Automated Mapping of Stream Features with High-Resolution Multispectral Imagery: An Example of the Capabilities

Donald G. Leckie, Ed Cloney, Cara Jay, and Dennis Paradine

Abstract
The capabilities of high-resolution, multispectral remote sensing imagery to map important stream features is investigated. Eighty centimeter spatial resolution CASI imagery was acquired in eight spectral bands over Tofino Creek on the west coast of Vancouver Island, British Columbia. A spectral angle mapping algorithm was used to classify stream habitat including hydraulic habitat, substrate material, and woody debris. Subclasses were attempted in terms of streambed material and water depth, but results were not reliable. A classification of deep water, moderate depth water, shallow water, sand, gravel and cobble, and woody debris in sunlit conditions, however, proved accurate (80 percent on average). Individual logs and piles of woody debris were consistently detected. Silty substrate in a tidal flats zone was also classified, but results indicated that different substrate material beneath the water may require separate classes and can result in problematic water depth classification. Patterns of general classes were reasonably represented within shadowed areas cast by isolated trees or groups of trees. However, problems do arise within lengthy shadowed stretches. Some boundaries of stream features with surrounding forest and between some zones of sand, gravel, and cobble were also misclassified. High-resolution, multispectral imagery in four or more bands combined with good geometric correction, image mosaicking, and appropriate automatic classification techniques offer a viable tool for stream mapping to meet a variety of issues and applications. In the future, a powerful suite of stream information may be compiled from multispectral classification combined with high-resolution thermal and lidar data.

Introduction
There is a broad need for mapping and monitoring stream channel features. Fisheries surveys need to determine quantities of different habitat. For example, pools, large woody debris, and overhanging vegetation all provide good habitat (Hardy and Shoemaker, 1995; Crowther *et al.*, 1995). Sediment available for transport is important environmentally and from an engineering point of view (Gardiner, 1995). Due to potential for serious blockage of stream channels or sudden release of large quantities of debris, large woody debris either as piles or individual pieces can be important for hazard identification and management on some streams. It is a feature that is often surveyed (Bilby, 1984; Bilby and Ward, 1989; Murphy and Koski, 1989; Robison and Beschta, 1990; Bilby and Ward, 1991; Marcus *et al.*, 2002). Restoration of streams is a growing activity and includes modification of stream channels, woody debris, streamside vegetation, and other features to restore the state of a disturbed stream or to improve fish habitat (Frissel *et al.*, 1993; Stanford *et al.*, 1996; Egan, 1998; Nienhuis and Leuven, 2001; Kondolf *et al.*, 2003). This requires knowledge of the current state of streams to determine candidate locations and for planning specific restoration activities. The effects of forest practices on streams is also an important issue (Murphy and Hall, 1981; Hartman and Scrivener, 1990; Bilby and Ward, 1991; Ralph *et al.*, 1994); knowledge of typical changes, conditions before logging, and those during and after logging are of interest to determine if there is an impact. Because streams are dynamic, it is often desirable to conduct monitoring with repetitive mapping or with surveys after catastrophic events like flooding (Werrity and Ferguson, 1980; Gilvear and Winterbottom 1992; Snider *et al.*, 1994; Gilvear *et al.*, 1995; Hardy and Shoemaker, 1995; Bornette and Amoros, 1996; Bryant and Gilvear, 1999; Meyer, 2001; Mount *et al.*, 2002). There is, therefore, a need for survey methods that can effectively map a variety of stream features in an efficient timely manner.

Traditionally, stream surveys are conducted on the ground. These are time-consuming and costly, often lack spatial detail, and are difficult to repeat at high temporal resolution (Poole *et al.*, 1997; Legleiter *et al.*, 2002; Leuven *et al.*, 2002). Access to remote streams can also be a problem. Remote sensing such as aerial photography or digital multispectral imagery provide an alternative that alleviates these issues and complements field surveys. For example, interpretation of aerial photography, usually of 1:20 000 to 1:5 000 scale, is used, often combined with varying degrees of field observations (Lapointe and Carson, 1986; Gilvear *et al.*, 1995; Church and Hassan, 1998; Gilvear *et al.*, 1999; Leuven *et al.*, 2002; Whited *et al.*, 2002; Gilvear and Bryant, 2003). It, however, can suffer from interpreter error and inconsistency and from poor or lack of interpretation in areas of cast shadow from adjacent trees or terrain, and can also be time-consuming, particularly if high spatial or temporal detail is required. Automated analysis of data from multispectral sensors provides several advantages. There is a potential for consistent, accurate, and cost-effective high

Donald G. Leckie and Dennis Paradine are with the Canadian Forest Service, Pacific Forestry Centre, 506 West Burnside Road, Victoria, B.C. V8Z 1M5 (dleckie@pfc.forestry.ca).

At the time of the study, Ed Cloney, Cara Jay, and Dennis Paradine were with Weyerhaeuser Ltd. (B.C. Coastal Group) 65 Front Street, Nanaimo, B.C. V9R 5H9

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spatial resolution mapping. Spectral band selection can often be tailored to help distinguish a single or multiple features for applications such as mapping aquatics, surrounding riparian zone vegetation, exposed substrate, water depths, and penetration of water for detection of submerged features. Mapping within shaded areas is a problem. The high radiometric resolution of some multispectral sensors may permit analysis within these areas. With precise positioning and geometric correction now available with current technology, quick and accurate georeferencing is possible. In addition, multispectral data can be combined with information from scanning lidar and thermal imagery acquired simultaneously to provide a wide variety of the needed information for stream mapping (Torgersen *et al.*, 1999; Witte *et al.*, 2001; Leuven *et al.*, 2002).

In the 1990s, airborne video, digital frame cameras, and airborne multispectral imagers began to be investigated and used for stream mapping with both manual and automated techniques. These studies often addressed single variables such as hydraulic habitat, water depth, and woody debris: typically on a limited extent of the stream or single reach (Marcus *et al*, 2003). Most used supervised maximum likelihood classification or unsupervised spectral clustering techniques, data with resolutions of 1 m, and many, although not all, used a limited band set. Hydraulic or in-stream habitat (e.g., eddy drop zones, glides, low and high gradient riffles, and pools) has been a key focus (Hardy *et al.*, 1994; Panja *et al.*, 1995; Wright *et al.*, 2000; Marcus, 2002; Whited *et al.*, 2002). Depth has been examined with regression relationships, radiometric modelling, and to a lesser extent classification methods (Lyon *et al.*, 1992; Gilvear *et al.*, 1995; Winterbottom and Gilvear, 1997; Bryant and Gilvear, 1999). Several studies have emphasized or included woody debris mapping and classification (Wright *et al.*, 2000; Marcus *et al.*, 2002). Substrate material either exposed or subaqueous has been the main focus of some investigations, but more commonly is included as a feature mapped as part of a study with another focus with few projects addressing differentiation of detailed substrate types (Lyon *et al.*, 1992; Crowther *et al.*, 1995; Thomson *et al.*, 1998; Paradine *et al.*, 1998). Marcus *et al.* (2003) used principal components derived from 128 band 1 m resolution hyperspectral data to examine supervised classification of hydraulic habitats, depths using regressions, and a matched filter approach for woody debris detection.

This study focuses on the automated classification of high-resolution (80 cm) multispectral imagery acquired from the Compact Airborne Spectrographic Imager (CASI) with a spectral angle mapping approach. CASI is a high-quality imaging spectrometer, capable of recording imagery in programmable multiple spectral channels at high spatial resolution (Anger *et al.*, 1994). The study explores the combined capabilities for mapping multiple variables (substrate material, woody debris, and hydraulic habitat including depth classes). It examines a mountain stream over a 5 km stretch, from where it ceases to be a very narrow, steep stream completely overtopped by trees to its estuary. The types of stream features that can be identified are investigated by extending the classification to finer classes than are expected to be separable. It also examines the difference between the riverine section and estuarine environment of the stream and the issue of mapping within shaded areas using an imager with high radiometric resolution. In addition, the capability of classifications using different band sets was examined including natural colour and colour infrared band combinations. The spectral angle mapper classification method (Kruse *et al.*, 1993) utilized in this study is used in hyperspectral analysis, but has not often been applied to stream mapping. It uses the orientation of the multispectral vector for classifying surface type and has the advantage of alleviating the effect of varying illumination conditions. The objective of the study is to provide an example to help define the capabilities and limitations of such data and analysis methods for mapping stream features.

Study Site

The study site is Tofino Creek (49° 12′ N; 125° 36′ W), a mountain stream typical of the west coast of Canada in the Clayoquot Sound area of Vancouver Island, British Columbia, Canada (Figure 1). The study area consists of a 5 km length that rises 250 m from tidewater to the start of an upper, more mountainous stream portion. Typical flow rates averaged over an annual period are 7.2 m^3/sec. At the time of the acquisition, surface turbulence ranged from quiet pools to sections of fast flow, some with ripples or small standing waves. White water was rare, only occasionally being present in some of the shallow riffles. Turbidity values were low. The stream has some straight reaches, but generally

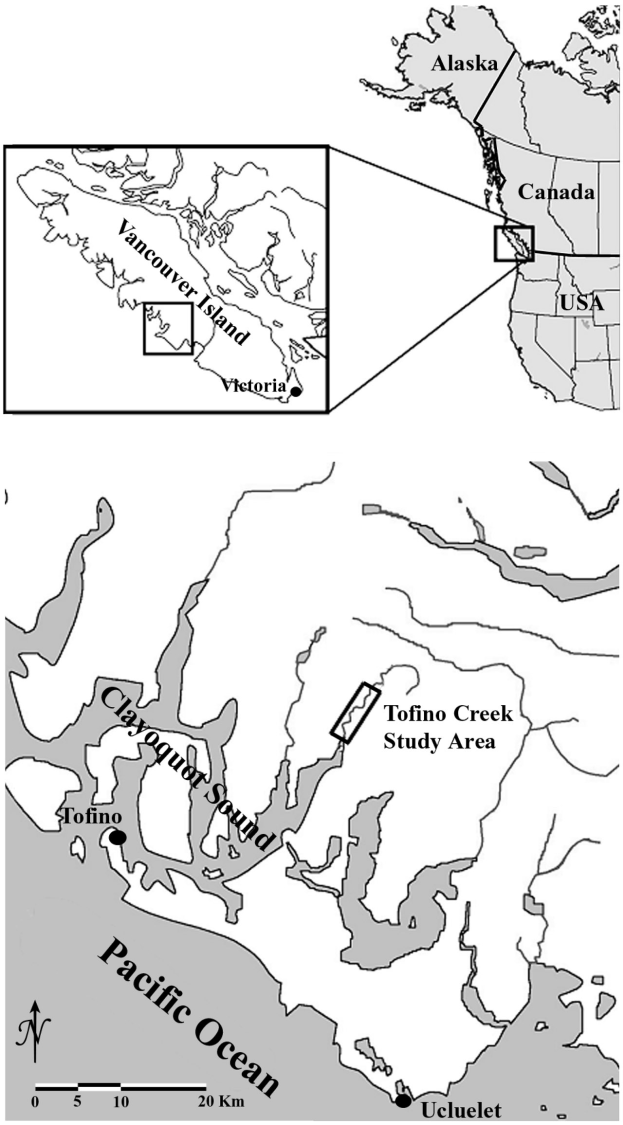


Figure 1. Study area location.

follows a sinuous course with channel widths ranging from 10 to 40 m. Substrate material varies from sand, through cobble, with some boulder and bedrock. It was predominantly light in color, and generally, there was no algae on the substrate. Aquatic plants were not common and were contained within small localized sites. At and near the mouth of the stream, silt substrate material occurs. The stream is surrounded by forested mountains rising steeply on both sides. Adjacent to the stream, trees are mainly mature conifers (e.g., western hemlock (*Tsuga heterophylla*), amabilis fir (*Abies amabilis*), Sitka spruce (*Picea stichensis*), and western redcedar (*Thuja plicata*)), but there are some deciduous trees and regenerating areas.

Image Data, Conditions, and Preprocessing

Imagery was acquired at 80 cm resolution in three adjacent and overlapping flight lines with a CASI imager. Each flight line was orthorectified using differential GPS, aircraft attitude data and existing British Columbia 1:20 000 topographic map (TRIM) data. CASI is a sensor that can produce imagery in 288 spectral bands in the visible and near-infrared spectral region (Anger *et al.*, 1994), but it was operated in spatial mode for this study to obtain high spatial resolution imagery in eight spectral bands. These bands were centred on 438 nm, 489 nm, 550 nm, 601 nm, 656 nm, 715 nm, 795 nm, and 861 nm with spectral bandwidths of approximately 50 nm (i.e., ±25 nm). Imagery was recorded with 12-bit radiometric resolution, but processed to 16-bit data. It was acquired at 80 cm resolution. No radiometric corrections for bi-directional reflectance affects or normalization between flight lines were conducted. This was not deemed necessary as the data were acquired over a short period of time with similar illumination conditions, a strong bi-directional reflectance influence was not observed or expected for the water and substrate material under the illumination and view angle conditions of the study, and the spectral angle approach is somewhat insensitive to these effects. The three flight lines of imagery were then mosaiced into one data set, and the whole mosaic was analyzed (Plate 1).

Data were flown between 1237 and 1315 on 25 September 1996 which resulted in a solar azimuth and elevation of 194° and 39°, respectively. Flight lines were oriented along the stream course, and each line was flown in the same direction from the upper reaches down the valley to the stream mouth (approximately 210°). There were high-scattered, thin cirrus clouds present in the region. The ground surface was dry as there was no recent rainfall. There was some senescence of ground vegetation, but deciduous trees were generally still green with only occasional early signs of senescence. Water levels were moderate with the last major rainfall being 13 and 14 September. Although flow measurements were not taken during 1996, typical September flows for non-storm event periods are in the neighbourhood of 0.7 m^3/sec. Plate 2 gives several ground photographs taken the day after the flights showing typical conditions.

Ground Reference Data

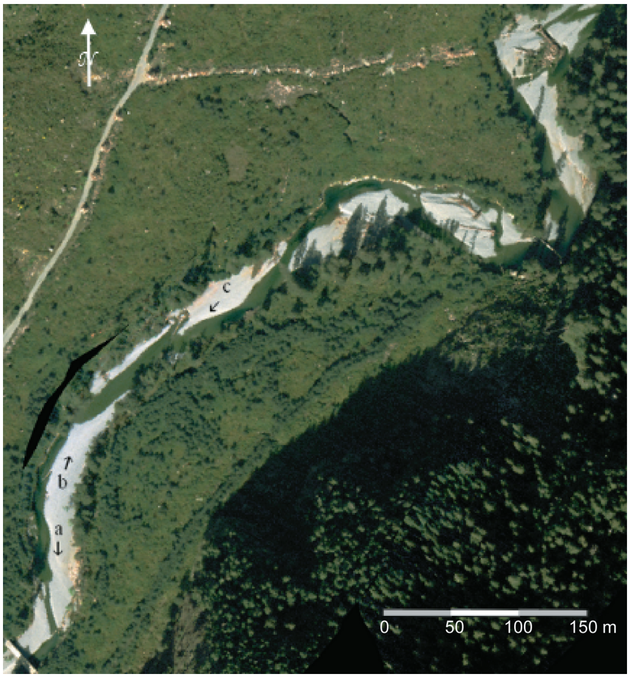
A "walk over" survey of the stream was conducted one and two days after the over-flights along a 4.5 km section of the 5 km stretch of the stream within the study area. Over 70 locations distributed along the stream course were documented. At each location, 35 mm colour photographs were taken of the channel features. Each site may have several stream features and conditions represented and recorded. In addition, three detailed plots (typically 25 by 60 m) were established, gridded, and mapped for surface type and water depth. These field sites and plots were chosen to capture the range of conditions along the whole study area. From this information surface conditions were determined for selected areas on the imagery. Water depth (deep (>1.0 m), moderate depth (0.35–1.0 m), shallow (<0.35 m)), riffles (very shallow with riffles or riffles with partly exposed usually wet gravel or cobble), substrate material (sand, gravel, cobble, boulder or bedrock), woody debris (large or small scattered), and surrounding forest condition (mature and regenerating hardwood and softwood plus open shrub areas) were assessed. Some finer differentiation of gravel and cobble sizes was also done. These data formed the basis for identifying sites for training the classifier and testing its accuracy, and for qualitative visual analysis of the correspondence of classified stream classes with reality. Natural colour aerial photography at 1:19 000 scale (late summer, 1994) was also available for the area and used as an ancillary source of stream form information. A 1:5 000 digital orthophoto was produced from the photography and used to aid the fieldwork and analysis.

Methods

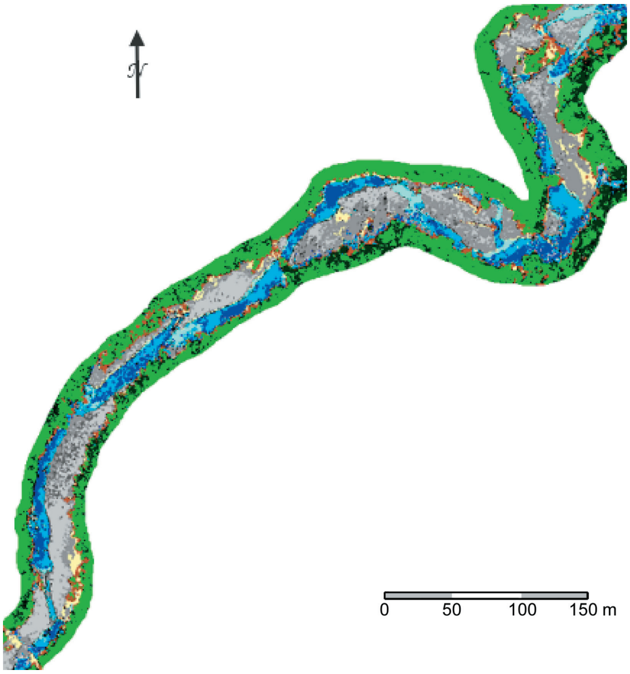
A spectral angle mapper approach (Kruse *et al.*, 1993), a supervised multispectral classification method, was implemented with *ENVI* software and was used to extract surface types. The approach treats the multispectral pixel values as a vector and determines the vector's angle in 'n' dimensional space. One defines individual input pixels that form a set of reference vectors (spectra) or angles for each class. Every input reference vector is used independently, so each class has more than one reference vector. The spectral angle for each pixel of the image is then examined and assigned to the class of the reference vector it is closest to. There is however a threshold angle; any pixel that does not match any of the reference vectors within this angle is designated unclassified.

Pixels of the different classes distributed throughout the study area were chosen to generate the reference spectra for each class. A series of very fine classes and reference spectra were defined to determine the types of features that could be differentiated (Table 1). Classes were then successively eliminated or combined to achieve a set of classes that can be reliably classified. For example, it was found that eliminating the reference spectra for the large cobble class altogether, resulted in better overall classification of both small-medium cobble and large cobble than retaining both reference spectra as part of a combined class. In contrast, combining the existing two woody debris classes resulted in a good classification of a combined woody debris class since much of the confusion within each class was due to misclassification as the other woody debris class. Table 2 gives a second reduced set of sunlit (non-shaded) classes. In order to handle specific issues in the classification, specialized classes were created and reference spectra generated for such cases as cobble, sand, or water under the shadow of trees. A deciduous and a conifer tree class were also included.

The spectral angle classifier was then run. All eight bands were used for the main analysis, but special runs examining various reduced band sets were also conducted. Several threshold angles were tested and a threshold of 0.2 radians was used for each class. As well, the classification results were filtered with a 2 × 2 sieve function (minimum size of area of 2 × 2 pixels and pixels removed by the filter were replaced with spatially adjacent classes by an erosion process). It consolidated the classification into larger mapping units and eliminated small and single pixel units.



(a)



(b)

Plate 1. Subsection of study area. (a) Natural color band combination (letters indicate locations of ground photographs of Figure 3). (b) Final classification of subsection. (deep water = dark blue; moderate depth water = blue; shallow water = light blue; sand = yellow; gravel = light gray; cobble = dark gray; rock/boulder = very dark gray; logs and woody debris = brown; conifer = dark green; deciduous = light green)

(a)

(b)

(c)

Plate 2. Field survey photographs of different planform classes along Tofino Creek. See Plate 1a for the location of these photographs. (a) sand, gravel and small woody debris. (b) cobble, shallow and deep water, woody debris. (c) gravel, woody debris and shallow and deep water.

Test areas of known surface type were identified on the imagery based on the ground reference data. The number of independent sites ranged from 3 to 15 for each class, with most having 5 to 10 sites each. Tables 1 and 2 list the total number of pixels in the test areas. The accuracies of the classifications were tested against the class determined for these predefined test areas. These sites were independent of the reference spectra used to generate the classes. Accuracies

TABLE 1. CLASSIFICATION ACCURACY (PERCENT) OF FINE CLASS SET

	Ground Reference Class																	
Classification	Deep Water	Moderate Water	Shallow Water	Sand	Gravel	Small-med. Cobble	Rock/ Boulder	Large Cobble	Wet Cobble/ Riffle	Scatt. Woody Debris	Logs with Bark	Shaded Deep Water	Shaded Moderate Water	Shaded Shallow Water	Shaded Gravel	Shaded Cobble	Conifer	Deciduous
Deep water	94.2	10.4	0	0	0	0	0	1.1	0.7	0	0	0.7	8.5	0	0	0.1	0	0.1
Moderate water	1.6	86.8	0	0	0	0	0	0	0	0	0	0	19.1	0	0	0	0	0
Shallow water	0	1.2	87.3	0	0	0	1.0	0	0.7	0	0	0	4.6	0.5	0	0	0	0.3
Sand	0	0	0	75.2	0	0.7	0	10.0	0	5.1	14.8	0	0	0.5	0	0	0	0.1
Gravel	0	0	0	0.6	76.6	7.8	4.7	1.1	3.5	0.3	0	0	0	0	0	0	0	0
Small-medium cobble	0	0	0	21.2	11.7	57.0	14.0	64.7	7.1	0	0.3	0	0	0	0	0	0	0.1
Rock/boulder	0	0	5.0	0	2.2	0.1	45.2	0.0	14.8	0.3	0	0	1.4	0	0	1.5	0	0
Large cobble	0	0	0	0.3	5.6	33.1	3.0	16.8	11.3	0	0	0	0	0	0	0	0	0
Wet cobble/riffle	0	0	2.2	0	0	0	24.1	0	50.7	0	0	0	1.1	0	0	0	0	0
Scattered woody debris	0	0	0	2.1	2.2	0.2	0	4.7	0	71.7	50.3	5.1	1.1	3.1	0.6	1.2	1.8	7.2
Logs with bark	0	0	0	0.3	0	0	0	0	0	13.0	23.0	0	0	0	0	0	0	0.8
Shaded deep water	3.7	0	0	0	0	0	0	0	0	0	0	33.0	28.4	15.2	7.5	3.0	0	0.1
Shaded moderate water	0.5	1.3	4.3	0	0	0	0	0	0.7	0	0.6	31.0	17.0	28.3	8.6	4.7	0.5	0.6
Shaded shallow water	0	0	0.2	0	0	0	0.3	0	0	0	0	0	0	22.0	0	0.4	0	0
Shaded gravel	0	0	0	0	0	0	0	0	0	0	0.3	7.4	10.6	16.2	23.0	5.3	0	0
Shaded cobble	0	0	0	0	1.2	0.6	0.7	0.5	4.2	5.8	4.4	13.1	0	4.2	55.7	79.2	0	0.1
Conifer	0	0	0	0	0	0	0	0	0	0	0	0.7	0	0.5	0	1.6	73.9	11.9
Deciduous	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	20.7	76.6
Unclassified	0	0.3	1.0	0.3	0.5	0.5	7.0	1.1	6.3	3.8	6.3	8.8	8.2	9.4	4.6	2.9	3.1	2.1
Number of pixels	622	607	603	633	1294	1236	299	188	142	293	318	297	282	191	174	730	777	1459

Table 2. Classification Accuracy (Percent) of Reduced Set of Sunlit Classes

	Ground Reference Class									
Classification	Deep Water	Moderate Water	Shallow Water	Sand	Gravel	Cobble	Rock	Wood Debris*	Conifer	Deciduous
Deep water	97.9	10.4	0	0	0	0	0	0	0	0.2
Moderate water	2.1	88.1	4.3	0	0	0	0.3	0.3	0.5	0.6
Shallow water	0	1.2	87.4	0	0	0	1.0	0	0	0.3
Sand	0	0	0	75.2	0	0.7	0	10.1	0	0.1
Gravel	0	0	0	0.6	76.6	7.8	4.7	0.3	0	0
Cobble	0	0	2.3	21.5	18.5	90.6	41.8	5.2	0	0.2
Rock	0	0	5.0	0	2.2	0.1	45.2	0.2	0	0
Wood debris*	0	0	0	2.4	2.2	0.2	0	78.7	1.8	8.0
Conifer	0	0	0	0	0	0	0	0	73.9	11.9
Deciduous	0	0	0	0	0	0	0	0	20.7	76.6
Unclassified	0	0.3	1.0	0.3	0.5	0.5	7.0	5.1	3.1	2.1
Number of pixels	622	607	603	633	1294	1236	299	611	777	1459

*Scattered woody debris and logs with bark.

of the classifications were also visually checked against the identifiable stream features from the imagery itself, the 1:20 000 photography, and field sites not formally used as test areas.

Results and Discussion

Substrate Material

This section examines the classification of sunlit substrate areas that are exposed (i.e., not submerged). There is little confusion of sunlit substrate with other surface types. The results regarding discrimination among various sunlit substrate types (Table 1) however were mixed. The differentiation of substrate material into sand, gravel, small-medium cobble, large cobble, boulder/rock classes was too fine. Although some general patterns matched the ground truth, the small-medium cobble and large cobble classes were severely confused. The large cobble class being very poorly classified (only 17 percent accuracy) with most being classified as small-medium cobble. Figure 2 indicates similar spectral values and shapes for the two classes. A second classification with a combined small-medium cobble/large cobble (cobble) class improved results with 75 percent accuracy for sand, 77 percent for gravel, 91 percent for cobble, and 45 percent for boulder/rock (Table 2). Gravel and sand were not confused, but there were considerable amounts of sand and gravel classed as cobble (22 percent and 19 percent, respectively) and some cobble classed as gravel (8 percent). If the gravel and cobble classes are combined accuracy was 97 percent for gravel/cobble. The rock class had poor classification, but removal from the classification resulted in the accuracy of some of the other classes being reduced. In general, with this data set, it appears that

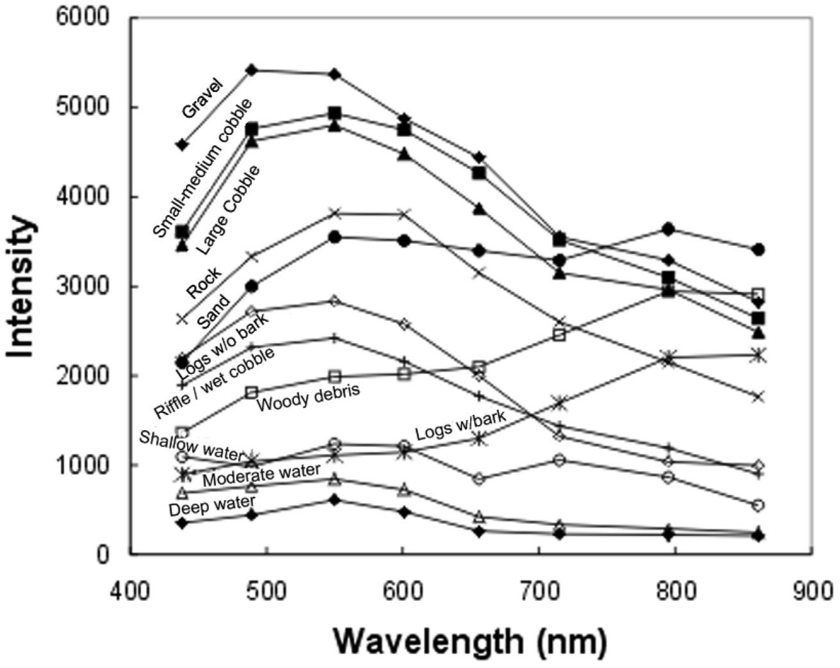


Figure 2. Selected reference spectra for different planform classes.

four substrate classes of sand, gravel, cobble, and boulder/rock could be reliably differentiated and accurate sand, gravel/cobble differentiation was fairly easy to achieve. It must be remembered, however, that these substrate classes are gradational, and there are often no clear boundaries in terms of classes and their spatial distribution.

In the tidal reach of Tofino Creek the substrate becomes silt. It was determined that two classes, wet and dry silt, were needed to represent the intertidal area. These classes were well-separated from the sand, gravel, and cobble classes from higher in the stream course, with accuracies of 92 percent and 80 percent for wet and dry silt respectively and 86 percent for a combined silt class. Confusion of wet silt was with moderate depth water and dry silt with shallow water. Field and laboratory spectra of estuarine sediment (Bryant *et al.* 1996) also indicated differences between silt substrate and sands and in a study with 4 m resolution CASI imagery of an intertidal site (Thomson *et al.*, 1998); wet and dry classes of substrate were also used.

Water

Three water classes were designated representing depths: shallow <0.35 m, moderate 0.35–1.0 m, and deep >1.0 m. A fourth class representing riffles/wet cobble included very shallow water with riffles, and areas of riffles with partly exposed cobble or sometimes gravel, usually wet. Accuracies are good for the three water depth classes at 94 percent, 87 percent and 87 percent for deep, moderate and shallow, respectively (Table 1). Some shallow areas were confused with rock and riffle/wet cobble. The riffle/wet cobble class was unsuccessful with only 51 percent accuracy. Areas of riffle/wet cobble were classed as one of the substrate, either cobble, rock, or gravel, and there were some commission errors with test pixels of rock and shallow water also having pixels being classed as riffle/wet cobble.

Other studies have also shown good results for differentiating stream depth, but mixed and variable results differentiating hydraulic habitats such as pools, eddy drop zones, riffles, and glides. Lyon *et al.* (1992) with a radiometric modeling approach achieved high accuracy for 60 cm depth classes, on average 93 percent accuracy. Gilvear *et al.* (1995) and Winterbottom and Gilvear (1997) with digitized aerial photography and Bryant and Gilvear (1999) with 2 m multispectral imagery used bathymetric techniques involving regression and a radiometric model to map water depth. Gilvear *et al.* (1995) determined similar depth classes as this study, although shallow water and riffles were combined in one class. A series of studies using 1 m resolution hyperspectral data (Legleiter *et al.*, 2002; Marcus, 2002; Marcus *et al.*, 2003) achieved an overall classification accuracy of 68 percent to 86 percent, depending on the study reach, for pools, eddy drop zones, glides and riffles. Riffles were the most difficult to classify at 52 percent to 76 percent accuracy. More specific classes could not be differentiated with overall classification accuracies being approximately 20 percent lower for seven habitat classes (Legleiter *et al.*, 2002). Wright *et al.* (2000) with 1 m resolution four-band visible infrared imagery had poor results using narrow habitat classes, and variable results from 28 percent to 80 percent depending on the stream reach for general habitat classes. Similar to the results of this study, there was confusion of riffles with exposed substrate. Another study using similar data achieved classification accuracies of approximately 70 percent for four depth-flow rate classes (Whited *et al.*, 2002).

At the mouth of Tofino Creek where the substrate is silty, it was found that for the shallow and moderate water depth classes, new classes were needed (shallow water with a silt substrate; moderately deep with silt substrate). This is in keeping with other studies which have shown that substrate material will affect depth estimates and classifications (e.g., Lyon *et al.*, 1992). Use of river reference spectra for water depth in the estuary area produced a pattern related to water depth, but not similar depth classes as in the river classes. Alternately, using reference spectra for the estuary area for classifying the river gave poor results. Accuracies of the moderate and shallow water classes in the estuary area using reference spectra for the estuary were lower than achieved for the moderate and shallow water river classes in the river section using river reference spectra. For example, accuracy of moderate depth water was 69 percent with 27 percent being classed as deep water. Shallow water (silty substrate) accuracy was 70 percent with 27 percent being classified as wet silt and some confusion even with dry silt. However, deep water was classified well (97 percent). An additional class of silty water was included. It also achieved approximately 70 percent accuracy, having some confusion with wet silt and areas of the other water classes being classified as silty water.

Woody Debris

Woody debris occurred as several distinct components (logs, scattered small woody debris, and root mat). Logs generally were 3 to 18 m long and 20 to 75 cm in diameter; some however, were up to 25 m long by 90 cm wide. Some of the logs had lost their bark and were bleached. Visually, the bleached logs appear quite similar to the sand, gravel, and cobble areas, and it was felt there may be considerable confusion among these classes. Other logs had not lost their bark and were darker. There were also incidences of scattered woody debris with small pieces of wood (20 cm to 2 m long by 0.3 to 8 cm wide) concentrated in a debris zone. Smaller pieces were sometimes associated with these zones. Pieces varied from being bleached with no bark too having bark on, and most were dry. Coverage by the debris varied from 25 percent to 80 percent of the area and the size of the affected area was generally small (1 m^2 to 25 m^2). They tended to be concentrated in areas of sand or gravel substrate rather than cobble. A class of root mat was included in the analysis. Root mats occurred at the end of some logs or as separate entities usually associated with a stump. Because of the different nature of the bark or bleaching, but mainly the structure and corresponding reflectance difference, the root mats had varied and often different reflectance from the other wood debris. It was not the intent to actually identify root mat as a different class, but to use it to combine with the other classes to produce an overall woody debris class.

There is not a strong application need in stream mapping to differentiate the type of woody debris except between the scattered smaller debris and larger pieces, such as root mat and logs. The main classification was run with reference spectra representing scattered small debris and others representing a log class, which included logs with bark and root mat. An additional trial with separate reference spectra of bleached logs was conducted and will be discussed later. The spectral characteristics for the scattered debris and logs with bark are variable in shape and intensity and are sometimes similar. Figure 2 gives example spectra of each. There was confusion between the two classes, especially logs with bark being classed as scattered debris (Table 1). There was however minor commission error in the scattered woody debris class (5 percent of the pixels classed as scattered debris were gravel and 2 percent sand). Combining both classes, scattered woody debris and logs with bark, classification accuracy was excellent at 79 percent. Error resulted mostly from woody material being classed as sand. It was also noted that the woody debris and especially large logs had properly classified pixels associated with them, but these were in a discontinuous pattern along their length. This is due mainly to the issue of log width versus pixel size and the presence of mixed pixels. The post-classification filtering process used also tended to enhance this effect and reduce the number of pixels classed as the woody debris classes. It is anticipated that with some post-classification processing using algorithms to check for linearity, width limits and continuity analysis, the identification of logs would be strengthened.

Wright *et al*. (2000) and Marcus *et al*. (2002) with four-band multispectral imagery were unable to classify large woody debris due to small spectral differences versus sand and gravel and the 1 m resolution of the imagery. They recommend higher resolution and more spectral bands, as is used in this study. The better results of this study may be due to higher spatial resolution imagery, on average larger woody debris size, and the spectral angle mapping classification approach. Marcus *et al*. (2003) using 1 m hyperspectral data achieved 85 percent accuracy but with 49 percent commission using a match filtering approach that only identified presence or absence of large woody debris.

Woody debris in the form of large, white/gray bleached logs was examined in an additional analysis. Separate spectra (Figure 2) and test areas were used. The spectral shape was quite similar to the substrate classes and confusion might be expected. One meter resolution multispectral imagery of Marcus *et al*. (2002) also indicated the spectral characteristics of large woody debris and sand and gravel to be similar. Classification was poor. Only 9 percent of the test pixels were classed as bleached logs; just over half were misclassified as one of the substrate classes. However, a third of the test pixels were classified as one of the other two woody debris classes (scattered debris and barked logs). Accuracy of some of the other classes such as sand, gravel, and rock decreased due to confusion caused by the bleached log class.

The scattered woody debris areas sometimes have small amounts of vegetation associated with them, and this can cause confusion in the classification. There was also a phenomenon of misclassification at the edge of the stream channel. There was often a narrow strip of pixels classed as the scattered woody debris class at the boundary between the vegetated forest and the stream channel either substrate material or water (Plate 1). This was more common and somewhat wider along shadowed edges. There were also some pixels within the deciduous test area that were classified as scattered woody debris. These were usually associated with small shadowed gaps in the canopy of the deciduous test areas.

Shadow

Presence of shadow cast by trees adjacent to a stream is a major problem in stream mapping. It is particularly problematic when using automated interpretation techniques (Crowther *et al*., 1995; Neale *et al*., 1995). The CASI sensor, however, with its large dynamic range provides some detail within the shaded areas. If particular shadow classes were not included in the classifications conducted for this study, shadowed areas produced misclassified or unclassified pixels. The spectral angle mapper approach by dealing with the orientation of the multispectral vector somewhat mitigates against the difficulties caused by different illumination conditions such as sunlit versus shade. There was moderate success at classification within shadow areas using sunlit reference spectra. Nevertheless, without select shadow classes of each surface type there are considerable problems. Shadowed classes were made for the predominant surface types (gravel, cobble, and deep, moderate and shallow water). There were few sites of shaded sand, so it was not included as a class. These classes generally constituted shade from individual trees or clump of trees rather than deep continuous shaded zones along long stretches of the stream channel.

The shaded classes increased classification accuracy of the shaded areas over that without the shaded classes, but were not very accurate in themselves at the individual class level. There was confusion between neighbouring shaded water depth classes and between shaded gravel and cobble (Table 1). For example, 56 percent of the shaded gravel test pixels were classed as shaded cobble. Shaded shallow water was confused with shaded deep and moderate water and shaded gravel. The shaded water classes also had approximately 9 percent unclassified. There was some classification of sunlit water areas as shaded water of the correct depth class. Except for shaded moderately deep water there was very little classification of shaded areas as a sunlit class. Considerable shaded moderate depth areas were classed as one of the sunlit water depth classes (Table 1). Accuracy was quite good if one permits classification of pixels in the test area to be considered correct if it is classed as an adjacent shaded class or equivalent or adjacent sunlit class. For example, accuracy of shaded deep water under these criteria (i.e., permitting shaded moderate and sunlit deep and moderate water to be correct) was 68 percent, shaded moderate was 73 percent, 50 percent for the shallow shaded class, and 79 percent and 85 percent for shaded gravel and cobble, respectively. Although not accurate at the class level, use of shaded classes produced good general classification with improved accuracy over classifications not using shaded classes. Visually, the classification does help eliminate most of the distinct patterns of the cast shadow (Plate 1). Many of the cast shadow areas are not discernible on the classification, while others appear as a pattern of speckled or patchy mixes of correct and incorrect, but often neighbouring classes. However, in the shade associated with long stretches of adjacent dense forest canopy, the classification was not reliable. In these deep large shadow zones the pixels were generally still classified as one of the classes (rather than being unclassified), but the class was often a water class even in the case of substrate areas.

Overall Classification

Overall accuracy can be assessed qualitatively by comparing patterns of stream classes with that known from the ground sites and photographs, and quantitatively by class accuracies. Overall accuracy will depend on the quantity of each class in the survey area. For example, because the accuracies of the shaded classes are poor, especially for deep large shadow areas, the overall accuracy will depend on the quantity and nature of shadow cast upon the stream channel. In this study, for the time of image acquisition, 65 percent of the 5 km study stretch of the stream was totally sunlit, 20 percent was mostly shaded and 15 percent had approximately one-fourth of the channel width shaded or with scattered tree shadows. The average class accuracy for the classes of Table 1 (minus deciduous and conifer) was 54 percent, but this includes an uncombined cobble class (large cobble and small-medium cobble classes) and equal weighting to the poorly classified shaded areas. As well, some shaded class pixels do get classed as the equivalent sunlit class and are considered an error in Table 1. Table 2 gives the accuracy when only sunlit classes and test pixels are used, combined cobble and wood debris classes are included, and the riffle/wet cobble class eliminated. Average accuracy of the classes was 80 percent (without deciduous and conifer).

Visual inspection indicated that, overall, the classification effectively represented the pattern of water depth and substrate material. Misclassification of strips along the boundary of the stream channel and surrounding vegetated areas as woody debris caused a misleading pattern. The shallow and deep water classes were classed well. The sand to gravel boundary is gradational and some overlap in these classifications is expected, but nevertheless sand versus gravel differentiation and mapping was good. The log and debris class detected logs well and even detected zones of scattered small woody debris. Large single logs were identified but often were not represented as a contiguous series of pixels. Spurious areas classed as rock/boulder occurred within gravel and cobble areas. Visually reasonable portrayals of stream features were classified in shaded areas caused by individual trees or tree clusters, although artifacts of the shade pattern occurred. Deep continuously shaded stretches were not well classified.

New classes were needed to represent different substrate and water clarity conditions near the mouth of the river. Accuracies were good, but reference spectra representing all the estuary and upriver regions used in a single classification of the whole study area produced poor results. This indicates that, for complete classification of the whole area, it would be best to conduct separate classifications.

Band Set Analysis

The above classification results were generated from the complete band set of all eight bands. The CASI sensor is capable of producing imagery in 288 narrow visible and near-infrared spectral bands and high spatial resolution imagery in the order of 8 to 10 bands. However, these may not all be needed. As well, video camera imagery and digital frame camera data with only three or four spectral bands are being used for various stream mapping projects (Snider *et al.*, 1994; Hardy and Shoemaker, 1995; Neale *et al.*, 1995; Wright *et al.*, 2000; Whited *et al.*, 2002; Marcus *et al.*, 2002). Classifications with several band sets were conducted (Table 3). The first classification included all bands as above and produced the best results. Similar results were obtained with a classification without the 438 nm band which was somewhat noisy. The accuracy of the substrate classes, however, were lowered somewhat. A four-band classification with a spectral band in the near-infrared, red, green, and blue spectral bands had reduced accuracy for the main sunlit classes, but results were still good. If either the near-infrared or blue band were removed, specific classes became poorly classified (e.g., the shallow water and gravel classes were poorly classified for the near-infrared, red, and green (color infrared) band combination, and the moderate water class had low accuracy for the red, green, blue (natural color) band combination). The infrared band was needed to separate deciduous from conifer. Classification of the shadowed classes was erratic among the different band sets.

Four bands were needed for good stream planform classification. Classifications improved slightly with more bands. The blue spectral bands appeared useful for substrate classification with the spectral angle mapping approach. For example, accuracy of the substrate classes was reduced when the 438 nm band was removed. There was erratic classification of substrate and other classes with both the color infrared and normal color band combinations. A blue band was needed to classify shallow water and a near-infrared band for moderate depth water. It is desirable to have sensors capable of acquiring at least four bands (blue, green, red, and near-infrared). Three channel sensors producing colour infrared or natural colour imagery such as most video and digital frame cameras may suffer difficulties classifying stream features.

TABLE 3. CLASSIFICATION ACCURACY (5) OF DIFFERENT BAND SETS[1]

Class	Classification Accuracy Per Bandset Bands: 1–8	Bands: 2–8	Bands: 7,5,3,2	Bands: 7,5,3	Bands: 5,3,2
Deep water	94	92	86	77	65
Moderate water	87	78	79	80	20
Shallow water	87	91	88	27	75
Sand	75	69	68	61	45
Gravel	77	70	73	29	80
Small-medium cobble	57	66	58	60	19
Large cobble	17	5	6	2	65
Wet cobble/riffle	51	51	50	43	26
Rock/boulder	45	45	40	49	9
Wood debris*	76	76	65	70	56
Conifer	74	69	79	44	1
Deciduous	77	77	78	73	31
Shaded deep water	33	34	52	59	56
Shaded moderate water	17	19	22	52	14
Shaded shallow water	22	40	18	10	1
Shaded gravel	23	14	21	10	22
Shaded cobble	79	75	59	32	66
Overall Accuracy	58.3	57.1	55.4	45.8	38.3

*Scattered woody debris and logs with bark.
[1]Band numbers are: 1 = 438 nm, 2 = 489 nm, 3 = 550 nm, 4 = 601 nm, 5 = 656 nm, 6 = 715 nm, 7 = 795 nm, and 8 = 861 nm.

Summary and Conclusion

Application of spectral angle classification to multiband CASI imagery over a 5 km clearwater length of Tofino Creek gave good classifications of the following classes: deep, moderate and shallow water, sand, gravel and cobble, and woody debris. Overall accuracy of sunlit stream channels was 80 percent and accuracy of the three water classes was 91 percent and 72 percent for substrate classes (sand, gravel and cobble, plus rock/boulder). It may in some cases be possible to gather useful information regarding finer classes. Tidal flat and estuary classes that had silty substrate could be distinguished from other stream features. Alternately, this indicated that water depth classes are sensitive to the substrate material, silty substrate requiring separate classes from the sand through cobble substrate material found in the main part of the stream. Woody debris in the form of both logs with bark and scattered small woody debris was identified by the classification method. Bleached logs without bark were not classified well. The classification worked moderately well in isolated shadow areas, but not for long zones of deep shadow. The method also seems robust; it was conducted on a mosaic representing data from three flight lines flown sequentially and the data was not normalized.

Good capabilities were shown for mapping the important stream habitat features using high-resolution, multispectral imagery with at least four spectral bands. The study area included a variety of conditions and extended from near the upper reaches of the stream with moderate gradients down to the outflow of the stream in a low gradient tidal flats zone. However, specific results, class types, and choice of classification options will vary for other stream conditions and settings and further testing and refinement of methods for different conditions is needed. Turbidity, organic content and sediment load of the water would be factors. Different parent materials for the substrate and presence of sub-aqueous and floating vegetation would have to be factored into the methods. The spectral angle approach and judicious use of shadowed reference pixels produced some good mapping of generalized classes for cast shadow areas from single trees or tree clusters. However, long continuous zones of deep shadow caused difficulties.

The timing of imagery acquisition should be planned to minimize cast shadow.

Such automated techniques and multispectral sensors provide a viable tool for mapping stream features suitable for a variety of applications. Information can be efficiently summarized for individual reaches and spatially analyzed regarding such parameters as size, shape, and adjacency. With the addition and data fusion of high-resolution lidar and thermal imagery collected simultaneously or in separate surveys, it may be possible to gain even more information. Examination of this combination and indeed further development and validation of automated stream planform classification is needed. However, multispectral classification of high-resolution imagery with appropriate use of current methods and adaptation for specific survey needs and stream conditions is a tool available to be utilized by those interested in stream mapping.

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