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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.

Software availability

Name of model: Bedload from Impact Plates (BLIP)
Developers: Philip Soar, University of Portsmouth, U.K. (philip.soar@port.ac.uk); Peter Downs, Plymouth University, U.K. (peter.downs@plymouth.ac.uk)
Program language: Visual Basic for Applications (VBA)
Hardware required: Microsoft Windows PC
Software required: Microsoft Excel
Availability: A working version has been developed as a VBA-coded model in Microsoft Excel and is proposed for general release as a software package in the near future. For the current version, please contact the authors

1. Introduction

Fluvial system sciences have seen the enthusiastic uptake of 'big data' over recent decades, with high-resolution, passively-sensed data sets becoming integral both to spatial analyses of terrain and to time-series investigations of water quality and suspended sediment transport. One outstanding challenge is the adequate characterization and prediction of bedload, with technological innovation considered the catalyst to developing detailed insights into transport processes (Ashmore and Rennie, 2012) that are critical to better understand physical habitat dynamics, underpin sustainable flood risk management and ensure the resilience of river restoration schemes.

Active, direct measurement of bedload using samplers or traps (Bunte et al., 2004, 2008) are costly in terms of labour (portable samplers) and/or infrastructure (permanent installations), logistically challenging to achieve with acceptable accuracy over geomorphologically-relevant time periods (Ryan and Porth, 1999; Sterling and Church, 2002; Vericat et al., 2006) and often involve hazardous working conditions. Alternatively, transport rates are estimated using empirical formulae, although such methods are characterized by marked differences in performance (e.g. Barry et al., 2004; Gomez and Church, 1989; Martin and Ham, 2005; Wilcock, 2001) arising from the computational simplifications required to represent the complex physics of bedload movement in a practicable manner. In particular, these numerical expressions cannot account for the inherently stochastic nature of bedload transport (see Recking et al., 2012) and are incapable of capturing intra- and inter-event variations in supply (Gomez, 2006). Sediment routing models and mobile boundary simulations (Bruner and

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Gibson, 2005; Cui et al., 2011; Papanicolaou et al., 2008) offer the potential to overcome some of these issues but are currently extremely difficult to set up and parameterize (except by an experienced modeller) and are rarely validated in practice (Thorne et al., 2011; Wallerstein et al., 2006). Recognizing the difficulties and limitations of direct measurement and unreliability of sediment transport equations, Wilcock (2001) appealed for new methods to be sought that strike a balance between accuracy and practicability.

Passive approaches to bedload monitoring are centred on recording the passage of bedload using an acoustic or seismic sensor that records an electrical wave (hydrophones, geophones, respectively) or simply an impulse (impact plates) as particles pass or strike the sensor. Modern data loggers provide a means of obtaining high-resolution spatial and temporal measurement of coarse bedload transport intensity over time periods of geomorphological relevance (Gray et al., 2010a). Such devices are relatively low cost (e.g. USD 900 per plate for those used here), portable and non-intrusive and, as a passive technique, offer far safer data collection. Depending on the sensor used, the minimum particle size recorded is usually in the range of 4–30 mm (Gray et al., 2010b; Rickenmann et al., 2012). There is a rapidly growing body of literature associated with these devices (summaries in Gray et al., 2010a, b; Rickenmann, 2017; Rickenmann et al., 2014), and an evolving understanding of their performance characteristics in relation to experimental set-up, grain-size dependent and transport-style effects (Beylich and Laute, 2014; Gray et al., 2010b; Rickenmann and Fritschi, 2010; Rickenmann and McArdell, 2007, 2008; Rickenmann et al., 2012, 2014; Tsakiris et al., 2014; Turowski and Rickenmann, 2009; Wyss et al., 2016a, 2016b, 2016c) and the dynamics of sediment supply during individual events (Downs et al., 2016).

There is now growing evidence for a robust correlation between summed impact counts and total bedload mass over event-scale and longer time periods (Beylich and Laute, 2014; Rickenmann et al., 2012, 2014). However, a significant question concerns the calibration of passive devices to convert data collected on bedload transport *intensity* into estimates of bedload transport *rates* (see review by Rickenmann, 2017). Research focussed initially on direct calibration of either summed impulse counts or a summary measure of acoustic signal against a measured sediment load to produce a rating curve but has more recently centred on extracting grain size information from the acoustic signal (Barrière et al., 2015; Bogen and Møen, 2003; Møen et al., 2010; Rickenmann et al., 2014; Wyss et al., 2014, 2016b) and correlating the signal strength to bedload transport rate as a function of sediment grain size (Wyss et al., 2016a). While acoustic fingerprinting techniques offer considerable promise for reconstructing continuous rates of bedload transport by size fraction, the approach is subject to time-consuming direct measurements (Turowski and Rickenmann, 2011), may require a lengthy refinement period and cannot facilitate rate estimates to be derived in the vast majority of rivers where bedload monitoring is not undertaken routinely. As such, environmental managers cannot as yet benefit from the 'revolutionary' potential afforded to bedload understanding from passive sensors (Gray et al., 2010b).

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

2. Model development

2.1. Model overview

The overarching assumption of the model is that in gravel-bed streams with variable sizes of bed material, impacts detected by a seismic plate are generated by a probabilistic array of 'possible' particle sizes in transit that reflects a proportion of the distribution of bed material grain sizes, constrained by a minimum size detectable by the equipment and a maximum size at the threshold for bedload motion.

The process for generating cross-sectional sediment rates from impact plate count data consists of four principal stages, illustrated in Fig. 1 and discussed below. Experimentally, the approach requires deployment of a cross-sectional array of impact plates in conjunction with one or more pressure transducers. As depth of flow is a critical parameter in the model, deployment of a pressure transducer as a component of the experimental set-up is essential and, therefore, it is recommended investigators consider strongly the deployment of two or more pressure transducers to facilitate logging of water surface slope. While a single impact plate can be used to explore temporal patterns of bedload occurring at or near the thalweg, sediment paths have been found to shift markedly with discharge (Downs et al., 2016). Therefore, resources permitting, multiple plate deployment across a section is recommended to better represent the natural spatio-temporal variation in sediment transport intensity over the channel bed and should improve accuracy. The discernible improvement in accuracy of empirical methods of transport rate estimation with increasing number of samples taken, and beneficial performance over sediment transport formulae, is illustrated for gravel-bed rivers by Wilcock (2001).

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 kth 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 (kilograms) over time step t ($\bar{Y}_{(total)t}$) 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.