Map-Guided Classification of Regional Land Cover with Multi-Temporal AVHRR Data

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Abstract

Cartographers often need to use information in existing land-cover maps when compiling regional or global maps, but there are no standardized techniques for using such data effectively. An iterative, "map-guided" classification approach was developed to compile a spatially and thematically consistent, seamless land-cover map of the entire Intermountain Semi-Desert ecoregion from a set of semi-independent subregional maps derived by various methods. A multi-temporal dataset derived from AVHRR data was classified using the subregional maps as training data. The resulting regional map attempted to meet the guidelines of the proposed National Vegetation Classification System for classification at the alliance level. The approach generally improved the spatial properties of the regional mapping, while maintaining the thematic detail of the source maps. The methods described may be useful in many situations where mapped information exists but is incomplete, has been compiled by different methods, or is based on inconsistent classification systems.

Introduction

Cartographers are often asked to compile land-cover maps of specific regions for which land-cover mapping already exists for smaller subsets of the region. These existing maps are rarely ideal for the assigned task because they may be outdated, use a classification scheme designed for a different set of objectives from the current task, or are not at the desired spatial resolution. Sometimes several maps, perhaps covering the entire study area, will be available but have different temporal, thematic, and spatial properties from each other as well as from the target product. The two most commonly used options for dealing with existing maps are remapping and mosaicking. With the first option, the cartographer chooses to ignore the information in the original maps and to remap the area rather than attempting to resolve their differences. The second option is to mosaic the maps together, perhaps with some attempt to match their classification scheme (i.e., "cross-walking") but retaining any mismatches that will likely occur at map boundaries. If the maps overlap, rules for determining the preferred map source must be identified. In addition, the cartographer could do the cross-walking plus attempt to smooth or adjust the mismatches in polygon boundaries and thematic labeling at map edges (i.e., "edge-matching"). If the region is quite large, both options (remapping and edge-matching) can entail more effort than is practical. Remapping is a particularly unsatisfying option given that it ignores so much available, if imperfect, data. Merely cross-walking maps into a common scheme may also be inadequate, not only for esthetic reasons, but also because the regional map may still lack the consistency necessary for the kinds of analyses for which it is being compiled. If the classification scheme of the source maps is too incompatible, the cross-walk may only be reasonable at a grosser level of aggregation than is useful for the analysis.

As a case in point, the Gap Analysis Program (GAP) (Scott *et al.*, 1993), coordinated by the Biological Resources Division of the U.S. Geological Survey (formerly the National Biological Service), is conducting assessments of the management status of native plant communities over entire multistate ecoregions. Maps of plant community types are compiled over the individual states within the region. Although GAP has standards for mapping land-cover, the maps produced for individual states are not entirely consistent, due to the evolution of the standards over the duration of the program, differences in interpretive methods, and differences in available ancillary information.

The objective of a regional gap analysis is to evaluate the conservation status of cover types at the "alliance" level, as surrogates for biodiversity as a whole. Alliances are defined by the dominant canopy plant species (FGDC, 1996). This is a more detailed classification than most regional-scale remote sensing applications that focus on structural rather than floristic differences (e.g., Running *et al.*, 1995; Cihlar *et al.*, 1996). There has been concern about the feasibility of edge-matching the state-level GAP maps to make a seamless regional land-cover map (Zube, 1994; DellaSala *et al.*, 1996).

Initial examination of the state-level land-cover maps of a region in the western United States suggested that simply mosaicking them would not provide the consistent product needed for gap analysis. Some classes were too general, while others were too detailed. The spatial resolution varied considerably according to the mapping method and the remote sensing and ancillary data sources used. Mapping the region again but using a single method was considered an unacceptable alternative given the large investment in producing the state maps. The task then was to synthesize a regional map from the existing GAP state maps, improving the

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spatial and taxonomic consistency while maintaining their best information. The desired consistency refers not only to the vegetation classification but also to the spatial resolution of the map and to the absence of artificial seams at state boundaries created by independent mapping.

An innovative approach was developed for this research project using existing maps as training data for classifying NOAA Advanced Very High Resolution Radiometer (AVHRR) meteorological sensor data. The objectives of this paper are to present this "map-guided classification" technique with an example from a region of the Intermountain West and to determine whether AVHRR data products could provide the desired spatial consistency and thematic detail. The generality of the technique to similar applications for compiling land-cover maps will be discussed as well as the limitations. This effort marks one of the first applications of the proposed National Vegetation Classification System (NVCS) (FGDC, 1996) at a regional mapping scale and, therefore, provides one test of the feasibility of implementing these standards in real-world situations.

Background on Broad Scale Land-Cover Mapping

Regional to global land-cover mapping has become an increasingly important data source in a variety of scientific studies, including land-use change, biogeochemistry cycle modeling, climate modeling, water-energy-vegetation interactions, and ecosystem response to environmental change (summarized in Townshend *et al.* (1994)). For such studies, land cover often needs to be determined only at a structural level, perhaps discriminating life-forms (tree versus shrub versus herbaceous), leaf longevity (evergreen versus deciduous), and leaf type or shape (needle- versus broad-leaved). However, knowledge of the floristic variation in plant community types is critical in planning conservation strategies that will protect all species and communities (Scott *et al.*, 1993).

Landsat Thematic Mapper (TM) data are generally not a viable option for mapping land cover over large regions because of the immense data volumes required, particularly if multi-date imagery is necessary to discriminate between land-cover types. With its relatively narrow swath width, TM imagery can not always be obtained from the same date over the entire region, which adds atmospheric and phenological variability to the dataset and complicates accurate classification. With few satellite passes during the growing season, Landsat also provides few opportunities to obtain cloud-free images of an entire region.

AVHRR imagery has become a popular alternative for land-cover mapping at regional to global scales because it is relatively inexpensive, has high temporal frequency for avoiding cloud cover, and has more manageable data volumes than TM. Most often, multispectral AVHRR data are first transformed into a single index such as the Normalized Difference Vegetation Index (NDVI) and composited over a 10- to 30-day period to reduce cloud cover (Holben, 1986). Loveland *et al.* (1991), for example, used eight monthly composites of NDVI to classify land cover of the conterminous United States. Kremer and Running (1993) were able to separate big sagebrush, introduced cheatgrass, and native bunchgrass at the Department of Energy's Hanford Reservation in Washington state by utilizing phenological differences detected from multi-temporal composites of NDVI. Lloyd (1990) derived phenological variables from similar NDVI composites and classified them. Lambin and Ehrlich (1995) integrated NDVI with land-surface temperature from AVHRR thermal infrared data to improve classification of land cover in Africa. Cihlar *et al.* (1996) also worked with NDVI, reflective red and near-infrared channels, and one thermal band to classify land cover in Canada. They used principal components analysis to extract the main phenological patterns in each channel or index. In discriminating relatively simple classes on a global scale, combinations of NDVI-derived phenological variables (e.g., amplitude of NDVI from annual minimum to annual maximum) and thermal data (e.g., maximum annual land-surface temperature) produced results superior to applying the NDVI composites directly (DeFries *et al.*, 1995). Running *et al.* (1995) have proposed a classification logic based on these phenological variables (i.e., derived from NDVI) for global land-cover mapping into 12 basic structural categories. Thus, there have been many datasets derived from AVHRR images that have been successfully used as inputs in regional land-cover classification, including direct indices such as NDVI, principal components of time-series data, and biophysical metrics derived from NDVI.

Several methods have been applied to classify land cover from these AVHRR-based indices over regional domains. The standard method is some form of statistical clustering such as maximum likelihood. Decision trees not only perform the classification, but also can reduce the dimensionality of the dataset while providing useful insights into the interrelations between variables (Lloyd, 1990; Running *et al.*, 1995; Hansen *et al.*, 1996). Only the input channels that best discriminate between classes are used, and the set of channels used to classify a given output class can vary between classes. Neural networks and evidential reasoning have also been applied to image classification (Gong, 1996) but are generally less familiar to most practitioners. The "best" classification method for land-cover mapping is still an open research question (Lloyd, 1990).

Existing Mapping of the Intermountain Semi-Desert Ecoregion

The study area for developing the map-guided classification methodology was the Intermountain Semi-Desert (ISD) ecoregion (Bailey, 1995). This ecoregion consists of the plains of the Columbia and Snake rivers and the Wyoming Basin in portions of Washington, Oregon, Idaho, Nevada, California, Utah, Wyoming, Colorado, and Montana (Figure 1). The ISD ecoregion is primarily characterized as sagebrush steppe, or

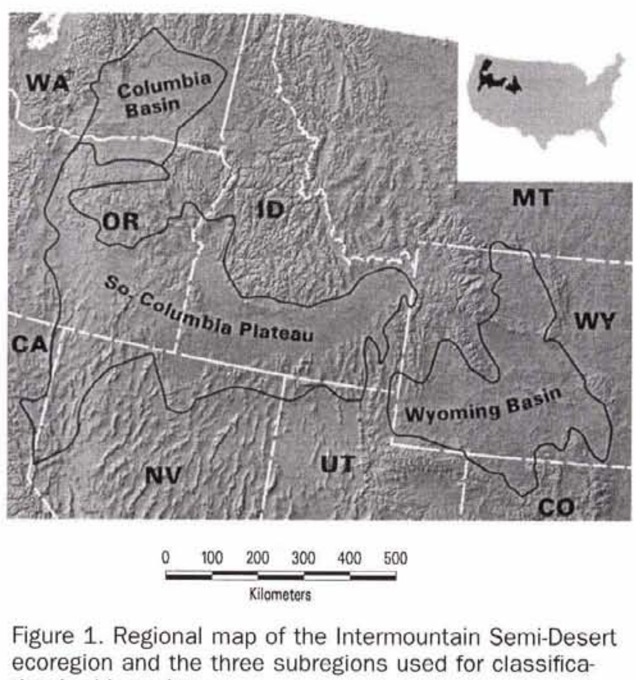

Figure 1. Regional map of the Intermountain Semi-Desert ecoregion and the three subregions used for classification in this project.

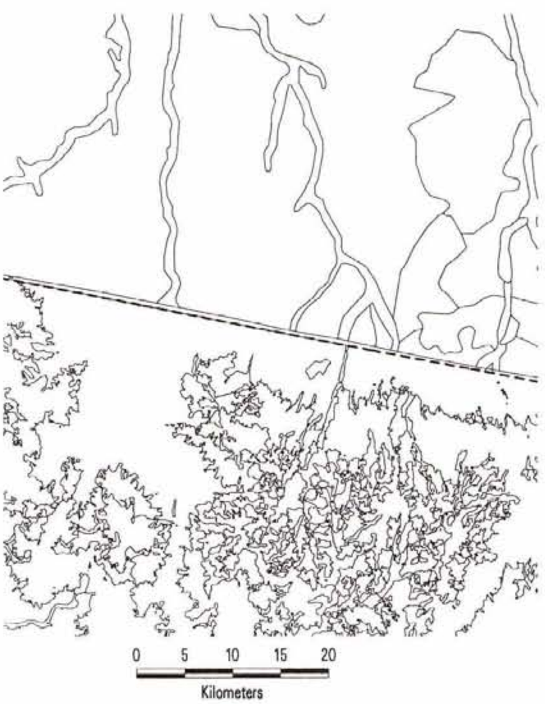

Figure 2. Detailed map of the original polygons from the state GAP maps of the Idaho-Nevada border.

sparse shrub cover (*Artemisia* species) interspersed with native bunchgrass (Küchler, 1970). The sparse shrub, grass, and woodland cover challenge most remote sensing techniques for determining land cover at the alliance level (Knick *et al.*, 1997). The various state-level GAP projects in this ecoregion were among the first to complete their land-cover mapping, but these semi-independent maps have not been compiled previously into a consistent, alliance-level, regional map. GAP and The Nature Conservancy were both eager to conduct regional conservation assessments and thus needed such a map as the basis.

The ISD ecoregion encompasses 412,000 km^2 (equivalent in size to the state of California) and a range of environmental conditions. The rainshadow effect produced by the Cascade-Sierra Nevada ranges favors shrub cover and limits tree cover to higher elevations, narrow riparian corridors, or sparse pinyon or juniper woodland. In low-lying areas that are subject to periodic flooding, sagebrush is replaced by saltbush (*Atriplex*) and greasewood (*Sarcobatus*) communities. Shrub species are replaced by perennial grasses where deeper soils occur. Most relatively level areas with adequate water supplies and suitable soils have been converted to agriculture (West, 1988). Annual grasses, especially cheatgrass (*Bromus tectorum*), have invaded the region since the 1870s. Cheatgrass is better adapted to frequent disturbance than is native bunchgrass for multiple reasons. It also creates self-perpetuating stands even when mechanical disturbance is removed because its dense cover burns hotter and more frequently than native grasses (Mack and Thompson, 1982; Rickard and Sauer, 1982). As a consequence, cheatgrass is now the dominant grass of the ISD ecoregion.

Despite the relatively homogeneous appearance of sagebrush steppe, the ecoregion is floristically complex. There are eight species or subspecies of *Artemisia* that dominate various plant communities. Three juniper and two pinyon species occur in different portions of the ecoregion. Additionally, many of these cover types have sparse canopies so that soils strongly affect the surface reflectance. Remote sensing alone would be an inadequate data source to distinguish the communities formed by these closely related and spectrally similar species.

The cover types in the ecoregion also display differences in their phenology which may be detectable with multitemporal remote sensing (Kremer and Running, 1993). The grasses flourish in the late spring and early summer while soil moisture from winter precipitation still remains (West, 1983). Cheatgrass becomes senescent by late May while bunchgrass (*Pseudoroegneria-Poa-Festuca* species) lasts until the end of June (Kremer and Running, 1993; Knapp, 1996). Deep-rooted sagebrush (*Artemisia* spp.) has a later growing season.

The purpose of gap analysis is to evaluate the extent and level of protection of mappable surrogates of biological diversity at a regional scale. To accomplish the objective, mapping can be moderately coarse in spatial detail but requires relatively fine discrimination of land-cover types to capture all the habitats important for biodiversity. The current standards for GAP land-cover maps are a minimum mapping unit of 100 ha (1 km^2) and a classification at the level of alliances. Two recent land-cover maps cover the region of interest: the seasonal land-cover regions map derived from 1 km^2 AVHRR time series data (Loveland *et al.*, 1991) and Küchler's map of potential natural vegetation (Küchler, 1970). The former has a suitable spatial resolution, but the classification is not sufficiently detailed floristically to meet GAP objectives. Küchler's map was at an extremely small scale and did not portray actual vegetation and thus was also not suitable for regional conservation assessment (Scott *et al.*, 1993).

Land cover has been mapped more or less independently for each of the nine states in the ISD ecoregion by the individual state GAP projects. Although most state GAP projects used 1990 ($\pm$2 years) satellite imagery from the Landsat Thematic Mapper (TM) sensor, combined with field inventories and existing maps of vegetation, in compiling their land-cover data, there were significant differences in methods and products. Maps for Idaho (Caicco *et al.*, 1995) and Oregon (Kagan and Caicco, 1992) were developed as prototypes and used photointerpretation techniques with older Multispectral Scanner images and larger minimum mapping units than did the other states. In contrast, land-cover mapping in Nevada and Utah was done with digital image processing of TM image mosaics and ecological modeling with topographic variables (Homer *et al.*, 1997). The 30-m pixels in the classified image were aggregated to the 100-ha minimum mapping unit (MMU). This approach generally achieved greater spatial resolution at some expense in classification detail. The other state GAP projects photointerpreted TM data (e.g., Davis *et al.*, 1995; Cassidy, in press; Driese *et al.*, 1997). Most of the maps have not yet been validated with a formal accuracy assessment (except see Caicco *et al.* (1995) and Edwards *et al.* (1995)) although some field data collection is underway.

Despite general similarities in these land-cover maps, they differ to some extent in the cover classifications used and in their spatial resolution. Further work was needed in cross-walking the separate classifications into a consistent regional scheme. Edge-matching is also a problem because the spatial grain of the maps changed across many of the state boundaries due to the methods rather than actual vegetative patterns (Figure 2). Grain tended to be much finer in states that used supervised classification of digital imagery than in those that used the photointerpretation approach.

The potential consequences of simply mosaicking and cross-walking the state GAP maps into a "patchwork quilt" regional map without some attempt at edge-matching are not only technical. Because these maps are intended to provide information to policy makers about the protection of plant communities and animal habitat, it is important that the final product be visually credible. A mosaic, while retaining the information in the state maps, has the effect of highlighting the inconsistencies and raising questions about the validity of the analysis. For these technical and policy-oriented reasons, we developed a methodology that retains much of the information in the original maps while minimizing inconsistencies between them.

Methods

The map-guided classification procedure requires four basic steps. The state maps are cross-walked to a common land-cover classification; AVHRR time series data and elevation data are preprocessed; the AVHRR and elevation data are classified using the cross-walked state maps as training data, and the output classified map is post-processed to deal with special cases.

The GAP land-cover maps for the individual states were cross-walked into consistent cover types according to the proposed National Vegetation Classification System (FGDC, 1996). This hierarchical scheme begins with structural and broad ecological properties at higher levels, with floristic divisions at the lower levels, even for Planted/Cultivated categories (Table 1). Although some of the GAP map classes matched directly with NVCS alliances, some classes could only be assigned at a higher classification level. Three main difficulties in the cross-walking arose: (1) not all states distinguished forest from woodland (a structural difference). This omission created uncertainty in assignment to a formation at the top of the classification tree even when the floristic assignment was certain. (2) Some GAP cover classes were labeled as mosaics of more than one type, often from two different structural formations. Furthermore, four states (California, Washington, Wyoming, and Colorado) labeled map units as landscape mosaics comprised of two or three cover types. Although this technique provides more thematic information than a single-value classification, the location within a polygon of the secondary cover types is not specified. Thus, these attributes are difficult to use in a traditional image classification approach. (3) Taxonomic (floristic) detail varied between states and between classes. In some cases, this occurred where the dominant species came from mixed types in more than one formation such as lodgepole pine-aspen. Alternatively, some cover types do not have a diagnostic species but contain a mix of species which varies from place to place. "Mountain brush" is an example of one of these diverse cover types that does not fit the NVCS scheme well. Some grouping of types was necessary where individual dominant species were impossible to determine. For example, grasses were aggregated into four types at the formation or subformation level: dry perennial grassland (dominated by *Pseudoroegneria* and *Poa* species), moist perennial grassland (dominated by *Festuca* species), artificial seedings of *Agropyron cristatum* and related species for rangeland improvement, and annual grasses (usually *Bromus tectorum*). These aggregations follow the NVCS hierarchy to the "group" level but constitute formations not in the standards to represent collections of alliances that could be identified with satellite data.

Multi-temporal AVHRR imagery was selected as an independent data source to provide a consistent spatial resolution for the regional map and to add plant phenologies as detected from space to aid classification. AVHRR can be effective in discriminating the sparse vegetation types of the Intermountain West (Kremer and Running, 1993). For map-guided classification, AVHRR data similar to the NDVI time series were compiled but with several differences. First, daily AVHRR images for the 1990 growing season were processed into ten-day (or 14-day during cloudy periods) composite images. This compositing process (Stoms *et al.*, 1997) uses a weighted combination of thermal infrared and satellite zenith angle to remove cloud contamination as well as to minimize the distortion in spatial and radiometric properties associated with off-nadir viewing. AVHRR datasets were generated for four periods throughout the 1990 growing season (5-16 April, 17-28 June, 20-31 July, and 19-30 September) to capture the main intra-annual variation of the phenology of the semiarid vegetation of this region. In particular, June was added to help discriminate between native bunchgrasses and cheatgrass. Selection of time periods was partially constrained by the number of dates for which imagery was available from the USGS EROS Data Center.

TABLE 1. LEVELS, PROPERTIES, AND EXAMPLES OF THE PROPOSED NATIONAL VEGETATION CLASSIFICATION SYSTEM (FGDC, 1996).

Level	Defining Properties	Examples
Order	Lifeform	Tree-, shrub, or herbaceous-dominated
Class	Lifeform and relative cover	Closed tree canopy (60-100% cover); open tree canopy (25-60%); shrubland with shrub cover >25% and tree cover <25%; herbaceous with shrub and tree cover <25%
Subclass	Leaf phenology, leaf type, periodicity	Evergreen or deciduous or mixed; perennial or annual
Group	Climate, leaf morphology and phenology	Temperate needle-leaved; Cold-deciduous
Subgroup	Source	Natural/Semi-natural or Planted/Culivated
Formation	Broad environmental and physiognomic factors	Rounded-crowned temperate or subpolar needle-leaved evergreen open tree canopy; Extremely xeromorphic deciduous subdesert shrubland with or without succulents
Alliance	Diagnostic or dominant species of overstory	*Juniperus occidentalis; Sarcobatus vermiculatus*
Community Association	Diagnostic or dominant species of overstory and understory	*Juniperus occidentalis/ Artemisia tridentata/ Poa secunda; Sarcobatus vermiculatus/Distichlis stricta*

The derived datasets included AVHRR Band 2 (near infrared), Band 4 (thermal infrared), and NDVI for each of the four composite periods (three bands for each of the four dates). Principal components analysis was used to reduce the large, relatively correlated dataset (Cihlar *et al.*, 1996; Hirosawa *et al.*, 1996). Five of the principal components, accounting for 85 percent of the variance in the 12 input channels, were then selected for use with the classifier. The first component is primarily an average annual reflectance of the near infrared or Band-2 data. The second component appears to contrast average annual thermal infrared with NDVI. The interpretation of the third and fourth components is less obvious, but the fifth component contrasts July near infrared with that of the other months, possibly reflecting the difference in grass phenologies. The AVHRR dataset provided a consistent, 1-km spatial resolution over the entire ecoregion.

Sometimes information classes in quite distinct ecological settings can have similar spectral characteristics. In such cases, the use of elevation or topographic data can assist in properly separating them (e.g., Franklin *et al.*, 1986; Cibula and Nyquist, 1987; Homer *et al.*, 1997). Therefore, as an additional input channel for the classifier, a 1-km-resolution digital elevation dataset (U.S. Geological Survey, 1993) was modified. The ISD region spans more than 8 degrees of latitude, which is large enough to produce shifts in elevational ranges of plant communities from the southern to the northern limits (Allen *et al.*, 1991). Consequently, the digital elevation pixels were adjusted 0.625 m higher per km of northness (Schoenherr, 1992) to generate an "equivalent elevation" image. All five principal components and the equivalent elevation data were normalized to the same dynamic range prior to classification by giving each band the same mean (126.5) and standard deviation (126.5).

The cross-walked state GAP maps were sampled to create training signatures. Rare and special land-cover classes were addressed differently than were the widespread map classes. Several of the 48 alliances in the ecoregion are relatively rare and tend to drop out of the output map if not given extra weighting in the sampling for training the classifier. A square root sampling strategy was applied for all other classes with more than 200 pixels in the input maps. For remaining types with fewer than 200 pixels, the entire population of the class was used in developing training signatures.

Map-guided classification is an iterative, two-step procedure. In the first step, unsupervised clustering is performed on a random sample of pixels using the ISOCLUSTER function in ARC/INFO GRID. Next, a standard maximum-likelihood classifier (MLCLASSIFY) in ARC/INFO GRID assigns unsampled pixels to these clusters. The information classes in the input map are compared with the spectral clusters, and the spectral cluster with the highest level of association (i.e., the highest ratio of pixels in a cluster and information class combination relative to the sum of pixels in the cluster in all classes) is assigned to its corresponding information class. The algorithm then removes pixels in that spectral cluster from the data set and repeats the two-step procedure with the remaining data. The level of association from the first iteration is multiplied by 0.95, and this value is set as the threshold for assignment in the next iteration. If no cluster reaches the threshold in subsequent iterations, the current highest association becomes the new threshold. Processing continues iteratively until all pixels are assigned to the alliance type that best matches their spectral signature or until a stopping rule is invoked. Based on initial runs, we decided to classify three subregions (the Columbia Basin, the southern Columbia Plateau, and the Wyoming Basin; Figure 1) independently to preclude types being extrapolated inappropriately to other subregions.

Three post-processing steps complete the map classification. First, a majority filter was applied to smooth the classified image and remove isolated pixels, which were likely to contain mixed classes. In addition, some land-cover types that had been accurately delineated in the original GAP maps were overlaid onto the classified image data. These classes were not mapped with AVHRR data because they were clearly visible in TM data (e.g., lakes, salt flats), were easier for human interpreters to see than computers (e.g., urban and developed areas), or were rare and of special conservation interest but hard to detect at the resolution of AVHRR (e.g., narrow riparian forests). Areas with these special cover types were masked from the image data and then incorporated from the original maps into the newly classified version in a post-processing step so that this information would not be over-generalized or lost. The total area of 35 classes region-wide and five classes in particular subregions that were "burned-in" from the source GAP maps amounted to 17 percent of the total area of the ecoregion. Eight classes were mapped entirely from the AVHRR dataset. In other words, 83 percent of the region was classified through the map-guided classification procedure. The last step was to vectorize the final raster land-cover map.

Validating regional-scale land-cover maps lacks an accepted methodology such as the error matrix used with larger scale maps (Stoms, 1996; Zhu *et al.*, 1996). Reference data of 1-km² sample plots are likely to contain mosaics of cover types, making an assignment to a single class unlikely. Also, the cost of collecting enough plots in each of the several dozen classes over a vast study area was prohibitive. As an alternative to a formal error matrix analysis, a more qualitative approach was used to evaluate both the input GAP maps and the map-guided classifications in order to gauge whether the derived map was actually improving the accuracy of the original along with the spatial consistency. An existing dataset of 1-km² field-based plots (Burgan *et al.*, 1993) was obtained from the USGS EROS Data Center. This dataset was originally compiled to validate the 1990 seasonal land-cover regions database (Loveland *et al.*, 1995). The plots had been located by randomly selecting 700 7.5-minute quadrangles in the conterminous United States and picking up to five plots in each of the selected quadrangles. Plots were accumulated so that the number of plots was proportionally distributed in relation to the area of each land-cover region in the Loveland *et al.* map. U.S. Forest Service personnel visited each accessible plot and recorded information about the structure and composition of the dominant trees, shrubs, grasses, and cultural land uses. Data were ultimately collected for 2,284 plots nationally, of which 78 occurred within the ISD ecoregion. The field data sheets distinguished between tree cover of 30 to 60 percent and 60 to 100 percent, which was virtually the same as the NVCS divisions between open and closed tree canopy. Based on the species composition and canopy cover data, each plot in the ISD was assigned to one of the alliances in the GAP land-cover maps. Tree-dominated and some shrub-dominated types could be assigned to specific alliances. Other shrub types were only identified at the genus level (i.e., sagebrush—*Artemisia* species) which could be any of eight alliances. Grasses were coded as annual or perennial, but the GAP dry versus moist bunchgrass types had not been distinguished in the plots. Various revisions of the derived map were compared to the plot data to assess whether the improved appearance of the map-guided classification (MGC) map was at the expense of reduced classification accuracy. The plot data were compared using a fuzzy sets approach (Gopal and Woodcock, 1994) to the final GAP land-cover map. In fuzzy accuracy assessment, samples are categorized by linguistic values (i.e., absolutely right, good answer, reasonable or acceptable answer, understandable but wrong, and absolutely wrong). This method recognizes the inherent ambiguity, or fuzziness, of land-cover classes which is obscured in traditional correct/incorrect assessment techniques. In addition, several revisions of the MGC map were reviewed by the cartographers who had compiled the original GAP data as a check that the classification was meeting our objectives without abusing their efforts.

Results

A regional land-cover map with 48 alliances/cover types was generated by the map-guided classification and post-processing procedures. Over 50 percent of the region was mapped as one of three widespread cover types: *Artemisia tridentata*, *A. tridentata-A. arbuscula*, or agriculture. Seventeen types had mapped distributions with less the 1,000 km² each (or 0.25 percent of the total region).

Average polygon size of the vectorized output map was 16.7 km², compared to 13.2 km² in the combined source

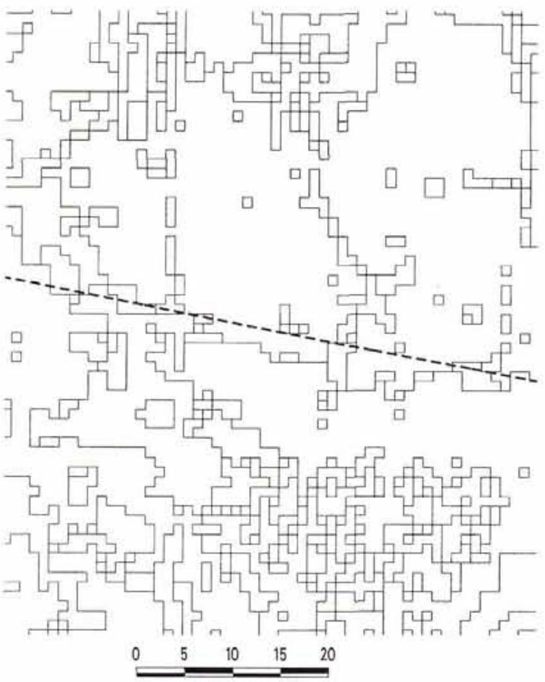

Figure 3. Detailed map of the final polygons from the map-guided classification of the Idaho-Nevada border.

maps. Thus, there was a small decrease in overall spatial resolution, but, by inspection, the gains in spatial consistency compensate for the loss of small polygons. Many of these smaller map units were apparently lost when the maps were rasterized prior to classification (mean size after rasterization and revectorization = 33.1 km²). Once the smallest polygons were filtered out by the rasterization process, the map-guided classification actually improved the spatial resolution (number of polygons) roughly by a factor of two. The output map is virtually seamless across state lines as can be seen by comparing Figures 2 and 3 for an enlargement of the Idaho-Nevada boundary.

Use of the 78 plots provided a qualitative evaluation of the major strengths and limitations of the land-cover map, but observations were too few to allow a statistically rigorous accuracy assessment. Forty percent of the plots were mapped with the "best" class according to the fuzzy sets method (i.e., absolutely right or good answer). These plots were completely consistent with the MGC map in both structural and floristic attributes. Another 22 percent were partially consistent with the map (e.g., having the correct dominant species present but in different percent cover in terms of the structural classification). For instance, ten plots were recorded in the field as grassland types but were classified as shrub types on the map. Of these ten plots, however, six had between 15 and 20 percent cover by the same shrub species as the mapped alliance and thus were reasonably considered a shrub type, even though this would not be the best class assignment. Four plots mapped as sagebrush were recorded as non-vegetated in the field. These four plots occur on a lava flow area in Idaho, which had a special class in the original GAP map for sagebrush on lava fields. In the cross-walking, this type was assigned to *Artemisia tridentata*, even though the percent cover may be less than the NVCS threshold.

Seventeen plots (22 percent) were labeled incorrectly but with understandable misclassification. A few of these plots had some overlap in species with the map class but there was clearly a better type that they should have been labeled. Most of the disagreements, however, occurred at the ecotones between cover types, and thus could be the result of registration error (in either the imagery, the GAP maps, or the plot locations) or of problems with mixed pixels. Many of the 78 plots occur within 1 km, the width of the pixels, from a boundary between cover types. For 15 of these plots that differed from the map, the cover types in the neighboring MGC map polygon agreed with the plot data. If these are also considered as consistent observations, the level of complete agreement increases to 62 percent. Thirteen plots (17 percent) were completely inconsistent with the map class assignment, including comparisons with polygons within 1 km of their locations. Seven of these inconsistencies were in polygons that had been "burned-in" from the source maps and thus were probably due to generalization of the source maps or problems with cross-walking rather than the product of the map-guided classification itself.

The source maps were also compared with the 78 plots to evaluate the relative accuracy of the map-guided classification. Thirty-two plots (41 percent) were completely consistent with the source maps, compared with 31 plots in the map-guided classification. Both the source maps and the map-guided classification map had an additional 17 plots (22 percent) with a "reasonable" label. Thus, 63 percent were at least partially consistent (62 percent for the map-guided classification). The source maps had more absolutely wrong labels (19 percent) compared to 17 percent for the map-guided classification. However, some of the source maps contained additional attributes for secondary or tertiary cover types in the polygon. When these attributes are also taken into account, a total of 88 percent of the plots were labeled with correct or reasonable types. The raster map produced by map-guided classification allows only one cover type per pixel. So, while the map-guided approach could not consider these additional attributes, it should be remembered that their true spatial location within polygons is undetermined.

Discussion and Conclusions

AVHRR data products were classified using an iterative, map-guided classification technique developed for this research project. The map-guided classification appears to be a practical approach for synthesizing land-cover maps from a set of source maps that are only partially consistent. The greatest strength of the MGC approach is that it uses whatever data are available to guide the classification. It differs from traditional supervised classification, however, in that it uses entire mapped classes rather than limited training sites. The MGC procedure is also iterative and only assigns class labels in each iteration to clusters with a strong association with a training map class signature. Low-probability class assignments that might be made in a single-pass algorithm are avoided in MGC. The most obvious classes with unambiguous spectral signatures, such as most agriculture in this semi-desert region, are classified in early iterations. The MGC method should work as well with TM imagery or other multispectral data as it did with AVHRR data. We are currently using the same basic technique for mapping land-use change over a large region with multiple TM scenes by using a classified image map for one year to classify image data for a later year. The MGC method should also work at other mapping scales, and even where there is incomplete input mapping, so long as adequate training data exists in the source maps for all desired output classes.

AVHRR-derived variables and equivalent elevations were used in this research to provide a consistent 1-km spatial resolution to the final regional map. Multi-temporal AVHRR composites through the 1990 growing season helped discriminate alliances by their distinct phenologies in addition to their spectral values. The regional land-cover map retains only small inconsistencies across state boundaries that was more evident in the source maps. This improvement is a product of both the consistent spatial resolution of the AVHRR data but also of the single regional classification, as opposed to the independent classifications done within individual states for the source maps. The MGC methodology should be robust with data from any year, despite inter-annual variation in weather-driven phenologies (Reed *et al.*, 1994), because it does not pattern-match observed greenness trajectories to a library of known phenological responses. Instead, the map-guided classification takes the observed spectral values and matches their empirical clusters to information classes in an existing map.

The proposed National Vegetation Classification System is explicitly defined to use existing capabilities of remote sensing for mapping the structural levels of the hierarchy, with floristic detail for determining alliances provided by quantitative field inventory data. As one of the first applications of the proposed NVCS scheme for regional scale land-cover mapping, this case study provides some insights into the technical limitations and ecological realities encountered in a real-world situation. The greatest difficulty and source of uncertainty in mapping NVCS alliances at a regional scale involved the highest structural levels of classification, particularly between open- and closed-canopy tree-dominated types (i.e., at the level of Classes in NVCS) and between grassland and shrubland (i.e., Orders). Because canopy density can have a strong effect on the habitat suitability for wildlife and understory plants, an incorrect assignment to woodland instead of forest, or shrubland instead of grassland, could be as serious as floristic errors in biodiversity assessments such as gap analysis. Much of the confusion between the map and the plot data occurred where the map was labeled as a shrub formation, but the plot contained only sparse shrub cover (i.e., less than 25 percent). Tree-dominated types were relatively minor in the ISD ecoregion or clearly belonged in open canopy types (e.g., pinyon-juniper), so this issue was less of a concern than it might be in an ecoregion characterized by both forest and woodland classes. This problem in the regional mapping could have been reduced if the source maps had followed the NVCS hierarchy more precisely with regard to canopy cover. Unfortunately, some types in the source maps spanned a range of cover densities, such as "sage-brush-steppe" which could indicate sparse to denser shrub cover. Therefore, the cross-walk created for the regional map was forced to assign such ambiguous types into a single NVCS Order (e.g., *Artemisia tridentata* shrubland). The NVCS Group for Herbaceous temperate perennial grassland with a shrub layer of 10 to 25 percent was never used in this application even though it is common in the ecoregion. Thus, this was a limitation of the source maps rather than of the NVCS scheme itself, but accurate discrimination of types that are in reality a continuum of canopy cover will continue to be a major obstacle for regional mapping from remotely sensed data.

A second difficulty we encountered in trying to meet the NVCS standards involved types that could not be conveniently divided into alliances even though the formation was unambiguous. Some land-cover types were aggregated to formations either because they were too small to be mapped as a separate class or because the source GAP maps did not consistently distinguish alliances within formations. For instance, the alliances within the seasonal/temporarily flooded cold-deciduous closed tree canopy formation were often aggregated in the source map classification. Because of the spectral similarity of these alliances, there was no simple method to extract them from the AVHRR data. This aggregation was more of a cartographic decision than a weakness in the proposed NVCS. For types like Mountain brush, the problem is that the type has no clear diagnostic or dominant species and is more of a general category for highly diverse shrub communities that share many of the same canopy species. The NVCS framework does not appear to handle such types well below the formation level. These issues indicate that what is possible using remotely sensed data over large geographic regions will continue to fall short of the ideal of completely achieving the NVCS standards.

The map-guided classification method provided an innovative means of compiling a regional land-cover map, but additional improvements may be possible. The NVCS scheme for classifying land cover is hierarchical, beginning with structural or physiognomic features at the highest levels. This suggests that a hierarchical approach to mapping might be appropriate as a two-stage classifier. Logic rules could be used for structural classification, similar to those proposed by Running *et al.* (1995). If the source map labels are consistent with the inference of logic rules applied to AVHRR data at the formation level, the source map alliance label would be assigned. If not, the map-guided classification or further ecological rules would be invoked. It should be noted that the classification logic in Running *et al.* (1995) uses AVHRR-derived variables to determine leaf type and phenology and permanence of aboveground live biomass, but does not distinguish life form or canopy density. Therefore, that particular hierarchical approach would not directly lead to a classification scheme compatible with the NVCS. Alternatively, a map-guided classification could be used as part of an evidential reasoning approach (Gong, 1996) which would integrate spectral data and derived indices or biophysical metrics with the source map labels and environmental variables. Such a two-step approach may lead to higher accuracy but would require greater effort to develop the set of deductive rules.

The procedures described in this paper successfully met the objectives to produce a seamless regional land-cover map at the alliance level. The multi-temporal AVHRR data provided consistent spatial resolution throughout the region and minimized the inconsistencies across state boundaries while preserving the best information in the source maps. Further improvement in accuracy is certainly possible. Based on the reviews from regional botanists, however, we believe the map-guided classification land-cover map is of sufficient quality to be useful for regional conservation assessment and for stratifying the ecoregion for detailed field survey.

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