Fusion of LiDAR Orthowaveforms and Hyperspectral Imagery for Shallow River Bathymetry and Turbidity Estimation

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Abstract—We propose an approach to voxelize bathymetric full-waveform LiDAR (Light Detection and Ranging) to generate orthowaveforms and use them to estimate shallow water bathymetry and turbidity with a nonparametric support vector regression (SVR) method. Two distinct shallow rivers were investigated ranging from clear to turbid water; hyperspectral imagery and traditional full-waveform LiDAR processing were also investigated as a baseline for comparison with the proposed orthowaveform strategy. The orthowaveform showed significant correlation to water depth in both scenarios and outperformed hyperspectral imagery for water depth estimation in more turbid water. The orthowaveforms showed similar performance to full-waveform LiDAR point observations for bathymetry estimation in clear water and outperformed the bathymetry performance of full-waveform processing in turbid water. The orthowaveforms also showed similar performance to hyperspectral imagery for predicting water turbidity in turbid water, with a root mean square error (RMSE) of 1.32 NTU. The fusion of both hyperspectral imagery and orthowaveforms was also investigated and gave superior performance to using either data set alone. The fused data set was able to estimate depth in clear and turbid water with an RMSE of 10 and 21 cm, respectively, and turbidity with an RMSE of 1.16 NTU.

Index Terms—Bathymetry, full-waveform light detection and ranging (LiDAR), hyperspectral imagery, support vector regression (SVR), turbidity.

I. INTRODUCTION

REMOTE mapping of river bathymetry is an important environmental tool that is widely used in hydrodynamic modeling and other fluvial applications. Remote sensing makes a significant contribution to river research by providing extensive and accurate quantitative depth, water column, and bottom composition observations for understanding fluvial processes [1]. The ease of deployment, cost effectiveness, and quick response for macroscale fluvial environments make remote sensing a viable tool for fluvial research. Ship- or boat-based acoustic sonar systems have also been applied to readily produce detailed bathymetric maps and can operate in water depths ranging from meters to thousands of meters [2], [3]. However, it is financially challenging to map shallow water using acoustic instruments, due to their reduced collection swath with decreasing water depth [4]. Safety is another significant limitation to boat-based methods for bathymetric mapping in very shallow water. Passive multi/hyperspectral imagery and airborne bathymetric LiDAR are two of the most widely used remote sensing tools for shallow water bathymetry [5], [6].

Satellite multi/hyperspectral imagery is a feasible tool for bathymetry estimation because it provides spatially continuous and optically based observations of water depth and bottom composition. However, its relatively low spatial resolution limits its application in fluvial environments with small spatial scale [7]. Airborne multi/hyperspectral imagery has emerged to provide finer spatial and spectral resolution, which is, thus, an attractive method for monitoring inland shallow river environments [8]. High-resolution imagery may also become more prevalent for river monitoring due to the recent proliferation of unmanned aerial vehicles (UAVs) in remote sensing. For example, results using a UAV for fluvial system mapping with a structure-from-motion (S/M) photogrammetric technique were reported in [9].

Many algorithms have been proposed to retrieve water depth from passive hyperspectral imagery dating back several decades; Lyzenga [10] and Philpot [11] presented the theoretical basis of retrieving water depths from passive multispectral imagery and proposed a linear method with a deep-water correction to map bathymetry in coastal waters. However, a substantial tuning/calibration is required to account for varying benthic albedo using this model [7]. Due to the limitations of the deep-water correction strategy, Legleiter et al. [8] proposed a band ratio method using the logarithm of the ratio of reflected radiance for shallow fluvial environments and demonstrated its robustness with a statistically determined optimal band pair. However, this band ratio method neglects less optimal bands that have potential additional information, which may enhance water bathymetry estimates. In contrast to conventional
physics-based spectral methods, machine learning techniques have improved rapidly in recent years, and many novel algorithms have been applied to remote sensing observations for water depth estimation. For example, Sandidge and Holyer [12] applied a trained neural network to retrieve water bathymetry from the AVIRIS data set, and Pan et al. [13] proposed support vector regression (SVR) to retrieve water depths from airborne hyperspectral imagery, for two shallow fluvial environments, with improved performance over the band ratio method.

Passive multi/hyperspectral optical systems need to account for spatiotemporal substrate changes, and their performance is also significantly affected by water column reflectance [8], and therefore, alternative methods to determine water depths have been investigated. Airborne bathymetric LiDAR has emerged as a remote sensing technique that uses active emission of green laser pulses to penetrate the water surface [14], and conventional airborne LiDAR Bathymetry (ALB) systems typically utilize photomultiplier tubes (PMTs) or combinations of avalanche photodiodes (APDs) and PMTs in the green channel(s) [4], [15], [16]. The laser flight time is converted to a range with a known constant speed of light in the transmission medium [17]. The spatial position of each LiDAR return can be derived using the navigational information provided by the Global Navigation Satellite System (GNSS) and inertial navigation system (INS) co-located with the LiDAR sensor. As an active remote sensing technology that utilizes relatively high-power laser pulses, bathymetric LiDAR acquisition can sometimes be successful in areas too deep or turbid for bathymetry retrieval from passive imagery [14]. Airborne bathymetric LiDAR can directly measure water depth by subtracting benthic elevations from simultaneously detected water surface elevations. The majority of bathymetric LiDAR systems are also full-waveform systems, i.e., they record a time-sampled representation of the full backscattered laser pulse signal. The recorded full waveforms enable post-mission investigation of the laser pulse interaction with targets along the laser cone of diffraction. A bathymetric full waveform is a composite of returns backscattered from the water surface, water column, and benthic layer. The shape and magnitude of the returned full waveform are determined by wave structure, laser incidence angle, bottom material, water physical and optical characteristics, and receiver and transmit pulse characteristics [18].

The conventional approach to utilizing full-waveform LiDAR is to decompose the sampled waveform into multiple distinct returns to extract the echo locations [5]. Pan et al. [19] showed the benefits of using a representative single-band full-waveform LiDAR system for shallow river bathymetry. In addition to decomposing the full waveform for return locations, the shape of the return pulse energy has also been exploited because it contains information related to environmental parameters, e.g., Parrish et al. [20], Rogers et al. [21] also found good correlation between full-waveform shape parameters and biophysical characteristics for a salt marsh area. However, the parameters derived from full waveforms do not preserve all the information contained in the backscattered return profile because they are normally derived from a model-based assumption of how the return energy should behave. Furthermore, the majority of recorded full waveforms have a varied and irregular sampling of look angles, which make it difficult to apply conventional image processing algorithms to the full-waveform analysis. Hence, Park et al. [22] proposed a voxelization of full-waveform returns to transform them to an equivalent 3-D image with subsequent detection of underwater environmental changes using the generated 3-D voxelized waveforms. The voxelized full waveform approximates a nadir laser pulse interaction with targets and facilitates the use of image processing strategies. A voxelized waveform was also shown to have potential for enhancement of land cover classification [23]. However, the potential of voxelized full waveforms for shallow water bathymetry and estimation of water characteristics has not been explored.

Herein, we propose a methodology to encapsulate the full-waveform LiDAR return signal in a voxelized structure, which we refer to as an orthowaveform. To investigate the potential of orthowaveforms for bathymetry and turbidity estimation, we suggest the use of SVR as a supervised learning method to analyze the generated voxelized full waveforms. To validate the orthowaveform performance, we compare it against hyperspectral imagery and traditional full-waveform LiDAR. We also investigate the fusion of hyperspectral imagery and orthowaveforms for both bathymetry and water turbidity estimation. The remainder of this paper is organized as follows: Section II presents the study area and remote sensing data sets used in the analysis; Section III presents the theoretical background, including methods for generating the orthowaveforms, and provides a brief introduction to SVR; Section IV presents the experimental results, Section V offers some discussion of the results, and finally, Section VI provides the study conclusion along with future directions.

II. STUDY AREA AND DATA SET DESCRIPTION

Both the Snake River in Wyoming’s Grand Teton National Park (see Fig. 1.1) and the confluence of the Blue and Colorado Rivers in North Central Colorado (see Fig. 1.2) were investigated in this study. Clear water was present for the Snake River in the summer when data acquisition occurred. The study focused on a sinuous area referred to as Rusty Bend, where the north bank consists of a large gravel bar and the southern portion features a deep pool along a high outer bank. The bed material consists mostly of cobble and gravel. The Colorado River originates in Rocky Mountain Park, and the Blue River enters the Colorado River from the south near Kremmling, CO. The bed material consists of sand, fine sediment, and lesser amounts of gravel. This site has variable water conditions because the Colorado River is also joined by Muddy Creek, which, as the name implies, was turbid due to rainfall immediately preceding data acquisition.

For both study sites, hyperspectral imagery was collected with an ITRES Compact Airborne Spectrographic Imager (CASI)-1500 sensor. CASI-1500 is a pushbroom camera with 1500 across-track pixels spanning a 40° field of view and has a programmable spectral range that extends from 380 to 1050 nm with a maximum of 288 bands. The CASI image data were georeferenced using trajectory information from the GNSS and INS on board the aircraft.

The hyperspectral imagery was calibrated with manufacturer-provided software and calibration constants to convert the raw
measurements into spectral radiance. The ATCOR-4 software was used for atmospheric correction and to retrieve surface reflectance [24]. This program uses a Digital Elevation Model (DEM) and a database derived from a Modtran-5 radiative transfer simulation to account for topographic and atmospheric effects on surface reflectance.

Both near-infrared (NIR, Optech Gemini) LiDAR and green (Optech Aquarius) LiDAR data sets were collected. The Aquarius system is a single-band laser system emitting 532-nm laser pulses with programmable pulse-repetition frequencies (PRFs) of 33, 50, and 70 kHz, a pulse energy of 30 μJ (at 70 kHz), and a beam divergence angle of 1 mrad. The scanner contains a side-to-side oscillating mirror with an adjustable scan angle up to ±25°. The return signal is digitized with a 12-bit amplitude quantization at a sampling speed of 1 GHz. The Gemini system is similar to the Aquarius system, but it emits 1064-nm laser pulses with PRFs up to 167 kHz. The Gemini system is also capable of recording full waveforms, but the full waveform was only recorded for the Aquarius system in both study areas. Table I shows the principal acquisition parameters for the remote sensing data sets [25]. The NIR LiDAR and the hyperspectral imagery data were collected simultaneously on August 21, 2012, for the Snake River, and September 6, 2012, for the Blue/Colorado River. The green LiDAR was collected separately on August 26, 2012, for the Snake River, and September 5, 2012, for the Blue/Colorado River.

**TABLE I**

| Summary of the Airborne Remote Sensing Data Set Acquisition Parameters |
|--------------------------------|----------------|----------------|----------------|
| A. ADCP Data |

ADCP reference data were collected with a SonTek River Surveyor S5 ADCP deployed from a kayak. SonTek reports a depth resolution of 0.001 m and an accuracy of 1% over the range of 0.2–15 m. These ADCP data were our primary ground reference data. We optimistically estimate that the accuracy values of the ADCP depths are better than 3 cm, for the two study sites, as all water was shallower than 3 m (see Fig. 1.3(a) and (b) for the Snake River and the Blue/Colorado River depth histograms, respectively). ADCP measurements were collected from August 14 to August 22, 2012, for the Snake River; all data (including both ADCP and water turbidity data) were collected from September 4 to September 5, 2012, for the Blue/Colorado River. A real-time kinematic (RTK) GPS...
was co-located with the ADCP, and the measurements were cross-calibrated with a separate wading RTK GPS survey. An adjustment was made to account for the depth of the ADCP probe beneath the water surface, the position of the ADCP on the kayak, and any datum offset for the ADCP measurements. The influence of temporal gaps between field and airborne data collections are negligible, when considering the changes in the water discharge rates provided by the USGS stream gauges for both rivers over the field collection campaign dates.

**B. Water Turbidity Measurements**

Water attenuation is a sum of absorption \((a)\) and scattering \((b)\), and the backscattering \((b_\text{b})\) can be represented by the scattering that is composed of the scattered radiation redirected toward to the optical detector [25]. A WET Labs EcoTriplet was deployed from a kayak on the Blue/Colorado River to measure the portion of the total backscattering \((b_\text{b}(700 \text{ nm}))\) associated with particulates in the water column, and turbidity was then derived from the measured backscatter in nephelometric turbidity units (NTU) (see Fig. 1.4). The distribution of the turbidity measurements is shown in Fig. 1.3(c), which is bimodal due to the introduction of higher turbidity water from Muddy Creek (see Fig. 1.4).

**III. METHODS**

**A. Theoretical Background**

Passive multi/hyperspectral remote sensing of water measures the visible and near-infrared reflected solar radiance that interacted with the water surface, water column, and benthic layer. The radiance received at the passive optical sensor for a specific wavelength over optically shallow water can be described as follows [8], [10], [11]:

\[
L_D = L_B \exp(-gh) + L_W
\]

with

\[
L_B = E_d T_w T_a (R_b - R_c) \\
L_W = E_d T_w T_s R_c + L_S + L_P
\]

where \(L_D\) denotes the radiance received at the detector; \(L_B\) is the bottom radiance; which is sensitive to substrate reflectance \((R_b)\); \(L_W\) is the deep water radiance; \(E_d\) is the downwelling irradiance; \(T_w\) accounts for the transmittance across the air–water interface; \(T_a\) is the atmosphere transmittance; \(R_c\) is the water column reflectance; \(g\) is the effective water attenuation coefficient; \(h\) is the water depth; \(L_S\) is the upwelling radiance from the water surface determined by the Fresnel equation; and \(L_P\) is radiance from the atmosphere that can be compensated with atmospheric correction. Except for physical water depth \((h)\), all parameters are wavelength dependent.

Lyzenga [10] and Philpot [11] proposed a linear algorithm to retrieve water depth from passive imagery, with a deep-water correction and an assumption of consistent water conditions. Legleiter et al. [8] proposed a band ratio method for optically shallow water depths because it is not feasible to perform a deep-water correction; in shallow water stream channels, any deep water radiance would contain a contribution from the benthic radiance. However, the band ratio method also has some limitations. First, only two bands are used to retrieve water depth, while all other bands are neglected; thus, there is potential for further improvement if more bands can be simultaneously incorporated into the estimation process. Second, the consideration of a nonzero \(L_W\) value can also improve depth estimates, particularly for turbid shallow water environments, where the water column radiance is significant [13].

If we consider all available spectral imagery bands and assume consistent water clarity and substrate type, at least three known water depths are required to estimate the three unknown parameters \((L_B, g, L_W)\), which are dependent on each study site. However, more known water depths are necessary for multivariate regression to account for the noise present in the remotely sensed radiance. Furthermore, it is clear that varying benthic composite reflectance \((L_B)\) and varying water column characteristics \((g\) and \(L_W)\) can make the bathymetry estimates more complex, and a multivariate exponential regression is thus impractical.

Instead of recording the returned solar radiance of hyperspectral imagery, full-waveform bathymetric LiDAR records the time-sampled full laser energy backscatter, and the signal can be presented as follows:

\[
S_D(t) = S_S(t) + S_C(t) + S_B(t)
\]

where \(t\) is the laser pulse propagation time, \(S_D(t)\) is the received bathymetric full waveform, \(S_S(t)\) is the water surface return, \(S_C(t)\) is the water column return, and \(S_B(t)\) is the benthic return. However, it should be noted that the magnitude of \(S_B(t)\) is dependent on both \(S_S(t)\) and \(S_C(t)\) because the magnitude of the benthic return is dependent upon the energy penetrating both the water surface and the water column. Furthermore, a bathymetric LiDAR is normally tilted to reduce \(S_S(t)\), while \(S_C(t)\) is mainly affected by the water column optical properties and laser path length through the water column and thus increases with higher water backscattering and longer propagation path in the water. Both of these components are functions of time, and also dependent upon the shape and amplitude of the emitted laser pulse, which is generally modeled as Gaussian function [19], [26]. Full-waveform processing algorithms detect both the water surface and benthic returns to determine the corresponding water depths. The water surface and benthic return can be described using convolution of the incident laser pulse with the target impulse functions. If we assume a Lambertian model of reflectance [26], [27], the return waveforms can therefore be modeled as Gaussian functions as well. However, one potential challenge in analyzing full waveforms is modeling the water column reflection, which is highly spatially variable and not Lambertian. If we assume single scattering and vertically homogeneous water attenuation, the laser energy in the water column can be expressed as follows [27]:

\[
E(R_W) = E_0 \exp(-c_3 R_W)
\]
where \( E(R_W) \) is the laser energy at path range \( R_W \); \( E_0 \) is the amount of energy refracted into the water column; \( c_\lambda \) is the beam attenuation coefficient, which is dependent on the water conditions and related to water turbidity. Thus, the water column return can be expressed as a convolution of emitted laser pulse and water column attenuation, as follows:

\[
S_C(t) = S_0(t) * \exp(-c_\lambda C_w t)^2
\]

where \( S_0(t) \) is the laser pulse time-series beneath the water surface, and \( C_w \) is the speed of light in water. The squared term accounts for the two-way laser propagation in the water column. If we assume that the water column is vertically homogeneous (constant \( c_\lambda \) and \( C_w \)) and that the refracted laser pulse in water \((S_0(t))\) is Gaussian, the shape of water column return can be modeled with preknown water depth and beam attenuation coefficients.

From (3) and (5), the return full waveform contains both target and water quality coefficients, which can be derived from full-waveform observations directly [16]. Nevertheless, due to the complex mixture of water surface, column, and benthic returns in shallow water, it is challenging to accurately estimate water column characteristics from the full-waveform returns.

The brief theoretical presentations earlier show that both hyperspectral imagery and full-waveform LiDAR contain information about water bathymetry and water column characteristics [see (1), (3), and (5)]; hyperspectral imagery records the received radiance at multiple wavelengths, while the full waveform records the time-series response signal at a single wavelength. Thus, both data sets have the potential to estimate water bathymetry and water column characteristics, simultaneously. With the different nature of their respective recorded signals, fusion of these two data sets has the potential to provide a better estimate than treating each observation source independently.

### B. Generation of Orthowaveforms

Because airborne LiDAR systems usually use mirrors to direct laser pulses across the field of view of the scanner and a forward tilt angle or a circular scan pattern to maintain a fixed incidence angle on the water surface, the return full waveform is generally along a slanted laser path. This variable slant direction makes the application of conventional image processing algorithms problematic. An orthorectified waveform (referred to here as an orthowaveform) would be preferable for extracting informative features using image processing techniques. The concept of voxelizing an irregular point cloud has been used previously in topographic LiDAR studies to determine structural characteristics of forests to estimate biomass parameters [28], and to fuse hyperspectral imagery and LiDAR for land cover classification [23]. To illustrate the voxelization process used in this study, Fig. 2 conceptually shows the generation of orthowaveforms from slanted full waveforms. Each laser point in the full waveform is georeferenced in space, and the ground and water surfaces are used to convert all waveform samples to an equivalent above ground height (AGH). The ground layer (DTM) is extracted from the discrete point cloud using a classification algorithm in the Terrascan software package similar to the approach described in [29]. The benthic portion of the waveform will reside under the 0-m surface, while features, such as vegetation and buildings, will be above it.

To produce a 3-D image, a gridding method, which is referred to as voxelization, was applied to the irregularly distributed waveform samples [30]. The pixel size and vertical resolution of the voxels are critical for generating orthowaveforms, as larger pixel sizes and vertical resolution result in more samples belonging to the same voxel. For our purpose, to accommodate the subsequent comparison with hyperspectral imagery and fusion strategies, the generated orthowaveforms have the same spatial pixel size as the hyperspectral imagery (see Table I). The vertical resolution is set as 0.2 m; this is slightly larger than the waveform sample resolution (1 GHz for full-waveform digitization). The mean amplitude value of all points falling in one voxel is used as the approximate voxel amplitude, due to the relatively low water depths [see Fig. 1.3(a) and (b)] and small scan angles (see Table I). The voxelization process averages the nearby full waveforms, and thus, the generated orthowaveforms approximate the geometric and spectral information contained in the waveform assuming homogeneous characteristics of the water area at the pixel scale.

Figs. 3 and 4 show the hyperspectral imagery and generated orthowaveform 3-D cube for the Snake River and the Blue/Colorado River, respectively. Only the portion of AGH (above ground height) less than 0 m (bathymetric returns) was used for subsequent analysis. The generated orthowaveforms have similar texture to the hyperspectral imagery, and the river channel is clearly observable with the dark pixels denoting the deep channel.

### C. SVR

The explicit physics-based relationship between observed optical radiance, water depth, and turbidity is difficult to model as a multivariate exponential regression [see (1)]. Varying benthic composition and water column characteristics can affect both the observed pixel radiance spectra and the received full-waveform returns; thus, only a qualitative assessment can be
Fig. 3. (a) Hyperspectral imagery 3-D cube for the Snake River with true RGB channels displayed. (b) Generated orthowaveform 3-D cube for the Snake River with three bands (R: −1.0 m; G: −1.4 m; B: −1.8 m).

Fig. 4. (a) Hyperspectral imagery 3-D cube for the Blue/Colorado River with true RGB channels displayed. (b) Generated orthowaveform 3-D cube for the Blue/Colorado River with three bands (R: −1.2 m; G: −1.6 m; B: −2.0 m).

given without thorough prior knowledge of these characteristics of study site, which is generally unavailable. Therefore, a data-driven machine learning technique is proposed as a quantitative way to connect the observations with physical characteristics of the fluvial environment. SVR is a nonparametric regression method, and therefore, no explicit physical model is required. SVR projects the original observational features into a higher dimensional space by implementing a kernel function, and hence, a hyperplane is utilized to fit the observation with physical parameters [31].

As SVR is a supervised learning strategy, calibration samples are essential to build and train the model. We define $\{(x_1, z_1), (x_2, z_2), \ldots, (x_n, z_n)\}$ as the observations, $x_i \in \mathbb{R}^N$ is the feature vector (hyperspectral spectra and orthowaveform in this study), and $z_i \in \mathbb{R}^1$ is the physical parameter vector (water depth and turbidity in this study). Here, $N$ is the dimension of the feature space, and $n$ is the number of samples. A hyperplane $f(x)$ for calibration samples is targeted for an $\varepsilon - SV$ regression. By introducing the slack variables $\xi_i$ and $\xi_i^*$ to accommodate a soft-margin SVR [32], the standard form of $\varepsilon - SV$ is given by

$$\begin{align}
\text{Min} & : \frac{1}{2}||w||^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \\
\text{Subject to} & \begin{cases}
z_i - f(x_i) & \leq \varepsilon + \xi_i \\
f(x_i) - z_i & \leq \varepsilon + \xi_i \\
\xi_i, \xi_i^* & \geq 0, \quad i = 1, \ldots, n.
\end{cases}
\end{align}$$

Here, $C$ adjusts the tradeoff between model generalization and accuracy of fitted hyperplane, and $\varepsilon$ is the maximum allowed deviation from the fitted hyperplane. A larger value of $C$ gives higher fitting accuracy but may cause overmodeling, and a smaller $C$ improves the flatness of the fitted hyperplane but is less effective at modeling the calibration samples, while $\varepsilon$ is the maximum allowed deviation from the fitted hyperplane.
Kernel functions are critical to project the features to the higher dimensional space for hyperplane fitting. Many kernel functions are available, e.g., linear, polynomial, radial basis function (RBF), and hyperbolic tangents [33]. RBF is a widely used form of kernel function and has been implemented in many software packages [31] because of its good performance and smaller number of tuning parameters. The RBF kernel is given as follows:

\[
K(x_i, x_j) = \exp\left(-\lambda \|x_i - x_j\|^2\right).
\]

Here, \(K\) is the kernel function for the two sample vectors \(x_i\) and \(x_j\); \(\lambda\) is the kernel width, which determines the projection and requires tuning to achieve optimal performance. Hence, the performance of SVR with the RBF kernel is highly correlated to the three input parameters: \(C\), \(\epsilon\), and \(\lambda\). A general \(k\)-fold cross-validation method and a grid-searching scheme are used to optimize the selection of the three parameters [34].

**D. Accuracy Assessment**

To evaluate the performance of both full-waveform LiDAR and hyperspectral imagery for prediction of bathymetry and turbidity, root mean square error (RMSE) and R-squared \(R^2\) value are used to compare the predicted values with field-measured reference data. The field-measured reference data set was gridded using averaged values, to ensure that it was at the same spatial pixel size as the hyperspectral imagery and generated orthowaveforms. The prediction error associated with each field measurement was calculated as follows:

\[
\epsilon = z_f - z_r,
\]

where \(z_f\) and \(z_r\) denote the field-measured and remotely sensed water depth (or turbidity), respectively. Then, the RMSE and \(R^2\) were then calculated as follows:

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \epsilon_i^2}{n}},
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (\epsilon_i^2)}{\sum_{i=1}^{n} (z_f - \bar{z})^2},
\]

where \(n\) is the number of field measurements, and \(\bar{z}\) is the average field measurements. A larger RMSE or lower \(R^2\) indicates that the remotely sensed water depth (or turbidity) deviates from field measurements; conversely, a lower RMSE or higher \(R^2\) implies that the remote sensing observations match the field measurements well.

**IV. Experimental Setup and Results**

To investigate the capability of orthowaveforms and their fusion with hyperspectral imagery, each individual data set was regressed using the proposed SVR method and the orthowaveforms were also concatenated to the hyperspectral imagery as a fused feature set. The calibration sample size was incrementally increased from 100 to 500, with an interval of 100, whereas the validation sample size was fixed at 1000. Both the calibration and validation samples were selected through random sampling. A fivefold cross-validation scheme was implemented to search for the optimal SVR parameters through a grid search. The same calibration and validation data sets were applied for each individual feature (hyperspectral imagery and orthowaveforms) and the fused feature set. Each experiment was repeated 20 times, and the average RMSE and \(R^2\) were calculated; the standard deviation calculated from the 20 iterations for each experiment was also reported in this study.

**A. Snake River Bathymetry Estimation**

Table II shows the results for the Snake River bathymetry estimation, and Fig. 5 shows the generated water depth maps. Each individual data set shows improved performance with increased calibration data set size. For hyperspectral imagery, the best average RMSE is 11 cm with a standard deviation of 3 cm, and an \(R^2\) of 0.96 with a standard deviation of 0.03; for orthowaveforms, the best average RMSE is 17 cm with a standard deviation of 1 cm, and an \(R^2\) of 0.91 with a standard deviation of 0.01. The orthowaveforms showed acceptable accuracy for water depth prediction but were outperformed by hyperspectral imagery. However, the standard deviation of orthowaveforms is lower than that of the hyperspectral imagery, indicating that the orthowaveforms are a more consistent feature for the Snake River.

The fused feature set showed the best performance with an average RMSE of 10 cm with a standard deviation of 1 cm and an \(R^2\) of 0.96 with a standard deviation of 0.01. Comparing the fusion results to hyperspectral and orthowaveforms, respectively, the average RMSE and \(R^2\) are similar to those of the hyperspectral imagery, which showed superior performance, but the standard deviations of both the RMSE and \(R^2\) are smaller than those of the hyperspectral imagery alone, which indicates that the fused feature set is more stable than hyperspectral imagery for water depth estimation.

To further investigate the estimation for varying water depths for the Snake River, Fig. 6 shows the distribution of RMSE for varying water depths. The RMSE increases dramatically after the water is deeper than 2 m, likely because of the saturation of the optical radiance signal in deeper water, such that the further increases in depth produce less significant changes [25]. Hyperspectral imagery performs better than the generated orthowaveforms for most depths, and the fused feature set performs similarly to hyperspectral imagery but does improve the spike in hyperspectral-imagery-only RMSE at 0.9-m water depth.
Fig. 5. Water depth maps for the Snake River retrieved by (a) hyperspectral imagery; (b) orthowaveforms; (c) fusion of hyperspectral imagery and orthowaveforms. Water depth error for water depths retrieved by (d) hyperspectral imagery; (e) orthowaveforms; (f) fusion of hyperspectral imagery and orthowaveforms ($Z_f$: ADCP water depth; $Z_r$: remote sensed water depth).

Fig. 6. RMSE distribution of water depths with varying water depths for the Snake River.

TABLE III
BLUE/COLORADO RIVER BATHYMETRY RESULTS FOR HYPERSONAL IMAGERY, ORTHOWAVEFORMS, AND FUSED FEATURE SETS USING SVR. (STANDARD DEVIATION IN BRACKETS; $\kappa$: CALIBRATION SAMPLE SIZE)

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>RMSE(m)</th>
<th>$R^2$</th>
<th>RMSE(m)</th>
<th>$R^2$</th>
<th>RMSE(m)</th>
<th>$R^2$</th>
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<td>0.69(0.04)</td>
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<tr>
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<td>0.32(0.05)</td>
<td>0.21(0.01)</td>
<td>0.70(0.03)</td>
<td>0.22(0.01)</td>
<td>0.69(0.03)</td>
</tr>
<tr>
<td>400</td>
<td>0.26(0.01)</td>
<td>0.55(0.03)</td>
<td>0.21(0.01)</td>
<td>0.71(0.02)</td>
<td>0.21(0.01)</td>
<td>0.70(0.03)</td>
</tr>
<tr>
<td>500</td>
<td>0.26(0.01)</td>
<td>0.55(0.04)</td>
<td>0.21(0.02)</td>
<td>0.70(0.04)</td>
<td>0.21(0.01)</td>
<td>0.71(0.03)</td>
</tr>
</tbody>
</table>

B. Blue/Colorado River Bathymetry Estimation

The Blue/Colorado River is more turbid than the Snake River, and the overall performance degrades due to excessive water column radiance. Table III shows the results for Blue/Colorado River bathymetry estimation, and Fig. 7 shows the retrieval of water depths, and again, each individual feature retrieval shows improved performance with an increase in calibration sample size. The best performance for hyperspectral imagery is an average RMSE of 26 cm with a standard deviation of 1 cm and an average $R^2$ of 0.55 with a standard deviation of 0.03. The best orthowaveform performance is an average RMSE of 21 cm with a standard deviation of 2 cm, and the best average $R^2$ is 0.70 with a standard deviation of 0.04. The orthowaveforms show superior depth retrieval in the more turbid water of the Blue/Colorado River because they are less affected by water turbidity. However, the higher standard deviation of the orthowaveforms indicates that water turbidity still has a significant influence on the accuracy of depth retrieval.

The fusion of the imagery and orthowaveform feature sets yields the best average RMSE of 21 cm with a standard deviation of 1 cm and the best average $R^2$ of 0.71 with a standard deviation of 0.03. A marginal improvement is found with fusion (compared to orthowaveforms alone); however, the lower standard deviations of the RMSE and $R^2$ for the fused feature set results indicate that they are more consistent. Fig. 8 shows the RMSE distribution of depth retrieval error with varying water depths for the Blue/Colorado River. RMSE increases for water depths larger than 1.5 m likely because of approaching the maximum detectable depth (see [25, Fig. 6]). The fused feature set shows similar performance to the orthowaveforms.

C. Comparison of Full Waveform and Orthowaveform for Bathymetry

According to Pan et al. [19], full-waveform bathymetric LiDAR processing significantly improves water depth estimation compared to depths estimated solely from the discrete bathymetric LiDAR point cloud. Therefore, it is reasonable to compare water depths derived from the full waveform to...
Fig. 7. Water depth maps for the Blue/Colorado River retrieved by (a) hyperspectral imagery; (b) orthowaveforms; (c) fusion of hyperspectral imagery and orthowaveforms. Water depth error for water depths retrieved by (d) hyperspectral imagery; (e) orthowaveforms; (f) fusion of hyperspectral imagery and orthowaveforms ($Z_f$: ADCP water depth; $Z_r$: remote sensed water depth).

Fig. 8. RMSE distribution of water depth errors with varying water depths for the Blue/Colorado River.

For the clear water of the Snake River, the bathymetry estimate from full-waveform LiDAR shows similar performance to the orthowaveforms, but with a slightly smaller standard deviation. Both bathymetry estimates show strong correlation to the field-measured water depths. However, for the more turbid water of the Blue/Colorado River study site, the bathymetry estimates from the orthowaveforms show significantly better performance than the bathymetry estimates from full-waveform processing. The standard deviation is reduced to 20 cm from 27 cm, while $R^2$ increases to 0.73 from 0.57. This indicates that the physically...
based full-waveform processing algorithm needs to more effectively remove the water column effect on the full-waveform shape to accurately estimate depths. The superior performance of the orthowaveforms indicates that the water column effect is indeed encapsulated in the LiDAR return pulse profiles and that it can be used to more accurately estimate bathymetry.

D. Blue/Colorado River Turbidity Estimation

Theoretically, the observed hyperspectral imagery and orthowaveforms both contain information pertaining to water column characteristics; however, it is difficult to explicitly define a physical model to relate the remote sensing observations to field-measured turbidity. However, the availability of field-measured water turbidity for the Blue/Colorado River enables us to investigate the applicability of both the individual and fused features for prediction of turbidity using a nonparametric SVR approach. Table V shows the results for turbidity estimation for the Blue/Colorado River, and Fig. 9 shows the retrieval of water turbidity. Similar to the bathymetry estimation results, the average RMSE and $R^2$ of turbidity estimation are improved with an increase in the calibration sample size; hyperspectral imagery yields the best RMSE of 1.20 NTU with an $R^2$ of 0.88; orthowaveforms yield the best RMSE of 1.32 NTU with an $R^2$ of 0.86. Both hyperspectral imagery and orthowaveforms show similar performance, indicating that the hyperspectral imagery and orthowaveforms observe similar water column characteristics for the Blue/Colorado River. Comparing Tables III–V, we can conclude that orthowaveforms are more applicable to water depth estimation than hyperspectral imagery for the turbid Blue/Colorado River; however, the hyperspectral imagery performs better for water turbidity estimation than orthowaveforms with a higher $R^2$ relating to turbidity. This again not only implies that bathymetric LiDAR is less affected by water turbidity but also suggests that the additional observed spectral channels from hyperspectral imagery are better able to estimate turbidity than the single spectral band reflectance of the bathymetric LiDAR. However, both hyperspectral imagery and orthowaveform show stronger correlation to water turbidity than water depth (i.e., higher $R^2$ value) indicating that the excessive water column reflectance overwhelmed the benthic return for the Blue/Colorado River.

The fused feature set shows an optimal performance of 1.16-NTU RMSE with an $R^2$ of 0.89. The fusion has marginally improved the performance compared using either the hyperspectral imagery or orthowaveforms alone; the standard deviations of the RMSE and $R^2$ are better for the fused data set and therefore gives a more consistent turbidity prediction. Fig. 10 shows the RMSE distribution of turbidity estimation error with varying water turbidity for the Blue/Colorado River for each observation type. The RMSE of the retrieved water turbidity is lowest, in the areas where the training samples had sufficient observed turbidity. The actual turbidity measurements showed a bimodal distribution [see Fig. 1.3(c)], and therefore, limited training samples were available outside the bands at $\sim$2 and 10 NTU.

V. DISCUSSION

Orthowaveforms generated from full-waveform bathymetric LiDAR contain both the shape and amplitude information of the reflected energy within the laser cone of diffraction, and SVR is an effective method to bridge the observational information contained in the LiDAR to physical water depths and turbidity. Orthowaveforms did not perform as well as hyperspectral imagery for water depth retrieval in the clear water of the Snake River, but outperformed hyperspectral imagery in the
more turbid water of the Blue/Colorado River study site. The water depths retrieved from orthowaveforms were similar to
water depths retrieved from full-waveform bathymetric LiDAR
processing for the Snake River; however, the water depths retrieved from orthowaveforms were significantly better than
water depths retrieved from full-waveform processing for the
Blue/Colorado River. The comparison of the full-waveform
processing results and the orthowaveform depth determination
clearly showed that, for more turbid water, the encapsulation
of the entire waveform shape better estimates depths than the
determination of return locations from full-waveform process-
ing. This suggests that, for turbid water, full-waveform LiDAR
processing needs to be extended to properly model the non-
Gaussian LiDAR energy returned from the water column.
There has been some initial work on this using simulated
data [35], but detailed studies using actual bathymetric LiDAR
data sets are required in order to develop a physical model
for the return energy from the water column. The regression
between generated orthowaveforms with water turbidity shows
its capability to derive additional environmental characteristics.
The promising capability of machine learning coupled with
orthowaveforms suggests that this approach could be extended
to estimating other biophysical and ecological parameters,
which currently can be estimated through the full-waveform
analysis [21].

In contrast to conventional processing strategies for bathym-
etry from hyperspectral imagery, the SVR approach used in this
study is purely data driven. As a supervised learning method,
calibration samples are necessary to connect the observations
with the results; the improvement of prediction with an increase
in calibration sample size indicates that better regression can
be found with more calibration samples if we can neglect the
increased computational load. However, the optimal number
of field measurements as training samples is still unknown,
and it is likely highly correlated to the variability in water
depths, turbidity, and bottom reflectivity found in the fluvial
environment under study. The projection of features into a
high-dimensional mathematical space and the fitting with a
hyperplane gives remote sensing users a new tool for data
analysis and interpretation. However, the one obvious disad-
vantage of using SVR is that accurate field data are required to
build the mathematical models, whereas the primary motivation
for using remote sensing is to directly quantify physical and
environmental characteristics remotely. Thus, the collection of
field measurements is not always feasible, particularly for non-
accessible areas, where temporal changes in observational pa-
rameters and difficult measurement environments are present.
Even for accessible sites, the requirement of excessive field
measurements can limit the applicability of using SVR, and
therefore, it is also necessary to develop strategies with fewer
field observations or which only require remotely sensed data.
The success of combining hydraulic principles with a linear
relation between image and water depth to derive river bathym-
etry without field data demonstrates outstanding potential in
fluvial remote sensing studies [36].

Both the orthowaveform and hyperspectral imagery showed
better correlation to water turbidity than water depth for the
Blue/Colorado River, i.e., a consequence of a major limitation
of optical remote sensing: returned radiance from the benthic
layer is required for accurate depth estimation. Preflight plan-
ning for data collection is critical to acquire the desired quality
of data and to ensure that the acquisition is done under ideal
conditions (e.g., low water flow and low turbidity). However,
overall, the orthowaveforms show better correlation to water
depth than hyperspectral imagery, while hyperspectral imagery
shows better connection to water turbidity than the ortho-
waveforms. This indicates that active optical airborne bathymetric
LiDAR is more tolerant to water turbidity.

Data fusion, on the other hand, is also currently a hot topic
for the remote sensing community. As Hossain et al. [37]
concluded, there is no single remote sensing strategy that is
suitable for all remote sensing tasks, and therefore, an optimal
combination of all available observations has the potential to
improve the quantitative determination of physical parameters
from remote observations. Although the fused feature sets in
this study only marginally improved estimates for both clear
and turbid water, it did stabilize the overall solution by yielding
smaller standard deviation (i.e., more consistent results). This
would suggest that additional analysis of fused feature sets, in-
cluding consideration of the physical radiative transfer models,
may allow additional improvement in the fused observations.
However, the determination of the optimal data fusion strategy
is beyond the scope of this study. Hence, more focus should
be applied to enhancing observational techniques for fusing
different remote sensing data sources.

VI. CONCLUSION

This study has shown that orthowaveforms are a useful
technique for analyzing bathymetric LiDAR return waveforms.
For orthowaveforms alone, in the clear water of the Snake
River study site, the best average RMSE is 17 cm with an $R^2$
of 0.91, and for the more turbid water of the Blue/Colorado
River study site, the best average RMSE is 21 cm with an $R^2$
of 0.70. Hyperspectral imagery showed superior performance
for the Snake River study but was outperformed by ortho-
waveforms in the turbid water of the Blue/Colorado River.
Through the comparison of orthowaveforms with full-waveform
processing strategies, it was found that orthowaveforms showed
similar performance to full-waveform processing in clear wa-
ter but improved the bathymetry estimates in turbid water,
significantly. This would suggest that additional modeling,
to account for water turbidity, is required in full-waveform
processing strategies. The turbidity derived from ortho-
waveforms has similar performance to hyperspectral imagery
for the Blue/Colorado River. Only marginal improvements were
observed by fusing orthowaveforms and hyperspectral im-
agery as fused feature sets for both the Snake River and
Blue/Colorado River; however, the fused feature sets did yield
more stable and consistent solutions by providing smaller stan-
dard deviations. The concept of orthowaveforms can also be
potentially applied to estimating other biophysical parameters,
and furthermore, a spectrally based fusion strategy for full-
waveform bathymetric LiDAR and hyperspectral imagery de-
serves further consideration in fluvial or shallow coastal water
mapping research.
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REFERENCES


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