LIMITATIONS OF ASSESSING SYNTHETIC NATURAL BOUNDARIES IN THE CHIHUAHUAN DESERT

BY

ANNA KLIMASZEWSKI PATTERSON, B.A.

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Dr. Michael N. DeMers, Chair

"Assessing Synthetic Predictive Vegetation Boundaries in the Chihuahuan Desert", a thesis prepared by Anna Klimaszewski Patterson in partial fulfillment of the requirements for the degree, Masters of Applied Geography, has been approved and accepted by the following:

Linda Lacey
Dean of the Graduate School

Michael N. DeMers
Chair of the Examining Committee

Date

Committee in charge:

Dr. Michael N. DeMers

Dr. Daniel P. Dugas

Dr. H. Curtis Monger

VITA

September 19, 1976	Born in Parma, Ohio
1994	Graduated from Klein High School, Klein, Texas
1998-1999	Adjunct Professor, Department of Business Management Technologies, University of Toledo
2006	Graduated from San Diego State University with a B.A. in Geography
2009-2010	Teaching Assistant, Department of Geography, New Mexico State University
2011	Research Assistant, Department of Geography, New Mexico State University

Professional and Honorary Societies

American Society of Photogrammetry and Remote Sensing

Association of American Geographers

Gamma Theta Upsilon

Publications [or Papers Presented]

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Field of Study

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DEDICATION

This document is dedicated to my family, for always encouraging me to pursue my dreams through education. Especially my daughter, Julia Serene, for not only tolerating, but thriving with two parents in Graduate School. I can’t imagine that it was an easy childhood, but hopefully it was a good one.

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ABSTRACT

Boundary delineations are constantly used in our everyday lives. Boundaries determine management practices and help formulate expectations; however, boundaries are mostly human constructs, and crisp delineations rarely occur in nature. Synthetic boundaries, or those boundaries established through a synthesis of implicit and explicit data, are purely human constructs. Yet synthetic boundaries are relied upon to delineate ecosystems and transition zones. The question becomes not only whether the placement of the boundaries is accurate, but also whether or not the accuracy of the boundaries can be assessed given their synthetic nature.

Dramatic ecosystem transitions in semi/arid environments have been of interest to researchers for several decades. At issue are the degradation of rangeland for human use and the associated extent of anthropogenic versus natural change. Semi/arid environments, by nature, have sparse, patchy vegetation; the predominant land cover type is exposed soil. Remotely sensed images of these landscapes allow for examination of geomorphology without the visual impediment of dense vegetation. Considerable research has been done on the correlation between geomorphology and vegetation types, opening the possibility of geomorphology acting as a proxy for expected vegetation given current climate conditions. In 2003, DeMers et al. (2010) created a rapid bioassessment model (REAL) predicting vegetation based on geomorphology, but extensive field verification of the model was not performed. My research examines the accuracy of REAL's synthetic boundaries from two scales: human (fine) and model (broad). To test the boundaries at the human

scale, two tests were performed: 90 meters continuous line-intercept transect sampling (LIS) within selected sampling areas, and an automotive random walk. For the model scale, a coefficient of areal correspondence (CAC) was calculated on two different computer-assisted classification types: unsupervised and supervised classification.

Testing REAL's synthetic boundaries posed issues at both scales. At the human scale, LIS proved mostly unsuccessful given that the extent of most vegetative ecotones was greater than 90 meters. The automotive random walk better allowed for boundaries to be seen, but exact accuracy could not be assessed. All the approaches used to test REAL's boundary accuracy at the model scale are themselves models, leading to mixed results and the possibility of circular reasoning. Unsupervised classifications did not work, as correspondence between the unsupervised classes and REAL's could not be determined. Supervised classifications showed greater success, but only where strong spectral signatures were present (lava flows, mountain slopes, and playas).

Overall, this research determined that though some synthetic boundaries can be partially assessed, the exact position of any boundary cannot be specifically determined. At the human scale, an automotive random walk allows boundaries to be most readily assessed, but not located precisely. Automotive random walk works best for determining confidence in synthetic boundary placement, as the method is the juxtaposition of the human and model scales. Expecting a quantifiable accuracy assessment on precise boundary placement of a synthetic model, such as REAL, is largely unreasonable. At best, an agreement on the general location of polygons can be reached, especially when using a method such as an automotive random walk.

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1. INTRODUCTION

Boundary delineations are constantly used in our everyday lives. Boundaries determine management practices and help formulate expectations; however, boundaries are mostly human constructs, and crisp delineations rarely, if ever, happen in nature. Synthetic boundaries, or those boundaries established through a synthesis of implicit and explicit data, are purely human constructs. Yet synthetic boundaries are relied upon to delineate ecosystems and transition zones. The question becomes, not only whether the placement of the boundaries is accurate, but whether or not the accuracy of the boundaries can be assessed given their synthetic nature.

Identification of ecosystem transitions in arid and semiarid environments has been the topic of great interest to researchers for the past several decades (Scheffer et al. 2001; Rietkerk et al. 2004; Bestelmeyer et al. 2006; Bestelmeyer, Ward, and Havstad 2006). As more land exhibits signs of the desertification process, the boundaries between vegetation shifts and the patchiness of the land increases. However, unless accurate boundaries are established in the first place, the ability to detect, predict, and possibly reverse the vegetative shifts due to degradation are difficult, if not impossible (Bestelmeyer, Ward, and Havstad 2006; Rietkerk et al. 2004). Boundaries are important in creating management zones where a uniformity of process is expected. If validation of boundary locations is not done, land managers and researchers do not have an accurate sense of expectations.

At issue is the ability to identify the degradation of rangeland for human use and determining the extent of anthropogenic impact versus natural change. Most research uses historical data such as land survey notes (Buffington and Herbel 1965), repeat imagery, both aerial and satellite (Gile, Ahrens, and S. P. Anderson 2003; G. S. Okin et al. 2001; Bestelmeyer, Ward, and Havstad 2006), and vegetation maps (Gibbens et al. 2005). While these researchers have demonstrated significant changes to vegetation types in anthropogenically impacted areas, teasing out the variables for natural vegetative progression based on current climate regimes has proven difficult. A method that would allow for expected vegetation mapping based on current climate could be used as an additional input for impacts comparison between current vegetative communities and expected ones.

Ecosystem degradation research has not focused explicitly on either the accuracy of boundaries drawn, nor taken climate-induced vegetation progression into account. Arid and semiarid environments, by nature, have sparse, patchy vegetation and a predominant land cover of bare soil. As a result, vegetation in such an environment is difficult to discern from remotely-sensed imagery; however, the landscape's geomorphology can easily be examined (Dwivedi et al. 1993; D. B. Clark, Palmer, and D. A. Clark 1999; G. S. Okin et al. 2001). Considerable research has been done on the correlation between geomorphology and vegetation types (Hunt 1966; Olsvig-Whittaker, Shachak, and Yair 1983; Burke, Reiners, and Olson 1989; Wondzell, Cunningham, and Bachelet 1996; G. S. Okin et al. 2001; Monger and Bestelmeyer 2006; Bestelmeyer et al. 2006; Saco, Willgoose, and Hancock 2007). Past research has not focused on establishing the accurateness of vegetation boundaries with respect to geomorphology, but instead focused on determining vegetation based on various spectral analysis of remotely sensed imagery (G. S. Okin et al. 2001), or examining different sides of an obvious ecotone (Bestelmeyer et al. 2006). Additionally, the research typically focused on either developing models (Wondzell, Cunningham, and Bachelet 1996; Saco, Willgoose, and Hancock 2007), or using pure remote sensing techniques (G. S. Okin et al. 2001; Bestelmeyer, Ward, and Havstad 2006), which typically required high-end computer systems and/or software to run the analyses. For instance, the Gap Analysis Program (GAP), launched in 1989 under the United States Geological Survey, aims to delineate animal and plant boundaries. The program, however, has a high cost in terms of time, manpower, and computing power. GAP also does not focus on the accuracy of the vegetation boundary, assuming the error to be small given the scale at which the program is being implemented (Crist and Deitner 2007). In 2003, DeMers *et al*. (2010; Dugas et al. 2011) developed a low-tech rapid bioassessment model with geomorphologic boundaries as a proxy for vegetation boundaries, using only Landsat 7 ETM imagery and visual analysis. This model was later named the Rapid Evaluation of Arid Lands (REAL) (Dugas et al. 2011). The goal of REAL was to provide a triage-level, inexpensive, rapid analysis tool for range managers and researchers. Field verification of REAL was done in 2003 with random-walk convenience sampling (Dugas et al. 2011).

My research determines whether the locational accuracy (accuracy) of synthetic boundaries, such as REAL, can be assessed. Accuracy is assessed at two different scales: the human scale and the model scale. Overall, this research provides an improvement in verification methods for categorical boundaries, as well as providing a sampling scheme for semi/arid-environment remotely sensed imagery. Broader impacts include providing range managers the ability to assess and manage their land based on accurate management boundaries, as well as provide a scheme for establishing management boundaries in other semi/arid regions.

2. LITERATURE REVIEW

2.1. Geomorphology, Soils, and Vegetation

Geomorphology is the study of landforms, which are discrete units of the earth's surface (Peterson 1981). Examples of landforms include: mountains, hills, valleys, plains, stream terraces, lava flows, and alluvial fans. Landforms may be composed of different types of parent material, including organic matter, unconsolidated sediments, or hard rock (Certini and Scalenghe 2007). Examples of parent material include: granitic mountains, sandstone hills; fluvium in valleys; and basalt in lava flows. Peterson (1981) provides a thorough discussion of how landforms are created in the Basin and Range Province. Regardless of the specifics in their formation, a landform's parent material and topographic disposition becomes the foundation of that unit's soil. In other words, soil patterns tend to correspond with landforms (Peterson 1981). Though landforms can have soils that differ from the original parent material due to addition (*i.e.*: loess), subtraction (*i.e.*: wind erosion), translocation (*i.e.*: bioturbation), and transformation (*i.e.*: leaching) (Monger pers com 2010), landforms are the initial basis for soil maps (Peterson 1981).

Soil, a three-dimensional body capable of supporting rooted vegetation, is created through a process known as pedogenesis. Dokuchaev (1883), the father of pedology, recognized that the following factors contributed to the formation of soil: climate, organisms (biota, including humans), relief (topology), and parent material. In 1941, Hans Jenny revised the soil forming factors to also include time. The five soil forming factors can be depicted in a soil-geomorphic template (Figure 1)

(Monger and Bestelmeyer 2006). Ultimately, parent material is a factor towards soil type, which is a factor towards vegetation type (Jenny 1941; Monger and Bestelmeyer 2006).

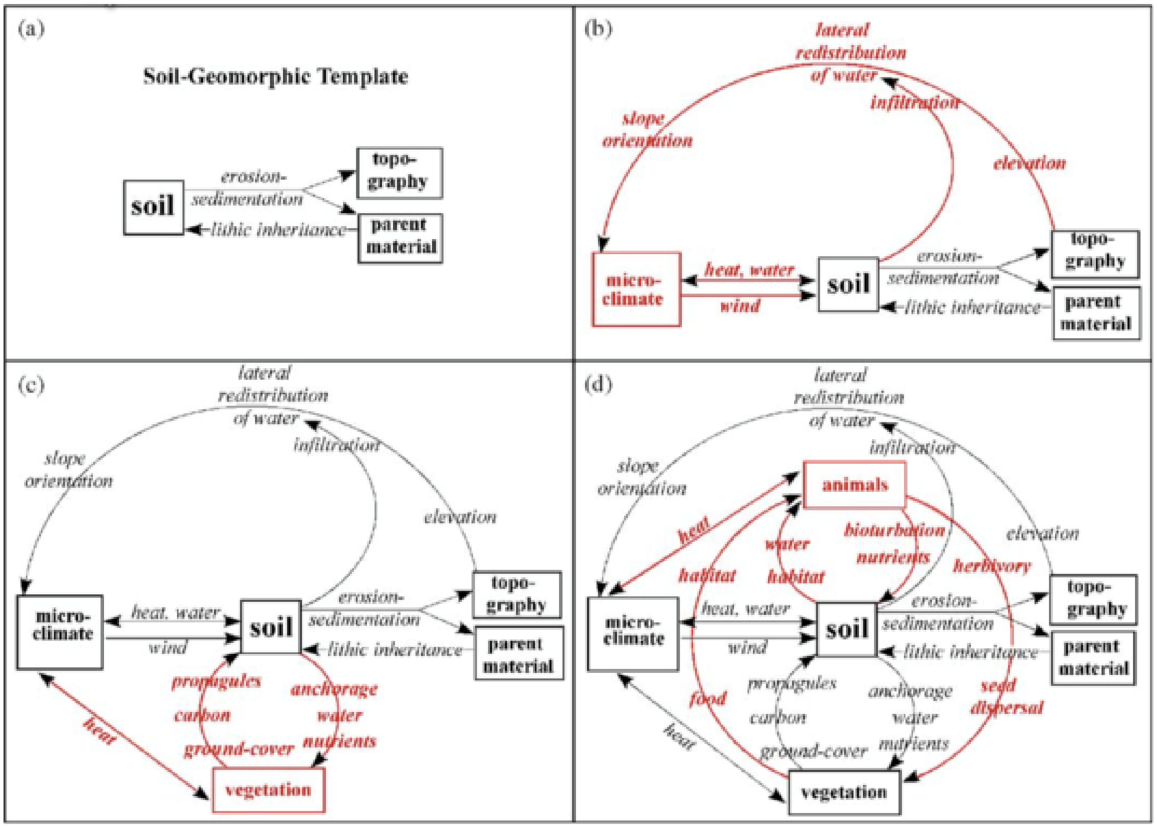


FIGURE 1
SOIL-GEOMORPHIC TEMPLATE
(Monger and Bestelmeyer 2006)

Soil has a major effect on vegetation type through three mechanisms: plant-available water, nutrients, and root anchorage (Figure 2) (Burke et al. 1998; Monger and Bestelmeyer 2006). For instance, less water is plant-available in sand, where porosity allows water to drain quickly from the root area. Soil lacking in nutrients, such as phosphorous, nitrogen, or potassium, limits the kinds of vegetation that can grow based on biological needs. Finally, if soil is too loose, too shallow, or too indurated, certain types of vegetation can have difficulty rooting (Bestelmeyer, Ward, and Havstad 2006; Monger and Bestelmeyer 2006).

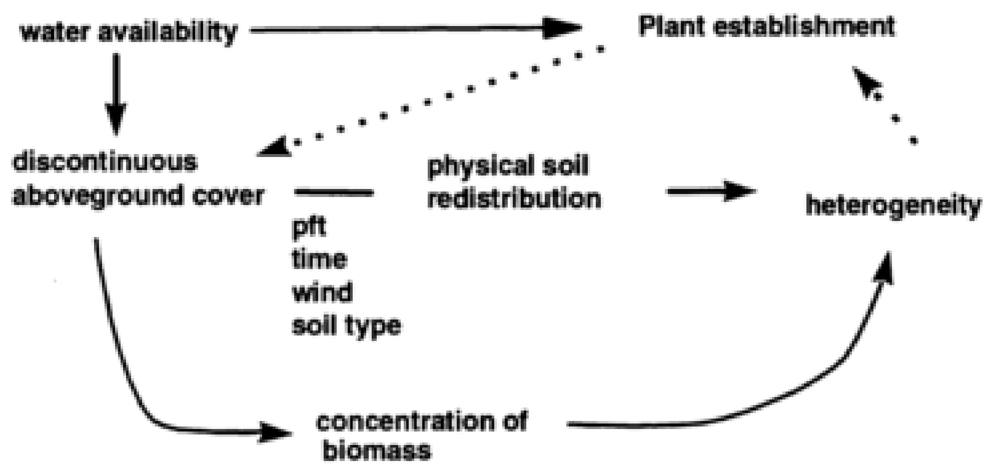


FIGURE 2
SOIL-VEGETATION INTERACTION IN DESERT GRASSLANDS
(Burke et al. 1998)

Vegetation, in turn, can affect soil and geomorphology. As is demonstrated in the soil-geomorphic template (Figure 1), vegetation can: slow soil erosion; introduce nutrients and carbon; slow runoff, thus increasing infiltration; and improve soil texture by introducing organic matter. By slowing soil erosion through root anchorage, vegetation also slows the erosion of landforms. Additionally, by introducing nutrients and improving soil texture, one vegetation type can create an ideal environment for another vegetation type (*i.e.*: plant succession). In semi/arid environments, soil-vegetation interaction is dominated by “resource islands”, which helps explain the patchy above-ground pattern of desert grasslands (Burke et al. 1998). Geomorphology and soils are contributing factors in the spatial arrangement of vegetation on the landscape. However, natural movement of land, soils, and vegetation results more in gradations across the landscape than in crisp boundaries.

2.2. Synthetic Boundaries

In the context of this research, synthetic boundaries are boundaries established through a synthesis of implicit and explicit data. Implicit data is data that cannot be readily seen or assessed, such as soil types or land-use history, while explicit data is data that can be readily interpreted, such as a lake boundary or current land use. Synthetic boundaries are important in delineating management zones at the local, ecosystem, and ecoregions level.

Ecoregions are large, regional-scale ecosystems, wherein interrelated biotic and abiotic systems are linked together (Tansley 1935; Bailey 2002; 2004). Though ecosystems have been mapped since the time of the ancient Greeks (Bailey 1996), the first world-wide ecoregion map was created in 1905 by Professor Andrew J. Herbertson (Unstead 1916). In his map, Herbertson took topography, elevation, climate, vegetation, and human population density into account (Herbertson 1905). In the following century, ecoregion maps have been recreated and evaluated. While many ecoregion maps (Küchler 1964; Omernik 1987; Bailey 1996; 2002; 2004; The Nature Conservancy 2010) continue to use some of Herbertson’s ecoregion factors, there exists little consensus in the placement of synthetic boundaries. This is due to varying factors used in the creation of the boundaries (scale, soil, landforms, land use, potential natural vegetation vs. existing vegetation, climate, topography, hydrology, wildlife, slope, aspect, etc), as well as creating boundaries within ecotones (transitional zones between ecosystems) instead of treating the ecotone as its own system. The same issues occur when mapping at different scales, such as the landscape scale. Yet, in order for any map to gain credibility, an accuracy assessment of some sort needs to be performed. Typical accuracy assessments of this type check the thematic accuracy within the region, and assume the boundary to be accurate enough (Crist and Deitner 2007). Thematic accuracy of remotely sensed imagery does not take scale into account. Typically, high resolution aerial photos are compared to low resolution satellite images. However, whether scale needs to be taken into consideration when assessing positional accuracy of synthetic boundaries has yet to be determined.

2.3. Issues of Scale

Scale, in the context of this research, is defined as the spatial dimension (Figure 3) of a process or object (Turner, Gardner, and O'Neill 2001), such as a tree, stand, ecosystem, or landscape. Map scale is defined as the ratio of distance on a map to distance on the ground (DeMers 2008), while grain size (Figure 4) is defined as the level of spatial resolution (Turner, Gardner, and O'Neill 2001). Human scale in this research is defined as the scale at which a person can interact with their environment, while model scale is defined as the map scale at which the model was created. An

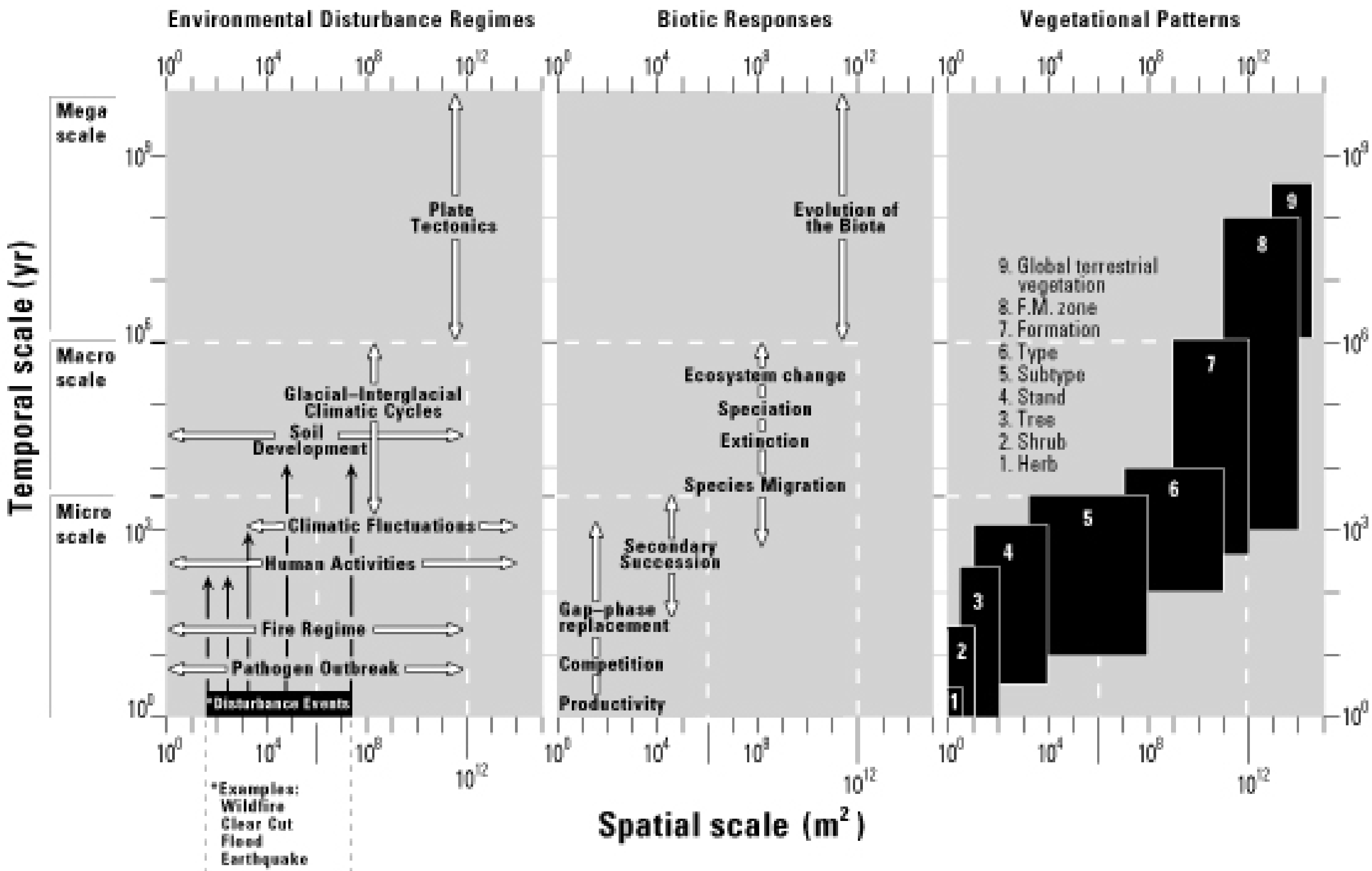


FIGURE 3
SPATIAL SCALE IN SQUARE METERS
(H. R. Delcourt, P. A. Delcourt, and Webb 1983; Turner, Gardner, and O'Neill 2001)

example of human scale would be domestic dwellings, with doors, stairs, windows, etc. designed to accommodate the average person's dimensions. One additional scale to consider in the context of human scale is automotive scale. Walking at 3.2 kilometers per hour (kph; 2 miles per hour (mph)), a person can walk 100 meters in 1 minute and 48 seconds. However, driving the same distance at 72 kph (45 mph) takes five seconds. Details perceived at automotive scale are less than the details perceived at the slowly walked human scale due to compressed space over time. As a result, perceived patterns change (Figure 5) because the map scale at which a person interacts with the environment is modified through an external force. In the same context, delineations on a map, such as boundaries, become more generalized the smaller (coarser) the map scale becomes.

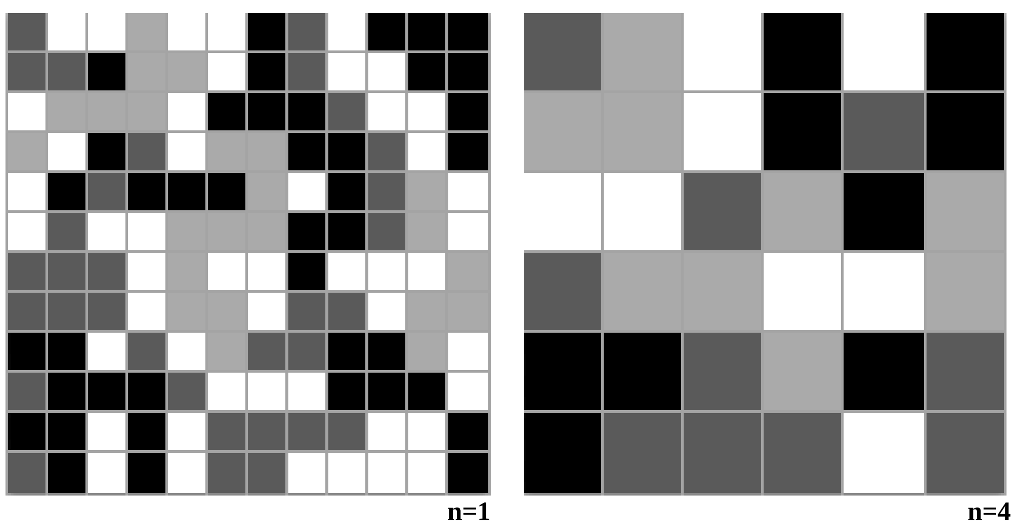


FIGURE 4
SMALL AND LARGE GRAIN SIZE COVERING THE SAME AREA

REAL was created at the landscape scale (model scale), using remotely sensed imagery from Landsat 7 ETM+ sensor. Landscapes are the extent which can be observed by a person (Peterson 1981). A landscape's extent is arbitrary (Turner, Gardner, and O'Neill 2001) and can be influenced by line of sight and elevation; however, when observed with a satellite sensor, landscape scale can be observed without line-of-sight impedance. Because patterns and processes are scale dependent (Figures 3, 4, and 5) (Turner, Gardner, and O'Neill 2001), only larger grain ecosystem patterns within the landscape can be explored due to Landsat 7's 30 square meters spatial resolution.

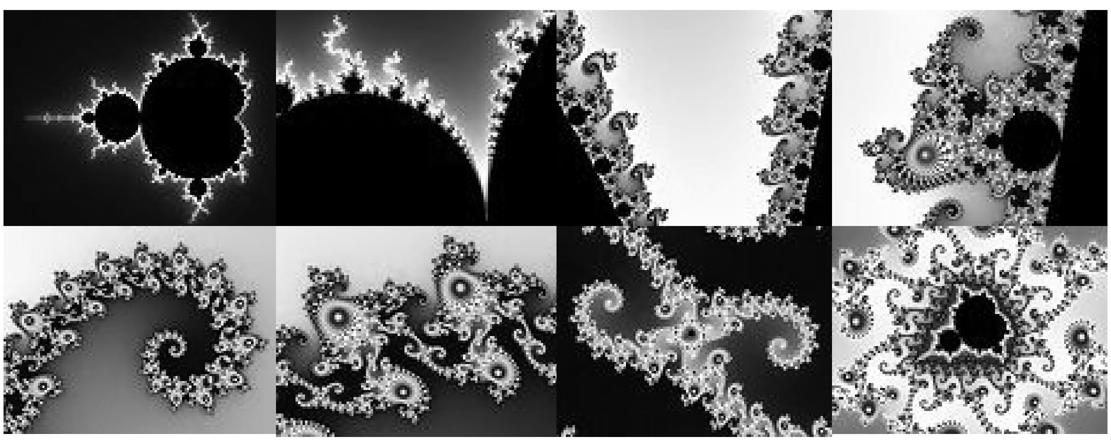


FIGURE 5
CHANGE IN PATTERN WITH CHANGE IN MAP SCALE
Demonstrated using a Mandelbrot set zoom sequence
(Demidov 2008; Wikipedia 2010)

2.4. Remote Sensing and Image Classification

For the purposes of this research, remote sensing is defined as spectral data of the earth's surface acquired from satellites (Richards and Jia 2006). Different satellite sensors have varying spatial, spectral, temporal, and radiometric resolutions. Spatial resolution refers to the amount of space represented in a single pixel. Spectral resolution refers to the depth and fineness of spectra, or wavelength bands. Temporal resolution refers to the time interval between image acquisition, and radiometric resolution refers to how finely intensity can be determined (levels of grayness). Optical satellite data is recorded as two-dimensional images containing multiple spectral bands, and is dependent on the four resolutions mentioned above. Data costs range from free to several thousand dollars.

Since July 23, 1972, the United States' Landsat satellite program has continuously recorded data about the earth's surface (NASA 2010). To date, there have been seven Landsat satellites launched. Landsat 6 was the only satellite to not achieve orbit. Landsat 5 and 7 have a temporal resolution of 16 days and a radiometric resolution of eight bits (256 shades of gray). Landsat 4-7 sensors provide 30 square meters spatial resolution for six spectral bands of visible, near-infrared, and mid-infrared. In addition, Landsat 7's Enhanced Thematic Mapper Plus (ETM+) sensor has a panchromatic band of 15 square meters spatial resolution, and a thermal band of 60 square meters (Table 1) (USGS 2010). Unfortunately, on May 31, 2003, the ETM+ sensor on Landsat 7 suffered a Scan Line Corrector (SLC) failure, causing data gaps in the imagery. Imagery used in this research was acquired from Landsat 7 ETM+ in October 2001 (DeMers et al. 2010), prior to the SLC failure (Table 2). In 2009, the Landsat archive became free to all users, making Landsat the most cost-effective source of satellite imagery at a moderate resolution (USGS 2010).

TABLE 1
ETM+ BAND DESIGNATIONS (USGS 2010)

Spectral Band	Use
1 Blue-green	Distinguishes soil from vegetation
2 Green	Assess plant vigor
3 Red	Emphasis on vegetation slopes
4 Reflected near-infrared	Emphasis on biomass
5 Reflected near-infrared	Moisture content of soils and vegetation
6 Thermal infrared	Thermal mapping and soil moisture
7 Reflected mid-infrared	Mineral deposits
8 Panchromatic	Panchromatic band for sharpening multi-spectral images

TABLE 2
SATELLITE SCENE AND METADATA

Type	Bands	Path	Row	Date	Scene ID
L7 ETM+	7	33	37	03 Oct 2001	LE70330372001276EDC00

To use remotely sensed imagery for categorical data analysis, it must be classified into land cover classes. Through the process of classification, each pixel will be assigned to a pre-determined number of categories. Classifications can be performed through two different means: supervised and unsupervised (Richards and Jia 2006). In a supervised classification approach, representative pixels known as "training sites" are selected for each category (Schowegerdt 2007). Training sites should be homogenous areas free of anomalies while representing variation within the land cover class. Remaining pixels are then statistically placed into each category based on a spectral signature analysis. Statistical methods include, but are not limited to, maximum likelihood and minimum distance. In maximum likelihood, pixels are classified according to the highest probability of a class, whereas minimum distance is based on a pixel's spectral proximity to the mean vector of each class, not physical distance. In unsupervised classification, pixels are assigned to a pre-determined number of spectral classes without the use of training sites (Schowegerdt 2007). The premise is that each pixel will be more related spectrally to pixels within its class than to pixels in another class (Richards and Jia 2006; Tangjaitrong 2010). Changing the number of classes into which each pixel can be classified will invariably change the results of the classification.

Both supervised and unsupervised classifications can result in a "salt and pepper" effect, whereby pixels are classified into categories dissimilar from the pixels surrounding them (Tangjaitrong 2010). Polygons can be made more homogeneous using either a clump-and-sieve or clump and eliminate approach. Clump minimally combines pixels within a specified neighborhood, while Sieve and Eliminate merge polygons smaller than a set size into the most appropriate neighboring class. The difference between the two is that Sieve reclassifies the polygons, while Eliminate maintains the original data.

Once completed, classifications undergo an accuracy assessment to determine how well the classification matches actual conditions. Typically, 85 percent accuracy is considered an acceptable classification, while field-collected data is considered to be 100 percent accurate.

While several types of land cover classification schemes exist, this research uses the descriptive landform and vegetation classification scheme from DeMers *et al*. (2010) and Dugas et al. (2011) (Table 3). Landform classifications were based primarily on Peterson's (1981) desert Basin and Range landforms, while vegetation classifications are mostly equivalent to those of Buffington and Herbel (1965), Dick-Peddie (1993), and Stubbendieck, Hatch, and Butterfield (1997). However, vegetation classifications were made more descriptive and applicable based on expert knowledge by renowned desert ecologist Dr. Walter H. Whitford.

Supervised and unsupervised classifications are typical assessment methods used by remote sensors. Because REAL is derived from remotely sensed imagery, I thought it appropriate to use these classification schemes to test REAL at the model scale.

TABLE 3
LANDFORM AND VEGETATION CLASSIFICATIONS

Landform	Vegetation (simplified)
Aeolian terrain	Alkali sacaton with burro grass OR burro grass flats with some tobosa
Alluvial fan	Creosote with scattered black grama and three awn-bush muhly
Alluvial flat	Alkali sacaton with burro grass OR tobosa grass and burro grass
Ballena	Black grama with scattered shrubs
Depression	Alkali sacaton with burro grass
Disturbed	N/A
Fan piedmont	Black grama with either creosote, yucca, or three awn-bush muhly OR presence of tarbush, with alkali-sacaton
Fan skirt	Presence of tarbush, with alkali-sacaton OR burro grass flats
Inset Fan	Tobosa and burro grass OR burro grass flats with some tobosa
Lava flow	Mixed black grama with creosote or tarbush OR burro grass flats
Lake plain	Alkali sacaton with burro grass
Mountain slope	Black grama with scattered shrubs
Playa	Alkali sacaton with burro grass
Sedimentary bedrock hill	Black grama grassland with yucca

2.5. Natural Resources Conservation Service Soil Maps

The Natural Resources Conservation Service (NRCS) is a federal agency responsible for leading all soil survey-related activities under the U.S. Department of Agriculture. The National Cooperative Soil Survey (NCSS), a partnership of private, federal, regional, state, and local entities, falls under the leadership of NRCS. NCSS inventories, documents, classifies, investigates, and disseminates information about soils in the United States (NRCS 2011). The soil surveys that NCSS creates and updates for NRCS are originally based on geomorphic features (NRCS 2011). Though the primary purpose of soil surveys is the classification of soil types, not geomorphology, soil scientists use geomorphology-soil-vegetation relationships to determine their soil boundaries (Neher 1984), making the NRCS soil maps a potential method to compare with REAL's geomorphic boundaries.

Given the amount of area to cover, and the verification of collected data involved, soil surveys are constantly underway on a rotating basis. The most current soil survey performed in Sierra County, New Mexico was completed in 1980 and published in 1984 (Neher 1984). Soil surveys are typically conducted by digging soil profiles to test for thematic accuracy. No testing is done to determine the accuracy of soil boundaries on the surface.

2.6. Line-Intercept Transect Sampling

Transect sampling, specifically line intercept-transect sampling (LIS), is the most appropriate field method for determining boundary location on the surface (Klimaszewski-Patterson 2009). LIS quantifies any element of interest (element) that breaks the plane, or intercepts, a line (transect). Elements can include, but are not limited to, trees, shrubs, grass, slow-moving animals, signs, or any other item that is nearly stationary (D. R. Anderson et al. 1979). LIS is not the same as a line transect. With line transects, the observer travels along transect, counting and recording the distance, direction, and angle to elements (Buckland et al. 2001; Melville and Welsh 2001). Line transects are typically used for wildlife. LIS quantifies elements either continuously or at standard intervals (Rich et al. 2005). Elements recorded include any portions touching, underlying, or overhanging transect (Roth 1984). To perform LIS, a tape measure is stretched between two points. The observer records the starting and ending points of all elements, including bare soil, intersecting the transect. Observer bias can occur for the following reasons: bends in transects due to wind, shrubs, and/or stems; interpretation of gap sizes; and vertical estimates due to canopy cover. These observer biases can be mitigated by: suspending the transect line between two points, establishing a gap threshold (*e.g.* 5 centimeters), and using a pole to site the canopy along transect (NBII 2005). In addition to observer bias, statistical bias can also occur due to transect's direction, length (random vs. fixed), and placement of transect's center (Kaiser 1983). Direction and length are relevant biases for vegetation surveys, but boundary verification requires a specific direction and consistent length (Klimaszewski-Patterson 2009). Random direction methods are also inappropriate because transect's direction may run parallel with the boundary (Figure 6). To ensure the boundary is tested, transect must be placed perpendicular to the boundary (Figure 7) (Buckland et al. 2001). Fixed-length transects ensure the transition zone is consistently covered to best estimate the boundary's location. Randomly locating transect's central point mitigates some statistical bias while ensuring the boundary is the object tested, not the vegetation coverage and/or density. LIS is recommended for open vegetation types such as steppes, open grassland, and shrub lands (Küchler and Zonneveld 1988). LIS also works well in relatively natural desert grassland environments (Klimaszewski-Patterson 2009) and can be quickly and easily implemented.

FIGURE 6
RANDOM LENGTH AND DIRECTION TRANSECTS
Shades of grey indicate polygons
(Klimaszewski-Patterson 2009)

FIGURE 7
FIXED LENGTH WITH PERPENDICULAR TRANSECTS
Shades of grey indicate polygons
(Klimaszewski-Patterson 2009)

LIS is performed at the human scale. Because a moving average can be used to determine where a vegetation shift occurs along transect, LIS is appropriate for determining boundary locations. Therefore, LIS is an appropriate technique to test REAL at the human scale.

2.7. Coefficient of Areal Correspondence

A quantifiable value, such as a coefficient of areal correspondence (CAC), is necessary to assess REAL at the model scale. Simply stated, CAC is the amount of overlap between two polygons (P. Muehrcke and J. O. Muehrcke 1992). CAC is used primarily when the data being tested is nominal, and the emphasis is on the correspondence between two data sets. CAC is calculated as:

$$\frac{\text{Overlap of regions } A \cup B}{\text{Area covered by regions } A \cap B}$$

No overlap results in a CAC of 0.0, and perfect correspondence results in a CAC of 1.0 (Figure 8). CAC quantifies how well boundaries between two datasets compare (Johnston et al. 2009), making it an ideal measure for testing the spatial accuracy of REAL against other models at the same scale.

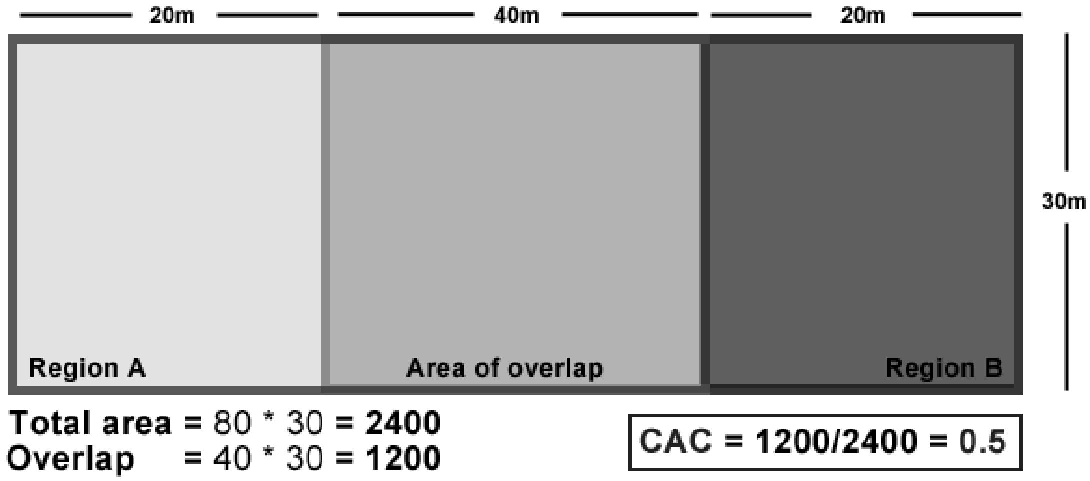


FIGURE 8
SAMPLE COEFFICIENT OF AREAL CORRESPONDENCE (CAC) CALCULATION

Landscape boundaries imply an abrupt change in the landscape that rarely occurs in nature due to the fuzzy nature of ecotones. Most research to this point has assumed landscape boundaries to be accurate and a subjective interpretation of polygon variance (Crist and Deitner 2007). This research, therefore, determines whether the accuracy of synthetic landscape boundaries can be assessed. To accomplish this goal, the accuracy of REAL's synthetic boundaries is assessed at two scales: the human scale and the model scale. Line-intercept transect sampling will be used to assess accuracy at the human scale. Common remote sensing techniques of supervised classification, unsupervised classification, and image segmentation will be used to create alternative boundary models at the model scale. CAC will then be used to assess the comparative overlap between the alternative boundaries and REAL's boundaries. A conservative strategy of 0.5 CAC (50%) will be considered successful agreement (Crist and Deitner 2007) of the land type boundary, given that one model is being compared against another. Determining CAC's statistical significance is inappropriate for this research because the data does not relate to the Central Limit Theorem.

Geomorphology, soils, and vegetation interrelate on the landscape; however, they rarely leave crisp boundaries under natural conditions. Therefore, synthetic boundaries are created to manage the land, creating a thematic expectation within the polygon. Traditional accuracy assessments test thematic accuracy and assume the boundary's location to be accurate enough (Crist and Deitner 2007). My research tests whether the accuracy of synthetic boundaries can be assessed, and if so, at what scale – human or model. At the human scale, surface boundaries are most appropriately tested with LIS and an automotive-assisted random walk. CAC is the most appropriate quantification to determine overlap between REAL and computer-assisted classifications at the model scale.

3. METHODS

3.1. Research Design

I assessed the accuracy of REAL's predictive synthetic boundaries at two scales: human and model, with model being the scale at which REAL was created. These two scales were chosen to determine the appropriate scale at which REAL could be assessed. Given the primary goal of REAL was to rapidly "triage" an arid environment using "low-tech" methods, the human scale assessment method was designed to keep with this spirit of the original work. I did not assign this restriction to the model scale assessment because computer accessibility and retail software was required.

3.2. Study Area

The same study area used in the development of a model, such as REAL, needs to be used when testing the accuracy of synthetic boundaries. This is because the model's boundaries are being examined. REAL was developed for use in semi/arid environments, and was calibrated in the northern Chihuahuan Desert ecoregion.

The northern Chihuahuan Desert (Figure 9) is sparsely vegetated and has elevations ranging from 600 m to 1675 m. In southern New Mexico, the Chihuahuan Desert has grass-shrub ecotones with very clumped and patchy vegetation (Chopping et al. 2004). Grasses include black grama (*Bouteloua eriopoda*), blue grama (*Bouteloua gracilis*), mesa dropseed (*Sporobolus flexuosus*), red threeawn (*Aristida purpurea*), tobosa (*Hilaria mutica*), and burro grass (*Scleropogon longisetus*). Shrubs include mesquite (various), creosote bush (*Larrea tridentata*), tarbush (*Flourensia cernua*), and alkali sacaton (*Sporobolus airoides*) (Chopping et al. 2004; DeMers et al. 2010; Dugas et al. 2011). The topography is predominantly Basin and Range.

FIGURE 9
RANCH AND THE CHIHUAHUAN DESERT

Chosen as the calibration site by DeMers *et al*. (2010), Armendaris Ranch (Ranch; Figure 9) is located in Sierra County near the town of Engle (33.2042 N, -106.9183 W), 120 kilometers north of Las Cruces, New Mexico. Situated within the Rio Grande rift zone, the Ranch lies in the basin between the Fra Cristobal Range to the west, and San Andres Range to the east (Figure 10). Precipitation varies greatly, both

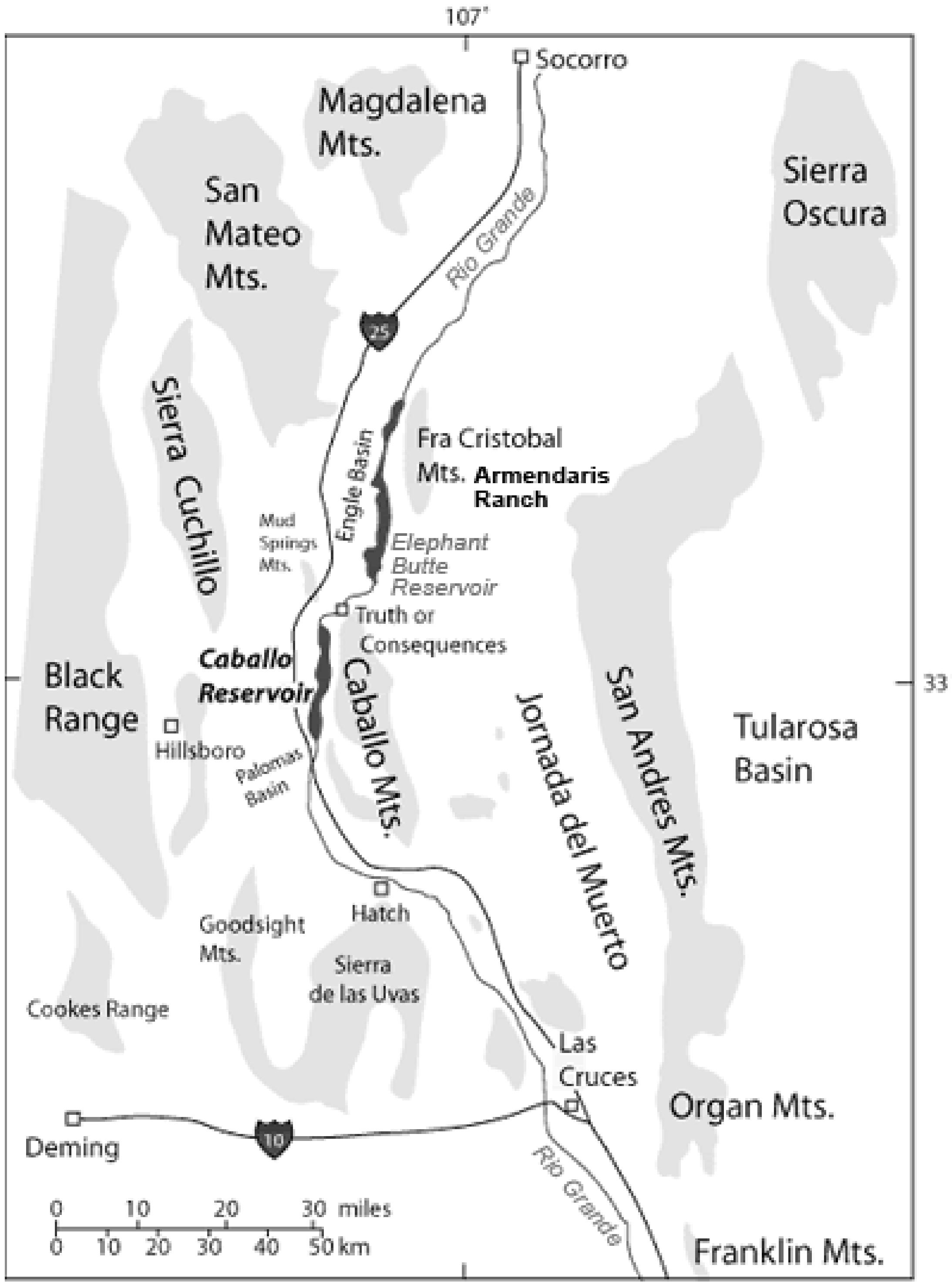


FIGURE 10
TOPOGRAPHIC PLACENAMES SURROUNDING ARMENDARIS RANCH
(Adapted from Kelley (2008))

between years and throughout the entire study area (Figure 11; Table 4). The Ranch's 355,600 acres are considered to have some of the last "pristine", minimally impacted desert grasslands in the northern Chihuahuan Desert (Bowser 2003). Privately owned for over 300 years, the Ranch was created via Spanish land grant in 1819, and patented in 1881. William Bell purchased the Ranch in 1895, followed by Victorio Land and Cattle Company in 1903, the Armendaris Corporation in 1968, and finally Ted Turner in 1994 (Bowser 2003). Though Ranch is used in commercial bison production (approximately 12,000 heads), the site has been used to reintroduce and provide habitat to endangered desert grassland species such as bison (*Bison bison*), aplomado falcons (*Falco femoralis septentrionalis*), willow flycatcher (*Empidonax traillii*), and bolson tortoises (*Gopherus flavomarginatus*) (Truett 2002; Bowser 2003; Edwards et al. 2009). An additional advantage of Ranch is that its geomorphology and vegetation are identical to the Jornada Long Term Experimental Research Station (Jornada), located near Las Cruces, New Mexico. Jornada is an anthropogenically-impacted area with over 100 years of ecological records and research, allowing for a comparison of the calibrated model (Ranch) against another control.

Given the vast size of Ranch, the study area was limited to Sierra County (Figure 11), and smaller sample areas (SAs) within the study area were selected for this analysis so that vegetation boundaries tested are at least 1,000 meters in length or the length of the boundary itself, whichever was greater. SAs were selected to maximize the number of unique boundaries on Ranch into the smallest number of

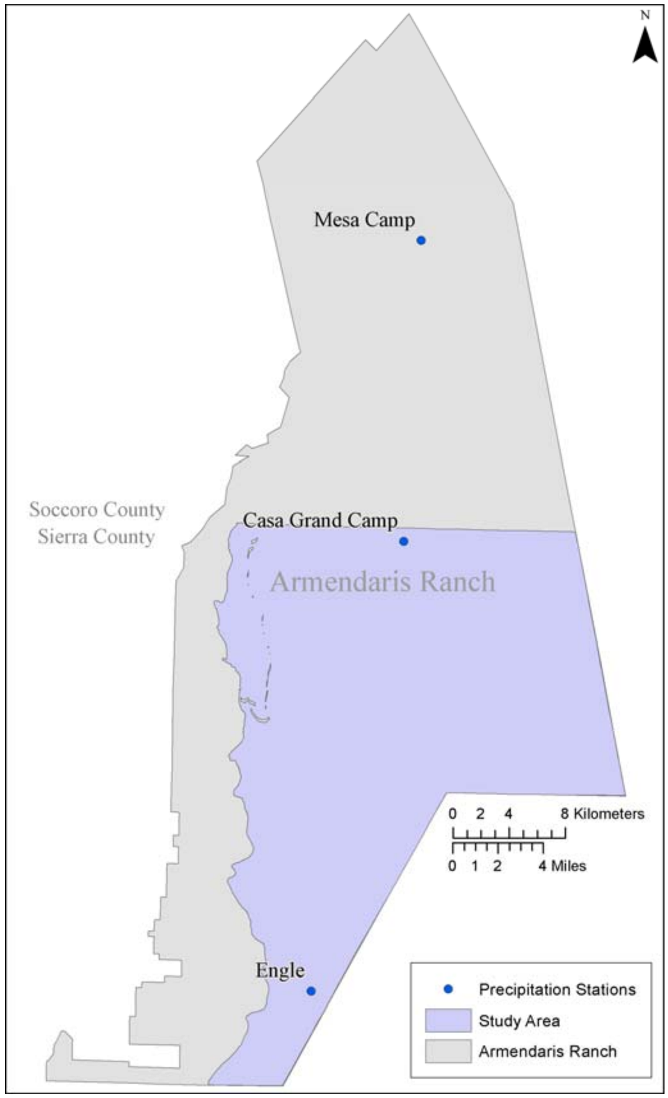


FIGURE 11
RANCH PRECIPITATION STATIONS

TABLE 4
VARIATION IN AVERAGE PRECIPITATION THROUGHOUT RANCH IN CENTIMETERS (INCHES)
(Waddell pers com; APPENDIX A)

	1998	2002	2003	2005	2007
Engle	27.97 (11.01)	18.19 (7.16)	10.24 (4.03)	24.66 (9.71)	31.19 (12.28)
Casa Grand	14.22 (5.60)	27.03 (10.64)	9.50 (3.74)	25.02 (9.85)	42.06 (16.56)
Mesa Camp	19.05 (7.50)	34.32 (13.51)	12.62 (4.97)	23.62 (9.30)	19.86 (7.82)

SAs (Figure 12). SAs were selected *a priori*, without any knowledge of roads, fence lines, other forms of anthropogenic impact, or accessibility.

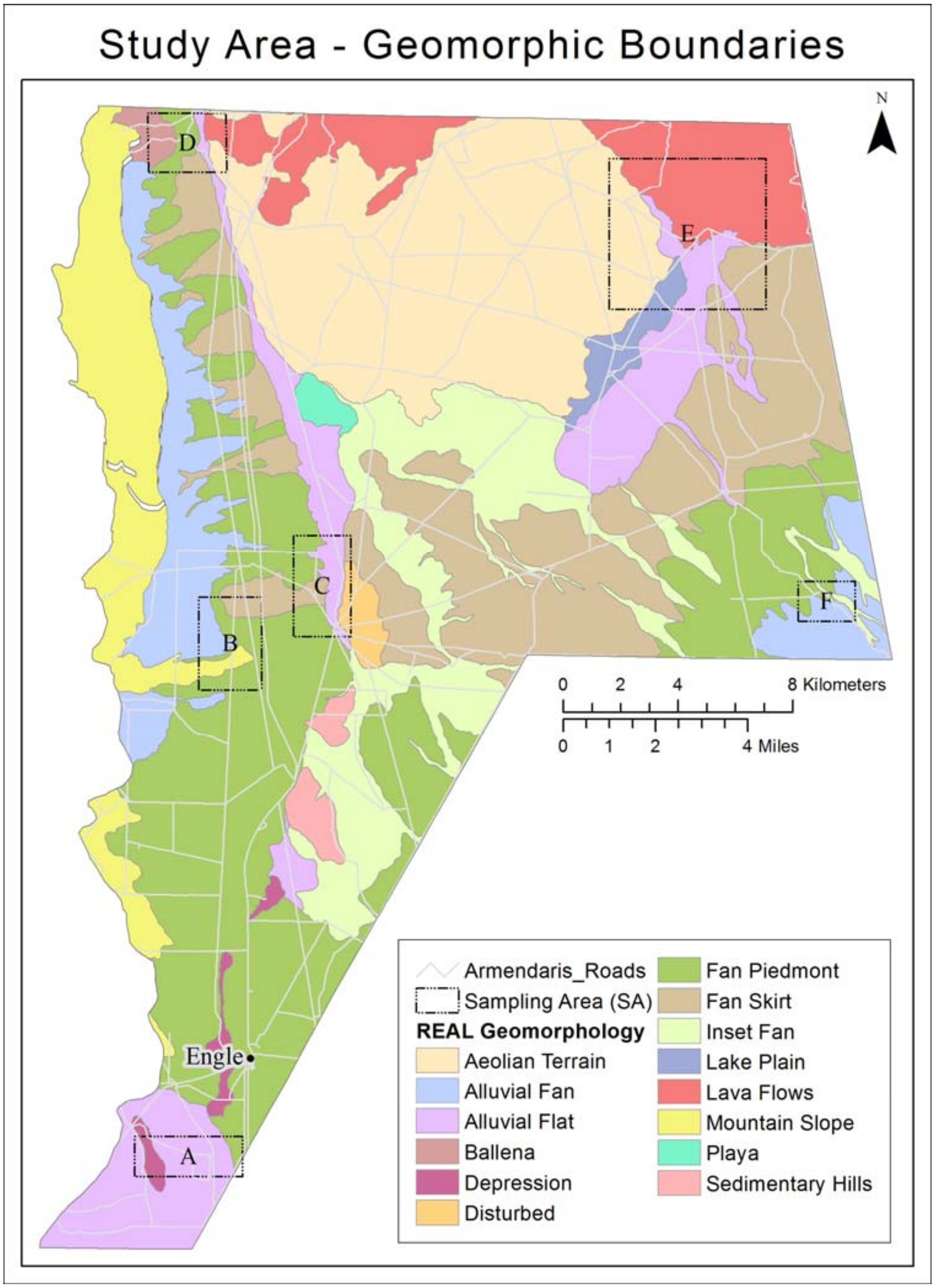


FIGURE 12
ORIGINAL STUDY AREA WITH PLANNED SAMPLING AREAS

3.3. Human Scale – Line-Intercept Transect Sampling

Line-intersect transect sampling (LIS) is used to quantify objects that intercept, or break the plane, of a line transect. Based on conclusions by Klimaszewski-Patterson (2009) and Küchler and Zonneveld (1988), I used line-intercept transect sampling as the human scale method for assessing the synthetic boundaries' accuracy. The following sampling rules, based on Klimaszewski-Patterson (2009), were used:

1. A minimum sampled boundary length of 450 m long, with transects placed perpendicular to the boundary (Figure 13);
2. Three transects per boundary type;
3. A 90 m buffer from the boundary of the study area and other vegetation types, to help eliminate edge issues (Figure 13); and
4. Transects spaced at least 90 m from each other

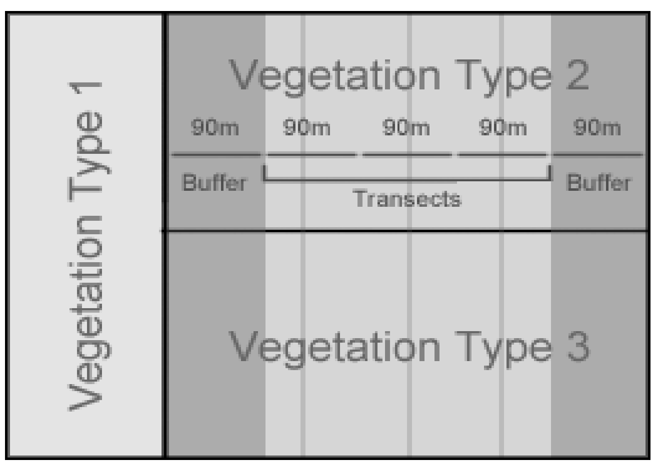


FIGURE 13
TRANSECT BUFFERS
(Klimaszewski-Patterson 2009)

For human-scale testing only, which is based on vegetation (Table 5), land was excluded from the original study area based on a high likelihood of human-induced impact. ArcGIS shapefiles indicating roads, streams, rail, sections, properly boundary, and vineyards (past and present) within the study area were acquired from Tom Waddell, Ranch Manager. Vineyards and military bases were excluded in entirety from the revised study area. Based on recommendations by renowned desert ecologist Dr. Walt Whitford (pers comm.), a one-mile exclusion buffer was placed around all known wells, tanks, mills, and camps/residences. As a result, two of the original SAs (B and F) were excluded from field sampling, and all but one SA (D) were affected with reduced area/boundary types (Figure 14).

I used a stratified random sampling with 90 meter LIS perpendicular to the tested boundary. To minimize edge effect, I buffered boundary edges 90 meters from the SA edge, and/or where a neighboring boundary ran near the LIS. Locating a 30 meters "pixel" in the field can be difficult; therefore, I also applied a 30 meters (one pixel) buffer on either side of the tested boundary for my positional inaccuracy. This was done to ensure that transect would cross the modeled boundary. As such, 90 meters became the standard distance from the SA/neighboring boundary edge, the distance between transects, and the length of a LIS. For each tested boundary, the initial LIS was determined by selecting a random number between 1-2. The number 1 represented north and west, and the number 2 represented south and east. The random

TABLE 5
REVISED HUMAN-SCALE STUDY AREA – VEGETATION TYPES
(Legend modified from Dugas et al. (2011))

V1. Black-grama (*Bouteloua eripoda*) grassland with scattered creosote (*Larrea tridenta*) and ocotillo (*Fourquiera slendens*) [Shrub-Mixed Grass Series]

V3. Creosote (*Larrea tridenta*) with scattered black grama (*Bouteloua eripoda*), three-awn (*Aristida* spp.), and bush muhly (*Muhlenbergia porteri*) [Grama-Threeawn Series]

V4. Black grama (*Bouteloua eripoda*) grassland, with blue grama (*Bouteloua gracilis*) and hairy grama (*Bouteloua hirsuta*) [Grama-Grass Series]

V5. Tobosa (*Hilaria mutica*) and burrograss (*Scleropogon brevifolius*), vinemesquite (*Panicum obtusum*) in clay-loam soils [Closed Basin-Playa-Alkali Sink Riparian]

V6. Burrograss (*Scleropogon brevifolius*) flats with Tobosa (*Hilaria mutica*) [Tobosa Series]

V7. Black grama (*Bouteloua eripoda*) grassland with soaptree yucca (*Yucca elata*). Localized mesquite due to disturbance [Grama Grass Series]

V8. Mixed black grama (*Bouteloua eripoda*) grassland with creosote (*Larrea tridenta*) and tarbush (*Flourensia cernua*) [Shrub-Mixed Grass Series]. Burrograss (*Scleropogon brevifolius*) flats on silty, clay-loam soils

V9. Grass cover mixture of alkali sacaton (*Sporobolis airoides*) and burrograss (*Scleropogon brevifolius*) [Sacaton Series/Closed Basin-Playa-Alkali Sink Riparian]

V10. Mosaic of mesquite (*Prosopsis glandulosa*), creosote (*Larrea tridentate*), and alkali sacaton (*Sporobolis airoides*) [Chihuahuan Desert Scrubland]

V11. Creosote (*Larrea tridentate*) with black grama (*Bouteloua eriopoda*) [Disturbed Chihuahuan Desert Scrubland]

V12. Occurances of tarbush (*Flourensia cernua*), alkali sacaton (*Sporobolis airoides*) [Disturbed Chihuahuan Desert Scrubland]

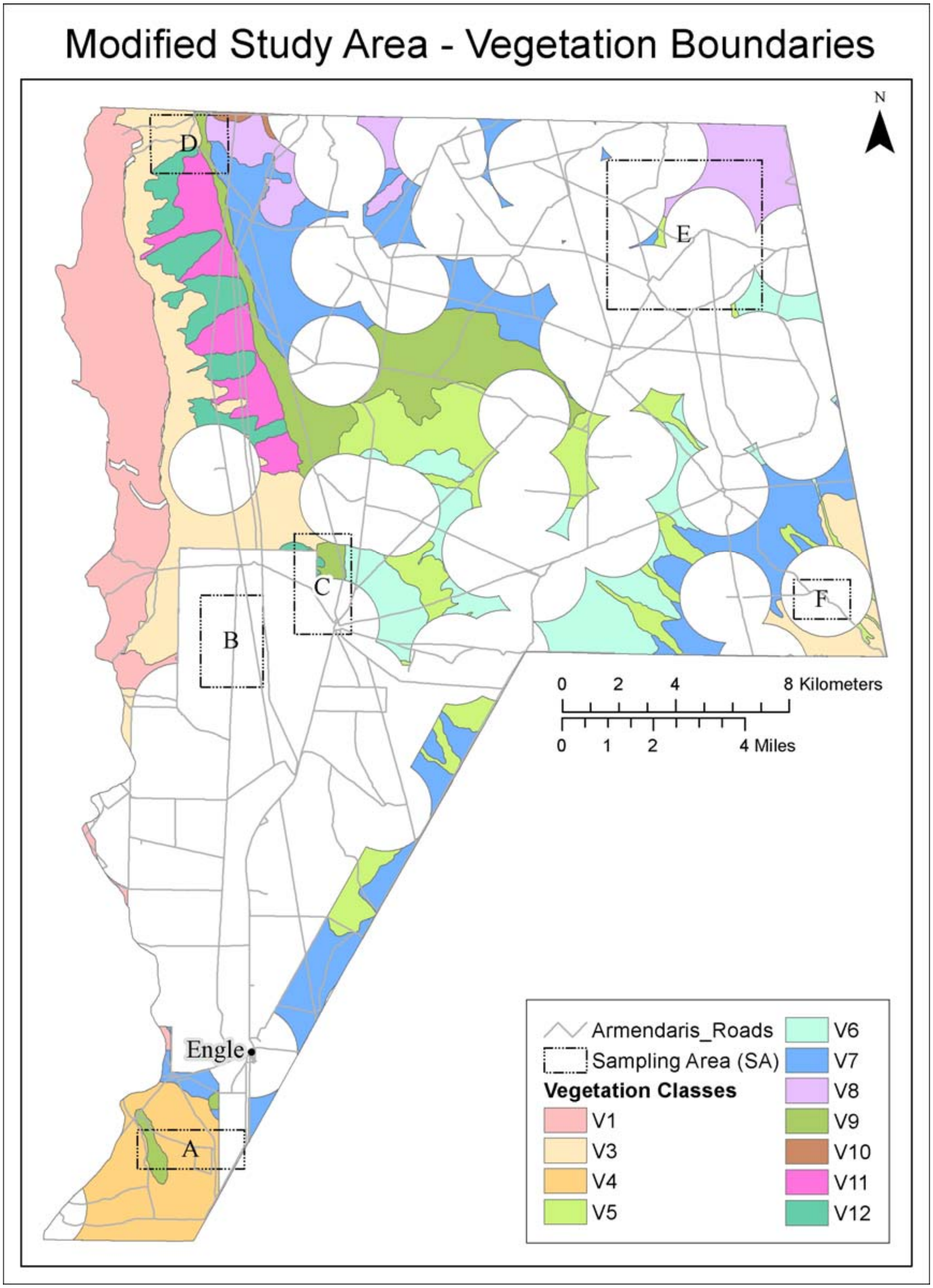


FIGURE 14
REVISED HUMAN-SCALE STUDY AREA

number determined the starting edge of the SA from which the following steps were performed:

1) Buffer in 90 meters from the SA or neighboring boundary edge;

2) Select a random number from 0-5;

3) Multiply the random number by 30 meters and move along the boundary by the additional amount;

4) Place the center of the LIS on the boundary and extend by 45 meters in either direction; and

5) Place all subsequent LIS in 90 meter increments along the tested boundary

I used a five centimeters gap-threshold when performing LIS. Readings were taken from the point where vegetation crossed (intercepted) the transect in a vertical plane. A minimum of three transects were performed for each boundary type.

Considering that homogeneity is not typical in the natural environment (Stohlgren 2007), dominant plant species coverage was used to establish the actual location of the tested boundary with a moving average (Figure 15). The boundary is considered accurate for that transect if it falls along the transect length (equivalent to three pixels on the base image). Agreement of 75% of the transects per boundary type indicates that the boundary placement is accurate, correlating to two of three transects per boundary (majority rule).

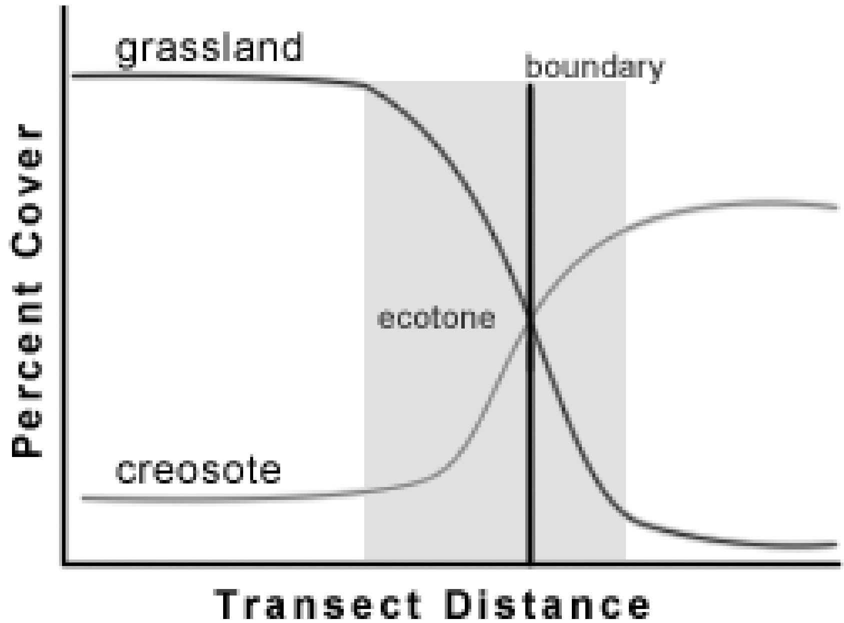


FIGURE 15
DETERMINING BOUNDARY LOCATION
(Klimaszewski-Patterson 2009)

Alternatively, as the goal of REAL was a "rapid" assessment, I took a GPS reading at the point where the visible vegetation boundary crossed the transect if the boundary between vegetation types was self-evident (a sharp ecotone). I performed an ocular estimate using a 20 centimeters quadrat (Küchler and Zonneveld 1988) along transect at 10 meters intervals to collect ancillary data for dominant vegetation types and coverage (eight total quadrats). These quadrat data could be used to confirm the vegetation types on either side of the boundary, as well as offer additional coverage data to aid in quantifying the descriptive nature of the vegetation classes.

I performed fieldwork from September to November 2009, and again in July 2010. The 2009 fieldwork was sporadic due to logistical issues, and was conducted primarily when the grasses were senesced but towards the end of their flowering period. I conducted fieldwork towards the end of the flowering season so that all grasses had flowered to make species identification easier. The 2010 fieldwork was conducted at the beginning of senescence due to logistics. Species identification was still possible, but the amount of cover each plant provided may have been less than expected later in the season.

3.4. Human Scale – Automotive Random Walk

In 2003, DeMers et al. assessed REAL with an automotive random walk (DeMers et al. 2010). The use of this random walk technique led to an automotive scale being incorporated into the original assessment. I thought it appropriate to recreate the original assessment method as another human scale method of accuracy assessment.

I performed automotive-based random walks in July and September 2010 on roads that appeared accessible to my field vehicle. I determined positioning using both a Trimble Juno SB and an HTC G1 Dream (G1) Android smartphone running OruxMaps. A discussion on G1's viability as a GPS device is available in Klimaszewski-Patterson (2010). I recorded approximate location on a paper map displaying REAL vegetation boundaries when I saw a vegetative transition occur. When crossing a REAL boundary, I visually determined whether a vegetative transition occurred or not, and often left the vehicle to confirm general vegetation types before and after the hypothetical REAL boundary.

3.5. Model Scale – Computer-Assisted Classifications

Different remote sensing classification schemes, and even variable settings within a scheme, can cause different polygon (and boundary) configurations. Because remote sensing classification schemes are in themselves constructs, REAL's geomorphic boundaries were compared to computer-assisted supervised and unsupervised classifications created in ERDAS IMAGINE 2010 (Erdas; Tables 6-7) (ERDAS 2010). All classification schemes used the same ETM+ imagery (Table 2) and were performed on a layerstack of bands 1-3 a mosaicked digital elevation model (DEM). These setting were used to most closely approximate methodology used by Dugas et al. (2011) when creating REAL boundaries. The unsupervised classification used 14 classes (the same number of geomorphic classes in REAL), 1,000 maximum iterations, and a convergence threshold of 0.999. The supervised classification used 15 training sites per land cover type (Buenemann pers comm.), except where the geomorphic type spanned multiple visible colors (*i.e*. Alluvial Flat). In this case, similar areas within the spectrum were classed separately and merged together post-classification to minimize pixel confusion.

TABLE 6
UNSUPERVISED CLASSIFICATION SETTINGS

Initialize From	Max. Iterations	Convergence Threshold	Skip Factors X/Y	Classify Zeros	Standard Deviation
Statistics	1,000	0.999	1/1	No	

TABLE 7
SUPERVISED CLASSIFICATION SETTINGS

# Training Sites	Fuzzy Classification	Non-Parametric Rule	Parametric Rule	Standard Deviation
15	No	None	Maximum Likelihood	

I performed post-processing on all classifications. Due to the “salt-and-pepper” effect that can occur in a classification, functions Clump and Eliminate were used in Erdas to create more homogeneous areas (polygons). I performed Clump with a neighborhood setting of 8. I subsequently performed Eliminate for clumped polygons smaller than 40 hectares (400,000 square meters). I chose 40 hectares as the minimum mapping unit (MMU) because (1) it corresponds most closely to the smallest dissolved polygon created by REAL, and (2) it is the MMU under GAP (Crist and Deitner 2007).

I calculated Coefficient of Areal Correspondence (CAC) for each geomorphic class (Appendix B) to compare the overlap of REAL and supervised classifications (Appendix C). Next, I converted the classified raster data to vector for analysis, as Raster Calculator does not perform actions for cells with “NoData”.

I did not perform accuracy assessments for any of the classifications, as REAL would have been used as the source for expert knowledge. Using REAL in this way would have resulted in circular logic, with REAL being both the truth set and the source being tested.

Third, at the model scale, training sites used for supervised classifications are a matter of personal assessment, and more art than science. A different technician could create a supervised classification with the same dataset and achieve a differing set of CAC results, while maintaining the same aspatial overlap in area.

4. RESULTS

4.1. Human Scale

Human scale testing using LIS was performed before exclusion zones were created (Figure 14). I also performed LIS before realizing that the originally digitized boundaries were misregistered, and approximately 200 meters too far west. Therefore, most LIS fieldwork is invalid for the purposes of this research because (1) the examined boundaries fall within excluded areas, and (2) examined boundary locations are off by 200 meters. The only field data remaining where exclusion zones are not a factor is for SA D (Table 8), as I was unable to gain access to SA A's V4-V9 boundary. Within SA D, boundaries V11-V12 and V12-V3 may not have been significantly impacted by the eastward correction of boundary locations, as the boundaries themselves were mostly east-west. However, while conducting LIS, I misunderstood the definition of vegetation class V12 to mean that its polygon should be dominated by tarbush. I later learned through consultation with Dr. Dugas (pers comm.) that V12's definition meant that tarbush could be present, but not necessarily the dominant type (creosote is dominant type in SA D). Because there was no tarbush along the proposed transect's path, V11-12 and V12-3 were recorded as incorrect boundaries and no LIS was performed.

Automotive-based random walk scale testing was performed before exclusion zones were created, but after correction of misregistered boundaries. Outside of exclusion zones, vegetation types and REAL boundaries matched well with REAL.

Inside of exclusion zones, vegetation types within polygons and bordering REAL boundaries were mostly incorrect (Figure 16).

TABLE 8
LINE-INTERCEPT TRANSECT SAMPLING (LIS) RESULTS

Sample Area	Boundary 1	Boundary 2	Exists?	Comments
D	V9	V11	N/A	Too close to road
D	V11	V12	No	No tarbush along transect
D	V12	V3	No	Creosote to creosote transition
D	V3	V9	N/A	Too close to road
D	V9	V8	N/A	Mislocated
D	V8	V7	N/A	Mislocated
D	V7	V9	N/A	Too close to road

4.2. Model Scale

The unsupervised classification proved unusable for analysis due to uncertainty in class allocation. I was unable to perform either a CAC or an accuracy assessment for the unsupervised classifications because I could not confidently determine which unsupervised class corresponded to which REAL geomorphic class (Figure 16). Based on polygon placement, the unsupervised classification seems to have given greater weight to the topographic layers (DEM, slope, and aspect) than to the spectral signature (Figure 17). As a result, I performed an unsupervised classification using only a layerstack of ETM+ bands 1, 2, and 3 to remove the perceived topographic bias and possibly improve the classification results (Figure 18). Uncertainty in class allocation persists, and the two unsupervised classifications demonstrate the variability in polygon placement based on inputs.

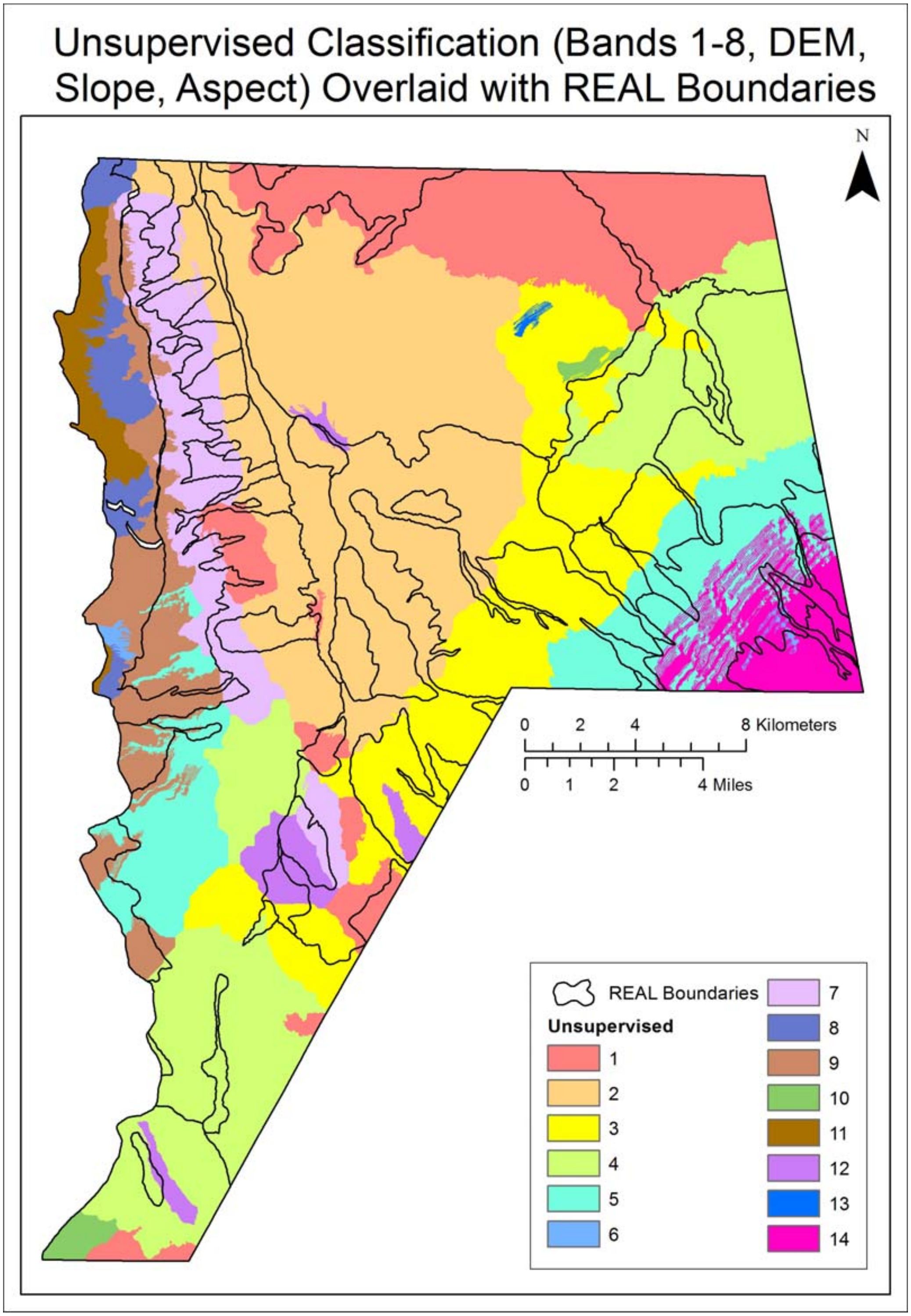


FIGURE 16
UNSUPERVISED CLASSIFICATION OVERLAID WITH REAL BOUNDARIES FOR VISUAL COMPARISON

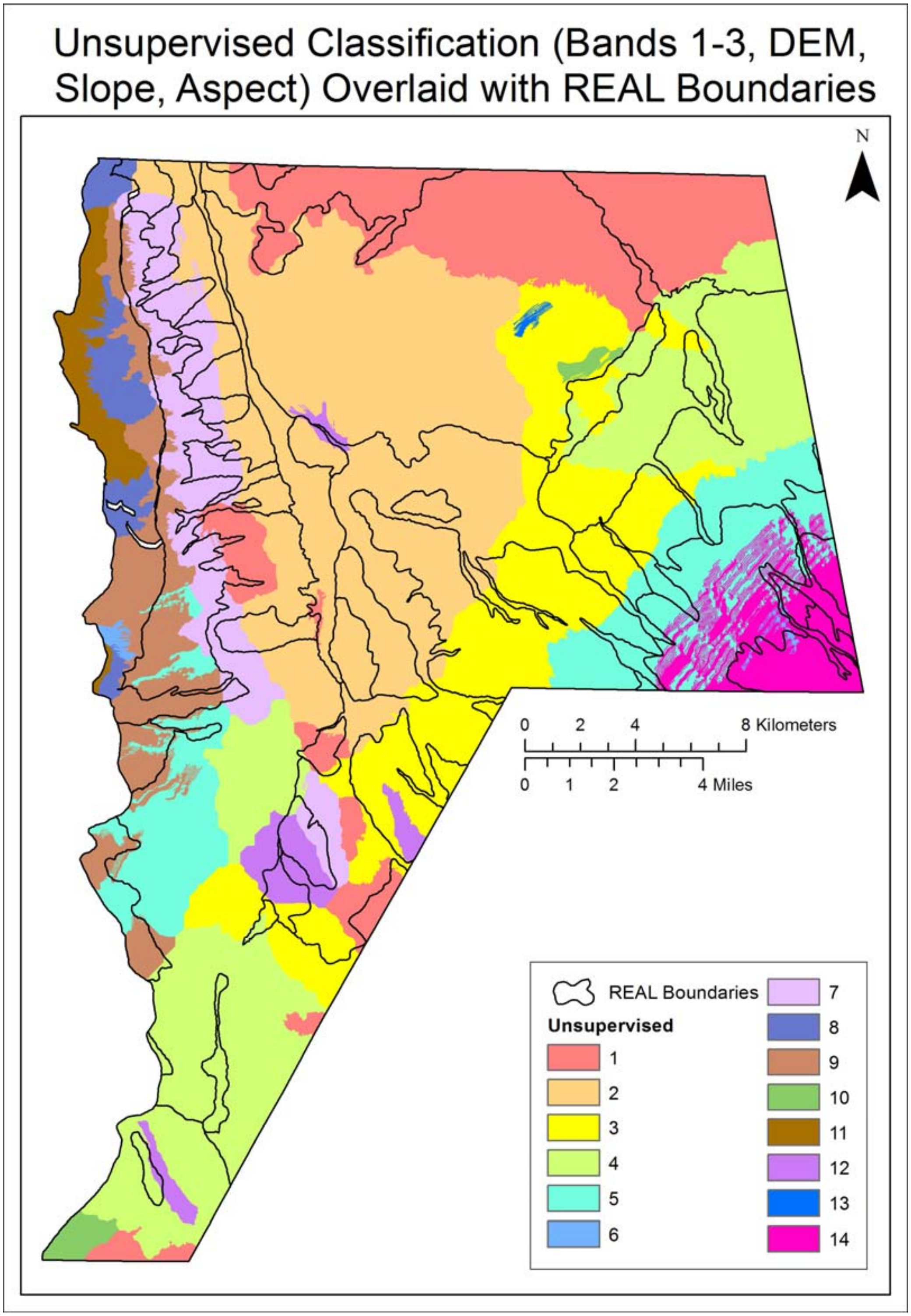


FIGURE 17
UNSUPERVISED CLASSIFICATION OVERLAID WITH 60M CONTOUR LINES (TOPOGRAPHY)

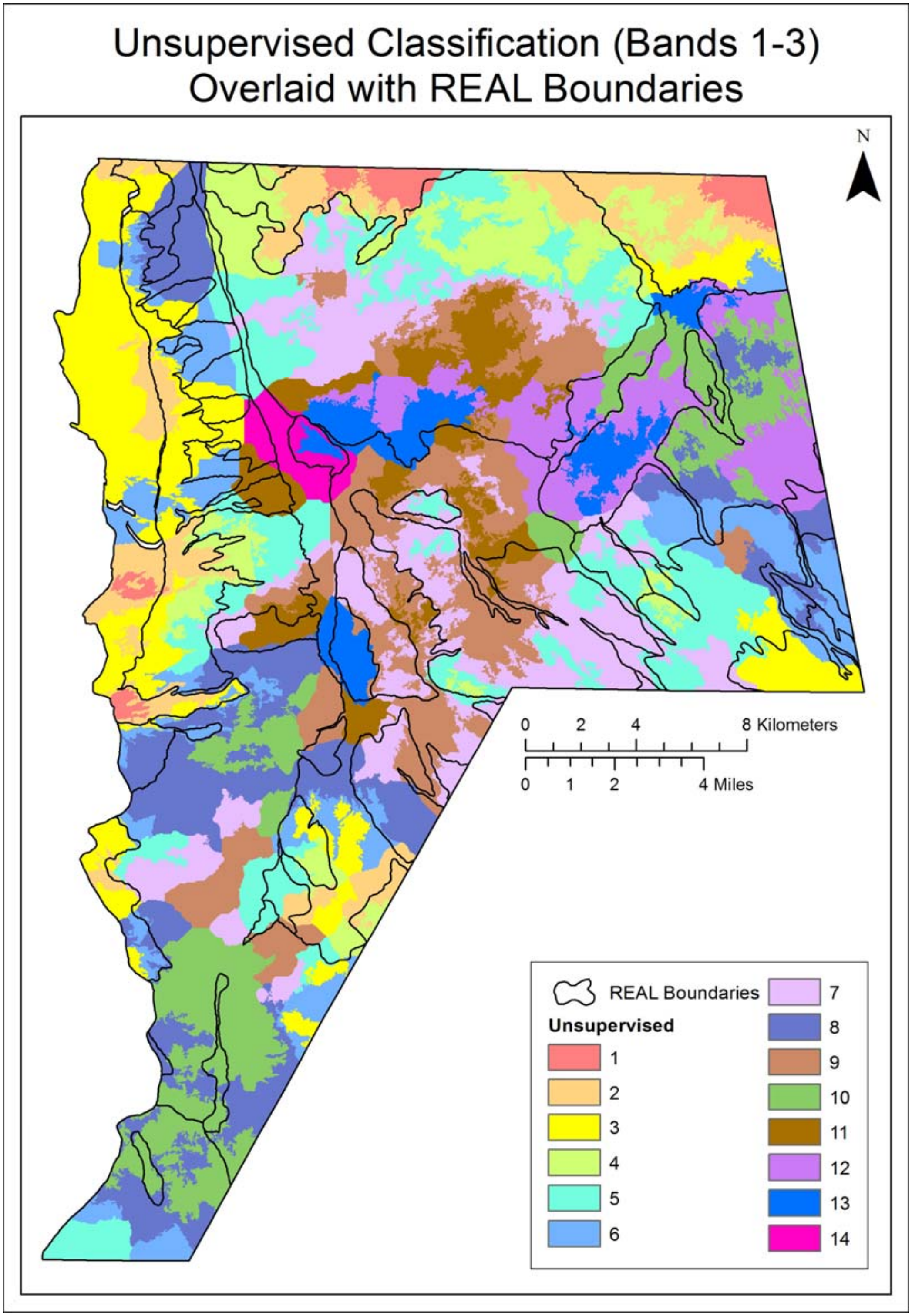


FIGURE 18
UNSUPERVISED CLASSIFICATION USING ONLY LANDSAT 7 ETM+ BANDS 3, 2, AND 1

The supervised classification had mixed results when compared to REAL (Figure 19). Spatial correspondence (Figure 20) meeting the established 50% threshold (0.5 CAC) occurred for only three of the 14 the geomorphic classes: lava flows (0.60 CAC), mountain slopes (0.64 CAC), and playas (0.74 CAC). Geomorphic classes with the least overlap (<0.2 CAC) include: ballena, depression, disturbed, lake plain, and sedimentary hills (Table 9). These same classes were considerably overestimated by the supervised classification (10,000+ sq km). Inset Fans had no spatial correspondence between REAL and the supervised classification. Aspatially, geomorphic classes with area values overlapping by at least 50% were: aeolian terrain (97.4%), alluvial fan (88.0%), alluvial flat (56.2%), fan skirt (75.9%), lava flows (91.9%), mountain slopes (85.5%), and playa (97.8%; Table 9). Though half the geomorphic classes had similar aspatial values for area, the results of CAC are more valid because CAC takes the spatial position of the geomorphic classes into account.

Overlaying both computer-assisted classifications (supervised and unsupervised) showed no visual correlation (Figure 21). I did this to determine if the two computer-assisted models shared greater similarities with each other than they did with REAL. Based on a visual assessment, there does not appear to be any greater similarity between the supervised and unsupervised classifications than there is with REAL and the unsupervised classifications.

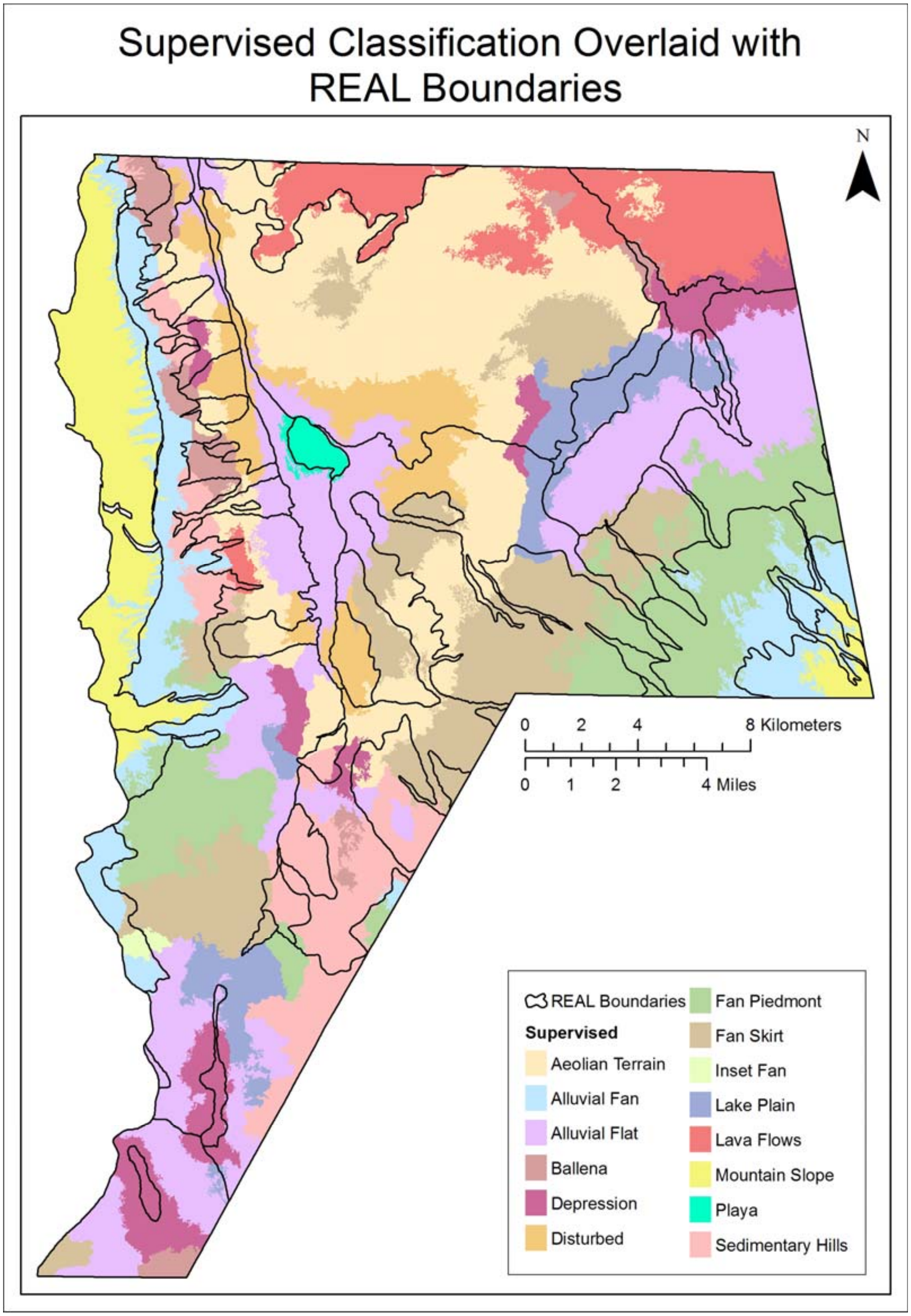


FIGURE 19
SUPERVISED CLASSIFICATION OVERLAID WITH REAL BOUNDARIES FOR COMPARISON

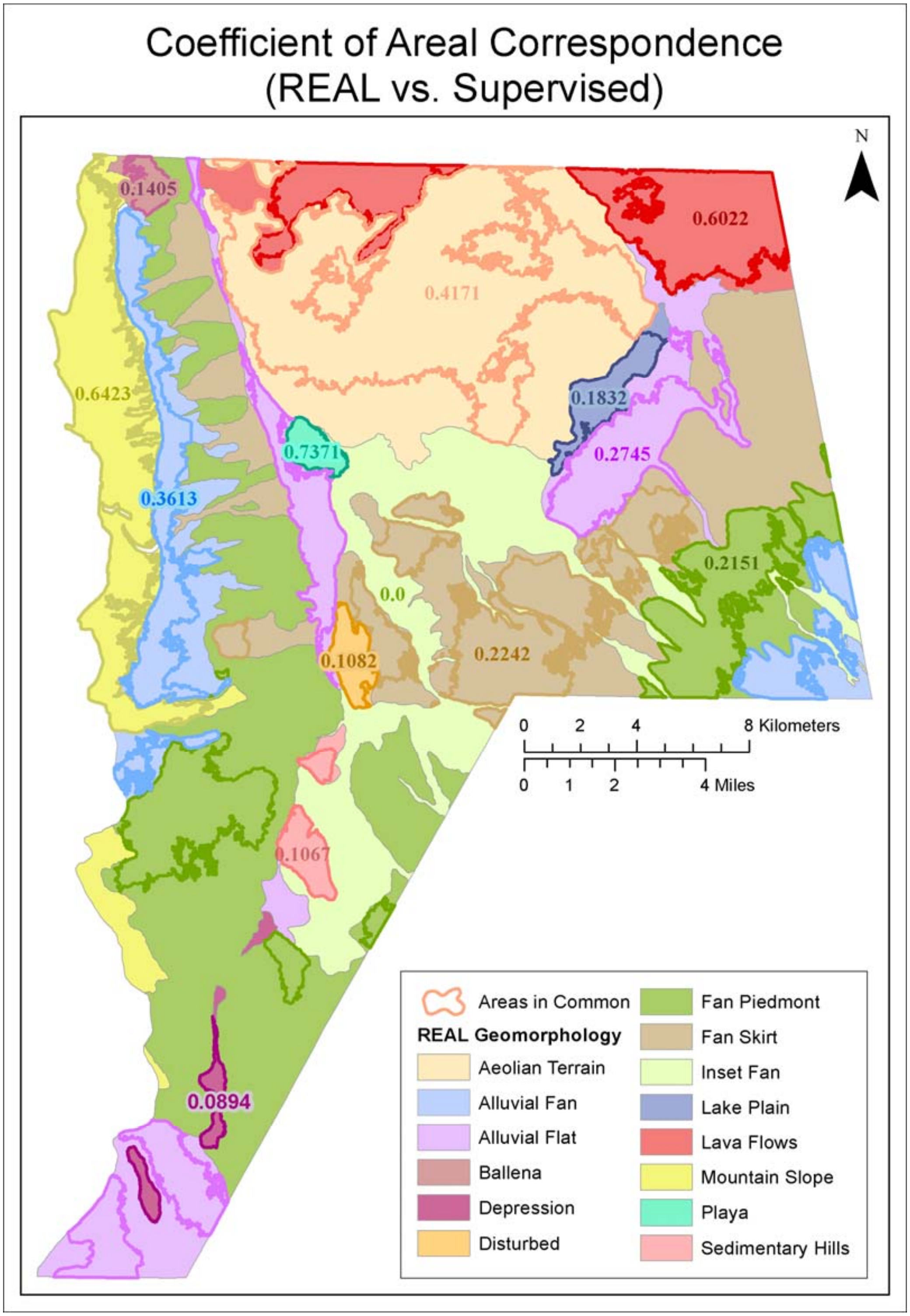


FIGURE 20
COEFFICIENT OF AREAL CORRESPONDENCE (CAC) FOR REAL AND SUPERVISED CLASSIFICATION, BY GEOMORPHIC CLASS

TABLE 9
COEFFICIENT OF AREAL CORRESPONDENCE (CAC) AND AREA BETWEEN REAL AND SUPERVISED CLASSIFICATION, BY GEOMORPHIC CLASS

Geomorphic Class	CAC	REAL Area (sq km)	Supervised Area (sq km)	Difference in Area (sq km)	Similar Area
Aeolian Terrain	0.4171	116,211.948	119,304.236	-3092.288	97.4%
Alluvial Fan	0.3613	44,545.380	50,622.619	-6,077.239	88.0%
Alluvial Flat	0.2745	60,265.067	107,291.181	-47,029.144	56.2%
Ballena	0.1405	2,736.114	14,253.641	-11,517.527	19.2%
Depression	0.0894	3,976.297	31,616.962	-27,640.665	12.6%
Disturbed	0.1082	3,967.259	33,266.423	-29,299.164	11.9%
Fan Piedmont	0.2151	158,072.970	68,185.155	89,887.815	43.1%
Fan Skirt	0.2242	110,128.323	83,625.737	26,502.586	75.9%
Inset Fan	0.0000	656.525	131.096	525.429	20.0%
Lake Plain	0.1832	6,388.781	28,942.012	-22,553.231	22.1%
Lava Flows	0.6022	39,880.338	43,392.771	-3,512.433	91.9%
Mountain Slope	0.6423	48,934.145	41,834.535	7,099.610	85.5%
Playa	0.7371	2,664.003	2,605.118	58.885	97.8%
Sedimentary Hills	0.1067	5,572.843	41,977.494	-36,404.651	13.3%

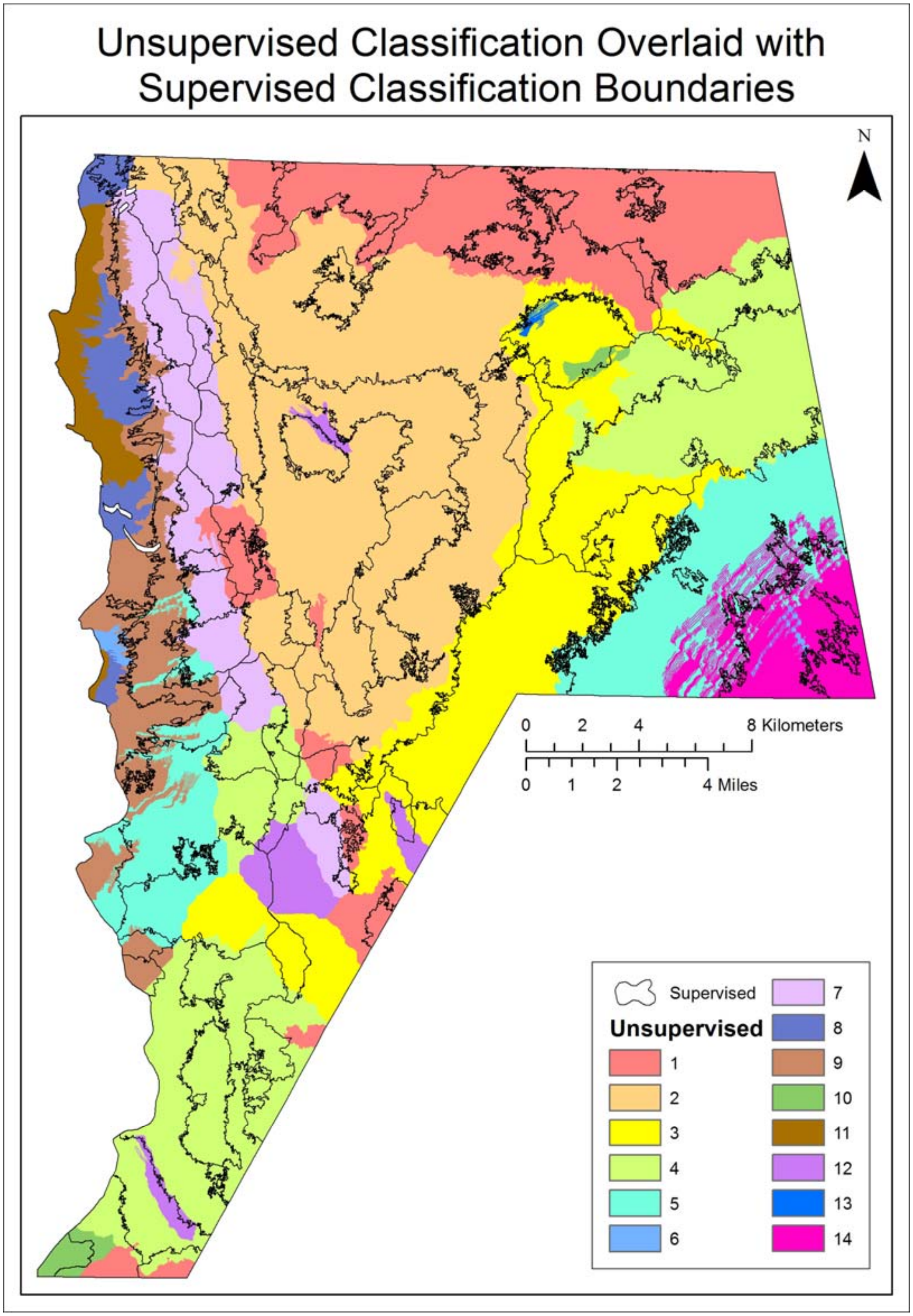


FIGURE 21
UNSUPERVISED CLASSIFICATION OVERLAID WITH SUPERVISED BOUNDARIES FOR COMPARISON

5. SUMMARY

Classifying land to establish management boundaries predates Carl Sauer (1921); however, Sauer clearly established two questions that classifications seek to answer: (1) how is the land used, and (2) what is the land's potential. This research aims to see if it is possible to not only assess boundary accuracy, but to assess that accuracy for a model that maps a land's potential. All while using existing land conditions for the assessment under the assumption that minimally impacted land will demonstrate the land's potential vegetation based on geomorphology. I tested REAL's boundaries at two scales: the human scale, and the model scale.

I used LIS and automotive-based random walk to test boundaries at the human scale. Though fieldwork was invalidated for most SAs, I could clearly see that the LIS method I had established would not work well in capturing ecotones. If a 90 meters transect could capture an ecotone, then I could just as well approximate the transition at an accuracy of 30 meters (the size of a Landsat 7 ETM+ pixel). I do not think any intercept-transect sampling method would work well because specific vegetation types, such as *yucca elata*, would have to fall on the transect. Instead, line transects, similar to those performed in wildlife surveys, may be more appropriate. However, labor and time costs remain factors given the quantity and length of line transects that would need to be performed. The automotive random walk was far more successful at the human scale. Though limited to roadways, the compression of space in time allowed me to notice boundaries that were not self-evident when walking through the same area. This is likely because small patches appear larger the closer you are to them, both in space and time. The overlapping nature of ecotones is less evident at an increased speed, allowing for the boundary to be perceived. Granted, the random walk is pre-defined in a certain way, given road placement, but I could also look several hundred feet in to the tested polygon to determine whether the vegetative boundary appeared to be correct or not. Of all the methods tested, automotive random walk seems the most promising, both in terms of assessing boundaries closer to the scale they were created in, and in maintaining the "rapid" in REAL.

I used computer-assisted supervised and unsupervised classifications to test boundaries at the model scale. Unsupervised classifications were unsuitable because I could not decipher class correspondence between the classification and REAL. In addition, the original unsupervised classification (bands 1-8, DEM, slope, and aspect) appeared to give greater weight to topography than to spectral signatures (Figure 17). While topography was a factor in the creation of REAL boundaries, it was used to determine breaks in the landscape. Because REAL was created based on an image using bands 3, 2, and 1, I decided to perform a simplified unsupervised classification. The resulting unsupervised classes were even more chaotic, and showed no resemblance either to REAL or the supervised classification (Figure 18). Given the class correspondence issue, and the fact that included bands in the analysis will result in drastically different classifications, I highly recommend that unsupervised classification not be used for boundary analysis in the future.

The supervised classification demonstrated reasonable correspondence with REAL where geomorphic features exhibited strong spectral signatures, such as lava flows, mountain slopes, and playa. The result is to be expected, as even an untrained geomorphic eye can readily distinguish the three landforms in the satellite image. Unfortunately, the supervised classification I ran was limited to spectral signatures, and could not take texture (*i.e.* ballenas) or topography into consideration. As such, the CAC was below 0.50 for all other landforms. This limitation may have also been a major contributing factor to inset fans having a CAC of 0.0 (no overlap). In REAL inset fans were determined based on slope and topography, two factors which were not used in the supervised classification.

Though CAC is, for the purposes of this research, the best method for comparing classifications with REAL, there is a limitation. REAL is a smoothed vector model. Classifications are raster, and by nature, pixelated. Even when classifications are converted from raster to vector, the original "jaggedness" of the classification remains. Therefore, a CAC of 1.0, indicating perfect correspondence, is impossible (Figure 22). This limitation is best seen in the playa landform (Figure 23). Even with considerable visual correspondence, the CAC indicates only 74% overlap between the two models. Unfortunately, determining a maximum CAC other than 1.0 is not reasonable, because the maximum value would depend on the area being compared.

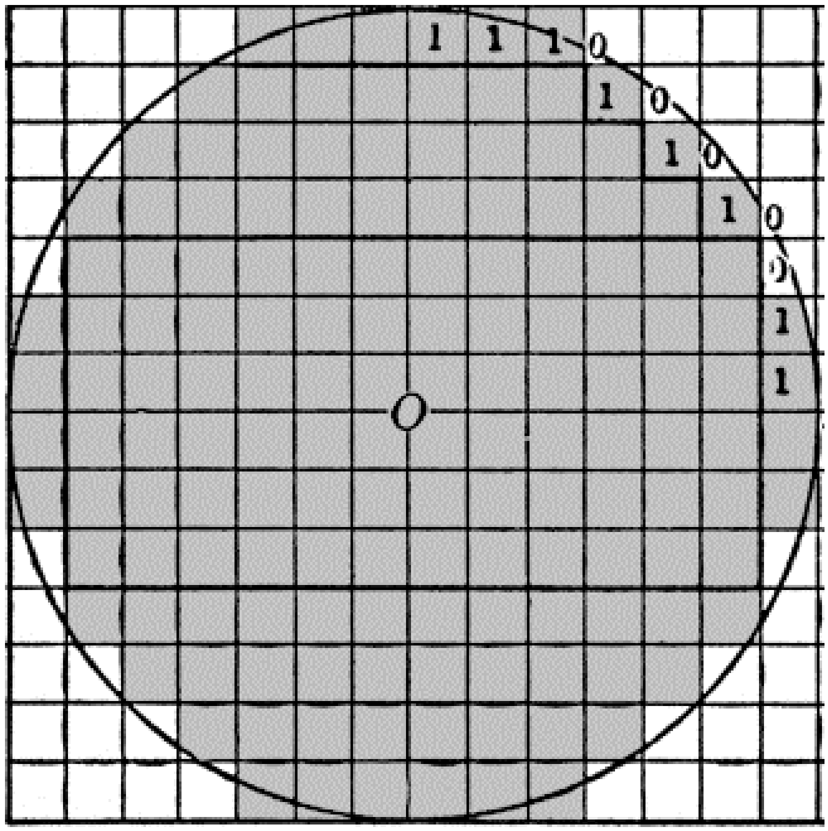


FIGURE 22
VISUALIZATION IN OVERLAPPING VECTOR AND
RASTER DATA FOR CAC

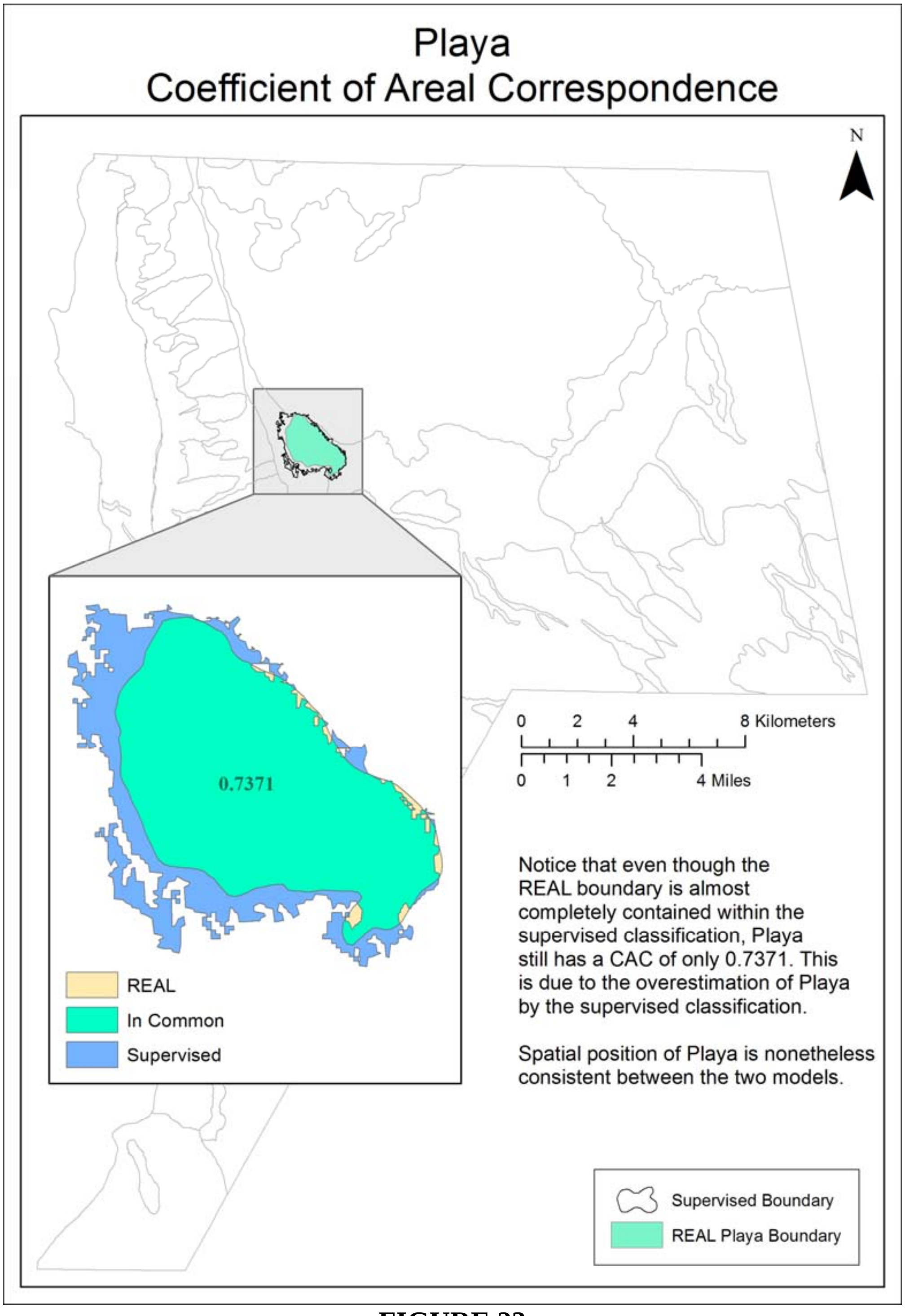


FIGURE 23
PLAYA EXAMPLE OF COEFFICIENT OF AREAL CORRESPONDENCE (CAC) LIMITATION

6. CONCLUSIONS

Assessments need to be performed at the scale relative to the patterns being observed. Assessments taken at a finer scale may demonstrate unrelated trends to those observed at a broader scale, as was the case with LIS at the human scale. LIS can capture specific information about the landscape, but cannot be reasonably performed over the entire width of an ecotone due to the high cost of time and labor. However, expanding the human scale to include an automotive scale may allow researchers to rapidly, and with reasonable confidence, assess a boundary's location at a scale closer to landscape patterns and processes. This is possible because space becomes compressed in the same amount of time, and the human eye more readily skips over minor differences in the landscape. The landscape at an automotive scale can be assessed with a broad stroke, allowing the researcher to see the forest instead of the trees. Though pinpoint accuracy should not be expected with an automotive random walk, such an assessment can provide researchers with reasonable confidence to the model's accuracy.

All the approaches used to assess REAL's boundary accuracy at the model scale are themselves models, leading to mixed results. Comparing the classified models to REAL is similar to asking different impressionist artists to paint the same subject – though there are similarities, each model is a unique result of the attributes used to assess the subject. Unsupervised classifications are unviable because I cannot confidently determine class correspondence with REAL. In addition, class boundaries can change based on the inputs used (area of interest, spectral bands, ancillary data, etc.) when creating the unsupervised classification. Supervised classifications eliminate the class correspondence issue, but do not take texture, elevation, or ancillary data into account – pixels are simply assessed by their spectral signature. Geomorphic classes with highly distinct spectral signatures, such as playas, mountain slopes, and lava flows, can be extracted reasonably with a supervised classification; however geomorphic classes with less distinct spectral signatures, or where texture may play a part in their delineation, are poorly extracted. Therefore, the use of supervised classifications is restricted as a comparative accuracy assessing method.

Overall, this research determined that though some synthetic boundaries can be partially assessed given caveats, the exact position of any boundary can not be specifically determined. At the human scale, an automotive random walk allows boundaries to be most readily assessed, but not located precisely. At the model scale, supervised classifications can extract highly distinct spectral signatures, but boundary placement can differ depending on training sites used in the classification. Expecting a quantifiable accuracy assessment on precise boundary placement of a synthetic model, such as REAL, is largely unreasonable. At best, an agreement on the general location of polygons can be reached, especially when using a method such as an automotive random walk.

7. DISCUSSION

In conducting this research, I made two important assumptions: that the study area exhibits minimal anthropogenic impact, and that vegetation within polygons is correctly labeled. I use these assumptions so that I am examining purely whether synthetic categorical boundaries can be assessed. While the study area has been privately owned for nearly 300 years, there is some impact from cattle grazing and human use. While I made efforts to remove from the original study area portions of the Ranch known to have some kind of impact, there may be some unknown impacted areas that remained in the study area (*i.e.*: faunal grazing patterns impacting perceived dominant vegetation cover). Additionally, the buffers applied to areas of impact may not have been broad enough (*ex*: 1.6 kilometers around sources of water, 90 meters from man-made structures such as roads and fences). I assumed vegetation within the boundaries to be accurate based on informal random walk conducted in 2003 and 2010. These assumptions were made so that I could examine purely whether the accuracy of categorical boundaries can be determined.

I encountered several issues when conducting this research, especially at the human scale. First, I used misregistered boundary data when performing LIS. Former students created the boundaries using a digitizing tablet around the year 2001. I assumed the data to be valid, and never verified the data against the satellite imagery. I did not realize the misregistration until I zoomed in on the map when visualizing my imported transects. At that point I could see the misregistration because even my untrained eye could detect certain geomorphic boundaries on the satellite image (notably the lava flows and alluvial fans). Upon consultation with Drs. DeMers and Dugas, I rubber sheeted the original REAL boundaries approximately 200 meters east. The boundaries then lined up well with the satellite image, though I could see some minor areas where I would have digitized the boundary differently. I think that if REAL were updated and digitized directly on the satellite image today, some boundaries may shift slightly, but not enough to impact general land use.

Second, I had a misconception of the term “pristine”. I thought pristine meant wholly and completely untouched, in a perfect, non-impacted state. Instead, “pristine” should be interpreted to mean that minimally impacted areas exist and are as close to natural as is possible in the modern day. Because of my semantic misunderstanding, it never occurred to me to gather infrastructure information (roads, fencelines, vineyards, etc.) for the study area prior to determining SAs. Nor did I realize that prior cattle use in the study area would have impacted the land so greatly in such a short time. It wasn’t until late 2010, when I spoke with Dr. Walter H. Whitford, that I learned of the cattle impact within the study area, and the need to create exclusion zones around known tanks and wells. If I had gathered infrastructure and impact data before creating the SAs, I would have placed SAs outside of exclusion zones to and made sure that testable boundaries met my LIS rules.

Third, I was forced by circumstance to conduct fieldwork over a protracted period of time; therefore, seasonality may have had an impact on quantifying dominant plant species by coverage. After fieldwork was performed in 2009 and 2010, I concluded that 90 meters transects rarely captures the entire width of an ecotone, especially with the descriptive categorical boundaries involved. Unfortunately, capturing an ecotone several kilometers long would be time and cost prohibitive, especially when testing a model based on a rapid assessment.

Last, I misunderstood REAL's descriptive vegetation categories, especially V12 (tarbush and alkali sacaton). I thought each category meant that the vegetation listed would be the dominant vegetation in the polygon. Instead, some categories, such as V12, indicate that the vegetation is present, but not necessarily the dominant type. REAL's vegetation categories should be described more clearly to indicate whether the class indicates that the vegetation can appear, versus being dominant. Doing so would eliminate this type of confusion.

When performing human scale testing in the future, I would recommend verifying all data prior to use, speaking with persons intimately familiar with the study area to gather land use history and infrastructure data, and clearly understanding definitions being used to describe categorical data. Doing so will eliminate, or at least minimize, main issues I encountered with human scale research.

For computer-assisted classifications, results may vary based on inputs used, study boundaries, training sites, bands used, auxiliary data, and the skill of the technician performing the classification. The key is computer-*assisted*, not computer-independent. While the computer is assisting in the classification, the resulting classification ultimately depends on the skill and knowledge of the technician. I performed unsupervised and supervised classifications to the best of my ability. Unsupervised classifications carry an inherent uncertainty because the technician has no control over how classes are created. Therefore, some ambiguity in determining correspondence between unsupervised classes and known classes is expected. Additionally, unsupervised classification boundaries can change based on using software other than Erdas. However, results can vary (Figure 24), even with supervised classifications. Ultimately, model scale testing uses one construct to test another. As such, expert knowledge is required to determine which model is more accurate than the other. REAL is based on expert knowledge.

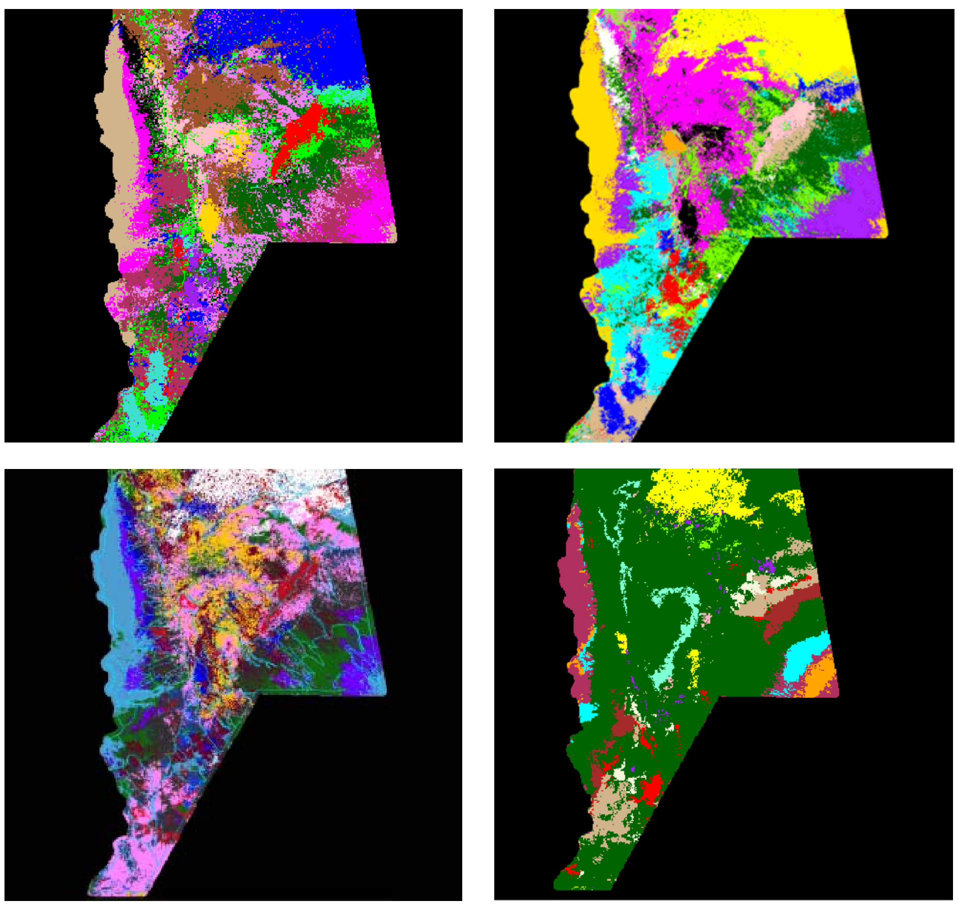


FIGURE 24
EXAMPLES OF A SUPERVISED CLASSIFICATION BY DIFFERENT TECHNICIANS

I looked at NRCS soil maps as a comparative method; however, a establishing a relationship between NRCS and REAL was not reasonable for a variety of reasons. First, the geomorphic definitions between the two models did not appear to match. The fieldwork for the Sierra County soil map was completed in 1980, with soil descriptions approved in 1981 (Neher 1984). 1981 is the same year Peterson's *Landforms of the Basin and Range Province Defined for Soil Survey* was published, the foundation from which REAL geomorphic units were defined. Therefore, the NRCS soil map could not have used Peterson's geomorphic definitions. The disparity in geomorphic definitions could explain items such as why NRCS soil maps placed alluvial fans at the very top of mountain slopes, or why piedmont and fan piedmont definitions varied greatly between NRCS and REAL. Attempting to crosswalk the two models proved ineffective, as the amount of categorical joining left only five categories for analysis: depression, lava flow, mountains, piedmont, and playa/basin (Figure 25). NRCS's low hills did not fall into any appropriate REAL geomorphic unit. Second, NRCS soil maps are created from a three-dimensional view of the soil through use of soil profiles. REAL was created purely from what is visible on the surface (*i.e.*: a two-dimensional satellite image), without knowledge of underlying soil structure. Third, NRCS takes the approach of studying the soil first, considering soil-vegetation relationships to establish boundaries (Neher 1984), and assigning soil units to a geomorphic unit. REAL looks at geomorphic units and then assigns a vegetation relationship to the unit. In short, the two models approach mapping from two different methodological directions.

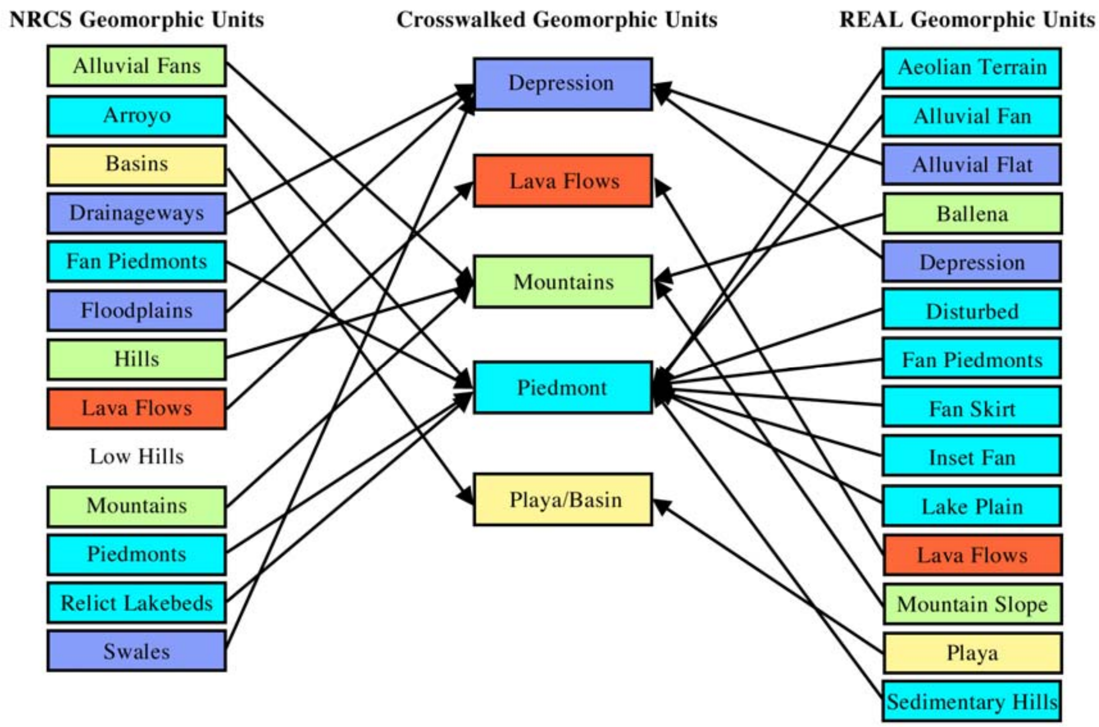


FIGURE 25
CROSSWALK OF NRCS SOIL MAP AND REAL

Another method that could be used to examine correspondence with REAL is image segmentation. Image segmentation takes the approach of dividing images based on shape, similar to the way the human eye perceives. Pixels are divided into segments, also known as superpixels, based on context. Segments are typically determined based on edge detection, intensity, color, and texture. Image segmentation software, such as Definiens eCognition (Trimble 2010), is typically expensive and difficult to learn. Given the power of segments, several geographic programs are attempting to incorporate the technology, with varying degrees of success. Thus far, eCognition is recognized as a leader in image segmentation software. In eCognition, object-based analysis is possible through defined rule sets. Rule sets may consist of a segmentation algorithm, classification algorithm, and layer operation (Trimble 2010). Segmentation algorithms include multiresolution and quadtree segmentations. With the multiresolution algorithm, objects are based on a scaling factor, where pixels are merge into segments based on their "degree of fitting" (Baatz and Schape 2000). Image segmentation does not automatically identify all objects at their final scale. Instead, smaller segments are created that are grown into larger segments through classification (Baatz and Schape 2000). A classification algorithm, such as nearest neighbor, compares and classifies each pixel based on its neighbors (Schowegerdt 2007). Layer operations are additional means by which segments can be further distinguished. Layer operations include slope, aspect, and edge detection (Trimble 2010). Slope is the steepness in changes of value, aspect is the cardinal direction in which a surface faces, and edge detection seeks sharp contrasts between pixels. A combination of segmentation, classification, and/or layer operation algorithms creates a rule set with which software such as eCognition can perform image segmentation.

Image segmentation can be difficult and costly to perform, both in time and money – two resources I did not have at the time of this research. However, the process works similarly to the human eye, and requires expert knowledge of the image being segmented. Because expert knowledge was used in creating REAL, I find it circular logic to use REAL as both the test set and truth set.

Given all of the above issues and observations, several future research opportunities exist. First, I would explore whether 90 meters is a sufficient distance from roads, fences, etc. to minimize impact on vegetation, with regard to field testing.

Second, I would examine if vegetation boundaries can be determined if integrating line transects (for rare vegetation, such as *yucca elata*) with point-intersect transect sampling of vegetation, assuming transects than span the entire ecotone. Third, I would explore how a supervised classification that takes elevation, texture, and spectral signature into account compare to REAL. Finally, I would determine how image segmentation compares to REAL, both spatially and in the time needed to create the segmentation.

APPENDICES

APPENDIX A

PRECIPITATION RECORD FOR ARMENDARIS RANCH, NEW MEXICO
2002 - 2009

	2002			2003			2004			2005		
	Engle	C.G.	Mesa	Engle	C.G.	Mesa	Engle	C.G.	Mesa	Engle	C.G.	Mesa
Jan.	0.08	0.08	0.15	0.02	0.06	0.10	0.16	0.15	0.10	1.11	2.62	1.55
Feb.	0.36	0.34	0.20	0.69	0.51	0.60	0.07	0.10	0.23	1.24	1.53	1.20
Mar.	0	0	0	0.02	0.02	0.02	0.71	0.48	0.40	0.66	0.43	0.90
Apr.	0.03	0.04	0	0.05	0	0.15	2.21	2.25	2.10	0.62	0.49	0.70
May	0.43	0.91	1.50	0.04	0.04	0.05	0.40	0.26	0.30	1.22	0.52	0.30
June	0	0.10	0.75	0.11	0.02	0.40	0.10	0	0.30	0	0.10	0.15
July	1.45	3.00	5.55	0.43	0.12	0.30	0.39	2.00	1.35	0	0	0.40
Aug.	0.58	1.50	1.15	1.26	0.50	1.00	1.64	0.80	0.75	3.31	2.31	1.60
Sept.	2.10	2.38	1.86	0.11	0.35	0.10	0.89	1.50	1.45	0.67	1.00	0
Oct.	0.74	0.47	0.70	0.58	1.49	1.50	0.99	1.20	1.19	0.88	0.85	2.50
Nov.	0.47	0.59	0.60	0.72	0.63	0.75	2.03	1.40	1.00	0	0	0
Dec.	0.92	1.23	1.05	0	0	0	0.34	0.55	0.95	0	0	0
Total	**7.16**	**10.64**	**13.51**	**4.03**	**3.74**	**4.97**	**9.93**	**10.69**	**10.12**	**9.71**	**9.85**	**9.30**

	2006			2007			2008			2009		
	Engle	C.G.	Mesa	Engle	C.G.	Mesa	Engle	C.G.	Mesa	Engle	C.G.	Mesa
Jan.	0.09	0.10	0.02	1.13	1.10	1.50	0.08	0.15	0.05	0	0	0
Feb.	0.05	0.05	0	0.12	0	0.75	0.10	0.15	0.10	0	0	0
Mar.	0	0.01	0.05	0.15	0.20	0.40	0	0	0	0.14	0.05	nr
Apr.	0.07	0.02	0	0.44	1.12	0.60	0	0	0	0	0	0
May	0.10	0.50	0.50	4.40	3.94	1.80	0.30	2.31	0.85	2.25	1.30	nr
June	0.76	0.53	0.36	0.19	3.06	0.25	0.03	0	1.11	0.28	0.20	0.10
July	2.64	3.13	2.77	1.38	0	0.85	5.36	5.30	1.50	1.08	3.65	nr
Aug.	3.64	1.80	2.06	1.82	3.87	0.72	0.36	1.55	0.90	0.02	0.03	nr
Sept.	2.95	0.95	1.05	0.90	2.12	0.55	3.85	3.85	2.35	0.15	0.10	nr
Oct.	2.40	2.25	1.40	0.70	0	0	0.42	0.80	0.85	0.40	0.30	nr
Nov.	0	0	0	0.45	65	0.30	0.15	0.05	0.35	0.48	0.32	nr
Dec.	0.39	0.70	0.25	0.6	0.5	0.10	0.05	0	0	0.97	0.80	nr
Total	**13.09**	**10.04**	**8.46**	**12.28**	**16.56**	**7.82**	**10.70**	**14.16**	**8.06**	**5.77**	**6.75**	**0.10**

Engle: **Engle, NM**
C.G.: **Casa Grand Camp, Armendaris Ranch**
Mesa: **Mesa Camp, Armendaris Ranch**

APPENDIX B

ACTIONS FOR CREATING COEFFICIENT OF AREAL CORRESPONDENCE (CAC)

1). For each REAL geomorphic class:

Step	Action	Toolbox	Settings	Purpose
1	Dissolve	Spatial Analyst	Default, on GEOMORPH	Create solid, multipart geomorphic polygons
2	Export Data	Spatial Analyst	Default	Separate SHP for each geomorphic class

2). For each supervised class:

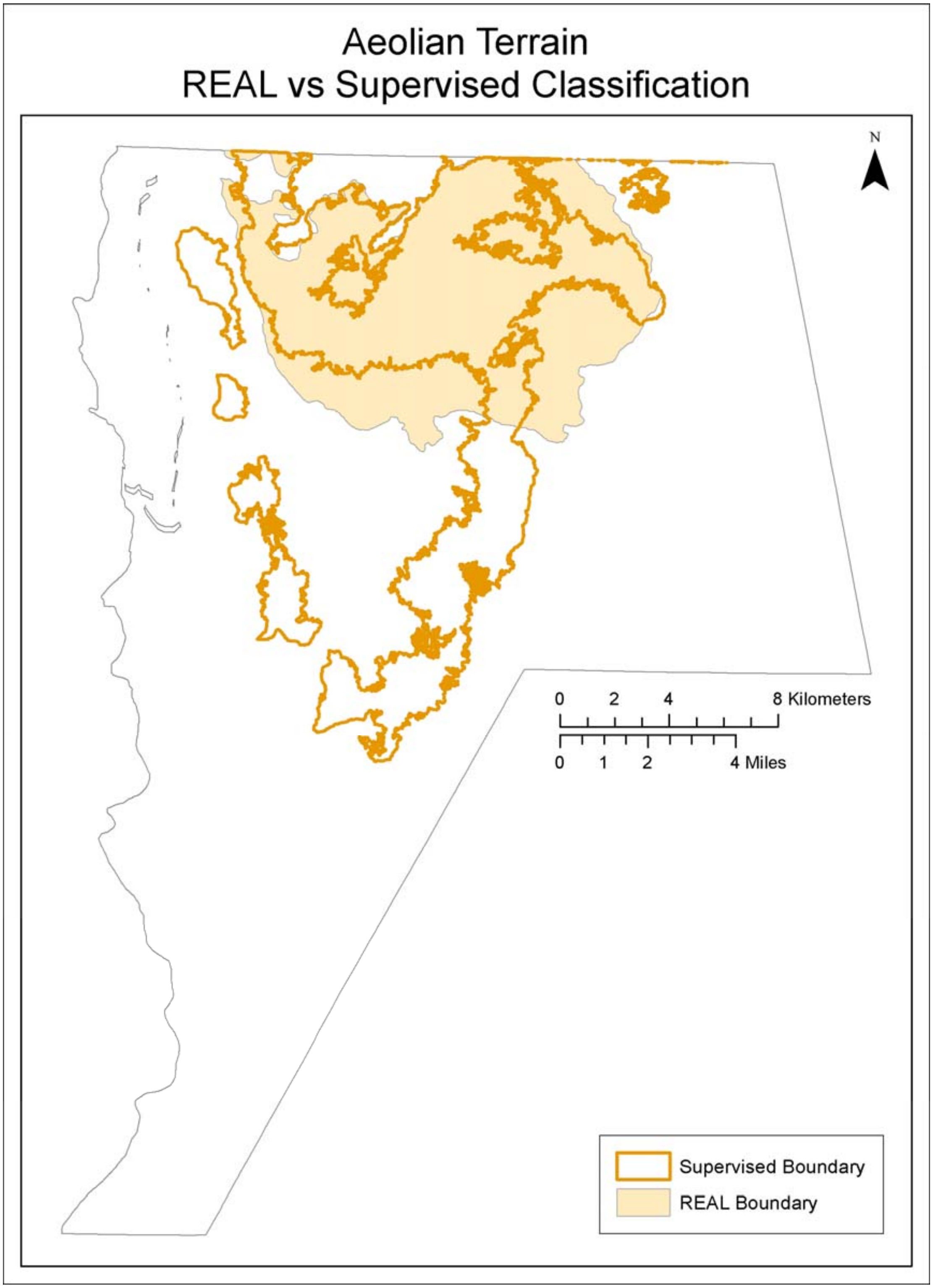
Step	Action	Toolbox	Settings	Purpose
3	Extract by Attribute	Spatial Analyst	Default	Separate raster file for each geomorphic class
4	Raster to Features	Spatial Analyst	Default	Convert raster to vector (polygons)
5	Dissolve	Spatial Analyst	Default, on GRIDCODE	Create solid, multipart geomorphic polygons

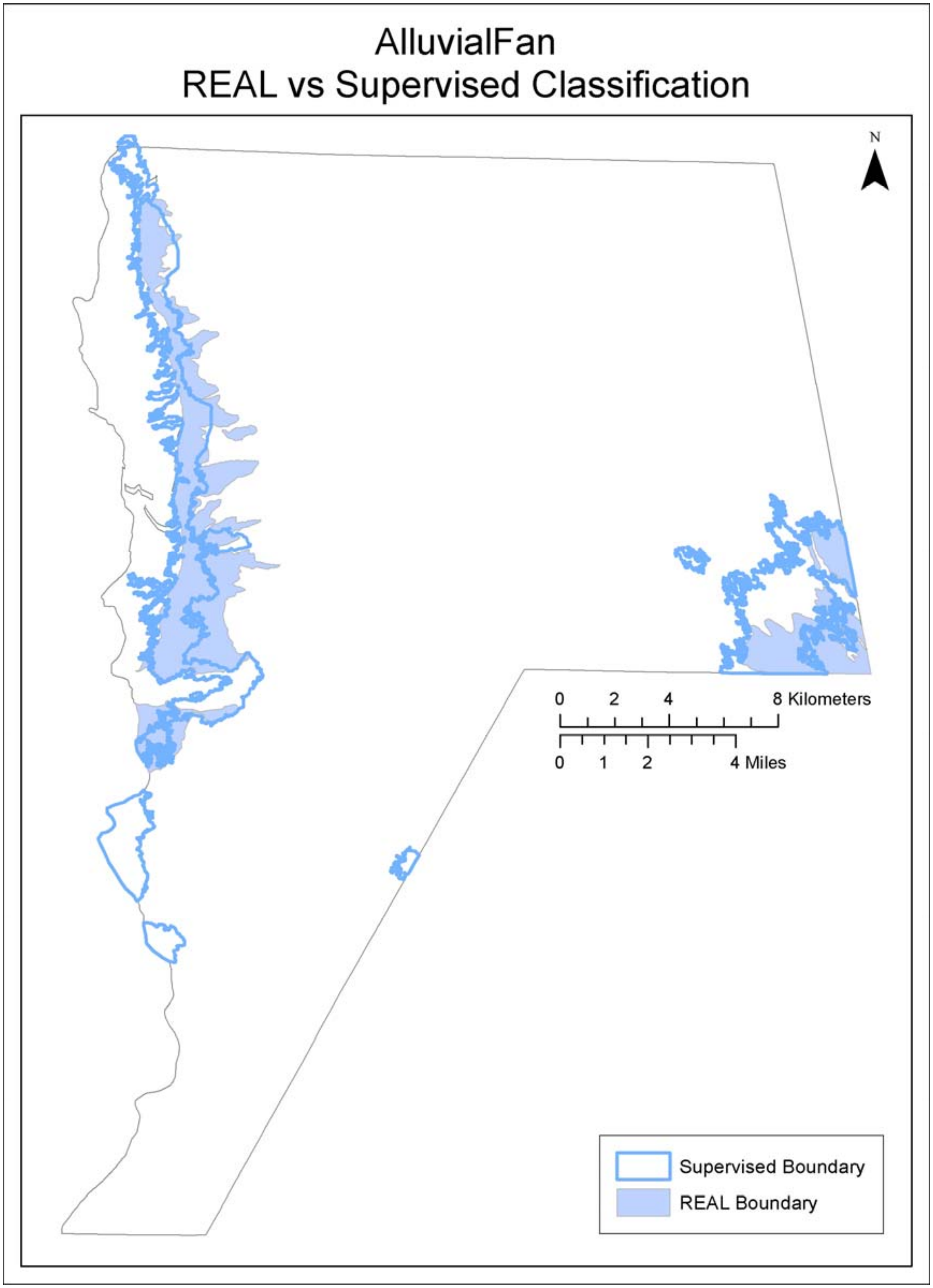
3). For each class created in parts 1 and 2:

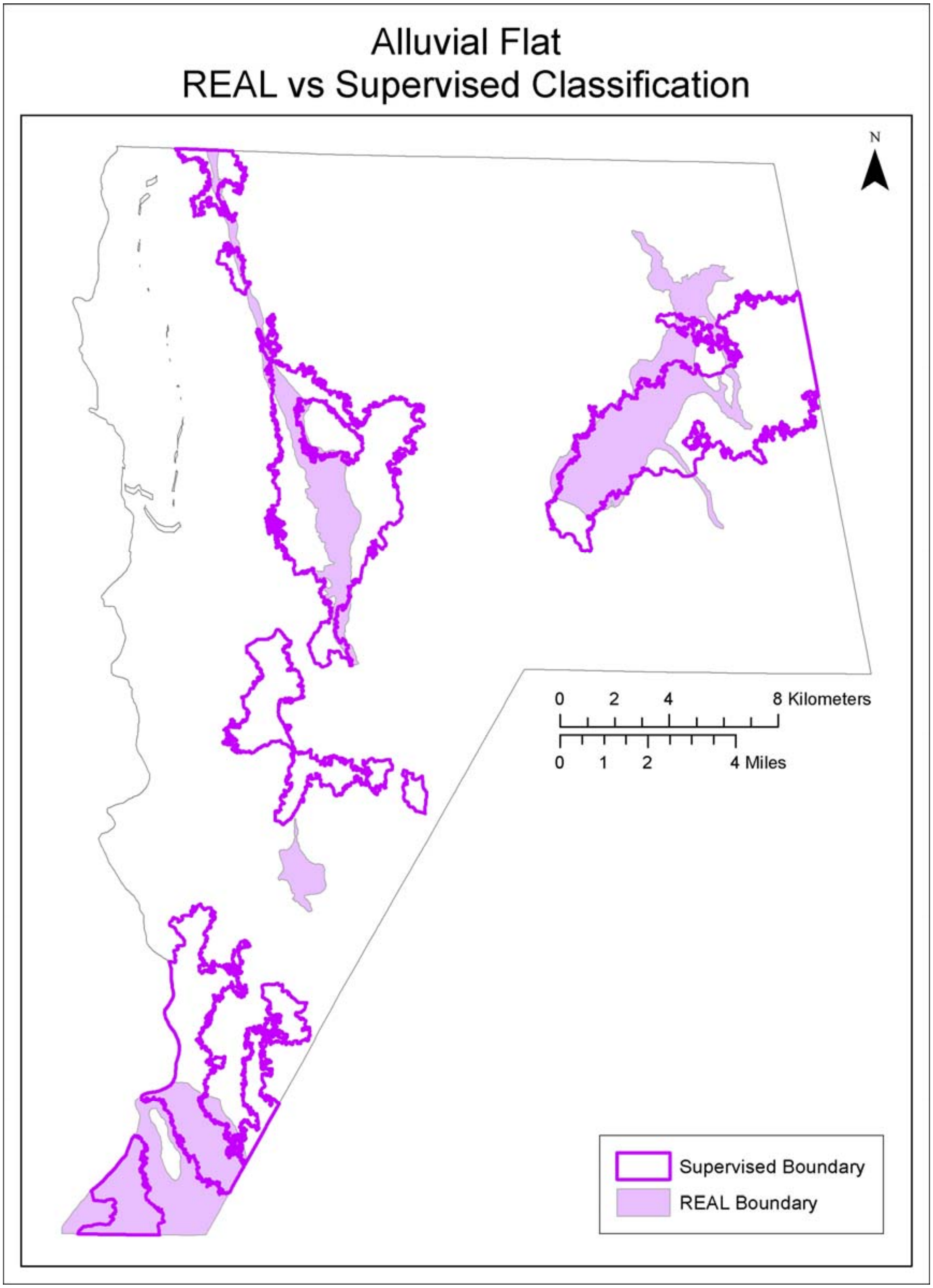
Step	Action	Toolbox	Settings	Purpose
6	Union	Spatial Analyst	Default (Join all)	Union the supervised and REAL class
7	Edit Table Add Column AREA CAC	Spatial Analyst	Default Sq. Meters (LONG) (FLOAT)	Add data to support calculations and display For calculating CAC Store calculated CAC

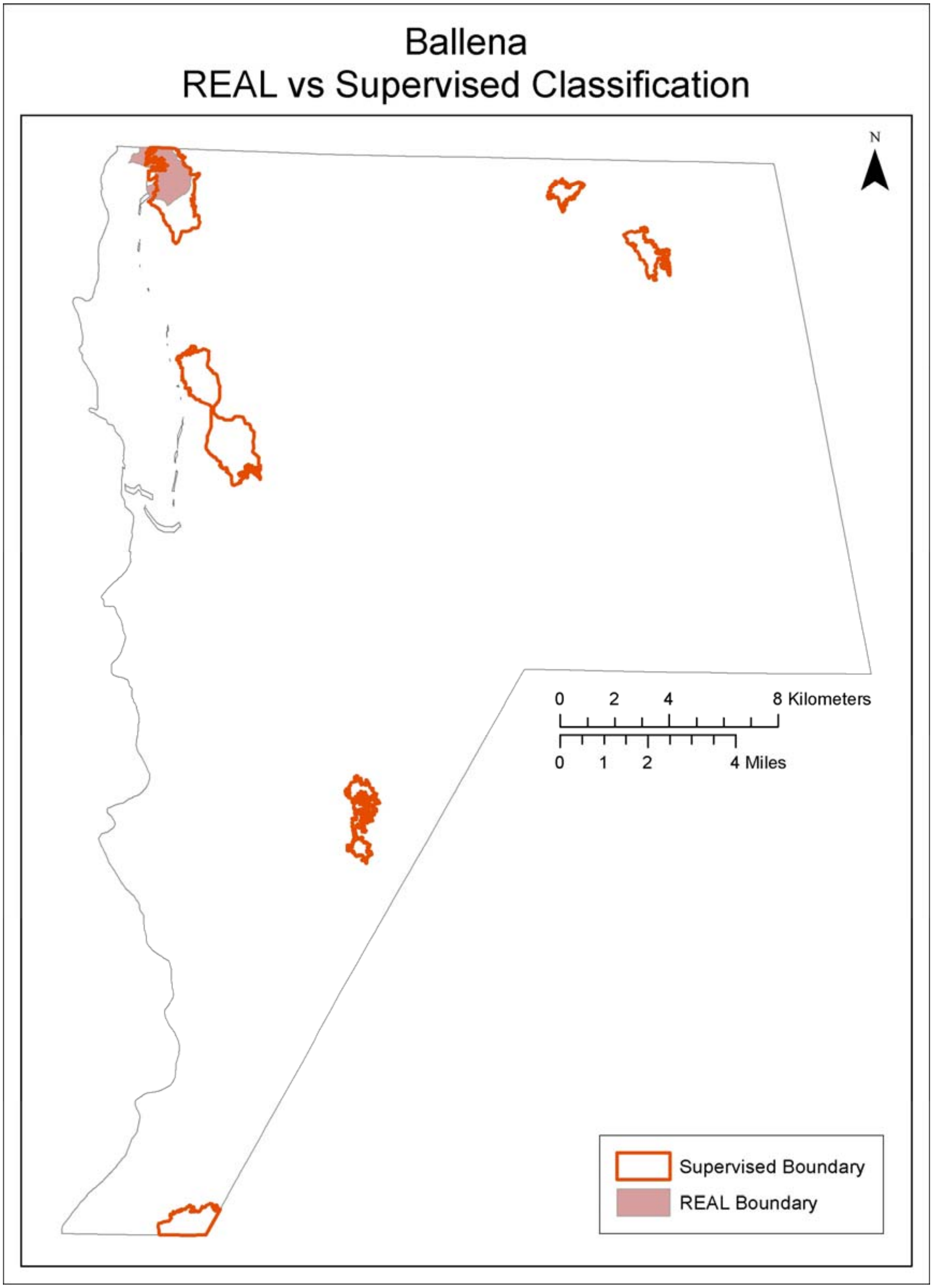
APPENDIX C

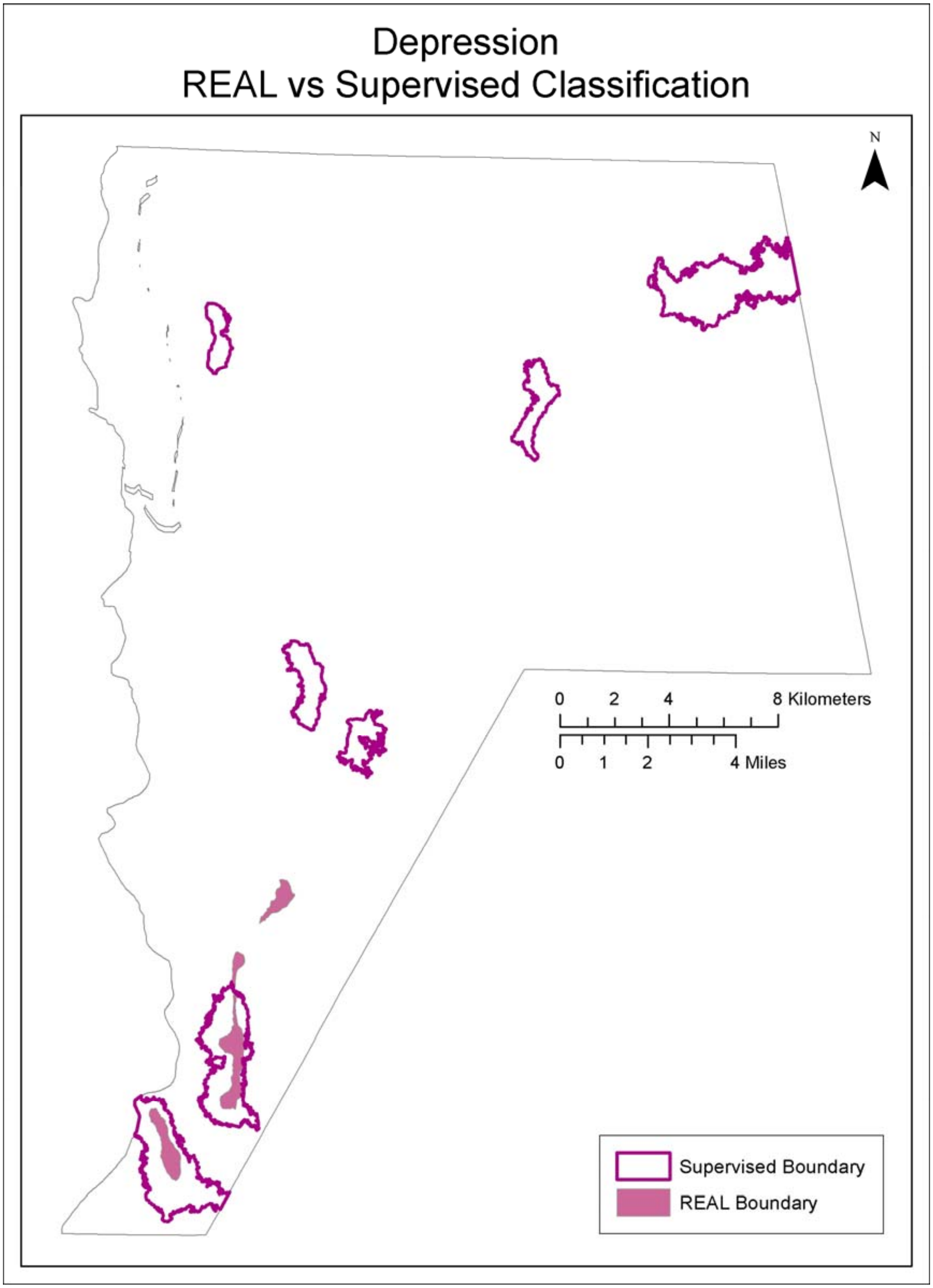
COEFFICIENT OF AREAL CORRESPONDENCE (CAC) FOR EACH GEOMORPHIC CLASS, REAL VS. SUPERVISED CLASSIFICTION

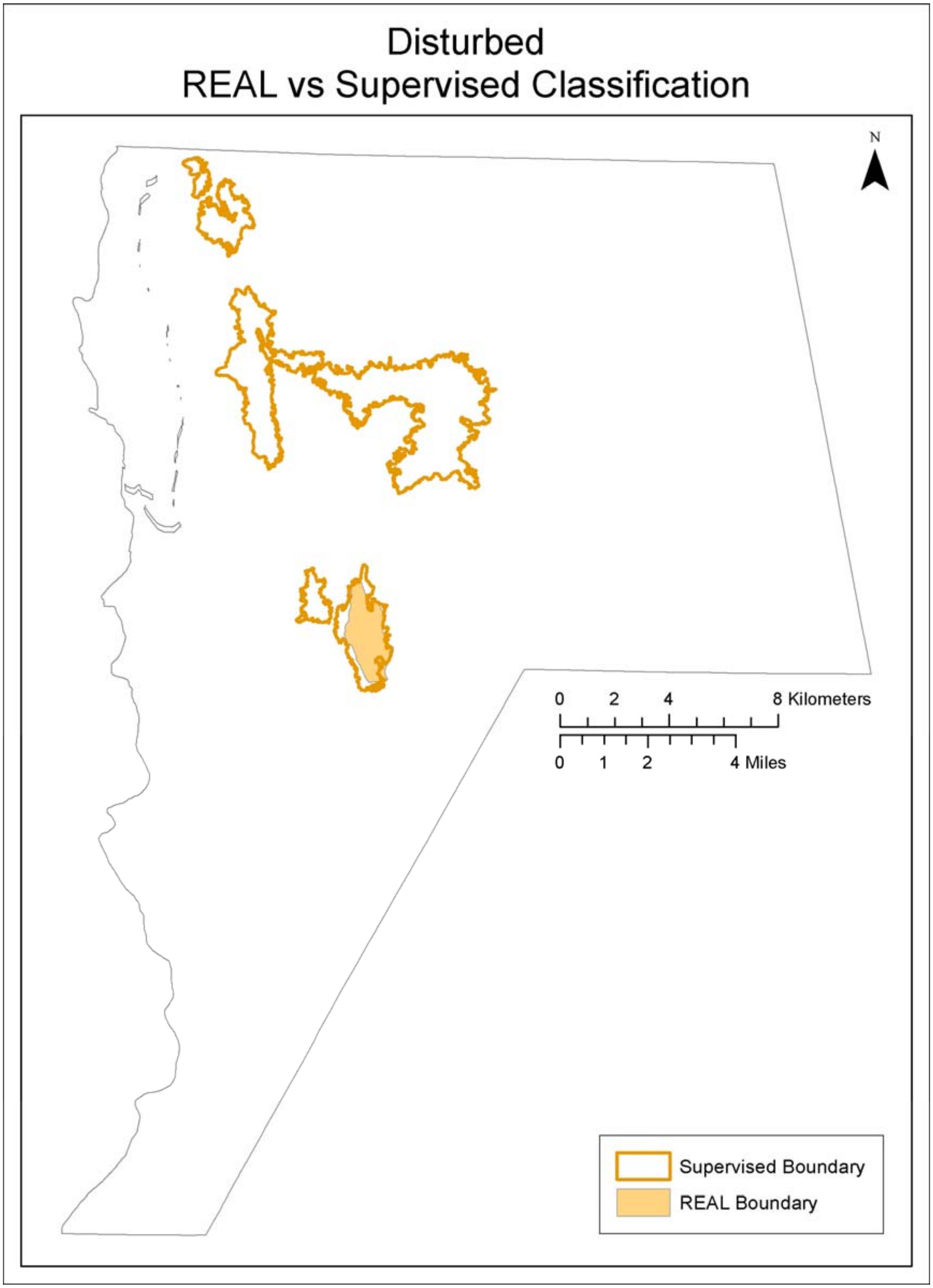

Aeolian Terrain
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

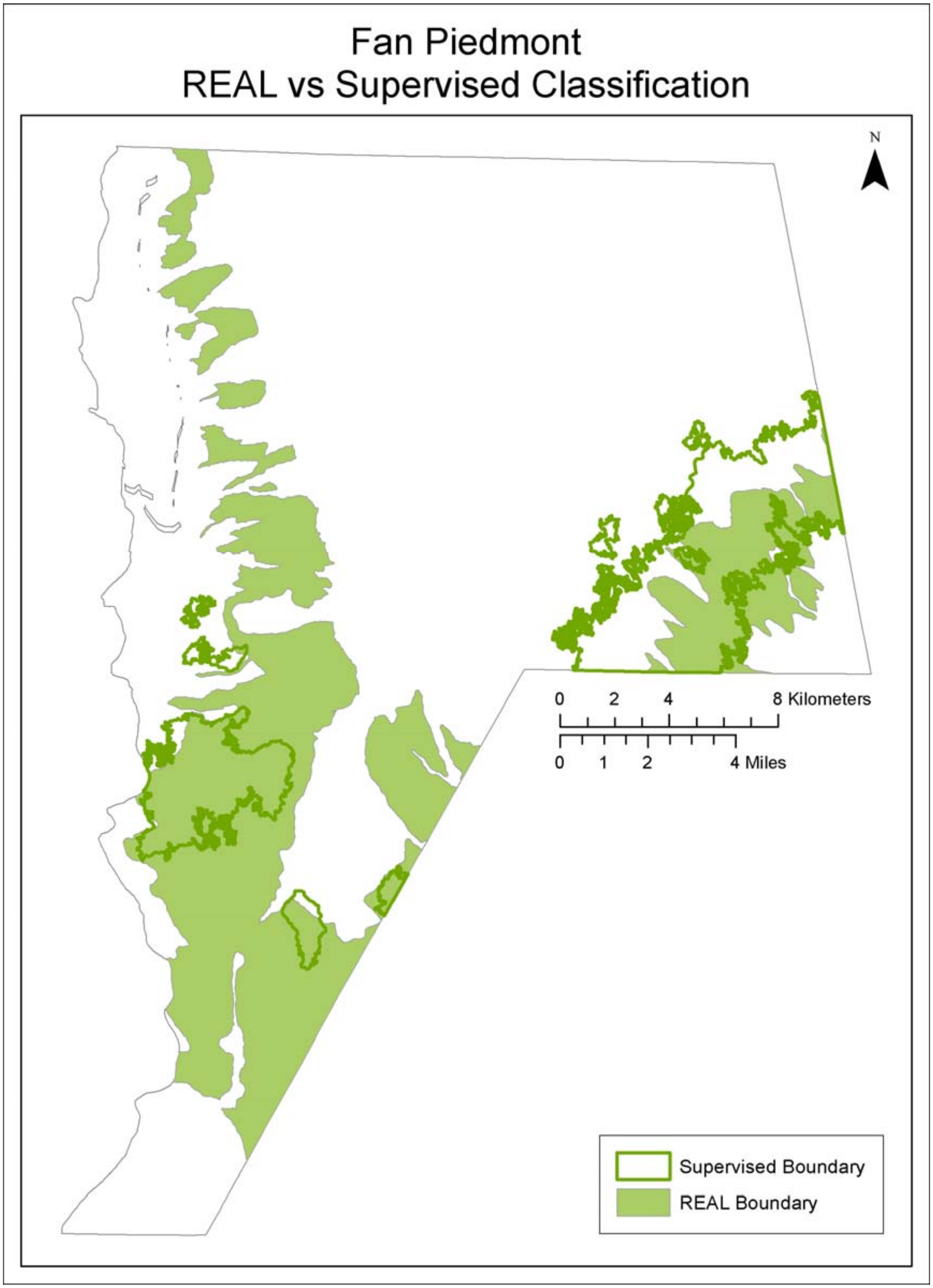

AlluvialFan
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary


Alluvial Flat
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

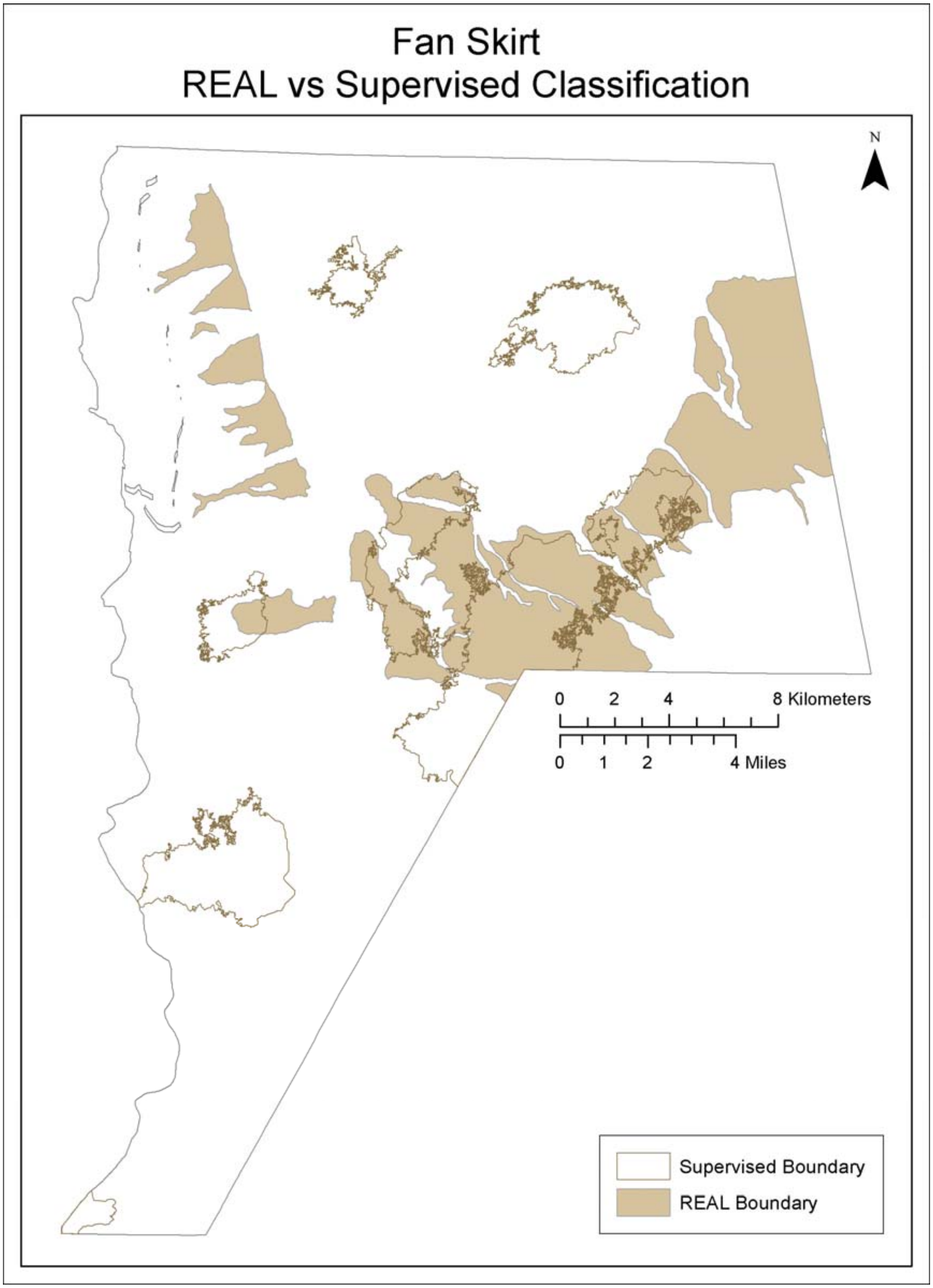

Ballena
REAL vs Supervised Classification
N
0
2
4
8 Kilometers
0
1
2
4 Miles
Supervised Boundary
REAL Boundary

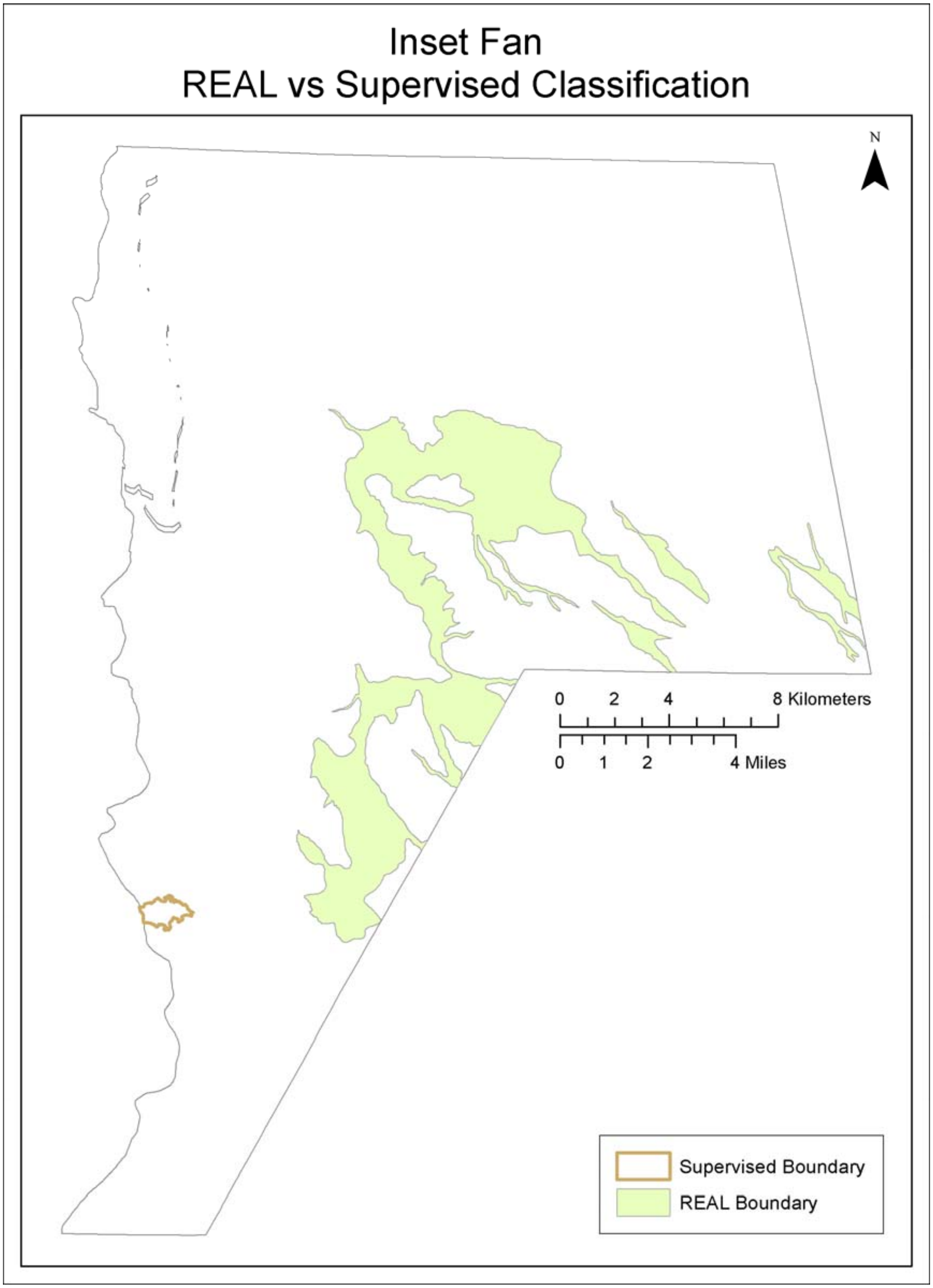

Depression
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

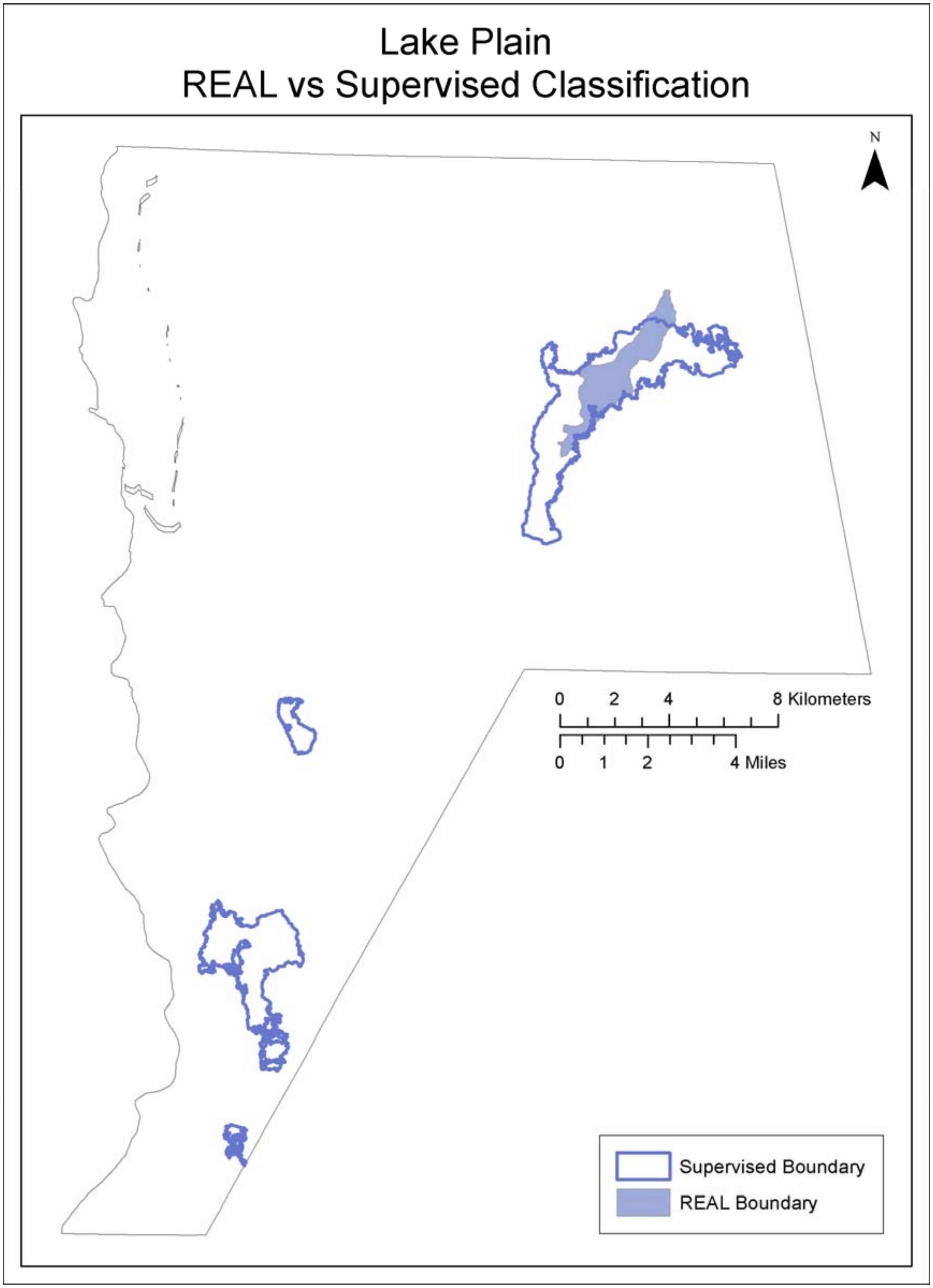

Disturbed
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

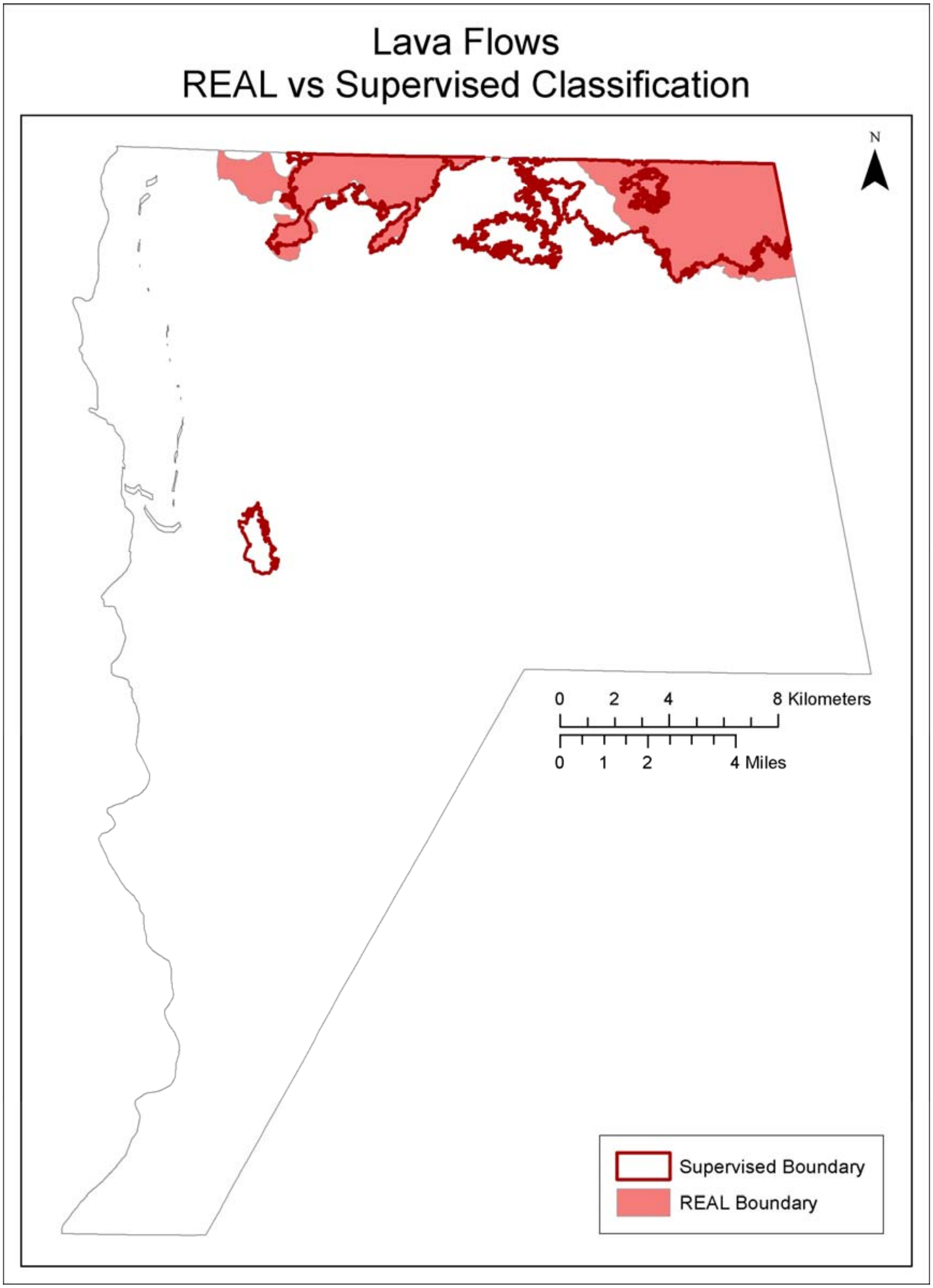


Fan Piedmont
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

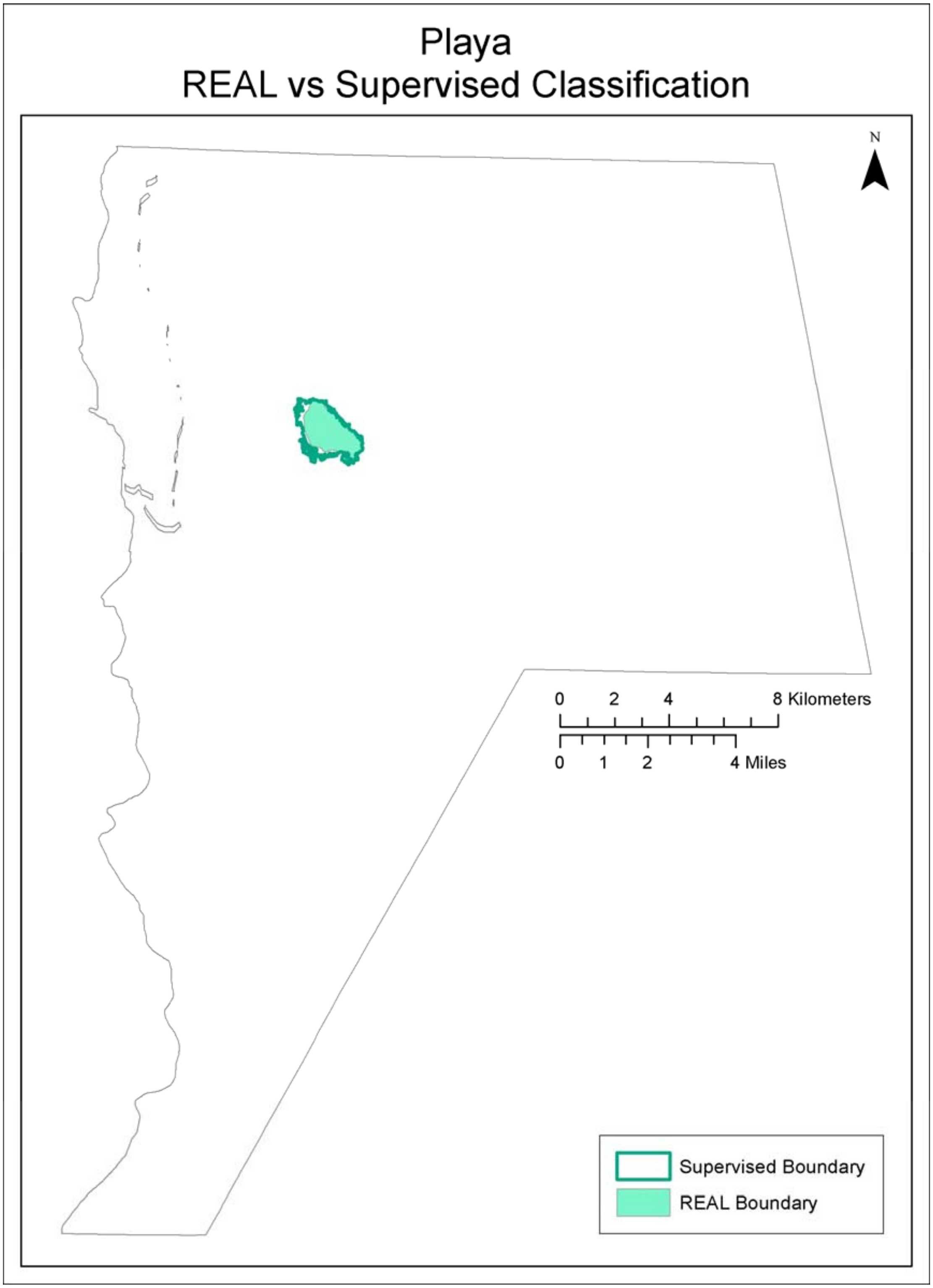

Fan Skirt
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

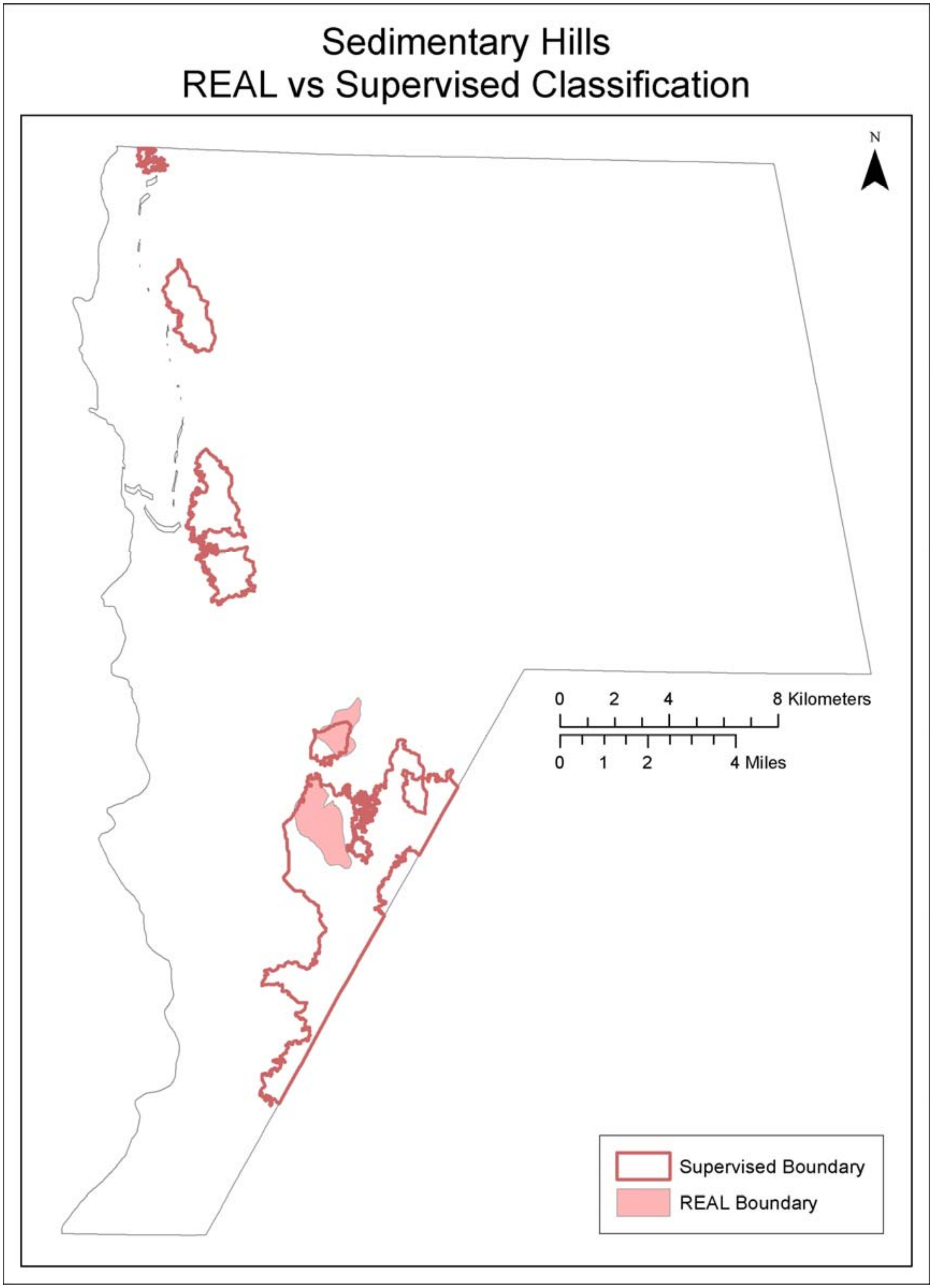

Inset Fan
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary


Lake Plain
REAL vs Supervised Classification
N
0
2
4
8 Kilometers
0
1
2
4 Miles
Supervised Boundary
REAL Boundary


Lava Flows
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary


Mountain Slope
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary


Playa
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary


Sedimentary Hills
REAL vs Supervised Classification
N
0 2 4 8 Kilometers
0 1 2 4 Miles
Supervised Boundary
REAL Boundary

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