The Southwest Regional Gap Analysis Project

Final Report on Land Cover Mapping Methods

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This report represents the land cover portion of the final project report for the Southwest Regional Gap Analysis Project

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Abstract

For more than a decade the USGS Gap Analysis Program has focused considerable effort on mapping land cover to assist in the modeling of wildlife habitat and biodiversity for large geographic areas. The GAP Analysis Program has been traditionally state-centered; each state having the responsibility of implementing a project design for the geographic area within their state boundaries. The Southwest Regional Gap Analysis Project (SWReGAP) was the first formal GAP project designed at a regional, multi-state scale. The project area comprises the southwestern states of Arizona, Colorado, Nevada, New Mexico and Utah. Project duration lasted approximately 5 years, beginning in 1999 and ending in 2004. The land cover map was generated using regionally consistent geospatial data (Landsat ETM+ imagery and DEM derivatives), similar field data collection protocols, a standardized land cover legend, and a common modeling approach (decision tree classifier). Partitioning of mapping responsibilities amongst the 5 collaborating states was organized around ecoregion based "mapping zones." Over the course of three field seasons approximately 93,000 field samples were collected to train the land cover modeling effort. Land cover modeling was done using a decision tree classifier. This report presents an overview of the methodologies used to create the regional land cover dataset and highlights issues associated with achieving this collaborative product through a regionally coordinated process.

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Introduction

In its "coarse filter" approach to conservation biology (Jenkins 1985, Noss 1987) gap analysis relies on maps of dominant land cover as the most fundamental spatial component of the analysis for terrestrial environments (Scott et al. 1993). For the purposes of GAP, most of the land cover of interest can be characterized as natural or semi-natural vegetation defined by the dominant plant species.

Vegetation patterns are an integrated reflection of physical and chemical factors that shape the environment of a given land area (Whittaker 1965). Often vegetation patterns are determinants for overall biological diversity patterns (Franklin 1993, Levin 1981, Noss 1990) which can be used to delineate habitat types in conservation evaluations (Specht 1975, Austin 1991). As such, dominant vegetation types need to be recognized over their entire range of distribution (Bourgeron et al. 1994) for beta-scale analysis (*sensu* Whittaker 1960, 1977). Various methods may be used to map vegetation patterns on the landscape, the appropriate method depending on the scale and scope of the project. Projects focusing on smaller regions, such as national parks, may rely on aerial photo interpretation (USGS-NPS 1994). Mapping vegetation over larger regions has commonly been done using digital imagery obtained from satellites, and may be referred to as land cover mapping (Lins and Kleckner 1996).

Generally, land cover mapping is done by segmenting the landscape into areas of relative homogeneity that correspond to land cover classes from an adopted or developed land cover legend. Technical methods to partition the landscape using digital imagery-based methods vary. Unsupervised approaches involve computer-assisted delineation of homogeneity in the imagery and ancillary data, followed by the analyst assigning land cover labels to the homogenous clusters of pixels (Jensen 2005). Supervised approaches utilize representative samples of each land cover class to partition the imagery and ancillary data into clusters of pixels representing each land cover class. Supervised clustering algorithms assign membership of each pixel to a land cover class based on some rule of highest likelihood (Jensen 2005). Supervised-unsupervised hybrid approaches are common and often offer advantages over both approaches (Lillesand and Kieffer 2000).

It is important to point out that a land cover map is never considered a perfect representation of the landscape. Improvements to land cover maps can, and should be made as additional “ground truth” information about actual land cover components and spatial patterns is acquired through time. These improvements should be based on independent assessments of the map’s quality (Stoms 1994).

This chapter is divided into three main sections. The first section discusses land cover map development. It begins by providing background information on the regional division of labor and the regional land cover legend. It then focuses on our land cover mapping methods, including a description of data sources, the land cover modeling approach, and the general flow of the mapping process. It concludes with a description of the resulting land cover map product. The second section describes the process of validating the land cover product. Background information on our approach is presented along with descriptions of the methods and results of the land cover product validation. The final section provides a discussion of the land cover mapping experience in general. In this section we discuss some of the "lessons learned" from the regional mapping effort with hopes that future mapping efforts of this nature will benefit from our experience.

Land Cover Map Development

Background:

Division of Regional Responsibilities:

The use of "spectro-physiographic" mapping areas has proven useful for satellite-based land cover mapping by maximizing spectral differentiation between areas with relatively uniform ecological characteristics (Bauer et al. 1994, Homer et al. 1997, Lillesand 1996, Reese et al. 2002). Dividing the 1.4 million square kilometer region into spectro-physiographic "mapping zones" provided working units distributed among the five collaborating states. With the diversity of biogeographic divisions across the region, we recognized the importance of leveraging local knowledge of the biota in each sub-region. We consequently determined that a geographical approach, assigning state teams to work in their local landscapes was the most appropriate means for distributing regional mapping responsibilities. Overall project tracking and management was conducted by the regional land cover lab at Utah State University.

Ecoregions defined by Bailey et al. (1994) and Omernik (1987) provided a starting point for determining the project mapping zone boundaries. These boundaries were refined by screen digitizing at a scale of approximately 1:500,000 using a regional mosaic of Landsat TM imagery resampled to 90 meters. Initial efforts yielded 73 mapping zones for the region. Through a process of iterative and collaborative steps involving all land cover mapping teams and NatureServe, the final number of mapping zones was reduced to 25 (Figure 1). A more detailed explanation of mapping zone development is found in Manis et al. (2000).

Each state was responsible for between four and six mapping zones roughly corresponding to state jurisdictional boundaries. Initial field data collection protocols were established at a workshop in Las Vegas, Nevada in the spring of 2001. Field data collection occurred during 2002 and 2003. Land cover workshops dedicated to ensuring regionally consistent mapping methods were conducted during the winters of 2002 and 2003. Yearly meetings and monthly teleconferences involving key land cover mapping personnel from all five states and NatureServe ecologists proved invaluable throughout the collaborative mapping process. Mapping efforts were completed on a mapping zone by mapping zone basis by individual states, with the final integration of all mapping zones performed by the regional land cover lab. The seamless land cover map was completed and made available to the public in September 2004.

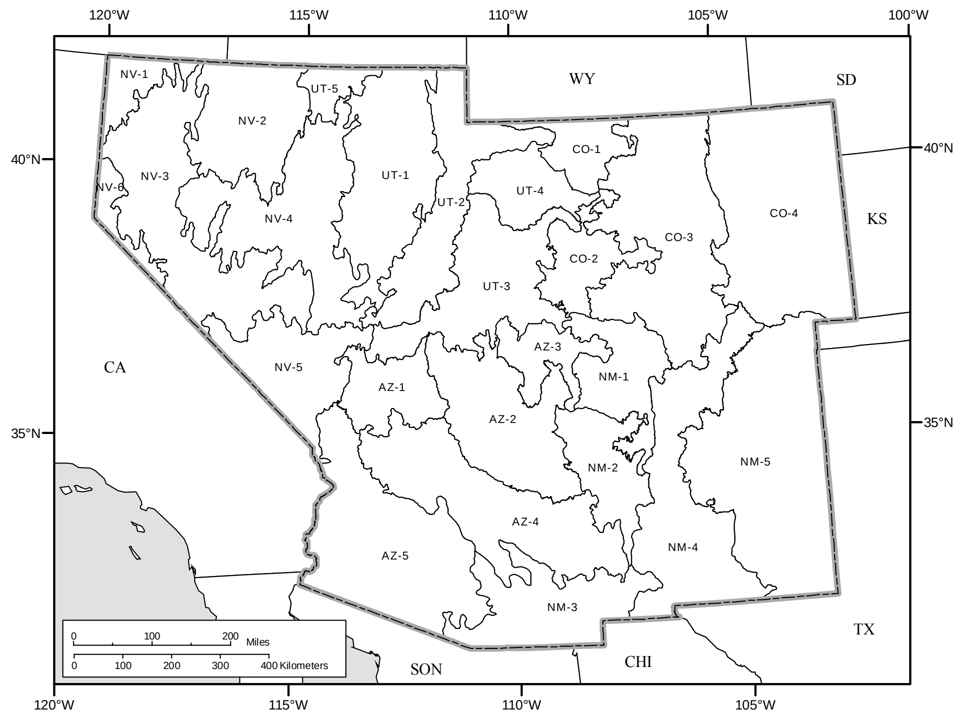

Figure 1. Mapping zone boundaries for SWReGAP land cover mapping effort.

Land Cover Legend:

The US National Vegetation Classification System (US-NVCS) has been adopted by the Federal Geographic Data Committee as the classification standard for all federal mapping projects (FGDC 1997) [1]. A nested hierarchical structure of the US-NVCS defines classification units at the highest levels as heterogeneous units based solely on vegetative

[1] The FGDC set standards and policy for vegetation classification and map products to enable agencies to collect, report and map vegetation information in a standard format (FGDC 1997). Although the policy for applying the standard is only through the formation level (physiognomy only), agencies are encouraged to aid in the development of the floristic alliance and the association levels (FGDC 1997, pg. 4, 7). FGDC recognized that mapping applications need to be based on the requirement of the project "The specific application of this standard to any mapping activities is dependent on the goals and objectives of the mapping activities…the classification standard merely sets a hierarchical list of classes that should be intelligently employed by the user based on the specifications and limitations of their particular mapping program" (FGDC 1997, pg. 9). Thus, the current FGDC standard is primarily for *describing and classifying* vegetation, whereas mapping units will reflect (1) the needs of the mapping project, (2) the technical tools, methods, and data available for mapping, and (3) the interactions of those factors with the vegetation classification concepts. The nested hierarchical structure was intended to ease applications of these classification concepts to the many and varied circumstances of vegetation mapping. At the time of its adoption, however, there had been limited experience in its mapped application at each hierarchical level. Because of difficulties in mapping at all levels, 'compliance' with the FGDC standard almost always requires some sort of crosswalk between resultant mapping units and classification units from one or more levels of the current FGDC hierarchy.

physiognomy and at the lower levels as more narrow and homogenous floristic units (figure 2). The upper physiognomic levels of the NVCS framework are adapted from the World Physiognomic Classification of Vegetation (UNESCO 1973) and later modified for application to the United States by Driscoll et al. (1983, 1984). The lower floristic levels (e.g. Alliance and Association) are based on both structural and compositional characteristics of vegetation derived by Mueller-Dombois and Ellenberg (1974). The Nature Conservancy, and now NatureServe—along with the network of Natural Heritage Programs—have worked with others since 1985 on the systematic development, documentation, and description of vegetation types across the United States (Grossman et al. 1994, 1998). NatureServe and the Natural Heritage Network have been improving upon this system in recent years with significant funding supplied by GAP. Products from this on-going effort include a hierarchical vegetation classification standard (FGDC 1997) and the description of vegetation Alliances for the United States (Drake and Faber-Langendoen 1997, Reid et al. 1999, Sneddon et al. 1994, Weakley et al. 1996). An alliance is a physiognomically uniform group of Associations sharing one or more dominant or diagnostic species, that as a rule are found in the uppermost strata of the vegetation (see Mueller-Dombois and Ellenberg (1974). The basic assumptions and definitions for this system have been described by Jennings (1993) and Grossman et al. (1998).

Link to FGDC standard	***Hierarchy level***	***U.S. National Vegetation Classification***	***Ecological systems***
Included		Division Order	
Included	Physiognomic levels	Formation Class Formation Subclass Formation Group Formation Subgroup Formation	
Hierarchically linked			Ecological systems
Proposed	Floristic levels	Alliance Association	

Table 1. Hierarchical structure of the U.S. National Vegetation Classification and the linkage with ecological systems.

When the SWReGAP project began in 1999 the intended thematic mapping unit was the NVC alliance. However, recognizing that over 500 alliances occur in the project area and that many alliances would be difficult to map as they do not occur in large and distinctive patches, we anticipated the need for a "meso" scale thematic mapping unit. In response to this need, a regionally consistent meso-scale land cover legend, NatureServe developed the Terrestrial Ecological Systems Classification framework for the conterminous United States (Comer et al. 2003). Ecological systems are defined as "groups of plant community types that tend to co-occur within landscapes with similar ecological processes, substrates and/or environmental gradients" (Comer et al. 2003). Although distinct from the US-NVC, the vegetation component of an ecological system is described by one or more NVC alliances or associations, though this relationship is not strictly hierarchical. While the ecological system concept emphasizes existing dominant vegetation types, it also incorporates physical components such as landform position, substrates, hydrology, and climate. In this manner, ecological system descriptions are modular, having multiple diagnostic classifiers used to identify several ecological dimensions of the mapping unit (Di Gregorio and Jansen 2000). Diagnostic classifiers include environmental and biogeographic characteristics, which are incorporated in the ecological system name thus providing descriptive information about the system through a standardized naming convention. More detailed information about the Terrestrial Ecological Systems Classification for the United States is available at http://www.natureserve.org/publications/usEcologicalsystems.jsp.

NatureServe Terrestrial Ecological Systems present one approach for mapping efforts to comply with Federal Geographic Data Committee standards. They are defined in terms of the base units (alliances and associations) of the US-NVC, and may be readily attributed to upper-most levels of the FGDC hierarchy (e.g., Division, Order, Class, Subclass). We follow this approach by attributing all mapping units to NLCD land cover classes 1 and 2 (Appendix LC-3 and LC-13) which closely follow these upper FGDC levels. This approach facilitates application of these mapped data to these hierarchical levels.

The initial SWReGAP target legend developed by NatureServe and the mapping teams identified approximately 110 potentially mappable ecological systems from the 140 that occur in the five-state region. Omitted ecological systems were mostly small patch (below minimum mapping unit) or peripheral to the region and lacked adequate training sites. The Terrestrial Ecological Systems Classification focuses on natural and semi-natural ecological communities. For SWReGAP, altered and disturbed land cover and land use classes were considered separately. These classes were incorporated into the SWReGAP legend using descriptions adopted from either the National Land Cover Dataset 2001 legend (e.g. Agriculture, Developed-Medium-High Intensity) (Homer et al. 2004) or were given special "altered or disturbed" designation within the SWReGAP legend (e.g. recently burned, recently logged areas, invasive annual grassland, etc.).

Land Cover Mapping Methods:

Data Sources:

Seventy-nine Landsat Enhanced Thematic Mapper Plus (ETM+) scenes (Figure 2) provided complete coverage of the five-state region, and were acquired from the USGS National Center for Earth Resources Observation and Science (EROS) through the Multi-Resolution Land Characteristics Consortium (MRLC). Spring, summer, and fall images were provided, raising the total number of images to 237 for the region. Optimal imagery dates varied across the region and were selected for peak phenological differences as well as clarity and low cloud cover. Image acquisition dates ranged from 1999 to 2001. All ETM+ scenes were terrain-corrected and provided to Utah State University in NLAPS (National Landsat Archive Processing System) format.

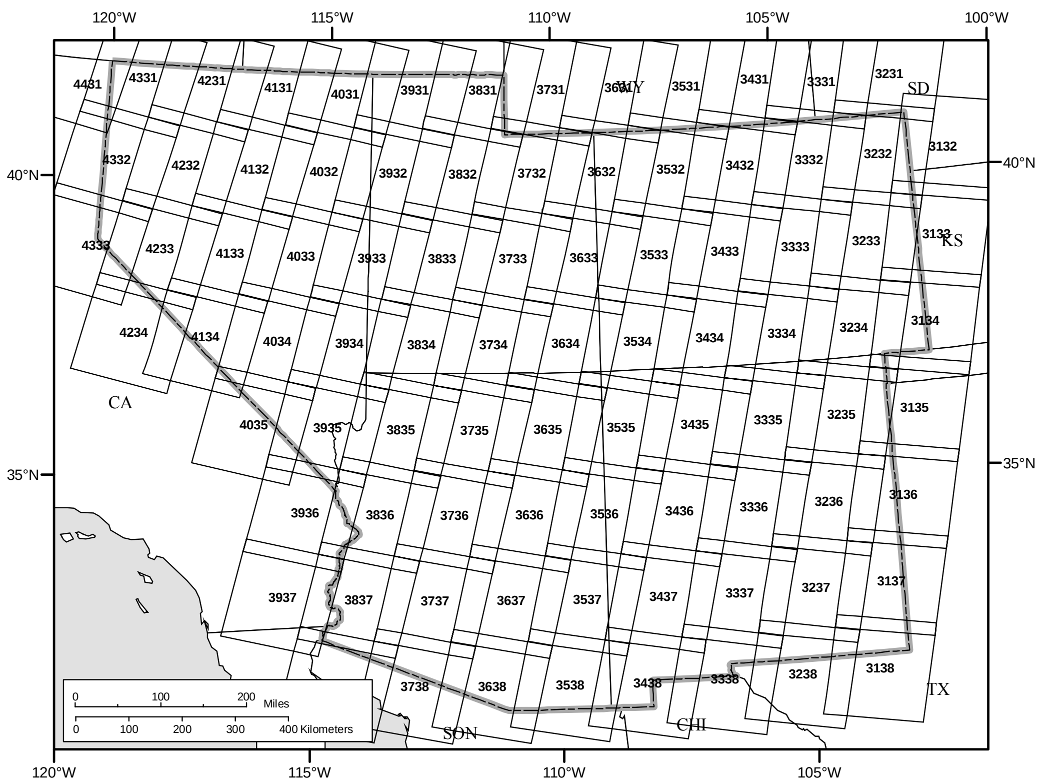

Figure 2. SWReGAP area showing Landsat ETM+ scenes

Our approach involved modeling image mosaics for each mapping zone (see Figure 1) including a 2 kilometer buffer (i.e. a 4 kilometer overlap between mapping zones). To improve image matching, image standardization for solar angle illumination, instrument calibration, and atmospheric haze (i.e. path radiance) was necessary. We determined the most practical approach was to use an image-based method as described by Chavez (1996). Standard protocol was to use a modified COST method (Chavez 1996). We found that using Chavez' COST method over-corrected atmospheric transmittance, particularly for scenes in the arid Southwest. To address this over-correction, we used COST without TAU_z (approximate atmospheric transmittance component of the COST equation). To facilitate image standardization, web-based scripts were developed to automate the process of generating corrected images on a scene-by-scene basis. [2]

Spatial data layer preparation included both image-derived and ancillary data sets. Core image-derived data sets included individual ETM+ bands, the Normalized Difference Vegetation Index (NDVI), and brightness, greenness and wetness bands created using Landsat ETM+ coefficients from Huang et al. (2002). Ancillary data sets were derived from 30 meter digital elevation models (DEM) obtained from the USGS National Elevation Dataset. Digital elevation model-derived data sets were created for each mapping zone and included elevation, slope (in degrees), a 9-class aspect data set, and a 10-class landform data set (Manis et al. 2001). Other ancillary data sets prepared for the region, but not used, included a "stitch map" of 1:500,000 scale state geology digital maps, a soil data set (STATSGO), and 1 kilometer resolution meteorological data (DAYMET). These data sets were not used because their scale was determined to be incompatible with the core Landsat ETM+ and 30 meter DEM-derived data sets.

"Ground truth" data were collected primarily through ground-based field work. Field samples were collected by traversing navigable roads in a mapping zone and opportunistically selecting plots that met criteria of appropriate size (1-hectare minimum) and composition (stand homogeneity).[3] Plot data were collected using ocular estimates of biotic and abiotic land cover elements, including percent cover of dominant species by life form (i.e. trees, shrubs, grasses, and forbs) and physical data such as elevation, slope, aspect and landform. Laptop computers using ArcView® software, Landsat imagery, digital orthophoto quads, and other ancillary information were also used for navigation and plot identification whenever possible. Each plot was identified with a paired UTM coordinate using a GPS and a visually interpreted polygon representing the survey plot.[4] Generally two digital photos were taken at each plot. Field data were recorded onto hardcopy field forms and subsequently entered into a database. Sufficient data were collected to assign a NVC alliance (Grossman et al. 1998) and/or ecological system (Comer et al. 2003) label to each plot. Of an approximate total of 93,000 samples

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[2] Scripts for image standardization were web-enabled making it possible for each land cover team to standardize their own images (see http://www.gis.usu.edu/docs/projects/swgap/ImageStandardization.htm). Users upload the image header file from which the script extracts the gain and bias coefficients, the solar zenith angle, and Julian date to produce an Imagine model (.gmd) file populated with extracted values for the specified correction equation. Because dark object brightness values were sometimes unavailable, or their selection was ambiguous in some mapping zones, an alternative script was available that converted brightness values to at-sensor reflectance. A single method, either the modified COST or at-sensor reflectance, was used within any given mapping zone (i.e. the standardization method was consistent within mapping zone mosaics).

[3] The ability to traverse all navigable roads varied by state and subsequently Colorado relied heavily on obtaining sample data from existing databases and visual image interpretation. In Arizona, navigable roads were sampled using a distance criteria coupled with assessment of vegetation homogeneity.

[4] Arizona collected field samples as point features (GPS x/y location) with an estimate of the radius of vegetation type, which were subsequently polygonized using an appropriately sized buffer for each sample plot.

obtained for the project, roughly 45,000 were collected via ground surveys during the course of the two field seasons (Appendix LC-1).

In addition to the SWReGAP ground-truthed samples as described above, these data were supplemented with sample plot data obtained from other projects roughly contemporary with the time period of our imagery (1999-2001), and via visual interpretation of aerial photography, digital orthophoto quads, or other remotely sensed imagery. Samples obtained from visual interpretation of remotely sensed imagery were given only a label identifying the land cover class. Appendix LC-1 presents the distribution of samples used in the land cover modeling process.

Land Cover Modeling Using Decision Tree Classifiers:

At the onset of the project Utah State University investigated several avenues for image classification. In particular we experimented with methods similar to those used in previous large landscape mapping efforts such as the 1995 Utah GAP land cover project (Homer et al. 1997) and the WISCLAND project (Reese et al. 2002). Supervised-unsupervised hybrid approaches, such as those used in the Utah Gap Analysis Project and WISCLAND Project have proven effective for the groups that have used them. However, an important consideration for our project was the need to develop a common methodology that could be applied by five separate land cover teams to create a regionally consistent product.

Classification and regression trees (CART) were developed by Breiman et al. (1984) and were quickly recognized as a valuable tool for discriminating complex relationships among environmental variables (Verbyla 1987). Early spatial applications of decision trees for remote sensing-based land cover classification focused on continental and global scale mapping using coarse resolution imagery (Hansen et al. 1996, Friedl and Brodley 1997, DeFries et al. 1998, Friedl et al. 1999, Hansen et al. 2000, Friedl et al. 2002). More recently, decision tree classifiers have produced repeatable, accurate results in meso-scale mapping with Landsat Thematic Mapper imagery (Lawrence and Wright 2001, Brown de Colstoun et al. 2003, Pal and Mather 2003, Lawrence et al. 2004).

Decision tree classifiers are well suited for land cover mapping. First, as a non-parametric classifier, decision trees require no prior assumptions of normally distributed training data, which is useful as many land cover classes do not exhibit a normal distribution in spectral feature space. Second, while incorporating ancillary data sets can improve land cover class discrimination (Hutchinson 1982, Homer et al. 1997, Ricchetti 2000; Treitz and Howarth 2000), traditional parametric classifiers have difficulty dealing with differences in spectral and ancillary measurement scales. Decision trees readily accept a variety of measurement scales in addition to categorical variables. Decision tree classifiers have demonstrated improved accuracies over the use of traditional classifiers (Hansen et al. 1996, Pal and Mather 2003). Finally, decision tree software is readily available, computationally efficient, and by using a hierarchical approach to define decision rules, is intuitive to a variety of users.

Decision tree classifiers are considered an exploratory technique used to uncover structure in data (Breiman et al. 1984, Clark and Pregibon 1992). Decision trees use a binary partitioning algorithm to successively split a multidimensional "cloud" of explanatory data into increasingly homogenous subsets. Each binary split is considered a single rule in a chain of rules defining the characteristics of the response variable. Chains of rules can also be thought of as branches, with the final decision represented by a "leaf" or terminal node. For land cover mapping, explanatory variables are the spectral and ancillary data sets and the response variable is the land cover classes. Typically, decision trees recursively split the explanatory data set until no further splits are possible. Over-fitting the decision tree model in this manner usually requires "pruning" the tree, otherwise rules are generated for individual plots rather than groups of plots representing land cover classes. The challenge with pruning is to establish optimal criteria so the final decision tree is neither too precise nor so general as to be meaningless.

As an alternative to pruning, "ensemble techniques" can be used to produce optimal trees. Ensemble techniques involve generating multiple trees to improve model accuracy and include "bagging" and "boosting" methods. With bagging, multiple trees are generated from randomly selected subsets of the data, where the final tree is produced from a majority "vote" by all the trees. Boosting similarly subsets the data, but generates multiple trees in succession focusing on branches of the tree that are most difficult to classify (based on misclassification rates). In this sense, boosting provides a way for an optimal tree to be generated by "learning" from previous tree models. This is an important benefit considering each split in a single, non-boosted decision tree determines all subsequent splits in the branch, some of which may be sub-optimal. Boosting, rather than bagging, has been more often employed for land cover mapping applications and has produced improved accuracies relative to non-boosted approaches (Pal and Mather 2003, Brown de Colstoun 2003, Lawrence et al. 2004).

A significant technical challenge with using decision trees for land cover mapping lies in the need to spatially apply the decision tree rules within a geographic information system. To successfully implement a boosted decision tree approach for such a large area among five separate teams, an effective tool for applying the decision trees in a spatially explicit context was imperative. Concurrent with our project, the USGS National Center for Earth Resources Observation and Science (EROS) began developing a land cover mapping tool capable of integrating the decision tree software See5/C5.0 (Quinlan 1993) with ERDAS Imagine. The tool, developed for the National Land-Cover Dataset 2001 (Homer et al. 2004) project (hereafter "NLCD mapping tool") provided the ideal solution to our need for an efficient integration of the decision tree software within a spatially explicit modeling environment.

SWReGAP Mapping Process:

Land cover modeling was performed on a mapping zone by mapping zone basis with each mapping zone overlapping its adjacent mapping zone(s) with a 2 kilometer buffer (4 km overlap). The project's primary objective was to produce the most accurate and complete map possible. To accomplish this, our mapping procedures required steps we determined made best use of all available training samples. In general, this meant two things:

First, we would rely on the decision tree classifier to discriminate the bulk of the land cover classes. However, recognizing that the classifier had difficulty discriminating certain classes adequately, other methods were employed to map these classes. Natural land cover classes such as lava flows and sand dunes, which are relatively rare and/or isolated on the landscape, were typically not modeled with the decision tree, nor were anthropogenic classes such as recently chained areas, agriculture, or developed land uses.[5]

Second, we conducted our assessment of map quality on an intermediate land cover map generated with a subset of samples rather than the final land cover map which was generated from 100 percent of the samples. We refer to this approach as an internal validation, which should not be confused with an accuracy assessment of the final map. The internal validation involved randomly selecting 20 percent of available samples stratified by land cover class, and withholding them from the decision tree model generation. The intermediate map (generated with 80 percent of the available samples) was assessed with the 20 percent withheld dataset, producing an error matrix and kappa statistic. The land cover modeling process concluded with the generation of the final map using 100 percent of the available data. Validation results therefore represent an assessment of land cover maps created using 80 percent of the training data. No assessment of the final map produced from 100 percent of the data was made. Details of our validation approach are presented in the validation section of this chapter.

The following steps correspond with Figure 3 and describe the general mapping process in greater detail:[6]

1) **Delineate non-modeled classes:** Delineate land cover classes anticipated to not be modeled with the decision tree classifier. These may include agriculture, developed, water, recently logged, chained, mined, etc. If GIS data exist, particularly for agriculture and developed classes, these may be used. Alternative methods for mapping these classes include screen digitizing and unsupervised clustering.

2) **Prepare explanatory data sets:** Explanatory data sets may be a combination of image- and DEM-derived data sets (see Data Sources). The choice of explanatory data sets may vary by mapping zone and is determined by the land cover analyst.

3) **Prepare sample data:** Sample data may be obtained from a number of sources (see Data Sources). All sample polygons are randomly divided into a training data set (80%) and validation data set (20%) using ArcView. The NLCD mapping tool requires individual

[5] The adequacy of the decision tree classifier for mapping any given land cover class was driven primarily by availability of sample data. Our field data collection protocol focused on natural and semi-natural classes with the assumption that many anthropogenic classes could be mapped from existing GIS data, or could be more easily delineated via screen digitizing. Given the abundance of anthropogenic classes in eastern Colorado, the Colorado team used the decision tree to discriminate developed and agriculture land cover classes using a substantial amount of image interpreted sample plots.
[6] Steps 1-10 outline the general mapping process as established by the regional land cover lab. Steps taken by state mapping teams may have diverted slightly from this general process.

pixels for sample observations. While each sample polygon is recognized as an independent observation, we use sub-samples (i.e. cluster sampling) within each polygon to account for spectral and environmental variability within the sample polygon. Sub-samples are randomly selected from each polygon with a maximum of 20 sub-samples per sample polygon using the Randpts extension (Jenness Enterprises 2005) in ArcView.

4) **Model land cover classes with decision tree classifier using 80% of sample data:** Using the NLCD mapping tool, explanatory variables are queried by the response variable data set to produce input files required by See5/C5.0. The decision tree model is created using the boosting option with 10 iterations in See5/C5.0. Output files from See5/C5.0 are spatially applied in Imagine using the NLCD mapping tool. Modeling is an iterative process. After model evaluation (see step 5 below) a different combination of explanatory data sets, or additional samples may be tried to improve the model. At this time the analyst decides which land cover classes are "mappable" given the availability of training data and the discriminating capabilities of the model. When model improvement reaches a point of diminishing returns, proceed to step 6.

5) **Internal validation of intermediate land cover map using 20% withheld sample data:** Model validation is only for those land cover classes being modeled with the decision tree. Using the 20% withheld sample polygons, use the ArcView Kappa extension (Garrard 2003) to create an error matrix and calculate the kappa statistic (Congalton 1991). The Kappa extension intersects the validation sample polygons through the completed map. When the mode (i.e. most frequent) value of pixels in the land cover map agree with the validation polygon label, the reference site is considered correctly mapped.

6) **Create final decision tree model and map using 100% of sample data:** This procedure is the same as step 4 with the exception that 100% of the sample data are used to generate the decision tree.

7) **Map refinement:** The land cover map produced in step 6 is carefully examined to determine where errors exist through a combination of visual examination and evaluation of the error matrix. The decision tree classifier may not have produced good decision rules for a number of possible reasons, such as not having an adequate number of samples for a given land cover class, not having sufficient samples in a given geographic region, or limitations of the explanatory data (spectral and/or ancillary) to discriminate between land cover classes. Known geographic errors can be fixed using Imagine's Recode utility and an *.aoi file. Known environmental errors (e.g. mapping on incorrect slope, elevation or aspect) can be fixed using a conditional statement in a post-classification model (e.g. Imagine *.gmd file). If possible additional sample plots for a geographic area or land cover class are added and the preceding steps repeated.

   At this step, it is also possible to correct errors associated with clouds. For example, where clouds exist in one date of imagery but not in others, separate models can be run (see step 4) to correctly classify the land cover classes in the cloud covered areas. Using a conditional post-classification model replace the cloud covered pixels in the final map with those from an alternate decision tree model/map that was not as good overall, but was not impaired by cloud cover (e.g. model using imagery from one season rather than two).

8) **Overlay non-modeled classes onto final land cover map:** Non-modeled classes retained from step 1 are converted to an Imagine file format, given the proper integer value, and combined (i.e. overlaid) with the map from step 7. This can be done with a conditional statement in an Imagine *.gmd model.

9) **Convert to minimum mapping unit:** Use Imagine's Clump and Eliminate functions to generalize the image to the minimum mapping unit (i.e. 1 acre). Parameters are set to use 4 connected neighbors for Clump and a minimum of 1 acre for Eliminate. When used

together these steps eliminate clumps of 3 pixels or less, where the eliminated pixels assume the majority value of adjacent pixels.

10) **Edge-match to adjacent mapping zones:** Edge-matching requires that the integer values for land cover classes be standardized in accordance with SWReGAP Handbook guidelines (e.g. S001 has value 1, S112 has value 112, D05 has value 305, etc.). Once standardized, adjacent images are mosaiced using Imagine's Mosaic tool with cutline and overlap functions. Cutlines can be drawn as needed within the 4 km overlap area using an *.aoi file.

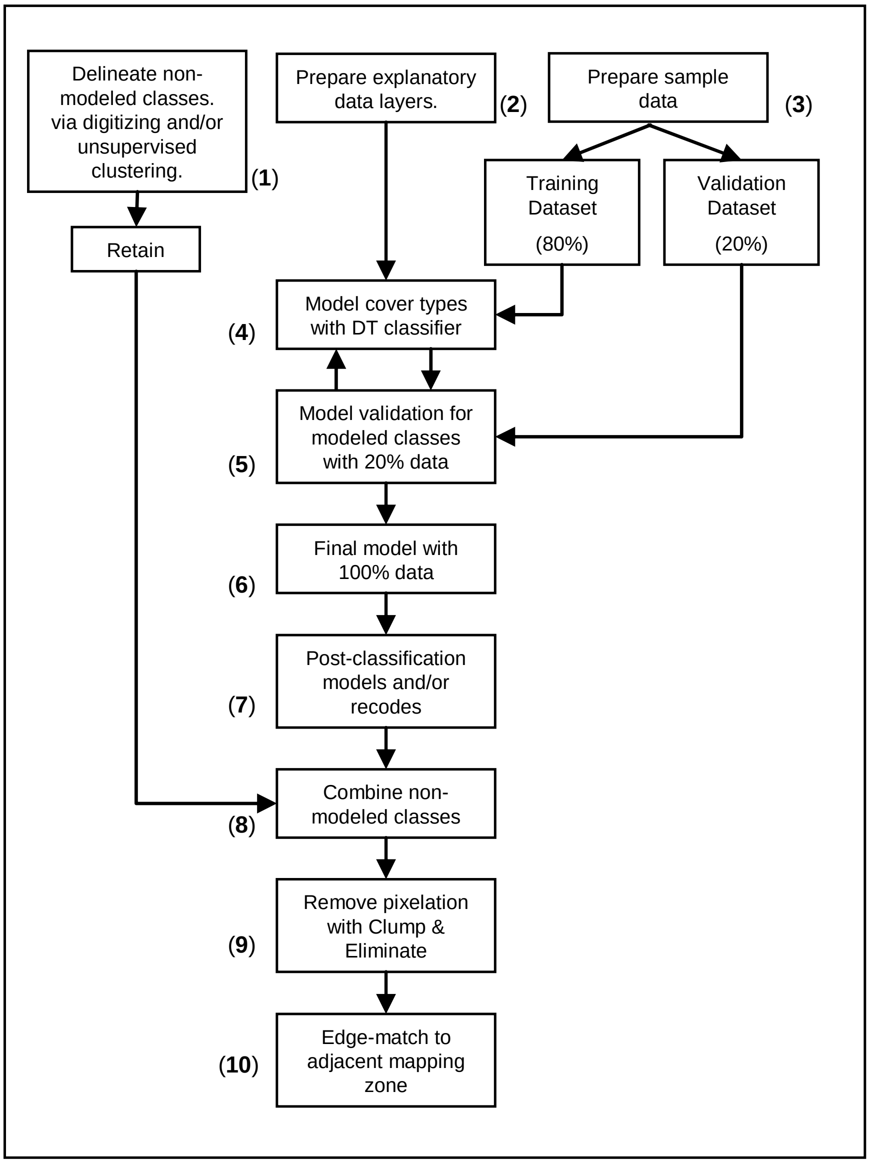

Figure 3. Overview of the SWReGAP Mapping Process

Land Cover Map Results:

State land cover mapping teams were responsible for all steps in the mapping process and edge-matched adjacent mapping zones within their responsibility area. Utah State University assembled the state mosaics to create the final regional mosaic. The final map product contains 125 land cover classes, 109 of which are ecological systems. The data set retains the 30 meter pixel resolution of the core data sets with a minimum mapping unit of 1 acre (0.40 hectares). The representative fraction scale of the data set is considered to be 1:100,000. Appendix LC-2 provides a summary of land cover classes mapped for the 5-state region. The Map Section of this report contains a figure of the final land cover map.

Land Cover Map Validation

Introduction:

Assessing land cover map quality is an important concern for land cover mapping projects. Map quality assessment provides useful information to map users about the reliability of the map product. Various approaches to map quality assessment are recognized (Foody 2002), however, making the assessment helpful to the map user should be of primary importance (Smits et al. 1999). Typically the quality of land cover maps are assessed using a probability based sampling design (Stehman and Czaplewski 1998) with relatively large sample sizes per class (Congalton and Green 1999). These probability based approaches utilize data collected specifically for map quality assessment, and are commonly referred to as "map accuracy assessments."

We consider our approach an internal validation; "validation" in the sense that our purpose is to validate the quality of the map, and "internal" because we use data collected for, and used within, the modeling process (Shtatland et al. 2004). The approach may be viewed as a "split sample" or "hold out" method. This type of validation is not as accurate as a k-fold cross-validation (Goutte 1997) or as robust as an external validation (Shtatland et al. 2004). However, given the size and scope of our project, we determined this to be the most feasible approach providing a useful quantitative measure of map quality.

Land Cover Map Validation Methods:

Quantitative validation methods were described briefly in the previous section dealing with the mapping process. Here we provide a more detailed explanation about the quantitative validation process used by SWReGAP, focusing on our use of fuzzy set analysis. We also describe our approach to performing a qualitative assessment of the map product.

Quantitative Assessment using Fuzzy Sets:

The Gap Analysis Handbook recommends the use of "fuzzy set" analysis as a means of providing map users additional information about the quality of the map product (Crist and Deitner 2000). Our approach to fuzzy set assessment is based on the work of Gopal and Woodcock (1994) and described by Congalton and Green (1999). Using fuzzy set analysis for map quality assessment has proven useful in various land cover mapping efforts (Falzarano and Thomas 2004, Laba et al. 2002, Woodcock and Gopal 1992, Reiners et al. 2000). The premise behind fuzzy set theory for thematic map assessment is that thematic mapping involves placing a continuum of land cover into (somewhat artificially) discrete land cover classes. This continuum suggests that there can be different magnitudes of error between/among classes. The objective of using fuzzy sets for thematic map assessment is to provide map users with information about the frequency *and* magnitude of map error. In other words, a reference site may have been mapped incorrectly, but how incorrect was it? An answer to this question can be provided by re-evaluating the error matrix within the context of recognized similarities among land cover classes.

The essence of fuzzy set assessment lies in the construction of a "linguistic measurement scale" to assign degrees of correctness to misclassification errors. Gopal and Woodcock (1994) suggest five levels of linguistic values ranging from "absolutely wrong" to "absolutely right" which experts to use when evaluating a map product relative to the reference sample plots. Determining the appropriate linguistic class, or error type, for any given reference plot is subject to the judgment of the error assessment "expert." Establishing objective criteria for assigning the level of error, therefore, is an important component to a fuzzy set assessment. Criteria for error assignment type may be based on seriousness of the error for its intended application (Reiners et al. 2000) or on some aspect of similarity among land cover classes.

Establishing criteria for defining error assessment types was particularly important for a collaborative project such as SWReGAP. For our project, each land cover team acted as the "expert" responsible for error type assignment. For the fuzzy assessment to be as regionally consistent as possible, establishing a regional framework for error assessment was critical. Our approach focused on criteria based on "ecological similarity." Fuzzy assessments were created for each mapping zone independent of other mapping zones rather than the region as a whole. Typically, fuzzy assessments are conducted as part of an accuracy assessment after map completion. Our approach however used the error matrices produced from the internal validation (see *SWReGAP Mapping Process*). Figure 4 provides an overview of the process describing the steps in greater detail.

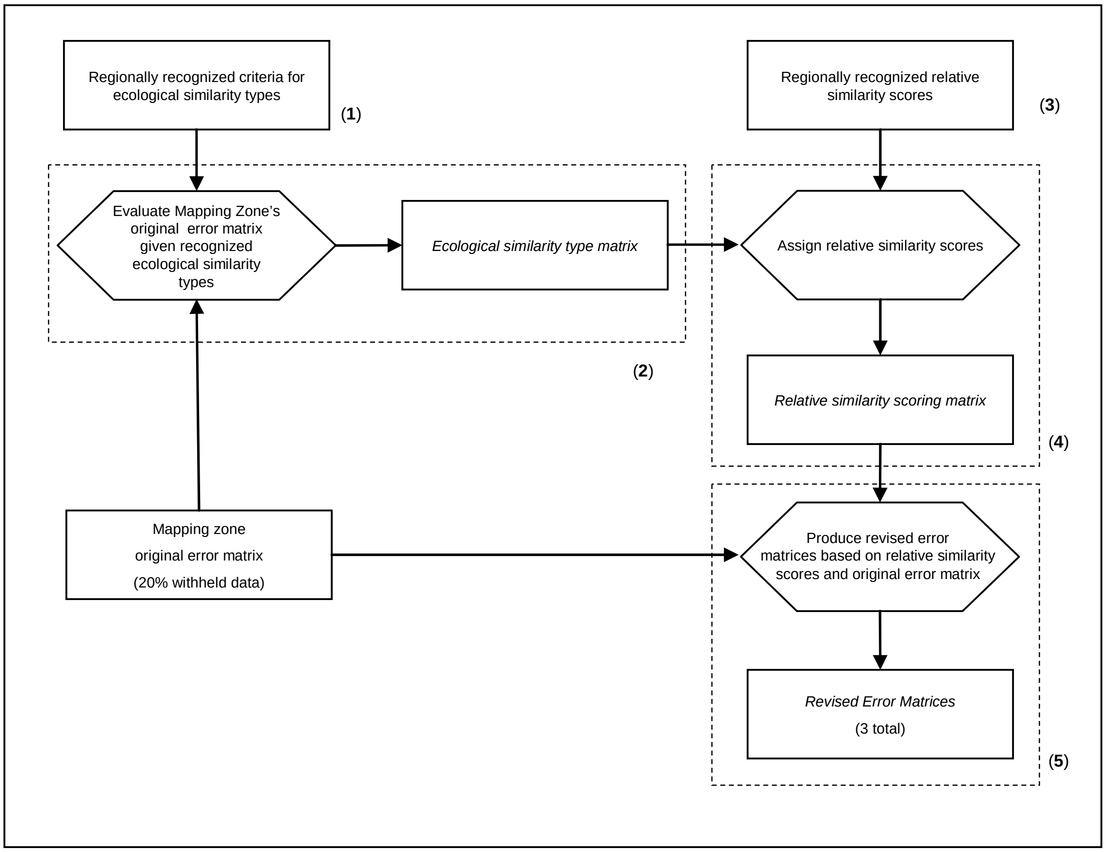

Figure 4. Overview of the SWReGAP fuzzy assessment process.

1) **Regionally recognized criteria for ecological similarity types.** Four major types of ecological similarity form the criteria from which similarity among land cover classes are recognized: physiognomic structure, dominant species, juxtaposition of ecological systems, and special substrates. Appendix LC-3 presents the regionally recognized ecological similarity types.

2) **Evaluate original error matrix for ecological similarity types to create *ecological similarity type matrix*.** The analyst evaluates each pair of land cover classes for every off-diagonal error (misclassification) cell in the original error matrix within the context of the regionally recognized ecological similarity types. While the ecological similarity types are regionally recognized, it is incumbent upon the analyst to assign ecological similarity codes. This is done based on the analyst's knowledge of the mapped ecological systems, and familiarity with the particular mapping zone being analyzed. An ecologist from NatureServe reviewed the state analysts' assignment of ecological similarity codes to ensure a regionally consistent application of the ecological criteria. Appendix LC-4 provides an example of the original error matrix for UT-5 and Appendix LC-5 presents the resulting *ecological similarity type matrix*.

3) **Regionally recognized relative similarity scoring system based on ecological similarity types.** Based on the ecological similarity type or combination thereof, each cell that is misclassified in the original error matrix must be ranked with a numeric relative similarity score. A regionally recognized scoring system (Appendix LC-6) provides a consistent method for the numeric scoring and ranking of ecological similarities between land cover classes.

4) **Assign relative similarity scores (numeric) to off-diagonal cells to create *relative similarity scoring matrix*.** The analyst uses the regional similarity scoring system (Appendix LC-6) to assign a relative similarity score to each off-diagonal error cell (Appendix LC-7).

5) **Produce revised measure of agreement matrices:** The original error matrix (Appendix LC-4) is re-evaluated in conjunction with the matrix of relative similarity scores (Appendix LC-7) to produce revised "measure of agreement" matrices (i.e. fuzzy set assessment) for each mapping zone. Three revised error matrices are produced including: revision recognizing land cover classes that are correctly mapped, or are incorrect, but are "very similar" (scores of 4 and 5) (Appendix LC-8); revision recognizing land cover classes that are correctly mapped, or are incorrect, but "very similar" or "moderately similar" (scores of 3, 4 and 5) (Appendix LC-9); and revision recognizing land cover classes that are correctly mapped, or are incorrect, but "very similar," "moderately similar," or "somewhat similar" (scores of 2, 3, 4 and 5) (see Appendix LC-10). Revised error matrices (Appendices LC-8, LC-9 and LC-10) can be summarized for both errors of commission and errors of omission to show overall improvement as well as by-class improvement given the recognized ecological similarities among mapped classes. Appendices LC-11 and LC-12 present summaries of fuzzy set assessments for all levels for user's and producer's accuracy respectively.

Qualitative Assessment:

It is important to recall that some land cover classes were not modeled with the decision tree classifier but were instead incorporated into the map as a post-modeling step. In addition, for some classes, withholding 20% of the available samples resulted in very few reference samples. Because of these shortfalls with the quantitative assessment, and because we believe there is value in a qualitative summary, we provide qualitative assessment summaries for each land cover class by mapping zone.

Land cover qualitative summaries are brief descriptions provided by the teams involved in the mapping process for each mapping zone. They are intended to provide a qualitative evaluation from the perspective of the land cover mapping analyst of how well the land cover class appeared to be mapped, taking into consideration the number of training and reference samples available for the cover class and the team's knowledge or familiarity with the mapping area. Often, the summary provides a narrative interpretation of the error matrix, identifying in qualitative terms where a particular land cover class is being misclassified geographically and with which land cover classes it is being confused.

Land Cover Map Validation Results:

Mapping Zone Assessments:

Model validation as described above was performed for each mapping zone separately. While reporting kappa statistics and presenting error matrices for all 25 mapping zones is beyond the scope of this paper, these data are available to the public at http://earth.gis.usu.edu/swgap/mapquality.html. The website provides errors of omission, errors of commission, overall percent correctly modeled, as well as the kappa statistic for each mapping zone. Since our validation approach involved withholding 20 % of available sample plots proportionally stratified across the land cover classes, few reference plots for several rare land cover classes were available for validation. Rather than exclude the rare, or non-modeled classes (e.g. anthropogenic classes) in our final product, we chose to include them without validation.

In addition to these quantitative data on model validation, the website also provides the qualitative evaluations provided by each state's land cover mapping team for every land cover class by mapping zone. The qualitative evaluations provide brief narratives summarizing perceived strengths and weaknesses of the mapped class. These evaluations are provided for all land cover classes regardless of whether they were quantitatively validated or not.

Regional Assessment:

To provide a regional quantitative summary of individual mapping zone validations, percentages of correctly mapped reference samples, by class, were summed across all mapping zones to produce Appendix LC-13. Land cover/use classes with fewer than 20 available reference samples, and/or classes that were not modeled with the decision tree classifier were not included in this regional summary. Of the 125 classes that were mapped in the final product, 85 classes are presented in the summarized regional validation (Appendix LC-13). These 85 classes represent 91% of the total land area. A regional error matrix was produced by combining all error matrices for these 85 classes. Results determined an overall correct classification of 61% (kappa statistic 0.60; n = 17,030).

The overall figure of 61% provides a summary measurement for the region of the decision tree classifier's performance relative to the reference samples used for validation. It is important to recognize that validation results vary by land cover class (Appendix LC-13) and by mapping zone. For example, matrix-forming land cover classes (i.e. "extensive and contiguous…with wide ecological tolerances typically ranging in size from 2,000 to 100,000 ha" (Comer 2003)) such as certain forests, shrublands and grasslands typically represent a larger portion of the landscape and typically had a larger number of training and validation samples. These classes typically had better validation results than small or linear patch types with relatively few training and reference samples. Land cover classes on the fringe of their geographic range in some mapping zones may be more poorly mapped than elsewhere because the size and distribution of samples (both for training and validation) was limited. Lastly, it is important to note that the validation results are based on the intermediate land cover map using the 20% withheld dataset. Since the final map was produced using the withheld samples, we assume that the final map is an improvement over the intermediate map that was validated.

Discussion

Land Cover Mapping Methods:

A primary objective of our land cover mapping process was to develop a methodology that was repeatable and could be consistently applied by multiple land cover mapping teams. In this regard we believe the decision tree classifier method was successful. The intuitive nature of the decision tree classifier and the easy-to-use software met this objective very well. Compared to hybrid supervised-unsupervised image classification approaches used in large land cover mapping efforts (Homer et al. 1997, Reese et al. 2002, Ma et al. 2001) we found the decision tree classifier considerably more time-efficient. Whether decision tree classifiers are a more effective tool for discriminating land cover classes was not specifically researched by our project. However Hansen et al. (1996) and Pal and Mather (2003) observed a measure of superiority over traditional parametric image classification techniques.

The use of spectro-physiographic mapping zones appeared to be a successful strategy for dividing the region into manageable working units and an effective means of constraining spectrally and environmentally similar land cover classes to logical geographic boundaries. Production of multi-scene mosaics for each mapping zone appeared successful as well. While image standardization did not result in seamless mosaics, satellite scene boundaries that were apparent generally were not problematic.[7] This may be due to the slight effects of atmospheric attenuation in the arid southwest, and may be of greater concern in other environments.

Identifying the optimal combination of predictor data sets for the decision tree classifier was a major focus in our efforts to develop a regional mapping methodology. Initially, we considered establishing a regional set of standard predictor data sets for all mapping zones in the region. Our concern was that adjacent land cover maps would not edge-match adequately if different sets of predictors were used for model development. Eventually, it was decided that each land cover analyst would choose the predictor data sets they determined worked best for a given mapping zone. As expected, the availability of multiseason imagery did improve image classification in most areas. However, use of imagery from a single season occasionally produced better results. The suite of core predictor data sets to choose from was consistent throughout the region, namely three seasons of ETM+ imagery with the analyst's choice of image transformations, and any combination of DEM derivatives (slope, aspect, landform, etc.). Concerns about edge-matching adjacent land cover maps proved negligible in most instances. In fact, successful matching of adjacent land cover maps could indicate accurate land cover mapping since completely different models converged upon similar predictions of vegetation distribution (see Figure 4). Good edge-matching was also facilitated by frequent communication and coordination between the land cover mapping teams and the

[7] Given highly seasonal spectral variability in Colorado, it seemed that scene boundaries needed to be accounted for. Therefore, scene boundaries were included as a predictor layer in Colorado.

NatureServe ecologist who assisted in decision-making in order to maintain regionally consistent application of the ecological systems concepts across the project.

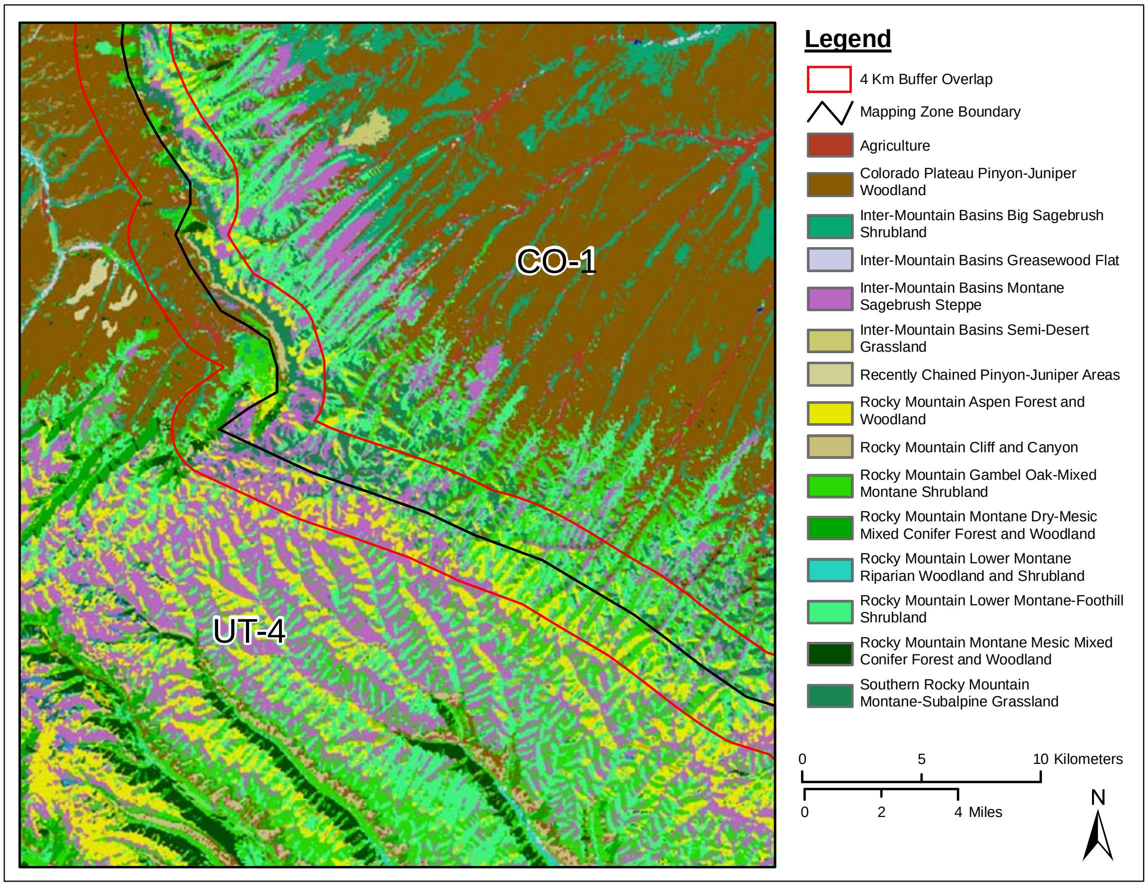

Figure 4. Example of edge-matching between UT-4 and CO-1

With the exception of work by Pal and Mather (2003), we found little published literature testing the training data requirements of decision tree classifiers for land cover mapping. Pal and Mather (2003) tested increasing training dataset size and found that classification accuracy increased linearly with size until reaching approximately 300 samples per class, whereupon additional training samples added little benefit. While not tested specifically, it is reasonable to assume that this is a general guideline and that the optimal number of samples for a given land cover class will vary with the spectral and environmental distinctiveness of each class, as well as the rarity of the class on the landscape. Identifying the optimal number of training samples per land cover class per mapping zone remained an elusive objective throughout the project and is certainly fertile ground for further study. We did discover, however, that sampling proportionally to the expected spatial abundance of land cover classes on the landscape produced superior results over using a roughly equal number of samples per class, which tended to over-map spatially rare classes. These findings are similar to those of McIver and Friedl (2002).

Given the importance of proportional sampling, the role of an adequate stratification strategy presents itself as another area where improvements could be made. As mentioned, our ground-truth collection strategy aimed primarily at obtaining as many samples as possible across the landscape via the road network. Some attempts were made to collect data in proportion to expected spatial abundance of land cover, and a minority of samples was collected via remote sources (e.g. aerial photography and digital orthophoto quads). While we were pleased with the number of samples collected for the region (approximately 93,000), in hindsight we recognize that more samples, more adequately stratified across the landscape within each mapping zone, could have been obtained using a more formal sampling design strategy combining ground based collection with a stronger effort at collecting remotely obtained samples.

Map Validation:

Throughout the course of the project we recognized the importance of providing a measure of map quality to users of the land cover map. While limitations of time, money and logistics prohibited a formal accuracy assessment (i.e. external validation with probability-based sample design), we believe the methods we employed provide useful information to map users. Our regional framework establishing criteria for fuzzy assessment helped standardize the process among the five mapping teams. However, in hindsight the criteria for the ‘moderate’ and ‘somewhat’ similar categories may be more liberal than advisable, and as such validation results at these levels of the fuzzy assessment are more optimistic than is warranted. The ‘very similar’ category we feel provides a reasonable assessment of map quality given the assumptions and rational of fuzzy set theory for map quality assessment. We recognize that not all land cover classes were quantitatively assessed throughout the region, but are satisfied that our assessment provided some measure of quantitative assessment for 85 of the 125 classes representing 91 percent of the land area.

Project Coordination:

Project coordination relied heavily on frequent communication between the regional land cover lab, the five land cover mapping teams, and the NatureServe ecologist who were familiar with the ecological systems for the project area. Correspondence via email—especially a project listserve—was critical for dissemination of information related to mapping methodologies and protocols. Also invaluable to project coordination were monthly teleconferences involving all land cover mapping personnel and the NatureServe ecologist. Face-to-face meetings (yearly) and hands-on workshops (three over five years) throughout the course of the project were essential not only for conveying important methodological techniques, but also as a means of fostering interpersonal relationships among team members. While the focus of this paper has been primarily on technical and methodological aspects of the land cover mapping effort, the importance of interpersonal relationships in a project of this nature should not be underestimated. Differing opinions regarding methodological and philosophical approaches to the effort were not uncommon. However, there was also a spirit of dedication to the work, and ultimately an understanding that in order to successfully complete the project, teamwork was essential.

From a project coordination standpoint, an important consideration was the recurring theme of how much autonomy each state would have in making decisions independent of group consensus. Perhaps the most difficult decision land cover analysts faced was deciding if a given land cover class should be mapped. Decisions to model a given land cover class were primarily driven by adequate representation within the training samples of a particular land cover class for a given mapping zone. Thus, the adequacy of the sample training set was a critical deciding factor for the land cover analyst. State analysts decided which classes to map based on their knowledge of the landscape or the perceived importance of the land cover class in the mapping zone. For example, riparian areas and invasive annual grasses, though difficult to map, may have been included if the analyst felt they were important features on the landscape. Also, when compiling the regional map some classes that were determined to be mappable in one state were aggregated or eliminated in the regional product to maintain regional consistency.[8]

In hindsight, more objective procedures could have been established to determine land cover class mappability. The ecological system classification as a regional target legend was developed by NatureServe during the course of the project, and must be recognized as a "working classification" (Comer et al. 2003). As such, the mappability of many classes using meso scale satellite imagery and ancillary data is not fully known. Developing better methods to determine land cover class mappability over large geographic areas is another area ripe for future research. Lastly, other regional, national and local projects such as LANDFIRE, SAGEMAP, several NPS Vegetation Mapping Program and USFWS refuge mapping projects are already benefiting from the great amount of effort that was involved on behalf of the SWReGAP and NatureServe in developing a stable legend suitable for a project of this scope.

Conclusion:

The goal of this project was to produce a land cover map that would not only be used for gap analysis, but would also be a useful product for individuals, agencies, and organizations. The methods outlined in this paper aimed at developing a land cover map using objective and replicable methods. We found the spatial and radiometric characteristics of the Landsat ETM+ sensor effective for mapping the vegetation of the Southwest into ecologically meaningful classes with reasonable accuracy. The decision tree classifier offered considerable benefits to the mapping process, and allowed us to map many land cover classes to our satisfaction. However, in addition to the sophistication of decision tree classifiers, the adequacy of training data, the establishment of objective criteria, and regional standards for consistency, we must recognize the importance of human reason in the mapping process.

One may ask whether we met our objectives of producing a map that improves upon the state-based, first generation GAP land cover maps for the region. A rigorous comparison

[8] For example not all states distinguished irrigated and non-irrigated agriculture and in the regional product these were combined into a single agriculture class. Also, Colorado mapped several land cover classes at the alliance level and mapped Conservation Reserve Program lands as a separate class. These have relevance for Colorado but were not included in the regional product.

between the SWReGAP map and previous maps would be time consuming but might prove useful. Another approach would be to design a statistically rigorous accuracy assessment of our product. One measure of the quality of this map relative to first generation state-based land cover maps, worth noting, is that more than ten times the number of training samples were used for the SWReGAP map than the previous maps combined. Furthermore, an important accomplishment of our effort is that instead of five different legends, there is now one to represent the region seamlessly. Ultimately, the value of the map will be determined by how frequently and how well the map is used. For that, only time will tell.

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Many individuals and organizations contributed to the SWReGAP project. Foremost we would like to thank Collin Homer, Bruce Wylie and Mike Coan at USGS EROS for their help with decision tree classifiers and the NLCD mapping tool. We would like to recognize both monetary and in-kind support provided by the Bureau of Land Management and in particular thank Diane Osborne formerly with the BLM National Science and Technology Center in Denver, CO for her contributions to the project. Other agencies and people we would like to recognize for their support include: Utah Division of Wildlife, U.S. Forest Service Region 4 (Ogden, UT), Bureau of Land Management (BLM) Salt Lake Field Office, BLM Nevada State Office (Reno, NV), BLM Ely Field Office (Ely, NV), Steve Knick and the SageMap Program at the USGS Forest and Rangeland Ecosystem Science Center, Snake River Field Station (Boise, ID) and Northern Arizona University.

We gratefully acknowledge the financial support of the USGS BRD, Gap Analysis Program, without which completion of this project could not have been possible. And finally, although we're many successive generations removed, where we are today is due in large part to the vision of J. Michael Scott, whose leadership in the early days of GAP fostered an intellectual climate still being realized today.

Literature Cited

Bailey, R. G., P. E. Avers, T. King and W.H. McNab, 1994. Ecoregions and subregions of the United States (1:7,500,000 map). With supplementary table of map unit descriptions, compiled and edited by W.H. McNab and R. G. Bailey. USDA Forest Service, Washington D.C.

Bauer, M. E., T.E. Burk, A. R. Ek, P.R. Coppin,, S. D. Lime,T. A. Walsh, Walters, D. K., W. Befort, and D. F. Heizen, 1994. Satellite inventory of Minnesota forest resources. *Photogrammetric Engineering and Remote Sensing 60*(3): 287-298.

Breiman. L., J. H. Friedman, R. A. Olshen, R. A., and C. J. Stone, 1984. Classification and regression trees. Wadsworth, Inc. Belmont, CA.

Brown de Colstoun, E. C., M. H. Story, C. Thompson, K. Commisso, T. G. Smith, T.G., and J. R. Irons, 2003. National Park vegetation mapping using multi-temporal Landsat & data and a decision tree classifier. *Remote Sensing of Environment 85*, 316-327.

Chavez, P. S. Jr. 1996. Image-based atmospheric corrections—Revisited and improved. *Photogrammetric Engineering and Remote Sensing* 62(9): 1025-1036.

Clark, L. A. and D. Pregibon, Tree-based Models. *In* J.M. Chambers & T.J. Hastie (Eds.). Statistical Models in S. Pacific Grove, CA: Wadsworth and Brooks; 1992; pp. 377-420.

Comer, P., D. Faber-Langendoen, R. Evans, S. Gawler, C. Josse, G. Kittel, S. Menard, S. Pyne, M. Reid, K. Schulz, K. Snowand, J. Teague, 2003. Ecological systems of the United States: A working classification of U.S. terrestrial systems. NatureServe, Arlington, Virginia. http://www.natureserve.org/library/usEcologicalsystems.pdf

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment 37*: 35-46.

Congalton, R. G. and K. Green. (1999). *Assessing the accuracy of remotely sensed data: principles and practices*. Boca Raton: Lewis Publishers.

DeFries, R. S., M. Hansen, J. R. G. Townshend and R. Sohlberg, 1998. Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. *International Journal of Remote Sensing* 19: 3141-3168.

Di Greogrio, A. and L. J. M. Jansen, 2000. Land cover classification system (LCCS): Classification concepts and user manual. Environment and Natural Resources Service, GCP/RAF/287/ITA Africover – East Africa Project and Soil Resources, Management and Conservation Service. FAO, Rome.

Driscoll, R.S., D.L. Merkel, D.L. Radloff, D.E. Snyder, and J.S. Hagihara. 1984. An ecological land classification framework for the United States. Miscellaneous Publication 1439. USDA Forest Service, Washington, DC.

Driscoll, R.S., D.L. Merkel, J.S. Hagihara, and D.L. Radloff. 1983. A component land classification for the United States: Status report. Technical Note 360. U.S. Department of the Interior, Bureau of Land Management, Denver, Colorado.

Eve, M. and J. Merchant. 1998. A national survey of land cover mapping protocols used in the gap analysis program. Final Report. Internet WWW page, at URL: http://www.calmit.unl.edu/gapmap/report.html.

Falzarano, S. R. and K. A. Thomas. 2004. Fuzzy set and spatial analysis techniques for evaluating thematic accuracy of a land-cover map. In Remote Sensing and GIS Accuracy Assessment R. S. Lunetta and J. G. Lyon, editors. CRC Press, Boca Raton, FL.

Federal Geographic Data Committee, Vegetation Subcommittee. 1997. FGDC Vegetation Classification and Information Standards--June 3, 1996 Draft. FGDC Secretariat, Reston, Virginia. 35 pp.

Foody, G., 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment 80*: 185-201.

Franklin, J.F. 1993. Preserving biodiversity: Species, ecosystems, or landscapes? *Ecological Applications* 3(2):202-205.

Friedl, M. A, and C. E. Brodley, 1997. Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment* 61:399-409.

Friedl, M. A., C. E. Brodley, and A. H. Strahler, 1999. Maximizing land cover classification accuracies produced by decision trees at continental to global scales. *IEEE Transactions on Geoscience and Remote Sensing* 37(2): 969-977.

Friedl, M. A., D. K. McIver, J. C. F. Hodges, X. Y. Zhang, D. Muchoney, A. H. Strahler, C. E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, and C. Schaaf, 2002. Global land cover mapping from MODIS: algorithms and early results. *Remote Sensing of Environment 83,* 287-302.

Garrard, C. M., 2003. Kappa tool user's guide. Unpublished document. RSGIS Laboratories, Utah State University. http://bioweb.usu.edu/chrisg/download/

Gopal, S. and C. Woodcock., 1994. Theory and methods for accuracy assessment of thematic maps using fuzzy sets. *Photogrammetric Engineering and Remote Sensing* Vol. 60, No. 2: 181-188.

Goutte, C., 1997. Note on free lunches and cross-validation, *Neural Computation*, 9, 1211-1215

Grossman, D., K.L. Goodin, X. Li, C. Wisnewski, D. Faber-Langendoen, M. Anderson, L. Sneddon, D. Allard, M. Gallyoun, and A. Weakley. 1994. Standardized national vegetation classification system. Report by The Nature Conservancy and Environmental Systems Research Institute for the NBS/NPS Vegetation Mapping Program. National Biological Service, Denver, Colorado.

Grossman, D. H., D. Faber-Langendoen, A. S. Weakley, M. Anderson, P. Bourgeron, R. Crawford, K. Goodin, S. Landaal, K. Metzler, K. D. Patterson, M. Pyne, M. Reid, and L. Sneddon. 1998. International classification of ecological communities: terrestrial vegetation of the United States. Volume 1. The National Vegetation Classification System: development, status, and applications. The Nature Conservancy, Arlington, Virginia, USA.

Hansen, M., R. Dubayah, and R. DeFries, 1996. Classification trees: An alternative to traditional land cover classifiers. *International Journal of Remote Sensing* 17(5): 1075-1081.

Hansen, M. C., R. S. DeFries, J. R. G. Townsend, J. R. G. and R. Sohlberg, 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *International Journal of Remote Sensing* 21(6,7): 1331-1364.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan, 2004. Development of a 2001 national land cover database for the United States. *Photogrammetric Engineering and Remote Sensing* 70(7):829-840.

Homer, C. G., R. D. Ramsey, T. C. Edwards, Jr. and A. Falconer, 1997. Landscape cover-type modeling using a multi-scene Thematic Mapper mosaic. *Photogrammetric Engineering and Remote Sensing 63*(1): 59-67.

Hutchingson, C. 1982. Techniques for combining Landsat and ancillary data for digital classification improvement. *Photogrammetric Engineering and Remote Sensing*, 48:123-130.

Huang, C., B. Wylie, C Homer, L. Yang, L., and G. Zylstra, 2002. Derivation of a Tasseled cap transformation based on Landsat 7 at-satellite reflectance. *International Journal of Remote Sensing* 23(8): 1741-1748.

Jensen, J. R. 2005. *Introductory Digital Image Processing.: A Remote Sensing Perspective*. Third Edition. Upper Saddle River, NJ, Prentice Hall.

Jenness Enterprises. 2005. Random Point Generator, v 1.3. ArcView Script. Internet WWW URL at http://www.jennessent.com/arcview/random_points.htm.

Jennings, M.D. 1993. Natural terrestrial cover classification: Assumptions and definitions. Gap Analysis Technical Bulletin 2. Idaho Cooperative Fish and Wildlife Research Unit, University of Idaho, Moscow.

Laba, M., S. K. Gregory, J. Braden, D. Ogurcak, E. Hill, E. Fegraus, J. Fiore, and S. D. DeGloria. Conventional and fuzzy accuracy assessment of the New York Gap Analysis Project land cover map. *Remote Sensing of Environment*. 81:443-455.

Lawrence, R. L. and A. Wright. 2001. A. Rule-based classification systems using classification and regression trees (CART) analysis. *Photogrammetric Engineering and Remote Sensing* 67(10):1137-1142.

Lawrence, R., A. Bunn, S. Powell, S., and M. Zambon, M. 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment* 90:331-336.

Lillesand, T. M. 1996. A protocol for satellite-based land cover classification in the Upper Midwest. Pages 103-118 in J. M. Scott, T. H. Tear, and F. W. Davis, editors. Gap Analysis: A Landscape Approach to Biodiversity Planning. ASPRS, 320 pp.

Lillesand, T.M. and R. W. Kiefer. 2000. *Remote Sensing and Image Interpretation.* Fourth Edition. John Wiley & Sons, Inc., New York.

Lins, K.S., and R.L. Kleckner. 1996. Land cover mapping: An overview and history of the concepts. Pages 57-65 in J.M. Scott, T.H. Tear, and F. Davis, editors, Gap Analysis: A landscape approach to biodiversity planning. American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland.

Ma, Z., M. M. Hart and R. L. Redmond. 2001. Mapping vegetation across large geographic areas: Integration of remote sensing and GIS to classify multisource data. *Photogrammetric Engineering and Remote Sensing* Vol. 67, No. 3, 295-307.

Manis, G., C. Homer, R. D. Ramsey, J. Lowry, T. Sajwaj, and S. Graves, 2000. The development of mapping zones to assist in land cover mapping over large geographic areas: A case study of the Southwest ReGAP project. GAP Analysis Bulletin No. 9. U.S. Geological Survey, Biological Resources Division. http://www.gap.uidaho.edu/Bulletins/9/bulletin9/default.html

Manis, G., J. Lowry, J. and R. D. Ramsey, 2001. Pre-classification: An ecologically predictive landform model. GAP Analysis Bulletin No. 10. U.S. Geological Survey, Biological Resources Division. http://www.gap.uidaho.edu/Bulletins/10/preclassification.htm

McIver, D. K. and M. A. Friedl. 2002. Using prior probabilities in decision tree classification of remotely sensed data. *Remote Sensing of Environment 81*: 253-261

Mueller-Dombois, D., and H. Ellenberg. 1974. Aims and methods of vegetation ecology. John Wiley & Sons, New York. 547 pp.

Noss, R.F. 1987. From plant communities to landscapes in conservation inventories: A look at The Nature Conservancy (USA). *Biological Conservation* 41:11-37.

Omernick, J. M. 1987. Ecoregions of the conterminous United States. Map (scale 1:7,500,000). *Annals of the Association of American Geographers 77*(1):118-125.

Pal, M. and P. M. Mather, 2003. An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment 86*, 554-565

Quinlan, J. R. 1993. C4.5: programs for machine learning. San Mateo, CA: Morgan Kaufmann Publishers.

Reiners, W. A., K. L. Driese, & D. Schrupp. 2000. Statistical evaluation of Wyoming and Colorado landcover map thematic accuracy using aerial videography techniques. Final Report. Department of Botany, University of Wyoming, Laramie, WY. WWW page at URL: http://ndis1.nrel.colostate.edu/cogap/report/colandcov_acc.pdf

Reese, H. M., T. M. Lillesand, D. E. Nagel, J. S. Stewart, R. A. Goldmann, T. E. Simmons, J. W. Chipman, and P. A. Tessar, 2002. Statewide land cover derived from multiseasonal Landsat TM data: A retrospective of the WISCLAND project. *Remote Sensing of Environment* 82: 224-237.

Ricchetti, E. 2000. Multispectral satellite image and ancillary data integration for geological classification. *Photogrammetric Engineering and Remote Sensing* 66(4):429-435.

Scott, J.M., F. Davis, B. Csuti, R. Noss, B. Butterfield, C. Groves, H. Anderson, S. Caicco, F. D'Erchia, T.C. Edwards, Jr., J. Ulliman, and G. Wright. 1993. Gap analysis: A geographic approach to protection of biological diversity. *Wildlife Monographs* 123.

Shtatland, E. S., K. Klienman and E. M. Cain. 2004. A new strategy of model building in PROC LOGISTIC with automatic variable selection, validation, shrinkage and model averaging. SUGI 29 Proceedings, paper 191-29. Montreal, Canada. WWW URL: http://www2.sas.com/proceedings/sugi29/191-29.pdf

Smits, P. C., S. G. Dellepiane and R. A. Schowngerdt 1999. Quality assessment of image classification algorithms for land-cover mapping a review and a proposal for a cost-based approach. *International Journal of Remote Sensing 20*, 1461-1486.

Sneddon, L., M. Anderson, and K. Metzler. 1994. A classification and description of terrestrial community alliances in The Nature Conservancy's Eastern Region: First approximation. Unpublished report to USDI Fish & Wildlife Service, Gap Analysis Program. The Nature Conservancy, Eastern Heritage Task Force, Boston, MA. 116 pp.

Stehman, S. V. and R. L. Czaplewski. 1998. Design and analysis for thematic map accuracy assessment: Fundamental principles. *Remote Sensing of Environment 64*:331-344.

Stoms, D.M. 1994. Actual vegetation layer. In J.M. Scott and M.D. Jennings, editors. A handbook for Gap Analysis. Idaho Cooperative Fish and Wildlife Research Unit, University of Idaho, Moscow.

Treitz, P. and P. Howarth, 2000. Integrating spectral, spatial, and terrain variables for forest ecosystem classification, *Photogrammetric Engineering and Remote Sensing*, 66(3):305-317.

UNESCO. 1973. International classification and mapping of vegetation. Paris.
Verbyla, D. L. 1987. Classification trees: A new discrimination tool. *Canadian Journal of Forest Research* Vol. 17.
USGS-NPS Vegetation Mapping Program. 1994. Field Methods for Vegetation Mapping. The Nature Conservancy and Environmental Systems Research Institute. December, 1994.
Weakley, A. S., K. D. Patterson, S. Landaal, M. Gallyoun, and others, compilers. 1996. International classification of ecological communities: Terrestrial vegetation of the Southeastern United States. Working draft of April 1996. The Nature Conservancy, Southeast Regional Office, Southern Conservation Science Department, Community Ecology Group. Chapel Hill, NC.
Whittaker, R.H. 1960. Vegetation of the Siskiyou mountains, Oregon and California. *Ecological Monographs* 30(3):279-338.
Whittaker, R.H. 1977. Species diversity in land communities. *Evolutionary Biology* 10:1-67.
Woodcock, C. and S. Gopal. 1992. *Accuracy assessment of the Stanislaus Forest vegetation map using fuzzy sets*. Proceedings of the 4th Biennial Remote Sensing Applications Conference, Orlando FL.

Appendix LC-1

	Source					Total Samples by Land Cover Class
	Air Photo Interpretation	Image (Landsat) Interpretation	DOQ/Terra Server Interpretation	Cooperator Databases	SWReGAP Fieldwork	
SPARSELY VEGETATED/BARREN CLASSES						
Barren Lands, Non-specific			45	55	222	322
Colorado Plateau Mixed Bedrock Canyon and Tableland	82	54	332	64	393	925
Inter-Mountain Basins Active and Stabilized Dune	1		38	27	161	227
Inter-Mountain Basins Cliff and Canyon	12	3	67	17	309	408
Inter-Mountain Basins Playa		3	43	59	306	411
Inter-Mountain Basins Shale Badland		13	86	53	117	269
Inter-Mountain Basins Volcanic Rock and Cinder Land	38	7	42	140	53	280
Inter-Mountain Basins Wash		66		32	56	154
Mediterranean California Alpine Bedrock and Scree					5	5
North American Alpine Ice Field	4		25	2		31
North American Warm Desert Active and Stabilized Dune				137	30	167
North American Warm Desert Badland					12	12
North American Warm Desert Bedrock Cliff and Outcrop			2	9	204	215
North American Warm Desert Pavement			3	15	33	51
North American Warm Desert Playa				44	131	175
North American Warm Desert Volcanic Rockland				13	11	24
Rocky Mountain Alpine Bedrock and Scree	117	6	27	236	83	469
Rocky Mountain Alpine Fell-Field	41			97	25	163
Rocky Mountain Cliff, Canyon and Massive Bedrock	180	34	94	244	108	660
Sierra Nevada Cliff and Canyon					22	22
Western Great Plains Cliff and Outcrop		22		14	9	45
Subtotal	***475***	***208***	***804***	***1,258***	***2,290***	***5,035***
DECIDUOUS FOREST CLASSES						
Rocky Mountain Aspen Forest and Woodland	358	59	328	1,040	893	2,678
Rocky Mountain Bigtooth Maple Ravine Woodland	30		87	16	46	179
Subtotal	***388***	***59***	***415***	***1,056***	***939***	***2,857***
EVERGREEN FOREST CLASSES						
Colorado Plateau Pinyon-Juniper Woodland	66	92	128	1,648	2,320	4,254
Great Basin Pinyon-Juniper Woodland			36	424	1,753	2,213
Inter-Mountain Basins Subalpine Limber-Bristlecone Pine Woodland					121	121
Madrean Encinal				116	74	190
Madrean Pine-Oak Forest and Woodland				40	398	438
Madrean Pinyon-Juniper Woodland				469	617	1,086
Madrean Upper Montane Conifer-Oak Forest and Woodland				2	28	30
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland					7	7
Mediterranean California Ponderosa-Jeffrey Pine Forest and Woodland					46	46
Mediterranean California Red Fir Forest and Woodland					33	33
Northern Pacific Mesic Subalpine Parkland					26	26
Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	44	51	4	895	752	1,746
Rocky Mountain Foothill Limber Pine-Juniper Woodland		12				12
Rocky Mountain Lodgepole Pine Forest	136	23	7	590	218	974
Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	92		37	76	243	448
Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	92	19	75	1,187	480	1,853
Rocky Mountain Subalpine Mesic Spruce-Fir Forest and Woodland	158		12	108	203	481
Rocky Mountain Subalpine-Montane Limber-Bristlecone Pine Woodland	21		1	90	45	157
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland					17	17
Southern Rocky Mountain Pinyon-Juniper Woodland	39	136		449	227	851

Southern Rocky Mountain Ponderosa Pine Woodland	128	162	39	1,209	2,255	3,793
Subtotal	***776***	***495***	***339***	***7,303***	***9,863***	***18,776***
MIXED FOREST CLASS						
Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	98	27	59	312	267	763
Subtotal	***98***	***27***	***59***	***312***	***267***	***763***
SCRUB/SHRUB CLASSES						
Apacherian-Chihuahuan Mesquite Upland Scrub				228	816	1,044
Chihuahuan Mixed Desert and Thorn Scrub				601	475	1,076
Chihuahuan Mixed Salt Desert Scrub				104	104	208
Chihuahuan Stabilized Coppice Dune and Sand Flat Scrub				216	78	294
Chihuahuan Succulent Desert Scrub				15	15	30
Coahuilan Chaparral				43	6	49
Colorado Plateau Blackbrush-Mormon-tea Shrubland		2	6	36	450	494
Colorado Plateau Mixed Low Sagebrush Shrubland	11	4	39	46	162	262
Colorado Plateau Pinyon-Juniper Shrubland	105	56	168	155	311	795
Great Basin Semi-Desert Chaparral		11		13	115	139
Great Basin Xeric Mixed Sagebrush Shrubland				82	1,821	1,903
Inter-Mountain Basins Big Sagebrush Shrubland	28	107	156	1,622	4,524	6,437
Inter-Mountain Basins Mat Saltbush Shrubland		18	16	141	151	326
Inter-Mountain Basins Mixed Salt Desert Scrub		60	36	613	3,313	4,022
Inter-Mountain Basins Mountain Mahogany Woodland and Shrubland	32	8	30	62	284	416
Mogollon Chaparral			2	303	480	785
Mojave Mid-Elevation Mixed Desert Scrub				429	548	977
Rocky Mountain Alpine Dwarf-Shrubland	26		3	1	12	42
Rocky Mountain Gambel Oak-Mixed Montane Shrubland	188	437	105	1,039	763	2,532
Rocky Mountain Lower Montane-Foothill Shrubland		124		221	26	371
Sonora-Mojave Creosotebush-White Bursage Desert Scrub			74	821	736	1,631
Sonora-Mojave Mixed Salt Desert Scrub			2	67	147	216
Sonora-Mojave Semi-Desert Chaparral					65	65
Sonoran Mid-Elevation Desert Scrub				15	133	148
Sonoran Paloverde-Mixed Cacti Desert Scrub			106	520	687	1,313
Southern Colorado Plateau Sand Shrubland			44	34	316	394
Western Great Plains Mesquite Woodland and Shrubland						0
Western Great Plains Sandhill Shrubland		554		145	153	852
Wyoming Basins Low Sagebrush Shrubland		3		21	1	25
Subtotal	***390***	***1,384***	***787***	***7,593***	***16,692***	***26,846***
GRASSLAND/HERBACEOUS CLASSES						
Apacherian-Chihuahuan Semi-Desert Grassland and Steppe				1,187	501	1,688
Central Mixedgrass Prairie		35		3	3	41
Chihuahuan Gypsophilous Grassland and Steppe				119	3	122
Chihuahuan Sandy Plains Semi-Desert Grassland				77	57	134
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland		6		276	233	515
Inter-Mountain Basins Big Sagebrush Steppe	3	1		7	448	459
Inter-Mountain Basins Juniper Savanna		13		96	286	395
Inter-Mountain Basins Montane Sagebrush Steppe	228	118	260	1,405	1,869	3,880
Inter-Mountain Basins Semi-Desert Grassland		24	18	389	1,505	1,936
Inter-Mountain Basins Semi-Desert Shrub-Steppe		4	27	845	2,649	3,525
Madrean Juniper Savanna				30	100	130
North Pacific Montane Grassland					19	19
Rocky Mountain Dry Tundra	66		1	219	68	354
Rocky Mountain Subalpine Mesic Meadow	67	37	27	242	188	561
Southern Rocky Mountain Juniper Woodland and Savanna		89		71	135	295
Southern Rocky Mountain Montane-Subalpine Grassland	31	29	45	791	497	1,393
Western Great Plains Foothill and Piedmont Grassland		436		360	44	840
Western Great Plains Sand Prairie		4		2		6
Western Great Plains Shortgrass Prairie		1,180		1,125	889	3,194
Western Great Plains Tallgrass Prairie						0
Subtotal	***395***	***1,976***	***378***	***7,244***	***9,494***	***19,487***

WOODY WETLAND CLASSES						
Great Basin Foothill and Lower Montane Riparian Woodland and Shrubland			83	4	381	468
Inter-Mountain Basins Greasewood Flat		45	22	294	1,601	1,962
North American Warm Desert Lower Montane Rip. Woodland & Shrubland				101	118	219
North American Warm Desert Riparian Mesquite Bosque			33	22	33	88
North American Warm Desert Riparian Woodland and Shrubland			4	113	42	159
North American Warm Desert Wash			6	58	160	224
Rocky Mountain Lower Montane Riparian Woodland and Shrubland	73	37	155	383	207	855
Rocky Mountain Subalpine-Montane Riparian Shrubland	47	9	35	453	141	685
Rocky Mountain Subalpine-Montane Riparian Woodland	2			164	59	225
Western Great Plains Floodplain		398			2	400
Western Great Plains Riparian Woodland and Shrubland		723		84	31	838
Subtotal	***122***	***1,212***	***338***	***1,676***	***2,775***	***6,123***
EMERGENT HERBACEOUS WETLAND CLASSES						
Mediterranean California Subalpine-Montane Fen					4	4
North American Arid West Emergent Marsh			42	104	194	340
Rocky Mountain Alpine-Montane Wet Meadow	93	6	110	352	141	702
Temperate Pacific Subalpine-Montane Wet Meadow					9	9
Western Great Plains Saline Depression Wetland					7	7
Subtotal	***93***	***6***	***152***	***456***	***355***	***1,062***
ALTERED OR DISTURBED CLASSES						
Disturbed, Non-specific		1		1	10	12
Disturbed, Oil well						0
Invasive Annual and Biennial Forbland		50		209	483	742
Invasive Annual Grassland	6	57	4	275	528	870
Invasive Perennial Forbland				21	16	37
Invasive Perennial Grassland	1	194	33	330	217	775
Invasive Southwest Riparian Woodland and Shrubland	31	226	11	114	179	561
Recently Burned	21	27	1	15	35	99
Recently Chained Pinyon-Juniper Areas	37	28	42	91	4	202
Recently Logged Areas	73	16	6	113	46	254
Recently Mined or Quarried		52		54	32	138
Subtotal	***169***	***651***	***97***	***1,223***	***1,550***	***3,690***
OTHER CLASSES						
Agriculture	10	4,625		1,290	977	6,902
Developed, Medium - High Intensity		104		77	6	187
Developed, Open Space - Low Intensity		189		51	7	247
Barren Lands, Non-specific			45	55	222	322
Open Water	18	756		182	216	1,172
Subtotal	***28***	***5,674***	***45***	***1,655***	***1,428***	***8,830***
Grand Total by Source	**2,934**	**11,692**	**3,414**	**29,776**	**45,653**	**93,469**

Appendix LC- 1. Distribution of all samples used for mapping in the SWReGAP region. Samples collected via air photo interpretation (3 % of total) were collected exclusively by the Utah team. Samples collected via DOQ/Terra Server interpretation were collected by the Arizona and Utah teams (4%). Samples collected via image (Landsat) interpretation (12%) were collected exclusively by the Colorado team, often with interpretive cues from Terraserver. Samples obtained from existing databases (32%) and collected through SWReGAP fieldwork (49%) represent the collective efforts of the five mapping teams.

Appendix LC-2

	Land Cover in Square Kilometers					
	Arizona	Colorado	Nevada	New Mexico	Utah	Region Wide
SPARSLEY VEGETATED/BARREN CLASSES						
Barren Lands, Non-specific	1,119	11	195	54	42	1,421
Colorado Plateau Mixed Bedrock Canyon and Tableland	6,974	675	2	2,466	14,196	24,313
Inter-Mountain Basins Active and Stabilized Dune	352	130	79	735	1,807	3,103
Inter-Mountain Basins Cliff and Canyon		4	2,487		382	2,873
Inter-Mountain Basins Playa	14	46	6,234	2	11,284	17,581
Inter-Mountain Basins Shale Badland	730	258		482	1,828	3,297
Inter-Mountain Basins Volcanic Rock and Cinder Land	573			470	317	1,360
Inter-Mountain Basins Wash	4	20	18	3	1	46
Mediterranean California Alpine Bedrock and Scree			23			23
North American Alpine Ice Field		2			21	23
North American Warm Desert Active and Stabilized Dune	1,016		16	1,695		2,728
North American Warm Desert Badland	34		78			112
North American Warm Desert Bedrock Cliff and Outcrop	761		1,842	838	127	3,568
North American Warm Desert Pavement	45		168	180		393
North American Warm Desert Playa	48		527	535	6	1,115
North American Warm Desert Volcanic Rockland	205		78	700	8	992
Rocky Mountain Alpine Bedrock and Scree	5	2,888	148	7	815	3,863
Rocky Mountain Alpine Fell-Field		584			177	761
Rocky Mountain Cliff, Canyon and Massive Bedrock	92	989		417	1,467	2,965
Sierra Nevada Cliff and Canyon			123			123
Western Great Plains Cliff and Outcrop		88		221		309
Subtotal	***11,972***	***5,695***	***12,018***	***8,805***	***32,478***	***70,969***
DECIDUOUS FOREST CLASSES						
Rocky Mountain Aspen Forest and Woodland	443	11,436	1,289	1,483	6,335	20,986
Rocky Mountain Bigtooth Maple Ravine Woodland			1		887	888
Subtotal	***443***	***11,436***	***1,290***	***1,483***	***7,222***	***21,874***
EVERGREEN FOREST CLASSES						
Colorado Plateau Pinyon-Juniper Woodland	32,495	15,136		27,864	22,360	97,855
Great Basin Pinyon-Juniper Woodland	3,414		36,376		10,986	50,776
Inter-Mountain Basins Subalpine Limber-Bristlecone Pine Woodland			635		32	666
Madrean Encinal	3,008			1,350		4,358
Madrean Pine-Oak Forest and Woodland	4,008			1,725		5,733
Madrean Pinyon-Juniper Woodland	13,163			8,754		21,917
Madrean Upper Montane Conifer-Oak Forest and Woodland	123			672		795
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland			2			2
Mediterranean California Ponderosa-Jeffrey Pine Forest and Woodland			209			209
Mediterranean California Red Fir Forest and Woodland			106			106
Northern Pacific Mesic Subalpine Parkland			42			42
Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	1,030	3,152	196	2,865	1,710	8,953
Rocky Mountain Foothill Limber Pine-Juniper Woodland		6				6
Rocky Mountain Lodgepole Pine Forest		6,940		7	1,817	8,764
Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	439	3,603	216	1,610	1,427	7,295
Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	223	10,189	190	982	3,230	14,814
Rocky Mountain Subalpine Mesic Spruce-Fir Forest and Woodland	120	8,151	175	640	1,273	10,359
Rocky Mountain Subalpine-Montane Limber-Bristlecone Pine Woodland	2	369	14	376	39	801

Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland			20			21
Southern Rocky Mountain Pinyon-Juniper Woodland	1	4,835		10,468		15,305
Southern Rocky Mountain Ponderosa Pine Woodland	16,240	10,792	7	21,163	2,019	50,221
Subtotal	***74,266***	***63,173***	***38,188***	***78,476***	***44,893***	***298,998***
MIXED FOREST CLASS						
Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland		1,951	84	182	1,222	3,439
Subtotal		***1,951***	***84***	***182***	***1,222***	***3,439***
SHRUB/SCRUB CLASSES						
Apacherian-Chihuahuan Mesquite Upland Scrub	16,546			15,137		31,683
Chihuahuan Mixed Desert and Thorn Scrub	6,319	9		21,079		27,407
Chihuahuan Mixed Salt Desert Scrub	2,816			1,597		4,413
Chihuahuan Stabilized Coppice Dune and Sand Flat Scrub	187			5,538		5,725
Chihuahuan Succulent Desert Scrub	109			78		187
Coahuilan Chaparral				93		94
Colorado Plateau Blackbrush-Mormon-tea Shrubland	4,037	97	4	141	9,031	13,310
Colorado Plateau Mixed Low Sagebrush Shrubland	489	66		329	1,517	2,401
Colorado Plateau Pinyon-Juniper Shrubland	354	1,765			9,417	11,535
Great Basin Semi-Desert Chaparral			162			163
Great Basin Xeric Mixed Sagebrush Shrubland			31,799		3,635	35,434
Inter-Mountain Basins Big Sagebrush Shrubland	5,200	13,384	66,020	3,934	19,941	108,480
Inter-Mountain Basins Mat Saltbush Shrubland	75	1,019			3,037	4,130
Inter-Mountain Basins Mixed Salt Desert Scrub	7,005	2,324	50,646	3,791	15,527	79,294
Inter-Mountain Basins Mountain Mahogany Woodland and Shrubland		1	1,924		626	2,550
Mogollon Chaparral	9,637		425	870	583	11,515
Mojave Mid-Elevation Mixed Desert Scrub	5,416		10,520		826	16,762
Rocky Mountain Alpine Dwarf-Shrubland					109	110
Rocky Mountain Gambel Oak-Mixed Montane Shrubland	128	10,229	108	1,888	6,597	18,950
Rocky Mountain Lower Montane-Foothill Shrubland		2,305		266	252	2,823
Sonora-Mojave Creosotebush-White Bursage Desert Scrub	38,922		19,030		808	58,760
Sonora-Mojave Mixed Salt Desert Scrub	1,011		1,528		10	2,549
Sonora-Mojave Semi-Desert Chaparral			86		3	89
Sonoran Mid-Elevation Desert Scrub	5,391			2		5,393
Sonoran Paloverde-Mixed Cacti Desert Scrub	39,790					39,791
Southern Colorado Plateau Sand Shrubland	6,074	13		79	855	7,021
Western Great Plains Mesquite Woodland and Shrubland		10		1,787		1,797
Western Great Plains Sandhill Shrubland		8,682		5,212		13,894
Wyoming Basins Low Sagebrush Shrubland		43			4	47
Subtotal	***149,506***	***39,947***	***182,252***	***61,821***	***72,778***	***506,307***
GRASSLAND/HERBACEOUS CLASSES						
Apacherian-Chihuahuan Semi-Desert Grassland and Steppe	11,353			34,358		45,711
Central Mixedgrass Prairie		120				120
Chihuahuan Gypsophilous Grassland and Steppe				804		804
Chihuahuan Sandy Plains Semi-Desert Grassland	16			970		986
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland						
Inter-Mountain Basins Big Sagebrush Steppe			1,275		523	1,798
Inter-Mountain Basins Juniper Savanna	4,002	281	1	1,298	9	5,590
Inter-Mountain Basins Montane Sagebrush Steppe	1	8,504	17,817	283	14,049	40,654
Inter-Mountain Basins Semi-Desert Grassland	11,250	863	3,114	16,400	2,014	33,640
Inter-Mountain Basins Semi-Desert Shrub-Steppe	15,474	3,354	5,974	14,486	8,330	47,618
Madrean Juniper Savanna	336	1		657		994
North Pacific Montane Grassland			27			27
Rocky Mountain Dry Tundra		2,447	20	19	293	2,779
Rocky Mountain Subalpine Mesic Meadow		1,507	24	147	499	2,177
Southern Rocky Mountain Juniper Woodland and Savanna		2,149		9,808		11,956
Southern Rocky Mountain Montane-Subalpine Grassland	587	7,252	2	1,859	594	10,294
Western Great Plains Foothill and Piedmont Grassland		4,365		701		5,066
Western Great Plains Sand Prairie		18				18
Western Great Plains Shortgrass Prairie		45,651		67,511		113,162

Western Great Plains Tallgrass Prairie		1				1
Subtotal	***43,019***	***76,513***	***28,254***	***149,301***	***26,311***	***323,395***
WOODY WETLAND CLASSES						
Great Basin Foothill and Lower Montane Riparian Woodland and Shrubland			1,068		293	1,360
Inter-Mountain Basins Greasewood Flat	1,237	2,281	10,673	2,269	7,310	23,770
North American Warm Desert Lower Montane Riparian Woodland and Shrubland	180		32	194	20	426
North American Warm Desert Riparian Mesquite Bosque	801		25	3	3	832
North American Warm Desert Riparian Woodland and Shrubland	283		5	125	10	422
North American Warm Desert Wash	153	1	288	199	10	652
Rocky Mountain Lower Montane Riparian Woodland and Shrubland	24	569		787	847	2,226
Rocky Mountain Subalpine-Montane Riparian Shrubland		2,820	3	103	298	3,224
Rocky Mountain Subalpine-Montane Riparian Woodland		215	68	5	4	292
Western Great Plains Floodplain		836				836
Western Great Plains Riparian Woodland and Shrubland		859		855		1,714
Subtotal	***2,678***	***7,581***	***12,162***	***4,540***	***8,795***	***35,754***
EMERGENT HERBACEOUS WETLAND CLASSES						
Mediterranean California Subalpine-Montane Fen			2			2
North American Arid West Emergent Marsh	32	45	409	86	482	1,053
Rocky Mountain Alpine-Montane Wet Meadow		1,331	10	136	479	1,956
Temperate Pacific Subalpine-Montane Wet Meadow			2			2
Western Great Plains Saline Depression Wetland				41		41
Subtotal	***32***	***1,376***	***423***	***263***	***961***	***3,054***
ALTERED OR DISTURBED CLASSES						
Disturbed, Non-specific		2			90	93
Disturbed, Oil well					46	46
Invasive Annual and Biennial Forbland	127	634	1,134	48	695	2,638
Invasive Annual Grassland	72	372	4,611		3,237	8,291
Invasive Perennial Forbland		1				1
Invasive Perennial Grassland	13	2,083	187	30	526	2,839
Invasive Southwest Riparian Woodland and Shrubland	484	493	149	27	456	1,609
Recently Burned	168	313	574	806	172	2,033
Recently Chained Pinyon-Juniper Areas		231			458	689
Recently Logged Areas		541		8	287	836
Recently Mined or Quarried	470	89	322	182	177	1,240
Subtotal	***1,334***	***4,759***	***6,977***	***1,101***	***6,144***	***20,315***
OTHER CLASSES						
Agriculture	5,635	52,901	2,223	6,025	9,197	75,981
Developed, Medium - High Intensity	4,048	1,074	210	1,108	1,099	7,539
Developed, Open Space - Low Intensity	1,711	2,013	726	977	1,997	7,425
Open Water	702	1,316	1,481	792	6,733	11,023
Subtotal	***12,096***	***57,304***	***4,640***	***8,902***	***19,026***	***101,968***
Total by State Political Boundary	**295,346**	**269,735**	**286,288**	**314,874**	**219,830**	**1,386,073**

Appendix LC- 2. Total land cover mapped in square kilometers summarized by land cover class and state political boundaries.

Appendix LC-3

Ecological Similarity Code	Ecological Similarity Type	Ecological Similarity Description
A	Physiognomic Structure (Map and reference have same NLCD class)	Where reference and mapped classes share the same NLCD Class, such as: N30 Barren (Includes all Barren Lands) N40 Forest (Includes all Deciduous Forest, Evergreen Forest and Mixed Forest types) N50 Shrubland (Includes all Shrub, Dwarf Shrub and Shrub/Scrub types) N70 Herbaceous (Includes all Grassland, Herbaceous, Savanna and Shrub-Steppe types) N90 Wetlands (Includes all Wetland, Riparian, Emergent Wetlands, Wet Meadows and Greasewood Flats)
B	Dominant Species Composition	Where reference and mapped classes share dominant/diagnostic species as specified in concept of Ecological Systems. For example, if systems share *dominant* or *codominant* species, then species composition is similar. If systems share species that are only *present*, then species composition is not similar. Would also apply if the confusion occurs between systems where the dominant/codominant species is common, but has been identified to a different subspecies (i.e. *Artemisia tridentata* spp.).
C	Juxtaposition	Where reference and mapped classes commonly form a mosaic, such as where patch or linear systems occur within matrix systems, or where broad ecotonal boundaries between the classes occur with regularity. This often relates to minimum mapping unit (scale) issues with mosaics of similar landcover types. Refrain from using this code when the possibility of juxtaposition is only a rare occurrence.
D	Special Substrates	Where reference and mapped classes share substrates with special properties that ecologically define each Ecological System. Apply with the following substrates only: - Eolian (sandsheets and dunes) - Bedrock (exposed weathering parent material); sparse vegetation (Barren) classes only - High Salinity (exposed marine shales, saline overflow /playas)

Appendix LC- 3. Ecological similarity codes, types, and descriptions for four major types of ecological similarity recognized within the region.

Appendix LC-4

			REFERENCE														
	LAND COVER CLASS NAME	class code	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118	TOTAL	ACCURACY
MAPPED	Inter-Mountain Basins Cliff and Canyon	S009	5	0	0	0	0	0	1	0	0	0	0	0	0	6	83%
	Rocky Mountain Aspen Forest and Woodland	S023	0	4	0	0	0	0	0	0	0	0	0	0	0	4	100%
	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	S028	0	0	5	0	0	0	0	0	0	0	0	0	0	5	100%
	Great Basin Pinyon-Juniper Woodland	S040	0	0	0	17	0	0	0	0	0	0	1	0	0	18	94%
	Inter-Mountain Basins Mountain Mahogany Woodland and Shrubland	S050	0	0	0	0	1	0	0	0	0	0	0	0	0	1	100%
	Inter-Mountain Basins Big Sagebrush Shrubland	S054	0	0	0	1	0	54	12	2	2	6	3	1	0	81	67%
	Great Basin Xeric Mixed Sagebrush Shrubland	S055	0	0	0	0	0	2	8	1	2	1	0	0	0	14	57%
	Inter-Mountain Basins Mixed Salt Desert Scrub	S065	0	0	0	0	0	0	1	2	0	0	0	0	0	3	67%
	Inter-Mountain Basins Montane Sagebrush Steppe	S071	1	2	0	0	1	1	3	0	18	2	1	1	0	30	60%
	Inter-Mountain Basins Big Sagebrush Steppe	S078	0	0	0	0	0	1	0	0	0	0	0	1	0	2	0%
	Inter-Mountain Basins Semi-Desert Grassland	S090	0	0	0	0	0	1	0	0	0	0	3	0	0	4	75%
	Inter-Mountain Basins Greasewood Flat	S096	0	0	0	0	0	0	0	1	0	0	0	1	0	2	50%
	Great Basin Foothill and Lower Montane Riparian Woodland and Shrubland	S118	0	0	0	0	0	0	0	0	0	0	0	0	6	6	100%
		TOTAL	6	6	5	18	2	59	25	6	22	9	8	4	6	176	
		ACCURACY	83%	67%	100%	94%	50%	92%	32%	33%	82%	0%	38%	25%	100%		70%

Kappa: 0.603367

Standard error of kappa: 0.0304283

Z-Score for kappa: 19.8291

Appendix LC- 4. Example of an original error matrix for mapping zone UT-5. This matrix was produced using 20% withheld data. This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

Appendix LC-5

		REFERENCE												
	CLASS	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118
MAPPED	S009	ABCD						0						
	S023		ABCD											
	S028			ABCD										
	S040				ABCD							C		
	S050					ABCD								
	S054				C		ABCD	ABC	AC	ABC	ABC	C	C	
	S055						ABC	ABCD	AC	AC	AC			
	S065							AC	ABCD					
	S071	C	C			AC	ABC	AC		ABCD	ABC	0	0	
	S078						ABC				ABCD		C	
	S090						C					ABCD		
	S096								CD				ABCD	
	S118													ABCD

Appendix LC- 5. Example for UT-5 of *ecological type similarity matrix* showing the application of recognized similarity codes (Appendix LC-3) to off-diagonal (misclassification) cells from the original error matrix (Appendix LC-4). This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

Appendix LC-6

Ecological Similarity Code	Relative Similarity Category	Example	Explanation	Relative Similarity Score
No Similarity (0)	INCORRECT	*Intermountain Basins Mixed Salt Desert Scrub* versus *Rocky Mountain Aspen Forest & Woodland*	No *Major Types of Ecological Similarity* are shared between these two Ecological Systems. Relationship is Incorrect.	**1**
A C D	SOMEWHAT SIMILAR	*Rocky Mountain Gambel-Oak Mixed Montane Shrubland* versus *Inter-Mountain Basins Mixed Salt Desert Scrub*	These two Ecological Systems are nested within the same NLCD Class for shrub/scrub and therefore share A- Physiognomy. No other *Major Type of Ecological Similarity* is shared. Relationship is Somewhat Similar.	**2**
B AB AC AD BC BD CD	MODERATELY SIMILAR	*Inter-Mountain Basins Greasewood Flat* versus *Inter-Mountain Basins Playa*	These two Ecological Systems are similar in terms of C- Juxtaposition and D- Special Substrates. Relationship is Moderately Similar.	**3**
ABC ABD ACD BCD ABCD	VERY SIMILAR	*Inter-Mountain West Aspen - Mixed Conifer Forest & Woodland* versus *Rocky Mountain Aspen Forest & Woodland*	These two Ecological Systems are similar relative to A- Physiognomic Structure, B- Dominant Species Composition and C- Juxtaposition. Relationship is Very Similar.	**4**
Diagonal Cell (blank)	CORRECT	*Mogollon Chaparral* versus *Mogollon Chaparral*	The reference and mapped classes are identical. Relationship is Correct.	**5**

Appendix LC- 6. Relative similarity scoring system based on four major ecological similarity types (Appendix LC-3).

Appendix LC-7

		REFERENCE												
MAPPED	**CLASS**	**S009**	**S023**	**S028**	**S040**	**S050**	**S054**	**S055**	**S065**	**S071**	**S078**	**S090**	**S096**	**S118**
	S009	5						1						
	S023		5											
	S028			5										
	S040				5							2		
	S050					5								
	S054				1		5	4	2	4	4	2	2	
	S055						4	5	2	2	2			
	S065							2	5					
	S071	1	1			2	4	2		5	4	1	1	
	S078						4				5		2	
	S090						1					5		
	S096								2				5	
	S118													5

Appendix LC-7. Example for UT-5 *relative similarity scoring matrix* showing the application of relative similarity scores to off-diagonal (misclassification) cells of the ecological similarity matrix (Appendix LC-4). This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

Appendix LC-8

		REFERENCE														
	CLASS	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118	TOTAL	ACCURACY
MAPPED	S009	5	0	0	0	0	0	1	0	0	0	0	0	0	6	83%
	S023	0	4	0	0	0	0	0	0	0	0	0	0	0	4	100%
	S028	0	0	5	0	0	0	0	0	0	0	0	0	0	5	100%
	S040	0	0	0	17	0	0	0	0	0	0	1	0	0	18	94%
	S050	0	0	0	0	1	0	0	0	0	0	0	0	0	1	100%
	S054	0	0	0	1	0	58	0	2	0	0	3	1	0	65	89%
	S055	0	0	0	0	0	0	20	1	2	1	0	0	0	24	83%
	S065	0	0	0	0	0	0	1	2	0	0	0	0	0	3	67%
	S071	1	2	0	0	1	0	3	0	20	0	1	1	0	29	69%
	S078	0	0	0	0	0	0	0	0	0	8	0	1	0	9	89%
	S090	0	0	0	0	0	1	0	0	0	0	3	0	0	4	75%
	S096	0	0	0	0	0	0	0	1	0	0	0	1	0	2	50%
	S118	0	0	0	0	0	0	0	0	0	0	0	0	6	6	100%
	TOTAL	6	6	5	18	2	59	25	6	22	9	8	4	6	176	0%
	ACCURACY	83%	67%	100%	94%	50%	98%	80%	33%	91%	89%	38%	25%	100%	0%	85%

Appendix LC- 8. Revised error matrix: Correct and very similar are considered "correct" (i.e. scores 4 moved to diagonal). This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

Appendix LC-9

		REFERENCE														
	CLASS	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118	TOTAL	ACCURACY
MAPPED	S009	5	0	0	0	0	0	1	0	0	0	0	0	0	6	83%
	S023	0	4	0	0	0	0	0	0	0	0	0	0	0	4	100%
	S028	0	0	5	0	0	0	0	0	0	0	0	0	0	5	100%
	S040	0	0	0	17	0	0	0	0	0	0	1	0	0	18	94%
	S050	0	0	0	0	2	0	0	0	0	0	0	0	0	2	100%
	S054	0	0	0	1	0	58	0	0	0	0	3	1	0	63	92%
	S055	0	0	0	0	0	0	24	0	0	0	0	0	0	24	100%
	S065	0	0	0	0	0	0	0	6	0	0	0	0	0	6	100%
	S071	1	2	0	0	0	0	0	0	22	0	1	1	0	27	82%
	S078	0	0	0	0	0	0	0	0	0	9	0	1	0	10	90%
	S090	0	0	0	0	0	1	0	0	0	0	3	0	0	4	75%
	S096	0	0	0	0	0	0	0	0	0	0	0	1	0	1	100%
	S118	0	0	0	0	0	0	0	0	0	0	0	0	6	6	100%
	TOTAL	6	6	5	18	2	59	25	6	22	9	8	4	6	176	0%
	ACCURACY	83%	67%	100%	94%	100%	98%	96%	100%	100%	100%	38%	25%	100%	0%	92%

Appendix LC- 9. Revised error matrix: Correct, very similar, and moderately similar are considered "correct" (i.e. scores 4 and 3 moved to diagonal). This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

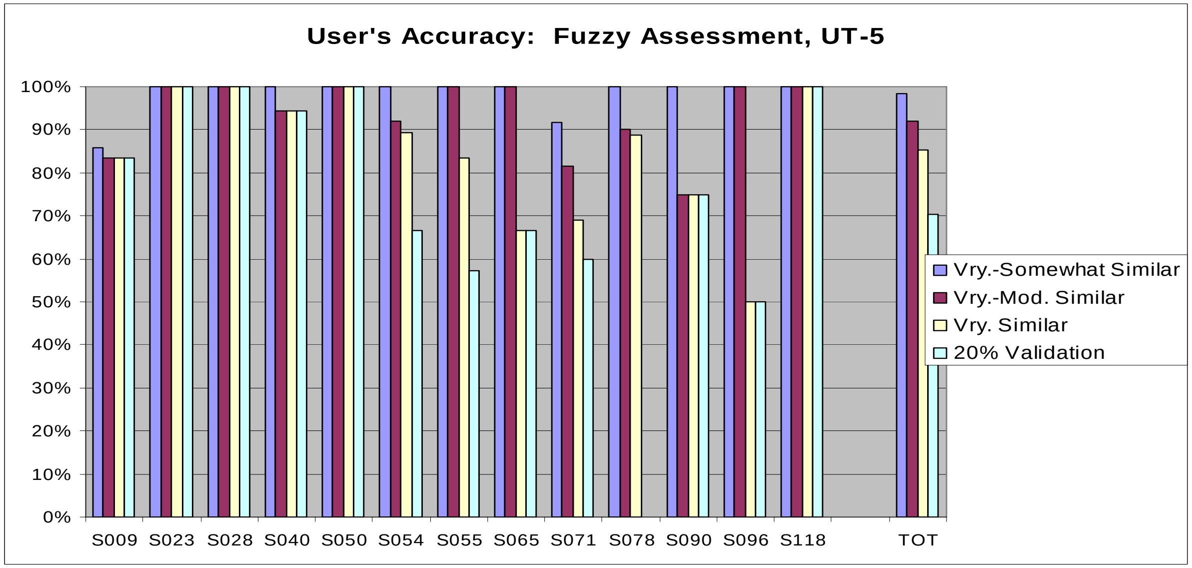
Appendix LC-10

		REFERENCE														
	CLASS	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118	TOTAL	ACCURACY
MAPPED	S009	6	0	0	0	0	0	1	0	0	0	0	0	0	7	86%
	S023	0	6	0	0	0	0	0	0	0	0	0	0	0	6	100%
	S028	0	0	5	0	0	0	0	0	0	0	0	0	0	5	100%
	S040	0	0	0	18	0	0	0	0	0	0	0	0	0	18	100%
	S050	0	0	0	0	2	0	0	0	0	0	0	0	0	2	100%
	S054	0	0	0	0	0	59	0	0	0	0	0	0	0	59	100%
	S055	0	0	0	0	0	0	24	0	0	0	0	0	0	24	100%
	S065	0	0	0	0	0	0	0	6	0	0	0	0	0	6	100%
	S071	0	0	0	0	0	0	0	0	22	0	1	1	0	24	92%
	S078	0	0	0	0	0	0	0	0	0	9	0	0	0	9	100%
	S090	0	0	0	0	0	0	0	0	0	0	7	0	0	7	100%
	S096	0	0	0	0	0	0	0	0	0	0	0	3	0	3	100%
	S118	0	0	0	0	0	0	0	0	0	0	0	0	6	6	100%
	TOTAL	6	6	5	18	2	59	25	6	22	9	8	4	6	176	0%
	ACCURACY	100%	100%	100%	100%	100%	100%	96%	100%	100%	100%	88%	75%	100%	0%	98%

Appendix LC- 10. Revised error matrix: Correct, very similar, moderately similar, and somewhat similar are considered "correct" (i.e. scores 4, 3 and 2 moved to diagonal). This table and similar tables for other mapping zones can be found at: http://earth.gis.usu.edu/swgap/mapquality.html

Appendix LC-11

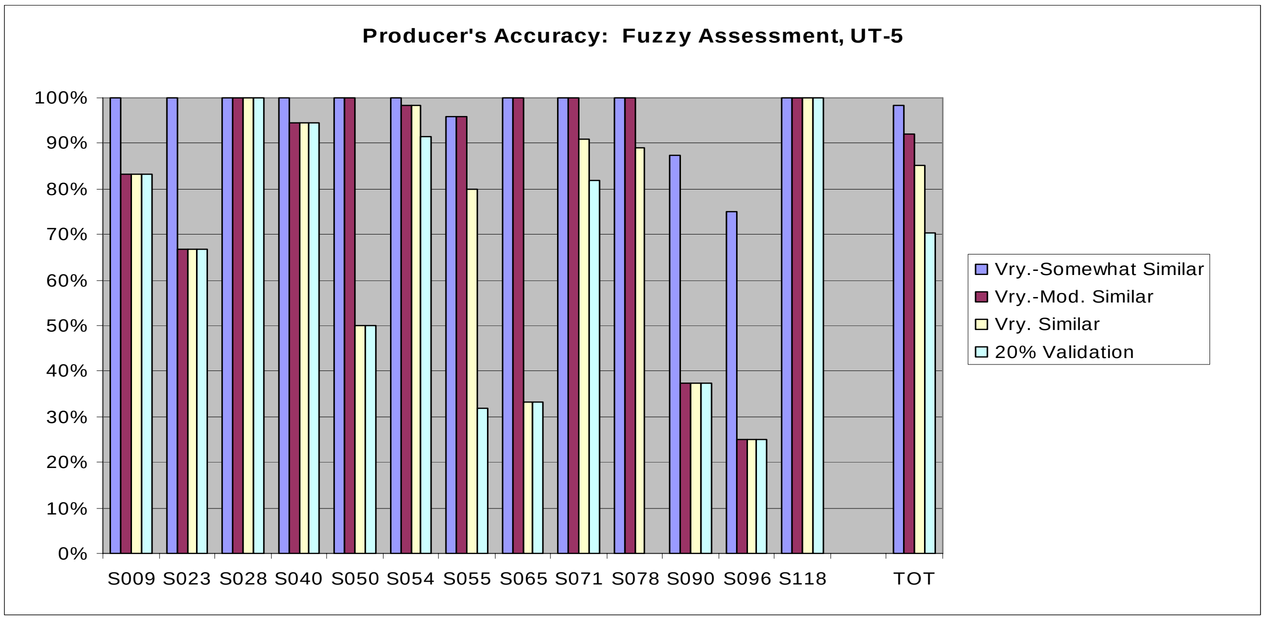
USER'S ACCURACY	Land Cover Class													
	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118	TOT
Vry.-Somewhat Similar	86%	100%	100%	100%	100%	100%	100%	100%	92%	100%	100%	100%	100%	98%
Vry.-Mod. Similar	83%	100%	100%	94%	100%	92%	100%	100%	82%	90%	75%	100%	100%	92%
Vry. Similar	83%	100%	100%	94%	100%	89%	83%	67%	69%	89%	75%	50%	100%	85%
20% Validation	83%	100%	100%	94%	100%	67%	57%	67%	60%	0%	75%	50%	100%	70%
No. Samples	6	4	5	18	1	81	14	3	30	2	4	2	6	176



Appendix LC- 11. Example for UT-5. Summary of user's accuracy for all levels of fuzzy assessment and the original error matrix. This table and graph summarize map quality given different levels of multiple class membership (expressed by recognized ecological similarities) among classes. For example, recognizing the possibility of multiple class membership between cover class S055 (Great Basin Xeric Sagebrush Shrubland) and other mapped classes at the 'very similar' level, "user accuracy" for S055 increases from 57% to 83%.

Appendix LC-12

PRODUCERS'S ACCURACY	Land Cover Class														
	S009	S023	S028	S040	S050	S054	S055	S065	S071	S078	S090	S096	S118		TOT
Vry.-Somewhat Similar	100%	100%	100%	100%	100%	100%	96%	100%	100%	100%	88%	75%	100%		98%
Vry.-Mod. Similar	83%	67%	100%	94%	100%	98%	96%	100%	100%	100%	38%	25%	100%		92%
Vry. Similar	83%	67%	100%	94%	50%	98%	80%	33%	91%	89%	38%	25%	100%		85%
20% Validation	83%	67%	100%	94%	50%	92%	32%	33%	82%	0%	38%	25%	100%		70%
No. Samples	6	6	5	18	2	59	25	6	22	9	8	4	6		176



Appendix LC- 12. Example for UT-5. Summary of producer's accuracy for all levels of fuzzy assessment and the original error matrix. This table and graph summarize map quality given different levels of multiple class membership (expressed by recognized ecological similarities) among classes. For example, recognizing the possibility of multiple class membership between cover class S055 (Great Basin Xeric Sagebrush Shrubland) and other mapped classes at the 'very similar' level, "producers accuracy" for S055 increases from 32% to 80%.

Appendix LC-13

	Land Cover Area		Validation Results		
	Area (Sq. Km)	Percent Total Area	Number Reference Samples	Producer	User
SPARSELY VEGETATED/BARREN CLASSES					
Barren Lands, Non-specific	1,421	0.10%	54	19%	56%
Colorado Plateau Mixed Bedrock Canyon and Tableland	24,313	1.75%	248	75%	72%
Inter-Mountain Basins Active and Stabilized Dune	3,103	0.22%	39	44%	71%
Inter-Mountain Basins Cliff and Canyon	2,873	0.21%	83	43%	64%
Inter-Mountain Basins Playa	17,581	1.27%	81	68%	77%
Inter-Mountain Basins Shale Badland	3,297	0.24%	59	37%	50%
Inter-Mountain Basins Volcanic Rock and Cinder Land	1,360	0.10%	na	na	na
Inter-Mountain Basins Wash	46	0.00%	na	na	na
Mediterranean California Alpine Bedrock and Scree	23	0.00%	na	na	na
North American Alpine Ice Field	23	0.00%	na	na	na
North American Warm Desert Active and Stabilized Dune	2,728	0.20%	37	43%	67%
North American Warm Desert Badland	112	0.01%	na	na	na
North American Warm Desert Bedrock Cliff and Outcrop	3,568	0.26%	38	53%	67%
North American Warm Desert Pavement	393	0.03%	21	14%	33%
North American Warm Desert Playa	1,115	0.08%	20	70%	64%
North American Warm Desert Volcanic Rockland	992	0.07%	na	na	na
Rocky Mountain Alpine Bedrock and Scree	3,863	0.28%	100	81%	84%
Rocky Mountain Alpine Fell-Field	761	0.05%	27	48%	59%
Rocky Mountain Cliff, Canyon and Massive Bedrock	2,965	0.21%	143	56%	67%
Sierra Nevada Cliff and Canyon	123	0.01%	na	na	na
Western Great Plains Cliff and Outcrop	309	0.02%	na	na	na
Subtotal	***70,969***	***5.12%***			
DECIDUOUS FOREST CLASSES					
Rocky Mountain Aspen Forest and Woodland	20,986	1.51%	582	81%	74%
Rocky Mountain Bigtooth Maple Ravine Woodland	888	0.06%	34	68%	74%
Subtotal	***21,874***	***1.58%***			
EVERGREEN FOREST CLASSES					
Colorado Plateau Pinyon-Juniper Woodland	97,855	7.06%	972	81%	69%
Great Basin Pinyon-Juniper Woodland	50,776	3.66%	441	84%	65%
Inter-Mountain Basins Subalpine Limber-Bristlecone Pine Woodland	666	0.05%	21	38%	50%
Madrean Encinal	4,358	0.31%	45	51%	44%
Madrean Pine-Oak Forest and Woodland	5,733	0.41%	104	42%	46%
Madrean Pinyon-Juniper Woodland	21,917	1.58%	233	71%	54%
Madrean Upper Montane Conifer-Oak Forest and Woodland	795	0.06%	na	na	na
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodlan	2	0.00%	na	na	na
Mediterranean California Ponderosa-Jeffrey Pine Forest and Woodland	209	0.02%	na	na	na
Mediterranean California Red Fir Forest and Woodland	106	0.01%	na	na	na
Northern Pacific Mesic Subalpine Parkland	42	0.00%	na	na	na
Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	8,953	0.65%	458	52%	57%
Rocky Mountain Foothill Limber Pine-Juniper Woodland	6	0.00%	na	na	na
Rocky Mountain Lodgepole Pine Forest	8,764	0.63%	199	60%	60%
Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	7,295	0.53%	na	na	na
Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	14,814	1.07%	466	76%	66%
Rocky Mountain Subalpine Mesic Spruce-Fir Forest and Woodland	10,359	0.75%	na	na	na
Rocky Mountain Subalpine-Montane Limber-Bristlecone Pine Woodland	801	0.06%	31	13%	44%
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	21	0.00%	na	na	na

Southern Rocky Mountain Pinyon-Juniper Woodland	15,305	1.10%	172	64%	63%
Southern Rocky Mountain Ponderosa Pine Woodland	50,221	3.62%	785	77%	66%
Subtotal	***298,998***	***21.57%***			
MIXED FOREST CLASS					
Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	3,439	0.25%	159	30%	49%
Subtotal	***3,439***	***0.25%***			
SHRUB/SCRUB CLASSES					
Apacherian-Chihuahuan Mesquite Upland Scrub	31,683	2.29%	215	41%	41%
Chihuahuan Mixed Desert and Thorn Scrub	27,407	1.98%	174	45%	45%
Chihuahuan Mixed Salt Desert Scrub	4,413	0.32%	45	22%	33%
Chihuahuan Stabilized Coppice Dune and Sand Flat Scrub	5,725	0.41%	59	49%	48%
Chihuahuan Succulent Desert Scrub	187	0.01%	na	na	na
Coahuilan Chaparral	94	0.01%	na	na	na
Colorado Plateau Blackbrush-Mormon-tea Shrubland	13,310	0.96%	106	73%	54%
Colorado Plateau Mixed Low Sagebrush Shrubland	2,401	0.17%	50	28%	50%
Colorado Plateau Pinyon-Juniper Shrubland	11,535	0.83%	149	61%	57%
Great Basin Semi-Desert Chaparral	163	0.01%	21	43%	50%
Great Basin Xeric Mixed Sagebrush Shrubland	35,434	2.56%	417	47%	55%
Inter-Mountain Basins Big Sagebrush Shrubland	108,480	7.83%	1394	77%	59%
Inter-Mountain Basins Mat Saltbush Shrubland	4,130	0.30%	64	55%	51%
Inter-Mountain Basins Mixed Salt Desert Scrub	79,294	5.72%	826	59%	53%
Inter-Mountain Basins Mountain Mahogany Woodland and Shrubland	2,550	0.18%	81	27%	55%
Mogollon Chaparral	11,515	0.83%	169	49%	52%
Mojave Mid-Elevation Mixed Desert Scrub	16,762	1.21%	168	71%	75%
Rocky Mountain Alpine Dwarf-Shrubland	110	0.01%	na	na	na
Rocky Mountain Gambel Oak-Mixed Montane Shrubland	18,950	1.37%	524	69%	71%
Rocky Mountain Lower Montane-Foothill Shrubland	2,823	0.20%	102	44%	68%
Sonora-Mojave Creosotebush-White Bursage Desert Scrub	58,760	4.24%	292	68%	76%
Sonora-Mojave Mixed Salt Desert Scrub	2,549	0.18%	23	26%	30%
Sonora-Mojave Semi-Desert Chaparral	89	0.01%	na	na	na
Sonoran Mid-Elevation Desert Scrub	5,393	0.39%	36	36%	50%
Sonoran Paloverde-Mixed Cacti Desert Scrub	39,791	2.87%	280	83%	74%
Southern Colorado Plateau Sand Shrubland	7,021	0.51%	81	56%	56%
Western Great Plains Mesquite Woodland and Shrubland	1,797	0.13%	na	na	na
Western Great Plains Sandhill Shrubland	13,894	1.00%	159	72%	74%
Wyoming Basins Low Sagebrush Shrubland	47	0.00%	na	na	na
Subtotal	***506,307***	***36.53%***			
GRASSLAND/HERBACEOUS CLASSES					
Apacherian-Chihuahuan Semi-Desert Grassland and Steppe	45,711	3.30%	343	63%	51%
Central Mixedgrass Prairie	120	0.01%	na	na	na
Chihuahuan Gypsophilous Grassland and Steppe	804	0.06%	25	56%	56%
Chihuahuan Sandy Plains Semi-Desert Grassland	986	0.07%	28	11%	21%
Chihuahuan-Sonoran Desert Bottomland and Swale Grassland	0	0.00%	104	32%	41%
Inter-Mountain Basins Big Sagebrush Steppe	1,798	0.13%	82	12%	26%
Inter-Mountain Basins Juniper Savanna	5,590	0.40%	89	36%	51%
Inter-Mountain Basins Montane Sagebrush Steppe	40,654	2.93%	781	72%	63%
Inter-Mountain Basins Semi-Desert Grassland	33,640	2.43%	392	32%	41%
Inter-Mountain Basins Semi-Desert Shrub-Steppe	47,618	3.44%	699	38%	52%
Madrean Juniper Savanna	994	0.07%	32	6%	25%
North Pacific Montane Grassland	27	0.00%	na	na	na
Rocky Mountain Dry Tundra	2,779	0.20%	68	76%	78%
Rocky Mountain Subalpine Mesic Meadow	2,177	0.16%	120	48%	56%
Southern Rocky Mountain Juniper Woodland and Savanna	11,956	0.86%	59	53%	53%
Southern Rocky Mountain Montane-Subalpine Grassland	10,294	0.74%	292	58%	64%
Western Great Plains Foothill and Piedmont Grassland	5,066	0.37%	135	65%	63%
Western Great Plains Sand Prairie	18	0.00%	na	na	na
Western Great Plains Shortgrass Prairie	113,162	8.16%	668	88%	72%
Western Great Plains Tallgrass Prairie	1	0.00%	na	na	na

Subtotal	***323,395***	***23.33%***			
WOODY WETLANDS CLASSES					
Great Basin Foothill and Lower Montane Riparian Woodland and Shrubl	1,360	0.10%	102	60%	68%
Inter-Mountain Basins Greasewood Flat	23,770	1.71%	405	46%	52%
North American Warm Desert Lower Montane Riparian Woodland and Shru	426	0.03%	43	19%	32%
North American Warm Desert Riparian Mesquite Bosque	832	0.06%	na	na	na
North American Warm Desert Riparian Woodland and Shrubland	422	0.03%	45	18%	35%
North American Warm Desert Wash	652	0.05%	50	24%	34%
Rocky Mountain Lower Montane Riparian Woodland and Shrubland	2,226	0.16%	177	45%	67%
Rocky Mountain Subalpine-Montane Riparian Shrubland	3,224	0.23%	135	49%	62%
Rocky Mountain Subalpine-Montane Riparian Woodland	292	0.02%	46	7%	50%
Western Great Plains Floodplain	836	0.06%	66	67%	70%
Western Great Plains Riparian Woodland and Shrubland	1,714	0.12%	153	75%	80%
Subtotal	***35,754***	***2.58%***			
EMERGENT WETLAND CLASSES					
Mediterranean California Subalpine-Montane Fen	2	0.00%	na	na	na
North American Arid West Emergent Marsh	1,053	0.08%	64	38%	65%
Rocky Mountain Alpine-Montane Wet Meadow	1,956	0.14%	118	35%	48%
Temperate Pacific Subalpine-Montane Wet Meadow	2	0.00%	na	na	na
Western Great Plains Saline Depression Wetland	41	0.00%	na	na	na
Subtotal	***3,054***	***0.22%***			
ALTERED OR DISTURBED CLASSES					
Disturbed, Non-specific	93	0.01%	na	na	na
Disturbed, Oil well	46	0.00%	na	na	na
Invasive Annual and Biennial Forbland	2,638	0.19%	138	17%	52%
Invasive Annual Grassland	8,291	0.60%	174	22%	42%
Invasive Perennial Forbland	1	0.00%	na	na	na
Invasive Perennial Grassland	2,839	0.20%	136	38%	67%
Invasive Southwest Riparian Woodland and Shrubland	1,609	0.12%	116	59%	66%
Recently Burned	2,033	0.15%	na	na	na
Recently Chained Pinyon-Juniper Areas	689	0.05%	na	na	na
Recently Logged Areas	836	0.06%	35	37%	93%
Recently Mined or Quarried	1,240	0.09%	23	61%	67%
Subtotal	***20,315***	***1.47%***			
OTHER CLASSES					
Agriculture	75,981	5.48%	na	na	na
Developed, Medium - High Intensity	7,539	0.54%	na	na	na
Developed, Open Space - Low Intensity	7,425	0.54%	na	na	na
Open Water	11,023	0.80%	na	na	na
Subtotal	***101,968***	***7.36%***			
Grand Total	**1,386,073**	**100.00%**	**17,030**	**61%**	**61%**

Appendix LC- 13. Area and validation summary for the 5-state region. Only land cover classes with a minimum of 20 reference samples are presented in this summary ("na" indicates fewer than 20 reference samples were used for validating that land cover class in the entire region). Land cover classes that were validated by individual states, but not validated by all states in the region are not included. For example, Colorado validated agriculture and developed land use classes (with > 20 samples) but other states did not; subsequently Colorado's validation data are not included in this regional summary for these classes. Validated land cover classes in this table represent 85 of 125 mapped cover classes and 91% of the land area. Overall validation of 61% represents the percent correctly mapped (sum of diagonals) for the 85 cover classes with validation results.