MAPPING MIXED AND FRAGMENTED FOREST ASSOCIATIONS WITH HIGH SPATIAL RESOLUTION SATELLITE IMAGERY: CAPABILITIES AND CAVEATS

by

Shanley Dawn Thompson

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ABSTRACT

Satellite imagery such as Landsat has been in use for decades for many landscape and regional scale mapping applications, but has been too coarse for use in detailed forest inventories where stand level structural and compositional information is desired. Recently available high spatial resolution satellite imagery may be well suited to mapping fine-scale components of ecosystems, however, this remains an area of ongoing research.

The first goal of this thesis was to assess the capacity of high spatial resolution satellite imagery to detect the variability in late seral coastal temperate rainforests in British Columbia, Canada. Using an object-based classifier, two hierarchical classification schemes are evaluated: a broad classification based on structural (successional) stage and a finer classification of late seral vegetation associations. The finer-scale classification also incorporates ancillary landscape positional variables (elevation and potential soil moisture) derived from Light Detection and Ranging (LiDAR) data, and the relative contribution of spectral, textural and landscape positional data for this classification is determined. Results indicate that late seral forests can be well distinguished from younger forests using QuickBird spectral and textural data. However, discrimination among late seral forest associations is challenging, especially in the absence of landscape positional variables.

Classification accuracies were particularly low for rare forest associations. Given this finding, the objective of the third chapter was to explicitly examine the caveats of using high spatial resolution imagery to map rare classes. Classification accuracy is assessed in several different ways in order to examine the impact on perceived map accuracy. In addition, the effects on habitat extent and configuration resulting from post-classification implementation of a minimum mapping unit are examined. Results indicate that classification accuracies may vary considerably depending on the assessment technique used. Specifically, ignoring the presence of fine-scale heterogeneity in a classification during accuracy assessment falsely lowered the accuracy estimates. Further, post-classification smoothing had a large effect on the spatial pattern of rare classes. These findings suggest that routinely used image classification and assessment techniques can greatly impact mapping of rare classes.

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CO-AUTHORSHIP STATEMENT

This thesis contains two submitted scientific papers of which I am lead author. The idea for the overall project was initially proposed by Dr. Sarah Gergel. Specific project objectives were subsequently refined with input from Dr. Nicholas Coops, and Mr. Andy MacKinnon. I performed all research, and data analyses, with the exception of the initial creation of the Digital Elevation Model, which can be credited to Mr. Christopher Bater, and the creation of the Light Detection and Ranging (LiDAR) intensity image, prepared by Dr. Nicholas Goodwin. I prepared the final manuscripts, with co-authors providing advice on methodology and editing earlier drafts.

1. INTRODUCTION

Forest structure refers to tree age, size, density and composition, as well as the vertical and horizontal arrangement of these variables. This information can be recorded at a range of spatial scales ranging from stand to landscape level. Typically forest management requires information at the stand level, as the ecological, economic and cultural value of a forested landscape may vary according to the structure of each stand. For example, tree and snag size is important for birds and mammals that nest and den in cavities (Bunnel et al. 2002; Franklin and Spies 1991), while branch size and tree spacing is an important factor determining habitat suitability for bird species such as the endangered marbled murrelet (Burger and Bahn 2004). Beyond ecological values, many First Nations have traditionally relied on certain species as a key resource and different species are valued more than others in commercial timber markets.

Mapping forest structure over large areas necessitates the use of remote sensing. The choice of which type of remotely sensed imagery to be used will depend largely on the spatial resolution needed to accurately capture the desired ground elements (Woodcock and Strahler 1987). In general, image pixels should be considerably smaller than the ground elements of interest. Imagery with this characteristic is known as H-resolution (Woodcock and Strahler 1987). In contrast, L-resolution imagery is the term given to imagery where image pixels are larger than the elements of interest which are therefore not resolvable. Aerial photographs are the conventional source of remotely sensed information for mapping forest structure and composition at the stand level (Goetz et al. 2003; Wulder et al. 2004a). Satellite imagery, while superior to aerial photographs with respect to spatial coverage and temporal resolution, has, until recently, only been available at spatial resolutions too coarse to provide a detailed characterization of forest structure at the stand level. For example, Landsat imagery (30m spatial resolution) is generally capable only of distinguishing general vegetative types (e.g., deciduous versus coniferous) (Wulder et al. 2004a). In some cases, multi-date imagery has enhanced the discriminating power of Landsat imagery by capitalizing on phenological differences among various vegetative species (Townsend and Walsh 2001). However, multi-seasonal imagery of an area is not always available.

Within the last decade, high spatial resolution optical satellite imagery has become available with a spatial resolution closely matching that of aerial photographs. For example, the QuickBird and IKONOS satellites provide multispectral imagery at spatial resolutions of 2.8 and 4m (70cm and 1m panchromatic) respectively. The spectral and textural information contained in a high spatial resolution forest scene may be related to fine-scale compositional differences, as well as to structural characteristics such as canopy gaps and crown size (Treitz and Howarth 2000; Wulder et al. 2004a). In some cases, high spatial resolution satellite imagery can be used to detect individual tree crowns (Gougeon et al. 2003; Wulder et al. 2004b). Studies of high spatial resolution satellite imagery for characterizing stand structure have by and large focused on stand age (Franklin et al. 2001b; Nelson et al. 2004), structural variables such as stand density and basal area (Kayitakire et al. 2006), or to the classification of stands dominated by one of only a few species (Chubey et al. 2006). Classifications of compositionally complex stands have generally been limited to airborne imagery (Treitz and Howarth 2000).

Applications of High Spatial Resolution Imagery to Fragmented Ecosystems

High spatial resolution imagery is particularly suited to mapping small or fragmented ecosystems (often of high conservation concern) as such classes may be missed if they occupy a small portion of a pixel in medium to coarse resolution imagery (Cunningham 2006; Silva et al. 2005). To this end, high spatial resolution satellite imagery has been used in a number of studies to successfully map a range of small land cover classes. As examples, multitemporal IKONOS imagery has been used to map Prairie wetland vegetation communities in Saskatchewan, Canada (Dechka et al. 2002) and heather (*Calluna vulgaris*) moorlands in northern England (Mehner et al. 2004) Elsewhere, riparian vegetation structure, traditionally difficult to detect remotely because of its thin, linear nature, has been characterized and classified into various types using QuickBird imagery (Johansen and Phinn 2006).

Using high spatial resolution imagery to map small and fragmented ecosystems results in estimates of extent and landscape pattern that differ from those estimated on the basis of coarser resolution imagery. In a comparison of NOAA-AVHRR (1km spatial resolution) and Landsat TM (30 m spatial resolution) datasets, estimates of the spatial extent of rare classes were shown to be more accurate at higher spatial resolutions (Konarska et al. 2002). One study suggests that the spatial resolution of an image should be 2-5 times smaller than the feature of interest or risk biasing landscape pattern indices such as the frequency distribution of patch sizes (O'neill et al. 1996). In a study of the effect of changing spatial scale on landscape pattern, rare cover types were found to be lost most readily with increasing spatial resolution, with the rate of loss greatest for fragmented classes (Turner et al. 1989).

Estimates of the extent and pattern of small, fragmented classes may be also impacted by various image processing techniques. Often high spatial resolution imagery is classified with an object-based classifier, whereby, prior to classification, image pixels are merged into homogeneous clusters (objects), the size of which is determined by the user. In their object-based classification of forest stand structural stages, Johansen et al. (2007) found that small patches (width ≤ 30m) of various features were poorly classified because they were merged with adjacent patches of a larger size during the creation of image objects. This finding indicates that a given image analysis technique may not be appropriate for all classes of interest, particularly those which are small or fragmented.

Although high spatial resolution satellite imagery may have an enhanced capability to detect small patches of classes, whether or not this capability is recognized will depend on the spatial resolution of the reference data utilized to assess classification accuracy as well as the accuracy assessment technique chosen by the map producer. Often, preexisting vector-based data that has been generalized to polygons is utilized as the truth data; this data may contain thematic ambiguity, with polygons labeled with multiple ecosystems. Traditional accuracy assessment only allows for one reference label to be considered per polygon, resulting in classification estimates that may be misrepresentative (Stehman et al. 2003; Wulder et al. 2007).

Previous Applications of High Spatial Resolution Satellite Imagery in Coastal British Columbia

In the forests of coastal British Columbia, QuickBird imagery has been used to distinguish among several stand-level structural classes (shrub/herb, pole/sapling, young forest, and old-forest) with an overall accuracy of 79% (Johansen et al. 2007). However, the classification accuracies reported may be misrepresentative (that is, falsely low) as the authors only considered the dominant label of reference polygons during accuracy assessment. In the same area of coastal BC, QuickBird imagery has also been used to distinguish among five riparian-specific structural classes (shrub dominated, deciduous dominated, overstocked conifer, suppressed conifer and old-growth) with per-class accuracies generally over 70% (Gergel et al. 2007).

These studies utilizing QuickBird imagery in coastal British Columbia's forests indicate strong potential for high spatial resolution satellite imagery to be used for classifying the globally rare coastal temperate rainforests. In particular, late seral coniferous stands in this region, Canada's oldest, largest and most fought-over forests (MacKinnon 2003), can be well separated from forests in other successional stages with producer's accuracies ranging from 84% to 88%. However, both of these studies were limited in spatial extent and utilized classification schemes that did not address finer-scale aspects of forest structure such as species composition.

Objectives

Building on previous work that used high spatial resolution satellite imagery to map forest structural classes in coastal BC, the objective of Chapter 2 was to assess the suitability of high spatial resolution (2.8m) QuickBird satellite imagery for mapping the fine-scale variability in the species composition of late-seral forests in coastal British Columbia, Canada. Forest associations defined by provincial ecosystem classification standards are mapped. These associations differ with respect to their plant communities as well as to their environmental site conditions (e.g., soil moisture and soil nutrient regimes). In coastal British Columbia, associations are variable in size and heterogeneous in composition, with many of the same overstory species occurring in multiple forest associations. Given this compositional variability as well as the importance of localized site characteristics to stand differentiation, an additional objective of this study was to explore the contribution of QuickBird imagery relative to ancillary landscape positional data (elevation and potential soil moisture) when classifying fine-scale forest associations.

Beyond assessing the capability of QuickBird imagery to map late-seral forest associations in coastal BC, this project also serves to examine how maps derived from high spatial resolution remotely sensed data can misrepresent locally rare ecosystem classes. As the use of automated classification of high spatial resolution digital imagery continues to increase (and as the use becomes simpler due to computer software advances), it is important to consider that the technology may be misused or used without an understanding of the limitations or caveats associated with a particular application (Fassnacht et al. 2006). The remote sensing community tends to use, unquestioningly, certain map production and accuracy assessment techniques, yet these approaches may not be appropriate in all situations. One goal of Chapter 3 was to compare the classification accuracies of rare classes derived from several different accuracy assessment techniques. An additional objective was to examine the effects on habitat extent and configuration resulting from the post-classification implementation of a minimum mapping unit. A minimum feature size is commonly imposed to maintain simplicity in a map, or to reduce fine-scale heterogeneity perceived as error. The implications for rare ecosystems resulting from the generalization of a fine-scale classification are explored.

A synthesis of Chapters 2 and 3 concludes this thesis. Recommendations for the application of high spatial resolution satellite imagery, and suggestions for research questions that should be addressed in the future are also addressed.

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2. CLASSIFICATION OF LATE SERAL COASTAL TEMPERATE RAINFORESTS WITH HIGH SPATIAL RESOLUTION QUICKBIRD IMAGERY[1]

Introduction

The age, size, composition and distribution of forest types across the landscape are critical variables for forest managers to consider when making decisions regarding the harvest, protection and restoration of forests. Remote sensing of the fine-scale structure and composition of forest stands conventionally necessitated the use of aerial photography and subsequent interpretation by trained analysts, particularly in complex, heterogeneous forest types. However, within the last decade, high spatial resolution satellite imagery has become available with a resolving power closely matching that of airborne imagery, and with its broad spatial coverage has a potential for even greater efficiency. Interest in the application of satellite imagery to map the fine-scale structure and composition of forest stands is increasing, with examples in Canada's western coniferous forests (Chubey et al. 2006; Gergel 2007; Johansen et al. 2007; Nelson et al. 2004) and elsewhere (Wang et al. 2004b). These and other studies suggest that not only spectral, but also textural and landscape positional information are useful for the classification of forested scenes captured at high spatial resolution.

In some cases, species composition can be differentiated on the basis of spectral response, particularly coniferous versus deciduous species which differ significantly with respect to their near-infrared reflectance (Lillesand et al. 2004). However, with increasing image spatial resolution comes an increase in within-class spectral variability (Franklin et

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al. 2001a). Therefore, image texture, which measures the spatial arrangement of brightness values in an image, is a useful addition to spectral information for the classification of forest structure and composition. Image texture is key for the estimation of stand structure, as it relates to physical characteristics of the canopy such as crown size and density (Wulder 1998). Texture may also be useful for the classification of forest species composition, because structural differences among species causes differences in the spatial distribution of reflectance values (Franklin et al. 2001a).

In addition to spectral and textural information, classification of forest species may be aided by data related to landscape position. Landscape position can influence the pattern of vegetation types across a landscape in several ways. Topographic variables (e.g. elevation, slope, and aspect) affect ground and air temperatures, precipitation patterns, surface and groundwater flows, and nutrients (Swanson et al. 1988; Whittaker 1956). Position in the landscape (e.g. distance to stream, or distance to coast) may be important by affecting energy and material flow (e.g., wind, water, particulates) as well as the type and severity of natural disturbance (Swanson et al. 1988; Wimberly and Spies 2001). Thus, topographic variables and contextual rules related to landscape position are often used to enhance remotely sensed vegetation classification (Chubey et al. 2006; Wright and Gallant 2007; Yu et al. 2006). Landscape positional data may be particularly useful when fine-scale phenomena (e.g. trees) cannot be well distinguished on the basis of spectral and textural information alone.

We assess the capacity of high spatial resolution satellite imagery to document the variability in late seral coastal temperate rainforests in British Columbia, Canada, typified by heterogeneous stands with a highly complex structure. Many of the tree species found within the study area display similar and partially overlapping signatures, particularly in stands containing trees of varying age and health (Leckie et al. 2005). Thus, it is uncertain whether spectral information provided by high spatial resolution imagery can be used to map these late seral forests at fine scales. Our approach uses a hierarchical classification scheme: First, we broadly classify the imagery based on structural (successional) stage. Secondly, the late seral forests were classified at a more detailed level into different vegetation associations. We specifically explore the relative contribution of spectral, textural, and landscape positional data (i.e., elevation and potential moisture) to improving the classification accuracy of fine-scale forest associations. Lastly, we present recommendations for using high spatial resolution satellite imagery to aid ecosystem inventories at fine spatial resolutions.

Methods

Study area

The focus of our research is the coastal temperate rainforests of the outer coast of western Vancouver Island, British Columbia (Figure 2.1). <INSERT FIGURE 2.1> Climate is characterized by cool summers and mild winters (mean annual temperature ~ 8°C) and very high amounts of precipitation (1000 - 5000 mm annually) (Green and Klinka 1994; MacKinnon 2003). Forests are dominated by coniferous species including western hemlock (*Tsuga heterophylla*), western redcedar (*Thuja plicata*), amabalis fir (*Abies amabilis*), and sitka spruce (*Picea sitchensis*). Approximately 40% of stands in the study site are greater than 250 years old (EcoCat: Ecological Reports Catalogue), while the remaining landscape is a mosaic of younger stands. The abundance of younger forests is primarily a result of harvest within the last century, with some fine-scale gap disturbance resulting from windthrow.

High Spatial Resolution Satellite Imagery

QuickBird imagery consisting of four multispectral bands at 2.8 m spatial resolution was captured on June 21, 2005. The imagery was geometrically corrected prior to purchase by DigitalGlobe with a stated positional accuracy of less than 5m. Raw digital values were converted to top of atmosphere radiance units using pre-launch calibration coefficients in ENVI (v 4.3, ITT Industries Inc. 2006), and the image data were subset from the full extent of 248 km^2 to the extent of the reference data (162 km^2).

Image texture layers were created from the multispectral imagery to quantify the spatial structure of forest associations. To determine the appropriate scale at which to measure spatial variation, multi-directional semivariograms were calculated for representative regions of each forest association for each spectral band. Semivariograms indicated that pixels were independent at a distance greater than approximately three pixels for all classes and most bands, corresponding to previous work (Johansen et al. 2007). A window size of 3x3 pixels (radius of 1.5 pixels) was thus selected as the optimum window size for texture analysis. Using this 3x3 window, six texture statistics (angular second moment, contrast, correlation, dissimilarity, entropy and homogeneity) were calculated for each spectral band using the standard Grey Level Co-occurrence Matrix (GLCM) (Haralick 1973). Pair-wise Jeffries-Matusita (JM) distance statistics were calculated in ENVI for each of the six, four-band (blue, green, red, and near-infrared) subsets, in order to determine which texture measure provided the greatest class separability. The JM distance is a measure of the average distance between two class density functions with values increasing as the distance between class means increases (Richards and Jia 2006). The range of JM values as calculated in ENVI is from 0 to 2.0 with values greater than 1.9 indicating good separability. Here, none of the texture subsets achieved JM values of 1.9 or greater, however we chose the texture measure which achieved the highest JM value (correlation, with a value of 1.08) for use in the subsequent classification procedure.

Landscape Positional Data

Ancillary positional data (elevation and potential soil moisture) were used to enhance the classification of forest associations because the associations are partially defined by localized site characteristics (Figure 2.2). <INSERT FIGURE 2.2> These two data layers were derived from Airborne Light Detection and Ranging (LiDAR) data collected in July 2005 (Terra Remote Sensing, Sidney, BC, Canada) using a Mark II discrete return sensor. Ground and non-ground returns were separated using Terrascan v 4.006 (Terrasolid, Helsinki, Finland) and ground hits were converted to a Digital Elevation Model (DEM) using a natural neighbour algorithm (Bater and Coops In Review; Sambridge et al. 1995; Sibson 1981). Using a nearest neighbour algorithm, the resulting 1m DEM was resampled to the spatial resolution of the QuickBird image (2.8m). Using 19 ground control points, the QuickBird imagery was subsequently georectified (using a nearest neighbour resampling algorithm) to the LiDAR imagery which had a higher positional accuracy. From the DEM, ArcGIS (v9.2; ESRI Inc.) was used to calculate, on a cell-by-cell basis, a topographic wetness index:

$$\mathrm{TWI} = \ln(a/\tan\beta) \qquad (1)$$

where a is the specific catchment area (the upslope area per unit contour length) and β is the slope. The assumption behind this index is that topography influences the flow and accumulation of water, and thus, soil moisture patterns (Schmidt and Persson 2003). Potential soil moisture is a common predictor in vegetation modeling and classification (Taverna et al. 2004; Townsend and Walsh 1998).

Classification Scheme

High spatial resolution imagery was classified into classes derived from the Terrestrial Ecosystem Mapping (TEM) framework routinely used for ecosystem mapping in BC. TEM is a hierarchical system that integrates biotic and abiotic components of the landscape to classify ecosystems and traditionally relies on manual interpretation of aerial photographs and field data for map production. First, we performed a simple classification of the imagery to demarcate areas of late seral forests using QuickBird multispectral and textural imagery. Then, with the addition of ancillary data relating to landscape position, we classified TEM *site series* which are forest associations characterized by the climax plant communities expected under specific soil moisture and nutrient regimes (Green and Klinka 1994; Meidinger and Pojar 1991). Because site series refer to potential climax vegetation, we restricted our mapping of site series to older stands only (> 250 years in age), ignoring early-seral forests. TEM classes used in this study are shown according to their defining nutrient and moisture regimes in Figure 2.2. The forest classes include three swamp/bog forests, a floodplain class, two dry upland associations, one shoreline class (a combination of two very rare associations found only along coastal fringes) and the zonal vegetation association (intermediate in soil moisture and nutrient regime and thus best reflecting the vegetation of the regional climatic zone).

To ensure adequate sample sizes for rigorous classification and accuracy assessment, we did not classify site series which occupied only one or two polygons on the reference map.

Image Classification

A supervised classification approach was used, utilizing a Nearest Neighbour algorithm. Selection of training samples was guided by a digital, vector-based (1:20 000) Terrestrial Ecosystem Map (TEM) of the area from 2003 and 2004 (EcoCat: Ecological Reports Catalogue). Training samples were selected from an area representing 70% of the image, retaining 30% of the area for independent accuracy assessment to follow classification (Figure 2.3). <INSERT FIGURE 2.3> The imagery was classified using object-based classification software (Definiens Professional 5.0, Munich, Germany), which, unlike traditional pixel-based classifers, first creates groups of adjacent pixels, then classifies these groups (objects) based on their mean and/or standard deviation with respect to the various input layers. The process of grouping pixels is termed segmentation and is performed via a bottom-up region merging algorithm (Benz et al. 2004). Beginning with single pixels, region-growing continues until a heterogeneity threshold is reached (Benz et al. 2004). This heterogeneity threshold is defined by the user-controlled scale parameter, with larger values of this parameter resulting in larger image objects. Object-based classification is well-suited to high spatial resolution imagery because it reduces the high within-class variability inherent in high spatial resolution imagery where multiple pixels may comprise an object of interest (Hay et al. 2005; Wang et al. 2004a). Further, image objects can be meaningfully related to one another, allowing context to be directly incorporated into classification (Benz et al. 2004).

Two hierarchical levels of image-objects were created. At each level, the results of several values of the scale parameter were visually assessed before selecting values which created image objects that were as large as possible and as fine as necessary to delineate relatively homogeneous patches of the different classes (Definiens 2006). At the first level (mean object size of 7.6 ha), image objects distinguished late seral forests from young seral stages. At the finer level (mean object size of 0.9 ha), classification of site series was then constrained to areas classified as old-forest in the coarser classification. As the location of old and young forest stands in the study area is less directly related to topography but rather due largely to patterns of forest harvest, we only used QuickBird multispectral data and texture derivatives for the broad-scale classification of old forest versus other successional stages. However, LiDAR-derived landscape positional data were used in addition to QuickBird imagery for the finer scale classification of late seral forest associations because the distribution of these classes does correspond well to landscape position. A contextual rule relating to landscape position restricted the *Picea sitchensis* (shoreline) class to within 350m of the coastline, a distance chosen after consulting the Terrestrial Ecosystem Map (TEM) of the study site. Contextual rules were also created to restrict the drier upland classes of *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR) and *Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon* (RS) to higher elevations. Specifically, objects to be considered for these two classes must have a mean elevation value of at least 40m. This threshold was selected by looking at the range of elevation values of each of these classes based on their locations on the reference map. The mean and median elevations of these two classes are 67 m and 62 m, and 73 m and 67 m respectively, while the mean and median elevation of the next highest class (*Thuja plicata - Tsuga heterophylla / Gaultheria shallon, HS*) is approximately 32 m and 21m, respectively.

Ten data layers were used as input for the fine-scale classification of late seral forest associations (4 multispectral, 4 texture, elevation and the topographic wetness index layer). To examine the relative importance of the three types of information (spectral, textural and situational) utilized in the classification of forest associations, we once again employed the Jeffries-Matusita (JM) distance equation (previously used to indicate the optimum measure of texture) to examine statistical pair-wise separability of the classes for each subset of image data. We also compared the results of the classification when all ten data layers were used, to those resulting from the classifications using spectral data only, and from spectral and textural data only.

Accuracy Assessment

We performed a pixel-based accuracy assessment whereby classified pixels were sampled from the map using a stratified random sampling design and compared to the class attributed to the TEM polygon at that location. Misregistration between a classification and preexisting vector-based reference data is a potential problem (Wulder et al. 2006) and will negatively affect map accuracy, particularly as landscape heterogeneity increases (Smith et al. 2003). We therefore buffered the edges of each polygon to constrain sampling to polygon interiors. A visual assessment of the reference polygons overlain on the multispectral image indicated that a buffer width of 10 m would be sufficient.

Results

The broad scale classification of late seral forests versus other structural (successional) stages had an overall accuracy of 92% and a corresponding Kappa coefficient of 0.84. User's accuracy for late seral forests was 94% (commission error of 6%) and producer's accuracy was 92% (omission error of 8%). At the finer level of late seral forest associations, classification accuracies were lower than those obtained at the broader level of classification. Classification of late seral forests into eight site series was 41% accurate overall when spectral, textural and positional (elevation and potential soil moisture) data were used, 29% accurate when using only spectral and textural data, and 28% when using solely spectral data. However, it is important to note that these overall accuracies do not capture the fact that some late seral forest associations were quite well classified.

The separability of late seral forest associations varied for different types of data. Forest associations were poorly separable using spectral and textural information. Most pairs were best separated on the basis of landscape positional data (Table 2.1). <INSERT TABLE 2.1> Jeffries-Matusita (JM) distance values ranged from 0.08 to 2.0 (mean 1.44) for the DEM and Topographic Wetness Index subset, from 0.03 to 0.99 (mean 0.50) for the four-band spectral subset, and from 0.01 to 1.08 (mean 0.45) for the four-band correlation (texture) subset (Table 2.2). <INSERT TABLE 2.2> The average JM distance for all pairs discriminated using spectral, textural and situational data combined was 1.71. When only spectral/textural data was used for the classification, misclassification was common among forest associations that are unlikely to be found in the same location on the landscape (e.g., the dry upland associations versus the wetland associations) (Table 2.3a and b). In contrast, the addition of LiDAR-derived landscape position variables (elevation and potential soil moisture) reduced class confusion among classes with dissimilar environmental characteristics (Table 2.3c). <INSERT TABLE 2.3>

Consistently, the most accurately classified were two of the wetland classes (*Pinus contorta - Chamaecyparis nootkatensis / Sphagnum* and *Thuja plicata - Chamaecyparis nootkatensis / Coptis asplenifolia*) as well as the shoreline class (*Picea sitchensis*). User's accuracies for these most accurately classified forest associations were as high as 84%, with producer's accuracies up to 94% for the classification utilizing all data layers (Table 2.2). The other wetland class (*Thuja plicata - Picea sitchensis / Lysichiton americanum*) and one of the dry upland classes (*Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon*) were the least accurately classified forest associations, with accuracies as low as 0% (Table 2.3).

Discussion

We classified high spatial resolution remotely sensed imagery of a forested landscape into forest types using two hierarchical schemes. At the broadest level, late seral forests were differentiated from young successional stages with very high accuracy, exceeding 90%. The successional transition from recently disturbed regenerating stands to old-growth stands is characterized by a decrease in albedo and increase in shade (Roberts et al. 2004) and a corresponding increase in canopy complexity (Johansen et al. 2007). Though the classification of mature versus old forests in the forests of the Pacific coast of North America has been somewhat challenging (Cohen et al. 1995; Jiang et al. 2004), our findings agree that late seral forests can be well discriminated (75% to 90%

accuracy) from early seral stands solely on the basis of spectral and/or textural information.

Pair-wise separability statistics indicate that within late seral stands however, classes are not well separated using only spectral or textural information. Although in general, spectral and textural data contributed slightly to the separability of stands dominated by species with large crowns (e.g. *Thuja Plicata, Picea sitchensis*) and wide spacing (a "rough" texture) from less productive sites (e.g. waterlogged bogs) dominated by species with smaller crowns (e.g., *Pinus contorta*).

Texture did not significantly enhance separability of late seral forest associations from the use of spectral data alone. This likely indicates textural similarity among many late seral associations. In forest scenes, spatial variation in spectral reflectance may be a result of changes in species, crown closure and stem density (Franklin et al. 2001a) and semivariogram range has been found to differ between various forest ecosystem classes, attributable to differences in crown diameters (Treitz and Howarth 2000). Species composition, tree size and tree spacing are variable within these late seral associations and similar across all associations. Thus, similar semivariogram ranges among associations helps to explain why the calculated image texture did not enhance fine-scale class separability. Texture is likely more helpful for discrimination between forests which are structurally dissimilar, such as old and young forests (Franklin et al. 2001b; Johansen et al. 2007).

The use of ancillary data describing landscape position has been shown to increase land cover classification accuracy relative to that using reflectance data alone (Bolstad and Lillesand 1992). Class separabilities incorporating elevation and potential soil moisture layers were higher than those achieved using spectral or textural data, improving overall classification accuracy by 12% relative to the use of spectral and textural data. Moist, low lying classes (such as bogs and floodplain classes) were well separated from drier upland classes. The zonal forest association (characterized by intermediate soil moisture) was not as well separated as some other classes were on the basis of landscape position because it is found at a variety of elevations and overlaps with both wetter and drier associations. The shoreline (*Picea sitchensis*) and floodplain class (*Thuja plicata - Picea sitchensis / Oplopanax horridus*), both found on gentle to moderate slopes, are poorly separable in terms of Jeffries-Matusita (JM) separability distances measured with respect to elevation and soil moisture. However, using a contextual rule to restrict the shoreline class to the coastline resulted in greater separation than is indicated by the JM statistic.

Accuracies reported here may be unrepresentative for a number of reasons. First, restricting sampling to polygon interiors tends to slightly inflate accuracy estimates (Hammond and Verbyla 1996), yet it remains a commonly used method. Accuracies reported for the finer-scale classification of forest associations may actually be conservative, however. It is common for small patches of subdominant forest associations to be scattered throughout reference polygons, yet traditional accuracy assessment generally allows for assessment of agreement with respect to the dominant classes only. Higher accuracies may be possible if matches between classified pixels and any subdominant classes were quantified, as explored elsewhere (Stehman et al. 2003; Thompson and Gergel In Review; Wulder et al. 2007). Another factor to consider is spatial autocorrelation among image pixels (samples located close to one another are more similar than samples located further apart). Although non-independent samples will not bias the results of an accuracy assessment where the motive is not to infer or generalize to a broader population of pixels beyond that contained in the image (Stehman 2000), spatial autocorrelation does reduce the effective sample size as many of the samples are actually redundant or duplicative (Griffith 2005). As a result, the confidence level attributed to the results of an accuracy assessment is decreased (Stehman 2000).

Future Work for Ecosystem Inventories

QuickBird has shown potential for providing information at multiple scales, enabling one image to be used for multiple purposes. A dataset which can provide multi-scale information has great potential for cost savings, and will be relevant in decision making for multiple stakeholder management which strives to manage goals and objectives at the landscape and stand level. This multi-scale analysis has particular appeal in ecosystems such as late seral coastal temperate rainforests which are structurally very complex, and hold a vast array of cultural, economic and ecological values (Clayoquot Sound Scientific Panel 1995). One particular application of high spatial resolution satellite imagery may lie in the domain of fine-scale vegetation modeling. Predictive Ecosystem Mapping (PEM) in British Columbia is sometimes used as low-cost alternative to Terrestrial Ecosystem Mapping (TEM). Unlike TEM, PEM does not rely on manual interpretation of aerial photographs and field data. Rather, PEM uses ancillary spatial data (e.g. existing forest and soil inventory data) and known ecological-landscape relationships to predict the locations of ecosystem across a landscape (Meidinger et al. 2000; Terrestrial Ecosystem Mapping Alternatives Task Force 1999). Satellite imagery (Landsat) may be used as input PEM. However, given that Landsat is insufficient for fine-scale mapping in forests (Foody and Hill 1996; Harvey and Hill 2001), high spatial resolution satellite imagery such as QuickBird could potentially improve the predictive ability of such models. Furthermore, our work clearly demonstrates the utility of landscape positional variables in aiding forest association mapping with QuickBird imagery. Given PEM's framework based on ecological-landscape relationships, QuickBird imagery combined with appropriate terrain data may be particularly useful in this regard.

Tables

LR	LS	RC	RS	SD	Shoreline	YG	
positional	positional	positional	positional	positional	positional	positional	**HS**
	positional	positional	positional	positional	positional	positional	**LR**
		spectral	positional	textural	spectral & textural	positional	**LS**
			positional	positional	positional	positional	**RC**
				positional	positional	positional	**RS**
					spectral	positional	**SD**
						positional	**Shoreline**

Table 2.1. Type of data (spectral, textural, or landscape positional) yielding maximum separability for all pairs of classes.

HS = *Thuja plicata - Tsuga heterophylla / Gaultheria shallon,* LR = *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum*, LS = *Pinus contorta - Chamaecyparis nootkatensis / Sphagnum,* RC = *Thuja plicata - Picea sitchensis / Lysichiton americanum,* RS = *Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon,* SD = *Thuja plicata - Picea sitchensis / Oplopanax horridus,* Shoreline = *Picea sitchensis*, YG = *Thuja plicata - Chamaecyparis nootkatensis / Coptis asplenifolia*

LR	LS	RC	RS	SD	Shoreline	YG	
0.62	0.94	0.13	0.37	0.03	0.48	0.39	**HS**
	0.26	0.64	0.17	0.69	0.88	0.22	**LR**
		0.88	0.56	0.99	0.83	0.37	**LS**
			0.49	0.15	0.52	0.36	**RC**
				0.47	0.86	0.13	**RS**
					0.38	0.50	**SD**
						0.81	**Shoreline**

Table 2.2a. Jeffries-Matusita (JM) distances separating each pair of classes. Spectral data layers only.

LR	LS	RC	RS	SD	Shoreline	YG	
0.94	1.07	0.47	0.42	0.10	0.11	0.74	**HS**
	0.07	0.44	0.29	0.96	0.68	0.12	**LR**
		0.49	0.41	1.08	0.83	0.14	**LS**
			0.08	0.50	0.38	0.15	**RC**
				0.46	0.27	0.11	**RS**
					0.13	0.76	**SD**
						0.53	**Shoreline**

Table 2.2b. Jeffries-Matusita (JM) distances separating each pair of classes. Textural data layers only.

LR	LS	RC	RS	SD	Shoreline	YG	
1.47	1.19	1.41	1.04	1.02	0.84	1.46	**HS**
	2.00	2.00	1.62	2.00	2.00	2.00	**LR**
		0.62	2.00	0.45	0.37	1.74	**LS**
			2.00	1.14	0.92	1.79	**RC**
				2.00	2.00	2.00	**RS**
					0.08	1.79	**SD**
						1.48	**Shoreline**

Table 2.2c. Jeffries-Matusita (JM) distances separating each pair of classes. Landscape positional data layers only.

LR	LS	RC	RS	SD	Shoreline	YG	
1.80	1.82	1.61	1.35	1.05	1.19	1.74	**HS**
	2.00	2.00	1.74	2.00	2.00	2.00	**LR**
		1.43	2.00	1.67	1.47	1.84	**LS**
			2.00	1.47	1.4	1.87	**RC**
				2.00	2.00	2.00	**RS**
					0.6	1.9	**SD**
						1.78	**Shoreline**

Table 2.2d. Jeffries-Matusita (JM) distances separating each pair of classes. All data layers combined.

		Reference Data									
		HS	LR	LS	RC	RS	SD	Shoreline	YG	Row Total	User's Accuracy
Spectral Classification	HS	59	2	9	6	3	54	2	70	205	29%
	LR	78	17	28	1	8	17	1	48	198	9%
	LS	28	4	136	6	0	3	3	22	202	67%
	RC	58	0	4	4	2	13	0	124	205	2%
	RS	60	0	8	32	0	3	0	89	192	0%
	SD	50	2	5	12	2	50	0	79	200	25%
	Shoreline	82	0	7	3	2	7	61	31	193	32%
	YG	41	6	34	3	0	12	0	118	214	55%
	Column Total	456	31	231	67	17	159	67	581		
	Producer's Accuracy	13%	55%	59%	6%	0%	31%	91%	20%		

Overall Accuracy 28%
Kappa 0.17

Table 2.3a Confusion matrix resulting from the classification of late-seral forest associations using QuickBird multispectral layers (blue, green, red and near-infrared).

		Reference Data									
		HS	LR	LS	RC	RS	SD	Shoreline	YG	Row Total	User's Accuracy
	HS	87	3	9	0	6	103	6	89	303	29%
	LR	107	18	44	7	7	11	1	83	278	6%
	LS	20	2	233	1	0	5	0	60	321	73%
	RC	68	0	10	0	5	50	1	157	291	0%
	RS	45	0	0	38	0	4	0	151	238	0%
Spectral and	SD	130	1	0	8	8	63	0	87	297	21%
Textural	Shoreline	72	0	0	0	7	47	76	43	245	31%
Classification	YG	66	4	35	8	1	24	0	189	327	58%
	Column Total	595	28	331	62	34	307	84	859		
	Producer's Accuracy	15%	64%	70%	0%	0%	20%	90%	22%		

Overall Accuracy 29%
Kappa 0.18

Table 2.3b. Confusion matrix resulting from the classification of late-seral forest associations using QuickBird multispectral and textural data layers.

		Reference Data									
		HS	LR	LS	RC	RS	SD	Shoreline	YG	Row Total	User's Accuracy
All Data Classification	HS	94	0	3	1	1	14	0	91	204	46%
	LR	97	37	0	0	46	0	0	0	180	21%
	LS	34	0	260	2	0	1	1	12	310	84%
	RC	77	0	20	4	1	5	5	135	247	2%
	RS	246	56	0	0	12	0	0	13	327	4%
	SD	30	2	0	20	10	39	0	31	132	30%
	Shoreline	23	0	0	0	0	0	122	0	145	84%
	YG	58	0	37	10	0	5	2	183	295	62%
	Column Total	659	95	320	37	70	64	130	465		
	Producer's Accuracy	14%	39%	81%	11%	17%	61%	94%	39%		
	Overall Accuracy 41%										
	Kappa 0.32										

Table 2.3c. Confusion matrix resulting from the classification of late-seral forest associations using QuickBird multispectral and textural data layers, as well as elevation and potential soil moisture (derived from airborne LiDAR data).

Figures

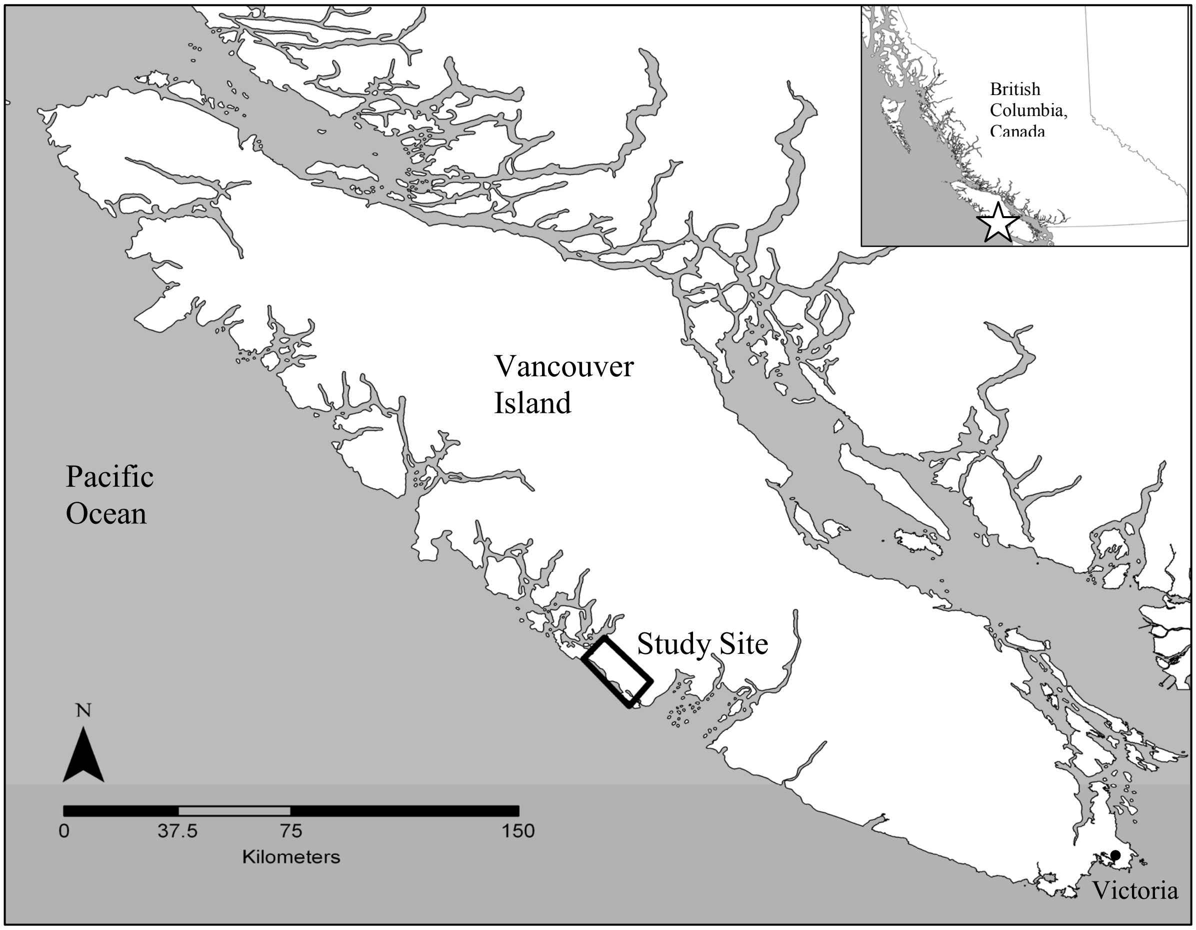
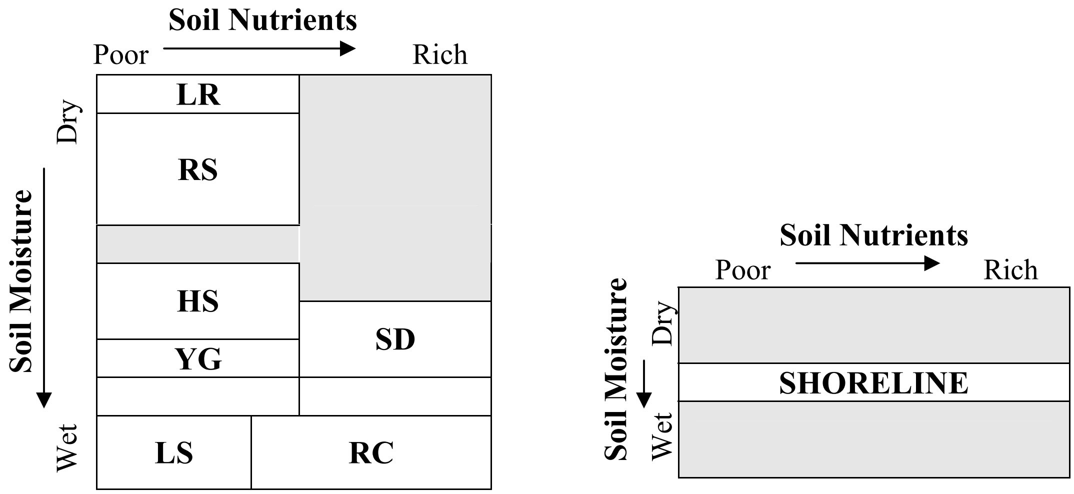


Figure 2.1. Study area (162 km^2) in the coastal temperate rainforests of western Vancouver Island, British Columbia, Canada.



HS	*Thuja plicata - Tsuga heterophylla / Gaultheria shallon*
LR	*Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum*
LS	*Pinus contorta - Chamaecyparis nootkatensis / Sphagnum*
RC	*Thuja plicata - Picea sitchensis / Lysichiton americanum*
RS	*Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon*
SD	*Thuja plicata - Picea sitchensis / Oplopanax horridus*
YG	*Thuja plicata - Chamaecyparis nootkatensis / Coptis asplenifolia*
SHORELINE	*Picea sitchensis*

Figure 2.2 Forest associations mapped in this study are characterized by particular soil moisture and nutrient regimes (represented by their relative position along a unitless edatopic grid). LS, RC and YG are wetland forest associations, SD is the floodplain class, LR and RS are the dry upland classes, and HS is the zonal vegetation association (intermediate soil moisture and nutrient regime). Shoreline refers to the blue-listed Sitka-spruce dominated associations found only along coastal fringes associated with high winds, salt spray from the ocean, and sandy or rocky substrate. Thus shoreline forest associations are on a separate grid reflecting their unique environment. Adapted from Green and Klinka 1994.

Figure 2.3. A supervised training approach was utilized in image classification. Prior to classification, the image was stratified into training and testing regions occupying 70% and 30% of the study area, respectively.

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3. CONSERVATION IMPLICATIONS OF MAPPING RARE HABITATS USING HIGH SPATIAL RESOLUTION IMAGERY: RECOMMENDATIONS FOR HETEROGENEOUS AND FRAGMENTED LANDSCAPES[2]

Introduction

Within the last several decades, natural resource management has struggled towards managing landscapes for ecosystem representation targets. Preservation of the full range of communities and ecosystems is important as it is assumed that by preserving a portion of each ecosystem the species and communities therein will be conserved (Noss 1996). Many nature reserve networks have been designed with this in mind (Margules and Pressey 2000). This perspective is also central to Ecosystem-Based Management (EBM), increasingly used in natural resource management and conservation in many areas of the world (Grumbine 1994; Slocombe 1993). Of particular concern in managing for ecosystem representation is the conservation of rare (uncommon, and potentially at risk or endangered) ecosystems. Thus, accurate and up-to-date information for all ecosystem types in a region, especially those which are rare, is crucial.

Fine-scale structural and compositional information of ecosystems (e.g., stand age, species diversity and dominance) is often required by managers, yet precise quantification of such fine-scale heterogeneity remains a challenge, especially over large areas. Conventional ecosystem inventories utilize aerial photograph interpretation and field surveys (Goetz et al. 2003; Wulder et al. 2004a). However, the costly and time-consuming nature of air photo processing and interpretation results in infrequent updates (Green 2000; Wulder 1998). Satellite remote sensing is a systematic, cost-effective

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[2] A version of this chapter has been submitted for publication: Thompson, S.D., Gergel, S.E. In Review. *Conservation implications of mapping rare habitats using high spatial resolution imagery: Recommendations for heterogeneous and fragmented landscapes.*

method to map and monitor land cover as the (digital) imagery has a broad coverage, and is acquired at regular time intervals. Until recently, the spatial resolution of satellite imagery has been too coarse to provide information beyond very general vegetative types (e.g., deciduous versus coniferous) (Wulder et al. 2004a). Within the last decade, high spatial resolution satellite imagery (such as QuickBird and IKONOS, with spatial resolutions of less than 4m) has become available, capable of characterizing ecosystem vegetation structure at much finer resolutions, including species (Chubey et al. 2006), age or structural (seral) type (Franklin et al. 2001b; Gergel et al. 2007; Johansen et al. 2007). Thus the use of high spatial resolution satellite imagery in ecosystem mapping continues to increase (Wulder et al. 2004a) and is particularly recommended for small ecosystems or when information regarding fine-scale heterogeneity is important.

Generally, classification errors on maps derived from remotely sensed imagery are greater for classes that occupy a small proportion of a study area than those that occupy a larger proportion (Smith et al. 2003; Smith et al. 2002). This is unfortunate as it is often a few select classes of conservation concern that primarily influence the conservation and management decisions made from maps. Inaccurate representation of rare cover types may have significant conservation implications. When the extent of a rare class is underestimated, missed areas would not be given the protection needed. In contrast, overestimation of the abundance of a rare ecosystem type is also problematic as it may result in that class no longer being considered rare and therefore not given the protection it requires. In addition to erroneous estimates of the overall area of an ecosystem, the size of an individual patch may be over- or underestimated, affecting patch-level conservation decisions. All of these types of map errors may also be problematic when such maps are used to delineate critical habitat for the protection and recovery of particular threatened and endangered species, or as input for automated decision support tools for reserve design such as Marxan (Ball and Possingham 2000; Possingham et al. 2000). Correct representation of the error associated with rare ecosystem maps is therefore essential.

The objective of this study is to evaluate how the portrayal and interpretation of rare habitat classes on maps derived from high spatial resolution satellite imagery may vary as a result of post-classification processing and chosen accuracy assessment technique. Imagery of a fragmented and heterogeneous landscape is classified and several accuracy assessment techniques are compared with respect to their representation of rare, and/or fragmented classes. To this effect, we perform (a) a standard, pixel-based accuracy assessment, (b) a modified assessment that acknowledges fine-scale heterogeneity, and (c) a polygon-level accuracy assessment. Also examined is the sensitivity of rare classes to the implementation of a Minimum Mapping Unit (MMU) with respect to several habitat fragmentation indices. Given the continuing increase in the use of high spatial resolution satellite imagery for detailed ecosystem inventories, explicit examination of techniques related to rare class mapping is particularly timely.

Methods

Study area

Our research focuses on the coastal temperate rainforests of the outer coast of western Vancouver Island, British Columbia, within and adjacent to Pacific Rim National Park (Figure 3.1). <INSERT FIGURE 3.1> Climate is characterized by cool summers and mild winters (mean annual temperature ~ 8°C) and very high amounts of precipitation (1000 - 5000 mm annually) (Green and Klinka 1994; MacKinnon 2003). Forests are dominated by coniferous species including western hemlock (*Tsuga heterophylla*), western redcedar (*Thuja plicata*), amabalis fir (*Abies amabilis*), and sitka spruce (*Picea sitchensis*). Several forest associations in the area have been blue-listed (designated as *of special concern*) by the Conservation Data Centre (CDC) (Table 3.1), BC's NatureServe counterpart responsible for collecting and disseminating information on animals, plants and communities at risk. <INSERT TABLE 3.1> Approximately 40% of the stands in the study site are greater than 250 years old (EcoCat: Ecological Reports Catalogue), while the remaining landscape is a mosaic of younger stands. This is primarily as a result of harvest within the last century, with some fine-scale gap disturbance resulting from natural processes such as windthrow.

Classification Scheme

The high spatial resolution imagery was classified into classes derived from the Terrestrial Ecosystem Mapping (TEM) framework used for ecosystem mapping in BC. TEM is a hierarchical system that integrates biotic and abiotic components of the landscape to classify ecosystems via the manual interpretation of aerial photographs and the use of supplemental field data. We chose to map at the level of *site series* as this is the ecosystem component utilized by the Conservation Data Centre. Site series are vegetation associations (ranging in size from less than 1 ha to several hundred hectares) characterized by the climax plant communities expected to develop under specific soil moisture and nutrient regimes (Green and Klinka 1994; Meidinger and Pojar 1991). Polygons on a Terrestrial Ecosystem Map may be labeled with more than one forest association (up to three), when multiple forest associations are present yet too limited in extent to be distinguished separately. In such cases, the proportion of each class is noted, although their exact spatial location is not.

The TEM classes used in this study are shown in Table 3.1. Because site series refer to potential climax vegetation, we restricted our mapping to old forests only (stands greater than 250 years in age), ignoring early-seral forests. In addition, to ensure adequate sample sizes for rigorous classification and accuracy assessment, we eliminated site series which were dominant in only one or two polygons on the reference map. However, rather than delete them, two very rare blue-listed associations with high ecological similarity (*Picea sitchensis / Eurhynchium oreganum* (SK) and *Picea sitchensis / Polystichum munitum* (SW)) were merged into one shoreline class (*Picea sitchensis)*. Both are spruce dominated shoreline/oceanspray associations with similar structural and site characteristics. Our classification scheme also contains one other blue-listed association, the swamp forest *Thuja plicata - Picea sitchensis / Lysichiton americanum* (RC). We decided to include *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR) in our rare class analysis as well. Though not formally recognized as rare on provincial lists, this ecosystem found on high, relatively dry sites, was locally rare, occupying a very small proportion of the total study area (< 1.5%), and thus provides another useful example of the challenges of mapping small, fragmented, locally rare plant associations.

Spatial Data

QuickBird imagery consisting of four multi-spectral bands at 2.8 m spatial resolution was captured on June 21, 2005. The imagery was geometrically corrected prior to purchase by DigitalGlobe with a stated positional accuracy of less than 5m. Raw digital values were converted to top of atmosphere radiance units using pre-launch calibration coefficients in ENVI (v 4.3, ITT Industries Inc. 2006), and the image data were subset from the full extent of 248 km^2 to the extent of the reference data (162 km^2).

Distinguishing among associations within coastal temperate rainforests on the basis of spectral information alone was expected to be very challenging as many of the tree species found within the study area display similar signatures, particularly in structurally complex late-seral stands with trees of varying age and health (Leckie et al. 2005), and forest associations in the region contain many of the same overstory tree species. Thus we created image texture layers to quantify the spatial structure of each forest association. To derive the size of the neighbourhood over which spatial variation would be measured, multi-directional semivariograms (for each spectral band) were calculated for representative regions of each forest association. Visual examination of the semivariograms indicated that pixels were no longer related at a distance of approximately three pixels for all classes and most wavelengths, as in our previous work in the area (Johansen et al. 2007). Using a 3x3 window, six texture statistics (angular second moment, contrast, correlation, dissimilarity, entropy and homogeneity) were calculated for each spectral band using the standard Grey Level Co-ocurrence Matrix (GLCM) (Haralick 1973). Pair-wise Jeffries-Matusita (JM) distance statistics were calculated in ENVI for each of the six, four-band (blue, green, red, and near-infrared) subsets to determine which measure provided the greatest class separability. The JM distance is a measure of the average distance between two class density functions with values increasing as the distance between class means increases (Richards and Jia 2006).

This analysis identified correlation as the measure which optimized class separability, thus it was chosen for use in the subsequent classification procedure.

Ancillary topographic data and derivatives were also used in this study because site series are partially distinguished by elevation, slope position and soil moisture (Table 3.1). We used a Digital Elevation Model (DEM) derived from airborne Light Detection and Ranging (LiDAR) data (Bater and Coops In Revision). The LiDAR data was collected in July 2005 (Terra Remote Sensing, Sidney, BC, Canada) using a Mark II discrete return sensor, with ground and non-ground returns separated using Terrascan v 4.006 (Terrasolid, Helsinki, Finland). Ground hits were converted to a DEM using a natural neighbour algorithm (Bater and Coops In Revision; Sibson 1981) and the resulting 1m DEM was resampled to the spatial resolution of the QuickBird image (2.8m). Using 19 ground control points, the QuickBird imagery was then georectified to the LiDAR imagery which had a higher positional accuracy. From the DEM, ArcGIS (v9.2; ESRI Inc.) was used to calculate, on a cell-by-cell basis, a topographic wetness index:

$$\mathrm{TWI} = \ln(a/\tan\beta) \qquad (1)$$

where a is the specific catchment area (the upslope area per unit contour length) and β is the slope. The assumption behind this index is that topography influences the flow and accumulation of water, and thus soil moisture patterns (Schmidt and Persson 2003). Potential soil moisture is a common predictor in vegetation modeling and classification (Taverna et al. 2004; Wright and Gallant 2007).

Image Classification

The imagery was classified using object-based classification software (Definiens Professional 5.0, Munich, Germany), which, unlike traditional classifers that classify each individual pixel, first clusters then classifies groups of adjacent pixels (image objects) based on the mean and/or standard deviation. Pixel clustering continues until a heterogeneity threshold is reached (Benz et al. 2004). This heterogeneity threshold is defined by the user-controlled scale parameter, with larger values of this parameter resulting in larger image objects. The use of image objects reduces the high within-class variability inherent in high spatial resolution imagery and thereby increases classification accuracy.

The imagery was first classified into a simple binary map demarcating areas of late-seral forests which were then classified into eight different forest associations, using a mean object size of 0.9ha. Objects much larger than this did not appear to delineate relatively homogeneous patches of the different classes as finely as necessary. A supervised classification approach was used, utilizing a Nearest Neighbour algorithm. Representative image objects of each class were selected to "train" the classifier, and the algorithm then assigned each image object to the class of the nearest sample object in feature space. Selection of training samples was guided by a digital, vector-based TEM (1:20 000) of the area which was developed in 2003 and 2004 (EcoCat: Ecological Reports Catalogue). Contextual rules were also created to restrict the drier upland classes of *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR) and *Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon* (RS) to higher elevations. These thresholds were selected by looking at the range of elevation values of each of these classes based on their locations on the reference map.

Accuracy Assessment

Site series on the classified image were compared to those on the vector-based TEM. Given that the TEM was to be used for both guiding and assessing the classification, the image was stratified *a priori* into training and testing regions (70% and 30% of the total area respectively) to ensure truth data were independent from information used to guide the classification (Figure 3.2a). <INSERT FIGURE 3.2> Both the training and testing regions contained a representative sample of all classes examined. Here, we focus on user’s accuracies and associated errors of commission. User’s accuracies indicate the probability that a pixel (or polygon) classified on the map actually represents that category on the ground (Jensen 2005). User’s accuracies also represent the reliability of the map and thus are often the measure of accuracy in which ecologists and managers are most interested.

We first performed a pixel-based accuracy assessment whereby classified pixels were sampled from the map using a stratified random sampling design. Several issues may arise when comparing pixels from raster data to preexisting vector-based reference data, including positional errors, and differences between the scale of polygon delineation in the truth layer and the spatial resolution of the satellite imagery (Wulder et al. 2006). Misregistration between the classified map and reference data will negatively affect map accuracy, particularly as landscape heterogeneity increases (Smith et al. 2003). We used a 10m buffer around each polygon to constrain sampling to polygon interiors, a method sometimes used to contend with this issue, despite the fact that it tends to inflate accuracy estimates (Hammond and Verbyla 1996). The issue of scale differences between the classified map and the reference data is important here because during air photo interpretation for TEM, a Minimum Mapping Unit (MMU) is used (Ecosystems Working Group Terrestrial Ecosystems Task Force Resources Inventory Committee 1998). The MMU of the TEM dataset utilized in this study is 2.0ha, which is a coarser scale of generalization than that of the object-based classification (average polygon size of 0.9ha) to which it was compared. The problem of comparing a fine-scale QuickBird classification to more generalized reference polygons was investigated by comparing the classified image to the dominant, as well as to the sub-dominant labels of the TEM reference polygons. These assessments are referred to UA1, UA2 and UA3 (user's accuracies for the first, second and third dominant site series in a reference polygon respectively). Several other studies have explored accuracy assessment techniques designed to account for the thematic ambiguity that may be present in reference maps, including the consideration of alternate labels associated with reference polygons (Stehman et al. 2003; Wulder et al. 2007).

In addition to the pixel-based accuracy assessment, we also performed a polygon-based assessment, given that we used a per-object classifier rather than a per-pixel classifier. Using an object-based classification and polygon-based reference data means that accuracy estimates actually refer to the accuracy of a more generalized area rather than at the scale of individual pixels. Thus per-pixel accuracy assessment estimates where pixels have been drawn from the same classified object may be unrepresentative as each classified pixel need only match one of the classes somewhere within the associated reference polygon. Furthermore, adjacent pixels of the same image object will not be independent. A polygon-level accuracy assessment whereby each classified image object is represented by only one pixel may be more appropriate because it avoids "double-counting" a single classified image object. Further it may also account for any remaining positional uncertainty between a classified map and the reference data (Wulder et al. 2006; Stehman et al. 2003). One potential problem however is that one large correct polygon (occupying a large portion of the map) is thus given the same weight as one very small incorrect polygon. On an areal basis, one could argue that this unfairly represents the accuracy/inaccuracy of the map as a whole. Therefore we perform a polygon-based accuracy assessment solely for the rare classes (which all occupy a similar range of average patch sizes and proportion of the landscape).

Finally, we examined the impact of the implementation of a minimum mapping unit (MMU), via post-classification smoothing, on the resulting accuracy and fragmentation of rare classes. Traditionally, post-classification smoothing is performed via a moving window of a fixed size whereby the value of the centre pixel becomes the mean or median class of the other pixels in its neighbourhood. In this study, smoothing was applied at the patch level in Definiens using the *merge* and *grow* reshaping algorithms. Adjacent image objects were merged together if they were smaller than 2ha in size (the MMU of the TEM dataset) and the resulting patch took on the value of the class which was dominant in the neighbourhood prior to the merger. For the rare classes, we calculated the percent change (with reference to the basic classification) in several Landscape Pattern Indices (LPIs) routinely used to evaluate fragmented habitat using the following equation:

$$\% \text{ change} = [(LPI_{unsmoothed} - LPI_{smoothed}) / (LPI_{unsmoothed})] * 100\% \qquad (2)$$

Results

Overall map accuracy in the pixel-based accuracy assessment was 41% with reference to the dominant site series label (Table 3.2). <INSERT TABLE 3.2> Gains of 15% and 5% resulted from consideration of the second and third dominant site series respectively. User's accuracies (Table 3.3a) for individual classes ranged from 2% to 84% when only the dominant site series label was considered (User's Accuracy 1, or UA1), improving 0% to 42% when considering the second site series (UA2) and 0% to 13% when the third site series was also considered (UA3). <INSERT TABLE 3.3> For UA1 the highest accuracies were achieved for *Thuja plicata - Chamaecyparis nootkatensis / Coptis asplenifolia* (YG), *Pinus contorta - Chamaecyparis nootkatensis / Sphagnum* (LS) and *Picea sitchensis* (shoreline). The classes seeing the largest increase in accuracy when UA2 and UA3 were also considered were *Thuja plicata - Tsuga heterophylla / Gaultheria shallon* (HS), *Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon* RS, and *Thuja plicata - Picea sitchensis / Lysichiton americanum* (RC). Relative to pixel-level accuracy estimates, polygon-level estimates (Table 3.4) for two of the classes (RC and shoreline) were no different, but were higher for LR (42% for the polygon-based assessment vs. 21% for the pixel-based assessment). <INSERT TABLE 3.4>

In the assessment of the agreement between the classified map and reference data (dominant class only), less common ecosystems were generally classified with lower accuracies than those more prevalent throughout the study area. However, accuracies were not directly proportional to their extent. An exception was the *Picea sitchensis* (shoreline) class, which although quite limited in extent, was classified with very high accuracy. Further, commission errors (with respect to UA1) for the shoreline class were relatively low (12% - 16%), while in contrast, commission errors for the two other rare classes (*Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR) and *Thuja plicata - Picea sitchensis / Lysichiton americanum* (RC) were very high (79% - 98%) (Table 3.3).

Smoothing the classification to implement a Minimum Mapping Unit (MMU) increased the overall accuracy of the map very slightly to 42%, up from 41% (UA1) (Table 3.3b). Smoothing increased some per-class accuracies and decreased others. The three classes most accurately classified in the smoothed map (UA1) were also those most accurately classified in the non-smoothed map. Rare class accuracies either increased or saw no change as a result of smoothing (Table 3.3b) with respect to the dominant reference label. However, the relative accuracies of these three rare classes (UA1) remained the same (shoreline was the most accurately classified and RC the least accurately classified) regardless of whether or not smoothing was used.

Implementation of a MMU greatly changed the spatial extent and pattern of classes. Two of the rare classes, *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR) and *Thuja plicata - Picea sitchensis / Lysichiton americanum* (RC) were reduced in extent by 19% and 7% respectively (Table 3.5). <INSERT TABLE 3.5> These classes were initially overestimated, thus the reduction in area improved their user's accuracies. Conversely, the extent of the rare class *Picea sitchensis* (shoreline) increased by 11% as it as it expanded at the expense of neighbouring pixels. Smoothing also reduced the number of patches of each rare class by an average of 63% (Table 3.5, Figure 3.2). The decrease in area and number of patches, combined with the increase in size of patches, means these rare classes became less fragmented as numerous small patches were eradicated during the smoothing process.

Discussion

We classified late-seral forest associations in a complex landscape using high spatial resolution multispectral QuickBird satellite imagery and LiDAR-derived topographic data. Accuracies were high (~85%) for two classes, but considerably lower for many other classes, including most of the rare ecosystems. The areal extent of rare classes was often overestimated. High rates of commission for rare classes have been partially attributed to class imbalances (Wright and Gallant 2007). Overestimating the extent of rare classes can occur when common classes are misclassified, even at a very low rate. As a result, the accuracy of common classes must be quite high to not impact the abundance of rare classes (Stehman 2005). While tradeoffs among class accuracies are expected, the impact on rare classes will be of greater magnitude (Stehman 2005). Further, because classification accuracy for common classes tends to decrease with increasing landscape heterogeneity (Smith et al. 2003; Smith et al. 2002), mapping rare classes may become even more difficult in complex landscapes with a high number of cover types.

Here, object-based image analysis software allowed us to introduce expert knowledge to reduce rates of misclassification partially caused by class imbalances. The inclusion of thresholds and contextual rules for two of the rare classes helped to improve their accuracies by reducing the possible interaction with the misclassification of more abundant classes. Finally, though not addressed here, it is possible that classification accuracies (particularly of rare classes) can be increased via the use of alternate classification methods such as Artificial Neural Networks (ANN), as well as decision trees and the use of bagging (bootstrap aggregating) or boosting (Lu and Weng 2007).

Here, as in other studies, when classified imagery was compared to a reference map with a larger Minimum Mapping Unit (MMU), traditional accuracy assessment tended to overestimate classification errors (Verbyla and Hammond 1995; Wulder et al. 2007). Others have suggested this conservative bias may increase as landscape heterogeneity increases (Verbyla and Hammond 1995). Our results (for both the pixel- and polygon-based accuracy assessments) showed that ignoring fine-scale heterogeneity within ecosystem types can result in misleading accuracy estimates. Here, many per-class accuracies differed substantially when fine-scale heterogeneity present within the reference map units was acknowledged. Several ecosystems routinely occur as subdominant classes as a result of fine-scale variability in site properties. For example, HS occurs on sites throughout the study area with an intermediate moisture and nutrient. In contrast RS, RC, and YG, are found towards the extremes of the soil moisture gradient, rarely occurring as contiguous 2ha patches. Accuracies for these classes at the subdominant level were important to consider, as the levels of overestimation indicated by UA1 were not representative of the truth.

Image smoothing is a commonly-used technique in mapping and image processing, and our results show it can greatly impact rare class mapping. The accuracy of all three rare classes increased after smoothing, yet this came at the expense of substantial changes in extent and configuration. Post-classification smoothing may be performed to reduce “salt-and-pepper” noise common in traditional pixel-based classifications. Where this type of error is present, the removal of small remnant patches via smoothing increases classification accuracy (Gergel 2007; Saura 2002). Smoothing may also be performed to mimic a Minimum Mapping Unit (MMU), as was the case here. Minimum Mapping Units commonly relate to the smallest area that can be drawn and labeled at the scale of the planned map, or to the smallest area that can be conveniently managed (Goodchild 1994). Smoothing commonly increases the dominance of those classes which occupy a large area of the map, and decreases the extent of smaller, more fragmented classes (Saura 2002). Smoothing has also been found to impact the accuracy of landscape pattern metrics association with fragmentation (Langford et al. 2006). Here, we smoothed a classified map to implement a MMU that corresponded with that used in the creation of the reference data. This resulted in a reduction in the extent and level of fragmentation of two of the three rare classes, while the extent of the rare class *Picea sitchensis* (shoreline) increased slightly.

Recommendations for Mapping Rare Classes

Based on our findings (and those of others) that show these different techniques may influence the perceived abundance and fragmentation of ecosystems, we suggest several recommendations for future work mapping rare classes in heterogeneous landscapes.

First, the method used to assess the accuracy of a classification should be transparent to the map user. A comprehensive discussion of the full range of accuracy assessment methods in existence is beyond the scope of this paper, however readers are encouraged to consult (Stehman and Czaplewski 1998; Stehman et al. 2003; Wulder et al. 2006). Suffice it to say that no method is perfect for all situations. Admittedly, the accuracy assessment method used in any situation does not change the actual accuracy of any map. Nonetheless, certain estimates may better represent the map errors of relevance to a particular management situation. Providing accuracy estimates from more than one definition of agreement allows map users to choose the definition most relevant to their application (Stehman et al. 2003). In the comparison of our classification to reference data that utilized a minimum mapping unit, we found that considering only the dominant class within a generalized reference polygon misrepresented accuracies by ignoring fine-scale heterogeneity. While the method used here is imperfect, we nonetheless show that an assessment using subdominant reference labels better represents the strengths and limitations of the map with respect to rare classes which are of limited abundance and occur in small, sometimes subdominant patches.

We also showed that polygon-level estimates of rare class accuracies may differ from pixel-based estimates. There are advantages and disadvantages to both pixel- and polygon- based accuracy assessments (Stehman and Czaplewski 1998). Polygon-level estimates, unlike pixel-based estimates show accuracies from a generalized map, and may be higher than pixel-based estimates because of the reduction in positional errors between the map and reference data as well as a reduction in spatial autocorrelation of pixels. For applications relying on patch-level information such as habitat fragmentation analysis, such polygon-based assessments may better represent the accuracy of the map. Given these issues, and it is imperative that producers of maps ensure the details of the accuracy assessment utilized (e.g., sample unit, sample size and definition of agreement) are transparent to the map user (Wulder et al. 2006).

Second, post-classification smoothing should be approached with caution. Smoothing can impact map accuracy as well as the extent and configuration of individual classes (Gergel 2007; Langford et al. 2006; Saura 2002) and inaccurate representation of the amount and configuration of rare classes may directly impact conservation decisions. Regardless of the rationale behind image smoothing (whether to establish a minimum mapping unit or to reduce salt-and-pepper error), image smoothing has considerable repercussions for fragmentation statistics such as average patch size and number of patches, particularly for rare classes. Therefore, post-classification smoothing may not be appropriate in heterogeneous and fragmented landscapes. More research is needed to fully understand the implications of this procedure for different mapping applications.

Conservation Implications

As the use of remotely sensed imagery for ecosystem mapping and monitoring continues to increase, it is essential to explicitly consider the techniques used to produce and assess the maps used for conservation and ecosystem management, particularly for rare classes. Troublingly, it is often the rare classes that drive important management decisions, yet it is often the rare classes which are mapped with the least accuracy. We examined changes in the classification accuracy and landscape pattern indices for three locally rare ecosystems which resulted solely from different mapping and assessment techniques. Accounting for the heterogeneity within reference polygons changed the estimated accuracy of one rare class by nearly ~12%. Post-classification implementation of a minimum mapping unit changed areal estimates by an average of 12%, decreased the number of patches by an average of over 60%, and increased mean patch size estimates by an average of more than 300%.

Key to the conservation of biodiversity is the protection of habitat. Decisions regarding the types and amounts of habitat to protect often rely on the relative proportions of the various habitats as shown on maps. We demonstrated that the use of a minimum mapping unit which ignores fine scale heterogeneity present in a landscape may result in erroneous estimates of the extent and configuration of these ecosystems. Such errors could greatly impact the management of rare ecosystems, particularly if small, fragmented patches are missed and not afforded the protection they require. Further, conservation and management decisions often rely on the results of spatially-explicit planning models utilizing classified ecosystem maps as input (e.g., Population Viability Analysis (PVA), which projects population losses or gains under current or future management plans). As the arrangement and size of patches of habitat will impact the output of such models, the mapping and assessment techniques used in mapping habitat for species of concern is of particular importance. Maps displaying the amount and location of habitat are also essential for assessing ecosystem representation targets, and are used as input into automated decision support tools for the design of nature reserves. Thus, mapping techniques should be avoided which alter the composition and arrangement of habitat patches or which inadvertently overlook landscape heterogeneity. Future research into the mapping of rare classes, especially in fragmented and heterogeneous landscapes is needed.

Tables

Site Series (Late-seral forest association)	Description	Conservation Status	% Of Study Site	Ecosystem Code (TEM)
Thuja plicata - Tsuga heterophylla / Gaultheria shallon (western redcedar - western hemlock / salal)	Association of intermediate moisture and nutrient regime (zonal vegetation type)		28.4	HS
Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum (lodgepole pine - yellow cedar / hoary rock-moss)	Driest association; found on hillcrests		1.4	LR
Pinus contorta - Chamaecyparis nootkatensis / Sphagnum (lodgepole pine - yellow cedar / sphagnum)	Treed bog/organic wetland; wet soils		12.8	LS
Thuja plicata - Picea sitchensis / Lysichiton americanum (western redcedar - Sitka spruce / skunk cabbage)	Poorly drained swamp forest; wet and nutrient rich soils	blue listed	2.1	RC
Tsuga heterophylla - Chamaecyparis nootkatensis / Gaultheria shallon (western hemlock - yellow-cedar / salal)	Intermediate-to-dry association; found on upper slopes to hillcrests		6.7	RS
Thuja plicata - Picea sitchensis / Oplopanax horridus (western redcedar - Sitka spruce / devil's club)	Moist-to-wet productive associations on lower/receiving sites		4.7	SD
Picea sitchensis / Eurhynchium oreganum (Sitka spruce - Oregon beaked-moss) **merged into the *Shoreline* class**	Shoreline association found on old beachplains	blue listed	0.56	SK
Picea sitchensis / Polystichum munitum (Sitka spruce / sword fern) **merged into the *Shoreline* class**	Shoreline association found on marine terraces/scarps	blue listed	0.58	SW
Thuja plicata - Chamaecyparis nootkatensis / Coptis asplenifolia (western redcedar - yellow-cedar / spleenwort-leaved goldthread)	Organic bog forest		20.9	YG

Table 3.1 Late-seral forest associations (site series) present in the study site according to BC Terrestrial Ecosystem Map (TEM) data which were discriminated in this study. Conservation status is defined by the BC Conservation Data Centre. Rare classes are shaded.

		Reference Data									
		HS	LR	LS	RC	RS	SD	Shoreline	YG	Row Total	User's Accuracy
Remotely Sensed Classification	HS	**94**	0	3	1	1	14	0	91	204	46%
	LR	97	**37**	0	0	46	0	0	0	180	21%
	LS	34	0	**260**	2	0	1	1	12	310	84%
	RC	77	0	20	**4**	1	5	5	135	247	2%
	RS	246	56	0	0	**12**	0	0	13	327	4%
	SD	30	2	0	20	10	**39**	0	31	132	30%
	Shoreline	23	0	0	0	0	0	**122**	0	145	84%
	YG	58	0	37	10	0	5	2	**183**	295	62%
	Column Total	659	95	320	37	70	64	130	465		
	Producer's Accuracy	14%	39%	81%	11%	17%	61%	94%	39%		
	Overall Accuracy = 41%										
	Kappa = 0.32										

Table 3.2. Confusion matrix evaluating classified high spatial resolution imagery to TEM reference data. Classification output is compared to the dominant class of reference polygons using a pixel-based classification. Statistics presented in Table 3.3 are derived from this and similar matrices (not shown). Refer to Table 3.1 for full description of each class. Rare classes are shaded.

Ecosystem Code	Sample Size (pixels)	Commission Errors 1	UA1	UA2	UA3	Cumulative User's Accuracies
HS	204	54	46.	42	7	95
LR	180	79	21	0	1	22
LS	310	16	84	1	2	86
RC	247	98	2	1	11	14
RS	327	96	4	32	13	49
SD	132	70	30	1	0	30
Shoreline	145	16	84	0	0	92
YG	295	38	62	30	0	84
Overall Accuracy			**41%**	**15%**	**5%**	**61%**

Table 3.3a Basic, non-smoothed classified image.

Ecosystem Code	Sample Size (pixels)	Commission Errors 1	UA1	UA2	UA3	Cumulative User's Accuracies
HS	262	56	44	48	2	94
LR	322	76	24	0	0	24
LS	315	11	89	0	3	91
RC	236	98	2	4	16	22
RS	327	99	1	36	10	47
SD	167	63	37	0	0	37
Shoreline	163	12	88	0	0	94
YG	290	35	65	30	0	88
Overall Accuracy			**42%**	**16%**	**4%**	**62%**

Table 3.3b Map which underwent post-classification smoothing to match the 2ha minimum mapping unit of the reference data.

Table 3.3 Accuracy assessment estimates for pixel-based assessment. UA1, UA2 and UA3 are the user's accuracies of the classified map relative to the dominant, second dominant and third dominant label of reference polygons respectively. Associated commission errors are shown for the traditional (dominant class) assessment only. Rare classes are shaded.

Ecosystem Code	Sample Size (polygons)	UA1	UA2	UA3
LR	12	42	0	0
RC	46	2	2	4
Shoreline	6	83	0	0

Table 3.4 User's accuracies for the three rare classes using a polygon-level accuracy assessment. The ecosystems are described in Table 2.

Ecosystem Code	**Extent (ha)**			**Number of Patches**			**Mean Patch Size (ha)**		
	Basic	Smoothed	Percent Change	Basic	Smoothed	Percent Change	Basic	Smoothed	Percent Change
LR	170	138	- 19 %	179	24	- 87%	0.78	5.8	+ 640 %
RC	647	601	- 7 %	236	100	- 58 %	2.4	6.3	+ 166 %
Shoreline	103	113	+ 11 %	35	20	- 43%	2.3	5.7	+ 144 %

Table 3.5 Comparison of landscape pattern indices (LPIs) for rare classes on the classified imagery before and after post-classification smoothing (implementation of a 2 ha minimum mapping unit). Percent change is calculated relative to original extent in the basic (non-smoothed) classification.

Figures

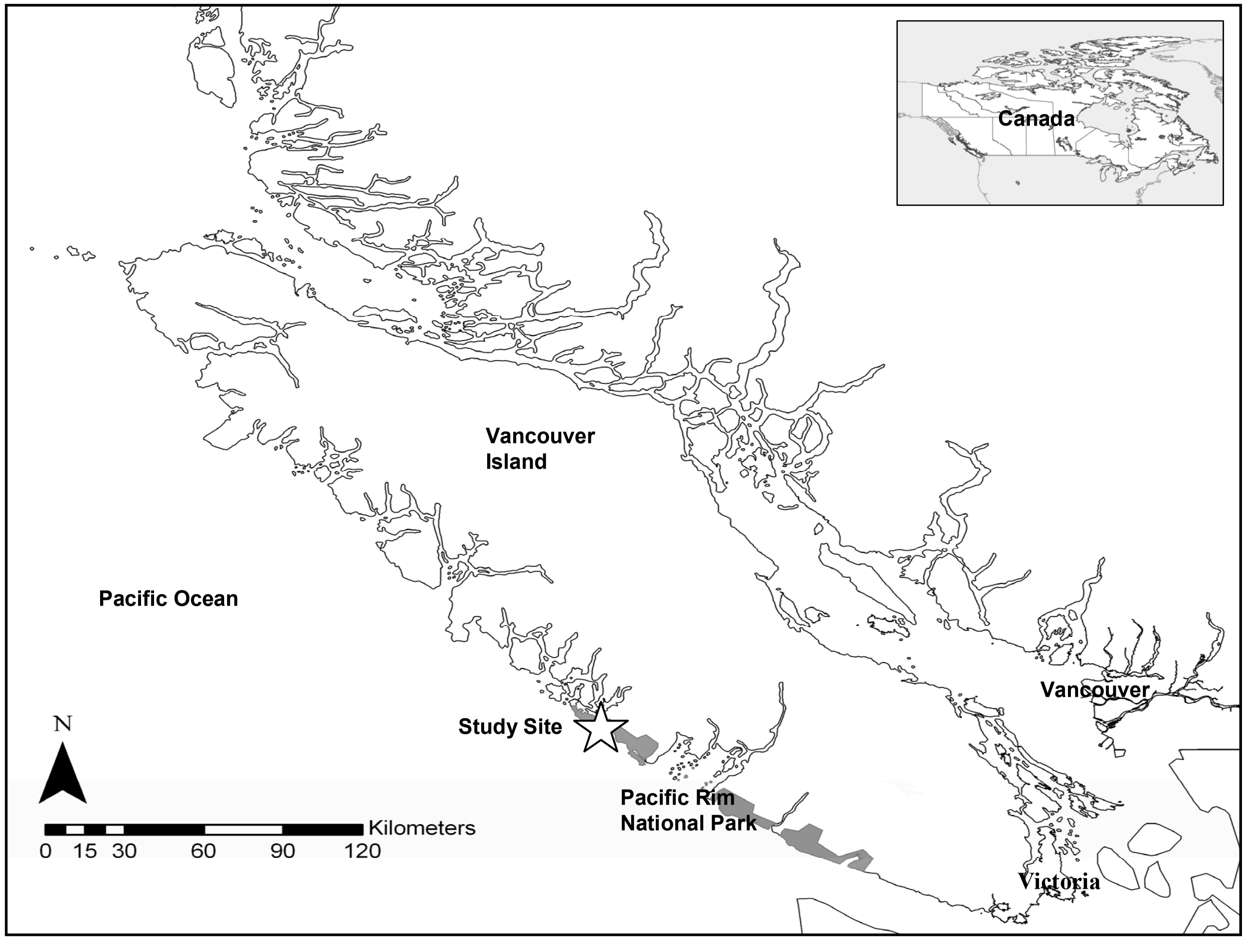

Figure 3.1. Study area (162 km^2) in the coastal temperate rainforests of western Vancouver Island, British Columbia, Canada.

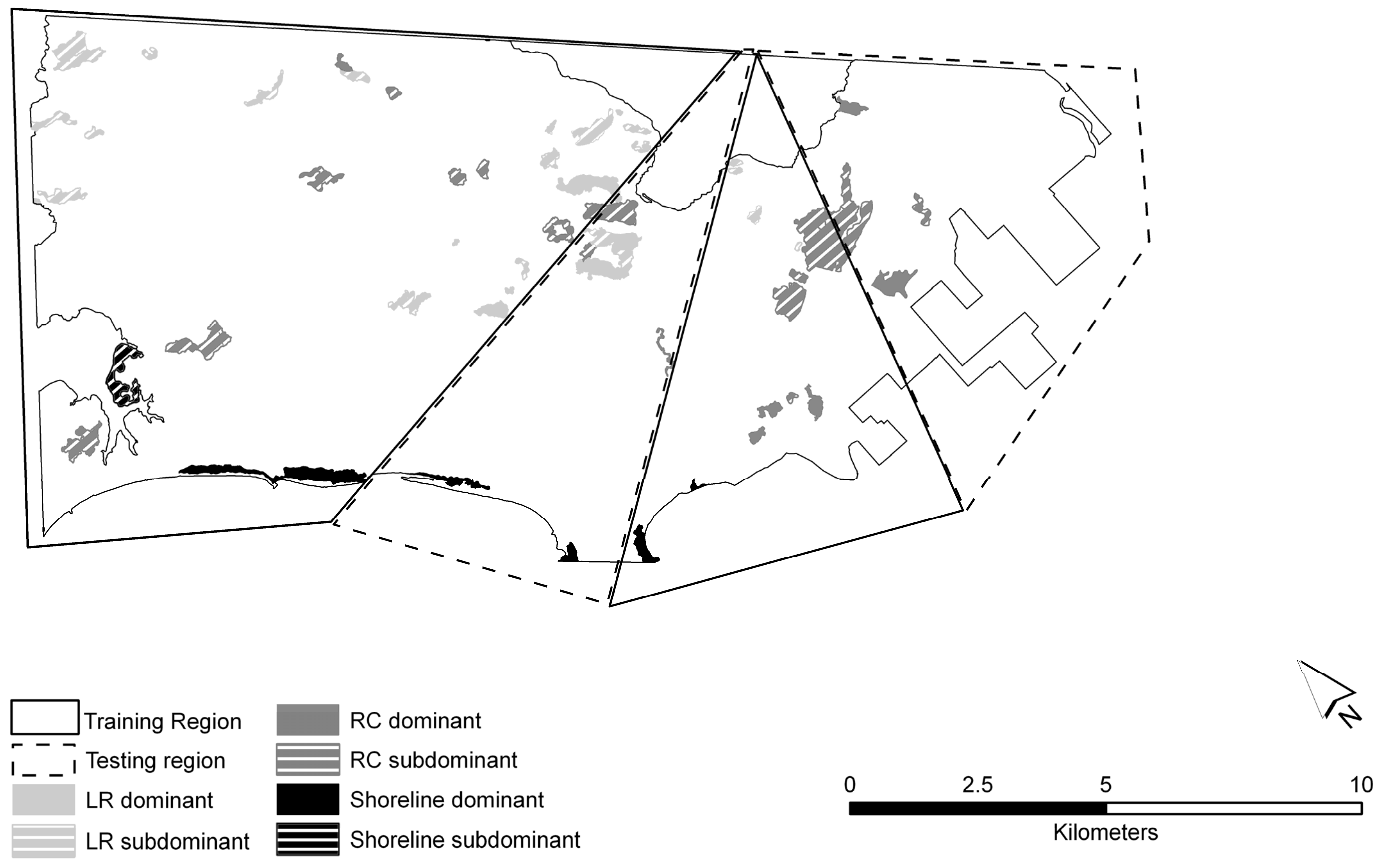

Figure 3.2a. Reference data (BC Terrestrial Ecosystem Map) depicting the three rare ecosystems analyzed in this study: *Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum* (LR), *Thuja plicata - Picea sitchensis / Lysichiton americanum* (RC) *and Picea sitchensis* (Shoreline). Both dominant and sub-dominant ecosystem classes within a given polygon are shown. Also shown are the training and testing regions used to guide and assess the classification.

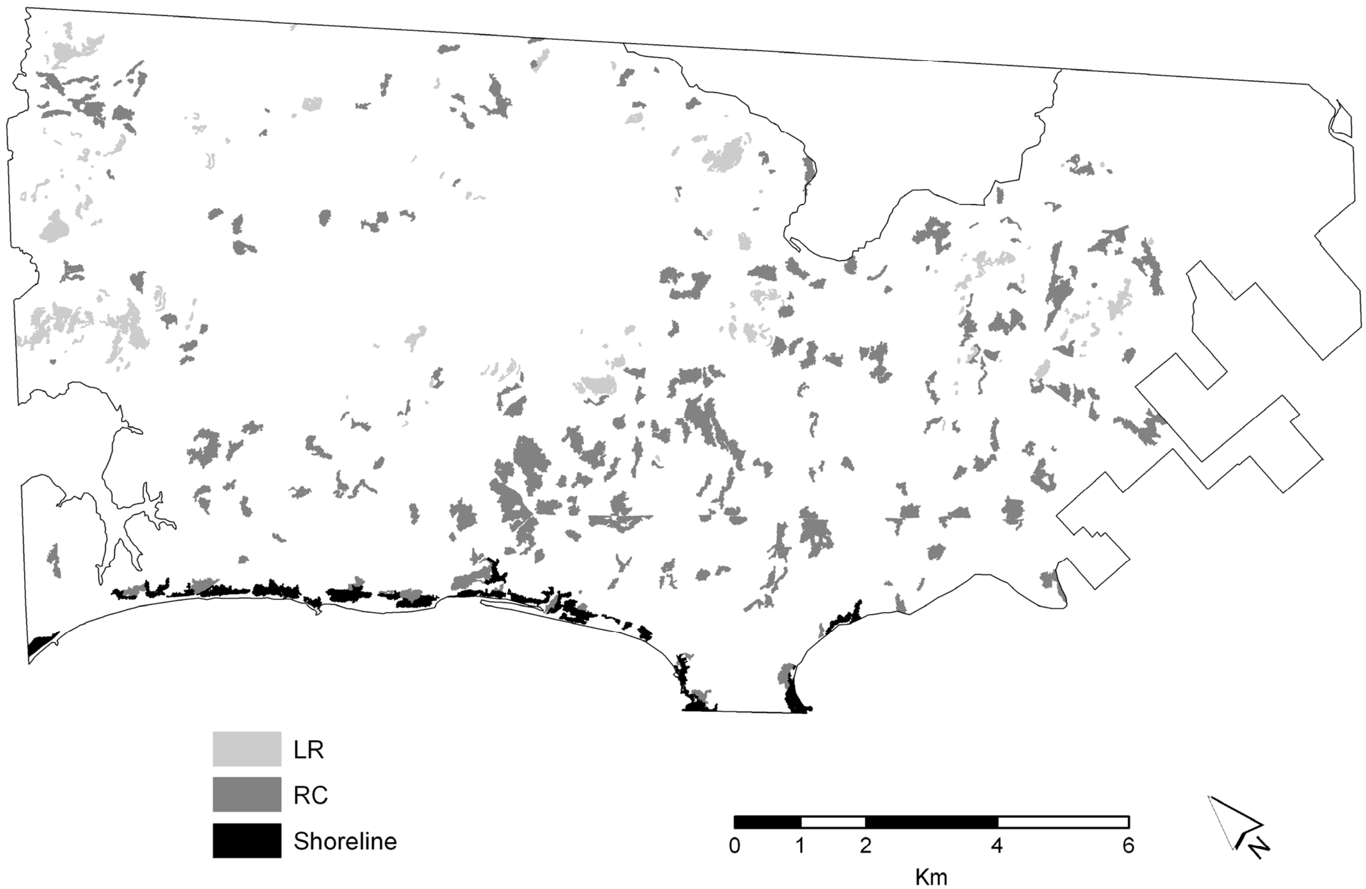

Figure 3.2b. Map of the three rare ecosystems analyzed in this study derived from the classification of high spatial resolution imagery.

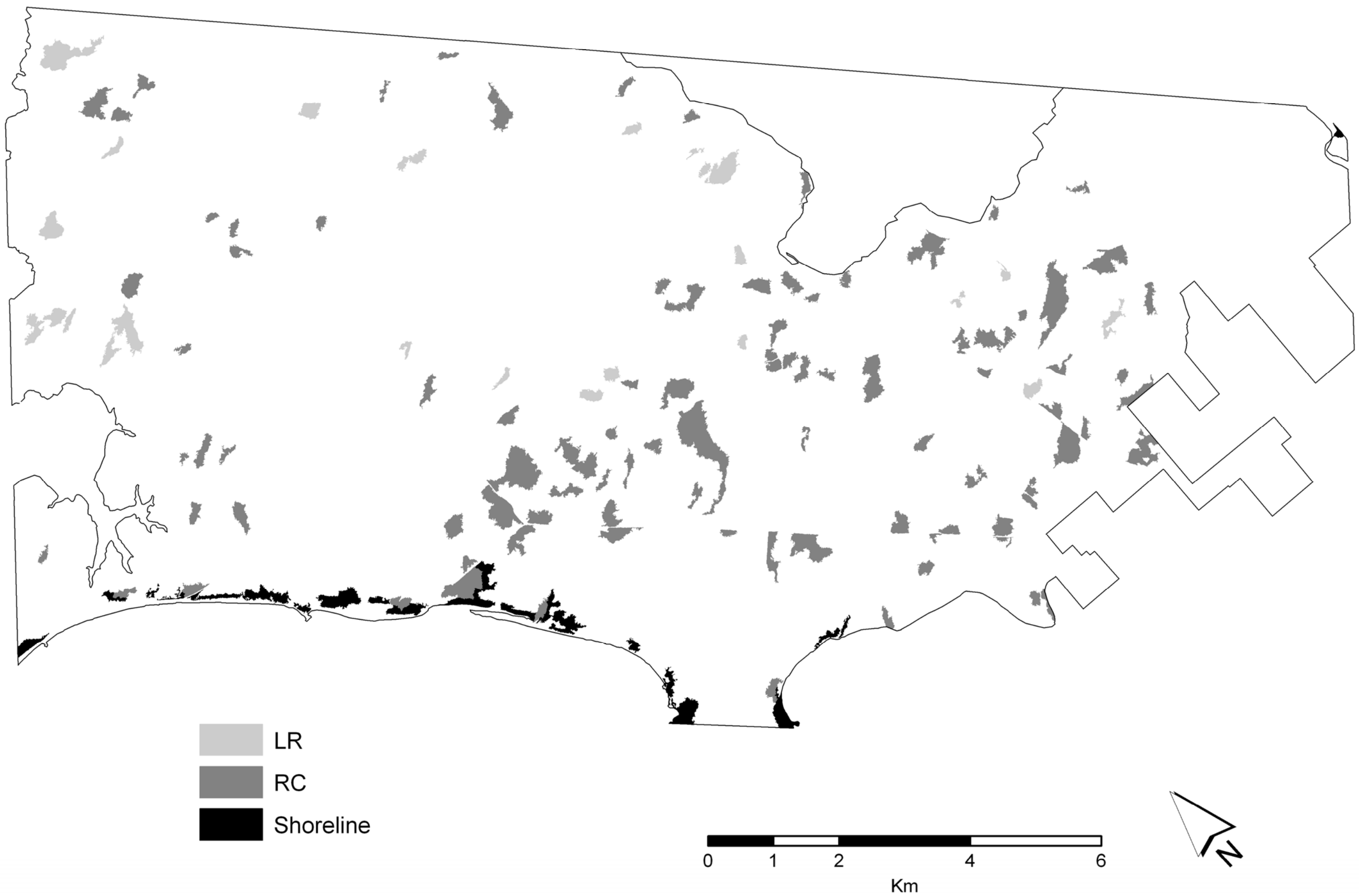

Figure 3.2c. The classification of the three rare ecosystems analyzed in this study site smoothed to implement a minimum mapping unit (MMU) of 2ha, which represents the MMU used in the creation of the Terrestrial Ecosystem Map (TEM) reference data.

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4. CONCLUSION

Remotely sensed imagery is often used to map and monitor land cover. High spatial resolution satellite imagery is a relatively new development of increasing interest. Chapter 2 demonstrated that this technology may have potential for use in ecosystem inventories because of its ability to map and monitor forest cover at multiple scales. Late-seral forests can be well distinguished from younger forests using QuickBird imagery, and with the addition of ancillary landscape positional data, some late-seral forest associations can be mapped with high accuracies. However many other late seral forest associations, particularly those which are locally rare, were mapped with significantly lower accuracies.

Rare classes are commonly classified with lower accuracies than more abundant classes, often because of the limited representation of these classes in the training data. For example, in their classification of forest stands in southwestern Alberta, (Chubey et al. 2006) found that accuracies of % pine and % crown closure were highest for classes comprising the greatest proportion of training data. Many classification algorithms may be impacted by class imbalances. For example, parametric classification algorithms (e.g., maximum likelihood classification) are not appropriate when there are some classes with very small sample sizes, as the training data for those rare classes is likely to be non-normal (Yu et al. 2006). Non-parametric algorithms (e.g., decision trees and nearest neighbour classification) may also be impacted by imbalanced training sets. The proportion of image pixels or objects classified as class *x* may increase as the proportion of class x in the training data increases (McIver and Friedl 2002), and class prediction accuracies may be proportional to training data as well (Breiman et al. 1984in; Wright and Gallant 2007).

In this study, classification accuracies of rare classes (and non-rare classes as well) may be improved by more advanced techniques such as artificial neural network classification. Further, oversampling the rare class or under-sampling the more common classes during training sample selection are other ways which may improve classification based on imbalanced representation in the training data (Barandela et al. 2004; Weiss 2004). These methods provide options for further work.

Given the challenge of mapping rare classes demonstrated here (Chapter 2), Chapter 3 of this thesis focused on how and why rare classes can be misrepresented on a map. Regardless of the classification accuracies obtained in this particular project, this analysis demonstrated that post-classification map production techniques (e.g. smoothing) may significantly impact an ecosystem's spatial distribution and representation on a map, and also its classification accuracy. Further, when comparing a high spatial resolution classification to coarser scale reference data (often the only option because of limited resources), classification accuracies may be misrepresentative.

The remote sensing community remains attached to the traditional confusion matrix approach to accuracy assessment where one classified map unit is compared to one reference unit, for which little or and no spatial or thematic ambiguity is allowed (Foody 2002). However, a non-traditional accuracy assessment may be more appropriate when reference data is at a coarser scale of generalization (Stehman et al. 2003). For example, *fuzzy* techniques allow for different degrees of agreement (Woodcock and Gopal 2000). This approach could be applied to Chapter 3 whereby different levels of correctness could be assigned according to whether the match is between the dominant or subdominant reference class (corresponding to how liberal is the definition of agreement), as has been discussed elsewhere (Stehman et al. 2003). A fuzzy accuracy approach could also be applied by weighting accuracies according to class similarity. Some fuzzy approaches to accuracy assessment have recently been made easier to implement via a new software package specifically developed for this purpose (The Map Comparison Kit, RIKS, The Netherlands) but have not yet been widely adopted. This thesis has demonstrated that how a map is assessed can have significant repercussions for rare ecosystems, and should therefore serve as an impetus to further research into, and adoption of, non-traditional accuracy assessment techniques. At the very least, this study indicates simple measures of overall accuracies are of limited value, a statement which is consistent with existing accuracy assessment literature (Foody 2002).

This work complements and builds upon previous studies testing the utility of high spatial resolution QuickBird satellite imagery for forest mapping in coastal British Columbia by demonstrating potential for the species-based classification of heterogeneous forest types. This research contributes to a growing body of literature indicating that high spatial resolution satellite imagery may soon be an additional tool used for detailed forest inventories. This thesis also draws attention to issues of mapping fragmented and rare classes, translating remote sensing analysis between map-makers and map-users and demonstrating that further research is needed. Only with further testing of high spatial resolution satellite imagery using non-traditional techniques will the full potential of high spatial resolution satellite imagery be known.

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