Terrestrial Laser Scanning for Delineating In-stream Boulders and Quantifying Habitat Complexity Measures

Jonathan P. Resop, Jessica L. Kozarek, and W. Cully Hession

Abstract
Accurate stream topography measurement is important for many ecological applications such as hydraulic modeling and habitat characterization. Habitat complexity measures are often made using visual approximations or total station (TS) surveying that can be subjective and have limited spatial resolution. Terrestrial laser scanning (TLS) can measure topography at a high resolution and accuracy. Two methods, TS surveying and TLS, were compared for measuring complex topography in a boulder-dominated 100 m forested reach of the Staunton River in Shenandoah National Park, Virginia. The mean absolute difference between the two datasets was 0.11 m with 82.3 percent of the TS data within ±0.1 m of TLS. The TLS dataset was processed to remove vegetation and create a 2 cm digital elevation model (DEM). An algorithm was developed for delineating rocks within the stream channel from the DEM. A common ecological metric based on the structural complexity of the stream, percent in-stream rock cover, was calculated from the TLS dataset, and the results were compared to estimates from traditional methods. This application illustrates the potential of TLS to quantify habitat complexity measures in an automated, unbiased manner.

Introduction
The complexity of stream habitat plays an important role in ecological processes such as organic matter processing, periphyton growth, and nutrient dynamics, and, in turn, affects aquatic species diversity and population dynamics (Gorman and Karr, 1978; Biggs and Stokseth, 1996; Brown, 2003; Lepori *et al.*, 2005). Habitat complexity is difficult to quantify objectively (Downes *et al.*, 2000), particularly at small scales (Sanson *et al.*, 1995), creating the need for improved, high-resolution techniques for measuring stream morphology (Legleiter *et al.*, 2004). The size and location of flow obstructions such as boulders are important factors influencing hydraulic habitat complexity by creating flow refugia, turbulence, and velocity gradients utilized by aquatic organisms (Fausch and White, 1981; Hayes and Jowett, 1994; Biggs *et al.*, 1997; Rempel *et al.*, 1999). Hydraulic models are being used to predict the influence of these obstructions on 2D and 3D flow patterns (Crowder and Diplas, 2000; Shen and Diplas, 2008; Kozarek *et al.*, 2010; Waddle, 2010). However, model accuracy is limited by the measured topography (Pasternack *et al.*, 2006) and for many studies individual boulder shapes are represented by only a few measured points (Crowder and Diplas, 2006; Clark *et al.*, 2008; Kozarek *et al.*, 2010). Other habitat complexity measures, such as in-stream rock cover and substrate composition, have long been recognized as important features for organisms at various scales, ranging from macroinvertebrate to fish (Wesche *et al.*, 1987; Beisel *et al.*, 2000; Peckarsky *et al.*, 2000; Venter *et al.*, 2008). However, percent rock cover is typically measured qualitatively or estimated visually (Kaufmann and Robison, 1998; Willis *et al.*, 2005). Additionally, accuracy and precision of rock-cover measures decrease as the substrate heterogeneity of the site increases (Wang *et al.*, 1996).

One strategy for quantifying habitat complexity is to measure the structural complexity of stream topography (Bartley and Rutherfurd, 2005). Two categories of surveying methods are: (a) point measurements, and (b) remote sensing. Field-based point measurements are surveyed with tools such as total station (TS) instruments or global positioning system (GPS) receivers. These methods can be accurate where points are taken; however, they can be time intensive, be affected by user bias choosing representative point locations, and have limitations in spatial resolution and scope (Heritage and Hetherington, 2007). Remote sensing is performed with tools such as aerial and satellite imaging systems or aerial laser scanning (ALS), also known as aerial lidar systems. ALS has been used in many studies to generate digital elevation models (DEMs) or canopy height models (CHMs) with typical resolutions ranging from 10 to 200 points/m^2 and elevation errors of ± 0.15 m (Charlton *et al.*, 2009; Devereux and Amable, 2009). Marchamalo (2007) implemented ALS to perform 2D hydraulic modeling for trout habitat characterization and noted the advantage of ALS for large-scale studies. While aerial remote sensing has the ability to provide greater spatial coverage, it has limited resolution and precision for measuring meso-habitat complexity such as individual boulders and undercut banks (Heritage and Hetherington, 2007).

Jonathan P. Resop is currently with the Crop Systems and Global Change Lab, USDA-ARS, 10300 Baltimore Ave., Beltsville, MD 20705, and formerly with the Department of Biological Systems Engineering, Virginia Tech (resop@vt.edu).

Jessica L. Kozarek is currently with the St. Anthony Falls Laboratory, University of Minnesota, and formerly with the Department of Biological Systems Engineering, Virginia Tech.

W. Cully Hession is with the Department of Biological Systems Engineering, Virginia Tech.

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Terrestrial laser scanning (TLS), or ground-based lidar, can generate high-resolution point clouds and is not limited to overhead views such as with ALS, therefore increasing data collection and decreasing shadow effects of complex topography. TLS data can be used to create surface models with resolutions ranging from 1,000 to 10,000 points/m^2 and absolute errors less than $\pm$ 0.02 m (Entwistle and Fuller, 2009). There is potential for using TLS to measure small-scale changes and spatial features in fluvial systems (Rosser *et al.*, 2005; Hetherington *et al.*, 2007). TLS has been utilized in both small- and large-extent applications ranging from measuring 1 m^2 gravel surface patches at 1 mm resolution (Hodge *et al.*, 2009) to measuring a 150 m $\times$ 15 m stream reach at 1 cm resolution (Heritage and Hetherington, 2007).

The accuracy and resolution of the surveying method combined with the spatial interpolation method play important roles in the creation of DEMs. The spatial error of a DEM is related to the topographic complexity of a stream with greater errors occurring at slope brakes with an insufficient number of point measurements (Heritage *et al.* 2009). As a result, there is a need for more measurements in areas of high spatial variability, such as streambank edges or in-stream boulders. The potential for TLS to provide high-resolution surface models has led to TLS being used to quantify the errors resulting from calculating streambed scour and fill (Milan *et al*., 2011) and streambank retreat (Resop and Hession, 2010), demonstrating the importance of accounting for spatial variability.

TLS has been applied to measuring parameters such as surface roughness and grain size, which are difficult to estimate for hydraulic models (Smith *et al*., 2007). Entwistle and Fuller (2009) derived grain size from a TLS DEM for a dry streambed based on the standard deviation of elevations within a moving window. Heritage and Milan (2009) used TLS to measure bed roughness for bar-scale stream topography (0.15 m moving window over a dry gravel point bar) and noted the potential for TLS to replace traditional manual sampling methods. A major advantage of lidar is its ability to measure high point densities from complex topographies in a short amount of time, providing small-scale measures of roughness and variability (Glenn, 2006). TLS has also been utilized for measuring vegetation density as a roughness factor for hydrodynamic floodplain flow models (Straatsma *et al*., 2008). The focus of this study, however, is to quantify structural elements (large cobbles and boulders) within the stream channel that create local flow and sediment diversity (Crowder and Diplas, 2002; Yarnell *et al*., 2006).

Figure 1. Study site map locating the 100 m reach of the Staunton River within Shenandoah National Park, Virginia.

The objectives of this study were to: (a) delineate the location and size of individual rocks within a stream channel from high-resolution DEMs created from TLS data, and (b) compare traditional methods (TS surveying and visual estimation) with TLS for deriving measures of habitat complexity, such as in-stream rock cover, at a sub-reach scale for a brook trout (*Salvelinus fontinalis*) stream in Virginia.

Methods

Study Site

The study site was a 100 m forested stream reach on the Staunton River located in Shenandoah National Park, Virginia (Figure 1). The second-order stream is classified as a combination of step pool and cascade morphology with an average stream width of 3.5 m (Roghair and Dolloff, 2005). The site is characterized by many cobbles and boulders, a large section of undercut bank, and mature bank vegetation with very little understory. Kozarek *et al.* (2010) studied this reach to model 2D hydraulic complexity for characterizing brook trout (*Salvelinus fontinalis*) habitat and visually estimated percent rock cover. This is a sub-reach of a 1 km reach of the Staunton River sampled bi-annually to monitor brook trout population (Roghair and Dolloff, 2005). The sub-reach encompassed six habitat complexes (HC), defined as 10 to 20 m sub-reaches with several pools and riffles divided by low-flow barriers to fish movement (Roghair and Dolloff, 2005).

Field Methods

The stream reach was surveyed with a Topcon GTS 230W TS in May 2007. The TS survey was completed over four days with approximately 10 hours of field work per day for a total of 40 hours. In addition, an Optech ILRIS-3D portable TLS was used to survey the reach over three days in July 2007 with approximately six hours of field work per day for a total of 18 hours. Six benchmarks were used for aligning both the TS data and the TLS data.

The TS survey resulted in 2,701 points for characterizing the complex topography of the streambed, banks, and boulders. Mean point density was approximately 2 points/m^2; however, point density was higher in complex areas and less dense in relatively uniform topography. The reported accuracy of the TS is $\pm$ 3 mm + 3 mm per km of measuring distance (Topcon, 2010). To characterize individual boulders, points were taken at the apex(es) and around the base. Because of the curvature of the stream, two traverses were required to survey the 100 m stream reach; therefore, six benchmarks were used on large boulders to align and error-check the data. Additional details for the TS data collection can be found in Kozarek *et al.* (2010).

TLS was used to survey the stream during baseflow conditions. The scanner was moved to 25 locations around the stream to collect data from different angles and minimize shadowing effects of the laser. A total of 89 scans were taken of the entire reach with an average of 1 cm point spacing or 10,000 points/m^2 (Figure 2). Overlap was required between scans to assist with the alignment process. Both first and last pulse returns were used during measurement. The average distance of the scanner to the stream was 12 m, with scan distances ranging from 5 to 20 m. Based on the beam divergence of the laser system (0.00974°), the scanner has a footprint of 14 mm at the average distance and has an accuracy of 7 to 8 mm at a distance of 100 m (Lichti and Jamtsho, 2006; Optech, 2010). Large triangular targets serving as physical reference points were placed at the six benchmarks and used to align the TLS data with the TS data.

Data Alignment and Processing

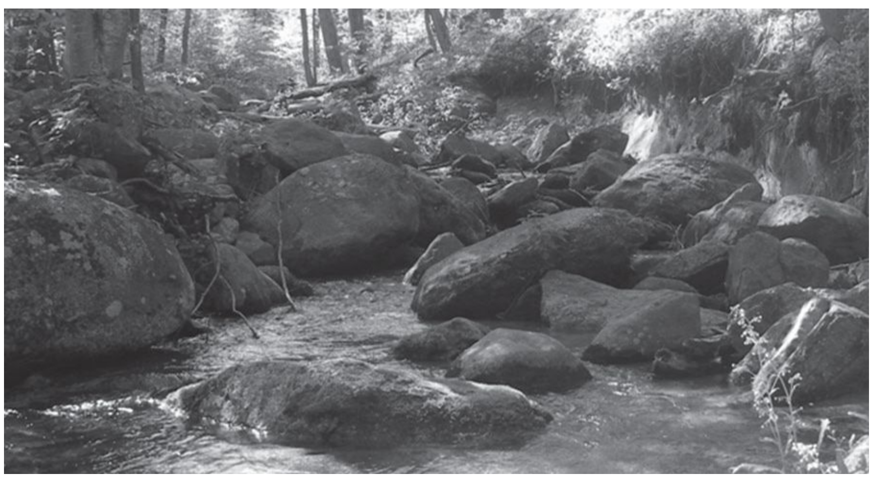
The TLS data were imported into PolyWorks version 10.1.6 (InnovMetric Software Inc., Quebec, Canada) one scan at a time and aligned into the same coordinate system using the IMAlign tool. Starting with the first two scans, similar identifiable features in the point clouds, such as rocks and fallen logs, were used to provide control points for a manual alignment. An automatic alignment algorithm was then used to best-fit the data to within a mean error of $\pm$ 0.0001 m. The rest of the scans were aligned in a similar, iterative manner. The entire TLS point cloud was then aligned to the same coordinate system as the TS survey data using the benchmarks and the best-fit algorithm. After alignment, the dataset was manually edited to remove large vegetation (shrubs and trees). TLS data processing in PolyWorks was performed over many days, with 9.5 million points in the final dataset.

Data Comparison

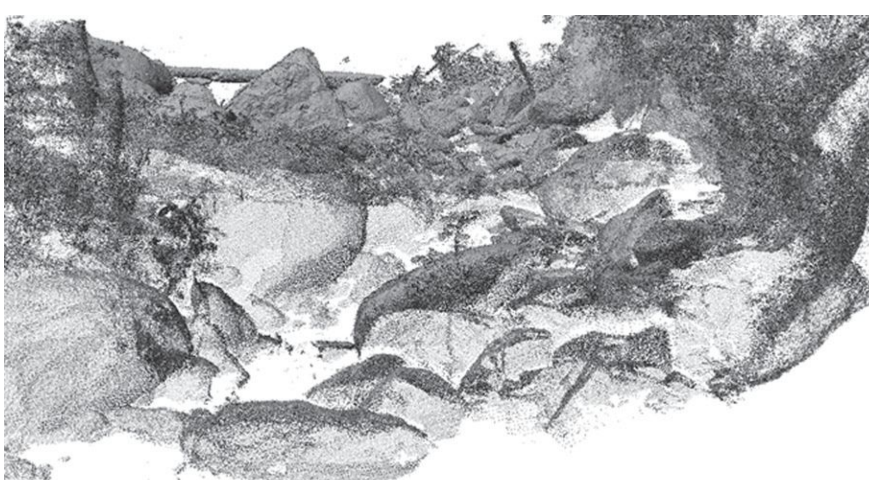
Once the datasets for both methods were aligned, the individual points from both datasets were compared. The point differences between TS and TLS were measured based on the point-to-point distances. TS point elevations were compared to the closest TLS data point within a 5 cm square grid around the point. The underwater streambed surface was not scanned by TLS due to the distortion of TLS near-infrared pulses by the water surface; as a result, TS streambed points were excluded from point comparison. While topographic data of the streambed is important for applications such as hydraulic modeling, the purpose of this paper is to extract information using TLS on stream topography above the baseflow water surface (such as protruding rocks).

Delineating In-stream Rocks

The TLS data were imported into MATLAB version R2009b (MathWorks Inc., Natick, Massachusetts) and converted into a 2 cm DEM. The minimum elevation was selected for each



(a)



(b)

Figure 2. (a) A section of the Staunton River (looking upstream), and (b) the same section represented by a TLS point cloud with an average 1 cm point spacing.

2 cm grid cell (Henning and Radtke, 2006) to increase the probability of using ground points for the DEM. Pixels in the DEM with a "no data" value were assumed to represent the water surface. A 5 × 5 majority filter was used to fill in small data holes in the DEM (isolated "no data" pixels located within the rock surface area) or remove isolated surface pixels from the water surface area. For "no data" pixels that were determined to be part of the rock surface area, the elevation was interpolated using a 3 × 3 mean filter. A binary grid was then created from the DEM representing either water surface or rock surface.

The rock delineation algorithm consisted of multiple image-processing functions designed to filter the TLS DEM and to define boundaries between rocks and the water surface and between rocks and other rocks. Similar algorithms have been developed in the field of forestry for delineating tree stands using remotely-sensed data (Andersen *et al.*, 2001; Culvenor, 2002; Koch *et al.*, 2006). The DEM pixels located within the stream channel were selected based on the stream-surface boundary defined by the water-edge locations measured at baseflow by the TS. Using the rock/water binary grid, continuous boundaries were created between the water surface and the rock areas.

Boundaries were then defined between individual rocks. A 5 × 5 low-pass (mean) filter was performed over the entire DEM to smooth the surface. A 7 × 7 local minima filter was used to determine the valley in the DEM and define the boundaries between rocks, similar to the method used by Culvenor (2002) to delineate tree boundaries. The rock-boundary layer was then merged with the water-boundary layer to create a single boundary layer. The boundary layer was processed with multiple filters to remove dead ends and connect small gaps, resulting in continuous, well-defined boundaries representing the areas of one or more rocks (Culvenor, 2002). An image-processing skeleton function was then used to reduce the width of the boundary to one pixel.

A sensitivity analysis was performed to evaluate the effect of the local minima filter size on the balance between Type I (false positives) and Type II (false negatives) errors in the delineation process. Type I errors occur when rock delineation boundaries are created that do not really exist and Type II errors occur when the algorithm fails to delineate a cluster of rocks. Minima filters of increasing size (3 × 3, 5 × 5, 7 × 7, and 9 × 9) were used in the algorithm and the resulting rock size distributions were compared.

The final step was to identify individual rocks in each area using a top-hat transformation, similar to the method used by Andersen *et al.* (2001) to identify tree crowns. A top-hat filter with a disc size of radius 15 pixels was used to identify the largest rocks in the DEM. A threshold and morphological open filter were then used to isolate the rock boundaries. Starting with the largest rock in the stream channel, the area defined by that rock was removed from the DEM. This process was repeated with smaller morphological filter sizes until all of the rocks were defined, using a 0.1 m minimum rock diameter threshold (a disc size of radius 3 pixels). The result was a database of rock size and location for the entire reach.

The results of the TLS rock delineation algorithm were compared to the locations and 2D plan-view area of 34 rocks measured from the TS survey. The number of TS points used to define the measured rock surfaces ranged from four to nine. The rocks in the TS dataset were matched to the nearest rock from the delineated TLS dataset. Due to the fact that the TS field measurements were of much lower resolution than the TLS dataset, they were used to compare with the general size and location of delineated rocks. Another limitation of the TS point data is that the boundaries of smaller rocks (those with diameters approaching 0.1 m) were not explicitly measured and as a result could not be compared with the TLS delineation results.

Ecological Metrics

The database of in-stream rocks delineated from TLS was then used to calculate two habitat complexity measures: (a) percent in-stream rock cover, and (b) distribution of grain size and rock area. These measures were then compared between traditional methods (i.e., visual estimation) and TLS for the six HCs within the stream channel. In-stream rock cover was defined as the percent area of rocks protruding from the stream surface during baseflow conditions. For visual estimation, two surveyors approximated the percent of the channel area covered by protruding boulders in August 2008. For TLS, grain size and plan-view area were calculated for each delineated rock. Grain size diameter was estimated from the plan-view area assuming a circular shape. Rocks were divided into two size classes based on their diameter: cobbles (greater than 0.1 m and less than 0.256 m) and boulders (greater than 0.256 m). Percent rock cover was calculated as the total plan-view area for all rocks within each HC divided by the total in-stream area. Similarly, percent rock cover was determined for both size classes (cobble and boulder). Within each HC the distribution of rocks was determined based on the mean, standard deviation, and maximum of individual rock areas as well as the number of rocks.

Results and Discussion

Data Comparison

Out of the 2,701 points measured with the TS, 596 were either located in the streambed (topography not scanned by TLS) or in small gaps in the TLS dataset. The other 2,105 TS points had a mean absolute elevation difference with the TLS data of 0.11 m and a standard deviation of 0.36 m. The point differences are comparable to results found by similar studies (Heritage and Hetherington, 2007), with 82.3 percent of the TS data within ± 0.1 m of the TLS data. The differences between the raw points measured by both methods are most likely due to the measurement error of the TS or any vegetation or large woody debris (LWD) that was not removed from the TLS data. Other potential errors include the measurement error of the laser scanner and the error from aligning the two datasets to the same coordinate system using the benchmarks.

Delineating In-stream Rocks

The delineation algorithm performed fairly well in terms of identifying individual rocks within the stream in an automated manner, based on comparing the TLS DEM to the delineation results (Figure 3). It is difficult to fully validate the results without a higher resolution TS survey or detailed field measurements, although some comparisons can be made with the existing TS data. There are obvious errors, such as rock clusters that were not fully delineated and other objects in the stream, such as LWD, which were delineated and classified as rocks. However, the method used for this study shows how relatively simple image-processing algorithms can be used with high-resolution stream topography data to delineate rock boundaries. The results would be valuable information for hydraulic modeling due to the influence that boulders have on flow complexity as shown by Crowder and Diplas (2000) and Kozarek *et al.* (2010).

A comparison was made between the TS point measurements and the TLS delineation algorithm using 34 rocks delineated from TLS (Figure 4b). The root mean square error (RMSE) was 0.27 m^2, or 55 percent with respect to the average delineated rock area and 74 percent of the delineated rocks had a center of mass within 0.2 m of the TS measured rock. In general, the TS data underestimated the size of individual rocks compared to TLS. While small differences in area between the two datasets can be attributed to the difference in resolution, larger differences are likely a result of errors within the TLS dataset and the delineation algorithm.

Sources of uncertainty in the rock delineation process include spatial variability (due to the complexity of the surface being scanned), parameter error, and model error. Parameter error consists primarily of measurement errors

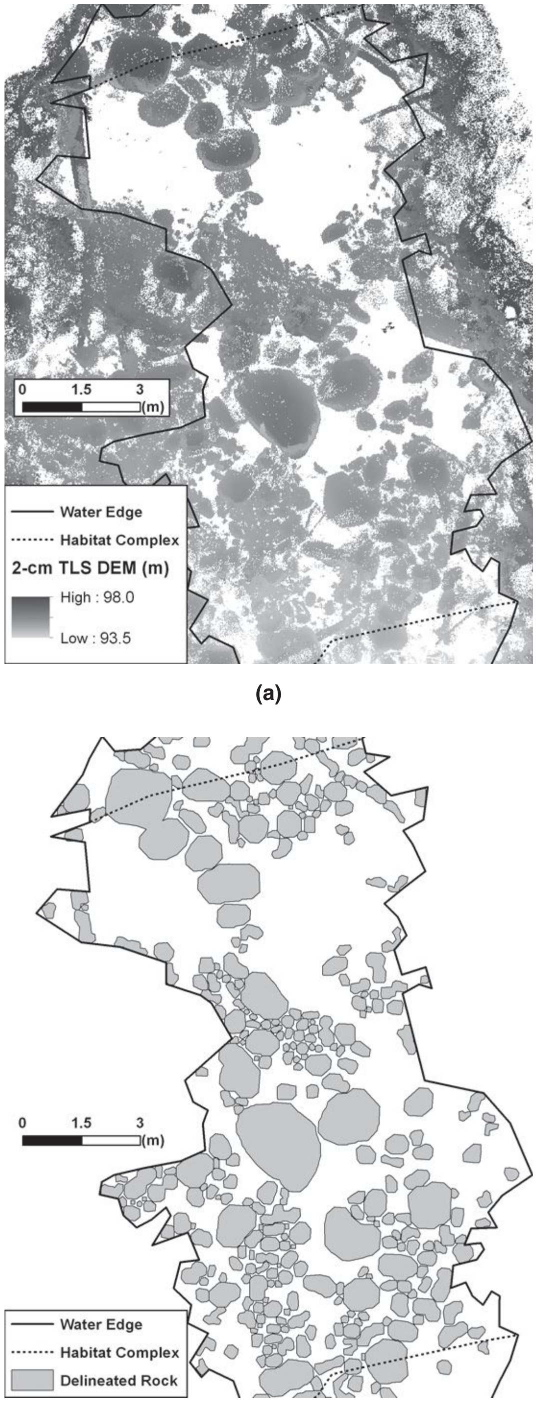


Figure 3. Plan-view maps of Habitat Complex 2 showing (a) the raw 2 cm TLS DEM with white space representing the water surface and small data gaps, and (b) individual delineated rock boundaries.

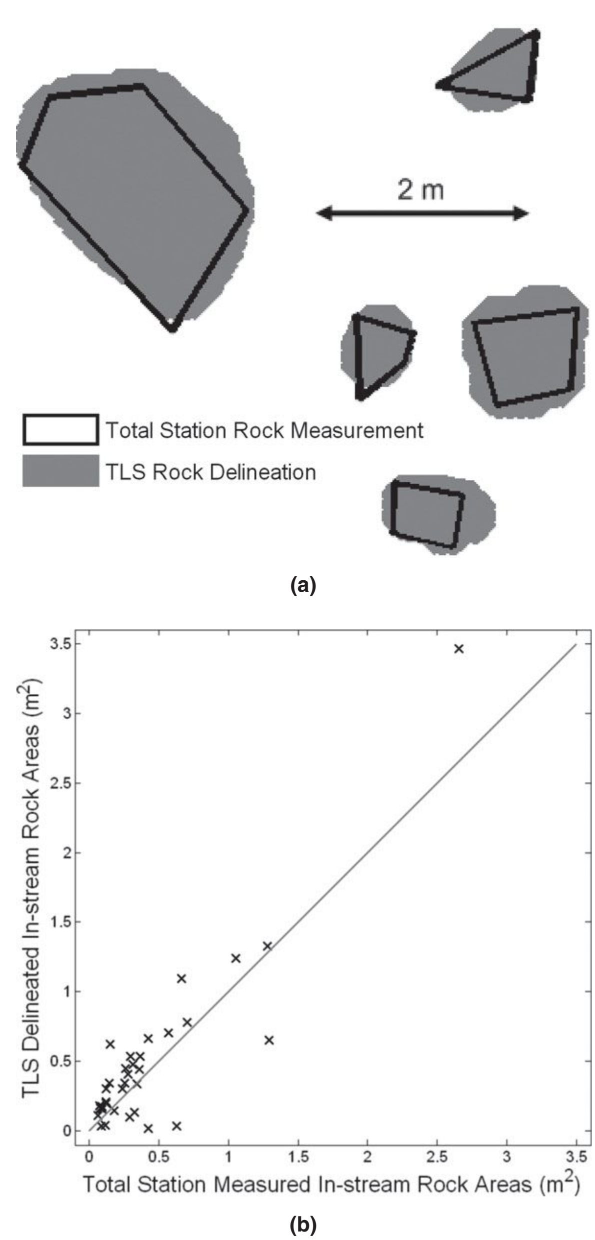


Figure 4. (a) Plan-view areas of example in-stream rocks measured with the both the TS and TLS, and (b) comparison between plan-view rock areas for 34 individual rocks measured by both TS surveying and TLS delineation.

selected from the stream reach (Figure 4a). The algorithm performed well at identifying the boundary, size and location of rocks measured in the field, based on the plan-view areas. There was general agreement ($R^2 = 0.83$) between the rocks measured with the TS and the rocks

Table 1. The Results of the Sensitivity Analysis Show How the Size of the Local Minima Filter used by the Rock Delineation Algorithm can Greatly Affect the Delineation Process

Size of Local Minima Filter	Number of Rocks	Mean Rock Area (m^2)
3 × 3	1,445	0.074
5 × 5	1,358	0.112
7 × 7	1,088	0.155
9 × 9	878	0.200

that occurred during the scanning process, such as gaps in the TLS data caused by shadowing and the presence of vegetation and LWD. Modeling error can be described by the Type I/Type II errors inherent to the delineation process. Type I errors occur when a rock is delineated that doesn't really exist, such as when a large rock is broken into many smaller rocks by the algorithm (which happened rarely) or when other in-stream objects were identified as rocks (such as LWD, which were not identified separately by the algorithm). Type II errors occur when the algorithm fails to delineate a cluster of rocks, identifying the cluster as a single, large rock.

A sensitivity analysis was performed by varying the size of the local minima filter used by the algorithm. Pixels identified as being local minima were used for defining the valleys that create the boundaries between rocks. As the filter size increased, it became less likely that a pixel was classified as a local minimum, fewer boundary pixels were identified over the entire reach, and as a result, the number of delineated rocks decreased and the average rock size increased (Table 1). Fewer individual rocks identified could lead to more Type II errors. As the local minima filter size decreased, pixels were more likely to be local minima. In this situation, the number of rocks increased and the average size decreased, making Type I errors more likely. The large range in the number of rocks and average area shows how sensitive the delineation algorithm is to the size of the local minima filter and demonstrates that more work is needed to optimize the algorithm.

Ecological Metrics

The visual estimates for percent rock cover and the values derived from TLS are summarized in Table 2. For the six HCs, the rock cover estimated in the field ranged from 10 to 65 percent, while the calculations made from the TLS data ranged from 24 to 44 percent. Ranking the HCs from smallest to largest percent rock cover, both methods had the same HCs for the lower three (1, 3, and 6) and upper three (2, 4, and 5). In general, the visual estimates overestimated rock cover with a mean absolute difference of 15 percent compared to the TLS calculations. The smaller range of values computed from TLS indicates the possibility that there is not as much difference in percent rock cover between the HC areas as estimated visually and demonstrates the advantage of an unbiased method for calculating rock cover. It is difficult to determine the true value of rock cover due to the uncertainty of both methods and the fact that rock cover depends on other variables such as stream flow (both methods were performed at baseflow).

The in-stream rocks delineated from TLS were right-skewed with respect to grain size, shown in Figure 5 by an empirical cumulative distribution function (CDF) with a sharp initial slope. It was determined that 71 percent of the 1,088 delineated rocks were classified as boulders (diameter greater than 0.256 m) with the rest classified as cobbles. Boulders

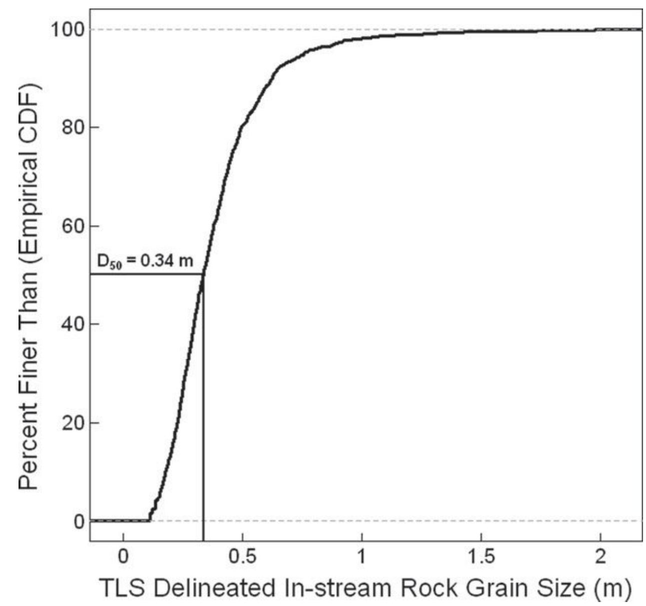


Figure 5. The distribution of in-stream rock grain size diameter for the 1,088 rocks in the stream reach identified by the TLS delineation algorithm (limited to rocks greater than approximately 10 cm).

Table 2. The Percent In-stream Rock Cover for each Habitat Complex (HC) Determined Using Visual Estimation and TLS Delineation; the Rocks Delineated Using TLS were also Classified as Cobble or Boulder Based on their Grain Size Diameter (D): Cobble (0.1 m < D < 0.256 m), Boulder (D > 0.256 m)

HC	Rock Cover (%)	Rock Cover (%)	Cobble Cover (%)	Boulder Cover (%)
	(Visual)	(TLS)	(TLS)	(TLS)
1	10	30.3	1.4	28.8
2	55	44.2	2.6	41.5
3	40	29.5	1.3	28.2
4	55	33.9	2.3	31.6
5	65	41.7	2.9	38.7
6	30	23.5	1.1	22.4

overwhelmingly contributed to the percent rock cover for each HU (94 percent of total rock area) (Table 2). The median grain size (D_{50}) of rocks larger than 0.1 m (the minimum detectable rock size by the delineation algorithm) was 0.34 m. The limitation with TLS is that particles below the water surface were not measured. The algorithm was also limited to identifying rocks larger than 0.1 m due to the data resolution. As a result, this TLS rock delineation only provides a partial, large-scale depiction of substrate composition.

Table 3 and Figure 6 show how the distribution of rocks varies between different HCs in the reach. From this information, one can observe in-stream areas defined by fewer, smaller rocks (HCs 1 and 6) as well as areas that are more densely covered (HC 2). These results are similar to the visual estimates of rock cover made in the field. However, with TLS more information can be quantified about the structural complexity of the stream and the spatial heterogeneity within and between HCs. Measures such as these could potentially be used to improve habitat characterization indices by providing automated, unbiased information.

Table 3. Plan-view Area Statistics of Individual Rocks Delineated from TLS for Each Habitat Complex (HC) Demonstrating the Diversity and Spatial Heterogeneity between Adjacent HCs

HC	Mean (m^2)	St. Dev (m^2)	Max (m^2)	Number of Rocks
1	0.159	0.151	0.789	124
2	0.169	0.334	3.462	304
3	0.158	0.282	3.064	182
4	0.133	0.194	2.358	230
5	0.158	0.271	2.416	173
6	0.144	0.116	0.705	75

Conclusions

TLS has potential for producing high-resolution, quantitative values for habitat complexity by enumerating cover provided by protruding bed substrate. The measures of topographic complexity generated from TLS could be used for further investigations involving habitat characterization. Measurements made using TLS for habitat metrics, such as in-stream rock cover, are unbiased and automated, thereby reducing the amount of uncertainty resulting from qualitative assessments. The surface models generated by TLS can potentially improve the accuracy of 2D and 3D hydraulic models and decrease the uncertainty associated with measurement and interpolation errors. The results from this study also have the potential to reduce the uncertainty in reach-wide measures for habitat assessment related to boulder and cobble representation.

Here we presented an application of tree crown delineation algorithms, previously used in forestry applications, for processing TLS-generated DEMs of stream topography. More research is needed to improve the data processing and rock delineation algorithms and optimize the balance between Type I and Type II errors. Optimization of the TLS rock delineation algorithm would be improved with high-resolution photography data for validation. More research is needed to quantify the uncertainty in TLS. While the feature extraction method presented in this study reduces the uncertainty from qualitative measurements and interpolation, the method introduces uncertainties resulting from the TLS tool and delineation algorithm. The sensitivity analysis demonstrates how the algorithm is sensitive to parameters such as the size of the window used for filtering.

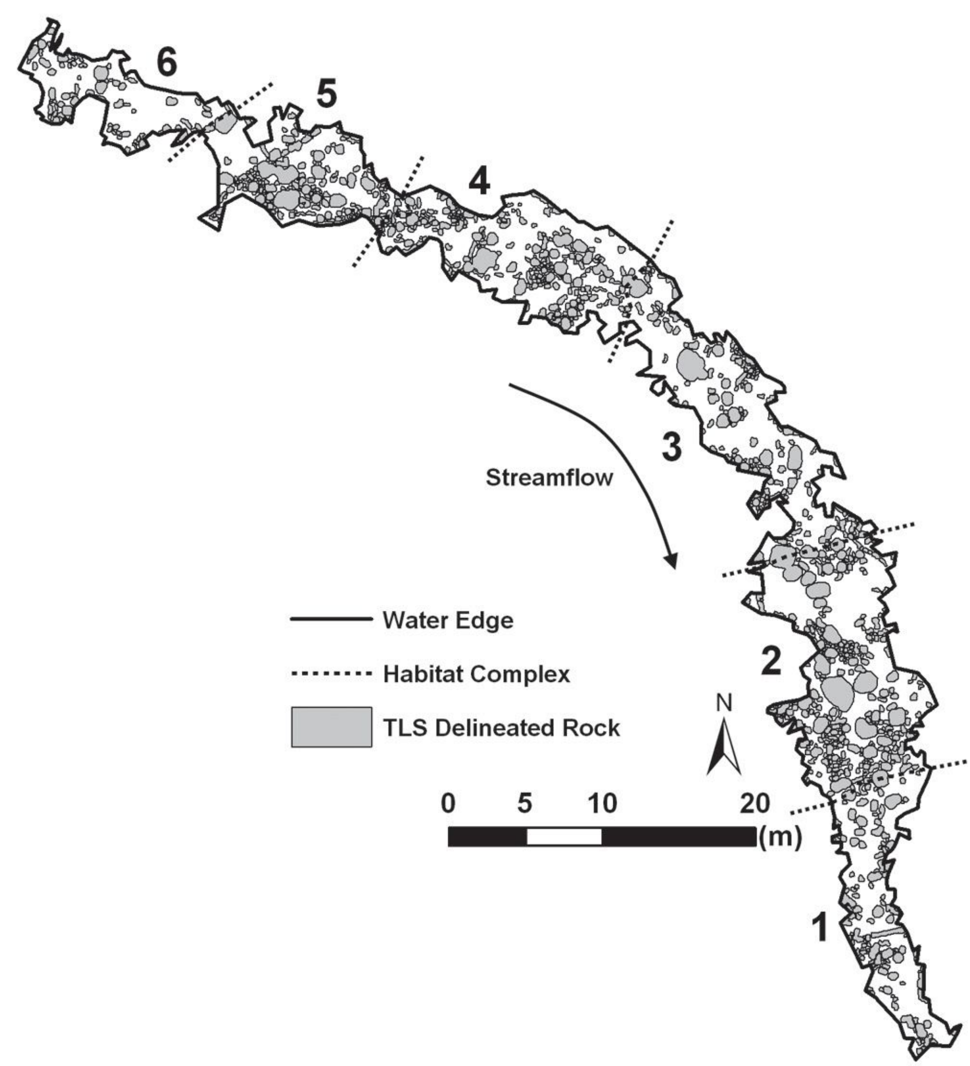


Figure 6. Plan-view showing the spatial distribution of individual in-stream rocks delineated within each Habitat Complex (HC).

TLS is limited by its inability to survey underwater topography; however, as demonstrated in this study, unbiased ecological metrics can be derived from TLS data above the baseflow water surface. Other potential ecological metrics derived from these data include quantifying large wood volume, shoreline vegetation, step-pool length, and topographic shading. However, the reflectivity of the laser is a limitation when studying other characterizations of channel morphology, such as bed substrate composition. TLS research has been performed on dry streambeds (Entwistle and Fuller, 2009; Heritage and Milan, 2009), although this is not a feasible option for sensitive fluvial systems, such as the one in this study. Blue-green wavelength laser scanners have been implemented for bathymetric surveys, although this technology is currently only available for ALS (Wedding *et al.*, 2008). Until this technology is ready for ground-based scanners, TLS should be combined with high-resolution bathymetric surveying tools to generate more complete surface models of stream topography for habitat complexity measures.

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