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Estimating bedload transport rates in a gravel-bed river using seismic impact plates: model development and application

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Abstract

A data-driven, uncertainty-bound estimation technique for bedload transport rates is developed based on passive sensing devices. The model converts sediment samples to a mass in transit for each instantaneous discharge according to impacts detected and a Monte Carlo simulation of the load determined at random from the particle size distribution. Using impact count data autogenically produces a supply-limited, location-specific and high-resolution time-series of bedload rates, while the probabilistic approach inherently accommodates the stochastic nature of bedload transport. Application to the River Avon (Devon, U.K.) provides cross-sectional bedload rate estimates within the bounds of experimental data and calibrated to observed field behaviour. This new procedure offers an alternative ‘class’ of bedload estimation to existing approaches and has the potential for wide-ranging applications in river management and restoration, while contributing to the integration of ‘big data’ into a progressive agenda for hydrogeomorphology research.

Keywords

Coarse bedload transport; Fluvial geomorphology; Monte Carlo simulation; Sediment monitoring; Seismic impact plate; Uncertainty

Software Availability

Name of model: Bedload from Impact Plates (BLIP)

1 *Developers:* Philip Soar, University of Portsmouth, U.K. (philip.soar@port.ac.uk); Peter Downs,
2 Plymouth University, U.K. (peter.downs@plymouth.ac.uk)

3 Program language: Visual Basic for Applications (VBA)

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5 *Hardware required:* Microsoft Windows PC

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7 *Software required:* Microsoft Excel

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9 *Availability:* A working model has been developed and is proposed for general release in the near
10 future. The model can be made available to researchers on request to the authors
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12 13 14 **1. Introduction**

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16 Fluvial system sciences have seen the enthusiastic uptake of ‘big data’ over recent decades, with
17 high-resolution, passively-sensed data sets becoming integral both to spatial analyses of terrain and
18 to time-series investigations of water quality and suspended sediment transport. One outstanding
19 challenge is the adequate characterization and prediction of bedload, with technological innovation
20 considered the catalyst to developing detailed insights into transport processes (Ashmore and Rennie,
21 2012) that are critical to better understand physical habitat dynamics, underpin sustainable flood risk
22 management and ensure the resilience of river restoration schemes.
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31 Active, direct measurement of bedload using samplers or traps (Bunte et al., 2004, 2008) are costly in
32 terms of labour (portable samplers) and/or infrastructure (permanent installations), logistically
33 challenging to achieve with acceptable accuracy over geomorphologically-relevant time periods
34 (Ryan and Porth, 1999; Sterling and Church, 2002; Vericat et al., 2006) and often involve hazardous
35 working conditions. Alternatively, transport rates are estimated using empirical formulae, although
36 such methods are characterized by marked differences in performance (e.g. Barry et al., 2004;
37 Gomez and Church, 1989; Martin and Ham, 2005; Wilcock, 2001) arising from the computational
38 simplifications required to represent the complex physics of bedload movement in a practicable
39 manner. In particular, these numerical expressions cannot account for the inherently stochastic
40 nature of bedload transport (see Recking et al., 2012) and are incapable of capturing intra- and inter-
41 event variations in supply (Gomez, 2006). Sediment routing models and mobile boundary
42 simulations (Bruner and Gibson, 2005; Cui et al., 2011; Papanicolaou et al., 2008) offer the potential
43 to overcome some of these issues but are currently extremely difficult to set up and parameterize
44 (except by an experienced modeller) and are rarely validated in practice (Thorne et al., 2011;
45 Wallerstein et al., 2006). Recognizing the difficulties and limitations of direct measurement and
46 unreliability of sediment transport equations, Wilcock (2001) appealed for new methods to be
47 sought that strike a balance between accuracy and practicability.
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1 Passive approaches to bedload monitoring are centred on recording the passage of bedload using an
2 acoustic or seismic sensor that records an electrical wave (hydrophones, geophones, respectively) or
3 simply an impulse (impact plates) as particles pass or strike the sensor. Modern data loggers provide
4 a means of obtaining high-resolution spatial and temporal measurement of coarse bedload transport
5 intensity over time periods of geomorphological relevance (Gray et al., 2010a). Such devices are
6 relatively low cost (e.g. USD 900 per plate for those used here), portable and non-intrusive and, as a
7 passive technique, offer far safer data collection. Depending on the sensor used, the minimum
8 particle size recorded is usually in the range of 4 to 30 mm (Gray et al., 2010b; Rickenmann et al.,
9 2012). There is a rapidly growing body of literature associated with these devices (summaries in Gray
10 et al., 2010a, b; Rickenmann, in press; Rickenmann et al., 2014), and an evolving understanding of
11 their performance characteristics in relation to experimental set-up, grain-size dependent and
12 transport-style effects (Beylich and Laute, 2014; Gray et al., 2010b; Rickenmann and Fritschi, 2010;
13 Rickenmann and McArdell, 2007, 2008; Rickenmann et al., 2012, 2014; Tsakiris et al., 2014; Turowski
14 and Rickenmann, 2009; Wyss et al., 2016a, 2016b, 2016c) and the dynamics of sediment supply
15 during individual events (Downs et al., 2016).

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30 There is now growing evidence for a robust correlation between summed impact counts and total
31 bedload mass over event-scale and longer time periods (Beylich and Laute, 2014; Rickenmann et al.,
32 2012, 2014). However, a significant question concerns the calibration of passive devices to convert
33 data collected on bedload transport *intensity* into estimates of bedload transport *rates* (see review
34 by Rickenmann, in press). Research focussed initially on direct calibration of either summed impulse
35 counts or a summary measure of acoustic signal against a measured sediment load to produce a
36 rating curve but has more recently centred on extracting grain size information from the acoustic
37 signal (Barrière et al., 2015; Bogen and Møen, 2003; Møen et al., 2010; Rickenmann et al., 2014;
38 Wyss et al., 2014, 2016b) and correlating the signal strength to bedload transport rate as a function
39 of sediment grain size (Wyss et al., 2016a). While acoustic fingerprinting techniques offer
40 considerable promise for reconstructing continuous rates of bedload transport by size fraction, the
41 approach is subject to time-consuming direct measurements (Turowski and Rickenmann, 2011), may
42 require a lengthy refinement period and cannot facilitate rate estimates to be derived in the vast
43 majority of rivers where bedload monitoring is not undertaken routinely. As such, environmental
44 managers cannot as yet benefit from the 'revolutionary' potential afforded to bedload understanding
45 from passive sensors (Gray et al., 2010b).

1 Addressing this issue, we focus here on a complementary, indirect, approach for estimating bedload
2 transport rates probabilistically from bedload counts detected by seismic impact plates using a
3 Monte Carlo simulation in conjunction with knowledge of particle size distribution of bed material
4 and parameters of the flow and cross-sectional geometry. The approach offers the prospect of
5 developing new insights into bedload transport dynamics while also enabling sensitivity testing and
6 scenario-modelling of future conditions. We illustrate the method with application to a gravel-bed
7 river in South West England during an extremely wet year, building on the insights offered from the
8 impact count data alone (Downs et al., 2016). Without the need for permanent bedload monitoring
9 infrastructure, this new procedure thus provides a potentially robust method of achieving indicative
10 measures of bedload transport load for wide-ranging practical applications and in so doing affords
11 one means of fulfilling the revolutionary potential of passive sensors in fluvial sedimentology.
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21 **2. Model Development**

22 *2.1 Model overview*

23 The overarching assumption of the model is that in gravel-bed streams with variable sizes of bed
24 material, impacts detected by a seismic plate are generated by a probabilistic array of ‘possible’
25 particle sizes in transit that reflects a proportion of the distribution of bed material grain sizes,
26 constrained by a minimum size detectable by the equipment and a maximum size at the threshold
27 for bedload motion.
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36 The process for generating cross-sectional sediment rates from impact plate count data consists of
37 four principal stages, illustrated in Figure 1 and discussed below. Experimentally, the approach
38 requires deployment of a cross-sectional array of impact plates in conjunction with one or more
39 pressure transducers. As depth of flow is a critical parameter in the model, deployment of a pressure
40 transducer as a component of the experimental set-up is essential and, therefore, it is recommended
41 investigators consider strongly the deployment of two or more pressure transducers to facilitate
42 logging of water surface slope. While a single impact plate can be used to explore temporal patterns
43 of bedload occurring at or near the thalweg, sediment paths have been found to shift markedly with
44 discharge (Downs et al., 2016). Therefore, resources permitting, multiple plate deployment across a
45 section is recommended to better represent the natural spatio-temporal variation in sediment
46 transport intensity over the channel bed and should improve accuracy. The discernible improvement
47 in accuracy of empirical methods of transport rate estimation with increasing number of samples
48 taken, and beneficial performance over sediment transport formulae, is illustrated for gravel-bed
49 rivers by Wilcock (2001).
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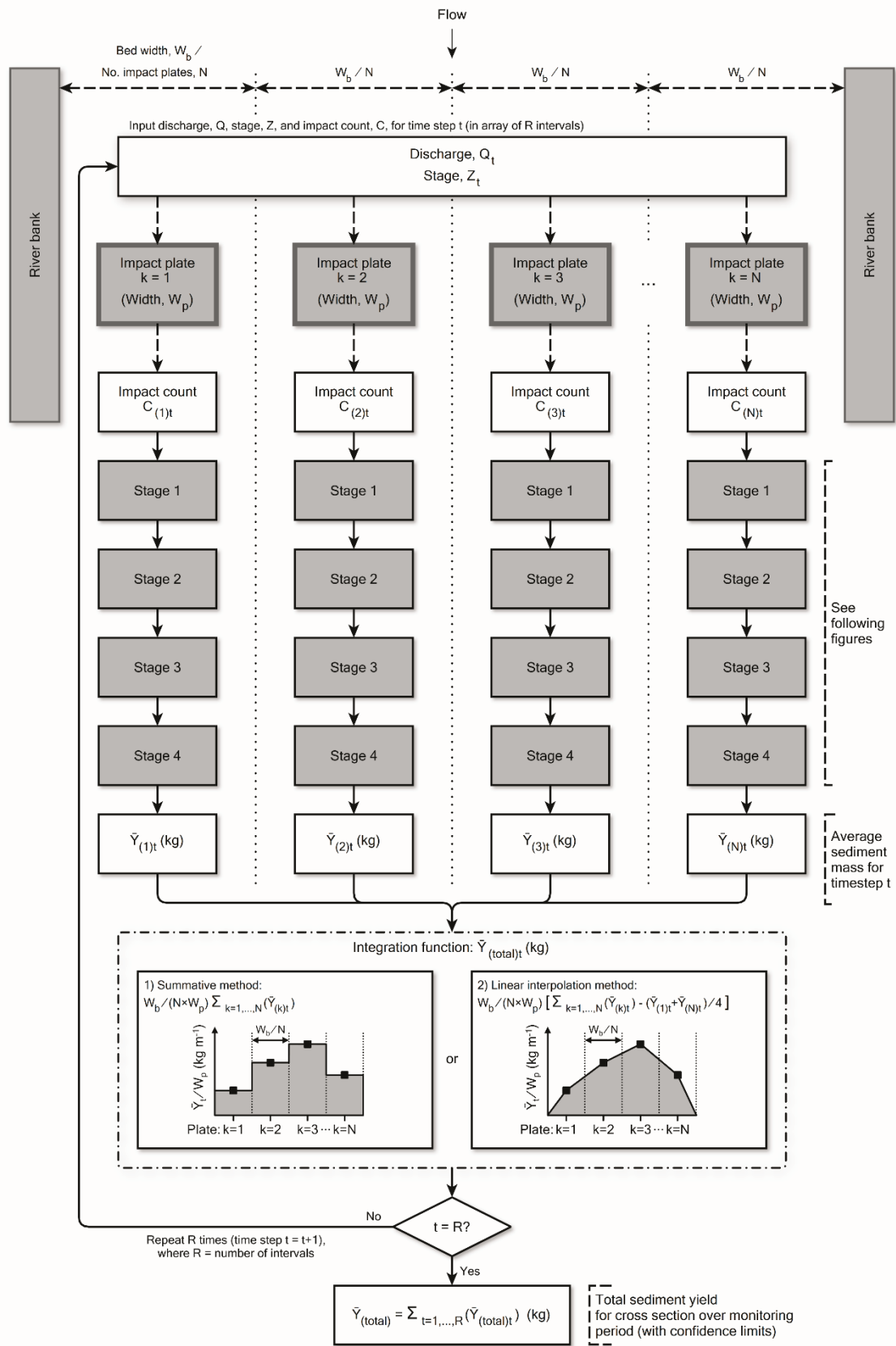


Fig. 1. Stages involved in generating probabilistic cross-sectional bedload yield using the ‘Bedload from Impact Plates’ (BLIP) model (see text for details).

Measurements made at each time step (t) in the time-series of impact counts thus comprise: the number of bedload impacts detected (count, C); water surface elevation (stage, Z), and; water surface slope (S). Discharge (Q) is not used directly in the model as the conversion of impacts to transport rates is a function of water depth, however a corresponding time series of discharge is critical for exploring relationships between derived bedload rate and flow. At ungauged sites, discharge can be simulated from the Manning equation (or alternative flow resistance equation) or if fortunate to be reasonably close to a gauging station, discharge can be extracted from the gauge record.

The working model 'Bedload from Impact Plates' (BLIP) is coded in VBA and integrates with field data tabulated in MS Excel. The model assumes a series of N impact plates are sited across the channel bed width (W_b) in the middle of equally spaced bed segments of width W_b/N . For each measurement time step (t), discharge, stage and water surface slope are updated and the model progresses through the four stages to convert impact counts ($C_{(k)t}$) to average sediment load ($\bar{Y}_{(k)t}$) in kilograms passing over the k^{th} plate (of width W_p). Here, 'average' refers to the mean of a Monte Carlo simulation, for which confidence limits can be derived. An estimate of the integrated cross-sectional sediment load over time step t ($\bar{Y}_{(\text{total})t}$) can be achieved either by assuming a constant sediment load per unit width over each plate's respective bed segment and summing the loads for each segment (summative method - Equation 1a), or through interpolation using a linear (Equation 1b) or non-linear (e.g. cubic spline) method.

Summative method:

$$\bar{Y}_{(\text{total})t} = \frac{W_b}{(N \times W_p)} \sum_{k=1}^N \bar{Y}_{(k)t} \quad (\text{kg}) \quad (1a)$$

Linear interpolation:

$$\bar{Y}_{(\text{total})t} = \frac{W_b}{(N \times W_p)} \sum_{k=1}^N \left[\bar{Y}_{(k)t} - \frac{(\bar{Y}_{(1)t} + \bar{Y}_{(N)t})}{4} \right] \quad (\text{kg}) \quad (1b)$$

Assuming a linear interpolation will only slightly reduce the load from the summative method, a function of reducing sediment transport to zero at the margins, but is recommended if only one or two plates are installed. With three or more plates the choice of lateral integration function becomes less important and the summative method can be adopted in most cases with reasonable

1 confidence in estimates. If necessary, unequal spacing of impact plates across the bed can be
2 accommodated in the model but with variants of Equations 1a and 1b. The use of multiple plates,
3 therefore, overcomes the tendency highlighted by Ferguson (2003) for width-averaging in one-
4 dimensional approaches to underestimate the true bedload transport rate for cases where hydraulic
5 conditions vary over a cross-section; such cross-sectional variability in transport is shown clearly by
6 Downs et al. (2016). $\bar{Y}_{(total)t}$ can then be converted into unit rate of bedload transport ($\text{kg s}^{-1} \text{m}^{-1}$), also
7 within confidence intervals, by dividing by the time step interval and bed width, offering the prospect
8 of evaluating the relationship between discharge and bedload transport rate that is frequently
9 derived in fluvial studies.
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11 The above procedure is iterated through the monitoring period to complete R time steps and derive
12 total cross-sectional sediment yield for that timeframe ($\bar{Y}_{(total)}$) within confidence limits. If monitoring
13 for a period of months or years (with the objective of capturing the full, or near-full, spectrum of
14 sediment transporting events), a longer-term sediment yield or, potentially, the average annual
15 sediment yield can then be derived and the distribution of sediment load with discharge class
16 explored (i.e. effective discharge analysis).
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18 *2.2 Converting bedload impacts to bedload mass in transit*

19 2.2.1 Characterizing sediment size and shape (Stage 1)

20 Analysis is initiated by deriving representative particle size and shape distributions from samples of
21 bed material retrieved from locations in close proximity to the impact plates (Figure 2). Sediment
22 size is equated to the intermediate (b-axis) diameter of particles. Both surface and bulk samples
23 (volumetric subsurface) are required as the surface sediments control the critical shear stress
24 required to disturb the bed and initiate bedload motion (Buffington and Montgomery, 1997), while
25 material in transit is generally much finer than the surface and closer in size distribution to the bed
26 substrate (Lisle, 1995). Composite size distributions from several samples are advised to
27 accommodate the spatial variability of material in the channel bed and to achieve a reasonably large
28 sample volume. Surface samples can be obtained in the field by using the standard grid-by-number
29 method (Wolman, 1954, and see Bunte and Abt, 2001), while bulk samples can be sieved in the
30 laboratory, acknowledging that coarse-grained beds require substantial sample sizes of tens of
31 kilograms or even several hundred kilograms depending on the coarseness of the bed (Bunte and Abt,
32 2001; Church et al., 1987; Ferguson and Paola 1996; Mosely and Tindale, 1985). For surface material,
33 a sample comprising 100 particles is suggested to yield an accurate median particle size whereas a
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sample of 400 or more is required to accurately portray the shape and extremes of the distribution, and is thus important here (Rice and Church, 1996).

In the model, frequency distributions are converted to phi-scale ($\phi = -\log_2(d)$, where ϕ is the negative of the logarithm of size to the base 2) classes to correct for the positive skew inherent to most sediment size distributions, and interpolated using a spline function to produce a smooth, monotonic cumulative distribution curve (Fritsch and Carlson, 1980 - monotone cubic Hermite method). Separate splines for composite surface and bulk samples are developed at this stage, with the average of the surface material median particle sizes (d_{50}) extracted to use as the reference size in the equation of incipient bedload motion (Equation 4 in Stage 4, below).

Estimates of particle volume (Stage 4) are also influenced by particle shape. As an optional (but highly recommended) step, sediment shape is analysed from measurements of a-, b- and c-axis diameters (d_a , d_b and d_c , respectively) of individual bedload particles. The model stores this dataset as 100 frequency percentiles of the ratios d_b/d_a and d_b/d_c (following the shape classification scheme of Zingg, 1935). In the absence of sediment shape data, the model defaults to assuming all particles are spherical, although recognizing this will be a source of considerable bias in most cases.

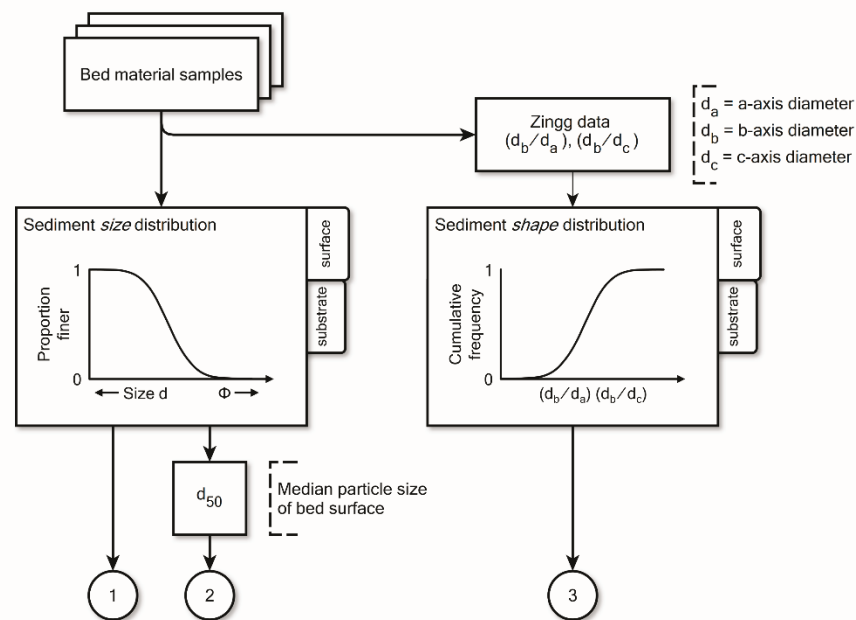


Fig. 2. Model Stage 1: Bed material characterization. Bed material particle size and shape distributions and median size of bed surface sediment are derived from composite bulk and surface samples. N.B. the connectors 1, 2 and 3 are subsequent inputs to Stage 4 (Fig. 5).

2.2.2 Estimating local water depth (Stage 2)

A representative cross-section is required, ideally surveyed at the site of the impact plates before their installation. In addition, a record of water surface elevation is needed to estimate the water depth over each plate for each instantaneous discharge (Figure 3). Depth here is used to estimate an average bed shear stress that drives the (theoretical) rate of sediment transport over and close to the impact plate and thus refers to a mean depth (D_m) within a ‘shear stress panel’ (SSP) centred on the plate. While hydraulic radius is conventionally used to estimate mean boundary shear stress for a cross-section, the SSP approach is preferred here with locally averaged depth restricting shear stress from being underestimated for plates sited close to the thalweg and overestimated for plates located in shallower water closer to the channel bank edge. This is particularly important where there is considerable variation in sediment transport rate across the section. For each plate, the default width of the shear stress panel is W_b/N - the bed width divided by the number of plates, although this can be set differently.

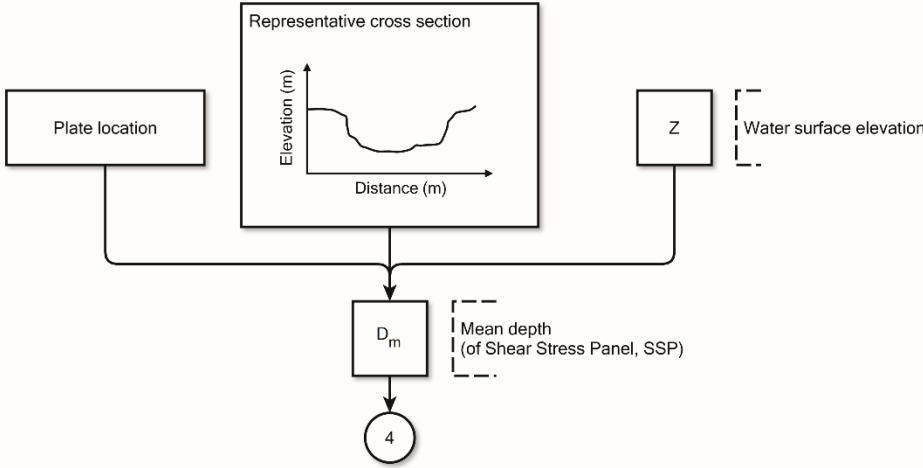


Fig. 3. Model Stage 2: Mean depth estimation over an impact plate, derived from the water surface elevation of each instantaneous discharge and the location of the plate within the cross-section. N.B. the connector 4 is a subsequent input to Stage 4 (Fig. 5).

2.2.3 Setup of model parameters (Stage 3)

A Monte Carlo routine attributes random combinations of sediment size (and therefore, mass) to each of the C recorded bedload impacts during time step t. This stage involves setting distributions for the parameters that constrain this process, using realistic bounds to the inputs rather than definitive values. The primary requirement is to set bounds to the minimum and maximum particle sizes that can be transported and detected as bedload by a given flow. This requires variables for the minimum particle size detectable by the impact plate (d_{min}), the Shields parameter (dimensionless

1 shear stress, a) and associated hiding factor (b), specific gravity (G), and the water surface slope (S) as
2 a surrogate for the energy gradient (Figure 4, and details below). During each model iteration, values
3 for each variable are selected at random from an assumed normal distribution, specifying an upper
4 and lower value for each parameter associated with the central 95% of the measured distribution (or
5 1.96 * 2 standard deviations). These bounds are used to estimate the mean and standard deviation
6 and thus the shape of the cumulative probability density function from which the Monte Carlo
7 simulation selects the values for each iteration corresponding to randomly chosen probabilities. This
8 is a conventional method for setting up the Monte Carlo process and has been applied, for example,
9 by Pitlick et al. (2009) to evaluate uncertainty in modelled sediment transport estimates.

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17 The minimum particle size detectable by the impact plate (d_{\min}) varies according to the impact plate
18 design and so requires laboratory and experimental calibration. The current design of 'Benson-type'
19 plates used here has a d_{\min} of c. 10±2 mm, established through limited flume testing (Downs et al.,
20 2016). Impacts are recorded whenever a threshold voltage of 20 mV is exceeded and a detection
21 frequency of approximately 5-7 Hz is used to restrict potential issues with over-counting rolling
22 particles (see footnote¹).

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30 The Shields parameter, hiding coefficient, specific gravity and slope relate to the critical shear stress
31 for mobilizing sediment of a particular maximum size, according to the following relationships.
32 Equation 2 is a simplified version of the original formula of Shields (1936) and Equation 3 is the
33 conventional expression for accounting for protrusion and hiding effects in mixed beds, as proposed
34 by Andrews (1983):

$$a_x = \frac{D_m S}{(G - 1) d_x} \quad (2)$$

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46 ¹ All bedload measurement techniques are subject to issues of potential bias and impact sensors and
47 geophones are no exception, with potential issues of consistency related to grain-size dependency and
48 transport-style effects that will vary with the design of the sensor. For example, experiments with the Swiss-
49 plate geophone indicate signal response is partially dependent on particle size (e.g. Rickenmann et al., 2012,
50 2014; Rickenmann and Fritschi, 2010; Rickenmann and McArdeall, 2007; Wyss et al., 2016a, 2016b, 2016c) and
51 other experiments have suggested that rolling particles may record more impacts than sliding or saltating
52 particles (Turowski and Rickenmann, 2009). Here, over-counting is limited by using a small plate to physically-
53 restrict multiple contacts and setting the detection frequency to suppress very closely timed impulses (the
54 sensor is set to approximately 5-7 Hz). Limited flume testing of the Benson-type plates used (R. Carrillo/P.
55 Downs, unpublished data; I. Benson, unpublished data) suggests variable recording efficiencies but no
56 consistent bias for grain size is yet proven to date. One advantage of using the BLIP model, wherein grain size
57 characteristics are estimated probabilistically, is that the model could readily be altered in a future revision to
58 offset a proven bias using a correction factor for grain size.

$$\frac{a_x}{a} = \left(\frac{d_x}{d_{50}}\right)^{-b} \quad (3)$$

Here, 'a' refers to a reference Shields Parameter, related to a reference grain size (considered here to be the median size of surface material, d_{50} , as specified by Buffington and Montgomery, 1997), 'a_x' is the Shields parameter related to individual particle size d_x and 'b' is the hiding factor. In Equation 2, mean depth, D_m , refers to depth for the SSP (see Stage 2).

Equation 2, alone, assumes for a given Shields parameter that shear stress (expressed by $D_m S$) is linearly proportional to sediment size (i.e. entrainment is purely size-selective). With the addition of the hiding coefficient in Equation 3, it is possible to model a range of conditions from pure size-selectivity ($b=0$) to equal mobility of all grain sizes ($b=1$), whereby protrusion of coarser than average sizes and hiding of finer than average sizes cancel out their size selectivity.

Substituting Equation 2 into 3 and rearranging to make d_x the subject yields an expression for the largest particle size that can be mobilized at this condition (renaming d_x as d_{max}), for $b < 1$:

$$d_{max} = \left[\frac{D_m S}{a(G-1)d_{50}^b} \right]^{\left(\frac{1}{1-b}\right)} \quad (4)$$

When $b=0$ in Equation 4, the expression reduces to a rearranged form of Equation 2. Critically, in the model d_{max} is capped by the largest particle size obtained from the field bulk samples. Entrainment of particles of diameters up to d_{max} requires specification of the Shields parameter (a) and hiding factor (b) in Equation 4 (see supplementary material: selection of Shields parameter and hiding factor).

In setting up the model, water surface slope can either be set to adjust with water surface elevation when stage is monitored with two or more pressure transducers (see insert in Figure 4), or held constant (recognizing that in many applications there may be difficulties in measuring slope over time). Upper and lower slope limits are entered that are assumed to correspond to the 95% confidence level.

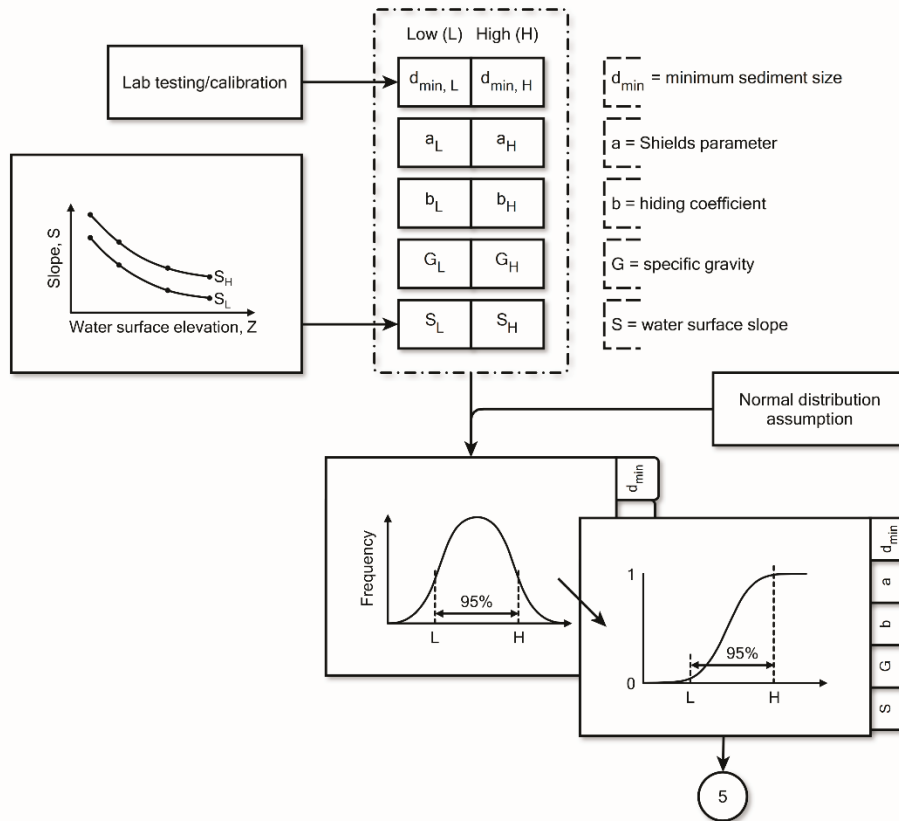


Fig. 4. Model Stage 3: Uncertainty-bounded parameterization of minimum (detectable) sediment size, Shields parameter, hiding factor, specific gravity and water surface slope. These bounds are used to estimate the corresponding cumulative probability density functions used in the Monte Carlo simulation. N.B. the connector 5 is the subsequent input of the cumulative distributions to Stage 4 (Fig. 5).

2.2.4 Monte Carlo simulation (Stage 4)

Accounting for uncertainty and investigation of sensitivity is important in developing any model (Jakeman et al., 2006) and Monte Carlo methods are the simplest means of conducting such analyses (Uusitalo et al., 2015) and highly flexible to any model code (Refsgaard et al., 2007). Here, uncertainty is integral to the modelling process and not considered as an ‘end-of-pipeline’ audit (Refsgaard et al., 2007). Monte Carlo analysis is well-suited for framing the variability of sediment transport potential in relation to discharge and has previously been applied in fluvial studies (e.g. Han et al., 2015; Little and Biedenharn, 2014; Rustomji and Wilkinson, 2008; Warrick, 2015).

In this main computational stage of the model process, sediment load is probabilistically estimated for each recorded discharge-impact count pairing (i.e. at each time interval of data) (Figure 5). The number of model iterations for each time interval can be fixed by the user, although 1000 is recommended. For each iteration (i) a random probability is generated and corresponding input

1 parameters ($d_{\min,i}$, a_i , b_i , G_i , S_i) are derived from their respective (bounded) cumulative normal
2 distributions. Investigators have the option of fixing any of these parameters by equating their low
3 and high bounding values in Figure 4, for example if specific gravity is known to be constant for a
4 particular physiographic region.
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8 Initially, with $d_{\min,i}$ constant, and $d_{\max,i}$ calculated from Equation 4, the bounds of the recorded
9 sediment size distribution (from the composite bulk sample) are reset with probabilities (proportion
10 finer) of 0 and 1 corresponding to the minimum and maximum values, respectively (inset in Figure 5).
11 As such, the revised distribution includes only those particle sizes that can be sensed by the impact
12 plate at the individual time step and discharge, within acceptable bounds of uncertainty. At each
13 iteration, multiple inner computational loops are performed to interpolate C random particle sizes
14 from the cumulative frequency distribution of sediments (where C is the number of recorded
15 bedload impacts at the current time step).
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24 For the j th particle size (of C) selected, d_j , the mass Y_j is calculated. This is achieved by assuming
25 either a random cuboid particle shape (sampling at random from the distributions of d_b/d_a and d_b/d_c
26 to estimate d_a and d_c , assuming the generated d_j corresponds to the b -axis diameter, d_b , in the above
27 ratios), or alternatively a sphere. In the former case, the simulated volume is likely to slightly
28 overestimate the true volume of a particle (as corners are somewhat rounded) but is probably more
29 accurate than assuming a sphere, particularly for more disc-shaped (oblate) or rod-shaped
30 (elongated/prolate) clasts. The summed logarithmic mass of the C particles is then stored in an array
31 and Stage 4 is repeated for the next ($i+1$) iteration. Upon completion of the i -loop (e.g. 1000
32 iterations), the geometric average mass from the array is computed, together with confidence limits
33 at a chosen significance level (default 95%). Two measures of uncertainty are employed: i)
34 confidence limits on the mean (mean response); ii) percentile confidence limits corresponding to the
35 range of mass between the tails of the distribution (single response, or 'prediction' limits), i.e. $(100-$
36 $\alpha)/2\%$ to $(100+\alpha)/2\%$ at the $\alpha\%$ confidence level. The percentile confidence limits are perhaps the
37 better representation of the variability and inherently non-deterministic nature of bedload transport.
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51 On completion of Stages 1 to 4, results are integrated from the series of plates across the section
52 (Figure 1) to derive the total cross-sectional load for the current time step (with confidence limits)
53 before proceeding to the next time step, and corresponding discharge and stage. The model
54 continues through the monitoring dataset for all recorded impact counts until a total cross-sectional
55 yield over time ($\bar{Y}_{(\text{total})}$) is obtained. Thus, a probabilistic rate of bedload transport is obtained from
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knowledge of impact counts, the bed material distribution and parameters of the flow and cross-sectional geometry.

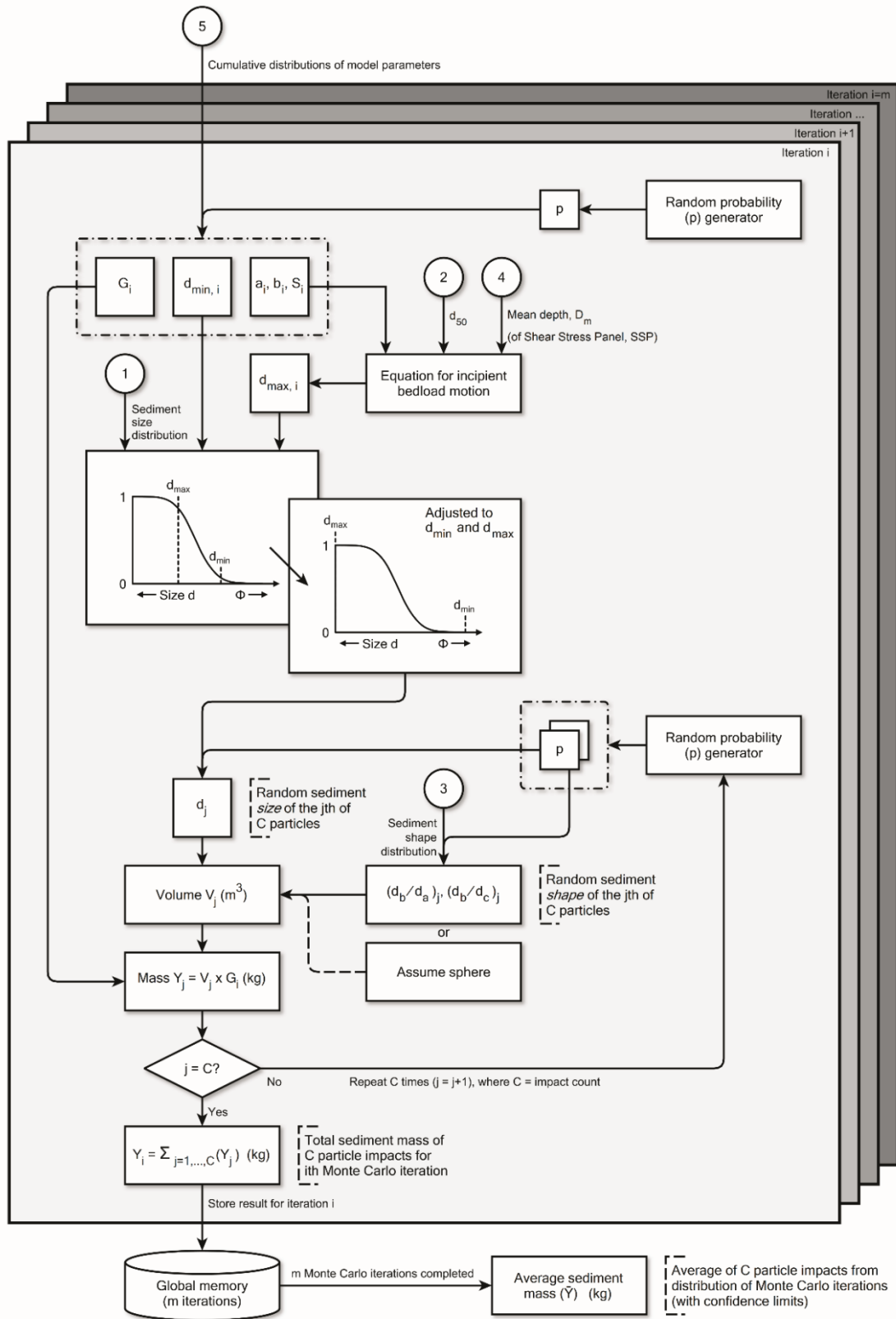


Fig. 5. Model Stage 4: Bedload mass calculation by Monte Carlo analysis. The input bedload size distribution is constrained to include only those particle sizes that can be detected and transported over the current time step, at the corresponding

1 discharge and stage. The mass of each particle detected over the time step is estimated randomly from the size distribution
2 and the total sediment mass (with confidence limits) derived iteratively through the Monte Carlo process. N.B. the
3 connectors 1-5 are inputs from Stages 1-3 (Figs. 2-4).
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6 **3. Application**

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8 The approach was applied to seismic impact plate data monitored near the mouth of the River Avon,
9 a flashy, gravel-bed river in South West England (drainage area 110 km²). The study reach is
10 characterized by an abundant supply of bed sediment fed from local sources during moderate flows
11 up to barfull but with notable sediment supply limitations during high in-bank events (Downs et al.,
12 2016). The bed material has a composite median (d_{50}) bulk grain size of 15 mm, surface d_{50} of 34 mm,
13 and water surface slopes vary typically from 0.0030 in moderate flow to 0.0025 during high overbank
14 flow. Fifteen-minute discharge data are recorded at a gauging station approximately 1 km upstream
15 of the monitoring site. Impact counts were recorded for 150 x 130 x 6 mm plates mounted on a 400
16 x 400 mm paving slab at 2.5-minute intervals. The data, aggregated to 5-minute intervals from May
17 2012 to April 2013, coincided with the wettest period on (gauged) record including twenty overbank
18 (>32 m³s⁻¹) events and the maximum gauged instantaneous peak flow (124 m³s⁻¹). The primary
19 impact plate, IP1, was installed in the mid-channel thalweg of a straight, 12.0 m active bed width
20 section of an otherwise geometrically complex alluvial meandering reach. Two further plates were
21 installed in December 2012 to provide an array of three equidistant devices. Data from IP1 indicated
22 a strong general correspondence between high flow events and high impact counts but with
23 considerable scatter between 5-minute interval discharges and impacts ($R^2 = 0.38$) which was only
24 slightly improved ($R^2 = 0.49$) when using an array of three impact plates (IP1 – IP3). The variability
25 was partly attributed to significant and consistent within-event hysteresis. Aggregating event-total
26 IP1 impacts against event-volumetric discharge (events averaged 32 hours in duration) increased
27 explanation ($R^2 = 0.74$) as intra-event and stochastic bedload factors were subsumed. Further details
28 on the catchment, reach and experiment are provided by Downs et al. (2016).
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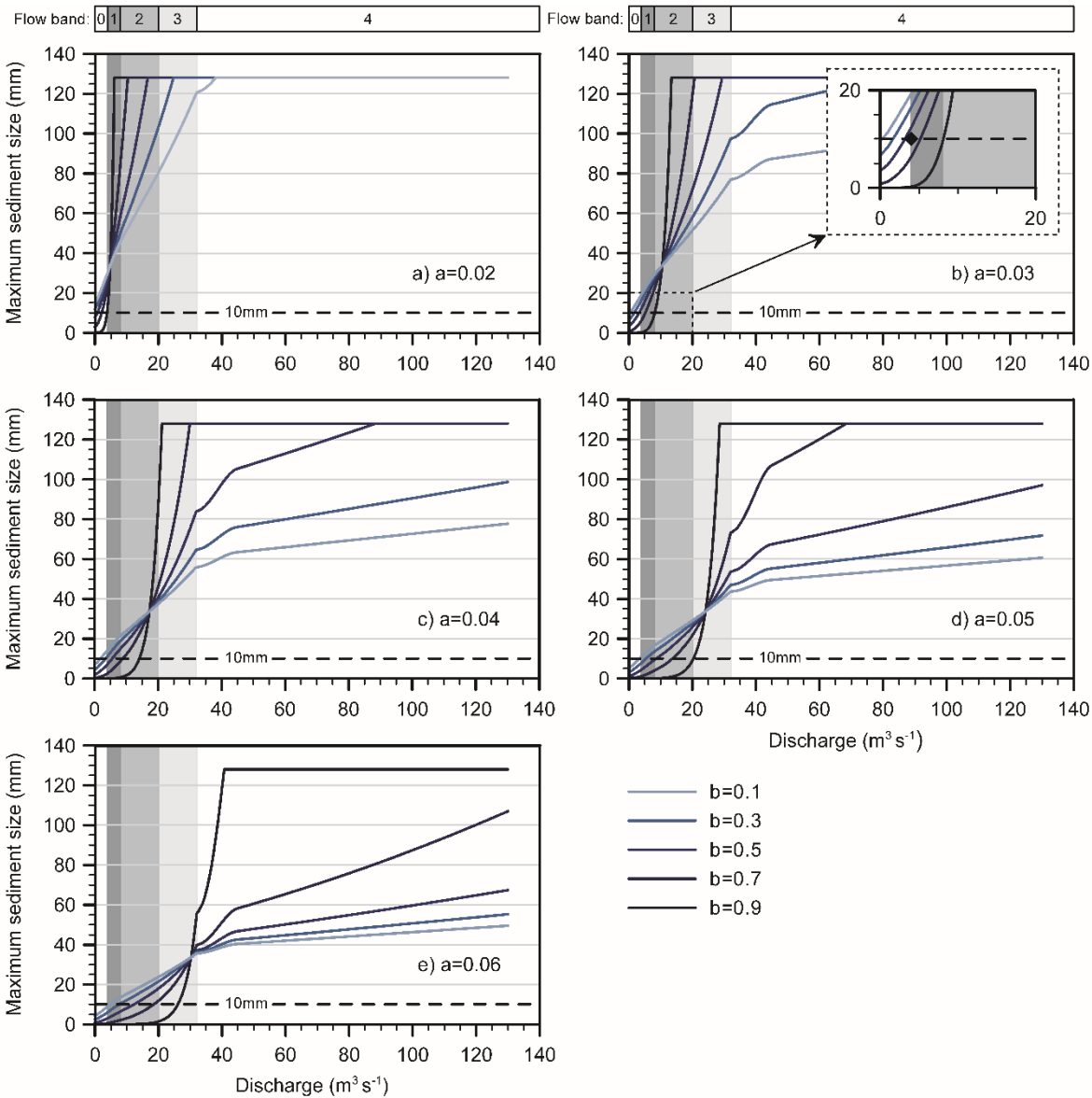
47 **4. Results**

48 *4.1 Calibration*

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50 In predicting the largest grain size in motion (Equation 4) at any individual flow it is important to
51 calibrate the method to a rational Shields parameter (a) and sediment hiding factor (b). In this
52 regard, the monitoring data provide two critical 'known' components (see Downs et al., 2016). First,
53 the minimum particle size capable of being recorded by the plate is c. 10±2 mm. On the River Avon
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1 this occurs at approximately $4 \text{ m}^3\text{s}^{-1}$ (i.e. threshold discharge of recorded impacts). Second, the
 2 majority of recorded transport occurs within a flow range of approximately $8\text{-}20 \text{ m}^3\text{s}^{-1}$.
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5 The sensitivity of Equation 4 in the model to variations in parameters 'a' and 'b' is illustrated in Figure
 6 6. By setting 'a' to 0.03 (the midrange value between 0.025 and 0.035 of Mueller et al., 2005), the
 7 resulting 'b' corresponding to a maximum entrained particle size of 10 mm (the threshold of bedload
 8 motion at $4 \text{ m}^3\text{s}^{-1}$) is approximately 0.6 (Figure 6b), invoking the midrange hiding factor suggested by
 9 Ferguson (2005).
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 57 **Fig. 6.** Calibration of the method to Shields parameter ($a=0.02$ to 0.06) and sediment hiding factor ($b=0.1$ to 0.9). The insert
 58 in (b) shows for the maximum entrained particle size of 10 mm the hiding factor is approximately 0.6 when the Shields
 59 parameter is set at 0.03. Flow bands illustrate important thresholds to characterize bedload transport activity (based on
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Downs et al., 2016) and are repeated through the sequence of Figs. 6 to 12. Band 0 ($<4 \text{ m}^3\text{s}^{-1}$) = no recorded bedload impacts. Band 1 ($4\text{-}8 \text{ m}^3\text{s}^{-1}$) = threshold of recorded impacts to point of rapidly increasing activity. Band 2 ($8\text{-}20 \text{ m}^3\text{s}^{-1}$) = peak rates and majority of recorded bedload activity, where $20 \text{ m}^3\text{s}^{-1}$ corresponds to the 'barfull' stage. Band 3 ($20\text{-}32 \text{ m}^3\text{s}^{-1}$) = significantly reduced rates of recorded bedload where $32 \text{ m}^3\text{s}^{-1}$ corresponds to the 'bankfull' stage. Band 4 ($>32 \text{ m}^3\text{s}^{-1}$) = progressive increase in recorded rates with larger overbank flows.

These settings also predict significant entrainment in the $8\text{-}20 \text{ m}^3\text{s}^{-1}$ range, known to account for most of the recorded sediment impacts. Applying much higher Shields parameter values (e.g. 0.05-0.06) requires a very low hiding factor indicative of conditions close to full selective entrainment in order to achieve 10 mm particle entrainment at $4 \text{ m}^3\text{s}^{-1}$ (Figure 6d, e). Such parameters contrast markedly with the armouring characteristic of observed field conditions and also do not predict entrainment of the coarsest fraction of the substrate material. At the other extreme, conditions indicative of (near) equal mobility (low a, high b) are incapable of predicting accurately the threshold of particle recording (Figure 6a) and imply full mobility of the bed (horizontal line capping maximum size) much earlier than indicated by the impact counts (see discussion by Downs et al., 2016). For the River Avon, at least, field and laboratory data suggest that the best calibration parameters correspond to the mid-ranges suggested by Mueller et al. (2005) and Ferguson (2005).

4.2 Predicted bedload rates

Following initial calibration, multiple model runs explored the bedload dynamics of the lower River Avon. Various data ranges were assumed to correspond to 95% confidence bands based on field data or values reported in the literature. Thus, the Shields parameter 'a' was varied between 0.025 and 0.035 (after Mueller et al., 2005), the hiding factor 'b' between 0.5 and 0.7 (after Ferguson, 2005) and specific gravity between 2.55 and 2.75 (field samples). Water surface slopes were assigned values ranging from 0.0030 at $4 \text{ m}^3\text{s}^{-1}$ to 0.0230 at $32 \text{ m}^3\text{s}^{-1}$ (bankfull stage) and 0.0250 thereafter, all ± 0.0003 based on field data from pressure transducers.

The primary impact plate (IP1), positioned centrally on the flow thalweg, recorded 27,850 'non-zero' intervals (i.e. five-minute intervals with at least one impact) from a total of nearly 92,300 intervals, implying bedload transport in approximately 30% of all five-minute intervals recorded in this wettest year of gauging records. In total there were approximately one million impacts, thus (with 1000 Monte Carlo iterations per impact) requiring approximately one billion model iterations to establish a confidence limit-bounded time-series of average impact mass. Processing time took approximately 2 hours 45 minutes on a PC with Intel quad-core i5 processor and 8 GB RAM. When performing model runs for different impact plates, and when investigating the effect of varying input parameters,

overall computation time was reduced by employing several computers. The basic time-series output of average mass from the model (Figure 7) indicates unit rates up to a maximum of nearly $0.7 \text{ kg s}^{-1} \text{ m}^{-1}$ passing across the plate/slab combination. Loads vary in general by at least two orders of magnitude explained in part by the geometric scale of the particle size distribution but also indicating the substantial role of supply limitations (see Section 5.1). Truncation of maximum transport rates can result from saturation of the impact plate data loggers (139 of 92,284 5-minute periods) and/or periods when flow exceeded that required to transport the coarsest bed sediment.

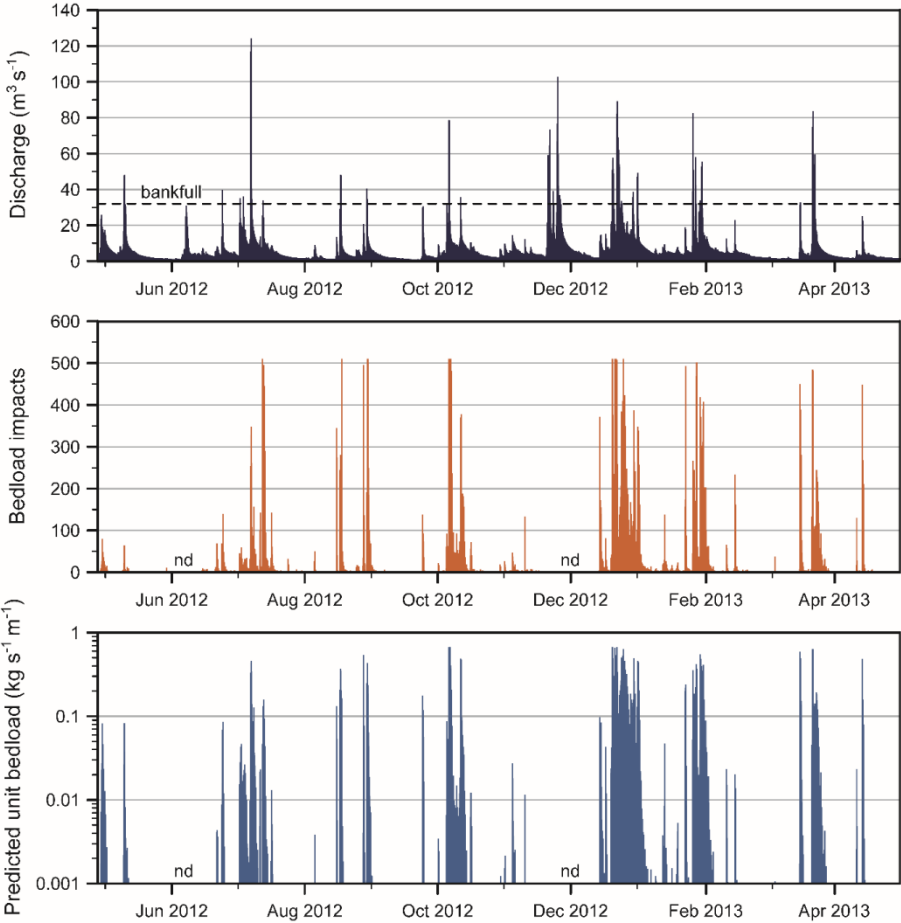


Fig. 7. Time-series of gauged discharge, impacts recorded by Impact Plate 1 and corresponding predicted (average) unit bedload rates from late April 2012 to early May 2013. Impacts are aggregated to 5-minute intervals with a maximum of 510 counts in each period. Data gaps (nd) occur where safe retrieval of the plates was impossible. The discharge record is interpolated from the series of 15-minute gauged flows.

The distributions of impacts and predicted unit rate of bed load at 5-minute intervals are illustrated in Figure 8 for the 12 month period of monitoring at plate IP1. Progressive entrainment of coarse bed material occurs after the $4 \text{ m}^3 \text{ s}^{-1}$ minimum threshold for instrument detection (Figure 8a) until

1 approximately $8 \text{ m}^3\text{s}^{-1}$. Subsequently, impacts rapidly peak (including occasional instrument
2 saturation) until decreasing again above about $20 \text{ m}^3\text{s}^{-1}$, which is morphologically the level of bankfull
3 discharge. The average number of impacts then decreases until the morphological bankfull discharge
4 of $32 \text{ m}^3\text{s}^{-1}$, beyond which impacts progressively increase with the magnitude of overbank discharge.
5 The physical explanation for these dynamics appears to relate strongly to significant within-event
6 hysteresis: analysis of 48 individual events (Downs et al., 2016) consistently demonstrated bedload
7 spikes occurring during both the rising and falling limb of the hydrograph. Such hysteresis is assumed
8 to represent supply variations related to break-up of the armour layer (rising limb) and bank failures
9 and flood-routing of non-local sediment sources (falling limb). Anticlockwise hysteresis is dominant,
10 particularly for the 20 overbank flow events, such that the peak in impacts, most clearly
11 demonstrated by the locally-weighted 95th percentile curve in Figure 8a, corresponds largely to
12 bedload transported in flows decreasing from 20 to $8 \text{ m}^3\text{s}^{-1}$, reflecting the complexity of local
13 sediment supply when monitoring sediment discharge at 5-minute intervals (Downs et al., 2016).
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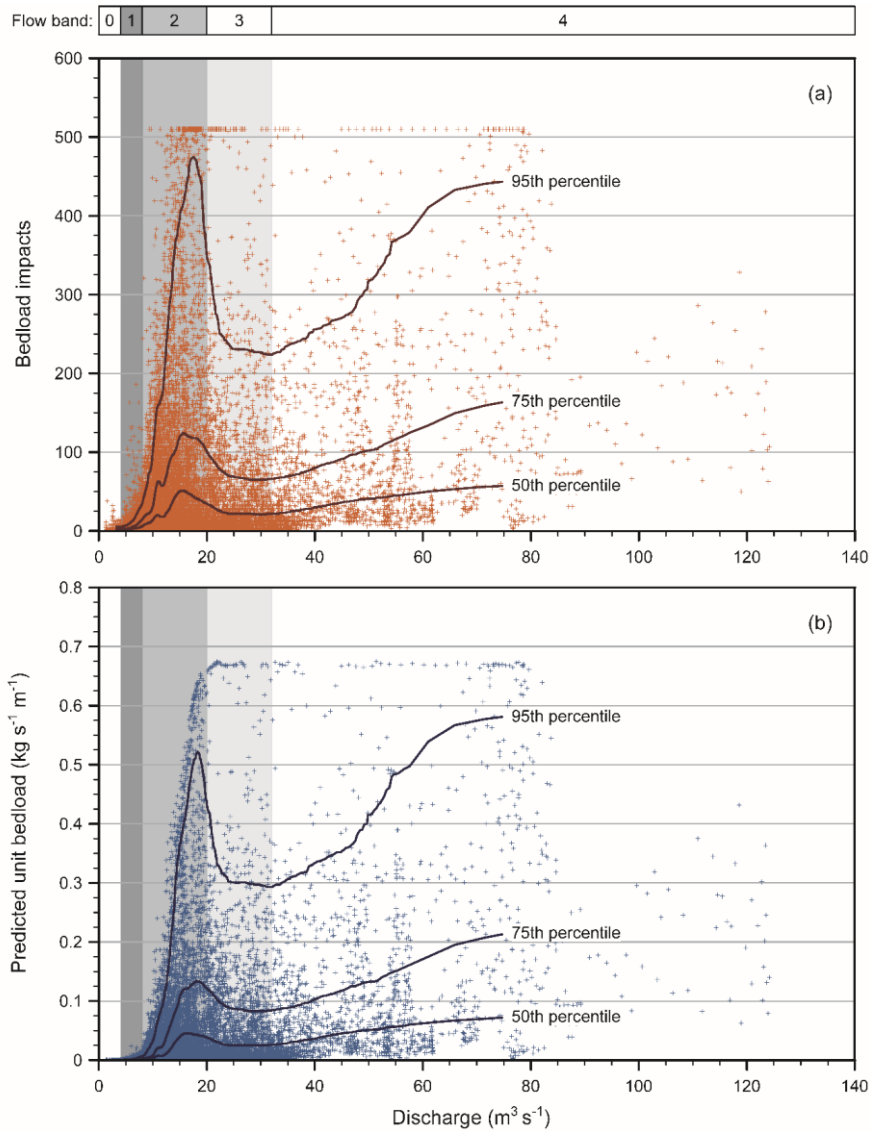


Fig. 8. Instantaneous discharge versus 5-minute impact count totals for Impact Plate 1 (a) and corresponding predicted (average) unit bedload rates (b) for 27,850 non-zero records during the 12 month study period (late April 2012 to early May 2013). Data saturation occurs in 139 (0.5%) of the total non-zero impact periods. Indicative ‘weighted’ percentiles highlight the variability with discharge (based on a moving window through 10% of the dataset and a Gaussian kernel smoothing algorithm to weight points according to proximity to the centre of the window).

A similar pattern is indicated in Figure 8b when impacts are processed through the model to produce unit bedload rates across plate IP1. Relative to the impacts in Figure 8a, appreciable sediment transport loads are offset towards slightly higher discharges, caused by multiplying the particle impacts by their volumetric mass. Also, there is a far clearer ‘leading edge’ to the predicted loads related to the monotonic increase in maximum transportable size with discharge and the averaging effect of the Monte Carlo simulation (Figure 8b). Despite the offset at low discharges, though, peak

1 rates of transport (most clearly depicted by the 95th percentile curve) occur at approximately the
2 same discharge ($18 \text{ m}^3 \text{ s}^{-1}$) as the peak rate of impacts.
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5 Records from the three plate array for mid December 2012 to early May 2013 miss the peak
6 instantaneous flow of record (7 July 2012; approximately 90-year recurrence interval) but do include
7 the wettest daily average flow of record during late December 2012. The lateral variability in
8 bedload transport (Figure 9) is evident in that at no point does saturation occur simultaneously in all
9 three plates (which would cap impacts at $510 \times 3 = 1530$ impacts). Indeed, the resulting pattern of
10 impacts generally reflects the combination of impacts at IP1 (thalweg) and IP3 (river right), with very
11 few impacts occurring over plate IP2 (river left) (see Downs et al., 2016, their Figure 12). Also, a
12 broader peak in impacts exists in Figure 9a than in Figure 8a because impacts at IP3 and IP1 are not
13 coincident. Impacts at IP3 occur primarily on the falling limb of the hydrograph; field evidence
14 suggests this reflects an increasingly diagonal flow path during flood recession that transports a large
15 volume of finer gravels over IP3. Changes to the pattern of impacts consequently alters the
16 distribution of modelled cross-sectional bedload rates (Figure 9b), with a few overbank unit peaks
17 now between $0.25 \text{ kg s}^{-1} \text{ m}^{-1}$ and $0.35 \text{ kg s}^{-1} \text{ m}^{-1}$. Comparing Figures 8b and 9b indicates that the out-
18 of-phase impacts at IP1 and IP3 result in peak cross-sectional transport rates of approximately 35 per
19 cent that of IP1 alone (i.e. based on comparison of the locally-weighted 95th percentile curves),
20 whereas the median transport rates shown by the 50th percentile curves are similar at approximately
21 $0.05 \text{ kg s}^{-1} \text{ m}^{-1}$ (acknowledging here that Figure 9b relates to a shorter monitoring period). The
22 discharges at which peak transport rates occur do not change.
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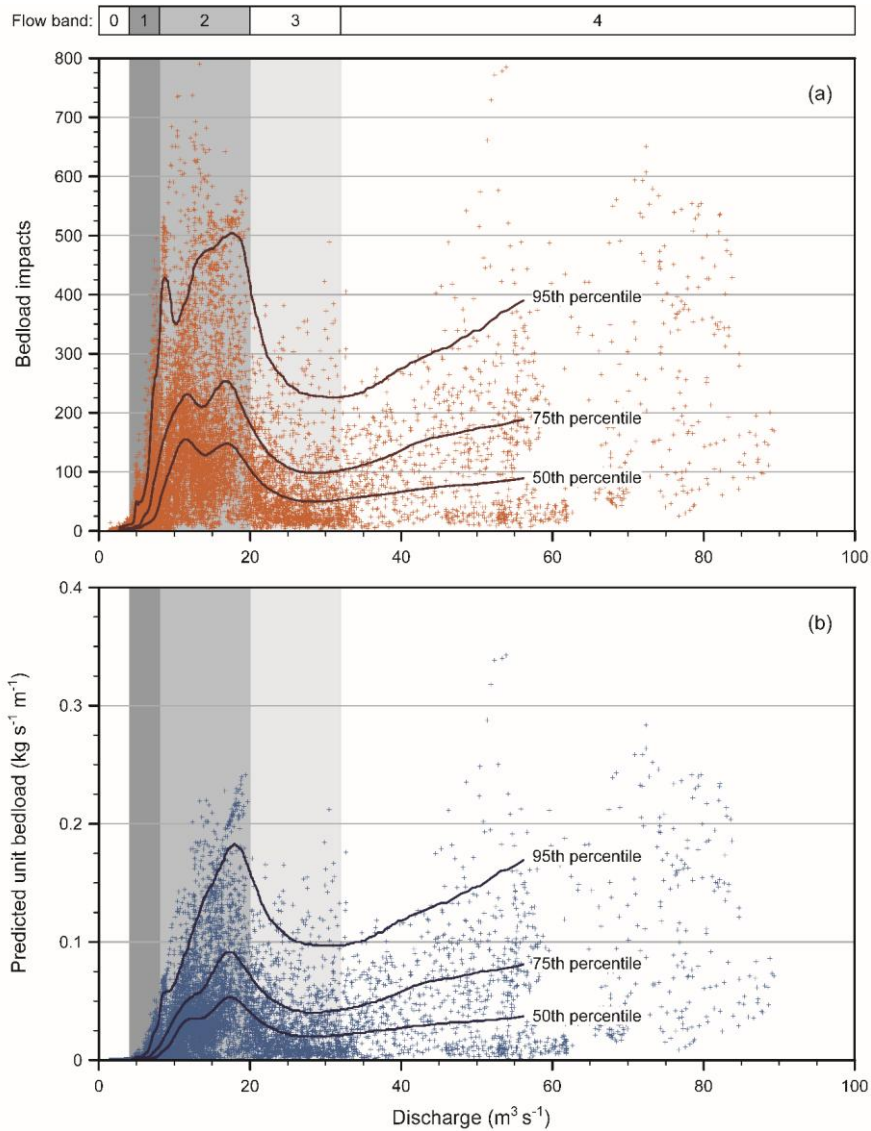


Fig. 9. Instantaneous discharge versus 5-minute impact count totals for Impact Plates 1 to 3 combined (a) and corresponding predicted (average) unit bedload rates (b) for the cross-section. Results are for 13,181 non-zero records during the 4.5 month period (mid December 2012 to early May 2013) in which all three plates were installed. Indicative weighted percentiles highlight the variability with discharge.

5. Discussion

This approach to bedload rate estimation constitutes a probabilistic estimate of transport derived directly from impact counts. It is semi-empirical and data-driven, an alternative to traditional approaches to bedload estimation that involve either direct measurements, producing a fully river-constrained estimate of bedload but requiring a lengthy calibration process, or those resulting from bedload transport formulae that can be achieved very rapidly but have very limited locational specificity. There are two particularly distinct attributes of this methodology. First, the approach is ‘autogenically moderated’ by incorporating the effect of near-instantaneous variations in sediment

1 supply derived from the high-resolution dataset obtained from impact plates (or other passive
2 measurement approaches). Second, the model enables rate estimates to be sensitivity tested and
3 statistically-bounded for uncertainty - a process that is inherently logical given the variable nature of
4 bedload transport.
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7 8 *5.1 Supply-limited bedload estimation* 9

10 We interpret the modelled transport rates not as 'potential' (see Gomez, 2006) but as veritable
11 representations of a river's bedload transport. This claim stems from an assumption that the high-
12 resolution input dataset faithfully represents the complex multiplicity of processes (the 'stochastic',
13 ontological uncertainty considered by Refsgaard et al., 2007) that results in sediment transport over
14 heterogeneous beds (and which will always defy deterministic sediment transport formulae). As
15 such, the modelled bedload rates are autogenically moderated by impact counts that are effectively
16 accommodating intra- and inter-event sediment supply variations. The model is thus intrinsically
17 unlikely to overestimate sediment loads, a known area of concern for sediment transport functions
18 in supply-limited conditions (Barry et al., 2004; Bathurst 2007; Bravo-Espinosa et al., 2003; Gomez,
19 2006; Recking, 2012; Vázquez-Tarrío and Menéndez-Duarte, 2015). As this moderation is internal to
20 the model as a verification process, the model is potentially portable to other sites and does not
21 require long periods of data 'training' to produce site specific estimates of bedload transport: a
22 considerable advantage over methods that are constrained by calibration to measured loads.
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24 Indicatively, the peak unit transport rates for the cross-section lie comfortably within the range of
25 values reported in the literature: a lower bound of 0.1-0.2 kg s⁻¹ m⁻¹ (e.g. Carling, 1989; Reid et al.,
26 1985; Vázquez-Tarrío and Menéndez-Duarte, 2015) and a guideline upper bound of 1-3 kg s⁻¹ m⁻¹ (e.g.
27 Bathurst, 2007; Habersack et al., 2008; López et al., 2014; Vericat and Batalla, 2010; Whitaker and
28 Potts, 2007). Conceivably, the modelled values here may fall below the suggestive upper bound
29 simply because the impact plates only detect particles greater than 10 mm.
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46 The accuracy of the approach instead depends on instrument factors, choice of a representative
47 cross-section and adequate characterization of the surface and bulk sediments, threshold of bedload
48 motion and water surface slope. The accuracy in estimating cross-sectional sediment loads
49 undoubtedly improves with number of plates deployed, enabling their measurements collectively to
50 reflect the bedload transport dynamics. Further, the high-resolution dataset enables the effects of
51 temporal variability in transport rates (over flow events and between years of data) to be examined,
52 while arrays of impact plates within a project reach enable the spatio-temporal variation in bedload
53 activity to be investigated (see Downs et al., 2016, for such exploration using bedload counts). In
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1 realizing these value-added prospects, the modelling approach represents a credible alternative to
2 commonly-utilized, time-invariant sediment transport equations (Recking et al., 2012) when
3 addressing river management concerns.
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6 *5.2 Bounding transport rate uncertainties*

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9 Uncertainty analysis is employed here to facilitate investigation of sensitivity associated with the
10 chosen entrainment parameters, the time-base of the rating relationship and bedload transport
11 volume when integrated over longer time periods.
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14 5.2.1 Entrainment

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17 The model is clearly sensitive to the choice of appropriate ranges of the Shields parameter and hiding
18 factor as constraints on the maximum size of sediment in transit. Thus, an important attribute of
19 model evaluation is to investigate the influence of these parameters ('a' and 'b', respectively) on
20 prediction of unit bedload transport rates. Three additional model runs were performed, estimating
21 average transport rates from the central impact plate (IP1), but varying the 'a' and 'b' values, as
22 illustrated in Figure 10 (here, Figure 10c reproduces the default condition in Figure 8b). These runs
23 included the case of complete relaxation of the threshold of bedload motion (i.e. without imposing
24 Equation 4) such that all sediment sizes were potentially available for transport (Figure 10a), a case
25 of near equal mobility with 'b' ranging between 0.7 and 0.9 (Figure 10b) and the case of near
26 selective entrainment with 'b' ranging between 0.1 and 0.3 (Figure 10d).
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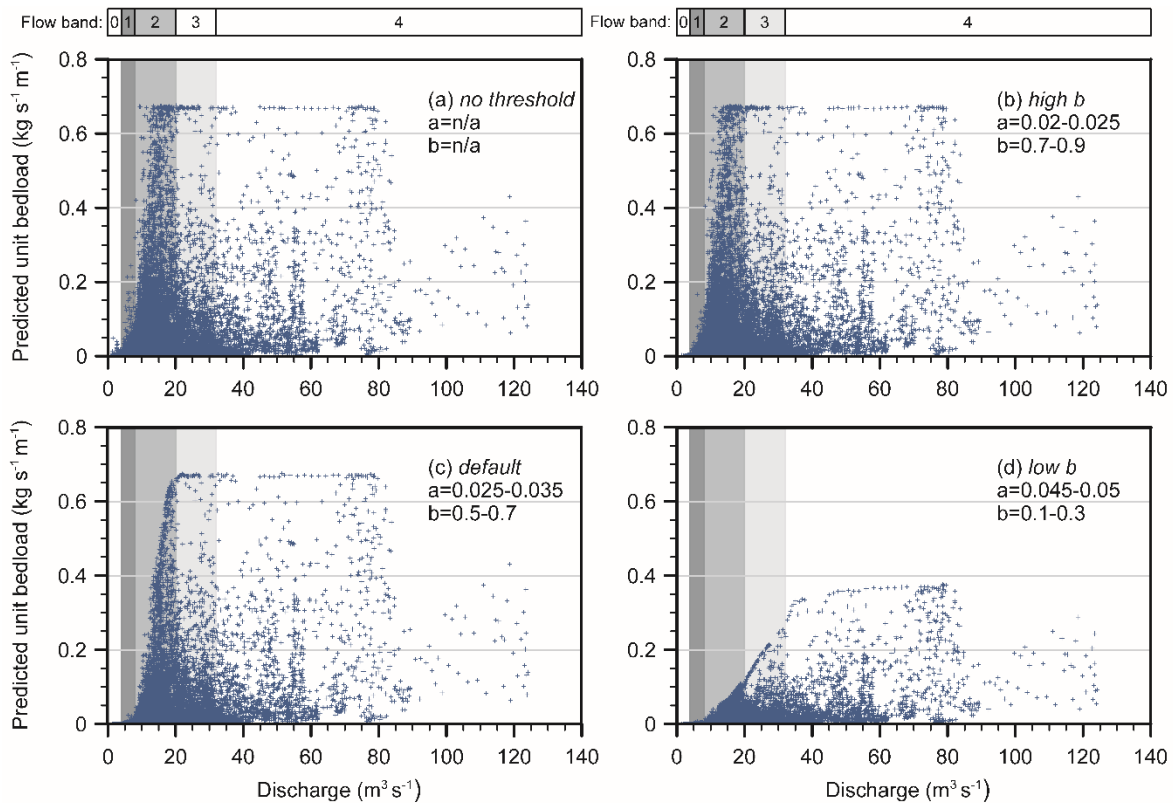


Fig. 10. Sensitivity analysis examining the influence of Shields parameter ‘a’ and hiding factor ‘b’ on the prediction of unit bedload transport rates. In (c) and (d) the Shields parameter was adjusted to maintain a minimum detection size of approximately 10 mm at the threshold of bedload motion of $4 \text{ m}^3 \text{ s}^{-1}$ (see Fig. 6).

Relaxing the threshold for bedload motion (Figure 10a, b) results in the achievement of maximum transport rates at approximately $12\text{-}14 \text{ m}^3 \text{ s}^{-1}$. Here, the mobility of smaller gravels is limited due to the hiding effects and the protrusion of larger particles is elevating their transport potential at low flows. Maximum transport rates are thus achieved at some $4\text{-}6 \text{ m}^3 \text{ s}^{-1}$ below those indicated by field data (Figure 8b, 10c), lending analytical support to observed partial bed armouring in delaying maximum rates of transport (see discussion in Downs et al., 2016), and indicating that using the Shields parameter at the lowest range of published values results in an unrealistic level of available sediment at flows only marginally above the threshold for entrainment ($4 \text{ m}^3 \text{ s}^{-1}$, here). With progressive reductions in hiding/protrusion effects due to particle interactions on the bed (i.e. moving from Figure 10a to 10d) and an associated trend toward wholly size-selective transport, the leading edge of the point distribution is flattened, offsetting full particle mobility and maximum transport rates to higher discharges. Therefore, in Figure 10d, which illustrates the extreme case of selective entrainment based on size alone, the larger particles are not mobilized at all (the maximum size transported is 70 mm, compared with particles up to 128 mm in the bulk sample). This effect nearly halves the maximum transport rate and reduces average annual bedload yield over IP1 by 73

1 per cent compared with Figure 10c. In particular, there is a significant suppression of predicted
2 transport activity at flows below bankfull discharge, a condition more akin to very stable armoured
3 beds and much lower rates of sediment supply than experienced here during the remarkably wet
4 study period.
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7 8 5.2.2 Time-base 9

10 The modelling approach also allows the indirect generation of sediment rating relationships for
11 detectable bedload using the high-resolution dataset to construct an autogenically moderated curve
12 that reflects variable sediment supply conditions rather than the supply-unlimited potential inherent
13 in sediment transport equations. It also allows an examination of the optimal time-base for rating
14 relationships in striking a balance between high data resolution and reduced data scatter (Figure 11).
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21 Ratings for plate IP1 (Figure 11a) reveal that with an increasing time-base and thus reduction in
22 sample size, the rating curve exponent increases and the coefficient decreases (up to a slight reversal
23 for the 24-hour time-base). Variance explained by the rating curves increases markedly from 5-
24 minute to 1-hour intervals, with the R^2 plateauing at nearly 80% thereafter. Comparing the ratings
25 between plate IP1 and the three plate cross-section (Figures 11a and b, respectively) suggests higher
26 explained variance for the cross-section at the 5-minute time-base, but slightly lower explained
27 variance for other periods (but note that Figure 11b relates to a shorter monitoring period).
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34 Conceivably, the plate array better captures the dynamic lateral variability of bedload transport at
35 very short time periods but, at longer time periods, the out-of-phase impacts recorded between the
36 different plates (see Downs et al., 2016) causes lower overall explanation.
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41 Increasing the time-base for the full cross-sectional bedload (Figure 11b) shows marginal
42 improvements in R^2 for rating curves capped at bankfull discharge ($32 \text{ m}^3\text{s}^{-1}$) but little improvement is
43 evident beyond the 1-hour time-base for rating curves capped at barfull discharge ($20 \text{ m}^3\text{s}^{-1}$).
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47 Nonetheless, previous work by Downs et al. (2016) revealed an R^2 of 0.45 (with discharge capped at
48 $20 \text{ m}^3\text{s}^{-1}$) based on impacts alone and thus the suite of unit transport rate exponents between 0.73
49 and 0.77 in Figure 11b appears to confirm an improvement in the predictive power of the rating
50 relationship when bedload impacts are converted to average rates of unit bedload transport using
51 the model.
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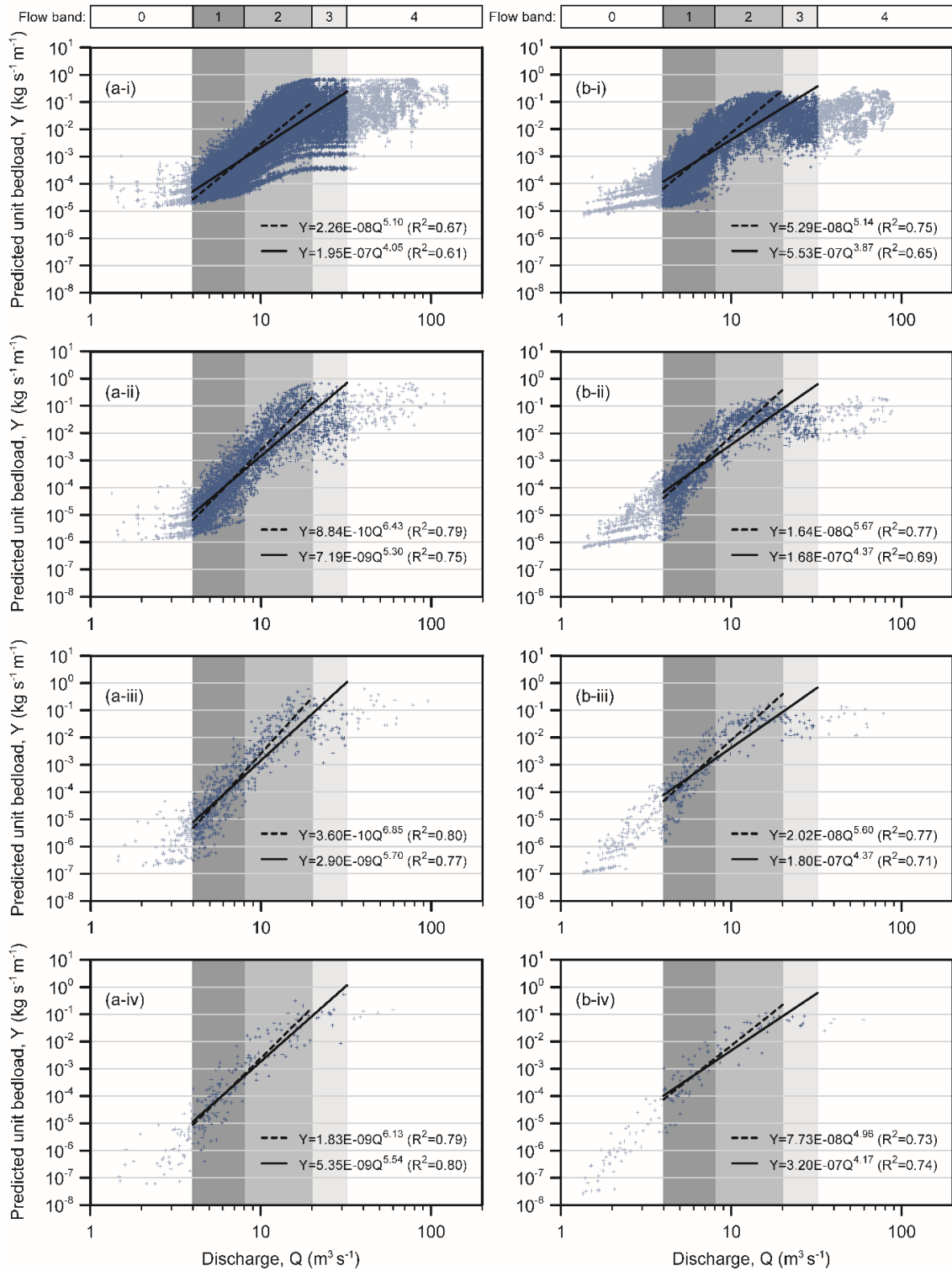


Fig. 11. Predicated (average) unit bedload rating relationships from 5-minute flow periods (i) compared to those derived by averaging discharges and aggregating impacts over 1-hour (ii), 6-hour (iii) and 24-hour (iv) periods, and for rating relationships constrained to the bankfull ($32 \text{ m}^3 \text{ s}^{-1}$ - solid line) and the barfull discharges ($20 \text{ m}^3 \text{ s}^{-1}$ - dashed line). The ratings for impact plate 1 (a) over the 12 month study period (late April 2012 to early May 2013) are set against those for the cross-section (b) over the 4.5 month period (mid December 2012 to early May 2013) with impact plates 1 to 3 installed.

1 Overall, the rating relationships capped at barfull discharge appear to be stronger than for those
2 capped at bankfull discharge, attributed to the decline in peak bedload activity between 20 and 32
3 m^3s^{-1} (flow band 3 in Figures 8b and 9b). The rating exponents lie toward the upper range of 2-4
4 based on Helley-Smith sampling and at the lower range of 5-20 for rates derived from trap sampling
5 (Bunte et al., 2014; Bunte and Abt, 2003). Using a large aperture sampler in a stream with many
6 similarities to the Avon, the exponent range of 2.4-6.7 derived by Whitaker and Potts (2007)
7 encompasses the values in Figure 11, giving further reassurances on average rating gradient. Very
8 provisionally for the River Avon, the results may also suggest that rating curves averaged over a 6-
9 hour time period provide the computationally most effective means of interpreting the coarse
10 bedload flux for management purposes, while confirming that, scientifically, such averages conceal
11 the significant variability inherent to sediment transport dynamics.
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21 5.2.3 Transport volume

22 The Monte Carlo basis for the approach enables uncertainty-bounded 'average' bedload yields to be
23 derived using a magnitude-frequency analysis (details in Downs et al., 2016). Figure 12a illustrates
24 the distribution of bedload corresponding to particles detected by plate IP1 for each $1 \text{ m}^3\text{s}^{-1}$ flow
25 interval based on the full one year monitoring period (with default run criteria described above). A
26 clearly defined effective discharge of $15\text{-}16 \text{ m}^3\text{s}^{-1}$ is evident, which compares with a range of $13\text{-}15$
27 m^3s^{-1} (and slightly less well defined peak) for the impact data alone (Downs et al., 2016). The offset
28 to a slightly higher discharge is attributed to the conversion to volume and capping of maximum size
29 of particles in transit within flow band 2 ($8\text{-}20 \text{ m}^3\text{s}^{-1}$). Although Figure 12a reveals a clearly defined
30 peak load, the 75% and 95% prediction limits reveal considerable uncertainty with the $15\text{-}16 \text{ m}^3\text{s}^{-1}$
31 peak bedload increment varying between approximately 6.7 and 11.4 t at the 95% level. The cross-
32 sectional sediment load over the 4.5 month winter monitoring period reveals a much broader
33 bedload peak (Figure 12b) with discharges in the range $11\text{-}17 \text{ m}^3\text{s}^{-1}$, corresponding to the trend in
34 recorded impacts (Figure 9a) and reflecting the lateral movement of the primary flow path over an
35 individual hydrograph and resultant out-of-phase impacts between plates IP1 and IP3 (detailed by
36 Downs et al., 2016). The total (>10 mm) cross-sectional load over the 4.5 month period averages
37 1455 t in this extremely wet period but is uncertainty-bounded to a range of 1273-1686 t (inter-
38 quartile range) and 981-2218 t (95% limits). The bedload across flow band 2 ($8\text{-}20 \text{ m}^3\text{s}^{-1}$) comprises
39 almost two thirds (64%) of the total yield but with approximately ± 10 per cent variation within the
40 inter-quartile range. The availability of such uncertainty-bounded and autogenically-moderated
41 estimates, when averaged over longer time periods, has potentially significant value in river
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1 management and restoration planning, not least as the basis for estimating future changes in
2 bedload fluxes.
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5 As an essential component of the modelling protocol, sensitivity testing is encouraged to reveal how
6 results might be affected by issues of data quality and to gain an understanding of potential sources
7 of uncertainty. This can be demonstrated for the River Avon case study with two examples. First, by
8 fixing slope to the average gradient of the bed (and thus unable to decrease with rising stage), it was
9 found that while there was little impact to rates at discharges above barfull, cross-sectional bedload
10 rates below this level were higher (with peak rates increased from 0.24 to 0.32 kg s⁻¹ m⁻¹), the
11 effective discharge was more clearly defined (but unchanged in value) and the average cross-
12 sectional bedload yield over the 4.5 month monitoring period increased from 1455 to 1831 t. Second,
13 by assuming all detected bedload particles are spherical, cross-sectional bedload rates were reduced
14 for all discharges (reducing the peak rates below barfull from 0.24 to 0.16 kg s⁻¹ m⁻¹), the effective
15 discharge was less well defined (but unchanged in value) and the average cross-sectional bedload
16 yield over the monitoring period decreased from 1455 to 1000 t; here, spherical particles (sized on
17 the intermediate axis) are clearly underestimating the volume of more disc- and rod-shaped gravels
18 typically found in the River Avon.
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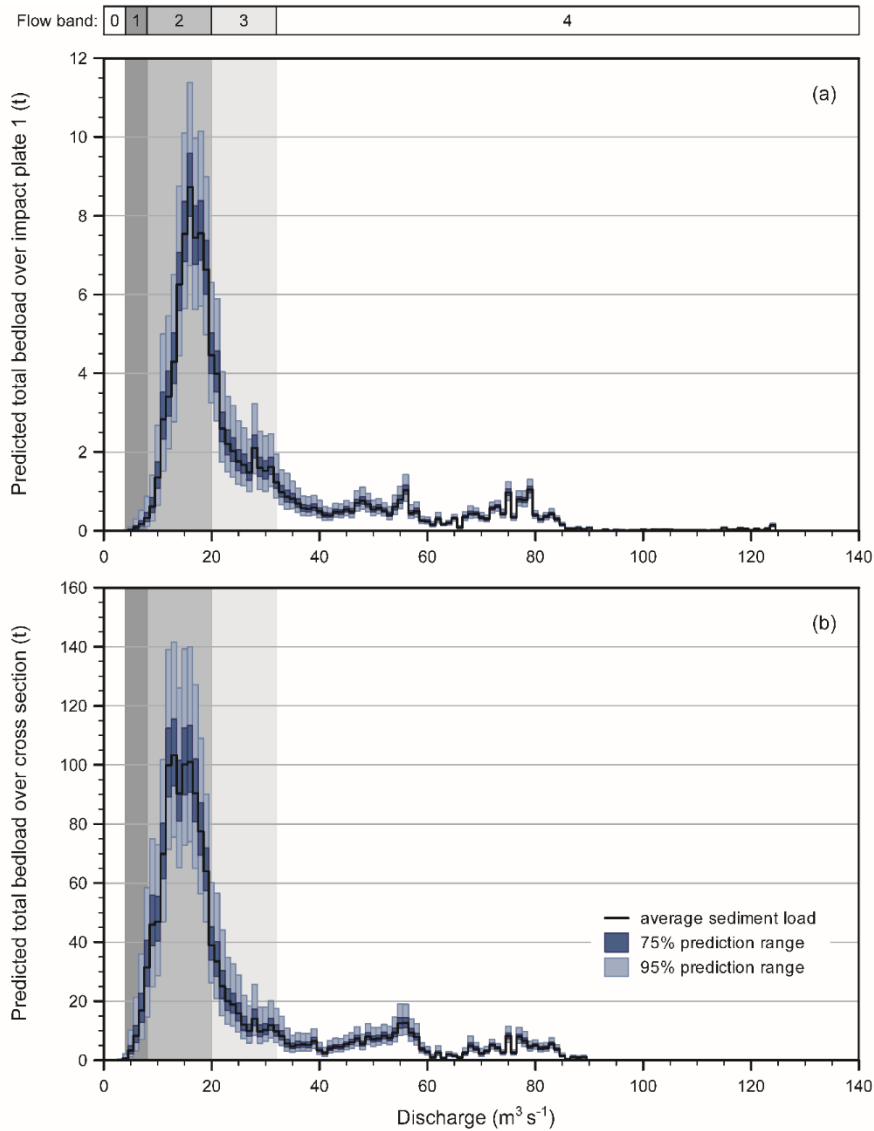


Fig. 12. Magnitude-frequency analysis of predicted total (>10 mm) bedload at $1 \text{ m}^3 \text{ s}^{-1}$ increments for Impact Plate 1 (a) during the 12 month study period, illustrating an effective discharge equivalent measure for coarse bedload transport of $15\text{-}16 \text{ m}^3 \text{ s}^{-1}$, and for the cross-section (b) during the 4.5 month period with impact plates 1 to 3 installed, illustrating a broad bedload peak of $11\text{-}17 \text{ m}^3 \text{ s}^{-1}$.

6. Conclusion

Improvements to the prediction of bedload transport rates have been suggested to hinge on technological innovation (Ashmore and Rennie, 2012) and approaches that strike a balance between accuracy and practicability (Wilcock, 2001). Passive sensing devices offer considerable potential for generating high-resolution data over extended time periods to facilitate detailed insights into bedload dynamics not achievable with direct measurement methods or sediment transport formulae. However, despite a burgeoning suite of investigations exploring the accuracy and output dynamics of such sensors, converting the raw time-series of impacts into bedload transport rates and volumes

continues to remain a challenge and a critical research impetus if the devices are to be deployed routinely for wide-ranging applications.

The method developed here represents a complementary ‘class’ of bedload estimation to those currently in existence: it is semi-empirical and minimizes the *a priori* assumptions of the model by ‘letting the data do the work’ in producing bedload estimates. The overarching assumption of the model is that in gravel-bedded rivers impacts detected by a seismic plate are generated by a probabilistic array of *possible* particle sizes in transit, derived from the distribution of bed material grain sizes but constrained by a minimum size detectable by the equipment and a maximum size at the threshold for bedload motion. The approach does not rest on direct calibration with measured sediment loads because it is empirically-attuned by impact count data and thus autogenically-moderated for sediment supply. This produces a supply-limited rather than transport-limited prediction of bedload transport rates, which is far less susceptible to overprediction than sediment transport formulae (Gomez, 2006). The approach is probabilistic in accommodating the inherently stochastic nature of bedload transport and uncertainty-bounded in its accounting for (largely field constrained) variability in model parameterization.

The approach is inherently sensitive to the particle size distribution that represents the domain of detectable sizes. The model is also sensitive to the recording device and its constraints (Downs et al., 2016) and is predicated on the assumption that plate performance is consistent between particle sizes and across different modes of bedload transport (Rickenmann and Fritschi, 2010; Rickenmann and McArdell, 2007; Turowski and Rickenmann, 2009); performance testing of the Benson-type impact plates utilized here is on-going (Benson, pers. comm., 2016). As the model is developed directly from impact count data, we can be fairly confident about the dynamics of, and *relative* rates of, detectable bedload transport indicated by the method. Further investigation of the accordance of (uncertainty-bound) bedload estimates with direct field measurements is recommended under a range of different environmental scenarios and field protocols and to better understand the ‘epistemic’ uncertainty (see Refsgaard et al., 2007) associated with equipment limitations and model structure/parameterization, but cognizant that such measurements themselves are very error-prone and reveal marked variation between methods (Bunte et al., 2004; Gray 2010a, b; Vericat et al., 2006).

There is considerable potential for the approach to be of benefit to river management projects, for instance in elucidating the geomorphological effectiveness of flows to inform stable channel design (see Soar and Thorne, 2011), and in baseline monitoring of project performance (see Downs et al.,

2011). The model facilitates sensitivity testing of its input parameters, understanding about event-scale bedload dynamics, and longer timeframe installations will provide the basis for understanding bedload sensitivity to hydrological conditions between water years and thus climate change impacts on sediment load, flood risk and aquatic habitats. In demonstrating its proof of concept, this new approach affords a practical and robust method of achieving uncertainty-bound, indicative measures of bedload transport variability and in so doing it contributes to the integration of big data bedload monitoring into a progressive hydrogeomorphic research agenda and the sustainable management of gravel-bed rivers.

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