# Back to Einstein: burial-induced three range diffusion in fluvial sediment transport

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November 21, 2022

#### Abstract

Individual grains move through gravel bed rivers in cycles of motion and rest with variable characteristics, so tracer grains spread apart as they transport downstream in a type of diffusion. Experiments and Newtonian simulations have demonstrated nuanced diffusion characteristics, with at least three distinct ranges of behavior as the observation time of tracers increases and each range exhibiting a different spreading rate. Although these observations are nearly 20 years old, no physical model has been developed to describe them, leaving us uncertain of the generating processes. In this work, we develop the first physical model describing three bedload diffusion ranges by incorporating sediment motion, rest, and burial into a random walk concept of individual bedload trajectories. Using the model, we attribute multiple bedload diffusion ranges to the interplay between motion, rest, and burial processes, and we relate the multi-range diffusion characteristics to measurable transport parameters.

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### Key Points:

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7	•	Random walk model describes coarse gravel tracers diffusing through a river as
8		they gradually become buried
9	•	Interchange of grains between motion, surface rest, and burial states generates
10		three diffusion ranges as the observation time increases
11	•	Sediment burial dominates long-time properties and may develop a fourth "ge-
12		omorphic" range of tracer diffusion

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#### 13 Abstract

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#### 1 Introduction

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Many environmental problems including channel morphology (Hassan & Bradley, 27 2017), contaminant transport (Macklin et al., 2006), and aquatic habitat restoration 28 (Gaeuman, Stewart, Schmandt, & Pryor, 2017) rely on our ability to predict the diffu-29 sion characteristics of coarse sediment tracers in river channels. Diffusion is quantified 30 by the time dependence of the positional variance  $\sigma_x^2$  of a group of tracers. With the 31 scaling  $\sigma_x^2 \propto t$ , the diffusion is said to be normal, since this is found in the classic 32 problems (Taylor, 1920). However, with the scaling  $\sigma_x^2 \propto t^{\gamma}$  with  $\gamma \neq 1$ , the diffu-33 sion is said to be anomalous (Sokolov, 2012), with  $\gamma > 1$  defining super-diffusion and 34  $\gamma < 1$  defining sub-diffusion (Metzler & Klafter, 2000). Einstein (1937) developed one 35 of the earliest models of bedload diffusion to describe a series of flume experiments 36 (Ettema & Mutel, 2014). Interpreting individual bedload trajectories as a sequence of 37 random steps and rests, Einstein originally concluded that a group of bedload tracers 38 undergoes normal diffusion. 39

More recently, Nikora et al. realized coarse sediment tracers can show either nor-40 mal or anomalous diffusion depending on the length of time they have been tracked 41 (Nikora, 2002; Nikora, Heald, Goring, & McEwan, 2001). From numerical simula-42 tions and experimental data, Nikora et al. discerned "at least three" scaling ranges 43  $\sigma_x^2 \propto t^{\gamma}$  as the observation time increased. They associated the first range with "lo-44 cal" timescales less than the interval between subsequent collisions of moving grains 45 with the bed, the second with "intermediate" timescales less than the interval between 46 successive resting periods of grains, and the third with "global" timescales composed 47 of many intermediate timescales. Nikora et al. proposed super-diffusion in the local 48 range, anomalous or normal diffusion in the intermediate range, and sub-diffusion in 49 the global range. They attributed these ranges to "differences in the physical pro-50 cesses which govern the local, intermediate, and global trajectories" of grains (Nikora 51 et al., 2001), and they called for a physically based model to explain the diffusion 52 characteristics (Nikora, 2002). 53

Experiments support the Nikora et al. conclusion of multiple scaling ranges 54 (Fathel, Furbish, & Schmeeckle, 2016; Martin, Jerolmack, & Schumer, 2012), but they 55 do not provide consensus on the expected number of ranges or their scaling properties. 56 This lack of consensus probably stems from resolution issues. For example, experiments 57 have tracked only moving grains, resolving the local range (Fathel et al., 2016; Furbish, 58 Ball, & Schmeeckle, 2012; Furbish, Fathel, Schmeeckle, Jerolmack, & Schumer, 2017); 59 grains resting on the bed surface between movements, resolving the intermediate range 60 (Einstein, 1937; Nakagawa & Tsujimoto, 1976; Yano, 1969); grains either moving or 61 resting on the bed surface, likely resolving local and intermediate ranges (Martin et 62 al., 2012); or grains resting between subsequent floods, likely resolving the global range 63

(Bradley, 2017; Phillips, Martin, & Jerolmack, 2013). At long timescales, a significant 64 fraction of tracers bury under the bed surface (Ferguson, Bloomer, Hoey, & Werritty, 65 2002; Haschenburger, 2013; Hassan, Church, & Schick, 1991; Hassan, Voepel, Schumer, 66 Parker, & Fraccarollo, 2013; Papangelakis & Hassan, 2016), meaning burial dominates 67 long term diffusion characteristics (Bradley, 2017; Martin, Purohit, & Jerolmack, 2014; 68 Voepel, Schumer, & Hassan, 2013), possibly at global or even longer "geomorphic" 69 timescales (Hassan & Bradley, 2017) than Nikora et al. originally considered. As a 70 result, three diffusion ranges can be identified by patching together multiple datasets 71 (Nikora, 2002; Zhang, Meerschaert, & Packman, 2012), but they are not resolved by 72 any one dataset. 73

Newtonian bedload trajectory models also show multiple diffusion ranges, al-74 though they also do not provide consensus on the expected number of ranges or their 75 scaling properties. The majority of these models predict two ranges of diffusion (local 76 and intermediate) without predicting a global range. Among these, Nikora et al. (2001) 77 used synthetic turbulence (Kraichnan, 1970) with a discrete element method for the 78 granular phase (Cundall & Strack, 1979); Bialik, Nikora, and Rowiński (2012) used 79 synthetic turbulence with a random collision model (Sekine & Kikkawa, 1992); and 80 Fan, Singh, Guala, Foufoula-Georgiou, and Wu (2016) used a Langevin equation with 81 probabilistic rests. To our knowledge, only Bialik, Nikora, Karpiński, and Rowiński 82 (2015) have claimed to capture all three ranges from a semi-Newtonian approach. 83 They incorporated a second resting mechanism into their earlier model (Bialik et al., 84 2012), implicitly suggesting that three diffusion ranges could result from two distinct 85 timescales of sediment rest. However, Newtonian approaches have not evaluated the 86 effect of sediment burial on tracer diffusion. 87

Random walk bedload diffusion models constructed in the spirit of Einstein 88 (1937) provide an alternative to the Newtonian approach and can include a second 89 timescale of rest by incorporating sediment burial. Einstein originally modeled bedload 90 trajectories as instantaneous steps interrupted by durations of rest lying on statistical 91 distributions (Hassan et al., 1991), but this generates only one range of normal diffu-92 sion (Einstein, 1937; Hubbell & Sayre, 1964; Nakagawa & Tsujimoto, 1976). Recently, 93 researchers have generalized Einstein's model in a few different ways to describe multi-94 ple diffusion ranges. Lisle et al. (1998) and Lajeunesse, Devauchelle, and James (2018) 95 promoted Einstein's instantaneous steps to motion intervals with random durations 96 and a constant velocity, providing two diffusion ranges – local and intermediate. Wu, 97 Foufoula-Georgiou, et al. (2019) retained Einstein's instantaneous steps but included 98 the possibility that grains can become permanently buried as they rest on the bed, 99 also providing two diffusion ranges – intermediate and global. Although no Einstein-100 type model of three bedload diffusion ranges has been developed, these earlier works 101 suggest the minimal required components are (1) exchange between motion and rest 102 intervals and (2) the sediment burial process. 103

In this study, we incorporate these two components into Einstein's original ap-104 proach to describe three diffusion ranges with a physically based model as called for by 105 Nikora (2002). Einstein was a giant in river geophysics and fostered an entire paradigm 106 of research leveraging and generalizing his stochastic methods (Gordon, Carmichael, & 107 108 Isackson, 1972; Hubbell & Sayre, 1964; Nakagawa & Tsujimoto, 1976; Paintal, 1971; Yang & Sayre, 1971; Yano, 1969). Einstein's model can be viewed as a pioneering 109 application of the continuous time random walk (CTRW) developed by Montroll and 110 Weiss (1965) in condensed matter physics to describe the diffusion of charge carriers in 111 solids. To incorporate motion intervals and sediment burial, we utilize the multi-state 112 CTRW developed by Weiss (1976, 1994) that extends the CTRW of Montroll and 113 Weiss (1965). Below, we develop and solve the model in section 2, and we discuss the 114 predictions of our model, present its implications for local, intermediate, and global 115

ranges of bedload diffusion, and suggest next steps for bedload diffusion research in sections 3 and 4.

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#### 2 Bedload trajectories as a multi-state random walk

#### 2.1 Model assumptions

We construct a three-state random walk where the states are motion, rest, and 120 burial, and we label these states as i = 2 (motion), i = 1 (rest), and i = 0 (burial). 121 Our target is the probability distribution p(x,t) to find a grain at position x and time t 122 if we know it started with the initial distribution  $p(x, 0) = \delta(x)$ . We characterize times 123 spent moving or resting on the surface by exponential distributions  $\psi_2(t) = k_2 e^{-k_2 t}$ 124 and  $\psi_1(t) = k_1 e^{-k_1 t}$ , since numerous experiments show thin-tailed distributions for 125 these quantities (Ancey, Böhm, Jodeau, & Frey, 2006; Einstein, 1937; Fathel, Furbish, 126 & Schmeeckle, 2015; Martin et al., 2012; Roseberry, Schmeeckle, & Furbish, 2012). 127 We expect our conclusions will not be contingent on the specific distributions chosen, 128 since all thin-tailed distributions provide similar diffusion characteristics in random 129 walks (Weeks & Swinney, 1998; Weiss, 1994). We consider grains in motion to have 130 characteristic velocity v (Lajeunesse et al., 2018; Lisle et al., 1998), and we model 131 burial as long lasting enough to be effectively permanent (Wu, Foufoula-Georgiou, et 132 al., 2019), with grains resting on the surface having a probability per unit time  $\kappa$  to 133 become buried, meaning  $\Phi(t) = e^{-\kappa t}$  represents the probability that a grain is not 134 buried after resting for a time t, while  $1 - \Phi(t)$  represents the probability that it is 135 buried. We specify the initial conditions with probabilities  $\theta_1$  and  $\theta_2$  to be in rest and 136 motion at t = 0, and we require  $\theta_1 + \theta_2 = 1$  for normalization. 137

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#### 2.2 Governing equations

Using these assumptions, we derive the governing equations for the set of probabilities  $\omega_{ij}(x,t)$  that a transition occurs from state *i* to state *j* at position *x* and time *t* using the statistical physics approach to multi-state random walks (Schmidt, Sagués, & Sokolov, 2007; Weeks & Swinney, 1998; Weiss, 1994). Denoting by  $g_{ij}(x,t)$ the probability for a particle to displace by *x* in a time *t* within the state *i* before it transitions to the state *j*, the transition probabilities  $\omega_{ij}(x,t)$  sum over all possible paths to the state *i* from previous locations and times:

$$\omega_{ij}(x,t) = \theta_i g_{ij}(x,t) + \sum_{k=0}^2 \int_0^x dx' \int_0^t dt' \omega_{ki}(x',t') g_{ij}(x-x',t-t').$$
(1)

Defining another set of probabilities  $G_i(x,t)$  that a particle displaces by a distance x in a time t within the state i and possibly remains within the state, we perform a similar sums over paths for the probabilities to be in the state i at x, t:

$$p_i(x,t) = \theta_i G_i(x,t) + \sum_{k=0}^2 \int_0^x dx' \int_0^t dt' \omega_{ki}(x',t') G_i(x-x',t-t').$$
(2)

Finally, the overall probability to be at position x at time t is

$$p(x,t) = \sum_{k=0}^{2} p_k(x,t)$$
(3)

This joint density is completely determined from the solutions of equations (1-2). We only need to specify the distributions  $g_{ij}$  and  $G_i$ .

#### 152 2.3 Joint probability distribution

<sup>153</sup> We construct these distributions from the assumptions described in section 2.1. <sup>154</sup> Since particles resting on the bed surface bury in a time t with probability  $\Phi(t)$ , and resting times are distributed as  $\psi_1(t)$ , we obtain  $g_{12}(x,t) = \delta(x)k_1e^{-k_1t}e^{-\kappa t}$  and  $g_{10}(x,t) = \delta(x)k_1e^{-k_1t}(1-e^{-\kappa t})$ . Since motions have velocity v for times distributed as  $\psi_2(t)$ , we have  $g_{21}(x,t) = \delta(x-vt)k_2e^{-k_2t}$ . Since burial is quasi-permanent, all other  $g_{ij} = 0$ . The  $G_i$  are constructed in the same way except using the cumulative probabilities  $\int_t^{\infty} dt' \psi_i(t) = e^{-k_i t}$ , since these characterize motions and rests that are ongoing (Weiss, 1994). We obtain  $G_1(x,t) = \delta(x)e^{-k_1 t}$  and  $G_2(x,t) = \delta(x-vt)e^{-k_2 t}$ .

To solve equations (1-2) with these  $g_{ij}$  and  $G_i$ , we take Laplace transforms in space and time  $(x, t \to \eta, s)$  using a method similar to Weeks and Swinney (1998) to unravel the convolution structure of these equations, eventually obtaining

$$\tilde{p}(\eta, s) = \frac{1}{s} \frac{(s + \kappa + k')s + \theta_1(s + \kappa)\eta v + \kappa k_2}{(s + \kappa + k_1)\eta v + (s + \kappa + k')s + \kappa k_2},\tag{4}$$

where  $k' = k_1 + k_2$ . Inverting this result using known Laplace transforms (Arfken, 1985; Prudnikov, Brychkov, Marichev, & Romer, 1988) obtains

$$p(x,t) = \theta_1 \Big[ 1 - \frac{k_1}{\kappa + k_1} \Big( 1 - e^{-(\kappa + k_1)t} \Big) \Big] \delta(x)$$
(5)

$$+\frac{1}{v}e^{-\Omega\tau-\xi}\Big(\theta_1\Big[k_1\mathcal{I}_0(2\sqrt{\xi\tau})+k_2\sqrt{\frac{\tau}{\xi}}\mathcal{I}_1(2\sqrt{\xi\tau})\Big] \tag{6}$$

$$+ \theta_2 \Big[ k_1 \delta(\tau) + k_2 \mathcal{I}_0 \Big( 2\sqrt{\xi\tau} \Big) + k_1 \sqrt{\frac{\xi}{\tau}} \mathcal{I}_1 \Big( 2\sqrt{\xi\tau} \Big) \Big] \Big)$$
(7)

$$+\frac{1}{v}\frac{\kappa k_2}{\kappa+k_1}e^{-\kappa\xi/(\kappa+k_1)}\Big[(\theta_1/\Omega)\mathcal{Q}_2(\xi/\Omega,\Omega\tau)+\theta_2\mathcal{Q}_1(\xi/\Omega,\Omega\tau)\Big]$$
(8)

for the joint distribution that a tracer is found at position x at time t. This result 166 generalizes the earlier results of Lisle et al. (1998) and Einstein (1937) to include 167 sediment burial. In this equation, we used the shorthand notations  $\xi = k_2 x/v$ ,  $\tau =$ 168  $k_1(t-x/v)$ , and  $\Omega = (\kappa + k_1)/k_1$  (Lisle et al., 1998). The  $\mathcal{I}_{\nu}$  are modified Bessel 169 functions of the first kind and the  $\mathcal{Q}_{\mu}$  are generalized Marcum Q-functions defined by  $\mathcal{Q}_{\mu}(x,y) = \int_{0}^{y} e^{-z-x} (z/x)^{(\mu-1)/2} \mathcal{I}_{\mu-1}(2\sqrt{xz}) dz$  and originally devised for radar 170 171 detection theory (Marcum, 1960; Temme, 1996). Burial generates the Marcum Q-172 functions, since we assumed resting grains could bury with an exponential probability, 173 while the rest probability follows a modified Bessel distribution (Einstein, 1937; Lisle 174 et al., 1998). 175

Figure 1 depicts the distribution (8) alongside simulations generated by a direct 176 method based on evaluating the cumulative transition probabilities between states on 177 a small timestep (Barik, Ghosh, & Ray, 2006). When grains do not become buried, 178 as in panel (a) of figure 1, the distribution becomes Gaussian-like at relatively large 179 observation times, exemplifying normal diffusion and satisfying the central limit the-180 orem. When grains become buried, as in panel (b) of figure 1, the Q-function terms 181 prevent the distribution from approaching a Gaussian at large timescales, exemplifying 182 anomalous diffusion (Weeks & Swinney, 1998) and violating the central limit theorem 183 (Metzler & Klafter, 2000; Schumer, Meerschaert, & Baeumer, 2009). 184

2.4 Positional variance

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To obtain an analytical formula for tracers diffusing downstream while they gradually become buried, we derive the first two moments of position by taking derivatives with respect to  $\eta$  of the Laplace space distribution (4) using an approach similar to Shlesinger (1974) and Weeks and Swinney (1998), and we use these to calculate the positional variance  $\sigma_x^2 = \langle x^2 \rangle - \langle x \rangle^2$ . The first two moments are

$$\langle x(t) \rangle = A_1 e^{(b-a)t} + B_1 e^{-(a+b)t} + C_1, \tag{9}$$

$$\langle x^2(t) \rangle = A_2(t)e^{(b-a)t} + B_2(t)e^{-(a+b)t} + C_2, \tag{10}$$

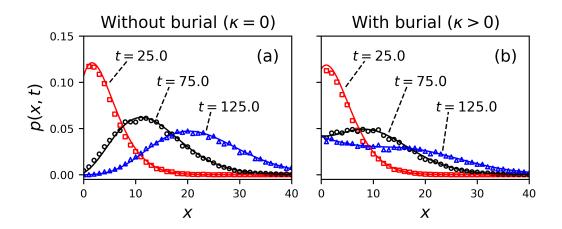


Figure 1. Joint distributions for a grain to be at position x at time t are displayed for the choice  $k_1 = 0.1$ ,  $k_2 = 1.0$ , v = 2.0. Grains are considered initially at rest ( $\theta_1 = 1$ ,  $\theta_2 = 0$ ). The solid lines are the analytical distribution in equation (8), while the points are numerically simulated, showing the correctness of our derivations. Colors pertain to different times. Units are unspecified, since we aim to demonstrate the general characteristics of p(x, t). Panel (a) shows the case  $\kappa = 0$  – no burial. In this case, the joint distribution tends toward Gaussian at large times (Einstein, 1937; Lisle et al., 1998). Panel (b) shows the case when grains have rate  $\kappa = 0.01$  to become buried while resting. Because of burial, the joint distribution tends toward a more uniform distribution than Gaussian.

<sup>191</sup> so the variance is

$$\sigma_x^2(t) = A(t)e^{(b-a)t} + B(t)e^{-(a+b)t} + C(t).$$
(11)

In these equations,  $a = (\kappa + k_1 + k_2)/2$  and  $b = \sqrt{a^2 - \kappa k_2}$  are effective rates having dimensions of inverse time, while the A, B, and C factors are provided in table 1.

**Table 1.** Abbreviations used in the expressions of the mean (9), second moment (10) and variance (11) of bedload tracers.

$$\begin{split} \overline{A_1 &= \frac{v}{2b} \Big[ \theta_2 + \frac{k_1 + \theta_2 \kappa}{b - a} \Big]} \\ B_1 &= -\frac{v}{2b} \Big[ \theta_2 - \frac{k_1 + \theta_2 \kappa}{a + b} \Big] \\ C_1 &= -\frac{v}{2b} \Big[ \frac{k_1 + \theta_2 \kappa}{b - a} + \frac{k_1 + \theta_2 \kappa}{a + b} \Big] \\ A_2(t) &= \frac{v^2}{2b^3} \Big[ (bt - 1)[k_1 + \theta_2(2\kappa + k_1 + b - a)] + \theta_2 b + \frac{(\kappa + k_1)(\theta_2 \kappa + k_1)}{(b - a)^2} [(bt - 1)(b - a) - b] \Big] \\ B_2(t) &= \frac{v^2}{2b^3} \Big[ (bt + 1)[k_1 + \theta_2(2\kappa + k_1 - a - b)] + \theta_2 b - \frac{(\kappa + k_1)(\theta_2 \kappa + k_1)}{(a + b)^2} [(bt + 1)(a + b) + b] \Big] \\ C_2 &= \frac{v^2}{2b^3} (\kappa + k_1)(\theta_2 \kappa + k_1) \Big[ \frac{2b - a}{(b - a)^2} + \frac{a + 2b}{(a + b)^2} \Big] \\ A(t) &= A_2(t) - 2A_1C_1 - A_1^2 \exp[(b - a)t] \\ B(t) &= B_2(t) - 2B_1C_1 - B_1^2 \exp[-(a + b)t] \\ C(t) &= C_2 - C_1^2 - 2A_1B_1 \exp[-2at] \end{split}$$

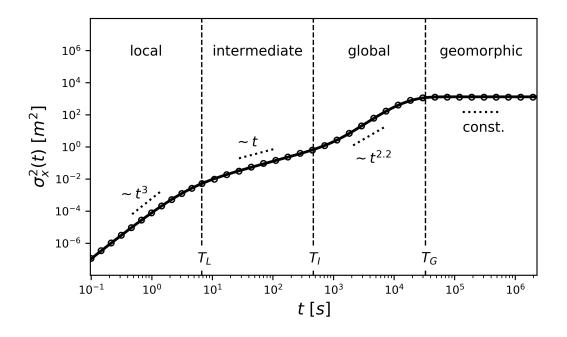


Figure 2. The variance (11) is plotted for the parameters  $1/k_2$ =  $1.5s, 1/k_1$ 30.0s. \_ and v0.1m/s. These values compare to laboratory flume experiments transporting small \_  $(\sim$ 5mm) gravels (cf., Lajeunesse et al., 2010; Martin et al., 2012). The timescale of burial is set to  $1/\kappa = 7200.0$  (two hours), and the initial condition is rest ( $\theta_1 = 1$ ). The solid line is equation (11) while the points are numerically simulated. When  $k_2 \gg k_1 \gg \kappa$  as in this plot, there are four distinct scaling ranges of  $\sigma_x^2$ : local, intermediate, global, and geomorphic. Within each range, a slope key is added to demonstrate the scaling  $\sigma_x^2 \propto t^{\gamma}$ . There are three crossovers between these ranges, denoted on the figure by vertical lines and labeled by timescales  $T_L$ ,  $T_I$ , and  $T_G$ . These timescales depend on  $k_2$ ,  $k_1$ , and  $\kappa$ .

The positional variance (11) is plotted in figure 2 for conditions  $\theta_1 = 1$  and 194  $k_2 \gg k_1 \gg \kappa$ . We interpret ">>" to mean "of at least an order of magnitude greater". 195 These conditions are most relevant to tracers in gravel-bed rivers, since they mean all 196 grains are initially at rest (Hassan et al., 1991; Wu, Foufoula-Georgiou, et al., 2019), 197 motions are typically much shorter than rests (Einstein, 1937; Hubbell & Sayre, 1964), 198 and burial requires a much longer time than typical rests (Ferguson & Hoev, 2002; 199 Haschenburger, 2013; Hassan & Church, 1994). Figure 2 demonstrates that under these 200 conditions the variance (11) shows three diffusion ranges with approximate power law 201 scaling  $(\sigma_x^2 \propto t^{\gamma})$  that we identify as the local, intermediate, and global ranges proposed 202 by Nikora et al., followed by a fourth range of no diffusion ( $\sigma_x^2 = \text{const}$ ) stemming from 203 the burial of all tracers. We suggest to call the fourth range geomorphic, since any 204 further transport in this range can occur only if scour re-exposes buried grains to the 205 flow (Martin et al., 2014; Nakagawa & Tsujimoto, 1980; Voepel et al., 2013; Wu, Singh, 206 Fu, & Wang, 2019). 207

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#### 2.5 Diffusion exponents

Two limiting cases of equation (11) provide the scaling exponents  $\gamma$  of the diffusion  $\sigma_x^2 \propto t^{\gamma}$  in each range. Limit (1) represents times so short a negligible amount of sediment burial has occurred,  $t \ll 1/\kappa$ , while limit (2) represents times so long motion intervals appear as instantaneous steps of mean length  $l = v/k_2, 1/k_2 \rightarrow 0$ 

while  $v/k_2 = \text{constant}$ . Limit (1) provides local exponent  $2 \le \gamma \le 3$  depending on the 213 initial conditions  $\theta_i$ , and intermediate exponent  $\gamma = 1$ . If grains start in motion or rest 214 exclusively, meaning one  $\theta_i = 0$ , the local exponent is  $\gamma = 3$ , while if grains start in 215 a mixture of motion and rest states, meaning neither  $\theta_i$  is zero, the local exponent is 216  $\gamma = 2$ . Limit (2) provides global exponent  $1 \leq \gamma \leq 3$  depending on the relative impor-217 tance of  $\kappa$  and  $k_1$ . In the extreme  $k_1/\kappa \ll 1$ , we find  $\gamma = 1$  in the global range, while 218 in the opposite extreme  $k_1/\kappa \to \infty$  we find  $\gamma = 3$ . We summarize when  $k_2 \gg k_1 \gg \kappa$ 219 so all three diffusion ranges exist, equation (11) implies: 220

- 1. local range super-diffusion with  $2 < \gamma < 3$  depending on whether grains start from purely motion or rest ( $\gamma = 3$ ) or from a mixture of both states ( $\gamma = 2$ ),
  - 2. intermediate range normal diffusion  $\gamma = 1$  independent of model parameters, and
    - 3. global range super-diffusion  $1 < \gamma < 3$  depending on whether burial happens relatively slowly  $(\gamma \to 1)$  or quickly  $(\gamma \to 3)$  compared to surface resting times.
- <sup>227</sup> Finally, the burial of all tracers generates a geomorphic range of no diffusion.

#### 228 3 Discussion

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#### 3.1 Local and intermediate ranges with comparison to earlier work

We extended Einstein (1937) by including motion and burial processes in a multi-230 state random walk (Weeks & Swinney, 1998; Weiss, 1994) to demonstrate that a group 231 of bedload tracers moving downstream while gradually becoming buried will generate 232 a super-diffusive local range (Fathel et al., 2016; Martin et al., 2012; Witz, Cameron, 233 & Nikora, 2019), a normal-diffusive intermediate range (Nakagawa & Tsujimoto, 1976; 234 Yano, 1969), and a super-diffusive global range (Bradley, 2017; Bradley, Tucker, & Ben-235 son, 2010), before the diffusion eventually terminates in a geomorphic range (Hassan 236 & Bradley, 2017). Nikora (2002) highlighted the need for such a physical description, 237 although they suggested to use a two-state random walk between motion and rest 238 states with heavy-tailed resting times, and they did not discuss sediment burial. In 239 the preliminary studies for this paper, we found that a two-state walk with heavy-240 tailed rests provides two diffusion ranges – not three: this conclusion is also suggested 241 by Weeks, Urbach, and Swinney (1996) and Fan et al. (2016). Although heavy-tailed 242 surface resting times have been documented (Fraccarollo & Hassan, 2019; Liu, Pelosi, 243 & Guala, 2019), they are more often associated with sediment burial (Martin et al., 244 2012, 2014; Olinde & Johnson, 2015; Pelosi, Schumer, Parker, & Ferguson, 2016; Voe-245 pel et al., 2013), and surface resting times usually display light tails (Ancev et al., 246 2006; Einstein, 1937; Habersack, 2001; Nakagawa & Tsujimoto, 1976; Yano, 1969). 247 These realizations and the need for a physical model of three diffusion ranges led us 248 to develop a three-state random walk for bedload trajectories with light-tailed surface 249 resting times and sediment burial. 250

The local and intermediate range diffusion characteristics resulting from our 251 model correspond closely to the original Nikora et al. concepts, while our global range 252 has a different origin than Nikora et al. described. Nikora et al. (2001) explained 253 that local diffusion results from the non-fractal (smooth) characteristics of bedload 254 trajectories between subsequent interactions with the bed, while intermediate diffu-255 sion results from the fractal (rough) characteristics of bedload trajectories after many 256 interactions with the bed. Our model represents these conclusions: non-fractal (and 257 super-diffusive) bedload trajectories exist on timescales short enough that each grain 258 is either resting or moving, while fractal (and normal-diffusive) bedload trajectories 259 exist on timescales when grains are actively switching between motion and rest states 260 (e.g., Einstein, 1937). We conclude that local and intermediate ranges stem from the 261 interplay between motion and rest timescales, as demonstrated by earlier two-state 262

random walk models (Lajeunesse et al., 2018; Lisle et al., 1998) and by all Newtonian
models that develop sequences of rests and motions (Bialik et al., 2012; Nikora et al.,
2001), even those including heavy-tailed rests (Fan et al., 2016).

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#### 3.2 Global and geomorphic ranges with next steps for research

Nikora et al. explained that divergent resting times generate a sub-diffusive 267 global range. However, studies have demonstrated that heavy-tailed resting times 268 can generate super-diffusion in asymmetric random walks (Weeks & Swinney, 1998; 269 Weeks et al., 1996), and both experiments (Bradley, 2017; Bradley et al., 2010) and 270 models (Pelosi et al., 2016; Wu, Foufoula-Georgiou, et al., 2019; Wu, Singh, et al., 271 2019) of bedload tracers undergoing burial have demonstrated global super-diffusion. 272 While our results also show global range super-diffusion, they do not refute the Nikora 273 et al. conclusion of sub-diffusion at large timescales. We assumed sediment burial 274 was a permanent condition which developed an extremely sub-diffusive geomorphic 275 range ( $\gamma \rightarrow 0$ ). In actuality, burial is a temporary condition since bed scour can 276 exhume buried sediment back into transport (Wu, Singh, et al., 2019), probably after 277 heavy-tailed intervals (Martin et al., 2014; Pelosi et al., 2016; Voepel et al., 2013). We 278 anticipate that a generalization of our model including heavy-tailed intervals separating 279 burial and exhumation would develop four ranges of diffusion, with a genuinely sub-280 diffusive scaling  $(0 < \gamma < 1)$  in the geomorphic range (Weeks & Swinney, 1998), 281 leaving Nikora et al. with the final word on long-time sub-diffusion. 282

The analytical solution of bedload diffusion in equation (11) reduces exactly to 283 the analytical solutions of the Lisle et al. (1998) and Lajeunesse et al. (2018) mod-284 els in the limit without burial ( $\kappa \to 0$ ), the Wu, Foufoula-Georgiou, et al. (2019) 285 model in the limit of instantaneous steps  $(k_2 \to \infty \text{ and } l = v/k_2)$ , and the original 286 Einstein (1937) model in the limit of instantaneous steps without burial. These re-287 ductions demonstrate that the majority of recent bedload diffusion models, whether 288 developed from Exner-type equations (Pelosi & Parker, 2014; Pelosi et al., 2016; Wu, 289 Foufoula-Georgiou, et al., 2019) or advection-diffusion equations (Lajeunesse et al., 290 2018; Lisle et al., 1998), can be viewed equivalently as continuous time random walks 291 applied to individual bedload trajectories. Within random walk theory, sophisticated 292 mathematical descriptions of transport with variable velocities (Masoliver & Weiss, 293 1994; Zaburdaev, Schmiedeberg, & Stark, 2008), correlated motions (Escaff, Toral, 294 Van Den Broeck, & Lindenberg, 2018; Vicsek & Zafeiris, 2012), and anomalous diffu-295 sion (Fa, 2014; Masoliver, 2016; Metzler, Jeon, Cherstvy, & Barkai, 2014) have been 296 developed. Meanwhile, in bedload transport research, variable velocities (Furbish et 297 al., 2012; Heyman, Bohorquez, & Ancey, 2016; Lajeunesse et al., 2010), correlated 298 motions (Heyman, Ma, Mettra, & Ancey, 2014; Lee & Jerolmack, 2018; Saletti & Has-299 san, 2020), and anomalous diffusion (Bradley, 2017; Fathel et al., 2016; Schumer et 300 al., 2009) constitute open research issues. We believe further exploiting the linkage 301 between existing bedload models and random walk concepts could rapidly progress 302 our understanding of these issues. 303

#### 304 4 Conclusion

We developed a random walk model to describe sediment tracers transporting 305 through a river channel as they gradually become buried, providing a physical descrip-306 tion of the local, intermediate, and global diffusion ranges identified by Nikora (2002). 307 Pushing their ideas somewhat further, we proposed a geomorphic range to describe 308 diffusion characteristics at timescales larger than the global range when burial and 309 exhumation moderate downstream transport. At base level, our model demonstrates 310 that (1) durations of sediment motions, (2) durations of sediment rest, and (3) the 311 sediment burial process are sufficient to develop three diffusion ranges. A next step 312

is to incorporate exhumation to better understand the geomorphic range. Ultimately,
we emphasize that the multi-state random walk formalism used in this paper implicitly underlies most existing bedload diffusion models and provides a useful tool for
researchers targeting landscape-scale understanding from statistical concepts of grainscale dynamics.

#### 318 Acknowledgments

K. Pierce acknowledges thoughtful exchanges with Eduardo Daly and Eric Weeks
 during the early stages of this work. Both authors would like to thank Conor McDowell,
 Matteo Saletti, and Will Booker for helpful discussions. M. Hassan is supported by an
 NSERC Discovery grant. The Python simulation code is freely available at https://
 zenodo.org/record/3659291#.Xj3p7XVKjIU.

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