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Earth Surface Dynamics Discussions

Rapid and objective characterization of channel morphology in a small, forested stream

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Abstract. Forested, gravel bed streams possess complex channel morphologies which are difficult to objectively characterise. The spatial scale necessary to adequately capture variability in these streams is often unclear, as channels are governed by irregularly spaced features and episodic processes. This issue is compounded by the high cost and time-consuming nature of field surveys in this type of environment. In larger stream systems, remotely piloted aircraft (RPAs) have proven to be effective tools for characterizing channels at high resolutions over large spatial extents, but to date their use in small, forested streams with closed forest canopies has been limited. This paper seeks to demonstrate an objective method for characterizing channel attributes over large areas, using easily extractable data from RPA imagery collected under the forest canopy in a small (width = 10 to 15 m) stream, and to provide information on the spatial scale necessary to capture the dominant spatial morphological variability of these channels. First, the accuracy and coverage of RPAs for extracting channel data was investigated through a sub-canopy survey. From this survey data, relevant cross-sectional variables were extracted and used to characterize channel unit morphology using a principal component analysis-clustering (PCA-clustering) technique. Finally, the length scale required to capture dominant morphological variability was investigated from analysis of morphological diversity along nearly 3 km of channel. The results demonstrate that sub-canopy RPA surveys provide a viable alternative to traditional survey approaches for characterizing these systems, with 87% coverage of the main channel stream bed. The PCA-clustering analysis provided a more objective means of classifying channel morphology with a correct classification rate of 85%. Analysis of morphological diversity suggests that reaches of at least 15 bankfull width equivalents are required to capture the channel's dominant heterogeneity. Altogether, the results provide a precedent for using RPAs to characterize the morphology and diversity of forested streams under dense canopies.

1 Introduction

Processes and features within forested, gravel bed streams may be transient, episodic, and possess irregular spatial patterns (Pryor et al., 2011; Wohl and Brian, 2015; Hassan et al., 2019). These characteristics can lead to a high degree of spatial variability and channel complexity, even within a relatively homogeneous channel type (Madej, 1999; Nelson et al., 2010; Gartner et al., 2015). From a practical management perspective, there is often a need to characterize such systems to obtain metrics related to channel geometry, flow hydraulics, sediment properties, and aquatic habitat (Buffington and Montgomery, 2013). A common challenge, however, arises in assigning a specific morphology to complex river sections, an issue compounded by

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difficulties in determining the minimum spatial extent necessary to capture the primary structural variability present in forested gravel bed streams. While approaches are often taken to select 'representative sites' when the characterisation of channel variables is necessary (Harrelson et al., 1994; Bisson et al., 2006), site selection is often based on a narrow subset of metrics (e.g. gradient, see Montgomery and Buffington, 1998) and 'rules of thumb' are frequently used to define the spatial extent of the surveyed area (Bisson et al., 2006). Given the logistical difficulty and cost of undertaking field surveys in small, forested gravel-bed streams, a more precise approach for site selection and resulting channel classification is warranted.

Channel classification serves to integrate the variability observed along a given length of channel into specific channel types or morphologies (Harrelson et al., 1994). In addition to describing channel types and patterns, classification schemes have served to facilitate discussions on stream management among disciplines (Buffington and Montgomery, 2013). This is evident in the array of classification schemes proposed to characterize channel morphology for both geomorphologists and ecologists alike (e.g. Hawkins et al., 1993; Rosgen, 1994; Montgomery and Buffington, 1997; Brierly and Fryirs, 2005). However, a common drawback of these classification approaches is their descriptive nature (Buffington and Montgomery, 2013; Hassan et al., 2017) and that their implementation can be subjective, differing between classifiers. Furthermore, traditional survey techniques often limit classification to short, accessible channel areas due to time and cost constraints, and these limitations may bias our understanding of the larger river network as a result of missing important channel areas and processes (Fausch et al., 2002; Hugue et al., 2016). More objective, flexible, and repeatable techniques for characterizing streams that can be applied at a scale relevant to the natural geomorphic and ecological processes within them are therefore desirable (see Fausch et al., 2002).

Traditionally, characterization and classification of channels through field surveys has required the use of a variety of GPS-based tools and linear-survey methods involving automatic levels, theodolites, and total-stations (e.g. Bangen et al., 2014; Reid et al., 2019). However, advances in our understanding of connections between geomorphological, hydrological and ecological processes across the riverscape require a new approach for fluvial characterization that can capture many variables concurrently and be conducted at scales relevant to key processes and their interactions (Beechie et al., 2010). In consideration of a river network, these spatial scales are often intermediate in length (in the order of kilometers), domains over which continuous, high-resolution characterisation of channel conditions is expensive and time consuming using ground-based survey methods (Fausch et al., 2002). Over the past decade, the use of remotely-piloted aircraft (RPAs) has enabled collection of high-resolution imagery over a range of scales for evaluation of stream bed topography (e.g. Tamminga et al., 2015; Woodget and Austrums, 2017), bathymetry (e.g. Kasvi et al., 2019), and ecological parameters (e.g. Roncoroni and Lane, 2019). However, much of this work has been limited to larger systems with relatively little obstruction from forest canopy or other overhead obstacles. This limitation therefore excludes a large fraction of river network length from RPA-based surveys, particularly in densely forested environments.

The primary objective of this paper is to develop and test a methodology using continuous RPA-derived data for objectively classifying channel morphology and characterising scales of variability in small, forested rivers under dense forest canopies. In an effort to improve the characterization of these channels, a new framework is developed to map and classify channel attributes

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through the use of RPA-based data collection under forest canopies. To build this framework, this paper aims to address the following research questions:

1. What are the capabilities and limitations of a survey approach using sub-canopy RPA flights to characterise channel morphology in small, forested streams?

2. Can RPA-derived continuous measurements be used to objectively characterize patterns in channel morphology?

3. What is the spatial extent of data collection necessary to capture the primary variability in geomorphic channel attributes?

To address these questions, a sub-canopy RPA survey was conducted along approximately 3.0 km of channel in Carnation Creek, B.C., a small coastal stream located on western Vancouver Island. This site serves as a valuable testing area due to the abundance of complementary channel attribute data available (Tschaplinski and Pike, 2017; Reid et al., 2019).

2 Study area

This research was conducted along Carnation Creek, a small gravel bed river located on the southwest coast of Vancouver Island, B.C. (Fig. 1). The watershed has been the site of a long-running fish-forestry interactions study focusing on the effect of different logging treatments on watershed response. The channel mainstem is approximately 8 km long and has a drainage area of 11.2 km^2 (Tschaplinski and Pike, 2017). The focus of research is along the lowermost 3 km of the channel, which possesses a low gradient (0.5–1%) and is dominated by a pool-riffle channel morphology. Upstream, the channel narrows into a canyon (Fig. 1) which contains predominantly a step-pool morphology and gradient above 5% (Reid et al., 2019). The average bankfull width (w_b) of the lower channel is close to 15 m. The channel is located within the Coastal Western Hemlock Biogeoclimatic Zone, common along coastal regions of the Pacific Northwest (Hartman et al., 1982). Visual estimates suggest that over 50% of the channel is hidden below a dense forest canopy composed of both coniferous and deciduous tree species. The environment is typical of the Pacific Northwest: precipitation rates are high and dominated by rain (between 2,900 – 5,000 mm/year), the majority of which falls during the autumn and winter months (Tschaplinski and Pike, 2017). Streamflow ranges from 0.1 m^3/s to 64 m^3/s in fall and winter months, (Tschaplinski and Pike, 2017), and is often very low ($<$ 0.01 m^3/s) for extended periods in the summer (Reid, 2020). Frequent storms in the winter months lead to multiple floods per year that are capable of mobilizing gravel in the system, with bankfull discharge between 20 and 30 m^3/s (Haschenburger, 2011).

The processes governing the morphological and hydraulic conditions in Carnation Creek are irregular in both time and space, creating a great deal of heterogeneity along the channel. Sediment is predominantly delivered from episodic landslides and debris flows located in the upstream half of the watershed, while large logjams intercept delivered material and lead to spatially variable sediment textures and morphological features (Reid et al., 2019). The sediment texture of the bed varies from small gravels near the stream outlet to coarser cobbles and boulders in the steeper canyon reach, but varies substantially over short distances (Reid et al., 2019). The bed surface and subsurface sediment textures are similar, representative of systems that experience comparatively high sediment supply conditions (Hassan et al., 2006).

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Detailed channel morphology data have been collected through annual topographic surveys in eight study sections (SAs 2–9), seven of which (SAs 2–8) are located downstream of a canyon (termed the 'canyon reach', see Fig. 1). The eighth study section (SA9) is located away from the others, upstream of the canyon. The lower study sections are 300–500 m apart and 5–10 w_b (50–150 m) in length (Reid et al., 2019).

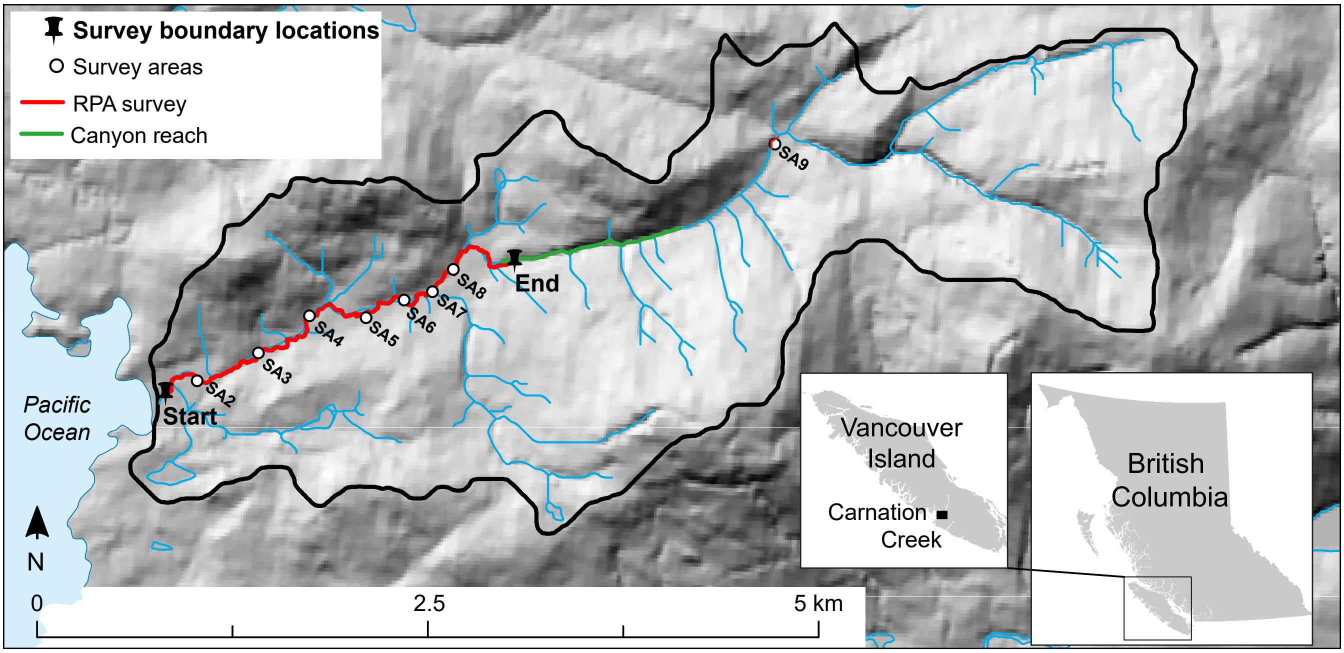

Figure 1. The Carnation Creek watershed, located on the south-west coast of Vancouver Island. The RPA survey extent is shown as a red line. An additional site (SA1) located in the channel estuary was active until the late 1980s, but has since been abandoned and was not included in this survey. Note that the RPA survey also included coverage of SA9, upstream of the other sites.

3 Methods

3.1 Remotely piloted aircraft survey

In July of 2018, approximately 3.0 km of channel was surveyed, with coverage extending from just upstream of the river mouth to the downstream limit of the canyon reach (Fig. 1), as well as over most of the SA9 study section. SA9 is farther upstream and possesses smaller channel dimensions, and therefore serves as a challenging test site to evaluate the coverage attainable with the RPA. Total survey time was approximately 12 full days, including flights over SA9. The RPA survey involved low-level flights conducted in tandem with placement of Ground Control Points (GCPs) that were surveyed with a Leica TPS 1100 total station. Flights were undertaken with a DJI Phantom 4 Advanced RPA, a consumer-grade RPA which contains a camera with a focal length of 8.8 mm (24 mm in 35 mm format equivalent) and a field of view of 84°. To avoid view obstruction

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of the channel bed, the RPA was flown manually below the canopy, with flying heights ranging from approximately 5–15 m above ground level. To obtain sufficient overlap between images, frames were acquired at two second intervals while moving at approximately 1 m/s horizontal velocity.

Due to flight obstacles (low-hanging branches, fallen trees, etc.), sightline obstructions, RPA battery life, and other practical survey challenges, the 3.0 km of channel was divided into roughly 80 segments, covered by 300–1,000 photos each. Each segment was initially flown following flight lines parallel to the channel direction, with imagery collected at 90° relative to the bed plane. While this in-flight photography strategy captured much of the channel, bank areas were often obstructed from overhead view by low-elevation shrubs, ferns, and brambles. To capture these obscured channel areas, each segment was flown with oblique and convergent imagery. 'Oblique imagery' refers to frames captured with a camera angle differing from bed-perpendicular, while 'convergent' refers to images capturing the same bed area but from different approach directions. This approach to image collection is likely advantageous in streams where riparian vegetation may prevent the RPA from flying directly over the bank, and has led to improvements in the quality of survey outcome in several studies (Wackrow and Chandler, 2011; James and Robson, 2014; Harwin et al., 2015). To collect this type of imagery, the RPA camera was tilted at a low angle (20–30° from vertical, see Figure 2 a) and a flight path parallel to the banks was taken (see Figure 2 b).

In order to provide precise imagery georeferencing, a minimum of ten ground control points (GCPs) were placed in each of the 80 segments, with additional points positioned in order to serve as independent checkpoints to assess the accuracy of the model outputs. The majority of the GCPs were distributed in a zig-zag fashion along dry exposed bars in the periphery of the channel segments, with a smaller number situated towards the centre. This configuration provided a balance between the suggested distributions of GCPs found in previously published studies (Harwin et al., 2015; Agüera-Vega et al., 2016; Tonkin and Midgley, 2016; Sanz-Ablanedo et al., 2018).

3.2 Basedata extraction

The software Agisoft PhotoScan Professional (AgiSoft, 2017) was used to generate georeferenced dense point clouds of each reach. As riparian vegetation often obstructed parts of the channel bed and introduced errors when digital elevation models are generated from point clouds (Tamminga et al., 2015), the Cloth Simulation Filter (Zhang et al., 2016) from the open source software Cloud Compare (Cloud Compare, 2017) was employed. This tool inverts the point cloud and generates an interpolated surface analagous to 'draping' a simulated cloth over the ground surface to approximate the terrain of an obscured area (Zhang et al., 2016). Following visual inspection of the filtered result, a cloth resolution of 0.1 m and maximum distance between 0.5 to 1.0 m was found to adequately filter the bed points.

The elevations of submerged channel bed areas are often overestimated due to the refractive effect of overlying water (Dietrich, 2017). To correct for this effect and to develop accurate bathymetry, a corrective script developed by Dietrich (2017) was employed. By determining the distance from a generated water surface mesh to the estimated bed elevations in the point cloud below, the corrected water depth for a location could be calculated as a function of the multiple viewing angles used to observe each point. Prior to applying this method, the clouds were sub-sampled to a spacing of 0.02 m while retaining the

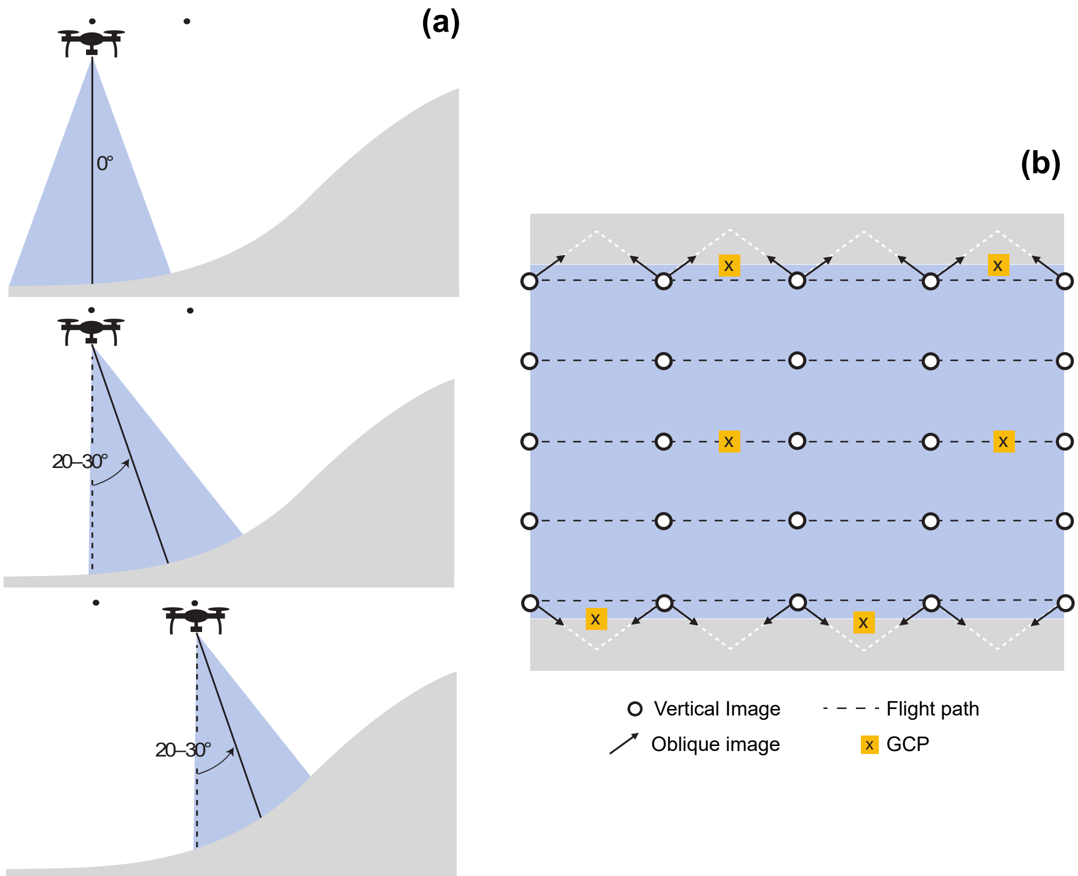

Figure 2. (a) Example partial channel cross-section showing the oblique angles of the RPA's camera (solid black line) for image acquisition of the banks. To characterize the channel banks, the camera was tilted 20–30° from vertical. (b) Plan view of the flight path of the RPA with the parallel flight lines shown as dashed lines. The outlined circles show the locations of a vertical image, and the arrows show the horizontal orientation of the camera towards the channel banks for the oblique images described in (a).

minimum height in each cell to further reduce cloud noise and ensure anomalous points from overhanging vegetation were removed in Cloud Compare.

Grain size estimates of the exposed bed were acquired by establishing a relationship between the roughness of the point cloud for 22 training sites and their median grain size (D_{50}) (see method described by Woodget and Austrums, 2017), a metric often of interest to river managers. Each roughness sampling site was approximately 1 m^2 and was photographed by hovering the RPA approximately 2 m above ground level. Using an in-house photo-sieving Matlab-based GUI (Matlab, 2017), the grain size distributions of each training site were determined and a linear model then fit between their D_{50} (Fig. 3) and their mean roughness value. Using a moving window analysis, grain size was then estimated across the exposed bed as described by Woodget and Austrums (2017).

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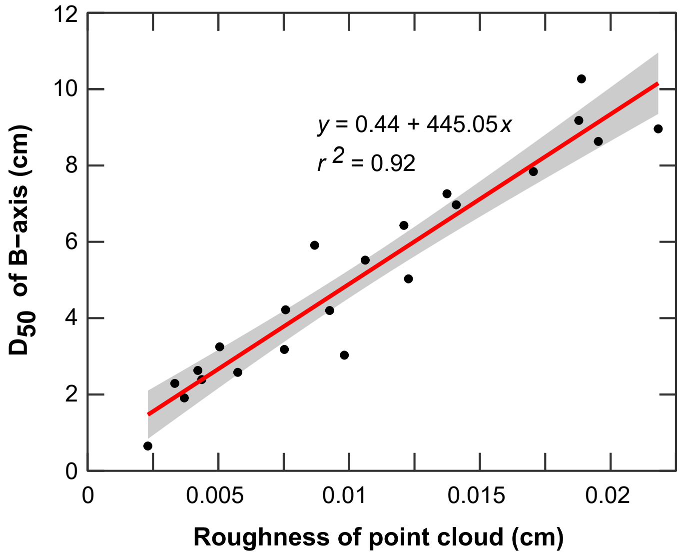

Figure 3. Predictive grain size relationships between the median surface sediment calibre (D_{50}) and the average roughness value of the training sites as determined from RPA-derived bed surfaces.

In-stream large wood (LW) was manually characterised and the area of each piece calculated using the DEMs and orthomosaics in ArcMap (ESRI, 2017). Pieces of wood (larger than approximately 0.1 m in diameter and 1 m in length), were digitized individually, whereas log jams were digitized as polygons as a result of difficulties in identifying individual pieces embedded within jams.

3.3 Selection of channel variables

To classify the channel along the longitudinal profile, the thalweg was first identified using the River Bathymetry Toolkit (RBT), an ArcMap add-in (McKean et al., 2009). The thalweg was used as a standardized location along which observations would be extracted at fixed intervals. To characterize patterns in channel morphology, five variables were extracted: the hydraulic radius (R_h), median grain size (D_{50}), local bed (S_l) and water surface slope (S_{ws}), and the reach bed slope (S_r). These variables were chosen as they are straightforward to extract from the data (a key requirement for a rapid classification scheme), and because they reflect larger basin-scale variables relevant to channel form, such as geology, climate and land-use. To provide a measure of grain roughness across the channel, the average D_{50} of the dry exposed bars in a 0.5 m buffer around each sampling location's cross-section was extracted. The local slopes of the bed and water surface were calculated for each sampling location by fitting a linear model through observations in a 15 m window around each sample site. This was repeated for the reach-scale bed slope using a 45 m window. Together these variables summarize the channel form (R_h and S) and roughness of each cross-section. Cross-sections where the channel banks were not discernible (due to channel obstructions or dense low-lying

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vegetation) were excluded from the analysis. Exclusion of these cross-sections, along with segments of the channel the RPA could not access, comprised approximatley 25% of the channel's thalweg.

3.4 Analysis

Following the extraction of the five channel variables, a principal component analysis (PCA) was applied to determine which variables were important for characterizing channel morphology, and a k-means clustering approach was then used to classify the PCA results into channel types. To implement the PCA and k-means clustering, the package 'stats' in R was employed (R Core Team, 2018). The general objective of a PCA is to reduce the number of dimensions in a dataset that contains interrelated variables while describing the maximum amount of variation present (Jolliffe, 2002). Because the dataset was multi-dimensional with five variables over 2,362 sampling sites, a PCA was an appropriate tool to help simplify and extract patterns in the data, a prerequisite for k-means clustering. The PCA was run using three of the five components, which together explained approximately 79.0% of the variation in the dataset, an appropriate cut-off according to Jolliffe (2002).

Following the PCA, the k-means clustering algorithm was run to identify groupings in the data along the first three components. A k-means clustering algorithm is an unsupervised classification that assigns observations from n dimensions to clusters that allow the within-cluster sum of squares to be minimized (Hartigan and Wong, 1979). Following guidelines for the method described by Flynt and Dean (2016), six clusters were chosen to group the dataset, a value which is in reasonable agreement with the number of morphologies one may expect at Carnation Creek.

Following clustering of the cross-sectional variables, the mean values of each channel variable for each cluster were examined and a morphology type attributed to each cluster. Morphologies were assigned to clusters based on obvious features (e.g. shallow water slopes and greater depth for pools) and criteria presented in Church (1992), Anonymous (1996), and Buffington and Woodsmith (2003). The resulting assignment of morphologies to clusters leads to a continuous classification of channel types found along the study reach at 1 m intervals, and provides insight into the survey extents necessary to adequately capture the heterogeneity of the system.

To characterize the diversity of channel morphology across the stream, a moving analysis using the Shannon diversity index (Shannon and Weaver, 1964) was conducted. This index provides a measure of the abundance and evenness of a property in an area (Lloyd and Ghelardi, 1964). While this index is often calculated with regard to species types in ecology, the approach can also be applied to channel morphology types, similar to the work of Harris et al. (2009). To calculate index values, the proportion of each channel type in an area is multiplied by the natural logarithm of the proportion. These values are then summed for all the channel types present in an area. In order to apply the method to the Carnation Creek data, the index values are first calculated by iteratively dividing the channel into segments based on window sizes ranging from 15–750 m in length (at 15 m intervals). For each iteration, the abundance of each channel morphology in each channel segment was determined. Using the 'vegan' package in R, the Shannon's diversity index of each channel segment was then calculated.

To determine the spatial scale required to capture the heterogeneity of the channel, the standard deviation of the diversity metrics across the channel was calculated for each iteration (using the increasing window size ranging from 1–50 w_b in length). For example, for the first iteration, a standard deviation value was calculated from all the diversity metrics across the channel

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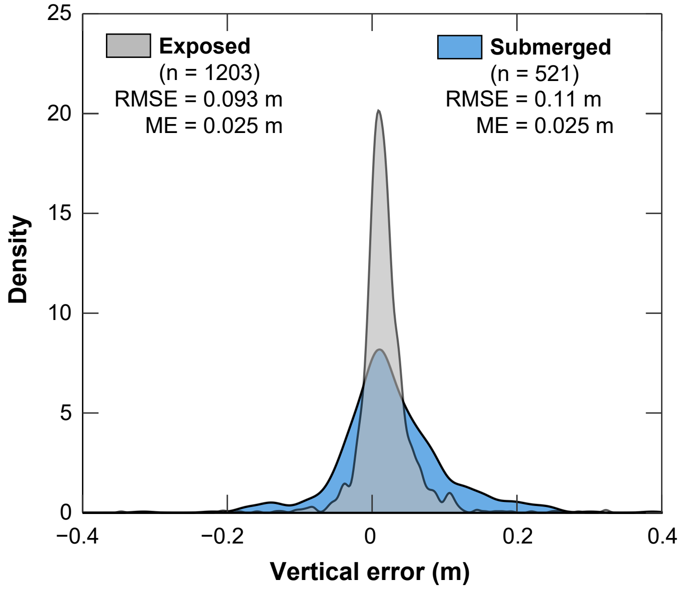

Figure 4. Density plot displaying the distribution of vertical errors between the modelled and field measured elevations. Summary statistics (root-mean-square-error (RMSE) and mean error (ME)) are provided for both the exposed and sumberged checkpoints.

that were based on 15 m channel segments. As sample size increases, the standard deviation of the channel segments tends towards an asymptote. The length scale required to approach this asymptote can therefore be interpreted as the scale beyond which diminishing returns arise in variability captured.

4 Results

4.1 Survey accuracy

The channel-averaged vertical survey error was estimated by calculating the root-mean-square-error (RMSE) and the mean error (ME) of differences between the elevations of check points collected with the total station survey and those estimated from the DEMs. The RMSE provides a measure of the spread of the squared residuals whereas the ME provides a measure of any potential positive or negative bias to the data, and are similar to other metrics used to evaluate RPA survey performance (e.g. Tamminga, 2016). The overall spread of this error and summary statistics are illustrated in Fig. 4. Vertical errors of the exposed bed points were found to be 0.093 m and 0.025 m for the RMSE and ME, respectively (n = 1,203), and similar values were obtained for the submerged bed points (RMSE = 0.11, ME = 0.025m, n = 521).

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4.2 Survey coverage

In order to evaluate the coverage extent obtainable with the sub-canopy RPA survey, the RPA-based results were compared to channel boundaries delineated with a total station in the eight established study sections (see example in Fig. 5). When including side channels, which were generally difficult to access with the RPA due to dense sub-canopy vegetation, it was possible to capture approximately 80% of the delineated study sections, a value which increased to 87% when side channels are excluded. When examining individual study sections that contained side channels, coverage ranged from a low of 54% in SA4, to a high of 89% in SA9. Generally, narrow (width < 3 m) side channels could not be effectively surveyed, but oblique imagery was advantageous in situations where a clear flight path was present alongside an obscured channel area (Fig. 6). Similarly, bank top elevations were difficult to capture in most locations due to understory vegetation obscuring the ground surface. The inclusion of bathymetric calibration greatly increased the area over which bed topography could be estimated (e.g. Fig. 6).

4.2.1 Principal component analysis, clustering analysis, and channel classification

The first three components from the PCA explained approximately 80% of the variation in the data, with components one, two and three reflecting 45.11%, 19.3% and 14.6% of the variation, respectively. The first component is dominated by S_r, D_{50} and S_{ws}, the second by R_h, and the third by S_l and D_{50}. After running the k-means clustering algorithm using six groupings on the first three components, these patterns were evident along the axis of the biplot (Fig. 7). For each cluster, the mean of each variable was calculated and the likely morphology corresponding to the cluster estimated from these values (Table 1). Moving from left to right along the first dimension (Fig. 7) there is a transition from morphologies with lower bed and water surface slopes and finer bed sediment, to those with steeper gradients and coarser material. This appears to represent a transition from pool to riffle morphologies along the first component. Overall, distinctions between most channel attributes arising from the clustering are clear and lead to relatively unambiguous classification of morphology types (Table 1). Within the riffle channel type, the classification also captures a distinction between riffle morphologies with slightly coarser bed material, defined here as 'Riffle-coarse' (Riffle$_C$, see Anonymous, 1996). When examining the second component (y axis of Fig. 7), hydraulic radius (R_h) decreases from top to bottom, as indicated by the transition from lower-velocity pool to higher-velocity glide morphologies, with remaining morphologies possessing intermediate R_h (Fig. 7).

Pools, riffles, glides and runs are relatively well distributed along the surveyed length of channel (Fig. 8). However, plane-bed and coarse riffle morphologies are mostly located near the upstream limit of the survey extent in this region. This area represents the outlet and downstream entrance of the canyon reach, where steeper gradients and coarser sediment are found.

4.3 Classification accuracy assessment

To assess the accuracy of the clustering algorithm, 100 locations along the surveyed length of channel were randomly selected and visually assigned to either glide, pool, run, riffle, riffle$_C$, or plane-bed morphologies. These values were then compared to the morphologies predicted by the PCA. A summary of agreement between the PCA and visual classification approach is shown

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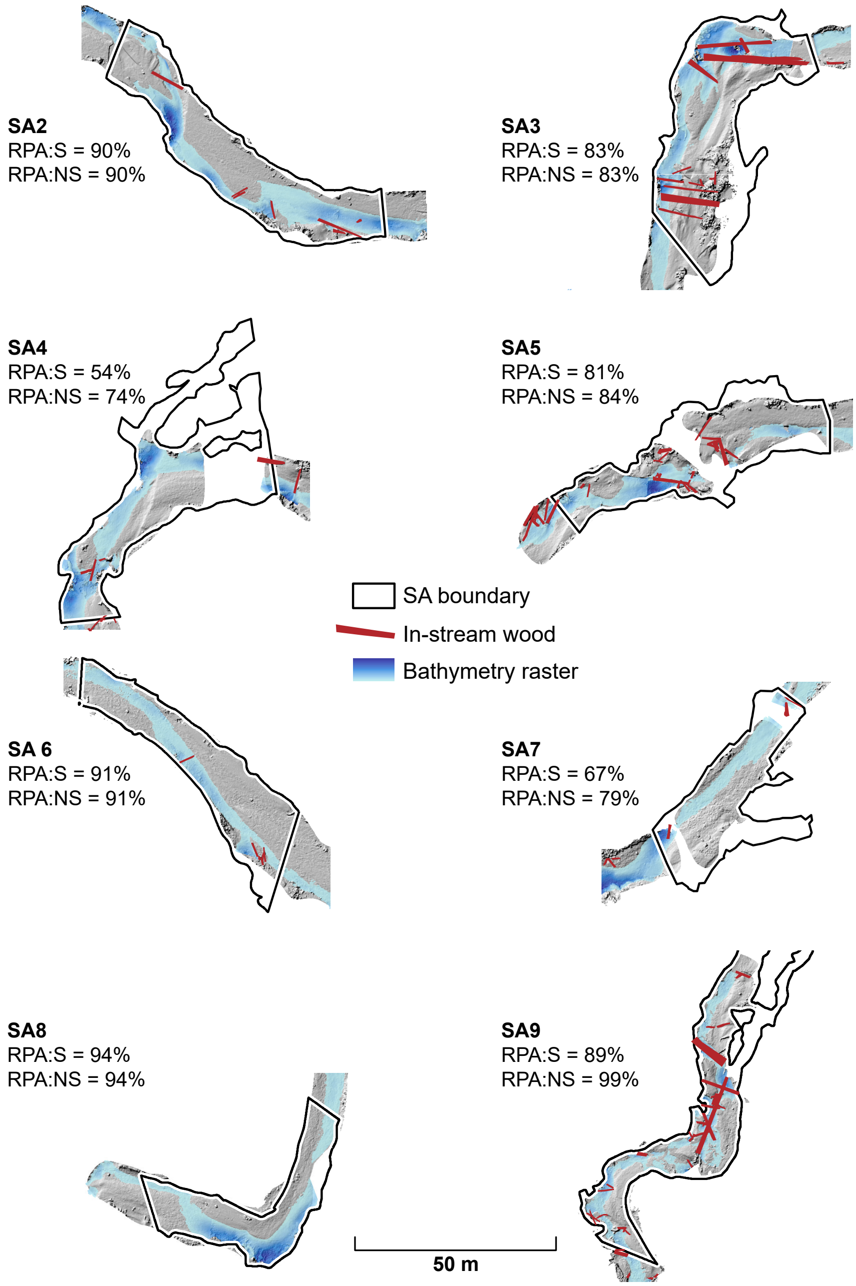

Figure 5. RPA coverage in comparison to the study section boundaries for SAs 2–9. Percentages of the study section covered with the RPA relative to the total station are based on whether the reference boundary included side channels (RPA:S) or just the main channel (RPA:NS).

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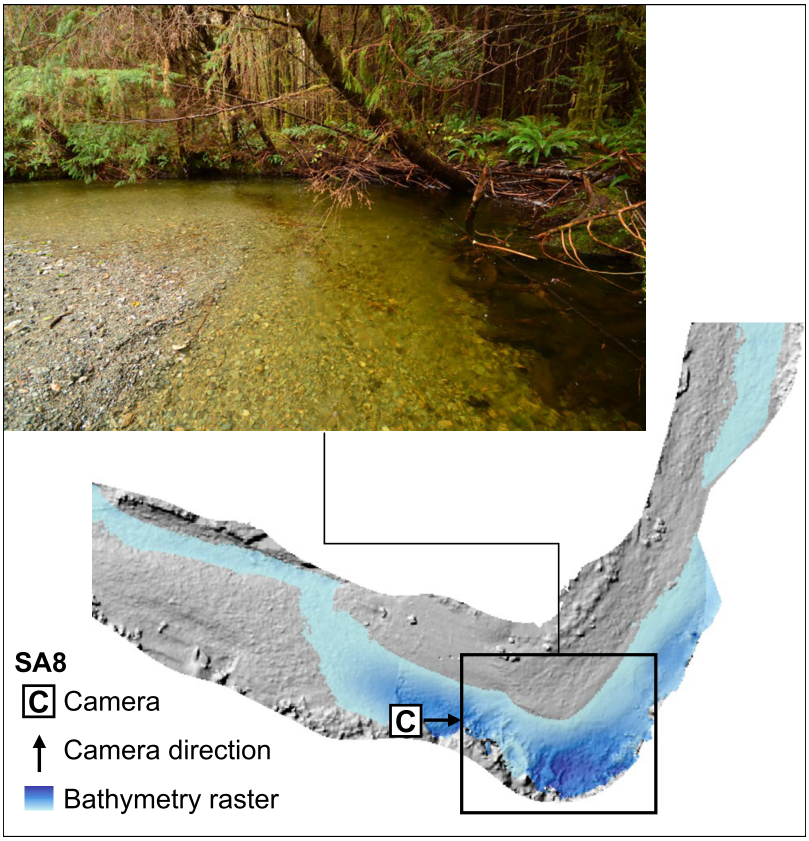

Figure 6. Coverage of a deep pool in SA8 under dense riparian vegetation. Note that the photo was taken in the autumn prior to the RPA survey, when the water level was higher than it was during the RPA survey. Photo courtesy of Iain Reid.

in Table 2. On average, 85% of sampled locations received the same morphology assignment between the two approaches, with riffle areas showing the lowest agreement (72%) and plane-bed areas the highest (100%). Overall, the classification matches the typical expected progression of channel morphologies in a pool-riffle system, as is shown in Fig. 9 . The exit of the pool is classified as a glide, with negative bed surface gradients. As gradient increases we see shallow riffle morphologies that meld into a deeper run at the entry of the pool (Fig. 9). It is likely that much of the disagreement can be attributed to 'transition' morphologies, which most classification schemes are unable to capture or define.

5 Discussion

5.1 Sub-canopy RPA surveys

The results of this study provide a precedent for using RPAs to characterize channel morphology in small, forested streams below the forest canopy. This approach provides several advantages over traditional ground-based surveys. Over twelve field

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Table 1. Means of channel variables for each cluster.

Cluster	l (m)^a	d (m)^b	R_h (m/m)^c	S_l (m/m)^d	S_{ws} (m/m)^e	S_r (m/m)^f	D_{50} (cm)^g	W (m)^h
Riffle$_C$	2980	0.16	0.12	0.018	0.018	0.024	6.74	4.13
Plane-bed	3160	0.20	0.14	0.054	0.047	0.042	8.21	3.47
Riffle	1650	0.13	0.090	0.027	0.016	0.012	4.10	3.65
Glide	1470	0.28	0.16	-0.020	0.003	0.003	3.68	4.99
Run	1435	0.61	0.35	0.044	0.005	0.016	3.92	4.94
Pool	1420	1.04	0.60	-0.031	-0.004	0.000	3.66	5.99

^{a} the midpoint of the longitudinal span where the morphology occurs

^{b} thalweg depth

^{c} hydraulic radius

^{d} local slope

^{e} water surface slope

^{f} reach-average slope

^{g} median grain size

^{h} wetted channel width

Table 2. Accuracy assessment of morphology classification.

Morphology	% Correctly classified
Riffle$_C$	78
Riffle	72
Plane-bed	100
Glide	97
Run	85
Pool	80
All	85

days, nearly three kilometers of channel were surveyed with an estimated coverage rate of 80% (including side channels) at a greater spatial resolution and extent than most traditional ground-based methods allow. Total station-based surveys in Carnation Creek typically result in point densities of 0.5–1.5 points/m^2, with 500–1000 points captured in a normal field day over a 70 m length of channel. In contrast, approximately 225 m of channel could be captured each day, more than three times the length coverage from the total station approach, and at a much higher resolution. The DEMs and orthophotos created from these images were of a very high resolution (0.02 m / pixel) with survey uncertainty between 0.01 m (for dry areas) and 0.1 m (for submerged bed areas). This magnitude of error is comparable to values observed in other studies (e.g. Flener et al.,

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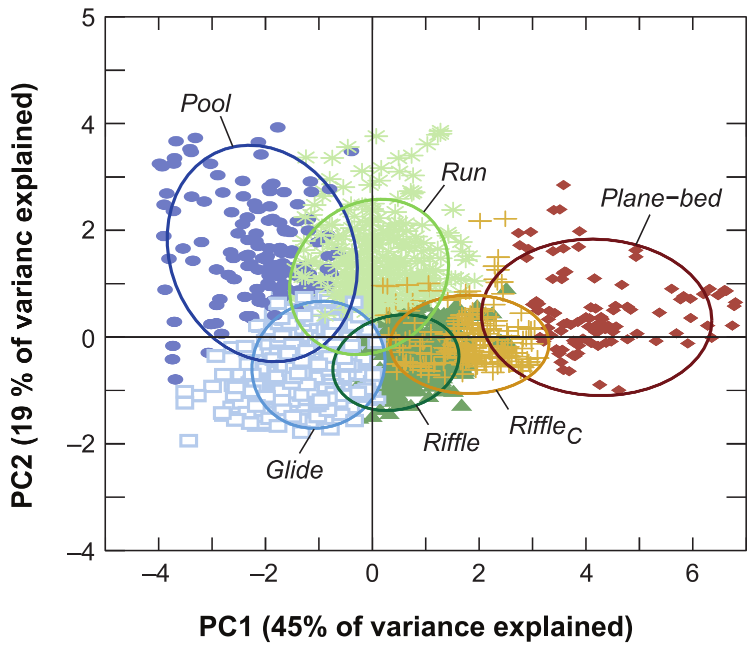

Figure 7. Biplot of each observation along the first two principal components PC1 and PC2. The groupings from the k-means clustering analysis are colour-coded and their centroid outlined.

2013; Tamminga et al., 2015), and is similar to error achieved using traditional ground or GPS-based point surveys (Reid et al., 2019).

Oblique imagery appears to provide good coverage of near-bank areas traditionally difficult to capture with vertical imagery, enabling the characterisation of low-velocity, near-bank channel areas which serve as critical fish habitat (Bjornn and Reiser, 1991). This additional imagery is generally straightforward to collect, but adds to the RPA power requirements and also increases survey time as a result of the need for additional flight passes. However, should repeat surveys be undertaken, a major reduction in survey time would be achieved through the installation of permanent ground control points. New RTK-GPS systems providing centimeter-level accuracy are also becoming available for consumer-grade RPAs, though signal attenuation through dense trees may reduce survey accuracy and limit their applicability for sub-canopy surveys.

While sub-canopy RPA surveys appear promising, certain environmental conditions and aspects of the survey approach continue to present limitations. First, the techniques for extracting the bathymetry may not be suitable for streams with turbid water that prevent observation of the submerged bed. While oblique imagery aided in characterisation of some bank areas, low elevation and dense riparian vegetation still pose a challenge for capturing bank topography in some locations, information which is necessary should the resulting survey be used for hydrodynamic modeling (Cienciala and Hassan, 2013) or to quantify bank erosion (Reid et al., 2019). In addition to bank vegetation causing obstructions, low-hanging branches (predominantly from riparian deciduous species) occasionally led to flight difficulties. Therefore, these techniques may be most suited to

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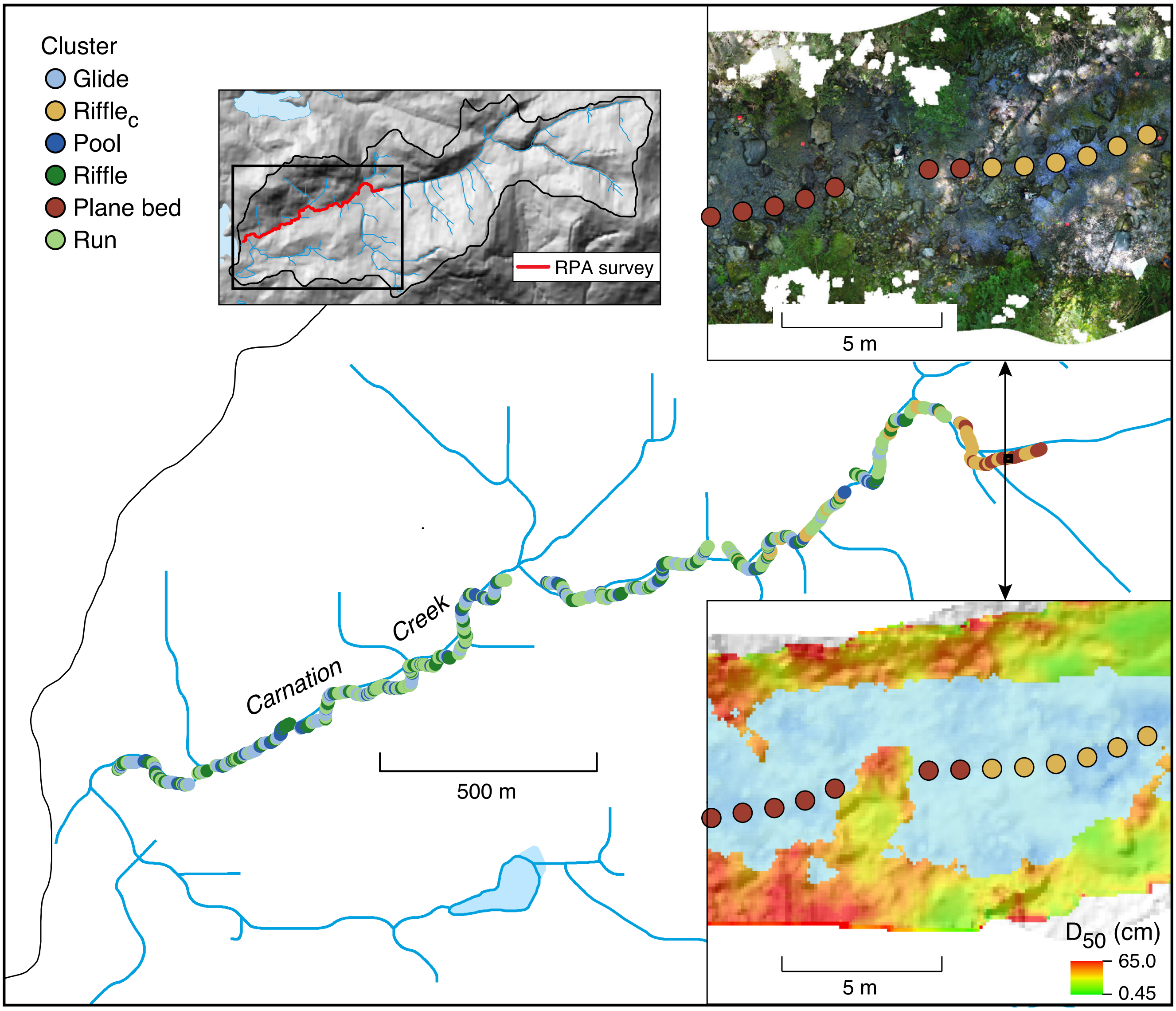

Figure 8. Distribution of channel morphologies along the surveyed reach of Carnation Creek. At approximately 2,500 m upstream, there is a marked change in channel morphologies from the typical riffle-pool morphologies to much steeper and shallower channel morphologies.

small channels in relatively mature forests that have an open understory, and flights in winter months when foliage is absent may prove beneficial. In certain circumstances, a hybrid survey with both RPA and total station data could provide complete coverage, even in locations highly obscured by dense understory foliage. In spite of these limitations, however, the sub-canopy RPA survey approach appears to offer substantial improvements over traditional survey methods.

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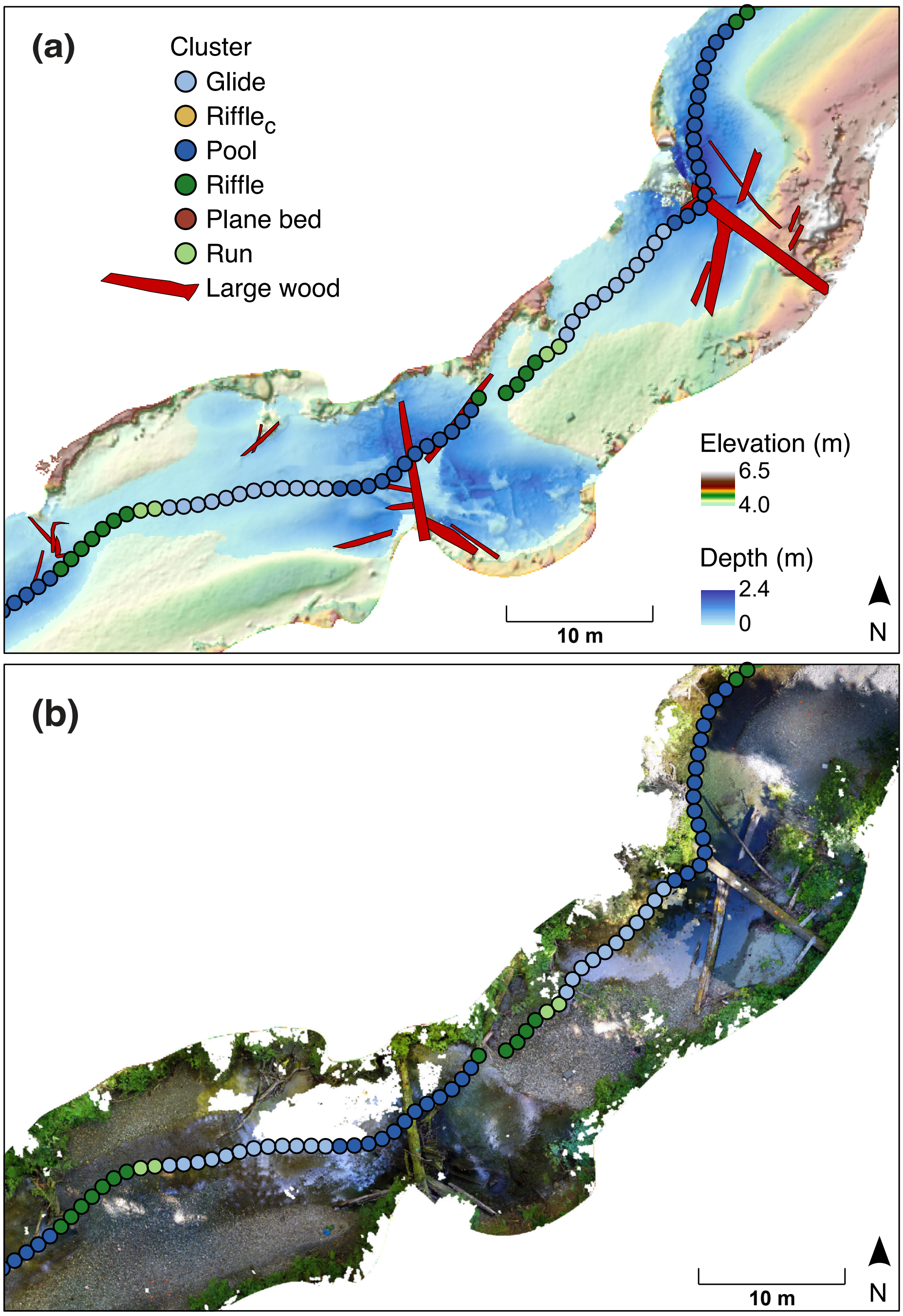

Figure 9. Example sequence of morphological units showing the transition from riffles to pools in a heterogeneous section of channel overlaid on (a) a DEM and (b) an orthomosaic.

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5.2 Classification approach

The PCA-clustering classification approach appears to present a viable and less-subjective method for evaluating morphology at the channel-unit scale, and incorporates a larger number of key variables than traditional methods. While some subjectivity remains in the interpretation of the k-means-derived clusters, examination of the classification from the PCA-clustering analysis revealed that there was good agreement between the characteristics of the morphologies derived from the clustering approach and morphologies identified visually (Table 2), with at least some remaining disagreement attributable to transition areas between morphological units. As shown in Table 3, the mean values of the variables for each assigned morphology are similar to reference values found for the slope, depth and grain size characteristics of similar channels classed in a number of other studies.

Including frequently measured channel metrics in a PCA-clustering analysis, as was conducted in this study, provides a sophisticated means not only for relating physical conditions to channel form (as descriptive schemes tend to do), but for identifying which key variables impact the relationship. Such an analysis may provide a precursory understanding of key variables worthy of investigation in the development of process-based classification schemes. A challenge encountered by many classification schemes is that they often lack the generality to be applied in environments outside of which they were developed. For example, although Whiting and Bradley (1993) provided a strong process-based classification of channel form, it was intended for headwater channels, limiting its wider applicability (Buffington and Montgomery, 2013). Similarly, the approach to classifying channels proposed by Montgomery and Buffington (1997) has a clear process basis where the channel is partitioned into source, transport and deposition zones, but was developed for mountain drainage basins. While the classification approach proposed here is also based in a mountainous environment, the PCA-clustering technique allows for the identification of morphologies in any fluvial environment where sufficient variation in bed topography is present. Unlike most classification schemes, identified clusters must be interpreted after the analysis to situate them within our conceptual understanding of river systems. While this consists of an additional step, it can provide opportunities to confirm our understanding of field observations in river systems or to guide further investigation when unexpected patterns appear.

Finally, it should be noted that in order to characterize the geometry of the channel, the PCA approach relies on wetted variables, in contrast to flow-independent features like bankfull width or depth. When considering things such as the needs of salmonids, the low flow conditions observed in late-summer may be of concern and will determine the connectivity and distribution of certain channel types across the riverscape. Depending on the application, however, consideration of flow-independent variables may be required, like the bankfull width or depth, which are less dependent on the particular wetted conditions observed at the time of the survey.

5.3 Insight into scales of spatial variability

The results of calculating the standard deviation of the diversity metric for channel types (Fig. 10 a) suggest that a window size of approximately 13–15 w_b (175–200 m in length) is necessary to capture the dominant variability along the channel. Beyond this scale, additional variability is captured, but at a decreasing rate. The 3.0 km of channel over which this analysis

Table 3. Comparison of average values for variables of each morphology to those found in previously published studies. Values from this study are indicated in bold.

Morphology	***S**$_{Church}$* *(m/m)*[a]	***S**$_{Hogan}$* *(m/m)*[b]	***S**$_{Buff.}$* *(m/m)*[c]	***S*** ***(m/m)***	***D/d**$_{Church}$* *(m)*[d]	***D/d**$_{Hogan}$* *(m)*[e]	***D/d*** ***(m)***
Riffle	0.02	0.005–0.015	0.001–0.02	**0.012**	<1.0	0.1–0.3	**0.33**
***Riffle**$_C$*	-	0.015–0.03	-	**0.024**	-	0.3–0.6	**0.41**
Plane-bed	0.02-0.04	0.03–0.05	0.01–0.04	**0.042**	$\sim$1	0.6–1.0	**0.42**
Glide	-	-	-	**0.003**	-	-	**0.13**
Run	-	-	-	**0.016**	-	-	**0.06**

[a] Slope values published from Church (1992)
[b] Slope values published from Anonymous (1996)
[c] Slope values published from Buffington and Woodsmith (2003)
[d] Relative roughness values published from Church (1992)
[e] Relative roughness values published from Anonymous (1996)

was conducted would likely be considered a relatively homogeneous riffle-pool reach under traditional channel classification schemes, such as that of Montgomery and Buffington (1997). The 15 w_b length scale is shorter than the 30–50 w_b equivalent often suggested for characterizing channel form (Bisson et al., 2006), and equivalent to 2–3 sets of pool-riffle units as defined by Keller and Melhorn (1978). This value fits in with the range of recommended study reach lengths that have been reported in the literature, though it is at the lower end (see Trainor and Church, 2003). For example, Montgomery and Buffington (1997) considered reaches 10–20 w_b in length for their research while Woodsmith and Buffington (1996) considered reaches 20 w_b in length. At the higher end, Hogan (1986) and Trainor and Church (2003) consider reaches greater than 30 w_b and reaches between 50–70 w_b to be conservative lengths for their research, respectively. Given that additional variability is still captured with a greater spatial survey extent, the 15 w_b value should be considered a minimum.

The explanation for the 15 w_b domain over which a threshold in variability is reached may be related to the spacing of major sediment storage areas in the system. Previous work in Carnation Creek by Reid et al. (2019) suggests that non-random spatial patterns in sediment storage are present along the channel (see Fig. 10 b and c). Both autocorrelation and spectral analysis methods applied to four sediment storage datasets collected between 1991 and 2017 revealed a periodicity in the data in the order of 12-20 w_b, providing information on the spacing of major sediment storage areas. Given the similarity in length scales between Figs. 10 a-c, it is possible that these storage zones (mainly large bars) serve as end members between which the typical progression of channel-unit morphologies would be expected.

The bar-to-bar spacing represented by length scales shown in Fig. 10 is within the range, but close to the upper limit, of values reported for gravel bed streams in Thompson (2013). The explanation for the relatively large feature spacing may be

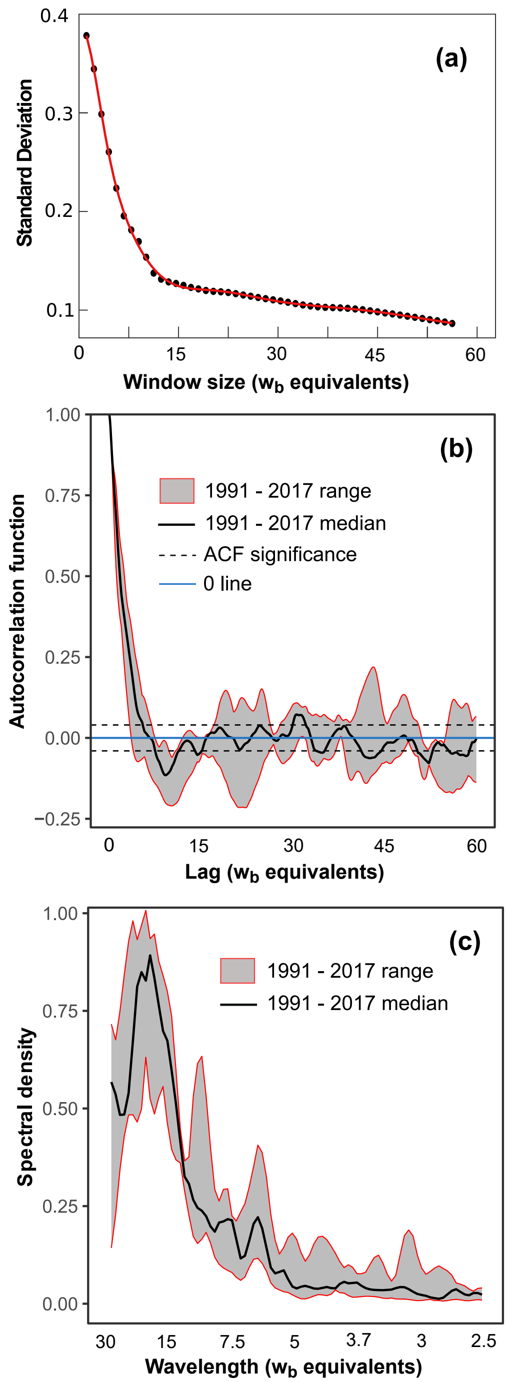

Figure 10. Notable length scales along the lower 3.0 km of Carnation Creek: (a) Standard deviation of channel diversity index values; (b) Autocorrelation function values extracted from channel longitudinal profile data collected four times between 1991 and 2017 (Fig. modified from Reid et al. (2019)); (c) Spectral density plot from analysis applied to longitudinal profile data in (b) (Fig. modified from Reid et al. (2019)). Note that channel width equivalents are given in relation to width determined as of 2017, equivalent to 13.4 m

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related to the presence of major logjams along the channel, which are commonly associated with areas of major sediment storage (Abbe and Montgomery, 1996; Davidson and Eaton, 2015; Wohl and Scott, 2017). However, as of 2017 (one year prior to the RPA survey) comparatively few major jams storing large quantities of sediment remained in the channel, and average jam spacing was only between 5 and 8 w_b (see Reid et al., 2019). Other factors which may explain the relatively large unit spacing in Carnation Creek may be related to patterns in channel width (Chartrand et al., 2018) or flow convergence (MacVicar and Roy, 2007; Thompson and Wohl, 2009).

It is important to note that the spatial scale of measurement needed to capture variability will depend on the particular variables of interest, and also the expected morphological character of the system. Carnation Creek is a channel which experiences episodic delivery of sediment from hillslopes (Hartman and Scrivener, 1990; Reid et al., 2019). As shown by the range of values in Fig. 10 b and c, temporal variability exists in the spatial pattern of dominant channel features. The 26 year period over which the data in Fig. 10 b and c was collected represents a comparatively inactive time interval in terms of colluvial sediment supply. This variability would be expected to increase during periods of episodic sediment supply, and could influence the resulting spatial scale over which dominant variance is captured. In this instance, a greater length of channel may be necessary to survey in order to increase the probability of capturing this type of localized feature. Similarly, practical survey limitations (such as site accessibility) may still factor strongly in decisions regarding site selection and survey extent. As others (e.g. Montgomery and Buffington, 1998) have suggested, examination of channel gradient or a channel profile will still provide useful preliminary information on regions of relatively homogeneous channel morphology.

6 Conclusions

The spatial extent needed to adequately capture variability and classify morphology of forested, gravel bed streams with closed canopies is often unclear, while the challenge of collecting comprehensive data in these environments necessitates efficient and low-cost data acquisition methods. This paper describes an approach to rapidly and objectively characterise and classify these channels through use of sub-canopy flights with Remotely Piloted Aircraft at the channel-unit to reach-scale. Through the incorporation of oblique-convergent imagery, it was possible to undertake a sub-canopy channel survey along 3 km of Carnation Creek, a small forested gravel-bed stream. This survey and resulting dataset allowed for the exploration of the spatial extent necessary to capture the dominant morphological variability of the channel. Use of RPA-derived rasters of bed morphology, bathymetry, and grain size in combination with a PCA-clustering analysis of channel morphologies provided characterization of this channel at an extent and resolution that would be difficult to attain using traditional methods. After calculating a diversity index describing the heterogeneity in channel morphology, a spatial scale equivalent to approximately 15 channel widths was found to capture much of the variability in channel unit morphology.

Overall, the methods were successful in demonstrating the use of RPAs for collecting channel attribute data below forest canopies and in providing an objective technique for characterizing patterns in channel morphology of small, forested channels at a variety of spatial scales. This research helps to expand the toolkit available to geomorphologists for characterizing small channels with complex morphology residing largely below forest canopies, and presents a classification approach with fewer

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drawbacks from subjective morphology identification. The results of this work are presented for a single catchment; additional study is needed to evaluate the limits of RPA approaches for data collection in similar environments.

Data availability. Data used for the analysis can be found at doi: 10.17632/jv9rftdmst.1 (Helm, 2020).

Author contributions. CH led all data collection, analysis and most manuscript preparation. MH provided supervisory support and assisted with project conceptualization and manuscript preparation. DR assisted with project conceptualization, data collection, and manuscript preparation.

Competing interests. The authors declare that they have no conflict of interest.

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