



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

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7 **Abstract.** The difficulties of measuring bedload transport in gravel bed rivers have given rise to the morphological  
8 method wherein sediment transport is inferred from changes in riverbed elevation and estimates of the distance traveled  
9 by sediment, its path length. Because current methods for estimating path length are time and labor intensive, we  
10 present a method to estimate path length from repeat digital elevation models (DEMs of difference i.e., DoDs). We  
11 propose an automated method to extract the spacing between erosional and depositional sites on the DoD by the  
12 application of Variational Mode Decomposition (VMD), a signal processing method, to quantify the spacing as a proxy  
13 for path length. We developed this method using flume experiments where bed topography and sediment flux were  
14 measured and then applied it to published field data with tracer measurements for validation. Our path length estimates  
15 had an error lower than 30% when compared to the measured mode of the tracer distances in the field and generated  
16 sediment transport estimates not significantly different than the measured sediment flux at lower discharges in the lab.  
17 However, we observed an underestimation of sediment flux at the higher discharges in the flume study. We explore  
18 explanations for the underestimation and how the time between survey acquisitions, the morphological active width  
19 relative to the channel width, and DoD thresholding techniques affect the proposed method and the potential issues they  
20 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 coupled with an estimate of how far sediment  
26 travels, the path length (Ashmore and Church, 1998), or a known flux at one boundary (Grams et al., 2013). With the  
27 increasing availability of high-resolution topography, it is now easier to quantify the volume of mobilized sediment  
28 needed for the morphological method from the comparison of repeat topographic surveys known as digital elevation  
29 models (DEMs) whereby the older survey is subtracted from the newer survey to obtain a DEM of difference (DoD).  
30 However, the estimation of path length remains a challenge.

31 Implementation of the path length-based approach requires an estimation of typical particle travel distances for the reach  
32 in question. Historically, these distances have been estimated using tracers, either electronically tagged or painted clasts.  
33 Unfortunately, tracer studies are time and labor intensive, requiring multiple site visits and intensive recovery campaigns  
34 which often have low recovery rates, especially for painted clasts (Hassan and Bradley, 2017; Brenna et al., 2019).  
35 Furthermore, tracer studies are often applicable only to exposed bars, ignoring a large portion of in-channel transport, and  
36 can be sensitive to the seeding location (Liébault et al., 2012). To overcome these limitations, several methods have been  
37 proposed to estimate path length based on the connection to morphology.



38 Given that morphological units are the cumulative result of the displacement of sediment particles, it follows that the two  
39 would be related. Neill (1971) proposed that path length in meandering rivers should be equal to the distance from an  
40 erosional site (eroding bank) to the next depositional site (point bar) downstream. Many others have observed similar  
41 relationships based on the spacing of erosional and depositional sites and channel morphology (Beechie, 2001; Hundey  
42 and Ashmore, 2009; Kasprak et al., 2015; Pyrcce and Ashmore, 2003b, a; Vázquez-Tarrío et al., 2019). A synthesis of  
43 tracer studies demonstrated that at formative discharges, particle path length distributions often exhibit primary or  
44 secondary modes corresponding to the location of bars, where deposition occurs (Pyrcce and Ashmore, 2003a). Further,  
45 depositional areas (typically bars), have demonstrated a higher probability of ‘trapping’ particles than erosional  
46 morphological units (McDowell and Hassan, 2020; McDowell et al., 2021). Finally, experimental research has confirmed  
47 the preferential deposition of particles specifically at bar heads and margins even in channels with more complex  
48 morphology, for example, in braided rivers (Kasprak et al., 2015) but it is reasonable to assume that in multithreaded  
49 channels, multiple path lengths might exist at different flow stages in primary and secondary channels.

50 Given the observations linking path length to morphology, we hypothesize that path length can be inferred from changes  
51 in morphology at near event scale comparisons. If during a flood, sediment is mobilized from an area of erosion to an  
52 area of deposition as represented on the DoD, the distance between the two should correspond to a typical path length.  
53 Following this hypothesis, this work has the following objectives: i) to propose an efficient and semiautomatic method to  
54 quantify the distance between sites of erosion and deposition from the DoD; ii) to use these estimates of path length to  
55 explore the feasibility and accuracy of sediment transport flux estimations, using direct measurements at the laboratory  
56 scale; iii) to compare these estimates to measured path lengths obtained from tracer data in the field; iv) and finally to  
57 evaluate the potential sources of error when estimating sediment flux from changes in morphology.

## 58 **2 Methods**

59 To meet our objectives, we use flume experiments at varying discharges with direct measurement of output sediment flux  
60 and sets of repeat DEMs from which DoDs are created and used to identify patterns of erosion and deposition. We then  
61 develop a semiautomated method to extract these distances between erosion and deposition and compare our estimates to  
62 measured sediment flux. Finally, we test this method using published field data with tracer measurements as validation  
63 of the path length estimates.

### 64 **2.1 The morphological method**

65

66 The morphological method is based on the sediment continuity equation.

$$67 \quad (Q_{b_{in}} - Q_{b_{out}})\Delta t = (1 - p)\Delta V \quad (1)$$

68 Where  $Q_{b_{in}}$  and  $Q_{b_{out}}$  are the volumetric sediment flux in and out of the reach respectively,  $\Delta t$  is the time between  
69 surveys,  $p$  is the sediment porosity, and  $\Delta V$  is the change in volume. The sediment continuity equation can be solved in  
70 several ways, one requires that either the incoming flux  $Q_{b_{in}}$  or the outgoing flux  $Q_{b_{out}}$  be defined. This has been  
71 estimated by setting a zero-flux boundary, such as a dam or gravel sand transition (McLean and Church, 1999), by  
72 segmenting the reach such that a zero-flux boundary is set between a section of net deposition to one of net erosion  
73 (Vericat et al., 2017) or by measuring flux either into or out of the reach (Grams et al., 2013).



74 Alternatively, Eq. (1) can be modified so that the virtual velocity,  $v_b$  is used.

75 
$$v_b = \frac{L}{T} \quad (2)$$

76 Where  $L$  is the distance the particles travel and  $T$  is the time over which the particles are traveling. Vericat et al. (2017)  
77 proposed an equation to use the path length with the volume of erosion derived directly from the DoD

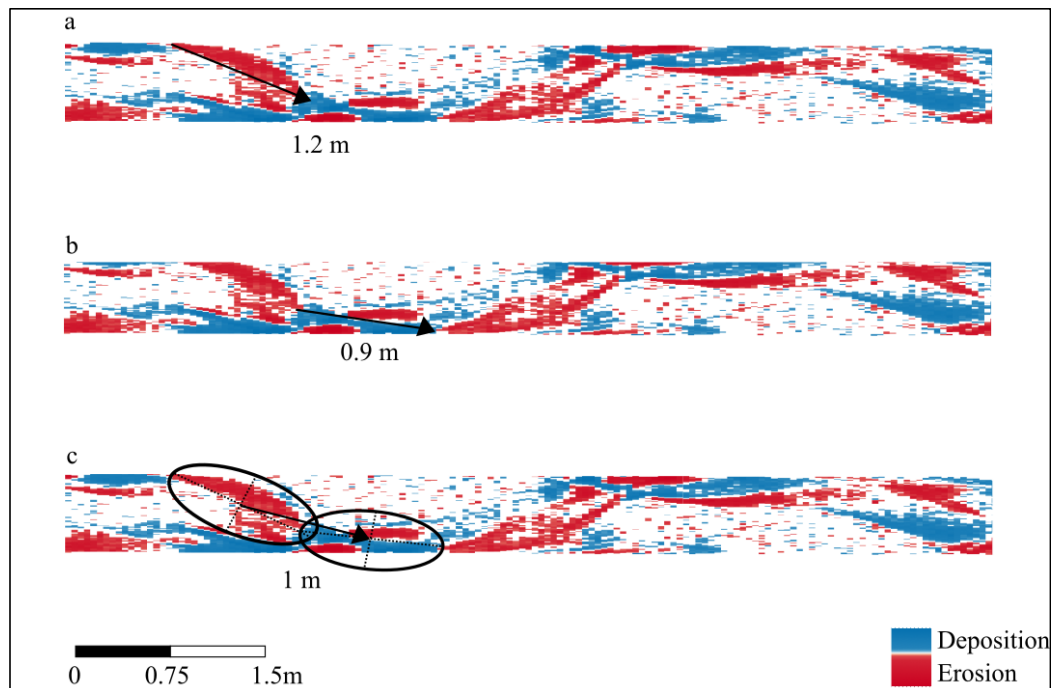
78 
$$Q_b = (v_b \sum V_e (1 - p)\rho_s)/L_c \quad (3)$$

79 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  
80 of erosion is normalized (Vericat et al., 2017). To use this method,  $L_c$  must be long enough for average path lengths ( $L$ )  
81 to occur and  $T$  must be short enough to prevent repeated erosion and deposition, known as compensation (Lindsay and  
82 Ashmore, 2002).

### 83 **2.2 Path length**

84

85 The crux of our hypothesis is that sediment moves from an area of net erosion to an area of net deposition during the  
86 time period between DEM acquisitions and that this represents a characteristic path length. The most obvious method to  
87 quantify this distance between erosional and depositional sites on the DoD is to measure the spacing manually using a  
88 GIS program however, this requires many subjective evaluations. Firstly, we must decide where on the patches of  
89 erosion and deposition to begin and end the measurements. Because patches of erosion and deposition are not  
90 symmetrical or of equal size, the distance between the two depends on which area of the patch we choose to begin and  
91 end the measurements (Fig. 1). For consistency, we choose the center of the patch (Fig. 1c). Next, we must determine  
92 which patch of erosion matches with which patch of deposition which is not always obvious, especially when multiple  
93 channels are present, and again requires subjective evaluation. Here we used our knowledge of morphological processes  
94 to make a best estimate. For example, a patch of erosion on an outside bend likely corresponds to the deposition of the  
95 next point bar downstream. Although this method is capable of producing estimates of path length, to overcome the  
96 subjectivity and time required to manually measure the distances we developed a method to extract the spacing that is  
97 objective and semiautomated.



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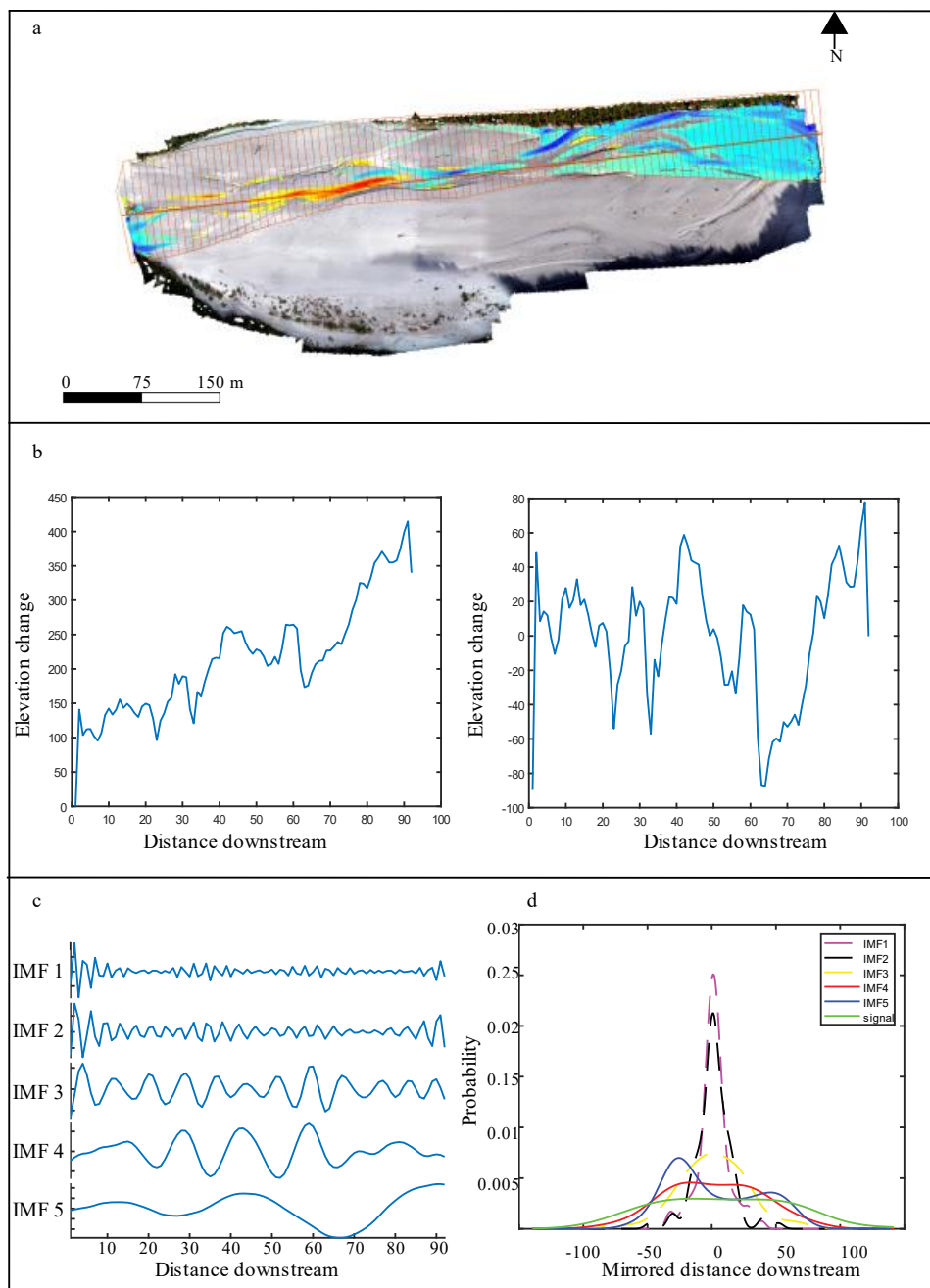
100 **Figure 1: Manual method to measure spacing of erosional patches (red) and depositional patches (blue) on a**  
101 **DoD. (a) Beginning of patch to beginning of next patch (b) end to end (c) center to center.**

101

### 102 2.3 Semiautomated extraction of path length

103

104 To visualize and then quantify the spacing of erosional and depositional sites on the DoD we simplify the spatial  
105 heterogeneity of the DoD into a vector of the net change in elevation in a streamwise direction (Fig. 2a). Because  
106 natural rivers are rarely straight, for field case studies, we must enforce a linear downstream directionality essentially  
107 straightening the bends in the river. This is achieved by segmenting the DoD into a series of equally sized “bins” using  
108 the segmentation tool of the Fluvial Corridor Toolbox (Roux et al., 2015) (Fig. 2a). We then sum the values in each bin  
109 to obtain a vector of the net change in elevation in a streamwise direction (Fig. 2b). In the flume studies, where there is  
110 no sinuosity, we simply sum each column of the DoD matrix. Oftentimes a reach is aggrading or incising and therefore  
111 the net vector will have an increasing or decreasing trend (Fig. 2b). Because we are interested in the spacing between  
112 areas of erosion and deposition rather than the overall trend, we remove it by subtracting a best-fit linear trend from the  
113 net vector (Fig. 2b).



114

115 **Figure 2: VMD- HD method (a) Segmentation of the DoD. (b) Plot of the net original and detrended vector. (c)**  
116 **Variational mode decomposition (VMD) with 5 intrinsic mode functions (IMFs). (d) Probability density function**  
117 **(PDF) of each IMF and the original net vector.**

118 From Fig.2b, it is clear that the pattern of erosion and deposition exhibits periodicity but there is also variation and  
119 “noise”. To see the pattern more clearly and quantify the periodicity we turn to the field of signal processing where the



120 problem of de-noising is ubiquitous. There are many approaches to de-noising including Fourier transform, empirical  
121 mode decomposition (EMD), and wavelet analysis. We chose to use variational mode decomposition (VMD) due to its  
122 robustness with respect to sampling and noise (Dragomiretskiy and Zosso, 2014; Huang et al., 2016; Ma et al., 2017).  
123 VMD decomposes the signal into a set of intrinsic mode functions (IMFs) each with a different central frequency  
124 (Dragomiretskiy and Zosso, 2014; Ma et al., 2017) (Fig. 2c). In this case of our static 'signal' the frequency is more  
125 accurately described as the wavelength. It is beyond the scope of this paper to describe the mathematics of VMD in  
126 detail, therefore, for a complete explanation see (Dragomiretskiy and Zosso, 2014; Huang et al., 2016; Ma et al., 2017;  
127 Upadhyay and Pachori, 2015). Once the original vector is decomposed into the various IMFs, we need to select the IMF  
128 or IMFs that most accurately represent the periodicity of the original data. Ma et al. (2017) proposed a method to select  
129 the most relevant IMF, and therefore periodicity of the signal, by computing the probability density function (PDF)  
130 using kernel density smoothing for each of the five IMFs and of the original data vector (Fig. 2d), then to calculate the  
131 Hausdorff distance (HD), a metric of geometric similarity, between each IMF's PDF and the PDF of the original data  
132 and select the IMF most geometrically similar to the original data (Ma et al., 2017) (hereafter VMD-HD method). In  
133 most cases, the longer wavelength IMFs most closely resemble the original signal whereas the IMFs with shorter  
134 wavelengths are more likely associated with noise (Boudraa et al., 2005). The computed wavelength is converted to a  
135 meaningful physical quantity by multiplying by the bin spacing in meters. Because we are interested in the distance  
136 from peak to trough, we divide the period by two to obtain the path length proxy (Neill, 1971; Ashmore and Church,  
137 1998). All calculations were performed in MatLabR2020b.

### 138 3 Flume and field data

139 The method was tested using data from a set of runs performed in the Hydraulic Laboratory of the University of Trento,  
140 where DEMs were generated for fixed time intervals and varying discharges, and direct measurements of the bedload  
141 flux were also collected. To test the efficacy of the method in the field, we selected a published dataset of measured  
142 path lengths with corresponding DoDs for the San Juan River in British Columbia Canada (McQueen et al., 2021). In  
143 this case, DoDs and corresponding tracer data were available for three separate bars (bar 6, bar 7, and bar 15) for the  
144 2018-2019 period. Detailed information on their collection and processing can be found in McQueen et al., 2021.

#### 145 3.1 Flume experiments

146 The Trento laboratory experiments were carried out in a 0.6 m wide and 24 m long flume, filled with sand characterized  
147 by a median diameter ( $D_{50}$ ) of 1 mm. The flume slope was set to 0.01 m/m. Topographic surveys were performed over  
148 the final 14 m of the flume, to limit the upstream inflow effects, using a laser gauge, mounted on a movable deck. The  
149 longitudinal and crosswise spacings were 0.05 m and 0.005 m, respectively. Four sets of runs were performed, with the  
150 flow discharge set to 0.7, 1, 1.5, and 2 l/s, which correspond to a range of different planform morphologies (see Fig. 3).  
151 The runs were performed following the same procedure, involving three phases of different lengths, based on the  
152 transport condition of each discharge. These durations were estimated referring to the time scale for morphological  
153 evolution computed from the sediment balance mass equation (Garcia Lugo et al., 2015), which can be expressed as:

$$154 \quad T_{ex} = \frac{DW^2}{Q_b}, \quad (4)$$

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

157 **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 <sup>3</sup> /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 <sub>50</sub> (m)	0.001	0.001	0.001	0.001	0.05	0.056	0.042
Time scale T <sub>ex</sub> (min) (eq.4)	94	50	38	30	-	-	-
Time between surveys (0.5 T <sub>ex</sub> )	47	25	19	15	1 year	1 year	1 year
$\omega$ * 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

158

159 First, an initial phase of about 12 times this time scale  $T_{ex}$  with constant flow was run, to ensure the formation of a  
 160 near-equilibrium morphological condition, starting from a flat sand bed scraped to the prescribed slope. This was  
 161 followed by a long run, at constant discharge, lasting 19 times the time scale  $T_{ex}$ , aimed at measuring the output  
 162 sediment flux. This was continuously monitored at the channel outlet, through a permeable basket placed on four load  
 163 cells. Sediment flux was measured every minute. After a bed topography survey, the third phase was a sequence of nine  
 164 shorter runs, lasting 0.5 times the time scale  $T_{ex}$ , each followed by a bed topography survey, which produced nine  
 165 corresponding DoDs. The duration of these nine runs (and therefore the time interval between surveys) was decided to  
 166 have easily measurable changes of the bed morphology, without having significant compensation processes. The use of  
 167 the time scale  $T_{ex}$  (and therefore a different absolute time interval between surveys for the four discharges) ensured to  
 168 have similar volumes of erosion and deposition in each run.

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

### 178 3.2 San Juan River data

179 The San Juan River DoDs were downloaded directly from the Scholars Portal Dataverse  
 180 (<https://doi.org/10.5683/SP2/UQGZCG>). The time in between acquisitions is one year, in which it is estimated there  
 181 were five flood events able to generate sediment transport using a threshold of 500 m<sup>3</sup> s<sup>-1</sup>, which was visually  
 182 estimated by the authors to be equivalent to the bankfull discharge (McQueen et al., 2021). DEMs were generated by  
 183 LIDAR acquisitions and have a spatial resolution of 10 cm and a vertical root mean square error lower than 10 cm.  
 184 Topographic changes between survey dates were then calculated by processing the LiDAR DEMs using the  
 185 Geomorphic Change Detection (GCD) software (Wheaton et al., 2010). More information on how they were obtained  
 186 and processed including the spatially variable thresholding techniques can be found in McQueen et al., 2021. The



187 LiDAR-derived DoDs were used to interpret patterns of tracer displacement and burial depths and to provide  
188 information on the morphological development of the bars during the study period. However, they do not provide  
189 complete reach-scale sediment budgets due to the lack of in-channel topographic data and stage differences during each  
190 LiDAR survey affecting the relative portion of the river bed that was exposed. Nevertheless, we believe the exposed  
191 part of the channel, the bars, and associated patches of erosion and deposition (see Fig. 8b) are sufficient to be used with  
192 our proposed method to estimate path lengths and be compared with field measured path lengths from the tracer data.

### 193 3.3 Validation data

194

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

$$198 \quad \omega^* = \frac{Q \cdot S}{W \sqrt{g \Delta D_{50}^3}} \quad (5)$$

199 Where  $Q$  is the peak discharge,  $S$  is slope,  $W$  is the average wetted width,  $\Delta$  is the relative submerged density,  $D_{50}$  is the  
200 median grain size, and  $g$  is the acceleration due to gravity.

201 For the flumes, we used estimates of path length generated by the VMD-HD method to calculate the virtual velocity Eq.  
202 (2) and sediment flux Eq. (3) which we then compared to measured flux data. The measured sediment flux during the  
203 initial long run showed high variability, with phases of high and low sediment flux lasting several tens of minutes. For  
204 this reason, we prefer to use the data from the long runs, from which we estimated an average sediment flux of 0.33 g/s  
205 (SD=0.17) for the 0.7 l/s 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  
206 discharge, and 3.22 g/s (SD=0.79) for the 2 l/s discharge (Fig. 3). We subdivided the second phase into 38 intervals of  
207 0.5  $T_{ex}$  duration, equal to the duration as the short runs in phase 3, and computed the variability of the flux over this  
208 range.

209 We used ANOVA to compare path length, virtual velocity, and erosion across the four discharges ( $\alpha=0.05$ ) and a Post-  
210 hoc Tukey test to explore significant differences between discharges. To compare the measured sediment flux to the  
211 estimates from the VMD-HD method we used a student's t-test ( $\alpha=0.05$ ). And finally, to compare the error of our path  
212 length and sediment transport estimates we calculated the symmetrical mean absolute percent error (SMAPE).

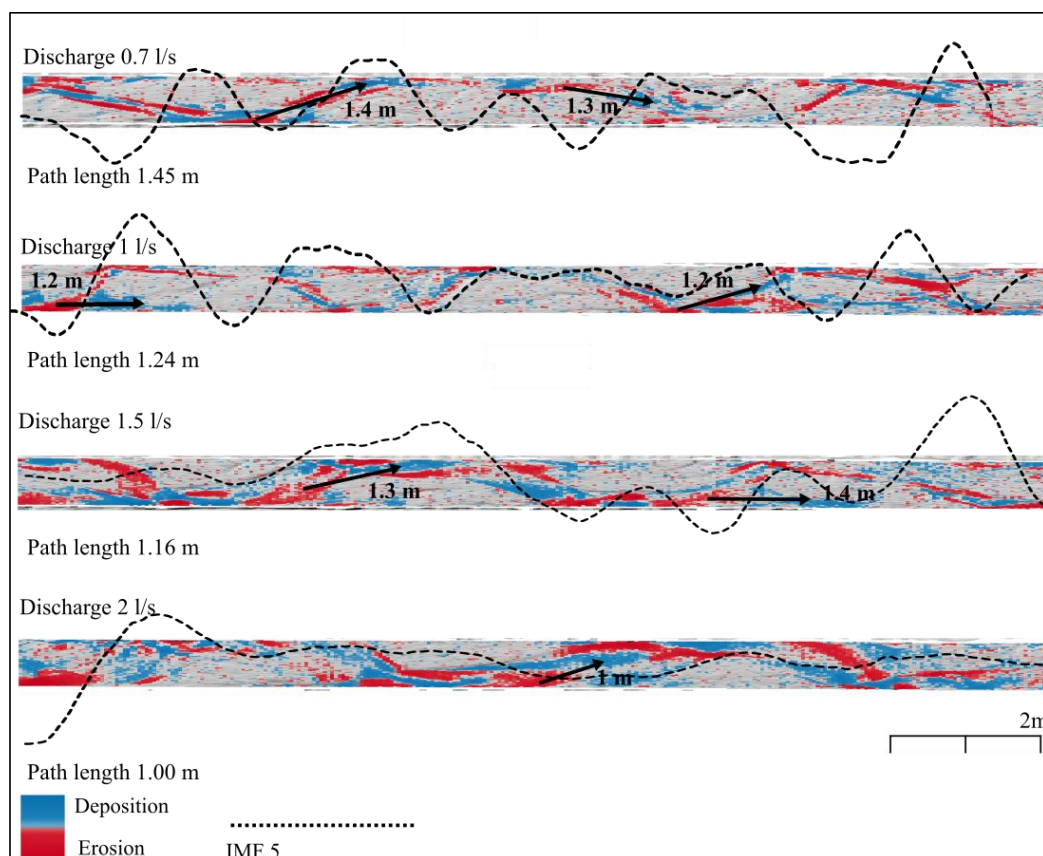
213 For the San Juan River we compared the VMD-HD estimates of path length to the published path length distributions.  
214 The tracer recovery locations were accessed in spreadsheet form and in keeping with the analysis of the authors we  
215 disregarded any tracers that moved less than 10 m before calculating the path length distributions.

## 216 4 Results

### 217 4.1 Flume experiment

218 To aid in the interpretation of the results, Fig. 3 shows a DoD from each of the discharges with the IMF 5 vector laid  
219 over the top. Oftentimes the areas of deposition and erosion from the DoD correspond clearly to the IMF 5 vector as  
220 with the 0.7 l/s discharge where areas of deposition are concave and areas of net erosion correspond to convex areas of  
221 the vector. At the higher discharges (1.5 l/s and 2 l/s) the total area of morphological activity increases and patches of  
222 erosion and deposition begin to overlap, creating a more chaotic and difficult to discern pattern (Fig. 3).



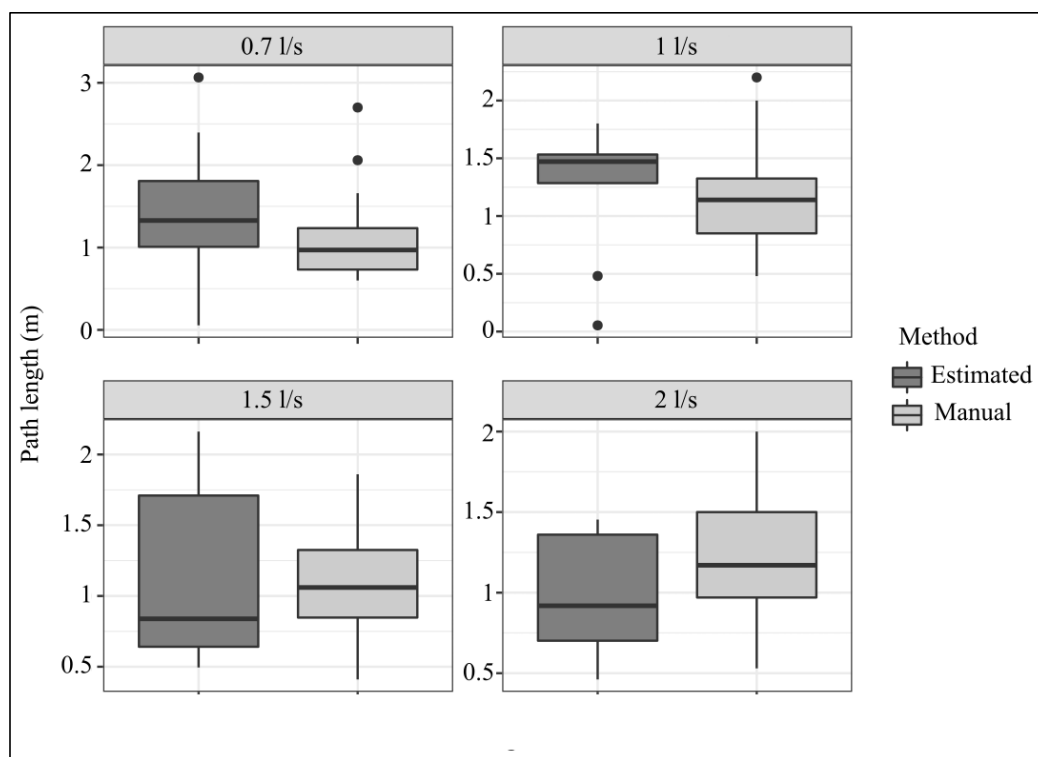


223

224 **Figure 3: All four discharges from the flume experiment DoDs with arrows showing manually derived distances**  
225 **from erosion to deposition, path length estimates using the VMD-HD method, and the IMF 5 vector.**

226 In the flume experiment, the VMD-HD method of choosing the most relevant IMF selected the longest wavelength IMF  
227 5 74% of the time and IMF 4 34% of the time. IMFs 2 and 3 were never selected and IMF 1 was selected only once.

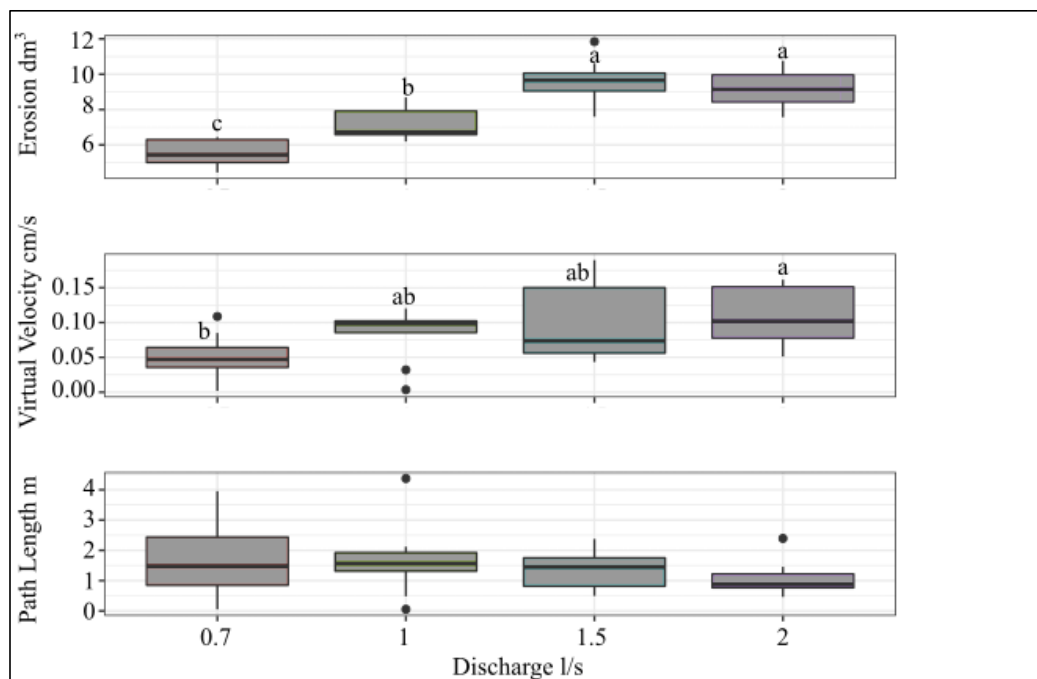
228 Using the selected IMFs, the method estimated a similar average path length for all of the discharges (Fig. 4 & 5). The  
229 averages were, 1.45 m (SD = 0.93) for the 0.7 l/s discharge runs, 1.24 m (SD=0.58) for the 1 l/s runs, 1.21 m (SD =  
230 0.58) for the 1.5 l/s runs, and 1 m (SD = 0.37) for the 2 l/s runs (Fig. 3). The path length estimates derived from the  
231 VMD-HD method matched closely with the manually measured distances and there were no statistically significant  
232 differences for any of the discharges (p-value > 0.05) (Fig. 4).



233

234 **Figure 4: Path length estimates from the VMD-HD method (dark gray) and the estimates derived from the**  
235 **manual method (light gray). The two groups were not statistically significant (p-value > 0.05).**

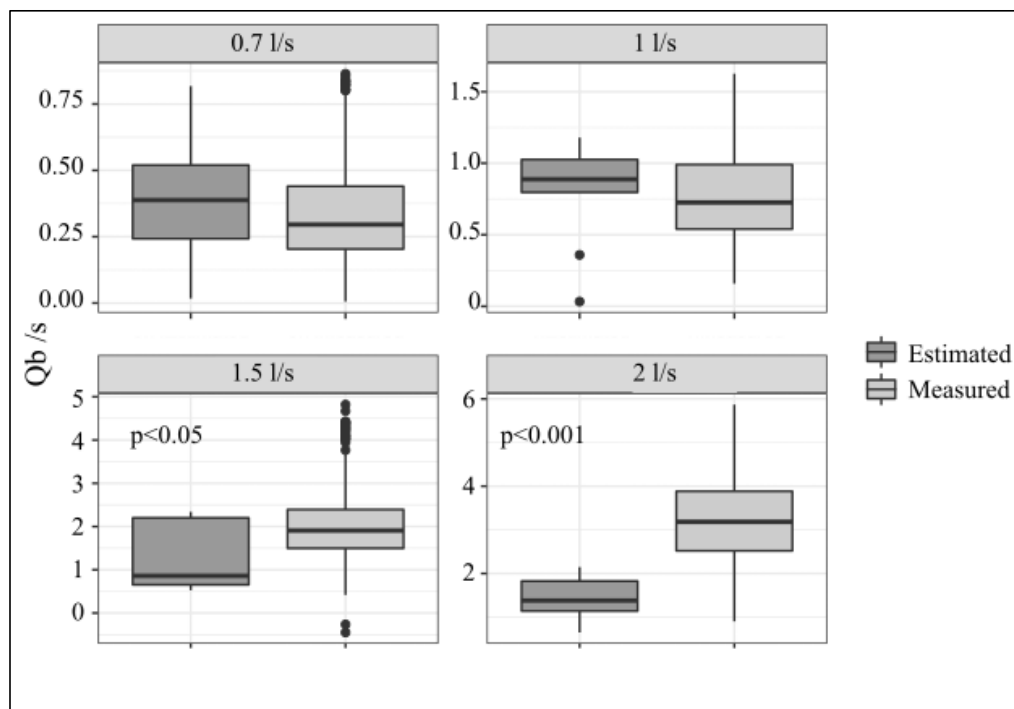
236 The estimated path lengths were not significantly different between the discharges (p-value >0.05) (Fig. 5) and showed  
237 no obvious trend of increasing or decreasing with discharge. However, when used to calculate the virtual velocity ( $v_b$ )  
238 wherein the path length is divided by the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



241

242 **Figure 5: Estimated path length using the VMD-HD method for all discharges in the flume experiment,**  
 243 **calculated virtual velocity using these estimates, and measured volumes of erosion. Significant differences from**  
 244 **the Post hoc Tukey test are denoted by letters a-c.**

245 When used to calculate sediment transport Eq. (3) the VMD-HD method corresponds well to the measured average for  
 246 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  
 247 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  
 248 (SD = 0.25) averaged over the nine runs, which was not significantly different than the measured average of 0.33 g/s  
 249 (SD = 0.18) and the SMAPE was 4%. For the 1 l/s discharge the method estimated 0.81 g/s (SD = 0.38) and was not  
 250 significantly different than the measured average of 0.78 g/s (SD = 0.30) with a SMAPE of 11%. At the higher discharge  
 251 of 1.5 l/s the average estimated by the VMD-HD method was 1.21 g/s (SD = 0.47) whereas the measured average was  
 252 1.98 g/s (SD = 0.70) (p-value < 0.05) with a SMAPE of 53%. Finally, for the 2 l/s runs the estimated average was  
 253 1.44 g/s (SD = 0.46) whereas the measured average was 3.22 g/s (SD = 0.98) (p-value < 0.001) (Fig. 6) with an SMAPE  
 254 of 90%.

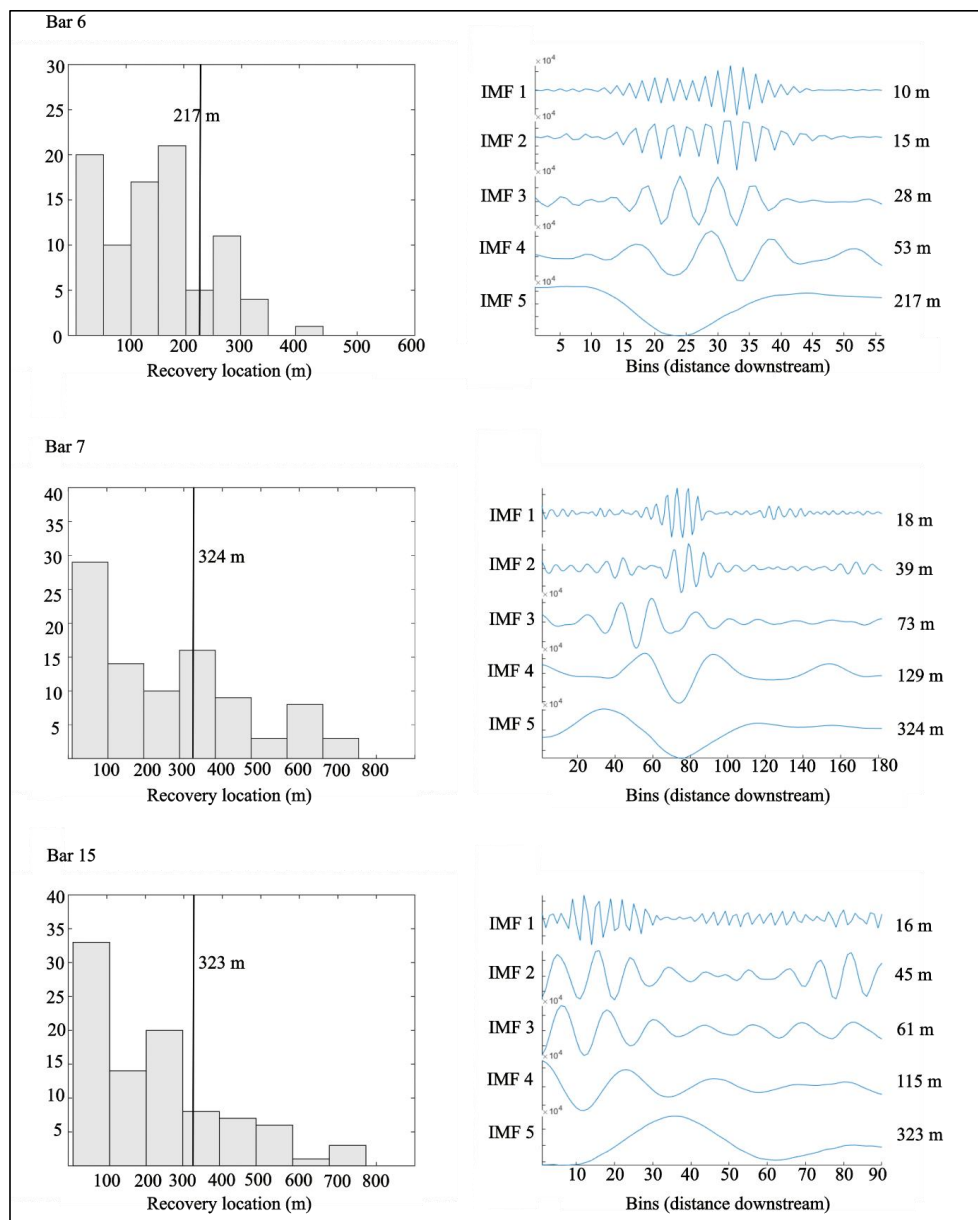


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256 **Figure 6: Estimated sediment flux (dark gray) compared to the measured average (light gray) for each of the 4**  
257 **discharges from the flume experiment. Significant p values ( $\alpha<0.05$ ) from a student's t-test are shown for the 1.5**  
258 **l/s and the 2 l/s discharges.**

#### 259 4.2 San Juan River

260 For the three bars in the San Juan River dataset, the path length calculated from the VMD-HD method for bar 6 was  
261 approximately 217 m whereas the field measured average from tracers was 153 m (SMAPE=35%), and the mode range  
262 was 150-200 m. For bar 7 the method calculated a path length of 324 m whereas the measured average was 255 m  
263 (SMAPE=24%), and the secondary mode range was 280-380 m. Finally, for bar 15 the method calculated a path length  
264 of 323 m whereas the measured average was 221 m (SMAPE=38%), and the secondary mode range was 200-300 (Fig.  
265 7).



266

267 **Figure 7: Tracers-based path length distributions (on the left) and VMD derived IMFs for bars 6,7, and 15 from**  
 268 **the San Juan River dataset. The VMD-HD method selected IMF 5 for all three bars and is reported on the**  
 269 **histograms on the left for visual comparison.**

270 **5 Discussion**

271 We developed a method to estimate the representative path length during a given flood using information inherent to the  
 272 DoD by applying the principle that at channel-forming flows, the majority of particles move from an area of erosion to  
 273 the next area of deposition downstream (Pyrcie and Ashmore, 2003b, a). Therefore, we hypothesized that the distance  
 274 between net erosional and depositional sites should provide a reasonable estimate of the path length. Our method

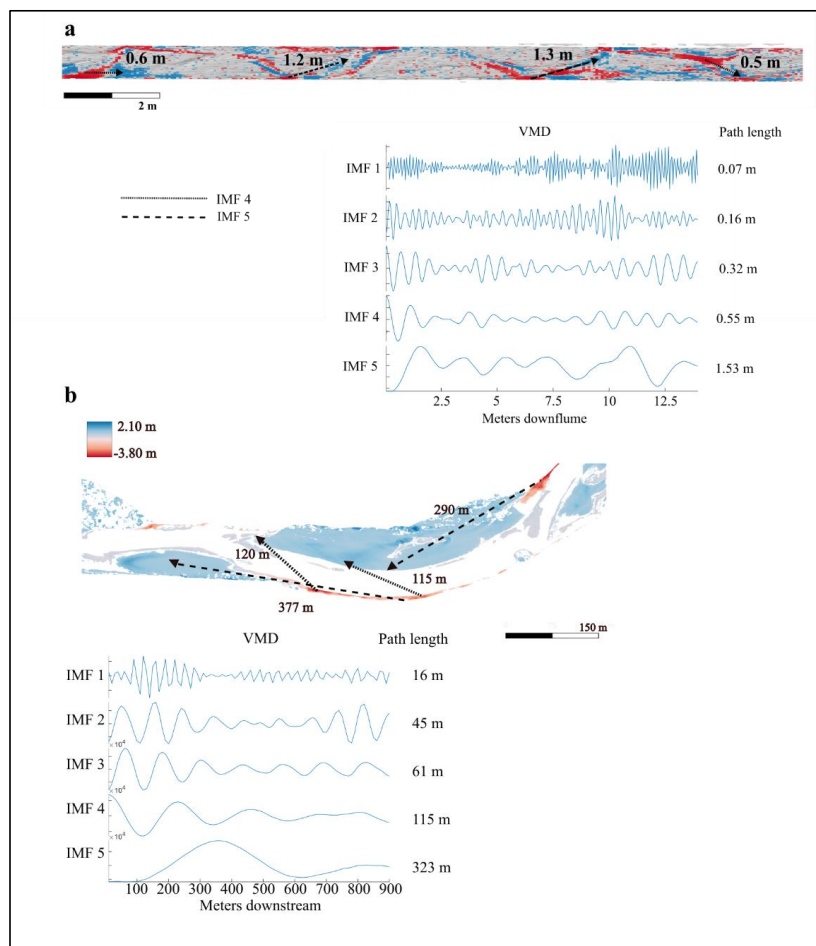


275 overcomes the subjectivity and time involved in measuring these distances manually while aligning closely with these  
276 manually measured distances (Fig. 4). Further, our estimates have an error lower than 30% when compared to the  
277 measured mode of tracer-derived path length estimates in the field (Fig. 7). When used to calculate sediment flux our  
278 estimates are not significantly different than direct measurements of sediment flux for the lower discharge ranges in the  
279 lab (Fig. 6). Importantly, we observed that the method underestimates the sediment flux significantly for the two highest  
280 discharges in the lab where the bed shows a higher percentage of topographic change (Fig. 6). The method presented to  
281 estimate path length using only remotely sensed data shows promising results under certain conditions and provides  
282 insight into conditions where it is not applicable.

### 283 **5.1 Path length estimation by VMD-HD method: limitations and perspectives**

284 Previous studies have shown a relationship between path length and hydrologic variables such as discharge, stream  
285 power, and excess shear stress (Hassan et al., 1991; Pyrcce and Ashmore, 2003b). A notable result of the flume  
286 experiment is that the estimated path length did not significantly differ between the four discharges (Fig. 4 & 5). We  
287 propose two possible explanations for this discrepancy with the literature. First, it is possible that the actual path length  
288 is increasing with discharge as has been observed in previous studies (Hassan et al., 1991; Pyrcce and Ashmore, 2003b)  
289 but the method fails to capture it because the VMD-HD method is based on the spacing of erosion and deposition which  
290 does not change for the varying discharges under the flume conditions. It is possible that at higher discharges the  
291 characteristic path length is not equal to the spacing of erosion and deposition because the particles are moving farther  
292 than the next depositional site downstream. For instance, if we double the estimated path length, hypothesizing a  
293 sediment is not trapped in the first depositional area but in the second one, we more closely estimate the sediment  
294 transport at the higher discharges (i.e., estimates are not significantly different than the measured averages ( $p > 0.05$ ) but  
295 overestimate the sediment transport at the 0.7 l/s and 1 l/s discharges ( $p < 0.05$ ) (Appendix Fig. A1). A second  
296 explanation is that the actual path length does not change with the increase in discharge because the channel width and  
297 morphological unit spacing exert a stronger control than any hydrologic variable which has also been observed in  
298 previous studies (Beechie, 2001; Pyrcce and Ashmore, 2003b; Vázquez-Tarrío et al., 2019). The width may exert an  
299 outsized effect in this case because the flume is laterally confined and unable to widen in response to an increase in  
300 discharge. Because we do not have tracer data in the flumes for comparison, we can only rely on the sediment transport  
301 measurements for validation which indicate that we are underestimating the sediment transport at higher discharges,  
302 thus supporting the first explanation, but further flume studies with both sediment flux and tracer data for validation  
303 could help resolve this question.

304 The VMD-HD method presented here selects one of the five IMFs to be used as an estimate of path length based on the  
305 geometric similarity, as measured by the Hausdorff distance, of the IMF to the original data vector. However, we  
306 presume that not only does the method occasionally select an erroneous IMF (IMF 1 for example) but it also reasons  
307 that in some cases more than one IMF could represent the pattern of erosion and deposition in the DoD and thereby the  
308 characteristic path length. In the flume experiment, the VMD-HD method selected the longest wavelength, IMF 5, 74%  
309 of the time and IMF 4, 24% of the time. There was only one instance in which IMF 1 was selected and neither IMF 2 or  
310 3 were ever selected. Likewise, IMF 5 was selected for all three bars in the San Juan River dataset. This result agrees  
311 with observations from the signal processing literature wherein the lower frequency (in our case wavelength) IMFs (4  
312 and 5) are thought to represent the true signal whereas the higher frequency (shorter wavelength) IMFs are attributed to  
313 noise (Boudraa et al., 2005). In our case we can verify visually that IMF 5 is most likely representative of the path  
314 length by tracing the path from erosional site to depositional site within the DoD using the manual method (Fig. 3 & 8).



315

316 **Figure 8: DoD with arrows showing possible path lengths between areas of erosion (red) to deposition (blue)**  
 317 **corresponding to both IMF 4 and IMF 5. The VMD breakdown including all IMFs and the corresponding path**  
 318 **lengths are shown for an experimental run from the 1.5 l discharge (a) and bar 15 from the San Juan River (b).**

319 We also see shorter path lengths in the DoDs that may correspond to IMF 4 (Fig. 8). The method we present here to  
 320 select one of the IMFs to represent the periodicity is convenient for assigning a characteristic path length to be used in  
 321 sediment transport calculations. However, we recognize that in reality there is not one path length but rather a  
 322 distribution. The path length-based method for calculating sediment transport necessitates that a single path length be  
 323 selected and this is surely an oversimplification of reality. Encouragingly, the flume experiment shows that by using the  
 324 VMD-HD method to select the path length, we are able to reasonably approximate sediment transport at the lower  
 325 discharges (Fig. 6) even with an occasional erroneous result (i.e., IMF 1). However, when applying this method to a real  
 326 case study, like that of the San Juan River, it is important to consider if the results make sense given what is known  
 327 about the channel and the time and magnitude of flood events between surveys, potentially taking into account both  
 328 IMF 4 and IMF 5 to generate a range of plausible transport.

329 The periodicity we extract from the DoDs as an estimate of path length corresponds to previous observations of  
 330 preferential particle deposition at specific morphological units and relationships to channel morphology (Beechie, 2001;



331 Kasprak et al., 2015; Pyrcce and Ashmore, 2003b). In the San Juan River study, our estimates aligned closely with the  
332 secondary modes in the particle path length distributions (Fig. 7) consistent with observations that at channel forming  
333 flows, particle path lengths tend to be bi or multimodal with secondary modes corresponding to the location of bars  
334 (Pyrcce and Ashmore, 2003b). This preliminary result should be further examined with additional field data in multiple  
335 channel types.

336 We expected that the path length in more complex channels such as braided configurations would be more difficult to  
337 estimate due to the possibility of multiple path lengths active at different flow stages. In this study both the flume  
338 experiment and the field study exhibited a wandering morphology although in the flume experiment, the channel began  
339 to simplify at higher discharges. This is likely due to the inability of the channel to widen in response to the increase in  
340 discharge. Further, path length estimates did not change significantly between the discharges whereas the erosion  
341 volume increases with discharge, and that, as mentioned previously, potentially contributed to the underestimation of  
342 sediment flux at the higher discharges. Additionally, at the 1.5 l/s, and 2 l/s discharges, the patches of erosion and  
343 deposition began to overlap, therefore, the wavelike pattern from areas of erosion to deposition represented by the IMF  
344 5 vector became flattened (Fig. 3). Further, when multiple channels are present and active, it may be beneficial to  
345 segregate the DoD, treating each channel as a separate system and generate multiple path length estimations. Further  
346 investigations are needed in the lab and in the field to propose robust methodologies to assess realistic ranges of path  
347 lengths from DoD for varying river patterns.

## 348 **5.2 DoD related uncertainties**

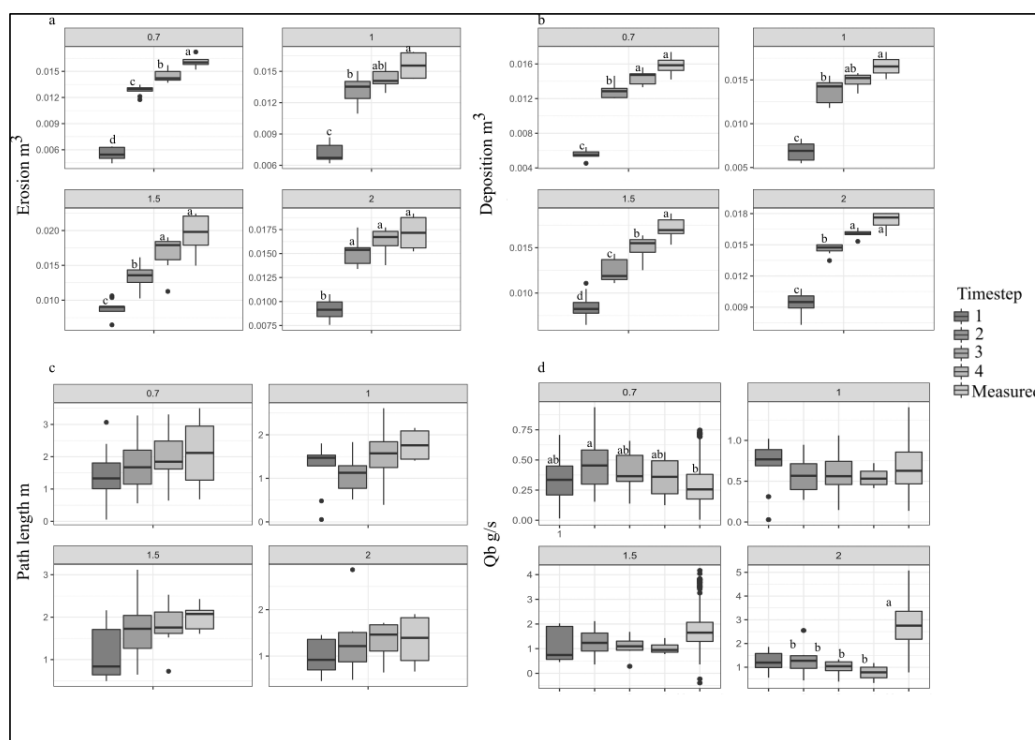
349 Any application of the morphological method using DoDs is sensitive to the error thresholding method used due to the  
350 way in which different thresholding techniques influence both the volumes of erosion and deposition as well as their  
351 spatial patterning (Brasington et al., 2003; Wheaton, 2008; Wheaton et al., 2010; Vericat et al., 2017). Because our  
352 method relies on the spacing between areas of erosion and deposition which is related to the size of the patches as well  
353 as which patches are detected, we considered that thresholding techniques could greatly affect the estimates of path  
354 length. We tested this hypothesis by applying the method to both the raw and filtered DoDs for the Trento flume  
355 experiment and found that while the volumes of erosion and deposition were lower after thresholding as expected  
356 ( $p < 0.001$ ), the path length estimates were not significantly different ( $p > 0.05$ ) (Appendix Table A1). While the  
357 thresholding here did not affect the path length estimates, we might imagine a scenario in which an entire area of  
358 erosion or deposition is removed through aggressive thresholding techniques, thereby potentially affecting the path  
359 length estimates and therefore caution that appropriate thresholding is important for the application of this method and  
360 the morphological method in general.

361 The time between surveys is of equal importance to the path length in the estimation of virtual velocity Eq. (2) and in  
362 the field can be highly uncertain due to poor availability of hydrologic data and/or the uncertainty of estimating the  
363 onset of transport based on a critical shear stress. Further, as time between surveys increases, so too does the probability  
364 of compensating erosion and deposition which can affect both the volumes of erosion and deposition and the  
365 topographic signatures (Lindsay and Ashmore, 2002; Vericat et al., 2017) necessary for VMD-HD method. We tested  
366 how the time between surveys might affect both the volumes of erosion and deposition and our path length estimates by  
367 differencing DEMs not every time step but between two, three, and four timesteps, each time step being one of the nine  
368 runs in the lab of phase 3 (see method). Not surprisingly the volume of erosion and deposition increased significantly  
369 with increasing time between surveys with the largest increase between the 1<sup>st</sup> timestep and 2<sup>nd</sup> timestep (Fig. 9). The  
370 path length estimates did not increase significantly for any of the discharges (Fig. 9c) indicating that the path length





371 estimate is stable, likely because, as already noted, the spacing of erosion and deposition is related to the position of  
 372 erosional and depositional features which do not change much in a confined experiment. When both of these parameters  
 373 are used in the sediment transport calculations and normalized by the increased time between surveys, we found no  
 374 statistically significant difference between the estimates (Fig. 9d). However, though not statistically significant, there is  
 375 an apparent decreasing trend in the sediment flux with the increased time between surveys, especially for the 2 l/s  
 376 discharge that may indicate compensation (Fig. 9d). Despite the apparent trend at the highest discharge this is a  
 377 promising result in that even by increasing the time interval by a factor of 4 we are still able to estimate sediment  
 378 transport reasonably at the lower discharges. In the field there are often multiple flood events of differing magnitude in  
 379 the year between surveys as was the case with the San Juan River study (McQueen et al., 2021). Although there were  
 380 five flood events of differing magnitudes between the San Juan River surveys, we were still able to estimate path  
 381 lengths corresponding to the RFID tracer data with an error of less than 30% (Fig. 7).



382  
 383 **Figure 9: (a) Erosion measured from the flume experiments for each discharge and each timestep (b) deposition**  
 384 **(c) path length estimates using VMD-HD method (d) sediment flux estimated using VMD-HD method and**  
 385 **measured. Significant post-hoc Tukey results are denoted by letters a-d ( $\alpha=0.05$ ).**

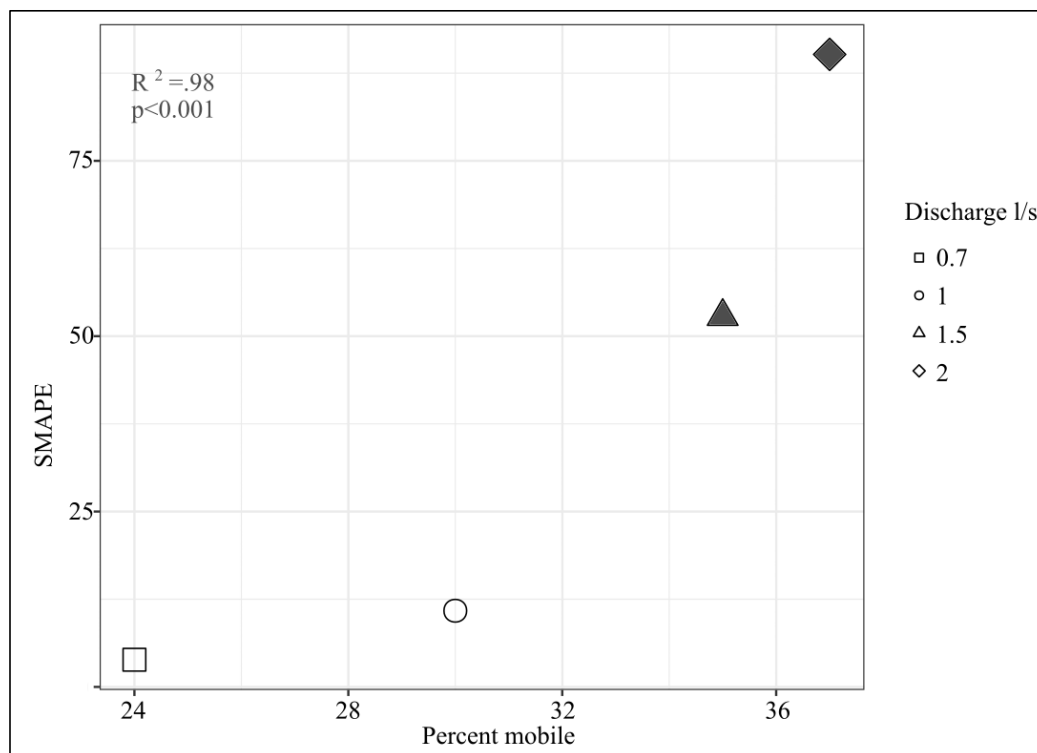
386 **5.3 Applicability of the method**

387 When evaluating the efficacy of our proposed method it is important to keep in mind the uncertainty of even direct  
 388 measurement of sediment transport. The spatial and temporal frequency required to overcome the noise of measurement  
 389 uncertainty (i.e., achieve an acceptable signal to noise ratio) in some cases can require sub-daily monitoring with  
 390 precise equipment (Grams et al., 2019). The variability of sediment transport measurements in the flume study ranged  
 391 from a standard deviation of approximately 30% to over 50% of the averaged flux (Fig. 3). Given this high variability,  
 392 our reach scale averages were not significantly different from the measured averages for the 0.7 l/s and 1 l/s discharges



393 (Fig. 6). Further, our method produced path length estimates which correspond to the distance between erosional and  
394 depositional sites on the DoD in both the flumes and field (Fig. 7).

395 In the flume experiment, we found that the VMD-HD method performed better at the lower discharges of 0.7 l/s and 1  
396 l/s but significantly underestimated the sediment transport at the 1.5 l/s and 2 l/s discharges (Fig. 6). In Sect. 5.1 we  
397 discussed that this underestimation is likely due to our limitations in the deriving realistic path lengths from DoDs. The  
398 underestimation at higher discharges could be related to the amount of morphological change relative to the sediment  
399 transport. Recently, Booker and Eaton (2022) quantitatively explored the link between sediment transport and  
400 morphology and proposed an index to represent the intuitive notion that as sediment transport increases relative to  
401 morphological change, the processes become decoupled and inferences from one to another become more difficult.  
402 They developed a ‘throughput index’ which is the ratio between sediment flux and morphological change and  
403 represents how much sediment moves through a reach without leaving a topographic signature of equal magnitude.  
404 Therefore, the ratio represents how well the flux is represented morphologically with the ratio approaching 1 when all  
405 of the flux is shown as morphological change and exceeding 1 when there is transport without equivalent morphological  
406 change. In our case the flume experiments were confined, therefore, as discharge increased the channel was not able to  
407 widen and deform laterally potentially causing the sediment to move through the flume without leaving an equivalent  
408 topographic signature. To explore the applicability of the method proposed we calculated the morphological active  
409 width by counting the percentage of pixels in the DoD that showed topographic change after filtering (we applied this  
410 metric only for the flume experiments since the San Jose DoDs do not include the submerged part of the channel). The  
411 morphological active width increased with discharge as expected and was positively correlated with the error of our  
412 estimates (Fig. 10). We found a strong exponential relationship between the percent of the flume that was active and the  
413 error of our estimates ( $R^2=0.98$ ,  $p<0.01$ ) (Fig. 10). This result exposes a limitation of the morphological method in  
414 general and our application specifically, that is, confined channels with high transport relative to morphological change  
415 are likely poor candidates for the morphological method as inferences between changes in morphology and sediment  
416 transport become decoupled. Further applications of this method in the field and in the lab could identify a potential  
417 threshold defined by the throughput index (Booker and Eaton, 2022) or the morphological active width described in this  
418 study. The advantage of using the morphological active width as opposed to the throughput index is that it can be  
419 determined from the DoD without direct sediment transport measurements.



420

421 **Figure 10: Symmetrical mean absolute percent error (SMAPE) between estimated and measured flux in the**  
 422 **flume experiments vs the percentage of the DoD showing morphological change. Different discharges are**  
 423 **denoted by shape. Filled shapes are where the sediment transport was significantly underestimated ( $\alpha=0.05$ ).  $R^2$**   
 424 **and p value from exponential regression is shown.**

425 **6 Conclusion**

426 The feasibility of estimating sediment flux using the morphological method has increased dramatically with the advent  
 427 of high-resolution topography but has thus far been limited by the high labor demand of acquiring estimates of path  
 428 length or the uncertainty of defining zero or known flux boundary. Given the observed connections between  
 429 morphology and path length at channel forming flows, we hypothesized that the pattern of erosion and deposition can  
 430 be a proxy for particle path length in gravel bed rivers. We applied tools from signal processing to quantify this  
 431 periodicity and found that our method provides estimates path length within 30% of measured tracer data and  
 432 corresponds to the spacing of erosion and deposition visible on the DoD. Further, our method provides estimates of path  
 433 length coherent with channel morphology and previous observations of preferential particle deposition at given channel  
 434 units, specifically bar heads and margins. When extended to calculate sediment flux our estimates were not significantly  
 435 different from the measured average at low discharges. Importantly we found that limits arise where discharge increases  
 436 in confined channels and sediment transport becomes decoupled from morphological changes. Our method provides a  
 437 reasonable estimation of path length based solely on remotely sensed data and a novel method to estimate sediment  
 438 fluxes associated with specific channel morphological processes through DoD interpretation.

439 **Appendix A**

440 Table 1A. 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	1.773259	1.307314	0.689433	0.302282	0.009159	0.008549	0.005447	0.005563
0.7	0.795361	0.754067	0.29032	0.142154	0.008599	0.008908	0.004441	0.004537
0.7	3.046668	3.064947	1.199591	0.707274	0.009275	0.009918	0.005436	0.005387
0.7	2.535835	2.396349	0.968185	0.510259	0.008994	0.009598	0.005016	0.005359
0.7	2.295464	0.054816	1.013183	0.014801	0.010397	0.010241	0.006361	0.006194
0.7	0.871326	1.093539	0.346255	0.232138	0.009361	0.009446	0.005001	0.005344
0.7	1.566474	1.610973	0.699181	0.429163	0.010514	0.010212	0.006275	0.006408
0.7	1.244291	1.348844	0.564266	0.368507	0.010683	0.009538	0.006436	0.00574
1	1.24835	1.40561	1.038306	0.88725	0.010422	0.010825	0.007909	0.007682
1	1.365147	0.481025	1.276647	0.310621	0.011718	0.011387	0.008091	0.00773
1	1.247054	1.47142	1.096304	1.020008	0.011015	0.01074	0.008686	0.008282
1	1.228217	1.801574	1.179758	0.998633	0.012036	0.011354	0.006946	0.007335
1	1.479481	1.593984	1.46079	0.837967	0.012372	0.012056	0.006587	0.00651
1	1.829563	1.532486	1.573845	0.767802	0.010779	0.011239	0.006278	0.005849
1	1.537466	1.524962	1.265276	0.753475	0.010312	0.01053	0.006191	0.005744
1	1.513476	1.285303	1.214192	0.688794	0.010052	0.009902	0.006715	0.005483
2	1.406256	1.401221	2.526716	1.855525	0.013508	0.013539	0.009956	0.009756
2	0.908098	0.918657	1.582438	1.193736	0.013101	0.013743	0.009769	0.010142
2	1.258225	1.359801	2.048964	1.578538	0.012243	0.013183	0.008727	0.009491
2	1.127641	1.256842	1.665162	1.265188	0.011102	0.011877	0.007568	0.008187
2	0.055676	1.453594	0.088489	1.610442	0.011949	0.010872	0.008329	0.0073
2	0.464373	0.461198	0.776033	0.561071	0.012564	0.012399	0.009146	0.00892
2	1.31982	0.826137	2.035505	1.182625	0.011595	0.013636	0.010762	0.009229
2	0.712963	0.65993	1.29628	0.740195	0.013669	0.014229	0.008432	0.010081

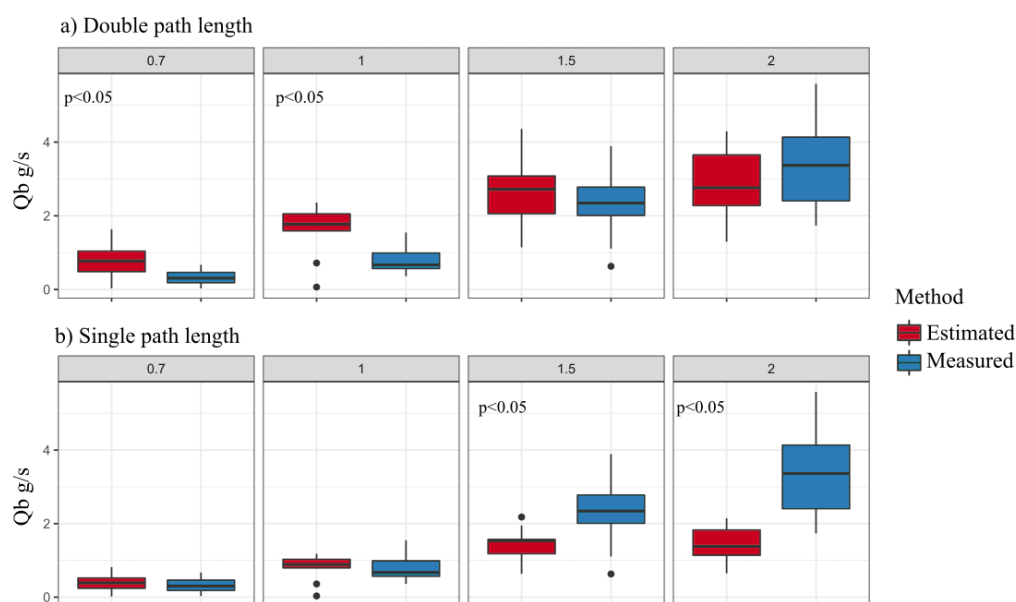
Summary

Discharge	Erosion	Deposition	Path Length	Qb
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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*
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



441

442

443

Figure 1A. 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.

444

**Code availability**

445

Data and code are available upon request form the corresponding author.

446

**Author contribution**

447

448

449

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

450

**Competing interests**

451

The authors declare they have no competing interests.

452

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453

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454

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