



Evaluating satellite-based depth mapping for large river monitoring: A case study of Peace River, British Columbia, Canada

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Abstract Accurate and reliable methods to measure water depth are essential for informed river research and management. Remote sensing presents a powerful tool for efficient characterization of fluvial systems, but more research is needed into the applicability of bathymetric mapping in a range of conditions and environments. This study assessed the utility of mapping water depth from satellite imagery in a large, seasonally turbid river. Steps included analysis of relationships between image properties and water depth, assessment of the effects of image pre-processing, and comparison of two methods for calibrating image values to depths. It was determined that spectral depth mapping is applicable in the system, with a depth signal described by the ratio of green to red wavelengths. Pre-processing steps including the automated removal of shadows and water surface reflections and the application of a median filter improved the quality of depth calibrations, and calibration methods gave similar results with errors of 25% of reach average depth. The resulting depth maps reliably captured the overall hydromorphic forms and distribution of habitat features, although results were less reliable in deep areas (> 2 m) due to the saturation of the depth signal. Overall, satellite depth mapping can be an appropriate tool for repeat, broad-scale, long-term large river monitoring in general, and could potentially improve flood inundation models based primarily on subareal LiDAR surveys.

Non-technical summary Mapping patterns of water depth is an important part of river monitoring and management, with implications for aquatic habitat studies and flood risk predictions. On large rivers, methods are needed that can reliably characterize depth over broad extents with limited additional fieldwork (which can be costly, inefficient, or hazardous to workers). This study tested whether satellite images can be used to measure depth, working from the basic idea that water in shallow areas has different colours than water in deep areas. Two methods of creating a depth map from imagery were tested, along with several steps to clean up the satellite image and create clearer maps. It was found that both methods provided high quality depth predictions, and that image cleaning steps improved the final results. Although results were less reliable in deeper areas, the overall approach can be useful for long-term river studies and can provide high quality depth maps that complement other ways of measuring river forms.

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1 Introduction

Measuring river water depth is crucial to support the study of spatial and temporal patterns of aquatic habitat, flood inundation mapping of communities and transportation corridors adjacent to streams, and long-term monitoring of river dynamics in the face of changing climate, land use, and other external stressors. Most instream hydrometric and physical data are collected using field sampling methods such as total station or GPS surveys and point- or transect-based depth and velocity measurements. These methods can be time consuming and hazardous to workers, and may potentially miss heterogeneity at scales that are important to river ecosystems (Poff and Ward, 1990; Ward, 1998; Fausch et al., 2002; Carbonneau and Piégay, 2012). To support river science and management, techniques that are ef-

ficient, accurate, repeatable, objective, high resolution, and spatially continuous are needed to measure three-dimensional physical structure and hydraulic distributions (Vaughan et al., 2009; Poole, 2010; Woodget et al., 2015).

In recent decades, remote sensing has emerged as a valuable method for measuring river hydromorphology and habitats (Lyon and Hutchinson, 1995; Fonstad and Marcus, 2010; Lane et al., 2010; Carbonneau and Piégay, 2012). In bathymetric applications, progress has been made in approaches based on through-water photogrammetry (Fryer, 1983; Lane, 2000; Westaway et al., 2001; Butler et al., 2002; Javernick et al., 2014; Dietrich, 2017), spectral depth techniques that rely on relationships between water depth and colour properties of imagery (Winterbottom and Gilvear, 1997; Legleiter et al., 2004; Feurer et al., 2008), physically based models incorporating hydraulic principles into depth estimation

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(Fonstad and Marcus, 2005; Legleiter, 2015), and active sensing methods including terrestrial and airborne laser scanning (Kinzel et al., 2007; Hildale and Raff, 2008; McKean et al., 2009) or ground penetrating radar (Costa et al., 2000).

In particular, spectral depth methods have been developed for river depth quantification. These methods are based on the differential attenuation of different wavelengths of light as they propagate through water: the absorption coefficient of clear water increases by an order of magnitude as wavelength increases across the spectrum from blue to near infrared. Spectral depth methods leverage this phenomenon by relating a ratio of two spectral bands in an image with geolocated flow depth data acquired in the field to create a correlation between image values and depth. Because radiance leaving the water column depends primarily on depth and riverbed albedo, and the reflectances of different substrates typically only vary by a few percent, a ratio of band values varies with depth while remaining relatively insensitive to bottom composition (Legleiter et al., 2009; Legleiter and Fonstad, 2012). The modeled empirical relationship can then be used to create a continuous map of depth from the image. Spectral depth methods have been shown to be accurate in appropriate conditions, with mean errors in the 10 cm range (Lejot et al., 2007; Tamminga et al., 2015; Woodget et al., 2015). Such approaches are also valuable because they can take advantage of widely available, frequently collected passive optical imagery (Bevington et al., 2018). Advances in the use of multi- and hyperspectral aerial and satellite imagery have also facilitated wider application and better understanding of the detailed spectral characteristics of water column optical properties (Philpot, 1989; Marcus et al., 2003; Legleiter et al., 2015).

However, relationships between spectral information and water depth are most applicable in shallow, clear water systems (Marcus et al., 2003; Legleiter et al., 2004), and factors such as water surface roughness, turbidity, substrate variability, and shadows from riverbank vegetation can complicate depth estimation (Gilvear et al., 2007; Kay et al., 2009; Overstreet and Legleiter, 2016). The majority of studies to date have focused on method development and evaluation under ideal water clarity and shallow depths, although examples exist that investigate deeper applications (Kumar et al., 1997; Hugue et al., 2016; Legleiter and Fosness, 2019) and more turbid conditions (Lafon et al., 2002; Legleiter et al., 2011). To ensure that optical spectral depth mapping can be used with broad confidence in river research and management, continued detailed quantitative testing of applicability and accuracy in a wide range of conditions is needed (Shintani and Fonstad, 2017), along with consideration of the technology's potential contributions to link hydrogeomorphology and aquatic ecology in a riverscape management context (Vaughan et al., 2009; Poole, 2010; Carbonneau and Piégay, 2012). This research contribution aims to evaluate the utility of multispectral satellite imagery for depth mapping and aquatic habitat assessment on a large, seasonally turbid river by addressing three specific questions:

1. To what extent is spectrally based depth mapping applicable in Peace River?
2. How do image pre-processing steps and different methods of calibrating image values to measured depths affect results?
3. What are the limits of depth estimation under limited water clarity conditions?

2 Methods

The workflow followed for this analysis is summarized in Figure 1, detailed in the subsequent subsections. All analysis steps were performed with R (R Core Team, 2024) and QGIS (QGIS Development Team, 2024).

2.1 Site description

The study site used in this research was a 3.6 km reach of Peace River near the town of Fort St. John, British Columbia, Canada (Figure 2). Peace River is a northward flowing boreal river that drains 293,000 km² of western Canada as part of the Mackenzie River watershed. In the study region, the river is entrenched into the Alberta Plateau, an area of high plains underlain by weakly lithified, Cretaceous-age shale and sandstones (Church, 2015). Based on morphology, the river can be classified as a large river, where fluvial processes and geologic constraints dominate channel form, bed structure is primarily pool riffle sequences with the presence of major bar forms, and a floodplain is present in non-constrained sections (Church, 1992); typical water depth and turbidity at the study site are at the upper range of conditions where satellite depth mapping has been applied (Legleiter et al., 2018; Legleiter and Fosness, 2019). Although the river originally exhibited a nival regime with a peak flow influenced by precipitation in early summer, flow is now regulated by the British Columbia Hydro and Power Authority (BC Hydro) through the upstream W.A.C Bennett (1967) and Peace Canyon (1980) dams. Flow regulation has resulted in a seasonal flow regime based on energy demand in western North America. Flows are generally higher in the winter throughout much of the upper river, although tributary inflows result in the re-establishment of a weak spring freshet near the study reach (Church, 2015). At the Water Survey of Canada station downstream of the study reach (Taylor, WSC No. 07FD002), the regulated mean annual flow for the period of 1973–2010 was 1456 m³ s⁻¹ and mean annual flood was 2837 m³ s⁻¹. Bed sediment in the reach is dominantly gravel ($D_{50} = 43\text{--}67$ mm, $D_{90} = 93\text{--}139$ mm), and bed slope ranges from 0.047% to 0.062%.

The study reach is of interest because it is downstream of the construction of a large hydroelectric facility, the Site C Clean Energy Project. In support of this project, BC Hydro is carrying out an extensive, multi-decade Fisheries and Aquatic Habitat Monitoring Plan aimed at assessing and mitigating effects on associated fluvial ecosystems (BC Hydro, 2015). As part of this plan, indicator species including Bull Trout, Kokanee, Mountain Whitefish, Goldeye, and Walleye are

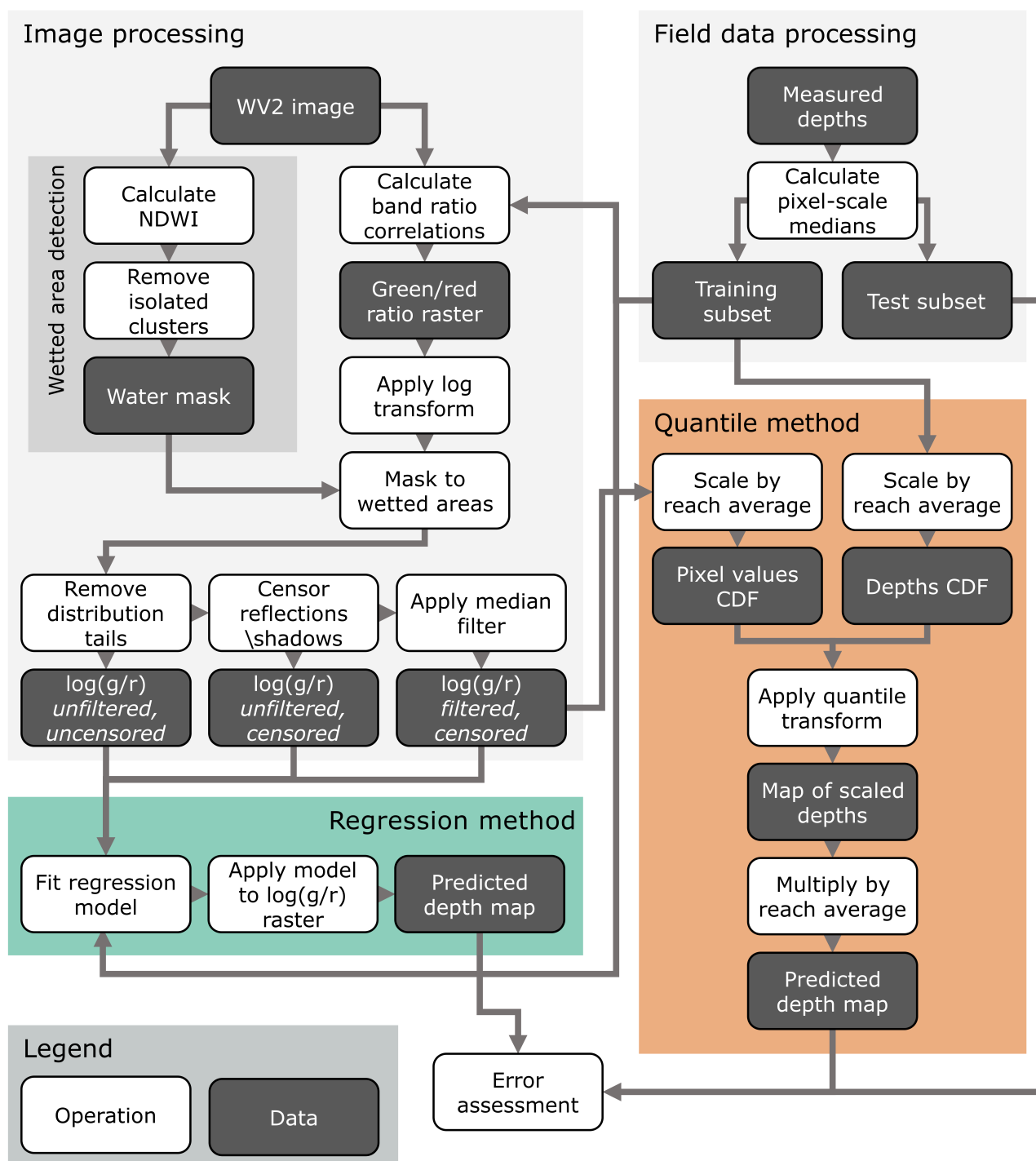


Figure 1 Flowchart of steps applied in this analysis, including relevant data pieces and operations for field data handling, satellite image processing, and two depth calibration methods

monitored along with aspects of habitat and ecosystem status. Within the study reach itself, several fish habitat mitigation/offset projects have also been constructed or are in progress, consisting of large-scale (10s of hectares) enhancement efforts to increase habitat that remains functional throughout the range of regulated flows, in both mainstem and side channel river areas. Repeatable and reliable methods for characterizing channel structure and habitat dynamics are therefore of extra importance to support informed monitoring and management of instream environments and constructed habitat features over a long time period and un-

der changing flow regulation regimes.

2.2 Satellite imagery

The satellite imagery used as the basis for bathymetric mapping was acquired by WorldView-2 (WV2). This multispectral imaging system collects eight spectral bands (2 m pixels) spanning the visible and near infrared (NIR) spectrum: coastal (401–453 nm), blue (447–508 nm), green (511–581 nm), yellow (588–627 nm), red (629–689 nm), red edge (704–744 nm), NIR1 (772–890 nm), and NIR2 (862–954 nm). A higher resolution

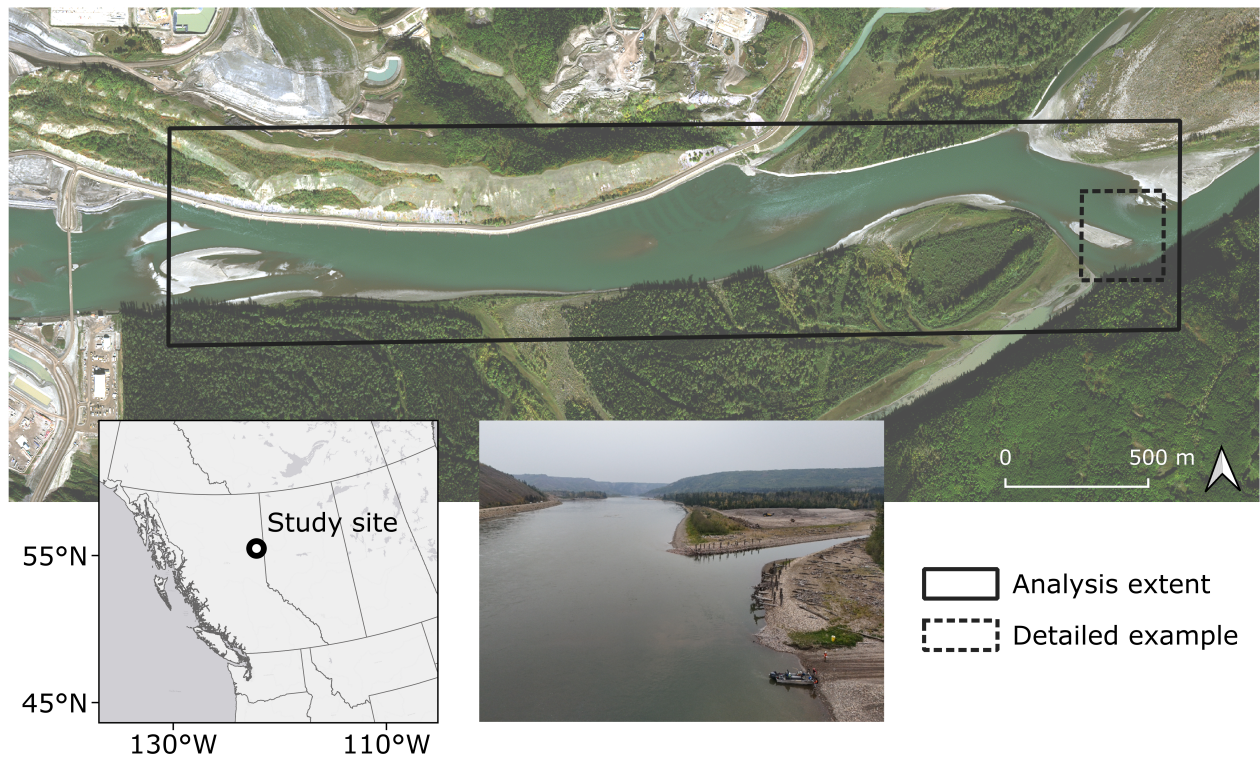


Figure 2 Peace River study reach, with full analysis extent denoted by solid black rectangle and detailed example close-up section (used in some later figures) denoted by dotted black rectangle. Flow is from left to right; background image is true colour RGB composite from WorldView-2. Also pictured are the study site location in western Canada and a low-level oblique photo of the site for context.

panchromatic band (0.5 m pixels) is also collected. The sun-synchronous satellite sensor has been operational since 2010 and provides frequent revisit time (1.1–3.7 days), a 16.4 km imaging swath, and a dynamic range of 11 bits per pixel. The Peace River imagery used in this study was captured September 19, 2018 at 10:30am and deliverables included 2 m orthorectified eight band spectral radiance data with no dynamic range adjustment (Figure 2). This date corresponded to a prolonged period of seasonally low flow and low turbidity on the river ($422 \text{ m}^3 \text{ s}^{-1}$ and 8.5 NTU, respectively).

2.3 Bathymetric survey

The field-measured depth dataset was collected on October 30, 2018. The survey consisted of two methods: GPS total station surveys with a Trimble R10 real-time kinematic GPS (Trimble Inc., Sunnyvale CA) system to measure bed and water surface elevations in shallow areas that could safely be accessed by wading (up to approximately 0.6 m), and a SonTek RiverSurveyor M9 dual-beam acoustic doppler current profiler (ADCP) system (SonTek/Xylem Inc., San Diego, CA) to perform depth surveys in deeper areas. Depth measurements were conducted at eight cross sections spaced along the 4 km reach as well as in a dense survey consisting of streamwise profiles spaced 25 m across the channel along a 700 m section (Figure 3). Because the field survey was conducted at a higher discharge than when the satellite image was captured, depths were adjusted by a constant offset based on a stage difference between the two dates based on nearby Water Survey of Canada water

surface elevation readings. Although this asynchronous data collection can introduce uncertainty into the process, this type of post-hoc analysis represents a common situation where this approach might be applied in practice, and the application of a constant offset is reasonable in the low gradient study reach with a relatively flat water surface profile. Points were then converted to pixel-scale median values to match the spatial resolution of the satellite image (Legleiter and Overstreet, 2012). This reduced-density survey of 5007 values had a mean and standard deviation of $1 \text{ m} \pm 0.68$ and a maximum of 4.72 m. Depth points were then divided into a training subset drawn from half of the points from the eight cross sections ($n = 678$), and a test subset comprising the other half of the cross section points and the entirety of the dense longitudinal survey ($n = 4329$). The dense survey was not included in the training subset because it does not represent an unbiased sample of channel depth distribution, but it was retained in the test subset for model evaluation.

2.4 Water index and censoring

An advantage of multispectral imagery is the utility of NIR bands for the discrimination of wetted areas. To create a water mask, the normalized difference water index was calculated as $\text{NDWI} = (\text{green} - \text{NIR2}) / (\text{green} + \text{NIR2})$ (McFeeters, 2013). This index was highly effective at finding wetted pixels (defined as $\text{NDWI} > 0.3$ throughout the image). To refine the water mask to the main wetted channel only, a cell cluster calculation using the ‘clump’ function from R ‘raster’ package (Hijmans, 2023) was used to identify spatially separate con-

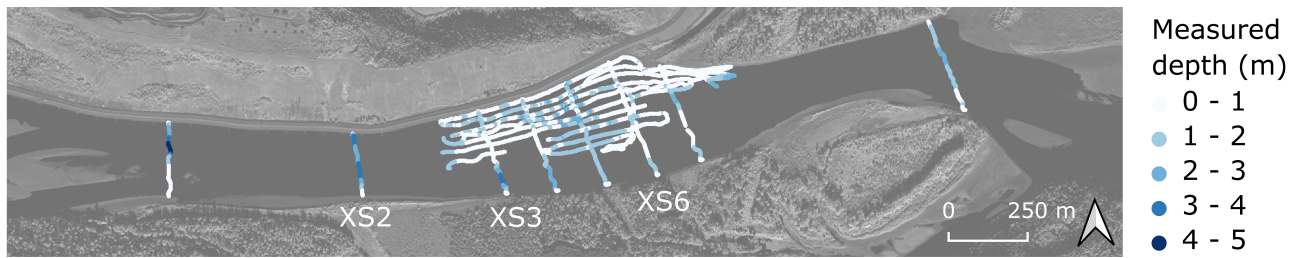


Figure 3 Field-measured depth points from October 30, 2018 survey, including cross sections and more intensive survey at a habitat enhancement site. Cross sections used as examples to show results are labeled. Background is grayscale version of the NIR2 WV2 band.

tiguous groups of raster cells. The cell cluster with the largest size represented the main wetted channel and was retained as the water mask; smaller clusters were isolated floodplain pools or unconnected side-channels that were not relevant to the analysis and were discarded. This raw water mask identified the entire wetted area of the main channel, which can be useful for applications requiring assessment of factors such as total wetted width and channel pattern. However, for spectrally based depth mapping, complications such as aerated surface water, sunglint, and shadows behind submerged large sediment clasts or under bank vegetation can compromise the approach within wetted areas (Gilvear et al., 2004; Visser et al., 2015). To ensure the depth/DN (digital number) relationship was only calculated for unobstructed areas where the radiance signal is dominantly controlled by reflectance from the bed and the water column, two image censoring operations were applied. A threshold on the NIR2 band was used to remove aerated water surfaces, reflections, and mixed wet/dry pixels at the water's edge, taking advantage of the fact that this range of wavelengths is strongly absorbed by pure water (Hochberg et al., 2003a; Hedley et al., 2005; Overstreet and Legleiter, 2016). A threshold of $\text{NIR2} > 8 \text{ W m}^{-2} \text{ sr}^{-1} \text{ m}^{-1}$ was used to identify and remove these anomalous reflections within the overall wetted mask. Similarly, a simple single-band threshold of $\text{red} < 45 \text{ W m}^{-2} \text{ sr}^{-1} \text{ m}^{-1}$ within the channel identified dark areas caused by shadows. Removing both shadows and bright reflections from the full NDWI-identified water mask resulted in a censored water mask where depth calibration is appropriate.

2.5 Band ratios

Spectral depth bathymetry methods are based on finding an appropriate pair of wavelengths to create a ratio that is related to water depth. Typically, the natural logarithm of this ratio is taken to account for the exponential attenuation of light by the water column (Legleiter et al., 2004). Accompanying field-measured datasets allow for empirical investigation into which image spectra are most strongly related to depth. To determine which ratio of spectral bands contained the most depth information in the Peace River image, each ratio combination of the eight bands was calculated and the correlation between ratio value for each pixel and associated measured depth was determined (Legleiter et al., 2009). The band ratio that had the strongest correlation

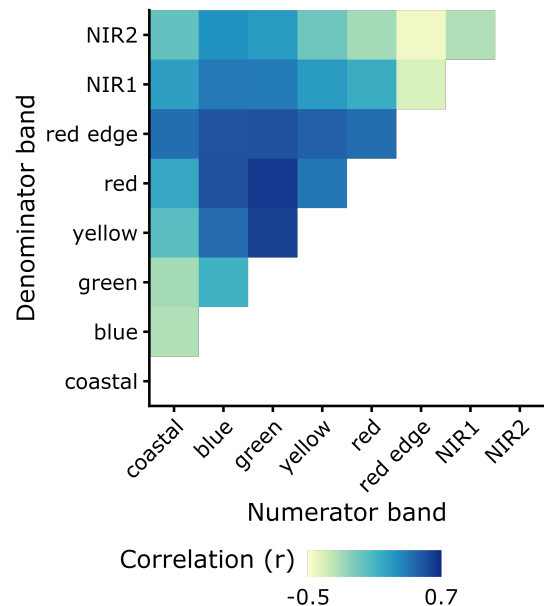


Figure 4 Correlation coefficients (r) between satellite band combinations and measured depths.

to depths and therefore best represented bathymetry under these conditions was found to be $\log(\text{green}/\text{red})$ ($\log(g/r)$), which was positively correlated with depth ($r = 0.65$). Correlation coefficients for all band pairs are presented in Figure 4; only $\log(g/r)$ was retained for further analysis (Figure 5). The use of red and green wavelengths in spectral depth mapping is common in a range of fluvial settings due to the physical properties of water: red frequencies are subject to strong absorption by pure water, and green wavelengths are more affected by scattering from suspended sediment in the water column; a ratio of the two can account for the main controls on depth signal (Legleiter et al., 2004, 2009; Tamminga et al., 2015). To account for mixed wetted and dry pixels at the water edge, the top and bottom 1% of the $\log(g/r)$ raster cell value distribution were also removed.

2.6 Image filtering

Calculating $\log(g/r)$ for the areas within the censored water mask resulted in a raw band ratio raster that can be considered a representation of relative depth. However, before calibrating and creating the final absolute depth maps, a spatial filtering step was taken to im-

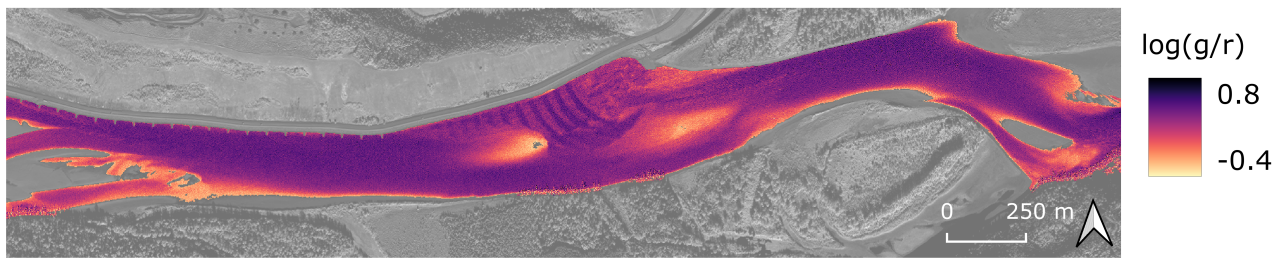


Figure 5 Log(g/r) raster (unfiltered, uncensored). Background is grayscale version of the WV2 NIR2 band.

prove the signal quality. Satellite images are inherently affected by noise, which is variation in brightness or colour unrelated to the desired information in a digital image (Ye et al., 2005). In earth science and fluvial mapping settings, various filtering techniques have been shown to improve image signal-to-noise ratios, aid in feature detection and creation of realistic topographic surfaces, and improve the accuracy of bathymetric calibrations (Hochberg et al., 2003b; Feurer et al., 2008; Legleiter, 2013; Tarolli, 2014). Low pass filters, such as median filters, can reduce fine scale noise while retaining information on features of interest (Hamza et al., 1999); a filtering step can also account for small georegistration mismatches between field data points and raster cells during calibration. In this study, a median filter with a three cell or 6 m window was employed using the ‘focal’ function in the R ‘raster’ package (Hijmans, 2023). This window extent is comparable to the reach maximum depth.

2.7 Calibrating depths

The final step to produce maps of absolute depths throughout the study region was to calibrate the censored and filtered log(g/r) raster to measured depths. In this study, two methods of calibrating image values to the measured depths (training subset ($n = 678$)) were compared. The first method, referred to here as the regression method, is an approach where an empirical model is fit between field-measured depth points and image values extracted at the same locations. The band ratio raster is then transformed to calibrated depths based on the model coefficients. This approach is widely used and applicable in many settings, provided a strong enough relationship exists between image spectral values and depth (Winterbottom and Gilvear, 1997; Legleiter et al., 2004; Feurer et al., 2008; Williams et al., 2014). In this study, a function of the form $\log(\text{depth}) = a \cdot \log(g/r) + b$ was applied after examining the shape of the distribution of depths versus band ratio. To assess the effects of image pre-processing operations, separate models were fit for depth points extracted from: (1) the entire wetted area identified by NDWI (‘unfiltered, uncensored’), (2) the wetted area with shadows and surface reflections censored out by band thresholding (‘unfiltered, censored’), and (3) the censored wetted area with the median filter applied (‘filtered, censored’).

Although regression type methods are intuitive and are accurate in many situations, the need to collect calibration data in the field at the time of the image cre-

ates an extra labor burden that undermines some of the main advantages of remote sensing. As an alternative, a second method of depth calibration based on Legleiter (2016)’s image-to-depth quantile transformation (IDQT) framework was tested. In this process, a non-spatial calibration is achieved through quantile matching between cumulative distribution functions (CDFs) of depths and pixel values under the assumption that pixel values are monotonically related to depth. The distribution for the pixel values within the reach is the entire set of pixels of the wetted area, and the distribution of depths is a measured depth dataset that could be collected at the time of imagery or at a different time provided the discharge is similar and no large-scale morphologic change has occurred. If field calibration data are unavailable, the depth distribution can alternatively be derived from an empirical or theoretical model; see discussion of the frequency distributions of reach scale hydraulic variables in the ecological and geomorphic literature (Lamouroux, 1998; Ferguson, 2003; Schweizer et al., 2007; Rosenfeld et al., 2011; Gleason, 2015; McParland et al., 2016). The pixel values and depths are scaled by mean values and CDFs are computed for each, yielding comparable non-dimensional distributions. For each pixel location, the probability of that pixel value as defined by the CDF is equated to the inverse CDF of depths to determine a scaled depth value at each pixel throughout the image. Multiplying scaled depth values by mean depth results in a final absolute depth map. This approach, referred to here as the quantile method, aims to alleviate some of the drawbacks of regression methods such as the need for simultaneous calibration data collection, the potential to predict negative depths at channel margins, the misrepresentation of deep areas affected by signal saturation, and errors introduced by georegistration mismatches between the depth and image datasets. In this study, the quantile method was applied by scaling the calibration depth set and the log(g/r) values at each pixel. Empirical CDFs were then determined for both and probabilities were matched based on distribution quantiles, allowing for the calculation of a continuous depth map.

3 Results and discussion

Overall, image pre-processing steps were successful in improving the quality of the band ratio raster and therefore the depth calibrations. The calculation of NDWI accurately identified wetted pixels in the image and

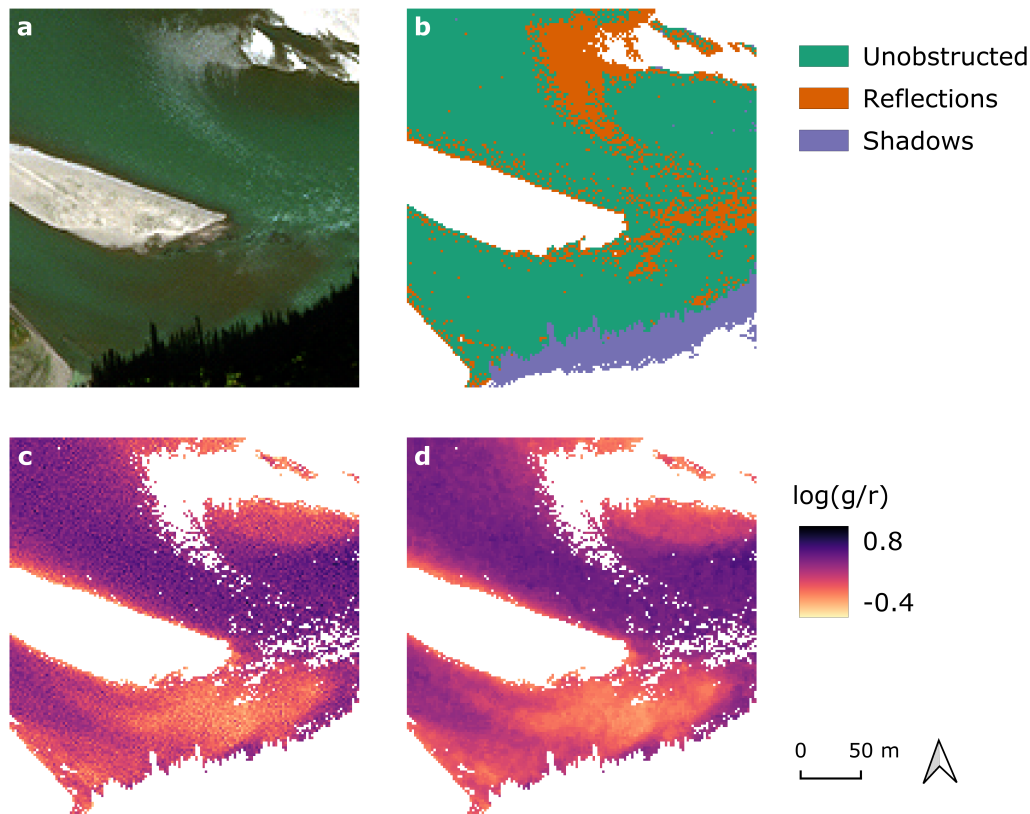


Figure 6 Detailed view of wetted area identification, image censoring, and image filtering, showing (a) the true colour RGB WV2 image, (b) the total wetted area identified by NDWI, including areas of reflections and shadows subsequently removed through image censoring, (c) unfiltered $\log(g/r)$ raster calculated for censored wetted areas, and (d) filtered $\log(g/r)$ raster calculated for censored wetted areas.

yielded a clean delineation of mainstem wetted areas after removal of contiguous patches below a certain size, even in areas with complex flow paths through dissected bars. Image censoring based on simple single-band thresholds effectively identified pixels affected by surface reflections and shadows; a detailed view of censoring is shown in Figure 6a-b. In this example, broken water surfaces through a riffle and a band of south-bank shadows were removed from analysis, leaving unobstructed areas for calibration and depth prediction. Of the reach total wetted area identified by the NDWI, 11.3% was censored out as surface reflections, and 2.9% was censored out as shadows, leaving 85.9% of the wetted area for further processing.

Figure 6c-d show the effects of the median filter on $\log(g/r)$ patterns. Prior to filtering, pixel-scale variation in ratio values was present throughout the area. This pattern mostly results from noise in the satellite image bands, but it could also be influenced by fine scale features like water surface waves or uneven submerged sediment clasts. The median filter reduced visible noise being contributed by both bands in the ratio calculation while qualitatively preserving the definition of relevant meso-scale hydrogeomorphic features such as individual bars, riffles, and pools.

The effects of pre-processing were also evident in the depth-ratio calibrations used in the regression method. Figure 7 shows the $\log(g/r)$ values extracted from the locations of the calibration measured depth set, along

with a model of the same form fit for each case. Although the models were fit as a linear log-log function, depths are shown in absolute values for ease of interpretation. The benefits of censoring and filtering are evident in the shape of the depth-ratio scatter and in the strength of the model fits. The first case (Figure 7a), where points were sampled from all wetted areas identified by NDWI (unfiltered, uncensored), showed the largest variation from the model and the widest range of ratio values, due to the inclusion of areas with surface reflection and shadows where the method is not applicable. A positive depth-ratio relation was evident but there was substantial scatter, particularly at larger $\log(g/r)$ values. The censoring operation to remove shadows and reflections (unfiltered, censored) led to slight improvement in R^2 and the removal of some of the largest residuals from the model, but the shape of the scatter was largely the same (Figure 7b).

Effects of median filtering (filtered, censored) were more noticeable; the variance was reduced as values collapsed around the model (Figure 7c). There was also a truncation effect on both tails of the $\log(g/r)$ distribution as filtering reduced individual extreme pixels. This truncation was most evident in points from deeper water, where the maximum $\log(g/r)$ value was reduced from 0.76 to 0.59. This was likely due to these areas being optically deep in the sense that the bottom is not visible and changes in depth no longer result in changes in water-leaving radiance that are detectable by the satel-

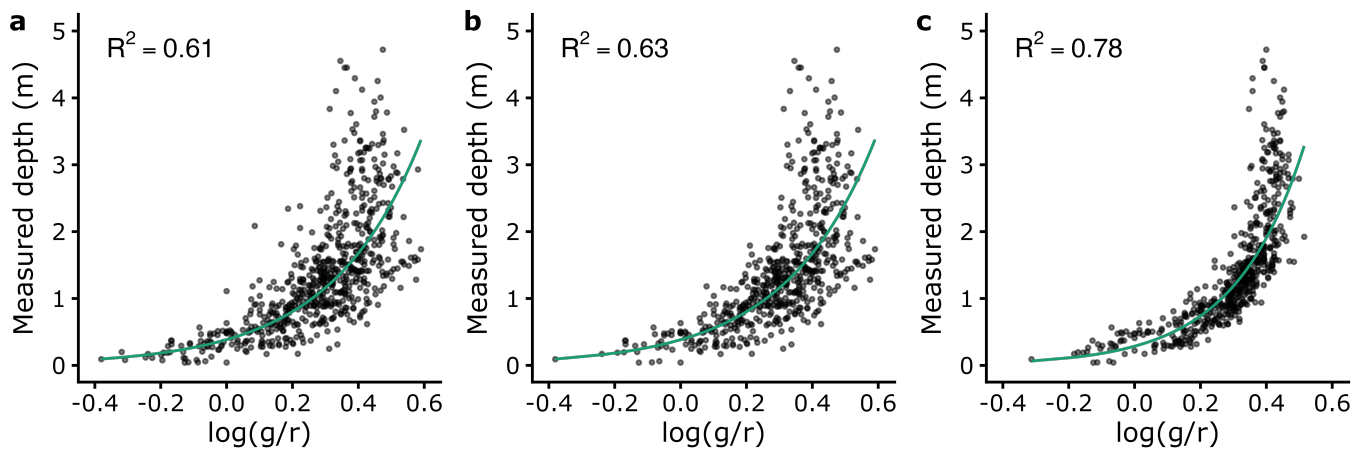


Figure 7 Regression method calibration models between band ratio and measured depths for (a) unfiltered, uncensored $\log(g/r)$ raster, (b) unfiltered, censored $\log(g/r)$ raster, and (c) filtered, censored $\log(g/r)$ raster.

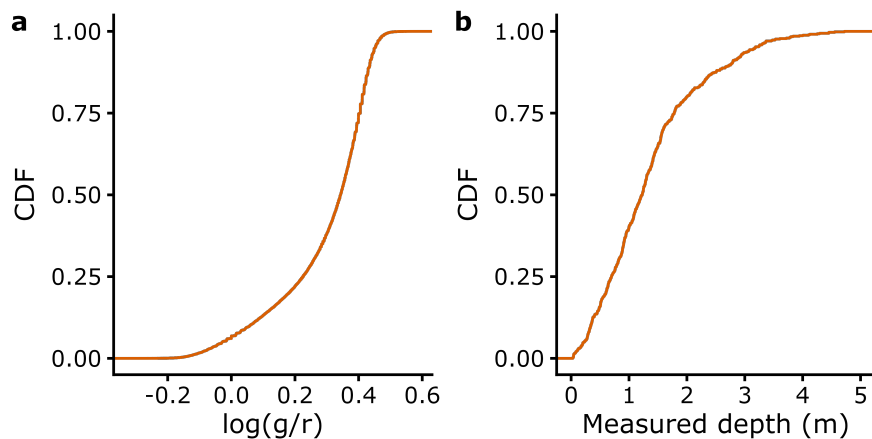


Figure 8 Empirical cumulative distribution functions used in the quantile method for (a) image band ratio values and (b) measured depth training subset.

lite sensor (Legleiter and Fosness, 2019). Therefore, there is only a small finite set of $\log(g/r)$ values in these areas and the median filter acts to further reduce the differences, even though these differences may reflect true changes in depth. This effect gives rise to the near vertical shape of the depth-ratio scatter above $\log(g/r)$ values of about 0.4. For all three cases, the regression model adequately described the positive relation between ratio and depth and the shape of the functions was similar. Although none of the models fit deep areas (> 2 m) very well, the fit of the filtered and censored model (Figure 7c) was good for the rest of the range and the reduction in scatter due to filtering was valuable; this model was used to produce the final predicted depth map for the regression method.

The calibration process for the quantile method is summarized in Figure 8, where CDFs of pixel values and measured depths are shown. The process of matching the two distributions through quantile transformation can be demonstrated by considering a single band ratio value, for example, a value of 0.2. According to the CDF of $\log(g/r)$ this corresponds to a probability of approximately 0.25. To assign a pixel of this value an absolute depth, the depth value for the 0.25 quantile from the measured depth CDF is found, which is just under 1 m. The CDFs in Figure 8 also demonstrate the same saturation pattern as the extracted values in the regression

method: pixel quantiles above about 0.75 correspond to only a few finite $\log(g/r)$ values, as indicated by the steep increase and slight stepped pattern. However, this represents a rather large range of depths as indicated by the measured depth CDF, where the upper quartile corresponds to a depth range of approximately 2 m to 4.7 m.

The overall depth maps predicted by the two methods give similar qualitative representations of river depth patterns (Figure 9). Both maps portray relative depth differences well, highlighting variations between shallow regions along bars and deeper areas along the north bank in the upper part of the reach and along the outer bend in the downstream part of the reach. Relevant geomorphic features are also evident, such as the elongate scalloped depressions constructed about halfway along the reach length to provide hydraulic habitat variability, or the mostly submerged mid channel bar slightly upstream. However, the inability of the regression method to properly characterize deep regions with the chosen model is evident in a consistent under-prediction of depth in pools, with a maximum predicted depth of approximately 3 m. This gives the impression of flat pool bottoms as predicted depths quickly reach this limit at pool edges and then stop increasing. The quantile method gives a better sense of true pool depth because the distribution is forced to include the full range

of measured depths, but the pattern in deep areas is spotty and highly variable given the lack of a reliably detectable change in band ratio and the fact that small changes in band ratio represent large changes in depth.

The quality of depth predictions can also be assessed by comparing cross section profiles (Figure 10). Extracting predicted depths from three example cross sections (XS2, XS3, XS6, see Figure 3) demonstrates the vertical errors and facilitates comparison to field-measured data. In general, depth predictions from both methods closely match field depths in shallow areas and become less reliable in deep areas. Local stream morphology therefore dictates how applicable spectral depth mapping will be for a given cross section, with better predictions in wide shallow sections (Figure 10c, XS6) compared to narrow deep sections (Figure 10a, XS2). Regression and quantile method predictions are similar in shallow areas and diverge in deeper areas, where depth predictions become highly variable. In these areas, the regression method consistently under-predicts, whereas the quantile method can over-predict or under-predict depending on slight differences in band ratio value.

The depth residuals (calculated as measured - predicted, Figure 11) and summary error statistics (Table 1) confirm the same patterns observed in the maps and cross sections. Both sets of residuals generally plot close to the 1:1 line, and linear models fit between measured and predicted depths indicate reasonably strong relations (regression $R^2 = 0.67$, quantile $R^2 = 0.60$). For both methods, absolute residuals increase with depth. The regression method (Figure 11a) consistently over-predicts depth, as indicated by the negative intercept and slope close to 1 of the linear fit ($y = 0.93x - 0.12$), leading to a negative mean bias (-0.21 m, Figure 11c). However, the under-prediction of pool depth is evident in the grouping of positive residuals above measured depths of about 2 m. The quantile method (Figure 11b) has a slight negative mean bias (-0.09 m, Figure 11c) but is less precise (quantile standard deviation of errors = 0.43 m, regression standard deviation of errors = 0.36 m) especially at higher depths, leading to a lower R^2 . The linear model of measured versus predicted values for the quantile method ($y = 0.74x + 0.19$) indicates that depths are under-predicted in shallow areas and over-predicted in deep areas. Root mean square errors were similar for both methods (regression = 0.41 m, quantile = 0.44 m), which is in the range of 25% of mean channel depth. Mean absolute error was smaller for the quantile method than the regression method, at 15.4% of mean channel depth compared to 18.7%.

Table 1 Error statistics for evaluation of regression and quantile methods.

Error statistic	Regression	Quantile
R^2 of measured vs. predicted	0.67	0.60
Root mean square error (RMSE, m)	0.41	0.44
Mean absolute error (MAE, m)	0.32	0.26
Mean bias (m)	-0.21	-0.09
Standard deviation of error (m)	0.36	0.43
RMSE as % of mean channel depth	24.4%	25.7%
MAE as % of mean channel depth	18.7%	15.4%

The residuals scatterplots (Figure 11a-b) also highlight the small number of $\log(g/r)$ values in deep areas, which is evident in the vertical banding patterns and poor predictions in both plots. This effect is due to the inherent radiometric resolution of the satellite sensor, which works by converting the continuous signal of radiance leaving the water column into finite digital numbers. For a change in depth to be detectable, it must result in a change in radiance that exceeds the amount corresponding to one digital number. Upwelling radiance is low in deep areas, so changes in depth are difficult to detect and uncertainty is high (Legleiter et al., 2004). This pattern is further evidence that the depth signal in the study reach approaches saturation in deep areas (depth values exceeding approximately 2 m) under these conditions.

Comparing the depth density distributions (Figure 11d) supports qualitative interpretations of the depth maps, with both methods predicting depth distributions that are realistic for river channels. The regression method predicts few depths above 3 m, but the quantile method spans to the maximum measured depth of 4.7 m. Given the finely discretized quantile transformation employed, the quantile method's density distribution closely replicates that of the measured depth training subset.

Despite the limits on depth estimation imposed by water depth, clarity, and sensor capabilities, the results indicate that spectral depth calibration is a useful method for broad-scale bathymetric mapping on Peace River. Analysis of modelled depth patterns and depth prediction residuals indicates that both tested methods can provide realistic qualitative maps of depth that would be suitable for investigations of hydraulic habitat patterns or relative geomorphic change. While both methods are biased to some degree and depth accuracy is not comparable to that of field-measured data, the increased areal coverage is likely more important in many applications (Carbonneau et al., 2006; Fonstad and Marcus, 2010). The methods appear most useful in shallow areas, however, consideration of both absolute errors and errors relative to depth is important in assessing utility for a given purpose. Although absolute errors are greatest for deeper areas (Figure 11a-b), applications concerned with nearshore habitats and issues such as fish stranding on bars under changing flows should also be considerate of relative errors. For example, a 5 cm error seems insignificant in the context of the entire depth range, but a 5 cm error in 20 cm water is 25% of depth and represents an important elevation change and wetted width difference on a low gradient bar surface with shallow water.

Model bias in the regression method is likely caused by the inability of the simple statistical model to fully describe the saturation effect in deep water and by the addition of the dense survey of depth points (which were primarily in shallow to medium depths) in the test depth set. Further investigation could include fitting different forms of models or progressively truncating depths during calibration to remove unreliable areas (Legleiter and Fosness, 2019). The quantile method could have been affected by spatial biases in the depth

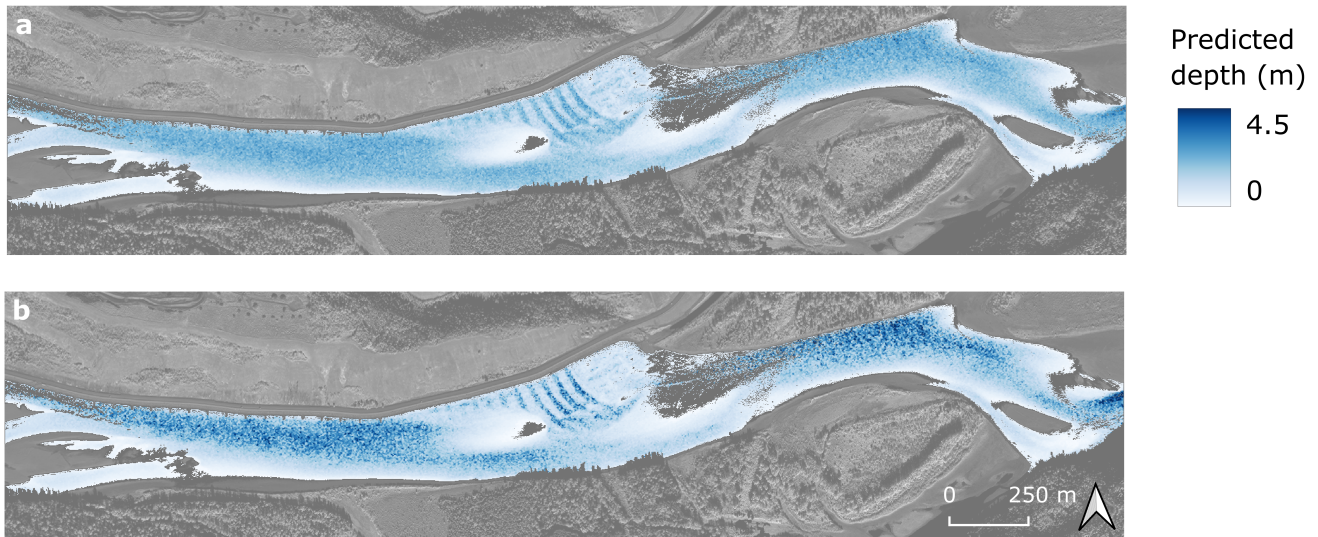


Figure 9 Predicted depth maps for (a) regression method and (b) quantile method.

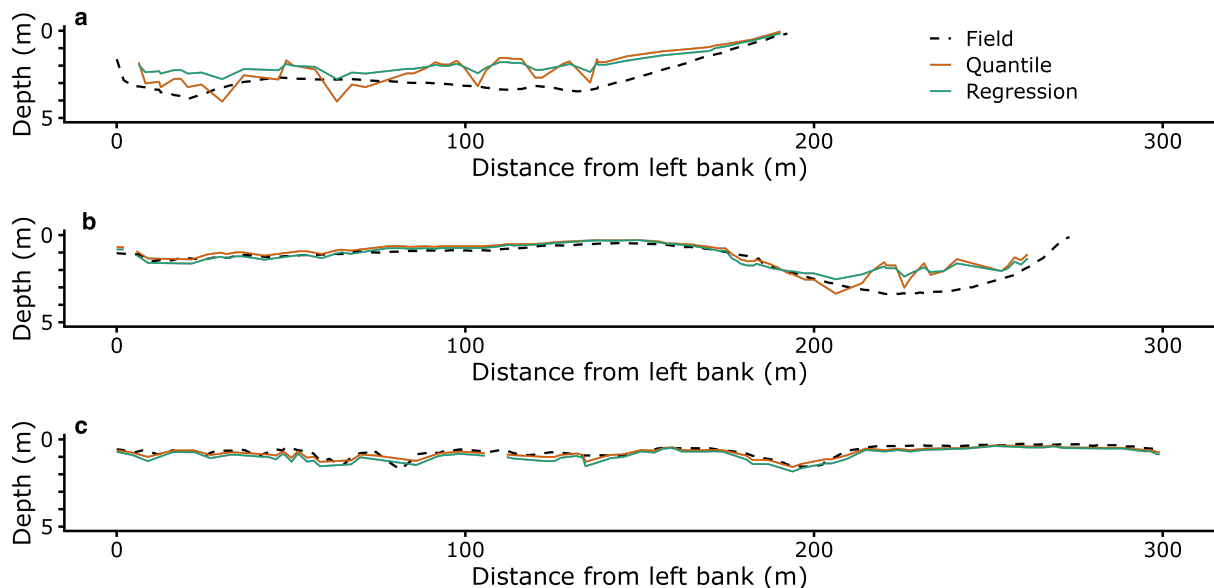


Figure 10 Example cross sections showing predicted and measured depths for (a) XS2, (b) XS3, and (c) XS6. Cross sections are shown with 5x vertical exaggeration.

collection related to cross section placement, or by the image censoring steps that removed areas in a non-random way to create a biased sample of the full wetted area. Both methods were also potentially subject to errors introduced by adjusting the measured depths by a constant stage adjustment to compensate for different flows between the field measurement and image date timing. While this assumption may be more valid for the large, low gradient Peace River than for steeper systems with more slope variability, a depth survey at the time of imagery or at the same discharge would reduce this uncertainty.

In a practical operational context, Peace River is approaching the limits for where satellite depth mapping is appropriate. The conditions shown in the September 19, 2018 WV2 image represent a near ideal combination of low flow and low turbidity. These conditions

are uncommon throughout the year and vary strongly along the length of the river, as tributary confluences often introduce visible plumes of turbid water that do not fully mix with the main flow for long distances. Methods exist to account for spatially variable water clarities (Legleiter et al., 2015), but calibration becomes more complex and the limited visibility may obscure the depth signal completely. Similarly, the inability to see the complete river bottom even at low flows makes methods based on cross sectional hydraulic approximations (e.g. Fonstad and Marcus, 2005; Legleiter, 2015) difficult, so some form of field calibration depth measurements may remain necessary. Further experimentation to assess the effects of weather conditions, water clarity, and riverbed characteristics on Peace River and in other settings would be valuable to determine influence of external factors. Although the deepest areas

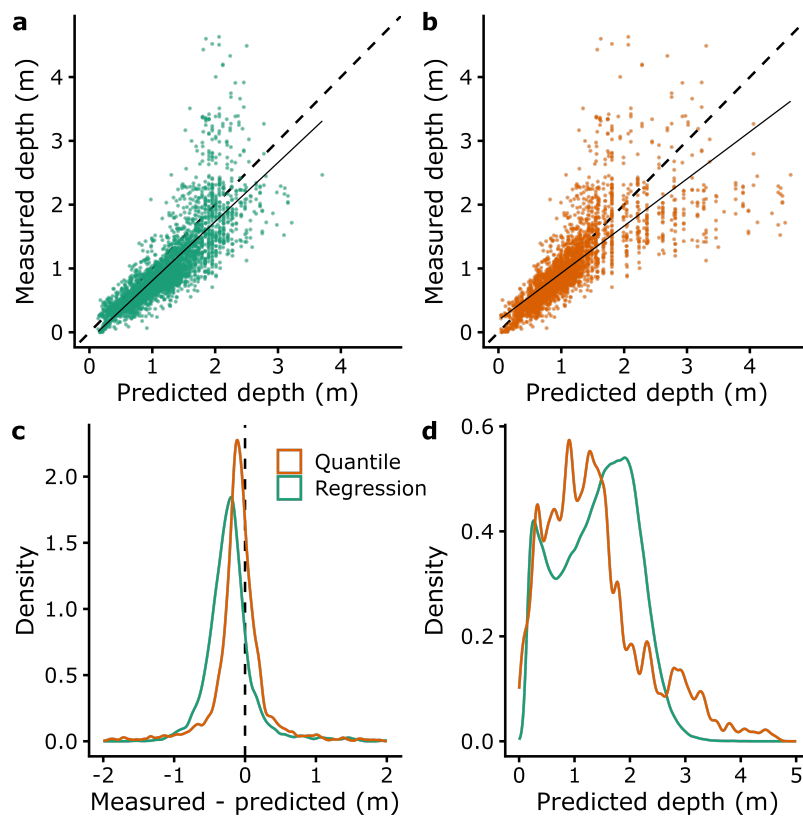


Figure 11 Measured versus predicted depths for (a) regression method and (b) quantile method. Dashed line indicates 1:1 for reference; solid line indicates linear model. (c) Distributions of depth residuals for both methods. (d) Predicted depth distributions for both methods.

were not predicted reliably, the regression and quantile methods tested in this study yielded useable data for much of the wetted channel. Further, the methods reliably identified locations deeper than a set value (here, > 2 m) which is helpful in itself for certain types of aquatic habitat monitoring (where knowing exact depth of deep areas may not be as important as knowing the size, extent, and location of those areas). In a long-term operational monitoring context downstream of a dam where flows can be controlled to coincide with image acquisition and water clarity is likely to be high, spectral depth mapping from satellites has the potential to fill an important niche in spatial analyses of ecosystem structure and dynamics.

4 Conclusions

This study aimed to assess the utility of depth mapping using satellite imagery on a large river system. Two methods of calibrating field-measured depth values to spectral properties from a multispectral WorldView-2 satellite image were tested, along with several image pre-processing steps. Analyses revealed that spectral depth mapping is suitable to characterize bathymetry, with a depth signal described by a ratio of a short wavelength numerator band (green) subject to scattering by suspended sediment and a longer wavelength band (red) dependent on absorption in pure water. Image censoring to remove unwanted shadows or reflections and a spatial median filter both improved depth calibration accuracy and the quality of resultant depth maps. A regression calibration approach relating measured

depths to image values at the same locations gave similar overall results to a non-spatial calibration based on quantile transformation between cumulative distribution functions of pixel values and a measured depth set, with root-mean-square errors in the range of 25% of mean channel depth. Under the water depth and clarity conditions at the time of the image, the reliability of depth predictions fell rapidly above depths of about 2 m. While neither method could account for this lack of detectable changes in upwelling radiance in deep areas, the quantile method did ensure that the full range of depths was represented in predictions, and tended to accentuate deep areas more than the regression method. The lack of reliable information in deep areas (> 2 m) may not matter if data are being used for general habitat classifications or geomorphic analyses; a field-based survey is likely necessary if greater accuracy is desired in deep areas. The methodology also offers promise for use in flood inundation mapping. Typically in Canada and the United States, flood inundation for 100-year or 200-year floods is modelled using a 2D hydraulic model. Because the details of the low-flow channel are less important in determining the flooding extent for such large magnitude events, a remote sensing approach combined with an aerial LiDAR survey of the subareal parts of the channel and adjacent floodplain could offer a cost effective and practical alternative to direct measurement of the channel bathymetry. Overall, the techniques outlined in this paper have the potential to support monitoring of hydraulic habitat conditions and complement existing measurement methods in a long-term river management context.

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Land Recognition

We acknowledge this research was conducted on the traditional territory of Treaty 8 First Nations of Dunne Zaa, Cree, and Tse'khene cultural descent.

Data and Codes Availability

Code and data are available on a Zenodo repository: <https://doi.org/10.5281/zenodo.15723177>. Note: the original WorldView-2 image cannot be shared due to the terms of the commercial license under which it was purchased; please contact the authors for more information.

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Conflict of Interest Disclosure

The authors have no competing interests.

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The authors declare that no artificial intelligence tool was used to assist in or generate any part of the contents in this manuscript.

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