

Joint stochastic model of bedload transport and bed elevations: derivation of heavy-tailed resting times

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Key Points:

- We model fluvial bedload activity and local bed elevation as a two-species stochastic birth-death process.
- Computations show heavy-tailed power-law distributions of resting times for sediment undergoing burial with tail parameter $\alpha \approx 1.18$.
- We discuss implications for bedload diffusion and propose a new modeling framework for fluvial morphodynamics.

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Abstract

We present a model of bedload transport and bed elevation changes as a joint stochastic process and use it to obtain resting time distributions for sediment undergoing burial. Our model predicts heavy-tailed power-law distributions of resting times with tail behavior completely characterized by the mean erosion rate and its scaling with bed elevation changes. Resting time distributions of sediment undergoing burial are remarkably independent of bedload fluctuations. Drawing upon concepts from the stochastic physics literature, we hypothesize this follows from the disparate characteristic timescales of bedload activity and bed elevation fluctuations. Our results show sediment burial generates heavy-tailed resting times and anomalous super-diffusion of bedload at large timescales.

1 Introduction

The movement patterns of individual sediment grains through river channels ultimately control a wide set of environmental processes, including the export of contaminants (e.g., Macklin et al., 2006; Malmon, Reneau, Dunne, Katzman, & Drakos, 2005), the success of ecological restoration efforts (e.g., Gaeuman, Stewart, Schmandt, & Pryor, 2017), and the response of channel morphology to disturbances (e.g., Hassan & Bradley, 2017), highlighting these patterns as an important area of geophysics research. Although the displacements of individual grains are certainly a mechanical consequence of forces imparted to them as they interact with the flow, bed, and other grains (e.g., Vowinkel, Kempe, & Frohlich, 2014; Wiberg & Smith, 1985), accurate characterization of these forces within river channels is practically impossible. This realization has motivated a stochastic concept of the sediment transport process (e.g., Einstein, 1937), whereby the displacement patterns of grains are modeled as random walks (e.g., Weiss, 1994).

In these stochastic models, individual displacements are considered to result from alternate step-rest sequences where step lengths and resting times are random variables following statistical distributions (Bradley & Tucker, 2012; Einstein, 1937; Hassan, Church, & Schick, 1991; Nakagawa & Tsujimoto, 1976; Yano, 1969). Differences between the random-walk motions of one grain and the next imply bedload diffusion, or a spreading apart of grains through time. Over long timescales, the diffusion characteristics predicted by these models critically differ depending on whether the step length and resting time distributions have light or heavy tails (e.g., Weeks & Swinney, 1998). Heavy-tailed distributions have exceedance functions $P(X > x) \sim x^{-\alpha}$ with tail parameters $\alpha < 2$, meaning large values of x

are relatively common, while light-tailed distributions have $\alpha \geq 2$, meaning large values of x are relatively rare. If both resting time and step distance distributions have light tails, the diffusion is said to be normal, with the variance of particle positions σ_x^2 scaling with time t as $\sigma_x^2 \propto t$. However, if either distribution has a heavy-tail, the diffusion is called anomalous, with the variance of particle position scaling as $\sigma_x^2 \propto t^\gamma$, where $\gamma \neq 1$. In this expression, $\gamma < 1$ is called sub-diffusion and $\gamma > 1$ is super-diffusion. In strongly asymmetric random walks such as bedload transport, heavy-tailed step lengths imply super-diffusion, while heavy-tailed resting times imply either super or sub-diffusion, depending on α (Bradley, 2017; Weeks & Swinney, 1998; Weeks, Urbach, & Swinney, 1996).

Tracer experiments in gravel-bed rivers show anomalous bedload diffusion (Bradley, 2017; Phillips, Martin, & Jerolmack, 2013), light-tailed step lengths (Bradley & Tucker, 2012; Hassan, Voepel, Schumer, Parker, & Fraccarollo, 2013; Phillips et al., 2013), and heavy-tailed resting times (Bradley, 2017; Olinde & Johnson, 2015; Pretzlav, 2016; Voepel, Schumer, & Hassan, 2013), forming a coherent experimental picture of super-diffusive bedload transport, at least at long observation timescales (e.g., Martin, Jerolmack, & Schumer, 2012; Nikora, 2002). However, field studies have not resolved the generating mechanism of the observed heavy-tailed resting times (e.g., Bradley, 2017), and empirical distributions display clear differences in their forms and characteristics, with different tail parameters (e.g., Olinde & Johnson, 2015; Pretzlav, 2016) and sometimes truncation (e.g., Bradley, 2017) or tempering to light tails at large resting times (e.g., Voepel et al., 2013). These differences and the mechanism generating heavy-tailed resting times deserve further research attention.

A predominant hypothesis is that heavy-tailed resting times and anomalous diffusion originate from sediment burial (Martin, Purohit, & Jerolmack, 2014; Voepel et al., 2013; Wu et al., 2019). Conceptually, when grains rest on the bed surface, material transported from upstream can deposit on top of them, preventing entrainment until it's removed, driving up resting times and imparting a heavy tail to the distribution. To our knowledge, Martin et al. (2014) have provided the only direct support for this hypothesis. They traced grains in a narrow flume with clear sidewalls, directly resolving burial as the mechanism of heavy-tailed resting times, and they described their results with a mathematical model that is formally similar to an earlier effort by Voepel et al. (2013). The models of Voepel et al. (2013) and Martin et al. (2014) consider bed elevations as a random walk and interpret resting times as return periods from above in the bed elevation time-series (e.g., Redner, 2007). Both models are successful in describing different experimental resting time distributions. However, their

assumptions and results are inconsistent with one another, and their treatment of bed elevations as a process independent of sediment transport is questionable at first glance, since the erosion and deposition of individual grains are the source of bed elevation changes (e.g., Wong, Parker, DeVries, Brown, & Burges, 2007).

In this work, we study heavy-tailed resting times by making an extension of the stochastic bedload transport model of Ancey, Davison, Böhm, Jodeau, and Frey (2008) to link bed elevation changes to the erosion and deposition events of individual grains. The key assumptions of our model are: (1) bedload erosion and deposition can be characterized by probabilities per unit time, or rates (e.g., Ancey et al., 2008; Einstein, 1950); and (2) these rates are contingent on the local bed elevation, encoding the property that erosion of sediment is emphasized from regions of exposure, while deposition is emphasized in regions of shelter (e.g., Sawai, 1987; Wong et al., 2007). Our model generates heavy-tailed distributions with no tempering and a universal tail parameter $\alpha \approx 1.18$ for a particular non-dimensionalization of the resting time, showing close correspondence to the findings of Martin et al. (2014) and suggesting a correction to their results. We conclude by framing our work in relation to earlier ideas and discussing its implications open problems in bedload transport and anomalous diffusion.

2 Stochastic model

We define a volume of downstream length L that contains some number n of moving particles in the water flow and some number m of stationary particles composing the bed at time t as depicted in figure 1. For simplicity, we consider all particles as approximately spherical with the same diameter $2a$, so their mobility and packing characteristics are similar. Following Ancey et al. (2008), we prescribe four events that can occur at any instant to modify the populations n and m , and we characterize these events using probabilities per unit time, or rates. These are: (1) migration of a moving particle into the volume from upstream ($n \rightarrow n+1$); (2) the entrainment (i.e., erosion) of a stationary particle into motion within the volume ($m \rightarrow m-1$ and $n \rightarrow n+1$); (3) the deposition of a moving particle to rest within the volume ($m \rightarrow m+1$ and $n \rightarrow n-1$); and (4) the migration of a moving particle out of the volume to downstream ($n \rightarrow n-1$). These four events are depicted as arrows in figure 1. As the events occur at random intervals, they set up a joint stochastic evolution of the populations n and m characterized by a joint probability distribution $P(n, m, t)$ having

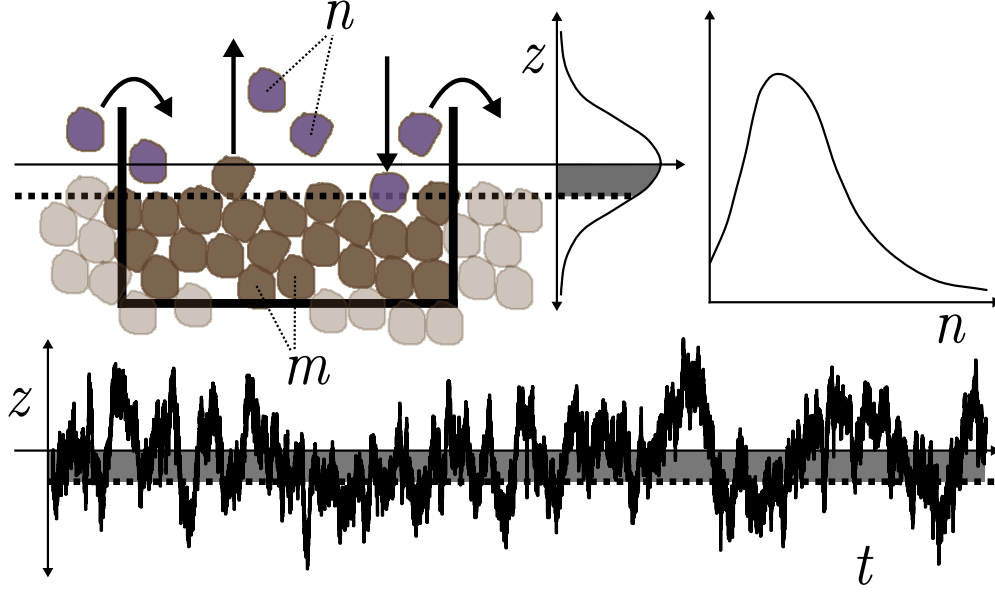


Figure 1. Definition sketch of a control volume containing n moving grains and m resting grains. Migration, entrainment, and deposition processes are represented by arrows, and the instantaneous bed elevation is depicted by dotted lines. The bed is displayed in a degraded state, where $m < m_0$. The marginal distributions of n and m are indicated in the upper right panel, while the lower panel is a realized time-series of bed elevations computed from m using (1).

marginals $P(n, t) = \sum_m P(n, m, t)$ and $P(m, t) = \sum_n P(n, m, t)$ for the number of particles in motion and at rest in the volume at t .

The populations n and m provide the bulk bedload flux q_s and the local bed elevation z . The mean bedload transport rate is given by $q_s \propto u_s \langle n \rangle$, where u_s is the characteristic velocity of moving bedload and $\langle n \rangle = \sum_{n,m} n P(n, m)$ is the mean number of grains in motion (e.g., Ancey et al., 2008; Charru, Mouilleron, & Eiff, 2004; Furbish, Haff, Roseberry, & Schmeeckle, 2012). The bed elevation is related to m though the packing geometry of the bed. To derive this, we prescribe a mean number of grains at rest m_0 and introduce a packing fraction ϕ of grains in the bed (Torquato, 2018). Considering a two-dimensional bed (e.g., Einstein, 1950; Paintal, 1971), the deviation from the mean bed elevation is

$$z(m) = \frac{\pi a^2}{\phi L} (m - m_0) = z_1 (m - m_0). \quad (1)$$

The constant $z_1 = \pi a^2 / (\phi L)$ is an important scale of the problem. z_1 is the magnitude of bed elevation change (in an average sense across the control volume) associated with the addition or removal of a single grain. We write the rates of the four possible transitions as

(e.g., Ancey et al., 2008):

$$R_{MI}(n+1, m|n, m) = \nu \quad \text{migration in,} \quad (2)$$

$$R_E(n+1, m-1|n, m) = \lambda(m) + \mu(m)n \quad \text{entrainment,} \quad (3)$$

$$R_D(n-1, m+1|n, m) = \sigma(m)n \quad \text{deposition,} \quad (4)$$

$$R_{MO}(n-1, m|n, m) = \gamma n \quad \text{migration out.} \quad (5)$$

These rates are independent of the past history of the populations and depend only on the current populations (n, m) . As a result, the system is Markovian (e.g., Cox & Miller, 1965; van Kampen, 1992), meaning time intervals between any two subsequent transitions are exponentially distributed (e.g., Gillespie, 2007).

In (2-5), ν and γ are constants characterizing migration rates of individual grains into and out of the volume. They lack any dependence on the populations n and m . In contrast, $\lambda(m)$, $\mu(m)$, and $\sigma(m)$, characterizing the entrainment, collective entrainment (e.g., Ancey et al., 2008; Heyman, Ma, Mettra, & Ancey, 2014; Heyman, Mettra, Ma, & Ancey, 2013), and deposition rates of individual grains are considered to depend on m . As is well-known, bed elevation changes modify the likelihood of entrainment and deposition in a negative feedback (Sawai, 1987; Wong et al., 2007); that is, aggradation increases the likelihood of entrainment, while degradation increases the likelihood of deposition. Wong et al. (2007) concluded that bed elevation changes induce an exponential variation in entrainment and deposition probabilities, while Sawai (1987) concluded that the variation is linear. For simplicity, we incorporate the scaling of Sawai (1987) and note its equivalence to the Wong et al. (2007) scaling when bed elevation changes are small. Because experimental distributions of bed elevations are usually symmetrical, (Martin et al., 2014; Singh, Fienberg, Jerolmack, Marr, & Foufoula-Georgiou, 2009; Wong et al., 2007), we expect the erosion and deposition feedbacks to be anti-symmetrical. That is, as bed elevation changes drive up (down) erosion rates, so they drive down (up) deposition rates to the same degree.

Summarizing these ideas, the entrainment and deposition rates can be written $\chi(m) = \chi_0(1 \pm z_1 z(m)/(2l)^2)$, where $\chi = \lambda, \mu, \sigma$, and the entrainment parameters take the plus sign, while deposition takes the minus, and we have introduced a length scale l . The variance of bed elevation turns out to be given by $\text{var}(z) = (l/z_1)^2$. Accordingly, l characterizes the range of bed elevation variations, which could be interpreted as an active layer depth (e.g., Church & Haschenburger, 2017). Another perspective is that l is the distance of bed elevation change at which the entrainment and deposition rates are significantly affected.

With these substitutions, the local bed elevation-dependent entrainment and deposition rates (3-4) can be written:

$$R_E(n+1, m-1|n, m) = [\lambda_0 + \mu_0 n] \left[1 + \frac{z_1 z(m)}{(2l)^2} \right], \quad \text{entrainment,} \quad (6)$$

$$R_D(n-1, m+1|n, m) = \sigma_0 \left[1 - \frac{z_1 z(m)}{(2l)^2} \right] n, \quad \text{deposition.} \quad (7)$$

At $z(m) = 0$, the rates reduce to those of the Ancey et al. (2008) model. Away from this elevation, entrainment and deposition are alternatively suppressed and accentuated depending on the sign of $z(m)$.

In terms of the transition rates (2-7), we can obtain the Master equation for the probability flow using the forward Kolmogorov equation $\partial P(n, m; t) / \partial t = \sum_{n', m'} R(n, m) P(n', m'; t)$ (e.g., Ancey et al., 2008; Cox & Miller, 1965; Gillespie, 1992) as

$$\begin{aligned} \frac{\partial P}{\partial t}(n, m; t) = & \nu P(n-1, m; t) + \{\lambda(m+1) + [n-1]\mu(m+1)\} P(n-1, m+1; t) \\ & + [n+1]\sigma(m-1) P(n+1, m-1; t) + [n+1]\gamma P(n+1, m; t) \\ & - \{\nu + \lambda(m) + n\mu(m) + n\sigma(m) + n\gamma\} P(n, m; t). \end{aligned} \quad (8)$$

The joint probability distribution $P(n, m; t)$ solving this equation will fully characterize the statistics of n and m . We anticipate that solutions will adjust from the initial conditions to a steady-state distribution $P_s(n, m)$, independent of time, if the constant factors in the transition rates are representative of steady bedload transport conditions. This Master equation describes a two-species stochastic birth-death model (e.g., Cox & Miller, 1965) of a type well-known in population ecology (e.g., Pielou, 1977; Swift, 2002) and chemical physics (e.g., Gardiner, 1983). In our context, the two species are the moving and stationary grains in the volume.

3 Numerical simulations

Unfortunately, (8) does not appear to admit an analytical solution (but see Swift (2002) for a standard method that fails in this case). The difficulty stems from the product terms between n and m . In response, we resort to numerical methods, simulating (8) with the Gillespie algorithm (Gillespie, 1977, 1992, 2007). The Gillespie algorithm leverages the defining property of a Markov process: when transition rates do not depend on the past, time intervals between transitions are exponentially distributed (e.g., Cox & Miller, 1965). As a result, to step the Markov process through a single transition, it's enough to draw a random value from the exponential distribution of transition intervals to determine the time

of the next transition. Then drawing another random value to choose the type of transition that occurs using the relative probabilities (2-7), the transition can be enacted by shifting t , n and m by the appropriate values (i.e., entrainment is $m \rightarrow m - 1$ and $n \rightarrow n + 1$, and so on). This procedure can be iterated to form an exact realization of the stochastic process (e.g., Gillespie, 2007).

Table 1. Parameters from Ancy et al. (2008) experiments describing the rates of migration in, entrainment, deposition, and migration out when $z(m) = 0$. All units are s^{-1} (probability/time). In our model, bed elevation changes modulate these rates in accord with (2-7).

Flow	ν	λ_0	μ_0	σ_0	γ
(a)	5.45	6.59	3.74	4.67	0.77
(g)	7.74	8.42	4.34	4.95	0.56
(i)	15.56	22.07	3.56	4.52	0.68
(l)	15.52	14.64	4.32	4.77	0.48
(n)	15.45	24.49	3.64	4.21	0.36

and set $L = 22.5\text{cm}$ and $a = 0.3\text{cm}$ in accord with the Ancy et al. (2008) experiments. Each simulation was run for 1500hrs of virtual time, a period selected to ensure convergence of the resting time statistics.

4 Results

Our simulations show dynamic time-series of bedload activities and bed elevations (as seen in the lower panel of figure 1). From our chosen initial conditions, all simulations show a rapid attainment of steady-state stochastic dynamics of n and m which support a time-independent joint distribution $P_s(n, m)$. We compute this joint distribution by counting

In this way, we simulated 5 transport conditions with 10 different values of l taken across a range from $l = a$ (a single radius) to $l = 10a$ (10 radii). These values lie in the range exhibited by the majority of available experimental data (Martin et al., 2014; Singh et al., 2009; Wong et al., 2007). For the migration, entrainment, and deposition parameters at each flow condition $(\nu, \lambda_0, \mu_0, \sigma_0, \gamma)$, we used values measured by Ancy et al. (2008) in a series of flume experiments. These are summarized in table 1. Flow conditions are labeled (a), (g), and so on, roughly in order of increasing bedload flux (see Ancy et al. (2008) for more details). In all simulations, we take the packing fraction $\phi = 0.6$, a typical value for a pile of spheres (e.g., Bennett, 1972),

occurrences of the states (n, m) in the simulated time series. From this joint distribution we compute marginals $P(n)$ and $P(m)$ as explained in section 2.

A representative subset of these marginal distributions is displayed in figure 3. In their model, Ancey et al. (2008) analytically derived negative binomial distributions for the bedload activity n , and this functional form appears preserved through our inclusion of feedbacks between bedload transport and bed elevation changes. All our computed distributions admit clean negative binomial fits (figure 3a). For the bed elevation m (or z), our computations show Gaussian distributions (figure 3b), consistent with our assumptions of a symmetric scaling of erosion and deposition rates with bed elevation changes (e.g., Wong et al., 2007).

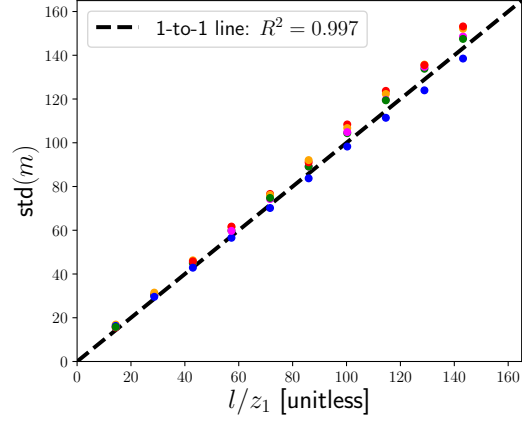


Figure 2. Data from all simulations is plotted to show that l controls deviations of bed elevations: $\text{var}(m) = (l/z_1)^2$.

From the marginal distributions, we calculate means and variances of bedload activity (n) and bed elevation (m). The mean bed elevation is m_0 , the parameter in (1). m fluctuates around this value because it sets the equilibrium position of the elevation-related feedbacks within (1). The variance of m follows $z_1^2 \text{var}(m) = l^2$, as demonstrated in figure 2, consistent with our interpretation of l as a measure of bed elevation fluctuations. The variance of n ($\text{var}(n)$), characterizing the magnitude of bedload activity fluctuations, has a more nuanced dependence on the coupling of transport to bed elevation changes. Generally speaking, our simulations show relatively small $\text{var}(m)$ increases $\text{var}(n)$ from its decoupled value (i.e., its $l \rightarrow \infty$ value), while relatively large $\text{var}(m)$ decreases $\text{var}(n)$ from its decoupled value. Since $\text{var}(m)$ reflects the coupling between entrainment/deposition rates and the local bed elevation, we see a relatively strong coupling (small l) increases bedload fluctuations, while a relatively weak coupling (large l) reduces them. In simple terms, when bed elevation variations are tightly linked to the mobility of surface grains, bedload fluctuations are enhanced.

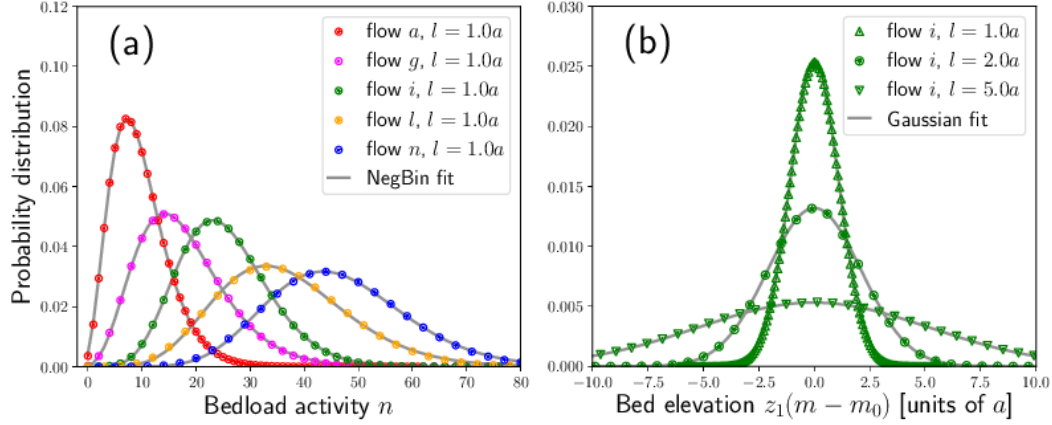


Figure 3. Marginal distributions of n and m for a representative subset of simulations. Some points have been omitted for clarity.

Resting times for sediment undergoing burial are obtained from the time-series of m . Following Voepel et al. (2013) and Martin et al. (2014), we concentrate on a particular bed elevation m' , and find all time intervals separating deposition events at $m = m'$ from erosion events at $m = m' + 1$. These are the return times from above of the sedimentary bed conditional to the elevation m' . Binning these conditional return times (using logarithmically-spaced bins to reduce computational load) and counting the occurrences in each bin, we obtain a non-exceedance distribution of return times t_r held conditional to the elevation m' : $P(T > t_r|m')$. Using the marginal probability distribution of bed elevations $P(m)$, we derive the unconditional non-exceedance distribution of resting times as a sum over all elevations (Martin et al., 2014; Nakagawa & Tsujimoto, 1980; Voepel et al., 2013; Yang & Sayre, 1971):

$$P(T > t_r) = \sum_{m'} P(m') P(T > t_r|m'). \quad (9)$$

Some of these results are displayed in figure 4. In contrast to earlier works our analysis does not require an additional binning step over the elevation, since our elevation series is discrete (multiples of z_1). This provides enhanced resolution of the resting time distributions. Comparing panels 4(a) and 4(c) shows the resting time distributions scale with the intensity of bedload transport and the standard deviation of bed elevations (l) in different ways. However, as shown in panels 4(b) and 4(d), a characteristic timescale T_0 is found to collapse away both of these types of differences. We obtain T_0 heuristically by finding a characteristic speed of bed elevation change. Formally, the mean erosion rate is $E = \sum_{n,m} R_E(n + 1, m - 1|n, m) P_s(n, m)$. This is the mean number of grains leaving the bed per unit time. Since

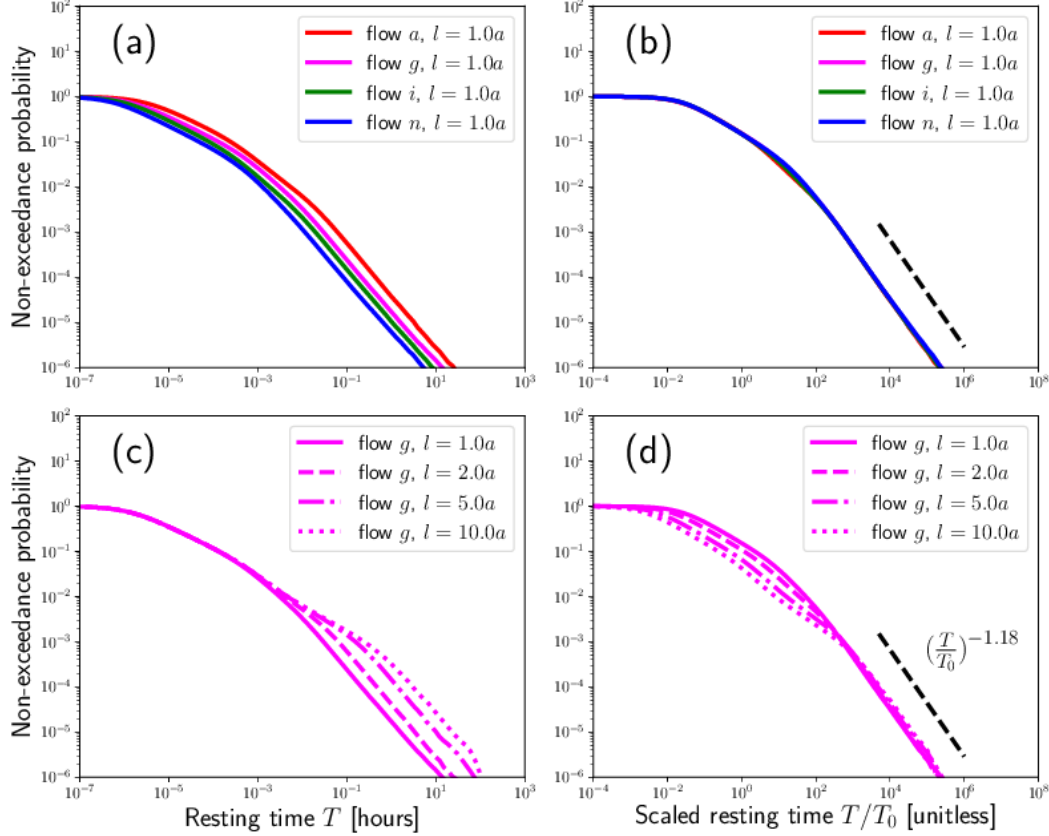


Figure 4. Resting time statistics scale differently with transport conditions and the bed elevation variance. Panel (a) shows differing flow conditions at a fixed l value, while panel (c) shows fixed flow conditions at differing l . When scaled by T_0 (10), both types of difference collapse in the tails of the distributions, as shown in panels (b) and (d). In panels (b) and (d), the black dotted lines indicate a power law decay of the collapsed tails having parameter $\alpha \approx 1.18$.

the removal of a single grain changes the bed elevation by z_1 , bed elevations change with a characteristic speed $z_1 E$. Since the range of elevation deviations is l , the time required for the bed to shift through this characteristic distance is

$$T_0 = \frac{l}{z_1 E}. \quad (10)$$

When scaling the resting time by this T_0 , we obtain the collapse shown in figure 4. Using the log-likelihood estimation technique described by Newman (2005), we estimate the scaled resting time non-exceedance distributions decay as a heavy-tailed power law with parameter $\alpha = 1.18 \pm 0.32$ for all return times satisfying $T/T_0 > 10^3$. These distributions are sufficiently heavy-tailed to violate the central limit theorem and drive anomalous super-diffusion of bedload, a result which supports the earlier conclusions of (Martin et al., 2014).

5 Discussion

Einstein (1937) developed the first model of individual bedload motions and bedload diffusion, and his ideas can be viewed as the historical nexus of an entire paradigm of research that extends into the present day (e.g., Ancey et al., 2008; Hassan et al., 1991; Hubbell & Sayre, 1964; Nakagawa & Tsujimoto, 1976; Wu et al., 2019). Works in this paradigm attempt to understand properties of bedload transport from applying a stochastic concept of individual sediment motions. With some exceptions (e.g., Nakagawa & Tsujimoto, 1980; Pelosi, Schumer, Parker, & Ferguson, 2016; Wu et al., 2019; Yang & Sayre, 1971), existing descriptions are spatially one-dimensional, concentrating on the motion of grains in the downstream direction without including the vertical dimension wherein local bed elevation changes imply sediment burial (e.g., Martin et al., 2014; Voepel et al., 2013) and modify the mobility of surface grains (e.g., Nakagawa & Tsujimoto, 1980; Yang & Sayre, 1971).

Our model builds upon several earlier works (e.g., Ancey et al., 2008; Martin et al., 2014) to include this vertical dimension and provide a joint description of bedload transport and bed elevation changes. We find negative binomial distributions of bedload activity and normal distributions of bed elevations, reproducing a wide set of experimental findings (Ancey et al., 2008; Heyman, Bohorquez, & Ancey, 2016; Martin et al., 2014; Singh et al., 2009; Wong et al., 2007). More importantly, we interpret resting times of sediment undergoing burial as return times from above in the bed elevation time series (e.g., Martin et al., 2014; Voepel et al., 2013), and predict the form and characteristics of this distribution. Of course, modeling complex geophysical phenomena (such as expressions of coupled fluid and granular phases) necessitates simplifying assumptions (e.g., Larsen et al., 2016), and our work is no exception. We believe the key limitations of our work are (1) our assumption that local (as opposed to non-local) deviations in bed elevation are the dominant control on the mobility of grains; and (2) those assumptions inherited from the underlying bedload transport model of Ancey et al. (2008), which essentially incorporates the earlier assumptions of Einstein (1950) into a stochastic framework. The first assumption can be somewhat justified under conditions in which the formation of organized bed structures is not favored (e.g., Hassan et al., 2008), while the second has been discussed in earlier works and appears justified in near-threshold transport conditions when the intermittent aspect of bedload transport is emphasized (e.g., Ancey et al., 2008; Heyman et al., 2014) whenever organized bed structures are not present (e.g., Dhont & Ancey, 2018).

The joint description (8) reproduces earlier descriptions of bedload activities by Ancey et al. (2008) and bed elevations by Martin et al. (2014) in simplified limits. The Ancey et al. (2008) bedload model is obtained when bed elevation fluctuations δm are considered small: $m \approx m_0$. Taking account of this change in (8) obtains the master equation of Ancey et al. (2008) for the bedload activity distribution $P(n, t)$. Hence the differences between our bedload activity statistics and those of the Ancey et al. (2008) model are induced by bed elevation fluctuations. When relatively large bed elevation fluctuations are possible (i.e., l is large), bed elevation changes act to buffer bedload activity fluctuations. In contrast, when bed elevation changes are tightly linked to the mobility of moving and stationary grains (i.e., l is small), bed elevation changes enhance bedload fluctuations. We hypothesize this enhancement/suppression of bedload fluctuations is primarily due to the collective entrainment term in (7), since the Ancey et al. (2008) variance is most sensitive to the collective entrainment process. However, more research will be required to clarify the linkage between bed elevation changes and bedload fluctuations. Given recent observations of sudden local elevation changes being induced by avalanches on the downstream face of bars (Dhont & Ancey, 2018), we identify the interplay between collective motions of bedload and bed elevation changes as an emerging research theme, and we suggest our joint description may hint toward a modeling framework to address these issues.

The Martin et al. (2014) bed elevation model based upon the Ornstein-Uhlenbeck (OU) process is obtained in the converse limit when bedload activity fluctuations δn are small: $n \approx \langle n \rangle$. In this case, neglecting the migration terms and identifying the mean entrainment and deposition rates as $E = \lambda_0 + \mu_0 \langle n \rangle$ and $D = \sigma_0 \langle n \rangle$ before using the steady-state transport condition $E = D$ (e.g., Einstein, 1950) gives

$$\frac{\partial}{\partial t} P(m, t) = E \left\{ \left[1 + \left(\frac{z_1}{2l} \right)^2 m \right] P(m+1, t) + \left[1 - \left(\frac{z_1}{2l} \right)^2 m \right] P(m-1, t) - 2P(m, t) \right\}, \quad (11)$$

This is a discrete state analogue of the OU process Martin et al. (2014) used to model bed elevation changes, and it provides excellent correspondence to the bed elevation statistics and resting time distributions computed from our joint model. Our resting time distributions of sediment undergoing burial essentially correspond with those of Martin et al. (2014) given our computational uncertainty. These authors proposed $\alpha \approx 1$ from a continuum analogue of (11). Incidentally, they scale resting times by an "activity parameter" $1/a$ which is equivalent to $1/(2E)$ in our notation. Our work suggests the incomplete collapse displayed by Martin et al. (2014) may be corrected by including a bed elevation variance factor in

their scaling as in (10), further justifying the correspondence of our model to (11). In fact, we note T_0 is the autocorrelation time of the limiting OU process (10) (e.g., Gardiner, 1983).

In light of the coupling between elevation fluctuations and the entrainment/deposition rates in (8), and the non-negligible elevation fluctuations our model produces (figure 3b), this correspondence to Martin et al. (2014) is initially surprising. However, we can understand it through the lens of "fast" and "slow" stochastic variables advanced by Haken (1983). Since appreciable bed elevation changes are the compound result of many bedload entrainment or deposition events ($O(l/z_1)$ of them), bed elevation fluctuations persist for a typical timescale which is much longer than the timescale of bedload activity fluctuations, so n is a "fast" variable while m is a "slow" one. This statement could be formalized by comparing the autocorrelation times of n and m (e.g., Gardiner, 1983). Accordingly, the value of m does not change appreciably during the period of time required for n to vary through a wide range, meaning the slow variable m is influenced by many n values during the course of its incremental evolution, justifying the mean-field limit (11) equivalent to Martin et al. (2014). This is a so-called adiabatic slaving principle, whereby fast stochastic variables are coordinated to slow ones but not the converse. Hence (11) is justified from a more rigorous adiabatic approximation of (8) based on integrating out the fast variable n (e.g., Gardiner, 1983; Haken, 1983), and not only by an ad hoc mean-field limit. We believe such ideas may find widespread application to future river science considerations. Indeed, rivers display a wide set of temporally evolving attributes, exhibiting apparent randomness on disparate scales (Chartrand, Jellinek, Hassan, & Ferrer-Boix, 2019), including hydraulic flow (e.g., Ferrer-Boix & Hassan, 2015), morphological structure (e.g., Dhont & Ancey, 2018), and sediment supply regime (e.g., Elgueta-Astaburuaga & Hassan, 2019). This increasing realization has encouraged investigators to approach river science problems from a stochastic physics standpoint, driving a contemporary increase in the popularity of this approach (e.g. Ancey et al., 2008; Furbish, Ball, & Schmeeckle, 2012). In the present context, we have provided evidence that simpler one-dimensional stochastic models (e.g., Martin et al., 2014) can aptly describe more complex geophysical phenomena when a scale mismatch is present in their coupled components.

The computed resting time distributions (figure 4) provide several implications for bedload diffusion. Our simulations show asymptotic power law tails with parameter $\alpha = 1.18 \pm 0.32$ after scaling by T_0 related to the characteristic speed of bed elevation changes. For a general power law, if $\alpha > 1$, neither the mean or variance of the resting time will

converge, while if $1 < \alpha < 2$, the mean will converge while the variance will not (e.g., Bradley, 2017). Within our computational uncertainty stemming from the finite duration of our simulations and the log-likelihood estimation of α (e.g., Newman, 2005), we are unable to conclude whether the mean resting time will diverge, but we can conclude the variance will diverge. According to Weeks and Swinney (1998), if the step length distribution has a light tail (e.g., Hassan et al., 2013), our computed power-law resting times are sufficiently heavy-tailed to imply diffusion scaling as either $\sigma_x^2 \propto t^{3-\alpha} \approx t^{\{1.82 \pm 0.32\}}$ or $\sigma_x^2 \propto t^{2\alpha} \approx t^{\{3.64 \pm 0.45\}}$ at asymptotically large times. In either case, the process of sediment burial induces an extreme super-diffusion of bedload: at long timescales, some grains will continue to transport downstream in alternate motion-rest sequences while others will become trapped under the bed for relatively long periods of time, driving a rapid spreading of the population. In relation to solid contaminant export from river channels (e.g., Malmon et al., 2005), long-time super-diffusion implies contaminants will eventually dilute over a relatively vast region. However, heavy-tailed resting times mean total evacuation could take an exceedingly long time.

Finally, we propose a possible extension of the joint model (8) by following its linkage to Ancey et al. (2008) and follow-ups (e.g., Ancey & Heyman, 2014; Heyman, Bohórquez, & Ancey, 2015; Heyman et al., 2014). These works are based on chaining many Ancey et al. (2008) single-cell models together along a line, with migration out of one cell being migration into another. In this way, they provide a framework to study spatial correlations in bedload transport (e.g., Heyman et al., 2015, 2014). Similar approaches have been used to formulate reaction-diffusion and flow problems in stochastic physics (e.g., Gardiner, 1983). One can imagine using the model (8) in the same way, chaining an array of volumes (as in figure 1) together along a line to generate a fluvial morphodynamics model ultimately rooted in a stochastic concept of individual motions (e.g., Einstein, 1937). Such a model could provide spatial correlations in bed elevation changes and bedload transport while taking account of their inherent granularity. Given the increasing realization that granular physics phenomena initiated by individual grains, such as avalanches and jamming, play a non-negligible role in fluvial processes (e.g., Dhont & Ancey, 2018; Saletti, 2016), we speculate such a model, if suitably extended, might provide unique traction on future research problems centered around processes initiated by individual grains.

6 Conclusion

We have developed a joint stochastic model of bedload transport and bed elevation changes based upon the motions of individual grains, fusing earlier works in the research paradigm of Einstein (1937). This is a two-population stochastic birth-death process of a type often encountered in mathematical ecology (e.g., Pielou, 1977) and chemical physics (e.g., Gardiner, 1983), and it reproduces empirical expectations for Gaussian bed elevation and negative binomial bedload activity distributions (e.g., Ancey et al., 2008; Wong et al., 2007). Interpreting resting times of sediment undergoing burial as return times from above in the bed elevation time series (e.g., Voepel et al., 2013), we predict asymptotic heavy-tailed power-law resting times with parameter $\alpha = 1.18 \pm 0.32$, corroborating the results of Martin et al. (2014). These distributions imply sediment burial will induce bedload super-diffusion at long timescales (e.g., Phillips et al., 2013). Finally, this work draws some concepts from the stochastic physics literature into river science for the first time, and it points out several difficult problems for future research. The limit of our description to the model of Martin et al. (2014) provides a geophysical example of Haken’s slaving principle concerning the interaction of fast and slow stochastic variables (Haken, 1983), and its comparison to Ancey et al. (2008) suggests a nuanced linkage between collective transport and bed elevation changes which requires further study.

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