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Mapping of Forest Alliances and Associations Using Fuzzy Systems and Nearest Neighbor Classifiers

F. Jack Triepke
US Forest Service Southwestern Region

C. Kenneth Brewer
US Forest Service Washington Office

Daniel M. Leavell
US Forest Service Kootenai NF

Stephen J. Novak
Boise State University

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Abstract
The study and management of biological communities depends on systems of classification and mapping for the organization and communication of resource information. Recent advances in remote sensing technology may enable the mapping forest plant associations using image classification techniques. But few areas outside Europe have alliances and associations described in detail sufficient to support remote sensing-based modeling. Northwestern Montana has one of the few plant association treatments in the United States compliant with the recently established National Vegetation Classification system. This project examined the feasibility of mapping forest plant associations using Landsat Enhanced Thematic Mapper data and advanced remote sensing technology and image classification techniques.

Suitable reference data were selected from an extensive regional database of plot records. Fifteen percent of the plot samples were reserved for validation of map products, the remainder of plots designated as training data for map modeling. Key differentia for image classification were identified from a suite of spectral and biophysical variables. Fuzzy rules were formulated for partitioning physiognomic classes in the upper levels of our image classification hierarchy. Nearest neighbor classifiers were developed for classification of lower levels, the alliances and associations, where spectral and biophysical contrasts are less distinct.

Maps were produced to reflect nine forest alliances and 24 associations across the study area. Error matrices were constructed for each map based on stratified random selections of map validation samples. Accuracy for the alliance map was estimated at 60%. Association classifiers provide between 54 and 86% accuracy within their respective alliances. Alternative techniques are proposed for aggregating classes and enhancing decision tree classifiers to model alliances and associations for interior forest types.

Keywords: vegetation mapping, map design, image classification, fuzzy logic, nearest neighbor, plant association, accuracy assessment

1. Introduction

Land cover maps are basic to the study and management of natural resources. As natural resources have become more scarce they have become more valuable, as evidenced by increased controversy over their management (Congalton & Green, 1999; Cohen et al., 2001), elevating the need for more current and accurate spatial data (Bobbe et al., 2001; Jennings et al., 2003).

While using satellite imagery has been used for coarse-scale vegetation mapping for over three decades now, satellite data has rarely been applied successfully for mapping at the floristic level. Recent advances in remote sensing technology and interpretation techniques has made imagery useful for vegetation type mapping at finer scales (e.g., Daniel & Fox, 1999; Brown de Colstoun et al., 2003). Stemming from needs expressed by the Kootenai National Forest (NF) in northwestern Montana, the goal of this project was to determine a process for the image classification and mapping of forest alliances and associations. Specific objectives were to: 1) identify key relationships between model data and the associated training samples for each alliance and plant association; 2) use remote sensing data to delineate map unit boundaries; 3) classify feature space to map forest alliances and associations in the study area at the scale of 1:24,000; and 4) test the accuracy of map products systematically to determine the feasibility of implementing similar projects elsewhere in the Pacific Northwest.

2. Background

Associations express characteristic patterns in their composition, beyond that which would be expected by chance (Drake, 1990). Different plant taxa that occupy the same plant community are not identical in habitat niche; rather, the particular community is an expression of where their ecological amplitudes overlap. Certain plant assemblages can reappear over the landscape wherever there are similar environments (Daubenmire, 1968; Leavell, 2000). Being able to recognize patterns within natural systems makes possible the statistical (classification) and spatial (mapping) depiction of plant communities.

While a *potential* vegetation type provides an *interpretive* classification of a plant community, the *existing* vegetation type provides a *descriptive* classification of current vegetation (Arno et al., 1985). Most of the resources directed toward the classification, inventory, and mapping of plant communities in much of the western United States have been focused on potential vegetation (e.g., Daubenmire & Daubenmire, 1968; Pfister et al., 1977; Cooper et al., 1991; Muldavin et al., 1996). Existing vegetation has received far less attention. The National Vegetation Classification system (NVC) has brought about needed consistency in classification standards for existing vegetation across federal lands in the United States (TNC and ESRI, 1994). Included in the NVC are both physiognomic and floristic hierarchies as originally identified by the Federal Geographic Data Committee in 1997 (FGDC, 1997). Physiognomic levels include *division*, *order*, *class*, *subclass*, *group*, *subgroup*, and *formation*. Floristic levels, at the bottom of the hierarchy, include plant *associations* nested under *alliances* according to floristic similarity. The Ecological Society of America (ESA) has established protocols for the classification of existing vegetation in the United States (Jennings et al., 2003). Critical to mapping applications is the ability to uncouple physiognomic and floristic hierarchies. In this way, alliances and associations can be mapped without requiring subclassification based on the degree of canopy cover imposed at the level of *class* (see below).

A plant community classification of existing vegetation was recently completed on the Kootenai NF according to NVC standards (Leavell, 2000). Leavell's treatment in conjunction with later supplemental classification work (Triepke, 2003) has resulted in the ordination and classification of 9 forest alliances and 24 associations (Table 1). Unlike the original classification, woodland and forest associations (and alliances) are referred to here collectively as *forest* associations, since we make no distinction in the degree of tree canopy cover that normally sets *woodland* and *forest* physiognomic classes apart further up in the NVC hierarchy (Jennings et al., 2003). Leavell analyzed relationships between vegetation types he described and the latent environmental gradients associated with those plant communities and identified precipitation, solar insolation, and land type as the three highest correlated variables to their occurrence.

Alliances are nearly equivalent in spatial scale and floristic resolution to dominance types or cover types (Eyre, 1980; Shiflet, 1994; Triepke et al., 2005). They differ greatly in that they are statistically analyzed and validated. Associations are equivalent in floristic detail to the plant communities conceptualized in theoretical synecology (Mueller-Dombois & Ellenberg, 1974). What appears as a homogeneous vegetation unit on an aerial photo may represent one or more plant associations depending on diagnostic flora of the understory. For this reason, the success of image classification and mapping plant associations is as likely to depend on abiotic variables, as indicators of understory composition, as on spectral information, given that satellite data are normally an expression of the overstory.

Image classification is the process of assigning land cover classes to pixels or polygons on the mapping surface (Lillesand & Kiefer, 2000). As with our project, model-based classifications are often accomplished through rule-based decision trees that divide feature space into finer and finer units in a divisive, top-down approach (Safavian & Landgrebe, 1991). Decision trees mitigate the potential enormity of image classification problems by creating additional but less complex decisions with each added level of (sub)classification. The classifiers employed at each node of the tree can either be expert systems, automatically generated algorithms (Gong et al., 1996), or manually generated algorithms based on statistical relationships between plant communities (i.e., training data) and spectral or biophysical variables (i.e., model data).

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Table 1
Summary of floristic map units of the Kootenai NF included in this study

Alliance Association	Common Name	Alias
Tsuga heterophylla / Thuja plicata	western hemlock – western redcedar	TSUHET_THUHET
Tsuga heterophylla – Thuja plicata / Tiarella trifoliata	western hemlock – western redcedar / threeleaf foamflower	TSUHET_THUPLI / TIATRI
Thuja plicata – Thuja plicata / Paxistima myrsinites	western hemlock – western redcedar / Oregon boxleaf	TSUHET_THUPLI / PAXMYR
Thuja plicata / Mnium spinulosum – Gymnocarpium dryopteris	western redcedar / largetooth calcareous moss – Pacific oakfern	THUPLI / GYMDRY
Abies grandis	grand fir	ABIGRA
Abies grandis / Acer glabrum – Linnaea borealis	grand fir / Rocky Mountain maple – twinflower	ABIGRA_PSEMEN / ACEGLA
Larix occidentalis – Betula papyrifera	western larch – paper birch	LAROCC_BETPAP
Larix occidentalis – Betula papyrifera / Acer glabrum	western larch – paper birch / Rocky Mountain maple	LAROCC_BETPAP / ACEGLA
Picea glauca – Galium triflorum	white spruce – bedstraw	PICGLA_GALTRI
Picea glauca / Mitella nuda	white spruce / naked miterwort	PICGLA / MITNUD
Pinus contorta	lodgepole pine	PINCON
Pinus contorta – Larix occidentalis / Vaccinium myrtillus	lodgepole pine – western larch / dwarf bilberry	PINCON_LAROCC / VACMYR
Pinus contorta – Larix occidentalis	lodgepole pine – western larch	PINCON_LAROCC
Pinus contorta – Larix occidentalis / Alnus viridis	lodgepole pine – western larch / green alder	PINCON_LAROCC / ALNVIR
Abies lasiocarpa	subalpine fir	ABILAS
Abies lasiocarpa / Alnus viridis	subalpine fir / green alder	ABILAS / ALNVIR
Abies lasiocarpa – Larix occidentalis / Vaccinium globulare (V. membranaceum)	subalpine fir – western larch / globe huckleberry	ABILAS_LAROCC / VACGLO
Abies lasiocarpa – Pinus contorta / Vaccinium myrtillus	subalpine fir – lodgepole pine / dwarf bilberry	ABILAS_PINCON / VACMYR
Abies lasiocarpa – Picea engelmannii / Menziesia ferruginea	subalpine fir – Engelmann spruce / fool's huckleberry	ABILAS_PICENG / MENFER
Abies lasiocarpa – Pinus albicaulis / Vaccinium globulare (V. membranaceum)	subalpine fir – whitebark pine / globe huckleberry	ABILAS_PINALB / VACGLO
Pinus contorta / Xerophyllum tenax	lodgepole pine / beargrass	PINCON / XERTEN
Abies lasiocarpa – Pinus albicaulis / Vaccinium scoparium	subalpine fir – whitebark pine / grouse whortleberry	ABILAS_PINALB / VACSCO
Abies lasiocarpa / Luzula hitchcockii	subalpine fir / Hitchcock's woodrush	ABILAS / LUZHIT
Picea / Ledum glandulosum	spruce / Labrador tea	PICEA / LEDGLA
Larix lyallii / Poa cusickii	alpine larch / Cusick's bluegrass	LARLYA / POACUS
Larix occidentalis – Pseudotsuga menziesii	western larch – Douglas-fir	LAROCC_PSEMEN
Larix occidentalis – Pseudotsuga menziesii / Vaccinium myrtillus	western larch – Douglas-fir / dwarf bilberry	LAROCC_PSEMEN / VACMYR
Larix occidentalis – Pseudotsuga menziesii / Vaccinium globulare (V. membranaceum)	western larch – Douglas-fir / globe huckleberry	LAROCC_PSEMEN / VACGLO
Larix occidentalis – Pseudotsuga menziesii / Shepherdia canadensis	western larch – Douglas-fir / buffaloberry	LAROCC_PSEMEN / SHECAN
Larix occidentalis – Pseudotsuga menziesii / Mahonia repens	western larch – Douglas-fir / Oregon grape	LAROCC_PSEMEN / MAHREP
Pseudotsuga menziesii – Pinus ponderosa	Douglas-fir – ponderosa pine	PSEMEN_PINPON
Pseudotsuga menziesii – Pinus ponderosa / Mahonia repens	Douglas-fir – ponderosa pine / Oregon grape	PSEMEN_PINPON / MAHREP
Pseudotsuga menziesii – Pinus ponderosa / Physocarpos malvaceus	Douglas-fir – ponderosa pine / ninebark	PSEMEN_PINPON / PHYMAL

Map units include nine forest alliances and 24 associations

3. Study area

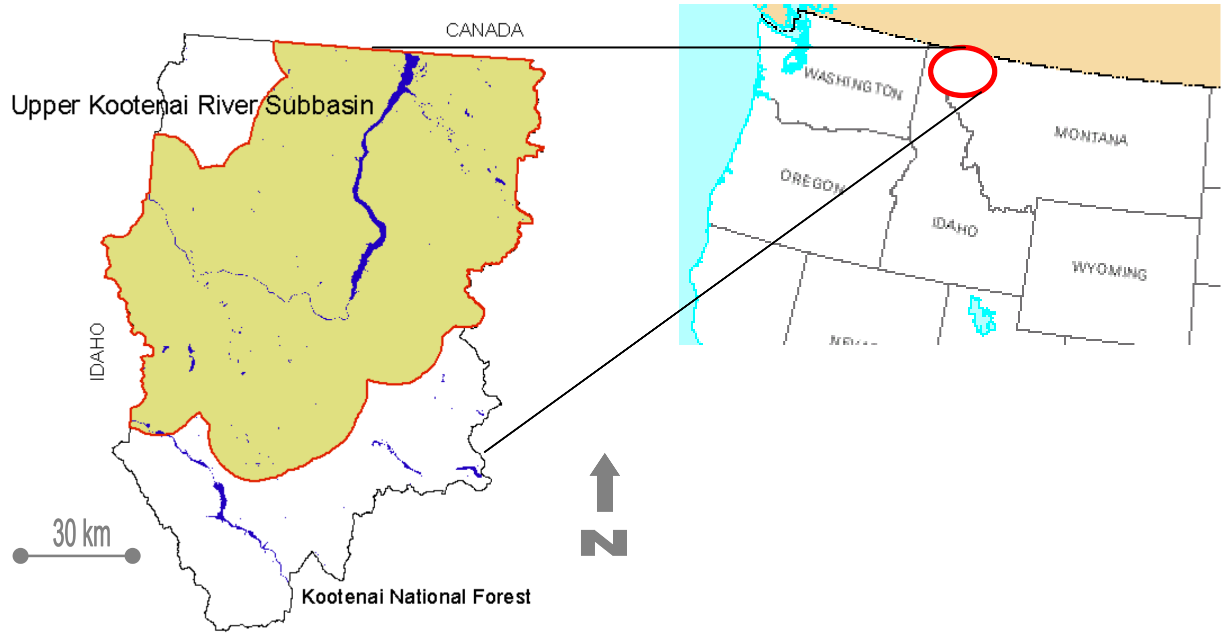

Fig. 1. Study area and vicinity map showing upper Kootenai River basin in northwestern Montana, USA.

The upper Kootenai River basin is located in the northwestern corner of Montana, bounded by Canada to the north, and Idaho to the west, and by the Kootenai River watershed in all other portions (Fig. 1). The 590,000 hectare study area occurs as part of the greater 'Steppe – Coniferous Forest', ecoregion M333, described and mapped by Bailey (1998). Elevation ranges from 555m to 2663m, and the overall climate of the area is 'cool temperate' with temperature extremes moderated by mountainous terrain. Despite the inland position of the area, climate and vegetation are significantly affected by residual, easterly, submaritime moisture and humidity. Annual precipitation of the upper Kootenai River drainage varies from about 35cm in the driest valley bottoms to the east to over 250cm at the uppermost elevations in the west. The influence of continental glaciation is evident in the Kootenai landforms – glaciated mountains, moraines, troughs, and glacial and lacustrine basins. Parent material consists primarily of pre-Cambrian metasediments (Kuennen & Nielsen-Gerhardt, 1995), and most soils are moderately deep with loamy to sandy textures. Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco), subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.), Engelmann spruce (*Picea engelmannii* Parry ex Engelm.), white spruce (*Picea glauca* (Moench) Voss), whitebark pine (*Pinus albicaulis* Engelm.), lodgepole pine (*Pinus contorta* Dougl. ex Loud. var. *latifolia* Engelm. Ex S. Wats.), and ponderosa pine (*Pinus ponderosa* P. & C. Lawson var. *ponderosa*) occur across the study area, while Pacific indicators such as western redcedar (*Thuja plicata* Donn ex D. Don), western hemlock (*Tsuga heterophylla* (Raf.) Sarg), western white pine (*Pinus monticola* Dougl. ex D. Don), and grand fir (*Abies grandis* (Dougl. ex D. Don) Lindl. var. *idahoensis* Silba) are concentrated to the west where maritime influence is the strongest.

4. Data

Reference data include both the basic information for 'training' map models, and separate data used for the accuracy assessment of map products (Stehman & Czaplewski, 1998). *Reference data* provide a link between the vegetation types being mapped and the differential variables that distinguish them from one another in feature space. Reference data for this study were obtained from vegetation plot records and processed into data sets for model training and map validation (see Reference Data Synthesis).

Model data represent spatially continuous variables of two main categories: 1) spectral data derived from satellite sensors and 2) *biophysical* data usually derived from other models that are used to represent the physical environment. All spectral and biophysical data were coregistered and clipped to the boundaries of the study area. Data were prepared using the ERDAS Imagine software (ERDAS, 1997) with each data file stored in **.img** format and input into eCognition, an advanced segmentation and image classification program (Definiens Imaging, 2003). Individual eCognition projects are stored as single **.dpr** files. Through the course of our experiment all spectral and biophysical variables were analyzed in eCognition for their utility in image classification.

4.1. Spectral data

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite data was selected for this project. The spatial, radiometric, and spectral resolution of Landsat imagery is well suited for mapping temperate vegetation (Brown de Colstoun et al., 2003; Cohen & Goward, 2004). At 30 meters, the spatial resolution of Landsat imagery is commensurate with the scale of forested plant communities in the interior northwest. Also, the high level of radiometric resolution (8-bit) is useful for detecting subtle contrasts in land cover features.

A satellite scene (Path 42, Row 26) taken near peak greenness (08.18.02) was acquired and preprocessed by the US Forest Service Region One geospatial group in Missoula, Montana. A second image (11.06.02) was processed to leverage seasonal change and phenological variation for image classification. A third 'difference' image was made based on the change in reflectance values for each band between the summer and fall images. In all, three primary data sets were created – 'summer', 'fall', and 'change'. These sets were compiled into single images (image stacks) each containing values for spectral channel data – the blue, green, red, near infrared (near-IR), first mid infrared (mid-IR 1), and second mid infrared (mid-IR 2) bands.

Six spectral indices were generated that had proven useful in previous vegetation mapping efforts (Jordan, 1969; Lillesand & Kiefer, 2000; Weiss et al., 2004; Cohen & Goward, 2004; Epting et al., 2005): 1) NDVI – the normalized difference vegetation index; 2) NIRM – near infrared and mid infrared index; 3) NIRR – near infrared and red index; 4) MSAVI – modified soil adjusted vegetation index; 5) VI – the simple vegetation index; and 6) SI – the structural index. Linear transformations were also employed to accentuate relationships between spectral data and vegetative characteristics (Coppin et al., 2001). Tasseled cap transforms have been formulated so that the majority (97%) of useful information from spectral data is expressed in three dimensions – *brightness* (soils), *greenness* (vegetation), and *wetness* (relating canopy and soil moisture) (Cohen et al., 2001; Maiersperger et al., 2001). Transformations were produced for the summer, fall, and change imagery.

4.2. Biophysical data

Biophysical data were selected for model development based on known relationships to interior forest plant communities (Pfister et al., 1977; Cooper et al., 1991; McNab & Avers, 1994; Kuennen & Nielsen-Gerhardt, 1995; USDA-Forest Service, 1999; Leavell, 2000). It was important to include key biophysical variables in the model, given that satellite data are an expression of overstory reflectance and that associations are defined by collective floristics, including understory vegetation. Biophysical variables used in this study are listed in Table 2.

4.3. Reference data

Our reference data were taken from an existing database (Ecodata) of over 4000 plot records from the Kootenai NF. The majority of these data were collected during the field seasons of 1993 to 1998 for purposes other than mapping. Most plot samples were collected using representative sampling within 6th-code level watersheds that had been stratified by vegetation response units (VRUs), each similar in potential vegetation and disturbance history. Plot data relevant to this study included location information and plant composition, the data necessary to identify alliances and associations.

Table 2. Listing of all biophysical data used in this study

Biophysical Variable	Description
precipitation	PRISM annual precipitation continuous data model, derived from weather station data and digital elevation model.
land type	Thematic data of topoedaphic types taken from the Kootenai NF land systems inventory (Kuennen & Nielsen-Gerhardt, 1995) – 16 classes.
vegetation response units	Thematic data based principally on potential vegetation, land type, and fire ecology relationships – 15 classes.
solar insolation (2 models; east-west, north-south)	Continuous data models of solar radiation based on slope, aspect, and digital elevation model.
elevation	Digital elevation model of land surface terrain (continuous).
subsection	Thematic data of subsection level ecological delineations taken from McNab and Avers (McNab & Avers, 1994) – 7 subsections.
potential vegetation	Thematic data of USFS PNV model representing potential vegetation, modeled according to existing vegetation, succession, climate, geology, and soils – 38 types.

Data summaries and sources are included in the description for each variable.

5. Methods

The project was carried out in five stages – map unit design, image object development, image classification, reference data synthesis, and map validation of alliance and association maps.

5.1. Map unit design

Map unit design is an iterative process and ideally balances mapping objectives, the vegetation type classification, and the capabilities of technology and resources. The goal in solidifying a map unit legend reflects an optimization between the accuracy and precision of map units. Given the limitations in technology and resources and the error inherent in map unit generalization, a one-to-one relationship between the vegetation classification and the map units is uncommon; however, in this study, vegetation types and map units *were* one in the same (Table 1).

In the NVC, life form dominance is identified according to a canopy cover threshold of 10% (TNC & ESRI, 1994), giving tree species first priority, followed by shrubs, and then herbs. Plant communities with a total tree canopy cover of 10% or more are considered 'tree dominated'. Early in our image classification tree-dominated plant communities were split into 'conifer' and 'broadleaf' classes based on the respective abundance of conifer and broadleaf components. To date, broadleaf communities have not been classified in terms of existing vegetation for northwestern Montana. As a result, an additional map unit was added to the legend, 'broadleaf', to collectively represent all broadleaf-dominated tree communities. And since the classification of non-forest vegetation in the study area has not been comprehensive, only conifer forest alliances and associations were mapped with this project. Non-forest feature space was mapped as one of four generic map units, either 'shrub', 'herbaceous', 'sparsely vegetated', or 'water'. For the final map products, shrub and herb communities were grouped into one 'herbaceous/shrub-dominated' map unit that collectively makes up a minor percentage of the study area (<5%). With the exceptions of 'cloud' and 'shadow' (see Image Classification – Upper Levels), the map units presented here provide an accounting of all feature space.

5.2. Image object development – segmentation

Spectral data were first used to develop a configuration of *object primitives* over the spatial extent of the study area. Object primitives are the basic, unclassified map polygons created through the union, or *segmentation-merge*, of contiguous pixels with similar values (Lillesand & Kiefer, 2000). We modified segmentation parameters in eCognition to locally minimize heterogeneity and to optimize the delineation of the dominant vegetation, canopy density, and tree size class. In eCognition the user selects 1) which variables (spectral or biophysical) to include in the segmentation process, 2) how each variable is weighted, 3) the level of desired heterogeneity ('scale parameter'), and 4) to what degree spectral values ('color') are weighted against continuity ('shape') of the image objects. Numerous object configurations were generated to arrive at the most suitable segmentation product for our image classification work. Parameters of the selected version of segmentation are listed in Table 3. Figure 2 illustrates a subset of the image object configuration chosen for this study. These image objects, averaging 1.6ha, formed the base model units for the subsequent image classification.

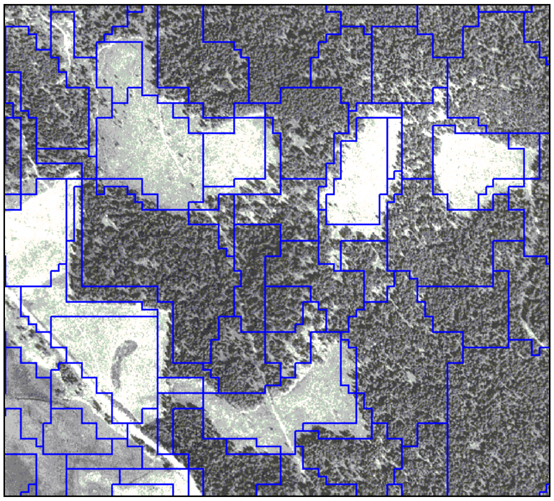

Fig. 2. Polygon configuration of image object primitives (unclassified polygons) in the vicinity of Fortine, Montana.

Table 3
Segmentation parameters used to generate the selected image configuration in eCognition

Variables	Weighting	
Blue	0.5	
Green	0.5	Scale parameter – 7
Red	1	Color-shape ratio – 7/3
Near-IR	1	
Mid-IR 1	4	
Mid-IR 2	4	
NDVI	1	

The 'weighting' is a relative measure of the emphasis placed on the variable in the segmentation process

5.3. Image classification – upper levels

Figure 3 shows the classification hierarchy used for in this study. The hierarchy served as a blueprint for the partitioning of feature space, starting with coarse physiognomic units at the upper levels, and finishing with the classification of floristic units at the lower levels. In eCognition, rule sets are comprised of *membership functions* at each node of the decision tree. Membership functions are either Boolean, fuzzy, or nearest neighbor expressions, that, alone or in combination, are structured to the demands of the classification, weaker contrasts requiring more sophisticated classifiers. For the most part, we employed fuzzy logic to classify upper level classes where contrasts between classes were often subtle. Where the classification utility of any one variable may have been marginal, the collective utility of several select variables in a fuzzy rule set was made suitable for image classification. As an approximate form of reasoning, fuzzy systems leverage *trends* between classes where there are no definitive boundaries (Eberhart et al., 1996).

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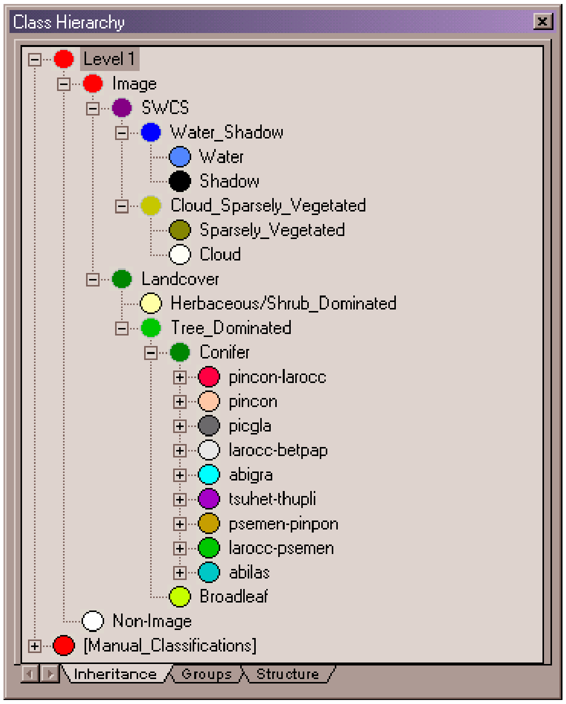

Fig. 3. eCognition user interface showing upper and lower levels of the classification decision tree.

Based on an understanding of local ecological gradients, we employed visual, on-screen interpretations of vegetation conditions for the image classification of upper-level classes (á la Bobbe et al., 2001). Qualitative assessments were based on aerial photography coupled with various image data (pan-sharpened TM data, Landsat TM panchromatic, digital orthoquads) suited for interpretation of coarse-scale land cover attributes. The classification process for the upper levels is summarized here: 1) digital band combinations were adjusted in the eCognition view window to highlight vegetation and land cover features (ETM+ band weighting 3, 5, 4 for blue, green, and red, respectively (USDA-Forest Service, 2002)); 2) a heads-up selection of sample objects was performed to adquately represent the spectral and biophysical variance of opposing classes at a given node in the decision tree – upwards of 200 samples selected for each class depending on variability and abundance of the class; 3) sample frequency histograms and the degree of overlap between classes were assessed to identify the variables that best divulged contrasts between opposing classes; 4) 'feature space optimization' analysis was performed in eCognition to identify the strongest differentia (see following description); 5) mathematical logic was written to partition classes based on the selection and variance of key differentia; 6) image classification was run using the new rule set; and 7) the performance of the models were reassessed. eCognition's accuracy assessment tool was especially useful in the classification of upper level classes. In this case, the accuracy assessment tool did not provide a true accuracy assessment since there were no independent samples. But it did provide an easy means for assessing the distribution of training samples among modeled classes. Coupled with a visual inspection of the classification results, the accuracy assessment tool allows for the rapid analysis of classification results for basing modifications to the mathematical logic.

The upper level image classification involved the separation of basic entities – 'image'/'non-image', 'water', 'cloud', and 'vegetated'/'sparsely vegetated'. Classification progressed to the levels of tree-dominated vs. herbaceous/shrub-dominated, and conifer vs. broadleaf (Fig. 3). For the most part, fuzzy functions were written for partitioning upper level classes. Fuzzy logic allows for fewer rules (Rickel et al., 1998) and simpler, more exacting manipulation of the functions themselves. Occasionally objects were manually classified where membership functions provided a poor rendering of land cover classes. While the majority of clouds, water, and shadow could be modeled, it was still necessary to manually classify many of these objects. At the completion of the upper level classification, 'conifer' feature space, under tree-dominated, was ready for the application of training data and image classification into alliances and associations.

5.4. Reference data synthesis

All 918 suitable plot records were analyzed and labeled by alliance and association with the aid of a field key and the constancy tables included with the community classification (Leavell, 2000). Each plant composition form was assessed individually, making this the most labor-intensive step of the project. Fifteen percent of the plots from each class of alliance and association were reserved as map validation samples, the remaining plots designated as training data.

5.5. Image classification – lower levels

The image classification of the floristic types occurred in five stages: feature space optimization, identification of outliers, nearest neighbor sampling, and the analysis and application of biophysical limiters. Where as fuzzy rules were used for feature space classification of the upper levels of the classification hierarchy, a nearest neighbor function was used for classification of the lower levels, alliances and associations. At the floristic levels contrasts between classes were weakest, too inconspicuous for visual assessment and expert classification systems based on fuzzy rule sets. At this point nearest neighbor sampling was used for classification of alliances and associations by using training samples and key biophysical and spectral variables for differentiating classes. Nearest neighbor is used to predict the class values of the majority of image objects based on the observed values of the minority of image objects that bear knowledge as training data. All nine alliances were classified based on a single nearest neighbor function, followed by the development of separate nearest neighbor classifiers for each set of associations within their respective alliance. Prior to the classification of associations, all reference data (training and validation samples) were used to generate a final alliance map to enable an independent assessment of association classifiers, based on a separate stratified selection of association validation samples.

While numerous biophysical variables were evaluated for their correlative value to alliances and associations, spectral variables were not included in the original classification work and canonical correspondence analysis on the Kootenai NF (Leavell, 2000). *Feature space optimization*, (FSO) a classification support tool in the eCognition program, was used to identify optimal differentia from the suite of available biophysical and spectral variables, according to patterns expressed in the training data. All variables were selected for analysis, first for the classification of alliances, and then for the classifications of associations within each alliance. As five of the nine alliances include only one association, only four sets of associations were analyzed. Along with the best differentia, FSO reports separation distances so that the user can evaluate the relative separation between classes (of training samples). Separation distances are represented by coefficients, typically reported on a scale of 0 to 1, which provide a relative measure of the ability of nearest neighbor to separate classes in feature space according to the selected variables.

Outliers were removed from the pool of reference data with the intention of reducing noise and improving the performance of nearest neighbor classifiers as well as the effectiveness of the map validation. Reference samples were assessed based on the ten best variables identified in the feature space optimization of alliances. Individual outliers were identified in Excel using the 'histogram' function in the data analysis tools. Only the most obvious outliers were removed owing to the potential variability of conditions within each class and the paucity of available samples in some classes. In two instances it was necessary to perform additional random selections to replace map validation samples that had been removed as outliers.

Once outlier samples were eliminated, nearest neighbor sampling was performed for classification of alliances and associations. The nearest neighbor function in eCognition samples every target object (predicted) against every training site (observed) based on the variables from FSO used to build the nearest neighbor function. The sample routine uses a Euclidean distance measure to determine the degree of separation between target and training objects, and then imputes the class label from a given training sample to the target object based on the least Euclidean distance. Likewise, FSO and nearest neighbor were used to classify each set of associations following the classification of alliances. After the classification of alliances and prior to the classification of associations, an intermediate alliance classification was carried out using *all* samples (both training and map validation) so that the error evident in the alliance classification would not be imposed on the association classification: in this way we could test the performance of alliance and association independently.

Biophysical value limiters were identified and combined with nearest neighbor classifiers to eliminate far reaching classification results and improve the overall performance of alliance and association classifiers. Limiters were developed for elevation, land type, subsection, and VRU according to the known limits of alliances and associations expressed in plant community descriptions (Leavell, 2000; Triepke, 2003; USDA-Forest Service, 1999). This analysis was completed in conjunction with a series of GIS exercises to determine the variability among training samples for elevation, land type, subsection, and vegetation response unit within each alliance and association. Simple Boolean expressions were joined to existing nearest neighbor functions in eCognition to complete alliance and association classifiers. For example, an elevation limit of 1680m was included with the nearest neighbor function for the PSEMEN-PINPON alliance to limit the image classification of this type to feature space below 1680m.

5.6. Map validation

Accuracy assessments are integral to vegetation mapping projects (Stehman & Czaplewski, 1998) and provide the map user with objective information on the utility of map products for practical applications (Congalton, 1991; RIC, 1995; Congalton & Green, 1999; Bobbe et al., 2001). Our assessment is more appropriately termed a *map validation* since a true accuracy assessment requires an independent probability sample: our training and validation samples were taken from the same preferential data set. We performed two separate validations for the alliance and association maps, using fifteen percent of the plots reserved from each class at the onset of image classification. Stratified random selections were made from each alliance and association using the 'random sampling function' in Excel. The procedure ensured an element of randomness desired for accuracy assessment (Stehman & Czaplewski 1998; Bobbe et al., 2001).

As in the case of this study, accuracy assessments for map products are normally presented in an error matrix (Congalton, 1991; Stehman & Czaplewski, 1998)(Table 5). Classes were ordered by similarity along the each axis of the error matrices according to distance values reported with FSO.

6. Results

Feature space optimization was performed on the set of nine alliances, and again on each set of associations within each alliance, to determine the variables best suited for use in image classification. The graph in Figure 4 shows the results of FSO for alliances, with the number of variables (dimensions) against separation distance, showing the peak separation of 0.655 at the 42nd dimension.

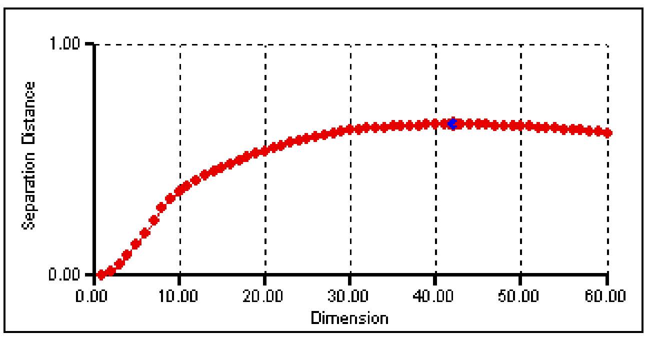

Fig. 4. Feature space optimization results for classification of alliances. Graph shows peak separation between alliances at the 42nd dimension (i.e., using 42 primary differentia).

The 'best separation distance' of 0.655 is actually the minimum separation value of all pair-wise comparisons of alliances. In this case, it was the separation distance between the LAROCC-PSEMEN alliance and the PSEMEN-PINPON alliance. Separation distances between all other classes were higher. The separation coefficients are listed in Table 4 along with the optimum number of differentia to use in the associated nearest neighbor functions (see Image Classification – Lower Levels).

The first ten of 42 differentia used in the classification of alliances included: 1) precipitation, 2) solar insolation – east-west, 3) near-IR, 4) NIRM, 5) VRU, 6) solar insolation – north-south, 7) land type, 8) potential vegetation, 9) elevation, and 10) mid-IR 1. The three most highly correlated variables identified with the original plant community classification work (land type, solar insolation, precipitation)(Leavell, 2000), were underscored by FSO analysis. Along with the list of key differentia, distance matrices were produced that indicated the degree of separability between classes in feature space.

Table 4
Feature space optimization results

FSO Analysis	Relative Separation	Dimension
All alliances	0.655	42
Western hemlock – western redcedar assoc.	0.663	23
Subalpine fir assoc.	0.636	38
Western larch – Douglas-fir assoc.	0.662	46
Douglas-fir – ponderosa pine assoc.	0.520	43

Relative separation based on the proportion of the 'best separation' to the reported scale (usually 0-1).

Overall accuracy for the alliance map was 59% while the *area-weighted user accuracy* was 60% (Table 5). User accuracy values for individual alliances ranged between 25% and 78%. The highest values occurred in the *western hemlock – western redcedar* alliance (78%) and the *subalpine fir* alliance (75%). The lowest values were in the two lodgepole pine alliances: *lodgepole pine* alliance (25%) and *lodgepole pine – western larch* alliance (36%).

Table 5
Alliance error matrix

Alliance	PSEMEN-PINPON	ABIGRA	TSUHET-THUPLI	LAROCC-PSEMEN	PINCON-LAROCC	PICGLA-GALTRI	LAROCC-BETPAP	PINCON	ABILAS	% User Accuracy
PSEMEN-PINPON	13	1	1	7	1					57
ABIGRA	2	4		1						57
TSUHET-THUPLI	1	1	7							78
LAROCC-PSEMEN	8	1	2	22	1		1	2	4	54
PINCON-LAROCC	1	1		4	4				1	36
PICGLA-GALTRI				1		2				67
LAROCC-BETPAP	1		1	1			2			40
PINCON			1					1	2	25
ABILAS	1	1	1	3	1			1	24	75
# Samples	27	9	13	39	7	2	3	4	31	
Area (hectares)	124456	37260	78879	163351	54453	3699	10764	18129	159179	
Overall accuracy		59%								
Area-weighted user accuracy		60%								

Columns in the error matrix show the distribution of validation samples among the mapped classes they intersect. Rows represent the classified image data. Strata occurring along the major, highlighted diagonal contain samples in agreement with mapped classes. All off-diagonal elements reflect mapping error: errors of commission are expressed in the distribution of samples to either side of the major diagonal, errors of omission are reflected in the distribution of samples above and below the diagonal. O*verall accuracy was* calculated by dividing the number of correct samples listed along the major diagonal by the total number of map validation samples. The *area-weighted user accuracy* was determined by weighting individual user accuracy values by the area in hectares mapped for each class of alliance.

Table 6
Summary of four association error matrices (not shown)

Associations	**# Samples**	**# Correct Samples**	**Overall Accuracy**
TSUHET-THUPLI Assoc.	14	12	86%
ABILAS Assoc.	32	19	59%
LAROCC-PSEMEN Assoc.	39	21	54%
PSEMEN-PINPON Assoc.	26	22	85%
Overall accuracy	**67%**		

Accuracy was similarly determined for associations within each alliance (Table 6). Since all reference data (training and validation samples) were used to generate a final alliance map prior to the classification of associations, the association map validation assumes 100% accuracy at the alliance level. Association user accuracy values ranged from 0% (four associations) to 100% (six associations), with a fairly even distribution of estimates across this range, and a concentration of values nearer 60%. Four of the nine subalpine fir associations had user accuracy values of 100%. Note that the user accuracy values in Table 6 are only reported for the associations with more than one association per alliance. The overall accuracy of the four sets of associations was estimated to be 67%.

7. Discussion

7.1. Feature space optimization

Of the five FSO analyses conducted with this study (Table 4), the TSUHET-THUPLI associations (see Table 1) required the least number of differentia (23) and received the highest separability value (separation distance 0.663). The image classification of TSUHET-THUPLI associations also resulted in the best overall accuracy (86%; Table 6). Conversely, LAROCC-PSEMEN associations required the highest number of differentia and received the lowest overall accuracy (54%). The dimension necessary to obtain peak separability may provide an indication of the contrast between classes and the classifier's ability to tease apart classes in feature space – the higher the required dimension, the more difficult the classification.

At least half of the top ten differentia for each classification group, one alliance and four sets of associations were biophysical indicators. Even with the classification of alliances, which are defined principally by one or few overstory components, seven of the first ten differentia were biophysical. Presumably an image classification of existing vegetation would be driven primarily by spectral reflectance, particularly in the case of overstory vegetation. There are two difficulties in modeling plant associations with remote sensing alone. First the association, and thus the parent alliance, are defined by the collective floristics. Even though there are often characteristic dominants, at any given time the association may be dominated by different plant species and provide different spectral patterns. Second, different associations with similar overstory components can have similar reflectance values. Our FSO results, with all of the indicated biophysical differentia, corroborate these concepts. The results further corroborate the importance that Daubenmire (1968) and others have placed on the biophysical environment in determining the collective presence (and absence) of plant community constituents (Leavell, 2000).

7.1. Map products summary

A qualitative assessment of the alliance map based on Forest Service inventory records and Kootenai NF land systems inventory (Kuennen & Nielsen-Gerhardt, 1995), regarding the distribution and amount of forest types across the study area, suggests that the alliances are correctly proportioned and in proper juxtaposition to one another from one drainage to the next. Likewise the distribution of alliances across larger geographic extents (e.g., subsections) also reflects the appropriate position and proportion. Similarly with the association map, the associations are generally arranged in predictable patterns along known elevation, moisture, and land type gradients (Pfister et al., 1977; Cooper et al., 1991). The ABILAS-PINALB / VACMEM association, having a relatively narrow ecological niche, was clearly overpredicted through lower elevation zones and across greater extents than have been previously characterized (Leavell, 2000). Also, the LAROCC-PSEMEN / VACMYR and ABILAS-LAROCC / VACMYR associations were sometimes confused in terms of moisture and elevation gradients, with LAROCC-PSEMEN / VACMYR occurring upslope of the ABILAS-LAROCC / VACMYR association, rather than in reverse as their habitat niches would suggest. Though these associations do not have particularly narrow amplitudes, they do have predictable distributions based on their biophysical correlates, implying that their misplacement may be due to noise in the reference data or to insufficient sample number. Otherwise, the spatial distribution of the remaining ABILAS and LAROCC-PSEMEN associations is consistent with their known ecology (Leavell, 2000). The TSUHET-THUPLI / TIATRI association was mapped over a greater extent than expected (over 8,000 hectares), possibly stemming from a low sample number (3) and exaggerated variance in the signature for this type. Otherwise, the associations of the TSUHET-THUPLI alliance and the remaining alliances follow predictable spatial patterns (USDA-Forest Service, 1999; Leavell, 2000; Triepke, 2003).

7.2. Map validation

With the alliance map, errors of commission (Table 5) are especially noticeable in the PSEMEN-PINPON, LAROCC-PSEMEN, and ABILAS alliances. Seven of the 23 validation samples that fell in PSEMEN-PINPON map features were LAROCC-PSEMEN samples; not surprising, given that the LAROCC-PSEMEN had the shortest separation distance from the PSEMEN-PINPON alliance, and vice versa. Errors of commission with the ABILAS alliance include single samples from all other classes except the LAROCC-BETPAP and PICGLA-GALTRI alliances, the two classes with the greatest separation distances from the ABILAS alliance. As the user accuracy values indicate, the TSUHET-THUPLI alliance had the fewest errors of commission.

Errors of omission were most evident in the PINCON alliance where classification is confused with the ABILAS and LAROCC-PSEMEN alliances. Patterns of ecological proximity and separation distances among these classes are evident in the distribution of user error, but for the most part the error is spread across several classes limiting the ability to manage error with our classifiers. More samples or other, untapped biophysical data may be needed to improve the alliance classification. That the omission error in the LAROCC-BETPAP alliance is shared with only one other class (LAROCC-PSEMEN) is as likely to stem from the low number of validation samples (three) as it is from low separability. Confusion between these two classes is understandable given their shared overstory dominants and the potential for spectral similarity.

At 60%, the area-weighted user accuracy of the alliance map falls short of the mid-scale mapping standard of 65% for Forest Service lands (Brohman & Bryant, 2005). The overall user accuracy was nearly the same at 59%. It is difficult to compare these results with other mapping studies given the novelty of mapping alliances (and associations) using remote sensing. For instance, the recent Southwest ReGAP land cover mapping (Lowry et al., 2005) resorted to mapping 'ecological systems', aggregations of alliances, due to the inherent challenges of mapping finer floristic units. Their map validation suggests an overall accuracy level of about 60% even with the compromise in thematic detail. Other efforts that have focused on existing vegetation, using similar regression classifier methods at similar or less thematic detail, have achieved similar results in overall accuracy in the high fifty and low sixty percentiles (e.g., Steele, 2000). A study conducted in the Rocky Mountains of southern Canada, using combinations of nearest neighbor classifiers to map subalpine forest types, with a superior sample set, produced high user accuracy estimates in the sixty percentiles and above (Collins et al., 2004).

When considering associations of all nine alliances (not just those with more than one association), the overall accuracy of the association map falls just short of mid-scale mapping standard of 65%, with an area-weighted user accuracy of 61% and an overall accuracy of 62%. In the association error matrices, commission error is particularly obvious in the TSUHET-THUPLI / TIATRI association where no samples were captured in feature space of the association. All TSUHET-THUPLI / TIATRI validation samples occurred as omission errors in TSUHET-THUPLI / PAXMYR feature space. Here again, misplacement may stem from the low sample size and an exageration in the breadth of the signature for this type. User accuracy of the remaining two associations in the alliance was 100%. In the ABILAS alliance, the ABILAS / ALNVIR, ABILAS-PINCON / VACMYR, and ABILAS-PINALB / VACGLO associations were nearly always in error, the former association exhibiting multiple samples in commission. Conversely, the user accuracy estimates of the remaining associations of this alliance are acceptable, most over 65%. The overall user accuracy of the LAROCC-PSEMEN associations is lower at 54%, the lowest overall accuracy of the four individual association matrices. The LAROCC-PSEMEN / VACMYR and LAROCC-PSEMEN / VACGLO classifications performed poorly, each with user accuracy estimates of less than 40%. The overall user accuracy of the PSEMEN-PINPON associations is exceptional at nearly 85%. The classification problems that did exist in the associations were primarily errors of omission within the PSEMEN-PINPON / PHYMAL association. Of the 21 accuracy samples of the PSEMEN-PINPON / MAHREP association, 20 were mapped correctly.

7.3. Aggregating classes to improve accuracy

The thematic resolution of map units often reflects an optimization between accuracy and precision. For some map applications, map units can be aggregated to improve accuracy, albeit at the expense of thematic detail. The previous map validation demonstrated the error structure of alliance and association maps. Based on the association map, the following exercise illustrates an approach to the logical aggregation of map units to achieve greater map accuracy. , We focused on the association map given that the aggregations of alliance map units would also impact the association map.

We aggregated associations according to the distance coefficients from their similarity matrices, analogous in approach to a technique employed by Zhenkui et al. (2001) in merging spectral classes based on a similarity matrix following an unsupervised classification. We applied the following rules: 1) all associations with user accuracy values of less than 50% were aggregated; 2) groupings were based on biophysical and spectral similarity, low-accuracy classes being combined with the next most similar class of acceptable accuracy; 3) only associations were combined to maintain the integrity of alliance-level detail (no single-association alliances were combined regardless of user accuracy value).

The map product resulting from this post-classification grouping of associations reflects a 40% reduction in thematic detail, from 24 to 17 map units; however, map accuracy increased significantly from 61% to 79% area-weighted user accuracy, and from 61% to 79% in overall accuracy. This map product surpassed the Forest Service mapping standard and nearly met the greater map accuracy goal of 80% for mid-scale mapping (Brohman & Bryant, 2005).

8. Conclusions

Remote sensing-based classification has become the primary means of vegetation mapping (Bobbe et al., 2001). Remote sensing technologies offer an affordable means for the consistent and accurate depiction of spatial features in an area of interest. Plant association maps and their associated community descriptions form a qualitative and quantitative, spatially delimited knowledge base of biological communities that can be used by researchers and land managers.

The map validations developed with this study suggest that map quality could be improved through sample design and increased sample number to generate a stronger reference database. These data could be gathered through sample methods specific to the purposes of mapping. For the mapping effort overall, and for some classes in particular, the sample numbers did not adequately represent the map units. The problem is accentuated in nearest neighbor sampling given the poor distribution that an incomplete sample set would portray. Congalton and Green (1999) suggests upwards of 50 samples per vegetation type for accuracy assessment alone, inferring that the total number of training samples collected be several times that amount. The actual sample number will depend on the complexity of vegetation types, the relationship of ecological variation to readily identifiable attributes present in plant communities (RIC, 1995), and the availability of time and resources to accomplish a suitable sampling campaign.

No doubt there are means of improving the classifiers developed with this project. We would, for instance, like to evaluate the effect of increasing the depth of the decision tree. The nearest neighbor function built for classification of alliances was likely too generic to classify any one class well. The same is likely the case for classification of *subalpine fir* associations where a step-wise approach would be preferable to taking on ten associations in one classifier. A more suitable approach would have been a classification hierarchy with more depth, several nodes with more exacting classifiers at each node.

We would also like to test a multistage nearest neighbor sampling technique that further leverages training data and the segmentation capabilities of the eCognition program. The premise of this technique is that the objects most confused spectrally are also the most difficult to classify correctly. Our strategy for managing these objects would be to execute nearest neighbor sampling in stages, over smaller and smaller, more homogenous areas. The eCognition program allows for *classification-based segmentation* so that a series of nearest neighbor classifiers can be developed according to the establishment of a set Euclidean distance rule. Objects not meeting the Euclidean distance rule, labeled as 'unclassified', would be further segmented into smaller, more homogenous units that are, in turn, subjected to the same nearest neighbor classifier. The classification proceeds in stages until all or most objects are classified according to the Euclidean distance rule.

The area-weighted user accuracy estimates of the alliance and association maps, 60% and 61%, respectively, do not meet the classification and mapping technical guide standard of 65% for mid-level mapping (Brohman & Bryant 2005). To help meet standards and facilitate some applications, an approach based on the aggregation of map units was discussed as a way to improve accuracy resulting in an increase in the area-weighted user accuracy of our association map from 61% to 79%. The quality of the alliance and association maps developed for the upper Kootenai River study area suggests an acceptable level of precision and a marginal level of accuracy for some purposes. A map based on the aggregation of some classes may be useful for applications that require greater accuracy and less precision (e.g., Forest Plan revision). Map products produced with this project may be useful for coarse-scale work involving landscape assessment, habitat modeling, old growth management, guiding inventory and monitoring plans, and other resource management purposes commensurate with this scale of work (Daniel & Fox, 1999; Cohen & Goward, 2004). Map units with higher accuracy may be suitable for base-level work that is being focused in those particular vegetation types. Finally, these maps should be used for further inventory and research regarding the characterization and analysis of existing vegetation types and their ecosystems. We would also encourage the routine maintenance and improvement of map products on a schedule in line with planning cycles, new information and technology, research requirements, and significant new directives and changes in management policies.

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