Spectrally based mapping of riverbed composition

Carl J. Legleiter^{a,b,*}, Tobin K. Stegman^b, Brandon T. Overstreet^b

^a*U.S. Geological Survey, Geomorphology and Sediment Transport Laboratory, Golden, CO, 80403, USA*

^b*Department of Geography, University of Wyoming, Laramie, WY 82071, USA*

Abstract

Remote sensing methods provide an efficient means of characterizing fluvial systems. This study evaluated the potential to map riverbed composition based on *in situ* and/or remote measurements of reflectance. Field spectra and substrate photos from the Snake River, Wyoming, USA, were used to identify different sediment facies and degrees of algal development and to quantify their optical characteristics. We hypothesized that accounting for the effects of depth and water column attenuation to isolate the reflectance of the streambed would enhance distinctions among bottom types and facilitate substrate classification. A bottom reflectance retrieval algorithm adapted from coastal research yielded realistic spectra for the 450 to 700 nm range; but bottom reflectance-based substrate classifications, generated using a random forest technique, were no more accurate than classifications derived from above-water field spectra. Additional hypothesis testing indicated that a combination of reflectance magnitude (brightness) and indices of spectral shape provided the most accurate riverbed classifications. Convolv-

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*Corresponding author. U.S. Geological Survey, Geomorphology and Sediment Transport Laboratory, 4620 Technology Drive, Suite #400, Golden, CO, 80403, USA; Phone +1 303-271-3651; Email: cjl@usgs.gov (Carl J. Legleiter).

ing field spectra to the response functions of a multispectral satellite and a hyperspectral imaging system did not reduce classification accuracies, implying that high spectral resolution was not essential. Supervised classifications of algal density produced from hyperspectral data and an inferred bottom reflectance image were not highly accurate, but unsupervised classification of the bottom reflectance image revealed distinct spectrally based clusters, suggesting that such an image could provide additional river information. We attribute the failure of bottom reflectance retrieval to yield more reliable substrate maps to a latent correlation between depth and bottom type. Accounting for the effects of depth might have eliminated a key distinction among substrates and thus reduced discriminatory power. Although further, more systematic study across a broader range of fluvial environments is needed to substantiate our initial results, this case study suggests that bed composition in shallow, clear-flowing rivers potentially could be mapped remotely.

Keywords: remote sensing; field spectroscopy; sediment grain size; submerged aquatic vegetation

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1. Introduction

Remote sensing has emerged as a powerful tool for characterizing river systems efficiently over large spatial extents (Marcus and Fonstad, 2010). Over the past two decades, a growing number of sensors, ranging from traditional passive optical systems (e.g., Marcus and Fonstad, 2008) to recently developed water-penetrating green LiDARs (e.g., McKean et al., 2008; Kinzel et al., 2013), have enabled a variety of riverine applications (Marcus et al., 2012). Recent examples include large-scale habitat mapping from satellite images (Hugue et al., 2016), identification of refugia from thermal infrared data (Dugdale et al., 2015), and assessment of riverbed stability based on LiDAR-derived topographic information (McKean and Tonina, 2013). Although such studies have demonstrated the potential utility of remote sensing, Legleiter et al. (2016) also identified challenges that must be addressed to scale up from reach-scale feasibility studies to synoptic, watershed-scale mapping. Progress toward this goal is closely linked to the riverscape concept (Carbonneau et al., 2011) and could yield novel insight on fluvial processes.

One of the earliest and most common applications of remote sensing to rivers is inferring water depth from passive optical image data (Lyon et al., 1992; Winterbottom and Gilvear, 1997; Gao, 2009). Legleiter et al. (2009) examined the radiative transfer processes involved as solar radiation interacts with stream channels and outlined the conditions under which bathymetric mapping is feasible. When depths are shallow, the water clear, and the streambed relatively bright, bottom-reflected radiance is the dominant component of the signal and accurate depth estimates are possible. Having established the physical basis for spectrally based depth retrieval, this study

26 seeks to build upon this framework and infer additional river attributes. More
27 specifically, because the bottom-reflected radiance depends not only on depth
28 but also the reflectance of the streambed itself, spectral information poten-
29 tially could be used to identify various bottom types. A strong precedent for
30 substrate mapping comes from coastal settings, where remotely sensed data
31 have been used to examine coral reefs and other benthic environments (e.g.,
32 Andrefouet et al., 2001; Hochberg et al., 2003; Mobley et al., 2005; Dekker
33 et al., 2011). Here, we adapt this approach to mapping riverbed composition.

34 In fluvial systems, spatially distributed information on the makeup of
35 the channel bed would be useful in geomorphic and ecological contexts. For
36 example, bed material sorting reflects complex interactions among the flow
37 field, the morphology of the channel, and the movement of various grain sizes
38 and often takes the form of distinct, persistent patches with characteristic
39 textures (Lisle et al., 2000; Nelson et al., 2010, 2015). This patchiness im-
40 plies that even a qualitative, facies-level mapping of spatial patterns of bed
41 material grain size could be highly informative (Buffington and Montgomery,
42 1999). Although various metrics of image texture have been used to estimate
43 grain size on exposed and/or shallow submerged gravel bar surfaces from very
44 high resolution image data (e.g., Carbonneau et al., 2004; Verdu et al., 2005;
45 Dugdale et al., 2010), we are not aware of any studies that have mapped
46 grain size within the wetted channel on the basis of spectral information.

47 From an ecological perspective, algae and other types of vegetation an-
48 chored on the channel bed form the photosynthetic foundation of lotic ecosys-
49 tems, converting light to biomass that nourishes higher trophic levels (Giller
50 and Malmqvist, 1998). Substrate-attached algae, known as periphyton, are

51 sensitive to particle size (e.g., Cattaneo et al., 1997), flow velocity (e.g., Biggs
 52 et al., 1998; Choudhury et al., 2015), and nutrient loading (e.g., Hoyle et al.,
 53 2014) and thus serve as an indicator of water quality and general stream
 54 health. Benthic algae also influence bed mobility by stabilizing sediment,
 55 although mature algal mats can detach from the bed to lift and transport
 56 sand and fine gravel even under low-flow conditions (Mendoza-Lera et al.,
 57 2016). Periphyton thus have geomorphic as well as ecological significance,
 58 and several previous studies have used remote sensing techniques to charac-
 59 terize algae and submerged aquatic vegetation in rivers; Marcus et al. (2012)
 60 provide a review. For example, Lee et al. (1999) used field spectra to dis-
 61 tinguish among various types of periphyton and macrophytes and to develop
 62 regression models for predicting chlorophyll and biomass. Their encouraging
 63 results — classification accuracies in excess of 95% and regression $R^2 > 0.92$
 64 — suggested that benthic vegetation could be mapped from hyperspectral
 65 image data. Lee et al. (1999) did not, however, consider the effects of depth
 66 or water column optical properties. More recently, Visser et al. (2014) per-
 67 formed object-based analysis of high resolution images and identified depth as
 68 an important factor limiting species-level classification of submerged aquatic
 69 vegetation. Similarly, Flynn and Chapra (2014) used images acquired from
 70 an unmanned aerial vehicle to map a nuisance green algae. Our study ex-
 71 tends earlier work by addressing the effects of depth and classifying riverbed
 72 composition from field spectra and hyperspectral image data.

73 Our investigation was founded on the premise that spectrally based sub-
 74 strate mapping could be enhanced by using information on depth and atten-
 75 uation to account for the influence of the water column and retrieve bottom

76 reflectance. This notion has a sound basis in the coastal literature where
77 Maritorena et al. (1994) and Dierssen et al. (2003), to name but two exam-
78 ples, used this approach to map coral reefs and seagrass, respectively. In
79 this study, we used field spectra measured above the water surface, direct
80 measurements of water depth, and a parameter summarizing water column
81 attenuation to retrieve bottom reflectance, as illustrated in Fig. 1. The right
82 side of this flow chart outlines how we visually interpreted photos of the
83 streambed to provide training data for a random forest algorithm that ul-
84 timately produced classifications of sediment facies and algal density. This
85 investigation evaluated the potential for spectrally based mapping of riverbed
86 composition and primarily used field measurements, but these methods also
87 were applied to a hyperspectral image to assess the feasibility of identifying
88 bottom types remotely.

Fig. 1. Flow chart for retrieving bottom reflectance from above-water field spectra or remotely sensed data and using this information to delineate various bottom types.

Our primary research objective was to establish a framework for mapping the substrate of relatively shallow, clear-flowing rivers amenable to remote sensing. More specifically, we used field spectra to determine the extent to which disparate sediment facies and different levels of algal development could be delineated based on above-water measurements and/or retrieved bottom reflectances. Several research questions motivated this inquiry:

- Can different grain size categories be distinguished from one another: sand, gravel, cobble, and various mixtures thereof?
- Similarly, can patches of high algal density be distinguished from areas with lesser amounts of submerged aquatic vegetation?

- 99   • Can these distinctions be made from reflectance spectra collected in
100   the field from above the water surface?
- 101   • Does accounting for the effect of the water column to retrieve bottom
102   reflectance enhance these distinctions and facilitate substrate mapping?
- 103   • Which variables — reflectance magnitudes or indices of spectral shape
104   — are most informative in distinguishing among various bottom types?
- 105   • Do multispectral satellites and hyperspectral imaging systems provide
106   sufficient spectral resolution to support streambed mapping?

107   **2. Methods**

108   *2.1. Study area and field data collection*

109   To evaluate the potential for spectrally based mapping of riverbed com-
110   position, we collected field data along the Snake River within Grand Teton
111   National Park WY. This site was the subject of several channel change stud-
112   ies (Marston et al., 2005; Erwin et al., 2011; Nelson et al., 2013) and previous
113   efforts to develop remote sensing methods (Legleiter and Overstreet, 2012;
114   Legleiter, 2013, 2015; Legleiter et al., 2016). Location maps and descriptions
115   of the study area are available in these publications. The present investiga-
116   tion was based on field observations of depth, reflectance, and bottom type
117   collected between Swallow Bend and Deadman’s Bar on 17 August 2012. In
118   addition, an image of Rusty Bend was used to illustrate how this approach
119   to riverbed mapping might be applied to remotely sensed data.

120   Whereas prior work along the Snake emphasized spectrally based depth
121   retrieval, herein we focused on the river’s bed, which is composed primarily
122   of gravel to cobble-sized material, with lesser amounts of sand. We did not

attempt to infer absolute particle sizes but rather adopted a facies-level classification of sediment grain size distributions (Buffington and Montgomery, 1999). The substrate tends to be coated with varying degrees of periphyton and macrophytes, filamentous algae, and other forms of submerged aquatic vegetation that occur in irregular patches. Species-level classification was beyond the scope of this study so we referred to all photosynthetic organisms attached to the bed as algae and distinguished various algal densities.

Field data were collected from a specially designed research cataraft that served as a mobile, highly maneuverable platform for deploying the following instrumentation: Trimble R8 real-time kinematic (RTK) and ProXH differential GPS receivers, used to establish the locations of all measurements; a Seafloor Systems Hydrolite-TM echo sounder for recording water depths with an accuracy of 1 cm/0.1% of depth; an Analytical Spectral Devices (ASD) FieldSpec3 spectroradiometer for measuring spectra; and a GoPro camera encased in a waterproof housing for photographing the riverbed. Simultaneous, georeferenced observations of depth, reflectance, and bottom composition were obtained while traveling along the river. We sampled a series of transects at Swallow Bend, including a deep backwater with a sand substrate and patches of dense aquatic vegetation, and then made a single downstream pass through the remainder of the study area. Water column optical properties were clear and homogeneous throughout this river segment.

Field spectra were measured above the water surface using a fore-optic mounted on a spar projecting from the rear of the cataraft and connected to the ASD with a waterproof fiber optic cable. This configuration allowed us to avoid self-shading effects and ensured that the water surface was not affected

148 by wake from the cataraft. The fore-optic had a 7.5° field of view and was
149 typically 0.25 m above the water surface, implying a 0.0034 m^2 measurement
150 area at the water surface and 0.085 m^2 of the bed for a typical depth of 1 m.
151 Spectra were recorded in reflectance mode by first measuring the instrument
152 response when viewing a Spectralon white reference panel and then dividing
153 subsequent readings by this standard. Every 10 to 15 minutes we optimized
154 and calibrated the ASD by extending the Spectralon panel along the spar into
155 the sensor's field of view. By default, the ASD averages 10 individual spectra
156 recorded at a sampling frequency set by the integration time to obtain a single
157 output spectrum saved to the computer controlling the instrument. However,
158 because the cataraft was moving while these measurements were being made,
159 we did not perform any averaging and recorded individual spectra once each
160 second. This protocol avoided aggregating spectra collected above variable
161 bottom types. The spectral sampling interval of the ASD was 1 nm over the
162 range from 350 to 1025 nm, with a 3-nm full-width half maximum.

163 To link these observations of the river's spectral characteristics to bottom
164 composition, we used a downward-facing camera to obtain photos of the
165 streambed beneath the cataraft at the same sampling frequency as the field
166 spectra. For a typical distance above the bed of 1 m, the GoPro camera's
167 effective focal length and detector array dimensions translated into a pixel
168 size of 0.56 mm and an image extent of $1.61 \times 2.15 \text{ m}$. Each substrate
169 photo thus encompassed an area substantially larger than the footprint of an
170 individual field spectrum. The camera's fisheye lens produced some distortion
171 along the margins of each photo, but we did not attempt quantitative digital
172 grain size analysis (e.g., Buscombe, 2013); these effects did not preclude

173 qualitative, visual interpretation of sediment facies and algal density.

174 In addition to the reflectance spectra, we also used the ASD to charac-
175 terize attenuation of light within the water column (Legleiter et al., 2016).
176 Briefly, we measured a vertical profile of downwelling spectral irradiance by
177 mounting an upward-facing fore-optic with a cosine response on the end of a
178 measurement crane that allowed us to lower the sensor to various positions
179 within the water column. A pressure sensor adjacent to the fore-optic was
180 used to define the depth of each measurement.

181 *2.2. Field data processing*

182 Because the ASD, camera, and echo sounder were mounted on the cataraft
183 in different positions, georeferencing the data required additional processing.
184 We used simultaneous positions from the two GPS receivers to determine
185 the location and orientation of the cataraft and then calculated the coordi-
186 nates of each measurement based on the sensor-mounting geometry relative
187 to the GPS receivers. Having established the locations of each measurement,
188 we interpolated depth measurements from the echo sounder to estimate the
189 depth of each spectrum and photo; kriging was used within Swallow Bend,
190 where data density was highest, and linear interpolation for the remainder
191 of the study area. We linked reflectance to bottom composition by pairing
192 each field spectrum with the nearest photo.

193 Processing field spectra involved truncating the data to 400 to 900 nm
194 and then smoothing each spectrum by twice applying a cubic Savitzky-Golay
195 (Savitzky and Golay, 1964) filter with a 15-nm frame width. In addition to
196 meaningful differences in reflectance driven by variations in depth and bottom
197 type, several types of noise affected the field spectra. For example, reflectance

198 tended to drift between observations of the Spectralon panel because of mo-
 199 tion of the sun through the sky, even though atmospheric conditions were
 200 clear and consistent throughout our measurement period. Another, more
 201 variable factor was sun glint from the water surface, which depends on view-
 202 ing and illumination geometry and can fluctuate from one second to the next
 203 caused by differences in water surface roughness (Mobley, 1999). Although
 204 various methods for removing sun glint from optical image data have been
 205 applied in coastal environments (Hedley et al., 2005; Kay et al., 2009; Martin
 206 et al., 2016), none of these techniques are directly applicable to field spectra
 207 from rivers. Instead, we used a simpler approach specifically intended to
 208 remove the effects of variable surface reflectance on above-water field mea-
 209 surements (O’Neill et al., 2011). Owing to strong absorption of near-infrared
 210 (NIR) light by water, water-leaving radiance at wavelengths greater than
 211 850 nm is negligible and any measured radiance can be attributed to sur-
 212 face reflectance. To account for these effects, we standardized each of our
 213 field spectra by calculating the mean reflectance from 850 to 900 nm and
 214 subtracting this value across the spectrum:

$$R'(\lambda) = R(\lambda) - \overline{R(850 - 900)} \quad (1)$$

215 where $R(\lambda)$ and $R'(\lambda)$ are the original and standardized reflectances, respec-
 216 tively, at each wavelength λ and the overbar indicates an average over the
 217 indicated range of wavelengths. This procedure provided a more internally
 218 consistent, less noisy reflectance data set (Fig. 2) and the resulting NIR-
 219 standardized reflectance spectra $R'(\lambda)$ were used for all subsequent analyses.

220 To characterize bed composition, the closest GoPro photo to each of the
 221 3377 field spectra was visually inspected by a single, trained operator. This

Fig. 2. (A) Original and (B) near-infrared standardized field spectra. Numbers in the legend refer to percentiles of the reflectance distributions ($n = 3377$). Optimal band ratio analysis (OBRA) of the (C) original and (D) standardized field spectra.

analysis was performed using a custom interface that indicated the location of each photo/spectrum on a background image. A scale bar was added to each photo based on the local flow depth, camera focal length, and pixel size of the detector array. Each photo was assigned to one of seven sediment textural facies (sand, sand/gravel, sand/gravel/cobble, sand/cobble, gravel, gravel/cobble, or cobble) and given an ordinal ranking of algal density from 1 (low) to 5 (high). The original categorizations also were aggregated to a set of three facies (sand, gravel/mixture, and cobble) and low (rank 1), medium (2 and 3), and high (4 and 5) algal densities. Though this approach was subjective, more automated procedures of analyzing the photos proved to be no more practical and far less reliable. Similar, visually based classifications of substrate images have been employed in coastal research (e.g., Fearn et al., 2011; Vahtmae and Kutser, 2013; Reshitnyk et al., 2014; Roelfsema et al., 2015) and are accepted as a robust approach to delineating bottom types more complex and variable than those encountered in this fluvial environment.

Pairing the field spectra to the classified streambed photos allowed us to associate each reflectance measurement with a particular sediment facies and algal density ranking. We summarized these data by calculating the mean and standard deviation of $R'(\lambda)$ for each facies and algal density, for the original and for the aggregated categorizations. In addition to bed composition, variations in water depth d influenced $R'(\lambda)$ and could affect our ability to distinguish bottom types. To account for this possibility, we used box plots and analysis of variance (ANOVA) to assess whether the various sediment facies and algal densities had significantly different distributions of

247 depth ($p < 0.05$).

248 To account for water optical properties in retrieving bottom reflectance
249 from above-water field spectra and/or remotely sensed data, we used paired
250 observations of depth and downwelling spectral irradiance from a vertical pro-
251 file measured at Swallow Bend to calculate a diffuse attenuation coefficient,
252 $K_d(\lambda)$ (Mishra et al., 2005). This apparent optical property summarized ab-
253 sorption and scattering of light within the water column and thus provided a
254 critical, site-specific input to subsequent calculations of bottom reflectance.

255 *2.3. Spectral analysis and variable selection*

256 Our field spectra were essentially continuous, with 500 bands spaced every
257 nm from 400 to 900 nm, but applying classification algorithms to such high
258 resolution data was impractical. The spectra also were statistically redundant
259 because of the smooth, gradual variation of reflectance with wavelength. Our
260 analysis thus involved an initial phase of data reduction and variable selec-
261 tion that closely followed O'Neill et al. (2011). First, we evaluated whether
262 NIR-standardization (Eq. 1) mitigated the noise associated with our raw
263 field measurements by performing optimal band ratio analysis of the orig-
264 inal and standardized spectra. Optimal band ratio analysis (OBRA) is an
265 established depth retrieval technique that identifies the band combination
266 that yields the strongest correlation between the spectrally based quantity
267 $X = \ln[R(\lambda_1)/R(\lambda_2)]$ and depth d (Legleiter et al., 2009). Because depth is
268 the primary control on reflectance in shallow, clear-flowing rivers such as the
269 Snake, comparing OBRA results from the original and standardized spec-
270 tra served as a means of assessing the extent to which NIR-standardization
271 improved the signal-to-noise characteristics of our field spectra.

Two methods were applied to the standardized field spectra to guide selection of a reduced number of spectral quantities for distinguishing among facies and algal densities. First, we quantified class separability by calculating M statistics for all class combinations and all wavelengths. The M statistic normalizes the difference between two class means by the sum of their standard deviations, with high values of $M > 1$ for a particular class combination at a given wavelength indicating clear separation between the two classes (Kaufman and Remer, 1994). The second method involved visually inspecting spectra to locate reflectance peaks and valleys that appeared capable of discriminating among substrates, followed by derivative analyses to identify specific wavelengths of local minima, maxima, and inflection points. This type of derivative analysis is widely used in remote sensing (e.g., Becker et al., 2005) and provides an effective means of highlighting variations in spectral shape that might be obscured by differences in overall brightness among classes.

These procedures allowed us to compile a condensed list of key wavelengths potentially useful for classifying bottom types. To further reduce the data and efficiently exploit spectral information, we defined a set of spectral indices as slopes $[R(\lambda_2) - R(\lambda_1)]/[\lambda_2 - \lambda_1]$ and ratios $R(\lambda_2)/R(\lambda_1)$ for each successive pair of wavelengths. The discriminatory power of all indices was evaluated using box plots and one-way ANOVAs, with index values grouped by sediment facies and by algal density ranking. The goal of this analysis was to identify a parsimonious collection of input variables for classifying bottom types. Three different sets of input variables were considered: (i) reflectances at 8 key wavelengths; (ii) a group of 16 spectral indices that in-

cluded reflectance at the two most important wavelengths as well as 7 spectral slopes and 7 band ratios; and (iii) a combination of all key wavelengths and spectral indices, a total of 22 spectral features.

Although this study developed an approach to riverbed mapping based on field observations, ultimately we intend to apply these methods to remotely sensed data. Motivated by this goal, we convolved the field spectra to three different sets of sensor band passes: (i) the WorldView2 (WV2) multispectral satellite used previously to map bathymetry (Legleiter and Overstreet, 2012); (ii) the hyperspectral Compact Airborne Spectrographic Imager (CASI) evaluated by Legleiter et al. (2016), consisting of 18 bands within the 400 to 900 nm range; and (iii) a higher spectral resolution CASI configuration with 35, narrower, visible and NIR bands. We repeated OBRA for each set of convolved spectra to evaluate the feasibility of depth retrieval, a prerequisite for inferring bottom reflectance from above-water measurements. In addition, we used the convolved spectra to quantify spectral separability among the original seven facies and five algal density rankings in terms of the Jeffries-Matusita distance metric described by Richards and Jia (2006, p. 273).

2.4. Bottom reflectance retrieval

Numerous methods for retrieving bottom reflectance have been developed by coastal researchers interested in mapping coral reefs, seagrass, and other benthic features; Zoffoli et al. (2014) provided a recent review of these techniques. One of the most popular approaches stems from the work of Maritorena et al. (1994) and remains widely used (e.g., Purkis and Pasterkamp, 2004; O'Neill et al., 2011). Briefly, we implemented the Maritorena model by (i) converting the NIR-standardized reflectance spectra to remote sens-

ing reflectances in air just above the water surface, denoted by $R_{rs,A}(\lambda)$,
 by assuming Lambertian behavior and dividing by π sr; (ii) accounting for
 transmission and refraction at the air-water interface to compute the remote
 sensing reflectance just beneath the water surface, denoted by $R_{rs,W}(\lambda)$, as
 (Lee et al., 2002):

$$R_{rs,W}(\lambda) = \frac{R_{rs,A}(\lambda)}{[0.52 + 1.7R_{rs,A}(\lambda)]} \quad (2)$$

(iii) defining the volume reflectance of optically deep water $R_{rs,D}(\lambda)$ as the
 mean of the $R_{rs,W}(\lambda)$ values for the deepest 0.5% of our field spectra; and
 (iv) rearranging the Maritorena et al. (1994) shallow-water reflectance model

$$R_{rs,W}(\lambda) = R_{rs,B}(\lambda)e^{-2K_d(\lambda)d} + R_{rs,D}(\lambda)[1 - e^{-2K_d(\lambda)d}] \quad (3)$$

to obtain an expression for the remote sensing reflectance of the bottom,
 denoted by $R_{rs,B}(\lambda)$:

$$R_{rs,B}(\lambda) = \frac{R_{rs,W}(\lambda) - R_{rs,D}(\lambda)[1 - e^{-2K_d(\lambda)d}]}{e^{-2K_d(\lambda)d}} \quad (4)$$

Equation (3) describes the total remote sensing reflectance, with the first
 term on the right-hand side representing the contribution from the bottom.
 This contribution is strongest in shallow, clear water ($R_{rs,W} \rightarrow R_{rs,B}$ as
 $d \rightarrow 0$ and/or $K_d \rightarrow 0$) but dampened in deeper, more turbid water. The
 second term in Eq. (3) represents the contribution to $R_{rs,W}(\lambda)$ from the
 water column and implies that $R_{rs,B} \rightarrow 0$ as $d \rightarrow \infty$ and/or $K_d \rightarrow \infty$. The
 denominator in Eq. (4) accounts for attenuation of light within the water
 column by using $2K_d(\lambda)$ to summarize the absorption and scattering that
 occurs as photons travel to and from the bed. After retrieving $R_{rs,B}(\lambda)$,
 we used the same key wavelengths and spectral indices as the above-water
 spectra in subsequent analyses.

343 2.5. Spectrally based classification and accuracy assessment

344 We performed classifications of sediment facies and algal density rank-
345 ings using above-water field spectra and inferred bottom reflectances. Field
346 data were randomly, evenly split into training and validation subsets, with
347 the same partition used across all classifications. We used six different sets
348 of predictor variables (spectral indices, key wavelengths, key wavelengths
349 and spectral indices, and spectra convolved to three different sensor band
350 passes) to perform classifications of sediment facies and algal density for the
351 original and for the aggregated categorizations, based on either above-water
352 field spectra or bottom reflectance. The various combinations of substrate
353 categories and input variables resulted in a total of 48 classifications.

354 All classifications were produced using random forests. This method was
355 developed by Breiman (2001) and has become a powerful tool for remote
356 sensing; Lawrence et al. (2006) and Cutler et al. (2007) summarized the
357 approach and its advantages. Random forests are well suited to the case
358 where no single variable or small group of variables can effectively distin-
359 guish among classes. The algorithm is essentially a bootstrap aggregation
360 operation in which a specified number of classification trees are developed,
361 each based on a random sample of training data as well as a random subset
362 of input variables. Observations are allocated to a particular class based on
363 votes cast by the individual trees. Unlike standard decision tree classifiers,
364 which require laborious and subjective pruning, random forests are robust to
365 overfitting. The method is easy to implement, requiring the user to specify
366 only the number of trees and the number of input variables used at each tree
367 split. Random forests also provide an estimate of classification error using

368 data randomly withheld from each tree, referred to as ‘out-of-bag’ observa-
369 tions (Lawrence et al., 2006). In addition, because only a subset of the input
370 variables are used in each iteration of tree development, the same out-of-
371 bag observations can be used to quantify variable importance (Cutler et al.,
372 2007). In a geomorphic context, Buscombe et al. (2014) mapped sand, gravel,
373 and rock along the Colorado River by applying a decision tree classifier to
374 high frequency acoustic backscatter data collected from a boat.

375 For each of the 48 classifications, random forests consisting of 100 deci-
376 sion trees were generated using the **TreeBagger** function in the MATLAB
377 Statistics and Machine Learning Toolbox (MathWorks, 2016). We plotted
378 the out-of-bag classification error against the number of trees to identify the
379 number of trees beyond which accuracy ceased to improve. Variable impor-
380 tance plots were used to identify which spectral features had the greatest
381 power to distinguish among substrates. We used the validation subset with-
382 held from training to perform a separate, independent accuracy assessment,
383 which we summarized in terms of overall classification accuracies and confu-
384 sion matrices.

385 2.6. Hypothesis testing

386 An important goal of this investigation was to determine which type(s)
387 of spectral information provided the most reliable classifications of bottom
388 type. We addressed this research question by formulating a set of hypothe-
389 ses to assess whether (1) retrieving bottom reflectance enabled more accurate
390 classification of the riverbed; (2) indices of spectral shape improved classifi-
391 cation accuracies relative to the original spectra; and (3) sensors with higher
392 spectral resolution provided greater classification accuracy. The hypothe-

Table 1

Hypotheses regarding spectrally based classification of river substrates

Hypothesis	Description
1_0	Classifications based on above-water field spectra are at least as accurate as classifications based on retrieved bottom reflectance
1_a	Classifications based on retrieved bottom reflectance are more accurate than classifications based on above-water field spectra
2_0	Classifications based on reflectance magnitude are at least as accurate as classifications based on reflectance and on spectral shape
2_a	Classifications based on reflectance and spectral shape are more accurate than classifications based on reflectance magnitude
3_0	Classifications based on sensors with lower spectral resolution are at least as accurate as classifications based on sensors with higher spectral resolution
3_a	Classifications based on sensors with higher spectral resolution are more accurate than classifications based on sensors with lower spectral resolution

ses listed in Table 1 were evaluated by performing one-tailed, mid p -value McNemar tests (Lancaster, 1961) with MATLAB’s `testcholdout` function. Separate tests were conducted for the validation subset for all combinations of features (original and aggregated categorizations of facies and algal density) and input variables (spectral indices, key wavelengths, and convolved spectra for above-water and bottom reflectance) relevant to each hypothesis.

2.7. Preliminary remote sensing case study: CASI image of Rusty Bend

To assess the feasibility of mapping riverbed composition from remotely sensed data, we applied the techniques we developed for field spectra to an image of Rusty Bend. This site was examined by Legleiter et al. (2016), who provide further information on the study area, sensor characteristics, image

404 processing, and depth retrieval. To summarize, Rusty Bend is a single-thread
 405 reach of the Snake River with a shallow point bar along the inner bank and
 406 a deep pool along the outer bank. Hyperspectral image data with 0.6-m
 407 pixels and 18 bands between 400 and 900 nm were acquired by the CASI
 408 sensor on 21 August 2012. Atmospheric correction was performed using
 409 ATCOR (ReSe, 2014), a mask highlighting the wetted channel was created,
 410 and a spatial smoothing filter applied. Optimal band ratio analysis based on
 411 field measurements of depth collected within a few days of image acquisition
 412 provided a relation between X and d that was applied throughout the image
 413 to produce a depth map. Validation using independent field data indicated
 414 highly accurate depth retrieval, with an observed vs. predicted R^2 of 0.93
 415 and a standard error of 0.15 m, relative to a reach mean depth of 0.85 ± 0.53
 416 m and a maximum depth of 2.82 m.

417 Bottom reflectance was retrieved from the CASI image by applying the
 418 procedure outlined in section 2.4 using the $K_d(\lambda)$ calculated from field mea-
 419 surements. A site-specific estimate of deep water reflectance was obtained
 420 by calculating $R_{rs,D}(\lambda)$ as the mean of the $R_{rs,W}(\lambda)$ values from the deepest
 421 0.5% of the pixels within the reach. Spectra were extracted from the original
 422 and bottom reflectance images at the locations of substrate photos acquired
 423 from the cataraft. We used the algal density rankings assigned to these pho-
 424 tos to calculate the mean and standard deviation of the CASI reflectance
 425 spectra and retrieved $R_{rs,B}(\lambda)$ spectra for each ranking.

426 The extracted spectra and corresponding rankings also were used to clas-
 427 sify algal density with the random forest algorithm. Separate classifications
 428 were produced for the CASI and bottom reflectance images, and an accu-

429 racy assessment similar to that of the field spectra was performed. Unlike
 430 the field data, which were restricted to point measurements at a small num-
 431 ber of locations, classifying the image resulted in continuous maps of algal
 432 density, with each pixel assigned to one of the four ranks we observed in
 433 Rusty Bend. In addition to the random forest classifications, we also created
 434 unsupervised, spectrally driven classifications from the CASI and $R_{rs,B}(\lambda)$
 435 images. A k -means algorithm (Lloyd, 1982) was used to create four clusters
 436 that served to identify natural spectral groupings within the original and
 437 bottom reflectance images.

438 **3. Results**

439 *3.1. Observations of river spectral characteristics and bed composition*

440 Raw field spectra from the Snake River were subject to several sources of
 441 noise, but the simple NIR standardization procedure adapted from (O'Neill
 442 et al., 2011) reduced these extraneous sources of variability. Subtracting the
 443 mean reflectance between 850 and 900 nm across the spectrum accounted
 444 for (i) reflectance drift due to the passage of time between readings of the
 445 white reference panel; (ii) variable sun glint caused by differences in viewing
 446 and illumination geometry and hydraulically driven water surface roughness;
 447 and (iii) potentially other sources of instrumental and environmental noise.
 448 Comparing the raw and standardized spectra in Figs. 2A and B indicates
 449 that bright outliers were removed and spectral features accentuated, such as
 450 a valley at 675 nm and a peak at 810 nm. The OBRA of the original and
 451 NIR-standardized spectra provided further evidence of the improvement re-
 452 sulting from this correction. Whereas the raw field spectra yielded a modest

OBRA R^2 of 0.736, R^2 increased to 0.865 for the standardized spectra, indicating a stronger correlation with depth. The OBRA matrices also indicated that a broader range of wavelengths, including some in the NIR around 810 nm, were potentially useful for depth retrieval (Figs. 2C and D). Because depth is the primary control on reflectance in shallow, clear rivers, stronger X vs. d relations obtained from the NIR-standardized spectra implied that $R'(\lambda)$ would be more useful for inferring other river attributes, such as bed composition.

Visual interpretation of streambed photos indicated that the substrate of the Snake River primarily consists of a gravel/cobble facies, with lesser amounts of clean gravel, sand, cobble, and various grain size mixtures (Fig. 3A). Aggregating the original seven facies to a more general set of three grain size categories further emphasized the predominance of gravel/mixture and the much less frequent occurrence of sand or cobble facies (Fig. 3B). Similarly, algal densities tended to be low, with 1 the modal rank and only 10.7% of the 3377 streambed photos assigned to the three highest rankings (3 to 5; Fig. 3C). Aggregating the original five ranks to low, medium, and high categories resulted in a vast majority classified as low; Fig. 3D illustrates the rarity of very dense patches of algae. To summarize the association of different sediment facies with various algal densities, we cross-tabulated the two attributes (Table 2). Whereas the lower algal densities (ranks 1 and 2) were distributed among all sediment facies, relatively dense patches of algae (ranks 4 and 5) occurred only in the gravel/cobble facies, the most common sediment texture along the Snake. For the aggregated categorizations, all 169 photos with high algal density were located in the gravel/mixture facies.

Fig. 3. Distributions of sediment facies and algal density rankings observed in riverbed photos for the (A) original seven and (B) aggregated three facies and for the (C) original five and (D) aggregated three algal density rankings.

Table 2

Cross-tabulation of sediment facies and algal density rankings observed in riverbed photos, for both original (left) and aggregated (right) categorizations ^a

Facies	Algal density					Facies	Algal density		
	1	2	3	4	5		Low	Medium	High
s	372	48	2	0	0	s	372	50	0
s/g	171	9	0	0	0	g/m	1977	722	169
s/g/c	159	0	0	0	0	c	22	65	0
s/c	153	15	0	0	0				
g	546	13	0	0	0				
g/c	948	506	179	86	83				
c	22	54	11	0	0				

^a Facies codes include: s = sand, g = gravel, c = cobble, and m = mixture. Algal densities are ordinal rankings from 1 (low) to 5 (high), or low, medium, and high for the aggregated categorization

478 The reflectance characteristics of various sediment facies and algal densi-
479 ties potentially were confounded with the effects of water depth. Box plots
480 and ANOVAs indicated that mean depths differed substantially among sed-
481 iment facies and algal densities (Fig. 4). Sand and mixed facies with sand
482 tended to occur in deeper water, although this observation could reflect pref-
483 erential sampling of a deep, fine-grained backwater at Swallow Bend. Gravel
484 and cobble were found in shallower water on average, but depth distribu-
485 tions for these facies were quite broad, particularly for the most commonly
486 occurring gravel/cobble bottom. Figure 4B shows that depth was inversely
487 correlated with algal density, with the most well-developed algae patches
488 tending to occur in shallower water than the lower density rankings.

489 Combining field spectra with streambed photos allowed us to link the re-
490 flectance characteristics of the Snake River to the composition of its bottom.
491 Mean spectra for the various sediment facies revealed an inverse correlation
492 between reflectance and grain size that was consistent from 400 to 900 nm
493 (Fig. 5A). On average, sand was brightest and cobble darkest; but all fa-
494 cies had fairly similar spectral shapes. Reflectance rose steadily throughout
495 the blue to a peak in the green followed by a sharp decrease in reflectance
496 from 570 to 600 nm, a more gradual decline through the red except for an
497 absorption band at 675 nm, followed by an abrupt decrease into the NIR
498 and very low reflectances beyond 735 nm except for a minor peak at 810
499 nm. For the aggregated categorization of facies in Fig. 5B, differences be-
500 tween the brighter sand, darker cobble, and intermediate gravel/mixture fa-
501 cies were more pronounced. For the original algal density rankings in Fig.
502 5C, reflectance magnitude varied less among rankings than among facies but

Fig. 4. Box plots of water depth grouped by (A) sediment facies and (B) algal density.

503 differences in shape were more evident. The most notable spectral feature
 504 was a valley at 675 nm, where stronger chlorophyll absorption caused lower
 505 reflectance for higher algal density rankings. Distinctions among algal densi-
 506 ties were more pronounced when aggregated to low, medium, and high; the
 507 much deeper chlorophyll absorption for high algal density stands out in Fig.
 508 5D.

509 Another important optical property that must be known to retrieve bot-
 510 tom reflectance is the rate at which light is attenuated by the water column,
 511 which we summarized by calculating the diffuse attenuation coefficient $K_d(\lambda)$.
 512 This analysis was reported previously in Fig. 3 of Legleiter et al. (2016).
 513 During late summer, the Snake River has low concentrations of suspended
 514 sediment and very little dissolved organic matter and thus is characterized
 515 by low values of $K_d(\lambda)$, particularly in the green and red wavelengths. At
 516 shorter blue wavelengths, greater attenuation is caused by scattering by sus-
 517 pended sediment and attenuation increases abruptly into the NIR because
 518 of strong absorption by pure water. Our field observations of water column
 519 attenuation thus imply a high degree of water clarity conducive to bottom
 520 reflectance retrieval, at least for green and red wavelengths with small $K_d(\lambda)$.

521 *3.2. Spectral analysis and variable selection*

522 Visual inspection of the mean spectra in Fig. 5 suggested that various
 523 sediment facies and algal densities could be distinguished by their reflectance
 524 characteristics, and we sought to make such distinctions based on a reduced
 525 set of input variables. The eight key wavelengths we identified, listed in
 526 Table 3 and illustrated in Fig. 5, included a peak in the green, inflection
 527 points on the descending limb from this peak, the chlorophyll absorption

Fig. 5. Mean above-water field spectra for (A) original and (B) aggregated sediment facies and (C) original and (D) aggregated algal density rankings. The vertical lines indicate key wavelengths listed in Table 3.

528 feature centered at 675 nm, and a smaller secondary peak in reflectance at 810
529 nm. Reflectance values for these wavelengths provided information on overall
530 brightness that might be useful for distinguishing among sediment facies. The
531 various algal densities had similar reflectance magnitudes, however, so we
532 defined indices of spectral shape (slopes and ratios) unaffected by brightness.

533 The potential of these 22 spectral features to distinguish among substrates
534 was confirmed by box plots and ANOVAs indicating that all key wavelengths
535 and indices had mean values that differed significantly among the various sed-
536 iment and algae categories ($p < 0.0001$), although the high level of statistical
537 significance was driven at least in part by large sample sizes. Nevertheless,
538 these results justified using the variables in Table 3 as inputs for riverbed
539 classification. For example, a simple chlorophyll absorption ratio defined as
540 $CAR = R'(695)/R'(675)$ provided clear separation among algal densities,
541 particularly for the two highest rankings (Fig. 6).

542 3.3. Bottom reflectance retrieval

543 We evaluated the hypothesis that inferring bottom reflectance would fa-
544 cilitate spectrally based mapping of riverbed composition by applying the
545 Maritorena et al. (1994) shallow water reflectance model to NIR-standardized
546 field spectra. This algorithm resulted in reasonable values of $R_{rs,B}(\lambda)$ from
547 450 to 700 nm but unrealistically high or negative values at shorter blue
548 wavelengths and particularly in the NIR caused by strong absorption by wa-
549 ter. A source of uncertainty that might have affected the $R_{rs,B}(\lambda)$ spectra
550 was our characterization of the deep-water reflectance $R_{rs,D}(\lambda)$ as the mean
551 of the deepest 0.5% of the spectra measured in the field. A radiative trans-
552 fer model such as Hydrolight (Mobley and Sundman, 2013) could have been

Table 3

Key wavelengths for distinguishing among sediment facies and algal densities; additional features used for classification included spectral slopes and ratios; numbers correspond to vertical lines in Figs. 5 and 7 and the horizontal axis of Figs. 9B and D

Spectral feature	Description
1	$R(435)$: Blue <i>base</i> where reflectance is similar for all facies and algal density rankings
2	$R(570)$: Green peak common to all facies and rankings
3	$R(605)$: Concave <i>shoulder</i> on descending limb from green peak
4	$R(650)$: Convex left <i>shoulder</i> of chlorophyll absorption feature
5	$R(675)$: Bottom of reflectance <i>trough</i> caused by chlorophyll absorption
6	$R(695)$: Convex right <i>shoulder</i> of chlorophyll absorption feature
7	$R(735)$: NIR base of descending limb from red into NIR caused by strong absorption by water
8	$R(810)$: Secondary peak caused by weaker attenuation by water
9	Spectral slope: $[R(570) - R(435)]/(570 - 435)$
10	Spectral slope: $[R(605) - R(570)]/(605 - 570)$
11	Spectral slope: $[R(650) - R(605)]/(650 - 605)$
12	Spectral slope: $[R(675) - R(650)]/(675 - 650)$
13	Spectral slope: $[R(695) - R(675)]/(695 - 675)$
14	Spectral slope: $[R(735) - R(695)]/(735 - 695)$
15	Spectral slope: $[R(810) - R(735)]/(810 - 735)$
16	Band ratio: $R(570)/R(435)$
17	Band ratio: $R(605)/R(570)$
18	Band ratio: $R(650)/R(605)$
19	Band ratio: $R(675)/R(650)$
20	Band ratio: $R(695)/R(675)$
21	Band ratio: $R(735)/R(695)$
22	Band ratio: $R(810)/R(735)$

Fig. 6. Box plot of the chlorophyll absorption ratio, $CAR = R'(695)/R'(675)$, identified as an effective spectral index for distinguishing among different algal density rankings.

553 used to simulate $R_{rs,D}(\lambda)$, but our empirical approach was simpler and more
554 direct. The noise at shorter and longer wavelengths lead us to truncate the
555 $R_{rs,B}(\lambda)$ spectra to 450 to 700 nm, implying that substrate mapping based
556 on bottom reflectance would be limited to a smaller range of wavelengths.

557 To assess whether inferring bottom reflectance would enhance differences
558 among various sediment facies and algal densities, we plotted mean $R_{rs,B}(\lambda)$
559 spectra for the original and aggregated categorizations of the riverbed (Fig.
560 7). For facies, the trend of higher reflectance for finer-grained bed material
561 evident in the above-water spectra became more pronounced for $R_{rs,B}(\lambda)$;
562 sand was brightest and cobble darkest across the 450 to 700 nm range.
563 Coarser facies also had more variable spectral shapes than sand or mixtures
564 with sand, most notably a deeper chlorophyll absorption feature. For algae,
565 differences in retrieved bottom reflectance were more subtle, with no consis-
566 tent trend in brightness across the original or aggregated density rankings.
567 The stronger absorption at 675 nm for the higher density rankings noted in
568 the above-water spectra remained evident for $R_{rs,B}(\lambda)$ as well.

569 Although this study was based on field spectra, we also sought to as-
570 sess whether our approach to inferring bottom reflectance and classifying
571 the riverbed could be applied to remotely sensed data. The Maritorena
572 et al. (1994) model requires information on water depth, so we first evalu-
573 ated whether field spectra convolved to the bands of the WV2, CASI 18-band,
574 and CASI 35-band sensors would yield accurate depth estimates. The results
575 summarized in Table 4 indicated that these instruments provide sufficient
576 spectral information to enable reliable depth retrieval, though somewhat less
577 so for the broader bands of the WV2 multispectral satellite. Doubling the

Fig. 7. Mean retrieved bottom reflectance spectra for (A) original and (B) aggregated sediment facies and (C) original and (D) aggregated algal density rankings. The letters textits, g , and c in the legend for (A) refer to sand, gravel, and cobble. The vertical lines indicate key wavelengths listed in Table 3.

Table 4

Summary of optimal band ratio analysis (OBRA) of standardized field spectra (Fig. 2B) convolved to the band passes of three different remote sensing instruments (for comparison to the full-resolution field spectra, refer to the OBRA results summarized in Fig. 2D); λ_1 and λ_2 refer to the center wavelengths of the numerator and denominator bands, respectively

Sensor	OBRA R^2	λ_1 (nm)	λ_2 (nm)	Regression slope	Regression intercept (m)	Standard error (m)
WorldView2	0.775	545	605	3.16	0.597	0.22
CASI-18	0.844	633.6	690.7	3.59	0.0709	0.183
CASI-35	0.849	561.3	703.7	1.13	0.191	0.18

number of bands for the hyperspectral CASI system did not substantially increase the OBRA R^2 .

Convolving above-water field spectra and inferred bottom reflectances to the band passes of these three sensors also allowed us to calculate metrics of spectral separability that were computationally intractable for the original, full-resolution spectra. The Jeffries-Matusita distance JM quantifies the degree to which spectra from a pair of classes are distinct from one another; $JM > 1.9$ implies a high degree of separability (Richards and Jia, 2006). We calculated JM for all combinations of the original seven sediment facies and five algal density rankings for above-water and $R_{rs,B}(\lambda)$ spectra convolved to the band passes of the WV2, CASI-18, and CASI-35 sensors (Fig. 8). All facies and algal densities were readily separable for the sensor with the most, narrowest bands (CASI-35), although to a slightly lesser degree for $R_{rs,B}(\lambda)$ than for the above-water field spectra. For the lower spectral resolution sensors, the facies were less separable, and for WV2 only a few pairs of sediment

categories exceeded the $JM > 1.9$ threshold. For algae, the distinctions between the five density rankings were even less strong, particularly for the relatively broad bands of WV2, for which $JM < 1.9$ for all combinations of rankings for the above-water field spectra (Fig. 8G). Unlike the sediment facies, comparison of Figs. 8G-J indicates that algal densities were distinguished more readily on the basis of bottom reflectance than above-water field spectra.

3.4. Riverbed classification

To assess the potential for mapping bottom type based on spectral information, we created 48 separate classifications and assessed their accuracy. This analysis allowed us to draw conclusions regarding the feasibility of identifying riverbed features from field spectra or remotely sensed data, to evaluate whether retrieving bottom reflectance would facilitate this objective, and to determine which input variables might provide the most reliable substrate maps. The random forest algorithm proved to be computationally efficient, with forests comprised of 100 trees and based on up to 35 input variables generated within a matter of seconds on a standard personal computer. Plots of classification error against the number of trees indicated that accuracy tended to stabilize more quickly for algal density than for sediment facies but that in both cases accuracy did not improve beyond about 50 trees (Fig. 9A and C). The random forest method also provided a means of determining which wavelengths and spectral indices were most useful for discriminating among bottom types. For example, variable importance plots for the most accurate classifications of sediment facies and algal density, based on a combination of key wavelengths and spectral indices derived from above-water

Fig. 8. Spectral separability of sediment facies and algal density rankings, quantified in terms of the Jeffries-Matusita distance JM , for above-water field spectra (left column) and inferred bottom reflectance (right column) convolved to the sensor band passes of the WorldView2 (WV2) satellite and Compact Airborne Spectrographic Imager (CASI) 18 and 35-band configurations. Facies codes are s = sand, g = gravel, and c = cobble.

spectra, are shown in Fig. 9B and D. For facies, spectral feature 1, $R'(435)$, stood out as particularly valuable and probably served to summarize overall brightness. For algae, chlorophyll absorption was highlighted as $R'(675)$ and $R'(695)$ were the first and third most important variables (Fig. 9D and Table S1).

Classification accuracies generally were > 0.7 but differed between facies and algae, original and aggregated categorizations, above-water and bottom reflectance, and types of predictor variables (Fig. 10 and Table S1). The single most accurate classification (0.924) was for the aggregated categorization of sediment facies and was based on a combination of 22 key wavelengths and spectral indices derived from above-water field spectra. The same predictor variables also provided the most accurate classification of algal density, but combining the original five ranks into a low/medium/high scheme had less of an impact than did grouping facies. Comparison of the light and dark blue bars in all four panels of Fig. 10 indicated that classification accuracies were higher for above-water field spectra than for inferred bottom reflectances, but variable importance plots failed to identify any obvious diagnostic wavelengths or spectral indices for differentiating among bottom types. The frequent occurrence of reflectances at 650, 675, and 695 nm, as well as slopes and ratios including these wavelengths, among the top four predictors in Table S1 implied that chlorophyll absorption at 675 nm was a useful spectral feature for classification, particularly of algal density.

3.5. Hypothesis testing

We used 48 classifications to statistically test the hypotheses listed in Table 1, which were designed to evaluate whether retrieving bottom reflectance,

Fig. 9. Examples of random forest classifications for the input variables providing the greatest classification accuracy for above-water field spectra: a combination of key wavelengths and spectral indices. Classification error rates as a function of the number of decision trees included in the random forest are illustrated for (A) facies and (C) algal density classifications. The error rates are out-of-bag classification errors. The corresponding variable importance plots (based on out-of-bag observations) are shown in panels (B) and (D). Spectral features are listed in Table 3.

Fig. 10. Classification accuracy for sediment facies and algal density rankings for the original (A and C) and aggregated (B and D) categories for different input variables.

643 incorporating indices of spectral shape, and using data from higher spectral
 644 resolution sensors might enable more reliable mapping of riverbed composi-
 645 tion. We hypothesized that inferring bottom reflectance would account for
 646 the confounding effects of a water column of variable depth and thus facilitate
 647 classification of bottom type, but our results did not support this notion. For
 648 all 12 tests comparing sediment facies classifications based on above-water vs.
 649 $R_{rs,B}(\lambda)$ spectra, we failed to reject null hypothesis 1_0 that retrieving bottom
 650 reflectance would not improve classification accuracy (Table S2). Similarly,
 651 for algal density we rejected null hypothesis 1_0 for 9 of 13 tests, the only
 652 exceptions being for the aggregated categorization and spectra convolved to
 653 the 18- and 35-band CASI configurations (Table S3). These results implied
 654 that retrieving bottom reflectance was not essential for mapping the bed and
 655 that classifications at least as accurate could be derived from above-water
 656 field spectra.

657 Our second hypothesis considered the selection of spectrally based input
 658 variables to drive these classifications. Indices of spectral shape, such as
 659 slopes and ratios, yield accuracies no higher than reflectance magnitudes,
 660 suggesting that distinctions among substrates were expressed primarily as
 661 differences in overall brightness rather than spectral shape. Although indices
 662 alone were not effective discriminators of sediment facies and algal density,
 663 McNemar tests provided strong evidence ($p < 0.0001$) against null hypothesis
 664 2_0 (Tables S2 and S3). These results implied that a combination of reflectance
 665 at key wavelengths, which provide information on brightness, and metrics of
 666 spectral shape enhanced classification accuracy. Because these indices did not
 667 impose a computational burden on the random forest algorithm, measures of

668 both reflectance magnitude and spectral shape should be included as input
669 variables for riverbed classification.

670 For our third hypothesis, concerning sensor spectral resolution, McNe-
671 mar tests indicated that a greater number of bands improved classification
672 accuracy in some cases but not others. In general, spectral resolution had
673 more of an effect on classification accuracy for facies ($p < 0.05$ for 3 of 8
674 tests; Table S2) than for algal density ($p < 0.05$ for only 1 of 8 tests; Table
675 S3). Significant improvements in accuracy were associated with an increase
676 in spectral resolution from the WV2 multispectral satellite to the 18-band
677 CASI configuration for facies classifications based on above-water and bot-
678 tom reflectance spectra and for algal density classifications based on $R_{rs,B}(\lambda)$.
679 In no case, however, did increasing the number of CASI bands from 18 to 35
680 enhance classification accuracy. These results implied that a moderate level
681 of spectral detail could be sufficient for delineating bottom types.

682 3.6. Preliminary remote sensing case study

683 Although this feasibility study was based on field observations of re-
684 flectance and bottom composition, ultimately our objective was to map river
685 substrates from remotely sensed data. As an initial step toward this goal, we
686 examined a CASI hyperspectral image of the Snake River. A green band is
687 displayed in grayscale in Fig. 11A, followed by the depth map and retrieved
688 bottom reflectance in panels B and C; Figs. 11A and C are displayed with an
689 identical 90% linear contrast stretch. Relative to the original CASI data, the
690 $R_{rs,B}(\lambda)$ image was more variable but remained spatially coherent, accentu-
691 ating features of the riverbed only subtly alluded to in the original image.
692 For example, the bottom reflectance image clearly highlighted brightly col-

693 ored clay bedrock and blocks of failed bank material exposed along the upper
 694 portion of Rusty Bend. Visual comparison of Fig. 11A and C suggested that
 695 inferring bottom reflectance might provide additional substrate information.
 696 Also overlain on Fig. 11 are symbols indicating algal density rankings
 697 assigned to streambed photos. To examine differences in reflectance among
 698 the four rankings observed along Rusty Bend, we extracted pixel values for
 699 all bands of the original CASI and inferred bottom reflectance images and
 700 calculated mean spectra for each rank. Spectra from the original CASI image
 701 exhibited only subtle differences among the four algal density rankings except
 702 for a greater reflectance for the lowest rank (Fig. 12A). Differences among
 703 ranks were more pronounced in the inferred bottom reflectance image, with
 704 a consistent decrease in brightness with increasing algal density (Fig. 12B).
 705 Similarly, whereas chlorophyll absorption was barely evident in the original
 706 CASI image, a decrease in reflectance in the red was more pronounced in
 707 the $R_{rs,B}(\lambda)$ spectra. The $R_{rs,B}(\lambda)$ also increased less at longer wavelengths
 708 approaching 700 nm for higher algal densities. These distinctions, primarily
 709 expressed as a contrast in overall brightness, could be confounded with differ-
 710 ences in depth among ranks, but the highest algal density had a median depth
 711 shallower than the two intermediate ranks and only slightly greater than the
 712 lowest density (Fig. 12C). The lack of a direct, consistent correlation between
 713 algal density and depth implies that lower reflectances for higher rankings
 714 were not driven entirely by greater depth. Instead, we attribute this inverse
 715 relationship to the greater coverage of relatively dark, strongly absorbing fil-
 716 amentous algae at the expense of brighter, more reflective bare sediment, as
 717 illustrated in the streambed photos in Figs. 12D to G.

Fig. 11. An example application of bottom reflectance retrieval from a CASI hyperspectral image of Rusty Bend. Flow is from upper right to lower left. (A) Reflectance in a green band displayed with a 90% linear contrast stretch. Point symbols overlain on the image represent algal density rankings. (B) OBRA-derived depth map (Legleiter et al., 2016), displayed with a 98% linear contrast stretch. (C) Bottom reflectance inferred for the same green band, also displayed with a 90% linear contrast stretch.

Fig. 12. Spectral characteristics of various algal density rankings from the Rusty Bend CASI image in Fig. 11. (A) Mean reflectance spectra from the CASI image. (B) Mean inferred bottom reflectance. (C) Box plot illustrating the distribution of depths for each algal density ranking. (D-G) Example riverbed photographs for each algal density ranking.

718 As an initial attempt to remotely sense riverbed composition, we used
719 spectra extracted from the original CASI and retrieved bottom reflectance
720 images to classify algal density. Half of the spectra were used as input to the
721 random forest algorithm with the remainder reserved for validation. Visual
722 comparison of the resulting classifications indicated that the algal density
723 map derived from the bottom reflectance image was much grainier (Fig. 13).
724 The assignment of pixels to the first two ranks also was reversed, with an
725 intermediate rank (2) along the bar margin followed by a low rank (1) closer
726 to the centerline in the classification based on the original CASI image and
727 an opposite pattern in the map derived from inferred bottom reflectance. Be-
728 cause we lack direct field observations from this area, we cannot verify which
729 is correct. In both cases, the two highest algal density rankings (3 and 4)
730 were located in deeper water near the outer bank. We assessed the accuracy
731 of each classification using streambed photos from the channel thalweg and
732 found that the original CASI image provided a more accurate classification
733 of algal density (0.686) than did the bottom reflectance image (0.451). The
734 variable importance plots in Fig. 13C and D indicated that red bands encom-
735 passing the chlorophyll absorption feature were more useful in classifying the
736 CASI reflectance image than the bottom reflectance image, for which blue
737 and green bands were most informative.

738 In addition to these supervised classifications, in which the random forest
739 assigned pixels to predefined classes based on training data, we also per-
740 formed unsupervised classifications to identify natural spectral groupings
741 that might correlate with bottom composition. We applied a k -means algo-
742 rithm to the original CASI and inferred bottom reflectance images to produce

Fig. 13. Supervised random forest classifications of algal density for Rusty Bend based on (A) the CASI reflectance image and (B) bottom reflectance retrieved from the image. The corresponding variable importance plots are shown in panels (C) and (D).

743 four clusters, the same number of categories as the supervised classifications
744 of algal density. Comparison of Fig. 14A and B indicates that the two images
745 resulted in k -means classifications with very different spatial patterns. The
746 clusters derived from the original CASI image were associated with water
747 depth, producing a classification that was essentially a bathymetric con-
748 tour map; note that because numbers were randomly assigned to clusters
749 by the k -means algorithm, the order of the clusters with increasing depth
750 (and thus decreasing overall brightness, Fig. 14C) was 3, 2, 1, 4. The bottom
751 reflectance-based unsupervised classification had a distinct spatial structure
752 that was not solely a function of depth. Although the clusters in Fig. 14B
753 are difficult to interpret, the mean spectra for each cluster (Fig. 14D) were
754 distinguished not only by brightness but also by spectral shape to a greater
755 degree than were the clusters produced from the CASI image. These results
756 suggest that retrieving bottom reflectance might reveal spectral characteris-
757 tics not evident in the original image and thus provide additional information
758 on riverbed composition.

Fig. 14. Unsupervised k -means classifications for Rusty Bend based on (A) the CASI reflectance image and (B) bottom reflectance retrieved from the image. The corresponding cluster centroid spectra are shown in panels (C) and (D).

759 4. Discussion

760 This study evaluated the potential for spectrally based mapping of riverbed
761 composition, primarily using field measurements but also a hyperspectral im-
762 age. Our results indicate that various sediment facies and algal densities ob-
763 served along the Snake River were sufficiently distinct for these bottom types
764 to be delineated on the basis of their reflectance characteristics. Moreover,
765 we found that accurate substrate classifications could be derived from above-
766 water field spectra; retrieving bottom reflectance was unnecessary. The algo-
767 rithm for inferring $R_{rs,B}(\lambda)$ was not cumbersome but did require knowledge
768 of depth and water column optical properties, summarized by the diffuse at-
769 tenuation coefficient $K_d(\lambda)$. If the bed could be mapped just as effectively
770 from above-water measurements, as our results suggest, additional informa-
771 tion on d and $K_d(\lambda)$ would not be necessary and substrate classification could
772 proceed directly from field spectra or remotely sensed data.

773 Another encouraging finding was that sensors with high spectral reso-
774 lution were not essential. Convolving field spectra to the band passes of a
775 multispectral satellite and 18- and 35-band configurations of a hyperspectral
776 system indicated that more, narrower bands did not significantly improve
777 classification accuracy. The importance of certain features, such as chloro-
778 phyll absorption at 675 nm, implied that wavelength location might be a
779 more important consideration than band width. A combination of reflectance
780 magnitude at key wavelengths and indices of spectral shape (e.g., slopes and
781 ratios) lead to greater classification accuracies. This improvement occurred
782 because although sediment facies were distinguished mainly by differences in
783 brightness, the various algal densities exhibited unique spectral shapes.

784 This investigation also highlighted two methodological innovations not
785 applied previously in a fluvial context. First, we demonstrated the effec-
786 tiveness of a simple method for standardizing field spectra: subtracting the
787 mean reflectance in the NIR (850 to 900 nm), where water-leaving radiance
788 is negligible even in shallow stream channels, across the spectrum. This ap-
789 proach accounted for extraneous sources of variability, such as drift caused
790 by the passage of time between reference panel measurements and sun glint
791 from the water surface, and enhanced the signal-to-noise characteristics of
792 our reflectance data. Second, the random forest algorithm proved robust,
793 computationally efficient, and capable of generating accurate classifications
794 along with metrics of variable importance; this technique can be implemented
795 using readily available software on a standard personal computer.

796 From a hypothesis-testing perspective, our most significant result was
797 negative. An established approach to mapping complex benthic environ-
798 ments in coastal settings involves accounting for water depth and optical
799 properties to retrieve bottom reflectance (e.g., Dierssen et al., 2003; Mobley
800 et al., 2005; Dekker et al., 2011; Garcia et al., 2015). Based on the utility
801 of inferred bottom reflectances for classifying coral reefs and other marine
802 features, we hypothesized that calculating $R_{rs,B}(\lambda)$ from above-water field
803 spectra would enhance our ability to delineate river substrates. The Mc-
804 Nemar test results in Tables S2 and S3, however, implied that above-water
805 field spectra provided superior classification accuracies, obviating bottom
806 reflectance retrieval. This outcome should be reevaluated through further
807 study, but if above-water data also prove sufficient in other cases, substrates
808 could be classified directly from field spectra or remotely sensed data.

809 A plausible explanation for the failure of bottom reflectance retrieval to
 810 improve classification accuracy could be a latent correlation between riverbed
 811 composition and water depth. If certain substrates tend to occur in deeper
 812 water while others are usually shallow, the different depths at which these
 813 bottom types are found could enhance their spectral separability by conflating
 814 the effects of depth with those of riverbed composition. Accounting for
 815 variations in depth thus might compromise discriminatory power and reduce
 816 classification accuracy, particularly for substrates with similar reflectance
 817 characteristics. In this study of the Snake River, box plots and ANOVAs
 818 indicated that various sediment facies and algal densities had different mean
 819 depths, implying that bottom reflectance retrieval might have eliminated a
 820 useful source of information — differences in reflectance driven by differences
 821 in depth — and thus made classes less spectrally distinct from one another.
 822 Although supervised classification of algal density from a hyperspectral im-
 823 age of Rusty Bend was more accurate for the original reflectance data than
 824 for inferred $R_{rs,B}(\lambda)$, a second, unsupervised classification produced distinct,
 825 spectrally based groupings in the bottom reflectance image. This analysis
 826 suggested that accounting for the effects of depth to isolate the reflectance
 827 of the streambed might provide additional river information.

828 In addition to the dependence of bottom-reflected radiance on depth and
 829 riverbed composition, several other caveats must be considered in assessing
 830 the generality of our results. For example, our field observations of bottom
 831 type were subjective, based on visual interpretation of streambed photos.
 832 Similarly, our nominal and ordinal categorizations of sediment facies and
 833 algal density, respectively, were qualitative and might not be a robust means

834 of describing the bottom. The homogeneity of the Snake River’s bed was
835 another limitation of this study, as the majority of substrate photos captured
836 a single gravel/cobble facies and relatively low algal densities; sites with
837 greater benthic diversity would provide a more stringent test of this approach.
838 More generally, because the observations reported herein were made on a
839 single river over the course of one day, our findings should be interpreted as
840 a proof of concept to justify further inquiry.

841 This initial study did not evaluate the true potential for spectrally based
842 mapping of river substrates at larger scales of greater interest to geomor-
843 phologists, ecologists, and managers. All the usual caveats regarding remote
844 sensing of rivers — such as the need for shallow, clear water, an unobstructed
845 view of the stream, and favorable atmospheric conditions — would apply to
846 any such effort. These considerations become even more important in the
847 context of substrate mapping because the effects of bottom type are sec-
848 ondary to and confounded with those of water depth. Water column optical
849 properties represent an additional constraint because turbidity limits the
850 range of depths over which the bed can be detected, let alone its compo-
851 sition inferred. By equating the second term in Eq. (3) with the sensor’s
852 detection threshold $R_{rs,T}(\lambda)$, Dekker et al. (2005) derived an expression for
853 the wavelength-dependent maximum detectable depth for a given substrate:

$$z_{max}(\lambda) = \frac{1}{2K_d(\lambda)} \cdot \ln \left[\frac{R_{rs,B}(\lambda) - R_{rs,D}(\lambda)}{R_{rs,T}(\lambda) - R_{rs,D}(\lambda)} \right] \quad (5)$$

854 Beyond this depth, the riverbed cannot be distinguished from optically deep
855 water with remote sensing reflectance $R_{rs,D}(\lambda)$. The sensor’s detection limit
856 can be characterized as the standard deviation of a homogeneous area of
857 optically deep water (e.g., Brando et al., 2009), although this approach can

858 be problematic in shallow rivers (Legleiter and Roberts, 2009).

859   Acknowledging these limitations, our results suggest that even though
860 depth is the primary control on reflectance in shallow river channels, streambed
861 composition exerts sufficient influence on the bottom-reflected radiance to en-
862 able spectrally based mapping of sediment facies and algal density. If this
863 approach to substrate characterization proves feasible in other fluvial sys-
864 tems, a number of potential applications in geomorphology and ecology could
865 emerge. For example, even a facies-level classification would provide informa-
866 tion on spatial patterns of sediment grain size sorting that could yield insight
867 on interactions among flow hydraulics, channel form, and patchy, localized
868 transport processes. Similarly, knowledge of the distribution and density of
869 algae and other forms of submerged aquatic vegetation, even at a qualitative
870 level, could highlight relationships among algal development, flow conditions,
871 and light and nutrient availability. The ability to infer riverbed composition
872 from field spectra and/or image data thus represents another way in which
873 remote sensing might advance our understanding of fluvial systems.

874   To realize this potential, however, further research will be required. For
875 example, future studies might attempt to disentangle the effects of depth and
876 bottom reflectance by building upon the work of Gilvear et al. (2007) and
877 conducting experiments in which data are collected from the same type of
878 substrate across a range of depths. This analysis also would constrain the
879 maximum detectable depth for specific bottom types. Similarly, additional,
880 more direct observations of the reflectance characteristics of various bed ma-
881 terials are needed. Although we have recorded field spectra within the water
882 just above the bed, these measurements did not provide reliable information

883 on bottom reflectance because they were affected by several other factors.
884 For example, even for measurements made near the bed, the small amount
885 of water between the sensor and substrate still must be accounted for. In ad-
886 dition, keeping the fore-optic a consistent distance above an irregular gravel
887 bed has proven difficult, as has placing the white reference panel to collect
888 data in reflectance mode, and disrupting the water surface during data col-
889 lection is inevitable. An alternative strategy that would avoid these problems
890 would involve obtaining samples of the bed materials of interest, removing
891 them from the channel, and measuring their reflectance on a raft or on the
892 bank where the sensor and target could be above water. O'Neill et al. (2011)
893 used this approach in a study of coastal eelgrass, but extracting pieces of the
894 bed and keeping them intact during measurement would be challenging even
895 in small rivers. If such data could be acquired, however, the resulting spec-
896 tral library would enable radiative transfer modeling and spectrum-matching
897 techniques developed by coastal researchers (e.g., Mobley et al., 2005) to be
898 applied to riverbed mapping.

899 5. Conclusion

900 Remote sensing methods have become an established means of charac-
901 terizing rivers across a range of scales. Whereas earlier studies focused on
902 retrieving water depth from passive optical image data, this investigation
903 used field spectra and a hyperspectral image to evaluate the potential for
904 spectrally based mapping of riverbed composition. We also introduced an
905 algorithm, adapted from the coastal research community, for inferring bot-
906 tom reflectance that accounts for the effects of depth and water column

907 attenuation. Referring back to the research questions posed in section 1, we
908 can summarize our primary conclusions:

- 909 • Field spectra from the Snake River indicate that various sediment facies
910 (including sand, gravel mixtures, and cobble) can be distinguished from
911 one another on the basis of their reflectance characteristics.
- 912 • Similarly, spectral information can be used to differentiate between
913 varying degrees of algal development.
- 914 • Distinctions among sediment facies and algal densities can be made
915 based on field spectra collected from above the water surface.
- 916 • Retrieving bottom reflectance did not enhance these distinctions and
917 thus failed to facilitate substrate mapping.
- 918 • A combination of reflectance magnitudes at key wavelengths and indices
919 of spectral shape was the most informative set of predictor variables
920 for classifying bottom type.
- 921 • Multispectral satellites and hyperspectral imaging systems provide suf-
922 ficient spectral resolution to support streambed mapping and a larger
923 number of narrower bands did not improve classification accuracy.

924 Further, more systematic study — involving field data collection from a
925 broader range of fluvial environments as well as radiative transfer modeling —
926 is needed to explore the potential for remote sensing of riverbed composition.

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