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Key issues in making and using satellite-based maps in ecology: A primer

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Abstract

The widespread availability of satellite imagery and image processing software has made it relatively easy for ecologists to use satellite imagery to address questions at the landscape and regional scales. However, as often happens with complex tools that are rendered easy to use by computer software, technology may be misused or used without an understanding of some of the limitations or caveats associated with a particular application. The results can be disappointment when maps are less accurate than expected or incorrect decisions when they are treated as truth. In this paper, we discuss several key issues which are critical to ensuring the effectiveness and value of remote sensing products, but which are also sometimes sources of confusion: (1) direct versus indirect models of land surface properties and processes, (2) differences between class-based and continuous mapping models, (3) scale, and (4) accuracy assessment. We illustrate our points with examples from the application of satellite imagery to forest management issues in the Pacific Northwest, USA. While our examples focus largely on Landsat image data, the issues we discuss have broad relevance across sensor data types, land cover properties, and geographic locations.

Keywords: Classification; Scale; Accuracy assessment; Remote sensing; Satellite

1. Introduction

In recent years, the use of satellite imagery in ecological research and ecosystem management has increased significantly. For example, 9 of 10 recent issues of the journal *Ecological Applications* contain at least one article in which satellite imagery was used to characterize vegetation or land cover. The widespread availability of imagery and image processing software has made it relatively easy for ecologists to employ satellite imagery to address questions at landscape and regional scales. However, as often happens with complex tools that are rendered easy to use by computer software, technology may be misused or used without understanding some of the limitations and caveats associated with a particular application. The promise of satellite imagery to solve landscape research and management problems has frequently been high (Green, 1994), but some assert that it has not delivered (Meyer and Werth, 1990; Holmgren and Thuresson, 1998). Some of the reasons for ''failures'' in the application of satellite imagery may derive from overly optimistic promises by remote sensing advocates, and from poor understanding by ecologists of the limits of the technology and the methods used to assess accuracy.

While there is a substantial body of literature exploring the application of remote sensing to ecological endeavors, there is a need for a non-technical overview of fundamental issues that ecologists should consider when using remote sensing. In this paper, we provide such an overview with respect to (1) feature description and spatial representation and (2) accuracy assessment, illustrating our points with examples from recent applications of remote sensing in ecological research and ecosystem management in western Oregon and Washington (Weyermann and Fassnacht, 2001; Cohen et al., 2001; Ohmann and Gregory, 2002; Spies et al., 2002; Nighbert et al., public communication[2]). We chose the Pacific Northwest for our examples because satellite imagery has been widely used in

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ecological research here and is increasingly being used to address ecosystem management problems (e.g., FEMAT, 1993; Weyermann and Fassnacht, 2001; Spies et al., 2002). Furthermore, the region is a center of considerable debate about forest management and biodiversity, creating a real need for landscape-scale information for assessment and policy decision-making.

2. Feature description and spatial representation

2.1. Is remote sensing the right tool?

It may seem trivial, but an important first question to address is: is remote sensing the right tool? When considering this question, the strengths of the technology must be balanced against its limitations. Remote sensing can be particularly useful when there is a need for (1) complete spatial coverage, especially over large areas; (2) monitoring, or frequently repeated measurements; or (3) measurements at inaccessible or sensitive locations. For environmental monitoring and management, Phinn et al. (2000) have identified four broad types of information which can be derived from remote sensing data: landscape composition, landscape pattern, biophysical parameters, and changes in time of these three elements.

The top-down view of remote sensing platforms restricts what can be ''seen'' by the sensor. Consequently, many important ecological variables measured beneath or within the canopy are not good candidates for direct remote measurement. For example, the Interagency Vegetation Mapping Project (IVMP; Weyermann and Fassnacht, 2001) attempted to map quadratic mean tree stem diameter directly using Landsat Thematic Mapper data with limited success. Overall accuracies for four to six structural classes were 33–44% (USDI, public communication[3]). Another limitation is that information recorded by airborne or satellite sensors is typically restricted to energy returned in one or more wavebands and relative geographic position. As a result, features that cannot be distinguished by ''color'' and spatial arrangement alone may be confused when using only spectral data.

Fortunately, there are ways to address these shortcomings. If a variable of interest is not visible from overhead (e.g., soil nitrogen mineralization rates), it can be calculated by using remotely sensed values of a visible variable (e.g., foliar lignin content; Wessman et al., 1988) if the two are statistically related. Furthermore, if variables cannot be distinguished by spectral values and spatial location alone, results can be improved by using ancillary data, such as topography, ownership, or soils data (e.g., Hutchinson, 1982; Palacio-Prieto and Luna-Gonzalez, 1996; Eiumnoh and Shrestha, 2000). In addition, multiple image processing techniques (e.g., per pixel classifiers and image segmentation) can be combined with other complementary analyses (e.g., GIS-based ecological modeling) and data sources (e.g., photointerpretation and field data) to enhance the capabilities of remote sensing alone (Franklin and Woodcock, 1997).

It is possible, however, that remote sensing technology may not be able to provide acceptable results for a given objective (Franklin and Woodcock, 1997; Cohen et al., 2003). In these cases, remote sensing may not be appropriate. A framework has been developed which can be helpful in making this evaluation (Phinn et al., 2000, 2003).

[3] IVMP Datasets, http://www.or.blm.gov/gis/projects/ivmp_data.asp, visited 26 February 2005.

2.2. Information classes

2.2.1. Defining a classification scheme

If data will be divided into groups, there are a number of factors to consider in developing a classification scheme. When hard class boundaries are desired, class definitions must be clear, mutually exclusive, and exhaustive to prevent confusion and to avoid unlabelled map regions (Congalton and Green, 1999). Mutual exclusivity is not required, however, if soft class boundaries are to be used (i.e., when features are allowed to belong to more than one class, e.g., a forest with 60% conifer might reasonably be considered to belong to either a ''conifer'' or ''mixed'' class). In either case, classes should be detailed enough to be useful, yet not so narrowly defined that they cannot be spectrally separated from other classes (Lillesand et al., 1998). Hierarchical classification schemes can help provide a balance between utility and accuracy by allowing users to define and organize desired detail, while permitting classes to be collapsed as needed if accuracies are not acceptable. For example, using the classification scheme presented in Table 1, Cohen et al. (2001) were able to provide a greater level of detail for forest compared to other land cover classes, and the most detail for closed canopy conifer forests.

If preexisting classification schemes or maps are to be used, it is important to know how the classes were defined in order to evaluate how well the scheme/map matches project objectives

Table 1
Hierarchical classification scheme used by Cohen et al. (2001)

Class
Water
Snow and ice
Cloud and shadow
Serpentine
Urban
Agriculture
Other non-forested
Forested
Open canopy
Semi-open canopy
Closed canopy
Broadleaf
Mixed
Conifer
Young
Mature
Old

(Cohen et al., 2001). For example, if a new study seeks to identify potential habitat for a forest dwelling creature, is a map that defines forest as any area with over 10% canopy closure (Anderson et al., 1976) suitable? It depends on the ecology of the creature being studied. Perhaps a classification scheme that required at least 60% canopy closure (Scepan, 1999) would be more appropriate. Without looking into how classes were defined, it would be easy to assume the map did a poor job of identifying forested areas or to misidentify areas of suitable habitat.

2.2.2. Classes versus continuous representations of information

When features of interest are categorical in nature (e.g., land cover/land use), techniques are typically used which place pixels or polygons into classes with either hard or soft boundaries. Franklin et al. (2003) provide a nice overview of many classification techniques including more traditional methods (e.g., maximum likelihood and minimum distance to mean classifiers) as well as newer methods (e.g., nearest neighbor and artificial neural networks).

When the features of interest are continuous in nature (e.g., leaf area index) or are based on such features (e.g., habitat suitability based on a tree-size threshold), using classes of any kind can be restrictive. Maps produced using classes divide continuous-variable data into arbitrary categories which can be rendered obsolete if class definitions are changed after the maps have been completed. Mapping variables continuously removes artificial class structure and allows multiple projects to use the same initial map by defining class boundaries for secondary maps to meet their individual needs (as in IVMP where four or more end users with still-developing needs would be using the maps being produced; Fassnacht, personal observation). For example, a single continuous map of tree density (Fig. 1a) is easily recoded into two classed maps to accommodate different habitat-suitability requirements for the marbled murrelet (*Brachyramphus marmoratus*) (Fig. 1b; McGrath, unpublished manuscript) and the northern spotted owl (*Strix occidentalis caurina*; Fig. 1c; McGrath, unpublished manuscript). In addition, changes in class requirements can be accommodated by reclassing the original continuous map, avoiding the need to remap the entire area. It should be noted, however, that at times sufficient data are not available to develop continuous models or the form of the relationship between independent and dependent variables is quite complex. Using classification methods may be preferred in these cases (Franklin et al., 2003).

Major projects in the Pacific Northwest are moving from using classification (e.g., Nighbert et al., public communication[2]) to using continuous mapping methods based on regression (e.g., Weyermann and Fassnacht, 2001) and gradient nearest neighbor (Ohmann and Gregory, 2002) analyses. Although earlier studies using continuous methods focused primarily on model development (e.g., Franklin, 1986; Running et al., 1986; Lathrop and Pierce, 1991; Cohen and Spies, 1992), more recent studies have used these models to map forest attributes over large areas (e.g., Cohen et al., 2001; Spies et al., 2002).

Multiple independent regression models, such as those used by Cohen et al. (2001), however, do not preserve the covariance among attributes. Joint variability, particularly of species occurrence and understory and overstory characteristics, is of interest to ecologists. To retain data covariance, Ohmann and Gregory (2002) developed a gradient nearest neighbor (GNN) method, which combines direct gradient analysis and nearest neighbor imputation (Moeur and Stage, 1995). Ground-inventory-based values (e.g., species basal area), satellite spectral data, and ancillary information related to ownership, topography, geology, climate, and location were combined in a canonical correspondence analysis to produce a distribution in eight dimensions. Each pixel was then assigned all the characteristics of whichever ground plot was closest to it in this eight-dimensional space.

2.3. Scale

2.3.1. Definitions

Scale is one of the most important characteristics to consider when matching remote sensing data with natural resource applications. Because the term ‘‘scale’’ has been inconsistently defined (Lam and Quattrochi, 1992; O’Neill and King, 1998), we want to be explicit in its definition here to avoid confusion (Raffy and Blamont, 2003). In this paper, *scale* will refer to the combination of extent, grain, and minimum mapping unit (MMU). Changing the value of any of these elements changes the scale. *Extent* is typically defined as the total physical area to be examined in a project (project extent) or covered by a data source (data extent; Fig. 2a), while *grain* is the smallest resolvable element in the extent (Turner et al., 2001). In a raster image, the grain is the pixel size (Fig. 2b); in a photograph, it is related to the size distribution of silver halide crystals (but is also influenced by atmospheric effects, uncompensated airplane or camera motion, etc.; Lillesand et al., 2003). *Minimum mapping unit*, in contrast, is the smallest area in the extent that will be mapped as a discrete unit (Fig. 2c). Because MMU is often larger than the grain, spatial and/or content information contained in the mapping unit is lost. For example, an aerial photograph polygon labeled as conifer may contain many conifer trees, a few hardwood trees, and a grassy opening. These different stand elements are resolvable because of the grain of the photo, but the analyst decided the latter two were too small to be considered separately for the map being made.

2.3.2. Choosing appropriate values for scale elements

To get the most from remote sensing data, it is important to make conscious decisions about scale (Phinn et al., 2000). Using popular data sources (e.g., Landsat Thematic Mapper (TM); grain = 28.5 m) or the defaults of the data (i.e., MMU = grain) will result in a view of the world that matches the sensor but not necessarily the question being asked. To facilitate decision-making, it is helpful to understand how changing scale elements can affect landscape information. Increasing extent, for example, increases the probability of sampling rare classes (Wiens, 1989), whereas increasing grain size reduces the number of landscape elements that can be

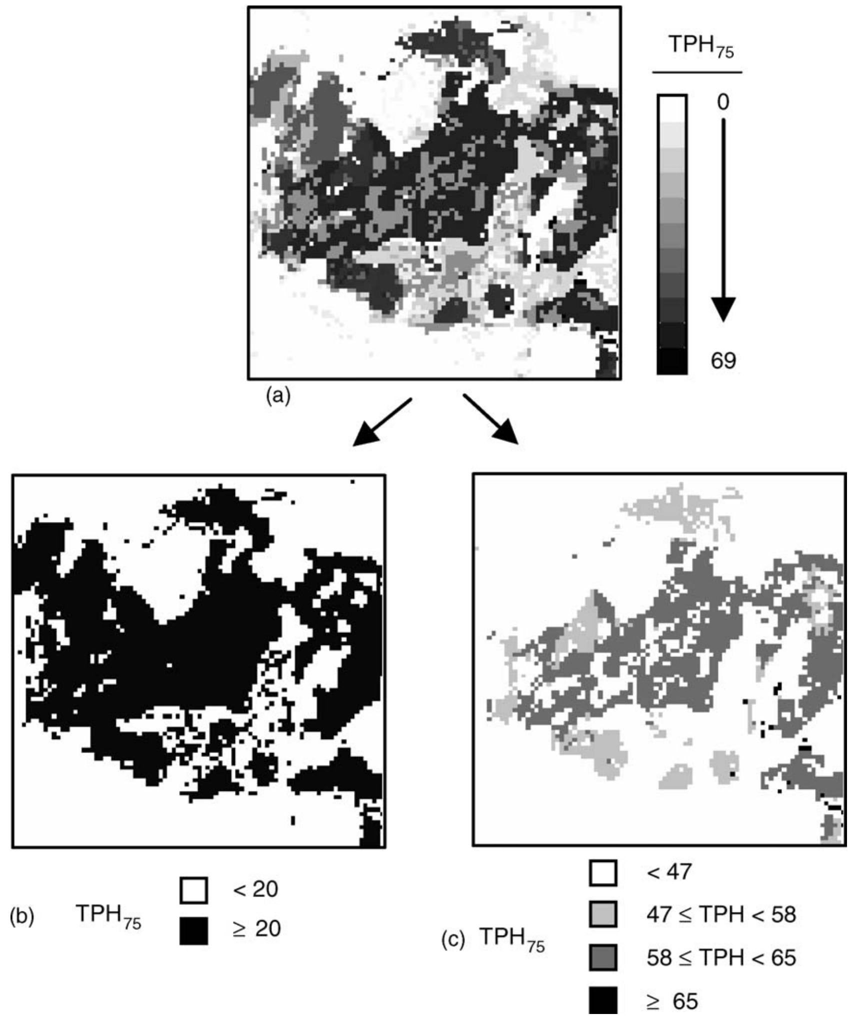

Fig. 1. (a) A continuous map of trees per hectare with diameter at breast height greater than 75 cm (TPH_{75}) used to create classed maps tailored to habitat-suitability requirements of (b) the marbled murrelet (*Brachyramphus marmoratus*) (platform tree index; McGrath, unpublished manuscript) and (c) the northern spotted owl (*Strix occidentalis caurina*) (diameter class 3 index; McGrath, unpublished manuscript). Data from Ohmann and Gregory (2002).

resolved. Changes in MMU affect the spatial expression of patches on the landscape (Fig. 3a–d). Smaller MMUs may result in large within-patch variability, making patches of interest difficult to discern (Fig. 3a) and reducing classification accuracies compared to maps where this variability has been removed (Fig. 3b and c; Toll (1985) and Irons et al. (1985), but see Markham and Townshend (1981) and Hsieh et al. (2001) for a discussion of the compensating effect of fewer mixed pixels). On the other hand, larger MMUs can result in patches of interest being artificially combined with surrounding patches (Fig. 3d).

So what are the optimum extent, grain, and MMU? There is a large body of literature devoted to this question, which speaks to both its importance and complexity. Phinn et al. (2003) have presented a framework for selecting appropriate remote sensing data for management issues which includes tackling the scale issue. In case studies presented (Phinn et al., 2000, 2003), initial grain size has typically been selected to equal the smallest feature that is to be resolved. This size is then evaluated in subsequent exploratory analyses which sometimes find that a different size would work better. Marceau et al. (1994a), in fact, found that the optimum grain size for best classification accuracy was different for different image elements. For example, to most accurately classify maple forest required a grain of 5 m while poplar and birch had optimal grains of 20 and 30 m, respectively. Likewise, at a coarser classification level, optimum grain sizes to classify deciduous, conifer, and mixed forest were 5, 10, and 30 m, respectively. Based on these results, Marceau et al. (1994a) recommend abandoning the common practice of selecting a unique resolution on which to perform analyses, instead pursuing multi-scale or hierarchical approaches which make use of logical decision rules.

In general, the factors involved in selecting optimum grain and MMU are complex. Considerations include not only project goals and the object of interest, but also the spatial arrangement of features on the landscape, the internal structure of objects of interest (e.g., stand characteristics), and the processing techniques to be used (Woodcock and Strahler, 1987). For additional discussion on this topic, see Quattrochi and Pelletier (1991, pp. 67–69), Marceau et al. (1994a,b), Cao and Lam (1997), Hsieh et al. (2001), and Franklin (2001, pp. 97–103).

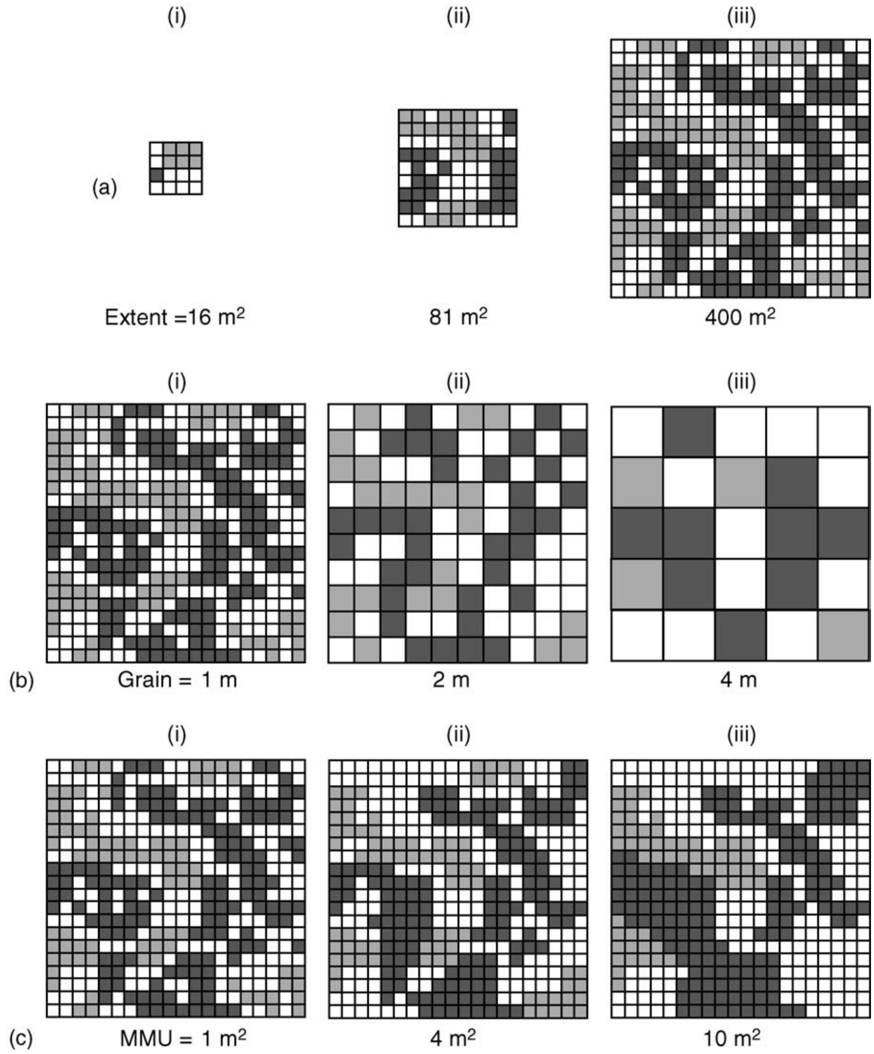

Fig. 2. Examples of increasing (a) extent, (b) grain, and (c) minimum mapping unit (MMU). Values held constant are (a) grain and MMU at 1 m and 1 m^2, respectively; (b) extent at 400 m^2; and (c) extent and grain at 400 m^2 and 1 m, respectively. Note that (b(ii)) and (c(ii)), both have extent = 400 m^2 and MMU = 4 m^2. Both were created from (b(i)) (the same as c(i)) rather than one being created from the other. Figure modified from Turner et al. (1989).

2.3.3. *Example*

The impacts of decisions about scale can be best appreciated through an example. To look at the effects of grain and MMU on landscape metrics, we will use a small area of classified imagery from the Coast Range of Oregon to compute landscape metrics for determining wildlife habitat suitability. We consider four scenarios: (1) grain = 25 m and MMU = 1/16 ha (i.e., one pixel), created by classifying the raw 25-m-grained imagery (Fig. 4a); (2) grain = 25 m and MMU = 1 ha, created by aggregating the map from scenario 1 to produce patches no smaller than 1 ha (Fig. 4b); (3) grain = 100 m and MMU = 1 ha, created by resampling the classified map from scenario 1 to obtain the desired grain and MMU (Fig. 4c); and (4) grain = 100 m and MMU = 1 ha as in scenario 3, but created by degrading the raw imagery to a grain of 100 m, and then reclassifying the image (Fig. 4d). Diagonals were not considered in determining patches for any scenario.

When the MMU is changed from 1/16 to 1 ha, the number of patches drops, and patch size and core area increase (Table 2), especially if the grain stays small (e.g., scenario 2). For a given MMU, smaller grained images can capture finer details in patch shape, and therefore, include more small areas into a patch. In contrast, by making the grain 100 m (scenarios 3 and 4), a 1-ha unit (pixel) belongs entirely or not at all to a given class, leading to more blocky, smaller patches (Fig. 4c and d; Table 2). When small grain is combined with small MMU (e.g., scenario 1), finer level ''salt-and-pepper'' variability is captured, leading to consistently higher edge densities and smaller solid blocks of any vegetation class (Table 2). Finally, increasing the grain of the raw imagery prior to classification (scenario 4) fundamentally changed the results, reducing the amount of ''broadleaf'', and increasing the amount of ''small and medium mixed'' (Fig. 4d; Table 2). The tendency of broadleaf cover in this image subset to form narrow linear features along rivers and drainage ways made this cover type particularly susceptible to changes in grain (Turner et al., 1989, 2000).

Obviously the four scenarios resulted in different characterizations of the landscape. None of these is wrong. A particular one, however, may be most appropriate given the species of wildlife being considered, the objectives of determining the

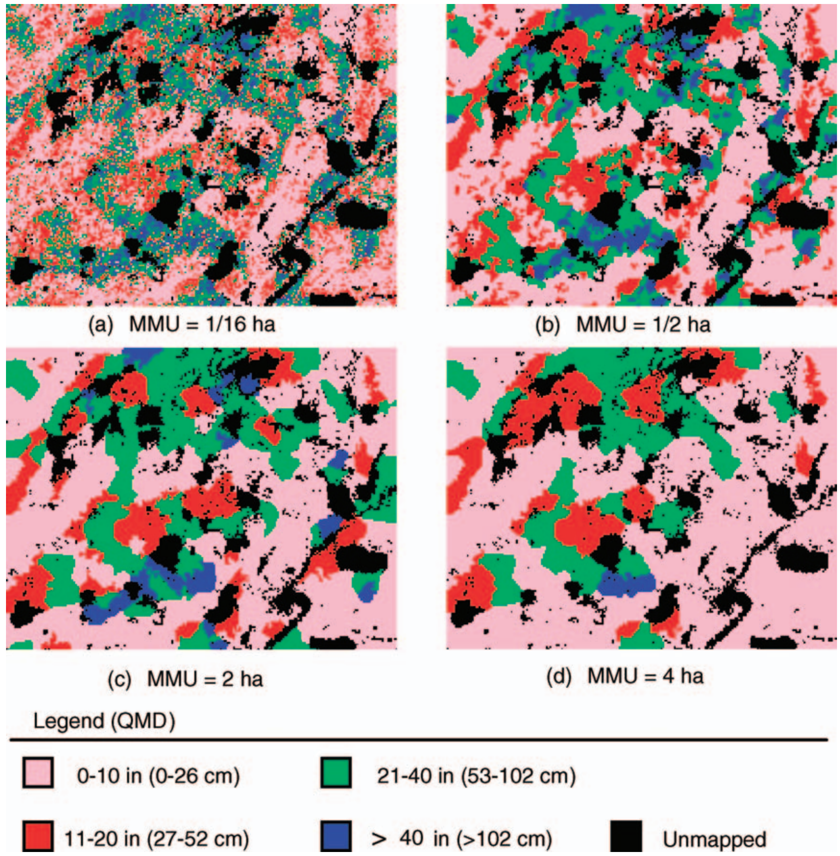

Fig. 3. The effect of increasing minimum mapping unit (MMU) on the expression of patches and heterogeneity on a landscape (a–d). The grain is 25 m in all cases, and the feature mapped is quadratic mean diameter (QMD). Unmapped areas (black) were not included in the increase in MMU. Data are from the Interagency Vegetation Mapping Project (Weyermann and Fassnacht, 2001).

landscape metrics, etc. Also noteworthy is the high degree of sensitivity of some landscape metrics to changes in scale. Such sensitivities have been widely noted in the literature (Turner et al., 1989; Moody and Woodcock, 1995; Wickham and Riitters, 1995; O'Neill et al., 1996; Cain et al., 1997; Wu et al., 2002). Wu et al. (2002) describe three categories of metrics having predictable, less-predictable staircase-like, and erratic responses to changes in scale. Given these sensitivities, they recommend the use of scalograms (which they describe as "response curves of landscape metrics to changing grain size or extent") for describing and comparing landscapes rather than seeking a single "optimum" scale at which to calculate metrics.

2.4. A word about preexisting maps

The decisions discussed in this section are extremely important for setting the foundation of a project and for maximizing the utility of remote sensing data. We recognize, however, that it is not always possible to make a new map for every project. Nonetheless, when using preexisting maps, there are tradeoffs: all the decisions made with respect to information classes, scale, and processing techniques were based on the needs of the original project. The scale selected for mapping owl habitat may not work well for studying carbon flux. Similarly, maps developed regionally may not capture local variation well (Fig. 5).

3. Accuracy assessment

Although error in remote sensing-derived maps is an important issue (Verbyla, 1995; Stehman and Czaplewski, 1998; Lowell and Jaton, 1999), users frequently treat error analysis in a *pro-forma* manner. That is, users will want to know if an accuracy assessment has been conducted but may not use the information in any way beyond establishing their general confidence level in the map. It is advisable, however, to take the time to study a map's accuracy assessment. The assessment provides not only a general idea of how "good" a map is but also details on how error is distributed both spatially and non-spatially, and insight into how further analyses of, or with, the map might be affected by error. Because a variety of accuracies can be obtained for the same map simply by modifying the methods used to calculate those accuracies, it is also worthwhile to understand how accuracies were computed. Below we discuss (1) sources of confusion with respect to accuracy, (2) effects of different methods on reported accuracy, and (3) impacts of error on further analyses.

3.1. Sources of confusion

Problems can arise when there is uncertainty about what accuracies are acceptable and misunderstandings about what accuracies are achievable. The acceptability of map accuracy

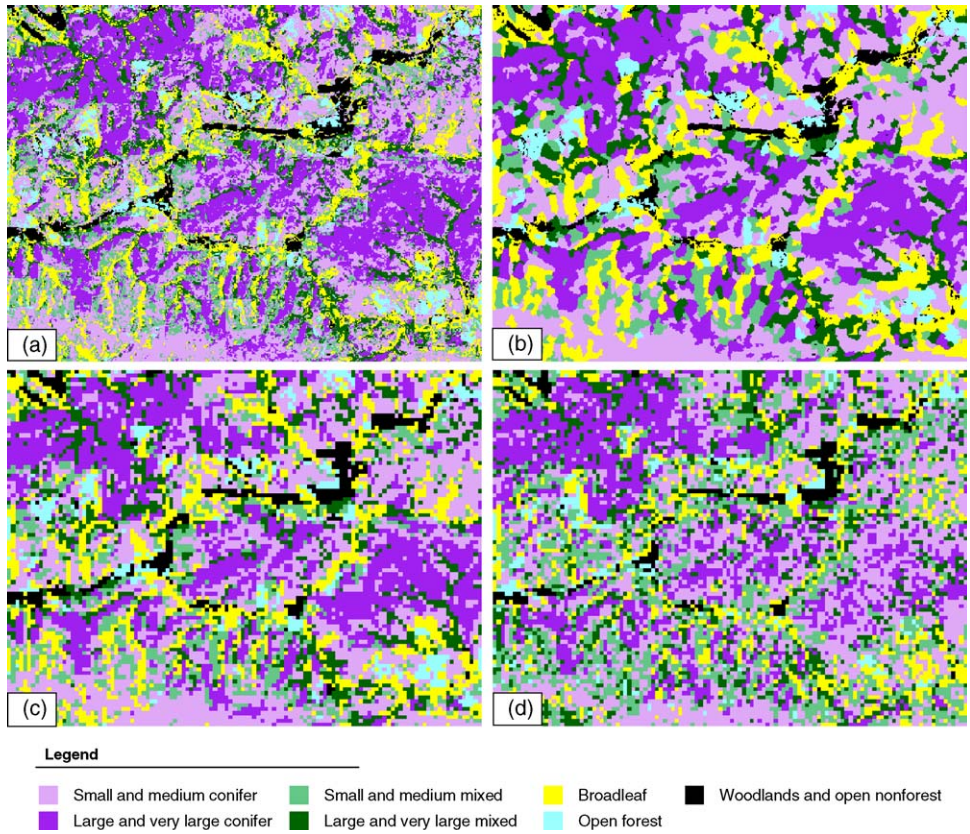

Fig. 4. Landscape scenarios used to illustrate the potential effect of changing grain and minimum mapping unit (MMU) on landscape metrics: (a) scenario 1, grain = 25 m, MMU = 1/16 ha; (b) scenario 2, grain = 25 m, MMU = 1 ha; (c) scenario 3, grain = 100 m, MMU = 1 ha; and (d) scenario 4, grain = 100 m, MMU = 1 ha. Scenarios 3 and 4 differ in their resampling procedure. See text for methods used to develop the scenarios, and Table 2 for associated landscape metrics. Data from Ohmann and Gregory (2002).

will depend not only on project objectives (e.g., map owl habitat suitability) and the cost of errors but also on the intended use of the product (e.g., to learn more about owls, make management decisions based on where owls live, evaluate policies in effect to protect owls, etc.). In scientific undertakings, more uncertainty may be tolerable, particularly if general trends are all that are needed. Conversely, in management and policy applications, higher accuracies may be required because information obtained will be used in decision-making. Given these differences, it is not possible to set a single threshold of accuracy below which a map is unacceptable.

The accuracy that is achievable will depend on a number of factors including the variables mapped, the sensor used, and the level of detail desired. Studies conducted in the Pacific Northwest suggest that, in this region, some forest variables are much harder to map accurately than others. Although accuracies from most of these studies cannot be compared directly because dissimilar methods were used to assess error, general trends are apparent that are consistent across studies. These trends suggest that, using TM data, forest structural attributes (e.g., tree stem diameter, basal area, height, etc.) are more difficult to map than forest composition (conifer cover, hardwood cover), which is more difficult to map than total green vegetation cover. For example, the overall accuracy of four to six structure classes was generally 35–45% (Cohen et al., 1995; Ohmann and Gregory, 2002; USDI, public communication[3]), compared to 50–70% for five composition classes (Cohen et al., 2001; USDI, public communication[3]) and 75–85% for five classes of green vegetation cover (Cohen et al., 2001; USDI, public communication[3]). Having realistic expectations of what accuracies are achievable will allow for informed decisions regarding the feasibility of a mapping effort and the advisability of subsequent analyses (e.g., mapping wildlife habitat suitability, modeling gross primary production, etc.).

Fortunately, if low accuracies are not acceptable for variables that are more difficult to map, there are a number of tradeoffs that can be made to improve results. Additional resources can be spent to obtain ancillary data or finer grained spectral data from another sensor (e.g., lidar, digital orthophotographs, etc.) to use with, or instead of, the original data source. Additional data, however, do not guarantee improved results. A more promising tradeoff involves decreasing the level of detail by combining classes. Cohen et al. (1995), for example, found that decreasing the number of tree-height classes from five to three increased overall accuracy from 38 to 56%. A decrease to two classes further increased accuracy to 77%. Similar results were observed for the other nine variables mapped. Collapsing five or six map classes into two or three, therefore, may result in relatively inexpensive wall-to-wall maps of variables of interest at an accuracy that is acceptable.

Confusion also can arise when users only look at a map's overall accuracy. Distribution of error among classes and

Table 2
The effect of grain and minimum mapping unit (MMU) on landscape metrics

Class/index	Scenario			
	1[a]	2[b]	3[c,d]	4[c,e]
Class				
Broadleaf				
Number of patches	2793	144	356	479
Mean patch size (ha)	0.46	12	4.3	2.2
Percent of landscape (%)	13	17	15	11
Edge density (m/ha)	62	29	31	29
Total core area (ha)	0.81	155	92	16
Number of core areas	8	145	59	15
Mean nearest neighbor distance (m)	18	105	70	74
Small and medium mixed				
Percent of landscape (%)	13	9	11	20
Large and very large mixed				
Number of patches	3523	153	433	673
Mean patch size (ha)	0.34	7.6	2.8	2.0
Percent of landscape (%)	12	12	12	13
Edge density (m/ha)	87	26	30	38
Total core area (ha)	0.00	57	38	14
Number of core areas	0	93	31	9
Mean nearest neighbor distance (m)	21	143	80	68
Small and medium conifer				
Percent of landscape (%)	33	32	33	32
Large and very large conifer				
Number of patches	2156	120	256	375
Mean patch size (ha)	1.2	21	9.3	5.6
Percent of landscape (%)	25	25	24	21
Edge density (m/ha)	89	34	35	39
Total core area (ha)	200.	714	599	304
Number of core areas	192	193	111	102
Mean nearest neighbor distance (m)	18	119	80	65
Landscape				
Number of patches	19871	794	2111	2961
Mean patch size (ha)	0.50	13	4.7	3.4
Edge density (m/ha)	278	83	95	113

[a] Grain: 25 m; MMU: 1/16 ha.
[b] Grain: 25 m; MMU: 1 ha.
[c] Grain: 100 m; MMU: 1 ha.
[d] Resampled classified image used for 1/16 ha MMU example.
[e] Resampled raw imagery, then reclassified it.

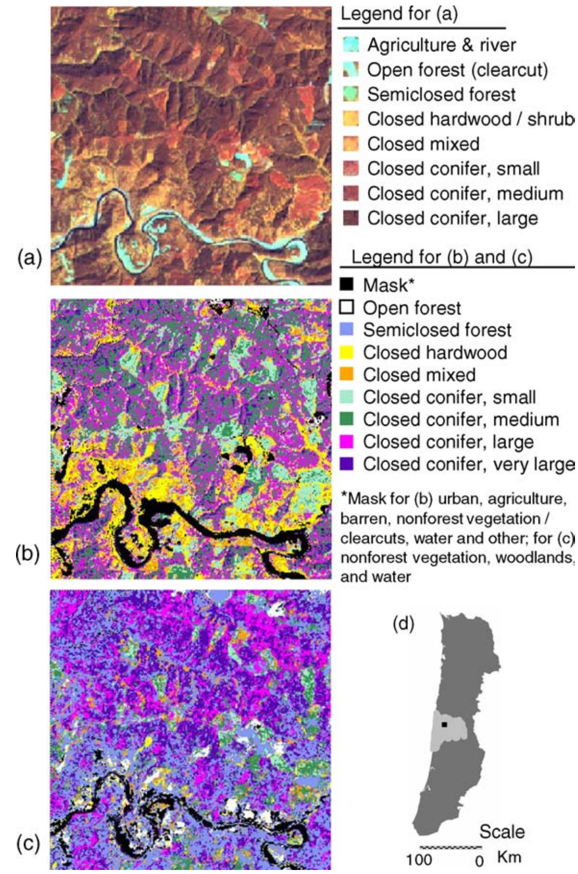

Fig. 5. Local variation evident in (a) raw imagery is often captured better by maps created by using (b) local compared to (c) regional data. In this case, the local data came from the approximately 300,000 ha, fourth-field Alsea watershed (shown in light grey in (d); Nighbert et al., public communication[2]), whereas the regional data came from the approximately 3 million ha Coast Province (shown in dark grey in (d); Ohmann and Gregory, 2002). The area covered by the image subset in (a–c) is show in black in (d).

regions must be considered as well (Franklin, 1991; Janssen and van der Wel, 1994). The overall accuracy reported from an error matrix does not imply equal error in all classes (Fig. 6a and b). Producer's and user's accuracies (accounting for errors of exclusion and inclusion, respectively) inform us of differences in error that may exist among classes (Fig. 6a and c). In addition, within a class, error is not necessarily distributed in a spatially uniform manner. Errors may be different at the center of a patch than at the boundaries between patches, particularly when the boundary between two cover classes is not sharp. Accuracy within a class also may differ spatially across a mapped region if local variation is not accommodated well by a regional model. In this latter case, separate mapping for each area of local variability is recommended, if possible.

Project objectives will affect where it is necessary to have acceptable accuracies. If high rates of error exist for the class or region of interest in a particular project, a map may be unacceptable for that project, despite having an acceptable overall accuracy. For example, using the Fuzz 2 numbers from Table 3 (discussed in detail below), the overall accuracy is 79%, which is respectable. The producer's and user's accuracies for ''very large conifer'', however, are 50% and 54%, respectively. These values may be unacceptable for a project whose main concern is with very large conifers. Conversely, if error is high in classes or areas not of interest in a particular project, a map may be still quite usable if the focus is on classes or areas with lower error (e.g., the ''broadleaf'' class in Table 3). Consequently, for a user to evaluate a map's appropriateness for a given objective, more must generally be known than an overall, and maybe even class, accuracy value (Franklin, 1991; Janssen and van der Wel, 1994).

3.2. Effect of methods

Problems can arise when there is uncertainty about how accuracy was computed and what types of assessment can be

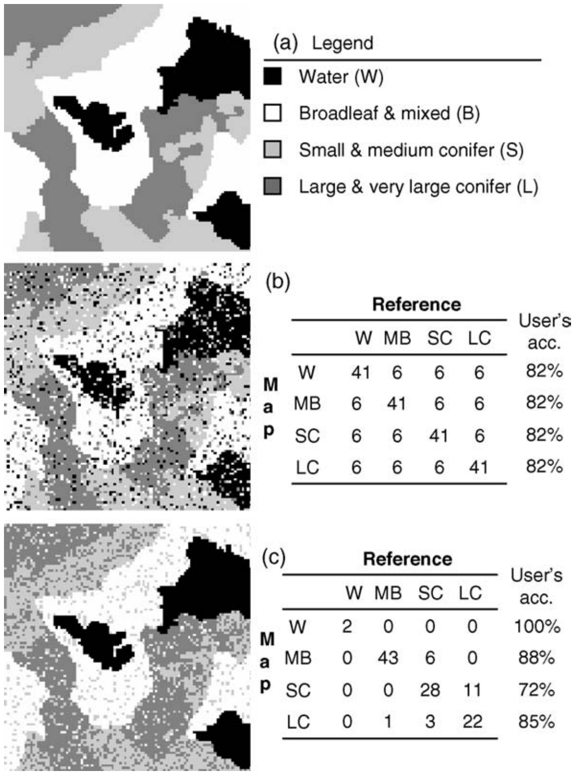

Fig. 6. Visualizing differences in error distribution among classes compared to the (a) error-free situation in a hypothetical landscape with four classes. Shown here are cases of (b) equal error and (c) error differing by class. Error matrices and user's accuracies for (b and c) are shown next to their corresponding maps. Error was assigned to pixels randomly (within the appropriate class for (c)) to achieve the user's accuracies shown for each map. See text for a definition of user's accuracy.

compared. In the following examples, we consider the effect on reported map accuracy of the fuzziness of class boundaries and sample heterogeneity.

3.2.1. Class boundary fuzziness

In recent years, some scientists have modified error calculations to reflect fuzzy rather than absolute class boundaries (Gopal and Woodcock, 1994; Congalton and Green, 1999; Townsend, 2000). Fuzzy boundaries are an acknowledgment that an area could reasonably be labeled as any one of several classes (e.g., hardwood or mixed); consequently, the area need not be mapped into only one specific class to be considered correct. In some cases, there has been a move away from traditional error matrices entirely (e.g., Gopal and Woodcock, 1994; McIver and Friedl, 2002). It is not within the scope of this paper to explore the many facets of this discussion. Rather, we examine the impact that the use of fuzzy boundaries can have on estimates of map accuracy and provide a caution to compare map accuracies only when they have been computed in a similar fashion.

In the following example, we examine class boundary effects by comparing three different ways to compute accuracy from the same data: the traditional hard-boundary approach (Trad; Table 3) and two fuzzy-boundary approaches (Fuzz 1 and 2; Table 3). The producer's accuracy of a class is calculated as the percentage mapped correctly (in black cells when using the traditional approach; Table 3) as a proportion of the total plots that actually were in that class (column total). So, for the "open" class, using the traditional approach, 16 plots were mapped correctly as "open" out of 21 total "open" plots in the reference data set to give a producer's accuracy of $100\% \times (16/21) = 76\%$. Similarly, user's accuracy is calculated as the percentage mapped correctly (in black cells using the traditional approach) as a proportion of the total plots that were mapped in that class (row total). So, for the "open" class, using the traditional approach, 16 plots were mapped correctly as "open" out of 18 total plots that were mapped as "open" to give a user's accuracy of $100\% \times (16/18) = 89\%$. Overall accuracy is calculated as the sum of all correctly mapped plots (in black cells using the traditional approach) divided by the total number of cells mapped. So, for the traditional method, the overall map accuracy is calculated as $100\% \times (2 + 16 + 11 + 15 + \cdots + 10 + 1)/152 = 61\%$.

In a simple example of fuzzy boundaries (Fuzz 1; Table 3), any class that is within one class (light gray cells) of the correct reference class is accepted as "correct" (Congalton and Green, 1999). For example, all "mixed" classes, regardless of tree size, are considered to be within one class of "broadleaf". Using the "open" class as an example again, the producer's accuracy increases to 100% because the five "open" plots misclassified as "semi-closed" in the traditional method will now be considered correct under this interpretation of fuzzy class boundaries. Likewise the user's accuracy for "open" has increased to 100%. In fact, producer's and user's accuracies of most classes and overall map accuracy have increased substantially. A more conservative version of error matrix modification can involve "floating" class boundaries, where the acceptability of an observation that was mapped differently than the reference is determined by a range centered on the reference value (Congalton and Green, 1999).

Another accuracy-assessment modification involves providing weights to classes considered acceptable, so that a fraction of the observations misclassified are considered correct (Cohen et al., 2001). As an example, the highlighting in Table 3 is used to represent a number of weights. A perfect match (black) is given a weight of 1.0. Plots mapped within one class of the reference (light gray) are given a weight of 0.5, whereas plots within two classes (dark gray) receive a weight of 0.25. Finally, all other plots are considered incorrect and receive a weight of 0 (Maiersperger, unpublished data). Accuracy values for this method (Fuzz 2), are higher than those from the traditional approach, but not to the extent seen for Fuzz 1.

Although accuracies will vary among different fuzzy-boundary techniques, in general, they can be expected to result in higher accuracies than traditional hard-boundary methods. This observation should be kept in mind when evaluating or comparing maps.

3.2.2. Sample heterogeneity

Most studies base their accuracy assessments on points or polygons located in homogeneous conditions (i.e., a single

Table 3
A comparison of accuracy[a] calculated using three different class boundary definitions: traditional (Trad), and unweighted (Fuzz 1) and weighted (Fuzz 2) fuzzy class boundaries

Predicted cover class[b]	Observed cover class[b]													User's (%)		
	Water	Open	Semi-closed	Blf	S mix	M mix	L mix	VL mix	S con	M con	L con	VL con	Total	Trad	Fuzz 1	Fuzz 2
Water	2												2	100	100	100
Open		16	2										18	89	100	94
Semi closed		5	11	2									18	61	100	81
Blf				15			2						17	88	100	94
S mix				1	2				4				7	29	100	64
M mix					3	4	3		1				11	36	91	66
L mix						4	4	3		1			12	22	92	65
VL mix							1	1					2	50	100	75
S con									17				17	100	100	100
M con									2	9	10	1	22	41	95	68
L con										3	10	7	20	50	100	75
VL con							1				4	1	6	20	83	54
Total	2	21	13	18	5	8	11	4	24	13	24	9	152			
Producer's (%)																
Trad	100	75	85	83	40	50	36	25	71	69	42	11		Overall accuracy (%)		
Fuzz 1	100	100	100	100	100	100	91	100	96	92	100	89		Trad	Fuzz 1	Fuzz 2
Fuzz 2	100	88	92	92	70	75	64	63	84	83	71	50		61	97	79

[a] Producer's accuracy (Producer's) measures the error of exclusion; user's accuracy (User's) measures the error of inclusion. Reference plots mapped correctly can be found along the main diagonal (black). See text for methodology and color coding. Data from Cohen et al. (2001).
[b]Blf, broadleaf; Mix, mixed conifer-broadleaf; Con, conifer; S, small; M, medium; L, large; VL, very large.

class; e.g., Perry, 1998; Cohen et al., 2001). Most landscapes, however, contain many heterogeneous areas. In IVMP, for example, data from five of the nine physiographic provinces covering western Oregon and Washington showed that, on average, almost 60% of inventory plots used were labeled as heterogeneous (i.e., plots containing roads, ravines, ridges or sharp edges between forest compositional or structural elements; Fassnacht, personal observation). This rate increased substantially (to 80%) for Forest Inventory and Analysis (FIA) plots (USDA FS, 1990, 1997), which are larger and located on private lands. Because the majority of inventory plots used in IVMP were located on systematic grids, these percentages should be representative of the landscape as a whole. Therefore, heterogeneous elements can comprise a significant portion of the landscape and should be considered.

How different are the accuracies of these heterogeneous areas compared to that of the homogeneous areas typically used for map production and assessment? To explore this question, we examined data from two of the nine IVMP provinces (USDA/USDI, unpublished data). Accuracy-assessment data were collected on systematic grids associated with FIA and Current Vegetation Survey (Max et al., 1996) inventories. Ground plots were located in a variety of conditions, with one to many cover classes present in a single plot. These plots were screened for homogeneity into three groups: A1 = homogeneous, A2 = heterogeneously homogeneous (for mixed classes, such as sparse cover or mixed conifer/hardwood), and A3 = heterogeneous (multiple classes with edge present, topographic ridge or ravine, and/or road present). For this analysis, the A1 and A2 plots were considered ''homogeneous'' and A3 plots were considered ''heterogeneous.''

Error was defined as the difference between observed and predicted values. Predicted values were derived from maps based on satellite imagery (Weyermann and Fassnacht, 2001); observed values were based on interpretation of aerial photographs for all cover variables (Fig. 7a–c) and from ground inventory data for tree size (Fig. 7d). Because preliminary exploration of our data suggested that assumptions of normality and homogeneity of variance had been violated in some cases, standard analysis of variance and *t*-tests could not be used. Rather, we used non-parametric tests to compare sample variances (Moses test; Daniel, 1978) and means (Tukey's quick test; Daniel, 1978). Data were analyzed by province (pooled across plot type) with homogeneity as the treatment.

Although results vary, some general trends are apparent. Estimated error variances were most often significantly different, with values for homogeneous plots being smaller, as expected (Fig. 7). Estimated error means were generally not significantly different (Fig. 7). These results are not surprising: heterogeneous data would be expected to have higher variability than homogeneous data. The general lack of difference in estimated error means, however, is reassuring. It suggests that the data used to produce the map (i.e., homogeneous plots) did not bias the estimate of vegetation characteristics for the landscape.

What are the implications of these findings? If data are to be left in continuous (versus class) format, using only homogeneous data will lead to a smaller error variance, and if the predictions are minimally biased, to a more favorable

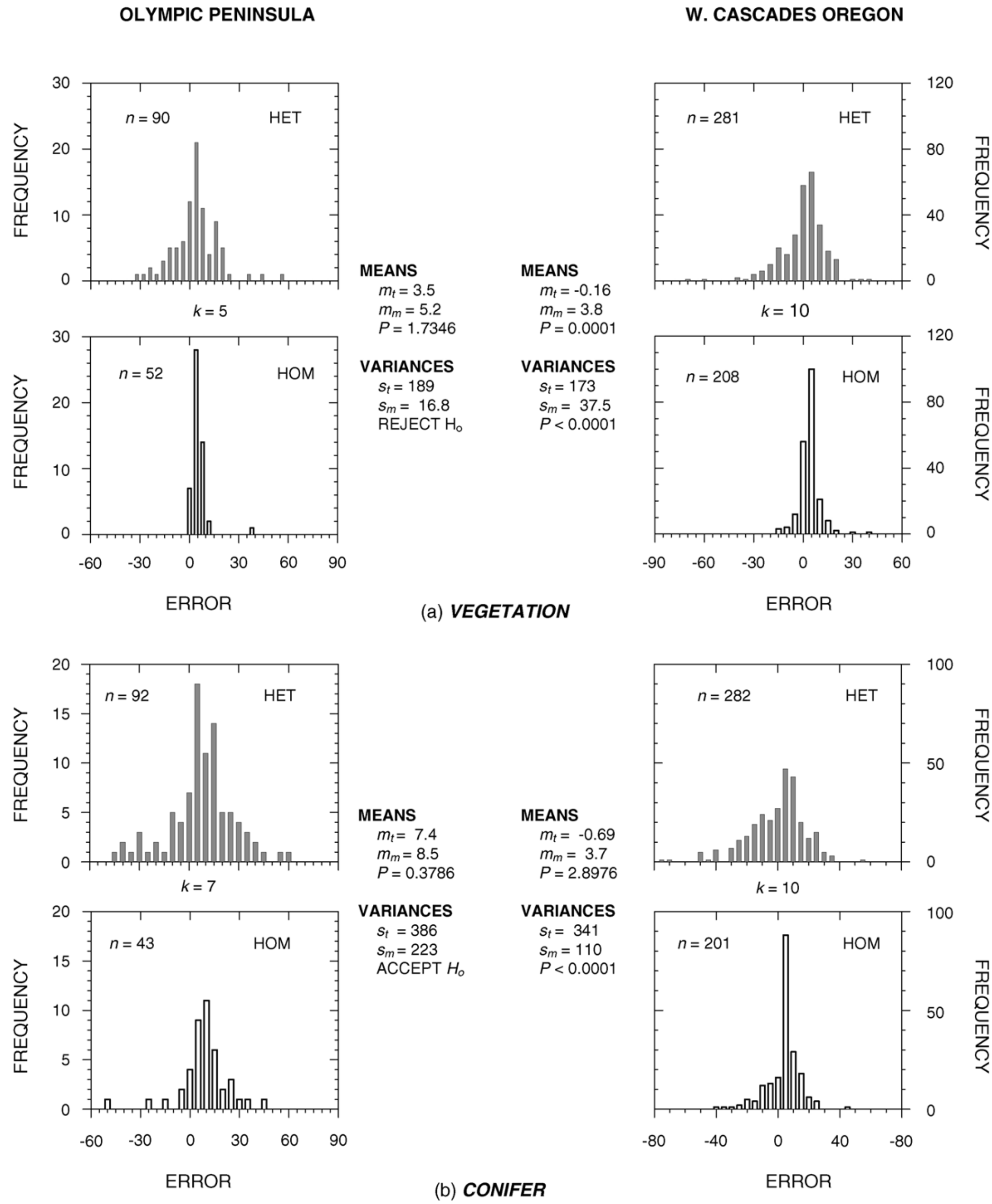

Fig. 7. Error distributions for heterogeneous (HET; grey) and homogeneous (HOM; white) samples of (a) percentage of total green vegetation cover, (b) percentage of conifer cover, (c) percentage of broadleaf cover, and (d) tree size (quadratic mean diameter in inches) from the Olympic Peninsula and western Cascades Oregon. *n* is the number of samples, *k* the number of subsamples per group (Moses test) for both heterogeneous and homogenous plots, *m* the estimated error mean, *s* the estimated error variance, H_o the null hypothesis of equal means or equal variances (two-sided), and subscripts *t* and *m* denote statistics for heterogeneous and homogenous samples, respectively. Note that *P*-values are not computed by using the Moses test when sample size is relatively small; rather, the H_o is rejected or accepted based on whether a test statistic falls between two critical values.

evaluation of the map than would be the case if data from all sources were used in the evaluation of accuracy. Given that heterogeneous data appear to make up a substantial portion of the landscape, this is important to consider. If data are to be broken into classes and an error matrix calculated, however, then any impact will be dependent on the size of the classes compared to the degree of variability. In this example, the estimated error variances of both homogeneous and heterogeneous data sets (Fig. 7) are smaller than the class sizes recommended for the IVMP data (i.e., 20–30% classes for

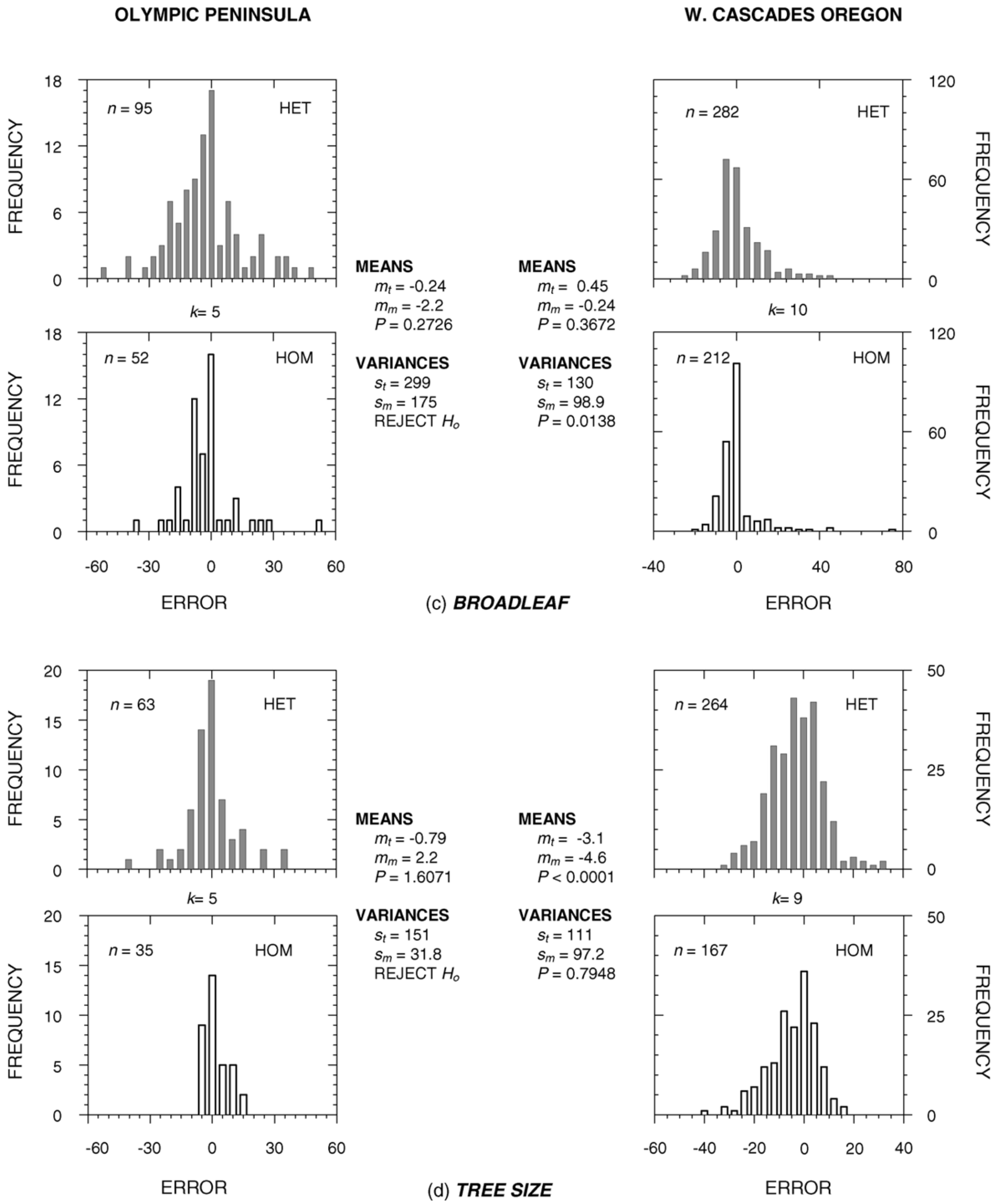

Fig. 7. (*Continued*).

cover, and ≥20 in (51 cm) classes for quadratic mean diameter (QMD); O'Neil et al., public communication[4]). Consequently, the impact on an error matrix of using only homogeneous data may be small in this example. Others, however, have found relatively large impacts. Hammond and Verbyla (1996) reported increases in accuracy of up to 11% for the same classification based on more versus less homogeneous accuracy-assessment data.

Given the results presented above, users of map products should keep in mind that (1) the calculated accuracies of maps as a whole may be optimistic if based solely on homogeneous data and (2) it may be inappropriate to compare map accuracies that have been calculated by using different sources of data (homogeneous only versus homogeneous and heterogeneous combined). It seems clear from the discussion above that further study is necessary to address the impact of excluding heterogeneous plots from accuracy-assessment calculations.

[4] Interagency Vegetation Mapping Project (IVMP): Western Cascades Washington Province Version 2.0, http://www.or.blm.gov/gis/projects/ivmp_-province.asp?id=3, visited 28 November 2003.

3.3. Impact of error

When remotely derived data are used as input to other spatial models, error will propagate with consequences that are typically not known or measured. Agumya and Hunter (1999) employ the term ''fitness for use'' to describe how scientists might employ information about the quality of geographic information. They describe two approaches, a standards-based approach in which error is compared against a set of existing standards, and a risk-based approach in which the impact of uncertainty in the information is expressed in terms of risk in the decision that is based on that information. The latter approach requires an understanding of both the limitations of the geographic information and the decisions that will be made by using that information. Users often have a reasonable knowledge of the error in their data but a poor understanding of the consequences of that error in subsequent decisions or models. As remote sensing is employed increasingly in policy and management decisions, users will have to incorporate estimates of risk associated with decisions based on models. However, in many natural resource applications, remote sensing maps are not the only information used in decision-making. Finer grained ground data that have higher accuracy are typically used at the project level to make final decisions. When employed as ancillary information, maps with relatively high error can still be useful to help set context, prioritize more intensive analysis, or communicate the big picture to the public.

4. Summary

Over the past two decades, there has been an explosion in the use of maps derived from remote sensing (particularly those from Landsat; Cohen and Goward, 2004) in ecological and resource management applications. Often, these maps are created or used without regard for, or knowledge of, a multitude of issues that can impact their value for specific applications. In this paper, we have discussed a number of critical issues, and provided a few examples to illustrate their impact.

- Is remote sensing the correct tool? Not all land cover properties are directly observable with remote sensing. For those that are not (e.g., amount of woody debris), it may still be possible to infer something about those properties based on observable vegetation characteristics (e.g., forest structure).
- What are the differences between class-based and continuous estimates? Maps based on classes can be limiting in their applicability to a potentially wide variety of uses. Using continuous models to derive maps facilitates a flexible definition of classes, and thus a broader applicability.
- Scale: what is it and what are the implications of data and methodological choices related to scale? We discussed three elements of scale: grain, extent, and minimum mapping unit, and demonstrated the effects of these scale elements on map quality and utility for a few specific purposes.
- Map errors: are they all the same? No map is perfectly correct, and those derived from remote sensing are commonly quite inaccurate. We discussed several issues related to this topic and the implications of errors for a variety of potential uses. By illustration, we demonstrated some differences between ''user's'' and ''producer's'' accuracy, class boundary fuzziness, and heterogeneity of accuracy-assessment sample data.

Perhaps the most important issue, however, is that of expectations. Sellers of remote sensing technology must manage expectations by resisting the desire to oversell their wares (Meyer and Werth, 1990), and users need to better understand the conditions under which remote sensing will provide the information they desire.

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