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Mapping moderate-scale land-cover over very large geographic areas within a collaborative framework: A case study of the Southwest Regional Gap Analysis Project (SWReGAP)

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Abstract

Land-cover mapping efforts within the USGS Gap Analysis Program have traditionally been 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. The land-cover map/dataset was generated using regionally consistent geospatial data (Landsat ETM+ imagery (1999–2001) 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 five collaborating states was organized around ecoregion-based "mapping zones". Over the course of $2^1/_2$ field seasons approximately 93,000 reference samples were collected directly, or obtained from other contemporary projects, for the land-cover modeling effort. The final map was made public in 2004 and contains 125 land-cover classes. An internal validation of 85 of the classes, representing 91% of the land area was performed. Agreement between withheld samples and the validated dataset was 61% (KHAT = .60, n = 17,030). This paper presents an overview of the methodologies used to create the regional land-cover dataset and highlights issues associated with large-area mapping within a coordinated, multi-institutional management framework.

Keywords: Large-area mapping; Meso-scale mapping; Moderate scale mapping; Land-cover mapping; Vegetation mapping; Southwestern U.S.; Collaborative projects; Remote sensing; Decision tree classifiers; Geographic information systems; Gap Analysis Program (GAP)

1. Introduction

Mapping the Earth's natural resources is fundamental to the inventory and subsequent monitoring of the Earth's biota, key to understanding environmental processes, and critical for effective natural resource planning and land management decision-making. The goal of the United States Geological

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Survey (USGS) Biological Resource Discipline (BRD) Gap Analysis Program (GAP) is to provide geographic information on biological diversity across large landscapes at moderate spatial resolutions for use by managers, scientists, planners, and policy makers to make informed decisions (Scott et al., 1993). A baseline GAP product is a land-cover map derived from satellite imagery.

GAP projects in the United States have traditionally operated within a state-based framework; that is, each state has had the responsibility of implementing a project design for the geographic area within their state boundaries. As a result, there have been considerable differences in mapping methodology, data collection efforts, and target land-cover legends among state-based GAP projects. To address these discontinuities, GAP was encouraged to consider adopting a regional operating framework for future gap analysis efforts (Eve & Merchant, 1998). One of the earliest state-based gap analysis efforts was the Utah project completed in 1995 (Edwards et al., 1995; Homer et al., 1997). Subsequently, GAP efforts in the adjoining states of New Mexico, Nevada, Colorado and Arizona were completed (Halvorson et al., 2001; Homer, 1998; Schrupp et al., 2000; Thompson et al., 1996). In 1999 representatives from these five states, and NatureServe (formerly with The Nature Conservancy) met to determine the feasibility of implementing a coordinated GAP project for the southwest region of the United States. Given advances in computing technologies, mapping methodologies, reduced costs of imagery and ancillary data, and perhaps most importantly—the perceived need for a regional GAP project, it was determined that a coordinated effort of this magnitude was possible. USGS BRD funded the Southwest Regional Gap Analysis Project (SWReGAP) beginning in 2000.

The primary objective of the SWReGAP effort was to create a seamless land-cover map approximating, or surpassing, the thematic level achieved by the earlier state-based gap analysis efforts for the region. The number of land-cover classes mapped in the earlier efforts for the five southwestern states ranged from 65 classes in Nevada (Homer, 1998) to 38 classes in Utah (Edwards et al., 1995). Overall map accuracy for the state maps ranged from a high of 83% to a low of 15% (Edwards et al., 1998; Falzarano & Thomas, 2004; Homer, 1998; Schrupp et al., 2000; Thompson et al., 1996). Given the results of these previous efforts, we anticipated being able to map roughly 100 land-cover classes with a goal of 80% overall map accuracy. The five-state region comprises roughly 1.4 million km^2 (540,000 sq. miles) representing approximately 1/5th the conterminous United States. Previous to SWReGAP the only U.S. land-cover mapping effort comparable to this in geographic scale was the 1992 National Land-cover Dataset (NLCD) (Vogelmann et al., 2001).

Utah State University, located in Logan, Utah was designated as the regional land-cover laboratory with the responsibility of coordinating the development of protocols for field data collection, image and ancillary data processing, and mapping methodologies for the region. Individual state teams were responsible for applying these protocols to their area of responsibility. This paper presents an overview of the methodologies used to create the regional land-cover dataset and highlights several of the issues associated with achieving this product through a regionally coordinated process.

2. Project organization

2.1. Project study area

The study area, lying between 102°–120° W longitude and 31°–42° N latitude, is diverse in its physical, climatic, and biological characteristics, and includes the states of Arizona, Colorado, New Mexico, Nevada, and Utah. Elevation ranges from approximately 22 m (72 ft) to 4405 m (14,500 ft). Precipitation, falling predominantly in summer or winter depending on location, ranges from 100 mm (4 in) to 770 mm (30 in). Vegetation covers the spectrum from sparse, hot desert scrub and cacti to more temperate shrub-steppe and grasslands, to montane and sub-alpine forests, meadows and alpine turf (Bailey, 1995).

2.2. Division of responsibilities

"Spectral-physiographic" mapping areas have 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). We developed areas of responsibility for participating state teams by dividing the study area into spectral-physiographic "mapping zones", (in lieu of political state boundaries) which also leveraged local knowledge of the biota in each sub-region.

Ecoregions defined by Bailey (1995) and Omernik (1987) provided a starting point for determining mapping zone boundaries and were refined using heads-up screen digitizing using a regional mosaic of Landsat TM imagery and a digital shaded relief map. Initial efforts yielded 73 mapping zones for the region. Through an iterative and collaborative process involving all land-cover mapping teams and NatureServe, the final number of mapping zones was reduced to 25 (Fig. 1). A more detailed explanation of mapping zone development is found in Manis et al. (2000).

2.3. Project coordination and timeframe

Each state was responsible for four to six mapping zones roughly corresponding to state boundaries. Initial field data collection protocols were established at a workshop in Las Vegas, Nevada in the spring of 2001. Field data collection primarily 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 were important to 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

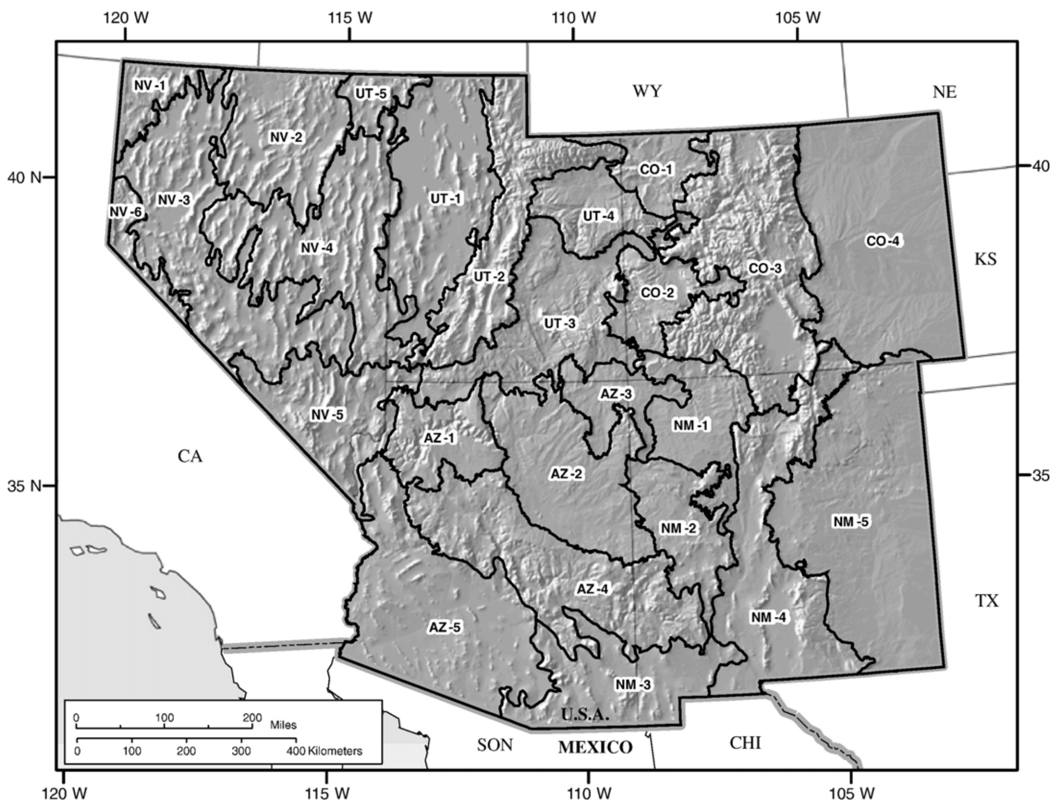

Fig. 1. Spectral-physiographic mapping zones delineated for the SWReGAP.

regional land-cover lab. The seamless land-cover map was completed and made available to the public in September 2004.

3. Methods

3.1. Image preparation

Seventy-nine Landsat Enhanced Thematic Mapper Plus (ETM+) scenes 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) (Fig. 2). Spring, summer, and fall images were provided for a total of 237 images. 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 with the majority of images collected in 2000. All ETM+ scenes were terrain-corrected and provided in NLAPS (National Landsat Archive Processing System) format, projected to an Albers Equal Area projection. All ETM+ scenes are available to the public at http://earth.gis.usu.edu/archive/.

Land-cover mapping teams created image mosaics for each mapping zone with a 2-km buffer, resulting in a 4-km overlap area 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 used the image-based COST method as described by Chavez (1996). However, we found that using Chavez's COST method as published, 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). We developed web-based scripts to automate the process of generating corrected images on a scene-by-scene basis (see http://www.gis.usu.edu/imgstandard.html).

3.2. Predictor layers

Geographic layers used to map land-cover included image-derived and ancillary datasets. Core image-derived datasets consisted of individual ETM+ bands, the Normalized Difference Vegetation Index (NDVI), and brightness, greenness and wetness derivatives generated using Landsat ETM+ coefficients from Huang et al. (2002). Ancillary datasets were derived from 30-m digital elevation models (DEM) obtained from the USGS National Elevation Dataset and consisted of elevation, slope (in degrees), a 9-class aspect dataset (eight cardinal directions plus flat), and a 10-class landform dataset (see Manis et al. (2001) for a detailed description of landform dataset).

3.3. Thematic mapping legend

A key factor related to the creation of a seamless land-cover map generated through a collaborative effort was the need to establish a single classification legend. Previous state-based GAP land-cover efforts developed target mapping legends *ad*

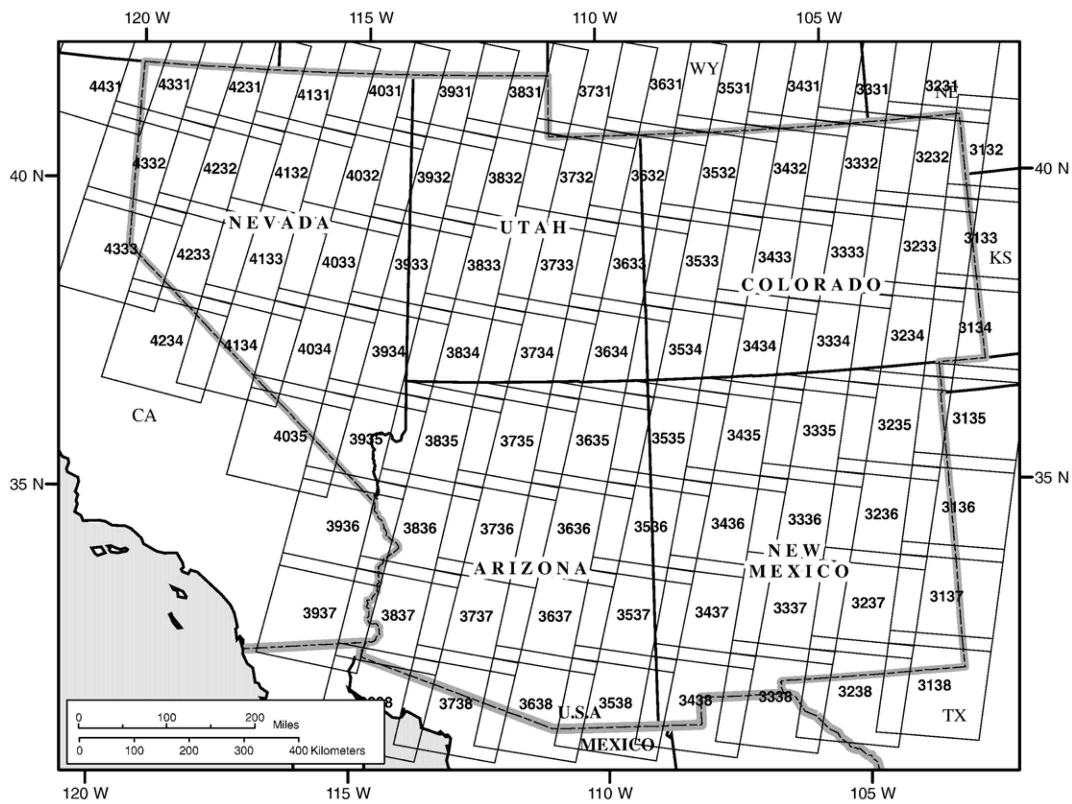

Fig. 2. Landsat ETM+ scenes (path and row) for the 5-state region.

hoc or based on a variety of vegetation classification systems. When SWReGAP began in 1999 our target thematic mapping unit was the National Vegetation Classification (NVC) alliance. However, recognizing that over 500 alliances occur in the project area and that many alliances would be difficult to map, we recognized the need for a thematic mapping scale between the alliance and formation levels (Grossman et al., 1998). In response to this need, NatureServe developed the Terrestrial Ecological Systems Classification framework (Comer et al., 2003). Using the "ecological system" as our moderate-scale thematic mapping unit, SWReGAP became the test-bed for a classification framework that would eventually be extended to the conterminous United States (Comer et al., 2003).

The initial SWReGAP target legend developed by NatureServe and the state mapping teams identified 110 ecological systems from the 140 that occur in the five-state region. Omitted ecological systems included those that had predominantly small patch sizes (<0.50 ha) or were peripheral to the region. 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 modified from the National Land-Cover Dataset 2001 legend (Homer et al., 2004) or given special "altered" or "disturbed" designations within the SWReGAP legend (e.g. recently burned, recently logged areas, invasive annual grassland, etc.). The final mapping legend for the region consisted of 125 natural and altered/disturbed land-cover classes.

3.4. Reference data collection

Training and validation data were collected through ground-based field work supplemented with existing field data from collaborating federal and state agencies determined to be roughly contemporary with the time period of our imagery (1999–2001). Additional data for land-cover classes in hard-to-reach locations (large wilderness areas, etc.) were obtained through visual interpretation of aerial photography, digital orthophotoquads, or other remotely sensed imagery. Samples obtained from these sources were given only a label identifying the land-cover class.

Ground-based field samples were collected by traversing navigable roads in a mapping zone and opportunistically selecting plots that met criteria of appropriate size (1-ha minimum) and composition (stand homogeneity). Field data were collected using ocular estimates of biotic and abiotic land-cover components, including percent cover of dominant species by life-form (i.e. trees, shrubs, grasses, and forbs) and site characteristics such as elevation, slope, aspect, and landform. Laptop computers using ArcView 3.x®, Landsat imagery, digital orthophotoquads, and other ancillary information were used for navigation and plot identification whenever possible. Each plot was identified with a UTM coordinate pair using a GPS. Sample areas were either digitized in the field as a polygon, or in the case of point samples, polygonized with an appropriate buffer distance from the center of the field site. Field data were recorded onto paper field forms and subsequently entered into a database. Typically, two digital photographs were taken at each plot to record current site conditions and provide a means for a visual comparison of differences between field plots. Sufficient data were collected at each plot to assign an NVC alliance label (Grossman et al., 1998) and/or ecological system (Comer et al., 2003) label to each plot. Of an approximate total of 93,000 samples obtained for the project, roughly 45,000 were collected via ground surveys during the course of two and a half field seasons. Field data collected via ground surveys are available to the public at http://earth.gis.usu.edu/swgap/trainingsites.html.

3.5. Modeling approach

The regional land-cover lab investigated several alternatives for image classification. In particular we experimented with methods similar to those used in previous large-area mapping efforts such as the 1995 Utah GAP land-cover project (Homer et al., 1997) and the WISCLAND (Wisconsin Initiative for Statewide Cooperation on Landscape Analysis and Data) project (Reese et al., 2002). We compared these supervised–unsupervised hybrid approaches to decision tree classifiers and found the decision tree approach more time-efficient and less unwieldy.

3.5.1. Decision tree classifiers

Early applications of decision trees (Breiman et al., 1984) for remote sensing-based land-cover classification focused on continental and global scale mapping using coarse resolution imagery (DeFries et al., 1998; Hansen et al., 1996, 2000; Friedl & Brodley, 1997; Friedl et al., 1999; Friedl et al., 2002). More recently, decision tree classifiers have produced accurate results in moderate-scale mapping with Landsat Thematic Mapper imagery (Brown de Colstoun et al., 2003; Lawrence et al., 2004; Lawrence & Wright, 2001; Pal & Mather, 2003).

As a non-parametric classifier, decision trees require no prior assumptions of normally distributed training data. Further, while incorporating ancillary datasets such as digital elevation model derivatives can improve land-cover class discrimination (Homer et al., 1997; Treitz & 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, and have demonstrated improved accuracies over the use of traditional parametric classifiers (Hansen et al., 1996; Pal & Mather, 2003).

Concurrent with our project, the USGS National Center for Earth Resources Observation and Science (EROS) developed a land-cover mapping tool capable of integrating the decision tree software See5 (RuleQuest Research, 2004) with ERDAS Imagine®. The tool, developed for the National Land-Cover Dataset 2001 (Homer et al., 2004) project (hereafter "NLCD mapping tool") provides an efficient integration of a decision tree algorithm within a spatially explicit modeling environment. While the tool is limited to the See5 decision tree algorithm, a significant benefit of the tool is the ability to apply boosting which has been shown to improve map accuracies in several land-cover mapping efforts (Brown de Colstoun et al., 2003; Lawrence et al., 2004; Pal & Mather, 2003).

3.5.2. SWReGAP mapping procedures

Our primary objective was to produce the most accurate and complete map possible. To accomplish this, our mapping process required two steps which made best use of all available training samples.

First, we relied on the decision tree classifier to discriminate the bulk of the land-cover classes. 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 classifier. In addition, land-use classes such as recently logged areas, agriculture, or developed land-uses were also excluded from the decision tree modeling process. 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.

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% of the training 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% of available training samples stratified by land-cover class, and withholding them from the decision tree model generation. The intermediate map (generated with 80% of the available samples) was assessed with the withheld samples to produce an error matrix and kappa statistic (Congalton & Green, 1999). The land-cover modeling process concluded with the generation of the final map using 100% of the available training data. Validation results therefore represent an assessment of the intermediate map, not the final map.

Fig. 3 provides a flow diagram of the general mapping process for each mapping zone. Land-cover and land-use classes not modeled by the decision tree classifier were delineated using extant GIS data [1]. Predictor layers were prepared as described previously [2]. Sample data were divided into a training and validation datasets. For model training, randomly selected sub-samples (i.e. cluster sampling) within each polygon were used as separate observations within the decision tree classifier. Sub-sampling within training polygons accounted for spectral and environmental variability within the sample polygon and possible positional miss-alignment of the imagery and/or GPS location. Specifying a maximum of 20 sub-samples per training polygon reduced modeling bias towards larger polygons [3]. Using the NLCD mapping tool, decision tree models were generated in See5 using 15 boosts (a minimum of 10 boosts are recommended for most datasets (RuleQuest Research, 2004)). The selection of predictor datasets varied by mapping zone depending on the strength of the relationship with land-cover as determined by the land-cover analyst. Modeling was iterative (i.e. after a model was created, it was evaluated (step 5) and revised with different combinations of predictor datasets or additional samples) [4]. Using the withheld 20% sample polygons, an error matrix was generated and the KHAT statistic calculated (Congalton & Green, 1999). A validation sample polygon was considered correctly mapped when the modal value of pixels in the land-cover map agreed with the

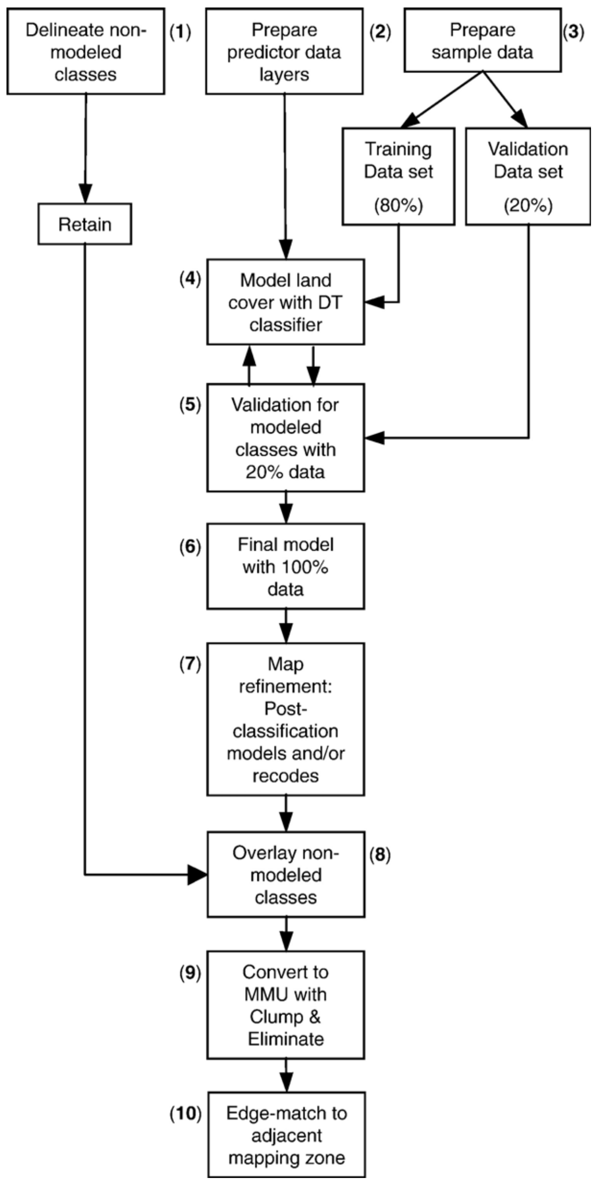

Fig. 3. General mapping process for the SWReGAP.

validation polygon label [5]. The final decision tree model and map was created using 100% of sample data [6]. The land-cover map was examined for errors by visually inspecting the map output and evaluating the error matrix. Known geographic errors (i.e. pixels known to be mapped incorrectly in a particular geographic location) were corrected by selective recoding. Known environmental errors (e.g. mapping on incorrect slope, elevation or aspect) were corrected using conditional statements in a post-classification model. Errors associated with cloud cover were often corrected in the same manner [7]. Non-modeled classes mapped in step 1 were incorporated into the final map with a post-classification conditional model [8]. The land-cover map was generalized to the minimum mapping unit (MMU) of 0.4 ha (1 acre) by aggregating (clumping) unique class pixels based on a rooks-move (4 connected neighbors) [9]. Land-cover classes were given identical integer pixel values across mapping zones to facilitate proper edge-matching and mosaicked using vector cutlines within the 4-km overlap area [10].

4. Results

4.1. Land-cover map

The final map product contains 125 land-cover classes, 109 of which are ecological systems (Fig. 4). The land-cover dataset retains the 30-m pixel resolution of the predictor layers with a minimum mapping unit of 0.40 ha (1 acre). The final map can be downloaded from http://earth.gis.usu.edu/swgap/landcover.html. Included at the website are detailed descriptions of mapping methods, specifying the suite of predictor datasets and training samples used for each mapping zone.

4.2. Map/model validation

Map/model validation was performed for each mapping zone separately. Publishing error matrices for each of the 25 mapping zones is beyond the scope of this paper. These data, however, are available to the public at http://earth.gis.usu.edu/swgap/mapquality.html. Overall validation results (sum of diagonals), with associated number of modeled classes, validation sample size, and KHAT statistic for each mapping zone are reported in Table 1.

To provide a regional validation by land-cover class, individual mapping zone error matrices were combined and summarized. Table 2 presents all 125 land-cover classes sorted into 5 validation groups and organized hierarchically into NLCD land-cover classes. The first validation group contains classes that were not assessed regionally because of limited validation plots ($n<20$ for the region) or were non-natural classes and not the primary focus of our mapping effort. These 40 classes comprise approximately 9.5% of the total land area for the region, with more than half (5.5%) as agriculture.

The second validation group contains land-cover classes with validation results from a user's perspective less that 30%. These three classes comprise less than 0.5% of the total land area for the region. All classes in this group are difficult to discriminate ecologically and spectrally (i.e. grassland, steppe and savanna). For example, the error matrices (not shown in Table 2 (see http://earth.gis.usu.edu/swgap/mapquality.html)) for these classes reveal that the *Chihuahuan Sandy Plains Semi-Desert Grassland* was most confused with the *Apacherian–Chihuahuan Semi-Desert Grassland and Steppe* class, and the *Inter-Mountain Basins Big Sagebrush Steppe* class was most often confused with the *Inter-Mountain Basins Big Sagebrush* class.

The next validation group contains classes where agreement between the validation samples and the map was between 30 and 49% from a user's perspective. These 17 classes represent approximately 9.5% of the land area. Most comprise very small portions of the region (less than 0.5%), with the exception of three classes. Two scrub/shrub classes (*Apacherian–Chihuahuan Mesquite Upland Scrub*, *Chihuahuan Mixed Desert and*

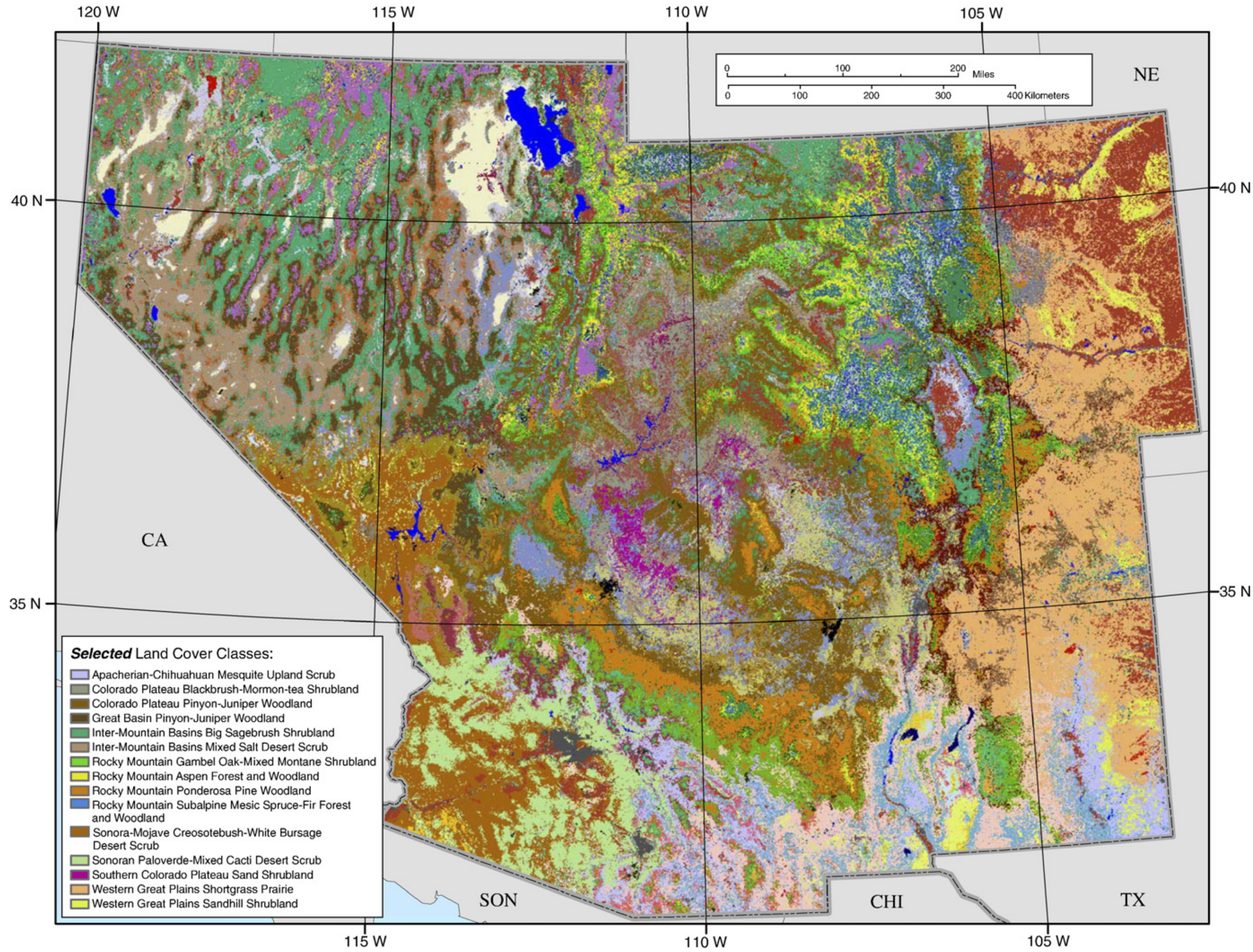

Fig. 4. Final SWReGAP land-cover map containing 125 mapped classes for the five-state region. Note only the 15 most abundant land-cover classes are depicted in the map legend.

Thorn Scrub) and one grassland/herbaceous class (*Inter-Mountain Basins Semi-Desert Grassland*) represent substantial portions of the land area, covering approximately 30,000 km^2 each. The two desert scrub classes are confused with the *Apacherian–Chihuahuan Semi-Desert Grassland and Steppe* class, and with each other. The *Inter-Mountain Basins Semi-Desert Grassland* is mostly confused with the *Inter-Mountain Basins Semi-Desert Shrub Steppe*, and the *Inter-Mountain Basins Big Sagebrush Shrubland* class. The obvious trend with these poorly and very poorly mapped classes is high confusion among classes that are ecologically very similar, sparsely vegetated, or both.

The largest number of mapped classes (50) comprising the greatest proportion of land area (56.5%) are presented in validation group 4. Here agreement between the validation samples and the map was between 50 and 70%. The most notable classes are the *Colorado Plateau Pinyon–Juniper Woodland* (7% land area) and *Inter-Mountain Basins Big Basin Sagebrush Shrubland* (8% land area) classes, with user validation rates of 69% and 59% respectively (producer's rates of 81% and 77%).

Fifteen classes were validated with results greater than 70% from a user's perspective (group 5). These 15 classes represent approximately 24% of the total land area. The 85 classes that were validated (groups 2–5, Table 2) represent 91% of the total land area. Overall correct classification for these 85 classes was 61% (KHAT statistic = 0.60; n = 17,030).

5. Discussion

While the remote sensing community has been mapping land-cover from satellite-based sensors for more than 30 years, it has not been until the last decade and a half that significant efforts have been made to map large geographic regions. In the U.S., these efforts are lead by the USGS Gap Analysis Program and the USGS National Land Cover Database program. McDermid et al. (2005) identify several unique challenges faced by large-area mapping efforts. One of the more obvious challenges is the temporal discontinuity between image dates. Atmospheric and/or topographic correction must be addressed for each scene, and phenological differences of just 2 weeks can sometimes present substantial radiometric differences. Another

Table 1
Overall validation results (sum of diagonals) for each mapping zone, with associated number of modeled classes, validation sample size, and KHAT statistic

Mapping zone	# modeled classes	# valid. samples	Overall validation (%)	KHAT
AZ1	20	471	60	0.51
AZ2	23	734	60	0.50
AZ3	19	264	55	0.47
AZ4	33	1116	59	0.53
AZ5	14	636	70	0.56
CO1 and 2	50	1452	66	0.64
CO3	50	2248	63	0.61
CO4	38	2594	80	0.76
NM1	21	224	52	0.45
NM2	34	104	31	0.22
NM3	26	289	39	0.31
NM4A	41	343	55	0.50
NM4B	46	886	47	0.39
NM5	40	513	51	0.35
NV1	23	127	49	0.39
NV2	31	439	49	0.43
NV3	31	1099	61	0.52
NV4	53	1192	52	0.44
NV5	30	340	65	0.61
NV6	33	185	44	0.37
UT1	21	732	59	0.53
UT2	35	1803	65	0.62
UT3	28	873	60	0.56
UT4	23	483	66	0.62
UT5	13	176	70	0.60

Note mapping zones CO1 and CO2 were combined for modeling and validation purposes, while mapping zone NM4 was divided.

challenge is that of "large-area diversity and spatial heterogeneity" or the concept of "signature extension" (Jensen, 1996). This refers to the idea that the extent to which training data in one location represent similar land-cover classes across space (Cartesian space and elevation) is finite. As the extent and spatial detail of the mapping area increase, a proportional increase in training data are needed. A related challenge is that of accuracy assessment by independent means (McDermid et al., 2005). Statistically valid methods for unbiased map accuracy assessments are well known (Congalton & Green, 1999; Stehman & Czaplewski, 1998) but implementing logistically feasible and economically viable strategies remains a challenge.

Throughout SWReGAP we encountered all of these challenges. Underlying these common challenges to large-area mapping, SWReGAP experienced the added challenge of developing a land-cover map through a coordinated process involving multiple mapping teams. The remainder of this discussion focuses on three general aspects of our experience we believe will be of interest to the remote sensing mapping community.

5.1. Mapping methods

An important goal in developing our mapping methodology was to develop procedures that could be independently applied by multiple land-cover mapping teams to yield similar results. We found the decision tree approach to be time-efficient and conceptually intuitive, making the methods easily transferable to multiple mapping teams.

Identifying the optimum combination of predictor layers for the decision tree classifier was a major focus of our efforts to develop a regional mapping methodology (see Falzarano et al., 2005). Initially, we considered establishing a regional set of standard predictor datasets 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. However, due to the wide environmental gradient across the study area, we decided that each land-cover analyst should choose the predictor datasets they determined were best suited for a given mapping zone since a single prescribed set of predictors would not work in all areas (e.g. mountains vs. plains).

We found that the choice of identical predictor layers across mapping zones was not critical to the edge-matching process. The use of multi-season imagery did appear to improve image classification as evidenced by their inclusion in most, but not all models. The suite of core predictor datasets 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.).

Edge-matching problems between adjacent mapping zones proved negligible in most instances. In fact, there was a high level of mapping agreement between several mapping zones, inferring accurate land-cover mapping since each mapping zone was modeled with an independent set of training data and different predictor variables (Fig. 5). In instances of less-than-favorable edge-matching, the use of a cutline within the 4-km buffer effectively improved the transition between mapping zones. The use of spectral-physiographic mapping zones proved to be effective work units and helped constrain spectrally and environmentally similar land-cover classes to logical geographic boundaries. Radiometric standardization through web-based tools was critical for quality control and efficient project management.

5.2. Map accuracy

Large geographic areas typically have greater spectral, environmental, and biological diversity, requiring a large number of samples to train and validate the map. Dealing with very large areas (even if subdivided into mapping zones—each of which may be a mosaic of 2–3 ETM+ scenes) we faced the challenge of obtaining sufficient training samples to account for the spectral and environmental variability *within* and *between* land-cover classes. When faced with this challenge, one must decide to either focus sampling efforts on the variability and internal heterogeneity of the most abundant land-cover classes, or to spend time searching for samples of the rarer land-cover classes. Unless specific attention is given to the rarer classes, the time and budgetary realities of a project of this magnitude will likely lead to more focused sampling efforts on the larger, more abundant land-cover classes.

Table 2
Regional summary of land-cover area and validation results sorted into 5 validation groups (based on user's perspective) and organized by NLCD land-cover class

Mapped land-cover classes (SWReGAP)	Land area		Validation results		
	Area (km²)	Percent total area (%)	Number reference samples	Producer	User
GRP 1: VALIDATION NOT ASSESSED					
Sparsely vegetated/barren classes					
Inter-Mountain Basins Volcanic Rock and Cinder Land	1360	0.10	na	na	na
Inter-Mountain Basins Wash	46	> 0.01	na	na	na
Mediterranean California Alpine Bedrock and Scree	23	> 0.01	na	na	na
North American Alpine Ice Field	23	> 0.01	na	na	na
North American Warm Desert Badland	112	0.01	na	na	na
North American Warm Desert Volcanic Rockland	992	0.07	na	na	na
Sierra Nevada Cliff and Canyon	123	0.01	na	na	na
Western Great Plains Cliff and Outcrop	309	0.02	na	na	na
Evergreen forest classes					
Madrean Upper Montane Conifer–Oak Forest and Woodland	795	0.06	na	na	na
Mediterranean California Dry–Mesic Mixed Conifer Forest and Woodland	2	> 0.01	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	> 0.01	na	na	na
Rocky Mountain Foothill Limber Pine–Juniper Woodland	6	> 0.01	na	na	na
Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	7295	0.53	na	na	na
Rocky Mountain Subalpine Mesic Spruce–Fir Forest and Woodland	10,359	0.75	na	na	na
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	21	> 0.01	na	na	na
Shrub/scrub classes					
Chihuahuan Succulent Desert Scrub	187	0.01	na	na	na
Coahuilan Chaparral	94	0.01	na	na	na
Rocky Mountain Alpine Dwarf-Shrubland	110	0.01	na	na	na
Sonora–Mojave Semi-Desert Chaparral	89	0.01	na	na	na
Western Great Plains Mesquite Woodland and Shrubland	1797	0.13	na	na	na
Wyoming Basins Low Sagebrush Shrubland	47	> 0.01	na	na	na
Grassland/herbaceous classes					
Central Mixedgrass Prairie	120	0.01	na	na	na
North Pacific Montane Grassland	27	> 0.01	na	na	na
Western Great Plains Sand Prairie	18	> 0.01	na	na	na
Western Great Plains Tallgrass Prairie	1	> 0.01	na	na	na
Woody wetland classes					
North American Warm Desert Riparian Mesquite Bosque	832	0.06	na	na	na
Emergent wetland classes					
Mediterranean California Subalpine-Montane Fen	2	> 0.01	na	na	na
Temperate Pacific Subalpine-Montane Wet Meadow	2	> 0.01	na	na	na
Western Great Plains Saline Depression Wetland	41	> 0.01	na	na	na
Altered or disturbed classes					
Disturbed, non-specific	93	0.01	na	na	na
Disturbed, oil well	46	> 0.01	na	na	na
Invasive perennial forbland	1	> 0.01	na	na	na
Recently burned	2033	0.15	na	na	na
Recently chained pinyon–juniper areas	689	0.05	na	na	na

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Table 2 (*continued*)

Mapped land-cover classes (SWReGAP)	Land area		Validation results		
	Area (km^2)	Percent total area (%)	Number reference samples	Producer	User
Other classes					
Agriculture	75,981	5.48	na	na	na
Developed, medium–high intensity	7539	0.54	na	na	na
Developed, open space–low intensity	7425	0.54	na	na	na
Open water	11,023	0.80	na	na	na
Total area not assessed	130,020	9.39			
GRP 2: VALIDATION RESULTS WITH <30% AGREEMENT					
Grassland/herbaceous classes					
Chihuahuan Sandy Plains Semi-Desert Grassland	986	0.07	28	11%	21%
Inter-Mountain Basins Big Sagebrush Steppe	1798	0.13	82	12%	26%
Madrean Juniper Savanna	994	0.07	32	6%	25%
Total area <30% agreement	3778	0.27			
GRP 3: VALIDATION WITH 30–49% AGREEMENT					
Sparsely vegetated/barren classes					
North American Warm Desert Pavement	393	0.03	21	14%	33%
Evergreen forest classes					
Madrean Encinal	4358	0.31	45	51%	44%
Madrean Pine–Oak Forest and Woodland	5733	0.41	104	42%	46%
Rocky Mountain Subalpine–Montane Limber–Bristlecone Pine Woodland	801	0.06	31	13%	44%
Mixed forest class					
Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	3439	0.25	159	30%	49%
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	4413	0.32	45	22%	33%
Chihuahuan Stabilized Coppice Dune and Sand Flat Scrub	5725	0.41	59	49%	48%
Sonora–Mojave Mixed Salt Desert Scrub	2549	0.18	23	26%	30%
Grassland/herbaceous classes					
Chihuahuan–Sonoran Desert Bottomland and Swale Grassland	>1	>0.01	104	32%	41%
Inter-Mountain Basins Semi-Desert Grassland	33,640	2.43	392	32%	41%
Woody wetland classes					
North American Warm Desert Lower Montane Riparian Woodland and Shrub	426	0.03	43	19%	32%
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%
Emergent Wetland Classes					
Rocky Mountain Alpine-Montane Wet Meadow	1956	0.14	118	35%	48%
Altered or disturbed classes					
Invasive Annual Grassland	8291	0.60	174	22%	42%
Total area 30–49% agreement	131,888	9.52			
GRP 4: VALIDATION WITH 50–70% AGREEMENT					
Sparsely vegetated/barren classes					
Barren lands, non-specific	1421	0.10	54	19%	56%
Inter-mountain basins cliff and canyon	2873	0.21	83	43%	64%
Inter-mountain basins shale badland	3297	0.24	59	37%	50%
North American Warm Desert Active and Stabilized Dune	2728	0.20	37	43%	67%
North American Warm Desert Bedrock Cliff and Outcrop	3568	0.26	38	53%	67%
North American Warm Desert Playa	1115	0.08	20	70%	64%
Rocky Mountain Alpine Fell-Field	761	0.05	27	48%	59%

Table 2 (*continued*)

Mapped land-cover classes (SWReGAP)	Land area		Validation results		
	Area (km^2)	Percent total area (%)	Number reference samples	Producer	User
Rocky Mountain Cliff, Canyon and Massive Bedrock	2965	0.21	143	56%	67%
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 Pinyon–Juniper Woodland	21,917	1.58	233	71%	54%
Rocky Mountain Dry–Mesic Montane Mixed Conifer Forest and Woodland	8953	0.65	458	52%	57%
Rocky Mountain Lodgepole Pine Forest	8764	0.63	199	60%	60%
Rocky Mountain Subalpine Dry–Mesic Spruce–Fir Forest and Woodland	14,814	1.07	466	76%	66%
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%
Shrub/scrub classes					
Colorado Plateau Blackbrush–Mormon-tea Shrubland	13,310	0.96	106	73%	54%
Colorado Plateau Mixed Low Sagebrush Shrubland	2401	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	4130	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	2550	0.18	81	27%	55%
Mogollon Chaparral	11,515	0.83	169	49%	52%
Rocky Mountain Lower Montane–Foothill Shrubland	2823	0.20	102	44%	68%
Sonoran Mid-Elevation Desert Scrub	5393	0.39	36	36%	50%
Southern Colorado Plateau Sand Shrubland	7021	0.51	81	56%	56%
Apacherian–Chihuahuan Semi-Desert Grassland and Steppe	45,711	3.30	343	63%	51%
Chihuahuan Gypsophilous Grassland and Steppe	804	0.06	25	56%	56%
Inter-Mountain Basins Juniper Savanna	5590	0.40	89	36%	51%
Inter-Mountain Basins Montane Sagebrush Steppe	40,654	2.93	781	72%	63%
Inter-Mountain Basins Semi-Desert Shrub-Steppe	47,618	3.44	699	38%	52%
Rocky Mountain Subalpine Mesic Meadow	2177	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	5066	0.37	135	65%	63%
Woody wetland classes					
Great Basin Foothill and Lower Montane Riparian Woodland and Shrub	1360	0.10	102	60%	68%
Inter-Mountain Basins Greasewood Flat	23,770	1.71	405	46%	52%
Rocky Mountain Lower Montane Riparian Woodland and Shrubland	2226	0.16	177	45%	67%
Rocky Mountain Subalpine–Montane Riparian Shrubland	3224	0.23	135	49%	62%

(continued on next page)

Table 2 (*continued*)

Mapped land-cover classes (SWReGAP)	Land area		Validation results		
	Area (km^2)	Percent total area (%)	Number reference samples	Producer	User
Rocky Mountain Subalpine–Montane Riparian Woodland	292	0.02	46	7%	50%
Western Great Plains Floodplain	836	0.06	66	67%	70%
Emergent wetland classes					
North American Arid West Emergent Marsh	1053	0.08	64	38%	65%
Altered or disturbed classes					
Invasive annual and biennial forbland	2638	0.19	138	17%	52%
Invasive perennial grassland	2839	0.20	136	38%	67%
Invasive southwest riparian woodland and shrubland	1609	0.12	116	59%	66%
Recently mined or quarried	1240	0.09	23	61%	67%
Total area 50–70% agreement	783,005	56.48			
GRP 5: VALIDATION WITH >70% AGREEMENT					
Sparsely vegetated/barren classes					
Colorado Plateau Mixed Bedrock Canyon and Tableland	24,313	1.75	248	75%	72%
Inter-Mountain Basins Active and Stabilized Dune	3103	0.22	39	44%	71%
Inter-Mountain Basins Playa	17,581	1.27	81	68%	77%
Rocky Mountain Alpine Bedrock and Scree	3863	0.28	100	81%	84%
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%
Shrub/scrub classes					
Mojave Mid-Elevation Mixed Desert Scrub	16,762	1.21	168	71%	75%
Rocky Mountain Gambel Oak–Mixed Montane Shrubland	18,950	1.37	524	69%	71%
Sonora–Mojave Creosotebush–White Bursage Desert Scrub	58,760	4.24	292	68%	76%
Sonoran Paloverde–Mixed Cacti Desert Scrub	39,791	2.87	280	83%	74%
Western Great Plains Sandhill Shrubland	13,894	1.00	159	72%	74%
Grassland/herbaceous classes					
Rocky Mountain Dry Tundra	2779	0.20	68	76%	78%
Western Great Plains Shortgrass Prairie	113,162	8.16	668	88%	72%
Woody wetland classes					
Western Great Plains Riparian Woodland and Shrubland	1714	0.12	153	75%	80%
Altered or Disturbed Classes					
Recently Logged Areas	836	0.06	35	37%	93%
TOTAL AREA >70% AGREEMENT	337,382	24.32			
TOTALS FOR 5-STATE REGION	1,386,073	100	17,030		

The first validation group contains classes that were not assessed regionally because of limited validation plots ($n<20$) or were non-natural classes and not the focus of the mapping effort.

Although we consider our assessment of map quality a validation rather than true accuracy assessment, the results reveal our sampling (and validation) bias toward the more abundant land-cover classes. Many of the rarer classes were either not validated (due to limited samples) or were validated with low results. Few samples in the rarer classes could explain low accuracies for these classes as decision tree classifiers are notably sensitive to under-represented classes (Weiss, 1995). Limiting our sample collection to the road network also biased the sample pool (training and validation) toward land-cover classes in proximity to roads. Because we used the same sample pool for both training and validation, this bias is likely undetected, and our validation results should be considered higher than would be expected from an independent dataset.

The task of collecting unbiased training samples and independent accuracy assessment data for most land-cover mapping efforts is a considerable challenge, and particularly so in a project of this size and scope. In retrospect, we believe improvements could be made to develop a more robust sampling design balancing the need for samples in both rare and abundant land-cover classes. This could be accomplished with reasonable cost-effectiveness by investing more project resources (time, effort and financial resources) in obtaining samples through air photo interpretation for training, and creating an independent validation dataset for accuracy assessment.

As a final note, our approach used sample polygons as the sample unit for error assessment. Using a cluster of pixels in this

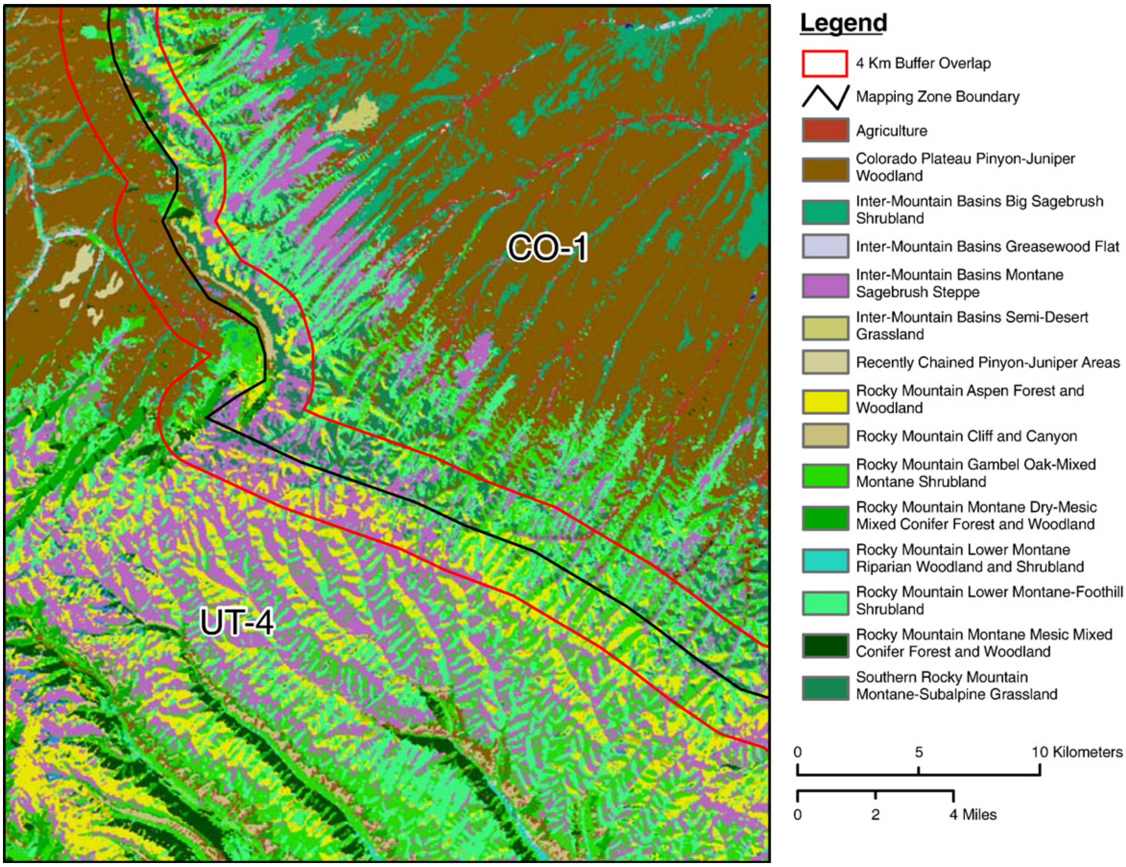

Fig. 5. Example of edge-matching between UT-4 and CO-1.

manner is a common choice for the sample unit and has the advantage of minimizing error attributed to miss-registration of the GPS sample site and/or the imagery (Congalton & Green, 1999). A disadvantage of this approach however, is that because the size of the sample unit dictates the level of detail of the accuracy assessment, this approach does not address the accuracy of individual pixels, nor larger homogenous patches of land-cover classes (Congalton & Green, 1999).

5.3. Project coordination

Project coordination relied heavily on frequent communication between the regional land-cover lab, the four other land-cover mapping teams, and NatureServe. Correspondence via email–especially a project listserve–was critical for dissemination of information related to mapping methodologies and protocols. Also invaluable were monthly teleconferences involving all land-cover mapping personnel and NatureServe. Face-to-face meetings (yearly) and hands-on workshops (3 over 5 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 for their mapping area. Perhaps the most difficult decision land-cover analysts faced was deciding if a specific land-cover class should be mapped. Decisions to model a specific land-cover class were primarily driven by adequate representation within the training samples of that class for a given mapping zone. Thus, the adequacy of the sample training set was a 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 determined to be mappable in one state may have been aggregated or eliminated in the regional product to maintain regional consistency (though this rarely occurred).

In hindsight, the project would have benefited by establishing more objective procedures 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 was therefore recognized as a "working classification" (Comer et al., 2003). As such, the mappability of ecological systems using moderate-scale satellite imagery and ancillary data was to some degree determined through this project. Developing better methods to determine land-cover class mappability over large geographic areas is an area for future work.

6. Conclusion

The objective of this project was to produce a land-cover map that would meet the needs for the GAP, and be an improvement over the 5 existing state land-cover maps in the region. The quantifiable objective of achieving a map product with an overall accuracy of 80% was not tested because a formal accuracy assessment was not performed. While the validation approach we used cannot be considered a true accuracy assessment, it does provide a quantifiable estimate of map quality. Assuming the validation results approximate what would be achieved with a formal accuracy assessment, we did not achieve the map accuracy goal. However we believe that the resulting "accuracy" of the land-cover map is not entirely an artifact of failures in the methodological procedures of our approach, but rather a manifestation of the challenges inherent in large-area land-cover mapping. In hindsight we recognize that more attention could have been placed on the decision to map or not map some of the rarer land-classes. Given that gap analysis in GAP is considered a "coarse filter" approach to biodiversity assessment, we may have attempted to map a number of rare classes that could have been grouped with other more widespread land-cover types, while still meeting the biodiversity assessment requirements of gap analysis.

In general, however, the results from this project are not inconsistent with other large-area mapping efforts. We concur with Laba et al. (2002) who suggest that user's and producer's accuracies for several recent large-area mapping projects (Edwards et al., 1998; Ma et al., 2001; Zhu et al., 2000) are "stabilizing in the 50–70% range" and that "artificial targets of 85% overall percent correct should not be used to measure the success or failure of a land-cover project".

Large-area mapping projects face challenges not found in smaller projects focusing on a single scene or within a limited geographic area. In this paper we presented a number of methodological approaches for dealing with some of these challenges. Unique to SWReGAP was our attempt to implement these approaches within a collaborative project management framework.

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