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Detecting translational landslide scars using segmentation of Landsat ETM+ and DEM data in the northern Cascade Mountains, British Columbia

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Abstract. Extensive landslide inventories are often utilized for hazard assessment studies and when investigating medium- to long-term evolution of alpine terrain. The predominant methodology for collecting these databases is aerial photographic interpretation, which can be time-consuming and expensive. Earlier work has demonstrated that spectral response patterns for satellite images, when used alone, are unreliable at detecting most types of landslides. Principal difficulties are related to inadequate image resolution and spectral methods of classifying image data that are not sensitive to the characteristics that identify landslide features such as their shape and topographic expression. This study in the Cascade Mountains of coastal British Columbia attempts to overcome the latter problem through image segmentation and the use of geomorphometric data derived from a digital elevation model (DEM). Image segmentation involved grouping pixels into discrete objects based on similarities and differences in their reflectance and the use of shape criteria. A hierarchical classification system was then developed such that the normalized difference vegetation index (NDVI) and slope data eliminated all areas in the image that were both vegetated and on a gradient of less than 15°. The remaining "unvegetated steeplands" were classified using a supervised classification based on spectral, geomorphic, and shape criteria. The technique produced an overall accuracy of 75% in the detection of landslides that were over 1 ha in area.

Résumé. Des inventaires exhaustifs de glissements de terrain sont souvent utilisés pour l'évaluation des risques ainsi que pour l'études de l'évolution a moyen et long termes du paysage alpin. L'interprétation de photographies aeriennes est la principale méthode utilisée pour la collecte des données relatives aux glissements de terrains. Elle s'avère toutefois lente et dispendieuse. Des études précédantes demontrent que l'analyse spectrale par images satellitaires, lorsqu'utilisée seule, est peu fiable pour la detection de la plupart des types de glissement de terrain. La principale difficultée est due à une résolution inadéquate de l'image ainsi qu'à des méthodes de classification de données spectrales insensibles aux charactérisiques permettant l'identification des glissements de terrain, tel que la formes et la topographie du terrain. Cette présente étude, réalisée dans les montagnes Cascade en Colombie Britanique, a pour but de surmonter ce problème en utilisant une technique de segmentation de l'image combinée a l'utilisation de données morphométriques dérivées d'un modèle numérique de terrain. La segmentation de l'image implique le regroupement de pixels en objets discrets en fonction de similarités et de différences de leur réflectances ainsi que l'utilisation de critères de formes. Un système de classification hièrarchique fut ensuite développé de façon à ce que la différence normalisée de l'indice de végétation et la pente élimine tous les aires de l'image qui ont à la fois un couvert végétal et ont une pente inférieure à 15°. Les aires résiduelles, i.e., non-végétalisées et à forte pente, furent soumises à une classification supervisée basée sur des critères spectrales, geomorphique et de forme. Cette technique a permis d'identifier de façon générale 75% des glissements de terrain dans un quadrat mesurant 1 ha.

Introduction

Landslides are widely recognized as an important process in the transport of sediment within alpine drainage basins (e.g., Hovius et al., 1997; 2000; Jakob, 2000). One of the major problems encountered in large-area studies of landsliding within mountainous landscapes is the acquisition of comprehensive databases. This is because of the inherent inaccessibility of alpine areas and the difficulty in identifying the mass-wasting events therein from the ground, particularly older events that have been subject to revegetation. Therefore, most large-area studies have adopted some form of remote sensing in their research methodology (e.g., Hovius et al., 1997; 2000; Martin et al., 2002). The most commonly used method is aerial photographic interpretation, although a number of studies have explored the feasibility of a computerized approach using satellite or airborne imagery (e.g., Sauchyn and Trench, 1978; Connors and Gardner, 1987; Epp and Beaven, 1988; McKean et al., 1991). Others have attempted to use a combination of satellite imagery and digital

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elevation models (DEMs) (e.g., Giles et al., 1994; McDermid and Franklin, 1995; Giles and Franklin, 1998) or interferometric radar data (Kimura and Yamaguchi, 2000).

Although primarily geared towards hazard assessment and geomorphic mapping, approaches involving both spectral and geomorphometric data could be successful in standardizing the accuracy of landslide inventories and in reducing the time demands required by the current methods. The main difficulties, however, have been related to data characteristics (e.g., spatial resolution) and methods of processing the data to detect and classify the landslide features. For example, McDermid and Franklin (1995) noted that in areas where geomorphic features and reflectance characteristics were unrelated, standardized supervised classification based on per-pixel spectral response patterns would fail to detect and classify accurately landslides and other mass-wasting features, such as debris flows. They suggested that an emphasis on extracting from imagery and DEMs the actual characteristics that distinguished landslide scars from surrounding terrain was needed. An approach focussed on landslide shape and topographic criteria over some local area would likely be more successful than a classification system that relied on pixel-based reflectance and geomorphometric properties alone.

This study involves the combination of Landsat enhanced thematic mapper plus (ETM+) imagery and geomorphometric data derived from a DEM to detect and classify fresh translational landslide scars within an area of the Cascade Mountains, British Columbia. Translational landslides (hereafter referred to as landslides) are defined as the mass movement of slope material owing to plane failure and transport downslope owing to gravity (Hutchinson, 1988). This broad definition is based on the mechanics of failure and transport rather than the type of slope material involved (i.e., unconsolidated material versus rock). This type of failure yields distinctive shape characteristics of the resultant scar and deposit that can be readily identified on the Landsat imagery. Fresh landslide scars refer to those that have not been subjected to significant revegetation and are therefore clearly visible on the aerial photographs.

Image segmentation groups pixels into objects based on their reflectance characteristics, shape criteria, and proximity. Such object-oriented classification is potentially of great value in the detection of landslide scars because it allows areal characteristics, such as the length to width ratio, to be included as class discriminators. This should produce a more accurate result than has been achieved in similar studies that have attempted to detect landslides using per-pixel spectral response patterns alone (e.g., Epp and Beaven, 1988). Because of the 30 m pixel size of the Landsat imagery, however, landslides having length dimensions that are less than 30–60 m (one to two pixels) will likely remain unresolvable. For this reason, we attempted to detect only those landslides that were over approximately 1 ha (10 000 m^2) in area.

Study area

The Chilliwack drainage basin, located approximately 160 km east of Vancouver on the U.S.–Canada border, was selected for this study. The Chilliwack River Valley roughly bisects the basin, with smaller tributary valleys feeding in from the north and south (**Figure 1**). Translational landsliding appears to be a dominant form of mass wasting within the basin. This dominance is attributable to the combination of glacial debuttressing, high relief, steep slope gradients, a shallow mantle of drift, and abundant precipitation (Howes, 1987). The inherent complexity of geomorphic systems in alpine areas is such that any inventory of discrete geomorphic forms will encounter classification errors owing to polygenesis. In the case of landsliding, similar forms can be the result of other geomorphic processes, in particular snow avalanching and the related breaks in vegetation. Such errors are expected to be minimal in the Chilliwack Basin, as the area exhibits little evidence of snow avalanche chutes along the valley walls.

The study area ranges in elevation from 13 m above sea level along the Fraser River floodplain to a maximum of 2283 m, with several peaks exceeding 2100 m. Bedrock geology is a complex sedimentary sequence of limestone, sandstone, and conglomerate, with large igneous outcroppings of predominantly granodiorite. The region is located on the fringe of what was the maximum extent of the Cordilleran Ice Sheet and has been subject to multiple glacial incursions during the Pleistocene (Armstrong et al., 1965). This glacial legacy is evident in the U-shaped valleys and cirques that typify the basin. The withdrawal of the valley glaciers has left slopes oversteepened and mantled with a layer of drift up to 2 m thick. Rock outcroppings are common near the mountain summits, where rock falls have produced long talus slopes.

The basin is subject to warm dry summers and cool moist winters. The densely forested slopes have been heavily logged, with many clear cuts in various stages of revegetation on all but the steepest of slopes. The higher and more exposed slopes have a combination of shrubs and alpine meadow or, in some cases, bare ground. Chilliwack, the only major urban centre within the study area, is located in the upper northwest corner along the Fraser River Valley, although there has been some settlement along the Chilliwack River Valley. The forest industry has developed a complex network of logging roads that provide access to all of the major valleys.

Data collection

Aerial photography

Colour 1 : 20 000 scale aerial photographs acquired in July 1996 were visually interpreted under a 10× power stereoscope to identify landslide scars within the study area. Interpretation was based on identification of breaks in vegetation that were located on slopes and showed evidence of surface rupture. The investigation yielded approximately 450 fresh landslide scars of various sizes. Of these, roughly 280 were of an area greater

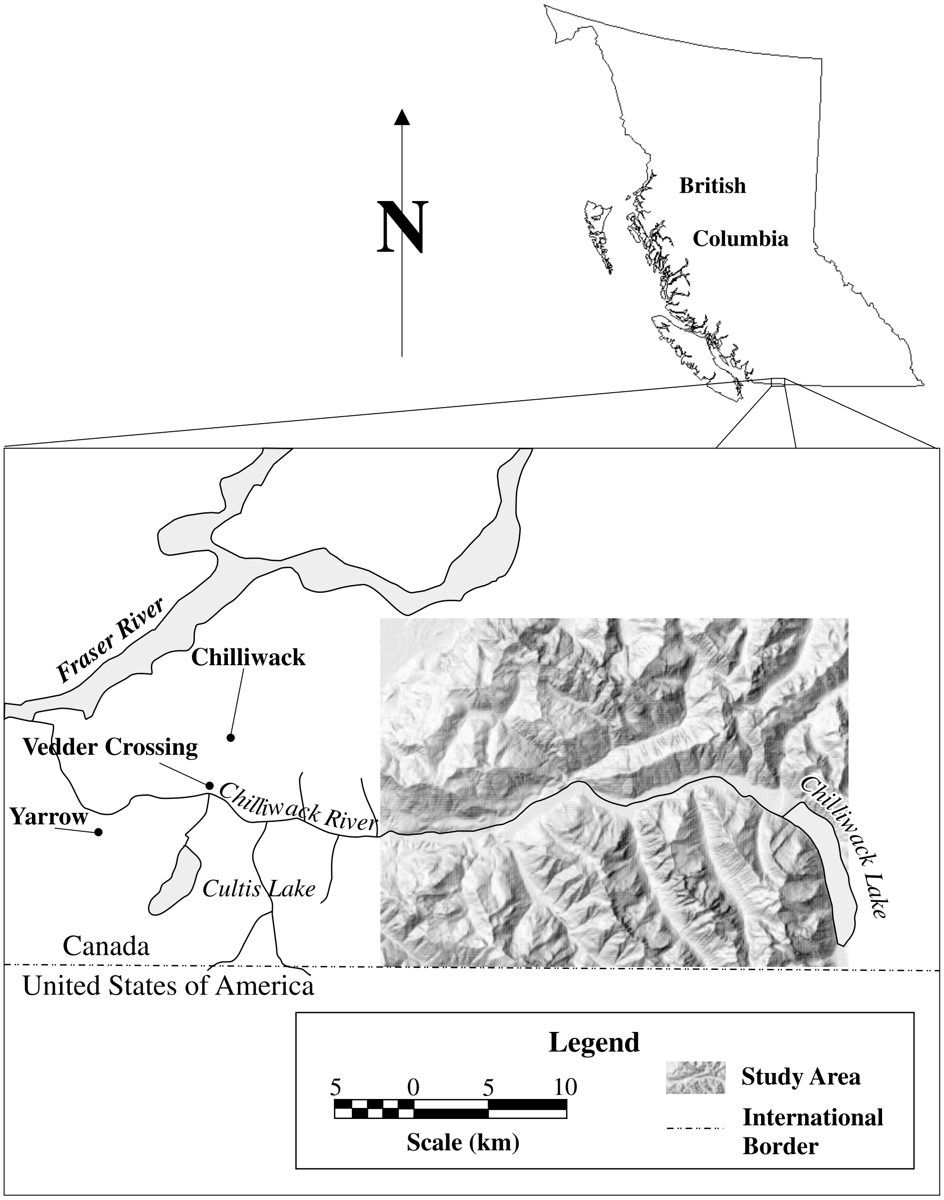

Figure 1. Geography of the Chilliwack Basin.

than 1 ha. Forty of these failures were randomly sampled and used in the accuracy assessment of the automated image classification. Training areas used in the supervised classification of the digital data were selected from areas identified on the aerial photographs. **Figure 2A** illustrates the identification of landslides and other features that were used to develop training area data for the supervised image classification.

Digital data

Data layers utilized for the image classification are illustrated in **Figure 3**. A Landsat ETM+ image acquired on 8 August 2001 was used in this analysis. Preprocessing of the six spectral channels involved atmospheric correction based on a standard atmosphere-model approach (Richter, 1998). Because of the proximity of the coast, the maritime atmospheric model was determined to be the most appropriate; we matched reflectance properties for pseudo-invariant features, such as lakes and roads, to the reflectance coefficients in the model atmosphere. Orthorectification was accomplished using geographic information system (GIS) vector road and stream data and a DEM interpolated from the provincial base-mapping program (1 : 20 000 scale Terrain Resource Information Management (TRIM) maps) of the area produced in 1998. We calculated slope and aspect from this DEM. A normalized difference vegetation index (NDVI) channel was created from the red and infrared spectral bands of the ETM+. We used this index to establish a threshold for vegetated and unvegetated pixels in the image (Hansen et al., 2000).

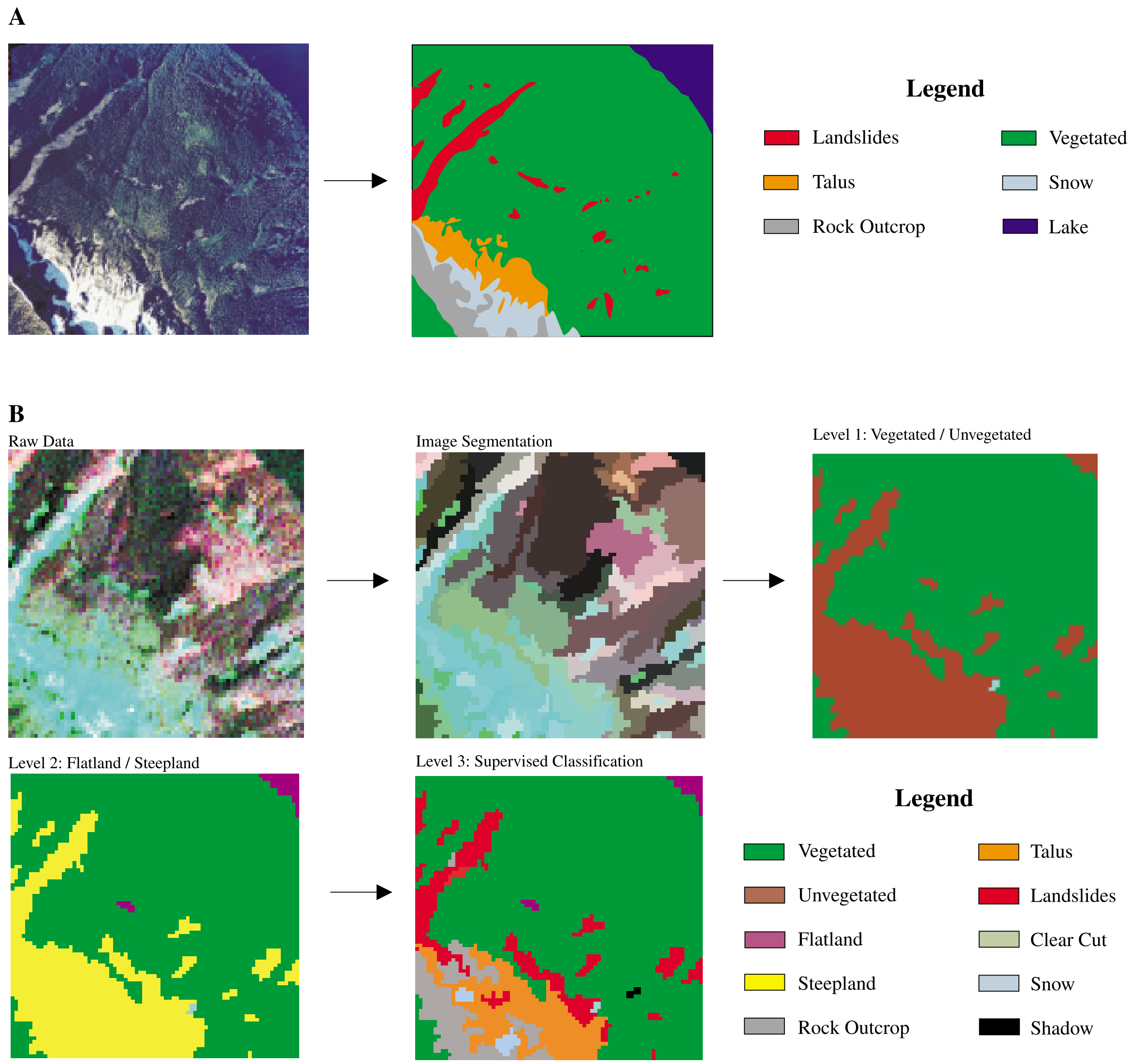

Figure 2. Aerial photographic interpretation of an area of the Chilliwack Basin (A) compared to the automated classification of the same area (B). Note the smaller slides that are not resolvable, the lower amount of snow cover, and the misclassification of some of the talus slope.

Field data

Ground truthing was conducted in the study area to test the accuracy of the aerial photographic interpretation and to gain insight into the geomorphic characteristics of the basin. A subset of 10 events was taken from the 40 used in the accuracy assessment and visually inspected to assess the type of slope material involved and the nature of the failure. In all cases, the areas identified as landslides in the aerial photographs were confirmed to be translational landslides on the ground. Of the 10 investigated, nine were found to involve bedrock (**Figure 4**). Failures that involved drift were confined to the lower slopes where stream migration had resulted in undercutting at the slope base or in areas where an accumulation of colluvial material had previously been deposited.

Methods

Digital image analysis was conducted with the eCognition software suite (Definiens, 2002). This software provides for image segmentation and classification hierarchy capabilities as illustrated in **Figure 2B**. Segmentation groups pixels into polygons based on similarities in user-defined data layers. Following segmentation, a classification hierarchy, mimicking the steps used in the aerial photograph interpretation of landslides, was followed. This involved progressively eliminating areas of the image where landslides would not be expected, such as those that were vegetated or on a low gradient. The remaining portions of the image were then classified using a supervised classification involving spectral, morphological, and shape criteria. An accuracy assessment was

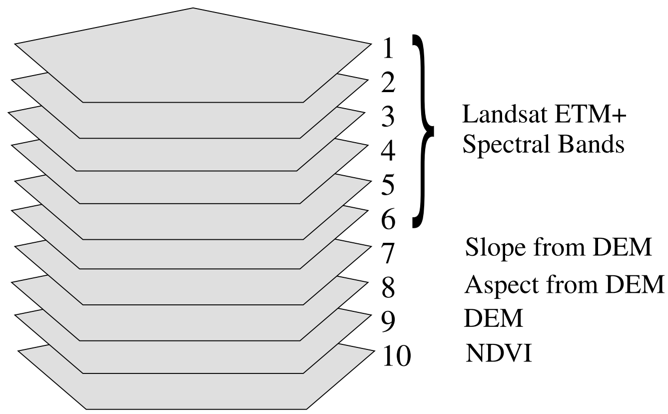

Figure 3. Data layers used in the classification.

conducted to determine the agreement between the aerial photographic interpretation and digital detection of landslides.

Image segmentation

Image segmentation within eCognition is based on a threshold fusion value that is a function of both spectral and shape heterogeneity (Definiens, 2002). The threshold is calculated from user-defined parameters of scale, colour, shape, compactness, and smoothness. Scale is a measure of the maximum change in heterogeneity allowable in the merging of two objects. Colour and shape are weighted relative to one another such that the sum of their assigned values must be 10. A similar weighting is given to compactness and smoothness (Definiens, 2002). We selected the plane neighbourhood and only considered the four pixels that are connected along a plane border as neighbours. The imagery was segmented using a scale of 10 and a ratio of 8:2 for the relative importance of reflectance versus shape and 7:3 for compactness versus smoothness. This combination of parameters was established after several iterations in which the produced segments or objects appeared to capture the shape and size of the landslides within the study area. We selected an equal weighting of the six ETM+ bands and the NDVI channel. This ensured that the segments or objects created were consistent with the spectral and vegetative patterns and were not dependent on the DEM data or the two morphological data layers.

Classification of segments

The classification scheme used to detect the landslides depends on a user-specified hierarchical structure used to eliminate image objects that are not of interest. The first level is the division of the image between vegetated objects and unvegetated objects based on their NDVI value. Those objects whose NDVI value was below 0.69 were considered to be unvegetated, and those whose NDVI values were above 0.69 were classed as vegetated. The selection of 0.69 was empirically based on an inspection of the image objects within the study area. This effectively eliminated the majority of the image objects, leaving only the barren areas for further consideration. These unvegetated areas were further subdivided to eliminate objects that had a mean slope gradient of less than 15°. This was accomplished by using a Boolean decision function within the class descriptor. The objects were then divided into unvegetated flatland and unvegetated steepland. This step was useful in eliminating all of the lakes in addition to the urban areas along the Chilliwack River Valley and those in the northwest corner of the study area. The unvegetated steepland was

Figure 4. Translational landslide within the Chilliwack Basin. The slide was successfully detected by the classifier.

then used as the target for a supervised classification using spectral, morphological, and shape descriptors.

Within the unvegetated steepland portion of the image, we identified classes of snow, rock, talus, shadow, clear cut, and landslides (see **Table 1**). The classification of snow and shadow was based solely on mean values obtained from each of the data levels because of their distinctiveness compared to the other classes. Rock was based on the layer values and a distance descriptor stating that rock outcrops were normally found within a certain proximity to one another. In this case, a threshold of 10 pixels was found to produce the best results. Talus, clear cuts, and landslides were extremely similar in terms of their reflectance, so morphological and shape criteria became important components of their class descriptions.

The discrimination of talus was accomplished through the use of related neighbour objects within the class description. To be classified as talus, an object had to border a classified rock outcrop object or another talus object. Similar measures were taken to discriminate between clear cuts and landslides. In this case, the class descriptor for clear cuts involved a requirement to border vegetated objects. A shape criterion was also included requiring clear-cut areas to have a length to width ratio in the range of 0.5–1.5. This is reflective of the blocky form that characterized the clear cuts located on steeper slopes. The result effectively eliminated much of residual misclassification between landslides and clear cuts. The class descriptor was completed by the inclusion of a morphological rule requiring clear cuts to be located on slopes that were no greater than 50°.

Landslides transport material along the path of steepest slope and are characteristically long, narrow, and somewhat symmetrical about their long axis. Therefore, the landslide class description was based on layer values and shape criteria. Because of similarities in the reflectance of landslide scars to that of other classes, landslides were discriminated by their distinctive length to width ratio and an asymmetry rule. The length to width ratio was set to fall within a range of values between 2 and 15. The asymmetry rule was similar in function and compared the long and short axes of an image object. The greater the difference between the two axes, the greater the likelihood of the object being classified as a landslide.

Table 1. Classes and class descriptions.

Class	Description
Vegetated	NDVI > 0.69
Unvegetated	NDVI < 0.69
Flatland	Slope gradient < 15°
Steepland	Slope gradient > 15°
Landslides	Layer values; length to width ratio between 2 and 15; high asymmetry
Talus	Layer values; border to rock outcrop – talus
Rock outcrop	Layer values; within 10 pixels of rock outcrop
Clear cut	Layer values; border with vegetated; length to width ratio between 0.5 and 1.5; slope gradient less than 50°
Snow	Layer values
Shadow	Layer values

Accuracy assessment

Testing of the classification was accomplished through a comparison of the aerial photographic interpretation to the classified imagery. Errors of omission were detected by matching landslides that had been identified on the aerial photographs to those identified on the classified imagery. Of the 287 landslides of over 1 ha in area that were identified within the study area, a random sample of 40 was taken for the comparison. The validity of the samples was tested through ground truthing a subset of 10 events within the study area to definitely identify each as a landslide. False positives (errors of commission) were identified using a randomly selected sample of 40 landslides identified by the classification scheme and comparing them to the aerial photographs.

Results and analysis

The classification hierarchy was useful in locating areas where shallow landslides were likely to have occurred. In particular, the grouping of image objects into vegetated and unvegetated classes eliminated the vast majority of the study area from further consideration. The second level in the hierarchy, steepland versus flatland, was useful in eliminating those unvegetated areas that were of anthropogenic origin. In particular, the urban areas located in the northwest corner of the image and those along the Chilliwack River Valley were all eliminated by this simple rule. Many of the fresh clear cuts in the image, particularly those located along the valley bottoms, were included in the flatland class. Those clear cuts not included in the flatland class were discriminated from landslides through the use of their shape characteristics later in the classification process.

The combination of data and techniques used in the detection of landslides for this study area yielded an accuracy of 75% for errors of omission and 77.5% for errors of commission. A summary of the accuracy assessments is shown in **Tables 2** and **3**. The most common error of omission occurred with the vegetated class; five of 40 features classified as vegetated areas in the satellite image segmentation and classification procedure were actually mapped as landslides in the aerial photographs. At least some of this error may be attributed to the 5-year time lag between the aerial photographs and the satellite imagery. Such an interval may be of sufficient length to permit vegetative recolonization to the degree that the NDVI value exceeds the 0.69 threshold value. Other errors include misclassification of landslides as talus and rock outcrops. These errors of omission are attributable to the high degree of similarity that exists between reflectance and other characteristics of these classes. For example, landslides that do not meet the shape criteria would have a high probability of being erroneously assigned to one of these classes. This might be relatively common for slopes that have experienced multiple failures. Although each individual failure will adhere to the specified shape criteria, when grouped together they will not possess the length to width ratio to be classed as landslides.

Table 2. Assessment of classification accuracy for errors of omission.

Class	No. of samples in class	Percentage of total no. of samples (n = 40)
Landslides	30	75.0
Talus	2	5.0
Rock outcrop	2	5.0
Clear cut	0	0
Snow	0	0
Shadow	1	2.5
Vegetated	5	12.5
Flatland	0	0

Table 3. Assessment of classification accuracy for errors of commission.

Aerial photograph interpretation	No. of samples	Percentage of total no. of samples (n = 40)
Landslides	31	77.5
Talus	4	10.0
Roads	3	7.5
Rock outcrops	1	2.5
Clear cut	1	2.5

Errors of commission were evident with talus slopes, logging roads, rock outcrops, and bare ground. Of these, talus slopes were most frequently misclassified as landslides, particularly those that were segmented into long, thin sections. Such misclassification between different types of mass movements is to be expected owing to the similarity of material and form that can exist between them. Significant errors of commission also occurred between landslides and logging roads. Of the 40 classified landslides selected, three were actually logging roads. Discriminating between the two proved to be difficult because of their similar reflectance and shape properties. A separate class for roads was not used in this study; in preliminary tests we found that use of general parameters resulted in large errors of commission with other classes in the third level of the hierarchy. The other errors were similarly owing to the nature of the segmentation in which long, thin objects within the unvegetated steepland class were mistaken for landslides by the classifier.

Conclusions

We used a segmentation approach to detect and classify translational landslides within a humid alpine basin. We stratified the study area into features that were likely candidates for landsliding and those that were not. Spectral and geomorphometric data in combination with the shape criteria proved to be an effective approach in the detection of landslides compared to the more traditional, per-pixel statistical classification of spectral data alone. For example, we obtained a 75% success rate in locating landslides, whereas most spectral classifications have obtained a 50% or less classification accuracy (e.g., Epp and Beaven, 1988). At least some of the misclassification of landslides as vegetated areas may have been a result of the 5-year time discrepancy between the aerial photographs and satellite imagery used in this study. These results are considered promising for the collection of large-area landslide inventories in alpine environments.

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