Remote sensing of stream depths with hydraulically assisted bathymetry (HAB) models

Mark A. Fonstad a,*, W. Andrew Marcus b,1

a Department of Geography, Texas State University, San Marcos, San Marcos, TX 78666, United States
b Department of Geography, University of Oregon, Eugene, OR 97403-1251, United States

Received 23 June 2004; received in revised form 17 June 2005; accepted 20 June 2005
Available online 29 September 2005

Abstract

This article introduces a technique for using a combination of remote sensing imagery and open-channel flow principles to estimate depths for each pixel in an imaged river. This technique, which we term hydraulically assisted bathymetry (HAB), uses a combination of local stream gage information on discharge, image brightness data, and Manning-based estimates of stream resistance to calculate water depth. The HAB technique does not require ground-truth depth information at the time of flight. HAB can be accomplished with multispectral or hyperspectral data, and therefore can be applied over entire watersheds using standard high spatial resolution satellite or aerial images. HAB also has the potential to be applied retroactively to historic imagery, allowing researchers to map temporal changes in depth.

We present two versions of the technique, HAB-1 and HAB-2. HAB-1 is based primarily on the geometry, discharge and velocity relationships of river channels. Manning’s equation (assuming average depth approximates the hydraulic radius), the discharge equation, and the assumption that the frequency distribution of depths within a cross-section approximates that of a triangle are combined with discharge data from a local station, width measurements from imagery, and slope measurements from maps to estimate minimum, average and maximum depths at a multiple cross-sections. These depths are assigned to pixels of maximum, average, and minimum brightness within the cross-sections to develop a brightness–depth relation to estimate depths throughout the remainder of the river.

HAB-2 is similar to HAB-1 in operation, but the assumption that the distribution of depths approximates that of a triangle is replaced by an optical Beer–Lambert law of light absorbance. In this case, the flow equations and the optical equations are used to iteratively scale the river pixel values until their depths produce a discharge that matches that of a nearby gage.

$R^2$ values for measured depths versus depths estimated by HAB-1 and HAB-2 are 0.51 and 0.77, respectively, in the relatively simple Brazos River, Texas. $R^2$ values for HAB-1 and HAB-2 are 0.46 and 0.26, respectively, in the Lamar River, a complex mountain river system in Yellowstone National Park. Although the $R^2$ values are moderate, depth maps and cross-sections derived from the HAB techniques are consistent with typical stream geomorphology patterns and provide far greater...
Detailed depth maps of streams can be a valuable tool for characterizing stream hydraulics (Waddle et al., 2000; Lane and Chandler, 2003), modeling flow dynamics and forecasting flood hazard (Brunner, 2002; Steffler and Blackburn, 2002), modeling pollutant dispersion (Coles and Wells, 2003), predicting channel change (Lane et al., 2002), documenting in-stream habitats (Whited et al., 2002; Marcus et al., 2003), and evaluating potential effects of management decisions. At present, accurate depth maps are generated from ground-based surveys, but these surveys are time consuming, costly, difficult to conduct in inaccessible areas, and require surveyors be in the field at the time of depth measurements. Ground-based depth surveys are therefore generally spatially limited to single reaches of a stream or to several cross-section locations throughout a watershed, and are temporally limited to periods when surveyors can be in the field, as well as to locations of known bed constraint.

Optical remote sensing of stream depths provides a useful, complementary alternative to ground-based surveys. Remote sensing-based depth maps could provide spatial coverage across entire watersheds and temporal coverage on a year-round basis, so long as the water column is not obstructed by trees, clouds, shadows, overhanging materials, ice, or significant turbidity. Indeed, accurate maps of stream depths (Lyon and Hutchinson, 1995; Winterbottom and Gilvear, 1997; Marcus et al., 2003) and marine bathymetry (e.g., Lafon et al., 2002; Liceaga-Correa and Euan-Avila, 2002; Louchard et al., 2003) have been generated by coupling remote imagery with ground measurements. However, the need for ground-based measurements imposes the same general constraints associated with field mapping of depths and reduces the relative advantages of these remotely sensed approaches.

In this article, we develop and evaluate two remote sensing models for estimating stream water depths without the use of ground crews. The two models are based on simple concepts of open-channel flow and require only slope data for the stream bed and discharge data from a nearby gaging station at the time of image collection. Because these hydraulically assisted bathymetry (HAB) models do not require ground data on depths or water optics, they remove the logistical obstacles associated with field surveys and radiometric calibration and enable depth estimates using historical and modern photos and digital data.

2. Background

Remote sensing of water depths dates at least to World War II, when photogrammetric techniques were used with aerial photos to measure near-shore depths in the Pacific (Lundahl, 1948). Likewise, some of the earlier work on use of digital imagery addressed techniques for estimating depth (Poclyn and Sattinger, 1969). Since these early studies, the large majority of research relevant to optical remote sensing of depth has focused on documenting and modeling optical characteristics of water (e.g., Gordon and Brown, 1974; Mobley, 1994; Gould and Arnone, 1997; Woodruff et al., 1999; Herlevi, 2002; Holden and LeDrew, 2002; Lafon et al., 2002; Louchard et al., 2003—to list just a few) and using variants of these radiant transfer models to estimate near-shore marine or lake depths (e.g., Lyzenga, 1978; Sandidge and Holyer, 1998; Roberts and Anderson, 1999; Lafon et al., 2002).

Similar radiant transfer models have generated useful depth estimates in large and relatively clear rivers. Lyon et al. (1992) and Lyon and Hutchinson (1995), for example, developed an optical model that, when coupled with ground-based measurements, estimated five depths classes with 95% accuracy in the St. Mary’s River of Michigan. While of value, these models do not readily transfer to the more spatially and temporally heterogeneous turbulent environments of relatively smaller and more shallow streams, where...
modeling the interaction of light in the substrate and water column is far more difficult (Dekker and Bukata, 2002; Legleiter et al., 2004). Moreover, parameters required for deep water models often cannot be readily measured in streams. Secchi disk measurements, for example, are often used to estimate turbidity and absorption coefficients, but cannot be used in shallow water systems where the disk remains fully visible at all depths. Furthermore, until recently, remote sensing of depths in relatively small streams was severely limited by the pixel sizes of satellite imagery, which were too large to resolve in-stream variations. Although airborne imagery provided finer resolution data, its cost and the relative scarcity of airborne multispectral imagery pushed research toward deep water environments with large surface areas that could be captured on satellite imagery.

Historically, approaches for remote sensing of shallow stream depths have therefore relied on simple regression models that do not require complex modeling or use of ground-based measurements of substrate, algae cover, turbulence, and turbidity, all of which can vary over distances of less than a meter in small streams. Winterbottom and Gilvear (1997) used Lyzenga’s (1981) linear depth function with simulated Daedalus AADS spectra to develop a stepwise regression between measured depths and Lyzenga adjusted reflectance. The model had an $R^2$ of 67% at depths up to 1.2 m, although the model was most effective at distinguishing variations in depths of 0.6 m or shallower. Remarkably, a regression of depths versus reflectance using fine spatial resolution (~0.8 m) scanned black and white photography yielded an $R^2$ of 55%, almost as high as that achieved with the multispectral data. Most impressively, the regressions developed by Winterbottom and Gilvear produced stream cross-sections that were remarkably true to form and generally accurate with +10 cm. Bryant and Gilvear (1999) used the Winterbottom and Gilvear regression on histogram-matched imagery from different dates to document flood effects on bathymetry throughout a 3-km reach.

Marcus et al. (2003) used a two-step process to estimate stream depths with Probe-1 128-band 1-m hyperspectral imagery. They first used a supervised classification to stratify the stream by in-stream habitat (e.g., riffles, pools, etc.), which provided an indication of surface turbulence and bottom character. A stepwise regression of principal component images versus measured depths in each of the unit types achieved $R^2$ values ranging from 67% for high gradient riffles to 99% for smooth water glides in the fifth order Lamar River, one of the sites examined in this study. Accuracy generally decreased as turbulence increased and streams became smaller, dropping as low as 20% for high gradient riffles in a third order channel. The decreasing accuracy in smaller streams probably resulted in large part from the greater proportion of mixed pixels in small streams.

The regression-based approaches of Winterbottom and Gilvear (1997) and Marcus et al. (2003) suffer from the need for ground-based measurements at the time of image acquisition. Alternatives that do not require nearly as many ground-based measurements include fine-resolution photogrammetry or use of active sensors. Photogrammetric approaches for depth measurements require multiple images, clear water, corrections for refraction, and accurate characterization of the observation geometry (Westaway et al., 2000, 2001, 2003; Lane and Chandler, 2003). Active sensors include dual-frequency lidar, which has shown promise in marine settings (Sinclair, 2002) but requires relatively clear water and raises concerns about eye damage for people and animals in the case of high-resolution, highly focused lidar beams (Guenter et al., 2000) and may not be able to distinguish depth variations at resolutions appropriate to shallow water streams. Ground penetrating radar can accurately measure stream depths even in turbid conditions (Spicer et al., 1997; Costa et al., 2000), but sufficiently accurate, aircraft mounted, imaging ground penetrating radar is not yet publicly available.

Existing techniques for depth measurement therefore face a number of obstacles in shallow stream settings. These include difficulties in applying radiative transfer models because of shallow water–substrate light interactions, problems with measuring all the parameters required for such optical models, requirements for ground data at the time of image acquisition, depth ranges that are smaller than the resolving power of the instrument, and requirements for clear water. Development of techniques that can use existing optical sensors and historic data but do not require complex optical models or ground crews would therefore enable much broader applications of remote sensing to river analysis.
3. Model development and methods

3.1. The HAB-1 model: hydraulically assisted bathymetry using the channel shape approximation

The HAB-1 model combines gage measurements of discharge, slope from maps, and stream widths taken from imagery with discharge and velocity equations to estimate stream depths at cross-sections. These cross-sectional depth estimates are used to derive a regression relating depth to pixel reflectance. The regression model is then applied to the entire image to develop a map of depth for each pixel within the stream.

In order to estimate the average depth at a site, we use the discharge measurement along with standard equations and assumptions that relate discharge \( Q \) to depth and average velocity \( V \). The discharge equation states that

\[
Q = AV = WD_a V \quad (1)
\]

where \( A \) is the cross-section area (m\(^2\)), also equal to width \( W \) times the average depth \( D_a \). Average velocity (m/s) is classically estimated using the Manning equation:

\[
V = R^{2/3} S^{1/2} / n \quad (2)
\]

where \( R \) is the hydraulic radius (m), equal to \( A/P \), where \( P \) is the wetted perimeter of the cross-section (m), \( S \) is the longitudinal energy gradient of the flow (m/m), and \( n \) is hydraulic resistance. In most rivers, \( R \) can be approximated by the average depth \( D_a \) of the river (Graf, 1988) and the average energy gradient \( S \) at the reach scale can be accurately estimated using channel slope measured in the field or from contour maps. Determining the value of \( n \) is less straightforward; we refer the reader to Knighton (1998) for various estimation methods. In the high gradient Yellowstone setting, this study uses Jarrett’s (1984) equation to estimate \( n \):

\[
n = 0.325^{0.38} R^{-0.16} \quad (3)
\]

Jarrett’s equation has been shown by Marcus et al. (1992) to be the most accurate approach in mountain streams similar to those of Yellowstone where much of our analysis is centered. Substituting Eqs. (2) and (3) into Eq. (1) and assuming that \( R \) equals \( D_a \), we find

\[
Q = W(D_a^{1.83})(S^{0.12}) / 0.32 \quad (4)
\]

or rearranging terms

\[
D_a = \left( \frac{Q/(3.125WS^{0.12})}{0.55} \right)^{0.55} \quad (5)
\]

Average depth, \( D_a \), can thus be estimated based on ground measurements of discharge, slope measurements from maps, and width measurements from imagery. In addition, the maximum depth \( D_{max} \) at each cross-section can be estimated using Robison and Beschta’s (1989) finding that the frequency distribution of depths in cross-sections and triangles are similar (note that this is not to say that a cross-section looks like a triangle). Fonstad (2000 and subsequent work) has confirmed the triangle approximation in different mountain river settings, where

\[
D_{max} = 2D_a \quad (6)
\]

If fine resolution imagery is available for a “clear” water stream (i.e., the depth is less than the extinction depth of light), then the quantities estimated in Eqs. (5) and (6) can be correlated to brightness values on the image. Along each cross-section where width is measured, the \( D_a \) is correlated to the average image brightness, \( D_{min} \) to the minimum brightness value, and \( D_{max} \) to the maximum brightness. Although we have not estimated \( D_{min} \), we can make an assumption that \( D_{min} \) is equal to some arbitrarily low value such as 5 cm (sensitivity analyses indicate that the technique is relatively insensitive to variations in \( D_{min} \) between 0 and 10 cm). These three points can then be collected at multiple cross-sections to fit an equation defining the “depth-to-brightness” relationship for the stream. We suggest that the easiest way to get a representative sample of points on the “depth to brightness” graph is to collect cross-sectional measurements from locations with significantly different widths. The fitted function can be applied to the rest of the imagery to produce maps of depth for each pixel.

3.2. HAB-2: hydraulically assisted bathymetry using the Beer–Lambert approximation

In cases where the triangle approximation is not justified or where substituting \( D_a \) for \( R \) is inappropri-
ate, we propose an alternative HAB technique based on the Beer–Lambert law. The Beer–Lambert law describes the exponential absorption of light in water columns where scattering is minimal:

\[ I = I_0 e^{-\beta \cdot D} \]  

(7)

where \( e \) is the base of natural logs, \( I \) is the intensity of light at some depth, \( I_0 \) is the intensity of light immediately prior to entering the water column, \( \beta \) is a constant indicating the strength of absorption per unit depth, and \( D \) is the distance that the light passes through water (Denny, 2003). The \( \beta \) value is a diffuse attenuation coefficient that can be quantified in deep water using the light extinction depth measured with a secchi disk. However, shallow, clear water streams where the water is not deep or turbid enough for the secchi disk to reach an extinction depth require measurement of light intensity off an underwater target at two different depths. Generally, the diffuse attenuation coefficient cannot be directly measured for every pixel of an image, so the value of coefficient must be estimated or derived. In most images, intensity \( I \) is unknown for each pixel, so that the digital number (DN) is substituted into Eq. (7), and the distance of light passage is identified as the depth of water:

\[ DN = DN_0 e^{-\beta \cdot D}. \]  

(8)

To solve for depth, rearrange Eq. (8):

\[ D = \ln(DN/DN_0)/ - \beta. \]  

(9)

From a physical standpoint, the value \( DN_0 \) should be equal to the DN of the riverbed when it is not covered by any significant water depth (in other words, before it is acted on by the absorbing properties of the water). To estimate \( DN_0 \), the image analyst can either find the river cross-sectional pixel with the highest DN (hence, a very shallow depth) or use the DN value of the dry shore material adjacent to the river, as long as it is the same material that makes up the majority of the wetted riverbed pixels.

Unfortunately, in the absence of field measurements, \( \beta \) is initially unknown. However, we can select a seed value for \( \beta \) (for example, \( \beta = 1 \)) to determine how well it estimates the discharge, for which we do have a measured value. Using this seed value of \( \beta \) to estimate discharge is done by selecting a transect of DN values across a gaged stream and inserting the DN values into Eq. (9) to estimate depths at multiple points along the cross-section. These depth estimates are then combined to calculate the hydraulic radius and the cross-sectional area (equal to \( WD_a \)). Velocity can be derived from Eq. (2) coupled with slope measurements from maps and approximations of resistance. Finally, discharge can be calculated by multiplying the resultant cross-sectional area by the average velocity (Eq. (1)).

This initial estimate of discharge will not match the measured discharge because \( \beta \) was estimating by guessing a seed value. However, one can continue to guess various values of \( \beta \) and run the calculations until the computed discharge matches the measured discharge, at which point one has the correct \( \beta \) for this section of the stream in the general area of the cross-section used for the HAB-2 derivation. In practice, this can be accomplished in a spreadsheet by tallying the DN values, the distance between each pixel center, and the depth for each DN value calculated using Eq. (9) and the estimate of \( \beta \). Once these “incorrect” depths are computed, we can estimate the corresponding \( Q \) for the section by calculating \( A, R, V \) and Eq. (1). This process is then iterated with new values of \( \beta \) until the difference between the estimated \( Q \) and the measured \( Q \) equals zero. Many spreadsheets have this “goal-seeking” type of iteration as a built-in function.

Additional image cross-sections could be used to derive more estimates of \( \beta \), which can be averaged to determine a value that is most representative of the stream, or to apply the function where it is known that the turbidity of the water is different (for example, above and below a confluence). Once a final value for \( \beta \) has been determined, Eq. (9) can be applied to the DN values for the remainder of the stream to develop a bathymetric map.

4. Field areas, field data and associated imagery

4.1. Overview

We evaluated the HAB models in the Brazos River, Texas, and the Lamar River, Yellowstone National Park, Wyoming. These two locations provide significantly different stream environments in terms of depth, substrate, and turbulence. Field data and imagery ranging from aerial photographs to airborne hyperspectral to satellite images are available because
of ongoing remote sensing research at each location (Allen et al., 1989; Wright et al., 2000; Legleiter et al., 2002; Marcus, 2002; Marcus et al., 2002, 2003). Use of the two sites thus allows a comparison of model results in significantly different stream environments using different types of imagery.

4.2. The Brazos River, Texas

The Brazos River study reach is ~1 km downstream of Whitney Dam (Figs. 1 and 2) in a partially bedrock, partially alluvial section of the river. Historical ground and air photo evidence (Allen et al., 1989)
shows significant channel alluviation since the construction of the dam in the early 1950s. The channel is wide (>80 m) and shallow (generally <2 m). The hydraulic resistance, backcalculated from USGS discharge measurements (Conyers, 2003), was high, with an $n$-value of ~0.070. The channel slope is 0.0003 as measured from a 1:24,000, 10-ft contour map, a commonly used and reasonably accurate source for downstream slope estimates (Graf and Randall, 1997). The estimates of $n$ and slope are probably within 10% of their actual values, because $n$ was directly backcalculated and the slope measurement is from an area with an easily measured, long, gradual slope. At the time of image acquisition, the stream bottom was clearly visible. The substrate is predominantly cobbles with no plants, although small areas contain algal mats or small plants. Surface turbulence is slight. Overall, the aquatic optics were dominated by the absorption of light with increasing depth rather than by variations in turbidity, substrate, or turbulence, an ideal situation for applying the HAB methods.

Fine resolution (0.2-m resolution), three-band (red, green, blue) digital aerial photographs were acquired on 13 May 2002, and this imagery was later resampled to 1-m resolution. Atmospheric conditions during the flight were optically clear. The day after the flight, we collected 90 ground-based depth measurements from a 100-m reach. Measured stream depths ranged from 0.02 to 1.6 m. Prominent markers visible on the images were mapped using a laser rangefinder (which has approximately 0.5-m accuracy) and coregistered to the imagery. The overall accuracy of the match between imagery and field points is ±1 m. The discharge the day of the flight and the day of field depth measurements was approximately 30 cm.
4.3. The Lamar River, Wyoming

The 2-km study reach within the Lamar River, Wyoming (Fig. 3), is a complex stream environment relative to the Brazos River. The Lamar switches between single channel and braided (Fig. 4), with individual channels varying from 5 to 55 m in width at the time of data collection. Surface turbulence ranges from smooth surfaces in glides to white water in high gradient riffles. The substrate ranges from cobbles in high energy environments to sand in backwater eddy zones. Algae were sporadically present as bottom-attached mats throughout the stream. Surface water gradients vary over just a few meters, changing from relatively steep (0.02 to 0.04) in high gradient riffles to nearly flat in nearby pools and glides. Average bed slopes along the reach varied from 0.0029 to 0.0039 as determined from 1:24,000 USGS topographic maps with 20-ft contours; we used these average slopes in the HAB analysis. Jarrett’s approximation (Eq. (3)) was used to estimate values for the Manning’s $n$ measure of flow resistance.

Discharge was estimated using USGS gage data from the Lamar River below the study reach and Soda Butte Creek (Fig. 3). Discharge at the study reach upstream of the gage was estimated by subtracting the gaged Soda Butte discharge and the discharge for the ungauged portion of the basin estimated with a basin area approximation. Discharge in the study reach on 3 August 1999, the day of image acquisition, was 7.08 cm. Water conditions were clear throughout the study reach, and observers in the field could see to the stream bottom at all locations. Color printouts of the imagery were generated within 24 h of the flight, enabling the field crew to map depths directly to the images and coregister field data and imagery to within ±1 m. Within 10 days of image acquisition, 105 depth measurements were collected along the 2-km reach. Discharge did not vary significantly during that period. Measured depths ranged from 0.05 to 1.5 m. Imagery consisted of 1-m resolution, 128-band hyperspectral imagery collected with Earth Search Sciences Probe-1 sensor mounted on an A-Star Aerospatiale helicopter flying 600 m above the ground surface. Atmospheric conditions were clear at the time of flight.

Previous studies have shown that principal component (PC) bands derived from hyperspectral imagery generate the highest correlations between measured depths and imagery (Liceaga-Correa and Euan-Avila, 2002; Marcus et al., 2003). We therefore derived PC bands from the hyperspectral imagery by calculating the covariance for water portion of the image, then used these statistics to determine PC values for the stream. This approach enhanced the within-stream variations captured by the PC images. We also resampled the hyperspectral imagery in ENVI to simulate Thematic Mapper 5 (TM5) bandwidths, which provided a comparison to imagery with lower spectral resolution.

5. HAB results

5.1. The Brazos River, Texas

DN values were collected from 10 cross-sections on the Brazos image and used with the HAB-1 model
to develop depth-to-brightness graphs (Fig. 5). We focus on the results with the blue band because correlations of HAB-1 depth versus DN are strongest for this band ($R^2 = 0.76$). Each of the reported regression equation results is significant at the 0.01 level. The exponential function for this regression can then be used to estimate depths throughout the remainder of the stream.

Fig. 6 shows the depths estimated using the exponential equation compared to depths measured by the field team. The HAB-1 model captures the trend of variations in depth with DN ($R^2 = 0.51$), but depths shallower than 0.8 m are consistently underpredicted. Application of the HAB-2 model required estimating $D_{0}$ and $\beta$ values. The $D_{0}$ value was estimated by measuring the brightness of wetted sediments adjacent to the waterline at one of the image cross-sections used for the HAB-1 method. Using the same cross-section, we then reiterated Eq. (9) with different $\beta$ values until estimated discharge equalled the known stream discharge, which occurred at $\beta = 0.952$. The resulting HAB-2 equation for predicting depth was:

$$D = \frac{\ln(DN/202)}{-0.952}.$$  \hfill (10)

Fig. 6 shows the HAB-2 modeled depths relative to measured depths. The HAB-2 model generates much better depth estimates ($R^2 = 0.77$) than the HAB-1 model in the Brazos River.

5.2. The Lamar River, Wyoming

5.2.1. HAB-1 results

In the Lamar River, the HAB-1 model was used to estimate depths at 29 image cross-sections corresponding to locations where depth had been measured in the field. All cross-sections were located in areas where the river flowed through a single channel, thus avoiding inaccuracies in estimating discharges in braided channels. These training cross-sections were also placed where bed slope approximated valley slope to insure that gradients derived from topographic maps and used in the Manning equation were approximately correct. In particular, this meant that cross-sections could not be located at places with obvious rapids where slopes were significantly steeper than the local valley gradient. The minimum depth at each cross-section was set to 5 cm. Like the Brazos River results, each of the reported regression results is significant at the 0.01 level.

Central to the HAB-1 method is the regression between DN values and depths estimated from HAB-1 at the cross-sections; it is this regression that generates the depth estimates throughout the remainder of the river. In the Lamar River, the more extensive ground data and the hyperspectral and simulated TM5 imagery (Marcus, 2002; Marcus et al., 2003) allowed us to examine several approaches for relating band values to estimated depths that were not possible in the Brazos River. These approaches included (1) multiple regression with principal component (PC) values; (2) multiple regression with TM5 bands; and
(3) Evaluation of HAB-1 depth estimates in different types of stream habitats.

The multiple regression of PC values versus HAB-1 estimated depths at the 29 cross-sections produced the equation:

$$D = 0.47 - (0.0047 \cdot \text{PC}4) - (0.0062 \cdot \text{PC}5)$$

(11)

where depth is in m and $R^2 = 0.78$. When this equation was used to estimate depths at the 105 measured depth locations, however, the $R^2$ value between measured and observed values fell to 0.22 (Fig. 7).

The HAB-1 model was used with the simulated TM5 imagery at both the original Probe-1 11-bit resolution and at resampled 8-bit resolution. The depth prediction equation relating HAB-1 estimated depths to DN values for the 11-bit imagery was:

$$D = 1.28 - (0.01035 \cdot \text{band}3) + (0.0059 \cdot \text{band}2)$$

(12)

where the $R^2 = 0.70$. Although significant at the 0.01 level, addition of the green band (band 2) only increased the $R^2$ for the stepwise regression from 0.69 to 0.70. Only the red band entered the stepwise regression for the 8-bit imagery, which generated a depth prediction equation:

$$D = 1.67 - (0.109 \cdot \text{band}3)$$

(13)

that has an $R^2 = 0.70$. Although the correlation value between HAB-1 estimated depths and DN values was not as high for the simulated TM5 ($R^2 = 0.70$) image as for the PC bands ($R^2 = 0.78$), the TM5-based equations for predicting depths produced better overall results when estimated depths were compared to observed depths (Fig. 8). The linear patterns on Fig. 8B reflect the small range of DN values within the low reflectance stream environment for 8-bit data.

Work by Marcus et al. (2003) showed that correlations between measured depths and DN values improve if the data are segregated by in-stream habitats (e.g., riffles, pools). We therefore segregated the data into three habitat types that could be identified visually on the imagery: (1) rough water, identified by the variable texture of the stream surface and local patches of brighter reflectance; (2) smooth water, as indicated by relatively constant reflectance; and (3) eddy drop zones, indicated by position downstream of obstacles. Because these features could be identified on the image, their use is representative of what a user...
could accomplish with historical data or without ground data. Spectral classification of specific habitat units from imagery would be less subjective, but there are currently few simple algorithms to achieve such stratification in an automated way. Some of the image-based identifications of rough versus smooth were questionable, a topic that is discussed later.

Segregating the stream into different habitats increases the $R^2$ from 0.34 for all sites to 0.40 for smooth water and 0.46 for rough water, but decreases the $R^2$ to 0.22 for eddy drop zones (Fig. 9). Beyond the improved $R^2$, the HAB-1 model appears to do a better job of capturing the absolute trend in measured depths, as indicated by slope of the regression line approaching 1.0 for smooth water and the $y$-intercept approaching 0.0 for smooth and rough water.

To apply the HAB-2 model, we estimated the DN0 value by selecting the highest DN value from among the 29 image cross-sections on the TM5, 11-bit, band 3 image. This brightest DN value was assumed to represent DN0; i.e., the shallowest water captured by the imagery. Calculations of $\beta$ for all 29 cross-sections demonstrated values ranging from 1.023 to 1.757, with the majority of values falling within ±0.20 of the average of 1.327. Using the average value of $\beta$, the HAB-2 model generates a depth prediction equation of:

$$D = \ln(\text{band3}/363)/ - 1.327.$$  \hspace{1cm} (14)

Application of this equation to estimate depths at the 105 validation points produced an $R^2$ of 0.26, lower than the overall results achieved with the HAB-1 analysis. This is in contrast to the Brazos River, where the HAB-2 model performed notably better than HAB-1 (Fig. 6).

6. Discussion

6.1. Performance of the HAB approaches

Based on the statistical comparisons of measured depths to estimated depths, the HAB models generated $R^2$ values of 0.77 for HAB-2 and 0.51 for HAB-1 in the Brazos River (Fig. 6). The Lamar River $R^2$ values were lower, ranging from 0.34 for HAB-1 (Fig. 8) to 0.26 for HAB-2 when using simulated TM5 imagery. We believe, however, that the $R^2$ values are poor indicators of the utility of the technique in the Lamar River and elsewhere. Slopes for regressions of measured versus HAB-estimated depths ranged from 0.79 to 1.0 and $y$ intercepts ranged from 3 to 10 cm, indicating that the technique approximates the overall trend in actual depths. The HAB models also generate
bathymetry and cross-sections consistent with normal stream geomorphology and our personal knowledge of the streams. Fig. 10, for example, shows a portion of the original image of the Brazos River and the HAB-2 depth estimates for this section. The HAB map fits with the classic model of asymmetric river deepening in meander bends and shallowing in wide stream areas.

Likewise, Fig. 11 is a bathymetric map of the Lamar River derived using HAB-1 with PC bands 4 and 5. The map provides depth measurements for 19,110 pixels along the 2-km reach. Given the relatively low $R^2$ value (0.22) for measured versus estimated depths, one is faced with the question of how far to trust this HAB-1 bathymetric map. Examination of the geomorphic patterns portrayed by the map helps provide an answer. Depths vary in the continuous manner typical of alluvial channels, avoiding abrupt jumps that would indicate instability in the model. Deep sections are along the outside corners of bends, in areas of convergent flow, or upstream of wood jams — all areas where channel scour occurs and which...
field teams observed to be deep. Likewise, the stream is shallow where flow diverges and the channel widens. Winterbottom and Gilvear (1997) noted similar results using stepwise regression to estimate depths, stating that their $R^2$ values of 0.55 for estimated versus measured depths did not reflect the power of the technique, which generated cross-sections that were remarkably similar to measured ones.

The HAB depth maps do, however, present problems. Depths typically fall within a ±15-cm error range which may be unacceptable for some applications. In the Lamar River, the HAB models also generated nonsensical “negative” depths in shallow water pixels which had high reflectance values (Fig. 12). Although the negative values only represent a small portion of the total number of mapped pixels, errors of this sort indicate the need to manually check HAB model results. Visual analysis of the Lamar depths maps clearly show that all the negative depth locations occur along channel margins or in shallow side channels where cobbles protrude above the surface (Fig. 12B).

HAB-estimated depths for individual pixels will thus be less accurate than field measurements on average, but a major purpose of the HAB approach is to estimate depths where field data are not available. Even in situations where estimates of slope and $n$ are grossly in error, sensitivity analysis of HAB shows that the effect on the errors of estimated depth are only in the range of 10% to 20%. In using HAB, one is giving up local accuracy, although one is generating measurements that are generally within ±15 cm (Fig. 8) and provide a more comprehensive, synoptic view of the river bathymetry.

Fig. 12. (A) Comparison of depths in the Lamar River estimated with HAB-1 and HAB-2 algorithms using the red band from simulated TM5 11-bit imagery. The “negative” depths represent shallow areas, generally less than 5 cm in depth and containing mixed pixels of both subaerial and subaqueous materials. (B) The locations of the negative depths were always in shallow side channels or along channel margins, as is typified by the gray pixels in this image from a small portion of the study reach.
The HAB map thus provides a better overall portrait of the fluvial system than can be achieved with ground surveys, at only a fraction of the total work and cost.

6.2. HAB-1 or HAB-2?

Based on $R^2$ values alone, our tests demonstrated that HAB-1 produced better depth estimates than HAB-2 in the Lamar River, but that HAB-2 produced better estimates in the Brazos River. Model results, however, varied with water depth in both settings. In the Lamar River, for example, the HAB-1 generated higher depth estimates than HAB-2 at depths greater than 0.2 m, but lower estimates in very shallow water (Fig. 12A). In both the Brazos and the Lamar Rivers, HAB-1 depth estimates were generally greater in deep water, while HAB-2 generated higher depth estimates in shallow water (Fig. 13). Possible reasons for these consistent variations are discussed further in following sections on spectral and hydraulic sources of variability in HAB depth estimates. Regardless of the source(s) of variability, our results do not provide clear guidance on which technique to use in a particular situation.

The most reliable way to determine which model to use would be to measure cross-sections, resistance, slope, and absorbance coefficients at the time of a flight, allowing a direct measure of the correlation between HAB-1 and HAB-2 estimates and actual water depths. Because ground data are generally not available, however, this validation approach is not an option for many applications. Alternatively, measurements of channel geometry can be made before or after a flight to assess the validity of the variables in

![Brazos River](image1)

![Lamar River](image2)

Fig. 13. Difference maps for portions of the Brazos and Lamar Rivers derived by subtracting HAB-2 from HAB-1 depth maps. Channel areas in light gray indicate HAB-2 > HAB-1 by more than 25 cm. Channel areas in black are where HAB-1 > HAB-2 by more than 25 cm. The portion of the Lamar River shown above had the poorest correspondence between HAB-1 and HAB-2 of any segment of the river.
the HAB equations, which should remain approximately constant over time if significant channel changes have not occurred.

The user may also wish to choose one approach over the other for reasons related to the form of the models. HAB-1, for example, works with multiple bands entered into a stepwise regression; while HAB-2 can only use one band at a time. The HAB-2 technique is slightly more sensitive to estimates of Manning’s $n$ and slope, but has an underpinning in optical theory that HAB-1 lacks. As a starting point, we suggest that if a stream’s cross-sections are known to fit a certain shape approximation (e.g., a distribution of cross-section depths similar to that of a triangle), HAB-1 is likely to be more reliable; otherwise HAB-2 provides a more robust approach.

6.3. Choice of spectral range and radiometric resolution

HAB could, in principle, be applied to any spectral band. The decision of which band or band combination to use is likely to be depth-dependant. Bryant and Gilvear (1999) had best results with red bands plus one IR band (0.91–1.05 μm), our Lamar River results were best with red and green bands combined, and the generally deeper Brazos River worked best with blue band. In general terms, the best band will probably have an attenuation depth approximately equal to the maximum water depth, thus generating a strong reflected signal at the surface, a near zero signal in the deepest water, and capturing variations across the full range of depths. However, if that same band(s) are strongly affected by surface turbulence, substrate, or organic material, other bands might provide better indicators of depth variations.

Use of PCA bands is an alternative to using just one band to drive the model. PC bands have the potential to compress useful depth information into a small number of bands, while isolating non-depth related signals into other bands. Our results, however, indicate that PC bands are not necessarily best for the HAB model, so we recommend caution in applying this technique.

A ratio-based technique could possibly highlight depth variations while suppressing variations in substrate and turbulence. However, bands close to one another in spectral range will have small differences in absorption coefficients, so we suspect choosing bands separated by at least 10 nm (e.g., red/blue or IR/green band ratios) will be most effective at maximizing differences due to depth. Legleiter et al. (2004) showed that a simple green/red band ratio was highly effective in highlighting depth variance while suppressing other optical signals from streams, and should be effective in conjunction with the HAB principle.

Alternatively, one could use multiple bands to generate multiple HAB estimations for a single image. Variations between the two (or more) HAB maps might be indicators of non-depth signals and provide an indication of variations in bottom composition, surface turbulence, or suspended material. In this case, HAB depth estimates could serve as a baseline reference that can be used to “subtract” the depth signal from the image, thus isolating the other, components that do not co-vary with depth.

The 11-bit resolution imagery performed significantly better than the 8-bit imagery (Fig. 8). The low reflectance from water meant that DN brightnesses were compressed into nine integer values on an 8-bit scale. This in turn forced depths into nine categories, thus missing the continuous variations in depth that are better shown with 11-bit resolution. Given the low reflectance of water and the potential for the signal to be compressed into a small range, higher radiometric resolution will usually significantly improve the accuracy of HAB estimates.

6.4. Hydraulic sources of variability in HAB depth estimates

In simple terms, the HAB approach estimates water depths using classical hydraulic equations of discharge and flow velocity, then correlates estimated water depth to image brightness. Factors that can throw off the estimates of depth include the applicability of Manning’s equation, the estimates of slope and resistance, the accuracy of the “known” discharge at the places used for HAB calibration, and the triangle shape approximation used for HAB-1. In particular, resistance is difficult to quantify and can lead to systematic over- or underpredictions. Ideally, one could estimate flow resistance from measurements at the site, but this requires field crews and negates many of the advantages of the HAB approach. The problem of estimating resistance, however, is ubiquitous to
Hydrology and use of Jarrett’s approximation in mountain systems is widely accepted (Marcus et al., 1992). Errors in HAB estimates from inaccuracies in resistance are therefore similar to errors in field-based flood prediction and paleoflow techniques that require estimates of resistance. HAB errors from resistance are thus within accepted ranges for standard hydrologic practice.

Inaccuracies in flow resistance estimates may have particularly affected HAB-2 estimates in the Lamar River, which displayed a systematic positive relationship of $\beta$ with width at the 29 cross-sections (Fig 14). Although we cannot definitely state why $\beta$ varies with width in this manner, it is likely an artifact of errors in flow resistance values. The wide cross-sections in the Lamar were also the shallowest. Shallow flows create higher resistance for a given discharge because of the increased interaction of the substrate and water column (Limerinos, 1970). Jarrett’s equation was developed for higher magnitude flows and may have underestimated resistance at the shallow cross-sections. This, in turn, would lead to underestimates of flow depth for a given discharge, thus generating higher estimates of $\beta$.

Alternative equations for estimating flow resistance might generate more consistent estimates of $\beta$ in this setting, but these alternative approaches require sediment size data not readily available from the optical imagery.

Errors due to discharge measurements will vary with proximity to the gage and the gage’s accuracy. Assuming there are no tributaries or diversions between the gage and study site, the study reach discharge will generally be similar to that at the gage. Even when tributaries enter the stream, standard methods of determining basin area-discharge relations can provide discharge estimates for ungaged portions of the basin. Like errors in resistance estimates, errors in HAB from discharge estimates will be within accepted ranges for standard hydrologic practice.

The assumption that depth distributions are similar to that of a triangle will also be incorrect in some settings. HAB-1 errors from the triangle approximation will probably be systematic, because channel geometry deviations from this approximation are generally systematic (Robison and Beschta, 1989). The triangle approximation is probably the reason for the systematic underestimation of mid-range depths by the HAB-1 model in the Brazos channel (Fig. 6), which is more “box-like” than “triangle-like” in its depth distribution. As with the resistance estimates, field observations are the obvious approach for determining the best shape approximation. In the absence of a clear rationale for choosing a certain shape distribution, the HAB-1 approach may be inappropriate.

6.5. Spectral sources of variability in HAB depth estimates

Errors in the HAB estimates can be generated by variations in turbulence, water clarity, and substrate that alter the relation between depth and image brightness. The single greatest constraint in applying the HAB techniques is that the channel bottom must be visible. If the light reaching the sensor from the river is composed entirely of path or surface radiance, as occurs in rivers with high turbidity or where depths exceed the absorption length for solar radiation, then river depths cannot be extracted with HAB. This knowledge is generally not known a priori, so the image analyst must decide whether or not the bottom is visible before HAB is used. In the absence of field observations, a simple approach is for the image analyst to look at the brightness values to decide if their spatial pattern match those expected in a river (e.g., darker near the channel center, brighter near shore, etc.). Alternatively, water quality data from nearby USGS discharge stations could provide an indicator of water clarity. These concerns did not apply in the Brazos and Lamar Rivers, where the water was clear and the channel bottoms could be seen.
One can minimize non-depth-related sources of spectral variability by choosing a band that maximizes the depth-to-brightness correlation, as we did in using the blue band reflectance in the Brazos and red band in the Lamar. One can also segregate the water into habitat types, as we did in the Lamar River (Fig. 9). This had the effect of improving overall depth estimates in most of the stream, with the exception of eddy drops zones. The poor performance of the HAB-1 technique in eddy drop zones is consistent with the highly variable nature of these local habitats. Eddy drop zones contain a wide range of substrates and organic litter and experience more shadow because of their locations near in-stream obstacles. This wide range of variability means that depth may not be the dominant factor controlling variations in brightness in these settings.

Other alternatives for reducing the non-depth related component of the reflectance might include band ratios, low pass filters to minimize the effects of pixel scale variations in substrate and turbulence, or further investigation of PC bands. However, neither a 3-by-3 low pass filter nor PC bands produced depth estimates in the Lamar River that were as good as those using just the red band DN values, suggesting that simpler may be better. Ideally, however, a model could be developed that allowed discrimination and mapping of all the key physical characteristics, including depth, substrate, algae, turbidity, and turbulence.

As just one example, the $\beta$ value for radiometrically corrected images is effectively twice the value of $k$, the diffuse attenuation coefficient. Work by Hedley and Mumby (2003) shows that when $k$ is known, a clear, shallow water bathymetry signal can be separated from the heterogeneous substrate signal through a modified linear unmixing algorithm. Coupled with HAB-2, such a procedure might produce bathymetric and substrate maps for modern and historical imagery. Substrate and depth maps might in turn be used to extract better estimates of resistance, which could in turn improve the HAB estimates of bathymetry.

Finally, the HAB techniques can be confused by shadows that make the channel look deeper than it actually is. Separation of shadow from water is difficult and we recommend avoiding areas with a large shadow component when using HAB. The HAB techniques will not also work in areas where the aerial view of the river is obstructed by trees.

6.6. Potential applications

The HAB techniques potentially increase the temporal and spatial scope of available data on depth variations in streams. It is notable that in a contemporaneous, independent study in another setting, Carbonneau et al. (in press) developed a depth estimation technique using the Beer-Lambert law that achieved accuracies similar to the HAB-2 results, indicating that such approaches will be widely applicable. Furthermore, Winterbottom and Gilvear (1997) found high correlations between water depths and black and white imagery. This suggests that HAB could be used to create bathymetric maps of rivers as early as the 1930s when widespread collection of aerial imagery began (Quackenbush et al., 1960). Given the grainy appearance and poor preservation of many of the photos, one would have to use caution in using the depth maps. At a minimum, however, the HAB maps could provide estimates of relative depth changes along the river at a given time and possibly indicate directions of depth change (i.e., entrenching or shallowing) over time. In some locales, the estimates could be validated using cross-sectional data from discharge gages. The accuracy of historical HAB depth maps should increase in later years with the addition of widespread color photography in the 1960s.

In addition, satellite images now have sufficient spatial resolution to view small rivers and streams, while also being large enough in spatial extent to map complete watersheds. In particular, both IKONOS and QuickBird have spatial resolutions that enable HAB estimates of stream bathymetry. Fig. 15 shows a depth map and channel cross-sections for Soda Butte Creek developed by applying the HAB-1 model to IKONOS 1-m panchromatic imagery which was resampled with a 3 by 3 low pass filter to remove local noise. The cross-sections highlight fine-scale fluvial landforms, clearly picking up the upstream development (cross-section 2), emergence (section 3), and submergence (section 4) of an in-channel bar. Although we have no ground data for validation, the HAB-estimated depths and fluvial features are consistent with our experiences in the reach. HAB depth estimation using space-
borne imagers such as IKONOS may be limited by the very low radiance values normally produced from rivers, and by the limited radiometric resolution of these instruments. However, the stable and global nature of such spaceborne platforms potentially makes them very useful to stream mapping worldwide. Furthermore, even if field data were available, it would be nearly impossible to survey ground-based maps that provide both the broad area coverage and the resolution that the 1-m IKONOS image provided.

Of course, HAB estimates (or any other spectrally driven measures of stream depth) only provide below-water depths. Above-water elevations or water surface elevations cannot be modeled by HAB. Classical photogrammetry, lidar, or radar interferometry can be used to map above-water elevations, and these could be used in combination with HAB to produce fully three-dimensional river maps of the fluvial–riparian environment. These three-dimensional maps would be of enormous utility in modeling hydrologic, hydraulic, and geomorphic features, for monitoring aquatic and riparian habitats, and for assessing flood hazard. In particular, two-dimensional models of hydraulic behavior, such as finite-element (Waddle et al., 2000) or cellular automata (Thomas and Nicholas, 2002) models, require exactly the kind of synoptic elevation coverage generated by these remote sensing methods. If other hydrologically important variables such as water slope, velocity, sediment size, and stream power can be remotely sensed, then the rapid assessment of entire fluvial systems becomes feasible.

7. Conclusions

The HAB models generate stream depth maps using remote sensing data, ground data from discharge stations and contour maps, and the discharge equation and Manning's equation. By iteratively applying these equations and values to imaged stream pixels, the values of these pixels can be scaled until discharge estimates across an imaged stream cross-section match that of a nearby gage recording. Testing of the HAB models in the Brazos River, Texas, and the Lamar River, Wyoming, indicate that the models work with airborne multispectral, airborne hyperspectral, and IKONOS satellite imagery. Although the accuracy of these methods varies between streams, the synoptic maps of stream environments are useful for characterizing stream depths. In addition, an advantage of the HAB technique over other sensor-based techniques for depth detection (e.g., radar) is that it can be used with historical imagery, making it possible to document three-dimensional changes in rivers.

The models will not work, however, when the stream is obstructed by trees or clouds, heavily shadowed, or turbid. Errors in HAB depth estimates can be generated by inaccuracies in the variable components of the models, especially flow resistance and slope. Additionally, errors can be generated by non-depth related changes in image brightness caused by

![Image of a depth map and cross-sections of Soda Butte Creek, WY, developed by applying the HAB-1 model to IKONOS imagery from 7 August 2001.](image-url)
variations in illumination angle, substrate, algae, turbidity, and turbulence. The HAB models could be significantly improved through the development of remote sensing approaches that either normalize for these factors or provide direct measurements of all the variables contributing to brightness variations.

Acknowledgements

We would like to thank Mindy Conyers for developing and running sensitivity analyses of HAB in various Texas river conditions. Model development and analysis were supported through the EPA Science to Achieve Results (STAR) program. Imagery and field data collection for the Brazos River, Texas, were funded by a faculty research enhancement grant from Texas State University. Hyperspectral imagery and field data collection for the Lamar River, Wyoming, were supported by the NASA Earth Observations Commercial Applications (EOCAP) program at Stennis Space Flight Center. IKONOS imagery was provided courtesy of the Yellowstone Ecological Research Center and Dr. Robert Crabtree, who also provided logistical field support. Carl Legleiter, Jim Rasmussen, and Robert Ahl collected the field data for the Lamar River. Derek Wu and David Jordan collected ground-truth data for the Brazos River, Texas. Six reviewers provided input that significantly improved the manuscript.

References


Carbonneau, P.E., Lane, S.N., Bergeron, N., in press. Feature based image processing methods applied to bathymetric measurements from airborne remote sensing in fluvial environments. Earth Surface Processes and Landforms.


Lane, S.N., Hardy, R.J., Elliott, L., Ingham, D.B., 2002. High resolution numerical modelling of three-dimensional flows...
over complex river bed topography. Hydrological Processes 16 (11), 2261–2272.


