CAPACITY OF HIGH SPATIAL RESOLUTION IMAGERY TO IDENTIFY STREAM GEOMORPHOLOGY

DEVELOPMENT AND TESTING OF METHODOLOGIES

Faculty of Forestry
University of British Columbia

Nicholas C Coops
Jessica Morgan
Christopher Bater
Sarah Gergel

FINAL REPORT

Submitted to
International Forest Products
June 06
1. Introduction

1.1 Mapping Fluvial Geomorphology

A critical piece of information in ecosystem based management (EBM) and watershed sensitivity analysis is understanding stream geomorphology, and identification and classification of alluvial reaches for coarse filter identification of high value fish habitat (HVFH). As a result, there is a heightened urgency to develop new methods to delineate and map alluvial reaches along stream lines in an efficient and timely manner. Detection, identification and monitoring of alluvial geomorphology and riparian vegetation using conventional field sampling and surveying is often infeasible, as these techniques are time-consuming and costly, and many areas are not easily accessible (Shanmugan et al. 2006). Spatially extensive and non-invasive remote sensing techniques are therefore often applied due to their synoptic and repetitive nature and ability to be utilized in areas which are not easily accessible. Conventionally stereoscopic interpretation of aerial photography (between 1:5,000 to 1:20,000 scale) has been highly useful (Lapointe and Carson 1986; Gilvear et al. 1995; Church et al. 1998; Gilvear and Bryant 2003) due to the high level of detail apparent on the photographs. However, aerial photography can suffer from error and inconsistency due to both interpreter error, and lack of interpretability in areas of shadow from adjacent trees or terrain. In addition, aerial photographic interpretation is time-consuming, particularly if high spatial or temporal detail is required (Leckie et al. 2005).

The application of satellite image data for mapping alluvial reaches and riparian vegetation with moderate spatial resolution image data from the Landsat and SPOT satellites has produced limited results as the spatial resolution of the sensors is too coarse to delineate narrow bands of vegetation or geomorphologic features along streams (Muller 1997; Congalton et al. 2002). At a 30 m spatial resolution, a number of cover types as well as the mixtures of water depth, woody debris and exposed cobble may be present within one pixel, often resulting in very spectrally noisy and thus poor classification.

Recent advances in high spatial resolution image data, both from satellites, and digital camera and scanner systems on airborne platforms, as well as ability to extract highly accurate information about the terrain surface using Light Detection and Ranging (LiDAR) technology, present important new datasets for delineating alluvial geomorphology and riparian vegetation. With nominal resolutions less than 4 m, there is the capacity to map and monitor complex riparian forest patterns to a greater detail (Johansen and Phinn 2006).

The objective of this research is to assess the capacity of high spatial resolution QuickBird imagery and terrain information extracted from LIDAR to discriminate alluvial areas along stream.
As a basis for comparison we utilized the Terrestrial Ecosystem Mapping (TEM) classification scheme, which consists of ecosystem mapping undertaken across the province using aerial photography at 1:20 000 to 1:50 000 scale (Mitchell et al. 1989; Demarchi et al. 1990). The TEM approach involves stratifying the landscape into map units according to a combination of ecological features, primarily climate, physiography, surficial material, bedrock geology, soil, and vegetation. From this classification, information on the underlying geomorphology can be extracted. Two approaches will be assessed in this research, the first involving object-based classification of the multispectral and LIDAR data fused together, and the second using a suite of rule-based indicators applied directly to a digital elevation model (DEM). If high spatial resolution satellite imagery and LIDAR data are able to accurately discriminate alluvial landforms as defined by the TEM, this technology may offer an alternative to air photo interpretation for identification and classification of alluvial reaches for coarse filter identification of high value fish habitat.

1.2 Object Based Classification of Remotely Sensed Data

With increased spatial resolution of both imagery and terrain data, however, comes added complexity with respect to the classification of the image into homogenous land cover classes. While the increased textural information available in fine spatial resolution image data allows for improved interpretation based on the shape and texture of ground features, the current techniques to process and analyze satellite image data (e.g. the use of vegetation indices or standard per-pixel based classifiers such as maximum likelihood ) may not be applicable to the additional information provided by high spatial resolution image data (Goetz et al. 2003). Object-based analysis provides an alternative methodology to per-pixel based analysis (de Kok et al. 1999) by developing region-growing image analysis techniques using a combination of the shape, size, and spectral data of the regions to classify image data (McKeown 1988; Hay et al. 2005).

The development of segments, or objects with homogenous properties, is achieved either by prior knowledge such as vector/polygon information or automatic division based on underlying statistics.

The applicability of an object-based classification approach on both high and low spatial resolution imagery has shown the technique is more suited to high spatial resolution data (Darwish and Reinhardt 2003), especially in situations were the derived image objects are paired with contextual knowledge (Blaschke 2003). In addition to simply using spectral data, object based classifiers can also incorporate terrain information such as a DEM, as well as data from other classification routines such as quadtree-based software which define merging criterion in relation to the degree of spectral heterogeneity among pixels of an object, and Bayesian neural networks (Song et al. 2005).
The introduction of high spatial resolution imagery has resulted in an increase in interest in the identification of geomorphic features (Mertes et al. 1995; Mertes 2002). With the introduction of object-based classification for identifying geomorphic features, there has been success in identifying features such as mires, wetlands, riparian areas and even alluvial fans. A study of mires (which include bogs, swamps and fens) used an object-based classifier to perform a hierarchical classification (Burnett et al. 2003). The classified output was further refined with feature heuristics and the exploration of boundary placements of segmented objects. Their methodology resulted in a successful visual result and an improvement in accuracy over pixel-based approaches.

Different types of imagery have also been found to have an impact on the accuracy of a classified image when using an object-based approach for surficial mapping. For instance, classification of wetlands was improved not only when an object-based method was applied to high spatial resolution imagery, but also when hyperspectral imagery was used rather than multi-spectral datasets (Sugumaran 2003). Recent studies targeted alluvial areas for identification using an object-based classification approach. By incorporating a DEM into an object-oriented classification procedure, geomorphologic terrain features were classified in Death Valley, Nevada by Ariagalas and Tzotsos (2003). Combining a priori knowledge of attributes for terrain classes and the statistical properties of the objects, fuzzy membership functions were derived. Through several stages of classification via segmentation and class fusion, satisfactory results were obtained in the extraction of terrain objects compared to a physiographic map. Using these results, alluvial fans were successfully identified by utilizing both supervised and unsupervised classifications paired with rules based on fuzzy logic (Argialas and Tzotsos, 2004).

Finally, the use of multi-resolution segmentation was very successful in improving the accuracy of the classification of complex riparian vegetation along the banks of streams (Antunes et al 2003). Along with emphasizing the importance of the spectral information of the infrared channel towards the classification of complex vegetation, they concluded that the contextual information gained from using a hierarchical classification led to consistently better classified classes than a Bayesian classifier.
2. Study Area and Data

2.1 The Study Area

The focus for this initial development was Lost Shoe Creek (49° 12' N; 125° 36' W) in the Clayoquot Sound area of Vancouver Island, British Columbia, Canada. The study site consisted of a 4 km x 7 km region, centered over the creek. The landscape rises gently 100m from tidewater to the start of an upper stream portion. The area receives prolonged and heavy precipitation in excess of 3000 mm per year. The width of the Lost Shoe Creek varies from 5-20m. The creek consists of substrate material varying from sand through cobble, with some boulder and exposed bedrock. The riparian zone on the stream banks of the creek consists of deciduous trees such as Alder (Alnus rubra) located on steep banks with dense understorey vegetation, while the adjacent land is occupied by a number of different tree species with varying age and vegetation structural characteristics.

The landscape surrounding the Lost Shoe Creek study site was partially deforested in the 1970’s, and as a result subsequent regeneration has created a complex mosaic of different stand structures. The entire study area is classified as Coastal Western Hemlock zone based on the Biogeoclimatic Ecosystem Classification (BEC) system used in British Columbia as a regional ecosystem classification scheme (Meidinger and Pojar 1991). Western hemlock (Tsugaheterophylla) is a dominant or codominant tree species throughout the study area, while western redcedar (Thuja plicata), amabilis fir (Abies amabilis), yellow-cedar (Chamaecyparis nootkatensis), Sitka spruce (Picea sitchensis), Douglas-fir (Pseudotsuga menziesii), and red alder (Alnus rubra) also occur under differing conditions.

2.2 Use of Terrain Ecosystem Mapping (TEM) to identify alluvial landforms.

The Terrestrial Ecosystem Mapping (TEM) classification has been designed to provide management-level information to a wide range of resource management applications, and is derived from aerial photography (1:20 000 to 1:50 000) (Mitchell et al. 1989; Demarchi et al. 1990). The TEM classification system used for mapping in this research are hierarchical, with broad scale regional and climatic landscape units and finer-scale polygons covering major, and then minor physiographic and macroclimatic variation. At the finest scale, TEM mapping provides polygons of similar vegetation composition with variations along a graduating scale of moisture and nutrient availability. TEM data are used in five broad subject areas: forest management, range management, wildlife management, biodiversity management, and terrain/soils. To identify polygons that are alluvial and therefore have increased potential to contain high value fish habitat, several parameters must be met.
a. One of the main geomorphological processes present in a given polygon must be Fluvial (F).

b. The state of activity of the geomorphological process [Active (A) or Inactive (I)] must be Active.

Table 1: Criteria used to identify alluvial landforms from TEM classification

<table>
<thead>
<tr>
<th>Description</th>
<th>Code</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process</td>
<td>F</td>
<td>Fluvial</td>
</tr>
<tr>
<td>State</td>
<td>A</td>
<td>Active</td>
</tr>
</tbody>
</table>

Figure 1 shows the distribution of alluvial landforms, as derived using Table 1 criteria, for the Lost Shoe study area.

2.3 High Spatial Resolution Remote Sensing Imagery

A QuickBird image was acquired on the 6th of June 2005 for Lost Shoe Creek (Figure 2), and comprises four multi-spectral bands of 2.8m spatial resolution and a panchromatic band of 0.70m spatial resolution. The QuickBird image data were converted to top of atmosphere radiance units using pre-launch calibration coefficients as described in the ENVI image process system (RSI 2005). The QuickBird radiances were not atmospherically corrected as time series analysis of consecutive image data was not required for this study, and detailed information on the atmospheric conditions at the time of overpass were not available. The image data was geometrically corrected prior to purchase by DigitalGlobe with a stated positional accuracy of less than 5m. This spatial accuracy was confirmed using available digital cadastral information.
Figure 1: Distribution of alluvial landforms (blue polygons) in the Lostshoe Creek region, as derived using Table 1 criteria, based on TEM Mapping.
Figure 2: Quickbird true colour multi-spectral satellite image of study area.
2.4 LIDAR DATA

Small footprint laser data were collected during July of 2005 by Terra Remote Sensing (Sidney, British Columbia). Pulse frequency, flight speed and altitude were optimized to achieve a nominal point spacing of one laser pulse return every 1.5 m². Separation of vegetation and terrain was carried out using Terrascan v. 4.006 (Terrasolid, Helsinki, Finland). A continuous DEM with a spatial resolution of 1.5 m was created using ArcGIS 9.1 (ESRI, Redlands, USA) by applying a natural neighbor interpolation algorithm to the ground returns (Figure 3). The final DEM has a nominal absolute accuracy of approximately 80 cm in forested areas.

A standardized DEM was created to minimize the systematic increase in elevation to the north and west as distance from the coast increases. By converting heights to z-scores, changes in the value of each raster cell should be more closely related to that cell’s relative position with respect to its immediate geomorphic setting (e.g. terrace, mid-slope, stream bed and so on), and less so with the broader general pattern of the study area. Heights were converted to z-scores using the following equation:

\[ Z_{xy} = \frac{(h_{xy} - \bar{h})}{S_h} \]

Where \( Z_{xy} \) are z-scores at location \( x \) and \( y \), \( h_{xy} \) are heights above the WGS 84 ellipsoid at location \( x \) and \( y \), \( \bar{h} \) is the mean height of the DEM, and \( S_h \) is the standard deviation of the DEM’s heights.
Figure 3: LIDAR image of study area and locations of cross-sectional profiles.
3. METHODS

3.1 Classification of QuickBird and LIDAR Data using an object-based classifier.

The multispectral orthorectified QuickBird image (with four bands) and the z-score DEM were classified using eCognition (V4.0, Definiens-Imaging, Germany) which is an object-oriented classification, involving the derivation of image clusters, which are polygons of roughly equal size exhibiting interior homogeneity (within-object variance is small compared with between-object variance). Classifying segments using both spatial and spectral characteristics allows separate objects that have quite different spectral features but similar spatial features to be classified similarly. These clusters are then automatically derived and then classified, based on both their spatial and spectral characteristics, following a supervised training model which involves, within training areas, allocating class labels to classified clusters. All of the input bands were assigned equal weights of 1.

The first step for classifying the image is called multiresolution segmentation. There are several user-controlled parameters that control the segmentation process. Firstly the scale of objects to be segmented is chosen. Taking into account the size of the image, the resolution and the classification goal, a scale parameter of 15 was assigned to the segmentation process. A second parameter is the homogeneity criterion, of which the color and shape weightings are most crucial. The weight of the spectral characteristics for this classification was set to 0.7, complimented by a shape setting of 0.3. More weighting was given to the spectral rather than spatial parameters due to the fact that broad patterns of forest structure are required. The second key step in the object based classification is the extraction of additional attributes for each object in addition to the standard spectral information that is provided within the image. For example, attributes on shape, texture, spectral and the relationship of each object to neighboring objects to the same, or different, classes are all calculated. To do this superclasses are defined, using a nearest neighbor classifier, from which individual image objects are marked as typical (representatives of a class), and the rest of the scene objects compared and contrasted.

Utilizing field-based information, TEM maps, as well as information from previous riparian vegetation classifications a class hierarchy was created. Three classes were created in order to allow differentiation of alluvial material (class 1) from all other cover types. These remaining three classes were coastal vegetation, coast, and non-alluvial areas. 150 image objects were then selected, generally stratified to the proportion of that class over the entire study area, grouped into one of the 4 classes based on the TEM maps, and used as training data for the nearest neighbor classification routine. Once the training area polygons were chosen as training sites the
Feature Space Optimization tool was used to define which attributes of the image objects contained maximum separability between classes and this should to be included in the classifier. The Feature Space Optimization allows the user to specify two or more classes and a set of attribute layers, then determines which layers statistically define the classes best, based on the samples that have been chosen for each class. Once adequate samples were selected for each class, and the attributes selected for the classification, the standard nearest neighbor classification was applied.

3.2 Processing of LIDAR Data to extract Fluvial Geomorphology

All data processing and analyses of the LIDAR data, in isolation, were performed using ArcGIS 9.1 Spatial Analyst and 3D Analyst extensions. In order to reduce random noise and minor variations in topography, which obscured larger-scale variations, the original 1.5 m LiDAR DEM was resampled to 10 m resolution and a low-pass filter applied.

Using the smoothed 10 m DEM, a number of additional raster data sets were created and analyzed, including:

- flow direction
- upstream flow length
- downstream flow length
- slope
- curvature
- profile curvature
- plan curvature.

In particular, the downstream flow length and profile curvature models were important DEM derivatives used to delineate alluvial areas. Downstream flow length indicates the distance downstream along a flow path for each raster cell (ESRI(a) 2006). Curvature is the second derivative of a surface, or the slope of the slope (ESRI(b) 2006). Profile curvature is referred to as either convex or concave, and determines the route water follows and locations where alluvium is deposited. A convex profile curvature indicates that slope is increasing in the downslope direction and is typically found near the top of hills, while concavity occurs in areas of diminishing slope, usually at the bottom of hills. The ArcGIS “curvature” tool calculates curvature based on the concepts found in Zeverbergen and Thorne (1987) and Moore et al. (1991) (ESRI(a) 2006; ESRI(b) 2006). The curvature of a surface is calculated on a cell-by-cell basis within a 3 x 3 window.
For each cell, a fourth-order polynomial is calculated using the following equation (ESRI(a) 2006):

\[ Z = Ax^2y^2 + Bx^2y + Cxy^2 + Dx^2 + Ey^2 + Fxy + Gx + Hy + I \]

The relationships between the coefficients and the values of elevation for the nine cells within the 3 x 3 window are determined in the following manner (ESRI(a) 2006):

- \[ A = \frac{[(Z1 + Z3 + Z7 + Z9) / 4 - (Z2 + Z4 + Z6 + Z8) / 2 + Z5]}{L^4} \]
- \[ B = \frac{[(Z1 + Z3 - Z7 - Z9) / 4 - (Z2 - Z8) / 2]}{L^3} \]
- \[ C = \frac{[(-Z1 + Z3 - Z7 + Z9) / 4 + (Z4 - Z6)] / 2}{L^3} \]
- \[ D = \frac{[(Z4 + Z6) / 2 - Z5]}{L^2} \]
- \[ E = \frac{[(Z2 + Z8) / 2 - Z5]}{L^2} \]
- \[ F = \frac{(-Z1 + Z3 + Z7 - Z9)}{4L^2} \]
- \[ G = \frac{(-Z4 + Z6)}{2L} \]
- \[ H = \frac{(Z2 - Z8)}{2L} \]
- \[ I = Z5 \]

where \( Z1, Z2, Z3... Z9 \) are elevation values of the cells within the 3 x 3 window, and \( L \) is the distance between cell centers. The profile curvature is a derivative of the polynomial surface, and in ArcGIS is calculated using the following equation (ESRI(b) 2006):

\[ \text{Profile Curvature} = 2*(DG^2 + EH^2 + FGH)/(G^2 + H^2)*100 \]

A logic-based approach was used to identify active fluvial areas within the DEM. First, cross-sectional profiles of the Lostshoe creek channel were extracted from the 1.5 m DEM and examined to develop an understanding of the stream's morphology (Figure 3). Global and focal statistics for the two classes were then calculated for the three DEMs and the derivatives of the smoothed 10 m DEM. Using the existing TEM definition of alluvial areas, the resulting statistical data were employed to identify datasets where alluvial areas differed from other classes. Thresholds were then manually selected to divide the landscape into alluvial and non-alluvial categories.

Cross-sectional profiles measured along Lost shoe Creek from the 1.5 m DEM are shown in Figure 4. The channel varied in width from approximately 30-100m, and the stream bed was generally 10-20 m below the surrounding landscape’s surface. As a result, focal windows with a width of 30-60 m were generally the most effective at delineating alluvial areas.
Figure 4: Cross-sectional profiles across Lostshoe Creek measured from a LiDAR-derived DEM. Refer to Figure 3 for locations.
4. RESULTS

4.1 Classification of QuickBird and LIDAR Data using an object-based classifier

The segmentation of the Quickbird multispectral imagery and the zscore-DEM produced approximately 18,000 objects with an average object size of 28 pixels (equating to 175 m$^2$). Statistics of the derived image objects are available in Table 2 and Figure 5. The output segmented multi-spectral image is shown in Figures 6 and the final classified image in Figure 7.

Table 2: Statistics of the image objects derived from the combined QuickBird and LIDAR dataset

<table>
<thead>
<tr>
<th>Segmentation</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Objects</td>
<td>18493</td>
</tr>
<tr>
<td>Mean size of Objects (pixels)</td>
<td>28.56</td>
</tr>
<tr>
<td>Standard deviation size of objects (pixels)</td>
<td>9.61</td>
</tr>
<tr>
<td>Smallest Object (pixels)</td>
<td>1</td>
</tr>
<tr>
<td>Largest Object (pixels)</td>
<td>80.86</td>
</tr>
</tbody>
</table>

Figure 5: Histogram of objects defined on the multi-spectral and LIDAR imagery.
Figure 6: Segmented objects of the Quickbird Scene (NIR) + raw NIR image.
Figure 7: Final object-based classification.
Once the image objects were defined the feature object extraction tool provided information on which of the spectral, textural, shape and object association attributes were the most significant in delineating alluvial reaches as defined by the training areas. Table 3 provides a list of the 14 most significant image attributes and indicates, in general, attributes associated with each objects association to its neighbour was the most significant variable in its classification to alluvial reaches. As the Table indicates the mean absolute difference in magnitude of the z-scored DEM between the alluvial objects and their neighbours was the attribute most able to discriminate classes. This was followed by the largest z-score difference between alluvial objects and their neighbours. In addition to these type of neighbourhood relationships the overall minimum value of Z score (i.e. the comparative lowest part of the landscape within the z-score window), variations in spectral values of Band 4 (NIR) and Band 2 (green) of the QuickBird image were also significant. Finally, image texture attributes also showed some capacity to differentiate classes all computed from band 3 (the red band) of the imagery.

Table 3: List of the most significant image attributes used to differentiate alluvial reaches from the three other cover classes in the image.

<table>
<thead>
<tr>
<th>Samples</th>
<th>Category</th>
<th>Overlap between alluvial category and other classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean diff to neighbors (abs) - DEM (z-scores)</td>
<td>Neighbour relationship</td>
<td>0.15</td>
</tr>
<tr>
<td>Mean Difference to brighter neighbors DEM (z-scores)</td>
<td>Neighbour relationship</td>
<td>0.17</td>
</tr>
<tr>
<td>Mean Difference to neighbors DEM (z-scores)</td>
<td>Neighbour relationship</td>
<td>0.25</td>
</tr>
<tr>
<td>Min pixel value - DEM (z-scores)</td>
<td>Spectral</td>
<td>0.27</td>
</tr>
<tr>
<td>Standard deviation to neighbor pixels - DEM (z-scores)</td>
<td>Neighbour relationship</td>
<td>0.34</td>
</tr>
<tr>
<td>Mean diff to scene - Band 4</td>
<td>Spectral</td>
<td>0.36</td>
</tr>
<tr>
<td>Ratio to scene - DEM (z-score)</td>
<td>Spectral</td>
<td>0.36</td>
</tr>
<tr>
<td>Standard Deviation - DEM (z-scores)</td>
<td>Spectral</td>
<td>0.37</td>
</tr>
<tr>
<td>Mean - Band 4</td>
<td>Spectral</td>
<td>0.38</td>
</tr>
<tr>
<td>Ratio - Band 2</td>
<td>Spectral</td>
<td>0.47</td>
</tr>
<tr>
<td>GLCM Entropy (all dir) - DEM (z-scores)</td>
<td>Texture</td>
<td>0.58</td>
</tr>
<tr>
<td>GLCM Entropy (0 deg) - Band 3</td>
<td>Texture</td>
<td>0.60</td>
</tr>
<tr>
<td>GLCM Homogeneity (45 deg) - Band 3</td>
<td>Texture</td>
<td>0.61</td>
</tr>
<tr>
<td>GLCM Entropy (90 deg) - Band 3</td>
<td>Texture</td>
<td>0.62</td>
</tr>
</tbody>
</table>
Figure 8(a) and (b) provide additional information on the separation of two selected attributes from the list of object features. The figure shows that the separability of a single attribute in isolation does not provide a clear classification result for alluvial reaches. Rather, a number of attributes applied in association are needed to provide a clear classification result.

Figure 8a: Separation in the mean ratio of Band 2 brightness between the 4 classes

Figure 8b: Separation in the absolute mean difference to neighbours of the DEM

4.2 Classification of LIDAR Data to extract Fluvial Geomorphology

Figure 9 displays the logic-based work flow used to identify alluvial areas within the study area. The most apparent problem in identifying alluvial landforms was the confusion created by the presence of coastal areas. The cross-sectional profiles of coastal wave-cut escarpments and stream banks are sufficiently similar that they could not be separated. Thus an important first step was to remove coastal areas completely from the classification. In order to do so, the 10 m DEM was further smoothed using a mean filter with a 200 m moving window, and then all areas ≤ -9.5 m above the ellipsoid were selected. This area was converted to a polygon, buffered by 125 m to ensure that the entire coastal escarpment was captured, and subsequently re-rasterized. All areas that fell below the specified height and/or were covered by the 125 m buffer were excluded from the classification.

In order to remove upland areas, the standardized DEM provided the best results. Areas with z-scores greater than 0.08 were removed from the classification. Removing coastal areas and uplands resulted in a classification identifying mid-elevations (Figure 10).
The mid-elevations DEM was then used as an input to calculate flow direction, or the steepest descent from each cell. Using the flow direction raster, downstream flow length was calculated.

Figure 9: Flow chart displaying logic-based process employed to identify active fluvial areas using LiDAR data.
Figure 10: Two temporary datasets (top and middle), and the final classification identifying alluvial areas (bottom).
Figure 11(a) shows the downstream flow lengths within each class, allowing the derivation of a simple threshold to define areas that are non-alluvial. Areas with a flow length greater than 115 m were then removed from the classification, leaving only areas with a relative “downstream position” on the landscape (Figure 10).

Profile curvature was then calculated for the remaining areas. The profile map describes to what degree a curved surface is concave or convex using positive and negative values. Of interest, however, was not only the type of curve, but the magnitude. Thus, the absolute values of the profile curvature were calculated. To enhance the boundaries between stream banks and adjacent areas, a high-pass filter was applied to the curvature surface. Focal standard deviations were then calculated using 30 m and 60 m windows.

Figure 11(b) shows the values for the 60 m focal standard deviations for each class. Although their ranges were similar, the curvature values for the classes were distributed about their means in such a way that some separation between the alluvial and non-alluvial categories could be identified. Thus, using the profile maps, areas where the topography’s surface exhibited a high degree of change in cross-sectional profile were identified. Because uplands and coastal areas had previously been removed, these areas generally corresponded to alluvial landforms. Areas were selected with 30 m focal standard deviations between 1.5 and 15, and with 60 m focal...
standard deviations between 1.8 and 10. Areas with standard deviations above or below these values were excluded. Finally, noise was removed from the classification using a 3x3 pixel median focal filter, resulting in the final classification of active alluvial areas (Figure 10).

Figure 11 displays both the rule-based and object-based classification results overlain with the alluvial TEM polygons for comparison.
Figure 12: Final object-based and rule-based classifications.
5. Discussion

The recent availability of object based classification routines have allowed two major advances in image classification. The first involves the use of image segments which allow the creation of scene objects which represent similar pixels grouped together in a coherent way. Secondly, the approach allows, for the first time, a large number of image attributes to be extracted from the image objects based on spectral, textural, shape and neighbor relationships.

The results of this pilot project show the classification of alluvial reaches is similar to that as defined by the TEM mapping and thus that these types of geomorphological features can be mapped from remotely sensed data using automated procedures. These results have been verified against the existing field data for the pilot area, and appear to have captured the major alluvial features present, however more verification is needed before this type of technology and approaches can be considered operational.

Initial results indicate close agreement between the location and size of polygons identified as alluvial landforms, based on the TEM mapping, and those identified using the remotely sensed imagery. Using the object based classifier it is apparent that the z-scored DEM contains most of the information needed to discriminate the alluvial classes from other land forms in the scene. The attributes extracted from the DEM were, in the majority, based on neighborhood relationships indicating it is the relative position of the objects, within their geomorphic context, that is the main identifier. The use of the near infrared band in the classification scheme can be attributed to its capacity to detect vegetation function which is likely to be greater in vegetation along streams. In addition, the lack of reflectance of water in the near infrared region of the spectrum allows very clear discrimination of water from soil and vegetation thereby enhancing discrimination.

The use of LIDAR data in isolation, using a rule based approach derived from height, slope and curvature information also proved to be effective in delineating alluvial reaches in the study area, and could be viewed as providing a more physically based alternative to that of the object based classifier. In reality, however, the difficulty of quantifying alluvial landforms statistically within this framework makes the implementation of this type of approach more time consuming than the object based image classification scheme.

While these preliminary findings show that both of these classification techniques accurately identify alluvial reaches when compared to the TEM, ongoing work is required to include a more refined definition of alluvial landforms based on slope classification from a digital terrain model,
as well as extending this study to a wider area, where more varied alluvial landforms are likely to be present.

6. Acknowledgements
We are grateful for Mr Warren Warttig (Interfor), and Dr Denis Collins and Dr Andy McKinnon (MOF&R) for ongoing support of this research. Dr Brett Eaton (UBC) provided valuable advice on interpretation of the TEM landform codes, and Kasper Johansen (University of Queensland) assisted with the object-based classification.

7. References


