Evaluation of the Potential for Providing Secondary Labels in Vegetation Maps

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Abstract

For thematic maps made from remote sensing at the resolution of polygons, there are frequently more data available than the single class assigned to the polygon. One way of using these additional data is to provide secondary labels in maps. A key question concerns the reliability of these data. The optimistic view is that the distribution of classes at the pixel level is representative of the polygon, while the pessimistic view is that classifications are noisy and thus unreliable at this level of detail. Secondary labels for a vegetation map of the Plumas National Forest mirror the errors in the original vegetation map, indicating caution in the use of secondary labels. Results from the analysis of three decision rules indicate that class-conditional thresholds perform better than either of the approaches based on a single threshold. The behavior of individual classes varies significantly as a function of a single threshold, but overall accuracy is generally stable. For future work, standards for accuracy of secondary labels in maps need to be established.

Introduction

Satellite remote sensing is now routinely used to make vegetation maps for resource management purposes (see, for example, Congalton *et al.* (1993) and Woodcock *et al.* (1994a)). Federal agencies, such as the U.S. Forest Service, Bureau of Land Management, and National Park Service, use these maps to assist in management of many resources, including timber, wildlife, and water. Frequently, the same map is used for many applications. One example is our recent work with the U.S. Forest Service in California. We have been making vegetation maps, where the initial concern was timber inventory. These same maps are now being used for a wide variety of applications, including wildlife habitat studies. Given that the same map is often used in many ways, there is growing interest in providing as much information as possible to potential users of the maps, as different users frequently have varying information requirements. One approach to this problem is to provide secondary vegetation labels for map polygons. This approach would provide information about the presence of vegetation types not indicated in the original vegetation map. While these "secondary" vegetation types explicitly are not the dominant vegetation type, their presence in the map could prove useful to some of the many map users. The purpose of this paper is to begin to explore the possibility of providing secondary vegetation labels. The approach adopted is to evaluate different methods of providing secondary labels and their accuracy.

An example from our work with the U.S. Forest Service helps illustrate the varying information needs of different map users. From our vegetation maps, it is possible to estimate the location and areal extent of the vegetation type *hardwood*. However, for a wildlife habitat study, a more pertinent question might concern the location and extent of hardwood trees. The difference here is that hardwood trees could occur in other vegetation types, whereas the current maps only showed areas where hardwood trees are dominant. Thus, it would be useful to be able to identify locations of other vegetation types that contain significant components of hardwood trees.

Recent experience indicates that vegetation maps for resource management are made typically using Landsat TM or SPOT imagery, and are generally intended for use at a scale of 1:24,000. This scale dictates polygons with a minimum size of approximately 2 hectares, which explicitly implies polygons comprised of groups of pixels. For our mapping projects, we have been using the most frequently occurring vegetation type within a polygon to provide the label to be used in the vegetation map. The vegetation types have been assigned to individual pixels by employing unsupervised classification. However, there are still considerable data available beyond the most frequently occurring class for each polygon. Two related questions remain:

> What methods can be used to provide secondary labels?
>
> What are the accuracies associated with these different methods?

Underlying the analysis presented in this paper is the idea that the accuracy of maps made from remote sensing increases as the class labels from individual pixels are aggregated to polygons. The primary label for a polygon is, in essence, an aggregation which stochastically smooths the errors occurring at the level of individual pixels. Secondary labels shift the level of aggregation closer to the individual pixels, and thus are likely to be inherently less accurate than primary labels. One of the key issues confronting the use of secondary labels will be whether or not they can be provided with sufficient accuracy to be useful.

There has been little explicit attention to the problem of secondary labels in vegetation maps, but considerable past research is relevant to this issue. Stenback and Congalton (1990) evaluated the ability to detect forest understory using Landsat TM data. In the context of the present study, their work constitutes an evaluation of the ability to detect one particular kind of secondary label (understory) within one vegetation type (conifer forest). There has been considerable attention devoted to the idea that remotely sensed measurements can be considered mixes of vegetation types. The problems caused by "mixed" pixels for image classification are well known and long lamented. One approach has been

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TABLE 1. THIS TABLE SHOWS THE HIERARCHICAL VEGETATION CLASSIFICATION SCHEME FOR THE PLUMAS NATIONAL FOREST. IN THIS STUDY OF SECONDARY LABELS, ONLY THE FIVE GENERAL LAND-COVER CLASSES ARE CONSIDERED.

General Land Cover Classes	Additional Specifications
water	
barren/grass	
brush	species associations
hardwood	species associations
conifer	species associations tree size tree cover

to use spectral mixing models to try to recover the various proportions of different surface materials (Nalepka and Hyde, 1972; Li and Strahler, 1985; Adams *et al.*, 1986; Roberts *et al.*, 1993). While these mixture models are usually applied to pixels rather than to polygons, the underlying model for the nature of landscapes and remotely sensed measurements is similar. While not considered in this study, spectral mixing models may prove a viable alternative for providing secondary vegetation labels. Additionally, the use of neural networks for vegetation mapping has provided indications of the mixed nature of remotely sensed measurements (Moody *et al.*, 1995).

Data

The dataset used in this analysis comes from a vegetation mapping project being conducted for the U.S. Forest Service in the Sierra Nevada of California. The vegetation maps are hierarchical, providing varying levels of detail within five general land-cover types (see Table 1). Landsat Thematic Mapper imagery and digital terrain data are the primary inputs to the mapping process. The maps are being produced for use at a scale of 1:24,000, and have a minimum polygon size of approximately 2 hectares (22 TM pixels) (Woodcock *et al.*, 1994a). The final maps come from the combination of the results from two independent steps. One of these steps is image segmentation, which is used to define the polygons. The image segmentation algorithm uses multiple passes and region growing (Woodcock and Harward, 1992). The inputs to the segmentation process are both spectral and texture bands (Woodcock *et al.*, 1994a) The second step is an unsupervised pixel-level classification, which is used to assign pixels to the general land-cover classes (Franklin *et al.*, 1986). The results of these steps are combined by assigning a land-cover class to each polygon based on the pixel-level classification. At this time, a simple plurality rule is used to assign land-cover labels. The key point for this paper is that each polygon contains many pixels (at least 22) and there is a distribution of land-cover classes within each polygon.

The map used in this analysis covers the Plumas National Forest. The ground reference data were collected in the field at the time of the accuracy assessment of the map (Woodcock *et al.*, 1994b). The methods used to assess map accuracy are based on fuzzy sets, as described by Gopal and Woodcock (1994). For the accuracy assessment, 165 sites randomly selected within the five land-cover classes were visited in the field, and ratings were given regarding the appropriateness of each possible map label. In addition to the data required for the map accuracy assessment, data relevant to secondary map labels were collected. These data are in the form of ratings of the appropriateness of each of the five general land-cover classes as a secondary label using the rating scale given in Table 2. This accuracy assessment approach is based on polygons rather than pixels out of practical necessity. In naturally vegetated landscapes it is typically impossible to identify precisely the location of individual pixels in order to assess their accuracy. Polygons are more readily identifiable features, and thus better suited for accuracy assessment.

The use of a linguistic scale in the accuracy assessment follows the approach of Gopal and Woodcock (1994), and is unusual in the sense that it requires a rating for each possible label in the map. Thus, the dataset for the analysis presented in this paper includes the following for each of 165 polygons visited in the field: (1) pixel counts for each of the five land-cover classes, and (2) ground reference data in the form of ratings of the appropriateness of each land-cover class as a secondary label in a vegetation map.

Methods and Results

To evaluate the potential for providing secondary labels for maps, a method of evaluating the accuracy of secondary labels is needed. Secondary labels in maps differ in two primary respects from the labels provided in more traditional maps: (1) there is no requirement that each polygon receive a secondary label, and (2) there is no explicit limit to the number of secondary labels a polygon might receive. Thus, the assessment of accuracy of secondary labels has to differ somewhat from traditional methods (Congalton, 1991). The method used in this paper is based on evaluating the presence or absence of each possible secondary label for each site. Because there are five land-cover types in the map, with one assigned as the primary label, there are four possible secondary labels for each site. Both errors of omission and commission are counted as incorrect, while the appropriate inclusion or exclusion of classes are both counted as correct (Figure 1). Given the data described above, classes given a rating of 0,1, or 2 are counted as correct if they are given as secondary labels, and incorrect if they are omitted. Classes given a rating of 3 are considered neutral and not counted as either right or wrong regardless of whether or not they are given as a secondary label. In essence, the rating of 3 is the borderline case. Classes with a rating of 4 are incorrect if included as secondary labels, and correct if not included.

In this paper, three decision rules for assigning secondary labels are evaluated. The simplest approach involves using a single threshold for all classes. In this approach, for each polygon all classes with proportions exceeding this single threshold are assigned as secondary labels. One question concerns how to establish the value for this threshold. In most mapping applications, the only available alternative is to select this global threshold on the basis of the intuition

TABLE 2. THIS TABLE SHOWS THE LINGUISTIC RATING SCALE USED IN THE COLLECTION OF FIELD DATA FOR ANALYSIS OF SECONDARY LABELS.

Rating Levels for Secondary Labels	Rating Description
0	should have been the primary map label; if it is not the primary label, it should appear as a secondary label
1	definitely should appear as a secondary label; it would be a problem to omit this class as a secondary label
2	desirable as a secondary label; less problematic if it didn't appear in the map
3	present, but borderline concerning its appropriateness in the map; probably not a problem to find it in the map, but its omission would also not be a problem
4	clearly inappropriate as a secondary label; its appearance in the map would definitely be a problem.

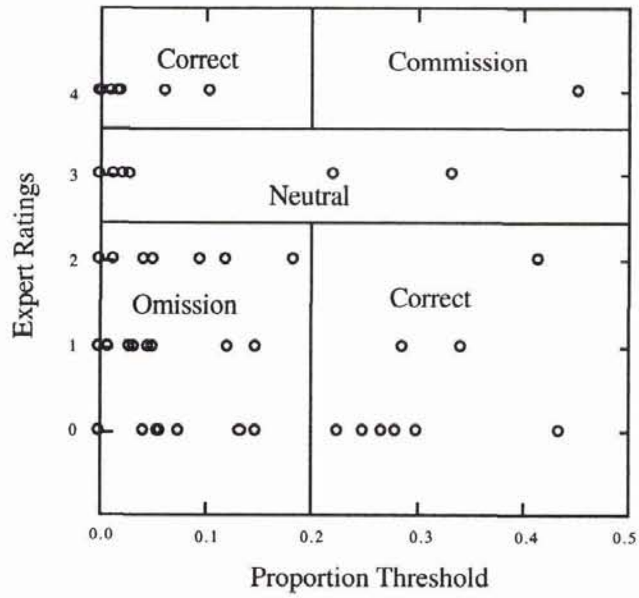

Figure 1. This figure illustrates the accuracy assessment scheme. Expert ratings of 0, 1, and 2 are combined, and 3 is neutral. The *x*-axis is the proportion of the pixels in a polygon in a particular class. In this example, the proportion threshold of 0.2 is used.

and experience of the people making the map. If the threshold is too low, many secondary labels will be assigned, and the most likely problems would be excessive errors of commission. Conversely, if the threshold is too high, the expected problem would be excessive errors of omission.

The first approach tested in this paper is a single threshold based on an educated guess—which was 20 percent of the pixels in a polygon. This means that if the proportion of pixels in a class is less than 20 percent and it received an expert rating of 0, 1, or 2, then it is an error of omission. If it has greater than or equal to 20 percent and received an expert rating of 4, then it is an error of commission. The accuracy for this single threshold is 80.4 percent (Table 3). This result is used as a baseline for comparison for the other decision rules.

TABLE 3. THIS TABLE SHOWS THE ACCURACY FOR THE THREE METHODS TESTED. THE SECOND COLUMN IS THE PERCENT IMPROVEMENT OVER THE FIRST METHOD. THE THIRD COLUMN IS THE PERCENT OF THE ERROR REMAINING AFTER THE FIRST METHOD EXPLAINED BY THE SECOND AND THIRD METHODS.

	Percent		
Decision Rules	Overall Accuracy	Improvement	Error Explained
1. Educated Guess	80.4	N/A	N/A
2. Best Single Threshold	81.5	1.1	6.4
3. Class Specific Thresholds	85.2	4.8	24.5

The second approach tested is the use of a single threshold which is determined through analysis of the accuracy assessment data. In this approach, the results from applying various thresholds are evaluated, with the threshold producing the highest accuracy being selected. This approach is biased, because the same data used to calibrate the decision rule are used to evaluate its quality. However, it is more objective than the first approach, which is simply an educated guess. Figure 2 shows the accuracy of secondary labels as a function of thresholds for 5 percent intervals in the range of zero to 50 percent. There is little fluctuation in this graph, although a decline is clearly evident for large thresholds. The highest accuracy (Table 3) occurs at a threshold of 5 percent, although it is only slightly larger than the accuracy for the initial guess of 20 percent.

The third approach tested uses class-specific thresholds. Again, the accuracy data are used to determine the optimum threshold for each class, which are given in Table 4. Using this approach, accuracy jumps to 85 percent. This method is

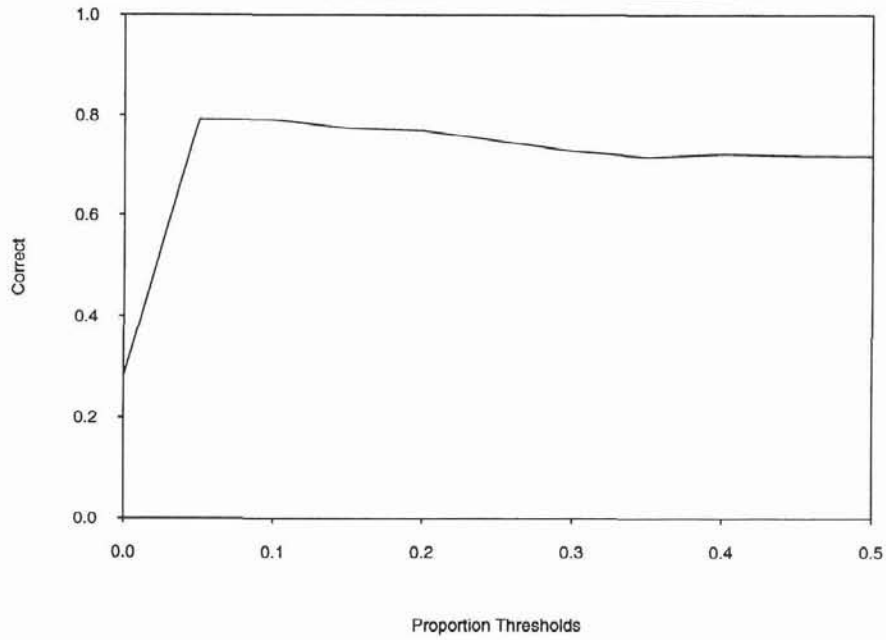

Figure 2. This graph shows accuracy as a function of various thresholds.

guaranteed to result in a higher answer, but the wide range of thresholds selected for each class is surprising.

The key to understanding the selection of 5 percent as the optimum single threshold and the reason the class specific thresholds are an improvement is to examine the behavior of the individual classes. Figure 3 shows the accuracy for each class separately as a function of thresholds. The shape of the curve for *brush* most closely resembles the expected form. At very low thresholds, many polygons would receive a secondary label of *brush*, resulting in many errors of commission. As the threshold increases, accuracy rises as the errors of commission decrease. However, eventually as the threshold increases, only a few polygons receive *brush* as a secondary label, and errors of omission increase and accuracy falls. Figure 4a illustrates the change in the distribution of errors between omission and commission for *brush*. One important note is the rule used for each threshold, in which the pixel-level proportion observed in a polygon exceeds the threshold. This rule is particularly important to remember when interpreting the results for a threshold of zero. In this case, only polygons that have pixels of the class in question would receive a secondary label. Notice from Figure 4a for the *brush* class, for example, that almost 20 percent of the errors for the zero threshold are errors of omission. This result implies that there are polygons with zero *brush* pixels that should have been assigned a secondary label of *brush*.

The behavior of the *conifer* class as illustrated in Figure 3 diverges significantly from the expected form. Accuracy increases as the threshold is reduced, with the highest accuracies occurring with a threshold of either zero or 5 percent. Two factors influence the shape of this curve for the *conifer* class. First, in the original vegetation map, there are many errors of omission for the *conifer* class (Woodcock *et al.*, 1994b). There are many polygons in both the *hardwood* and *brush* classes that would have been better mapped as the *conifer* class. Given that situation, there are many of the sample sites where *conifer* received a rating of 0 as a secondary label. Thus, when a strict, or high threshold is used which gives very few polygons a secondary label of *conifer*, accuracy for the *conifer* class is very low. Second, the original class definitions are skewed to reflect one of the primary purposes of this particular vegetation map, which is timber inventory. Only 10 percent cover of conifer trees is required for a polygon to be included in the *conifer* class. So it takes very small amounts of conifer trees for the *conifer* class to be a desirable secondary label. This situation helps explain why the accuracy of the *conifer* class as a secondary label continues to rise as the threshold is decreased. The trend for *conifer* accuracy to increase as thresholds are decreased appears to be the primary reason that the optimum single threshold is pushed back to 5 percent.

The distribution of errors between omission and commission for the *conifer* class is interesting (Figure 4b). The small proportion of commission errors at low thresholds is another indication that the *conifer* class is under-represented in the pixel-level classification. Also, the high magnitude of errors at the zero threshold, which are predominantly errors of omission, indicates the impossible nature of trying to provide accurate secondary labels of *conifer* using this dataset.

The situation for the *hardwood* class is quite different. One of the findings of the accuracy assessment of the Plumas vegetation map (Woodcock *et al.*, 1994b) was that the *hardwood* class was unreliable, and included many errors of commission. This trend is carried over into the secondary labels, where errors of commission are large for small thresholds (Figure 4c).

The behavior of *water* and *barren* are less informative.

TABLE 4. THIS TABLE SHOWS THE THRESHOLDS AND ACCURACIES FOR EACH CLASS FOR THE METHOD USING CLASS-CONDITIONAL THRESHOLDS.

Class	Optimum threshold	Accuracy
brush	10%	75.7%
barren	10%	79.8%
hardwood	35%	92.4%
conifer	0 or 5%	61.2%
water	10%	100%

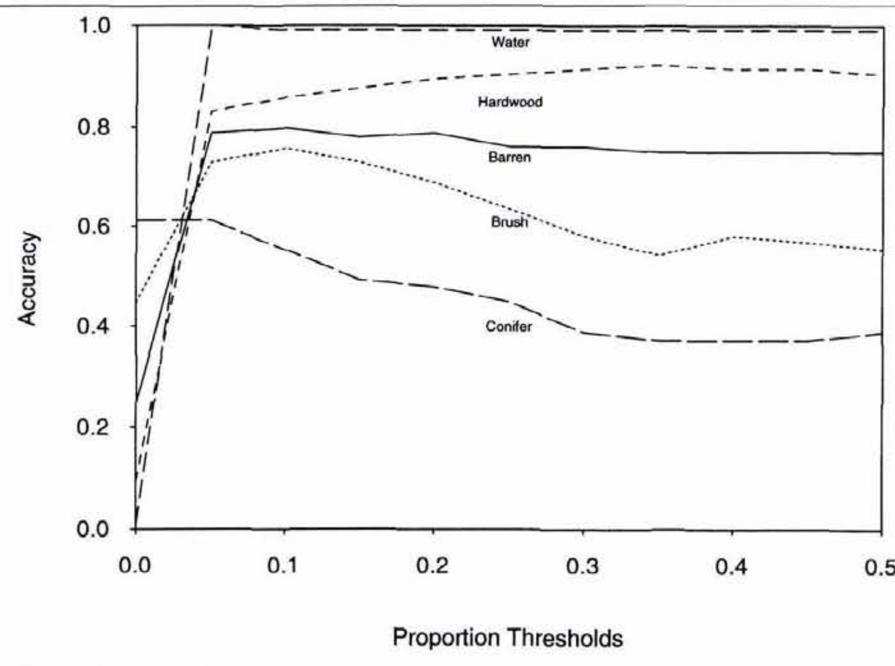

Figure 3. This graphs shows accuracy for each class as a function of various thresholds.

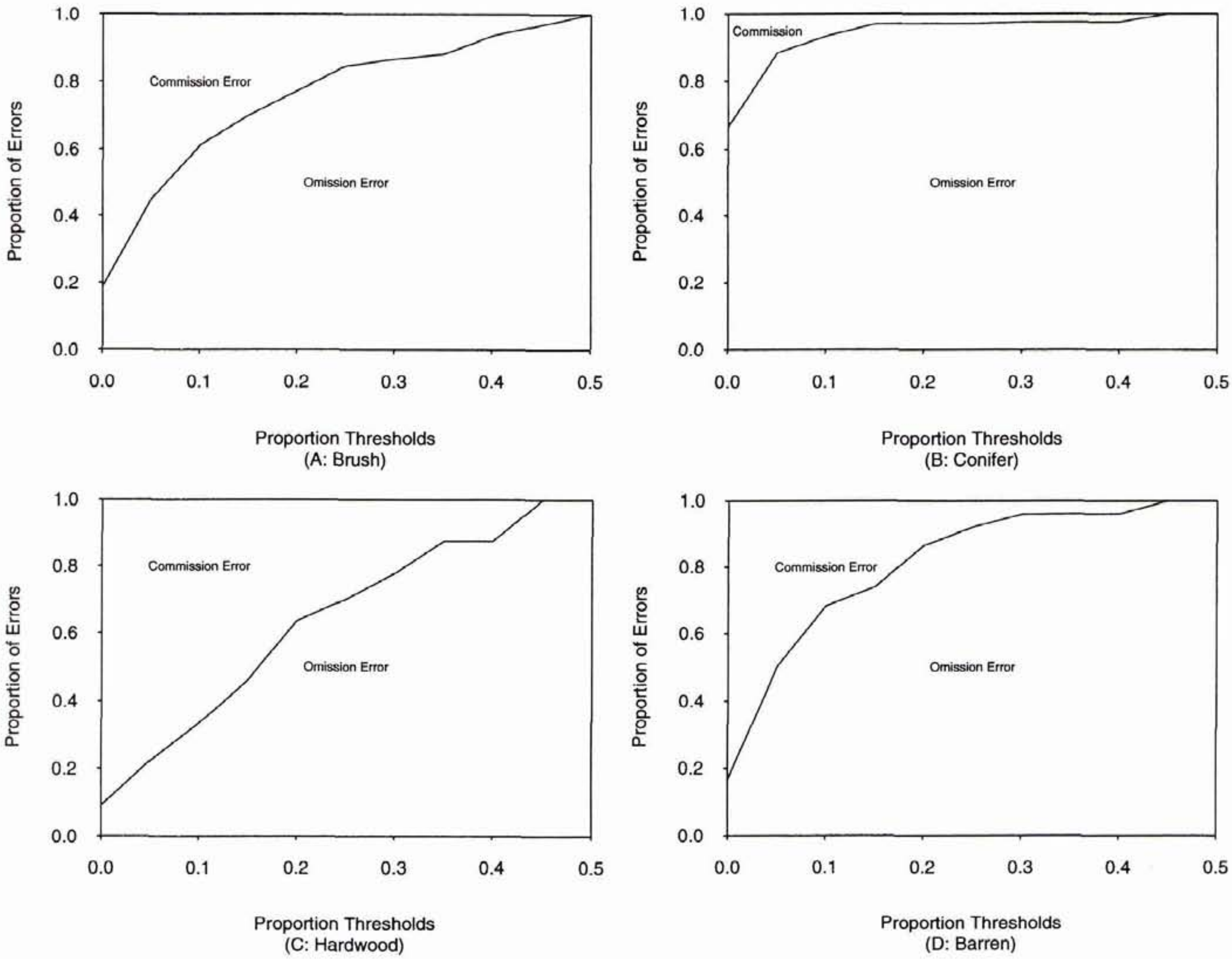

Figure 4. These graphs show the distribution of errors between omission and commission as a function of thresholds.

Barren behaves much the same as *brush*, which conforms closest to the expected behavior. The accuracy of *water* rises directly from zero to 100 percent as the threshold changes from zero to 10 percent. This result indicates high accuracy in the pixel-level classification for water, and is the reason a figure showing the breakdown of the omission and commission error is omitted.

Discussion

One issue that emerges from this analysis concerns how to interpret the magnitudes of the accuracies. Because the methods are clearly different from traditional map accuracy assessment, the results should not be directly compared. It must be remembered when interpreting the results in this paper that the appropriate omission of a secondary label is as important as the appropriate inclusion of a secondary label. Thus, as the number of choices for secondary labels increases, one would expect the accuracy to increase. Some future method that takes this effect into account would be desirable. One possibility might be a modification of the kappa statistic (Cohen, 1960).

Another question concerns the degree of accuracy that can be expected of secondary map labels. The idea of providing secondary labels in maps is based on the assumption that there is a relationship between the cover proportions on the ground, and the distribution of classes at the pixel level for each polygon. At one extreme would be the assumption that they match perfectly, in which case the proportions of classes in a polygon become a reliable estimate of the proportions of land covers in a polygon. A more skeptical view is that pixel-level classifications are frequently noisy, and, as a result, these relationships are unreliable. The key question then becomes, where along this continuum do pixel-level classifications exist? The results presented in this paper clearly indicate that there is error in the image classifications. The most obvious evidence are the errors of omission for classes at the zero thresholds, which indicate that there are no pixels in polygons for classes for which secondary labels would be desirable. While some smoothing of pixel-level error occurs in assigning secondary labels, they cannot be expected to be as accurate as the primary map. But what accuracies are high enough to warrant including the secondary labels in a map? That question remains to be answered. For example, it is not clear whether accuracies in the range of 80 to 85 percent as found in this study are sufficient to warrant their use in a map.

A related question concerns the significance of the improvements in accuracy associated with the different deci-

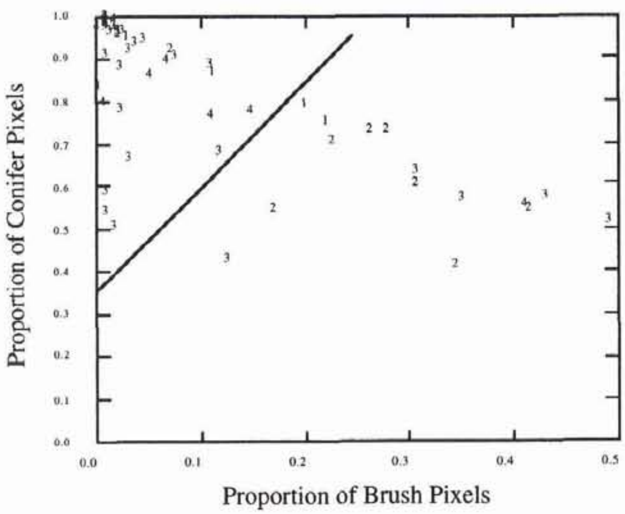

Figure 5. This graph is an example of a bi-variate decision rule. The numbers in the graph are expert ratings for the *brush* class as a secondary label for sites mapped as *conifer* in the primary map. The line shows an example of a decision rule.

sion rules. In Table 3, the accuracies for the different methods are given three ways. First, there is the overall accuracy. Second is the improvement relative to the first approach, or an educated guess at a single threshold. The last way accuracy is presented is as a percentage of the error in the first method explained by the second and third approaches. This last column helps illustrate the significance of different levels of improvement. For example, a 5 percent improvement in a classification that is 90 percent accurate may be more significant than a 5 percent improvement in a classification that is 70 percent accurate, as a greater proportion of the error in the classification has been resolved. The small improvement of the approach using a best single threshold over the educated guess is surprising. Given the method of determining the best single threshold, its accuracy is guaranteed to be greater than or equal to the educated guess threshold. The insensitivity of the results across a wide range of thresholds indicated by Figure 2 is one of the more interesting results of the analysis. The small changes for different single thresholds are particularly surprising given the large differences in the behavior of the individual classes shown in Figure 3. One way to understand this result is to remember that the points in Figure 2 are in essence the weighted means of the individual classes as shown in Figure 3. Given this perspective and the large increase associated with the use of class specific thresholds, one recommendation that emerges from this study is the importance of using class specific thresholds in mapping projects.

The analysis in this paper also clearly illustrates that the errors in the secondary labels are highly related to the errors in the primary map. This result should not be surprising, as they are both based on the same pixel-level classification. For example, one of the main findings of the assessment of the primary map was frequent errors of omission for the *conifer* class (Woodcock *et al.*, 1994b). Similarly, using any of the decision rules tried in this analysis, there are many errors of omission for *conifer* as a secondary label (see Figures 3 and 4b). Thus, it may be unrealistic to expect secondary labels to provide the correct primary label for polygons where the primary label is incorrect.

The three approaches tested in this paper only represent a subset of the approaches possible. A fourth approach would be to use class conditional rules. A bivariate example of class conditional rules is shown in Figure 5. In this example, each site in the accuracy assessment that was labeled *conifer* in the primary map is plotted as a function of the percentage of pixels in the polygon classified as *brush* and *conifer*. The numbers in the graph are the expert ratings for brush as a secondary label, and the line represents a bivariate decision boundary for assignment of *brush* as a secondary label given that the polygon was assigned the label of *conifer* in the primary map. The idea here is that the proportion of *brush* pixels in a polygon needed to include *brush* as a secondary label could easily be different depending on the composition of the other pixels in the polygon. Calibrating this kind of approach requires considerably more data than were available for the Plumas dataset. For example, in Figure 5, note that many of the polygons sampled have low proportions of *brush* pixels and, as a result, are not much help. This problem could be minimized by controlling the selection of sample sites so that they are more evenly distributed through the range of combinations covered in this graph. This sample selection process would bias the accuracy assessment, which could be easily solved through the use of weights. The benefits of this approach could be large, and it is an approach that merits attention in future studies.

One question not addressed in this paper is the influence of the methods used to define the polygons in the map. As previously mentioned, the method used here is image segmentation, which is based on the original spectral data and a texture channel. The image segmentation is performed independently of the pixel classification. Different methods of polygon definition might significantly influence the results with respect to secondary labels. Other possible methods of polygon definition include hand delineation and methods based on smoothing pixel-level classifications. Also, much of the current GIS analysis generates many sets of polygons which could be used. The underlying question with respect to polygon definition concerns the homogeneity of vegetation cover within polygons. The use of polygons implies generalization, in which patches of vegetation too small to constitute an entire polygon must be merged with a neighboring area. If alternative polygon-definition methods perform this generalization differently, the results of attempts to provide secondary vegetation labels would be influenced. This topic warrants consideration in future work.

This paper addresses only a subset of possible types of secondary labels that might be assigned in a map. Specifically, this paper focusses on providing additional nominal, or categorical, labels for polygons. Other possibilities might include estimates of the area covered by various vegetation categories.

Conclusions

Secondary labels in vegetation maps hold the promise of providing map users with additional information, helping make the maps useful for a wider range of applications. Secondary labels have different properties from the original primary map and thus require different methods for accuracy assessment. In the approach used here, all possible secondary labels are assessed, with errors of omission and commission weighted equally. Of the three methods tested for assigning secondary labels in vegetation maps, class conditional thresholds were the most accurate. There was little difference in accuracy for a single threshold based on an educated guess and an optimum single threshold despite the widely varying behavior of different vegetation classes as a function of thresholds. Errors in the secondary labels mirror the errors in the original map, as they are both based on the same pixel-level classification. Clearly, there is noise in the pixel-level classification, which causes problems in polygon-based secondary labels. The question of accuracy standards for secondary labels has not been addressed in the literature, and needs further attention prior to regular adoption.

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