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RESEARCH ARTICLE

Conservation implications of mapping rare ecosystems using high spatial resolution imagery: recommendations for heterogeneous and fragmented landscapes

Shanley D. Thompson · Sarah E. Gergel

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Abstract Protection of rare ecosystems requires information on their abundance and spatial distribution, yet mapping rare ecosystems, particularly those which are fragmented, is a challenge. Use of high spatial resolution satellite imagery is increasing, in part because it may be well-suited for mapping fine-scale components of landscapes. We classified high spatial resolution QuickBird imagery of coastal British Columbia, Canada into late seral forest associations. With an emphasis on rare forest associations, we compared the classification accuracies resulting from contrasting accuracy assessment techniques. We also evaluated the impact of post-classification image smoothing on the quantity and configuration of rare forest associations mapped. Less common associations were generally classified with lower accuracies than more abundant associations, however, accuracies varied depending on the assessment technique used. In particular, ignoring the presence of fine-scale heterogeneity falsely lowered the estimates of map accuracy by approximately 20%. Smoothing, while generally increasing the accuracies of rare forest associations, had a large effect on their predicted spatial extent and configuration. Simply due to smoothing, areal estimates of rare associations differed by as much as 36%, the number of patches decreased by 73% on average, and mean patch size increased by up to 650%. Our findings indicate that routinely used post-classification and map assessment techniques can greatly impact the portrayal of rare and fragmented ecosystems. Further research is needed on the specific challenges of mapping and assessing the accuracy of rare ecosystems in fragmented and heterogeneous landscapes.

Keywords QuickBird satellite imagery · Late seral forests · Conservation planning · Minimum mapping unit · Accuracy assessment · British Columbia · Coastal temperate rainforests · Landscape heterogeneity

Introduction

Ecosystem representation (preservation of a full range of the ecosystems present in the world, a region, or a single watershed) is a well-established conservation goal (Olson and Dinerstein 1998). Preserving examples of all ecosystems is an important way to conserve the unique assemblages of plant and animal species within the different ecosystems (Noss 1996). The spatial patterns of ecosystems across a landscape are

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S. D. Thompson (✉) · S. E. Gergel
Department of Forest Sciences and Centre for Applied Conservation Research, University of British Columbia, Vancouver, BC, Canada V6T 1Z4
e-mail: shanleyt@interchange.ubc.ca

also appreciated. Fragmentation of an ecosystem into smaller, isolated patches may lead to the decline of a population if movement among patches is not possible, as well as to negative edge-effects (e.g., increased predation) (Fahrig 2003).The concepts of ecosystem representation and spatial connectivity, particularly relevant for rare (uncommon, and potentially at risk or endangered) ecosystems, are central to Ecosystem-Based Management (EBM), increasingly used in natural resource management in many areas of the world (Grumbine 1994; Slocombe 1998). Explicit consideration of these ideas is also important in the context of designing nature reserve networks (Margules and Pressey 2000).

Information describing the abundance, structure, composition and spatial configuration of ecosystems is conventionally based on field work, or the interpretation of aerial photographs and satellite imagery (Goetz et al. 2003; Wulder et al. 2004). Recent advances in technology have led to increasing interest in high spatial resolution (<4 m) satellite imagery and digital processing techniques for ecosystem mapping and monitoring. Developments in object-based image classification techniques in particular (as distinct from pixel-based techniques) have accompanied and promoted the use of high spatial resolution imagery (Hay et al. 2005). While high spatial resolution imagery may offer great promise for mapping fine-scale ecosystems and structure (Dechka et al. 2002; Johansen and Phinn 2006; Mehner et al. 2004) several aspects of the use of this technology have not been explored within the context of rare class mapping.

Classification errors on maps derived from remotely sensed imagery are generally greater for classes that occupy a small proportion of a study area than for those that occupy a larger proportion (Smith et al. 2002, 2003). Studies examining the role of spatial resolution and land cover configuration on mapping accuracy have found that coarser spatial resolutions tend to produce less accurate maps of small, fragmented classes (Hlavka and Livingston 1997; Silva et al. 2005). Rare, fragmented classes are often underrepresented when the spatial resolution is decreased or the Minimum Mapping Unit (MMU) increased (Kendall and Miller 2008; Mayaux and Lambin 1995). However, most previous work discussing the impact of changing MMUs on rare classes has been based on medium- or coarse-grained imagery (Kendall and Miller 2008; Saura 2004; Turner et al. 1989). Others have utilized simulated landscapes where the effect of spatial resolution is unclear (Langford et al. 2006; Saura 2002; Turner et al. 1989).

As the automated classification of high spatial resolution digital imagery for mapping fine-scale ecosystems continues to increase, it is important to consider that the technology may be misused or used without an understanding of some of the associated limitations or caveats (Fassnacht et al. 2006). Our objective was to evaluate how a common mapping technique, as well as several different accuracy assessment techniques, may impact the portrayal of rare ecosystems on maps derived from high spatial resolution satellite imagery. Using an object-based classifier, we classified imagery collected over a heterogeneous landscape and compared the classification accuracies of rare, fragmented classes resulting from several different accuracy assessment techniques. We performed (a) a standard, pixel-based accuracy assessment, (b) a modified assessment that acknowledges fine-scale heterogeneity, and (c) a polygon-level accuracy assessment. We also examined the impact of implementing of a Minimum Mapping Unit (MMU) on several Landscape Pattern Indices (LPIs) of fragmentation for rare ecosystems.

Methods

Study area

Our research focused on the coastal temperate rainforests of the outer coast of western Vancouver Island, British Columbia (BC), within and adjacent to Pacific Rim National Park (Fig. 1). Climate is characterized by cool summers and mild winters (mean annual temperature ~8°C) and very large amounts of precipitation (1,000–5,000 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*).

Classification scheme

High spatial resolution QuickBird satellite imagery was classified into ecosystems defined by British

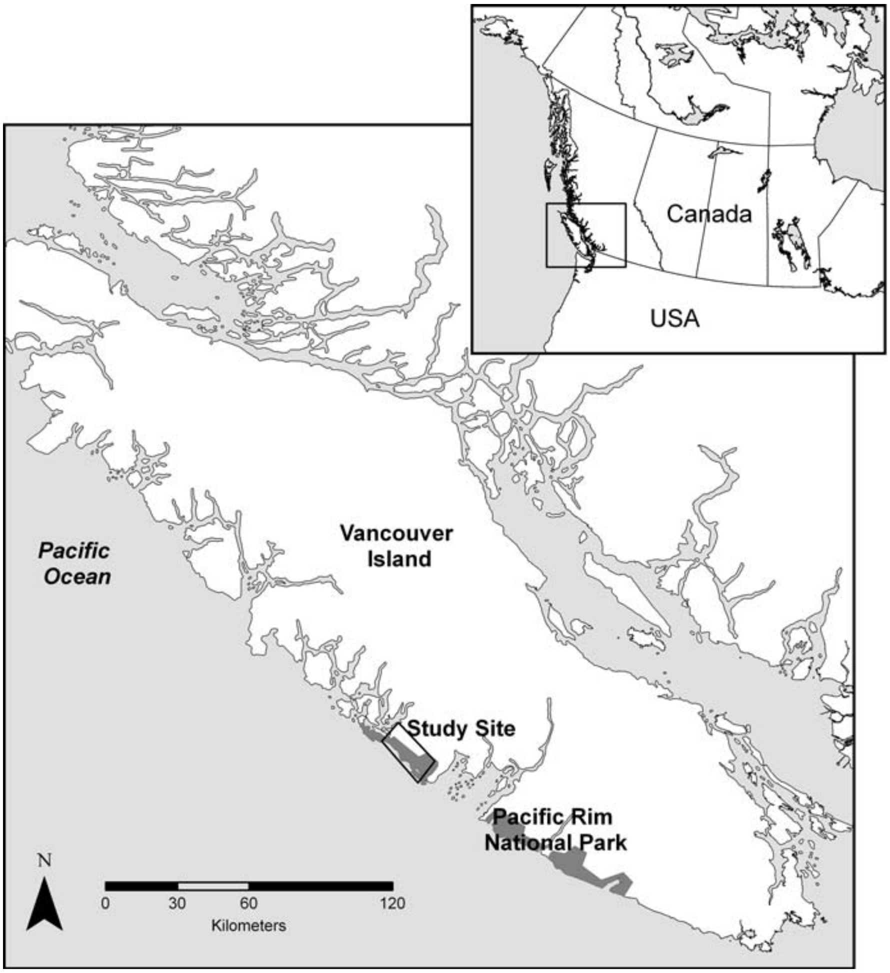


Fig. 1 This study concerns a number of late seral forest associations within a 162 km^2 area of the coastal temperate rainforests of western Vancouver Island, British Columbia, Canada

Columbia's Biogeoclimatic Ecosystem Classification (BEC) hierarchical framework. At the broadest scale, the province is classified into zones of similar climate. At the finest scale of classification are plant associations. These associations (ranging in size from less than 1 ha to several 100 ha) are characterized by the climax plant communities expected to develop under specific soil moisture and nutrient regimes (Green and Klinka 1994; Meidinger and Pojar 1991).

The BEC framework is used to create a Terrestrial Ecosystem Map (TEM) of a region in British Columbia, based traditionally upon the interpretation of aerial photographs and the use of supplemental field data. Polygons on a TEM 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 is noted, although the exact location of each is not.

The forest associations analyzed in this study are shown in Table 1. Several forest associations in the area have been blue-listed (designated as *of special concern*) by the Conservation Data Centre (CDC) (Table 1), BC's NatureServe counterpart responsible for collecting and disseminating information on animals, plants and communities at risk. Because the associations refer to potential climax vegetation, mapping was restricted to old forests (stands greater than 250 years in age). Additionally, associations were eliminated which were dominant only in one or two polygons on the reference map in order to ensure adequate sample sizes. However, two very rare blue-listed associations (*Picea sitchensis/Eurhynchium oreganum* (SK) and *Picea sitchensis/Polystichum*

Table 1 Late-seral forest associations discriminated in this study

FOREST ASSOCIATION	DESCRIPTION	CONSERVATION STATUS	% OF STUDY SITE	ECOSYSTEM CODE
Thuja plicata - Tsuga heterophylla / Gaultheria shallon (western redcedar - western hemlock / salal)	Zonal forest association (intermediate moisture and nutrient regime)		28.4	HS
Pinus contorta - Chamaecyparis nootkatensis / Racomitrium lanuginosum (lodgepole pine - yellow cedar / hoary rock-moss)	Dry 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, floodplain associations		4.7	SD
Picea sitchensis / Eurhynchium oreganum (Sitka spruce - Oregon beaked-moss) **merged into the *Shoreline* class**	Oceanspray association found on old beachplains	blue listed	0.56	SK
Picea sitchensis / Polystichum munitum (Sitka spruce / sword fern) **merged into the *Shoreline* class**	Oceanspray 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

These associations are drawn from British Columbia's Biogeoclimatic Ecosystem Classification (BEC). Extent of each association in the study area determined from a local Terrestrial Ecosystem Map (TEM) (EcoCat 2005). Conservation status is defined by the BC Conservation Data Centre. Locally rare classes are shaded

munitum (SW)) were merged into one Shoreline class (*Picea sitchensis*) because both are spruce dominated associations adjacent to the coast. Our classification scheme contains one other blue-listed association, the swamp forest *Thuja plicata–Picea sitchensis/Lysichiton americanum* (RC). We also included *Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum* (LR) in our rare ecosystem analysis. Though not formally recognized as rare on provincial lists, this forest association found on high, relatively dry sites, and occupies a very small proportion of the total study area (<1.5%). This association thus provides another useful example of the challenges of mapping fragmented, locally rare ecosystems.

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 16 m. 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).

In addition to spectral information, image texture layers were created to quantify the spatial structure of each forest association. Image texture may relate to changes in species, crown closure and stem density (Franklin et al. 2001) and may be particularly useful information when the features of interest, such as many of the tree species in coastal BC (Leckie et al. 2005), have similar spectral reflectances. Semivariograms were utilized to derive the size of the neighbourhood over which spatial variation was measured. Several polygons were drawn for each forest association within the centre of larger regions indicated by the reference data as belonging to the various classes. The number, size and shape of sample polygons varied for each association depending on its abundance and magnitude of fragmentation. Using these data, multidirectional semivariograms were calculated for each spectral band for each forest association, and the range subsequently identified via visual examination. Pixels appeared to be independent at a distance of approximately three pixels for all classes and most wavelengths, as in our previous work (Johansen et al. 2007). The Grey Level Co-occurrence Matrix (GLCM) (Haralick 1973) correlation measure was thus calculated for each spectral band using a 3×3 window. Further details regarding our choice of texture measure can be found in our previous work (Thompson et al. in press).

Ancillary terrain data were also used in this study because the forest associations are partially dependent on elevation, slope position and soil moisture (Table 1). We derived two terrain layers (elevation and potential soil moisture) from airborne Light

Detection and Ranging (LiDAR) data. 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 returns were converted to a Digital Elevation Model (DEM) using a natural neighbour algorithm (Sibson 1981) and the resulting 1 m DEM was resampled to the spatial resolution of the QuickBird image (2.8 m). Using 19 ground control points, the QuickBird imagery was then georectified to the LiDAR imagery (estimated horizontal error of 0.5 m), with a resulting Root Mean Squared Error of approximately 1 pixel.

ArcGIS (v9.2; ESRI Inc.) was used to calculate a Topographic Wetness Index (TWI) from the DEM:

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

where a is the specific catchment area (the upslope area per unit contour length) and β is the slope. High values of this index correspond to concave areas where water would be expected to accumulate, whereas low values are related to dry, convex areas. The TWI was chosen for use based on our previous forest classification study in the region (Thompson et al. in press). Given that soil moisture affects vegetation patterns across a landscape (Swanson et al. 1988; Whittaker 1956), 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 an object-based classifier (Definiens Professional 5.0, Munich, Germany). Object-based classifiers classify groups of adjacent pixels (image objects) based on the mean and/or standard deviation, unlike traditional classifiers that classify each individual pixel. This method is preferred for classifying high spatial resolution imagery, where multiple, adjacent pixels comprise a feature of interest, because pixel variance is divided into image objects approximating real objects (Hay et al. 2005). Thus the possibility of developing unique spectral signatures for a given feature or class is increased (Wulder et al. 2004).

Two hierarchical levels of image-objects were created. At the broadest scale (mean object size of 7.6 ha), the imagery was first classified into a binary map demarcating areas of late seral forests. At the finer scale, late seral forests were then classified into eight different forest associations, using a mean object size of 0.9 ha. A supervised classification approach was used, utilizing a nearest neighbour algorithm. Representative image objects of each forest association were selected to "train" the classifier, and the algorithm then assigned each image object to the forest association of the nearest sample object in feature space. Our selection of training samples was informed by a digital, vector-based TEM (1:20,000) developed in 2003 and 2004 (EcoCat: Ecological Reports Catalogue). A contextual rule was used to restrict the presence of the *Picea sitchensis* (Shoreline) class to within 350 m of the coastline, and minimum elevation thresholds were used to aid discrimination of *Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum* (LR) and *Tsuga heterophylla–Chamaecyparis nootkatensis/Gaultheria shallon* (RS).

Accuracy assessment

Forest associations on the classified image were compared to those on the vector-based TEM. The field sampling which occurs during the creation of a TEM informs and results in revisions to mapping while it is created to ensure a quality product. Further, there are generalized protocols for independent accuracy assessments of TEM (via additional field sampling) designed to ensure a minimum overall accuracy of 65% (Meidinger 2003). To date, not all TEM projects have been assessed in this manner and, results for specific TEM maps are not publicly available. Thus, quantitative knowledge of the accuracy of the TEM for the study site is unknown. However, it is considered by regional experts to be of higher quality than most (A. MacKinnon 2007, pers. comm.) while additional accuracy research, funded by the Province of BC, is underway in this regard.

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 (Fig. 2). Both the training and testing regions contained examples of all forest associations examined.

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 therefore used a 10 m 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 was important because a Minimum Mapping Unit (MMU) is used during air photo interpretation for Terrestrial Ecosystem Mapping (Ecosystems Working Group Terrestrial Ecosystems Task Force 1998). The MMU of the TEM dataset utilized in this study was 2.0 ha, which is a coarser scale of generalization than that of the object-based classification (average polygon size of 0.9 ha) 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 UA_1, UA_2 and UA_3 (user's accuracies for the first, second and third dominant forest associations in a reference polygon, respectively). Several other studies have indicated that accuracy assessment techniques should account for the thematic ambiguity that may be present in reference maps (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. This polygon-based assessment amounted to selecting only one point per classified object. In this way, we avoided "double-counting" a

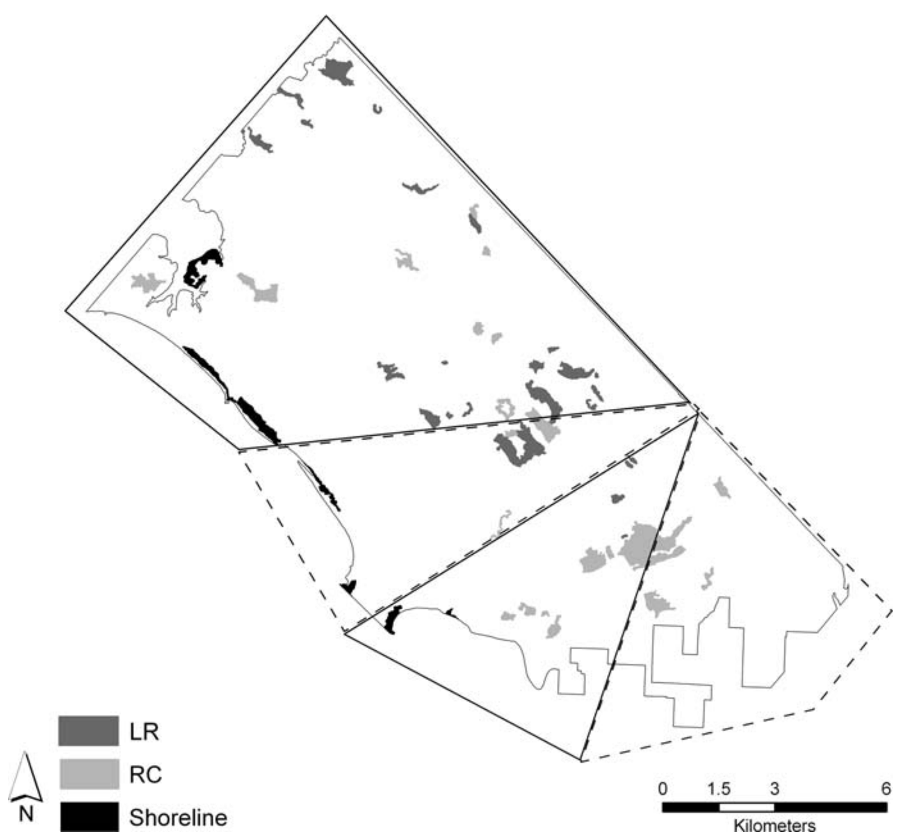


Fig. 2 The study area contains three locally rare forest associations, shown here on the Terrestrial Ecosystem Map (TEM) reference data derived from 1:20,000 aerial photographs (EcoCat 2005): *Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum* (LR), *Thuja plicata–Picea sitchensis/Lysichiton americanum* (RC) and *Picea sitchensis* (Shoreline). The area was divided into training and testing regions to guide and assess the classification

single image object, as well as accounted for any remaining positional uncertainty between the classified map and reference data (Stehman et al. 2003; Wulder et al. 2006). One potential problem, however, is that one large correct polygon 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 performed a polygon-based accuracy assessment solely for the rare forest associations (which all occupy a similar range of average patch sizes and proportion of the landscape).

In each case, accuracy was assessed via common descriptive measures, as well as Kappa (K_{hat}) (discrete multivariate) statistics, all based on the error, or confusion matrix. Descriptive measures (e.g. overall, user's and producer's accuracies) based simply on the proportion of correctly classified pixels, are the most common way to represent classification accuracy and are easy to understand. However, descriptive measures do not take into account chance agreement (Jensen 2005), and the fact that some classes may have a greater chance of being correctly mapped, such as in our study, where the proportion of classes (and sample sizes) is significantly unequal. When an accuracy assessment is based on unequal sample sizes, overall accuracy in particular may be misrepresentative, as it will be higher when there are more samples for a class that is well classified, than when there are fewer samples of that class (and more samples of a class more poorly mapped) (White et al. 2007). Furthermore, confidence in the estimated accuracy of each class may vary as a result of differences in sample sizes (White et al. 2007).

The Kappa coefficient, which can be calculated to measure the overall agreement between the classification and the reference data, as well as per-class (conditional) accuracies, incorporates chance agreement. It thus provides additional information regarding classification accuracy (Congalton 1991). The Kappa ranges from -1 to $+1$, with values less than 0 indicating poor agreement between the classification and reference data, and increasing accuracy with greater Kappa values, where values greater than 0.8 indicate "almost perfect" agreement (Landis and Koch 1977). We evaluated classification accuracy in terms of overall accuracy and overall Kappa, as well as user's accuracies and conditional Kappa statistics. We focused on per-class accuracies from the user's perspective, as this perspective represents the reliability of the map, and thus are often the measures of accuracy in which ecologists and managers are most interested.

Smoothing analysis

Minimum Mapping Units (MMUs) 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). Minimum Mapping Units may be applied after the automated classification of a digital image (Saura 2002) in a process referred to as spatial aggregation or image smoothing. Post-classification smoothing is also often performed to reduce "salt-and-pepper" noise common in traditional pixel-based classifications (Gergel 2007; Saura 2002). A common technique is the application of a moving window of a fixed size (e.g. 3 × 3 pixels) whereby the value of the centre pixel becomes the mean or median class of the other pixels in its neighbourhood (Jensen 2005). In this study, smoothing was applied on image objects (polygons) of various sizes and shapes, rather than at the pixel level. Using the reshaping algorithms available in Definiens classification software, a classified image object smaller than the MMU of the TEM dataset (2 ha in size, of any shape) was merged into the neighbouring image object with which it shared the largest border.

Following this post-classification smoothing, the difference in several routinely used class-level LPIs (with reference to the unsmoothed classification) was assessed for the rare forest associations using the following equation:

$$\% \,\text{difference} = [(\text{LPI}_{\text{unsmoothed}} - \text{LPI}_{\text{smoothed}})/(\text{LPI}_{\text{unsmoothed}})] * 100\% \quad (2)$$

Results

Overall map accuracy in the pixel-based accuracy assessment was 41% ($K_{hat} = 0.32$) with reference to the dominant forest association. Less common associations were often classified with lower accuracies than those more prevalent throughout the study area (Table 2a). An exception was the *Picea sitchensis*

Table 2 Pixel-based classification accuracies using a British Columbia Terrestrial Ecosystem Map (TEM) as reference data: (a) Unsmoothed classification and (b) Map which underwent post-classification smoothing to implement the 2 ha minimum mapping unit of the reference data

Ecosystem code	Sample size (pixels)	Conditional Kappa_1	UA_1	UA_2	UA_3	Cumulative UA	Cumulative conditional Kappa
(a)							
HS	204	0.160	46	42	7	95	0.924
LR	*180*	*0.162*	*21*	*0*	*1*	*22*	*0.174*
LS	310	0.805	84	1	2	86	0.832
RC	*247*	*−0.004*	*2*	*1*	*11*	*14*	*0.124*
RS	327	−0.001	4	32	13	49	0.466
SD	132	0.270	30	1	0	30	0.278
Shoreline	*145*	*0.829*	*84*	*0*	*0*	*84*	*0.829*
YG	295	0.492	62	30	0	92	0.886
Overall		0.32	41%			61%	0.55
(b)							
HS	262	0.094	44	48	2	94	0.901
LR	*322*	*0.182*	*24*	*0*	*0*	*24*	*0.182*
LS	315	0.865	89	0	3	91	0.895
RC	*236*	*0.019*	*2*	*4*	*16*	*22*	*0.204*
RS	327	0.003	1	36	10	47	0.469
SD	167	0.348	37	0	0	37	0.348
Shoreline	*163*	*0.868*	*88*	*0*	*0*	*88*	*0.868*
YG	290	0.523	65	30	0	94	0.925
Overall		0.33	42%			62%	0.56

Accuracy is assessed via metrics of User's Accuracy (UA) and Conditional Kappa. Agreement between the classified map and the dominant class in each reference polygon is indicated by User's Accuracy 1 (UA_1), and by Conditional Kappa_1. Agreement with respect to the second dominant and least dominant class in each reference polygon is indicated by User's Accuracy 2 and 3 (UA_2, UA_3), respectively. Cumulative UAs and cumulative conditional Kappas are also shown. Locally rare classes are italicized

(Shoreline) class, which although quite limited in extent, was classified with very high accuracy. Further, accuracies were quite high for the Shoreline class (User's Accuracy_1 = 84%, $K_{hat} = 0.829$), yet for the two other rare forest associations (*Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum* (LR) and *Thuja plicata–Picea sitchensis/Lysichiton americanum* (RC)), accuracies were comparatively very low (UA_1 = 21% and 2%, $K_{hat} = 0.162$ and −0.0004, respectively) (Table 2a). A full confusion matrix is contained in (Thompson et al. in press).

Accounting for the second and third dominant site series in the accuracy assessment increased the overall Kappa measure of agreement from 0.32 to 0.55, thus shifting the overall classification from a level of "fair" to "moderate" agreement (Landis and Koch 1977). When considering only the dominant forest association, per-class accuracies (Table 2a) ranged from user's accuracies of 2 to 84% (and corresponding conditional Kappa values of −0.004 to 0.829). Accuracies improved by up to 49% when considering the non-dominant forest associations (Table 2a). For UA_1, the highest accuracies were achieved for *Thuja plicata–Chamaecyparis nootkatensis/Coptis asplenifolia* (YG), *Pinus contorta–Chamaecyparis nootkatensis/Sphagnum* (LS) and *Picea sitchensis* (Shoreline). The forest associations seeing the largest increase in accuracy when moving from UA_1 to the Cumulative UA (Conditional Kappa_1 to Cumulative Conditional Kappa) 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

Table 3 Polygon-based classification accuracies using a British Columbia Terrestrial Ecosystem Map (TEM) as reference data

Ecosystem	Sample size (polygons)	User's accuracies (UA1)
LR	12	42
RC	46	2
Shoreline	6	83

User's accuracies are shown for the locally three rare forest associations (described in Table 1)

estimates (Table 3) for two of the forest associations (RC and Shoreline) were no different, but were higher for LR (42% for the polygon-based assessment vs. 21% for the pixel-based assessment).

Smoothing the classification to implement a MMU increased the accuracy of the map very slightly to 42% ($K_{hat} = 0.33$), up from 41% ($K_{hat} = 0.32$) (UA_1) (Table 2). Smoothing increased some per-class accuracies and decreased others. The three forest associations most accurately classified in the smoothed map (UA_1 and Conditional Kappa_1) were also those most accurately classified in the non-smoothed map. Rare association accuracies either increased or saw no change as a result of smoothing (Table 2) with respect to the dominant reference label. However, the relative accuracies of these three rare forest associations (UA_1 and Conditional Kappa_1) remained the same. Shoreline was the most accurately classified and RC the least accurately classified) regardless of whether or not smoothing was used.

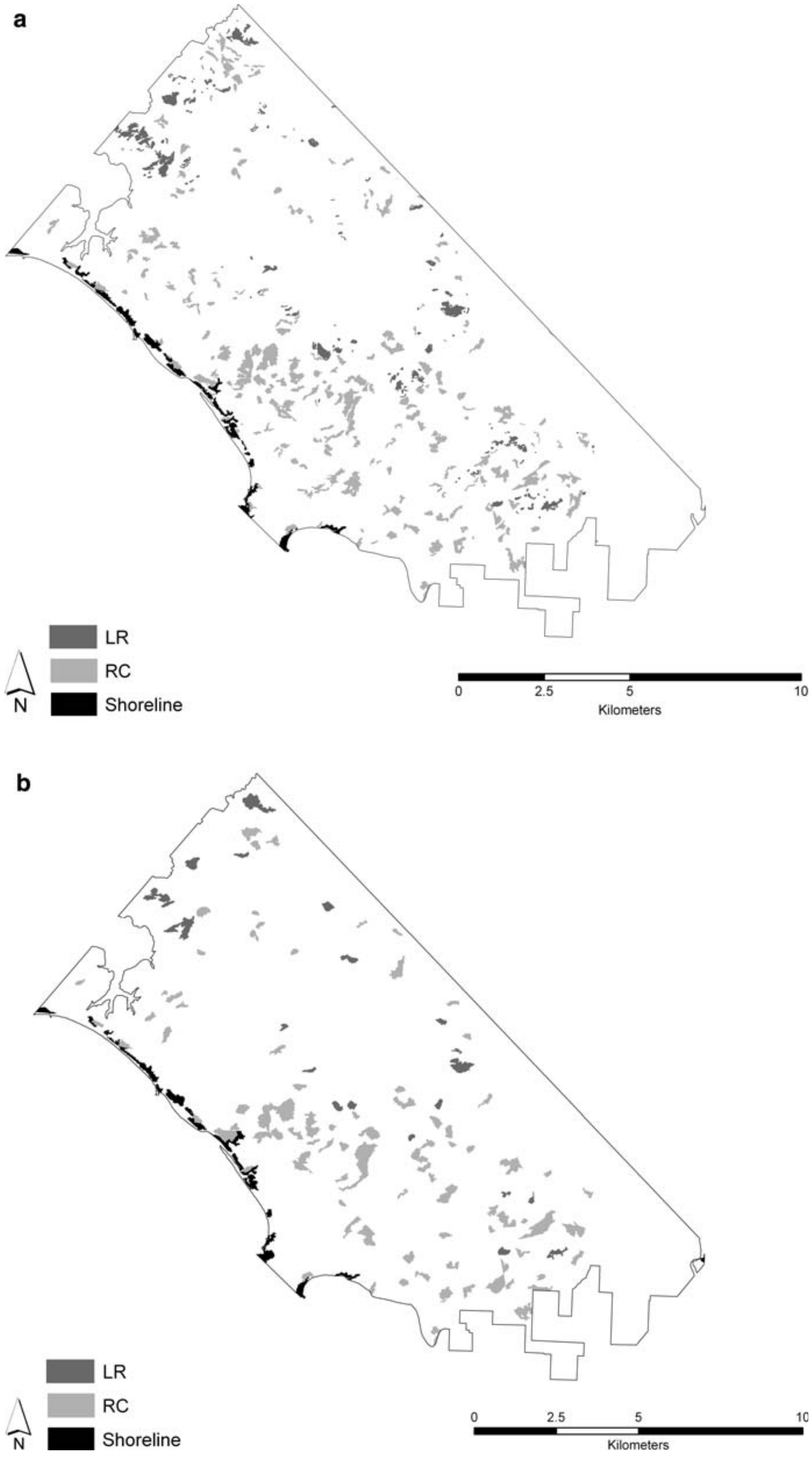
Implementation of a MMU greatly changed the quantity and configuration of the rare forest associations. The removal of small patches via smoothing reduced the number of patches of *Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum* (LR), *Thuja plicata–Picea sitchensis/Lysichiton americanum* (RC), and *Picea sitchensis* (Shoreline) by 92, 66, and 60%, respectively (Table 4; Fig. 3). Removal of small patches also resulted in large increases in the mean patch size for each association (Table 4), and a corresponding decrease in the abundance of LR, RC and Shoreline of 36, 32, and 20%, respectively (Table 4). These forest associations were initially overestimated, thus the reduction in area improved their user's accuracies. The decrease in abundance and number of patches, combined with the increase in size of patches, indicates the smoothed

Table 4 Comparison of Landscape Pattern Indices (LPIs) for rare classes on the classified imagery prior to and after post-classification smoothing was performed to implement a 2 ha minimum mapping unit

Ecosystem type	Extent (ha)			Number of patches			Mean patch size (ha)		
	Unsmoothed	Smoothed	Difference (%)	Unsmoothed	Smoothed	Difference (%)	Unsmoothed	Smoothed	Difference (%)
Pinus contorta–Chamaecyparis nootkatensis/Racomitrium lanuginosum (LR)	170	108	−36	212	18	−92	0.80	6.0	+650
Thuja plicata–Picea sitchensis/Lysichiton americanum (RC)	647	441	−32	236	79	−66	2.7	5.6	+107
Picea sitchensis (Shoreline)	103	82	−20	35	14	−60	3.0	5.9	+97

The difference is calculated relative to the non-smoothed classification

Fig. 3 Three rare forest associations were analyzed in this study (Table 1; Fig. 2). Panel A. The rare ecosystems were mappí using high spatial resolution QuickBird imagery and ancillary terrain data. Panel B. The classified image depicting the rare ecosystems was smoothed to implement a Minimum Mapping Unit of 2 ha, corresponding to that used in the TEM reference data



map presents the rare associations as being less fragmented than in the unsmoothed map.

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 ($K_{hat} = 0.83$) for two associations, but considerably lower for many others, including those uncommon in the study area. The abundance of rare forest associations was often overestimated. High rates of commission for rare classes may be partially attributed to class imbalances. Many classification algorithms (both parametric and non-parametric) may be impacted by class imbalances (Breiman et al. 1984; McIver and Friedl 2002; Wright and Gallant 2007; Yu et al. 2006). Further, overestimating the extent of rare classes can occur when common classes are misclassified, even at a very low rate. Thus, the accuracy of common classes must be quite high to not impact rare class abundance (Stehman 2005). While tradeoffs among class accuracies are expected, the impact on rare classes will be of greater magnitude (Stehman 2005). In addition, because classification accuracy for common classes tends to decrease with increasing landscape heterogeneity (Smith et al. 2003; Smith et al. 2002), mapping rare ecosystems may be even more difficult in complex landscapes with a high number of classes.

We introduced expert knowledge to help reduce misclassification partially caused by class imbalances. The inclusion of thresholds and contextual rules for two of the rare forest associations improved their accuracies by reducing misclassification with the more abundant associations. It is possible that classification accuracies (particularly of rare classes) could be increased further, for example, via the use of alternate classification methods such as Artificial Neural Networks (ANN), as well as decision trees and bagging (bootstrap aggregating) or boosting (Lu and Weng 2007). The goal of this paper, however, was not to explore techniques to improve the mapping of rare classes per se, but rather to examine effects of post-classification processing and accuracy assessment techniques on the portrayal of rare classes.

Similar to other recent studies of the effects of a Minimum Mapping Unit (MMU) on classification accuracies (Verbyla and Hammond 1995; Wulder et al. 2007), we found that a traditional accuracy assessment tended to inflate error estimates. Others have suggested this conservative bias may increase as landscape heterogeneity increases (Verbyla and Hammond 1995). Our results demonstrated that ignoring fine-scale heterogeneity within the dominant ecosystem can result in misleading accuracy estimates. Many per-class accuracies differed substantially when subdominant forest associations within the reference map units were acknowledged. Several forest associations routinely occur as subdominant classes within a patch as a result of localized variability in site properties. As an example, associations found towards the extremes of the soil moisture gradient (RS, RC, and YG), rarely occur as contiguous patches as large as the MMU. Accuracies for these forest associations at the subdominant level were important to consider, as the levels of error indicated by assessing only the dominant class were misrepresentative.

It is important to note that the accuracy statistics here are based on agreement between the classified QuickBird image and the TEM, and the true accuracy of the latter is quantitatively unknown. Error in the reference data may have caused some pixels to be identified as incorrectly classified when in fact they were correct. For this reason it may be more appropriate to view the accuracy statistics as referring to the agreement between the two maps and not necessarily true thematic accuracy.

The results of a pixel versus polygon based accuracy assessment differed slightly, with no evident trends. This finding likely resulted because the location and size of the boundaries of our classified objects were sometimes very different from those in the reference data. A trend may have been found with larger sample sizes. Others have suggested there are both advantages and disadvantages to both pixel- and polygon- based accuracy assessments (Stehman and Czaplewski 1998). One difference between the two methods is in the way the results are interpreted. A polygon based assessment is less spatially explicit than a pixel-based approach, with accuracies referring to (the center of) larger areas rather than individual pixels (Goodchild 1994). In our case, those areas were the classified image objects. For applications relying on patch-level information, such as landscape pattern analysis, polygon-based accuracy assessments may be more appropriate.

Image smoothing is a commonly-used technique in mapping and image processing. Post-classification smoothing may be performed to implement a MMU, as was the case here, or to reduce "salt-and-pepper" noise common in traditional pixel-based classifications (Gergel 2007; Saura 2002). Elsewhere, smoothing has been found to impact the accuracy of landscape pattern metrics association with fragmentation (Langford et al. 2006). We have shown this impact may be especially great for rare ecosystems. The accuracy of all three locally rare forest associations increased after smoothing, yet this came at the expense of substantial changes in the displayed extent and configuration. Post-classification implementation of a minimum mapping unit changed areal estimates by an average of 29%, decreased the number of patches by an average of 73%, and increased mean patch size estimates by an average of 285%. These differences in the described quantity and spatial pattern of rare forest associations resulting from post-classification smoothing correspond to the findings of others (Kendall and Miller 2008; Saura 2002; Turner et al. 1989) despite the methodological differences (e.g., in spatial resolution and classification approach) among studies.

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 ecosystems. It is clear that map users must be provided with a range of classification accuracy statistics (Foody 2002), as well as the methods used to assess the map accuracy. Indeed, it may be useful to provide accuracy estimates using more than one definition of map agreement in order to allow users to choose the definition most relevant to their application (Stehman et al. 2003). As an example, if the map were used to estimate broad-scale forest productivity (where only the dominant forest types are considered relevant), a traditional accuracy assessment that evaluates the agreement between dominant classes within a reference polygon and the classification will likely be sufficient. However, in conservation planning, where rare and fragmented classes are of concern, a traditional approach to accuracy assessment may be less appropriate. We found that when considering only the dominant forest association within a reference polygon, accuracies of rare classes were often falsely low. An assessment that accounts for fine-scale heterogeneity may better represent the strengths and limitations of a map of rare ecosystems which are of limited abundance, and which may also occur in small, subdominant patches. Given these issues, it is imperative that map producers ensure the details of the accuracy assessment utilized (including sample unit, sample size and definition of agreement) are transparent to the map user (Wulder et al. 2006).

Key to the conservation of biodiversity is the protection of a diversity of ecosystems. Decisions regarding the types, amounts and locations of ecosystems to protect often rely on the quantity and spatial configuration of ecosystems as indicated on maps, attributes which we have demonstrated will differ when a MMU is implemented. Such errors could greatly impact the management of rare ecosystems, particularly if small, fragmented patches are removed from a map after implementing a MMU. For example, small wetlands may be missed in this way, and thus not afforded the protection they require. Further, conservation and management decisions often rely on the results of spatially-explicit planning models such as Marxan (Ball and Possingham 2000; Possingham et al. 2000), utilizing classified ecosystem maps as input. Errors in the arrangement and size of patches of ecosystems may bias the output of such models, resulting in non-optimal conservation decisions. Therefore, post-classification smoothing may be less appropriate in heterogeneous and fragmented landscapes, and mapping techniques should be avoided which alter the description of the quantity and configuration of ecosystems.

Although the classification scheme utilized in our study has been developed for British Columbia, the portrayal of rare and fragmented classes on any map would be expected to be impacted by post-classification smoothing and different accuracy assessment techniques. It may be interesting to consider whether the direction or magnitude of impacts may differ in other regions or when scaling up to a broader spatial extent. Where the number of rare ecosystems is high, accounting for only the dominant class of reference polygons would likely lead to more misrepresentative accuracy statistics than in landscapes dominated by large, homogeneous ecosystems. In addition, one might expect changes in the spatial configuration of patches due to post-classification smoothing to be of greatest magnitude in landscapes with a high number of classes. Changes would also depend on the original spatial configuration itself. By systematically varying the level of landscape fragmentation, Saura (2002) demonstrated that the decrease in presence of rare classes on a map resulting from introduction of a MMU was positively related to their level of fragmentation. Such studies based on replicated, simulated landscapes together with case-studies such as ours provide useful information regarding the implications of post-classification smoothing as well as of issues of accuracy assessment with respect to rare classes. However, more research is needed to fully understand the implications of these mapping procedures and assessments for different mapping applications, and for different landscapes.

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