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Spectrally based remote sensing of river bathymetry

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Earth Surface Processes and Landforms

ABSTRACT: This paper evaluates the potential for remote mapping of river bathymetry by (1) examining the theoretical basis of a simple, ratio-based technique for retrieving depth information from passive optical image data; (2) performing radiative transfer simulations to quantify the effects of suspended sediment concentration, bottom reflectance, and water surface state; (3) assessing the accuracy of spectrally based depth retrieval under field conditions via ground-based reflectance measurements; and (4) producing bathymetric maps for a pair of gravel-bed rivers from hyperspectral image data. Consideration of the relative magnitudes of various radiance components allowed us to define the range of conditions under which spectrally based depth retrieval is appropriate: the remotely sensed signal must be dominated by bottom-reflected radiance. We developed a simple algorithm, called optimal band ratio analysis (OBRA), for identifying pairs of wavelengths for which this critical assumption is valid and which yield strong, linear relationships between an image-derived quantity X and flow depth d. OBRA of simulated spectra indicated that water column optical properties were accounted for by a shorter-wavelength numerator band sensitive to scattering by suspended sediment while depth information was provided by a longer-wavelength denominator band subject to strong absorption by pure water. Field spectra suggested that bottom reflectance was fairly homogeneous, isolating the effect of depth, and that radiance measured above the water surface was primarily reflected from the bottom, not the water column. OBRA of these data, 28% of which were collected during a period of high turbidity, yielded strong X versus d relations (R^2 from 0.792 to 0.976), demonstrating that accurate depth retrieval is feasible under field conditions. Moreover, application of OBRA to hyperspectral image data resulted in spatially coherent, hydraulically reasonable bathymetric maps, though negative depth estimates occurred along channel margins where pixels were mixed. This study indicates that passive optical remote sensing could become a viable tool for measuring river bathymetry. Copyright © 2009 John Wiley & Sons, Ltd.

KEYWORDS: remote sensing; fluvial geomorphology; river depth; bathymetry

Introduction

Considerable optimism has been expressed regarding the potential contribution of remote sensing to river research, providing extensive, quantitative data that could yield insight on the organization of fluvial systems from reach to catchment scales. For example, Marcus and Fonstad (2008) claim that 'optical remote sensing is the only viable method for measuring, monitoring, and mapping a large suite of inchannel river parameters continuously at sub-metre resolution.' On a more cautious note, these authors also emphasized the need for further methodological development and testing. In this paper, we examine the reliability of remote measurements of river bathymetry by evaluating a simple, spectrally based approach to retrieving depth from passive optical image data.

Remote sensing of water depth has a long history in shallow marine settings (e.g. Lyzenga, 1978; Philpot, 1989; Maritorena *et al.*, 1994; Lee *et al.*, 1999; Lesser and Mobley, 2007), and Gilvear and Bryant (2003) and Marcus and

Fonstad (2008) review an expanding body of literature on depth retrieval in rivers. This type of bathymetric mapping facilitates parameterization of hydrodynamic models (e.g. French, 2003), morphologic inference of bed material transport rates (Ashmore and Church, 1998), or any investigation requiring detailed characterization of river form. Although light detection and ranging (LiDAR) has become the preferred means of collecting topographic data for the study of surface processes (Slatton et al., 2007), the near-infrared (NIR) laser pulses emitted by most LiDAR systems are strongly absorbed by water and thus provide no information on submerged areas (Reusser and Bierman, 2007). Alternative technologies more readily applicable to rivers include waterpenetrating green LiDAR (Kinzel et al., 2007) and dualfrequency bathymetric LiDAR (Hilldale and Raff, 2008), but these systems were designed for coastal environments, require specialized processing algorithms, and yield relatively coarse spatial resolution for a given flying height due to a large laser spot size and spacing. These limitations imply that,

particularly in smaller streams, passive optical techniques might complement sub-aerial LiDAR topography from bars and floodplains by providing bathymetric information from the wetted channel.

Although previous efforts to map river bathymetry from image data have been largely empirical (e.g. Winterbottom and Gilvear, 1997; Marcus et al., 2003), recent studies in shallow coastal waters (e.g. Mobley and Sundman, 2003; Dierssen et al., 2003) have helped to establish the physical basis for remote sensing of rivers. For example, Legleiter et al. (2004) used the Hydrolight radiative transfer model (Mobley, 1994) to quantify the effects of depth, substrate type, water surface roughness, and water column optical properties. Analyses of these simulated spectra indicated that the logarithm of the ratio of the radiances for two bands was linearly related to water depth across a plausible range of stream conditions. Subsequent modelling suggested that this simple algorithm would be robust in morphologically complex channels, providing unbiased depth estimates when bed topography and substrate type vary within a pixel (Legleiter and Roberts, 2005).

These studies represented initial steps toward a more general theoretical framework but were limited in several important respects. First, although we advocated a spectrally based approach, we have not determined which wavelengths are most useful for mapping bathymetry. A second, related problem is a lack of information on the spectral properties of the streambed itself. Because bottom-reflected radiance is a function not only of depth but also substrate type, in situ observations of bottom reflectance would help to determine how effectively the bathymetric signal can be isolated. A recent experimental study documented the influence of distinctive bottom types using field spectroscopy of progressively submerged artificial substrates in a tidal channel (Gilvear et al., 2007), but the extent to which streambed spectral variability might confound depth retrieval in natural rivers remains unclear. Finally, the encouraging results obtained via radiative transfer modelling have been tempered by a lack of validation data - a small sample of field-based reflectance measurements and qualitative interpretations of image-derived relative depth maps. This paper addresses these shortcomings by pursuing the following objectives:

- 1. develop a simple algorithm for determining an optimal pair of ratio bands for depth mapping;
- 2. evaluate the sensitivity of ratio-based depth estimates to variations in bottom type, suspended sediment concentration, and water surface roughness using Hydrolight simulations;
- 3. quantify variability in bottom reflectance within a typical channel based on field spectra; and
- 4. assess the accuracy of spectrally based depth retrieval under a range of conditions using both ground-based reflectance measurements and hyperspectral image data.

Spectrally Based Depth Retrieval

Theoretical background

Passive optical remote sensing of rivers involves measurement of visible and near-infrared reflected solar energy that has interacted with the atmosphere, the water column, and the streambed. The relevant processes were summarized by Legleiter *et al.* (2004), based primarily upon the work of Philpot (1989), Mobley (1994), Maritorena *et al.* (1994), and a special issue of *Limnology and Oceanography* (Ackleson,

Table I. Notation

a_{η}	constant in Equation (9)
$a(\lambda)$	absorption coefficient
$a_{s}(\lambda)$	absorption coefficient for suspended sediment
$a_{w}(\lambda)$	absorption coefficient of pure water
$A(\lambda)$	constant in Equation (8)
$b(\lambda)$	scattering coefficient
$b_{\rm s}(\lambda)$	scattering coefficient for suspended sediment
Cs	suspended sediment concentration
$C(\lambda)$	constant representing transmission across air-water interface
d	water depth
D_x	grain size for which x percent of the distribution is finer
$E_{\rm d}(\lambda)$	downwelling solar irradiance
$K(\lambda)$	effective attenuation coefficient
$L_{\rm b}(\lambda)$	bottom-reflected radiance
$L_{c}(\lambda)$	radiance from the water column
$L_{\rm k}(\lambda)$	diffuse sky radiance
$L_{\rm P}(\lambda)$	path radiance from the atmosphere
$L_{\rm S}(\lambda)$	surface-reflected radiance
$L_{\rm T}(\lambda)$	total at-sensor radiance
$L_{\rm u}(\lambda)$	upwelling radiance
$L_{\rm w}(\lambda)$	radiance from optically deep water
n	number of spectral bands
Ν	number of spectral measurements
$R(\lambda)$	reflectance
$R_{\rm b}(\lambda)$	bottom reflectance of the streambed
$R_{\rm c}(\lambda)$	volume reflectance of the water column
$R_{\infty}(\lambda)$	volume reflectance of optically deep water
R^2	coefficient of determination for regression
$T(\lambda)$	transmittance of the atmosphere
U	wind speed
X	log-transformed band ratio
β_0	regression intercept
β_1	regression slope
θ	solar incidence angle
λ	wavelength
ρ	reflectance of the air-water interface
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- $\sigma_{\rm d}$ standard deviation of water depth
- σ_{η} standard deviation of water surface elevation

2003). The notation used here is summarised in Table I. For any wavelength λ , the upwelling spectral radiance $L_{T}(\lambda)$ can be expressed as the sum of four components:

$$L_{\rm T}(\lambda) = L_{\rm b}(\lambda) + L_{\rm c}(\lambda) + L_{\rm S}(\lambda) + L_{\rm P}(\lambda). \tag{1}$$

 $L_{\rm b}(\lambda)$ represents bottom-reflected radiance, which is related to both depth, due to the exponential attenuation of light with distance travelled through the water column, and substrate type, through a term representing the 'bottom contrast' between the reflectance of the streambed and that of the water column itself. For bathymetric mapping, $L_{\rm b}(\lambda)$ is the signal of primary interest and the remaining terms in Equation (1) represent additional, complicating factors. $L_c(\lambda)$ denotes radiance emanating from the water column, having been back-scattered upward before reaching the bed. The magnitude and spectral shape of $L_c(\lambda)$ are determined by the water's optical properties, which depend on absorption and scattering by pure water, suspended sediment, and possibly other optically significant constituents (e.g. chlorophyll, coloured dissolved organic matter; Bukata et al., 1995). $L_s(\lambda)$ represents radiance reflected from the water surface, which can be a large fraction of $L_{T}(\lambda)$ for certain viewing geometries (i.e. sun glint) or for roughened water surfaces. Finally, $L_{\rm P}(\lambda)$ indicates path radiance scattered into the sensor's field of view by the atmosphere.

Expanding terms in Equation (1) and suppressing the dependence on wavelength of all variables except for depth to simplify notation, we have (Philpot, 1989):



Figure 1. (a) Reflectance spectra for various in-stream and terrestrial features observed along Soda Butte Creek. The gravel and periphyton spectra were used to parameterize bottom reflectance for radiative transfer simulations with the Hydrolight numerical model. (b) Spectral differences in bottom reflectance are minor relative to spectral differences in attenuation by the water column, which is dominated by absorption by pure water. Data on the absorption coefficient for pure water $a_w(\lambda)$ are from Pope and Fry (1997). This figure is available in colour online at www.interscience.wiley.com/journal/espl

$$L_{\rm T} = E_{\rm d} \ CT(R_{\rm b} - R_{\rm c}) \exp(-Kd) + E_{\rm d}CTR_{\rm c} + T\rho L_{\rm k} + L_{\rm P}, \tag{2}$$

where E_d is the downwelling solar irradiance, *C* is a constant that accounts for transmission across the air–water interface, *T* is atmospheric transmittance, R_b denotes the reflectance or albedo of the streambed, R_c is the volume reflectance of the water column, *K* is an 'effective' attenuation coefficient with units of m⁻¹ that summarizes the effects of absorption and scattering of light within the water column (Maritorena *et al.*, 1994), d denotes the water depth, ρ is the reflectance of the air–water interface (Mobley, 1999), and L_k denotes the diffuse sky radiance. Although the following treatment is presented in terms of radiance, these components can also be expressed as reflectance values, which are dimensionless and thus facilitate comparison among datasets (Schott, 1997).

Because $L_b(\lambda)$ depends on both *d* and $R_b(\lambda)$, the effects of depth and substrate are intertwined; depth retrieval requires a means of accounting for variations in bottom reflectance. Figure 1(a) illustrates typical reflectance spectra for various features from our study area in Yellowstone National Park, USA (near 45° N, 110° W): bright limestone exposed locally

on the bed, darker gravel prevalent in most reaches, and periphyton present throughout much of the channel. Because $L_T(\lambda)$ measured above a streambed with a high $R_b(\lambda)$ is larger than that observed over a darker substrate at the same depth, d tends to be overestimated for the bottom type with lower $R_b(\lambda)$ and vice versa (Legleiter *et al.*, 2004). This problem can be severe in coastal environments, where benthic habitats with very different albedos are juxtaposed in a patchy mosaic (e.g. Hochberg *et al.*, 2003b), but marine researchers have found that for an appropriate pair of spectral bands, denoted by numeric subscripts, the ratio R_{b1}/R_{b2} is nearly constant across substrate types (e.g. Stumpf *et al.*, 2003; Mishra *et al.*, 2007).

This observation forms the basis of a popular ratio-based method – introduced by Lyzenga (1978), extended by Philpot (1989), and now widely applied (e.g. Dierssen *et al.*, 2003) – for distinguishing changes in depth from variations in bottom albedo. The underlying principle is illustrated in Figure 1(b): spectral differences in $R_b(\lambda)$ are small, on the order of a few percent, relative to the order-of-magnitude spectral differences in attenuation by the water column, summarized by the

coefficient $K(\lambda)$. For clear-flowing streams (i.e. those with low concentrations of suspended sediment and for which the influence of chlorophyll and dissolved organic matter on water column optical properties can be considered negligible), $K(\lambda)$ is primarily determined by the absorption coefficient of pure water $a_w(\lambda)$, which is lowest in the blue and increases rapidly with wavelength through the red and NIR. Thus, although substrate variability affects R_{b1} and R_{b2} to a similar degree, as *d* increases the radiance L_{T2} measured in the band experiencing stronger attenuation decreases faster than the radiance L_{T1} in the band with weaker attenuation, and for $K_2 > K_1$ the ratio L_{T1}/L_{T2} thus increases with depth. Using Equation (2), and taking the natural logarithm of the ratio to account for the exponential attenuation of light by water, we have

$$X = \ln \left[\frac{L_{T1}}{L_{T2}} \right]$$

$$= \ln \left[\frac{E_{d1}C_{1}T_{1}\{(R_{b1} - R_{c1})e^{-K_{f}d} + R_{c1}\} + T_{1\rho1}L_{k1} + LP1}{E_{d2}C_{2}T_{2}\{(R_{b2} - R_{c2})e^{-K_{2}d} + R_{c2}\} + T_{2\rho2}L_{k2} + LP2} \right].$$
(3)

Because only $L_{\rm b}(\lambda)$ is directly related to depth, the utility of the image-derived variable *X* for bathymetric mapping depends on the relative magnitude of the various radiance components and the extent to which the ratio of true interest, $L_{\rm b1}/L_{\rm b2}$, can be isolated. If the other terms can be accounted for, Equation (3) simplifies to a linear relation between *X* and *d*, as described below.

On the applicability of deep-water corrections to shallow stream channels

One solution to this problem, called the deep-water correction or Lyzenga (1981) algorithm, involves subtracting the radiance $L_w(\lambda)$ observed over deep water from $L_T(\lambda)$ values throughout an image; if water column optical properties, water surface state, and atmospheric conditions are (assumed) homogeneous,

$$L_{\rm w}(\lambda) = L_{\rm c}(\lambda) + L_{\rm S}(\lambda) + L_{\rm P}(\lambda)$$

and thus

$$L_{\rm b}(\lambda) = L_{\rm T}(\lambda) - L_{\rm w}(\lambda).$$

Although this method has been applied with reasonable success in fluvial environments (Winterbottom and Gilvear, 1997; Gilvear *et al.*, 2007), the approach is subject to a number of limitations.

First consider $L_c(\lambda)$. If the entire river is optically shallow – that is, if the product $dK(\lambda)$ is sufficiently small that a measurable proportion of $E_d(\lambda)$ reaches the bottom – a deepwater correction might not be possible because any estimate of L_w from within the channel would contain some contribution from the streambed. Truncation of the water column by even a perfectly absorbing, black substrate results in a volume reflectance $R_c(\lambda)$ that differs from that of a hypothetical, optically deep water body for which $dK(\lambda) \rightarrow \infty$, denoted by $R_{\infty}(\lambda)$ (Figure 2). Technically, Equation (2) should be expressed



Figure 2. Water column $R_c(\lambda)$ and bottom $R_b(\lambda)$ reflectance spectra. $R_c(\lambda)$ spectra were simulated with the Hydrolight radiative transfer model with a suspended sediment concentration of 2 g m⁻³ and perfectly absorbing, black substrates at the indicated depths. Truncation of the water column by a bottom at finite depth reduces $R_c(\lambda)$ relative to a hypothetical infinitely deep water column. Representative $R_b(\lambda)$ spectra measured in the field are included to illustrate the bottom contrast $R_b(\lambda) - R_c(\lambda)$ between the substrate and water column. This figure is available in colour online at www.interscience.wiley.com/journal/espl

in terms of $R_{\infty}(\lambda)$ (Philpot, 1989), but we use $R_c(\lambda)$ to emphasize that observations of $R_{\infty}(\lambda)$ might not be available in rivers.

 $L_{s}(\lambda)$ depends on water surface state, which is primarily a function of wind speed in marine settings and varies little from one pixel to the next. In rivers, water surface topography depends on flow hydraulics and is thus much more variable over small spatial scales; if $L_{s}(\lambda)$ is subsumed as a component of $L_w(\lambda)$ and subtracted uniformly across an image, these local variations in $L_s(\lambda)$ persist. Similarly, surface reflectance corrections developed for ocean colour remote sensing assume that the water-leaving radiance $L_{\rm b}(\lambda) + L_{\rm c}(\lambda)$ is zero in the NIR. Any radiance measured at 750 nm is attributed to surface reflectance, which is spectrally flat (i.e. $\rho(\lambda) = \rho$), and subtracted across the spectrum (e.g. Hooker et al., 2002; Hochberg et al., 2003a). This approach is not applicable to shallow rivers, however, because a large bottom contribution implies that the water-leaving radiance cannot be considered negligible for wavelengths up to 800 nm (Legleiter et al., 2004).

 $L_{\rm P}(\lambda)$ is also problematic. Because water has such low reflectance, atmospheric path radiance can be a sizable fraction of the total at-sensor radiance, particularly over deep water. Subtracting $L_{\rm w}(\lambda)$ from $L_{\rm T}(\lambda)$ can be considered a simplified form of atmospheric correction (Spitzer and Dirks, 1987), but the difficulties involved in estimating $L_{\rm c}(\lambda)$ and $L_{\rm S}(\lambda)$ imply that using observations of $L_{\rm w}(\lambda)$ would result in uncertain estimates of $L_{\rm P}(\lambda)$ as well. More sophisticated and robust methods of atmospheric calibration have been developed for ocean colour remote sensing (e.g. Gao *et al.*, 2000), but they require a level of data and expertise that make them less practical to apply.

Relative magnitude of radiance components

Given the difficulty of accounting for water column, water surface, and atmospheric effects in shallow rivers, a less restrictive approach involves considering the relative magnitude of the terms in Equation (2), keeping in mind that $L_b(\lambda)$ is the component of interest for bathymetric mapping. In streams with typical depths on the order of tens of cm (small *d*), relatively clear water (small $K(\lambda)$), and highly reflective substrates (large $R_b(\lambda)$), and with favourable viewing geometry (small $L_s(\lambda)$) and reasonably good atmospheric conditions (small $L_p(\lambda)$), the other radiance components can be considered negligible:

$$L_{\rm b}(\lambda) \gg L_{\rm w}(\lambda) = L_{\rm c}(\lambda) + L_{\rm S}(\lambda) + L_{\rm P}(\lambda).$$

More specifically, the contribution from the water column relative to that from the bottom diminishes as depth decreases, bottom albedo increases, and absorption predominates over scattering:

$$\frac{L_{\rm c}(\lambda)}{L_{\rm b}(\lambda)} \to 0 \quad \text{as} \quad d \to 0, \tag{4}$$

$$\frac{L_{\rm c}(\lambda)}{L_{\rm b}(\lambda)} \to 0 \quad \text{as} \quad \frac{R_{\rm c}(\lambda)}{R_{\rm b}(\lambda)} \to 0, \tag{5}$$

$$\frac{L_{\rm c}(\lambda)}{L_{\rm b}(\lambda)} \to 0 \quad \text{as} \quad \frac{b(\lambda)}{a(\lambda)} \to 0,$$
 (6)

where $a(\lambda)$ and $b(\lambda)$ are absorption and scattering coefficients, respectively. These inherent optical properties determine the

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magnitude and spectral shape of $K(\lambda)$, which is an apparent optical property that also depends on the angular distribution of the underwater light field (Mobley, 1994).

The relative contribution of $L_{\rm s}(\lambda)$ depends on illumination and viewing geometry, which completely specify the value of ρ when the water surface is level, a typical value being 0.028. For the more realistic case of an irregular water surface, ρ increases with roughness to values in excess of 0.1 as a greater proportion of the individual surface facets become oriented so as to reflect brighter, near-sun portions of the sky radiance distribution into the sensor's field of view (Mobley, 1999). The effects of water surface topography are examined later, but for now we reason that for shadowand cloud-free conditions and typical viewing geometries, illumination of the river is dominated by the direct solar beam rather than diffuse sky light and $L_{\rm s}(\lambda)$ is a small, constant fraction of $L_{\rm b}(\lambda)$.

The relative magnitude of $L_{\rm P}(\lambda)$ is difficult to generalize because atmospheric effects vary with elevation, visibility, and the distribution of water vapour and aerosols. Nevertheless, the following first-order approximation seems reasonable: because Rayleigh scattering scales as λ^{-4} , $L_{\rm P}(\lambda)/$ $L_{\rm b}(\lambda)$ can be significant in the blue but becomes small to negligible at longer wavelengths.

Simplification of the log-transformed band ratio

Where and when these scaling arguments are valid, $L_{\rm b}(\lambda) \gg L_{\rm w}(\lambda)$ and the bottom-reflected radiance can be considered the dominant term in Equation (1). Equation (3) then reduces to

$$X = \ln \left[\frac{L_{\text{T1}}}{L_{\text{T2}}} \right] \approx \ln \left[\frac{L_{\text{b1}}}{L_{\text{b2}}} \right]$$

$$= \ln \left[\frac{E_{\text{d1}}C_1 T_1 (R_{\text{b1}} - R_{\text{c1}})}{E_{\text{d2}}C_2 T_2 (R_{\text{b2}} - R_{\text{c2}})} \right] - d(K_1 - K_2).$$
(7)

This expression can be simplified further because $C(\lambda) = C$ is essentially constant (Mobley, 1999; Dierssen *et al.*, 2003) and $T(\lambda)$ typically does not vary appreciably across an image except for wavelengths affected by strong molecular absorption bands. The primary factors controlling irradiance (time, date, and location) are all fixed for a given scene. Although the angle of incidence and thus the magnitude of $E_d(\lambda)$ vary locally as a function of streambed slope and aspect, these topographic effects influence both wavelengths equally and cancel in the ratio (Legleiter and Roberts, 2005). Combining these terms into a single constant and rearranging (7), we obtain a dimensionally homogeneous, linear relationship between the image-derived variable X and water depth *d*:

$$X \approx (K_2 - K_1)d + \ln\left[\frac{(R_{\rm b1} - R_{\rm c1})}{(R_{\rm b2} - R_{\rm c2})}\right] + A,$$
(8)

where $A = \ln[E_{d_1}C_1T_1/E_{d_2}C_2T_2]$. The slope term in this relation is the difference in effective attenuation between the two bands, and *X* increases with depth for $K_2 > K_1$. The intercept includes the constant *A* and incorporates the bottom contrast between the streambed and water column.

With this simplification, we next consider which terms in Equation (8) might vary across an image and which are likely to remain approximately constant. Both $K(\lambda)$ and $R_c(\lambda)$ are

determined by the inherent optical properties of the water column, which can be assumed homogeneous over reach scales except where suspended sediment is introduced by tributaries or other sources. $R_{\rm b}(\lambda)$ depends on substrate composition but, to the extent that R_{b1}/R_{b2} is actually constant across bottom types, this ratio will not vary spatially, either. The only quantity in Equation (8) expected to vary on a pixelby-pixel basis is the one of interest, d, implying that the remotely sensed variable X is well-suited for bathymetric mapping. Furthermore, because the slope and intercept in Equation (8) are computed as a difference and a ratio, respectively, precise knowledge of absolute radiance values is not necessary, allowing depth information to be retrieved from uncalibrated image data. In this case, regression of in situ depth measurements against X values from the corresponding image pixels can be used to determine the coefficients of a linear relation between X and d.

Methods and Data

Optimal Band Ratio Analysis (OBRA)

The preceding theoretical development suggests that under certain circumstances, and for certain combinations of wavelengths, a linear relation between the remotely sensed variable X and flow depth d can be established and used to map bathymetry from passive optical image data. Ultimately, only two bands are needed to calculate the log-transformed band ratio, but because the terms in Equation (8) vary spectrally, the key to reliable depth retrieval is to consider a range of wavelengths and select band pairs that satisfy, to the fullest extent possible, the critical assumptions outlined above and are relatively insensitive to departures from these assumptions. We have developed a simple technique, which we call Optimal Band Ratio Analysis (OBRA), for identifying appropriate band combinations and calibrating Equation (8). This method exploits high spectral resolution data by determining the pair of wavelengths that yield the strongest linear relation between X and d.

Input data for OBRA consist of paired observations of depth and a radiometric quantity measured in n spectral bands - radiance, reflectance, or digital numbers. These data could be obtained through radiative transfer simulations, by field spectroscopy, or from coordinated field measurements and remotely sensed data collection. For each pair of bands (λ_1, λ_2) , the algorithm proceeds by calculating X values, performing a regression of d on X, and using the resulting coefficients to populate $n \times n$ matrices of intercept $\beta_0(\lambda_1, \lambda_2)$, slope $\beta_1(\lambda_1, \lambda_2)$, and coefficient of determination $R^2(\lambda_1, \lambda_2)$ values that summarize spectral variations in the nature and strength of the relationship between X and d; because these matrices are symmetric, only their upper diagonals are retained. The optimal band ratio is then taken to be that which yields the highest R^2 . The corresponding $R^2(\lambda_1, \lambda_2)$ matrix indicates whether this optimum is fairly broad, with adjacent bands also yielding strong relationships with depth, or rather narrow, implying that radiometric observations at those particular wavelengths are essential for accurate bathymetric mapping. Because the log-transformed band ratio X is the sole explanatory variable in the OBRA regressions, the only effect (in a statistical sense) considered explicitly is the interaction between bands. Including the individual bands as main effects would improve the predictive power of the regressions and could render X statistically not significant in some cases (e.g. Robinson et al., 2004; Maynard et al., 2007).

Radiative transfer simulations

To examine the effects of substrate type, water column optical properties, and water surface roughness on spectrally based depth retrieval, we performed OBRA of reflectance spectra simulated with the Hydrolight numerical radiative transfer model (Mobley, 1994; Mobley and Sundman, 2001). This model is widely used by marine scientists (e.g. Dierssen *et al.*, 2003; Lesser and Mobley, 2007) and additional detail on Hydrolight and our parameterization thereof can be found elsewhere (Legleiter *et al.*, 2004; Legleiter and Roberts, 2005). For our purposes here, the critical inputs to Hydrolight were:

- 1. water depth, varied in 5 cm increments from 5 to 100 cm;
- 2. bottom reflectance for two substrate types the gravel and periphyton spectra shown in Figure 1(a);
- 3. suspended sediment concentration c_{sr} , varied from 0 to 8 g m⁻³ and used to specify the optical properties of the water column by multiplying each c_s value by an optical cross-section (Bukata *et al.*, 1995) to compute absorption $a_s(\lambda)$ and scattering $b_s(\lambda)$ coefficients for suspended sediment; and
- 4. wind speed U, varied from 0 to 5 m s⁻¹ to represent varying degrees of water surface roughness.

Hydrolight accounts for the effects of water surface irregularity on the reflectance and transmittance properties of the air-water interface by simulating surface realizations that have a zero mean, Gaussian distribution of wave slopes with a variance related to wind speed (Cox and Munk, 1954). The corresponding water surface elevations are also normally distributed and have a standard deviation σ_{η} given by (Mobley, 1994)

$$\sigma_{\eta} = a_{\eta} \sqrt{U}, \qquad (9)$$

where $a_{\eta} = 0.0229 \text{ m}^{1/2} \text{ s}^{1/2}$ is a constant derived from the original work of Cox and Munk (1954). Radiative transfer simulations parameterized by wind speeds up to 5 m s⁻¹ thus represent significant water surface topography, with σ_{η} on the order of 5 cm. The extent to which this approach is appropriate for river channels, where surface roughness primarily results from turbulent flow processes, is not known, but Hydrolight simulations parameterized in terms of wind speed provide a useful surrogate for quantifying the influence of surface-reflected radiance on depth retrieval.

To isolate the effects of substrate, optical properties and surface state, spectra were simulated for all depths for different values of one variable while holding the other two constant. Performing OBRA for each of these simulated datasets in turn summarized the influence of each variable on depth retrieval across the full range of the variable of interest. In addition, to examine more realistic field conditions, we extracted from an existing Hydrolight database a random sample stratified by the probability distributions of depth and substrate type observed in our study area. This data-base included the same values of *d* and *c*_s but spanned a broader range of substrates and surface states by including limestone and andesite $R_b(\lambda)$ spectra and *U* up to 15 m s⁻¹ (Legleiter *et al.*, 2004).

Field spectroscopy

In an effort to validate this approach to remote mapping of river bathymetry, we performed ground-based spectral

Table II. Characteristics of study reaches along Soda Butte Creek

Reach	Drainage area (km²)	Bed slope (m m ⁻¹)	Width (m)	D ₁₆ (mm)	D ₅₀ (mm)	D ₈₄ (mm)
Hollywood (HW)	116	0.0079	10	25	51	96
Round Prairie (RP)	150	0.0062	21	22	39	70
Footbridge (FB)	239	0.0066	22	23	48	90

Reported width is the reach-averaged water-surface width at the time of spectral data collection. The notation D_x denotes the percentile of the grain size distribution for which x% are finer; percentiles are computed by averaging the percentiles for individual pebble counts distributed evenly throughout each reach.

Date	Reach*	θ_{s} (°)	Ν	$\bar{d} \pm \sigma_{\!_d} (\mathrm{cm})$	Max d (cm)	Notes			
27 July 2006	RP	32.8	15	26.9 ± 14.3	66	_			
28 July 2006	RP	30.7	26	26.4 ± 11.7	52	_			
10 Aug 2006	FB	33.4	23	21.8 ± 12.5	49	A few high cirrus clouds			
11 Aug 2006	FB	31.9	30	27.1 ± 13.2	49	Wind-roughened water surface			
19 Aug 2006	HW	36.0	20	28.5 ± 17.3	65	Includes backwater channel			
13 July 2007	RP	26.5	30	38.5 ± 14.8	73	Higher discharge, greater \overline{d}			
2 Aug 2007	RP	29.6	55	$24{\cdot}8\pm16{\cdot}9$	80	High c_s , no mat spectra			
All dates	All sites	31.0	199	$27{\cdot}6\pm15{\cdot}4$	80	72% clear water/28% turbid			

Table III. Summary of field spectral data collection on Soda Butte Creek

* see Table II.

 θ_s denotes the solar zenith angle at the mid-point of the data collection period for that date, N is the number of spectral measurements, and \overline{d} and σ_d denote the mean and standard deviation, respectively, of the flow depth d at the spectral measurement locations.

measurements along three reaches of Soda Butte Creek (Table II), a tributary to the Lamar River in the northeastern corner of Yellowstone National Park, USA. A number of previous remote sensing investigations have been conducted in this area (e.g. Legleiter et al., 2002; Marcus et al., 2003), and our ongoing research focuses on sediment transfer and channel change within the Lamar River watershed. The relevant channel attributes at the time of our spectral data collection are depth, substrate type, water surface roughness, and turbidity, which we use in a generic sense to refer to the optical properties of the water column. Flow depths at spectral measurement locations ranged from 4 to 80 cm, with an average depth of 27.6 cm (Table III). The bed of Soda Butte Creek is comprised of heterogeneous gravel derived from Eocene volcanics (andesite), glacial outwash, and Paleozoic carbonate rocks; grain sizes are reported in Table II. During the mid- to late-summer period when we made our radiometric observations, much of the streambed was coated with periphyton, which tended to be best-developed in shallow and/or low-velocity areas of the channel. Spectral data span a range of water surface states from highly turbulent, broken water in riffles to flat water over pool tailouts. Suspended loads within the snowmelt-dominated catchment typically decline to low levels by mid-July, and data from a gauging station on the Lamar River indicate typical c_s values of 2–8 g m⁻³ during late summer when most of our spectral data were collected. Over a quarter of our measurements, however, were obtained on 2 August 2007 following a thunderstorm that introduced significant amounts of suspended sediment, obscuring the streambed from view except along shallow channel margins. Spikes in the gauge record of 10–100 times base-flow c_s values suggest that these spectra represented concentrations an order of magnitude higher than our other measurements, and a surface water sample obtained on this date had a c_s of 61 g m⁻³.

wavelengths) was placed over the streambed and a second set of spectra collected. This experimental design served to isolate the bottom-reflected radiance by covering the bright bottom with an artificial 'black' control. Black mat spectra were not recorded on 2 August 2007 due to high turbidity and in a few other cases where flow strength was sufficient to lift the weighted mat off of the streambed. In addition to the reflectance data, flow depth was measured with a ruler for both the exposed bed and the black mat and the substrate was characterized by acquiring a digital image with a waterproof camera. In total, 199 ground-based spectral measurements were collected from three reaches on seven separate days (Table III).

Ground-based reflectance data were acquired with a

FieldSpec HandHeld spectroradiometer (Analytical Spectral

Devices, Inc., or ASD) that measured upwelling spectral radiance from 400 to 900 nm with a nominal sampling

resolution of 1 nm and a full-width half maximum (FWHM)

of 2-3 nm. Nadir-viewing measurements were made from

above the water surface (1.5 m above the bed) by mounting

the ASD on a large camera tripod; an 8° fore-optic provided a

field of view 21 cm in diameter. All data were collected in raw

digital counts and converted to reflectance by dividing target

spectra by the counts measured above a white reference

panel made of Spectralon (Labsphere, Inc.). Five spectra

were measured for each target and stored for subsequent inspection and averaging. Spectra were typically collected

during a 1-1.5 hr midday period, with solar zenith angles

ranging from 26.5° to 36.0° (Table III). Reflectance data were

collected along channel cross-sections that spanned a range

of depths, substrate types, and water surface states. For each

location, we positioned ourselves and oriented the tripod to

avoid both shadows and wakes. One set of spectra was measured under natural conditions and then a mat coated

with flat-black spray paint (reflectance ≈ 0.03 across all

Post-processing of these spectral data was performed within the Spectral Analysis and Management System (Rueda and Wrona, 2003). The five individual spectra for each sampling location and substrate type were plotted and any obvious outliers removed; the remaining spectra were then averaged to obtain a single mean spectrum. Reflectance was then calculated by dividing the raw digital counts by the counts for the Spectralon standard recorded closest in time and a third-order, 15 nm-wide Savitzky-Golay smoothing filter applied twice (Savitzky and Golay, 1964; Hochberg et al., 2003b). The resulting averaged, smoothed reflectance spectra were used as input to the optimal band ratio analysis (OBRA) procedure described above. In addition, we compared spectra for the exposed bed and black mat to determine the extent to which substrate reflectance varied within the channel and to assess the contribution of $L_{\rm b}(\lambda)$ to $L_{\rm T}(\lambda)$.

We also used these data to examine the effects of reduced spectral resolution on depth retrieval. Field spectra were convolved from the original 1 nm sampling interval of the ASD to 5, 10, 20, 50, and 100 nm wide, equally spaced bands using a Gaussian kernel with the specified FWHM; OBRA of the degraded spectra was then performed. We also evaluated two sensors for which spectral response information was available: Quickbird, a popular multispectral satellite, and the Airborne Imaging Spectrometer for Applications (AISA), a hyperspectral sensor used to acquire image data from our study area. In this case, the full-resolution field spectra were convolved to each sensor's band passes and the OBRA procedure applied to the resampled spectra.

Remotely sensed data

To evaluate how well results from field spectroscopy might scale up using remotely sensed data, we analyzed hyperspectral images from the Lamar River and Soda Butte Creek acquired on the morning of 1 August 2002 under clear skies during base-flow conditions. The AISA sensor measured upwelling spectral radiance at wavelengths from 495 to 898 nm in 34 bands with FWHM of 3.42 nm. Downwelling irradiance data were collected simultaneously using a diffuse collector mounted on top of the aircraft and used to calculate apparent at-sensor reflectance. Due to the low flying height (2000 m above ground) and high altitude of our study area (1975-2142 m), atmospheric effects were minimal and no atmospheric correction was applied. Geo-referencing based on position and orientation data logged during the flight resulted in a pixel size of 2.5 m, relative to a wetted channel width of up to 50 m on the Lamar River but on the order of 15 m for much of Soda Butte Creek.

On the day of the flight, depth measurements were made along several transects on Soda Butte Creek. Field data were related to specific pixels by marking each transect end point with a tarpaulin identifiable on the image and measuring the distance to each depth reading. Reflectance data for these locations were extracted from the image and inspected to exclude spectra contaminated by terrestrial features, which were obvious due to the much higher reflectance of gravel bars and riparian vegetation in the NIR. The remaining spectra and corresponding depth data (n = 21) were input to OBRA to select the optimal pair of bands and calibrate the resulting X versus d relation. In addition, to evaluate whether wavelengths suitable for remote bathymetric mapping could be identified via field spectroscopy, X values were computed using the optimal bands selected via OBRA of convolved field spectra and related to depth measurements collected during the flight.

Results

Assessment of ratio-based depth retrieval: OBRA of radiative transfer simulations

We performed OBRA of Hydrolight-simulated spectra to identify combinations of wavelengths that provide strong linear relationships with depth and are robust to the potentially confounding effects of suspended sediment concentration, bottom reflectance, and water surface roughness. These results were summarized using images organized with the numerator wavelengths λ_1 as rows, the denominator wavelengths λ_2 as columns, and colours representing the OBRA $R^2(\lambda_1, \lambda_2)$ matrices. Light (red) tones in Figures 3-6 thus indicate wavelength pairs for which the log-transformed band ratio X is strongly related to depth. Conversely, dark (blue) tones indicate combinations for which X is insensitive to variations in d. The band ratio yielding the highest $R^2(\lambda_1, \lambda_2)$ value is specified in the lower diagonal of each panel, along with the regression equation, R^2 , and standard error. The residuals from the optimal band ratio relationships are displayed on the right side of each figure and illustrate how variations in each factor might lead to systematic depth retrieval errors.

Suspended sediment concentration. The feasibility of retrieving depth information from remotely sensed data depends on the optical properties of the water column, which we have parameterized in terms of c_s using optical crosssections (Bukata et al., 1995). The spectra illustrated in Figure 3(c)-(h) are dominated by scattering by suspended sediment at shorter wavelengths, where reflectance increases with depth. For longer wavelengths, radiative transfer is dominated by absorption by pure water and reflectance decreases as depth increases. The transition between scattering- and absorption-dominated regimes is thus marked by a crossover wavelength at which reflectance is the same for all depths (Figure 3(c)-(e)); the location of this crossover shifts toward longer wavelengths with increasing c_s . Figure 3(f)–(h) also shows that the depth signal is obscured at shorter wavelengths because, for a fixed depth, reflectance can vary significantly due to differences in c_s .

This effect is indicated in Figure 3(a) by very low $R^2(\lambda_1, \lambda_2)$ values where both ratio bands are short, scattering-dominated wavelengths. Longer-wavelength denominator bands, for which absorption predominates over scattering, yield stronger relationships with depth, and the vertically oriented swath of high $R^2(\lambda_1, \lambda_2)$ values suggests that the numerator wavelength has little effect on the strength of the X versus d relation. For a constant depth, an increase in c_s causes reflectance to increase across the spectrum due to greater scattering, but the NIR is less sensitive than shorter wavelengths (Figure 3(f)–(h)). The optical properties of the water column are thus primarily accounted for by the numerator band, and the wavelength indicated by OBRA, $\lambda_1 = 594$ nm, is aligned with the reflectance peaks in Figure 3(c)-(h), the height of which is determined by c_s . Depth information is thus associated with the denominator band through the rapid increase in pure water absorption in the red and NIR (Figure 1(b)). Weaker relations result for $\lambda_2 > 735$ nm because relatively few photons survive the trip through the water column to the bottom due to very strong absorption, implying that a greater proportion of the total radiance is associated with scattering and thus sensitive to c_s . The low $R^2(\lambda_1, \lambda_2)$ values centred at (655 nm, 670 nm) are associated with a pronounced chlorophyll absorption feature in the periphyton spectrum used to parameterize $R_{\rm b}(\lambda)$.

Residuals from the optimal band ratio relationship illustrated in Figure 3(b) provide some additional insight. The



Figure 3. OBRA of Hydrolight radiative transfer simulations isolating the effect of suspended sediment concentration $c_{s'}$ the substrate was periphyton and the wind speed was constant at U = 0 m s⁻¹. (a) $R^2(\lambda_1, \lambda_2)$ matrix from OBRA, (b) residuals from optimal band ratio relation, (c)–(e) simulated spectra for fixed c_s and a range of depths, and (f)–(h) simulated spectra for fixed depths and a range of c_s . The vertical dashed lines in (c)–(e) indicate the transition from scattering- to absorption-dominated radiative transfer; see text for details. This figure is available in colour online at www.interscience.wiley.com/journal/espl

variance of the residuals increases with depth because the effects of c_s are more pronounced in deeper water: for a given concentration, a thicker water column contains more suspended sediment, resulting in greater scattering. Because fewer photons are absorbed and a larger proportion experience multiple scattering events, the classic exponential relation between radiance and distance travelled through the water column begins to break down and the X versus d relation becomes slightly nonlinear. The residuals exhibit a quadratic structure as a result, but the R^2 value of 0.989 indicates that a linear approximation is reasonable for the depths considered here; adding an X^2 term to the regression might be necessary for deeper water (Dierssen et al., 2003; Mishra et al., 2007). In practice, this nonlinearity would be less pronounced because depths would likely span a smaller range and would not be evenly distributed over this range as they were for our simulations.

Given this quadratic trend, considering the relative positions of the residuals for a given depth is more informative than their absolute magnitudes and indicates the

error that might be incurred due to variations in c_s. For shallow water (d < 0.2 m), depths are overpredicted for small $c_{\rm s}$ due to lower volume reflectance from the water column, which reduces the total reflectance and thus makes the water appear deeper. Conversely, depths tend to be underpredicted for high c_s because increased scattering results in greater volume reflectance that is mistaken for a shallower depth. For deeper water (d > 0.4 m), these relationships are reversed, and *d* is underpredicted for relatively low c_s values. As depth increases, the denominator band becomes more sensitive to c_s because strong absorption reduces the amount of radiance reflected from the bottom and allows radiance scattered within the water column to make a relatively large contribution to $L_{\rm T}(\lambda_2)$. As a result, the reduced scattering associated with a low c_s makes the water appear shallower. Conversely, relatively high c_s values lead to overpredictions of depth because the increased volume reflectance produced by higher sediment concentrations is confused with a thicker water column. As depth approaches 1 m, residuals for the highest c_s considered approach those for clear water, multiple



Figure 4. OBRA of Hydrolight radiative transfer simulations isolating the effect of bottom reflectance $R_b(\lambda)$ or substrate type; $c_s = 2 \text{ g m}^{-3}$ and $U = 0 \text{ m s}^{-1}$. (a) $R^2(\lambda_1, \lambda_2)$ matrix from OBRA, (b) residuals from optimal band ratio relation, (c) simulated spectra for periphyton substrates at a range of depths, (d) simulated spectra for gravel substrates at the same range of depths, and (e) the difference in reflectance between periphyton and gravel substrates at these depths. This figure is available in colour online at www.interscience.wiley.com/journal/espl



Figure 5. OBRA of Hydrolight radiative transfer simulations isolating the effect of water surface roughness, parameterized in terms of wind speed U using Equation (9); substrate is periphyton and $c_s = 2$ g m⁻³. (a) $R^2(\lambda_1, \lambda_2)$ matrix from OBRA, (b) residuals from optimal band ratio relation, (c) simulated spectra for a fixed depth of 0.3 m and the range of water surface states indicated in the legend, with the standard deviation of water surface elevation σ_η corresponding to each value of U given in parentheses, and (d) surface-reflected radiance $L_s(\lambda)$ contribution, expressed as a proportion of the total radiance $L_t(\lambda)$, for the same depth and range of water surface states as in (c). This figure is available in colour online at www.interscience.wiley.com/journal/espl



Figure 6. OBRA of 100 Hydrolight radiative transfer simulations sampled at random from a database parameterized for our field area; see text for details. Depth, substrate type, suspended sediment concentration c_{sr} and water surface roughness (wind speed *U*) are all allowed to vary. (a) $R^2(\lambda_1, \lambda_2)$ matrix from OBRA, (b) residuals from optimal band ratio relation grouped by c_{sr} (c) residuals grouped by substrate type, and (d) residuals grouped by *U*. This figure is available in colour online at www.interscience.wiley.com/journal/espl

scattering become significant, and interpretation of depth retrieval errors becomes difficult.

Bottom reflectance. Because $L_{\rm b}(\lambda)$ is a function of both d and $R_{\rm b\prime}$ spatial variations in bottom reflectance could adversely affect depth retrieval, and a pair of wavelengths must be identified for which X is sensitive to d but unaffected by substrate heterogeneity. We simulated reflectance spectra for two common bottom types, gravel and periphyton, and performed OBRA to examine spectral variation in the predictive power of the X versus d relationship. Figure 4(a) indicates that the range of wavelengths that provide strong linear relations with depth in the presence of mixed substrates is much narrower than was the case for variable c_s . The highest $R^2(\lambda_1, \lambda_2)$ values occur in two distinct regions: one horizontally oriented in Figure 4(a), with λ_1 centred around 630 nm and λ_2 extending from 590 to 655 nm, and the other vertically oriented with λ_2 more narrowly centered on 675 nm and λ_1 from 400 to 540 nm. The former region is the site of the optimal band ratio, which yields an R^2 value of 0.996 using the wavelength at which the scatteringabsorption crossover occurs for the gravel spectra $(\lambda_2 = 590 \text{ nm};$ Figure 4(d)) as the denominator and a wavelength for which the spectra for the periphyton substrate diverge for different depths ($\lambda_1 = 586$ nm; Figure 4(c)) as the numerator. Figure 4(e) also indicates that the difference in reflectance between the two substrate types is fairly constant across this range of wavelengths, which isolates the effect of depth. The latter region of high $R^2(\lambda_1, \lambda_2)$ values is associated

with the pronounced chlorophyll absorption feature evident in the periphyton spectra but absent from clean gravel. For denominator bands within this 675 nm absorption feature, the numerator experiences a 'blue shift' toward shorter wavelengths ($\lambda_1 < 540$ nm) for which the periphyton and gravel spectra are similar and dominated by scattering within the water column (c_s was held constant at 2 g m⁻³ for these simulations). These results illustrate how distinctive substrate spectral characteristics can dictate which specific, potentially quite narrow, ranges of wavelengths are most useful for depth retrieval.

Residuals from the optimal band ratio relationship for both substrate types are plotted against depth in Figure 4(b). For d < 0.4 m, depth is underpredicted for periphyton because the increased reflectance from this relatively bright bottom type is confused with a shallower depth, whereas depth is overestimated for the darker gravel substrate. Conversely, for d > 0.4 m, depth is underpredicted for gravel because the lower reflectance of this bottom type is mistaken for reduced water column volume reflectance due to a shallower depth. Increased reflectance from a brighter, periphyton-coated streambed has the opposite effect and leads to overestimation of d in deeper water. This interpretation of the residuals is contingent upon the wavelength position of the scatteringabsorption crossover, which in this case coincides closely with the bands identified via OBRA. Though suboptimal in that the $R^2(\lambda_1, \lambda_2)$ values might be slightly lower, band combinations from the second, vertically oriented region described above might yield relationships for which interpretation of residuals would be less ambiguous because the denominator band (~675 nm) is well within the absorptiondominated regime while the numerator is subject to greater scattering.

Water surface roughness. The effects of surface state, parameterized in terms of wind speed U using Equation (9), on depth retrieval are illustrated in Figure 5 for a range of conditions from calm to highly irregular. Figure 5(a) indicates that a broad range of wavelengths from 500 to 715 nm yield very strong linear relations with depth, and spectra for a fixed depth vary little over this range of U (Figure 5(c)). These results suggest that the effects of surface roughness on depth retrieval are less significant than those associated with water column optical properties and substrate composition.

Because c_s was held constant and a single periphyton substrate was used, there is little spectral variation in predictive power and many combinations of wavelengths yield $R^2(\lambda_1, \lambda_2)$ values nearly as high as the optimum band ratio identified through OBRA. $R^2(\lambda_1, \lambda_2)$ is lower in the blue due to stronger Rayleigh scattering by the atmosphere, which increases the diffuse sky radiance for these shorter wavelengths. For a level water surface, surface-reflected radiance $L_{s}(\lambda)$ is comprised entirely of diffuse sky light, except for the special case of specular reflection of the direct solar beam. For rougher surfaces, more surface facets reflect light from the brighter, near-sun portion of the sky and $L_{s}(\lambda)$ begins to resemble the solar spectrum rather than the background sky (Mobley, 1999). These different sources of $L_s(\lambda)$ are most distinct in the blue and cause the spectra in Figure 5(c) to diverge for wavelengths less than 500 nm, reducing the utility of this portion of the spectrum for bathymetric mapping. Predictive power is also low in the NIR because strong absorption by pure water dictates that the amount of radiance leaving the water column is relatively small and $L_s(\lambda)$ thus represents a larger proportion of the total radiance $L_{T}(\lambda)$ (Figure 5(d)).

In general, although surface reflectance is spectrally flat, implying that all wavelengths should be affected equally, variations in water surface roughness will have the greatest impact on bands for which $L_s(\lambda)$ is a large fraction of $L_T(\lambda)$. Our results indicate that ratio-based depth retrieval is robust to surface reflectance because this radiance component is effectively cancelled in the ratio, although high $L_s(\lambda)$ could saturate the remotely sensed signal and obscure the effect of of depth. Figure 5(d) also suggests that approaches relying on the absolute magnitude of $L_T(\lambda)$ for individual bands or additive combinations of bands will be more sensitive to surface roughness because much of the signal might be composed of surface-reflected radiance that is independent of depth.

Residuals from the optimal band ratio relationship are grouped by wind speed and plotted against depth in Figure 5(b). These residuals exhibit a parabolic trend but are not as heteroscedastic as the residuals from the optimal band ratio relationships for variable c_s and bottom type. Furthermore, unlike these other two factors, the relative position of the residuals for different values of U are consistent across the full range of depths considered. Depth is underpredicted for level or less rough water surfaces because reflectance from the surface is relatively small, resulting in a lower total reflectance that is mistaken for a greater depth. Conversely, rougher water surfaces are characterized by greater surface reflectance, which increases the total reflectance and leads to underpredictions of depth because the greater overall brightness is confused with shallower water.

Random sample from Hydrolight database. In practice, water column optical properties, substrate type, and water

surface state all vary within a river system and could complicate remote mapping of bathymetry. To obtain a more realistic indication of the performance of ratio-based depth retrieval under typical field conditions, and to determine which wavelengths might be most useful in general, we performed OBRA for 100 simulated spectra sampled at random from a Hydrolight database parameterized for our field area (Legleiter *et al.*, 2004). These spectra represent c_s values from 0 to 8 g m⁻³, wind speeds up to 15 m s⁻¹, and four different substrate types for depths distributed between 0.05 and 1 m in proportion to their occurrence along Soda Butte Creek.

Even with these broader, more representative ranges and simultaneous variation of all three factors, OBRA yields a strong ($R^2 = 0.945$) relation with depth for the ratio of reflectances at 586 and 614 nm. The numerator band is aligned with reflectance peak associated with c_s and thus accounts for water column optical properties related to scattering while the denominator is absorption-dominated for all but the highest sediment concentrations and is not unduly influenced by the high red and NIR reflectances of periphyton and limestone substrates. Figure 6(a) also indicates a horizontally oriented swath of high $R^2(\lambda_1, \lambda_2)$ values centred on $\lambda_1 = 580$ nm and denominator wavelengths from 590 to 660 nm. This region of high predictive power is interrupted by a vertical swath of lower $R^2(\lambda_1, \lambda_2)$ values centred on the chlorophyll absorption feature at $\lambda_2 = 675$ nm, with a narrower zone for which $R^2(\lambda_1, \lambda_2) > 0.9$ at $\lambda_2 = 690$ nm, outside the chlorophyll absorption band. The vertically oriented region of moderately high $R^2(\lambda_1, \lambda_2)$ values for $\lambda_2 = 720-725$ nm and $\lambda_1 = 400-650$ nm is associated with a rapid increase in the absorption coefficient of pure water in the NIR, which makes these wavelengths relatively insensitive to variations in c_s or substrate type. For any $\lambda_2 < 710$ nm, shorter-wavelength numerator bands yield low $R^2(\lambda_1, \lambda_2)$ values due to the effects of scattering by suspended sediment. For example, the region of high predictive power aligned with the chlorophyll absorption feature at $\lambda_2 = 675$ nm and extending throughout the green and blue portions of the spectrum that was evident when substrate was variable but c_s was held constant (Figure 4(a)) is truncated at $\lambda_1 = 510$ nm when the optical properties of the water column are also allowed to vary. These results illustrate the complex interactions among depth, water column optical properties, and bottom reflectance and suggest that successful spectrally based depth retrieval might require narrow, carefully selected bands.

To examine whether departures from the optimal band ratio relationship were systematically associated with cs, substrate type, or surface state, we plotted residuals against depth for each factor in turn (Figure 6(b)-(d)). When all three parameters are free to vary, residuals are larger but generally remain unbiased, although depth tends to be underpredicted in deeper water. This type of error is likely to be common in practice due to saturation of the radiance signal for absorption-dominated numerator bands (Figure 3(c)-(e)), and because X versus d relations calibrated primarily on the basis of observations from shallow depths might not perform as well in deeper water due to the nonlinearity introduced by scattering (Figure 3(b)). Positive residuals in Figure 6 tend to be associated with clear water, particularly for greater depths where reduced volume reflectance leads to underpredictions of depth, but the strongest trends in the residuals are related to substrate type. Bright limestone bottoms lead to underpredictions of depth in shallow water, where higher reflectance is confused with a smaller depth, and overpredictions in deeper water, where the brighter substrate



Figure 7. Comparison of field spectra for all depths for (a) the streambed, (b) the black mat used as a bottom reflectance control, and (c) the difference in reflectance between the bed and the mat. The thick white line in each panel represents the median spectrum and the solid areas encompass the indicated percentage of the distribution of spectra for which reflectance measurements were made for both the bed and the mat (n = 139). This figure is available in colour online at www.interscience.wiley.com/journal/espl

is mistaken for a thicker water column with higher volume reflectance. Conversely, dark andesite substrates lead to overpredictions of depth in shallow water, where the darker bottom appears similar to deeper water, and underpredictions for greater depths, where the presence of a dark substrate appears similar to a shallower water column with reduced volume reflectance.

Field observations of substrate spectral variability

The preceding analyses suggest that substrate heterogeneity influences the accuracy of image-derived depth estimates and implies that spatial variations in streambed spectral properties could complicate bathymetric mapping. Data on bottom reflectance are also valuable because the bottom contrast between the substrate and water column largely depends on $R_b(\lambda)$, and if, for a particular wavelength, $R_b(\lambda) - R_c(\lambda)$ is not of sufficient magnitude, depth cannot be estimated from radiometric observations at that wavelength. Furthermore, $R_b(\lambda)$ plays an important role in determining whether the bottom-reflected radiance is significantly greater than the radiance scattered within the water column, one of the critical assumptions leading to the simplified band ratio expression (8).

To investigate these issues, we made paired above-water, field-based reflectance measurements of the natural streambed and a low-albedo substrate control (black mat) at 139 locations along Soda Butte Creek. These data are summarized in Figure 7, in which median reflectance values for each wavelength indicate the central tendency of our measurements and are represented by the thick white lines. Variability is expressed using percentiles of the distribution of reflectance values to define areas that bracket 25, 50, and 75% of the data (Hochberg *et al.*, 2003b).

Considering that the data span the full range of measured depths and no attempt was made to account for the effect of varying water depth on reflectance, the streambed spectra in Figure 7(a) are remarkably similar. For example, the chlorophyll absorption feature at 675 nm is clearly expressed in not only the median reflectance spectrum but also the various percentiles of the distribution, implying that substrates throughout our study area are coated with periphyton during late summer. These spectra are also characterized by

1. an increase in reflectance with wavelength up to 580 nm, consistent with our radiative transfer modelling of the

effects of suspended sediment on water column optical properties;

- 2. a plateau from 580 to 650 nm on the shoulder of the chlorophyll absorption band;
- 3. a strong peak in reflectance at 700 nm on the opposite limb of the chlorophyll feature, followed by a sharp decrease due to strong absorption by pure water in the NIR; and
- 4. a smaller reflectance peak at 810 nm due to a decrease in the absorption coefficient of pure water at this wavelength, documented by Kou *et al.* (1993) but not incorporated into Hydrolight, which only considers wavelengths from 400 to 800 nm.

The consistency with which these features were observed implies that substrate spectral characteristics are fairly homogeneous within our study area. Although streambed photographs typically included a range of grain sizes and lithologies, these grain-to-grain differences in colour were apparently not significant at the scale of our radiometric observations, defined by the ASD's 0.21 m field of view. This result implies that the presence of different rock types does not introduce appreciable spectral variability as long as the lithologies are spatially well-mixed. Coating by periphyton also acts to homogenize the bottom reflectance.

Spectra measured when the black mat was placed over the streambed as a bottom reflectance control are relatively featureless by comparison (Figure 7(b)), and the pronounced difference between the bed and mat indicates that the streambed is relatively bright, implying a positive bottom contrast. The effects of depth are still present in the mat spectra through the influence of a water column of varying thickness, but the positive difference between the bed and mat spectra (Figure 7(c)) suggests that the majority of the total radiance measured above the river is reflected from the bottom rather than scattered within the water column. This result implies that, for most wavelengths, Equation (5) is at least approximately valid under the field conditions observed in our study area. The water column plays a greater role at shorter wavelengths and explains why reflectance above the black mat is greatest in the blue, exceeding the reflectance measured above the natural streambed in some cases. Because this portion of the spectrum is dominated by scattering, $R_{\rm b}(\lambda)$ has relatively little influence on the total reflectance, causing the bed and mat spectra to converge.

Optimal band ratio analyses of field spectra

Our radiative transfer simulations suggest that, by selecting an appropriate pair of bands, one can define a spectrally based variable *X* that exhibits a strong, linear relationship with water depth. To provide some empirical verification for this result, we performed separate optimal band ratio analyses for the individual datasets described in Table III, as well as the composite of all 199 field spectra. The results are summarized in Figure 8, which displays the $R^2(\lambda_1, \lambda_2)$ matrices as images and reports the optimal band combinations, corresponding *X* versus *d* relations, and regression statistics. Maximum $R^2(\lambda_1, \lambda_2)$ values ranging from 0.792 to 0.976 indicate the potential for highly accurate spectrally based depth retrieval under field conditions, with standard errors of a few cm.

Many of the features described in the context of our Hydrolight-generated spectra are evident in the field data as well; this agreement lends some credibility to our modelling efforts. For example, the $R^2(\lambda_1, \lambda_2)$ image for field data collected on 19 August 2006 (Figure 8(e)) bears a striking resemblance to the $R^2(\lambda_1, \lambda_2)$ image for the random sample from the Hydrolight database (Figure 6(a)). The vertically oriented swath of low $R^2(\lambda_1, \lambda_2)$ values centred on the chlorophyll absorption feature at $\lambda_2 = 675$ nm is present in all datasets except that acquired on 2 August 2007 under highly turbid conditions. Similarly, band combinations drawn from shorter, scattering-dominated wavelengths provide little predictive power, consistent with Figure 3 and our interpretation thereof.

For the overall dataset of 199 field spectra, 28% of which were collected during a period of high c_s on 2 August 2007, the optimal band ratio consisted of a green numerator ($\lambda_1 = 570$ nm), which primarily accounted for variations in water column optical properties related to scattering by suspended sediment, and a NIR denominator ($\lambda_2 = 716$ nm), which provided depth information across a broad range of conditions due to the strong absorption by pure water at this wavelength. The resulting *X* versus *d* relation had a high R^2 of 0.799 and a regression standard error of 0.069 m, demonstrating that the spectrally based depth retrieval algorithm we have examined via radiative transfer simulations also performs well when applied to real data collected from a natural setting.

One notable difference between OBRA results for simulated and field spectra is the selection of longer-wavelength denominator bands for the field data. Whereas OBRA of the random sample of Hydrolight-generated spectra identified a red band at λ_2 = 614 nm, NIR denominator wavelengths were optimal for all field datasets ($\lambda_2 = 694$ nm for 13 July 2007, but equally high R^2 values were obtained for $\lambda_2 > 700$ nm). Figure 8 suggests that the NIR region of the spectrum is the most valuable for depth retrieval, including the 810 nm band highlighted by reflectance peaks in our field spectra (Figure 7(a)). Strong absorption by pure water in the NIR dictates absorptiondominated radiative transfer, one of the key requirements for ratio-based depth retrieval (Equation (6)), but also implies that the radiometric signal saturates at greater depths, as shown in Figure 3(c)–(e). This saturation might account for the disparate OBRA results for modelled and field spectra; because the field data were generally obtained from shallower depths than those modelled with Hydrolight, these data would have been less susceptible to saturation in the NIR.

A salient feature of Figure 8 is the difference in OBRA results among datasets. These differences are difficult to examine quantitatively due to the limited ancillary data available; additional measurements of c_{s} , water column optical properties, periphyton biomass, and flow velocity, wind speed, or some other surrogate for water surface

topography would have been useful in this regard. Nevertheless, we attempt to explain a few observations based on our radiative transfer simulations and field experience. For both the Round Prairie and Footbridge reaches, spectra collected on successive days yield disparate optimal band ratios and $R^2(\lambda_1, \lambda_2)$ matrices, particularly in the NIR (Figure 8(a)-(d)). Bottom reflectance and water column optical properties did not vary from one day to the next, but closer inspection of our field data indicated that the different OBRA results might be a consequence of the distribution of depths sampled on each date. On 27 July 2006, 33% of our data were for d > 0.3 m whereas a greater proportion (42%) of the observations from 28 July were for d > 0.3 m. Similarly, more of the spectral data for the Footbridge reach were from d > 0.3 m on 11 August (43%) than on 10 August (30%). Although Kolmogorov-Smirnov tests indicated that depth distributions were not significantly different for either pair of dates, in general, a sample biased toward shallower water could tend to favour NIR wavelengths where small changes in depth correspond to large changes in radiance. Conversely, a sample drawn from deeper water might tend to indicate less predictive power in the NIR due to saturation at greater depths. High $R^2(\lambda_1, \lambda_2)$ values were observed throughout the NIR for the dataset (13 July 2007) with the greatest mean depth (Table III, Figure 8(f)), however, suggesting that saturation was not necessarily a problem. An alternative explanation for the reduced utility of the NIR on these dates could be a greater degree of water surface roughness, which would result in a higher ratio of surface-reflected to total radiance in the NIR; the greater $L_{s}(\lambda)$ might have overwhelmed the radiance signal related to depth. Spectral data were collected under very windy conditions on 11 August 2006 that presumably generated greater surface roughness than was present on 10 August; our field notes do not specifically indicate that 28 July 2006 was significantly windier than the day before. In any case, this day-to-day variability implies that variables other than depth influence which wavelengths are useful for bathymetric mapping and might affect depth retrieval accuracy.

The dataset collected in Round Prairie on 2 August 2007 is distinctive due to much greater turbidity on this date. The OBRA results in Figure 8(g) indicate that although the visible portion of the spectrum was rendered useless for depth retrieval by high concentrations of suspended sediment, a strong ($R^2 = 0.792$) relationship with water depth was still obtained using a pair of NIR bands separated by only 5 nm. Hydrolight simulations indicated that the transition from scattering- to absorption-dominated radiative transfer shifts toward longer wavelengths with increasing c_s , and the order of magnitude greater concentrations represented by this dataset dictated that wavelengths up to 690 nm were not useful band ratio denominators. Wavelengths as short as 520 nm yielded $R^2(\lambda_1, \lambda_2) > 0.6$ when used in the numerator with $\lambda_2 > 725$ nm, however, and predictive power was maximized when both ratio bands were from the NIR. Because the scattering coefficient for suspended sediment decreases steadily from 700 to 730 nm while the absorption coefficient of pure water increases rapidly over this range, this portion of the spectrum is responsive to changes in depth but insensitive to c_{st} even for relatively high concentrations. NIR bands thus extend the range of conditions under which river bathymetry can be remotely mapped.

Effects of spectral resolution on depth retrieval

Optimal band ratio analyses of both radiative transfer simulations and field spectra indicate significant spectral







Figure 9. OBRA of field spectra convolved to different sensor band passes; the composite dataset was used for this analysis. OBRA results for the original, full-resolution field spectra are shown in (a), and (b)–(f) represent OBRA results for hypothetical sensors with Gaussian-shaped bands with the specified widths. OBRA results for the hyperspectral AISA and multispectral Quickbird sensors are illustrated in (g) and (h), respectively. This figure is available in colour online at www.interscience.wiley.com/journal/espl

variation in the strength of the relationship between X and d, implying that accurate depth retrieval might require specific, fairly narrow ranges of wavelengths. These results suggest that spectral resolution could be a significant constraint because, whereas our reflectance measurements were essentially continuous, remote sensing instruments provide data from a smaller number of broader bands, which could obscure important spectral variations. To investigate this issue, we convolved the 199 spectra from our composite field dataset to different spectral response functions, including Gaussianshaped bands with full-width half maxima (FWHM) ranging from 5 to 100 nm as well as the AISA and Quickbird sensors. We then performed OBRA of the degraded spectra, and the resulting $R^2(\lambda_1, \lambda_2)$ matrices and regression equations are presented in Figure 9.

The optimal band ratio for the full-resolution field spectra $(\lambda_1 = 570 \text{ nm}, \lambda_2 = 716 \text{ nm})$ produced an X versus d regression R^2 value of 0.799, and for convolved spectra with FWHM up to 20 nm, typical of hyperspectral instruments, the optimal wavelengths remained consistent and R^2 was reduced by only 0.01. For broader-band multispectral sensors, shorter-wavelength numerators were identified as optimal, but R^2 values were only slightly lower: 0.760 and 0.735 for FWHM of 50 and 100 nm, respectively. Figure 9 indicates that reducing spectral resolution from our 1 nm-sampled field data to 100 nm multispectral bands did not significantly decrease the predictive power of the optimal band ratio - regression standard errors increased by only 0.01 m over this range. These results indicate that because variations in water depth exert a first-order control on the radiance signal, accurate bathymetric mapping does not necessarily require high-spectral-resolution data.

Although the results presented in Figure 9(a)–(f) represent hypothetical sensors with idealized Gaussian spectral response functions, convolution of our field spectra to the known band passes of AISA and Quickbird corroborated these findings. For the AISA hyperspectral sensor, the optimal wavelength combination was slightly different than that of the original field spectra due to the specific locations of the instrument's bands, but the R^2 and standard error were virtually identical (Figure 9(g)). For the Quickbird multispectral satellite, OBRA of convolved field data indicated that the ratio of the blue to the NIR band would be optimal, but with a lower R^2 value of 0.704. Because Quickbird's bands are not significantly wider than the hypothetical 100 nm-FWHM sensor considered in Figure 9(f), the selection of different optimal wavelengths and lower R^2 value for Quickbird are a consequence of the locations of the sensor's bands rather than their widths, implying that wavelength position is more important than spectral resolution *per se*.

Application to remotely sensed data

AISA hyperspectral image data from the Lamar River and Soda Butte Creek were used to evaluate how effectively remote sensing might allow us to extend these modellingand field-based results to larger, more geomorphologically relevant scales. First, we assessed whether pairs of wavelengths found to be strongly related to depth through OBRA of field spectra would also be useful for mapping bathymetry from remotely sensed data. *X* was defined using reflectance values for the band combination identified as optimal via OBRA of convolved field spectra (Figure 9(g)) and related to *in situ* depth data collected during the flight to obtain the following regression equation:

$$d = -0.142 + 2.18X, \quad X = \ln\left[\frac{R_{577}}{R_{711}}\right]; \quad (10)$$
$$R^2 = 0.747, \quad S.E. = 0.0996 \text{ m},$$

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Figure 10. (a) Spectrally based bathymetric map of the Lamar River, derived using the bands identified via OBRA of convolved field spectra (Figure 9(g)) and Equation (10). (b) compares image-derived depth estimates to data from a subsequent topographic survey; see text for details. This figure is available in colour online at www.interscience.wiley.com/journal/espl

where R_{577} and R_{711} denote reflectances measured by AISA at the specified wavelengths and *d* is in m. The predictive power of this expression indicates that wavelengths selected via field spectroscopy perform well when applied to airborne image data and, more importantly, that bathymetry can be accurately mapped via remote sensing. An example is presented in Figure 10, generated by applying Equation (10) to AISA data from the Lamar River. The resulting patterns are spatially coherent and hydraulically reasonable, with greater depth in zones of flow convergence, along the outer bank of the bend, and in backwater areas. The image also captures shallower riffles and shoaling over the point bar and onto the midchannel bar near the top of Figure 10.

In addition to their realistic spatial structure, the absolute magnitudes of the image-derived depth estimates are plausible, with a reach-averaged mean depth of 0.38 m and pools up to 0.8 m deep. No field measurements were collected from this area during the flight, but a subsequent cross-sectional survey provides some qualified support. Although depth estimates from 2002 cannot be related to topographic data from 2007 due to channel migration in the interim, extracting a bathymetric profile from a position along the bend analogous to the location of our 2007 survey allows for an indirect comparison, and Figure 10 indicates that the remotely sensed data and field survey yield similar point bar slopes. Depths are also comparable the mean and maximum depths derived from the image were 0.50 m and 0.86 m, as opposed to 0.45 m and 0.66 m for the field data. The agreement is quite strong considering that the discharge recorded at a nearby gauge was 37% lower during the field survey than during the AISA flight; this decrease in discharge affected the maximum depth more than the mean depth due to the asymmetry of the cross-section.

In practice, field spectra might not be available to guide wavelength selection for depth retrieval, and appropriate band combinations must be identified from the image data itself. To assess whether the OBRA procedure would be useful in this situation, we used spectra from the image pixels for which depths were measured in the field as input to OBRA. The results presented in Figure 11(a) indicate that the optimal wavelengths (624 nm, 693 nm) differ from those identified through OBRA of the convolved field spectra (Figure 9(g)), but the image-derived relation also yields a higher R^2 (0.806) and smaller standard error (0.0872 m) than the equation (10) based on field spectra. This result implies that a strong, linear relationship between a radiometric quantity and depth can be developed directly from image data, provided *in situ* depth measurements are also available.

A comparison of the $R^2(\lambda_1, \lambda_2)$ matrices derived from field spectra and AISA image data, illustrated in Figures 9(g) and 11(a), respectively, reveals some notable similarities and differences. Both datasets indicate that the 711 nm band is a useful denominator in combination with most visible wavelengths, with the vertically oriented swath of high predictive power extending farther into the green for the image data than for the field spectra, which include reflectance measurements from high c_s conditions under which visible bands were of little value (Figure 8(g)). Similarly, both $R^2(\lambda_1, \lambda_2)$ matrices reveal areas of reduced predictive power associated with the chlorophyll absorption feature at 675 nm and where both λ_1 and λ_2 < 530 nm. This latter region, in the upper-left corner of these diagrams, is presumably less extensive for the image data due to lower scattering than was observed in the high-turbidity field spectra. The most pronounced disparity between the two





Figure 11. Application of the ratio-based depth retrieval algorithm to the Footbridge reach of Soda Butte Creek. (a) shows the OBRA of spectra derived from the AISA image and depth measurements collected during the flight and (b) is the resulting bathymetric map, with thalweg profile shown as an inset; flow is toward the bottom of the image. (c) shows image spectra extracted from the transect near the bed apex together with associated depth estimates; see text for details. This figure is available in colour online at www.interscience.wiley.com/journal/espl

matrices is in the NIR, where the field data indicate fairly strong relationships with depth for λ_2 up to 820 nm and very low predictive power when $\lambda_1 > 734$ nm, presumably due to a low signal-to-noise ratio at longer wavelengths where water-leaving radiance is minimal. In contrast, the AISA data are weakly related to depth for $\lambda_2 > 720$ nm, which might be attributed to saturation of the radiance signal or possibly to atmospheric effects.

Another important difference between field spectra and image data is spatial resolution, which represents a fundamental constraint on remote mapping of small streams. For example, application of the optimal band ratio relation from Figure 11(a) to AISA data from the Footbridge reach suggests that reliable depth estimates might be difficult to obtain in very shallow water and along channel margins where pixels are mixed. The bathymetric map in Figure 11(b) features hydraulically reasonable spatial patterns consistent with our field experience at this site, and a thalweg profile indicates that useful information on pool-riffle morphology can be derived from image data. For this 20 m-wide channel, however, an important limitation of image-derived bathymetry becomes evident: depth estimates are negative along the margins of the point bar and, most notably, on the upstream end of the large mid-channel bar toward the top of the reach. As suggested by earlier work based on radiative transfer modelling (Legleiter and Roberts, 2005), channel banks present a challenging remote sensing problem due to the juxtaposition of terrestrial and aquatic features with very different spectral characteristics; these issues are most pronounced when the image pixel size is an appreciable fraction of the wetted channel width.

In this case, the river is spanned by as few as four 2.5 m pixels, and the spectral transect in Figure 11(c) indicates that contamination of the water-leaving radiance signal by adjacent terrestrial features can be significant. These spectra, extracted from eight sequential pixels across the channel, include unusually high NIR reflectances on both sides of the channel, influenced by exposed gravel toward the left bank and a vegetated cutbank on the right. The presence of vegetation within a pixel, such as that closest to the right bank (spectrum 8 in Figure 11(c)), causes reflectance to increase with wavelength through the NIR, whereas water has an opposite trend. Spectrum 7, extracted from the second pixel from the right bank, also bears the imprint of vegetation, suggesting that NIR radiance can be scattered into a pixel from nearby - these adjacency affects might be inevitable where bright vegetation and dark water are in close proximity. For the point bar on the left side of the transect, gravel has a less distinctive spectral shape than does vegetation and is expressed as an overall increase in brightness for spectra 1 and 2. In the middle of the channel, away from the influence of the banks, spectra are similar to both radiative transfer simulations and field-based measurements, with a pronounced chlorophyll absorption feature at 675 nm, a peak around 700 nm, and low reflectances through the NIR except for a smaller peak at 810 nm. Shallower areas (spectra 3 and 6) are brighter than deeper pixels from the thalweg (spectra 4 and 5), with the greatest difference at 693 nm, the optimal denominator band from OBRA.

For the mixed spectra near the margins of the channel, relatively high reflectances at longer wavelengths translate into large negative values of the log-transformed band ratio X and result in negative depth estimates for two pixels on either side of the eight-pixel transect (lower panel of Figure 11(c)). In general, because the underlying premise of the ratio-based depth retrieval algorithm is that reflectance for λ_2 is lower than for λ_1 due to stronger absorption in the denominator band, any spectrum for which $R(\lambda_2) > R(\lambda_1)$ is likely to yield a negative depth estimate. The extensive pale (orange/red) hues in Figure 11(b) suggest that this condition holds in shallow areas throughout the reach. These negative estimates do not necessarily preclude interpretation of bathymetric maps, however, and depth retrieval is more reliable in deeper areas not subject to adjacency effects. Nevertheless, the difficulty of obtaining accurate bathymetry in shallow water and along channel banks might limit the utility of spectrally based depth retrieval for some applications.

Summary and Conclusion

The prospect of measuring channel morphology with an unprecedented combination of resolution and extent has stimulated considerable interest in remote sensing of rivers. The potential for more accurate, more efficient mapping and monitoring clearly exists, but achieving the kinds of advances envisioned by Marcus and Fonstad (2008) will require a high degree of confidence in remotely sensed information. This confidence must first be justified. Establishing the reliability of image-derived data thus constitutes a critical research objective and has motivated this study.

Our results indicate that passive optical remote sensing of bathymetry is not only feasible but highly accurate under conditions typical of shallow river channels, supporting earlier experimental (Gilvear et al., 2007) and modelling (Legleiter et al., 2004; Legleiter and Roberts, 2005) studies. In this paper, we have more closely examined the theoretical basis for spectrally based depth retrieval, considered the relative magnitudes of various radiance components, and outlined the range of conditions under which this approach to bathymetric mapping would be appropriate. Depths estimated from band ratios are most reliable when the remotely sensed signal is comprised primarily of bottomreflected radiance $L_b(\lambda)$. This component will tend to be dominant when depths are shallow, the water is clear and dominated by absorption rather than scattering, the reflectance of the substrate is high relative to that of the water column itself, and little radiance is reflected from the water surface or scattered into the sensor's field of view by the atmosphere.

Because the radiometric quantities involved depend on wavelength, these conditions might hold for some portions of the spectrum but not for others. To examine these spectral variations, we developed a simple procedure, called Optimal Band Ratio Analysis (OBRA), for identifying pairs of wavelengths that yield strong, linear relations between the log band ratio X (Equation (8)) and flow depth d. Applying this technique to spectra simulated with the Hydrolight radiative transfer model allowed us to systematically examine the effects of water column optical properties, bottom reflectance,

- 1. The spectrum can be divided into a scattering-dominated regime at shorter wavelengths, which are thus sensitive to suspended sediment concentration c_s , and a longer-wavelength regime dominated by pure water absorption, which is more responsive to changes in depth.
- 2. The optical properties of the water column are primarily accounted for by the numerator band, which is aligned with reflectance peaks related to c_s , while depth information is provided by a longer-wavelength, absorption-dominated denominator band.
- 3. The range of wavelengths yielding strong relations with depth can be limited by the presence of spectrally distinctive substrates, such as periphyton with chlorophyll absorption features.
- 4. The effects of water surface roughness are minor relative to those of c_s and bottom reflectance, but radiance reflected from the surface constitutes a large proportion of the total for blue and NIR wavelengths and can thus limit the utility of these bands for depth retrieval.
- 5. When c_s , $R_b(\lambda)$, and water surface state were varied simultaneously, the ratio of reflectances at 586 and 614 nm was strongly related to depth ($R^2 = 0.945$). Residuals were generally unbiased with respect to these three factors but depth was underpredicted in deeper water.

The complex interactions among depth, water column optical properties, and bottom reflectance revealed by OBRA illustrate the value of spectral information and imply that collecting data from specific, fairly narrow ranges of wavelengths could facilitate remote mapping of river bathymetry.

The analyses presented here were substantiated not only by radiative transfer modelling but also by a large number of field-based spectral measurements from a gravel-bed river in Yellowstone National Park. Field spectra were collected from above the water surface for both the natural streambed and a low-albedo bottom reflectance control. These data indicate that substrate spectral characteristics are fairly homogeneous within our study area, which facilitates bathymetric mapping by isolating the effect of depth on the bottom-reflected radiance; this homogeneity is largely due to the ubiquitous presence of periphyton during late summer. Comparison with the black mat used as a control suggests that natural substrates are relatively bright, supporting the assumption that a significantly greater proportion of the at-sensor radiance is reflected from the bottom than is scattered within the water column. Application of the OBRA procedure to our field data yielded X versus d relations with R^2 values from 0.792 to 0.976, even for spectra collected under highly turbid conditions ($c_s = 61 \text{ g m}^{-3}$). The high predictive power of these relationships demonstrates that ratio-based depth retrieval is effective in a natural setting, validating previous modeling work and implying that the assumptions leading to the simplified band ratio expression (8) are reasonable. The similarity of OBRA results derived from field spectra and Hydrolight simulations further corroborates our modeling efforts, although some notable differences were observed, particularly in the NIR. Disparate OBRA results for individual field datasets suggest that additional factors could influence which bands are most useful for depth retrieval and might affect bathymetric accuracy.

Although results from radiative transfer modelling and field spectroscopy were encouraging, the utility of spectrally based depth retrieval depends on how well this approach can be applied to remotely sensed data. We examined the effects of

spectral resolution by degrading our field spectra to mimic hypothetical sensors with a range of band widths and real multi- and hyper-spectral instruments. OBRA of convolved spectra indicated that reduced spectral resolution did not significantly decrease the predictive power of the optimal band ratio and that the position of a sensor's bands might be more important than their widths. We also used hyperspectral image data and ground-based depth measurements to demonstrate that wavelengths identified via field spectroscopy are useful for remote sensing of bathymetry ($R^2 = 0.747$). An image-derived depth map of the Lamar River exhibited coherent, hydraulically reasonable spatial patterns, and comparison with a subsequent topographic survey suggested that depth estimates were of realistic magnitude. A separate Xversus d relation developed by extracting spectra directly from the image achieved greater predictive power (R^2 = 0.806) using a different pair of bands, but yielded negative depth estimates along shallow channel margins. Inspection of spectra from a transect across this image indicated that mixed pixels along channel banks contaminated by vegetation and/ or gravel have higher red and NIR reflectances that translate into large negative values of X and hence negative depth estimates; this issue becomes more important as the ratio of wetted channel width to image pixel size decreases.

Limitations of this kind will always be present and have been discussed extensively elsewhere (e.g. Legleiter *et al.*, 2004: Marcus and Fonstad, 2008). Nevertheless, through a combination of theoretical arguments, numerical modelling, field spectroscopy, and image processing of remotely sensed data, this study confirmed the potential for spectrally based depth retrieval in shallow rivers. Whether this approach will ultimately advance our understanding of fluvial systems is another question, the answer to which depends on the ability of remotely sensed data to satisfy the information requirements of specific geomorphic investigations. Addressing this issue will require careful consideration of the physical principles that both enable and limit remote sensing of rivers.

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