Analysis of Landscape Fragmentation in the Peloncillo Mountains in Relation to Wildfire, Prescribed Burning, and Cattle Grazing

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Abstract*—This paper examined the application of state-of-the-art remote sensing image enhancement and classification techniques for mapping land cover change in the Peloncillo Mountains of Arizona and New Mexico. Spectrally enhanced images acquired August 1985, 1991, 1996, and 2000 were combined with environmental variables such as slope and aspect to map land cover modifications using a machine learning classifier. Change-map accuracies ranged between 68% and 80%. Maximum land cover change occurred in grassland ecosystems (>25% change in cover), caused primarily by prescribed burning practices in the region.*

Introduction

Land cover is defined as the biophysical attributes of the Earth's surface, typically based on a classification system consisting of discrete classes and formulated for a specific purpose. Land cover patterns and related processes in the Southwest United States have recently received considerable attention in the conservation literature, due to the high levels of floral and faunal biodiversity in the region. In particular, the Peloncillo Mountains of southeastern Arizona and southwestern New Mexico have been the focus of long term ecosystem monitoring efforts (Rogan and Yool 2001).

Three general properties of land cover attributes affect the quantity and quality of information (signal) received by remote sensing instruments: (1) abundance (i.e., relative or absolute amount of an attribute, per amount of ground area); (2) composition (i.e., spatial and spectral properties of an attribute); and (3) condition (i.e., biophysical traits of an attribute). Therefore, alterations in any one, or all of these properties over various spatial and temporal scales may be detected as "change" (Singh 1989). Land cover change scientists are typically interested in either the magnitude (i.e., degree of modification) or direction (i.e., extent of modification) of change, or both.

Detection and monitoring land cover change across large areas are two of the most important tasks that remote sensing data and technology can accomplish. Land cover change detection, one of the most common uses of remote sensing data, is possible only if changes in the surface phenomena of interest result in detectable changes in radiance, emittance, or microwave backscatter values, which implicitly involves spatial patterns of change. The purpose of this paper is to map land cover changes, from 1985 to 2000, in a portion of the Peloncillo Mountains using state-of-the-art remote sensing data enhancement and classification techniques.

Study Area

The Peloncillo Mountains extend north/south along the Arizona-New Mexico border into Mexico (figure 1). The Peloncillos are one of a series of ranges in the Mexican Highlands section of the basin and range physiographic province (Rogan and Yool 2001).

Recently, maps of current vegetation, soils, and geology have been completed within the Malpais Borderlands area of southeastern Arizona and southwestern New Mexico (Muldavin et al. 1998; McGuire 1998; Biggs et al. 1999). Dominate vegetation types include mixed woodland, chaparral woodland, desert scrub, and mesquite scrubland (Muldavin et al. 1998). Two prescribed fires were ignited in the region: Baker Canyon in 1995, and Maverick in 1997. Other vegetation-disturbances in the region include cattle grazing and various human activities including mining and off-roading.

Data

Remote Sensing Data

Three Landsat Thematic Mapper images (August 1985, 1991, and 1996) and one Landsat Enhanced Thematic Mapper image (August 2000) were acquired for land cover characterization over a 15-year time period. Additional remote sensing
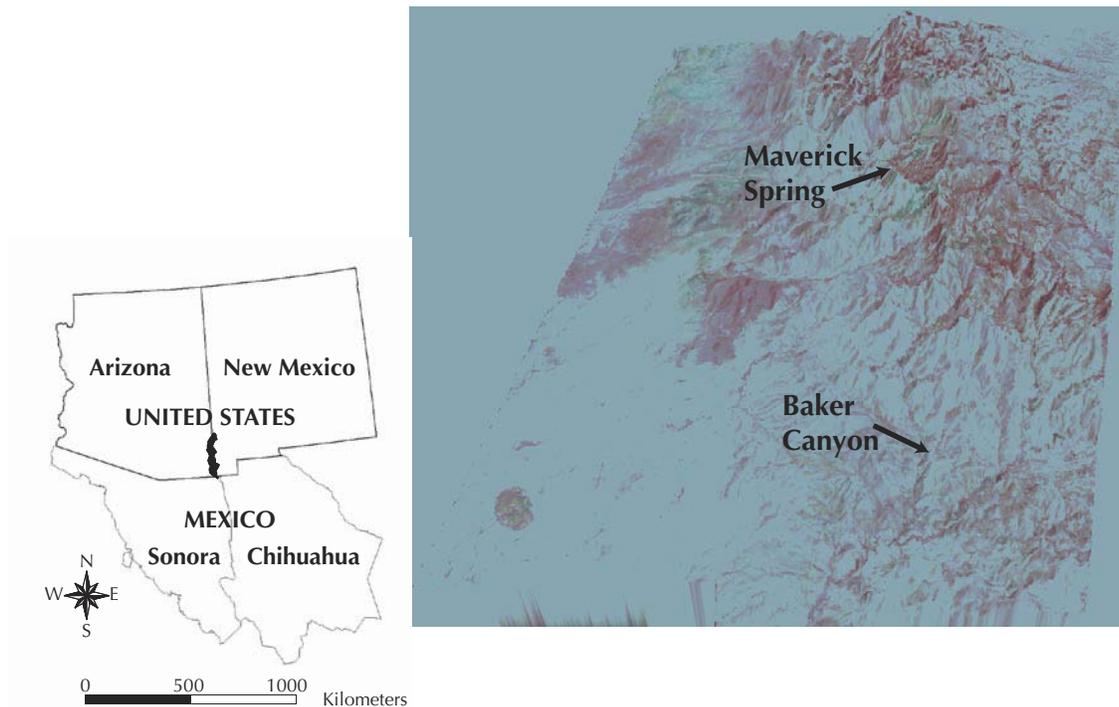
Figure 1—Location of the study area.

data included digital orthorectified photographs and hardcopy U.S. Forest Service resource aerial photographs.

Ancillary Data

Non-spectral ancillary data included a 30 m spatial resolution Digital Elevation Model mosaic that was then manipulated to produce slope and aspect spatial variables for inclusion in the change detection classification process. 60 x 60 m ground cover information was also available to aid in the change classification process. For more details on the collection of these data see Rogan and Yool (2001) and O'Neal (2004).

Methods

Image Pre-processing

Each scene was geometrically registered to the UTM WGS84 projection with an independent root mean square error of 0.4 pixels. A nearest neighbor algorithm was used to resample each image to 30 m. All images were then normalized for atmospherical illumination differences independently and converted to reflectance values using a dark object subtraction (DOS) approach described by Chavez (1989). Recent change detection studies have found the DOS approach robust for correction of atmospheric effects for change detection and mapping (Song and Woodcock 2003). Overlapping scenes in both study areas were then mosaicked and subset to the study area boundaries shown in figure 1.

Image Enhancement

In order to produce a suite of spectral features for change mapping the data sets were transformed using a Spectral Mixture Analysis (SMA) algorithm. Four endmembers were chosen for each study area because previous SMA-based change detection studies have found the dimensionality of Landsat data suited to spectral unmixing using shade, soil, green vegetation (GV), and non-photosynthetic vegetation (NPV) fractions. Further, the choice of these biophysically based endmembers helps reduce the inherent variability common in natural remote sensing scene elements. For more details on this process, see O'Neal (2004). As a result, four biophysically representative fraction images were generated for each image date in the study area and input to the classification process.

Change Map Legend

Land cover change categories used in this study are shown in table 1. This map legend describes three discrete categories of shrub canopy cover decrease and two classes of canopy cover increase. Further, a single forest cover increase and shrub decrease class is used, along with change in developed (urban) areas, and no change (+/- 15% cover change) categories. The +/- 15% class was designed to reduce the confusion caused by phenological differences between image dates and post-disturbance change classes (Rogan et al. 2003). This classification scheme was modified from that developed and in Statewide use by the U.S. Forest Service in California.

Land Cover Change Classification

Land cover change categorization was performed using an S-Plus classification tree algorithm. Classification trees are a type of MLA used to predict membership of cases or objects in

Table 1—Land cover change classification scheme.

Quantitative land cover change class
+/-15% shrub change
-71 to –100% shrub change
-41 to –70% shrub change
-16 to 40% shrub change
Forest decrease > 15%
+16 to +40% shrub change
+41 to 100% shrub change
Forest increase > 15%
Change in developed areas

the classes of a categorical dependent variable from their measurements on one or more predictor variables. Classification trees are developed using different measures to recursively split data sets into increasingly homogeneous subsets representing class membership, such as a measure of decreased deviance. All classification tree approaches employ hierarchical, non-linear recursive partitioning of the data until all pixels are uniquely identified. Classification trees are relatively easy to use, and the only user interaction required is the selection of a pruning rule, e.g., simple error rate pruning. They have a set of terminal nodes created for all classes and a path of decisions, or rules with associated input data thresholds leading to each node of the tree. All nodes have associated suitabilities or probabilities of class membership. MLAs have emerged as more accurate and efficient alternatives to conventional parametric algorithms, when faced with large data volumes and complex measurement spaces. SMA fraction images were input to the classification tree algorithm with elevation, slope, and aspect ancillary layers. The algorithm was calibrated using ground reference data, described previously, and the final change maps were validated using 20 independent validation points per image date.

Results

A comparison of the variables selected for classification in the S-Plus MLA is presented in table 2. The dominant variables used for change-class discrimination, for each time period, were GV followed by NPV and bare soil. Elevation and aspect variables were not used by any of the trees for the three time periods. The results of the change map accuracy assessment are shown in figure 2. The Kno statistic, representing percent overall map accuracy, was derived to compensate for some of

the shortcomings of the kappa statistic, as Kno is not a chance-corrected measure of agreement and does not make distinctions among various types and sources of disagreement (Pontius 2000). The Kno results reveal that the 1985-1991 change map was least accurate (Kno = 68%). The 1991-1996 change map had the second highest accuracy (Kno = 72%), while the highest accuracy was achieved with the 1996-2000 data set (Kno = 80%). These results can be considered reasonable to good when one considers the number of change classed resolved, and the heterogeneity of the study area. The high accuracy associated with the 1996-2000 data set can be attributed to the fact that more ground reference data for model calibration were available for this time period.

The Kno results revealed other important information about the change maps. For example, error due to quantity (disagreement between map categories and validation points) was lower than 10% for each time period. Error due to location (disagreement between position of changed pixels and validation pixels) was lowest for the 1996-2000 time period and highest for the 1985-1991 time period. This was possibly caused by positional errors in ground reference information and/or within-pixel shifting in the geometric registration process.

Finally, the results for the proportion of land cover that underwent change over the 15-year time period are presented in figure 3. Overall, vegetation cover has not changed dramatically over the 15-year time period. Riparian areas changed least (below 5%). Grassland areas have experienced maximum change over time, especially between 1991 and 1996 when the Baker Canyon prescribed burn was ignited. Mixed woodland and chaparral vegetation types underwent intermediate land cover change (i.e., ~15%).

Conclusions

This paper examined 15 years of land cover change in the Peloncillo Mountain region using state-of-the-art remote sensing image enhancement and classification techniques. Overall map accuracies were reasonable for a change-mapping endeavor involving nine land cover change classes in a heterogeneous landscape. Machine learning classification accuracies ranged between 68 and 80%. The most important variables in mapping land cover change were the SMA-based green vegetation and non-photosynthetic vegetation fraction images. Maximum land cover change occurred in grassland ecosystems (>25% change in cover), caused primarily by prescribed burning practices in the region.

Table 2—Variables selected by the S-Plus classification tree algorithm for each time period (numeric subscript indicates the number of times the variable was used as a discriminatory variable in the classification).

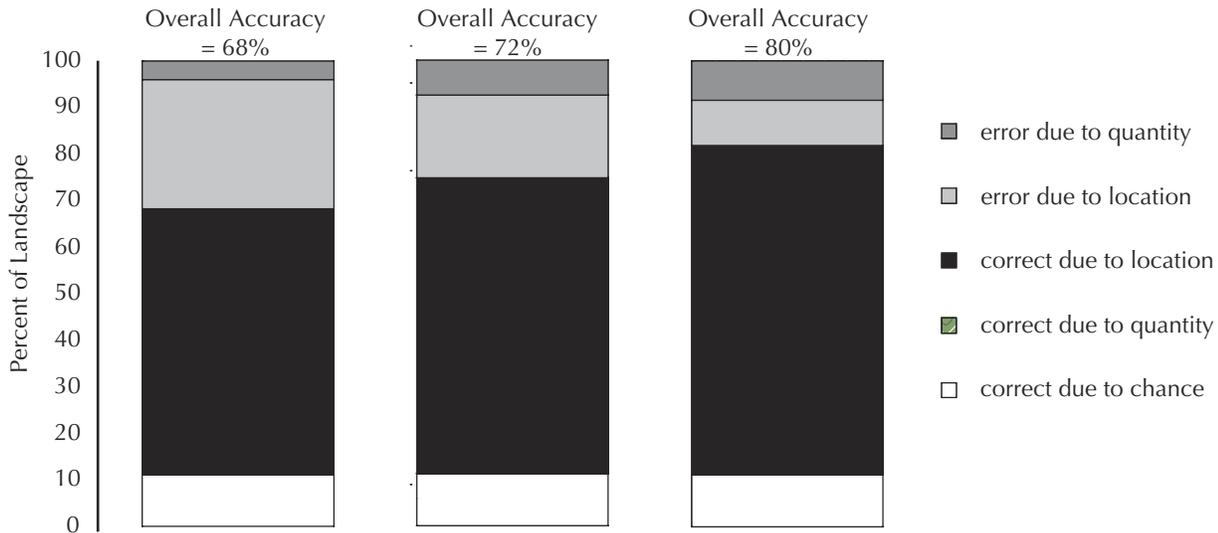| Date	Shade	GV	NPV	Soil	Elevation	Slope	Aspect
1985 - 1991	X_1	X_5	X_4	X_2	-	X_1	-
1991 - 1996	-	X_5	X_5	X_3	-	X_1	-
1996 - 2000	-	X_6	X_5	X_1	-	-	-

Figure 2—Kno statistic accuracy results for land cover change maps (1985-1991, 1991-1996, and 1996-2000). Contribution to both quantitative and positional errors are shown.

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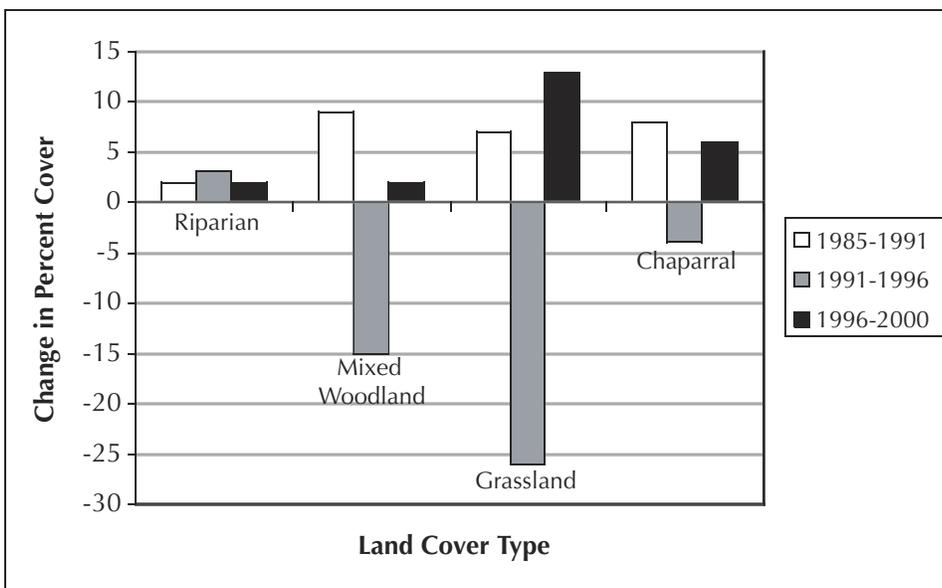
Figure 3—Percent land cover change statistics for dominant land cover types in the study area.