# Probability distributions of particle hop distance and travel time over equilibrium mobile bedforms

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#### Abstract

The joint probability distribution of streamwise particle hop distance, lateral particle hop distance, and travel time constrains the relationships between topographic change and sediment transport at the granular scale. Previous studies have investigated the ensemble characteristics of particle motions over plane-bed topography, however it is unclear whether reported distributions remain valid when bedforms are present. Here, we present measurements of particle motion over bedform topography obtained in a laboratory flume and compare these to particle motions over plane-bed topography with otherwise similar conditions. We find substantial differences in particle motion in the presence of bedforms that are relevant to macroscopic models of sediment transport. Most notably, bedforms increase the standard deviation of streamwise and lateral hop distances relative to the mean streamwise hop distance. This implies that bedforms increase the streamwise and lateral diffusion lengths and, equivalently, increase diffusive-like fluxes.

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## Key Points:

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10	•	Particle travel times over bedforms are exponentially-distributed as proposed for
11		planar beds.
12	•	Streamwise and lateral hop distances over bedforms are not Weibull-distributed
13		as proposed for planar beds.

• Bedforms increase the variance in streamwise and lateral hop distances and increase diffusive-like transport.

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#### 16 Abstract

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## <sup>29</sup> 1 Introduction

The joint probability distribution of particle hop distance and travel time encap-30 sulates the relationship between granular sediment motion and topographic change (Nakagawa 31 & Tsujimoto, 1976; Tsujimoto, 1978; Ancey, 2010; Furbish et al., 2012; Pelosi & Parker, 32 2014). Considerable attention has been devoted to the problem of discerning the forms 33 of the associated marginal distributions and predicting their parameters or moments un-34 der steady, uniform macroscopic flow conditions (Abbott & Francis, 1977; Lajeunesse 35 et al., 2010; Fathel et al., 2015; Furbish, Schmeeckle, et al., 2016; Hosseini-Sadabadi et 36 al., 2019; Liu et al., 2019). This objective represents an important step toward the de-37 velopment of models for large-scale fluvial morphodynamics that are consistent with the 38 physics of grain-scale sediment transport. 39

Likely forms for the marginal probability distributions of particle hop distances and 40 travel times can be obtained from simple assumptions about particle motion through statistical-41 mechanical arguments (Furbish & Schmeeckle, 2013; Furbish, Schmeeckle, et al., 2016). 42 These authors suggest that travel times are exponentially distributed while streamwise 43 and absolute lateral hop distances follow a Weibull distribution with shape parameter 44  $0.5 \leq k < 1$ , neglecting the small fraction of particles that move in the upstream di-45 rection. Previous experimental measurements of particle motion confirm these predic-46 tions for uniform flow conditions over a flat streambed (Lajeunesse et al., 2010; Fathel 47 et al., 2015; Campagnol et al., 2015; Furbish, Schmeeckle, et al., 2016; Liu et al., 2019; 48 Wu et al., 2020). This still leaves a gap in understanding for the wide range of condi-49 tions under which the coupled motion of fluid and sediment amplifies small perturba-50 tions in bed elevation leading to the development of ripples and dunes (Van den Berg 51 & Van Gelder, 1993; Southard & Boguchwal, 1990; García, 2008). We therefore seek to 52 determine the forms of these distributions in the presence of equilibrium mobile bedforms. 53

The processes governing growth, coarsening, and subsequent dynamical behavior 54 of bedforms involve a continual feedback between topography, flow, and sediment trans-55 port (Southard & Dingler, 1971; Costello, 1974; McLean, 1990; Best, 1992; Mclean et 56 al., 1994; Venditti et al., 2005a, 2006; Coleman et al., 2006; Coleman & Nikora, 2011; 57 Charru et al., 2013). A rich literature related to flow over bedforms reveals persistent 58 zones of flow acceleration, expansion, and separation which modulate the bed stress and 59 transport fields (Mclean et al., 1994; Maddux, Nelson, & McLean, 2003; Maddux, McLean, 60 & Nelson, 2003; Best, 2005, 2009; Muste et al., 2016; Kwoll et al., 2017; Nagshband et 61 al., 2017). Only recently have researchers begun to examine the effects of this interac-62 tion on particle kinematics through particle tracking and acoustic techniques. Exper-63 imental results indicate that instantaneous quantities like particle activity and velocity 64 vary systematically in relation to topographic position while retaining probability dis-65 tributions similar to those observed under plane-bed conditions (Wilson & Hay, 2016; 66

Leary & Schmeeckle, 2017; Tsubaki et al., 2018; Terwisscha van Scheltinga et al., 2019).
What remains unclear is how bedforms influence Lagrangian integral quantities like particle hop distance and travel time, particularly insofar as they relate to the ensemble average flux and its advective and diffusive components (Furbish et al., 2012; Ancey et al., 2015).

The purpose of this paper is to clarify how bedforms influence time-integrated par-72 ticle behavior by comparing observations of particle motion over bedforms and plane-73 bed topography. We consider intermediate-timescale hops, defined as periods of contin-74 75 uous motion separated by periods of rest (sensu Nikora et al., 2001; Ballio et al., 2018). Here, we present the results of experiments designed to reveal differences in the prob-76 ability distributions of particle hop distance and travel time over equilibrium mobile bed-77 forms compared with plane-bed topography. We focus on properties that are relevant 78 to macroscopic transport to determine whether existing theory developed for plane-bed 79 topography provides a suitable description of particle motion when bedforms are present 80 on the bed. 81

#### 82 2 Theory

The topography of a granular bed evolves through the processes of particle entrain-83 ment and disentrainment. Each entrainment or disentrainment event produces a small 84 change in bed elevation which, averaged over time, results in macroscopic topographic 85 change. This notion underlies the entrainment form of Exner equation (Nakagawa & Tsu-86 jimoto, 1976; Tsujimoto, 1978; Parker et al., 2000; Furbish et al., 2012), expressing the 87 time rate of change of bed elevation  $\eta$  (L) at time t, streamwise position x and cross-stream 88 position y in terms of the difference between the volumetric particle entrainment rate 89 E (LT<sup>-1</sup>) and disentrainment rate D (LT<sup>-1</sup>) per unit bed area: 90

$$c_b \frac{\partial \eta}{\partial t}(t, x, y) = -E(t, x, y) + D(t, x, y).$$
(1)

Here,  $c_b$  (-) is the concentration of particles in the bed.

Paired entrainment and disentrainment events are explicitly linked through the motion of individual particles, defining a spatiotemporal displacement vector with components of streamwise hop distance  $L_x$  (L), lateral hop distance  $L_y$  (L), and travel time  $T_p$  (T). Because these quantities are defined in terms of particle exchanges with the bed, they also form the basis for the relationship between sediment transport and topographic change. This statement can be demonstrated by invoking a master equation to rewrite D(t, x, y) as

$$D(t, x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{0}^{\infty} E(t - T_p, x - L_x, y - L_y) f_{T_p, L_x, L_y}(T_p, L_x, L_y; t - T_p, x - L_x, y - L_y) dT_p dL_x dL_y,$$
(2)

<sup>99</sup> where  $f_{T_p,L_x,L_y}(T_p,L_x,L_y;t,x,y)$  is the joint probability distribution of streamwise hop <sup>100</sup> distance, lateral hop distance, and travel time of particles entrained at (t,x,y). Equa-<sup>101</sup> tion (2) (Furbish et al., 2012) is fundamentally nonlocal in that it integrates conditions <sup>102</sup> over space and time, however it can be approximated in terms of local variables as a Fokker-<sup>103</sup> Planck equation (Furbish et al., 2012, 2017), given by

$$c_{b}\frac{\partial\eta}{\partial t}(t,x,y) = -\frac{\partial}{\partial x}E\overline{L_{x}} - \frac{\partial}{\partial y}E\overline{L_{y}} - \frac{\partial}{\partial t}E\overline{T_{p}} + \frac{1}{2}\frac{\partial^{2}}{\partial x^{2}}E\overline{L_{x}^{2}} + \frac{1}{2}\frac{\partial^{2}}{\partial y^{2}}E\overline{L_{y}^{2}} + \frac{1}{2}\frac{\partial^{2}}{\partial x\partial y}E\overline{L_{x}L_{y}}$$
(3)

where overbars denote ensemble averages. This approximation is valid as long as the marginal probability distributions of hop distance and travel time have finite first and second mo-

<sup>106</sup> ments and as long as the spatiotemporal scales of particle motion are small relative to

the scales of change in flow conditions (Furbish et al., 2012). The one dimensional fluxes  $q_x (L^2T^{-1})$  and  $q_y (L^2T^{-1})$  are obtained from (3) by assuming conditions are approximately steady in time and uniform in one spatial dimension. These assumptions are appropriate for many practical problems (Furbish et al., 2012; Furbish, Fathel, & Schmeeckle, 2016). Noting that the variance is equal to the mean squared hop distance minus the squared mean, (i.e.  $\sigma_{L_x}^2 = \overline{L_x^2} - \overline{L_x^2}^2$ ), the one dimensional fluxes are given by

$$q_x(t,x,y) = E\overline{L_x} - \frac{1}{2}\frac{\partial}{\partial x}E\overline{L_x}^2 - \frac{1}{2}\frac{\partial}{\partial x}E\sigma_{L_x}^2$$
(4)

113 and

$$q_y(t, x, y) = E\overline{L_y} - \frac{1}{2}\frac{\partial}{\partial y}E\overline{L_y}^2 - \frac{1}{2}\frac{\partial}{\partial x}E\sigma_{L_y}^2.$$
(5)

As noted by Furbish et al. (2017), these terms do not map directly onto conventional ad-114 vective and diffusive components of the flux containing the mean particle velocity and 115 diffusivity. Instead, the first two terms comprise an advective-like flux consisting of a lo-116 cal term that is equal to the total flux under uniform transport conditions and a non-117 local term that accounts for spatial variability in particle entrainment rate and mean hop 118 distance. The third term is like a diffusive flux in that it is driven by the variance in par-119 ticle hop distance. This interpretation differs from previous studies, reflecting the de-120 composition of the raw variance (i.e.  $\overline{L_x^2}$ ) into terms containing the squared mean and 121 variance. Under this interpretation, the squared coefficient of variation (the ratio of the 122 standard deviation to the mean) of particle hop distances is like an inverse Peclet num-123 ber in that it scales the relative propensity for diffusion-like and advection-like transport. 124 Similarly, the ratio of the variance to the mean is like a diffusion length in that it scales 125 the diffusive-like flux in the presence of gradients in the advective-like flux. This idea is 126 fully discussed in Section 4.4. 127

The objective of this paper is to reveal the manner in which bedforms influence the 128 marginal probability distribution of particle travel time  $f_{T_p}(T_p)$ , streamwise hop distance 129  $f_{L_x}(L_x)$  and lateral hop distance  $f_{L_y}(L_y)$ . This work is primarily motivated by macro-130 scopic morphodynamic modeling problems (e.g., Abramian et al., 2019) for which the 131 most important features of these distributions are the statistical moments contained in 132 Equations (3), (4) and (5). We consider multiple indicators of distribution fit, however 133 we place special emphasis on those which pertain to the estimation of these moments. 134 Results are interpreted in the context of probability distribution models proposed by Fathel 135 et al. (2015) which are consistent with various mechanical constraints (Furbish, Schmeeckle, 136 et al., 2016) as well as with empirical constraints imposed by an extensive dataset of par-137 ticle motion over plane-bed topography (Roseberry et al., 2012). These distributions ex-138 ist on the domain from zero to infinity and thus ignore hops in the upstream direction. 139 They also have thin tails and fixed coefficients of variation, implying that the propen-140 sity for diffusion-like transport varies in proportion to the advective component of flux 141 across a wide range of conditions as discussed in more detail below. We aim to deter-142 mine the extent to which the constraints that derive from the forms of these distribu-143 tions provide a realistic foundation for modeling macroscopic sediment transport phe-144 nomena when bedforms are present. 145

#### <sup>146</sup> 3 Experiments

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#### 3.1 Overview

In order to compare the ensemble statistics of particle motions that are characteristic of plane-bed and bedform topography, we conducted two flume experiments differentiated primarily by the presence or absence of equilibrium bedforms. For each experiment we recorded videos of fluorescent tracer particles that were used to construct empirical distributions of particle hop distance and travel time. In considering fixed distributions of these quantities, we appeal to the idea of an ensemble of nominally identical systems first described by Gibbs (1902) and elaborated recently with respect to bedload transport by Furbish et al. (2012). We designed our experiments so that the distributions measured over a finite temporal and spatial domain may be assumed to be
equivalent to the instantaneous ensemble distribution at any position and time. This assumption is reasonable as long as the macroscopic average conditions are steady and uniform over the domain of data collection.

Theory and analyses presented here assume a steady, uniform probability distri-160 bution of particle hop distance and travel time that is independent of x, y and t. Although 161 previous studies find that particle motion depends on location relative to bedform fea-162 tures (Wilson & Hay, 2016; Leary & Schmeeckle, 2017; Tsubaki et al., 2018; Terwisscha 163 van Scheltinga et al., 2019), we emphasize that the existence of bedforms does not pre-164 clude the possibility of considering a stationary distribution averaged over all possible 165 configurations of bedform topography. Bedforms are viewed as stochastic fluctuations 166 in bed elevation, and there is a timescale over which a single location on the bed expe-167 riences a representative sample of all possible configurations of topography character-168 istic of the macroscopic flow conditions (e.g. the bedform field timescale as envisioned 169 by Furbish et al., 2012). In this context, the term "macroscopic" implies averaging over 170 scales much larger than an individual bedform. 171

In order to ensure that measured distributions reflect ensemble probability distri-172 butions characteristic of macroscopic flow conditions, measured particle motions would 173 ideally contain a sample that is representative of all possible microconfigurations of flow 174 and topography. In practice, this means that particle hops should be measured over spa-175 tiotemporal scales that are much larger than those of significant autocorrelation in flow 176 velocity and bed elevation. Due to practical limitations, this was not possible for the bed-177 form condition: particle motions were recorded over a small region of the bed with stream-178 wise and cross-stream dimensions comparable to the bedform lengthscale which we as-179 sume is similar to the autocorrelation lengthscale of topography (Nordin, 1971; Nikora 180 et al., 1997). Nonetheless, we posit that these data are sufficient to reveal important fea-181 tures of particle motion over bedforms. We report distributions sampling hops originat-182 ing on both stoss and lee regions of a single bedform over two ten second intervals. All 183 tracer particle motions in the measurement window were included in our analysis such 184 that the empirical distributions approximately reflect the relative entrainment rates in 185 stoss and lee regions of one bedform. For additional discussion of issues related to the 186 finite sampling window, see Section 4.5. 187

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#### 3.2 Description of Experiments

Experiments were conducted in a 7.2 m long  $\times$  0.29 m wide flume capable of re-189 circulating both sediment and water. Bedforms were allowed to develop under constant 190 flow conditions over a period of 48 hours, at which point particle motions were recorded 191 using a downward-looking camera. Plane-bed conditions were then achieved by manu-192 ally grading the bed using a plastic paddle, and particle motions were recorded again. 193 Flume boundary conditions remained constant throughout this procedure: water discharge 194 was 18 L/s, the flume slope was 0.001, and flow depth at the outlet was set to approx-195 imately H = 0.16 m. The mean flow velocity was U = 0.39 m/s, and the Froude num-196 ber was  $Fr = U/\sqrt{gH} = 0.31$ . 197

The bed material consisted of natural sediment collected in an aeolian dune field near the Seminoe Reservoir in Wyoming. Fine sediment was removed prior to these experiments by continuously siphoning turbid water in the outlet reservoir and replacing it with clear water. The resulting bed material had a median diameter of 330  $\mu$ m and median settling velocity  $\omega_s = 4.4$  cm/s. The base-2 logarithmic standard deviation was 0.69 (68% of the bed material was within a multiplicative factor of  $2^{0.69} = 1.61$  of the mean). This is typical of hydraulically sorted natural sediment in fluvial systems, but is a significant departure from the single-grain size experiments reported in previous studies. The implications of this difference are discussed in Section 4.2.

Particle motions were measured using videos of fluorescent tracer particles. To this 207 end, a small fraction of the bed material was removed from the flume and coated with 208 a thin layer of fluorescent paint. Although we cannot rule out the possibility that the 209 paint caused small differences in particle properties, we expect that such effects are small 210 and do not influence the primary findings of this study. Approximately  $30 \text{ cm}^3$  (includ-211 ing pore space) of tracer particles were added back into the flume and allowed to mix 212 213 with the unpainted bed material over a period of several weeks of continuous run time under a range of flow conditions. The thickness of sediment within the flume was approx-214 imately 8 cm such that the total volume of sediment in the flume including pore space 215 was approximately 170000  $\text{cm}^3$  and tracer particles composed an estimated 0.017 % of 216 the bed material. For comparison, the tracer particle percentage estimated by compar-217 ing the tracer particle flux and the bedform bedload flux (discussed below) is 0.019 %. 218 Particles were illuminated with black lights (GE Black Light Blue bulbs, peak wavelength 219 = 368 nm) through the side windows of the flume test reach (Figure 1a, 1b), which in-220 creased the contrast of tracer particles against the bed and facilitated consistent track-221 ing (Nagshband et al., 2017). We assume this procedure provides an unbiased sample 222 of complete particle hops representing the full distribution of particle sizes. 223

Acoustic measurements of the near-bed flow velocity profile were collected over equi-224 librium bedforms to compute the bed stress condition (Bagherimiyab & Lemmin, 2013; 225 Le Bouteiller & Venditti, 2015). The sidewall-corrected shear velocity was  $u_* = 2.4$  cm/s. 226 This produced bedload dominated bedforms with a suspension number (the ratio of shear 227 velocity to sediment settling velocity) of 0.54. For comparison, the unit bedload flux es-228 timated from bedform migration using the bedform bedload equation of Simons et al. 229 (1965) was  $q_b = 4.1 \times 10^{-7} \text{ m}^2/\text{s}$ . Applying the Wong and Parker (2006) bedload equa-230 tion and solving for stress suggests that the effective shear velocity (i.e. skin friction) driv-231 ing sediment transport was  $u_{*sk} = 1.8$  cm/s. This is consistent with the notion that pres-232 sure differences across a bedform reduce the bedload transport rate associated with a 233 specified average bed stress. 234

Although fluid velocities were not measured directly for the plane-bed condition, 235 we may estimate of the shear velocity by comparing the relative magnitudes of the tracer 236 particle flux (discussed below) using the Wong and Parker (2006) bedload equation. The 237 tracer particle flux for the plane-bed experiment was 2.1 particles per second per me-238 ter width. The bedload flux is estimated to be  $1.9 \times 10^{-7} \text{ m}^2/\text{s}$  leading to an estimated 239 shear velocity of  $u_* = 1.7$  cm/s and a suspension number of 0.38. We emphasize that 240 this estimate requires substantial assumptions and is reported here as a rough approx-241 imation to contextualize our experiments. However, the specific values of the shear ve-242 locity are not central to any of the theoretical developments or interpretations presented 243 below. 244

Characteristic scales of bedform topography were computed from one-dimensional 245 scans obtained using an ultrasonic profiler mounted to a moving cart. Equilibrium bed-246 forms had a characteristic height  $H_c = 1.5$  cm, a characteristic length  $L_c = 16$  cm, and 247 a characteristic migration velocity  $V_c = 0.50$  cm/minute. Bedform height was determined 248 using  $H_c = 2\sqrt{2}\sigma_\eta$  where  $\sigma_\eta$  is the standard deviation of bed elevation (McElroy, 2009) 249  $L_c$  was determined from the spectral centroid of the bed profile and  $V_c$  was determined 250 from the maximum of the cross-correlation function of successive scans (Van der Mark 251 & Blom, 2007). The characteristic evolution timescale of bed elevation  $\eta$  computed as 252  $T_{\eta} = \eta/(\partial_{\eta}/\partial_{t})$ , was approximately 8 minutes, such that topography is effectively fixed 253 within the ten-second data collection intervals. 254

Videos of particle motion were recorded using a submerged downward-looking camera mounted near the centerline of the flume with the lens approximately 15 centime-



**Figure 1.** Experimental setup and tracked particle motions. (a) Oblique view of flume with bedforms. Black box indicates the approximate region of the bed where videos of fluorescent tracer particles were recorded. (b) Still image from video of fluorescent tracer particles during the bedform condition. Flow is from bottom to top. (c) Tracked particle motions over plane-bed and (d) bedform topography. Grey region in (d) indicates the position of a bedform lee face. Note that the particle transport direction exhibits conditional dependence on topographic configuration in the vicinity of the particle that is discussed in more detail in section 4.1. (e) Visualization of particle displacements over plane-bed and (f) bedform topography. Topographic effects manifest as qualitative differences in between (e) and (f).

ters from the bed. Videos were collected at a resolution of 1920 by 1080 pixels and at 257 a frame rate of 30 frames per second. This window covered a streamwise distance of 12.2 258 cm, and a cross-stream distance of 21.7 cm. Two ten-second intervals from each video 259 were used for this analysis. Image registration and rectification were performed using 260 OpenCV in Python (Bradski, 2000) Particles were digitized manually using TrackMate 261 (Tinevez et al., 2017), an open-source particle tracking package for ImageJ (Schindelin 262 et al., 2012; Rueden et al., 2017). All particles that moved during each interval were tracked 263 for their entire visible path, including rest times (Figure 1). 264

The position of the particle centroid was tracked to within roughly one pixel such that the total uncertainty in each estimate of particle hop distance is roughly 0.022 cm (or one pixel at the start and beginning of each hop). Note that this is comparable to the median particle diameter. The uncertainty in each particle hop distance is approximately 6.25% of the mean hop distance in the plane-bed experiment and 9.5% of the mean hop distance in the bedform experiment. This error may be positive or negative such that it is unlikely to bias estimates of the mean hop distance. In principle, this type
of uncertainty could result in a positive bias in estimates of the variance by adding normally distributed noise, however the magnitude of this effect is small and equivalent for
both experiments. As a result, it is ignored in the analysis presented below.

The timing of the end and beginning of particle motions can be constrained to within 275 one frame (0.033 s). Assuming perfect detection of particle motion, the measured hop 276 duration will always be greater than or equal to the true hop duration because motion 277 will always be registered as starting the frame before motion begins and ending the frame 278 279 after motion ends. This effect will introduces a positive bias to empirical estimates of the mean travel time if the particle is assumed to be moving for the full duration over 280 which motion is observed. Correcting for this bias is not trivial and depends on assump-281 tions about the underlying distribution of particle travel times, however we note that the 282 effect on the computed moments is small, biasing the estimate of the mean travel time 283 by approximately one frame time and introducing essentially no bias to the estimate of 284 the variance. A moderate bias correction does not influence the primary findings of this 285 paper and is not performed here. 286

#### 3.3 Definition of a Particle Hop

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The concept of a complete particle "hop" follows from the notion that particles may 288 occupy one of two mutually exclusive states: motion and rest (Hosseini-Sadabadi et al., 289 2019). This distinction is critical to the interpretation of particle-kinematic statements 290 of sediment mass conservation, namely, the divergence and entrainment forms of the Exner 291 equation. However, differentiating between active and stationary particles is not straight-292 forward: grains on the bed surface may wiggle in place without moving appreciably and 293 may accumulate significant displacements over long timescales due to granular creep (Houssais 294 et al., 2015). In fact, granular transport occurs via numerous phases (Houssais & Jerol-295 mack, 2017); the binary view of mobility is merely a convenience adopted to delineate 296 highly disparate scales of particle velocity and flux for the purposes of mathematical ab-297 straction. 298

This reasoning suggests that particles on or below the bed surface are not truly sta-299 tionary in the sense that they have detectable mean velocities averaged over long timescales. 300 Consequently, empirical studies of particle motion which attempt to differentiate between 301 mobile and immobile grains do so according to criteria that, despite their intuitive ap-302 peal, lack clear physical justification (Hosseini-Sadabadi et al., 2019). For example, par-303 ticles are often treated as mobile when their velocity exceeds a threshold value that is 304 either explicitly stated or set implicitly by the resolution of the technique used to dig-305 itize particle motions. Such criteria retain the important property of mass conservation 306 as long as the mobile and immobile states encompass all grains and are mutually exclu-307 sive, and mobile particles are not counted towards the elevation of the bed. Moreover, 308 velocity criteria are valid in scenarios where sediment transport and morphodynamics 309 are dominated by bedload transport rather than granular creep. 310

Other criteria that are equally valid from a theoretical perspective may lead to dif-311 ferent results as to whether certain particles are mobile or immobile, ultimately produc-312 ing differences in measured distributions of particle hop distance and travel time (Hosseini-313 Sadabadi et al., 2019). We recognize this issue but do not attempt to solve it here. In-314 stead, we use an approach that is similar to previous studies (Liu et al., 2019) and ac-315 knowledge where our results might be sensitive to this choice. Velocity criteria are an 316 objective, reproducible solution to this problem. Different velocity thresholds may pro-317 duce different distributions of particle hop distance and travel time but will lead to es-318 sentially the same estimate of the macroscopic flux as long as the velocity threshold is 319 sufficiently small. 320

	Plane Bed	Bedforms
Mean travel time $\overline{T_p}$	0.18 s	0.13 s
Variance $\sigma_{T_n}^2$	$0.042 \ {\rm s}^2$	$0.023 \ {\rm s}^2$
Coefficient of variation $\sigma_{T_p}/\overline{T_p}$	1.13	1.13
Mean streamwise hop distance $\overline{L_x}$	$0.32 \mathrm{~cm}$	0.21 cm
Variance $\sigma_{L_x}^2$	$0.43 \ \mathrm{cm}^2$	$0.47~{ m cm}^2$
Coefficient of variation $\sigma_{L_x}/\overline{L_x}$	2.04	3.25
Streamwise diffusion length $\ell_{D_r}$	$1.34 \mathrm{~cm}$	$2.22 \mathrm{~cm}$
Inverse Peclet number $Pe_x^{-1}$	4.2	10.6
Mean lateral hop distance $\overline{L_y}$	$-2.2 \times 10^{-3} \mathrm{~cm}$	$-2.8 \times 10^{-2} \text{ cm}$
Variance $\sigma_{L_u}^2$	$0.11 \ \mathrm{cm}^2$	$0.27~{\rm cm^2}$
CV of absolute values $\sigma_{ L_y }/\overline{ L_y }$	2.20	2.70
Coefficient of lateral transport $\sigma_{L_y}/\overline{L_x}$	1.03	2.49
Lateral diffusion length $\ell_{D_y}$	$0.34~\mathrm{cm}$	$1.29~\mathrm{cm}$
Inverse Peclet number $Pe_{u}^{-1}$	1.07	6.17

Table 1.	Summary	Statistics
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The exact value of the velocity threshold used here was chosen following the ap-321 proach of Liu et al. (2019). Specifically, we examined particle motions under a range of 322 velocity thresholds and found that values ranging from 0.2 cm/s to 0.5 cm/s reliably dis-323 criminated between visually-identified mobile and immobile states. The exact value of 324 the threshold within this range affects the absolute magnitude of empirical moments but 325 has almost no effect on the primary findings of this paper which concern their relative 326 magnitudes and the shape of the distribution functions. Reported results were obtained 327 using a velocity threshold of 0.3 cm/s. This value is significantly lower than the thresh-328 old velocities adopted by Liu et al. (2019) and Lajeunesse et al. (2010), perhaps because 329 the lower frame rate (30 frames per second in the present study compared with 90 frames 330 per second) allows more precise estimates of frame-averaged velocity. This number cor-331 responds to a one-frame displacement of 0.01 cm over  $1/30^{th}$  of a second, which is roughly 332 one pixel or one third of the median grain diameter. Particles with frame-averaged ve-333 locities greater than or equal to the threshold velocity are considered mobile, and all other 334 particles are considered immobile. A complete hop is defined as an uninterrupted period 335 in the mobile state that begins and ends with transitions to and from the immobile state. 336 Insofar as previous plane-bed studies necessarily employ some variant of this approach, 337 it is sufficient to reveal the extent to which particle motions over bedforms conform to 338 existing theory. 339

## 340 4 Results and Discussion

The experimental procedure described in the previous section yielded measurements of 360 complete particle hops for the plane bed condition and 1170 hops for the bedform condition. These data are visualized in Figure 1, which shows all tracked particle motions, and Figure 2, which shows the pairwise relationships between variables. Descriptive statistics are reported in Table (1).

Tracked particle paths reveal significant qualitative differences between the planebed and bedform experiments. Notably, particle behavior clearly depends on position relative to bedform features in a manner that is reminiscent of the backward facing step experiments of Leary and Schmeeckle (2017) and the particle velocity fields reported by Tsubaki et al. (2018) and Terwisscha van Scheltinga et al. (2019). Particle transport direction is highly variable in the region of flow separation immediately downstream of the

<sup>352</sup> bedform crest. On the stoss side, particle transport direction is more regular and the mean

 $_{353}$  local transport direction is approximately perpendicular to the nearest crest (Figures 1c,

1d). These behaviors produce significant qualitative differences in the characteristics of

<sup>355</sup> particle displacement as shown in figures 1e, 1f, and 2.



**Figure 2.** Pairwise comparison of measured particle hop distances and travel times. Dashed lines indicate particle hop distances of zero. Bedform data are shown in black diamonds and plane-bed data are shown in white circles. Panels (a) and (b) illustrate a conditional dependence of streamwise and lateral particle hop distance on travel time that is used by Fathel et al. (2015) to derive the Weibull distribution for particle hop distances. Panel (c) encompasses the primary qualitative differences between the plane-bed and bedform experiments; particle motions over bedforms exhibit a wider spread in both the streamwise and cross-stream directions, and upstream hops appear to occur more frequently and have larger magnitudes over bedforms than over planar topography.

Empirical moments are reported in Table 1. Although the mean particle travel time 356 and mean streamwise hop distance are slightly larger in the plane-bed experiment, we 357 find that the distribution of particle hop distances over bedforms has much larger vari-358 ance in the cross-stream and streamwise directions. This difference reflects the increased 359 variability in hop distances evident in Figure 2. The sample size in both experiments was 360 sufficiently large such that conventional measures of statistical uncertainty indicate that 361 moments are estimated with high precision. For example, the 95% asymptotic confidence 362 interval for the estimate of the mean travel time in the bedform experiment ranges from 363 0.12 s to 0.14 s. More sophisticated estimates of statistical uncertainty produce similar 364 results. However, these statistical measures only quantify uncertainty associated with 365

measurement error and finite sample size, and cannot quantify uncertainty associated with the finite measurement window (Section 4.5). We believe this effect is the primary source of uncertainty in our results. Due to the systematic misrepresentation of true uncertainty, confidence intervals for other parameters are not reported here.

370

## 4.1 Physical Mechanism for Observed Differences in Particle Behavior

Previous studies of particle motion find that particle velocities are conditionally 371 dependent on the local topographic configuration due to the coupling of topography, flow, 372 and sediment transport (Tsubaki et al., 2018; Terwisscha van Scheltinga et al., 2019). 373 Topographically-induced correlations in flow velocity exist over spatial scales that are 374 comparable to the bedform length; in contrast, we find that the average hop distance is 375 much smaller than a bedform length. As a result, individual particle hops do not con-376 verge on the ensemble statistics of motion (Fathel et al., 2016; Furbish et al., 2017), in-377 stead reflecting topographically-induced deviations from the mean flow field. 378

As an example, consider a particle that is entrained on a stoss slope that is oriented 379 obliquely relative to the mean flow direction. This topographic configuration usually re-380 sults in flow being redirected laterally (Best, 2005; Venditti et al., 2005b), causing a cor-381 responding lateral component of sediment movement (Tsubaki et al., 2018; Terwisscha 382 van Scheltinga et al., 2019) that is possibly amplified by gravitational effects (Parker et 383 al., 2003). Because particle motions are short relative to the spatial scales of topogra-384 phy, this particle is likely to spend the entire interval from entrainment to disentrain-385 ment on this oblique slope. A large lateral hop distance would be highly improbable over 386 plane-bed topography under similar mean flow conditions, but would be typical for particles entrained in this location. 388

We suggest that observed differences in probability distributions of particle hop dis-389 tance and travel time are the result of this effect. Over plane-bed topography, turbulent 390 fluctuations in flow velocity and collisions between particles are the primary sources of 391 variability (Nikora et al., 2001, 2002; Seizilles et al., 2014; Fathel et al., 2015; Hosseini-392 Sadabadi et al., 2019). We infer that localized fluctuations in flow velocity driven by bed-393 form topography cause variability in particle behavior that is superimposed on variabil-394 ity driven by turbulence and particle collisions. Tsubaki et al. (2018) and Terwisscha van 395 Scheltinga et al. (2019) report similar behaviors, which manifest as deviations from the 396 mean particle velocity field characterized by crest-normal transport on the stoss sides 397 of bedforms (Fryberger & Dean, 1979; Werner & Kocurek, 1997), and highly variable trans-398 port over lee faces and troughs (figures 1c, 1d). This causes a marked qualitative differ-399 ence in particle behavior that is apparent in Figures 1e, 1f, and 2 as enhanced variabil-400 ity in transport direction and distance. Quantitative analyses presented below contex-401 tualize these observations in terms of the entrainment forms of the flux and Exner equa-402 tions. 403

404

## 4.2 Effect of Naturally Sorted Sediment

Our analysis assumes that the marginal distributions of particle hop distance and 405 travel time have thin tails such that the mean and the variance are well defined. Although 406 previous studies suggest that this is true for monodisperse sediment undergoing low bed-407 load transport (Fathel et al., 2015; Furbish, Schmeeckle, et al., 2016; Liu et al., 2019), 408 heavy-tailed distributions of hop distance and travel time are possible if a range of grain 409 sizes are present and the mean hop distance varies with grain size (Ganti et al., 2010). 410 Our experiments involved naturally sorted sediment which is valuable insofar as we seek 411 to understand natural transport systems. However, it is important to consider the ex-412 tent to which theory developed for uniform sediment may be applicable to the present 413 research. 414

As a starting point, we consider the distribution of streamwise hop distance as a margin of the joint distribution of particle hop distance and grain size,  $f_{L_x,D}(L_x,D)$ :

$$f_{L_x}(L_x) = \int_0^\infty f_{L_x|D}(L_x|D) f_D(D) dD.$$
 (6)

Ganti et al. (2010) clarify how this integration may lead to a heavy-tailed distribution 417 of hop distance. Specifically, if  $f_{L_X|D}(L_x|D)$  is exponential with mean varying in pro-418 portion (or inverse proportion) to grain size and  $f_D(D)$  is a Gamma distribution with 419 shape parameter  $\alpha$ , then  $f_{L_x}(L_x)$  is a generalized Pareto distribution. This argument 420 also holds for particle travel times. In this scenario, the mean only converges if  $\alpha > 1$ 421 and the variance only converges if  $\alpha > 2$ . We note that the the coefficient of variation 422 of a Gamma distribution is equal to  $1/\sqrt{\alpha}$ . Thus, the weight of the tails depends on the 423 degree of sorting of the bed material, where well sorted sediments are less likely to have 424 heavy-tailed distributions of hop distance and travel time. The best-fit Gamma distri-425 bution for the bed material used in these experiments has a shape parameter  $\alpha = 4.83$ 426 such the mean and variance are well-defined. On this basis, we suggest that it is reason-427 able to expect that the distributions of hop distance and travel time are thin-tailed. 428

Even if the distributions have thin tails, variability in grain size implies that the 429 marginal probability distributions of hop distance and travel time depend on (a) the func-430 tional form of the grain-size specific distribution of hop distance and travel time (e.g.  $f_{L_r|D}(L_x|D)$ ), 431 (b) the relationship between the grain size and the parameters of this conditional dis-432 tribution, and (c) the relative entrainment rates of different grain sizes (which may dif-433 fer from the grain size distribution of the bed material due to selective entrainment and 434 vertical sorting). Each of these effects may be present in our data, however we focus on 435 the collective outcome and have not attempted to evaluate their importance individu-436 ally. 437

438

439

#### 4.3 Comparison of Theoretical and Empirical Distributions

#### 4.3.1 Travel Times

Previous studies suggest that the marginal probability distribution of bedload particle travel times is exponential (Fathel et al., 2015; Furbish, Schmeeckle, et al., 2016),
i.e.:

$$f_{T_p}(T_p) = \frac{1}{\tau} e^{-T_p/\tau},$$
(7)

where  $\tau$  is a characteristic travel time. This implies a fixed temporal disentrainment rate 443 for moving particles (Tucker & Bradley, 2010; Furbish, Schmeeckle, et al., 2016). In other 444 words, the probability that a particle in motion at time t is deposited over the next small 445 time interval dt does not depend on how long the particle has been in motion at t in the 446 absence of other information about the flow and topographic configuration. Previous stud-447 ies have suggested that this distribution is not strictly exponential (due to the pres-448 ence of truncated tails) but may be treated as such for most practical purposes (Fathel 449 et al., 2015). 450

Quantile-quantile (Q-Q) plots (figure 3a, 3b) and histograms (figure 3c, 3d) reveal 451 that the exponential distribution provides a reasonable fit to plane-bed and bedform par-452 ticle travel times (Figure 3). The coefficient of variation (the ratio of the standard de-453 viation to the mean) of an exponentially distributed random variable is 1, which is an 454 important diagnostic test of distribution fit. Measured coefficients of variation are 1.13 455 for both experiments (Table 1). Based on these observations, we suggest that (a) our data 456 confirm the findings of previous authors with regard to the exponential distribution of 457 particle travel times over plane-bed topography and (b) the presence of equilibrium mo-458 bile bedforms does not substantially influence the functional form of this distribution. 459 We also find no evidence that the distribution of travel times is heavy-tailed despite vari-460 ability in bed material grain size typical of natural fluvial systems. 461



Figure 3. Quantile-quantile (a, b) and density plots (c,d) comparing measured distributions of particle travel time with best-fit exponential distributions (dashed lines). Densities were computed using logarithmically-spaced bins. Error bars represent the 95% Bayesian credible interval for a binomial proportion obtained using Jeffrey's prior (Brown et al., 2001). Deviations from theory are similar in both experiments and do not cause a substantial difference in the coefficient of variation in travel times. We interpret observed deviations as measurement error rather than as genuine features of the dataset.

## 4.3.2 Streamwise Hop Distances

462

Theoretical distributions proposed by Fathel et al. (2015) to describe streamwise 463 hop distances follow from exponentially distributed travel times combined with the as-464 sumption that particles with longer travel times have the opportunity to attain higher 465 velocities (Roseberry et al., 2012). This suggests that a conditional dependence of par-466 ticle hop distance on travel time (evident in Figures 2a and 2b) that can be approximated 467 by  $L_x = a_x T_p^{b_x} + \epsilon_x$  (Fathel et al., 2015), where  $a_x$  is a characteristic acceleration,  $\epsilon_x$ 468 is a residual deviation term, and  $b_x$  is a scaling parameter that may be connected to sus-469 pension conditions. For bedload-dominated transport, particle travel times are short rel-470 ative to the timescale required to accelerate particles to the mean near-bed fluid veloc-471 ity and particle hops are dominated by the unsteady acceleration and deceleration phases 472 of motion (Campagnol et al., 2015). As a result, previous studies which report bedload-473 dominated transport over plane-bed topography (e.g., Fathel et al., 2015) find that  $L_x/T_p \sim$ 474  $T_p$  and leading to  $b_x = 2$ . It has been suggested that this dependence disappears at higher 475 suspension conditions (Ancey & Heyman, 2014; Heyman et al., 2016; Campagnol et al., 476 2015; Wu et al., 2020), however we restrict our attention to bedload-dominated trans-477 port similar to previous plane-bed studies. Ignoring the residual deviation and assum-478 ing exponentially distributed travel times leads to the expectation that hop distances fol-479 low Weibull distributions (Fathel et al., 2015). Thus, the marginal distribution of stream-480

wise hop distances is given by 481

$$f_{L_x}(L_x) = \frac{k_x}{\lambda_x} \left(\frac{x}{\lambda_x}\right)^{k_x - 1} e^{-(x/\lambda)^{k_x}}$$
(8)

482 483 484

where  $k_x = 1/b_x$  and  $\lambda_x = a_x \tau^{b_x}$ . If  $k_x = 1/2$ , then the mean and variance in particle hop distance can be expressed in terms of model parameters as  $\overline{L_x} = 2a_x\tau^2$  and  $\sigma_{L_x}^2 = 20a_x^2\tau^4.$ 



Figure 4. Quantile-quantile (a, b) and density plots (c, d) comparing measured distributions of streamwise hop distance with best-fit Weibull distributions with shape parameter k= 1/2(dashed lines). Densities were computed using logarithmically-spaced bins. Error bars represent the 95% Bayesian credible interval for a binomial proportion obtained using Jeffrey's prior (Brown et al., 2001). Red regions in panels (b) and (d) highlight systematic deviations from plane-bed theory.

485

In considering whether this distribution is suitable for hop distances over bedforms, we focus primarily on the considerations relevant to macroscopic morphodynamic mod-486 eling outlined in Section 2. Specifically, we ask whether estimates of distribution param-487 eters  $a_x$  and  $\tau$  can lead to accurate predictions of the mean hop distance  $\overline{L_x}$  and the vari-488 ance  $\sigma_{L_r}^2$ . This question is of central importance if the eventual goal is to construct macro-489 scopic morphodynamic models that are consistent with the physics of grain-scale sed-490 iment transport. The proposed Weibull distribution with shape parameter k = 1/2 pre-491 scribes a fixed coefficient of variation  $\sqrt{5} \approx 2.23$ . This implies that the variance  $\sigma_{L_x}^2$ 492 can be estimated from a measurement of the mean. If k is allowed to vary between 1/2493 and 1, the coefficient of variation must be between 1 and  $\sqrt{5}$ . The coefficient of varia-494 tion therefore is an important indicator of distribution fit; if it is significantly larger than 495  $\sqrt{5}$  or smaller than 1, no single estimate of model parameters appropriately character-496 izes the advective and diffusive components of the flux simultaneously. 497

Measured streamwise hop distances in the plane-bed experiment have a coefficient 498 of variation of 2.05 compared with 2.23 predicted from theory. Ignoring upstream hops 499

does not significantly affect the estimate of the mean because only 5% of hops occur in 500 the upstream direction and the average upstream hop distance is very small relative to 501 the average downstream hop distance (0.1 mm compared with 3.5 mm). As with travel 502 times, we find no evidence that the distribution of particle hop distance is heavy-tailed 503 for the moderately sorted sand used in this experiment. We suggest suggest that the dis-504 tribution of streamwise bedload hop distances over plane-bed topography in hydrauli-505 cally sorted, natural sediments can be sufficiently approximated using a Weibull distri-506 bution with shape parameter k = 1/2 in the context of macroscopic transport prob-507 lems. 508

In contrast, the distribution of streamwise hop distances over bedforms exhibits sig-509 nificant deviations from theory. Qualitative comparison of the histogram and a best-fit 510 theoretical distribution (figure 4d) reveals systematic differences in probability density 511 across the full range of observed hop distances that results in a concave-up relationship 512 between empirical and theoretical quantiles (Figure 4b). A much larger fraction of hops 513 occur in the upstream direction (15%) and these possess an average upstream displace-514 ment that are a significant fraction of the average downstream displacement (0.8 mm com-515 pared with 2.8 mm). We conclude that the presence of bedforms leads to an important 516 difference in empirical moments: the coefficient of variation in measured streamwise hop 517 distances is 3.25, meaning that the standard deviation does not vary with the mean as 518 expected. Instead, observed spatiotemporal correlations between particle behavior and 519 topography lead to an increased variance relative to the mean (figure 1d, 1f) that vio-520 lates constraints imposed by plane-bed theory. 521

#### 522

## 4.3.3 Lateral Hop Distances

The streamwise and lateral coordinates are defined such that lateral hop distances 523 have a mean of zero and are symmetrically distributed under steady, uniform transport 524 conditions considered here. Like with streamwise hop distances, Roseberry et al. (2012) 525 and Fathel et al. (2015) find that the absolute lateral displacement is correlated with travel 526 time leading to  $|L_y| = a_y T_p^{b_y} + \epsilon_y$ , where  $b_y \approx 2$ . The distribution of absolute lateral hop distances can therefore be approximated using a Weibull distribution with shape pa-527 528 rameter k = 1/2 and scale parameter  $\lambda = a_{y}\tau^{2}$ . For particle motions over plane-bed 529 topography, quantile-quantile (figure 5a) and histogram plots (figure 5c) reveal that ab-530 solute lateral hop distances over plane-bed topography are well-approximated by the best-531 fit Weibull distribution with fixed shape parameter k = 1/2. 532

Once again, we consider whether the proposed Weibull distribution can accurately quantify the first and second moments of measured lateral hop distances. This distribution implies that the mean absolute lateral hop distance is given by  $\overline{|L_y|} = 2a_y\tau^2$ , the variance is given by  $\sigma_{|L_y|}^2 = 20a_y^2\tau^4$ , and the coefficient of variation is  $\sqrt{5}$ . Because the distribution of signed lateral hop distances is symmetric with mean equal to zero, the variance is equal to the raw variance of absolute lateral hop distances, i.e.  $\sigma_{L_y}^2 = \overline{|L_y|^2} = \overline{|L_y|^2} + \sigma_{|L_y|}^2$ . The first and second moments that are relevant to macroscopic transport problems can be expressed in terms of distribution parameters as  $\overline{L_y} = 0$  and  $\sigma_{L_y}^2 = 24a_y^2\tau^4$ .

The empirical coefficient of variation for absolute lateral hop distances is 2.20, com-542 pared with 2.23 predicted from theory. For particle motions over bedform topography, 543 the coefficient of variation in absolute lateral hop distances is 2.7, while the histogram 544 plot (figure 5d) reveals systematic deviations from predicted bin frequencies resulting 545 in a concave-up relationship between theoretical and measured quantiles (figure 5b). Again, 546 this may indicate a heavy-tailed distribution of absolute lateral hop distances. If the dis-547 tribution is not heavy tailed, then bedforms cause a significant increase in the variance 548 of the signed lateral hop distances  $(0.27 \text{ cm}^2 \text{ compared with } 0.11 \text{ cm}^2)$ , both by alter-549 ing the shape of the distribution of absolute lateral hop distances and by increasing the 550



Figure 5. Quantile-quantile (a, b) and density plots (c, d) comparing measured distributions of absolute lateral hop distance with best-fit Weibull distributions with shape parameter k = 1/2 (dashed lines). Densities were computed using logarithmically-spaced bins. Error bars represent the 95% Bayesian credible interval for a binomial proportion obtained using Jeffrey's prior (Brown et al., 2001). Red regions in panels (b) and (d) highlight systematic deviations from plane-bed theory.

average absolute lateral hop distance. This result primarily reflects an increase in the
 variability in transport direction as characterized by the coefficient of lateral transport
 (Table 1).

#### 554 4.4 Bedload Diffusion

We have found that bedforms increase the variance of the ensemble probability dis-555 tributions of streamwise and absolute lateral hop distances. Here, we consider the sig-556 nificance of this observation in the context of macroscopic transport equations under the 557 assumption that these moments are in fact finite and well-represented by our data. As 558 noted previously, the Fokker-Planck approximation of the one dimensional entrainment 559 flux consists of three terms: a local advective term that represents the mean hop distance, 560 a nonlocal advective term that squared the squared mean, and a diffusive term that rep-561 resents the variance. These three terms are not guaranteed to map directly onto the typ-562 ical advective and diffusive terms contained in the activity form of the flux (Furbish et 563 al., 2012, 2017), thus we refer to the sum of the first two terms as the advective-like flux 564 and the third term as a diffusive-like flux. 565

Nonlocal advective-like and diffusive-like transport terms are zero under steady, uniform transport conditions (Furbish et al., 2012). In order to compare the advective and diffusive behavior associated with a fixed distribution of particle hop distances, we consider a simple disequilibrium scenario in which the sediment flux varies due to a constant spatial gradient in the particle entrainment rate,  $\partial E/\partial x = \beta$ . In this case, the total flux is steady, varying only as a function of x and is given by:

$$q_x(x) = E(x)\overline{L_x} - \frac{1}{2}\beta\overline{L_x}^2 - \frac{1}{2}\beta\sigma_{L_x}^2.$$
(9)

572 and the flux gradient is given by

$$\frac{\partial}{\partial x}q_x(x) = \beta \overline{L_x} \tag{10}$$

The diffusive flux is related to gradients in the advective flux by a diffusion length  $\ell_{D_x}$ (Seizilles et al., 2014) as

$$q_{x_{\text{diffusive}}} = -\ell_{D_x} \frac{\partial}{\partial x} q_x(x). \tag{11}$$

For the simple disequilibrium conditions considered here, this diffusion length reduces to  $\ell_{D_x} = \sigma_{L_x}^2 / \overline{L_x}$ .

If hop distances are assumed to follow a Weibull distribution with shape param-577 eter k = 1/2, the diffusion length is given by  $\ell_{D_x} = 5\overline{L_x}$ . The ratio of diffusion length 578 to hop length  $\ell_{D_x}/L_x$  is like an inverse Peclet number in that it scales the relative propen-579 sity for diffusion-like and advection-like transport in the presence of gradients in parti-580 cle entrainment rate. We recognize that the entrainment rate and the probability dis-581 tributions of particle hop distance vary together in response to changes in boundary con-582 ditions; however, this mathematical abstraction is useful in that it enables a direct char-583 acterization of the effects of bedform development on particle diffusion. 584

For the plane bed experiment reported here, we find that measured distributions of particle hop distance lead to  $\ell_{D_x} = 4.2\overline{L_x}$ . Thus, the Weibull distribution proposed by previous authors appropriately predicts the measured relationship between streamwise diffusion and streamwise advection for naturally sorted sediments transported over planar topography. In contrast, we find for the bedform condition that  $\ell_{D_x} = 10.6\overline{L_x}$ , deviating significantly from theory.

Following similar arguments presented above but assuming a constant lateral gra-591 dient in particle entrainment rate  $\partial E/\partial y$ , it is straightforward to show that the lateral 592 diffusive flux is related to the lateral gradient in the streamwise advective flux by a dif-593 fusion length  $\ell_{D_y} = \sigma_{L_y}^2 / \overline{L_x}$ . Though, we lack a clear basis for predicting the lateral 594 diffusion length as we have done for the streamwise diffusion length above, we assume 595 as a starting point that the lateral Peclet number is fixed over plane-bed topography (as 596 theory predicts for the streamwise Peclet number). For measured particle hop distances 597 over plane-bed topography, we find that  $\ell_{D_y} = 1.07 \overline{L_x}$ . In contrast, particle motions 598 in the bedform experiment have a lateral diffusion length of  $\ell_{D_u} = 6.17 \overline{L_x}$ . 599

An important assumption in this analysis is that the distribution of particle hop 600 distance is independent of the entrainment rate. Correlations between these variables 601 cannot be evaluated using data reported here and may serve to enhance or diminish macro-602 scopic diffusion. Nevertheless, bedform development appears to increase the propensity 603 for streamwise and lateral diffusive transport quantified by an inverse Peclet number that 604 is equal to the squared coefficient of variation (for streamwise diffusion) or the squared 605 coefficient of lateral transport (for lateral diffusion). This difference cannot be explained 606 by an increase in shear stress alone which would likely cause an increase in the mean stream-607 wise hop distance (Lajeunesse et al., 2010). Instead, bedform development results in a 608 decrease of the mean streamwise hop distance with a concurrent increase of the variance 609 of streamwise and lateral hop distances in our experiments. The notion that this differ-610 ence is primarily caused by the development of bedform topography is entirely consis-611 tent with previously observed differences in particle behavior described by Wilson and 612 Hay (2016), Leary and Schmeeckle (2017), Tsubaki et al. (2018), and Terwisscha van Scheltinga 613 et al. (2019). 614

## 4.5 Experimental Censorship

We have interpreted these data as representative of the ensemble distribution of particle hop distances and travel times characteristic of macroscopic flow conditions. In principle, this requires an unbiased sample of particle motions representing all possible microconfigurations of flow, topogrpahy, and sediment transport. However, practical considerations limited the spatiotemporal extent over which it was possible to measure particle motions. This has two effects which could potentially influence our results.

The first effect is related to the fact that particles with longer hop distances and 622 travel times are more likely to begin or end their motions outside of the measurement 623 window. This effect causes a systematic reduction in the sample mean and variance rel-624 ative to the true mean and variance because hops are censored at a rate that is propor-625 tional to their duration and length. In order to evaluate the importance of this effect, 626 we performed the correction proposed by Ballio et al. (2019). This correction resulted in almost no change in estimates of the mean or variance in either of our experiments. 628 Although this correction cannot account for all forms of censorship (for example, trun-629 cation of the distribution), we are confident that our results are not substantially influ-630 enced by this effect. 631

632 The second effect concerns the fact that our sampling window is not large enough to capture a representative sample of particle motions originating from all possible mi-633 croconfigurations of flow and topography characteristic of the macroscopic transport con-634 ditions. The importance of this effect cannot be evaluated directly from available data. 635 Nevertheless, we argue that our data are sufficient to provide unequivocal support for 636 the primary claims made in this paper. Observed differences in particle behavior are con-637 sistent with previous studies of particle motion over bedforms (e.g., Wilson & Hay, 2016; 638 Leary & Schmeeckle, 2017; Tsubaki et al., 2018) and qualitative differences illustrated 639 in figure 1. Additionally, the mean lateral hop distance in the bedform experiment is ap-640 proximately zero (-0.028 cm) despite clear spatial correlations in lateral hop distance within 641 the measurement window (Figure 1). Assuming the true mean lateral hop distance is zero, 642 we tentatively interpret this as an indicator that the spatiotemporal extent of our mea-643 surement window is sufficiently large such that the measured statistics have begun to 644 converge on the true ensemble statistics. By way of analogy, consider the problem of es-645 timating the mean and variance of bed elevation in a stable bedform field. Measurements 646 from a single bedform will provide reasonable first-order estimates of these quantities despite the fact that there is variability between bedforms (Robert & Richards, 1988; Nikora 648 et al., 1997). 649

We argue that the primary findings of this paper concerning the forms of the distributions of particle hop distance and travel time over bedforms are robust to possible censorship effects. Increases in streamwise and lateral diffusivity are consistent with observations of particle motion reported by previous authors cannot be explained by censorship or sampling biases.

655

## 4.6 Limitations and Future Work

Our theoretical and experimental approach has several important limitations that must be addressed in order to extend the utility of our results to a wide range of macroscopic morphodynamic modeling problems. Here, we outline these limitations and provides suggestions for future studies focused on particle motions over bedforms.

The first limitation discussed in Section 3.3 is that measured distributions of particle hop distance and travel time depend on the criterion used for differentiating between mobile and immobile particles. Bed elevation is also defined with respect to the positions of particles in the immobile phase such that different criteria potentially lead to different descriptions of topography. We report results obtained using a mobility criterion that

is consistent with previous work but ultimately subjective. Different criteria are valid 665 as long as they obey mass conservation (i.e., mobile and immobile states encompass all 666 particles and are mutually exclusive), and therefore provide alternative but compatible 667 descriptions of sediment transport and morphodynamics. Recognizing this, the next step is to investigate how different choices of mobility criteria influence measured statistics 669 of topogrpahy and particle motion. The morphodynamic interpretation of varying thresh-670 olds is similar to the scale-dependent active layer concept (Church & Haschenburger, 2017) 671 and could potentially lead to valuable insights regarding interactions between fluctua-672 tions in bed elevation at the grain, bedform, bar, and channel scale (e.g., Nikora et al., 673 1997).674

Another important issue is that the theoretical framework presented here is only 675 valid for quasi-steady, uniform transport. In principle, this condition is satisfied if we con-676 sider macroscopic transport averaged over bedform-scale fluctuations (i.e., averaged over 677 the bedform field timescale as envisioned by Furbish et al., 2012); however, an impor-678 tant caveat is that equations (4) and (5) assume that the entrainment rate and hop dis-679 tance are independent. This assumption is valid for planar topography befcause the en-680 trainment rate is effectively uniform, but bedforms potentially introduce correlations be-681 tween the entrainment rate and hop distance that can influence the macroscopic trans-682 port rate. 683

To clarify this point, consider that the entrainment rate may fluctuate under macroscopically steady, uniform boundary conditions when bedforms are present. In this case, the instantaneous entrainment rate may be viewed as a probabilistic quantity and the ensemble average flux (over all possible topographic configurations) is given by  $q_x = \overline{EL_x}$ . This becomes  $q_x = E\overline{L_x}$  if E is constant, or  $q_x = \overline{E}\ \overline{L_x}$  if E and  $L_x$  are independent. If they are not independent, the flux may be expressed in terms of a mean and deviatoric component as

$$q_x = \overline{E} \ \overline{L}_x + \overline{E'L'_x} \tag{12}$$

where  $E' = E - \overline{E}$  and  $L'_x = L_x - \overline{L}_x$ . The second term in this expression is a covari-ance and can be rewritten as  $\overline{E'L'_x} = \rho_{EL_x}\sigma_E\sigma_{L_x}$ , where  $\rho_{EL_x}$  is the correlation co-691 692 efficient for the entrainment rate and hop distance,  $\sigma_E$  is the standard deviation of the 693 entrainment rate, and  $\sigma_{L_x}$  is the standard deviation of the hop distance. The diffusive 694 contribution to the flux under disequilibrium conditions may similarly be expanded in 695 terms of mean and deviatoric components. This clarifies how correlations can influence 696 the macroscopic transport rate and leads to several unanswered questions. First, are the 697 entrainment rate and hop distance correlated over equilibrium mobile bedforms? Second, how does the correlation coefficient change under different conditions? Third, how 699 do entrainment rate and hop distance vary within a statistically homogeneous bedform 700 field as a function of local topography? 701

Because our experimental approach was aimed at quantifying the probability dis-702 tribution of particle hop distance and travel time averaged over all possible topographic 703 configurations, our results are limited in their capacity to elucidate the interaction be-704 tween particle motion and bedform evolution at the granular scale. Nevertheless, our re-705 sults clearly indicate that particle motions vary systematically in relation to topogra-706 phy. Future studies investigating this relationship may clarify (a) how morphodynamic 707 feedbacks lead to a stable condition where the motion of individual particles perpetu-708 ates an statistically steady, uniform topographic configuration, and (b) how bedforms 709 influence the advective and diffusive components of the flux under different flow condi-710 tions. 711

## 712 5 Conclusions

This paper presents results of an experimental study comparing the probability distributions that describe the spatiotemporal scales of particle motion linking particle entrainment and disentrainment events. Measured distributions of particle travel time,  $T_p$ , streamwise hop distance,  $L_x$ , and lateral hop distance,  $L_y$ , are compared with previously proposed theoretical distributions describing particle motions over plane-bed topography. We confirm that particle motions over plane-bed topography in natural sediments conform to existing theory. Travel times follow an exponential distribution while streamwise and absolute lateral hop distances follow a Weibull distribution with shape parameter k = 1/2.

In contrast, we find that particle hop distances over bedforms possess an increased 722 723 standard deviation in both the streamwise and lateral directions relative to the mean streamwise hop distance. We argue that this effect is consistent with observations of particle 724 motion over bedforms reported by previous authors; quantities like particle activity and 725 velocity vary systematically in relation to topographic position. Topographically-induced 726 deviations from mean-particle behavior coupled with local flow velocity result in an ad-727 ditional source of variability that is superimposed on turbulent flow and particle colli-728 sion effects. At the macroscopic scale, this means that the relative magnitudes of advec-729 tive and diffusive-like transport implied by plane-bed distributions cannot be assumed 730 when bedforms are present. Instead, bedforms increase the propensity for streamwise 731 and lateral diffusion-like transport. 732

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