

RESEARCH ARTICLE

10.1002/2013JF002897

Key Points:

- Accuracy of bathymetric lidar is tested for stream hydrodynamic modeling
- Tests used both synthetic lidar errors and field surveyed bathymetry
- Bed shear stress and mobility predictions largely unaffected by lidar errors

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Citation:

McKean, J., D. Tonina, C. Bohn, and C. W. Wright (2014), Effects of bathymetric lidar errors on flow properties predicted with a multi-dimensional hydraulic model, *J. Geophys. Res. Earth Surf.*, 119, 644–664, doi:10.1002/2013JF002897.

Received 21 JUN 2013

Accepted 18 FEB 2014

Accepted article online 19 FEB 2014

Published online 26 MAR 2014

Effects of bathymetric lidar errors on flow properties predicted with a multi-dimensional hydraulic model

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Abstract New remote sensing technologies and improved computer performance now allow numerical flow modeling over large stream domains. However, there has been limited testing of whether channel topography can be remotely mapped with accuracy necessary for such modeling. We assessed the ability of the Experimental Advanced Airborne Research Lidar, to support a multi-dimensional fluid dynamics model of a small mountain stream. Random point elevation errors were introduced into the lidar point cloud, and predictions of water surface elevation, velocity, bed shear stress, and bed mobility were compared to those made without the point errors. We also compared flow model predictions using the lidar bathymetry with those made using a total station channel field survey. Lidar errors caused < 1 cm changes in the modeled water surface elevations. Effects of the point errors on other flow characteristics varied with both the magnitude of error and the local spatial density of lidar data. Shear stress errors were greatest where flow was naturally shallow and fast, and lidar errors caused the greatest changes in flow cross-sectional area. The majority of the stress errors were less than ± 5 Pa. At near bankfull flow, the predicted mobility state of the median grain size changed over $\leq 1.3\%$ of the model domain as a result of lidar elevation errors and $\leq 3\%$ changed mobility in the comparison of lidar and ground-surveyed topography. In this riverscape, results suggest that an airborne bathymetric lidar can map channel topography with sufficient accuracy to support a numerical flow model.

1. Introduction

Numerical simulations are often used to investigate morphodynamics of channels as well as response of fluvial systems to natural and anthropogenic perturbations [e.g., Nelson and Smith, 1989; Lane and Richards, 1998; Wheaton et al., 2004; McKean and Tonina, 2013; Tonina and Jorde, 2013]. Computational fluid dynamics (CFD) models allow examination of the interactions of flow and sediment transport processes with fluvial forms and aquatic habitat at spatial and temporal scales relevant for scientific and management purposes [e.g., Leclerc et al., 1995; Lancaster and Downes, 2010; Tonina and McKean, 2010; McKean and Tonina, 2013]. These models can improve understanding of flow structure and sediment transport, more easily evaluate the effects of boundary conditions, and increase the spatial density of information relative to that gathered by field observations [Lane et al., 1999]. Numerical models can be employed to generate hypotheses and direct efficient field investigations [Wheaton et al., 2004]. They can also be used to explore adaptive management scenarios, i.e., “digital adaptive management,” with fewer logistical and economic demands and environmental risk than full-scale physical experiments.

In all CFD models of in-channel flows there is a trade-off between adequate spatiotemporal representation of hydraulic complexity over the modeling domain and computational efficiency and model data requirements [Hardy, 2008; Tonina and Jorde, 2013]. For example, some aquatic habitat studies may require knowledge of complex patterns of flow, velocity gradients, and depth that vary spatially over distances on the order of a meter and occur throughout kilometer-scale stream segments [e.g., Fausch and White, 1981; Tonina and McKean, 2010; Tonina et al., 2011; McKean and Tonina, 2013; Maturana et al., 2013]. Fully 3-D fluid dynamics models will make spatially explicit flow and sediment transport predictions, but model complexity and data and computational requirements currently restrict the 3-D domain to at most a few hundred meters of channel length [e.g., Bradbrook et al., 1998; Lane et al., 1999; Booker, 2003; Shen and Diplas, 2008; Tonina and Buffington, 2009; Tonina and Jorde, 2013]. Alternatively, 1-D models can represent kilometer-scale channel segments but use only average conditions in channel cross sections to define the flow domain and make

simplified flow and sediment transport predictions. An appropriate compromise for many problems is 2-D or quasi 3-D models that predict depth-averaged processes with meter-scale spatial resolution over domains up to several kilometers long [e.g., *Leclerc et al.*, 1995; *Crowder and Diplas*, 2000a, 2000b, 2002; *French and Clifford*, 2000; *Nelson et al.*, 2003; *May et al.*, 2009; *Harrison et al.*, 2011; *Legleiter et al.*, 2011a; *Tonina et al.*, 2011].

Channel topography can have a strong effect on hydraulics, and therefore it is important to properly describe the topography that defines the boundary of a CFD model flow domain [e.g., *ASCE*, 1988; *Lane and Richards*, 1998; *Horritt*, 2005; *Hardy*, 2008; *Legleiter et al.*, 2011b; *Conner and Tonina*, 2013]. A number of studies have demonstrated the influence of model topography and topographic errors on floodplain hydraulics predicted by CFD models [e.g., *Hardy et al.*, 1999; *Marks and Bates*, 2000; *Horritt and Bates*, 2001; *Bates et al.*, 2003; *French*, 2003; *Casas et al.*, 2006], but comparable research for 2-D simulations of in-channel flows is less common. In one investigation of the effects of model topography on 2-D CFD predictions of channelized flows, *Horritt et al.* [2006] used high-resolution sonar and other survey data to define the boundary of a channel with a relatively simple trapezoidal shape. For a single discharge condition equal to the mean annual flood, they found that model predictions were sensitive to the resolutions of both the model mesh and the topographic sampling, with the mesh resolution the more important of the two. However, the authors noted that the streambed topography was almost featureless compared to that of a natural channel. At low discharges, when flows tend to be steered by small features of the bed topography (with dimensions of tenths of a channel width) and in more complicated channels than that investigated by *Horritt et al.* [2006], the importance of topographic mapping presumably would have been greater. *Horritt et al.* [2006] also did not explore the effects of model domain boundary topographic errors on flow model performance.

Conner and Tonina [2013] investigated the effect of cross-section spacing on flow properties predicted with 2-D numerical models supported by cross-section derived bathymetries. They concluded that the spatial resolution of streambed topography has an important effect on predicted flow fields and cross-section spacings less than one channel width may be necessary to generate elevation rasters suitable for 2-D modeling in large streams.

Pasternack et al. [2006] observed a propagation of topographic errors through 2-D model predictions of flow depth, velocity, and shear velocity when compared to field measurements and estimates of these traits in a regulated gravel bed river. The model flow mesh was derived from a DEM that was, in turn, developed from relatively closely spaced point elevation measurements made during a field survey. Model flow depth errors averaged 21% and were all attributed to errors in the topographic survey. Model velocity errors averaged 29%, and greater than half of this was the result of depth errors, and thus again topographic errors. Despite the depth and velocity errors, model shear velocity corresponded well with the field estimates of this flow characteristic. *Pasternack et al.* [2006] used a constant value of Manning's n to describe channel roughness, and unrecognized spatial variations in this parameter may have also contributed to the model errors.

Legleiter et al. [2011b] used stochastic simulations to produce many realizations of channel topography in a short, simple reconstructed meander bend. They tested the effects of uncertainty in the model boundary condition on predictions of water surface elevation, flow depth, and velocity and near-bed shear stress. The channel topography was originally mapped with very sparse field-surveyed data (0.06 measurements m^{-2}). Then multiple variations of these data and even sparser subsets (as few as 0.01 measurements m^{-2}) were produced by introducing spatially correlated variations in point elevations. Thus, topographic uncertainty was the result of both a variable data density and data errors. Iterative model predictions were made using these varying topographic boundary conditions, and statistics from the many simulations defined distributions of outcomes at each node in the flow mesh. This study also used a spatially constant drag coefficient, calibrated for conditions in each simulation, to represent channel roughness throughout the model domain. *Legleiter et al.* [2011b] found that topographic uncertainty caused by decreased data density propagated through the multi-dimensional flow model and in some cases had a strong influence on predicted water surface elevations, depths, velocities, boundary shear stresses, bed mobility, and aquatic habitat suitability indices.

Traditional field methods, including wading surveys using levels, total station, or GPS technologies, can map channel topography with high precision, accuracy, and resolution but only over a limited area [e.g., *Brasington et al.*, 2000]. The locations and spatial extents of wading surveys and the survey data density are

restricted by logistical issues such as legal access, flow conditions of depth, velocity and water temperature, GPS signal quality, and the time required to make each measurement. Optical airborne remote sensing surveys have recently been used with some success to map bathymetry in local reaches of channels [e.g., Lyon *et al.*, 1992; Gilvear *et al.*, 1995; Winterbottom and Gilvear, 1997; Lane, 2000; Marcus *et al.*, 2003; Legleiter *et al.*, 2004; Marcus and Fonstad, 2008; Feurer *et al.*, 2008; Legleiter *et al.*, 2009]. These passive sensors must accommodate spatial and temporal variability in water column optical properties (e.g., from turbidity), bottom reflectivity, sun glint off the water surface, shadowing by overhanging stream bank vegetation, and mixed subaerial-subaqueous pixels on the margins of flowing water and generally require some local calibration [Feurer *et al.*, 2008; Gao, 2009; Legleiter *et al.*, 2009]. Passive optical methods also measure water depth rather than stream bed elevations. Wide swath sonar systems towed behind boats are capable of high-definition bathymetry over large areas [e.g., Parsons *et al.*, 2005; Horritt *et al.*, 2006; Conner and Tonina, 2013]. Horritt *et al.* [2006] report vertical and horizontal sonar map accuracies of about 10 and 25 cm, respectively, in recent kilometer-scale surveys by the UK Environment Agency. Navigable flow conditions are necessary, and Horritt *et al.* [2006] also noted poor system performance in shallow (undefined) water at the lateral margins of flow, and, in their study, the banks, islands, and other features along the edges of flow were mapped by non-sonar surveys.

Airborne near-infrared lidars are routinely used to map floodplain topography in support of flood routing models. Unfortunately, little near-infrared energy is returned from surface water bodies, and these terrestrial lidars have limited utility for in-channel mapping [Hofle *et al.*, 2009]. Bathymetric lidars usually operate at green wavelengths (normally 532 nm) and potentially can penetrate water to depths of several meters, depending on factors such as water clarity, laser power, beam divergence, and bottom reflectivity [e.g., Liu, 1990; Storlazzi *et al.*, 2003; Finkl *et al.*, 2005; Hildale and Raff, 2008]. Most bathymetric lidars have a footprint size of a few meters [Nayegandhi *et al.*, 2009; Bailly *et al.*, 2010], and this large footprint limits their use to lower spatial resolution mapping in larger channels and also accentuates errors in areas of abrupt topographic change, such as at stream banks.

New airborne bathymetric lidars have been developed that are designed for shallow water surveying using narrow-beam, full-waveform lasers with relatively low power and measurement footprints of around 15–20 cm. One of the pioneering narrow-beam, shallow-water bathymetric lidars is the Experimental Advanced Airborne Research Lidar (EAARL) [Wright and Brock, 2002; Brock *et al.*, 2002, 2004]. This instrument was initially used in near-shore marine surveys but has recently been deployed to map detailed stream and floodplain topography [Kinzel *et al.*, 2007; McKean *et al.*, 2008a, 2009a, 2009b]. During these projects the EAARL performance was evaluated by comparing how well it mapped basic topographic attributes relative to field surveys of point elevations [Kinzel *et al.*, 2007, 2013; McKean *et al.*, 2009b], stream profiles, cross sections, areas, and volumes [McKean *et al.*, 2009b]. But there has been limited testing of whether narrow-beam, shallow-water bathymetric lidars can define channel topography with sufficient accuracy to support a 2-D fluid dynamics model [McKean *et al.*, 2009b].

Here, we report results of such a test of the EAARL system. We first measured performance by introducing point elevation errors, with a pattern and magnitude typical of those produced by this instrument, into the original lidar data point clouds. These errors were propagated into the fluid dynamics model, and their effects on model predictions were evaluated. Finally, the lidar-based CFD model results, without introduced experimental errors, were also compared to the same model predictions supported by field-surveyed channel topography.

2. Field Area

The lidar errors were tested on a CFD model of Bear Valley Creek, a tributary to the Middle Fork Salmon River, Idaho. This stream is 10–15 m wide, the median substrate size in the channel bed is about 58 mm, and the channel gradient ranges from 0.17 to 0.61%, measured over 200 m channel lengths [McKean *et al.*, 2008a, 2009b; Gariglio *et al.*, 2013]. Two reaches were analyzed, one has a meandering planform with pool-riffle bed morphology (Figure 1a), and the other, located 2.5 km downstream, is a straight reach with plane bed morphology with randomly located large boulders (Figure 1b). Bankfull water depths in the pool-riffle channel range up to about 1.8 m with one standard deviation of 0.29 m, while depths in the plane bed reach are < 1.1 m and are more consistent with one standard deviation of 0.17 m. The channel banks are about 1 m tall and range from vertical to gently sloping on point bars and around islands in the meandering reach and are generally steeper in the plane bed reach. Vegetation along the meandering reach is dominantly grasses, sedges, and willows with occasional isolated conifers, while the straight reach is bordered mostly by a coniferous forest.



Figure 1. Field sites: (a) Low gradient meandering gravel bed, pool-riffle reach. Channel is approximately 15 m wide. View is downstream. (b) Straight gravel bed channel reach with plane bed morphology. Channel is approximately 15 m wide (see figure on right bank for scale). View is downstream.

3. Airborne Bathymetric Lidar Background and Methods

3.1. Lidar Errors

The error budget of all airborne subaerial or bathymetric lidars is complex and involves at least the instantaneous location and three-dimensional orientation of the aircraft, laser ranging accuracy, laser return sampling frequency, laser scan rate and angle, laser beam divergence and footprint, and the interactions of these system and mission parameters with terrain that has variable scales and amounts of topographic roughness and other target characteristics, such as reflectivity.

Bathymetric lidars also have several additional significant complications. The laser energy is refracted when crossing the air-water interface on both the outgoing and return travel legs of each laser pulse and the amount of refraction is proportional to the angle of incidence as described by Snell's Law. The EAARL instrument uses a cross-track scanner

that oscillates perpendicular to the line-of-flight, so a first-order correction is made for the increasing angle of incidence toward the edges of each scan line. However, finer corrections to compensate for the individual refraction of each laser pulse caused by the dynamic local water surface roughness, e.g., due to wind and waves, are not possible. The effects of refraction errors increase with water depth and primarily cause planimetric shifts in the data.

The velocity of laser energy drops from 15 cm ns^{-1} in air to about 11 cm ns^{-1} in water. Therefore, during data processing it is important to recognize the water surface in the return from each laser pulse and adjust the laser velocity during the portion of the travel time spent in water. If the air velocity is erroneously used for the travel time in water, this vertical error of about 4 cm ns^{-1} means the elevation of a point will be under predicted. At water depths less than about 15 cm it can be difficult to discriminate the water surface and correctly adjust the laser velocity, but a velocity error over this depth translates into a vertical error of only a few centimeters, within the normal vertical uncertainty of airborne lidar data. As water depths increase, the potential error associated with the incorrect velocity rises, but it also becomes easier to distinguish the water surface in the EAARL data and avoid the error.

To best retrieve the submerged ground elevations, it is normally necessary to record and interpret the full time-rate-of-return of reflected energy from each laser pulse, i.e., to use a "full-waveform" lidar and data interpretation methods. For example, the full waveform is employed to distinguish reflections at the water surface from those caused by sediment suspended in the water. The EAARL sensor is a full-waveform resolving lidar, and the custom-built processing software, the Airborne Lidar Processing System (ALPS), provides the user several algorithms and adjustable parameters to customize the processing in specific stream environments [see Bonisteel *et al.*, 2009, for further details about the ALPS software]. Adjustments in the ALPS algorithms and parameters can strongly affect the density of the bathymetric data and, to a lesser extent, the predicted elevations of point reflections.

Water depth and quality can also affect lidar performance as a result of both energy scattering and absorption. Suspended sediment particles and entrained air bubbles are point reflectors that scatter energy as each laser pulse makes the two-way transit through the water column. In-water reflections that still reach

the system detector can make the return energy waveform more difficult to interpret and identify true reflections from the channel bed. Some of the energy may also be reflected outside the field of view of the detector, reducing the returned signal strength, sometimes to the extent that it is not possible to detect the signal. In addition, some dissolved organic molecules, for example tannic acids, heavily absorb laser energy having a wavelength of 532 nm and can prevent laser pulses successfully traversing the water column twice to define a bed elevation. Thus, in poorer quality and deeper water, in-water reflections and absorption can locally cause either bed elevation measurement errors or data thinning and eventually complete loss of bed elevation data, all of which deteriorate the resulting channel DEM, but in different ways.

3.2. Lidar Data Acquisition and Error Assessment Methods

Lidar data were acquired by the EAARL in October 2007. The key attributes of this instrument are given by *Wright and Brock* [2002] and *Nayegandhi et al.* [2006]. Bear Valley Creek was in low-flow conditions during the lidar survey with very clear (unquantified) water and flow depths < 2 m. The data were processed using the bathymetric algorithm in the Airborne Laser Processing Software (ALPS) [*Wright and Brock*, 2002; *Nayegandhi et al.*, 2006; *Bonisteel et al.*, 2009]. The typical lidar bathymetric data density was about 0.3 points m^{-2} . The mean lidar elevation error was eliminated by vertically adjusting the lidar data after comparison of lidar point elevations with ground-surveyed GPS and total station point elevations made within 0.25 m, horizontally, of the lidar points. After this block adjustment of the lidar data, the elevation accuracy of individual bathymetric lidar measurements was about ± 15 cm (1σ) when compared to the ground measurements. In a similar 2004 survey of this field area with the same instrument, the point elevation accuracy was ± 17 cm (1σ) [*McKean et al.*, 2006, 2009b]. Point elevation errors calculated by this method are always somewhat uncertain as they include the effects of topographic variability in the up to 0.25 m distances between each ground and corresponding lidar point measurement. In our study channels, the local bed slope can approach 20%, with elevation changes of 5 cm over a 25 cm horizontal distance. Furthermore, there is planimetric ambiguity in each lidar measurement, which is often on the order of 50 cm, and each recorded lidar elevation is some representation of the range of elevations in the ~ 20 cm diameter lidar footprint. The 2004 lidar data also used a lower precision GPS solution due to problems with the on-site field base station during the mission.

Experimental elevation errors were introduced to all data in the EAARL bathymetric point clouds by sampling randomly from normally distributed error populations with a mean elevation error of zero [*McKean et al.*, 2008b]. The possibility of spatially correlated errors in the lidar data was examined in some detail by *McKean et al.* [2009b] in the same study stream, and no correlations were found. This is particularly obvious in Figures 6 and 8 from that publication where along two stream profiles the lidar data vary in an irregular fashion around a coincident ground-surveyed profile. The effects of error magnitude were tested by regenerating the error populations with one standard deviation equal to 10, 13, and finally 15 cm and then repeating the flow model predictions with each level of errors. This size range of errors is based on the 2004 and 2007 EAARL point accuracy assessments in this study area. It is slightly greater than that found by *Nayegandhi et al.* [2009], who used the EAARL in shallow clear-water marine studies and reported RMS elevation errors of 8–14 cm and slightly lower than that reported by *Kinzel et al.* [2007] who found EAARL elevation errors with an RMS of 18 and 24 cm in two reaches of the Platte River. In each realization with a different magnitude of errors, the errors also had an independent spatial distribution.

Ground-based total station surveys were made of 120–150 m long subsets of the pool-riffle and plane bed reaches to enable the lidar-to-ground survey comparison. The surveys extended beyond the channel banks for several meters in both reaches. The ground survey data had an average density of 0.08 points m^{-2} , and the internal horizontal and vertical point accuracies were about ± 1 –2 cm in the subaerial and shallow submerged portions of the surveys. In areas of deeper flows the survey accuracy probably declined, in some unquantified manner, due to effects such as difficulty maintaining a vertical rod position. To enable the lidar-to-ground comparison, the total station data were converted to the same datum and projection as the lidar data by GPS observations at the total station bench marks.

All point clouds from the ground surveys, the original lidar surveys, and lidar with experimental introduced errors were treated identically. Data were first gridded to make elevation rasters with 1 m grid cell spacing. A simple isotropic kriging method was selected to make the rasters after tests on the dense lidar data showed little effect of using anisotropic kriging or changing the spatial covariance of the kriging. These elevation rasters were then mapped onto a channel-centered flow mesh with a similar square 1 m grid spacing

[Lane, 1998; Tonina and Jorde, 2013] in the finite difference fluid dynamics model FaSTMECH, run under the user interface MD-SWMS [Nelson et al., 2003; McDonald et al., 2005]. FaSTMECH is a depth-integrated hydrostatic model that proceeds by solving the Reynolds-averaged momentum equations. It has two calibration parameters: a drag coefficient (cell-scale roughness flow resistance) and lateral eddy viscosity (turbulence resistance). The former can be spatially distributed and depends on streambed roughness including grain size and any other topographical irregularities at a scale smaller than the mesh size [Morvan et al., 2008]. The latter has a uniform value for the entire reach and is estimated with the equation $\nu = 0.01 \cdot U \cdot H$, where U and H are the mean flow and hydraulic depth of the flow at the reach scale [Barton et al., 2005]. Nelson et al. [2003] and McDonald et al. [2005] describe further details of flow calculations in FaSTMECH within the MD-SWMS environment. FaSTMECH was implemented in a quasi-3-D mode to predict spatially distributed water elevations, velocities, and near-bed shear stresses.

The FaSTMECH model was first calibrated, using the original lidar bathymetry, by comparison with the water surface elevation (surveyed along the channel centerline) and depth-averaged velocity distribution, both measured in the field at a low discharge of $0.96 \text{ m}^3 \text{ s}^{-1}$ [McKean and Tonina, 2013]. The calibration was accomplished by adjusting the flow resistance until the model predictions matched the two field measured variables. The resistance was described by a drag coefficient that varies spatially as:

$$C_d = \left[\frac{1}{h} \int_{z_o}^h f(z, z_o) dz \right]^{-2} \quad (1)$$

Here h is the local flow depth, z is height above the stream bed, and z_o is the height above the stream bed at which the velocity is equal to 0, assuming a logarithmic vertical velocity profile [McLean et al., 1999]. This exercise yielded a calibrated $z_o = 0.006 \text{ m}$ and an eddy viscosity of $0.05 \text{ m}^2 \text{ s}^{-1}$ [Figure 5 in McKean and Tonina, 2013]. A sensitivity analysis showed little change in transverse flow structure and water surface elevation when the eddy viscosity was varied by as much as $\pm 50\%$, so this parameter was kept constant at $0.05 \text{ m}^2 \text{ s}^{-1}$ during higher discharges. Comparable sensitivity analyses on the values of z_o and the lateral eddy viscosity are also reported in the work of McKean and Tonina [2013] for the same reach, and of Maturana et al. [2013] for a similar nearby reach. Note that flow resistance still varied spatially according to the flow depth even though z_o was constant.

The model was validated by comparing modeled and observed water surface elevations at a discharge of $1.6 \text{ m}^3 \text{ s}^{-1}$ and velocities over a range of discharges from 1.6 to $6 \text{ m}^3 \text{ s}^{-1}$ with the set z_o and ν values (see McKean and Tonina [2013], for calibration and validation data). The model was also validated empirically at a discharge of $0.96 \text{ m}^3 \text{ s}^{-1}$ by observing a close correspondence between two predicted recirculating eddies, shaded by meanders, and the same eddies mapped in the field by injecting a dye tracer into the water.

The 1 m square cells in the CFD mesh provided a detailed flow field and optimal convergence with local cross-sectional and reach mass balance errors within $\pm 3\%$ and below 1% , respectively [Tonina and McKean, 2010; McKean and Tonina, 2013]. The comparisons of the original lidar bathymetry to lidar-with-errors were then made by repeating the flow model predictions with the boundary condition errors while leaving constant the roughness and lateral eddy viscosity parameters as well as the discharge and downstream water stage. We used the same C_d and ν because our goal was to quantify the error caused solely by the bathymetry and not a combination of bathymetric uncertainties and energy losses due to flow resistance at the cell scale. Furthermore, our high-resolution topography constrained the local resistance to losses caused by topographic irregularities with scales smaller than the mesh size. Reach scale values, which are at a scale larger than the resistance accounted for by C_d , should not change by varying the local elevation data.

Previous modeling and field measurements had established that annual base flow and bankfull flow conditions existed in the study channel at discharges of about 1 and $6.7 \text{ m}^3 \text{ s}^{-1}$, respectively, and model calculations were made at 1 and $6 \text{ m}^3 \text{ s}^{-1}$. The same calibrated hydraulic model parameters and range of discharges were used to also compare model predictions of water elevation, velocity, and near-bed shear stress, made with the original lidar bathymetry, to those made with the ground-surveyed bathymetry.

Whether or not the water surface, velocity, and near-bed shear stress errors caused by topographic errors are functionally significant depends on the intended use of the model predictions. For example, a common application of CFD models is to analyze channel bed mobility [e.g., May et al., 2009]. We tested the effects of

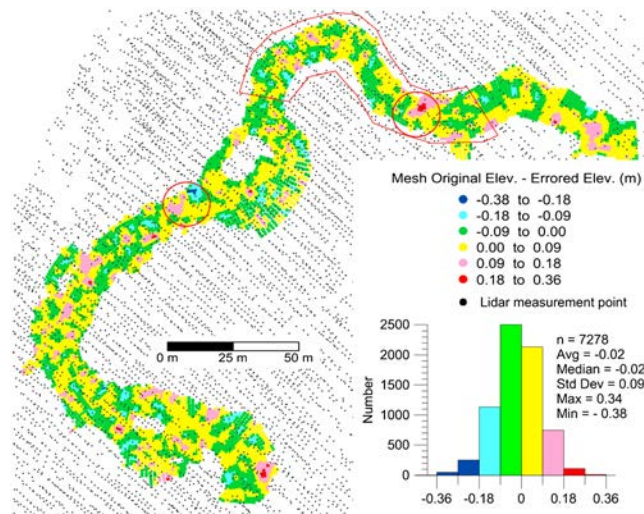


Figure 2. Elevation error pattern in MD-SWMS flow mesh of pool-riffle channel reach at bankfull flow ($6 \text{ m}^3 \text{ s}^{-1}$). Flow mesh has 1 m pixels, and errors are mapped in 1σ categories. Gray dots are lidar measurement locations in original EAARL point cloud. Two red circles are areas of largest elevation errors, and red polygon is area of the ground-surveyed reach shown in Figures 11a, 12, and 15. Flow is from lower left to upper right.

bathymetric lidar errors on modeled initial motion of particles on the beds of the pool-riffle and plane bed channel reaches. Particle motion was evaluated by first predicting local shear stress at each node of the flow mesh as a function of discharge, using each of the model bathymetric boundary conditions defined above. Then the shear stress at each mesh node was compared to a theoretical critical stress, τ_c , for initial particle motion estimated from the Shields criterion for a single grain size:

$$\tau_c = \theta g (\rho_s - \rho_w) d \quad (2)$$

Here θ is the dimensionless Shields number (0.047), g is the gravitational acceleration (9.81 m s^{-2}), ρ_s is the sediment bulk density (2500 kg m^{-3}), ρ_w is the bulk density of water (1000 kg m^{-3}), and d is the representative grain size.

While more sophisticated initial motion

models are available, this simple approach using a single particle size has been used successfully in other studies [e.g., May et al., 2009; Goode et al., 2013; Conner and Tonina, 2013] and suffices to investigate the effects of bathymetric errors. The grain size, d , was varied from 1 to 145 mm, corresponding to critical stresses from 0.5 to 100 Pa. The median grain size, defined by field surface pebble counts, is 58 mm and has a critical stress of about 40 Pa.

4. Results

4.1. Lidar to Lidar-With-Errors Comparisons

The results of the direct effects of experimental introduced bathymetric errors on mesh elevations and near-bed shear stress residuals are shown only for larger errors randomly sampled from populations with one standard deviation of 15 cm. For the assessment of bed mobility predictions, smaller and larger errors are compared at the high-flow condition of $6 \text{ m}^3 \text{ s}^{-1}$ by random sampling from error populations having one standard deviation of 10 and then 15 cm.

4.1.1. Patterns of Introduced Topographic Errors

The normally distributed (in magnitude) elevation errors introduced into the EAARL point cloud data produced a similar statistical distribution of MD-SWMS mesh errors (see error histograms in Figures 2 and 3). One standard deviation of the mesh elevation errors was 9 and 10 cm in the meandering and plane bed reaches, respectively, which is slightly less than that in the introduced point elevation error populations (15 cm s.d.). This is as expected due to the smoothing of data during production of the elevation rasters and then the mapping of those rasters to the flow mesh. In the pool-riffle reach the maximum errors were about $\pm 35 \text{ cm}$, while they were $\pm 43 \text{ cm}$ in the plane bed channel. In both reaches, elevation errors in the flow mesh occurred throughout the model domain with no apparent biases along the margins or center of the flows (Figures 2 and 3). In the pool-riffle reach, the smaller mesh elevation errors ($< \pm 9 \text{ cm}$) were often clustered in groups that are 4–5 m across and frequently extended for $>10 \text{ m}$ in either the downstream or cross stream directions. This pattern was most predominant in regions where the lidar point cloud was less dense, allowing each original elevation error to have an effect over a larger area, for example, in the last (downstream) 100 m of the pool-riffle reach (Figure 2). The larger errors ($> \pm 9 \text{ cm}$) occurred in smaller symmetrical clusters about 3–5 m in diameter. In the plane bed channel, groups of the smaller flow mesh elevation errors ($< \pm 10 \text{ cm}$) tended to have a planimetric asymmetry with the long axis parallel to the lidar scan lines which intersected this straight reach at about 70° to the channel long axis (Figure 3). The larger errors ($> \pm 10 \text{ cm}$) occurred in small symmetrical clusters about 2–4 m in diameter.

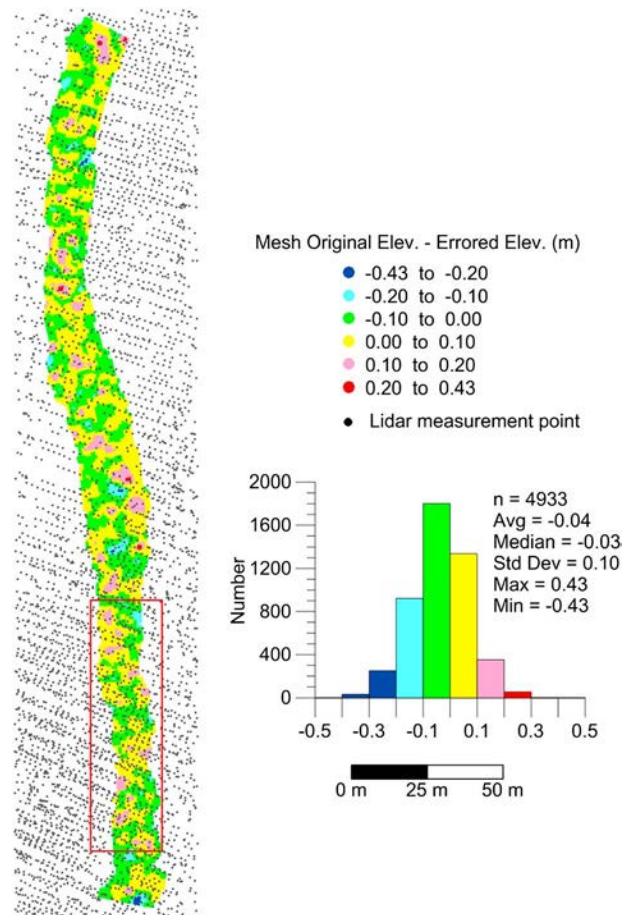


Figure 3. Elevation error pattern in MD-SWMS flow mesh of plane bed channel reach at bankfull flow ($6 \text{ m}^3 \text{ s}^{-1}$). Flow mesh has 1 m pixels, and errors are mapped in 1σ categories. Gray dots are lidar measurement locations in original EAARL point cloud. Red rectangle is area of ground survey shown in Figures 11b, 13, and 15. Flow is from bottom to top.

4.1.2. Patterns of Near-Bed Shear Stress Errors

Of the three modeled variables (water surface elevation, flow velocity and bed shear stress), only shear stress results at the lowest and highest discharges are presented. The bathymetry errors caused almost no change ($< 1 \text{ cm}$) in the predicted water surface elevations. FaSTMECH predicts shear stress from flow velocity, so bathymetric errors affect both of these variables in a similar fashion.

In the meandering pool-riffle channel reach, the magnitude of shear stress errors was normally distributed by magnitude with only a slight trend in the median toward more positive residual errors (see histograms in Figures 4 and 5). Relative to the original shear stresses, the errors were larger at low-flow conditions than at the greater discharge (the median original shear stress is noted at each discharge for comparison in Figures 4 and 5). The overall spatial patterns of shear stress errors in the meandering channel were similar from low-flow to high-flow conditions. However, at the higher stage there was flow around three islands that were still connected to the bank at the low flow. In these areas of complicated topography, such as around the island on the left side of the cross section A-A' in Figure 5, bathymetric errors sometimes caused greater shear stress and velocity errors. Along the margins of flow some nodes switched from wet-to-dry or vice versa when topographic errors were introduced.

The largest shear stress errors were generally in the main core of flow in places where the water was shallower and had a higher velocity. In those locations bathymetric errors of a given size make a relatively greater change in the cross-sectional area of flow. For example, a 15 cm bed elevation error in the bottom of a 2 m deep pool represents only a 7.5% change in depth, but the same error at a site with a flow depth of 40 cm causes a 37.5% change in depth. A consequence of this depth dependency is that higher shear stress errors were biased toward morphologic and habitat units that naturally have shallower and higher velocity flows (Figures 6a and 6b). In both low-flow and high-flow conditions, the smallest shear stress errors occurred in pools and planar areas, while riffles and point bars experienced greater errors. At low flows, the shear stress errors declined considerably where depths were greater than about 35 cm (Figure 6a). At bankfull flows, the water surface was about 45 cm higher, and the low-flow error pattern with depth and morphologic unit was essentially repeated, but shifted about 45 cm toward greater depths. Thus, at these high flows, errors decreased greatly where the water is deeper than about 80 cm (Figure 6b).

The direction of shear stress errors (increasing or decreasing when the topographic errors were introduced) consistently reflected the direction of the input bathymetric errors. Errors that locally raised the bed of the channel caused the cross-sectional area of flow to decrease and the flow velocity and bed shear stress increased correspondingly. Logically, some of the largest shear stress errors occurred where there was a combination of shallow and fast water and, by chance, larger positive and negative bathymetric errors occurred adjacent to one another. Examples include the areas defined by dotted circles in Figures 2, 4, and 5.

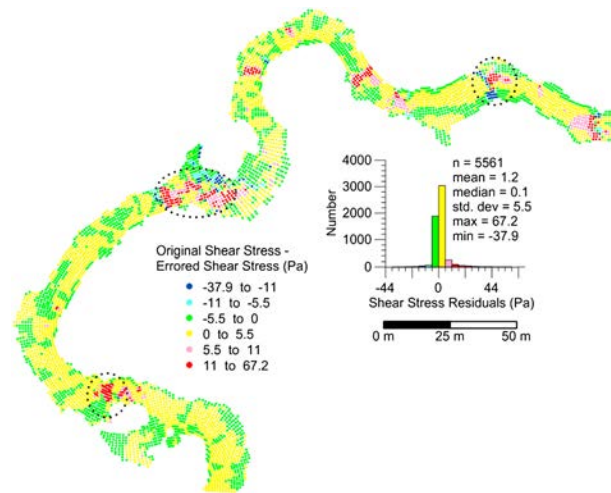


Figure 4. Pattern of near-bed shear stress residuals in pool-riffle reach with discharge of $1 \text{ m}^3 \text{ s}^{-1}$. Residuals calculated as shear stress in original bathymetric topography minus shear stress in bathymetric topography with introduced errors. Reach median shear stress in original topography is 1.1 Pa . Data are mapped in 1σ increments. Dashed circles are areas of large elevation errors discussed in text. Flow is from lower left to upper right.

Shear stress errors were smaller along the margins of flow in the plane bed reach where the channel morphology has a much simpler cross-sectional shape that approximates a trapezoid with steep sides (see cross section in Figure 7). A consequence was that changes in flow stage did not involve complex topography at the edges of the channel of the type seen in Figure 5, and in fact, there was relatively little increase in flow surface area with rising stage. Thus, bathymetric errors were not likely to cause more shear stress and velocity errors at the channel margin as it expanded upward and only slightly outward during higher flows.

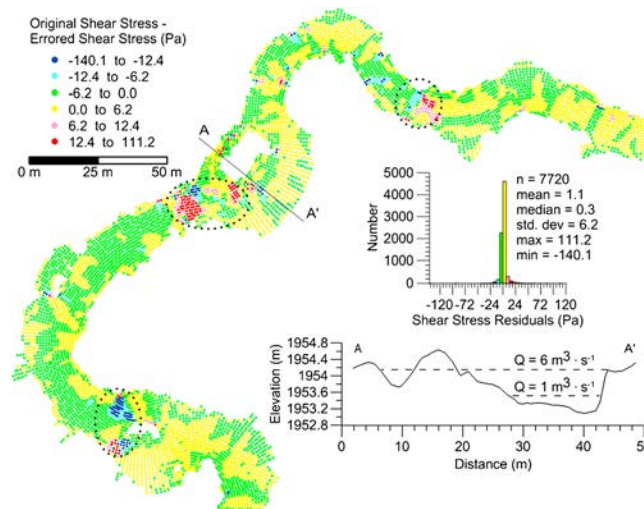


Figure 5. Pattern of near-bed shear stress residuals in pool-riffle reach with discharge of $6 \text{ m}^3 \text{ s}^{-1}$. Residuals calculated as shear stress in original bathymetric topography minus shear stress in bathymetric topography with introduced errors. Reach median shear stress in original topography is 4.9 Pa . Data are mapped in 1σ increments. Dashed circles are areas of large elevation errors discussed in text. Flow is from lower left to upper right.

Shear stress errors in the plane bed reach were also normally distributed with a slight trend toward more positive residuals, similar to the results of the pool-riffle channel (see histograms in Figure 7). Flow in the plane bed channel was not well structured by the bed morphology, and consequently the spatial pattern of shear stress errors was more poorly organized, particularly at low flows. The largest shear stress and velocity errors were where flows were shallowest and again higher stress and velocity were related to bathymetric errors that decreased flow depth. In low-flow conditions the errors declined greatly at flow depths greater than about 35 cm (Figure 6c). At bankfull flows the pattern of errors with depth shifted about 40 cm toward deeper flows (Figure 6d). The larger errors at this high stage were distributed over a wider range of depths but declined steadily and were less variable at flow depths greater than about 60 cm .

4.1.3. Patterns of Bed Mobility Errors

We calculated, for a range of potential critical shear stresses, the percentage of flow mesh nodes whose mobility state would change when a suite of bathymetric errors were introduced. For the pool-riffle topography, the result at near bankfull flow conditions is shown in Figures 8a and 8b for critical shear stresses ranging from < 1 to 100 Pa . At even very low critical shear stresses, less than 7% and 9% of the mesh had errors in predicted mobility state when smaller and larger random errors, respectively, were introduced (Figures 8a and 8b). During this high flow, the median reach shear stress of 4.9 Pa was equivalent to the critical stress for coarse sand material with a grain diameter of about 0.7 mm . As noted previously, this is a gravel bed channel, and the critical shear stress for the median grain size at this site was approximately 40 Pa . For this threshold stress and near bankfull

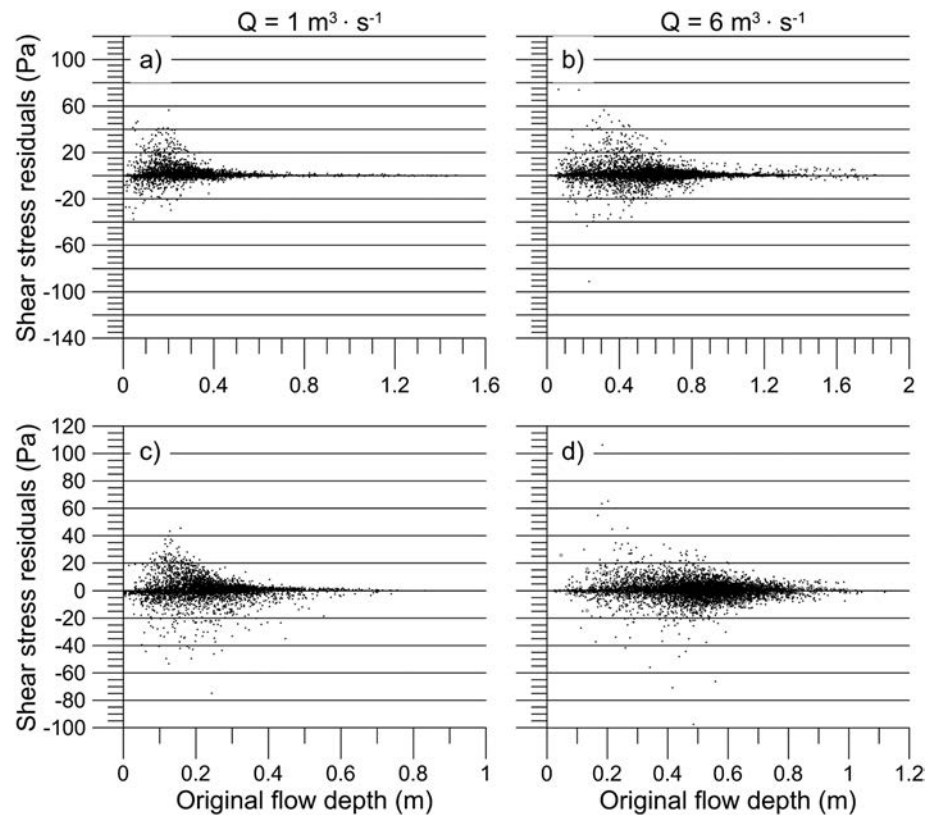


Figure 6. Shear stress residuals by flow depth and discharge: (a and b) Pool-riffle reach. (c and d) Plane bed reach. Lidar errors were introduced by random sampling of an error population with 1 standard deviation = 15 cm.

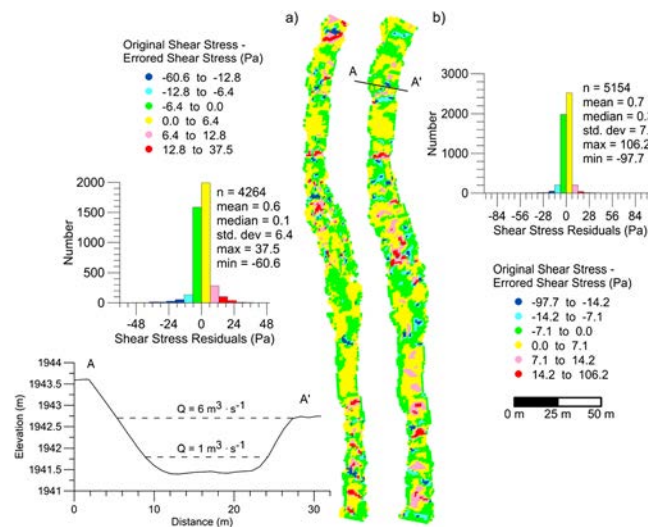


Figure 7. Pattern of near-bed shear stress residuals in plane bed reach: (a) discharge of $1 \text{ m}^3 \text{ s}^{-1}$. Reach median shear stress in original topography is 3.0 Pa, (b) discharge of $6 \text{ m}^3 \text{ s}^{-1}$. Reach median shear stress in original topography is 11.2 Pa. Residuals calculated as shear stress in original bathymetric topography minus shear stress in bathymetric topography with introduced errors. Data are mapped in 1σ increments. Flow is from bottom to top.

flow conditions, the smaller topographic errors caused about 0.8% of the nodes to switch from immobile to mobile and 0.6% became immobile (Figure 8a), while the larger introduced errors caused 0.3% and 0.9% to become mobile and immobile, respectively (Figure 8b).

In the pool-riffle reach, the spatial distributions of the mobility errors are shown in Figure 9. The mobility errors were concentrated in the same areas of greatest bathymetric errors (Figure 2) and highest shear stress residuals (Figure 5). The direction of mobility errors also corresponded to that of the original bathymetry errors. Where the elevation errors raised the bed, the shear stress increased, and any mobility errors tended to be those of increased mobility. The magnitude of the experimental errors had little effect on the spatial patterns (Figures 9a and 9b).

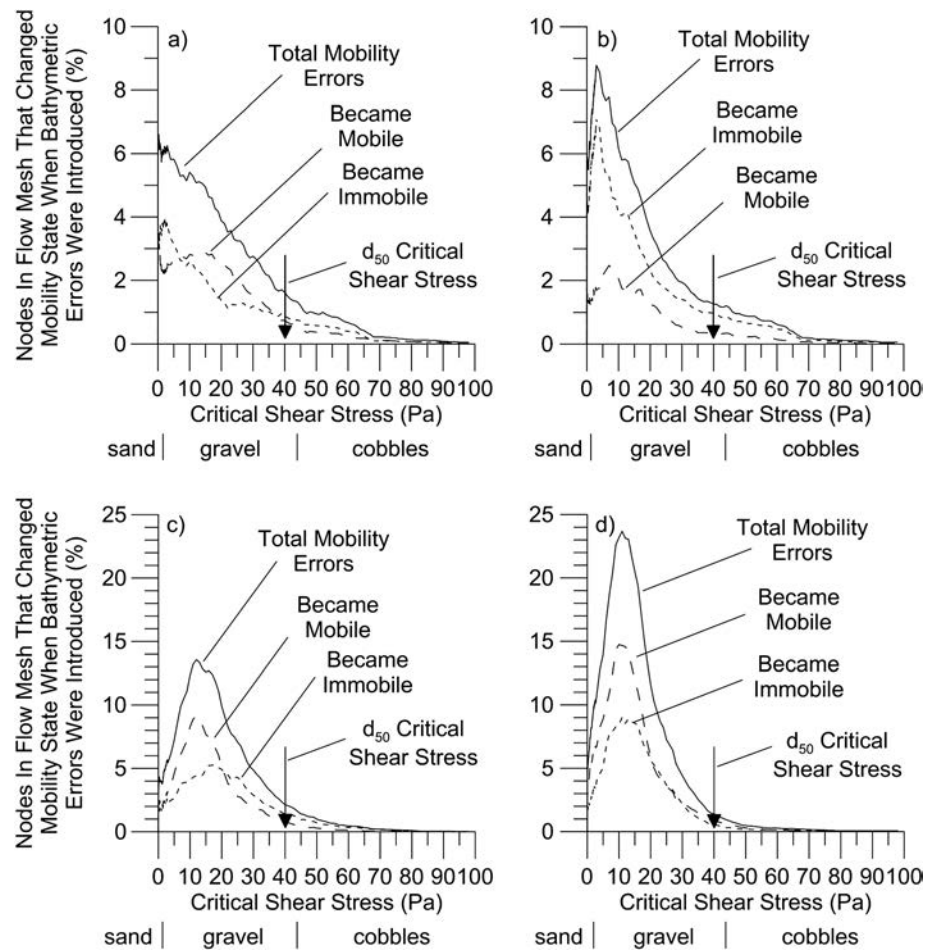


Figure 8. Bed mobility errors as a function of critical shear stress at near bankfull flows ($Q = 6 \text{ m}^3 \text{ s}^{-1}$): (a) pool-riffle with elevation errors having one standard deviation = 10 cm; (b) pool-riffle with elevation errors having one standard deviation = 15 cm; (c) plane bed with elevation errors having one standard deviation = 10 cm; (d) plane bed with elevation errors having one standard deviation = 15 cm. Local Bear Valley critical stress for the median grain size is 40 Pa. Typical ranges of critical stress for sand-, gravel-, and cobble-sized particles are indicated below graphs. [Figure 8c is modified from McKean *et al.*, 2009b.]

At near bankfull flow in the plane bed study reach, bathymetric errors caused more bed mobility errors than observed in the pool-riffle reach if critical shear stresses were greater than about 5 Pa (Figures 8c and 8d). This was probably a result of the overall lower water depth and the greater bed slope relative to the pool-riffle reach. The mean water depth of the plane bed reach is 11 cm less than that of the meandering reach, and the general slopes of the plane bed and pool-riffle reaches are 0.45% and 0.28%, respectively. The result is a median shear stress of 9.9 Pa in the plane bed channel versus 4.9 Pa in the pool-riffle case. These larger original shear stresses also meant that the size of the introduced elevation errors had a greater effect, especially in the range of critical shear stresses appropriate for smaller gravel sized particles (10–20 Pa). Still, at the d_{50} critical shear stress of 40 Pa, only about 0.8% of the mesh nodes changed from immobile to mobile and 1.5% became immobile when the population of smaller elevation errors was used (Figure 8c). Larger introduced errors changed these percentages only slightly to 0.5% and 0.8%, respectively (Figure 8d).

The sites and directions of mobility change shown in Figure 10 again corresponded predictably to changes in bed elevation and shear stress. At sites where the original shear stresses were near critical, mobility increased if large experimental errors raised the elevation of the stream bed, causing the near-bed shear stress to increase, and mobility decreased if elevation errors caused the bed to be lower and stresses to decline. The spatial patterns of bed mobility errors again varied only slightly between realizations of error populations (Figures 10a and 10b).

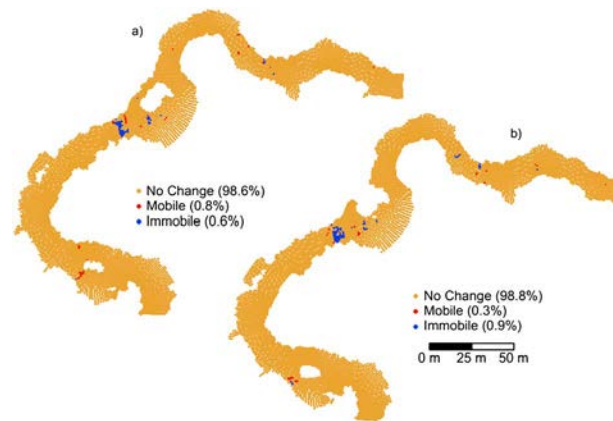


Figure 9. Predicted change in bed mobility at near bankfull flows ($6 \text{ m}^3 \text{ s}^{-1}$) in pool-riffle channel due to spatially random bathymetric errors sampled from a Gaussian distribution with: (a) 10 cm standard deviation, (b) 15 cm standard deviation. Mobility is assumed to occur when shear stress exceeds a critical value of 40 Pa. Change in mobility is defined as conditions at a node in the model flow mesh switching from mobile to immobile or vice versa when bathymetric errors are introduced to the model flow boundary. Flow is from lower left to upper right.

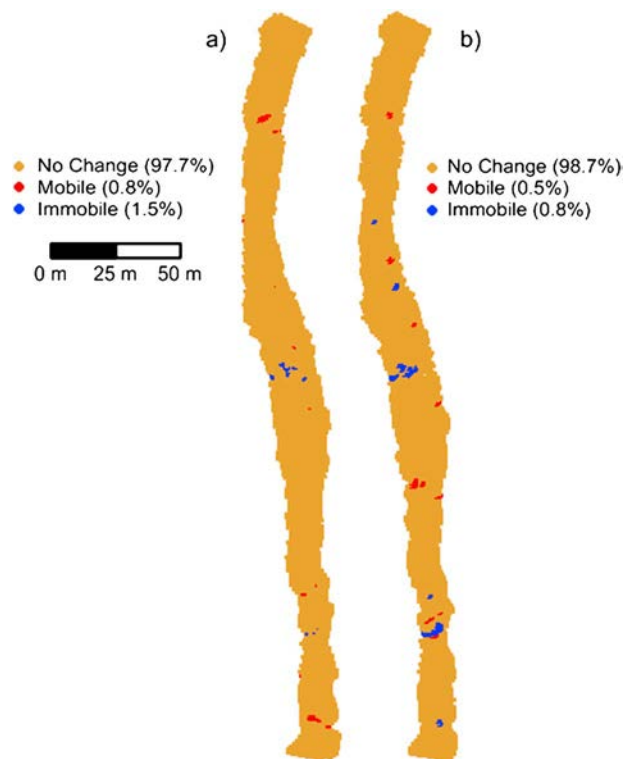


Figure 10. Predicted change in bed mobility at near bankfull flows ($6 \text{ m}^3 \text{ s}^{-1}$) in plane bed channel due to spatially random bathymetric errors sampled from a Gaussian distribution with: (a) 10 cm standard deviation, (b) 15 cm standard deviation. Mobility is assumed to occur when shear stress exceeds a critical value of 40 Pa. Change in mobility is defined as conditions at a node in the model flow mesh switching from mobile to immobile or vice versa when bathymetric errors are introduced to the model flow boundary. Flow is from bottom to top. [Figure 10a is modified from McKean *et al.*, 2009b.]

We also ran several additional simulations to test the reproducibility of our results as well as their sensitivity to the magnitude of introduced errors. In both the pool-riffle and plane bed reaches, for discharges of 1 and $6 \text{ m}^3 \text{ s}^{-1}$, we conducted two replications using different populations of errors with a standard deviation of 10 cm, and one simulation using errors with a standard deviation of 13 cm. In both stream morphologies the smaller elevation errors caused correspondingly smaller shear stress residuals and mobility errors. The global statistics were essentially identical for the two replications done using errors with a standard deviation of 10 cm. In the pool-riffle reach, all the tests produced similar spatial patterns of shear stress and mobility errors with the largest errors concentrated in the areas of shoaling water circled in Figure 5. In contrast, in the plane bed reach, each random population of elevation errors caused a unique spatial pattern of shear stress and mobility errors, as flow depths were not well structured by the bed morphology.

4.2. Ground Survey-To-Lidar Comparisons

4.2.1. Patterns of Elevation Errors

The elevation errors calculated by subtracting the lidar-generated flow mesh from the ground-survey-generated-flow mesh were normally distributed in magnitude (see histograms in Figure 11). In the pool-riffle reach there was a 5 cm bias in the median value toward more positive errors and in the plane bed reach this bias increased to 7 cm. The ranges and standard deviations of elevation errors were 2 to 3 times larger than those in the lidar to lidar-with-experimental-errors comparison, although the ground-to-lidar comparison study reach was only a small subset ($\sim 20\%$) of the model domain in the lidar to lidar-with-errors investigation. In the pool-riffle study site the smallest errors ($< \pm 21 \text{ cm}$) occurred throughout the reach while the largest errors ($> \pm 42 \text{ cm}$) tended to be on the channel banks along the edges of the mesh (Figure 11a). In the plane bed reach the larger errors ($> \pm 27 \text{ cm}$) were again concentrated along the margins of the flow mesh, and there was a systematic pattern of positive errors on the left bank and negative errors on the right bank (Figure 11b).

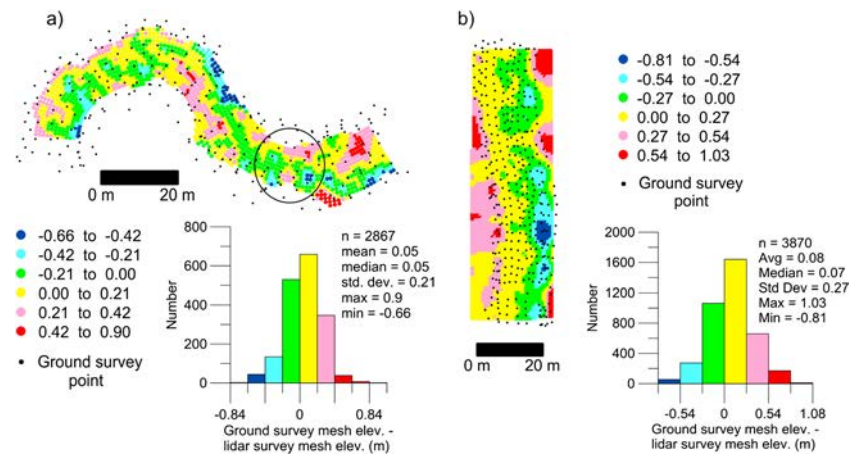


Figure 11. Patterns of elevation errors calculated as elevation in ground survey flow mesh minus elevation in lidar flow mesh: (a) Pool-riffle reach. Circle is location of higher shear stress and mobility errors discussed in the text. Flow is left to right. See Figure 2 for location of this study reach; (b) Plane bed reach. Flow is bottom to top. See Figure 3 for location of this study reach. Spatial resolution is 1 m, and errors are mapped in 1σ categories. Gray dots are ground measurement locations whose cross-stream extent is about 2–4 m beyond the channel banks.

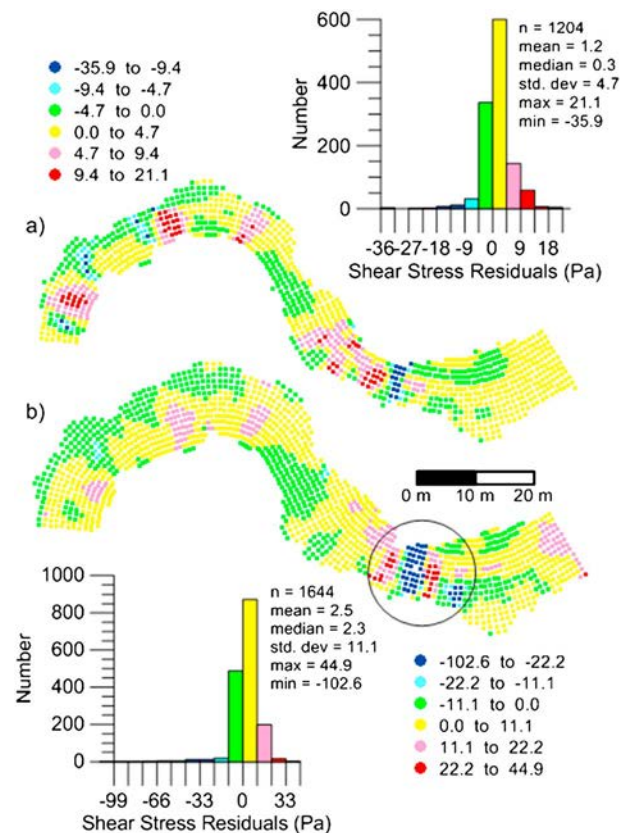


Figure 12. Pattern of near-bed shear stress residuals in pool-riffle reach with discharges of: (a) $1 \text{ m}^3 \text{ s}^{-1}$, (b) $6 \text{ m}^3 \text{ s}^{-1}$. Residuals calculated as shear stress in original ground-surveyed topography minus shear stress in bathymetric lidar topography. Reach median shear stress in the ground-surveyed topography is 1.7 and 11.2 Pa, in low-flow and high-flow conditions, respectively. Data are mapped in 1σ increments. Circle is the area of higher errors discussed in the text. Flow is from left to right.

This was due to an approximately 50 cm planimetric shift toward the left bank (looking downstream) of the lidar data in this reach, with unknown causes, that was noted by McKean *et al.* [2009a, 2009b].

4.2.2. Patterns of Near-Bed Shear Stress Errors

The differences between near-bed shear stresses modeled with the ground survey and lidar channel topographies were normally distributed by magnitude at low and high flows in both the pool-riffle and plane bed reaches (see histograms in Figures 12 and 13). In the pool-riffle channel the median, maximum, and minimum shear stress residuals all increased at the higher discharge, while in the plane bed reach there was less change with discharge and the median residual declined at the higher flow. In both morphologies during both flow conditions the median stress residuals were positive, indicating lower predicted stresses when using the lidar bathymetry. The spatial patterns of stress residuals were similar from low to high flows in each study reach (Figures 12 and 13). In the pool-riffle morphology the negative near-bed shear stress residuals occurred at sites where the lidar surveyed elevations were higher than those in the ground survey and the channel cross-sectional area for flow was reduced. The largest residuals, in the circled area in Figure 12b, were at the same location of large errors in the lidar to lidar-with-errors

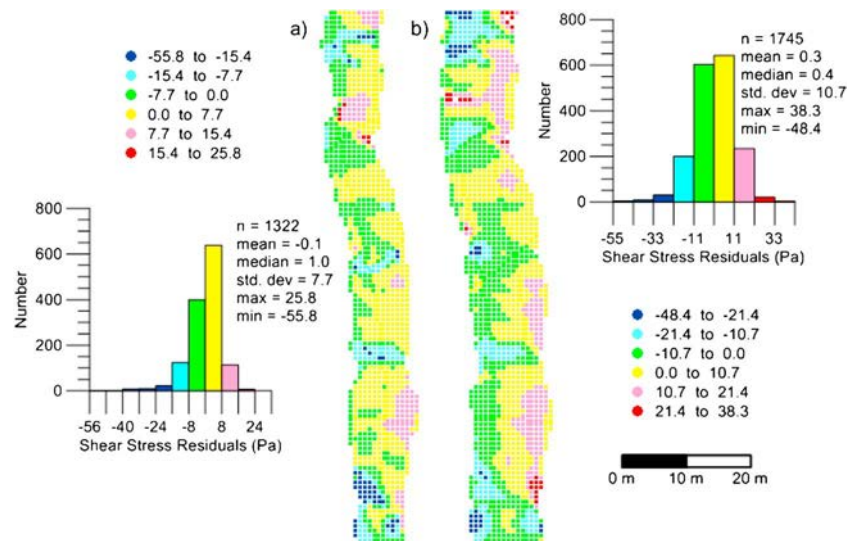


Figure 13. Pattern of near-bed shear stress residuals in plane bed reach with discharges of: (a) $1 \text{ m}^3 \text{ s}^{-1}$, (b) $6 \text{ m}^3 \text{ s}^{-1}$. Residuals calculated as shear stress in original ground-surveyed topography minus shear stress in bathymetric lidar topography. Reach median shear stress in the ground-surveyed topography is 7.5 and 18.3 Pa, in low-flow and high-flow conditions, respectively. Data are mapped in 1σ increments. Flow is from bottom to top.

comparison (see the downstream-most dashed circle in Figure 5). In the plane bed reach, the 50 cm eastward shift of the lidar data caused the water depth to increase along the left margin (looking downstream) and decrease on the right margin of the channel relative to the ground survey. This, in turn, caused the shear stress residuals to be negative on the left and positive on the right margins of flow, and the pattern was more pronounced at the high discharge (Figure 13).

4.2.3. Patterns of Bed Mobility Errors

At low flow in the pool-riffle reach, up to about 25% of the mesh changed mobility condition when the ground survey bathymetry was replaced with the lidar bathymetry (Figure 14a). However, this effect was predominantly in situations where the critical stresses were below about 10 Pa. During low flow in Bear Valley Creek, the critical shear stresses in the reach were generally well below those required to move the existing gravel bed, and using the d_{50} critical stress for the existing substrate (40 Pa) the change from ground-surveyed to lidar data had no effect on the predicted very limited mobility. At near bankfull flow, the peak in mobility errors shifted to between 5 and 25 Pa, reflecting the greater overall shear stress at that discharge, but the number of errors changed very little (Figure 14b). At the d_{50} critical stress in this high-flow condition, 2% of the model mesh shifted to mobile and 2% became immobile when the lidar bathymetry was used rather than the field surveyed topography.

At near bankfull flow in the meandering reach, all of the mobility errors were concentrated in one location (Figure 15). This area had a low density of lidar data (see downstream circled area in Figure 2), moderately high bed elevation differences between the ground and lidar surveys (Figure 11a), and higher shear stress residuals (Figure 12b). A natural local constriction in the channel also caused shear stresses to approach critical levels, which allowed the bathymetry differences between the lidar and ground surveys to cause changes in predicted mobility. The same area had larger shear stress residuals in the comparison of lidar to lidar-with-errors (see downstream dashed circle in Figure 5).

During low flow in the plane bed reach, mobility changed in up to about 44% of the mesh with the peak differences near a critical shear stress of 10 Pa (Figure 14c). As in the pool-riffle case, shear stresses were low throughout the plane bed reach at a discharge of $1 \text{ m}^3 \text{ s}^{-1}$, and the existing gravels, with a d_{50} critical shear stress of 40 Pa, were unaffected by the choice of model topography. During a discharge of $6 \text{ m}^3 \text{ s}^{-1}$, the peak in mobility errors occurred at approximately 20 Pa and using the d_{50} shear stress for the existing gravel substrate, 2.1% of the mesh became more mobile and 0.9% less so when the lidar topography was used in the model (Figure 14d). The pattern of mobility changes shown in Figure 16b is dominated by increased mobility in a small area at the downstream end of the model reach.

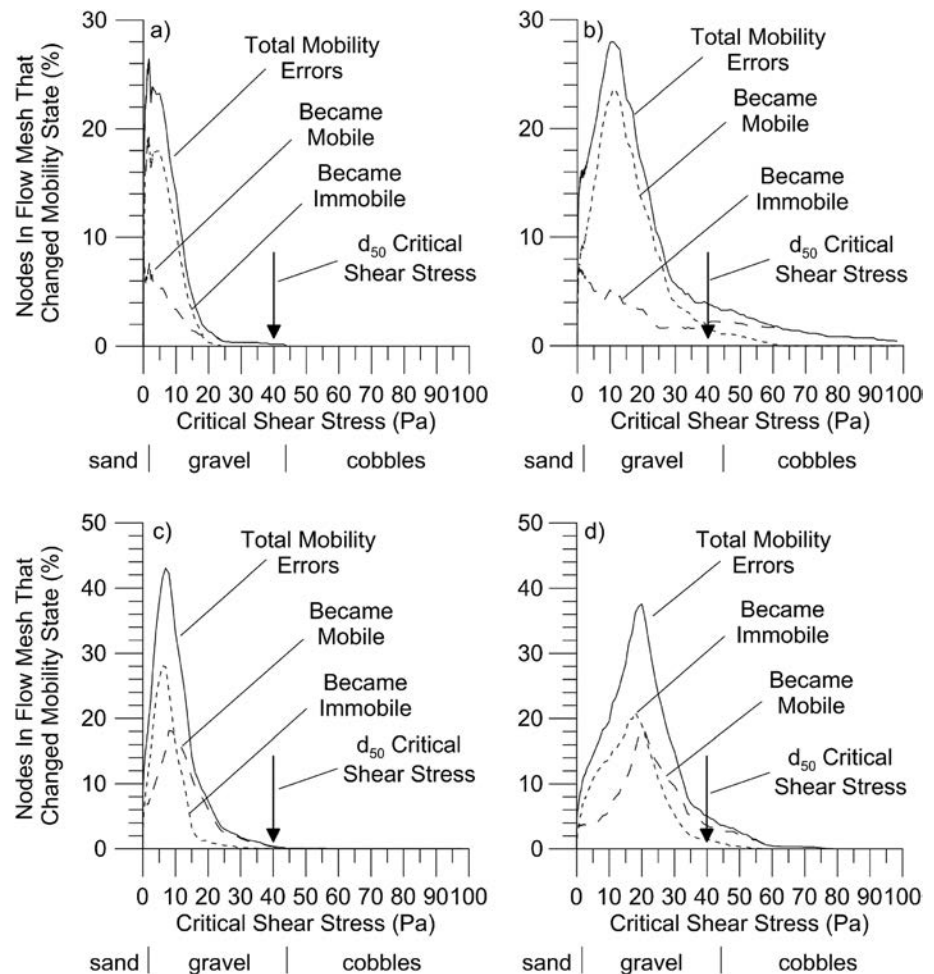


Figure 14. Lidar-to-ground survey comparison of bed mobility errors as a function of critical shear stress: (a, b) pool riffle at discharges of 1 and $6 \text{ m}^3 \text{ s}^{-1}$; (c, d) plane bed at discharges of 1 and $6 \text{ m}^3 \text{ s}^{-1}$. Peaks in the curves reflect the dominant bed shear stress at each discharge. Local Bear Valley critical stress for the median grain size of the existing substrate is 40 Pa. Typical ranges of critical stress for sand-, gravel-, and cobble-sized particles indicated below graphs.

5. Discussion

The goal of this study was to test the effects of point elevation errors, made with spatial patterns and magnitudes typical of those produced by the EAARL, on numerical flow models of streams. Furthermore, we were most interested in errors in the bed topography of the channels, and their effects on model predictions of near-bed flow conditions, rather than errors on the stream banks. In our comparison of the original lidar data to lidar data- with-introduced-errors, we created elevation errors in the lidar point cloud by randomly sampling from a Gaussian distribution. Therefore, there was no spatial correlation between input errors, i.e., the size of one point elevation error did not affect that of a neighboring error. *Legleiter et al.* [2011b] have criticized this approach and argued that in studies of this kind, *introduced* bathymetric errors must have a spatial correlation because hydrodynamic model *output* has a spatial structure, as conditions at one node in a flow mesh inevitably affect model predictions at nearby nodes. They assert that the use of spatially random input bathymetry errors represents a significant limitation of the work and cannot realistically capture the effects of topographic uncertainty on 2D flow model predictions.

Topographic errors with any spatial distribution, including random, always cause spatially correlated errors in a flow mesh, as the elevation raster is produced by interpolations between data in the original point cloud. The size and spatial scale of these correlated mesh elevation errors, e.g., the areal extent within a flow mesh affected by just a single input error, depends on the combination of the magnitude of the original point

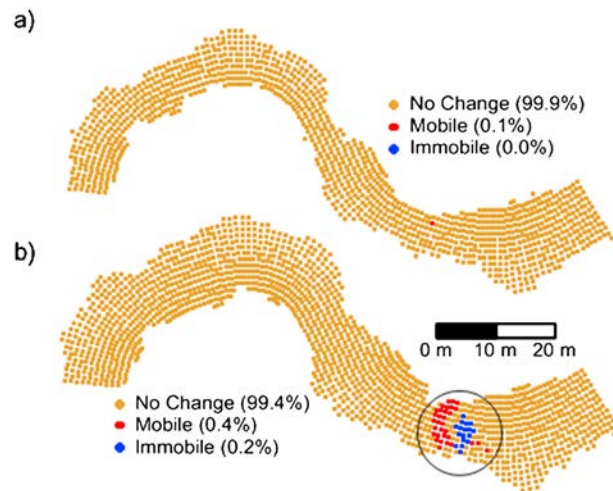


Figure 15. Predicted change in bed mobility in pool-ripple channel due to bathymetric errors with discharges of: (a) $1 \text{ m}^3 \text{ s}^{-1}$ and (b) $6 \text{ m}^3 \text{ s}^{-1}$. Mobility is assumed to occur when shear stress exceeds a critical value of 40 Pa. Change in mobility is defined as conditions at a node in the model flow mesh switching from mobile to immobile or vice versa when lidar topography replaces ground-surveyed topography defining the model flow boundary. Circle is the area of higher errors discussed in the text. Flow is from left to right.

ensuing model predictions, we argue that one cannot infer that the existence of such spatial structure in the modeled *output* dictates some non-random spatial structure in the original *input* bathymetric errors.

Nonetheless, for several reasons it is possible for the EAARL, or similar systems, to produce spatially correlated data errors. First, all data from airborne lidars have an intrinsic spatial structure caused by the scan pattern of the instrument. The effect of the EAARL cross-track scanner on the pattern of data can be readily seen in Figures 2 and 3. The data have an asymmetric spatial arrangement with more closely spaced data along the

elevation error(s), the local density of data, the local topographic complexity and the interpolation technique. This effect is well illustrated in our data where the random introduced point elevation errors caused clusters of elevation errors in the flow meshes of both the pool-ripple and plane bed study reaches (Figures 2 and 3). In areas with low data density, the spatial influence of single errors extended over many square meters in the flow mesh rasters. In contrast, in areas of high data density, the effects of larger point elevation errors were considerably reduced in both magnitude and spatial influence during the kriging interpolations to construct the elevation rasters. Furthermore, any pattern of errors, including random, in the flow mesh will also cause spatially structured effects in flow model predictions. Because all input elevation error patterns, including random, produce spatially correlated errors in derived flow mesh rasters and other

scan lines and sparser data in the direction of flight, perpendicular to the scan lines. This asymmetry is most developed at positions near nadir and least obvious at the edges of a scan swath. Any introduced errors will then occur within, and retain, this scan-related spatial structure.

Flight conditions and mission characteristics could also cause spatially correlated elevation errors. Temporal drift of the aircraft GPS and inertial navigation trajectories may lead to long wavelength error patterns that occur over whole stream segments and that are difficult to detect unless of high magnitude. Local air turbulence and curving stream geometries that require steeper roll of the aircraft can also cause direct elevation errors and planimetric displacements that indirectly lead to elevation errors [Kinzel *et al.*, 2013; Figure 4a].

Another possibility is lidar bathymetric errors that vary in magnitude and spatial

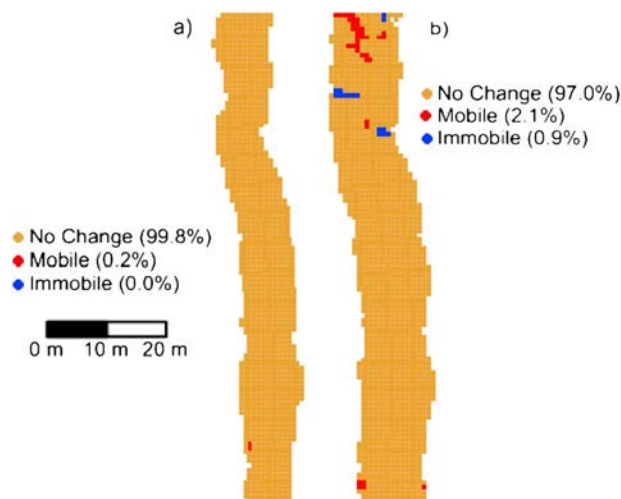


Figure 16. Predicted change in bed mobility in plane bed channel due to bathymetric errors with discharges of: (a) $1 \text{ m}^3 \text{ s}^{-1}$ and (b) $6 \text{ m}^3 \text{ s}^{-1}$. Mobility is assumed to occur when shear stress exceeds a critical value of 40 Pa. Change in mobility is defined as conditions at a node in the model flow mesh switching from mobile to immobile or vice versa when lidar topography replaces ground-surveyed topography defining the model flow boundary. Flow is from bottom to top.

pattern according to water depth. For example, *Bailly et al.* [2010] tested the accuracy of the Hawkeye II bathymetric lidar in the Gardon River, France, and found lidar biases with water depth. At depths less than about 20 cm, the lidar elevations were too high, and the suggested explanation was that many of these shallow data were on flow margins where the relatively wide footprint of the Hawkeye II instrument (2.25 m²) included reflected energy from both the bank and channel bed [*Bailly et al.*, 2010]. Conversely, at depths greater than about 2 m, the lidar elevations were too low relative to ground measurements. It is difficult to definitely explain this result in deep water, although it is what would be expected if the instrument did not properly identify the water surface and thus allow the processing algorithm to correctly reduce the laser velocity over the appropriate portion of the travel path. In the Trinity and Klamath Rivers of northern California, *Kinzel et al.* [2013] report difficulty mapping the stream beds in deep pools with the EAARL sensor due to a combination of in-water reflections from air bubbles and suspended sediment, laser energy absorption by organic compounds in the water, and poor reflectivity of the bed. However, at their Colorado River test site, the EAARL errors appear very poorly correlated with water depth [*Kinzel et al.*, 2013; Figure 9].

We tested for errors related to water depth by comparing 74 lidar point elevation measurements made within 25 cm, planimetrically, of ground survey elevation measurements in water depths that ranged from 0 to 1.2 m. A regression of bed elevation errors on water depth had a coefficient of -0.16 with an R^2 of only 0.08 and standard error of 0.17 m, indicating a very poor correlation, if any, between lidar errors and water depth. A visual inspection of the data also did not reveal any other spatial patterns of errors on the stream bed. As noted, there is a concentration of elevation errors along the banks of the plane bed reach, apparently caused by a systematic and uniform horizontal shift in the lidar data, but we found no spatial pattern of errors on the stream bed in that reach. Again, our field area has very clear water, with little suspended sediment, tannins or entrained air bubbles, and a highly reflective substrate. It is possible that in other fluvial settings, with poorer water quality or bed reflectivity, bed elevation errors would increase with water depth as a result of in-water reflections or absorption or poor bed reflectivity. It is also important to note that for hydrodynamic modeling, a non-random spatial pattern achieved by having the elevation error magnitude proportional to water depth would have a smaller influence on shear stress and velocity than would random errors. Furthermore, these smaller effects would be focused on pools where the local shear stress and bed mobility are already low.

The ground-to-lidar survey flow mesh elevation errors were greater than those in the lidar to lidar-with errors comparison, but the use of ground survey data raises several additional issues relevant to accuracy assessments [*Horritt*, 2005]. Each ground measurement is taken at a point, while the lidar records the three-dimensional location of a circular footprint about 20 cm in diameter, and the lidar-derived elevation represents some integrated measure of the different elevations in each footprint [*Jutzi and Stilla*, 2006]. As mentioned, the respective ground and lidar survey measurements also are never taken at exactly the same positions, and airborne lidar measurements have decimeter-level uncertainty in their locations, leading to further elevation discrepancies that cannot be separated from true local elevation measurement errors. These issues related to measurement technique are at least somewhat mitigated by interpolating each separate point cloud and then comparing elevation rasters or flow meshes as done in this study.

It is normally assumed that, because their individual point measurements can be made with greater accuracy, ground surveys are more accurate than those done remotely using airborne methods. Typically, a total station or differentially corrected GPS survey would have a point vertical accuracy of better than 1 cm, while the uncertainty of airborne lidar point elevations is an order-of-magnitude worse. However, as mentioned, the accuracy of an elevation raster, which is the goal in this application, depends in a complicated manner on the combination of not only the accuracy of the individual point elevations, but also the spacing and locations of measurements, the three-dimensional spatial scale of topographic roughness, and the raster interpolation technique. Bathymetric lidars typically record elevations at about 1 m planimetric intervals. It is tedious to gather data of this density in wading surveys, and this is seldom attempted in stream reaches longer than a few hundred meters. Furthermore, even in small streams like Bear Valley Creek it is common to encounter pools deeper than 1.5 m which are un-wadeable, and therefore even reach-scale field surveys are often incomplete. Thus, in airborne lidar surveys, there is a trade-off between poorer individual point measurement accuracy but much greater data density and spatial extent, and it may often be problematic to use field surveys as a standard, against which the accuracy of lidar data is measured.

The physical explanation of the effects of lidar elevation errors on shear stress predictions appears to primarily be simple water mass conservation, with upward elevation errors reducing the area for flow and causing the local velocity and shear stress to increase. In the pool-riffle morphology, this effect is accentuated at sites where the flow is shoaling and converging in a downstream direction, often approaching a riffle or bar, and depths decline to the ranges of peak error concentrations shown in Figures 6a and 6b. This illustrates the dominant control of flow conditions, forced by the basic bed morphology in the pool-riffle channel, on model prediction errors, regardless of the random pattern or magnitude of introduced bathymetric errors. In this channel type, a similar spatial pattern of predicted shear errors occurred in both low and high discharges and in the ground-to-lidar survey comparisons, and we expect that it would persist even if non-random bathymetric errors were introduced. Because of the lack of macro-bedforms in the plane bed reach, the original water depths are not strongly controlled by bed morphology, and shallow areas occur more randomly, often at larger than normal clasts on the bed. In addition to affecting the area for flow, we recognize that elevation errors also change the local bed slope and water divergence, which could further impact the velocity and shear stress.

At the two test reaches the bathymetric errors had little effect on predicted mobility of the gravel bed. This is partially because most of the flow domains are at considerably less than critical bed shear stress, even at bankfull flows. For example, the peaks between about 10 and 20 Pa in Figures 8c and 8d are near the most frequent shear stress for this plane bed reach and are well below the critical value of 40 Pa for grains of about the median size. If the critical shear stress had coincided with the reach median stress, i.e., the whole reach had been on the threshold of mobility of bed material comprised of smaller grain sizes, fewer than 24% of the mesh nodes at the plane bed reach would have changed mobility state as a result of the bathymetric errors introduced from a population with one standard deviation equal to 15 cm (Figure 8d). Consistent with the magnitude of shear stress errors, mobility errors were concentrated in areas where the original shear stress was within about ± 5 Pa of the critical level of 40 Pa. Again, in the pool-riffle morphology the flow structure focused the mobility errors on shoaling flows approaching riffles, bars, and islands, and this effect persisted at low and high discharges and in both the lidar-to-lidar and ground-to-lidar survey analyses. In the plane bed case the error pattern was less predictable.

We have not explored impacts of lidar bathymetry errors on other typical hydrodynamic model predictions beyond bed mobility. For example, it is difficult to anticipate the effects of lidar bathymetry errors on sediment transport predictions. Fluvial sediment transport varies strongly and often nonlinearly with shear stress, suggesting that the observed stress errors might have been intolerable. But on the other hand, sediment transport is notoriously uncertain due to other factors, such as flow turbulence, and thus bathymetric errors may not have been limiting.

We have concentrated on the effects of bathymetric errors on modeled depth and velocity in channelized flow, and on shear stresses on the bed of a channel. We have not investigated in any detail the impacts of EAARL inaccuracies on channel banks, although we recognize that bank topography can strongly affect momentum exchanges between the main channelized flow and floodplain flow, as well as analyses and predictions of bank erosion. Furthermore, previous research has shown that EAARL elevation errors are likely to be greater along channel banks, because of the combined effects of the lidar measurement footprint, the point density, and point horizontal and vertical accuracies in this area of rapidly changing topography [McKean *et al.*, 2009b].

One-dimensional fluid dynamics models calculate flow from the wetted area of channel cross sections and so are less sensitive to the details of boundary topography. Previous research in the same small streams in Idaho has shown that channel widths, depths, and cross-sectional areas of flow mapped in DEMs made from EAARL data were within 2% of those measured by field surveys [McKean *et al.*, 2009b]. Thus, the remotely measured channel boundaries appear adequate for 1-D flow models, and the necessary channel cross-sectional information can be automatically extracted from the EAARL-derived DEMs using software such as the River Bathymetry Toolkit [McKean *et al.*, 2009b, http://www.fs.fed.us/rm/boise/AWAE/projects/river_bathymetry_toolkit.shtml]. We have not tested the EAARL data in three-dimensional CFD models, but these are quite sensitive to the slope of the channel bed at the base of each discrete column in the flow mesh, and it is likely that typical EAARL point elevation errors will significantly affect model results.

6. Conclusions

In at least low gradient, clear-water, gravel bed streams, a new generation airborne bathymetric lidar appears to define the physical boundary of the channels with sufficient accuracy to support multi-dimensional computational fluid dynamics models of flow, bed shear stress, and bed mobility. This technological advance is significant as extensive high-resolution airborne lidar surveys offer the potential of metric-scale micro-habitat resolution over greater than kilometer-scale investigations of fluvial processes. Further research is required to define the range of poorer stream conditions (water depths/quality and bottom reflectivity) still acceptable for bathymetric lidar surveys. More experience is also needed with multi-temporal bathymetric lidar surveys to explore how accurately changes in channel hydrodynamics can be defined.

While our research is specific to the EAARL bathymetric lidar, it does provide information about the general effects of bathymetric errors on hydrodynamic models. Any mapping techniques that develop point elevation data with the spatial density and vertical accuracies we report should suitably support 2-D and quasi 3-D hydrodynamic models of velocity, bed shear stress, and bed mobility in similar riverscapes.

Where the bathymetric lidar method can replace short reach-scale field wading surveys, aquatic biophysical processes can be studied over a much fuller range of conditions. This is a particular advantage when investigating mobile species, for example anadromous fish, that use a wide variety of physical habitats over large stream extents during their various life stages. The problems of field access and selection of representative field sample reaches are also greatly reduced by using a synoptic airborne survey.

Acknowledgments

We gratefully acknowledge the financial support of the US Forest Service, Rocky Mountain Research Station. Comments from reviewers significantly improved the manuscript. Data are available upon request from the senior author.

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