

# Mapping of stream microhabitats with high spatial resolution hyperspectral imagery

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**Abstract.** Maximum likelihood supervised classifications with 1-m 128 band hyperspectral data accurately map in-stream habitats in the Lamar River, Wyoming with producer's accuracies of 91% for pools, 87% for glides, 76% for riffles, and 85% for eddy drop zones. Coarser resolution 5-m hyperspectral data and 1-m simulated multiband imagery yield lower accuracies that are unacceptable for inventory and analysis. Both high spatial resolution and hyperspectral coverage are therefore necessary to map microhabitats in the study area. In many instances, the high spatial resolution hyperspectral (HSRH) imagery appears to map the stream habitats with greater accuracy than our ground-based surveys, thus challenging classical approaches used for accuracy assessment in remote sensing.

**Key words:** Streams, habitats, hyperspectral, resolution, mapping, remote sensing

**JEL classification:** C63, C80, C93

## 1 Introduction

Mapping in-stream habitats such as riffles and pools has widespread applications for fisheries and wildlife management (Gorman and Karr 1978; Orth and Maughan 1983; Richards et al. 1997), stratification of streams for environmental sampling (Ladd et al. 1998), prediction of river change (Rosgen 1996), and inventory and assessment of channel change and human impacts

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(Gilvear et al. 1995). The use of ground-based surveys to map stream features can be prohibitively expensive and time consuming, however, especially when carried out at watershed scales or on multiple dates to document change over time. If these stream features could be accurately mapped using remotely sensed imagery, it would generate significant time and cost savings and improve spatial and temporal data coverage of stream systems.

This article evaluates the ability of high spatial resolution, hyperspectral (HSRH) imagery to map in-stream habitats. Specifically, I test the ability of 1-m and 5-m resolution 128 band Probel imagery to map microhabitats using a modified Bisson et al. (1982) classification scheme which is widely used by federal resource management agencies. In addition, I resample the imagery to test the ability of simulated 1-m and 5-m resolution TM5 and SPOT4 multiband sensors to map the same habitats.

Classifications in this article are developed using standard maximum likelihood classification approaches available with all commercially available remote sensing software, although I conduct the analysis on the principal component images rather than on the raw reflectance data. Results from this article thus provide examples of classical non-spatial, spectral classifications results which can be compared to the spatially explicit approaches used on the same and similar data sets in this special issue (Maruca and Jacquez; Goovearts; Griffith; Lagona; all this issue).

## 2 Previous research

Remotely sensed images have been used since the 1930s to map stream features, although the overwhelming majority of these projects have used framing cameras with film to map the planform of rivers (particularly width and sinuosity), changes in channel location, or floodplain extent. More recent studies have examined the utility of digital remote sensing for stream mapping, but have generally focused on large river systems or large features which can be detected by coarse resolution satellite data (e.g., Jacobberger 1988; Mertes et al. 1993; Nellis et al. 1998). Compared to air photo coverage, satellite-based monitoring of these coarse spatial resolution stream features covers wider areas, has superior temporal coverage, and provides a digital data base more readily utilized with GIS and other computer-based software (Muller et al. 1993).

In contrast, relatively little research has evaluated the use of remote sensing to map finer scale, in-stream features like riffles and pools, largely because of logistical constraints. Prior to this time, fine resolution digital remote sensing has required airborne platforms, but there have been relatively few digital imaging devices mounted on aircraft, which in turn has limited applications. Some of these digital monitors offer little spectral information beyond that of infrared film and thus fail to offer research opportunities beyond what could already be accessed by scanning air photos. Monitors with more bands have been limited historically to relatively coarse spatial resolutions due to inflexible scan speeds or mounts on high altitude aircraft. Only in the last few years have hyperspectral instruments such as AVIRIS, Probe1, and HyMap been mounted on aircraft that can fly at lower elevations, making possible the acquisition of the 2–5 m resolution imagery most useful for detecting in-stream features in 5th order and smaller streams.

The few existing studies on digital remote mapping of in-stream habitat features have therefore scanned aerial photos for input to remote sensing software, or have collected multiband digital images that do not provide a great deal more information than scanned infrared photos. Gilvear et al. (1995) used scanned panchromatic photos with approximately 1-m resolution to map runs, glides, riffles, and gravel bars before and after mining in Alaska. Multispectral 0.25–3.0 m imagery worked well in the Green River of Utah for separating pools, eddies, runs, and relative depths (Hardy et al. 1994). Both Gilvear et al. and Hardy et al. demonstrated the utility and potential for remote sensing of in-stream features, but did not carry out quantitative error assessment of their classifications.

When quantitative accuracy assessments of habitat classifications have been carried out, the results have been less than promising. Wright et al. (2000) used 1-m four band digital imagery to map in-stream habitats in the same watershed as the study reported in this article. They were only able to obtain overall classification accuracies ranging from 10–53% due to difficulties in precisely coregistering field maps to fine resolution imagery and inadequate spectral differentiation of classes. Marcus et al. (2002) encountered similar coregistration and spectral resolution problems in trying to map woody debris with the same 1 m imagery used by Wright et al. (2000), achieving maximum accuracies of only 42%. Both Wright et al. and Marcus et al. recommended evaluating the use of hyperspectral imagery to identify key stream features, thus laying the groundwork for this article.

### 3 Field area

Field data and remote sensing imagery were collected from a 2-km reach of the Lamar River, Wyoming, immediately upstream of its confluence with Soda Butte Creek (Fig. 1, Jacquez et al. in this issue). The Lamar River at this location has a braided channel displaying a wide variety of in-stream habitat types. Depths range from zero near many shorelines to 1.6-m in the deeper pools. Substrate sizes generally range from coarse gravels to cobbles, although sand dominates in small pockets (generally  $< 25 \text{ m}^2$ ) in backwater circulation areas or at the toes of emergent bars.

One meter and 5-m hyperspectral data were collected on August 3 and August 25, 1999, respectively. Based on U.S.G.S. gage records farther downstream, I estimate average daily discharges in the study reach were approximately 250 cfs on August 3, and 150 cfs on August 25, 1999. The changes in water level did not alter in-stream habitats (e.g., cause a glide to become a riffle due to changing water levels), although they did narrow the channel and reduce depths in some braids. The water was clear when imagery was flown and no channel changing or sediment mobilizing events occurred in August. There is very little overhanging vegetation or woody debris to obscure views of the river from the airborne platforms.

### 4 Methods

Hyperspectral imagery was collected with the Probel sensor, a cross track scanner operated by Earth Search Systems, Inc. The Probel sensor has

128 bands with 12–16 nm spectral resolution, ranging from 420–2543 nm. The 1-m resolution August 3 data were collected by mounting the sensor on an A-Star Aerospaiale helicopter that flew at approximately 600-m about the ground surface. Problems resulting from this previously untried approach are detailed in Aspinall et al. (this volume). The 5-m data were collected from a twin engine, fixed wing Cessna 320.

The 1-m hyperspectral data were downloaded the day of collection to generate color prints. These true color prints provided base “photos” for field mapping the stream habitats. Because map boundaries were drawn directly on the imagery, the 1-m field maps were precisely coregistered to the imagery.

Mapped habitat types were based on a modified Bisson et al. (1982) scheme. Units mapped in the Lamar River were:

- (1) eddy drop zones, which are areas of low surface turbulence where backwater circulation deposits fine grained sediments;
- (2) glides, which are areas of shallow, smooth flow with coarse gravel substrates;
- (3) runs, which are similar to glides but generally deeper and slightly more turbulent;
- (4) rough water runs, which are identical to runs but have more surface turbulence;
- (5) low gradient riffles, which are usually shallow, display significant surface riffles, and have slopes of 1–2% in the study area;
- (6) high gradient riffles, which display significant white water and typically have slopes of 2–4% in the study area; and
- (7) pools, which display little surface disturbance and usually have depths of 0.7 m or more.

All units were mapped by the same survey team to maintain consistency of unit identification throughout the study reach. The entirety of the Lamar River image was surveyed with the exception of the upper and lower 100–200-m where the spectral signal was severely compromised by bi-directional reflectance. Because of spectral and environmental similarities among classes, the rough water runs and runs were later merged with the glide category, and both high and low gradient riffles were merged into one riffle category for analysis with the 5-m data.

Field maps were manually digitized to the 1-m and 5-m images. Before classification, a two pixel buffer was removed from the edges of all units (e.g., the outside edges of all riffles) on the 1-m imagery and a one pixel buffer on the 5-m imagery. This reduced the amount of transitional area where class types were indistinct and removed minor location errors resulting from manually digitizing the unit boundaries.

To classify the morphologic units on the 1-m imagery, 129 training sites were randomly chosen from within each unit type, which is the minimal number of training sites required to conduct supervised classification with 128 bands. The 129 training sites per category exceeds standard minimum requirements for remote sensing accuracy assessment (Congalton and Green 1999).

The smaller number of in-stream pixels on the 5-m imagery limited the number of training sites. Fifty training pixels were used for glides, 30 for

riffles, and 16 each for eddy drop zones and pools. This number of training sites allowed at least half of the pixels in each class to be used for validation of the classifications.

The hyperspectral data were not atmospherically corrected. This is because the aircraft were flying at low altitudes, thus minimizing atmospheric effects, and because the standard atmospheric correction algorithms degrade signal to noise ratios over water surfaces.

The spectral resampling tool in ENVI provided simulated TM5 and SPOT4 imagery. The resampling process applies appropriate spectral sensitivity curves to the spectra covered by TM5 and SPOT4 to simulate the spectral responses of these sensors. The resampling does not, however, add noise to the image to simulate the lower signal to noise ratio of the TM5 and SPOT4 sensors relative to probe1.

Initial analyses using ENVI software indicated that the best classification results were generated by using principal component images rather than the raw data or other transformations. This is a common result with hyperspectral imagery, because the principal components isolate clear signals that cross multiple spectral bands, while also removing the noise component within those spectral bands. Principal components were calculated using the non-normalized covariance matrix for the stream with all other features masked out, thus enhancing the within-stream variance. Maximum likelihood supervised classification in ENVI followed standard procedures (Richards 1994), as did accuracy assessment with error matrices (Congalton and Green 1999). All the training sites were removed from the data set before evaluating the accuracy of classifications.

## 5 Results

Sensitivity analysis indicates that the best 1-m classifications result from using the first 25 principal component bands (Fig. 1a). The kappa statistic and overall accuracy for the 5-m data also increase with increasing numbers of principal components, but this “improvement” is brought at the cost of placing most pixels in the glides and riffle categories, while eliminating all pools and most eddy drop zones (Fig. 1b). From an environmental monitoring perspective, the best classification occurs when pools and eddy drop zones are detected, even if this leads to a somewhat larger number of riffle and glide pixels being misclassified. The following accuracy analysis therefore shows results for the 5-m data where the first 8 principal component bands are used for maximum likelihood classification.

Table 1 presents classification accuracies for the seven morphologic unit classes using the 1-m hyperspectral imagery. Glides, runs, and rough water runs are commonly confused by the classification algorithm, as are high gradient riffles and low gradient riffles. Most ground-based stream classifications only differentiate between glides, riffles, pools, and eddy drop zones, however, so I merged the seven stream habitats into these four categories, which resulted in significantly improved classification accuracies (Table 2). Table 3 presents the accuracy results for the 5-m hyperspectral data using the first 8 principal component bands.

The hyperspectral data were spectrally resampled in ENVI to generate simulated 1-m and 5-m SPOT4 and TM5 imagery. Table 4 compares

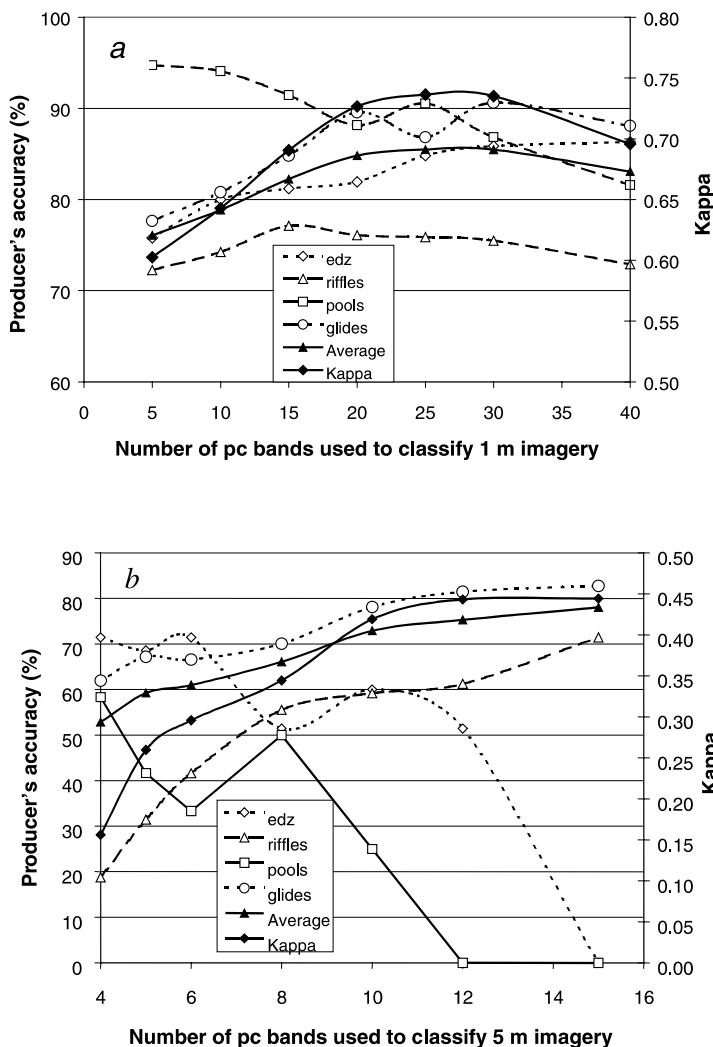


Fig. 1. Sensitivity analysis of variations in accuracy as a function of number of principal component bands included in the classification of glides, riffles, pools and eddy drop zones

accuracies of the simulated multiband and hyperspectral data at spatial resolutions of 1-m and 5-m.

## 6 Discussion

### 6.1 Classification accuracies with 1-m hyperspectral imagery

When all seven in-stream habitats are classified using the 1-m hyperspectral imagery, overall accuracy is 75%, with producer's accuracies ranging from 73% for rough water runs to 86% for eddy drop zones (Table1). Units that

are most commonly confused are high gradient riffles with low gradient riffles, and runs with rough water runs and glides. Merging the runs, rough water runs, and glides into one unit called glides, and the high and low gradient riffles into one riffle unit is more typical of how most habitat mapping occurs and improves overall classification results by 10% for the 1-m hyperspectral imagery (Tables 1 and 2).

The fact that some misclassification is occurring is further borne out by Fig. 2, which compares measured depths within units mapped by the field team to depths at the same locations within units as classified by the imagery. The field surveys were relatively consistent in differentiating pools, glides, and riffles on the basis of depth, although a 1.5 m deep point was mistakenly

**Table 1.** Error matrix for maximum likelihood supervised classification of seven in-stream habitat types using 1-m imagery and principal components 1 through 25. The data points used to classify the image are not included in the accuracy assessment

Classified pixels	Ground truth pixels							
	Eddy drop zone	High gradient riffle	Low gradient riffle	Pools	Rough water runs	Runs	Glides	Total
Eddy drop zone	<b>574</b>	120	8	2	7	10	149	870
High gradient riffle	12	<b>1458</b>	179	1	12	29	89	1780
Low gradient riffle	15	299	<b>1129</b>	12	0	14	128	1597
Pools	1	23	92	<b>128</b>	1	40	185	470
Rough water runs	10	45	39	3	<b>287</b>	241	135	760
Runs	1	32	15	2	59	<b>1671</b>	351	2131
Glides	52	20	40	4	27	162	<b>2864</b>	3169
Total	665	1997	1502	152	393	2167	3901	10777
Producer's accuracy	86.3%	73.0%	75.2%	84.2%	73.0%	77.1%	73.4%	
User's accuracy	66.0%	81.9%	70.7%	27.2%	37.8%	78.4%	90.4%	
Overall accuracy	75.3%							
Kappa	0.69							

**Table 2.** Error matrix for maximum likelihood supervised classification of four in-stream habitat types using 1-m hyperspectral imagery, principal components 1 through 25. The data points used to classify the image are not included in the accuracy assessment

Classified pixels	Ground truth pixels				
	Eddy drop zones	Riffles	Glides	Pools	Total
Eddy drop zones	<b>564</b>	142	139	2	847
Riffles	23	<b>2653</b>	174	6	2856
Glides	77	389	<b>6083</b>	12	6561
Pools	1	313	323	<b>132</b>	769
Total	665	3497	6719	152	11033
Producer's accuracy	84.8%	75.9%	90.5%	86.8%	
User's accuracy	66.6%	92.9%	92.7%	17.2%	
Overall accuracy	85.5%				
Kappa coefficient	0.74				

**Table 3.** Error matrix for maximum likelihood supervised classification of four in-stream habitat types using 5-m hyperspectral imagery, principal components 1 through 8. The data points used to classify the image are not included in the accuracy assessment

Classified pixels	Ground truth pixels				
	Eddy drop zones	Riffles	Glides	Pools	Total
Eddy drop zones	<b>18</b>	21	48	1	88
Riffles	12	<b>136</b>	159	3	310
Glides	1	41	<b>589</b>	2	93
Pools	4	47	45	<b>6</b>	642
Total	35	245	841	12	1133
Producer's accuracy	51.4%	55.5%	70.0%	50.0%	
User's accuracy	20.5%	43.9%	91.7%	6.5%	
Overall accuracy	66.1%				
Kappa coefficient	0.34				

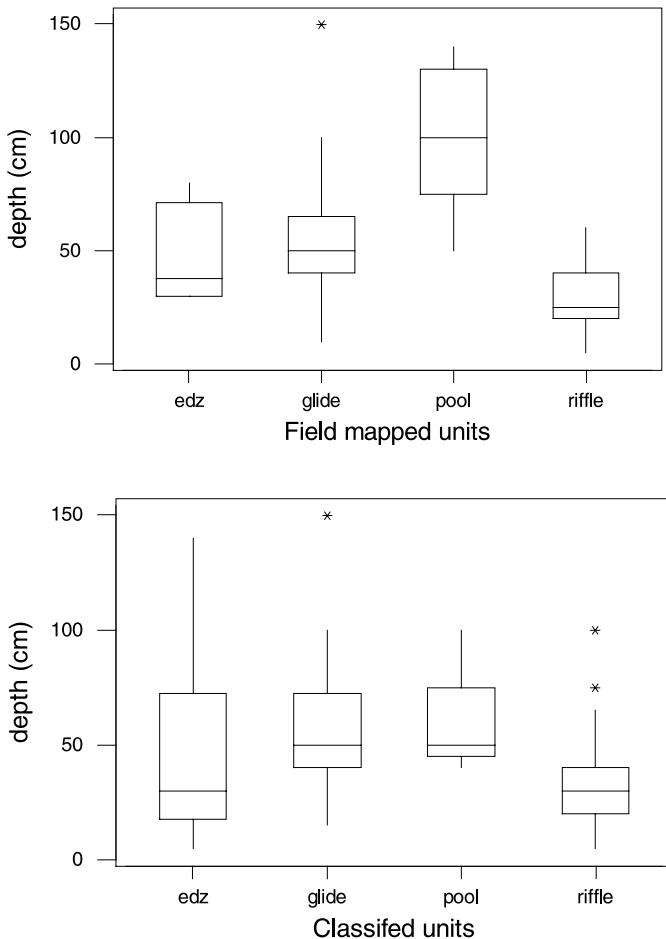
**Table 4.** Comparison of accuracies achieved with 1-m and 5-m hyperspectral and simulated multiband imagery

		Eddy drop zones	Riffles	Pools	Glides	Overall accuracy	Kappa
1-m image results							
Producer's accuracy	Probe1	84.8%	75.9%	90.5%	86.8%	85.5%	0.74
	SPOT4	78.2%	64.4%	95.3%	68.0%	67.9%	0.4944
	TM5		70.4%	92.1%	73.2%	73.0%	0.566
User's accuracy	Probe1	66.6%	92.9%	92.7%	17.2%		
	SPOT4	53.4%	80.6%	6.4%	91.4%		
	TM5	67.0%	86.6%	6.4%	94.2%		
5-m image results							
Producer's accuracy	Probe1	51.4%	55.5%	50.0%	70.0%	66.1%	0.34
	SPOT4	42.5%	40.0%	41.2%	62.9%	57.0%	0.22
	TM5	35.0%	55.5%	47.1%	77.7%	71.0%	0.41
User's accuracy	Probe1	20.5%	43.9%	6.5%	91.7%		
	SPOT4	18.9%	44.8%	3.3%	84.9%		
	TM5	26.4%	55.5%	60.2%	91.7%		

classified by the field team as a glide rather than a pool. In contrast, the hyperspectral image classification shows glides and pools having approximately the same median depth, which clearly indicates that the imagery is misclassifying at least some of the pools and glides. One would expect, however, some real world overlap in depths between unit types, which are defined by field observers on the basis of surface turbulence and substrate as well as depth. The overlapping depths of the classified unit types therefore partially reflect real phenomenon, as is indicated by the partial overlap in depths of field mapped units.

Although some misclassification is occurring, visual inspection of the classification maps raises serious questions about the degree to which many "misclassifications" are real. Many of the areas misclassified using the 1-m

data are single pixels or small clumps of pixels, often near the edges of units. With the exception of eddy drop zones, most in-stream units mapped by the field teams were generally 100 m<sup>2</sup> or more in size. Many of these mapped units, however, contained small patches with different characteristics within their boundaries. For example, most riffles had many smooth flowing “mini-glides” within the larger riffle unit. The frequency of these mini-glides within the riffles was greatest near downstream unit edges where the slopes of the riffles decreased, or along shorelines where velocity decreased. The survey teams, however, did not attempt to map these numerous smaller patches of only one or two square meters in size.



**Fig. 2.** Box plots of depth ranges of in-stream habitats mapped by field teams and of units as classified with the 1 m hyperspectral imagery. Edz refers to eddy drop zone. The median value for each unit type is indicated by the horizontal line in the middle of the box. The top and base of the box show the third and first quartile values, respectively. Whiskers show the range of values below or above the first and third quartile, except for values shown by asterisks, which are more than 1.5 times the range between the first and third quartiles from the median

All the field surveyors examining the classification images believed that the hyperspectral sensor was detecting spatial heterogeneity within the stream at a finer scale than that mapped by the field teams. The fact that 389 mapped riffle pixels were classified as glides therefore partially represents real internal heterogeneity within the riffle units rather than bad classification on the part of the imagery. Similar arguments can be made for many of the “misclassified” pixels among other units. This suggests that fuzzy logic or graded membership functions could be used to develop more realistic classifications or to assess the accuracy of the “crisp” classification scheme used in this study.

Subjectivity also played a role in misclassification. The point at which a glide becomes a riffle, or an eddy drop zone transitions into an adjoining glide, is partially dependent on who is doing the mapping. Despite training field surveyors as a team to improve consistency, disagreements among observers still occurred. When image-based “misclassifications” occurred over more than several pixels, it was usually near the edge of a unit where it was transitioning to another unit. It may well be that the imagery provides a more objective and therefore more accurate placement of these boundaries than the field survey teams.

The combination of inaccuracies in field maps due to unmapped fine scale features and inaccuracies in mapping unit boundaries indicates that the image classifications are more accurate than indicated by Tables 1 and 2. Based on the expert opinion of the field surveyors and others who have visited the field site, we believe, but cannot prove, that the image classifications are even more accurate than the field map at many locations. This challenges the standard approaches used to assess classification accuracy, suggesting that the image classification should be used to validate the field map rather than the other way around. If one accepts this argument, then the HSRH imagery is providing remote mapping rather than remote sensing as the term has classically been used.

## 6.2 *Spatial resolution*

Tables 2 and 3 indicate that the 1-m spatial resolution is needed to achieve the overall accuracies of 85% or better considered acceptable by much of the remote sensing community. Eddy drop zones and pools are often only 25 m<sup>2</sup> in size, which means they can be “lost” due to pixel mixing on 5-m imagery. Wright et al. (2000) state that pixel size should be less than 25% of the area (and preferably even smaller) of the smallest in-stream habitat unit to insure detection. This suggests the size of pixels could be increased to 2.5 m and still detect features such as pools and eddy drop zones in the Lamar River. The required spatial resolution for detecting flow habitats will vary from stream to stream, or from headwaters to downstream within the same system, depending on the scale of the features being detected.

In some instances, pixel unmixing to detect subpixel features can be an alternative to acquiring high spatial resolution data. Pixel unmixing, however, works best when there is a substance with a unique spectral signature (e.g., a mineral type) within a pixel. Variations in the reflectance of in-stream habitats probably result primarily from subtle variations in water reflectance rather than from compositional differences. It therefore seems

unlikely that pixel unmixing will enable the accurate identification of habitat units at the subpixel scales, which in turn suggests that coarser spatial resolution imagery will not be useful for in-stream habitat mapping. Although this issue requires further research, it seems likely that detection of in-stream features requires pixels at least as small as the feature of interest and preferably even smaller.

### *6.3 Spectral resolution*

Table 4 indicates that hyperspectral band coverage is needed to achieve classification accuracies of 85%. One meter imagery with only 6 bands (TM5) or 4 bands (SPOT4) achieves accuracies that are 12% and 18% lower than the hyperspectral-based classification. The accuracy of the SPOT4 and TM5 classifications should probably be even lower than is shown in Table 4, however, because noise was not added to the simulated multiband images to mimic the lower signal to noise ratio of these sensors relative to Probe1. Visual observation also suggests that the quality of the multiband classifications relative to the hyperspectral classification is even worse than suggested by Table 4. The 1-m SPOT4 and TM5 classification images show entire in-stream habitats classified incorrectly. In contrast, apparent errors on the hyperspectral 1-m classifications occur as isolated pixels or near transition zones between units. Finally, the spectral reflectance for each in-stream unit type varies across all wavelengths covered by the hyperspectral sensor (Fig. 3). This indicates that even a multiband sensor that focused on bands maximizing differences between in-stream habitats would not catch the full range of useful information captured by a hyperspectral sensor. Future analysis of principal component loadings associated with the different spectral channels in different stream microhabitats and different streams would help to determine how many bands and which spectra ranges are most valuable for identifying in-stream environments.

## **7 Conclusions**

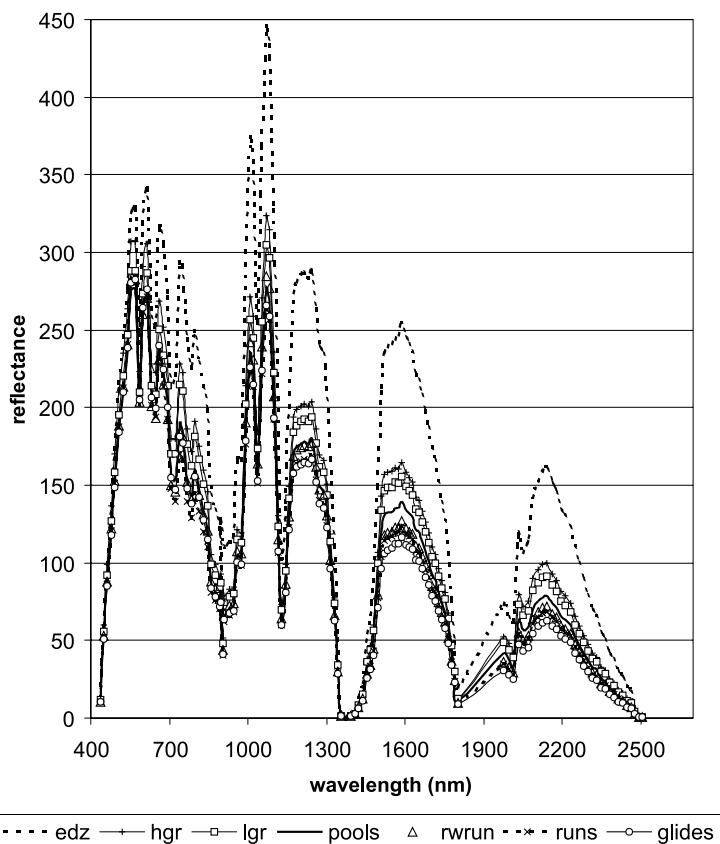
Results from this study indicate that HSRH imagery can be used to map fine scale in-stream features at reach to watershed scales. A number of issues, however, present obstacles to easily applying this technology in stream settings.

New approaches to accuracy assessment need to be developed beyond the ground truthing and contingency table approach used in this article. The simple one-to-one correspondence used to determine “right” or “wrong” in error matrices does not allow room for transitional regions between units, does not accommodate situations where image spatial resolution may be better than what can be mapped by the field surveys, and is inappropriate in situations where the image classifications may be more consistent and accurate than field maps created by subjective surveyors. Although one can devise solutions to all these problems, most existing solutions such as fuzzy classifications or clumping and sieving of the image classifications degrade the information provided by the imagery to make it fit the scale and quality

of ground truth information. New approaches must be developed that enable useful accuracy assessment without degrading the imagery. Rule-based post-classification sorting (e.g., Hutchinson 1982) using data on spatial locations of microhabitats relative to one another and fine resolution digital elevations of water surfaces may hold particular promise in this regard.

Even assuming field surveyors could create accurate field maps at the scale of 1-m size stream habitats, presently available commercial software cannot coregister features mapped at this fine scale to the imagery with sufficient precision. Overlaying fine scale features mapped in the field onto the wrong image pixel results in the kind of false misclassification problems reported by Wright et al. (2000).

Finally, the approach used in this article is a classic top down approach, where ground truth sites are used to choose image pixels, which in turn are



**Fig. 3.** Mean reflectance of the training sites used for the seven different morphologic units. “Edz” is eddy drop zone, “hgr” is high gradient riffle, “lgr” is low gradient riffle, and “rwrn” is rough water run. Runs and rough water runs have almost identical spectral reflectances and are hard to distinguish on the graph, although runs have slightly lower mean reflectances. The mean reflectance for pools falls between rough water runs and low gradient riffles, and glides have the lowest average reflectance of any unit type

used to train the classification algorithm. This empirical approach suffers from being suitable for only one-place and one-time, because light angles, light intensity, and atmospheric effects may generate different reflectance values for the same object at other sites or times. If possible, a spectral library-based deterministic model would allow extension of stream mapping to multiple sites and multiple dates without the extensive ground truthing necessary to recalibrate the classification algorithm. Lyon et al. (1992), Lyon and Hutchinson (1995), Winterbottom and Gilvear (1997) and Lee et al. (1999) have made significant progress in this arena, but the difficulties in incorporating the multiple sources of spectral variance indicate such a model will be some time in the development. Variations in reflectance due to spatial and temporal variations in water depth, surface turbulence, subsurface turbulence, turbidity, suspended sediment concentration and composition, substrate size and color, periphyton, and organic material in the water column create a level of complexity that may never be fully captured by models that operate independently of extensive ground truth field data.

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