Reconstruction of subgrid-scale topographic variability and its effect upon the spatial structure of three-dimensional river flow

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A new approach to describing the associated topography at different scales in computational fluid dynamic applications to gravel bed rivers was developed. Surveyed topographic data were interpolated, using geostatistical methods, into different spatial discretizations, and grain-size data were used with fractal methods to reconstruct the microtopography at scales finer than the measurement (subgrid) scale. The combination of both scales of topography was then used to construct the spatial discretization of a three-dimensional finite volume Computational Fluid Dynamics (CFD) scheme where the topography was included using a mass flux scaling approach. The method was applied and tested on a 15 m stretch of Solfatara Creek, Wyoming, United States, using spatially distributed elevation and grain-size data. Model runs were undertaken for each topography using a steady state solution. This paper evaluates the impact of the model spatial discretization and additional reconstructed-variability upon the spatial structure of predicted three-dimensional flow. The paper shows how microtopography modifies the spatial structure of predicted flow at scales finer than measurement scale in terms of variability whereas the characteristic scale of predicted flow is determined by the CFD scale. Changes in microtopography modify the predicted mean velocity value by 3.6% for a mesh resolution of 5 cm whereas a change in the computational scale modifies model results by 60%. The paper also points out how the spatial variability of predicted velocities is determined by the topographic complexity at different scales of the input topographic model.


1. Introduction

In hydraulic modeling, the representation of the river boundary shape is central to the analysis of river flow and has implications for conveyance, turbulence, sediment dynamics, and in-stream ecology [Lane, 2000]. Many environmental studies now recognize the importance of the complex variability of river topography for both sediment entrainment and transport [Van Oost et al., 2004; Hardy, 2005] and in-stream ecology (e.g., habitat for fish spawning) [Crowder and Diplas, 2000]. However, it is only recently that methods for handling the associated channel topographic complexities have been developed in computational fluid dynamics [Bates et al., 2005; Biron et al., 2007]. Such complexities include flow over and around individual gravel particles and clusters [Papanicolaou and Schuyler, 2003; Strom et al., 2004; Lane et al., 2003, 2004; Hardy et al., 2007], and complex flow patterns at the extremely small scales at which physical habitat operate can now be predicted using numerical models [Clifford et al., 2005; Leclerc, 2005; Crowder and Diplas, 2006]. However, the collection of high-resolution topographic data is one of the current limitations of these Computational Fluid Dynamics (CFD) environmental applications [Horritt, 2005; Hardy et al., 2005]. The discretization required to simulate flow patterns at scales significant to environmental applications determines the scale at which topographic effects are represented in the model. However, what is discretized also depends upon the topographic information content of measured river bed data, notably data from the bed surface [e.g., Casas et al., 2006]. The last 10 years have seen a revolution in data acquisition methods in relation to river and floodplain topography including media digital photogrammetry [e.g., Westaway et al., 2000, 2001; Butler et al., 2002], coupled photogrammetry and image analysis [e.g., Westaway et al., 2003], differential Global Positioning System (GPS) [e.g., Brasington et al., 2000], and now through water laser scanning [e.g., Kinzel et al., 2007]. However, there has been much less development of the theoretical and empirical methods required to link this topography into analysis of flow [Lane and Hardy, 2002].
In the case of gravel bed rivers, the surface topography is highly irregular due to clast size and the presence of bed forms at different roughness scales [Lawless and Robert, 2001; Butler et al., 2002; Lane et al., 2004]. These topographic irregularities exert a significant effect on flow variability as flow depth is usually shallow in relation to the height of bed forms [Hardy et al., 2009]. In an ideal situation, a high-resolution Digital Elevation Model (DEM) of the bed surface which incorporates all scales of roughness (e.g., grain scale, bed forms, reach scale) would be used to understand flows at the river reach scale; however, this is not feasible in cost nor time investment. In practice, an irregular set of distributed elevation points and grain-size data are measured at coarser spatial scales than the spatial discretization of the hydraulic model. In hydraulic modeling, these discrepancies between measurement and modeling scales may lead to problems of spatial parameterization and model validation [Schumann et al., 2000; Horritt, 2006]. The challenge, then, is to develop new ways of describing the topography at the different levels of detail required in hydraulic models that do not require time-demanding and expensive survey. The introduction at computational scale of a topographic variability data set to account for the roughness at those scales finer than that of measurement would eliminate this gap in spatial parameterization [Lane et al., 2004; Nicholas, 2005]. This is particularly important in CFD applications where derived flow variability is needed but surface data at the fine scale may not be available. The question here is how to reconstruct this topographic variability at scales finer than the measurement scale. This paper presents a new approach.

The downscaling process commonly used by hydraulic modelers to provide topographic values at a fine modeling scale using measured data at coarser scales usually involves some kind of interpolation. However, any interpolation method (e.g., kriging, spline) downscales the mesh resolution of the topographic representation but not the intrinsic topography; that is, no natural topographic variability is added to the DEM below the measurement scale [Atkinson, 2005]. Geostatistical methods make use of the spatial structure of measured data and provide complete coverage of values at the downsampled mesh resolution; but again, topographic variability between measurement sampling locations cannot be generated, though it is known that nature increases its geographic variability with the scale of observation [Mandelbrot, 1983; Klinkenberg, 1992; Fisher and Tate, 2006]. In addition, geostatistical methods involve smoothing, due to the averaging process of the neighbor data in the interpolation process [Atkinson and Tate, 2000].

Geostatistical approaches point to an alternative parameterization method, based upon fractal geometry. Fractal geometry principles can be used to generate surfaces of different complexities through its fractal dimension, D [Voss, 1988]. Fractal methods have already been used in both the analysis of surface roughness and in topographic generation [Goodchild and Mark, 1987; Xu et al., 1993; Lam and Cola, 1993; Lavallee et al., 1993; Tate, 1998] since the fractal dimension can describe the increasingly detailed features which appears at different spatial scales of natural surfaces [Barnsley, 1989; Herzfeld and Overbeck, 1999]. Specifically, in gravel bed rivers, fractal analysis has already been undertaken [Robert and Richards, 1988; Robert, 1991; Nikora et al., 1998; Butler et al., 2001]. For instance, Butler et al. [2001] used 2D fractal analysis of fluvial gravels to produce characteristic gravel scaling relationships, finding two structures at different scales, an isotropic and smoother at subgrain scale and an anisotropic and more complex at grain-size scale. With such information, it becomes possible to create gravel structures with the same scale-dependent statistical properties and so, potentially, to represent the effects of gravel grain-size variability upon flow structure more realistically, even if the exact detail of the river bed is not reproduced [Lane et al., 2004]. A fractal-based characterization of the grain-size roughness variability may then provide a way of representing the effects of unmeasured microtopography upon flow structure in a way that preserves the scale-dependent information of gravel bed river surfaces.

In this paper, we present a method to downscale topography to the required computational scales of interest. The method couples the representation of measured features of the reach morphology (riffle-pool morphology) to the reconstruction of microtopography, using measured grain-size data and fractal methods, as suggested by Lane et al. [2004]. To achieve this, we address three specific objectives: (1) the reconstruction of correlated microtopography at modeling scales finer than those of measurement, using grain-size data and its combination with topographic data at the mesh resolution of the hydraulic model; (2) the assessment of topographic effects upon 3D flow results due to reconstructed microtopography and mesh resolutions; and (3) exploration of topographic and velocity variability by looking at the spatial performance of the model at the correlation scales present in the flow. Finally, we assess the implications of these results for the representation of topography in CFD applications to natural river channels.

2. Methodology

2.1. Study Area and Initial Data

The study area is located at Solifluta Creek near Norris Junction in Yellowstone National Park, Wyoming (see Whiting and Dietrich [1991] for detailed field description). The river reach covered by the survey is about 15 m long and comprises a sinuous, clear-flowing gravel bed channel averaging 5.2 m wide and 0.2 to 0.7 m in minimum and maximum water depth with a water surface slope of ~0.001 (Figure 1a). The bed surface is composed of spatially sorted fine-to-medium gravel and coarse sand. The median size (D50) of the bimodal bulk distribution is 8 mm, and D84 and D16 are 16.1 and 0.7 mm, respectively. The largest grains are found along the left channel margin and on top of bar surface (Figure 1b). Along cross sections, depth was measured at 0.25 m intervals, with 0.2 m intervals near the channel margin. Cross sections were taken at 1.5 m intervals down the channel. The bed sediment size was determined at 0.4 to 0.6 m intervals across the sections by sampling 200–300 g from the bed. Sediment samples were dried in the laboratory and sieved at half-pitch intervals [Whiting and Dietrich, 1991]. The bed topography is controlled by the upstream bend and the downstream bar (Figure 1a). Bed elevation data were obtained subtracting depth from water surface elevation data at each station.

In total, the field and laboratory database gathered from this survey comprises (1) distances between measurement stations along each of the 11 cross sections from a...
Figure 1. Initial data location of Solfatara Creek reach: (a) elevation and velocity data location and (b) grain-size data location and area distribution of fractal scale-dependent squares. Cross section A-A’ refers to Figure 11.
defined channel centerline and distance to the banks; (2) 257 depth measurements with an accuracy of 1 cm; (3) 257 measurements of water surface elevation data with an accuracy of 0.5 cm; (4) 257 measurements of flow velocities at the 40% of the flow depth with an accuracy of ±0.3 cm s⁻¹ or ±1.2 per cent; and (5) 94 samples of grain-size data (φ5, φ16, φ25, φ50, φ65, φ75, φ84, φ100) at about 0.4 m intervals within cross stations (see Whiting and Dietrich [1991] and Whiting [1997] for further details).

2.2. Numerical Scheme and Solution

The numerical scheme solves the full three-dimensional Navier-Stokes equations discretized using a finite-volume method. The interpolation scheme used is hybrid-upwind, where upwind differences are used in high-convection areas (Peclet number > 2), and central differences are used where diffusion dominates (Peclet number < 2). Although this scheme can suffer from numerical diffusion, it is stable, and the Peclet condition implicitly counters the tendency to diffusion. The pressure and momentum equations are coupled by applying SIMPLEST, a variation on the SIMPLE algorithm of Patankar and Spalding [1972]. The convergence can precede either smoothly or with damped oscillations to the final solution. To achieve relaxation, either (1) realistic maximum and minimum values may be imposed on the solution; or (2) relaxation may be used to limit the amount of change allowed in any variable at a given iteration. Weak linear relaxation was used for the pressure correction, while weak false time step relaxation was used for the other variables. The convergence criterion was set such that the residuals of mass and momentum flux were reduced to 0.1% of the inlet flux. The computational domain was regular in the x, y directions with mesh resolutions of 5, 10, and 20 cm. The domain is contained within a 14.4 × 5.3 m rectangle. In the z direction the grid resolution was doubled, namely 2.5, 5, and 10 cm, respectively, to allow inclusion of elevation variability data using the mass flux scaling approach. The maximum extent of the domain depth (∼0.7 m) was set at 28, 14, and 7 mesh cells. Thus, the computational meshes dimensions are of 286 × 106 × 28 for the 5 cm mesh; 143 × 53 × 14 for the 10 cm mesh; and 72 × 27 × 7 for the 20 cm mesh.

The topography was subsequently included in the discretization using a mass flux scaling approach where the cell volume and faces are scaled and blocked according to the amount of topography included in the mesh. This approach has been developed [Hardy et al., 2005] and applied from the millimeter scale of gravel beds [Lane et al., 2004; Hardy et al., 2007] through the hundreds of meters scale of river reaches [Hardy et al., 2006]. The spatial discretization resolution does not change because topography is included using a mass flux scaling approach.

A wall function is applied because any topography at a scale smaller than that of the computational discretization cannot be represented directly. Here, the nonequilibrium form of the standard wall functions, which is suitable for flows with separation and assumes local equilibrium of turbulence, is used as proposed by Launder and Spalding [1974]. To parameterize the wall function, a roughness height is prescribed which is parameterized according to the spatial resolution and the fractal dimension. It is assumed that the maximum possible roughness that is not included in the discretization using the mass flux scaling approach is half the fractal dimension. It should be noted here that the CFD scheme is not as sensitive to roughness parameterizations as a depth-averaged numerical scheme, and uncertainty surrounds the validity of roughness parameterization in CFD scheme [Lane, 2005]. The wall functions are applied to the boundary cells, those which contain bed and water. The logarithmic velocity profile dependent on the value of subgrid-scale roughness is therefore modified by the presence of porosities on the cell faces. The reduction of flow velocity associated with the boundary is combined with the reduction due to the blockage to create realistic levels of flow retardation near the boundary.

Boundary conditions are specified at the upstream inlet and downstream outlet, at the sidewalls, and at the free surface. The upstream inlet was specified as a fully developed profile calculated from measured data of distributed water surface elevations and velocities (u- and v-component) of the flow. The downstream outlet is specified as a fully developed profile with the hydrostatic pressure set at the surface at the downstream outlet, and sufficiently far downstream that it did not influence the zone within which the numerical results were interpreted. The standard Renormalization group (RNG) theory k-ε turbulence model is not modified at the sidewalls or the bed, and the equilibrium wall function is used. At the free surface, the method applied by Bradbrook et al. [2000] was adopted, which uses a symmetry plane at the surface across which all normal resolutes are set to zero, with a correction to represent the effects of water surface variation: a nonzero pressure term on the symmetry plane is introduced to the momentum equations, commonly referred to as a rigid-lid treatment; and a porosity treatment is used to correct for the effects of this upon mass conservation. This treatment is acceptable for subcritical flows. For supercritical flows, it will not represent surface energy losses correctly.

This approach has previously been developed and validated [Lane et al., 2002, 2004; Hardy et al., 2005] for the inclusion of complex topography (individual gravel particles) in high-resolution (spatial resolutions of 0.002 m) CFD applications. The methodology has also been extended to consider greater spatial scales [Hardy et al., 2006] where the importance of the quality and resolution of the topographic boundary condition has been noted. This approach has been shown to reflect feature variability in the surface border cell and to replicate the effect of this on flow patterns [Lane et al., 2004; Hardy et al., 2005]. The methodology partially blocks the border cell that represents the bed topography, retains a hexahedral shape, and avoids instability and diffusion problems [Lane and Hardy, 2002; Lane et al., 2004; Hardy et al., 2006].

2.3. Spatial Parameterization: Interpolation Coupled to the Reconstruction of Topography

Measured elevation data were interpolated using geostatistical methods onto three different computational modeling scales (5, 10, and 20 cm). Experimental semivariograms were computed with elevation data, and a model was fitted visually. The spatial structure of the study reach was considered anisotropic given that a predominant terrain and bed form direction is observed. An elliptical model was fitted to experimental semivariograms where the major range in the direction of maximum continuity (α = 84.2°) is 11.11 m and 4.18 m is the minor range in the perpendicular direction.
The range of variability of fractally generated microtopography is calculated by the difference between grain-size diameters.

The nugget value is 0.00800, and the partial sill 0.0647 m (for a lag of 0.938 m; number of lags: 12). Geostatistically interpolated surfaces of elevation data are rasterized into the three mesh resolutions considered (5, 10, and 20 cm) which are coincident with the CFD computational scale.

Microtopography was reconstructed using grain-size data whose sampling locations are spatially distributed within the reach area (Figure 1b). A geostatistical model of the distribution of grain data is generated at modeling scales (5, 10, and 20 cm) using a mean value of D16 and D84 ((D16 + D84)/2). This continuous microtopographic surface arising from interpolation was then perturbed with fractal methods within a variability threshold given by the difference of grain-size diameters at each location (see Figure 2). The spatial structure of grains data was considered anisotropic, and a spherical model was fitted, where the major range in the direction of maximum continuity (\( \alpha = 83.6^\circ \)) is 12.07 m and 4.94 m is the minor range in the perpendicular direction. The nugget value is 4.70 mm, and the partial sill is 26.1 mm (for a lag of 0.94 m; number of lags: 12). The grain-size surface (G) was geostatistically generated with the average of grain-size diameters (D16 (mm) and D84 (mm)), therefore artificial microtopographic variability must range within the difference between grain-size diameters values (Figure 2). Grain-size data are spaced \( \sim 1.5 \) m along the reach and \( \sim 0.5 \) m within each cross section. Following the Nyquist rule, by which the lowest detectable periodicity is twice the sampling interval, the model will provide explicitly first-order representation of microtopography and its variability at scales greater than \( 3 \times 1 \) m. Scales below this resolution need to be reconstructed. In addition, one of the problems of fractals when simulating real surfaces is that self-similarity is exhibited for a small range of scales [Atkinson, 2002]. Therefore in this study, the channel domain is divided into square areas (\( 2 \times 2 \) m) where microtopographic variability is generated locally. Thirty-two (8 \times 4) windows are needed to cover the whole squared domain (\( 15.37 \times 7.59 \) m; see Figure 1b. Variations in microtopography were reconstructed for those scales that range from the grain scale to computational mesh scales (5, 10, and 20 cm).

Fractal Brownian motion (fBm) derived from random Brownian motion can be used to simulate fractional Brownian surfaces [Voss, 1988] which, ultimately, result in an irregular, self-similar surface that looks like natural topography [Goodchild, 1980]. The theory of fractals [Mandelbrot, 1977] is based on numerous iterations of a simple rule, producing complex shapes. By introducing a small random perturbation to each iteration, the resultant surface will be highly irregular. The resolution issue is solved through the number of iterations performed, and the scale of the inner variability is controlled with the magnitude of the perturbation. Because the basic rule is so simple, the initial required data are very small in number. These three characteristics make fractal generation of surfaces a particularly appropriate method to simulate natural terrain features with an implicit level-of-detail control with a small amount of initial data. Fractals reflect the scale dependency of the natural surfaces and provide the possibility to generate topography in a realistic and controllable way. There are various methods of generating a fractal surface (e.g., midpoint displacement method, the shear displacement, or Fourier filtering), and in any of them the result is that by changing the parameters, the degree of spatial structure can be varied, and the scale properties are controlled [Wood, 1996]. In this study the midpoint displacement methodology is used. Following Russ [1994], the methodology keeps the four corner points of the area fixed, whereas the center of each square is displaced up or down from the average of the four corners. This produces a finer grid consisting of points with spacing \( 1/2 \) of the original, which is oriented 45° to the original. Displacing the center of these squares produces a finer grid aligned with the original and \( 1/2 \) the spacing. The displacement is an amount taken from a Gaussian random number distribution with mean value \( h \). This mean value of the displacement \( h \) is reduced for each iteration according to \( h = wh, \) where \( w \) is the size of the square and \( H \) is a coefficient between 0 and 1. The surface that results will have a fractal dimension (Fd) of \( 3 - H \).

The generation of grain-size (i.e., microtopographic) variability (\( \Delta G \)) as fractal surfaces using the midpoint displacement algorithm [Russ, 1994] requires three input parameters: (1) the size of the area to reconstruct, which will be each one of the \( 2 \times 2 \) m square areas in which the channel domain has been divided; (2) the maximum perturbation value divided by \( 2 (h) \) (this parameter varies spatially for each one of the squares accordingly to the grain-size data information); and (3) the fractal dimension of the surface (Fd). The final size of the reconstructed area will depend on the number of iterations implemented within the initial \( 2 \times 2 \) m square following the rule \( 2n + 1 \). For this study, eight iterations result in a square of 257 cells. Therefore, each fractal square of \( 2 \times 2 \) m will have 257 \times 257 cells of 7.782 mm each. The overall perturbation of the surface (\( h \)) is calculated locally as half the value of the maximum difference (MaxDiff/2) between \( \text{d84} \) (mm) and \( \text{d16} \) (mm) within each square (Figure 2). Therefore, the variability threshold at which the surface is reconstructed varies spatially according to the measured grain-size data available within each square, and reconstructed variability will never exceed this maximum difference between grain-size diameters (Figure 2). The algorithm will perturb the surface upward and downward with this variability (\( h \) parameter). Finally, the fractal dimension (Fd) determines the complexity of the artificial surface. For this study, there are no available data to derive grain-size structure below the modeling scales; therefore two different fractal dimensions are used, and a sensitivity analysis is performed. Following Butler et al.’s [2001] results, low fractal dimensions are obtained at grain scales (\( \sim 25 \) mm) due to the smoothing effects of water working at this scale on particle orientation. Accordingly, grain-size variability was
Figure 3. Fractally simulated microtopographic variability for different dimensions for a 2 m squared area of the domain: (a) Fd = 2.5; (b) Fd = 2.3.
Table 1. Summary of Scaled DEMs

<table>
<thead>
<tr>
<th>Scaled DEMs</th>
<th>Composition</th>
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<tbody>
<tr>
<td>DEM&lt;sub&gt;1cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;1cm&lt;/sub&gt;</td>
</tr>
<tr>
<td>DEM&lt;sub&gt;2cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;2cm&lt;/sub&gt; + (G&lt;sub&gt;2cm&lt;/sub&gt; + ΔG&lt;sub&gt;2cm&lt;/sub&gt;)</td>
</tr>
<tr>
<td>DEM&lt;sub&gt;5cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;5cm&lt;/sub&gt; + (G&lt;sub&gt;5cm&lt;/sub&gt; + ΔG&lt;sub&gt;5cm&lt;/sub&gt;)</td>
</tr>
<tr>
<td>DEM&lt;sub&gt;7.5cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;7.5cm&lt;/sub&gt; + (G&lt;sub&gt;7.5cm&lt;/sub&gt; + ΔG&lt;sub&gt;7.5cm&lt;/sub&gt;)</td>
</tr>
<tr>
<td>DEM&lt;sub&gt;10cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;10cm&lt;/sub&gt; + (G&lt;sub&gt;10cm&lt;/sub&gt; + ΔG&lt;sub&gt;10cm&lt;/sub&gt;)</td>
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<tr>
<td>DEM&lt;sub&gt;20cm&lt;/sub&gt;</td>
<td>Z&lt;sub&gt;20cm&lt;/sub&gt; + (G&lt;sub&gt;20cm&lt;/sub&gt; + ΔG&lt;sub&gt;20cm&lt;/sub&gt;)</td>
</tr>
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</table>

Where Z is the surface model generated with elevation data, G is the grain-size model, and ΔG is the fractionally generated surface of grain-size variability. Subscripts define the mesh resolution of generated topography. The sign refers to the addition or subtraction of the grain-size information to the reference elevation model Z<sub>ref</sub>. DEM, Digital Elevation Model.

generated using the midpoint displacement algorithm for 2.3 and 2.5 fractal dimensions within each square. Figure 3 shows two 2 × 2 m surfaces generated for different fractal dimensions (Fd). Figure 3 shows that a high fractal dimension (Figure 3a) increases the complexity of the generated surface for a constant value of h. The squares are then merged to generate the surface (ΔG) of the whole domain for each fractal dimension, and grain-size variability data are extracted for each point in the computational meshes (ΔG<sub>5cm</sub>, ΔG<sub>10cm</sub>, and ΔG<sub>20cm</sub>). Finally, interpolated topography and reconstructed microtopography are combined at modeling scales (m) according to DEM = Z ± (G + ΔG). These downscaled DEMs with natural variability below the measurement scale are applied explicitly to the computational meshes. Table 1 summarizes the 15 DEMs generated and how they are constructed at modeling scales (Z<sub>f</sub> = Z ± (G + ΔG)).

2.4. Spatial Structure Analysis

The notion of surface roughness is used to encompass all the spatial structures of a natural surface at several scales. A simple nonspatial global statistic like the root-mean-squared error (RMSE) fails to describe the spatial pattern of this surface variability when comparing two surfaces with different roughness [Atkinson and Tate, 2000] and does not provide information on the contributing factors implied in the overall surface generation process. Following Herzfeld et al. [2006], a more valuable function for surface roughness estimation can be obtained from the spatial variability of local differences in attribute values, which results from the knowledge of the spatial structure of the elements comprising that surface. This spatial variability of local differences can be formulated as the difference between values averaged over all points that are located at the same distance. The variance function used in geostatistics matches this concept and is formally equivalent to the first-order variance function. The difference between both is that the variogram is defined in the stochastic framework, and the variance function theory is set in a discrete-mathematics framework; variance functions of first order always exist, whereas the variogram requires statistical assumptions to ensure their existence. The discrete-mathematical framework is suitable for parameter extraction and to explore spatial scaling effects.

In this study, characterization parameters identified by Herzfeld et al. [2006] are used. These parameters include first (1) the maximum variance-function value (max variance) which is related to the absolute variance (in spatial statistics); this parameter captures the overall spatial variability of the surface within the scale range of study and can be considered as a direct indicator of surface roughness; then, (2) the scale at which this occurs, i.e., the distance at which maximum variability is reached (scale max), is also extracted; and finally, (3) the fractal dimension and its level of adjustment (R<sup>2</sup>) is calculated using the semivariogram method [Mark and Aronson, 1984].

3. Results

Downscaling effects are evaluated looking at global aspatial statistics like the root-mean-squared difference (RMSD) whereas the spatial structure assessment is approached using the extraction of parameters from the variance functions constructed with simulated results, such as the characteristic spatial scale of flow results, the maximum overall roughness of the data, and/or the fractal dimension. Parameters are extracted from the variance function and no model derived parameters are used, as the modeling process includes an estimation error that for structure analysis purposes is not required (as it is for modeling purposes) [Herzfeld, 1999]. Spatial structure is evaluated at different modeling scales to assess (1) the impact of interpolation into different mesh resolutions and (2) the impact of reconstructed topography at different modeling scales. Scale relationships are established using variance values at concurrent lag scales between topography and flow variability.

3.1. Reconstructed Topography at Modeling Scales

Figure 4 represents the variance function for ranges below 3 m and a lag interval equal to the mesh resolution, respectively. It can be stated that (1) finer meshes are more sensitive to grain-size variability; and (2) within each mesh resolution, fractal dimension determines the correlation of the surface. Lower fractal dimensions result in surfaces with longer characteristic scales and a lower range of variability values which implies a smoother surface. The characteristic scales, maximum grain-size variability values, are less than 3 m which is the minimum distance at which any measured feature could be detected (calculated by the Nyquist rule).

3.2. Impact of Topography and Topographic Representation Upon Spatial Structure of Three-Dimensional Flow

Topography and its representation impact upon flow results is assessed: (1) globally through the root-mean-squared difference (RMSD) of velocity magnitude and individual components; and (2) spatially, looking at flow structure. Globally, computational mesh scale impact is calculated at different flow depths, through the comparison...
of the flow velocity results using a 10 and 20 cm mesh with those obtained using a 5 cm mesh. Table 2 summarizes these RMSD values, where the larger impact of mesh resolution upon flow velocity components toward the surface of the flow can be noted. At any flow depth, mesh resolution impact (RMSD) is higher for the downstream component (u-) and lower for the vertical one (w-). Topographic impact is presented in Table 3 where, at each modeling scale, velocity results obtained with topography with added variability are compared with those of the reference plain topography. Table 3 quantifies the stronger impact of topography close to the bottom (20% of the flow depth) and that the behavior is not systematic with mesh resolution. The 5 cm scale is the most sensitive to topographic changes whereas the 10 cm model shows the lowest variations. If we assume a reference value of velocity as the simulated mean velocity using the 5 cm model (~0.3 ms⁻¹), changes in the topography for a 5 cm mesh produce a variation of the 3.6% in velocity, whereas a change in mesh resolution from a 5 to a 20 cm mesh cell size produces a variation in velocity of 60%.

[24] Spatially, variance functions are calculated for velocity results using different topographies and mesh resolution. Figure 5 plots variance functions calculated at different flow depths for each mesh resolution. It is apparent from Figure 5 that once the variance value reaches a maximum, the function fluctuates with a lower frequency for finer meshes. This reflects the increment of spatial variability in flow velocities for fine mesh resolutions. From Figure 5, it can also be stated that 10 cm is the most sensitive approach to flow depth, where variance values differ more between depths.

[25] Figure 6 plots fractal dimension values extracted from these variance functions of simulated flow velocity. Figure 6 shows the depth dependence of the mesh resolution impacts upon velocity results. Shallow depths are more sensitive to mesh resolution variations. This is reflected in the larger difference in fractal dimension values for different mesh resolutions at 20% of flow depth. For each mesh resolution, fractal dimension is reduced closer to the surface, implying a smoothing of flow structure. Mesh resolution modifies the variability of simulated values and its characteristic scale; therefore the level of organization is also modified. Velocity complexity does not vary systematically with mesh resolution. In this model, at any flow depth, the 10 cm simulation shows the lower fractal dimension; therefore it provides the most organized velocity results in space, in correspondence with a smoother correlated variation in velocity predictions. At positions close to the surface (20% and 40%), the 5 cm approach shows higher variability in simulated velocity results (see Figure 5) followed by the 10 cm and then the 20 cm results. Thus, the heterogeneity of velocity values close to the bottom is better represented at finer scales, given the finer vertical resolution. However, the length of the characteristic scale (again modified by the mesh resolution) also determines the level of organization of the flow.

[26] The parameters from the variance function obtained for simulations with topography with different complexity show how the addition of topographic variability modifies variance values but not the flow structure (as characteristic scales remain constant at each mesh resolution). This suggests that the computational mesh scale controls the structure of the flow whereas topographic variations at a given mesh scale impacts upon the range of velocities and the level of organization of velocities at each depth. The topographic impact is plotted in Figure 7, which shows fractal dimension of velocities. Figure 7 shows how the topographic impact is stronger close to the bottom with higher differences in fractal dimension results. The behavior of the model is systematic with changes in topography: for any mesh resolution (m), an additional topographic scheme, namely, DEM⁺².⁺³, DEM⁺².⁺² (see Table 1) derives in an
Table 2. RMSE of Velocity Magnitude and Individual Components$^a$

<table>
<thead>
<tr>
<th>RMSE (ms$^{-1}$)</th>
<th>20% Depth</th>
<th>40% Depth</th>
<th>60% Depth</th>
<th>80% Depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{10cm}$</td>
<td>0.184</td>
<td>0.210</td>
<td>0.221</td>
<td>0.226</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.197</td>
<td>0.216</td>
<td>0.227</td>
<td>0.229</td>
</tr>
<tr>
<td>$U_{10cm}$</td>
<td>0.181</td>
<td>0.206</td>
<td>0.219</td>
<td>0.226</td>
</tr>
<tr>
<td>$U_{20cm}$</td>
<td>0.195</td>
<td>0.214</td>
<td>0.227</td>
<td>0.230</td>
</tr>
<tr>
<td>$V_{10cm}$</td>
<td>0.045</td>
<td>0.048</td>
<td>0.047</td>
<td>0.048</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.044</td>
<td>0.046</td>
<td>0.046</td>
<td>0.047</td>
</tr>
<tr>
<td>$W_{10cm}$</td>
<td>0.013</td>
<td>0.009</td>
<td>0.007</td>
<td>0.004</td>
</tr>
<tr>
<td>$W_{20cm}$</td>
<td>0.012</td>
<td>0.009</td>
<td>0.007</td>
<td>0.004</td>
</tr>
</tbody>
</table>

$^a$Using a mesh resolution of 10 and 20 cm compared with the 5 cm model results at different flow depths; $v$, velocity magnitude; $U$, $V$, and $W$, individual components. RMSE, root-mean-squared difference.

increment of the fractal dimension of predicted velocities, and therefore an increase in the complexity of the spatial organization of simulated flow. Maximum variations due to topography are observed at the 20% of the flow depth for the 10 cm scale model. The small effect of this in relation to the mesh resolution effect must be noted.

3.3. Efficacy of the Spatial Scale Parameterization Using Coarser Measured Velocity Data

[27] In this section, simulated flow results are compared with measured velocity data. The RMSE, the percentage of differences normalized (%dn), and a reduced major axis (RMA) regression is calculated for sampling locations, and results are summarized in Table 4. Table 4 shows that the 10 cm computational mesh provides the lower RMSE value ($\pm 0.203$ ms$^{-1}$). Additional topographic data reduce this value marginally, to $\pm 0.201$ ms$^{-1}$. The analysis of the percentages (%dn) shows that the 10 cm scaled simulated flow is also the best model, with a value of 17.3%. The RMA regression, however, produces the best adjustment for the 5 cm scale with an additional microtopographic scheme of grain-size data and a fractal variability of dimension 2.3 added, with an $R^2$ of 0.398. The maximum differences due to microtopography are produced in the 5 cm scale model. These validation data used here correspond to a coarser scale ($\Delta x \sim 1.5$ m, $\Delta y \sim 0.25$ m); therefore an adequate validation of the spatial scale approach is difficult to obtain. It may be that, in this case, validation data are not sufficient to resolve the topographic effects. The variability of simulated velocity is regressed against the variability in measured data at concurrent length scales ($R^2_{var}$) to assess the spatial parameterization approach looking at flow structure (Table 4). Table 4 shows the 10 cm modeling scale as the one with best agreement (i.e., the best spatial performance) in the variability of velocity values at each lag. The adjustment improves with the removal of microtopography with a complex variability, ($D = 2.5$).

3.4. Topographic and Flow Variability Relationships

[28] In this section, topographic and derived velocity variance values are related at concurrent ranges of analysis below the characteristic scale of the flow ($\ll 4.5$ m (mindist. scale; see Figure 5). This relation describes the behavior of the hydraulic model with spatial parameterization and is plotted in Figures 8 and 9. Figure 8 plots topography against velocity variance values, i.e., describes topographic variability effects upon flow variability, at concurrent lags within the characteristic scale of the flow (full waveform scale), for each mesh resolution (5, 10, and 20 cm) at different flow depths: 20% (Figure 8a), 40% (Figure 8b), 60% (Figure 8c), and 80% (Figure 8d).

[29] These figures confirm the topographically driven behavior of the hydraulic model given that at concurrent distances the wider range of elevation values in a DEM produce an increment in the range of velocity values. It is apparent from Figure 8 that this variability relation changes with mesh resolution. Therefore, the topography-velocity variability relation is (1) scale-dependent on mesh resolution (e.g., the slope of the relation is larger at the 20% of the flow depth for the 5 cm model; therefore it can be inferred that the impact of topographic content is better reflected in the range of derived velocities in finer meshes); and (2) this dependency is stronger toward the bottom of the flow (i.e., slopes between model resolutions at each depth differ more at the 20% and 40% of flow depth). Additional topography at fine scales also modifies this relationship. Figure 9 plots microtopographic variance values at the 20% of the flow depth against variance values of predicted velocity at common lags. Figure 9 shows how the removal of microtopography produces an increment of velocity variance values for the same length scale, and additional microtopography produces a decrease of predicted velocity values. Figure 9 shows the impact of microtopography in variance values of predicted velocities for each mesh resolution. The 10 cm model is the most sensitive to changes in the microtopography with different slopes for different microtopographic schemes (Figure 9b), and the 20 cm model is the less sensitive with similar slopes for every microtopographic scheme (Figure 9c).

4. Discussion

[30] Recent development of new methods to incorporate complex topographies in high-resolution CFD emphasizes the limitations that arise from difficulties of measuring topography at spatial scales (e.g., grain scale and bed forms) commensurate with the CFD analysis scale (computational

Table 3. RMSE of Simulated Flow Results$^a$

<table>
<thead>
<tr>
<th>RMSE (ms$^{-1}$)</th>
<th>20% Depth</th>
<th>40% Depth</th>
<th>60% Depth</th>
<th>80% Depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{5cm}$</td>
<td>0.0105</td>
<td>0.0062</td>
<td>0.0061</td>
<td>0.0081</td>
</tr>
<tr>
<td>$V_{10cm}$</td>
<td>0.0103</td>
<td>0.0056</td>
<td>0.0054</td>
<td>0.0061</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.0106</td>
<td>0.0063</td>
<td>0.0061</td>
<td>0.0077</td>
</tr>
<tr>
<td>$V_{5cm}$</td>
<td>0.0108</td>
<td>0.0072</td>
<td>0.0074</td>
<td>0.0088</td>
</tr>
<tr>
<td>$V_{10cm}$</td>
<td>0.0064</td>
<td>0.0038</td>
<td>0.0029</td>
<td>0.0022</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.0070</td>
<td>0.0034</td>
<td>0.0030</td>
<td>0.0029</td>
</tr>
<tr>
<td>$V_{5cm}$</td>
<td>0.0067</td>
<td>0.0039</td>
<td>0.0025</td>
<td>0.0020</td>
</tr>
<tr>
<td>$V_{10cm}$</td>
<td>0.0125</td>
<td>0.0105</td>
<td>0.0102</td>
<td>0.0103</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.0094</td>
<td>0.0063</td>
<td>0.0053</td>
<td>0.0041</td>
</tr>
<tr>
<td>$V_{5cm}$</td>
<td>0.0079</td>
<td>0.0058</td>
<td>0.0046</td>
<td>0.0034</td>
</tr>
<tr>
<td>$V_{10cm}$</td>
<td>0.0093</td>
<td>0.0063</td>
<td>0.0052</td>
<td>0.0039</td>
</tr>
<tr>
<td>$V_{20cm}$</td>
<td>0.0224</td>
<td>0.0228</td>
<td>0.0237</td>
<td>0.0242</td>
</tr>
</tbody>
</table>

$^a$At 5, 10, and 20 cm modeling scales with different microtopographic schemes compared with plain topographic models at different flow depths. The subscripts define the mesh resolution used, while the superscripts define the fractal dimension of generated topography $D_f$. The sign refers to the addition or subtraction of the grain-size information to the reference elevation model $Z_{ref}$. 

A previous study showed the importance of topographic representation at measurement scale, with a straightforward impact upon the spatial structure of predicted flow [Casas et al., 2010]. This paper provides a downscaling method to reconstruct topography at scales finer than that of measurement, to the grain scale that retains some of the scaling properties commonly observed for gravel surfaces. This topography is then combined with topography generated with elevation data, and the resultant DEM is used to parameterize the CFD scheme spatially. The spatial parameterization in this way accounts explicitly and in a spatially distributed way for the impact of topography upon computed flow results. Figure 10 shows the topographic impact throughout a vertical profile.

[31] The downscaling of topography by the reconstruction of boundary roughness at unsampled scales in gravel bed rivers was attempted by Nicholas [2001] using a scale-independent estimate of surface variance at those scales between grain size and mesh discretization scale. A random bed elevation model was incorporated into a boundary-fitted coordinate scheme to simulate vertical profiles of hydraulic variables for two-dimensional longitudinally uniform flows (the downstream and the vertical components). This method successfully introduced roughness at those scales into the boundary fitted coordinates (BFC) scheme but neglected the correlated nature of gravel bed rivers at different scales. In this study, the reconstruction of microtopography at scales not measured makes use of grain-size data and fractal geometry to generate the natural variability existing across scales (from coarse measurement to modeling scales). This procedure overcomes some of the common limitations of interpolation methods which are not able to generate topographic detail at fine scales.

[32] Herzfeld [1999] applied fractals to analyze and to simulate surfaces and processes with scale-dependent properties, with a specific application to seafloor morphology. The study [Herzfeld, 1999] successfully combines the simulation of scale-dependent surface processes at fine scales with simple interpolation methods for larger scale features. In the present study, Butler et al.’s [2001] characterization of gravel bed river surfaces is used to simulate microtopography at unsampled scales with natural characteristics. The midpoint displacement algorithm is applied for two different levels of complexities (2.3 and 2.5) given the low fractal dimensions found by Butler et al. [2001] at grain scales (~25 mm) which relates to the smoothing effects of water flowing at this scale on particle surfaces.

Figure 5. Variance function of flow structure at three different modeling scales: 5, 10, and 20 cm at different depths of the flow for (a) 5 cm; (b) 10 cm; and (c) 20 cm modeling scales.

Figure 6. Fractal dimension of flow velocity for different mesh resolutions at 20%, 40%, 60%, and 80% of the flow depth.
DEMs at different mesh resolutions (5, 10, and 20 cm) were generated from the same topographic source ($\Delta x \sim 1.5$ m; $\Delta y \sim 0.25$ m). The measurement scale is coarser than the mesh resolution; therefore changes in the mesh cell size will manifest the impact due only to mesh resolution, avoiding the smoothing impact of interpolation upon topography with the subsequent lost of “topographic content” in spatial modeling when modeling scales are coarser than measurement scale.

In this study, topography was generated at the grain scale (~mm) and interpolated onto modeling scales (~cm). Characteristic scales of this artificial surface generated are finer than ~3 m which is the minimum distance at which any measured feature could be detected (calculated by the Nyquist rule). Surfaces generated with a low fractal dimension (2.3) produced surfaces with lower variance values and longer characteristic scales, i.e., smoother surfaces (Figure 4). Mesh resolution modified the simulation structure in both characteristic scale and variance values, whereas changes in the topography are only reflected in differences in variance values (i.e., the rank of elevation values) at correlation scales (~4 m), which is quantified in ~±5 cm. The addition of topography, DEM$_m^{\text{Fd}}$ (see Table 1), increases variability of elevation values in relation to a plain DEM generated only with elevation data (DEM$_m$). Conversely, a removal of topography, DEM$_m^{\text{Fd}}$, decreases elevation variability. This is important in order to assess the blockage impact of topography upon flow results.

The impact of these topographic variabilities upon the velocity magnitudes can be characterized by their spatial patterns using geostatistics. The use of a structural function to characterize the flow provides not only the magnitude of variation of the attribute due to the scaling process but the scales at which these happen [Lam et al., 2004]. Variance functions also provide a clear visual impact of the analyzed attribute; for instance, the complexity of velocities represented by each modeling scale in Figure 5 is visually reflected in the frequency intervals of the fluctuations of variance values once the maximum scale is reached, which reflects the spatial structure of the surface [Herzfeld et al., 2003]. The topographic impacts (mesh and topographic scales) upon velocity results are shown to be depth–dependent (Figures 6 and 7). The RMSD quantifies it at the 20% of the flow depth as the ~60% and ~3.6%, respectively, in relation to the mean velocity of the 5 cm simulation results (~0.3 ms$^{-1}$). The RMSD is greater toward the surface for each mesh scheme, and differences between mesh resolution simulations are larger close to the surface (Figure 11). This is not associated with the topographic reconstruction. The 5 cm model provides the widest range of velocity values at 60% of the flow

### Table 4. Comparison Between Simulated and Measured Data at the 40% of Flow Depth

<table>
<thead>
<tr>
<th>DEMs</th>
<th>RMSD (ms$^{-1}$)</th>
<th>Percent Differences Normalized</th>
<th>R$^2$</th>
<th>$R^2_{\infty}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM$_{5cm}$</td>
<td>0.2096</td>
<td>214.081</td>
<td>0.389</td>
<td>0.9953</td>
</tr>
<tr>
<td>DEM$_{5cm}^{\text{+2.5}}$</td>
<td>0.2076</td>
<td>209.877</td>
<td>0.379</td>
<td>0.996</td>
</tr>
<tr>
<td>DEM$_{5cm}^{\text{+2.3}}$</td>
<td>0.207</td>
<td>207.995</td>
<td>0.397</td>
<td>0.9959</td>
</tr>
<tr>
<td>DEM$_{10cm}$</td>
<td>0.2027</td>
<td>172.996</td>
<td>0.387</td>
<td>0.997</td>
</tr>
<tr>
<td>DEM$_{10cm}^{\text{+2.5}}$</td>
<td>0.204</td>
<td>173.349</td>
<td>0.380</td>
<td>0.9973</td>
</tr>
<tr>
<td>DEM$_{10cm}^{\text{+2.3}}$</td>
<td>0.2022</td>
<td>182.254</td>
<td>0.393</td>
<td>0.9964</td>
</tr>
<tr>
<td>DEM$_{20cm}$</td>
<td>0.2042</td>
<td>174.176</td>
<td>0.379</td>
<td>0.9967</td>
</tr>
<tr>
<td>DEM$_{20cm}^{\text{+2.5}}$</td>
<td>0.204</td>
<td>179.073</td>
<td>0.391</td>
<td>0.9968</td>
</tr>
<tr>
<td>DEM$_{20cm}^{\text{+2.3}}$</td>
<td>0.204</td>
<td>233.028</td>
<td>0.371</td>
<td>0.9948</td>
</tr>
<tr>
<td>DEM$_{20cm}$</td>
<td>0.215</td>
<td>231.451</td>
<td>0.373</td>
<td>0.9949</td>
</tr>
</tbody>
</table>
depth and decreases toward the surface (Figure 5) whereas coarser modeling scales do not reflect this interaction between depth and surface complexity upon flow variability, and higher variance values are only related to the surface of the flow. This variation in the spatial structure of the 5 cm simulation results might be related to the greater impact of the downstream component at the 60% of flow depth; longer characteristic scales confirm this.

36 The spatial analysis of the mesh resolution impacts (Figure 11) shows how mesh resolution modifies the characteristic scale of velocity results and the variability of velocity, and therefore the organization of velocity results ($F_d$). These variations are not systematic with mesh resolution. Indeed, the 10 cm model shows the highest level of organization in terms of velocity results (Figure 6). The 10 cm DEM also presented the lowest fractal dimension. The spatial assessment of the mesh resolution impact allows us to assess if this change in flow scale due to the mesh resolution approach is important or not for the final application. A difference in the characteristic scale (full waveform of the flow) of 0.9 m can be important when, for instance, physical habitat is being studied [Crowder and Diplas, 2000; Clifford et al., 2005]. The longest characteristic scales are found in the 10 cm scale model (~4.84 m), which implies smoother and more correlated flow behavior. However, the variability in velocity values is greater at finer computational scales, which implies a more heterogeneous velocity layer, though less correlated.

37 Microtopographic impact is also depth-dependent, and it is reflected in velocity variability values as the characteristic scale remains constant for a given mesh resolution. Results show a stronger impact close to the bottom (Figure 7). The behavior of the velocity is systematic with topographic variability. The addition of microtopography slightly increases the complexity of velocity, and the removal of microtopography reduces the fractal dimension. Therefore the level of organization of velocity results is higher.

38 The comparison of measured flow velocity data at 40% of the flow depth with simulated results is not conclusive in assessing the efficacy of the spatial scale approach of the model, given that the measured velocity data scale is much coarser than the modeling scale. Different methods result in different optimum spatial schemes (see Table 4), though it is the 10 cm simulation that is most similar to the validation data. It must be noted here what little difference parameterizing microtopography makes in relation to the validation data but not with respect to other resolutions. So one implication from this analysis is that the improvement in grain-size representation achieved is not as important as other sources of errors, such as mesh resolution or topographic complexity represented [Casas et al., 2010]. If the measurement scale were closer to the modeling scale, any of these methods could be trusted to assess the adequacy

Figure 8. Spatial relationship between topographic and flow variance values at corresponding lag ($h$) distances at (a) 20%; (b) 40%; (c) 60%; and (d) 80% depth.
of the spatial parameterization approach (mesh resolution and topographic data scale), but discrepancies between computational and measured velocity values make this an unresolved problem. Validation data are not sufficient to resolve the topographic effects in this case. The assessment of changes in flow variability due to microtopography would require a finer measurement scale. The measurement density can be inferred

Figure 9. Scale relationship between topography and flow variance values at corresponding lag (h) distances due to different microtopographic contents at 20% flow depth for (a) 5 cm; (b) 10 cm; and (c) 20 cm model scales.

Figure 10. Vertical profile of velocity magnitude (see location in Figure 1a) for each microtopographic scheme at different mesh resolutions. The profile is located upstream from the midchannel bar (Figure 1), where the flow becomes shallower (0.34 m of flow depth), being dramatically accelerated because of the topographic forcing.
looking at the spatial distribution of flow departures (differences) between predicted velocities using plain topography and predictions with additional microtopography. Figure 12 represents variance function of these velocity deviations at a flow depth of the 20%. Figure 12 shows that the characteristic scale of the isolated impact of microtopography upon flow variability is 0.5 m. Therefore, at least a sampling interval of 0.25 m (Nyquist rule) would be required to detect roughness features at this grain-size scale. However, the measurement scale for this study was ∼0.5 m in the cross-stream direction and ∼1.5 m in the downstream direction. Point-measured velocity values at a coarser scale may fit better or worse at certain locations. This fit will depend in turn on the capacity of the model to simulate the spatial distribution of the flow which depends upon mesh resolution and the topographic variability of the DEM, as shown. Nevertheless, it is not enough to validate the spatial behavior of the flow at higher spatial resolution. Hardy et al. [1999] showed why sensitivity analysis was required to deal with spatial scale effects in hydraulic modeling. As discretization independence is difficult to achieve in CFD [e.g., Lane et al., 2005], a sensitivity analysis is required to assess the suitability of a certain spatial approach for the modeling purpose [Nicholas, 2001]. In this study, regression between the rank of velocity values present at concurrent lags in measured and simulated models (Table 4), considering lag units according to measured data scale, i.e., 1 m lag units, provided a means for evaluating the spatial performance of the model. This analysis concludes that the 10 cm model is the most effective scale approach; that is, simulated velocities present within different scales match better with those velocities present at correlated distances in measured data. This is consistent with RMSD and the normalized percentage difference results, which are lower for these (measurement) scales. The structure of the flow is simi-

Figure 11. Cross section A–A′ (see location in Figure 1a) showing the velocity magnitude at the upstream bend simulated for each mesh resolution (5, 10, and 20 cm from top to bottom, respectively).

Figure 12. Variance function of the spatial structure of flow deviation due to microtopography using a mesh resolution of 5 cm at 20% flow depth.
lar, and the ranges of velocity values match better at certain scales (e.g., measurement scale). This emphasizes the importance of validation scale in the assessment of model behavior. 

[39] The topographic-flow variability graphs (Figures 8 and 9) confirm the importance of topography and its depth-dependent impact upon velocity behavior. The graph represents at concurrent distances within correlation scales (~4.5 m in this case) the topographic values present at those scales (topographic variance values) against the velocity magnitude of values present in the simulation (velocity variance values), and can be used to understand spatial model behavior and decide measurement and modeling strategies.

[40] Given that this relationship quantifies within a range how a certain topographic content in the DEM produces more variability in velocity values as computational scale is finer, this relationship could be used to take decisions about the spatial parameterization of the hydraulic model. For instance, if model application requires velocity variations of ±0.1 ms⁻¹ (variance value = 0.005 m² s⁻²) at the 20% of the flow depth, Figure 8a shows that those variations will be reached using a mesh resolution 5 cm, with a topographic variability of 0.14 m (topographic variance ~0.01 m²). However, using a 10 cm mesh resolution approach, this variability in velocity will occur with a topographic variance of 0.017 m² in the mesh (variability of 0.2 m). These relations show that to obtain a certain variation of velocity values within a certain range of analysis, as the mesh resolution is coarser, additional topographic variability must be included in the DEM, and this is not always possible. Commonly, a certain topography is available at a certain measurement scale, and the modeling scale (mesh resolution) must match the computational scale of the CFD scheme, according to the hydraulic processes of interest in the application. Therefore, the mesh resolution should account for the required topographic variability, particularly the characteristic scale of the flow. The graph also shows that a given topographic variability obtained through different cell sizes produces different variability results. The computational mesh resolution is likely to produce a certain variability in flow results. However, topographic variability can modify this velocity variability according to result requirements. Therefore, topographic data scale decisions must be taken according to the scale of the spatial structure of the flow required by the application. This approach seems to be able to generate velocity variability values through reconstructed microtopography within a spatial flow structure controlled by the computational mesh scale approach.

5. Conclusions

[40] This paper has described a method to downscale topographic surfaces with natural characteristics for hydraulic modeling. This approach is based upon the reconstruction of topography from a combination of grain-size data and scaling analyses, the latter based upon fractal methods. These reconstructions were applied to different mesh resolutions. Results confirm that fractal geometry can be used to generate a topography below the topographic measurement scale (~3 m) using grain-size data to define the variability of the surface. The addition of this microtopographic variability modifies the level of organization of the surface but does not modify the characteristic scale of the DEM as determined by macrotopographic data to which the microtopographic variability was applied. Global and spatial assessment of simulation results shows the depth dependence of the mesh resolution and microtopography impacts upon velocity results. Assuming a reference value of velocity of the simulated mean velocity using the 5 cm mesh (~0.3 ms⁻¹), changes in the topography within a 5 cm mesh produce a variation of the 3.6% in the predictions of velocity, whereas a change in mesh resolution (from a 5 to a 20 cm mesh cell size) produces a variation in velocity of 60%. Mesh resolution modifies the characteristic scale and the variability of velocity values, and therefore the spatial organization of velocity (D), albeit not systematically. In this study, the 10 cm model shows the more organized velocities at any flow depth and is the most sensitive mesh resolution to depth and microtopographic variations. Microtopography impacts only upon velocity variability, and the characteristic length scale is constant for each mesh resolution. The behavior of velocity is systematic with microtopographic variations at any flow depth, additional microtopography increasing the complexity of velocity results, and the removal produces a more organized flow. A mesh resolution of 10 cm results in the simulation most effective in relation to measured validation data at 40% of the flow depth, although incorporation of microtopography improved agreement only marginally. In this model, velocity variability is related to topographic variability, and this relation depends upon the mesh resolution and the microtopography incorporated. Further work is required, using high-resolution validation data (~modeling scale) at different depths to assess the efficacy of the spatial performance of simulated flow due to the reconstruction of microtopography and the mesh resolution approach.

References


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