Geomorphology 308 (2018) 161–174

Contents lists available at ScienceDirect

Geomorphology

journal homepage: www.elsevier.com/locate/geomorph

Delineation of gravel-bed clusters via factorial kriging

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ARTICLE INFO

Article history:
Received 22 November 2017
Received in revised form 3 February 2018
Accepted 5 February 2018
Available online 16 February 2018

Keywords:
Gravel-bed rivers
Clusters
Delineation
Factorial kriging
Digital elevation model (DEM)

ABSTRACT

Gravel-bed clusters are the most prevalent microforms that affect local flows and sediment transport. A growing consensus is that the practice of cluster delineation should be based primarily on bed topography rather than grain sizes. Here we present a novel approach for cluster delineation using patch-scale high-resolution digital elevation models (DEMs). We use a geostatistical interpolation method, i.e., factorial kriging, to decompose the short- and long-range (grain- and microform-scale) DEMs. The required parameters are determined directly from the scales of the nested variograms. The short-range DEM exhibits a flat bed topography, yet individual grains are sharply outlined, making the short-range DEM a useful aid for grain segmentation. The long-range DEM exhibits a smoother topography than the original full DEM, yet groupings of particles emerge as small-scale bedforms, making the contour percentile levels of the long-range DEM a useful tool for cluster identification. Individual clusters are delineated using the segmented grains and identified clusters via a range of contour percentile levels. Our results reveal that the density and total area of delineated clusters decrease with increasing contour percentile level, while the mean grain size of clusters and average size of anchor clast (i.e., the largest particle in a cluster) increase with the contour percentile level. These results support the interpretation that larger particles group as clusters and protrude higher above the bed than other smaller grains. A striking feature of the delineated clusters is that anchor clasts are invariably greater than the D_{90} of the grain sizes even though a threshold anchor size was not adopted herein. The average areal fractal dimensions (Hausdorff-Besicovich dimensions of the projected areas) of individual clusters, however, demonstrate that clusters delineated with different contour percentile levels exhibit similar planform morphologies. Comparisons with a compilation of existing field data show consistency with the cluster properties documented in a wide variety of settings. This study thus points toward a promising, alternative DEM-based approach to characterizing sediment structures in gravel-bed rivers.

1. Introduction

Gravel-bed rivers exhibit a wide variety of bedforms ranging in scale from microforms (e.g., imbrication, cluster), mesoforms (e.g., transverse rib, stone cell, step-pool, pool-riffle), macroforms (e.g., bar), to megaforms (e.g., floodplain, terraces) (Hassan et al., 2008). Among these, clusters are the most prevalent microforms, observed to cover 10–50% of the bed surface (Wittenberg, 2002; Papanicolaou et al., 2012). Clusters have drawn much attention from river scientists and engineers due to their impacts on: (1) local turbulence structures (Buffin-Bélanger and Roy, 1998; Lawless and Robert, 2001a; Lacey and Roy, 2007; Strom et al., 2007; Hardy et al., 2009; Curran and Tan, 2014a; Rice et al., 2014), (2) flow resistance (Hassan and Reid, 1990; Clifford et al., 1992; Lawless and Robert, 2001b; Smart et al., 2002), (3) sediment transport (Brayshaw et al., 1983; Brayshaw, 1984, 1985; Billi, 1988; Paola and Seal, 1995; Hassan and Church, 2000; Strom et al., 2004), and (4) bed stability (Reid et al., 1992; Wittenberg and Newson, 2005; Oldmeadow and Church, 2006; Mao, 2012). Besides, clusters also provide insights into the flow and sediment supply conditions of their formation (Papanicolaou et al., 2003; Wittenberg and Newson, 2005; Strom and Papanicolaou, 2009; Mao et al., 2011).

The term "clusters" was traditionally used by many researchers to refer to the so-called "pebble clusters", which normally comprise three components: obstacle, stoss, and wake (Brayshaw, 1984). The obstacle is a large clast providing an anchor for cluster formation; upstream of the obstacle is an accumulation of smaller particles that constitute the stoss zone; downstream of the obstacle is a wake zone characterized by deposition of fine material. More recently, clusters have been perceived more broadly to refer to "*discrete, organized groupings of larger particles that protrude above the local mean bed level*" (Strom and Papanicolaou, 2008; Curran and Tan, 2014a). Using this broad working definition, researchers have identified cluster microforms with a variety of shapes, such as rhombic clusters, complex

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https://doi.org/10.1016/j.geomorph.2018.02.013

clusters, line clusters, comet clusters, ring clusters, heap clusters, triangle clusters, and diamond clusters (e.g., de Jong and Ergenzinger, 1995; Wittenberg, 2002; Strom and Papanicolaou, 2008; Hendrick et al., 2010). Papanicolaou et al. (2012) used the areal fractal (Hausdorff-Besicovich) dimensions of the projected areas to discriminate the planform morphologies of the clusters.

Although the broad definition of clusters has opened up new avenues for recent progress in cluster research, to date identification of clusters still relies largely on visual inspection (e.g., Entwistle et al. 2008; Strom and Papanicolaou, 2008; Hendrick et al., 2010; L'Amoreaux and Gibson, 2013). A set of predetermined criteria for cluster identification are normally adopted in these studies. A typical example is given here: (1) A cluster consists of a minimum number of (e.g., 3 or 4) abutting or imbricated particles; (2) at least one of these particles is an anchor clast greater than the specified grain size (e.g., D_{50} or D_{84}) of the bed surface; (3) a cluster protrudes above the surrounding bed surface (e.g., Oldmeadow and Church, 2006; Hendrick et al., 2010). As can be seen, specifying a minimum number of constituent particles and a threshold grain size for anchor clast is somewhat arbitrary and based on the rule of thumb. The subjectivity of the "gestalt sampling" could produce operational bias. In particular, researchers have found it extremely difficult to visually recognize bed structures whose dimensions are of the same order of magnitude as their spacing and the grain sizes of their constituent particles (Entwistle et al. 2008; L'Amoreaux and Gibson, 2013).

In laboratory settings, identification of clusters was recently advanced by a combined analysis of bed-surface images and digital elevation models (DEMs) (Curran and Tan, 2014a; Curran and Waters, 2014), with the procedure described as follows. First, clusters are visually identified by the particle arrangements shown in the digital photos. Then, the visually identified clusters are verified with the DEM, checking whether clusters are discrete and protruding above the mean bed level by a specified minimum height (e.g., D_{85} or D_{95}). Last, each verified cluster is confirmed by checking whether the cluster consists of a recognizable anchor clast $>D_{90}$, around which at least two particles $>D_{50}$ were deposited. In contrast to the previous laboratory approaches that used only images or DEMs to identify clusters (Mao, 2012; Piedra et al., 2012; Heays et al., 2014), the combined use of images and DEMs represents technological progress, providing a more robust approach. This approach, however, continues to rely on visual inspection at the identification stage and specification of some quantitative criteria (e.g., threshold protrusion height and grain sizes) at the verification and confirmation stages, thus is prone to a certain degree of subjective judgment.

Attempts to apply advanced methods to studies of field clusters have been made by two groups of researchers. The first group (Entwistle et al. 2008) used the DEM derived from terrestrial laser scanning (TLS) and an optimized moving window to compute the local standard deviations (SD) of bed elevation across a study reach. The resultant SD surface was interrogated to extract the SD that corresponded to the observed clusters. The statistics derived from the classified SD were then applied to a validation DEM to produce a map of predicted clusters. The density and spacing metrics of these predicted clusters were consistent with field observations, while the shapes and constituent grains of individual clusters were not resolvable with this statistical approach. By contrast, the second group (L'Amoreaux and Gibson, 2013) used image analysis and nearest neighbor statistics to quantify the relative abundance and spatial scale of clusters, yet individual clusters were not resolvable with such spatial statistics. The most debatable aspect of this approach is, perhaps, to collectively treat large grains ($>D_{84}$) and medium grains (between D_{50} and D_{84}) as clusters just because they were found in proximity to similar grains more frequently than the spatially random null hypothesis would predict. The lack of a topographic component in this type of analysis, however, made clusters a 2D statistical feature of plane sampling rather than a 3D morphological feature of bed structures.

While the use of DEMs in cluster identification has proved promising in laboratory settings, extending this approach to field studies would require: (1) high-resolution DEMs that resolve both the grain- and microform-scale topographies, and (2) DEM-based delineation of clusters. High-resolution DEMs that capture grain-scale details over the reach-scale extent are now achievable using the hyperscale survey methods, such as TLS or Structure-from-Motion photogrammetry (see reviews by Milan and Heritage (2012) and Brasington et al. (2012)). However, a standardized DEM-based method for delineating clusters is still lacking. Here we present a novel, DEM-based approach for cluster delineation. This approach is facilitated by the feature recognition capability of the factorial kriging that decomposes the grain- and microform-scale components of DEM. The grain-scale DEM serves as an aid for segmentation of grain boundaries, while the microform-scale DEM is used to identify individual clusters. The delineated clusters are compared with a compilation of existing field data to confirm the robustness of the presented approach.

2. Factorial kriging

The DEM of a gravel-bed surface may be considered as a random field of spatial elevation data (e.g., Matheron, 1971; Journel and Huijbregts, 1978; Furbish, 1987; Robert, 1988; Goovaerts, 1997; Nikora et al., 1998), where the dependency between the bed elevations at two locations is expressed as a function of the spatial lag, i.e., the separation distance and direction between the two locations. The organization of the gravel-bed surface has been investigated by many researchers using the semivariogram (or simply called variogram) (e.g., Robert, 1988, 1991; Nikora et al., 1998; Butler et al., 2001; Marion et al., 2003; Aberle and Nikora, 2006; Cooper and Tait, 2009; Hodge et al., 2009; Mao et al., 2011; Huang and Wang, 2012; Curran and Waters, 2014), which is a second-order structure function summarizing all the information about the spatial variation in bed elevation over a range of scales. The empirical (also termed sample or experimental) 2D variogram of the DEM, denoted as $\hat{\gamma}(\mathbf{h})$, may be expressed by a general form of semivariance as follows:

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(\mathbf{x}_i) - z(\mathbf{x}_i + \mathbf{h})]^2 \quad (1)$$

where $\mathbf{h}$= lag vector separating locations $\mathbf{x}_i$ and $\mathbf{x}_i + \mathbf{h}$; $z(\mathbf{x})$= bed elevation at $\mathbf{x}$; $N(\mathbf{h})$=number of data pairs separated by $\mathbf{h}$, typically $\mathbf{h}$ is limited to half of the DEM extent to ensure that sufficient data pairs are used. Use of Eq. (1) also requires that bed elevations are normally distributed and second-order stationary (Butler et al., 2001; Hodge et al., 2009). Hence, the elevation data must be normalized to a zero mean and detrended with a trend surface to remove first-order nonstationarity (Oliver and Webster, 1986; Hodge et al., 2009). The detrended (or residual) elevations retain the topographies of sediment grains and microforms, with the general bed slope removed.

Eq. (1) may be used to calculate the semivariance $\hat{\gamma}(\mathbf{h})$ over a range of $\mathbf{h}$, resulting in an empirical variogram surface that shows the spatial variability of bed elevation at different scales and along different directions. The variogram may be also plotted as a 1-D profile along a specific direction of interest. Such a 1-D directional variogram has been used extensively to investigate the multiscale properties of the gravel-bed surface (Robert, 1988; Nikora et al., 1998; Butler et al., 2001; Hodge et al., 2009; Huang and Wang, 2012). Depending on the resolution and extent of the DEM, and whether bedforms are present, the variogram profile may exhibit single or multiple scaling regions that correspond to different scales of the bed structures. Fig. 1 demonstrates a schematic empirical variogram profile (solid circles) that exhibits two scaling regions. The first region, with the lags ranging between $[0, a_1]$, corresponds to the grain-scale structure. The second region, with the lags ranging between $[a_1, a_2]$, corresponds to the microform-scale structure. At lags greater than a_2, the semivariance remains a constant sill value, which corresponds to a saturation region where the spatial