.1002/esp.3290170206

Lamb, M. P., Dietrich, W. E., & Venditti, J. G. (2008). Is the critical Shields stress for incipient sediment motion dependent on channel-bed slope? *Journal of Geophysical Research*, 113, F01020. https://doi.org/10.1029/2007JF000831

Lenzi, M. A., Mao, L., & Comiti, F. (2004). Magnitude effects on bed load data in an Alpine boulder bed stream. *Water Resources Research*, 40, W17201. https://doi.org/10.1029/2003WR002961

Leopold, L., & Maddock, T. (1953). The hydraulic geometry of stream channels and some physiographic implications. *Geological Survey Professional Paper* 252. Washington, DC: United States Government Printing Office.

Maniatis, G., Hoey, T. B., Hassan, M. A., Sventek, J., Hodge, R., Drysdale, T., & Vallyakis, M. (2017). Calculating the explicit probability of entrainment based on inertial acceleration measurements. *Journal of Hydraulic Engineering*, 143(4), 04016097. https://doi.org/10.1061/(ASCE)HY.1943-7799.0001262

Mao, L., Dell’Agnese, A., Hinincache, C., Penna, D., Engel, M., Niedrist, G., & Comiti, F. (2014). Bedload hysteresis in a glacier-fed mountain river. *Earth Surface Processes and Landforms*, 39(7), 964–976. https://doi.org/10.1002/esp.3593

Mao, L. C. (2012). The effect of hydrographs on bed load transport and bed sediment spatial arrangement. *Journal of Geophysical Research*, 117, F03024. https://doi.org/10.1029/2011JF002428

Marquis, G. A., & Roy, A. G. (2012). Using multiple bed load measurements: Toward the identification of bed dilation and contraction in gravel-bed rivers. *Journal of Geophysical Research*, 117, F01014. https://doi.org/10.1029/2011JF002120

Martin, R. L., & Jerolmack, D. J. (2013). Origin of hysteresis in bed form response to unsteady flows. *Water Resources Research*, 49, 1314–1333. https://doi.org/10.1002/wr.20993

Masteller, C. C., & Finnegan, N. J. (2017). Interplay between grain protrusion and sediment entrainment in an experimental flume. *Journal of Geophysical Research: Earth Surface*, 122, 274–289. https://doi.org/10.1002/2016JF003943

Masteller, C. C., Finnegan, N. J., Turowski, J. M., Yager, E. M., & Rickenmann, D. (2019). History-dependent threshold for motion revealed by continuous bedload transport measurements in a steep mountain stream. *Geophysical Research Letters*, 46, 2583–2591. https://doi.org/10.1029/2019GL081325

McNamara, J. P., & Borden, C. (2004). Observations on the movement of coarse gravel using implanted motion-sensing radio transmitters. *Hydrological Processes*, 18(10), 1871–1884. https://doi.org/10.1002/hyp.1453

Meirovitch, L., Laronne, J. R., & Reid, I. (1998). The variation of water-surface slope and its significance for bedload transport during floods in gravel-bed streams. *Journal of Hydraulic Research*, 36(2), 147–157. https://doi.org/10.1080/00221689809498630

Meyer-Peter, E., & Müller, R. (1948). Formulas for bed-load transport: Proc., 2nd Meeting, IAHR, Stockholm, Sweden, 39–64.

Milly, P. C. D., Wetherald, R. T., Dunne, K. A., & Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature*, 415(6871), 514–517. https://doi.org/10.1038/415514a

Moog, D. B., & Whiting, P. J. (1998). Annual hysteresis in bed load rating curves. *Water Resources Research*, 34(9), 2393–2399. https://doi.org/10.1029/98WR01658

Mueller, E. R., & Pitlick, J. (2005). Morphologically based model of bed load transport capacity in a headwater stream. *Journal of Geophysical Research*, 110, F02016. https://doi.org/10.1029/2003JF000117

Mueller, E. R., Pitlick, J., & Nelson, J. M. (2005). Variation in the reference Shields stress for bed load in gravel-bed streams and rivers. *Water Resources Research*, 41, W04006. https://doi.org/10.1029/2004WR003692

Okeefold, A. M., & Haynes, H. (2013). The impact of stress history on bed structure. *Earth Surface Processes and Landforms*, 38(7), 717–727. https://doi.org/10.1002/esp.3348

Olinde, L., & Johnson, J. P. L. (2015). Using RFID and accelerometer-embedded tracers to measure probabilities of bed load transport, step lengths, and rest times in a mountain stream. *Water Resources Research*, 51, 7572–7589. https://doi.org/10.1002/2014WR016120

Paintal, A. S. (1971). Concept of critical shear stress in loose boundary open channels. *Journal of Hydraulic Research*, 9(1), 91–113. https://doi.org/10.1080/0022168710950339

Paola, C., & Mohrig, D. (1996). Palaeohydraulics revisited: Palaeoslope estimation in coarse-grained braided rivers. *Basin Research*, 8(3), 243–254. https://doi.org/10.1111/j.1365-2117.1996.00253.x

Paphitis, D., & Collins, M. B. (2005). Sand grain threshold, in relation to bed ‘stress history’: An experimental study. *Sedimentology*, 52(4), 827–838. https://doi.org/10.1111/j.1365-3091.2005.00710.x

Parker, G. (1978). Self-formed straight rivers with equilibrium banks and mobile bed. Part II. The gravel river. *Journal of Fluid Mechanics*, 89(1), 127–148. https://doi.org/10.1017/S0022112078002505

Parker, G. (1990). Surface-based bedload transport relation for gravel rivers. *Journal of Hydraulic Research*, 28(4), 417–436. https://doi.org/10.1080/00221689009499058

Peiffer, A. M., Finnegan, N. J., & Willenbring, J. K. (2017). Sediment supply controls equilibrium channel geometry in gravel rivers. *Proceedings of the National Academy of Sciences*, 114(13), 3346–3351. https://doi.org/10.1073/pnas.1612907114

Phillips, C. B., & Jerolmack, D. J. (2016). Self-organization of river channels as a critical filter on climate signals. *Science*, 352(6286), 694–697. https://doi.org/10.1126/science.aad3348

Phillips, C. B., & Jerolmack, D. J. (2019). Bankfull transport capacity and the threshold of motion in coarse-grained rivers. *Water Resources Research*, 55, 11,316–11,330. https://doi.org/10.1029/2019WR025455
Segura, C., & Pitlick, J. (2015). Coupling
Segura, C., McCutchan, J. H., Lewis, W. M. Jr., & Pitlick, J. (2010). The in
Schneider, J. M., Rickenmann, D., Turowski, J. M., Bunte, K., & Kirchner, J. W. (2015). Applicability of bed load transport models for mixed
Sekine, M., & Parker, G. (1992). Bed
Yalin, M. S. (1972).
Viparelli, E., Gaeuman, D., Wilcock, P., & Parker, G. (2011). A model to predict the evolution of a gravel bed river under an imposed cyclic
Turowski, J. M., Badoux, A., & Rickenmann, D. (2011). Start and end of bedload transport in gravel
Strom, K., Papanicolaou, A. N., Evangelopoulos, N., & Odeh, M. (2004). Microforms in gravel bed rivers: Formation, disintegration, and
Venditti, J. G., Dietrich, W. E., Nelson, P. A., Wydzga, M. A., Fadde, J., & Sklar, L. (2010). Mobilization of coarse surface layers in
Torizzo, M., & Pitlick, J. (2004). Magnitude
Sanguinito, S., & Johnson, J. (2012). Quantifying gravel overlap and dislodgement forces on natural river bars: Implications for particle
Strom, K., & Papanicolaou, A., N. (2004). Microforms in gravel bed rivers: Formation, disintegration, and effects on bedload transport. *Journal of Hydraulic Engineering-Asce*, 130(6), 554–567. https://doi.org/10.1061/(asce)0733-9429(2004)130:6(554)
Torizzo, M., & Pitlick, J. (2004). Magnitude-frequency of bed load transport in mountain streams in Colorado. *Journal of Hydrology*, 290(1–2), 137–151. https://doi.org/10.1016/j.jhydrol.2003.12.001
Turowski, J. M., Badoux, A., & Rickenmann, D. (2011). Start and end of bedload transport in gravel-bed streams. *Geophysical Research Letters*, 38, L04401. https://doi.org/10.1029/2010GL046558
Venditti, J. G., Dietrich, W. E., Nelson, P. A., Wydzga, M. A., Fadde, J., & Sklar, L. (2010). Mobilization of coarse surface layers in gravel-bedded rivers by finer gravel bed load. *Water Resources Research*, 46, W07506. https://doi.org/10.1029/2009WR008329
Viparelli, E., Gaeuman, D., Wilcock, P., & Parker, G. (2011). A model to predict the evolution of a gravel bed river under an imposed cyclic hydrograph and its application to the Trinity River. *Water Resources Research*, 47, W02533. https://doi.org/10.1029/2010WR009164
Wilcock, P. R., & Crowe, J. C. (2003). Surface-based transport model for mixed-size sediment. *Journal of Hydraulic Engineering-Asce*, 129(6), 120–128. https://doi.org/10.1061/(asce)0733-9429(2003)129:2(120)
Wong, M., & Parker, G. (2006). Reanalysis and correction of bed-load relation of Meyer-Peter and Muller using their own database. *Journal of Hydraulic Engineering*, 132(11), 1159–1168. https://doi.org/10.1061/(ASCE)0733-9429(2006)132:11(1159)
Yager, E. M., Schmeeckle, M. W., & Badoux, A. (2018). Resistance is not futile: Grain resistance controls on observed critical Shields stress variations. *Journal of Geophysical Research: Earth Surface*, 123, 3308–3322. https://doi.org/10.1029/2018JF004817
Yager, E. M., Turowski, J. M., Rickenmann, D., & Mc Ardell, B. W. (2012). Sediment supply, grain protrusion, and bedload transport in mountain streams. *Geophysical Research Letters*, 39, L10402. https://doi.org/10.1029/2012GL051654
Yalin, M. S. (1972). Mechanics of sediment transport (p. 290). Oxford: Pergamon Press.