

1 Path length and sediment transport estimation from DEMs of 2 Difference: a signal processing approach

3 Lindsay Capito¹, Enrico Pandrin², Walter Bertoldi², Nicola Surian¹, Simone Bizzi¹

4 ¹Department of Geosciences, University of Padova, Padova, 35131, Italy

5 ²Department of Civil, Environmental, and Mechanical Engineering, University of Trento, Trento, 38122, Italy

6 *Correspondence to:* Lindsay Capito (lindsaymarie.capito@studenti.unipd.it)

7 **Abstract.** The difficulties of measuring bedload transport in gravel bed rivers have given rise to the morphological
8 method wherein sediment transport can be inferred from changes in riverbed elevation and estimates of the distance
9 traveled by sediment, its path length. Because current methods for estimating path length are time and labor intensive,
10 we present a method to estimate a characteristic path length from repeat digital elevation models (DEMs of difference
11 i.e., DoDs). We propose an automated method to extract the spacing between erosional and depositional sites on the
12 DoD by the application of Variational Mode Decomposition (VMD), a signal processing method, to quantify the
13 spacing as a proxy for path length. We developed this method using flume experiments where bed topography and
14 sediment flux were measured and then applied it to published field data with physical path length measured from tracer
15 measurements. Our sediment transport estimates were not significantly different than the measured sediment flux at
16 lower discharges in the lab. However, we observed an underestimation of sediment flux at the higher discharges in the
17 flume study. We interpret this as a limit of the method in confined settings, where sediment transport becomes
18 decoupled from morphological changes. We also explore how the time between survey acquisitions, the morphological
19 active width relative to the channel width, and DoD thresholding techniques affect the proposed method and the
20 potential issues they pose to the morphological method in general.

21 1 Introduction

22 In gravel bed rivers sediment transport fundamentally controls morphological processes but is notoriously difficult to
23 measure due to its spatial and temporal heterogeneity (Hoey, 1992; McLean and Church, 1999), measurement uncertainty
24 (Vericat et al., 2006), and the logistical challenges of field measurements. The morphological approach is a method to
25 estimate bedload transport based on observed changes in morphology. There have been many implementations of the
26 morphological method since its inception and it has been reviewed extensively (Ashmore and Church, 1998; Brewer and
27 Passmore, 2002; Church, 2006; Vericat et al., 2017). With the increased availability of hydrologic data and modeling
28 capabilities the morphological method has also been applied in two dimensions (x,y) by coupling a 2D hydraulic model
29 to account for sediment routing (Lane et al., 1995; Antoniazza et al., 2019; Bakker et al., 2019). These 2D applications
30 shed light on the functional links between topographic changes and spatial distribution of bedload transport. Antoniazza
31 et al., (2019) quantified the potential errors in estimating sediment transport using a 1D approach where 2D cross-stream
32 sediment fluxes are neglected. The error associated with neglecting the 2D fluxes may be especially important in
33 multithreaded channels. They also explored how DEM accuracy and the frequency of acquisitions affect the estimates of
34 sediment fluxes derived by the morphological method. These 2D applications enhance the accuracy of the morphological
35 method to estimate sediment transport, however, these studies benefited from intensive field campaigns and an accurate
36 accounting of upstream water and sediment supplies, often not available in real case studies. In this paper, the desire is to
37 explore novel approaches to apply the morphological method using topographic data alone, as hydraulic and sediment
38 supply data are not available in many applications and management situations.

39

40 The morphological method can be formalized based on the sediment continuity equation:

$$41 \quad (Q_{b_{in}} - Q_{b_{out}})\Delta t = (1 - p)\Delta V, \quad (1)$$

42 where $Q_{b_{in}}$ and $Q_{b_{out}}$ are the volumetric sediment flux in and out of the reach respectively, Δt is the time between
 43 surveys, p is the sediment porosity, and ΔV is the change in volume (Ashmore and Church, 1998; Church, 2006). The
 44 sediment continuity equation can be solved in several ways, but in addition to ΔV measured from the DoDs, it requires
 45 that either the incoming flux $Q_{b_{in}}$ or the outgoing flux $Q_{b_{out}}$ be defined. In most cases, neither of these fluxes are
 46 known, as they are the exact parameters that need to be estimated when applying the morphological method. This
 47 conundrum has been addressed by setting a zero-flux boundary, such as a dam or gravel sand transition (McLean and
 48 Church, 1999), by segmenting the reach such that a zero-flux boundary is set between a section of net deposition to one
 49 of net erosion (Vericat et al., 2017; Calle et al., 2020) or by measuring flux either into or out of the reach (Grams et al.,
 50 2013; Antoniazza et al., 2019).

51 Alternatively, Eq. (1) can be modified so that active layer depth, d_s and width w_s , and the virtual velocity, v_b are used:

$$52 \quad Q_b = v_b d_s w_s (1 - p)\rho_s \quad (2)$$

53

54 Where w_s is the active layer thickness, generally measured by chains and estimated by depth of scour (Church and
 55 Haschenburger, 2017), and v_b is equal to L/T , L being the distance the particles travel and T the time over which the
 56 particles are traveling (Church, 2006). The virtual velocity approach has been successfully applied using tracer gravels to
 57 estimate the path length parameter L in a variety of morphological settings (Liébault et al., 2012; Mao et al., 2017; Brenna
 58 et al., 2019, 2020; Brenna and Surian, 2023). Unfortunately, tracer studies are time and labor intensive, requiring multiple
 59 site visits and intensive recovery campaigns which often have low recovery rates, especially for painted clasts (Hassan
 60 and Bradley, 2017; Brenna et al., 2019). Furthermore, tracer studies are often applicable only to exposed bars, ignoring a
 61 large portion of in-channel transport, and can be sensitive to the seeding location (Liébault et al., 2012). To overcome
 62 these limitations, several methods have been proposed to estimate path length based on the connection to morphology.

63 The term path length describes the distance traveled by a particle from entrainment to deposition during a transport event
 64 and is punctuated by shorter bursts of movement termed step lengths (Einstein, 1937). Individual particles do not all
 65 entrain, travel, and deposit together in unison but rather form a distribution of path lengths potentially dependent on grain
 66 size, flow strength and duration, and channel morphology. The relative strength of these physical controls on path length
 67 has been explored with varied results. Some studies have found relationships between path length and flow metrics such
 68 as stream power (Hassan et al., 1992; Schneider et al., 2014; Vázquez-Tarrío and Batalla, 2019; Vázquez-Tarrío et al.,
 69 2019) but a considerable scatter in the data has reinvigorated the debate over the role of morphology as a primary control
 70 of path length (Hassan and Bradley, 2017; Vázquez-Tarrío and Batalla, 2019; Vázquez-Tarrío et al., 2019).

71 The connection between morphology and path length has long been discussed. Neill (1971) proposed that path length in
 72 meandering rivers should be equal to the distance from an erosional site (eroding bank) to the next depositional site (point
 73 bar) downstream. Many others have observed similar relationships based on the spacing of erosional and depositional

74 sites and channel morphology (Beechie, 2001; Pyrce and Ashmore, 2003a, b; Hundey and Ashmore, 2009; Kasprak et
 75 al., 2015; Vázquez-Tarrío et al., 2019). Further, depositional areas (typically bars), have demonstrated a higher probability
 76 of ‘trapping’ particles than erosional morphological units (McDowell and Hassan, 2020; McDowell et al., 2021). Finally,
 77 experimental research has confirmed the preferential deposition of particles specifically at bar heads and margins even in
 78 channels with more complex morphology, for example, in braided rivers (Kasprak et al., 2015) but it is reasonable to
 79 assume that in multithreaded channels, multiple path lengths might exist at different flow stages in primary and secondary
 80 channels.

81 The path length used for the virtual velocity approach is generally taken as the mean travel distance (Wilcock, 1997;
 82 Vericat et al., 2017; Mao et al., 2017; Brenna et al., 2019). However, as we have seen from tracer studies, particles tend
 83 to form a distribution of travel distances, therefore, it is unclear if the mean path length is the best representation of a
 84 ‘characteristic’ path length to estimate bedload transport. To obtain an estimate of reach scale sediment transport we want
 85 to approximate the distance travelled by the bedload that builds geomorphic units, this is what we will consider as a
 86 ‘characteristic path length’. Tracer studies have allowed us to see that this may not necessarily be the average distance,
 87 as evidenced by the wide variety of path length distributions, it is often the case that many or even most (the mode) of
 88 path lengths are very short, thus skewing the average depending on the distribution. For example, Pyrce and Ashmore
 89 published synthesis of tracer studies and demonstrated that at formative discharges, particle path length distributions often
 90 exhibit primary or secondary modes corresponding to the location of bars, where deposition occurs (Pyrce and Ashmore,
 91 2003a). Further, flume experiments with tracers showed that the majority of particles eroded from an upstream scour pool
 92 were deposited at the point bar apex and corresponded to peaks in bi or multimodal path length distributions (Pyrce and
 93 Ashmore, 2005). Therefore, the characteristic path length, i.e., the most representative and sound value to be used in
 94 sediment transport estimations, might be better described by these primary or secondary modes in channels with bar
 95 morphology at channel forming flows.

96 If a characteristic path length can be inferred from changes in morphology as previously discussed, advances in
 97 topographic survey techniques to acquire detailed digital elevation models (DEMs) and facilitate change detection,
 98 provide an opportunity to streamline the estimation of sediment transport. The high-resolution topography (HRT)
 99 revolution (Vericat et al., 2017) has provided an abundance of high quality surveys and an increased frequency of
 100 change detection based on the differencing of DEMs to create digital elevation models of difference (DoDs)
 101 (Brasington et al., 2000; Lane et al., 2003). Vericat et al. (2017) proposed an equation to use the path length with the
 102 volume of erosion derived directly from the DoD

$$103 \quad Q_b = (v_b \sum V_e (1 - p)\rho_s)/L_c, \quad (3)$$

104 where $\sum V_e$ is the total volume of erosion from the DoD and L_c is the length of the analyzed DEM by which the volume
 105 of erosion is normalized (Vericat et al., 2017). To use this method, L_c must be long enough for average path lengths (L)
 106 to occur and T must be short enough to prevent repeated erosion and deposition, known as compensation (Lindsay and
 107 Ashmore, 2002).

108 Redolfi (2014) attempted to estimate the path length parameter directly from the DoD using the length of individual
 109 erosional patches as a proxy for the length of the erosion-deposition sequence. This approach avoids the need to couple
 110 each erosional area to a downstream depositional area, which can be difficult to automate in multi-thread rivers. While
 111 this method scales well with flow metrics and provides reasonable estimates (Redolfi, 2014; Vericat et al., 2017), the

112 hypothesis that the length of erosional areas is equivalent to the erosion-deposition distance has not been tested in
113 different morphologies, and it is not clear how the survey resolution may affect the estimates by fragmenting the
114 erosional areas into smaller parts. Recently, Calle et al. (2020) used a method of river segmentation to visualize the
115 pattern of erosion and deposition and infer sediment connectivity as well as to estimate potential travel distances. They
116 defined boundaries between river segments and classified them into types based on their net erosional or depositional
117 characteristics. Focusing on the “type 1 depositional boundary” wherein the upstream section is erosional and the
118 immediate downstream boundary is depositional and depending on the volumes of deposition and erosion in these
119 segments they were able to estimate minimum or maximum transport distances (Calle et al., 2020). This approach
120 provides greater insight into the spatial connectivity of the river corridor and is useful to understand reach scale
121 processes. However, depending on the river, and the sections surveyed, the number of type 1 boundaries may limit the
122 applicability of the method in defining a characteristic path length and crucial information may be missed where the
123 pattern of erosion and deposition is not clear, or the periodicity spans multiple sections. For example, where there are
124 back-to-back patches of erosion or deposition or the overall pattern is separated by small areas of mixed boundaries.

125 Given the observations linking path length to morphology and building on the aforementioned methods, we seek to
126 expand on the idea that characteristic path length can be inferred from changes in morphology at near transport event
127 scale comparisons. If during a flood, sediment is mobilized from an area of erosion to an area of deposition as
128 represented on the DoD, the distance between the two should correspond to a characteristic path length. Following these
129 assumptions this work has the following objectives: i) to propose an objective and semiautomatic method to quantify a
130 characteristic path length as represented by the periodic nature of erosion and deposition from the DoD using flume
131 data; ii) to compare these estimates of a characteristic path length to measured path length distributions obtained from
132 tracer data in the field; iii) and finally to evaluate the conditions in which a characteristic path length is appropriate to
133 estimate sediment transport.

134

135 **2 Methods**

136 To meet our objectives, we use flume experiments at varying discharges with direct measurement of output sediment flux
137 and sets of repeat DEMs from which DoDs are created and used to identify patterns of erosion and deposition. We then
138 develop a semiautomated method to extract these distances between erosion and deposition as a proxy for the
139 characteristic path length and then compare our estimates of sediment flux calculated using the characteristic path length
140 to measured sediment flux. Finally, we compare the characteristic path length estimates from a published case study to
141 the physical path length distributions as measured by tracers in the field to see how the characteristic path length
142 corresponds to path length distributions.

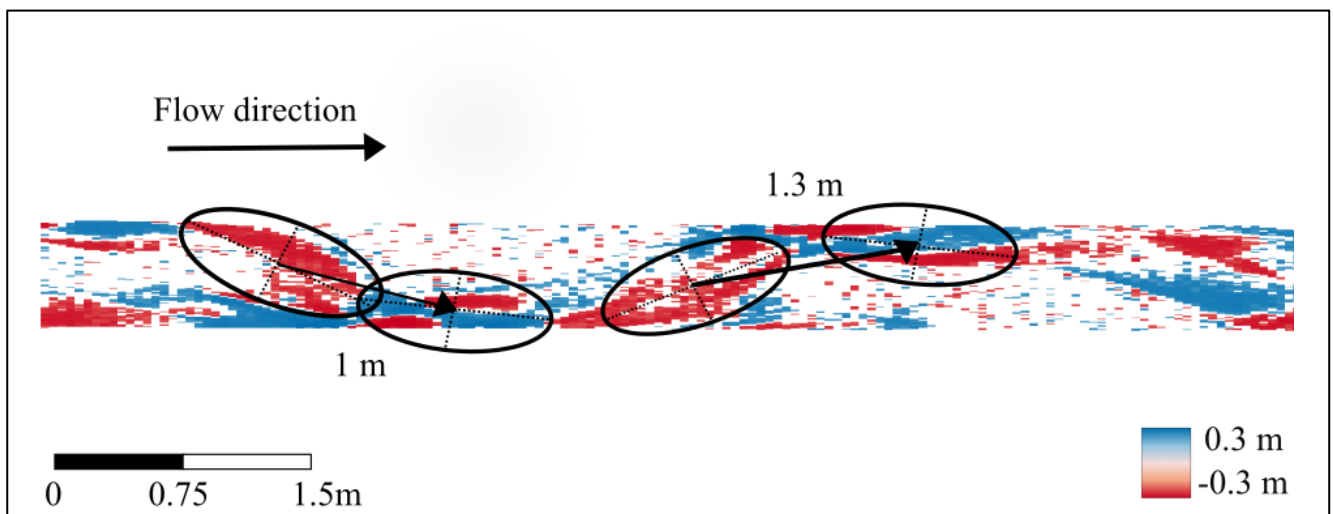
143

144 **2.1 Path length**

145

146 A key assumption inherent in our objectives is that sediment moves from an area of net erosion to an area of net
147 deposition during the time period between DEM acquisitions and that this represents a characteristic path length.
148 Ferguson and Ashworth (1992) proposed a similar method of matching specific erosional and depositional patches
149 albeit without the assistance of a DoD. This method was then implemented in the Sunwapta River, Canada (Goff and

150 Ashmore, 1994) although the authors note the difficulty in finding perfectly matching patches and conclude that
 151 erosional and depositional processes are likely more dispersed. Here we will implement this “manual method” as a
 152 means of comparison for the automated method presented later. The most obvious method to quantify this distance
 153 between erosional and depositional sites on the DoD is to measure the spacing manually using a GIS program however,
 154 this requires many subjective evaluations. Firstly, we must decide where on the patches of erosion and deposition to
 155 begin and end the measurements. Because patches of erosion and deposition are not symmetrical or of equal size, the
 156 distance between the two depends on which area of the patch we choose to begin and end the measurements. For
 157 consistency, we choose the center of the patch (Fig. 1) after Ashmore and Church (1998). Next, we must determine
 158 which patch of erosion matches with which patch of deposition which is not always obvious, and as noted previously,
 159 likely does not accurately represent the nature of bedload transport (Goff and Ashmore, 1994). Here we perform this
 160 method solely for comparative purposes and therefore used our knowledge of morphological processes to make a best
 161 estimate. For example, a patch of erosion on an outside bend likely corresponds to the deposition of the next point bar
 162 downstream (Fig. 1). Although this method is capable of producing crude estimates of path length to overcome the
 163 aforementioned biases (Ferguson and Ashworth, 1992; Goff and Ashmore, 1994; Ashmore and Church, 1998) we
 164 propose a method to estimate a characteristic path length without relying on the matching of erosion and deposition but
 165 rather to use the periodic nature of these processes. Additionally, we seek to create a method that is both objective and
 166 semiautomated.



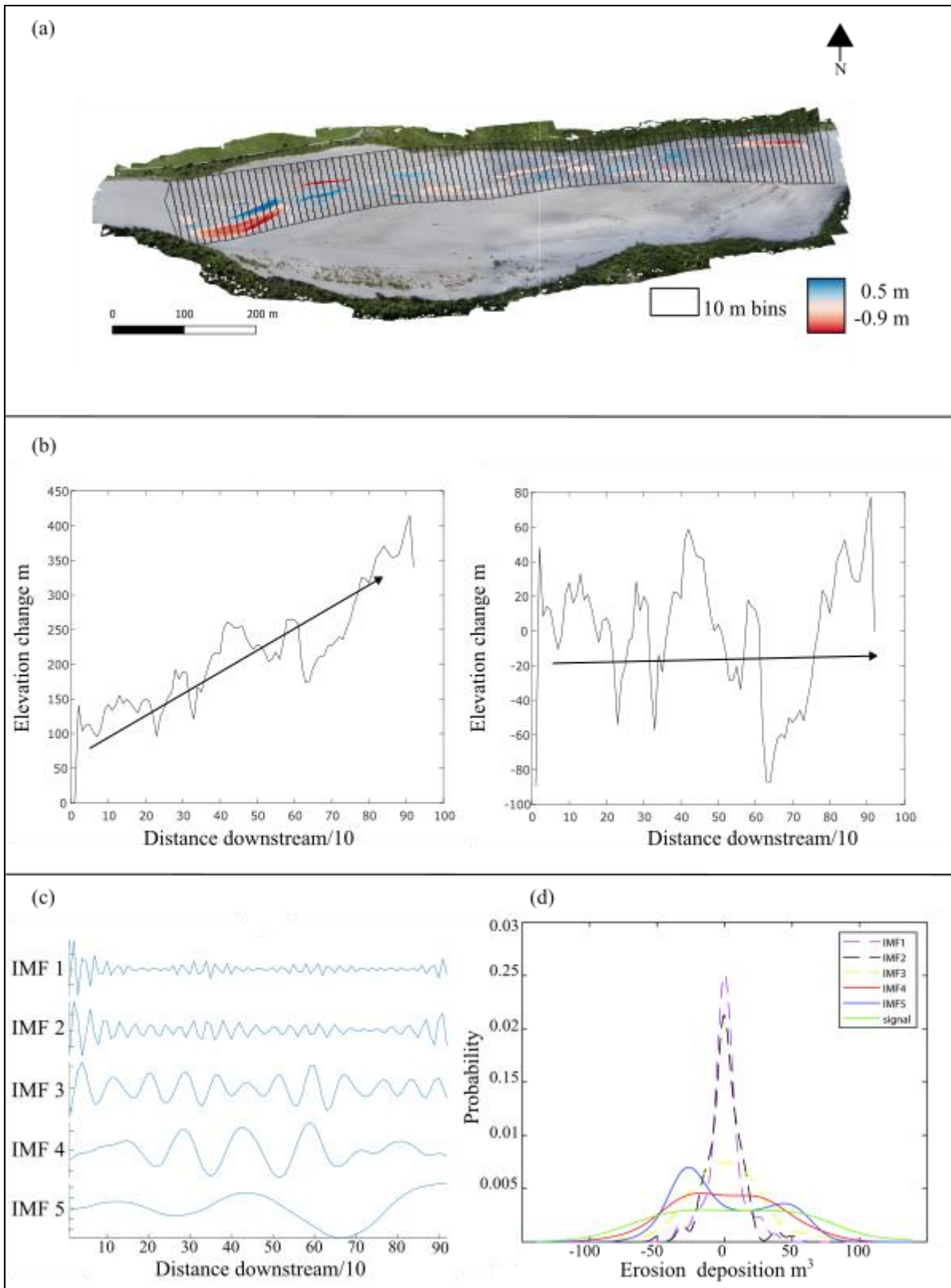
167

168 **Figure 1: Manual method to measure spacing of erosional patches (red) and depositional patches (blue) on a**
 169 **DoD.**

170 2.2 Semiautomated extraction of path length

171 To visualize and then quantify the periodic nature of erosion and deposition from the DoD we simplify the spatial
 172 heterogeneity of the DoD into a vector of the net change in elevation in a streamwise direction (Fig. 2a). Because
 173 natural rivers are rarely straight, for field case studies, we must enforce a linear downstream directionality essentially
 174 straightening the bends in the river. This is achieved by segmenting the DoD into a series of equally sized “bins” using
 175 the segmentation tool of the Fluvial Corridor Toolbox (Roux et al., 2015) (Fig. 2a). The bin size can affect the pattern of
 176 erosion and deposition in that by selecting too large of bins we may miss important erosional or depositional areas when
 177 they are summed in the same bin. Similar methods that require river segmentation have proposed using the reach
 178 averaged width for the length of the bins (McDowell et al., 2021) or half of the width of the reach (McDowell and
 179 Hassan, 2020) although these studies had different objectives. Calle et al. (2020) applied a segmentation method with a
 180 similar goal of identifying corresponding zones of erosion and deposition and set the bin sized based an assessment of

181 the river dimensions as well as the minimum transfer distance of interest. Therefore, depending on the river, the user
182 may select differently sized bins. Once the river is segmented, we then sum the values in each bin to obtain a vector of
183 the net change in elevation in a downstream direction (Fig. 2b). In the flume studies, where there is no sinuosity, we
184 simply sum each cross section of the DoD matrix. Oftentimes a reach is aggrading or incising and therefore the net
185 vector will have an increasing or decreasing trend (Fig. 2b). Because we are interested in the spacing between areas of
186 erosion and deposition rather than the overall trend, we remove it by subtracting a best-fit linear trend from the net
187 vector (Fig. 2b). Because we simplify the heterogeneity of erosion and deposition into a net vector of elevation change,
188 we risk compensating erosion and deposition within the same cross section, therefore we also create a vector of just
189 erosion and one of just deposition as well as the net allowing for a visual comparison of the relative contribution of
190 erosion and deposition to the net as well as the periodicity of the individual processes (Fig. A1). We can see that there
191 appears to be a periodicity as the net vector oscillates forming peaks and troughs and although this periodicity seems
192 apparent, quantifying the distance is not straightforward.



193

194 **Figure 2: VMD- HD method (a) Segmentation of the DoD (example orthophoto and DoD from the Tagliamento**
 195 **River, Italy). (b) Plot of the net original and detrended vector. (c) Variational mode decomposition (VMD) with 5**
 196 **intrinsic mode functions (IMFs). (d) Probability density function (PDF) of each IMF and the original net vector.**

197 One approach could be to count the zero crossings and then use that distance as the proxy for path length. However, we
 198 risk measuring low magnitude spikes that cross zero that may not necessarily represent the overall periodicity or large
 199 oscillations that don't cross the zero line. A smoothing filter may be used to remove these low magnitude oscillations

200 but we risk losing potentially relevant information. To solve this problem, we turn to the realm of signal processing
201 where the practice of “denoising” and extracting information from oscillations is ubiquitous.

202 Signal processing is a field that deals regularly with extracting information and patterns that are not visually apparent
203 and its applications have been used in a wide variety of settings including voice recognition (Sigmund, 2003; Upadhyay
204 and Pachori, 2015), medical applications (Boudraa et al., 2005; Liu et al., 2008), and even time series analysis of
205 climate data (Barnhart and Eichinger, 2011). There are many approaches to de-noising including Fast Fourier transform,
206 empirical mode decomposition (EMD), and wavelet analysis. Each of these methods come with inherent strengths and
207 weaknesses, for example wavelet analysis requires that a mother wavelet be selected a priori and may influence the
208 results (Boudraa et al., 2005). We chose to use variational mode decomposition (VMD) due to its robustness with
209 respect to sampling and noise and the ability to handle signals that exhibit non-linearity and non-stationarity
210 (Dragomiretskiy and Zosso, 2014; Huang et al., 2016; Ma et al., 2017). VMD decomposes the signal into a set of
211 intrinsic mode functions (IMFs) each with a different central frequency (Dragomiretskiy and Zosso, 2014; Ma et al.,
212 2017) (Fig. 2c). In this case of our static ‘signal’ the frequency is more accurately described as the wavelength. It is
213 beyond the scope of this paper to describe the mathematics of VMD in detail, therefore, for a complete explanation see
214 (Dragomiretskiy and Zosso, 2014; Huang et al., 2016; Ma et al., 2017; Upadhyay and Pachori, 2015).

215 Once the original net vector of erosion and deposition is decomposed into the various IMFs, we need to select the IMF
216 or IMFs that most accurately represent the periodicity of the original data and therefore our characteristic path length.
217 Ma et al. (2017) proposed a method to select the most relevant IMF, and therefore periodicity of the signal, by
218 computing the probability density function (PDF) using kernel density smoothing for each of the five IMFs and of the
219 original data vector (Fig. 2d), then to calculate the Hausdorff distance (HD), a metric of geometric similarity, between
220 each IMF’s PDF and the PDF of the original data and select the IMF most geometrically similar to the original data (Ma
221 et al., 2017) (hereafter VMD-HD method). In most cases, the longer wavelength IMFs most closely resemble the
222 original signal whereas the IMFs with shorter wavelengths are more likely associated with noise (Boudraa et al., 2005).
223 The computed wavelength is converted to a meaningful physical quantity by multiplying by the bin spacing in meters.
224 Because we are interested in the distance from peak to trough, we divide the period by two to obtain the path length
225 proxy (Neill, 1971; Ashmore and Church, 1998). Although this method allows for the selection of one IMF to
226 presumably represent the periodicity of the data, we record path lengths calculated from the other IMFs to evaluate the
227 range of estimates generated by the decomposition and determine if the VMD-HD method is appropriate for
228 determining a characteristic path length and the relative importance of other IMFs. All calculations were performed in
229 MatLabR2020b using the built in VMD function and the Hausdorff distance function (Danziger, 2023).

230 One important consideration when using VMD to decompose a signal is that the user must define the number of IMFs
231 beforehand. The number of IMFs is important as under binning, choosing too few IMFs, may mean that critical IMFs
232 are missed, whereas over binning, can cause duplication of components (Wu et al., 2020). In signal processing, there are
233 sophisticated methods for determining the number of IMFs, for a summary see (Wu et al., 2020). However, for our
234 purposes and simplicity’s sake, we performed a brief sensitivity analysis based on the property of convergence often
235 used in the signal processing methods (Wu et al., 2020; Huang et al., 2016; Ma et al., 2017). The default setting in the
236 MatLab function is 5 IMFs, we used 3, 5, 8, 15, and 25 IMFs to calculate path length and assessed how it changed for
237 the maximum IMF (Fig. A2). We found that using more IMFs generally increased the number of high frequency
238 components rather than the lower frequency IMFs (Fig. A3). Because these higher frequencies are generally associated
239 with noise and in our case are physically too small to likely represent meaningful path lengths (on the order of

240 millimeters) we decided more than 5 IMFs did not contribute physically meaningful information in that the IMFs with
 241 longer wavelengths did not change drastically. We also determined that 3 IMFs were too few as it was clear that the
 242 longer wavelengths were missing (Fig. A3). Therefore, we chose to use the default 5 IMFs as this provided a
 243 manageable number of components while effectively separating the lower frequencies. This is a convenient starting
 244 point for assessing the VMD method as a tool to extract the periodicity as a proxy for characteristic path length but is by
 245 no means the only option. We encourage further exploration of the IMF parameter in future applications and as the
 246 method is refined.

247 3 Flume and field data

248 The method was tested using data from a set of flume runs performed in the Hydraulic Laboratory of the University of
 249 Trento, where DEMs were generated for fixed time intervals and varying discharges, and direct measurements of the
 250 bedload flux were also collected. To test the efficacy of the method in the field, we selected a published dataset of
 251 measured path lengths with corresponding DoDs for the San Juan River in British Columbia Canada (McQueen et al.,
 252 2021). Although McQueen et al. deployed tracers in four separate periods, there was only one deployment (2018-2019)
 253 with corresponding DEMs (McQueen et al., 2021). DoDs and corresponding tracer data were available for three
 254 separate sites (bar 6, bar 7, and bar 15) for the 2018-2019 period. Detailed information on their collection and
 255 processing can be found in McQueen et al., 2021.

256 3.1 Flume experiments

257 The Trento laboratory experiments were carried out in a 0.6 m wide and 24 m long flume, filled with nearly uniform 1
 258 mm diameter sand. The flume slope was set to 0.01 m/m. Topographic surveys were performed over the final 14 m of
 259 the flume, to limit the upstream inflow effects, using a laser gauge, mounted on a movable deck. The longitudinal and
 260 crosswise spacings were 0.05 m and 0.005 m, respectively. Four sets of nine runs were performed, with the flow
 261 discharge set to 0.7, 1, 1.5, and 2 l/s, which correspond to a range of different planform morphologies (Table 1).
 262 Sediment input at the upstream end of the flume was constant in each run, with a flux equal to the average measured at
 263 the downstream end, as computed in a preliminary set of experiments. Therefore, the overall average bed elevation of
 264 the runs was in equilibrium, with no net erosion or deposition. The runs were performed following the same procedure,
 265 involving three phases of different lengths, based on the transport condition of each discharge. These durations were
 266 estimated referring to the time scale for morphological evolution computed from the sediment balance mass equation
 267 (Garcia Lugo et al., 2015), which can be expressed as:

$$268 \quad T_{ex} = \frac{DW^2}{Q_b}, \quad (4)$$

269 where D is the average flow depth and W is the flow width. Table 1 provides the values of T_{ex} for each flume
 270 experiment.

271 **Table 1: Initial conditions for each dataset including the type of validation data.**

	Flume 1	Flume 2	Flume 3	Flume 4	San Juan Bar 6	San Juan Bar 7	San Juan Bar 15
Peak discharge (m ³ /s)	0.0007	0.001	0.0015	0.002	942	942	942
Slope (m/m)	0.01	0.01	0.01	0.01	0.0038	0.0031	0.0009
Width (m)	0.6	0.6	0.6	0.6	150	150	130
D ₅₀ (m)	0.001	0.001	0.001	0.001	0.05	0.056	0.042

Time scale T_{ex} (min) (eq.4)	94	50	38	30	-	-	-
Time between surveys (min)	47	25	19	15	~1 year	~1 year	~1 year
ω^* Dimensionless stream power	0.15	0.22	0.33	0.43	0.76	0.61	0.31
Validation Data	Sediment Flux	Sediment Flux	Sediment Flux	Sediment Flux	RFID tracers	RFID tracers	RFID tracers
Planform	Wandering	Wandering	Wandering transitional	Alternate bar	Wandering	Wandering	Wandering

272

273 First, an initial phase of about 12 times this time scale T_{ex} with constant flow was run, to ensure the formation of a
274 near-equilibrium morphological condition, starting from a flat sand bed scraped to the prescribed slope. This was
275 followed by a long run, at constant discharge, lasting 19 times the time scale T_{ex} , aimed at measuring the output
276 sediment flux. This was continuously monitored at the channel outlet, through a permeable basket placed on four load
277 cells. Sediment flux was measured every minute. After a bed topography survey, the third phase was a sequence of nine
278 shorter runs, lasting 0.5 times the time scale T_{ex} , each followed by a bed topography survey, which produced nine
279 corresponding DoDs. The duration of these nine runs (and therefore the time interval between surveys) was decided to
280 have easily measurable changes of the bed morphology, without having significant compensation processes.

281 The DoDs were created by subtracting two consecutive DEMs, then underwent a three-step filtering process to highlight
282 the relevant erosion and deposition patterns, removing most of the noise associated with the surface roughness and
283 measurement accuracy. First, the DoDs were filtered considering a uniform detection threshold equal to 2 mm (2 times
284 the D_{50}), meaning that erosion or deposition values lower than this threshold are set to zero. Thereafter, a spatial average
285 was performed as a moving average on three values along the transversal direction where the DoD discretization is the
286 finest. Lastly, a despeckling algorithm removed all isolated cells, both considering single cells that show erosion or
287 deposition, as well as single cells that show no change. This last step was implemented to keep the detection threshold
288 as low as possible while removing unphysically small areas. Additionally, we calculated the morphological active width
289 by determining the percentage of the DoD that showed morphological activity (i.e., was not zero after filtering).

290 3.2 San Juan River data

291 To compare the characteristic path length to measured path length distributions in the field, we used data from the San
292 Juan River, located on Vancouver Island, British Columbia with a drainage area of approximately 730 km² and a mainly
293 rainfall driven hydrology (McQueen et al., 2021). The reach of interest in this study was alluvial in nature with a
294 wandering morphology and a substrate composed of gravel, cobble, and sand (McQueen et al., 2021). The time in
295 between acquisitions is one year, in which it is estimated there were five flood events able to generate sediment
296 transport using a threshold of 500 m³ s⁻¹, which was visually estimated by the authors to be equivalent to the bankfull
297 discharge (McQueen et al., 2021). DEMs were generated by LiDAR acquisitions and have a spatial resolution of 10 cm
298 and a vertical root mean square error lower than 10 cm. Topographic changes between survey dates were then
299 calculated by processing the LiDAR DEMs using the Geomorphic Change Detection (GCD) software (Wheaton et al.,
300 2010). More information on how they were obtained and processed including the spatially variable thresholding
301 techniques can be found in McQueen et al. (2021). The LiDAR-derived DoDs were used to interpret patterns of tracer
302 displacement and burial depths and to provide information on the morphological development of the bars during the
303 study period. However, they do not provide complete reach-scale sediment budgets due to the lack of in-channel
304 topographic data and stage differences during each LiDAR survey affecting the relative portion of the river bed that was

305 exposed. The submerged area represented 22% of the DoD for bar 6, 42% for bar 7, and 36% for bar 15. Nevertheless,
 306 we believe the exposed part of the channel, the bars, and associated patches of erosion and deposition (see Fig. 9b) are
 307 sufficient to be used with our proposed method to estimate path lengths and be compared with field measured path
 308 lengths from the tracer data as a first application to field data. This is because we are not calculating sediment flux for
 309 the San Juan River and are only interested in comparing our estimates of the characteristic path length to the measured
 310 tracer distributions. As far as the pattern of erosion and deposition and how that may be disrupted, we recognize that the
 311 pattern could change by including the underwater areas, however, looking at figures 15 and 16 from McQueen et al.
 312 (2021) we can see that the tracers were largely recovered from the exposed bar surfaces in the 2018-2019 deployment.
 313 This gives us confidence that the deposition we are measuring corresponds largely to the deposition associated with the
 314 tracers. Although this is not an ideal situation, we believe the benefits outweigh the limitations considering the difficulty
 315 of finding high quality RFID tracer data and corresponding DoDs. The San Juan River DoDs were downloaded directly
 316 from the Scholars Portal Dataverse (<https://doi.org/10.5683/SP2/UQGZCG>). The DoDs were segmented using similar
 317 principles to Calle et al. (2020) in a similarly sized river, therefore the bin size was conservatively set at 10 m.

318 3.3 Validation and error estimation

319

320 Each study had unique initial conditions including slope, discharge, grain size, channel configurations, and time/flood
 321 events between surveys (Table 1). Because the studies vary with respect to these initial conditions, we calculated the
 322 dimensionless stream power (ω^*) after Bertoldi et al. (2009) to compare them as:

$$323 \quad \omega^* = \frac{Q \cdot S}{W \sqrt{g \Delta D_{50}^3}}, \quad (5)$$

324 where Q is the peak discharge, S is slope, W is the average wetted width, Δ is the relative submerged density, D_{50} is the
 325 median grain size, and g is the acceleration due to gravity.

326 For the flumes, we used estimates of path length generated by the VMD-HD method and those associated with the two
 327 longest wavelengths, IMF 4 and IMF 5 separately to calculate the virtual velocity Eq. (2) and sediment flux Eq. (3)
 328 which we then compared to measured flux data. The measured sediment flux during the initial long run showed high
 329 variability, with phases of high and low sediment flux lasting several tens of minutes. For this reason, we prefer to use
 330 the data from the long runs, from which we estimated an average sediment flux of 0.33 g/s (SD=0.17) for the 0.7 l/s
 331 discharge, 0.78 g/s (SD=0.31) for the 1 l/s discharge, 1.98 g/s (SD=0.65) for the 1.5 l/s discharge, and 3.22 g/s
 332 (SD=0.79) for the 2 l/s discharge. We subdivided the second phase into 38 intervals of 0.5 T_{ex} duration, equal to the
 333 duration as the short runs in phase 3, and computed the variability of the flux over this range.

334 We used ANOVA to compare path length, virtual velocity, and erosion across the four discharges ($\alpha=0.05$) and a Post-
 335 hoc Tukey test to explore significant differences between discharges. To compare the measured sediment flux to the
 336 estimates from the VMD-HD method and the IMF 4 and IMF 5 estimates we used a student's t-test ($\alpha=0.05$). And
 337 finally, to compare the error of our path length and sediment transport estimates we calculated the relative percent error
 338 δ in order to compare the sediment flux estimates to that of the long runs of average sediment flux as:

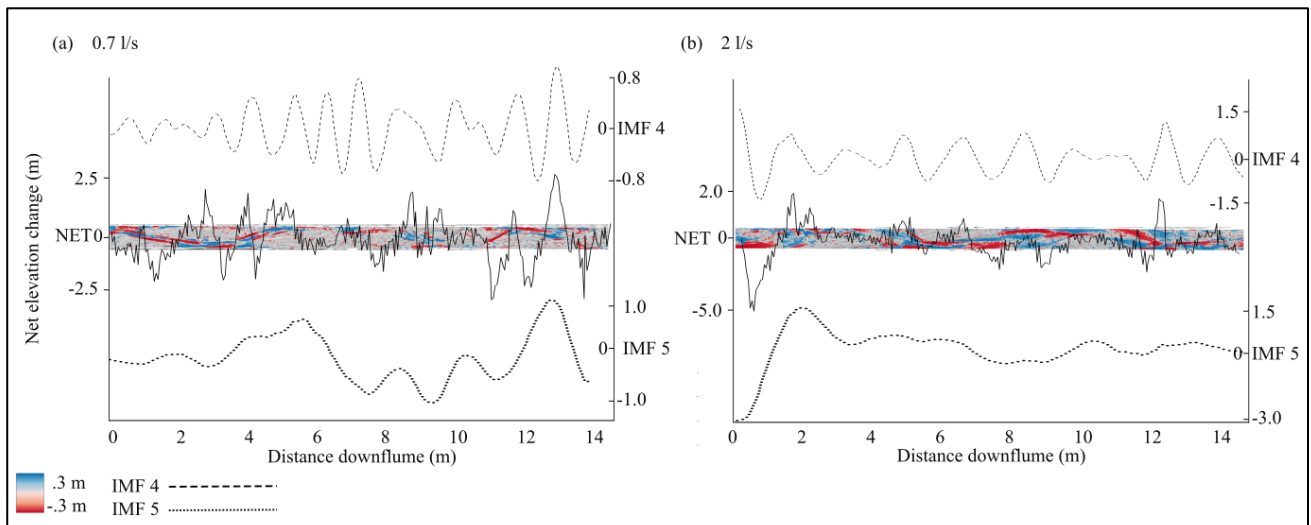
$$339 \quad \delta = \frac{|E-M|}{M}, \quad (6)$$

340 where E is the average of the estimated sediment flux for the 9 runs at a given discharge and M is the averaged
 341 measured sediment flux from the long run at the same given discharge. For the San Juan River we compared the VMD-
 342 HD estimates of path length and IMFs 4 and 5 qualitatively to the published path length distributions and the locations
 343 of mean, median, and modes. The tracer recovery locations were accessed in spreadsheet form and in keeping with the
 344 analysis of the authors we disregarded any tracers that moved less than 10 m before calculating the path length
 345 distributions.

346 4 Results

347 4.1 Flume experiment

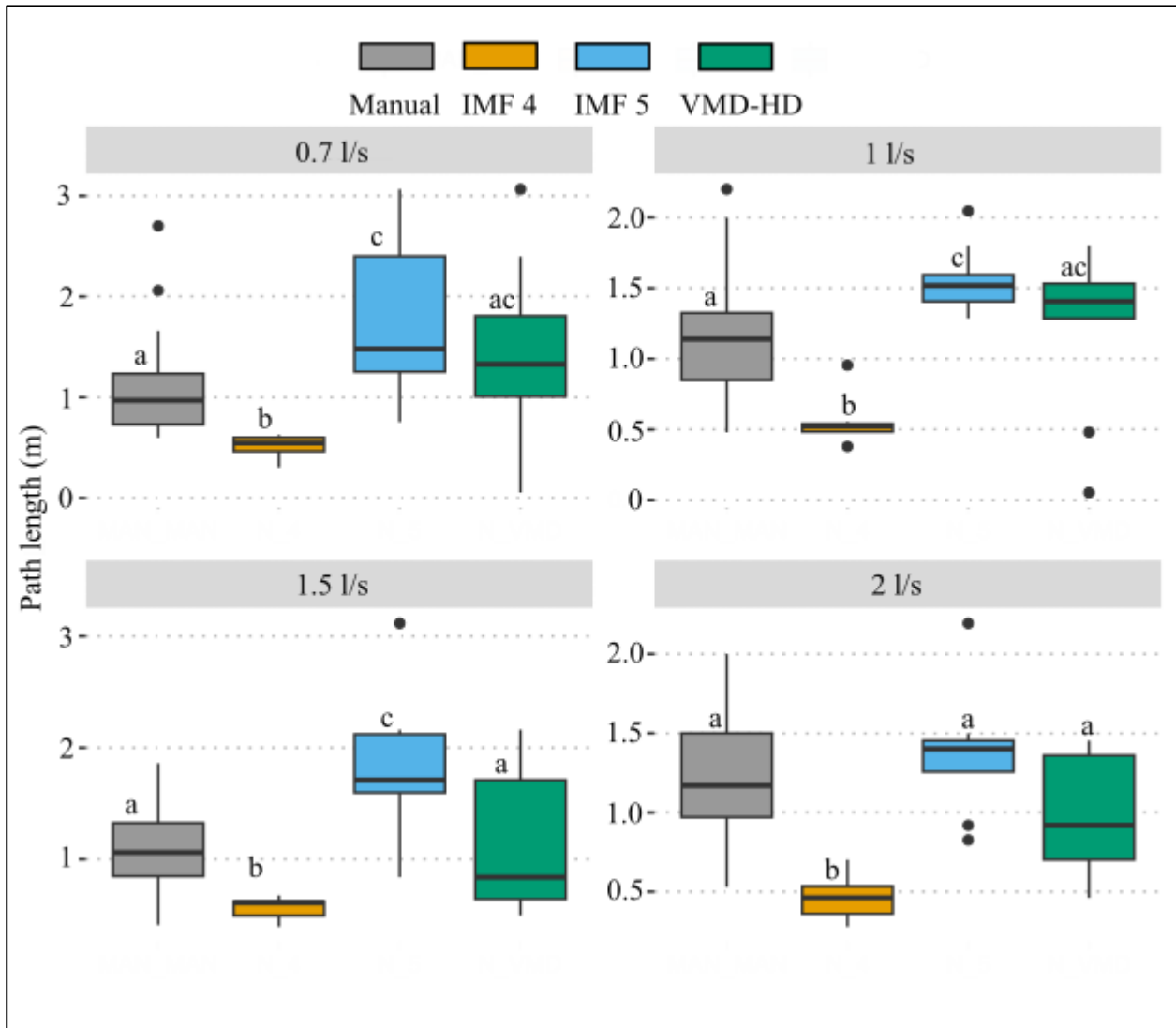
348 To aid in the interpretation of the results, Fig. 3 shows a DoD from the lowest discharge, 0.7 l/s (a) and the highest
 349 discharge, 2 l/s (b) with the net vector (continuous line), IMF 4 (dashed line), and IMF 5 (dotted line) as obtained from
 350 the VMD method. Oftentimes the areas of deposition and erosion from the DoD correspond clearly to the IMF 4 and 5
 351 vectors as with the 0.7 l/s discharge where areas of deposition are concave and areas of net erosion correspond to
 352 convex areas of the vector (Fig. 3a). At the higher discharges (1.5 l/s and 2 l/s) the total area of morphological activity
 353 increases and patches of erosion and deposition begin to overlap, creating a more chaotic and difficult to discern pattern
 354 (Fig. 3b, A1). We also observed a similar periodicity in the erosional and depositional vectors and at the 2 l/s discharge
 355 the depositional vector appears to show this most clearly (Fig. A1).



356
 357 **Figure 3: DoDs from 0.7 l/s discharge (a) and 2 l/s discharge (b) with the net vector of elevation change laid over**
 358 **the top. IMF 4 vector (above, dashed line) and IMF 5 vector (below, dotted line)**

359 In the flume experiment, the VMD-HD method of choosing the most relevant IMF selected the longest wavelength IMF
 360 5 71% of the time and IMF 4 23% of the time. IMFs 2 and 3 were never selected and IMF 1 was selected only twice.
 361 However, at the higher discharges (1.5 l/s and 2 l/s) IMF 4 was selected more frequently, thereby reducing the average
 362 path length when compared to the lower discharges (Fig. A4). Using the selected IMFs, the VMD-HD method
 363 estimated a similar average path length for all of the discharges (Fig. 4). The averages were, 1.45 m (standard deviation
 364 (SD) = 0.93) for the 0.7 l/s discharge runs, 1.24 m (SD=0.58) for the 1 l/s runs, 1.21 m (SD = 0.58) for the 1.5 l/s runs,
 365 and 1 m (SD = 0.37) for the 2 l/s runs (Fig. 4). The path length estimates derived from IMF 4 were similar for all
 366 discharges, 0.51 m (SD=0.12) for the 0.7 l/s discharge, 0.55 m (SD=0.16) for the 1 l/s discharge, 0.56 m (SD=0.91) at
 367 the 1.5 l/s discharge, and 0.46 m (SD=0.15) at 2 l/s (Fig.4) with no significant differences between the discharges ($p >$
 368 0.05). The path lengths derived from IMF 5 were also similar between the discharges with no significant differences (p

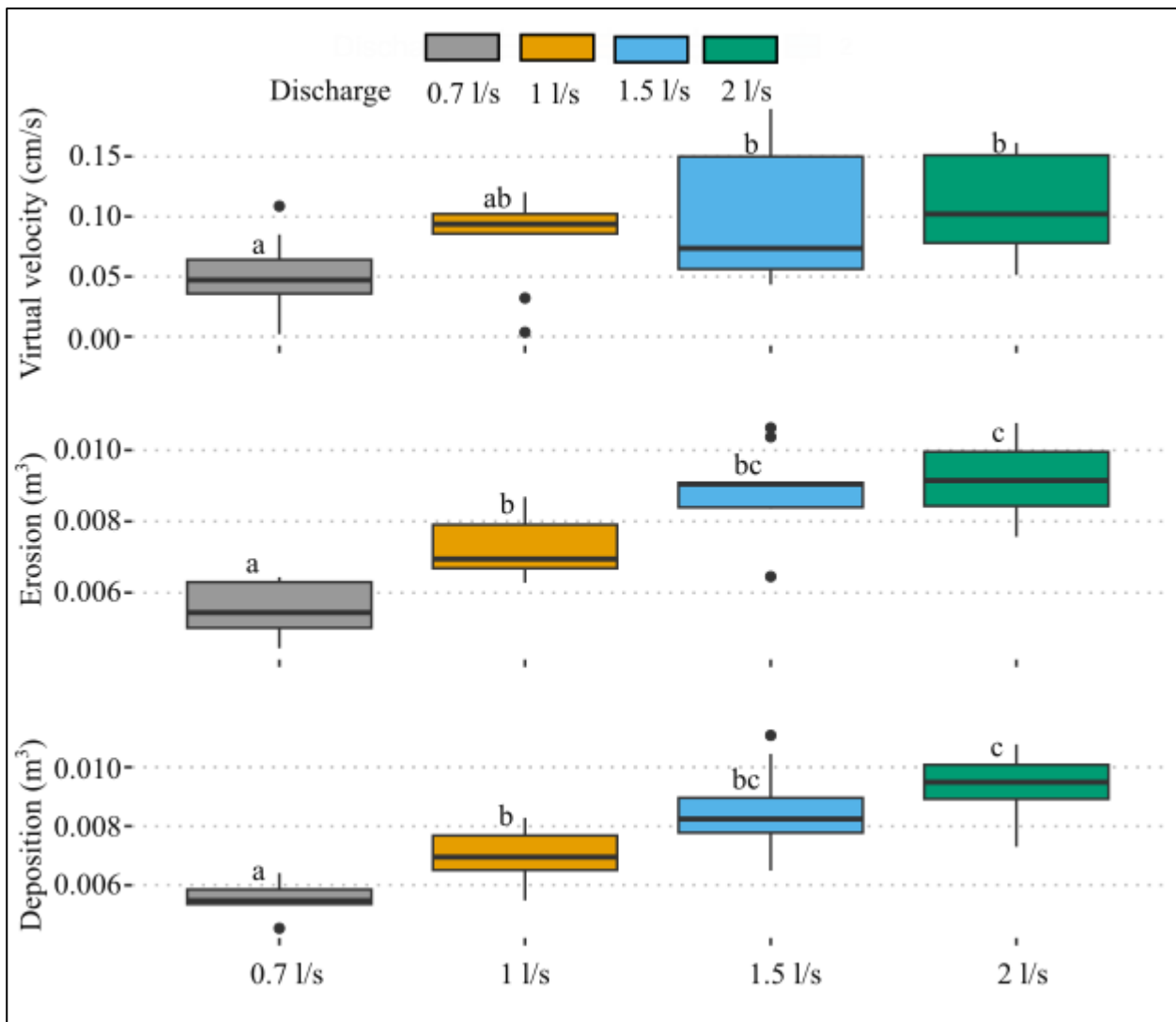
369 > 0.05) and were, 1.75 m (SD=0.79) for the 0.7 l/s discharge, 1.55 m (SD=0.24) for the 1 l/s discharge, 1.79 m
 370 (SD=0.67) for the 1.5 l/s discharge, and 1.37 m (SD=0.39) for the 2 l/s discharge (Fig. 4). The VMD-HD method
 371 matched closely with the manually measured distances and there were no statistically significant differences for any of
 372 the discharges (p-value > 0.05) (Fig. 4) while the IMF 4 and IMF 5 derived path lengths bracket the manually measured
 373 distances and the VMD-HD selected path lengths (Fig. 4).



374

375 **Figure 4: Path length estimates from the manual method (gray), IMF 4 (orange), IMF 5 (blue), and the VMD-HD**
 376 **method (green). Significant differences from the post-hoc Tukey test are denoted by letters a-c.**

377 The estimated path lengths were not significantly different between the discharges (p-value >0.05) and showed no
 378 obvious trend of increasing or decreasing with discharge. However, when used to calculate the virtual velocity (v_b)
 379 wherein the path length is divided by the time between surveys (Table 1), we see an increase in the virtual velocity with
 380 discharge (p-value < 0.05) (Fig. 5). Likewise, the average volumes of erosion and deposition calculated from the filtered
 381 DoDs increases significantly with discharge (p-value < 0.001) (Fig. 5).



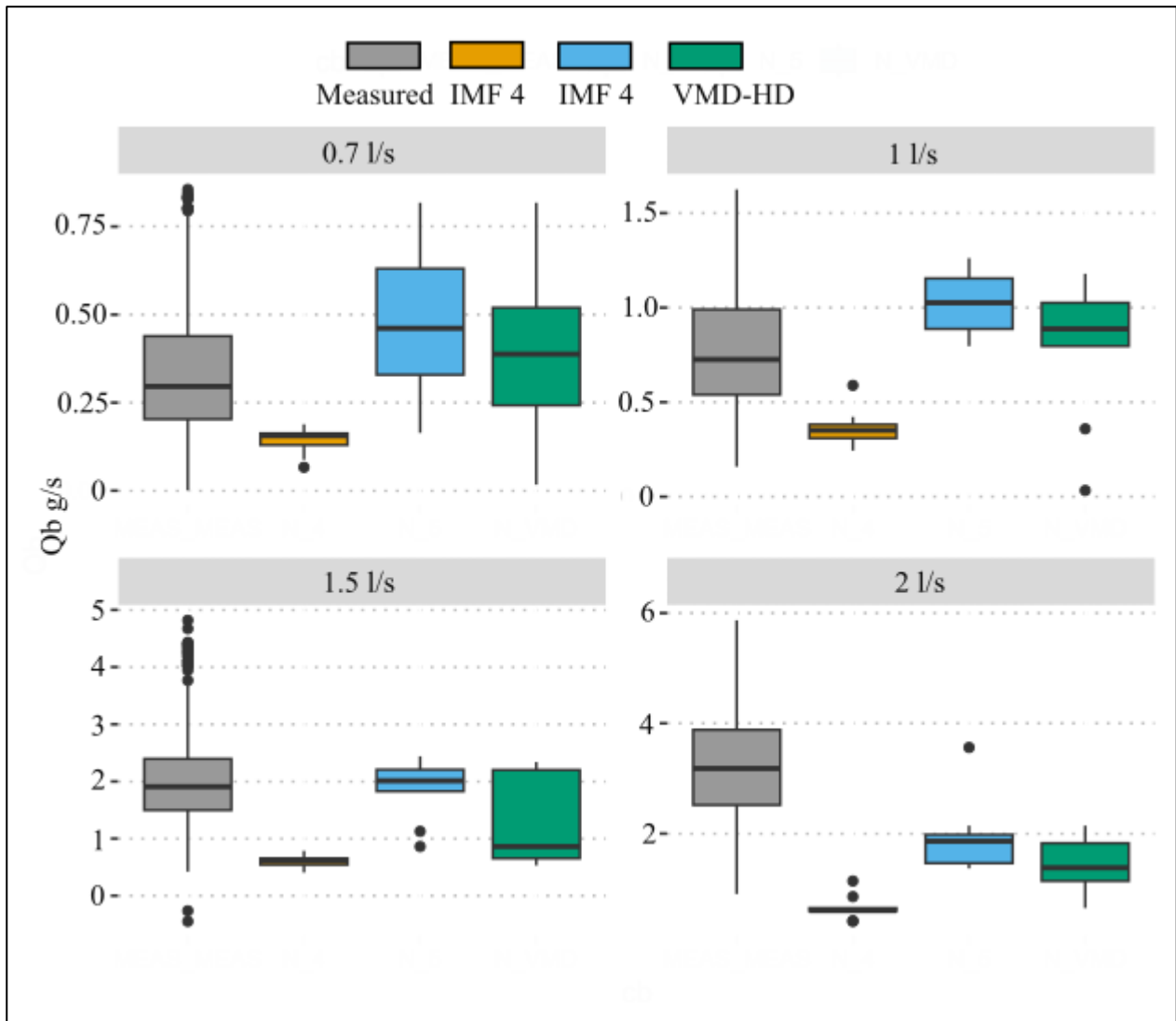
382

383 **Figure 5: Estimated virtual velocity using the VMD-HD path length estimates, measured volumes of erosion and**
 384 **deposition for each discharge. Significant differences from the Post hoc Tukey test are denoted by letters a-c.**

385 When used to calculate sediment transport Eq. (3) the VMD-HD method corresponds well to the measured average for
 386 the lower discharges (0.7 l/s and 1 l/s) whereas at the higher discharges (1.5 l/s and 2 l/s) the method significantly
 387 underestimated the measured flux (Fig. 6). For the 0.7 l/s discharge, the VMD-HD method estimated a rate of 0.39 g/s
 388 (SD = 0.25) averaged over the nine runs, which was not significantly different than the measured average of 0.33 g/s
 389 (SD = 0.18) and the relative percent error (δ) was 18%. For the 1 l/s discharge the method estimated 0.81 g/s (SD =
 390 0.38) and was not significantly different than the measured average of 0.78 g/s (SD= 0.30, δ = 4%). At the higher
 391 discharge of 1.5 l/s the average estimated by the VMD-HD method was 1.33 g/s (SD = 0.82) whereas the measured
 392 average was 1.98 g/s (SD = 0.70) (p-value < 0.05, δ =32%). Finally, for the 2 l/s runs the estimated average was 1.41g/s
 393 (SD = 0.48) whereas the measured average was 3.22 g/s (SD = 0.98) (p-value < 0.001, δ = 56%) (Fig. 6).

394 If we use just the IMF with the longest wavelength (IMF 5) to estimate path length and calculate sediment transport, we
 395 slightly overestimate sediment transport at the 0.7 l/s discharge, 0.48 g/s although not significantly ($p > 0.05$, δ = 45%)
 396 (Fig. 6). At the 1 l/s discharge IMF 5 significantly overestimates the average flux with an estimate of 1.03 g/s ($p < 0.01$,
 397 δ = 32%). At the 1.5 l/s discharge the estimated flux of 1.88 g/s using the IMF 5 path lengths was not significantly

398 different from the measured flux ($p > 0.05$, $\delta = 5\%$) (Fig. 6). However, using the IMF 5 path lengths still significantly
 399 underestimated sediment flux at the 2 l/s discharge, 1.95 g/s ($p < 0.001$, $\delta = 39\%$) (Fig. 6).



400

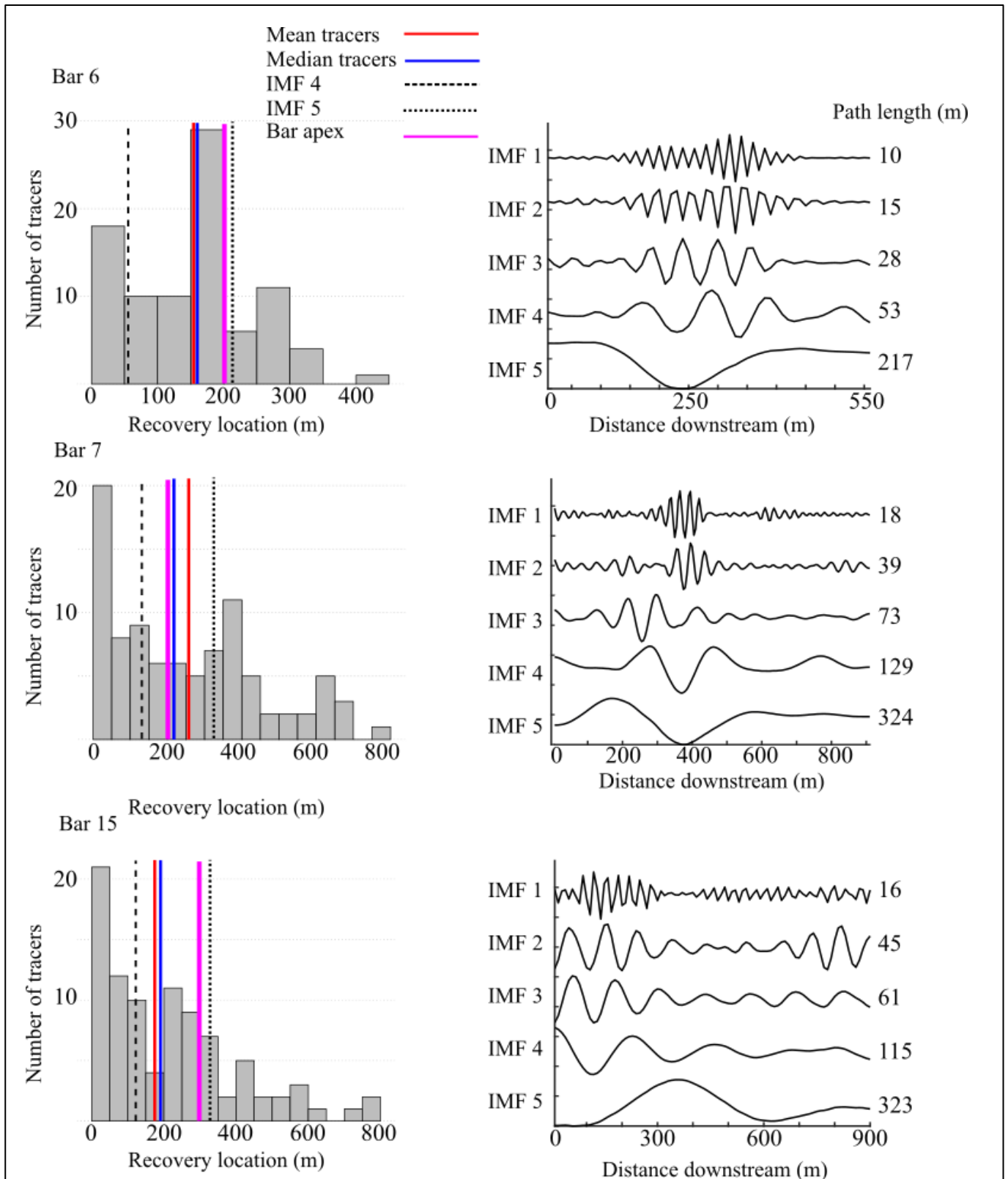
401 **Figure 6: Measured sediment flux (gray) compared to the estimates calculated using IMF 4 (orange), IMF 5**
 402 **(blue), and the VMD-HD method (green). Significant differences from the post-hoc Tukey test are denoted by**
 403 **letters a-c.**

404 Using the second longest wavelength, IMF 4, we underestimate at all of the discharges (Fig. 6). The estimated flux was
 405 0.14 g/s at the 0.7 l/s discharge ($\delta = 58\%$), 0.36 g/s at the 1 l/s discharge ($\delta = 54\%$), 0.61 g/s at the 1.5 l/s discharge
 406 ($\delta = 69\%$), and 0.65 g/s at the 2 l/s discharge ($\delta = 80\%$), (all p values < 0.001) (Fig. 6).

407 4.2 San Juan River

408 The 2018-2019 year for which we conducted our analyses, was moderate in terms of excess flow energy with 5 flood
 409 events exceeding a discharge of $500 \text{ m}^3 \text{ s}^{-1}$ and a peak discharge of $942 \text{ m}^3 \text{ s}^{-1}$. The path length distributions of bar 7
 410 and bar 15 are positively skewed although there is a secondary mode in the bar 7 distribution corresponding roughly to
 411 the bar tail (Fig. 7) whereas the distribution of bar 6 is bi-modal with the primary mode corresponding to the bar apex
 412 (Fig.7). This is potentially because bar 6 had the most pronounced curvature, perhaps contributing to the clustering of
 413 deposition just before the apex, where a migrating gravel sheet terminated (McQueen et al., 2021). This bar apex
 414 corresponds with the path length from IMF 5 of 217 m which was selected from the VMD-HD method (Fig. 7). IMF 5

415 was also selected by the VMD-HD method for bar 7 equaling 324 m, and here we see a correspondence to the small
416 secondary mode where the authors note there was a clustering of tracers (Fig. 7) (McQueen et al., 2021). Again, IMF 5
417 with a path length of 323 m was also selected for bar 15 and corresponds closely to the bar apex, although there was not
418 a clustering of tracer deposition in this deployment as observed in the year with higher discharge (Fig. 7). Additionally,
419 bar 15 had the highest proportion of sand which is not represented by the tracers, potentially contributing to the
420 discrepancy between our estimates and the tracers. IMF 4 was always well below the lengths associated with the bar
421 apexes, and the median and mean tracer distances (Fig. 7). However, the bar apexes and the median and mean tracer
422 distances were always between IMF 4 and IMF 5 (Fig. 7). The range between IMF 4 and IMF 5 accounted for 62% of
423 the path length distribution for bar 6, 36% for bar 7, and 45% for bar 15.



424

425 **Figure 7: Tracers-based path length distributions (on the left) and VMD derived IMFs for bars 6,7, and 15 from**
 426 **the San Juan River dataset. IMF 4 (dashed line), IMF 5 (dotted line), mean tracer distance (red), median tracer**
 427 **distance (blue), and the bar apex (pink) are shown over the path length distributions.**

428 5 Discussion

429 We developed a method to estimate the characteristic path length during a given flood using information inherent to the
 430 DoD by applying the principle that at channel-forming flows, the majority of particles move from an area of erosion to

431 the next area of deposition downstream (Pyrce and Ashmore, 2003a, b). By using the periodic nature of erosion and
432 deposition we overcome the subjectivity and time involved in measuring these distances manually while aligning
433 closely with these manually measured distances (Fig. 4). When evaluating the efficacy of our proposed method it is
434 important to keep in mind the uncertainty of even direct measurement of sediment transport. The spatial and temporal
435 frequency required to overcome the noise of measurement uncertainty (i.e., achieve an acceptable signal to noise ratio)
436 in some cases can require sub-daily monitoring with precise equipment (Grams et al., 2019). The variability of sediment
437 transport measurements in the flume study ranged from a standard deviation of approximately 30% to over 50% of the
438 averaged flux (Fig. 6). Given this high variability, our reach scale averages were not significantly different from the
439 measured averages for the 0.7 l/s and 1 l/s discharges (Fig. 6). Importantly, we observed that the method underestimates
440 the sediment flux significantly for the two highest discharges in the lab where the bed shows a higher percentage of the
441 width experiencing topographic change (Fig. 6). The method presented to estimate a characteristic path length using
442 only remotely sensed data shows promising results under certain conditions and provides insight into conditions where
443 it is not applicable.

444 **5.1 Path length estimation by VMD-HD method: limitations and perspectives**

445 **5.1.1 Flow effects**

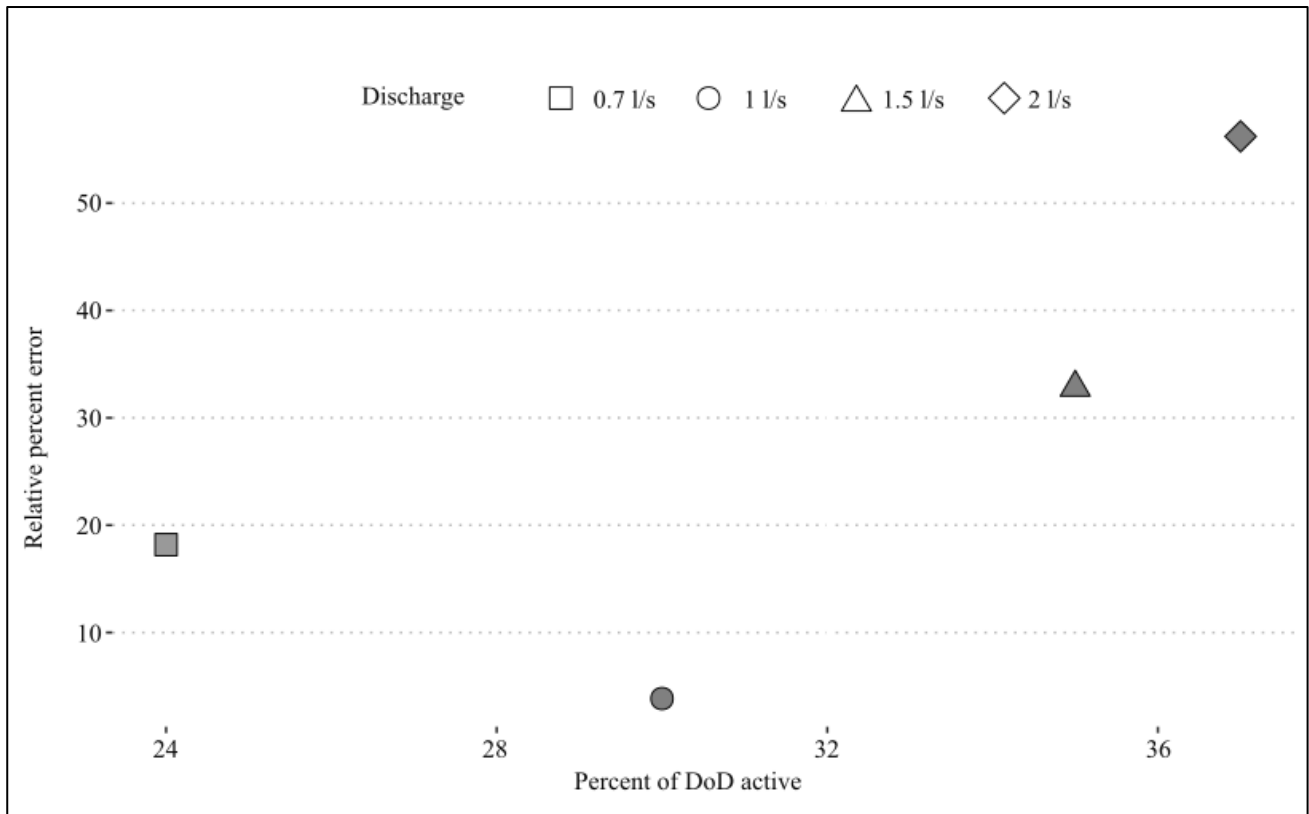
446 Previous studies have shown a relationship between path length and hydrologic variables such as discharge, stream
447 power, and excess shear stress (Hassan et al., 1991; Pyrce and Ashmore, 2003b). A notable result of the flume
448 experiment is that the estimated path length did not significantly differ between the four discharges (Fig. 5). We
449 propose two possible explanations for this discrepancy with the literature. First, it is possible that the actual path length
450 is increasing with discharge as has been observed in previous studies (Hassan et al., 1991; Pyrce and Ashmore, 2003b)
451 but the method fails to capture it because the VMD-HD method is based on the spacing of erosion and deposition which
452 does not change for the varying discharges under the flume conditions. It is possible that at higher discharges the
453 characteristic path length, that we define as the distance from net erosional areas to net depositional areas, is not
454 appropriate under the higher flow conditions because most particles are moving farther than the next depositional site
455 downstream. This violates the assumption on which our method is based and is impossible to prove in our experiment
456 without tracers. We can however look to literature to understand the conditions in which tracers tend to travel more than
457 one morphological unit (Liébault et al., 2012; Vázquez-Tarrío et al., 2019) and coupled with future studies, perhaps
458 determine the conditions under which a characteristic path length is inappropriate to estimate sediment transport.

459 From the San Juan River data we see that for a year with moderate flow, as characterized by the authors, that very few
460 tracers traveled further than the first depositional site downstream of their insertion point although it is possible that the
461 unrecovered tracers escaped the first bar, the recovery rates were high with 75% of tracers recovered for bars 6 and 15,
462 and 79% recovered for bar 7 (McQueen et al., 2021). However, the moderate flow year for which we had corresponding
463 tracer and DoD data resulted in two of the three sites with positively skewed distributions, and only bar six showing a
464 mode near the bar apex, which also corresponded to the IMF 5 path length (Fig. 7). The moderate flow conditions could
465 explain why our estimates lined up more closely with the bar apex for bar 15, where in the previous high flow year the
466 majority of tracers were deposited resulting in a symmetrical distribution (Fig. 8 from McQueen et al., 2021). It could
467 be that our method is strongly influenced by the morphology of the channel such that when flow is insufficient to create
468 symmetrical or bi modal path length distributions, we overestimate by using the characteristic path length because the
469 majority of particles are not reaching the next major depositional site downstream (i.e., a positively skewed
470 distribution). Additionally, when the flow exceeds a yet unidentified threshold, the majority of particles move more than

471 one depositional site downstream and therefore we underestimate sediment transport by using the characteristic path
472 length. We can speculate that this is happening to some extent in the flume experiment. We see that at the lowest
473 discharge, 0.7 l/s, we slightly overestimate the sediment flux especially using IMF 5 (Fig. 6) and underestimate the flux
474 at the highest discharge, 2 l/s, where we also see a simplification of channel morphology (Fig. 6, 3). Because we did not
475 have tracers in the flumes we can not say if the path length distributions were in fact different between the lowest and
476 highest discharges. Future applications of this method with tracer data both in the flumes and in the field could help to
477 understand when the characteristic length scale of morphology extracted by the method is an appropriate estimate of
478 sediment transport and if this corresponds to flow metrics and path length distributions. In the flume studies we tested
479 the idea that the majority of particles are bypassing the first depositional site simply by doubling the estimated path
480 length. Assuming that sediment is not trapped in the first depositional area but in the second one and doubling the path
481 length we more closely estimate the sediment transport at the higher discharges (i.e., estimates are not significantly
482 different than the measured averages ($p>0.05$) but overestimate the sediment transport at the 0.7 l/s and 1 l/s discharges
483 ($p<0.05$) (Fig. A5).

484 **5.1.2 Confinement**

485 It is possible that due to the confined condition of the flumes, channel width may exert an outsized effect on the average
486 bedload transport distance as the channel is unable to widen in response to an increase in discharge, therefore causing a
487 flushing effect. In the flume experiment, we found that the VMD-HD method performed better at the lower discharges
488 of 0.7 l/s and 1 l/s but significantly underestimated the sediment transport at the 1.5 l/s and 2 l/s discharges (Fig. 6). The
489 underestimation at higher discharges could be related to the amount of morphological change relative to the sediment
490 transport. Recently, Booker and Eaton (2022) quantitatively explored the link between sediment transport and
491 morphology and proposed an index to represent the intuitive notion that as sediment transport increases relative to
492 morphological change, the processes become decoupled and inferences from one to another become more difficult.
493 They developed a ‘throughput index’ which is the ratio between sediment flux and morphological change and
494 represents how much sediment moves through a reach without leaving a topographic signature of equal magnitude.
495 Therefore, the ratio represents how well the flux is represented morphologically with the ratio approaching 1 when all
496 of the flux is shown as morphological change and exceeding 1 when there is transport without equivalent morphological
497 change. In our case the flume experiments were confined, therefore, as discharge increased the channel was not able to
498 widen and deform laterally potentially causing the sediment to move through the flume without leaving an equivalent
499 topographic signature. To explore the applicability of the method proposed we calculated the morphological active
500 width by counting the percentage of pixels in the DoD that showed topographic change after filtering (we applied this
501 metric only for the flume experiments since the San Juan River DoDs do not include the submerged part of the
502 channel). The morphological active width increased with discharge as expected and was positively correlated with the
503 error of our estimates (Fig. 8). This result exposes a limitation of the morphological method in general and our
504 application specifically, that is, confined channels with high transport relative to morphological change are likely poor
505 candidates for the morphological method as inferences between changes in morphology and sediment transport become
506 decoupled. Further applications of this method in the field and in the lab could identify a potential threshold defined by
507 the throughput index (Booker and Eaton, 2022) or the morphological active width described in this study. The
508 advantage of using the morphological active width as opposed to the throughput index is that it can be determined from
509 the DoD without direct sediment transport measurements.



510

511 **Figure 8: Relative percent error between estimated flux using the VMD-HD method and the measured flux in the**
 512 **flume experiments (y-axis) vs the percentage of the DoD showing morphological change (x-axis). Different**
 513 **discharges are denoted by shape.**

514 5.1.3 Morphological controls

515 Previous studies have shown that in gravel bed rivers, macroform spacing is typically 5-7 channel widths (Montgomery
 516 and Buffington, 1997) and therefore half of that spacing, i.e. pool to bar, may be considered a proxy for the
 517 characteristic path length. We compared our estimates of path length to (half) of both 5 and 7 times the channel width in
 518 the flumes and found that the IMF 5 estimates of path length were between the 5 and 7 channel widths for all but the
 519 highest discharge (Fig. A6). Interestingly, the manually measured distances were less than the 5-7 channel widths for all
 520 discharges but approaching 5 channel widths at the 2 l/s discharge (Fig. A6). When used to calculate sediment flux, the
 521 estimates derived from using 5 and 7 channel widths were not significantly different than our VMD-HD estimates at
 522 discharges 0.7-1.5 l/s or the measured flux at all discharges (Fig. A5). Here we are likely seeing a good correspondence
 523 between the characteristic path length, width, and sediment transport, because at formative discharges, morphology is
 524 the primary control on bedload travel distance. Whereas at lower discharges, where the morphology is relatively stable,
 525 discharge may exert a stronger control on path length. Because we do not have tracer data in the flumes for comparison,
 526 we can only rely on the sediment transport measurements for validation but further flume studies with both sediment
 527 flux and tracer data for validation could help resolve this question. The periodicity we extract from the DoDs as an
 528 estimate of path length corresponds to previous observations of preferential particle deposition at specific
 529 morphological units and relationships to channel morphology (Beechie, 2001; Pyrcce and Ashmore, 2003a, b; Kasprak et
 530 al., 2015; McDowell and Hassan, 2020; McDowell et al., 2021). In the San Juan River study, our estimates aligned
 531 closely with the secondary modes in the particle path length distributions (Fig. 7) consistent with observations that at
 532 channel forming flows, particle path lengths tend to be bi or multimodal with secondary modes corresponding to the

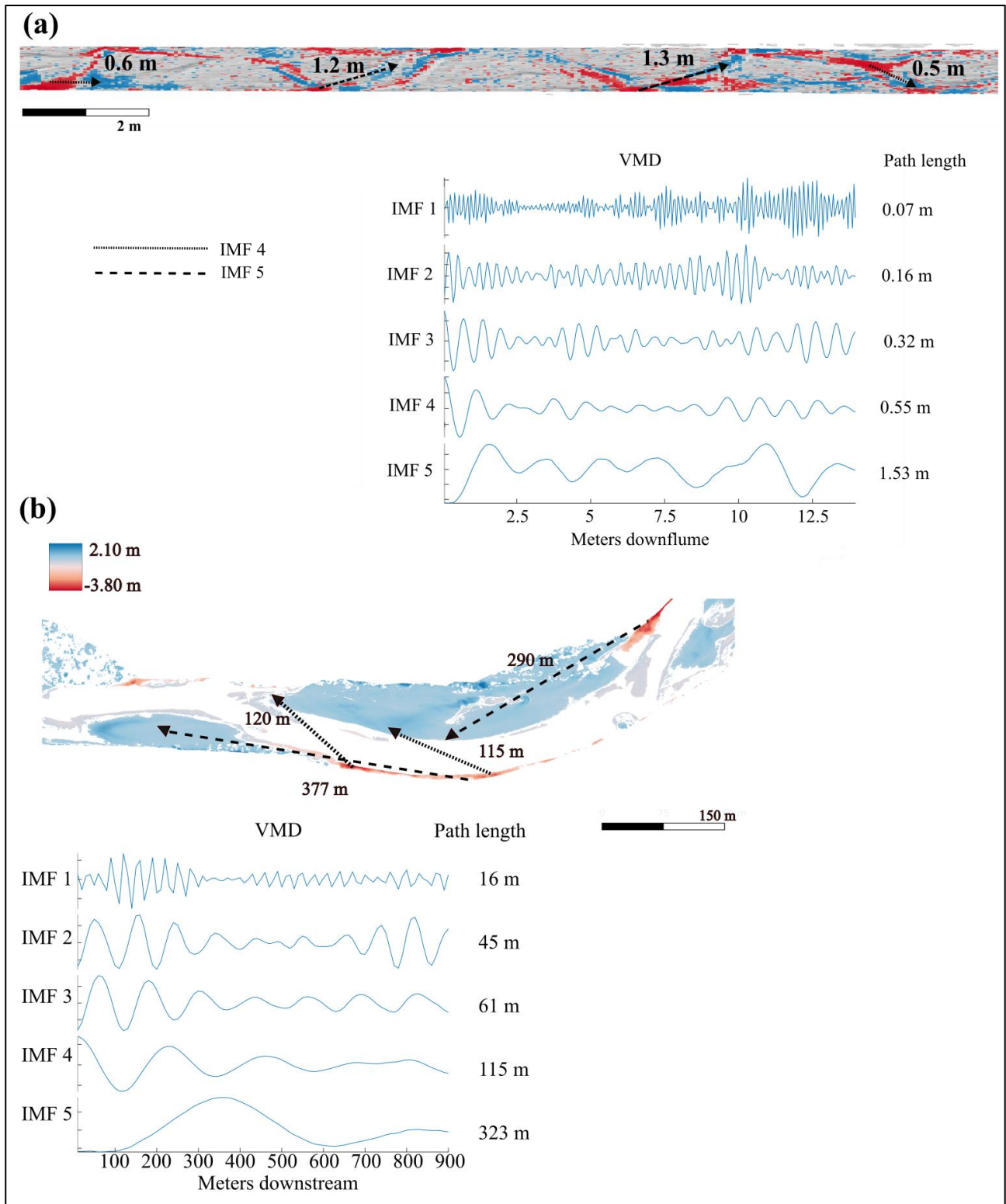
533 location of bars (Pyrce and Ashmore, 2003b). This preliminary result should be further examined with additional field
534 data in multi-threaded channel types.

535 We expected that the path length in more complex channels such as braided configurations would be more difficult to
536 estimate due to the possibility of multiple path lengths active at different flow stages. In this study both the flume
537 experiment and the field study exhibited a wandering morphology although in the flume experiment, the channel began
538 to simplify at higher discharges, likely due to the inability of the channel to widen in response to the increase in
539 discharge. Further, path length estimates did not change significantly between the discharges whereas the erosion
540 volume increases with discharge, and that, as mentioned previously, potentially contributed to the underestimation of
541 sediment flux at the higher discharges. Additionally, at the 1.5 l/s, and 2 l/s discharges, the patches of erosion and
542 deposition began to overlap, therefore, the wavelike pattern from areas of erosion to deposition represented by the IMF
543 5 vector became flattened (Fig. 3, A1). To disentangle the confounding erosion and deposition from the net vector, we
544 applied the VMD method to a vector created from erosion and deposition separately. When calculating the path length
545 using the erosion or deposition vectors, we took half of the resulting path length as we are still interested in the distance
546 from erosion to deposition rather than erosion to erosion. We found that the path lengths generated from these vectors
547 were not significantly different than the path lengths generated using the net vector ($p > 0.05$) (Fig. A6) nor were the
548 estimates of sediment transport (Fig. A5) This evidence supports the use of the net vector in this case because it appears
549 that erosion and deposition were similarly distributed. However, in rivers with differing morphology, perhaps braided
550 systems, we might suspect that erosion will be more localized than deposition which can be dispersed (Goff and
551 Ashmore, 1994). In these cases, using VMD to decompose the net, erosion, and deposition separately could give further
552 insight into how deposition and erosion are contributing to the net change. For example, deposition may contribute little
553 to net vector if the relative magnitude of the oscillations is small compared to erosion which tends to be more
554 concentrated. In addition to estimating a characteristic path length, this decomposition could give further insight into the
555 nature of depositional and erosional processes in a reach. We also recognize that perhaps when multiple channels are
556 present and active, it may be beneficial to segregate the DoD, treating each channel as a separate system and generate
557 multiple path length estimations and avoid compensating erosion and deposition within the cross section. Further
558 investigations are needed in the lab and in the field to propose robust methodologies to assess realistic ranges of path
559 lengths from DoD for varying river patterns.

560 **5.1.4 Using the IMFs**

561 The path length-based method for calculating sediment transport necessitates that a single path length be selected and
562 this is surely an oversimplification of reality. Encouragingly, the flume experiment shows that by using the VMD-HD
563 method to select the path length, we are able to reasonably approximate sediment transport at the lower discharges (Fig.
564 6). However, when applying this method to a real case study, like that of the San Juan River, it is important to consider
565 if the results make sense given what is known about the channel and the time and magnitude of flood events between
566 surveys, potentially taking into account both IMF 4 and IMF 5 to generate a range of plausible transport or path lengths.
567 The VMD-HD method presented here selects one of the five IMFs to be used as an estimate of path length based on the
568 geometric similarity, as measured by the Hausdorff distance, of the IMF to the original data vector. However, we
569 presume that not only does the method occasionally select an erroneous IMF (IMF 1 for example where the path length
570 is on the order of mm) but it also reasons that in some cases more than one IMF could represent the pattern of erosion
571 and deposition in the DoD or perhaps a range due to the heterogeneous nature of sediment transport. In the flume
572 experiment, the VMD-HD method selected the longest wavelength, IMF 5, 74% of the time and IMF 4, 24% of the

573 time. There were only two instances in which IMF 1 was selected and neither IMF 2 or 3 were ever selected. Likewise,
574 IMF 5 was selected for all three bars in the San Juan River dataset. This result agrees with observations from the signal
575 processing literature wherein the lower frequency (in our case wavelength) IMFs (4 and 5) are thought to represent the
576 true signal whereas the higher frequency (shorter wavelength) IMFs are attributed to noise (Boudraa et al., 2005). In our
577 case we can verify visually that IMF 5 is most likely representative of the characteristic path length by tracing the path
578 from erosional site to depositional site within the DoD using the manual method (Fig. 9). Here we see that the longest
579 IMF captures the spacing between erosional and depositional patches as estimated by other methods (Redolfi, 2014;
580 Vericat et al., 2017; Calle et al., 2020). This study, as the others, supports the idea that the periodic nature of erosion
581 and deposition can be used to estimate sediment transport and helps to clarify the conditions where this approach is
582 valid. Moreover, this study provides an objective and repeatable method to estimate the characteristic path length.



583

584 **Figure 9: DoD with arrows showing possible path lengths between areas of erosion (red) to deposition (blue)**
 585 **corresponding to both IMF 4 and IMF 5. The VMD breakdown including all IMFs and the corresponding path**
 586 **lengths are shown for an experimental run from the 1.5 l discharge (a) and bar 15 from the San Juan River (b).**

587 Different IMFs also allow us to explore multiple periodicities, such as shorter path lengths in the DoDs that may
 588 correspond to IMF 4 (Fig. 9). The method we present here to select one of the IMFs to represent the periodicity is
 589 convenient for assigning a characteristic path length to be used in sediment transport calculations. However, it is unclear
 590 if the range of IMFs may be used to estimate aspects of the path length distribution. As a first step, we see that in the

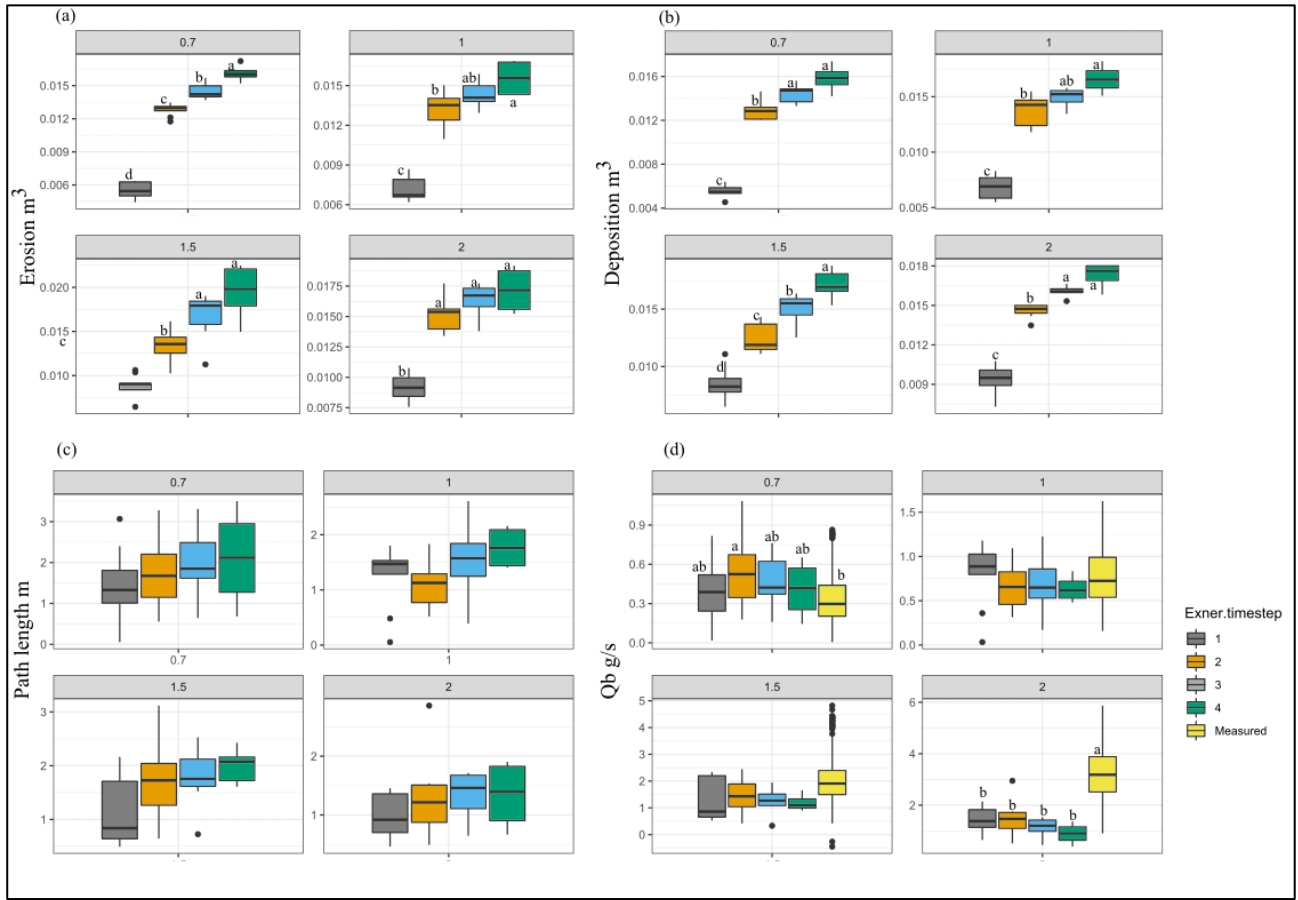
591 San Juan River the path lengths associated with IMF 4 and IMF 5 bracket the mean, median, and key depositional areas
592 associated with the path length distribution (Fig. 7). With future studies it may be possible to set a range of plausible
593 transport based on IMFs 4 and 5.

594 **5.2 DoD related uncertainties**

595 Any application of the morphological method using DoDs is sensitive to the error thresholding method used due to the
596 way in which different thresholding techniques influence both the volumes of erosion and deposition as well as their
597 spatial patterning (Brasington et al., 2003; Wheaton, 2008; Wheaton et al., 2010; Vericat et al., 2017). Because our
598 method relies on the spacing between areas of erosion and deposition which is related to the size of the patches as well
599 as which patches are detected, we considered that thresholding techniques could greatly affect the estimates of path
600 length. We tested this hypothesis by applying the method to both the raw and filtered DoDs for the Trento flume
601 experiment and found that while the volumes of erosion and deposition were lower after thresholding as expected
602 ($p < 0.001$), the path length estimates were not significantly different ($p > 0.05$) (Table A1). While the thresholding here
603 did not affect the path length estimates, we might imagine a scenario in which an entire area of erosion or deposition is
604 removed through aggressive thresholding techniques, thereby potentially affecting the path length estimates and
605 therefore caution that appropriate thresholding is important for the application of this method and the morphological
606 method in general. It is also important to consider the spatial resolution (i.e., raster cell size) of the DoD when applying
607 this method. Similarly to thresholding or selecting a bin size, the spatial resolution of the DoD could cause information
608 to be lost if the cell size is large enough to aggregate erosion and deposition within the same cell (see for instance the
609 comparison made in Antoniazza et al., 2019). We see less of a risk in using smaller cell sizes as the method already
610 calls for aggregation in the binning process and in theory VMD should be able to separate the small scale fluctuations as
611 short wavelength IMFs. However, this is an open question and should be evaluated by the user on a case by case basis.

612 The time between surveys is of equal importance to the path length in the estimation of virtual velocity and in the field
613 can be highly uncertain due to poor availability of hydrologic data and/or the uncertainty of estimating the onset of
614 transport based on a critical shear stress. Further, as time between surveys increases, so too does the probability of
615 compensating erosion and deposition which can affect both the volumes of erosion and deposition and the topographic
616 signatures (Lindsay and Ashmore, 2002; Vericat et al., 2017) necessary for VMD-HD method. We tested how the time
617 between surveys might affect both the volumes of erosion and deposition and our path length estimates by differencing
618 DEMs not every time step but between two, three, and four timesteps, each time step being one of the nine runs in the
619 lab of phase 3 (see method). Not surprisingly the volume of erosion and deposition increased significantly with
620 increasing time between surveys with the largest increase between the 1st timestep and 2nd timestep (Fig. 10). The path
621 length estimates did not increase significantly for any of the discharges (Fig. 10c) indicating that the path length
622 estimate is stable, likely because, as already noted, the spacing of erosion and deposition is related to the position of
623 erosional and depositional features which do not change much in the flume. When both of these parameters are used in
624 the sediment transport calculations and normalized by the increased time between surveys, we found no statistically
625 significant difference between the estimates (Fig. 10d). However, though not statistically significant, there is an
626 apparent decreasing trend in the sediment flux with the increased time between surveys, especially for the 2 l/s
627 discharge that may indicate compensation (Fig. 10d). Despite the apparent trend at the highest discharge this is a
628 promising result in that even by increasing the time interval by a factor of 4 we are still able to estimate sediment
629 transport reasonably at the lower discharges. In the field there are often multiple flood events of differing magnitude in
630 the year between surveys as was the case with the San Juan River study (McQueen et al., 2021). Although there were

631 five flood events of differing magnitudes between the San Juan River surveys, we were still able to estimate path
 632 lengths corresponding to potentially significant features of the path length distributions (Fig. 7).



633
 634 **Figure 10: (a) Erosion measured from the flume experiments for each discharge and each timestep (b) deposition**
 635 **(c) path length estimates using VMD-HD method (d) sediment flux estimated using VMD-HD method and**
 636 **measured. Significant post-hoc Tukey results are denoted by letters a-d ($\alpha=0.05$).**

637 **6 Conclusion**

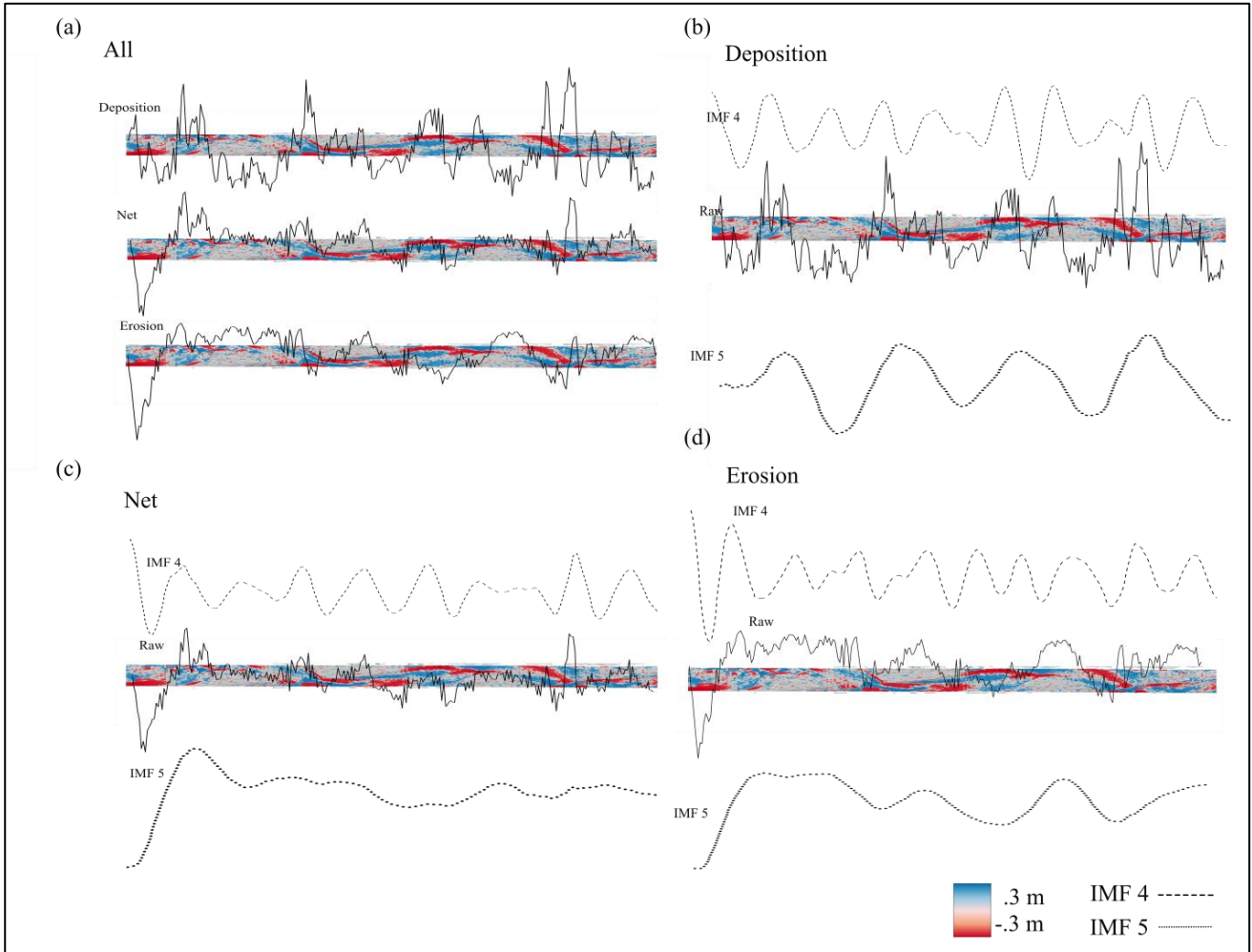
638 Given the observed connections between morphology and path length at channel forming flows, we proposed that the
 639 periodic nature of the pattern of erosion and deposition can be a proxy for a characteristic path length in gravel bed
 640 rivers. We applied tools from signal processing to quantify this periodicity and found that by the longest wavelengths
 641 from the decomposition, IMF 4 and IMF 5 may represent meaningful bedload transport processes and IMF 5 in
 642 particular may represent the characteristic path length. We found that the path length estimates generated by IMFs 4 and
 643 5 bracket a significant portion of measured path length distributions in the field and correspond to important
 644 morphological units. In the flume experiment we found that IMF 4 and 5 path lengths also bracket the manually
 645 measured distances between erosional and depositional patches and when extended to calculate sediment flux our
 646 estimates were not significantly different from the measured average at low discharges. Importantly we found an
 647 insensitivity of the method to increasing discharge and propose that perhaps limits arise where discharge increases in
 648 confined settings, such as in the flume, and sediment transport becomes decoupled from morphological changes. Our
 649 method provides a new view of the periodic nature of erosion and deposition in sediment transport and a novel way to
 650 extract sediment transport information using only DoDs.

651

652

653 **Appendix A**

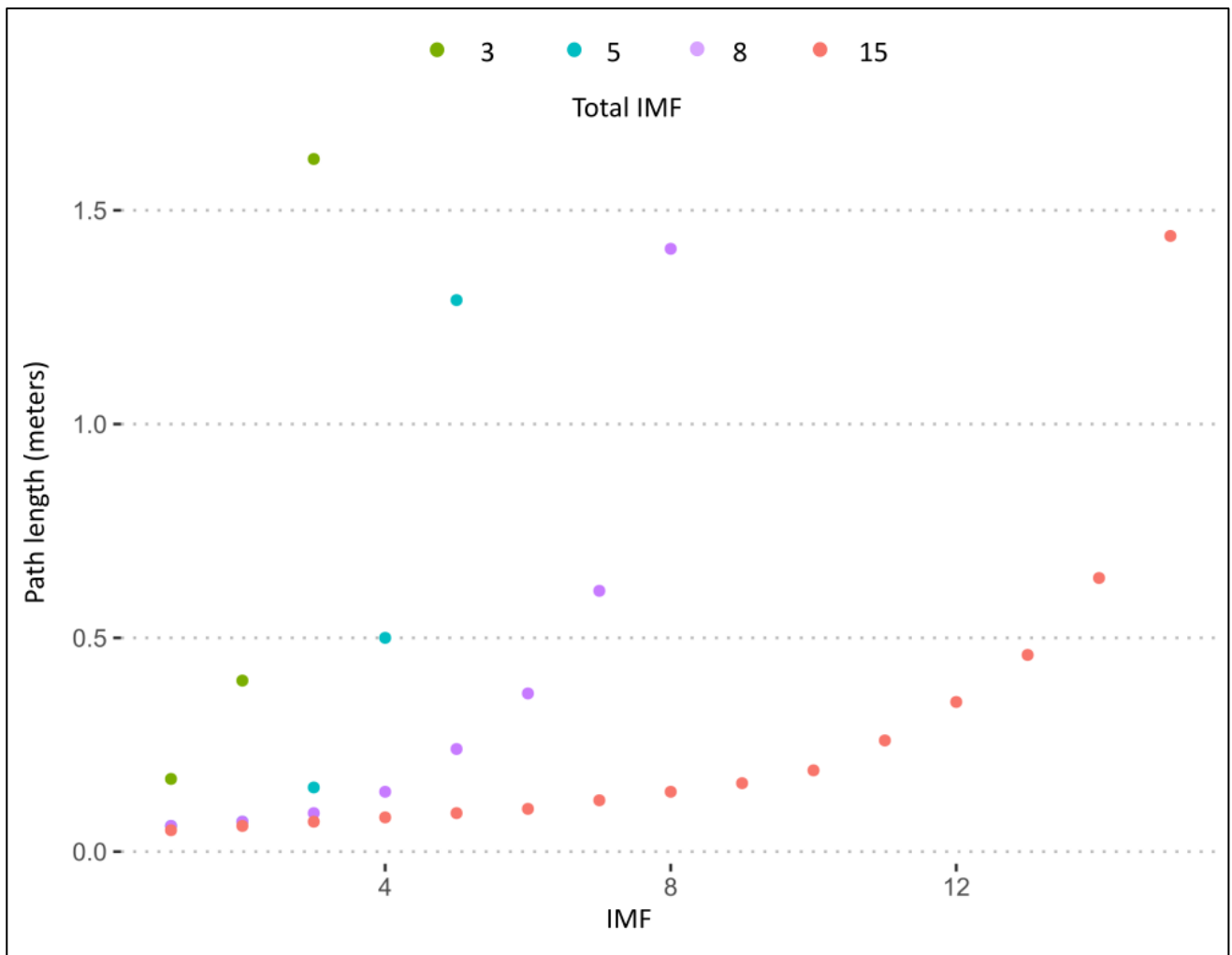
654



655

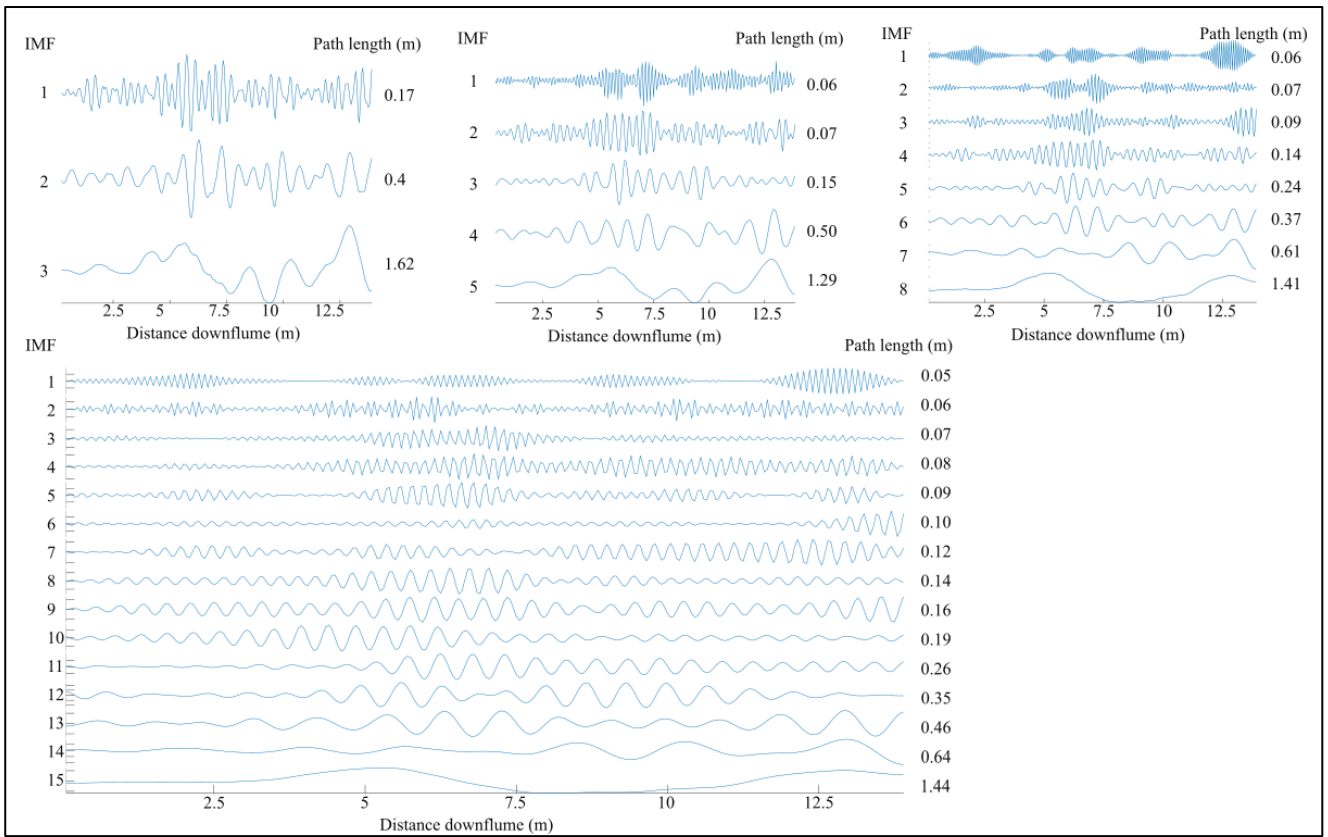
656 Figure A1. DoDs from the 2 l/s discharge. a) Vector of deposition, erosion, and the net. b) Raw depositional vector and
 657 the decomposition of IMF 4 and IMF 5 from that depositional vector. c) Net vector and the decomposition of IMF 4 and
 658 IMF 5 from that net vector. d) Raw erosional vector and the decomposition of IMF 4 and IMF 5 from that erosional
 659 vector.

660



661

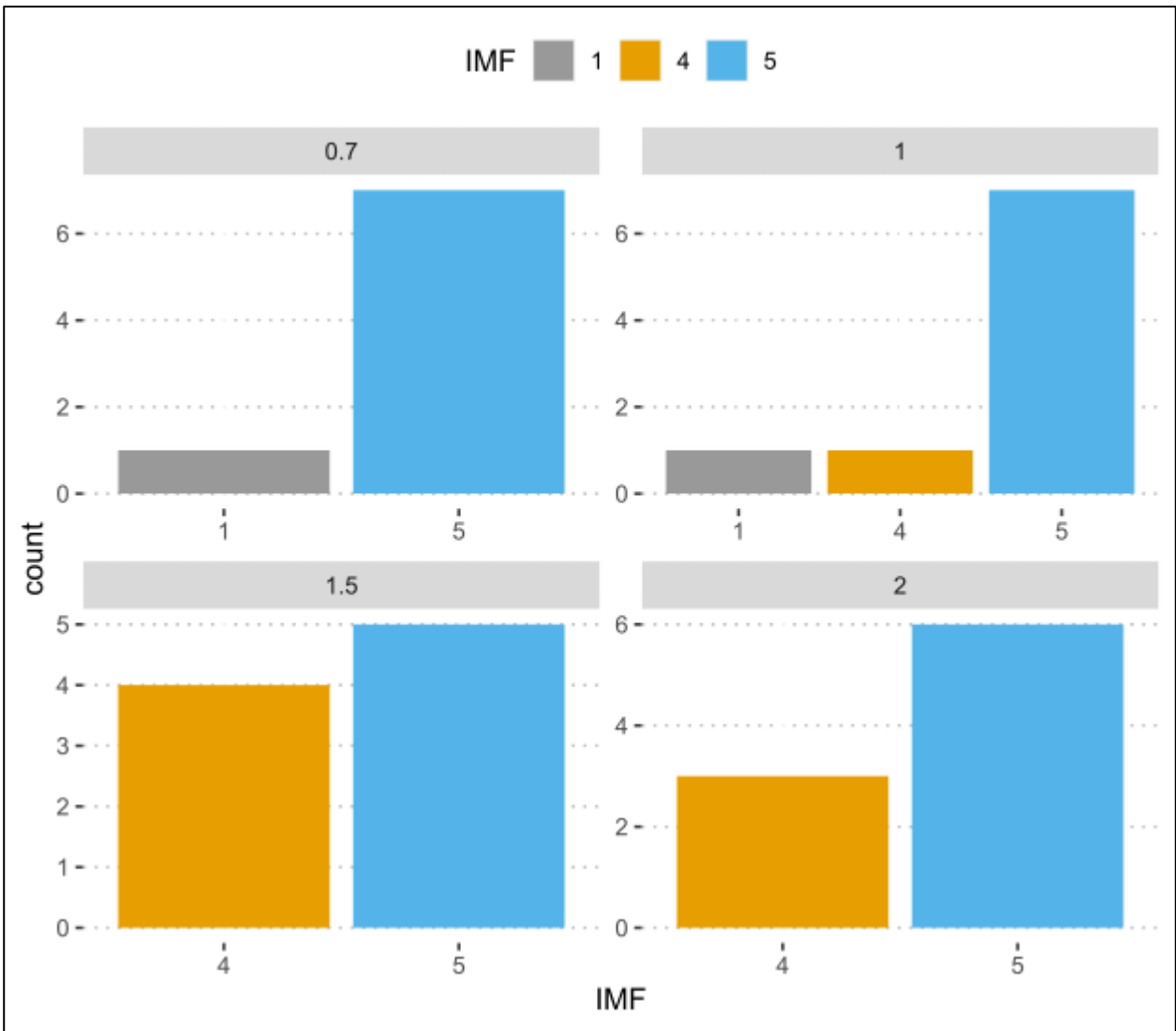
662 Figure A2. Path length estimates using a maximum of 3,5,8, or 15 IMFs.



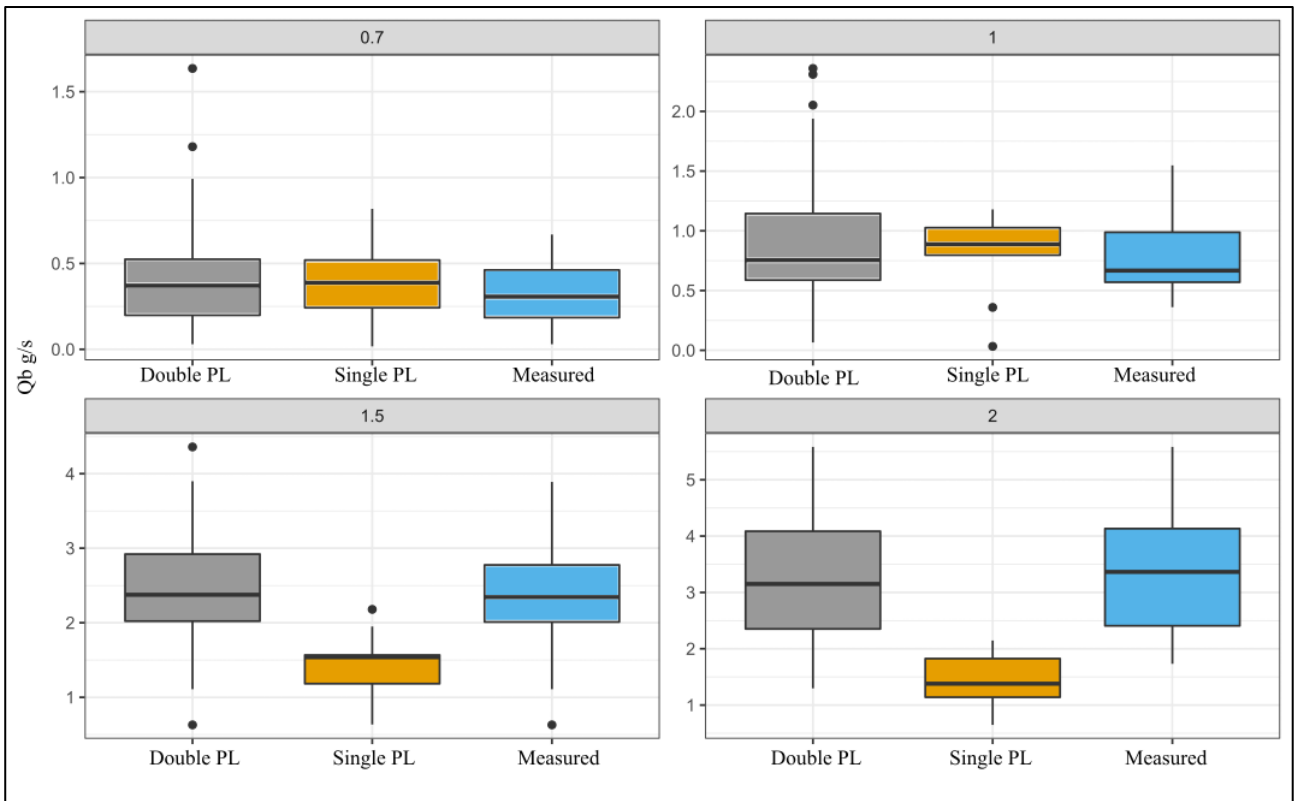
663

664 Figure A3. Path length estimates from VMD for 1.5 l/s discharge. Sensitivity of maximum number of IMFs.

665



666
 667 Figure A4. Number of times each IMF was selected by the VMD-HD method for each discharge.



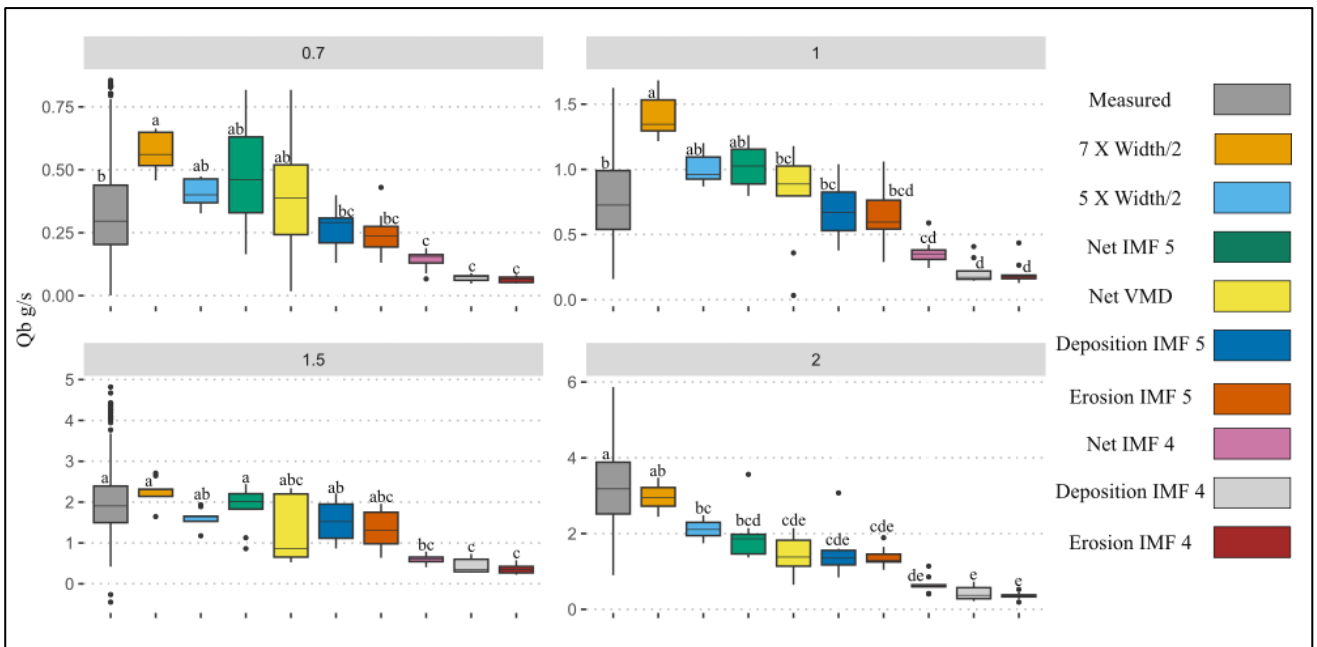
668

669

670

671

Figure A5. Sediment transport calculated using the single path length estimate from the VMD-HD method (b) and doubling the path length estimate (a). Estimated flux is red and measured flux is blue. Significant p values are shown.

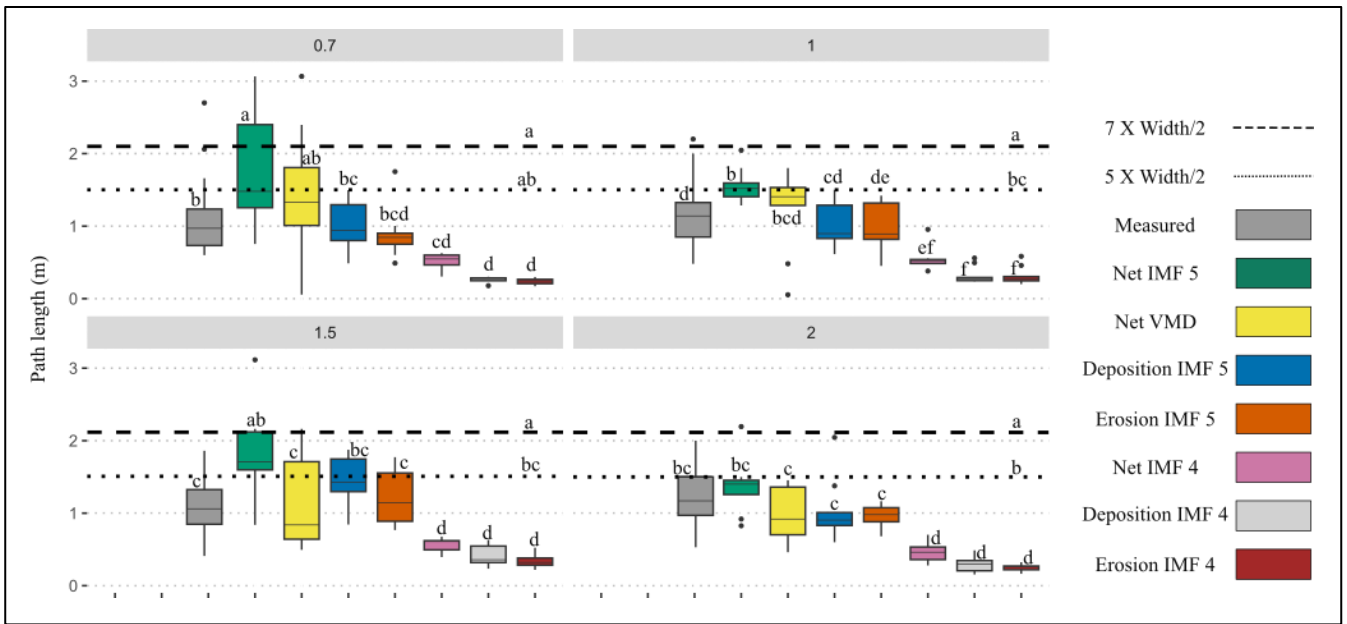


672

673

674

Figure A6. Sediment transport (g/s) calculated using channel dimensions, IMFs 4 and 5 for net, erosion, and deposition vectors. Compared to the measured flux for each discharge. Post hoc Tukey results denoted by letters a-f.



675

676

677

Figure A7. Path length estimates from the channel dimensions, IMFs 4 and 5 for net, erosion, and deposition vectors compared to manually measured distances for each discharge. Post hoc Tukey results denoted by letters a-f.

678

Table A1. Results from filtered vs raw DoDs from the flume experiments.

Discharge	Path length raw (m)	Path length filtered (m)	Qb estimated raw(g/s)	Qb estimated filtered (g/s)	Erosion raw (m3)	Deposition raw(m3)	Erosion filtered (m3)	Deposition filtered (m3)
0.7	1.77	1.31	0.69	0.30	0.01	0.01	0.01	0.01
0.7	0.80	0.75	0.29	0.14	0.01	0.01	0.00	0.00
0.7	3.05	3.06	1.20	0.71	0.01	0.01	0.01	0.01
0.7	2.54	2.40	0.97	0.51	0.01	0.01	0.01	0.01
0.7	2.30	0.05	1.01	0.01	0.01	0.01	0.01	0.01
0.7	0.87	1.09	0.35	0.23	0.01	0.01	0.01	0.01
0.7	1.57	1.61	0.70	0.43	0.01	0.01	0.01	0.01
0.7	1.24	1.35	0.56	0.37	0.01	0.01	0.01	0.01
1	1.25	1.41	1.04	0.89	0.01	0.01	0.01	0.01
1	1.37	0.48	1.28	0.31	0.01	0.01	0.01	0.01
1	1.25	1.47	1.10	1.02	0.01	0.01	0.01	0.01
1	1.23	1.80	1.18	1.00	0.01	0.01	0.01	0.01
1	1.48	1.59	1.46	0.84	0.01	0.01	0.01	0.01
1	1.83	1.53	1.57	0.77	0.01	0.01	0.01	0.01
1	1.54	1.52	1.27	0.75	0.01	0.01	0.01	0.01
1	1.51	1.29	1.21	0.69	0.01	0.01	0.01	0.01
1.5	1.12	0.68	1.82	0.53	0.01	0.01	0.01	0.01
1.5	1.63	0.84	2.30	0.86	0.01	0.01	0.01	0.01
1.5	1.50	0.64	2.74	0.65	0.02	0.01	0.01	0.01
1.5	0.50	0.61	0.82	0.67	0.01	0.01	0.01	0.01
1.5	0.85	0.49	1.41	0.54	0.01	0.01	0.01	0.01
1.5	0.51	1.60	0.76	2.01	0.01	0.01	0.01	0.01
1.5	1.67	1.71	2.28	2.21	0.01	0.01	0.01	0.01
1.5	1.50	2.16	2.54	2.20	0.01	0.01	0.01	0.01

1.5	1.13	2.12	1.73	2.34	0.01	0.01	0.01	0.01
2	1.41	1.40	2.53	1.86	0.01	0.01	0.01	0.01
2	0.91	0.92	1.58	1.19	0.01	0.01	0.01	0.01
2	1.26	1.36	2.05	1.58	0.01	0.01	0.01	0.01
2	1.13	1.26	1.67	1.27	0.01	0.01	0.01	0.01
2	0.06	1.45	0.09	1.61	0.01	0.01	0.01	0.01
2	0.46	0.46	0.78	0.56	0.01	0.01	0.01	0.01
2	1.32	0.83	2.04	1.18	0.01	0.01	0.01	0.01
2	0.71	0.66	1.30	0.74	0.01	0.01	0.01	0.01
Summary								
Discharge	Erosion	Deposition	Path Length	Qb				
0.7	p<0.001**	p<0.001**	p>0.05	p<0.05*				
1	p<0.001**	p<0.001**	p>0.05	p<0.05*				
1.5	p<0.001**	p<0.001**	p>0.05	p<0.05*				
2	p<0.001**	p<0.001**	p>0.05	p>0.05				
*p-values from student's t test between raw and filtered data								

679

680 Data availability681 Data is available at <https://doi.org/10.5281/zenodo.8014453>.**682 Author contribution**

683 LC, SB, WB and NS conceptualized the study. EP preformed the experiments. LC, SB and WB designed the method.
684 LC performed statistical analysis. LC, EP, and WB wrote the manuscript. LC, SB, EP, WB, and NS edited the
685 manuscript.

686 Competing interests

687 The authors declare they have no competing interests.

688 Financial support

689 This work was supported by the CARIPARO foundation and the University of Padova.

690 Acknowledgements

691 We would like to thank the three anonymous referees for their time and thoughtful suggestions which have considerably
692 improved the quality of this work. We would also like to thank the CARIPARO foundation and the University of
693 Padova.

694 References

695 Antoniazza, G., Bakker, M., and Lane, S. N.: Revisiting the morphological method in two-dimensions to quantify bed-
696 material transport in braided rivers, *Earth Surf. Process. Landf.*, 44, 2251–2267, <https://doi.org/10.1002/esp.4633>, 2019.

697 Ashmore, P. E. and Church, M.: Sediment transport and river morphology: a paradigm for study, *Gravel-Bed Rivers*
698 *Environ.*, 345, 115–139, 1998.

699 Bakker, M., Antoniazza, G., Odermatt, E., and Lane, S. N.: Morphological Response of an Alpine Braided Reach to
700 Sediment-Laden Flow Events, *J. Geophys. Res. Earth Surf.*, 124, 1310–1328, <https://doi.org/10.1029/2018JF004811>,
701 2019.

702 Barnhart, B. L. and Eichinger, W. E.: Empirical Mode Decomposition applied to solar irradiance, global temperature,
703 sunspot number, and CO2 concentration data, *J. Atmospheric Sol.-Terr. Phys.*, 73, 1771–1779,
704 <https://doi.org/10.1016/j.jastp.2011.04.012>, 2011.

- 705 Beechie, T. J.: Empirical predictors of annual bed load travel distance, and implications for salmonid habitat restoration
706 and protection, *Earth Surf. Process. Landf.*, 26, 1025–1034, <https://doi.org/10.1002/esp.251>, 2001.
- 707 Booker, W. H. and Eaton, B. C.: Morphodynamic styles: characterising the behaviour of gravel-bed rivers using a
708 novel, quantitative index, *Earth Surf. Dyn.*, 10, 247–260, <https://doi.org/10.5194/esurf-10-247-2022>, 2022.
- 709 Boudraa, A.-O., Cexus, J.-C., and Saidi, Z.: EMD-Based Signal Noise Reduction, *Signal Process.*, 1, 2005.
- 710 Brasington, J., Rumsby, B. T., and McVey, R. A.: Monitoring and modelling morphological change in a braided gravel-
711 bed river using high resolution GPS-based survey, *Earth Surf. Process. Landf.*, 25, 973–990,
712 [https://doi.org/10.1002/1096-9837\(200008\)25:9<973::AID-ESP111>3.0.CO;2-Y](https://doi.org/10.1002/1096-9837(200008)25:9<973::AID-ESP111>3.0.CO;2-Y), 2000.
- 713 Brasington, J., Langham, J., and Rumsby, B.: Methodological sensitivity of morphometric estimates of coarse fluvial
714 sediment transport, *Geomorphology*, 53, 299–316, [https://doi.org/10.1016/S0169-555X\(02\)00320-3](https://doi.org/10.1016/S0169-555X(02)00320-3), 2003.
- 715 Brenna, A. and Surian, N.: Coarse sediment mobility and fluxes in wide mountain streams: Insights using the virtual
716 velocity approach, *Geomorphology*, 427, 108625, <https://doi.org/10.1016/j.geomorph.2023.108625>, 2023.
- 717 Brenna, A., Surian, N., and Mao, L.: Virtual Velocity Approach for Estimating Bed Material Transport in Gravel-Bed
718 Rivers: Key Factors and Significance, *Water Resour. Res.*, 55, 1651–1674, <https://doi.org/10.1029/2018WR023556>,
719 2019.
- 720 Brenna, A., Surian, N., Ghinassi, M., and Marchi, L.: Sediment–water flows in mountain streams: Recognition and
721 classification based on field evidence, *Geomorphology*, 371, 107413, <https://doi.org/10.1016/j.geomorph.2020.107413>,
722 2020.
- 723 Brewer, P. A. and Passmore, D. G.: Sediment budgeting techniques in gravel-bed rivers, *Geol. Soc. Lond. Spec. Publ.*,
724 191, 97–113, <https://doi.org/10.1144/GSL.SP.2002.191.01.07>, 2002.
- 725 Calle, M., Calle, J., Alho, P., and Benito, G.: Inferring sediment transfers and functional connectivity of rivers from
726 repeat topographic surveys, *Earth Surf. Process. Landf.*, 45, 681–693, <https://doi.org/10.1002/esp.4765>, 2020.
- 727 Church, M.: Bed Material Transport and the Morphology of Alluvial River Channels, *Annu. Rev. Earth Planet. Sci.*, 34,
728 325–354, <https://doi.org/10.1146/annurev.earth.33.092203.122721>, 2006.
- 729 Church, M. and Haschenburger, J. K.: What is the “active layer”?, *Water Resour. Res.*, 53, 5–10,
730 <https://doi.org/10.1002/2016WR019675>, 2017.
- 731 Dragomiretskiy, K. and Zosso, D.: Variational Mode Decomposition, *IEEE Trans. Signal Process.*, 62, 531–544,
732 <https://doi.org/10.1109/TSP.2013.2288675>, 2014.
- 733 Ferguson, R. I. and Ashworth, P. J.: Spatial patterns of bedload transport and channel change in braided and near-
734 braided rivers, *Dyn. Gravel-Bed Rivers Billi P Hey RD Thorne CR Tacconi P Eds*, 1992.
- 735 Garcia Lugo, G. A., Bertoldi, W., Henshaw, A. J., and Gurnell, A. M.: The effect of lateral confinement on gravel bed
736 river morphology, *Water Resour. Res.*, 51, 7145–7158, <https://doi.org/10.1002/2015WR017081>, 2015.
- 737 Goff, J. R. and Ashmore, P.: Gravel transport and morphological change in braided sunwapta river, Alberta, Canada,
738 *Earth Surf. Process. Landf.*, 19, 195–212, <https://doi.org/10.1002/esp.3290190302>, 1994.
- 739 Grams, P. E., Topping, D. J., Schmidt, J. C., Hazel Jr., J. E., and Kaplinski, M.: Linking morphodynamic response with
740 sediment mass balance on the Colorado River in Marble Canyon: Issues of scale, geomorphic setting, and sampling
741 design, *J. Geophys. Res. Earth Surf.*, 118, 361–381, <https://doi.org/10.1002/jgrf.20050>, 2013.
- 742 Grams, P. E., Buscombe, D., Topping, D. J., Kaplinski, M., and Hazel, J. E.: How many measurements are required to
743 construct an accurate sand budget in a large river? Insights from analyses of signal and noise, *Earth Surf. Process.*
744 *Landf.*, 44, 160–178, <https://doi.org/10.1002/esp.4489>, 2019.
- 745 Hassan, M. A. and Bradley, D. N.: Geomorphic Controls on Tracer Particle Dispersion in Gravel-Bed Rivers, in:
746 *Gravel-Bed Rivers*, John Wiley & Sons, Ltd, 159–184, <https://doi.org/10.1002/9781118971437.ch6>, 2017.

- 747 Hassan, M. A., Church, M., and Schick, A. P.: Distance of movement of coarse particles in gravel bed streams, *Water*
748 *Resour. Res.*, 27, 503–511, <https://doi.org/10.1029/90WR02762>, 1991.
- 749 Hassan, M. A., Church, M., and Ashworth, P. J.: Virtual rate and mean distance of travel of individual clasts in gravel-
750 bed channels, *Earth Surf. Process. Landf.*, 17, 617–627, <https://doi.org/10.1002/esp.3290170607>, 1992.
- 751 Hoey, T.: Temporal variations in bedload transport rates and sediment storage in gravel-bed rivers, *Prog. Phys. Geogr.*
752 *Earth Environ.*, 16, 319–338, <https://doi.org/10.1177/030913339201600303>, 1992.
- 753 Huang, N., Chen, H., Cai, G., Fang, L., and Wang, Y.: Mechanical Fault Diagnosis of High Voltage Circuit Breakers
754 Based on Variational Mode Decomposition and Multi-Layer Classifier, *Sensors*, 16, 1887,
755 <https://doi.org/10.3390/s16111887>, 2016.
- 756 Inc, T. M.: MATLAB version: 9.13.0 (R2022b), 2022.
- 757 Kasprak, A., Wheaton, J. M., Ashmore, P. E., Hensleigh, J. W., and Peirce, S.: The relationship between particle travel
758 distance and channel morphology: results from physical models of braided rivers., *J. Geophys. Res. Earth Surf.*, 120,
759 55–74, 2015.
- 760 Lane, S. N., Richards, K. S., and Chandler, J. H.: Morphological Estimation of the Time-Integrated Bed Load Transport
761 Rate, *Water Resour. Res.*, 31, 761–772, <https://doi.org/10.1029/94WR01726>, 1995.
- 762 Lane, S. N., Westaway, R. M., and Murray Hicks, D.: Estimation of erosion and deposition volumes in a large, gravel-
763 bed, braided river using synoptic remote sensing, *Earth Surf. Process. Landf.*, 28, 249–271,
764 <https://doi.org/10.1002/esp.483>, 2003.
- 765 Liébault, F., Bellot, H., Chapuis, M., Klotz, S., and Deschâtres, M.: Bedload tracing in a high-sediment-load mountain
766 stream: BEDLOAD TRACING IN A HIGH-SEDIMENT-LOAD MOUNTAIN STREAM, *Earth Surf. Process. Landf.*,
767 37, 385–399, <https://doi.org/10.1002/esp.2245>, 2012.
- 768 Lindsay, J. B. and Ashmore, P. E.: The effects of survey frequency on estimates of scour and fill in a braided river
769 model, *Earth Surf. Process. Landf.*, 27, 27–43, <https://doi.org/10.1002/esp.282>, 2002.
- 770 Liu, S., He, Q., Gao, R. X., and Freedson, P.: Empirical mode decomposition applied to tissue artifact removal from
771 respiratory signal, in: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology
772 Society, 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3624–
773 3627, <https://doi.org/10.1109/IEMBS.2008.4649991>, 2008.
- 774 Ma, W., Yin, S., Jiang, C., and Zhang, Y.: Variational mode decomposition denoising combined with the Hausdorff
775 distance, *Rev. Sci. Instrum.*, 88, 035109, <https://doi.org/10.1063/1.4978029>, 2017.
- 776 Mao, L., Picco, L., Lenzi, M. A., and Surian, N.: Bed material transport estimate in large gravel-bed rivers using the
777 virtual velocity approach: Virtual velocity for bed material transport estimate, *Earth Surf. Process. Landf.*, 42, 595–611,
778 <https://doi.org/10.1002/esp.4000>, 2017.
- 779 McDowell, C. and Hassan, M. A.: The influence of channel morphology on bedload path lengths: Insights from a
780 survival process model, *Earth Surf. Process. Landf.*, 45, 2982–2997, <https://doi.org/10.1002/esp.4946>, 2020.
- 781 McDowell, C., Gaeuman, D., and Hassan, M. A.: Linkages between bedload displacements and topographic change,
782 *Earth Surf. Process. Landf.*, 46, 3127–3142, <https://doi.org/10.1002/esp.5221>, 2021.
- 783 McLean, D. G. and Church, M.: Sediment transport along lower Fraser River: 2. Estimates based on the long-term
784 gravel budget, *Water Resour. Res.*, 35, 2549–2559, <https://doi.org/10.1029/1999WR900102>, 1999.
- 785 McQueen, R., Ashmore, P., Millard, T., and Goeller, N.: Bed Particle Displacements and Morphological Development
786 in a Wandering Gravel-Bed River, *Water Resour. Res.*, 57, <https://doi.org/10.1029/2020WR027850>, 2021.
- 787 Montgomery, D. R. and Buffington, J. M.: Channel-reach morphology in mountain drainage basins, *GSA Bull.*, 109,
788 596–611, [https://doi.org/10.1130/0016-7606\(1997\)109<0596:CRMIMD>2.3.CO;2](https://doi.org/10.1130/0016-7606(1997)109<0596:CRMIMD>2.3.CO;2), 1997.

- 789 Pyrce, R. and Ashmore, P.: The relation between particle path length distributions and channel morphology in gravel-
790 bed streams: A synthesis, *Geomorphology*, 56, 167–187, [https://doi.org/10.1016/S0169-555X\(03\)00077-1](https://doi.org/10.1016/S0169-555X(03)00077-1), 2003a.
- 791 Pyrce, R. S. and Ashmore, P. E.: Particle path length distributions in meandering gravel-bed streams: results from
792 physical models, *Earth Surf. Process. Landf.*, 28, 951–966, <https://doi.org/10.1002/esp.498>, 2003b.
- 793 Pyrce, R. S. and Ashmore, P. E.: Bedload path length and point bar development in gravel-bed river models,
794 *Sedimentology*, 52, 839–857, <https://doi.org/10.1111/j.1365-3091.2005.00714.x>, 2005.
- 795 Redolfi, M.: Sediment transport and morphology of braided rivers: steady and unsteady regime, n.d.
- 796 Roux, C., Alber, A., Bertrand, M., Vaudor, L., and Piégay, H.: “FluvialCorridor”: A new ArcGIS toolbox package for
797 multiscale riverscape exploration, *Geomorphology*, 242, 29–37, <https://doi.org/10.1016/j.geomorph.2014.04.018>, 2015.
- 798 Schneider, J. M., Turowski, J. M., Rickenmann, D., Hegglin, R., Arrigo, S., Mao, L., and Kirchner, J. W.: Scaling
799 relationships between bed load volumes, transport distances, and stream power in steep mountain channels, *J. Geophys.*
800 *Res. Earth Surf.*, 119, 533–549, <https://doi.org/10.1002/2013JF002874>, 2014.
- 801 Sigmund, M.: Voice Recognition by Computer, Tectum Verlag DE, 114 pp., 2003.
- 802 Upadhyay, A. and Pachori, R. B.: Instantaneous voiced/non-voiced detection in speech signals based on variational
803 mode decomposition, *J. Frankl. Inst.*, 352, 2679–2707, <https://doi.org/10.1016/j.jfranklin.2015.04.001>, 2015.
- 804 Vázquez-Tarrío, D. and Batalla, R. J.: Assessing Controls on the Displacement of Tracers in Gravel-Bed Rivers, *Water*,
805 11, 1598, <https://doi.org/10.3390/w11081598>, 2019.
- 806 Vázquez-Tarrío, D., Recking, A., Liébault, F., Tal, M., and Menéndez-Duarte, R.: Particle transport in gravel-bed
807 rivers: Revisiting passive tracer data: Particle transport in gravel-bed rivers, *Earth Surf. Process. Landf.*, 44, 112–128,
808 <https://doi.org/10.1002/esp.4484>, 2019.
- 809 Vericat, D., Wheaton, J. M., and Brasington, J.: Revisiting the Morphological Approach, in: *Gravel-Bed Rivers*, John
810 Wiley & Sons, Ltd, 121–158, <https://doi.org/10.1002/9781118971437.ch5>, 2017.
- 811 Wheaton, J. M.: Uncertainty in morphological sediment budgeting of rivers, phd, University of Southampton, 2008.
- 812 Wheaton, J. M., Brasington, J., Darby, S. E., and Sear, D. A.: Accounting for uncertainty in DEMs from repeat
813 topographic surveys: improved sediment budgets, *Earth Surf. Process. Landf.*, 35, 136–156,
814 <https://doi.org/10.1002/esp.1886>, 2010.
- 815 Wilcock, P. R.: Entrainment, displacement and transport of tracer gravels, *Earth Surf. Process. Landf.*, 22, 1125–1138,
816 [https://doi.org/10.1002/\(SICI\)1096-9837\(199712\)22:12<1125::AID-ESP811>3.0.CO;2-V](https://doi.org/10.1002/(SICI)1096-9837(199712)22:12<1125::AID-ESP811>3.0.CO;2-V), 1997.
- 817 Wu, S., Feng, F., Zhu, J., Wu, C., and Zhang, G.: A Method for Determining Intrinsic Mode Function Number in
818 Variational Mode Decomposition and Its Application to Bearing Vibration Signal Processing, *Shock Vib.*, 2020, 1–16,
819 <https://doi.org/10.1155/2020/8304903>, 2020.
- 820