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Spectrally based mapping of riverbed composition

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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. Convolving 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.

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 seeks to build upon this framework and infer additional river attributes. More specifically, because the bottom-reflected radiance depends not only on depth but also on the reflectance of the streambed itself, spectral information potentially could be used to identify various bottom types. A strong precedent for substrate mapping comes from coastal settings, where remotely sensed data have been used to examine coral reefs and other benthic environments (e.g., Andrefouet et al., 2001; Hochberg et al., 2003; Mobley et al.,

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2005; Dekker et al., 2011). Here, we adapt this approach to mapping riverbed composition.

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

From an ecological perspective, algae and other types of vegetation anchored on the channel bed form the photosynthetic foundation of lotic ecosystems, converting light to biomass that nourishes higher trophic levels (Giller and Malmqvist, 1998). Substrate-attached algae, known as periphyton, are sensitive to particle size (e.g., Cattaneo et al., 1997), flow velocity (e.g., Biggs et al., 1998; Choudhury et al., 2015), and nutrient loading (e.g., Hoyle et al., 2014) and thus serve as an indicator of water quality and general stream health. Benthic algae also influence bed mobility by stabilizing sediment, although mature algal mats can detach from the bed to lift and transport sand and fine gravel even under low-flow conditions (Mendoza-Lera et al., 2016). Periphyton thus have geomorphic as well as ecological significance, and several previous studies have used remote sensing techniques to characterize algae and submerged aquatic vegetation in rivers; Marcus et al. (2012) provide a review. For example, Lee et al. (1999) used field spectra to distinguish among various types of periphyton and macrophytes and to develop regression models for predicting chlorophyll and biomass. Their encouraging results – classification accuracies in excess of 95% and regression $R^2 > 0.92$ – suggested that benthic vegetation could be mapped from hyperspectral image data. Lee et al. (1999) did not, however, consider the effects of depth or water column optical properties. More recently, Visser et al. (2014) performed object-based analysis of high resolution images and identified depth as an important factor limiting species-level classification of submerged aquatic vegetation. Similarly, Flynn and Chapra (2014) used images acquired from an unmanned aerial vehicle to map a nuisance green algae. Our study extends earlier work by addressing the effects of depth and classifying riverbed composition from field spectra and hyperspectral image data.

Our investigation was founded on the premise that spectrally based substrate mapping could be enhanced by using information on depth and attenuation to account for the influence of the water column and retrieve bottom reflectance. This notion has a sound basis in the coastal literature where Maritorena et al. (1994) and Dierssen et al. (2003), to name but two examples, used this approach to map coral reefs and seagrass, respectively. In this study, we used field spectra measured above the water surface, direct measurements of water depth, and a parameter summarizing water column attenuation to retrieve bottom reflectance, as illustrated in Fig. 1. The right side of this flow chart outlines how we visually interpreted photos of the streambed to provide training data for a random forest algorithm that ultimately produced classifications of sediment facies and algal density. This investigation evaluated the potential for spectrally based mapping of riverbed composition and primarily used field measurements, but these methods also were applied to a hyperspectral image to assess the feasibility of identifying bottom types remotely.

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?

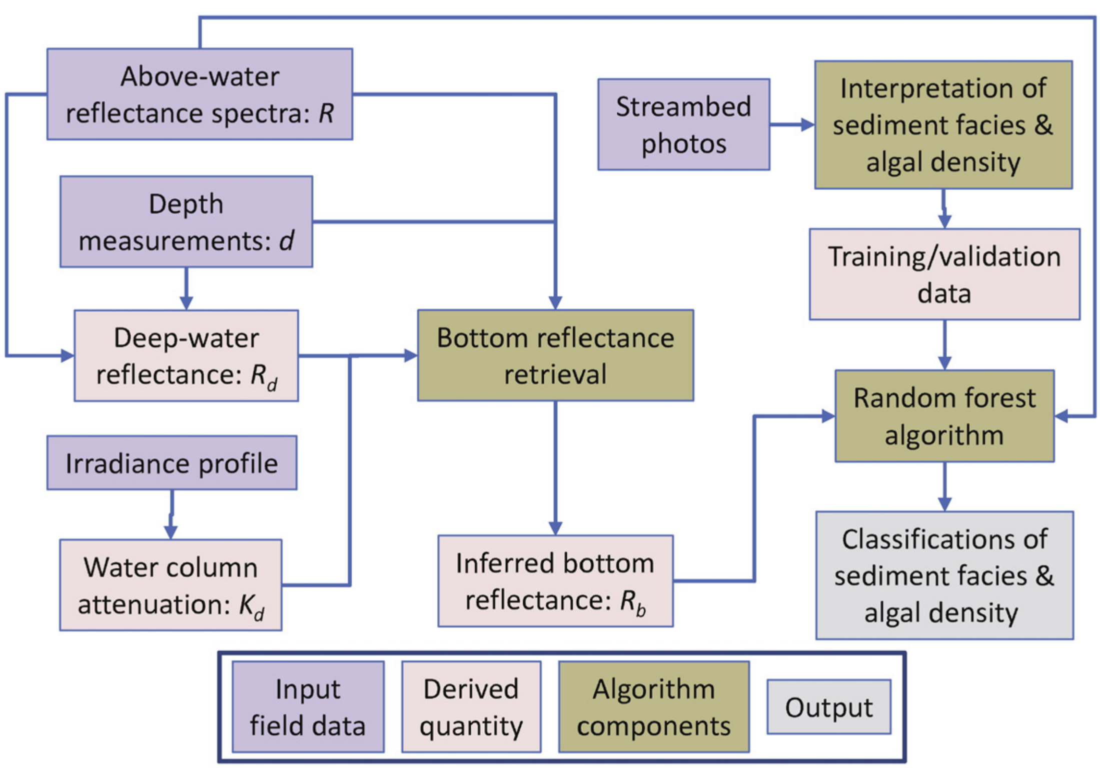

Fig. 1. Flow chart for retrieving bottom reflectance from above-water field spectra or remotely sensed data and using this information to delineate various bottom types.