MAPPING GRADATIONS AMONG VEGETATION COMMUNITIES ON SANTA CRUZ ISLAND WITH FIELD AND REMOTE SENSING DATA

Michelle Cobb and Leal A. K. Mertes

Department of Geography, University of California, Santa Barbara, CA, 93106-3060
(805) 893-7017, FAX (805) 893-3146, Email: leal@geog.ucsb.edu; mlcobb@yahoo.com

ABSTRACT

Vegetation changes on Santa Cruz Island, especially those due to changes in grazing impacts, have made it useful to prepare a new vegetation map that is complementary to maps such as reported by Minnich (1980). Through the combination of field and remote sensing data of Santa Cruz Island, vegetation maps that emphasize both distinct vegetation communities and gradations among them were produced. The stratified random sampling scheme for field plots resulted in a data set detailing species dominance in significant vegetation communities. TWINSPAN (two-way indicator species analysis) was used to produce a classification of the 93 field samples yielding eight major classes that were interpreted to represent: grassland, coastal sage scrub, fennel-invaded, mixed coastal sage scrub/grassland, mixed oak woodland/island chaparral, island chaparral, Bishop pine forest, and oak woodland. The 'mixed' classes represent the intergrading of vegetation associations described by Junak et al. (1995). These field data were used to assess classification accuracy for maps depicting locations and extent of the community types produced from a Bayesian and a map-guided classifier based on a Landsat image for October 1993. Spectral mixture analysis was used to map the gradations within and between the vegetation communities.

Keywords: Spectral mixture analysis, map-guided classification, Bayesian classification.

INTRODUCTION

Santa Cruz Island is one of the four Northern California Channel Islands, a westward extension of the Santa Monica Mountains. Santa Cruz Island is the largest of the eight California Channel Islands with an area of 249 km². It is located approximately 40 km off of the coast of southern California and is separated from the mainland by the Santa Barbara Channel (Figure 1). With the most rugged topography of the northern islands, Santa Cruz Island displays remarkable physiognomic diversity. Santa Cruz Island supports the widest variety of indigenous flora (420 species) of any of the Channel Islands, including seven endemic species (Raven 1967). Philbrick and Haller (1977) described ten plant communities: southern beach and dune, coastal bluff, coastal-sage scrub, valley and foothill grassland, island chaparral, southern coastal oak woodland, island woodland, Bishop pine forest, coastal marsh and southern riparian woodland. Minnich (1980) reported that oak-woodland, grassland, chaparral, and coastal sage scrub covered 89% of the island. Jones et al. (1993) reported percent cover of 11 vegetation classes derived from a digitized vegetation map based on 1:24,000 color infrared (CIR) aerial photographs: grasses (52.5%), chaparral (18.4%), barren (9.7%), riparian (7.2%), coastal sage scrub (5.1%), oaks (4.1%), pines (1.5%), island oak (0.7%), island ironwoods (0.4%), woody exotics (0.3%), and coastal bluff (0.1%). Junak et al. (1995) described 16 plant associations: southern beach and

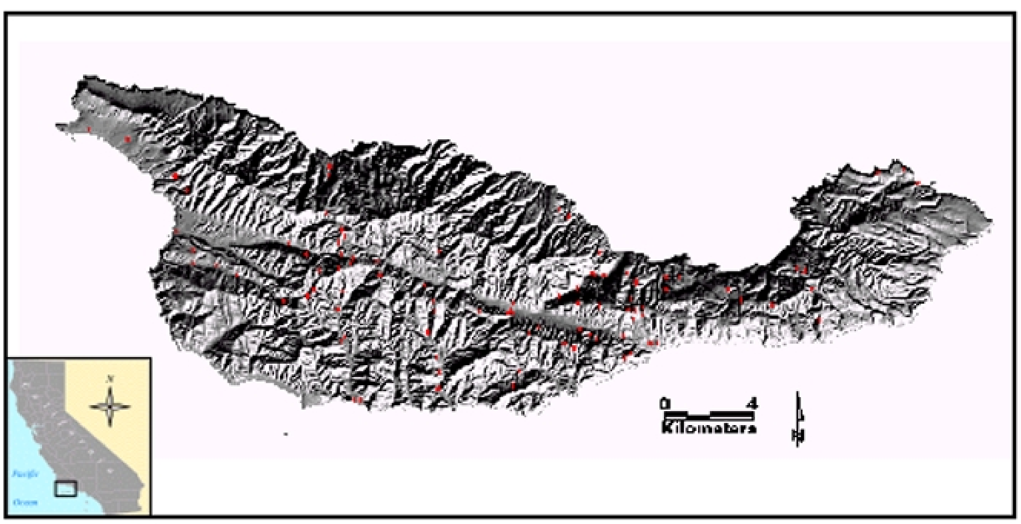

Figure 1. Shaded relief image using the sun angle and azimuth of the satellite at the time of data capture and a DEM. Plot locations are indicated by red markers.

dune, valley and foothill grassland, coastal-bluff scrub, coastal-sage scrub, coyote-brush scrub, island chaparral, island woodland, southern coastal oak woodland, Bishop pine forest, intertidal and subtidal marine, coastal marsh and estuary, freshwater seeps and springs, vernal ponds, riparian herbaceous vegetation, mule-fat scrub, southern riparian woodland.

As a result of decades of extensive overgrazing by feral sheep and cattle, the island suffered severe environmental degradation (Brumbaugh 1980; Minnich 1980; Hobbs 1980; Van Vuren and Coblentz 1987). Due to this damage, The Nature Conservancy (TNC), proprietor of the western 90% of Santa Cruz Island, removed approximately 38,000 sheep and 20,000 cattle during the 1980s (Schuyler 1993). The objectives of this program were to "preserve, protect, and restore the natural systems, flora and fauna of the island" (Klinger et al. 1994: 341). Unfortunately, one result of these control efforts was the accelerated invasion of exotic species, especially fennel (*Foeniculum vulgare*), into many of the island's plant communities (Beatty and Licari 1992). TNC not only continues restoration of native floral communities, but also works to control the expansion of invasive exotic plant species (Brenton and Klinger 1994).

Given Santa Cruz Island's ecological diversity and TNC's current management philosophy to promote restoration, the island is a virtual mecca for many types of research. Much of this research relies on basic ecological descriptors for the island, including topography, geology, hydrology, and climate. Information on the island's vegetation cover, which results from the synthesis of ecological factors, is often fundamental to many research projects. Surprisingly, no contemporary or field-verified vegetation cover map of the island exists. The most recent vegetation map utilized by some researchers was published by R. Minnich in 1980. This classification was derived from 1:22,000 CIR photography acquired during July 1970, a period of intense grazing by feral sheep (Van Vuren 1981). The classification was not comprehensively verified in the field; instead "… the primary role of fieldwork was the characterization of photographic data" (Minnich 1980: 124). Using laboratory and field techniques, the physiognomic vegetation classes were identified based on crown structure, height, spread, and other morphological characteristics using aerial photographic interpretation. As experienced by Minnich and other researchers, the island's large size and rugged terrain limits the use of traditional field techniques for land-cover mapping. If the spatial scale is appropriate, remotely sensed imagery can efficiently analyze a large area for vegetation cover. However, simultaneous collection of traditional field, or ground-verified, habitat data is crucial to the calibration of the remotely sensed imagery. Using geographic information systems technology, the remote sensing and field data can be entered into a database using software designed to input, store, manipulate, analyze, and output spatial information. In this case, the various pertinent themes of data, such as satellite imagery, locations of field plots, attributes of the field plots and elevation contours, can be combined and/or compared with each other in order to perform the desired spatial analysis.

One of the major obstacles encountered when attempting to describe the type, location, and size of areas of similar land-cover is that geographical information is imprecise, meaning that the boundaries between different phenomena are fuzzy or there is heterogeneity within a class (Jensen 1996). Satellite imagery contains pixels with mixtures of land-cover categories that are not easily classified or labeled. The mixtures are not strictly limited to land-cover but also represent topographic variation. Shading of or shadows in a pixel will dramatically affect the reflectance measured by the satellite. However, the typical approach to classification is to determine to which class a pixel belongs. This type of classification uses a hard classification algorithm which is based on classical set theory that requires precisely defined boundaries for which an element either is or is not a member of a given set (Jensen 1996). It is understandable to want to be able to label an entity as one thing or another; such as a tree that is a pine, oak, cottonwood, or cypress. Yet, in the case of a pixel in a satellite image, the entity is a portion of the earth that is covered by a variety of types of natural and human-made substances. Fuzzy set theory provides a tool for dealing with the real-world issues of land-cover mapping. Fuzzy set theory allows a given pixel to have percentages or portions of membership in different classes, such as soil, shade, and vegetation.

The objective of this paper is to present the results of three classification algorithms to determine the most appropriate method, or a combination of methods, to employ in land-cover mapping of rugged terrain. Maps depicting locations and extent of the primary community types were generated from two hard classification methods: Bayesian (Jensen 1986) and an iterative, map-guided (Stoms et al. 1998). Spectral mixture analysis (Smith et al. 1990; Adams et al. 1994; Mertes et al. 1995) was used to map the intergrading of the communities as expressed in the TWINSPAN results.

METHODS

Field Data Collection

During the fall of 1993 through the spring of 1994, 93 vegetation plots were established using a stratified-random sampling scheme (Figure 1). Nine vegetation cover classes were surveyed island-wide, including the eight physiognomic types mapped by Minnich (1980): grassland, island chaparral, coastal sage scrub, woodlands, Bishop pine forest, riparian, barren, and woody exotics. The vegetation cover class of fennel grassland was also included due to the recent invasion of *Foeniculum vulgare* into many of the shrub communities (Beatty and Licari 1992). The island's vegetation types were first stratified using interpretations of 1991 CIR photos (scale 1:24,000). Then field plots were randomly located within the identified stratified stands. The plots measured 60 by 60 m in order to include sufficient areal coverage for ground verification of remotely sensed imagery with a spatial resolution of 30 by 30 m. Each plot's location was recorded on the 1991 CIR photos and the following attributes were measured in the field: 1) slope and aspect, 2) dominant species, 3) percent cover of dominant species, 4) percent cover of litter, exposed litter and soil, and 5) soil color. The flora referenced during field data collection was The Jepson Manual: Higher plants of California (Hickman 1993). The emphasis of this paper will be on the presence/absence and percent cover of dominant species. For further details on the field data collected, refer to Cobb (1999).

Field Data Analysis

All of the field data were entered into a spreadsheet in preparation for both integration into the Geographical Information System (GIS) database and the species and sample ordination analysis. The locations of the plots, represented as points in the database, were screen-digitized using USGS digital data (Digital Line Graph files of hydrography and hypsography) to transfer their locations from 1991 CIR photos into the GIS database. The attributes of the plots were imported into the GIS, appended to the field plot location data layer. Elevation values were calculated by overlaying the points on a Triangulated Irregular Network (TIN) of Santa Cruz Island. The TIN was derived from a mosaic of USGS Digital Elevation Models (DEM) which have a spatial resolution of 30 m by 30 m. Next, the attributes were exported from the GIS database and formatted for import into a FORTRAN based vegetation analysis program, TWINSPAN.

Hill (1979) describes TWINSPAN as a two-way indicator species analysis used to produce a classification of the field samples in two definitions of space (species in species space and species in sample space) using both frequency and presence/absence data. TWINSPAN is a polythetic divisive classification technique that analyzes the presence/absence data of dominant species within each sample (or plot). The program employs a two-way ordination technique that groups species with other similar species and the same with the samples. Among the results listed are the differential species which are those that have distinct ecological preferences and can be used to identify particular environmental conditions. TWINSPAN is designed to construct ordered two-way tables identifying the differential species using reciprocal averaging of samples. The program performed a dichotomized ordination analysis of the samples and qualitatively identifies the differential species on each side of a crude dichotomy. Using these differential species, the ordination was further divided to achieve a user-defined level of dichotomy. Although indicator species analysis is not the focus of TWINSPAN, indicator ordination or a simplified ordination based upon differential species was performed. The main result of TWINSPAN is a table of the samples classified into groups, or classes, to which labels are attached. The number of these classes depends on the number of iterations requested by the user. In this case, data for 85 plots were analyzed (the riparian, barren and woody exotic plots were removed for the final analysis because they were extreme outliers) with three iterations within TWINSPAN, and eight final classes resulted.

Image Analysis

A Landsat 5 Thematic Mapper (TM) scene of central California dated October 20, 1993, was selected based on the absence of cloud cover and coincidence with collection of field data. Elements of an image processing software package, Image Processing Workbench (Frew 1990) and spatial analysis tools embedded in ARC/INFO®, a GIS software package (Environmental Systems Research Institute, Redlands, California) were employed to generate a land-cover map of Santa Cruz Island. Following pre-processing of the image, three classification methods were applied to the data: 1) Bayesian classification, 2) map-guided classification, and 3) spectral mixture analysis. Then two post-processing procedures were performed to complete the three classifications. Lastly, the accuracy of the three methods was assessed using both a quantitative and a qualitative approach.

Image pre-processing begins with geometric rectification, the process by which the "geometry of an image area is made planimetric" (Jensen 1986:103). First, the image coordinates were translated to real-world coordinates using 20 ground control points and United States Geological Survey (USGS) Digital Line Graph files as the basemap. Next, intensity interpolation was performed to calculate each pixel's digital number (DN) at the new spatial location. The nearest-neighbor interpolation method, where the DN of the pixel closest to the original pixel location is assigned to the pixel at its new spatial location, was chosen because this method does not alter the original DNs (Jensen 1986). Lastly, the images were corrected for atmospheric effects through the minimum DN subtraction method to account for path radiance (Jensen 1986).

The Bayesian classification is a supervised method based on maximum likelihood statistics that yields a hard classification. Using the field data, training sites were identified and used as input to the statistical portion of the supervised classification process (Richards 1986). These sites provided sample DNs, or relative values of reflectance, on which the classification was based. The statistics generated from the training sites set the rules for the maximum likelihood classes. To determine the best bands, or wavelengths, of the satellite imagery for use in the classification, a divergence operation was performed (Jensen 1986). Given the six possible bands, the four most informative bands (TM bands 3, 4, 5 and 7) were chosen for the analysis. The Bayesian classification method analyzes covariance values, user-defined a priori probabilities as weights for each class, and chi-square values as classification thresholds (Jensen 1986). This approach weeds out atypical values and highlights previously unidentified spectral classes, which otherwise would simply have been assigned to the 'most similar class' in a standard Boolean classification (Jensen 1986).

The map-guided classification (MGC) method was developed by the Institute for Computational Earth System Science at the University of California at Santa Barbara

(Stoms et al. 1998). MGC is an iterative procedure consisting of two steps using functions within the GRID module of ARC/INFO®. The first step is to perform unsupervised clustering on the image with ISOCLUSTER. Next, the MLCLASSIFY function assigns unclassified pixels to the clusters determined with ISOCLUSTER. MGC requires an input map to be used as training data. As described in Stoms et al. (1998:14):

> "The information classes in the input map are compared with the spectral clusters, and the spectral cluster with the highest level of association (i.e., the highest ratio of pixels in a cluster and information class combination relative to the sum of pixels in the cluster in all classes) is assigned to its corresponding information class. The algorithm then removes pixels in that spectral cluster from the data set and repeats the two-step procedure with the remaining data. Processing continues iteratively until all pixels have been assigned to [a class] that best matches their spectral signature or until a stopping rule is invoked."

In this case, the training sites used in the Bayesian classification were used as the input map data and the program performed 17 iterations.

Given the natural tendency of vegetation classes to lack distinct borders, vegetation communities commonly mix or overlap resulting in gradients. Based on the theory that pixels tend to be inherently heterogeneous, standard classification techniques do not accurately represent reality (Jensen 1986). The fact that pixels contain varying proportions of vegetation, soil, and topography complicates attempts to assign pixels into predefined vegetation community classes. Spectral mixture analysis (SMA) is based on defining endmembers that are represented by spectral data for a homogeneous pixel of, for example, vegetation, shade, and soil (Smith et al. 1990; Mertes et al. 1993; Adams et al. 1994). From the results of the mixing model with the image spectral endmembers, the amount that each image endmember contributed to the composition of each pixel was computed as a fraction value. The fraction images were combined and the patterns of fraction combinations were interpreted to represent the different vegetation categories. Using additive color combinations as a guide, the final SMA map retains information on both the locations of distinct classes as well as the gradations among them.

A traditional approach to the assessment of image classification accuracy is the quantitative comparison of test site data to the classified values in terms of correct or incorrect. This assessment is typically expressed by calculating the mapping accuracy (MA). The MA is the percentage of the number of pixels classified correctly over the summation of the number of pixels classified correctly and classified incorrectly by both errors of commission and omission (Jensen 1986; Richards 1986):

$$\mathrm{MA} = \left(\left(\frac{\text{correct}}{(\text{correct} + \text{omission} + \text{commission})} \right) * 100 \right)$$

The data from the training and test sites were used to calculate the MA for the hard classification methods. In an attempt to evaluate the accuracy of the hard classifications within a descriptive context, a fuzzy sets approach was applied to the 93 field samples' observed vegetation class versus their assigned values from the hard classification methods. Fuzzy accuracy assessment "recognizes the inherent ambiguity, or fuzziness, of land-cover classes" (Stoms et al. 1998:835). This method replaces the traditional labels of correct or incorrect categories with "linguistic values" (Gopal and Woodcock 1994:183), such as, absolutely right, good answer, reasonable or acceptable, understandable but wrong, and absolutely wrong (Gopal and Woodcock 1994; Stoms et al. 1998).

Lastly, the total areal coverage for each vegetation community was calculated for the Bayesian and MGC vegetation maps. To calculate correctly the coverage area of a given land-cover class from the image data, it is necessary to account for the difference between the apparent pixel area (1141 m²) versus the true area as it varies with slope. Therefore, for each vegetation category total true area (TTA) was calculated according to:

$$\mathrm{TTA} = \left(\left(\frac{\text{width of pixel}}{\cos(\text{slope of pixel})} \right)^2 * (\text{number of pixels in class}) \right)$$

RESULTS

Field Data Results

The field data analysis using TWINSPAN resulted in eight major classes which were interpreted as representing the following communities: grassland, mixed coastal sage scrub, fennel-invaded, mixed coastal sage scrub/grassland, mixed oak woodland/island chaparral communities, island chaparral, Bishop pine forest, and oak woodland (Table 1). The classes labeled as 'mixed' appear to represent intergrades described by Junak et al. (1995). The dominant species associated with each vegetation community type are listed in Table 2.

The following discussion includes a description of each TWINSPAN class and the logic behind the labeling process. Class 000 was labeled grassland, as all 12 samples in the group were field plots of grassland. There were no indicator species for this class; however, the preferential species included: *Atriplex spp., Brassica nigra, Bromus mollis, Dichelostemma capitatum, Erodium spp., Lamarckia spp.,* and *Foeniculum vulgare*. Class 001 was labeled mixed coastal sage scrub/grassland, as the majority of the samples

Table 1. TWINSPAN groupings and fuzzy accuracy assessment values for field plots. Abbreviations for the vegetation type: CH = island chaparral, CS = coastal sage scrub, F = fennel-invaded, G = grassland, OW = oak woodland, and P = Bishop pine forest. The fuzzy accuracy assessment (FAA) values translate as follows: 1 = absolutely right, 2 = good answer, 3 = reasonable, 4 = understandable, but wrong, and 5 = absolutely wrong.

Plot Name	Bayesian Class	Bayesian FAA	MGC Class	MGC FAA	TWINSPAN Class	TWINSPAN Description
CH-01	CH	1	CH	1	101	island chaparral
CH-02	CH	1	CH	1	101	island chaparral
CH-03	P	4	CH	1	101	island chaparral
CH-04	CH	1	CH	1	101	island chaparral
CH-05	OW	2	CH	1	100	mixed oak woodland/chaparral
CH-06	OW	3	CH	1	101	island chaparral
CH-07	CH	1	P	4	101	island chaparral
CH-08	CH	1	CH	1	101	island chaparral
CH-09	OW	3	OW	3	101	island chaparral
CH-10	CH	1	P	5	100	mixed oak woodland/chaparral
CH-11	P	5	CH	1	100	mixed oak woodland/chaparral
CH-12	CS	5	G	5	100	mixed oak woodland/chaparral
CH-13	P	4	P	4	101	island chaparral
CH-14	CH	1	CH	1	100	mixed oak woodland/chaparral
CH-15	CH	1	CH	1	110	Bishop pine forest
CS-01	CS	1	OW	5	10	fennel-invaded
CS-02	G	2	G	2	11	mixed coastal sage
CS-03	CH	5	CS	1	10	fennel-invaded
CS-04	G	2	G	2	1	mixed coastal sage/grassland
CS-05	G	2	G	2	11	mixed coastal sage/grassland
CS-06	CH	5	F	3	1	mixed coastal sage/grassland
CS-07	OW	4	none	5	1	mixed coastal sage/grassland
CS-08	CS	1	OW	4	1	mixed coastal sage/grassland
CS-09	CS	1	G	2	10	fennel-invaded
CS-10	G	2	G	2	11	mixed coastal sage
CS-11	6	3	F	3	11	mixed coastal sage
CS-12	OW	4	F	3	11	mixed coastal sage
CS-13	G	2	G	2	11	mixed coastal sage
CS-14	CH	5	CH	5	11	mixed coastal sage
F-01	6	1	F	1	11	mixed coastal sage
F-02	6	1	G	2	10	fennel-invaded
F-03	6	1	F	1	10	fennel-invaded
F-04	none	5	G	1	10	fennel-invaded
F-05	CH	5	CH	5	10	fennel-invaded
F-06	none	5	CH	5	10	fennel-invaded
F-07	CH	5	F	1	10	fennel-invaded
F-08	G	2	G	2	10	fennel-invaded
F-09	CH	5	F	1	10	fennel-invaded
G-01	none	5	CS	2	0	grasslands
G-02	CS	2	OW	4	10	fennel-invaded
G-03	G	1	G	1	10	fennel-invaded
G-05	CH	5	CH	5	11	mixed coastal sage
G-06	OW	4	F	2	0	grasslands
G-07	P	4	P	4	0	grasslands

Table 1. Continued.

Plot Name	Bayesian Class	Bayesian FAA	MGC Class	MGC FAA	TWINSPAN Class	TWINSPAN Description
G-08	OW	4	CS	2	0	grasslands
G-09	G	1	F	2	0	grasslands
G-10	none	5	G	1	11	mixed coastal sage
G-11	CH	5	F	2	10	fennel-invaded
G-12	OW	2	CH	5	1	mixed coastal sage/grassland
G-13	G	1	G	1	0	grasslands
G-14	CS	2	OW	4	0	grasslands
G-15	CS	2	CS	2	0	grasslands
G-16	CH	5	CH	5	0	grasslands
G-17	CH	5	CS	2	1	mixed coastal sage/grassland
G-18	none	5	G	1	0	grasslands
G-19	G	1	G	1	0	grasslands
G-20	none	5	OW	4	0	grasslands
OW-01	CH	4	P	5	111	oak woodland
OW-02	OW	1	CH	4	111	oak woodland
OW-03	CH	2	OW	1	100	mixed oak woodland/chaparral
OW-04	6	4	OW	1	1	mixed coastal sage
OW-05	CH	2	CH	2	101	island chaparral
OW-06	none	5	OW	1	100	mixed oak woodland/chaparral
OW-07	CH	2	CH	2	100	mixed oak woodland/chaparral
OW-08	CH	2	CH	2	100	mixed oak woodland/chaparral
OW-09	G	4	G	4	10	fennel-invaded
OW-10	P	5	CH	5	10	fennel-invaded
OW-11	CH	3	CH	3	11	mixed coastal sage
OW-12	CH	3	CH	3	111	oak woodland
OW-13	CH	3	CH	3	111	oak woodland
OW-14	CS	4	OW	1	100	mixed oak woodland/chaparral
OW-15	CS	3	OW	1	1	mixed coastal sage
OW-16	CH	2	CH	2	100	mixed oak woodland/chaparral
OW-17	CS	5	OW	1	111	oak woodland
P-01	OW	5	OW	5	110	Bishop pine forest
P-02	CS	5	OW	5	110	Bishop pine forest
P-03	CH	3	CH	3	110	Bishop pine forest
P-04	CH	3	P	1	110	Bishop pine forest
P-05	CH	3	CH	3	110	Bishop pine forest
P-06	CH	3	CH	3	110	Bishop pine forest
P-07	CH	3	CH	3	110	Bishop pine forest
P-08	P	1	P	1	110	Bishop pine forest
P-09	none	5	OW	5	110	Bishop pine forest
P-10	none	5	OW	5	110	Bishop pine forest
P-11	OW	5	none	5	110	Bishop pine forest

were identified as coastal sage scrub in the field. This group of samples consists of four coastal sage scrub, three grassland, and two oak woodland plots. Class 001 had two indicator species that helped to distinguish it from Class 000: *Bromus rubens* and *Quercus agrifolia*. These two species are typically dominant species of grassland and oak woodlands plots, respectively (Junak et al. 1995). The preferential species included *Artemisia californica, Baccharis pilularis, Bromus rubens, Eriogonum arborescens, Gnaphalium spp., Lotus scoparius, Opuntia spp., Quercus agrifolia,* and *Rhus integrifolia*. Species that held no preference for either class were: *Avena spp., Bromus diandrus, Lolium spp., Nassella spp.,* and *Hordeum spp.* Class 010 was labeled fennel-invaded due to the overwhelming number of samples in the group that were identified in the field as fennel grasslands. This class consisted of eight

Table 2. Dominant species typically found in each community type and the related TWINSPAN code(s) for each community type.

Grassland 000 and 001	
Atriplex semibaccata	*Brassica nigra*
Avena spp.	*Bromus diandrus*
Baccharis glutinosa	*Bromus mollis*
Baccharis pilularis	*Lolium* spp.
Oak woodland 111 and 100	
Adenostoma fasciculatum	*Heteromeles arbutifolia*
Arctostaphylos spp.	*Quercus agrifolia*
Ceanothus arboreus	*Quercus dumosa*
Cercocarpus betuloides	
Island chaparral 101 and 100	
Adenostoma fasciculatum	*Heteromeles arbutifolia*
Arctostaphylos spp.	*Quercus agrifolia*
Ceanothus arboreus	*Quercus dumosa*
Ceanothus megacarpus	*Rhus integrifolia*
Cercocarpus betuloides	*Rhus ovata*
Eriogonum arborescens	
Coastal Sage Scrub 001 and 011	
Artemisia californica	*Eriogonum arborescens*
Avena spp.	*Eriogonum grande*
Baccharis pilularis	*Haplopappus squarrosus*
Bromus diandrus	*Lotus scoparius*
Bromus mollis	*Rhus integrifolia*
Encelia californica	*Salvia* spp.
Bishop Pine Forest 110	
Arctostaphylos spp.	*Quercus agrifolia*
Pinus muricata	
Fennel-invaded 010	
Artemisia californica	*Bromus mollis*
Avena spp.	*Eriogonum arborescens*
Baccharis pilularis	*Eriogonum grande*
Bromus diandrus	*Foeniculum vulgare*
Riparian not included in the analysis	
Avena spp.	*Eriogonum grande*
Baccharis glutinosa	*Hordeum californica*
Baccharis pilularis	*Mimulus* spp.
Eriogonum arborescens	*Salix* spp.
Woody Exotics not included in the analysis	
Eucalyptus globulus	

fennel grassland, three coastal sage scrub, three grassland, and two oak woodland plots. Along with *Foeniculum vulgare*, the indicator species for the class included *Eriogonum grande, Hordeum spp.,* and *Artemisia californica*, which are either typical dominant species of grassland or coastal sage scrub associations (Junak et al. 1995). The preferential species included: *Baccharis pilularis, Bromus mollis, Eriogonum grande, Hordeum spp.*, and *Marrubium vulgare*. Class 011 was labeled mixed coastal sage scrub, as the 11 samples were a mixture of seven coastal sage scrub, two grassland, one oak woodland, and one fennel grassland. The indicator species were *Artemisia californica* and *Eriogonum arborescens*, which Junak et al. (1995) identify as dominant species of coastal sage scrub. The preferential species included *Artemisia californica*, *Eriogonum arborescens, Quercus dumosa,* and *Rhus integrifolia*. Species that held no preference for either class were *Avena spp.* and *Bromus diandrus*. Class 100 was labeled mixed oak woodland/island chaparral, as the 11 plots were almost evenly split between the two classes (six oak woodland and five island chaparral). Two species of *Bromus* were indicator species: *Bromus mollis* and *Bromus diandrus*. The occurrence of these grasses is indicative of oak woodlands' understory; however, this is not true of typical chaparral plots, which tend to lack any understory (Holland and Keil 1990). Preferential species in this mixed oak woodland/chaparral class included: *Avena spp., Bromus diandrus, Bromus mollis, Ceanothus arboreus, Quercus agrifolia,* and *Rhus integrifolia*. Class 101 was labeled island chaparral, as the ten plots were dominated by nine plots identified as island chaparral in the field and with one oak woodland plot. This class did not have any indicator species; however, the preferential species included: *Ceanothus arborescens, Dodecatheon clevelandii, Eriogonum grande, Erodium spp., Hordeum spp., Pinus muricata,* and *Solanum spp.*. Species that held no preference for either class were: *Adenostoma fasciculatum, Arctostaphylos spp., Bromus rubens, Cercocarpus betuloides, Gnaphalium spp., Heteromeles arbutifolia, Lotus scoparius, Mimulus spp.,* and *Quercus dumosa*. Class 110 was labeled Bishop pine forest, as all 11 pine forest field plots fell into this group, along with one chaparral plot. *Pinus muricata* and *Mimulus spp.* were the indicator species while the preferential species included: *Arctostaphylos spp., Baccharis pilularis, Ceanothus arboreus, Comarostaphylis diversifolia, Lotus scoparius, Mimulus spp., Pinus muricata* and *Rhus integrifolia*. Class 111 was labeled oak woodland, as all samples were identified as oak woodland plots in the field. There were no indicator species; however, the preferential species included: *Bromus diandrus, Claytonia perfoliata, Encelia californica, Foeniculum vulgare, Marah macrocarpus, Marrubium vulgare,* and *Solanum spp*. The non-preferential species were *Heteromeles arborescens* and Quercus agrifolia.

Image Analysis Results

The eight vegetation classes from the TWINSPAN results were used as a guide in the analysis of the remote sensing data. The Bayesian (Figure 2a) and map-guided (Figure 2b) classification methodologies produced maps depicting the locations and extent of primary community types. Table 3 contains the error or confusion matrices for the classification results which were used to calculate the MA for the Bayesian and the map-guided classifications, respectively. The MA for the Bayesian method was 65.3% for training sites and 15.7% for test sites. The MA for the map-guided classification was 40.9% for training sites and 31.5% for test sites.

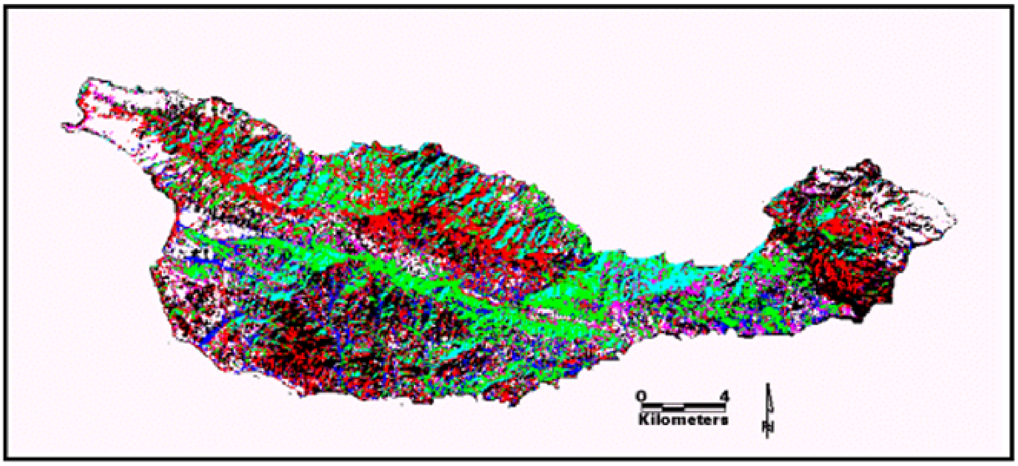

Figure 2a. Bayesian classification results (white = grassland, red = oak woodland, green = Island chaparral, blue = coastal sage scrub, cyan = Bishop pine forest, magenta = fennel-invaded).

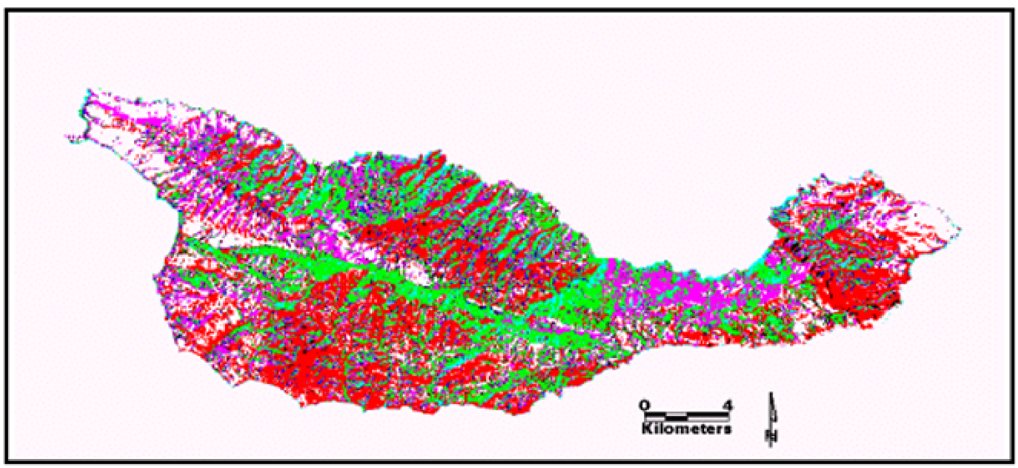

Figure 2b. Map-guided classification results (white = grassland, red = oak woodland, green = Island chaparral, blue = coastal sage scrub, cyan = Bishop pine forest, magenta = fennel-invaded).

In order to analyze the results of the hard classifications methods, 85 of the field samples were analyzed using the fuzzy accuracy assessment (FAA) method (Table 1). Forty-one percent of the plots were in the 'best' class category (i.e., 'absolutely right' or 'good answer'; FAA values 1 and 2, respectively) for the Bayesian method compared to 56% for MGC. These plots were completely consistent with the results from the image classification schemes and the TWINSPAN analysis. For example, an island chaparral plot (CH-05) was classified as oak woodland in the Bayesian method and in the TWINSPAN mixed oak woodland/chaparral class; thus, it was assigned a FAA value of 2 or 'good answer'. Another 14% were categorized as 'reasonable' (FAA value 3) values for the Bayesian method compared to 13% for the MGC method. Examples for this category are two Bishop pine forest plots (P-06 and P-07) that were classified as island chaparral by both methods; however, field data document the presence of dominant species which frequently occur in both the island chaparral and Bishop pine forest communities (i.e., *Arctostaphylos spp.* and *Quercus agrifolia*). Another example is coastal sage scrub plot CS-11 which was classified as fennel-invaded by both classifiers and as mixed coastal sage/grassland by the TWINSPAN analysis; thus, the label of reasonable was assigned due to the degree of mixing these two vegetation communities. Eleven plots (13%) were labeled 'understandable, but wrong' (FAA value 4) for the Bayesian method and 9 plots (11%) for MGC. Plot OW-14 was assigned a FAA value of 4, as it was classified as a mixed oak woodland/chaparral plot by TWINSPAN and as coastal sage scrub by the Bayesian method. Although some oak woodland plots were analyzed by TWINSPAN to 'mix' with coastal sage scrub, the species within this plot were not indicative of the mixed coastal sage class. Hence, the Bayesian classification of coastal sage scrub for this plot was understandable, but not correct. Twenty-six plots (34%), nine (11%) of which were unable to be classified in the Bayesian method, were labeled 'absolutely wrong,' representing values completely inconsistent with field observations. Within the same category there were seventeen plots (20%) , two (2%) of which were unclassified in the map-guided classification. Thus, 54% of the field plots were at least partially consistent (i.e., 'absolutely right', 'good answer', or 'reasonable') for the Bayesian classification method and 69% for MGC.

Even though the accuracies as assessed by both classical and fuzzy methods appear to be low, it is of interest to compare the total true area covered by each vegetation class of the two hard classification methods. Of the reported total area for Santa Cruz Island (249 km²), the Bayesian classification yielded the following percent cover results: grassland = 16.7% (41.7 km²), oak woodland = 23.9% (59.4 km²), island chaparral = 21.8% (54.2 km²), coastal sage scrub = 7.8% (19.4 km²), Bishop pine forest = 12.0% (29.8 km²), and fennel-invaded = 5.6% (14.0 km²). In comparison, the MGC yielded the following percent cover results: grassland = 16.7% (41.6 km²), oak woodland = 18.2% (45.4 km²), island chaparral = 24.3% (60.5 km²), coastal sage scrub

Table 3. Confusion matrices for Bayesian and map-guided classifications.

	Bayesian	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total	Correct %	Omission %	Commission %	MA %
	Grassland	**266.0**	7.0	0.0	4.0	0.0	0.0	277.0	96.0	4.0	13.7	84.4
	Oak Woodland	8.0	**27.0**	26.0	8.0	3.0	3.0	84.0	32.1	67.9	48.8	21.6
Training	Island Chaparral	2.0	25.0	**293.0**	8.0	13.0	13.0	369.0	79.4	20.6	17.3	67.7
Sites	Coastal Sage Scrub	13.0	6.0	4.0	**73.0**	0.0	1.0	103.0	70.9	29.1	22.3	57.9
	Bishop Pine Forest	0.0	2.0	30.0	0.0	**142.0**	2.0	180.0	78.9	21.1	8.9	72.4
	Fennel-invaded	15.0	1.0	4.0	3.0	0.0	**52.0**	92.0	56.5	43.5	20.7	46.8
									77.2	**22.8**	**18.2**	**65.3**

	Bayesian	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total	Correct %	Omission %	Commission %	MA %
	Grassland	**29.0**	16.0	0.0	0.0	1.0	9.0	96.0	30.2	69.8	35.4	84.4
	Oak Woodland	2.0	**12.0**	74.0	0.0	13.0	7.0	112.0	10.7	89.3	42.9	21.6
Test	Island Chaparral	0.0	2.0	**129.0**	1.0	66.0	0.0	201.0	64.2	35.8	160.2	67.7
Sites	Coastal Sage Scrub	27.0	27.0	6.0	**36.0**	0.0	2.0	128.0	28.1	71.9	2.3	57.9
	Bishop Pine Forest	0.0	1.0	205.0	2.0	**3.0**	0.0	220.0	1.4	98.6	67.3	72.4
	Fennel-invaded	5.0	2.0	37.0	0.0	68.0	**26.0**	169.0	15.4	84.6	10.7	46.8
									25.4	**74.6**	**61.9**	**15.7**

	Map-guided	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total	Correct %	Omission %	Commission %	MA %
	Grassland	**245.0**	15.0	1.0	2.0	0.0	14.0	277.0	88.4	20.2	11.6	73.6
	Oak Woodland	8.0	**14.0**	23.0	17.0	8.0	10.0	84.0	16.7	122.6	83.3	7.5
Training	Island Chaparral	6.0	13.0	**263.0**	4.0	50.0	17.0	369.0	71.3	33.1	28.7	53.6
Sites	Coastal Sage Scrub	18.0	73.0	3.0	**1.0**	0.0	5.0	103.0	1.0	23.3	99.0	0.8
	Bishop Pine Forest	0.0	1.0	90.0	1.0	**68.0**	20.0	180.0	37.8	39.4	62.2	27.1
	Fennel-invaded	24.0	1.0	5.0	0.0	13.0	**42.0**	92.0	45.7	71.7	54.3	26.6
									57.3	**40.0**	**42.7**	**40.9**

	Map-guided	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total	Correct %	Omission %	Commission %	MA %
	Grassland	**29.0**	16.0	0.0	0.0	1.0	9.0	96.0	72.9	44.8	25.0	51.1
	Oak Woodland	2.0	**12.0**	74.0	0.0	13.0	7.0	112.0	1.8	71.4	92.0	1.1
Test	Island Chaparral	0.0	2.0	**129.0**	1.0	66.0	0.0	201.0	77.6	118.4	20.4	35.9
Sites	Coastal Sage Scrub	27.0	27.0	6.0	**36.0**	0.0	2.0	128.0	3.1	8.6	89.8	3.1
	Bishop Pine Forest	0.0	1.0	205.0	2.0	**3.0**	0.0	220.0	35.9	20.5	59.5	31.0
	Fennel-invaded	5.0	2.0	37.0	0.0	68.0	**26.0**	169.0	68.6	28.4	30.2	54.0
									46.1	**74.6**	**50.2**	**31.5**

= 4.5% (11.2 km²), Bishop pine forest = 5.1% (12.7 km²), and fennel-invaded = 15.1% (37.5 km²).

Due to the low accuracies and inconsistencies between the Bayesian classification and MGC and to portray the TWINSPAN results spatially, spectral mixture analysis was used as an alternative method to map the intergrading of the communities. Figure 3 is a ternary plot of a field sample for each TWINSPAN class within the context of the mixing model fractions. Interpretation of the ternary plot requires consideration of how the components (soil, vegetation, and shade) would physically mix in the landscape. Although island chaparral is more open compared to the mainland communities (Holland and Keil 1990; Junak et al. 1995), for the sake of explanation we refer to the characteristics of typical chaparral. Chaparral has a dense, complex crown resulting in a high level of self shading while the dense canopy cover prevents an aerial view of soil. The reasonable fraction combination for typical chaparral would be 0.0 soil, 0.5 vegetation, and 0.5 shade. In the case of island chaparral, the fraction combination was approximately 0.1 soil, 0.5 vegetation, and 0.4 shade. In contrast, during the fall season the grasslands are dominated by senesced or dry grass and characteristically have effectively no self-shading. The spectral signature of senesced or non-photosynthetic vegetation is similar to barren areas (e.g., Jensen 1986: 159, Figure 7-31). Therefore, the fraction combination for the grassland plot is approximately 1.0 soil, 0.0 vegetation, and 0.0 shade. To aid in the interpretation of both Figure 3 and the vegetation map shown in Figure 4, the mixing of the fractions can also be interpreted with respect to the mixing of additive primary colors (i.e., red = 100% bright soil, green = 100% healthy vegetation, and blue = 100% deep shade). For example, the dark green-blue color (mixture of vegetation and shade) representing an island chaparral plot is in sharp contrast to the red color (100% soil) of the grasslands and barren areas.

DISCUSSION AND CONCLUSIONS

Through the combination of field and remote sensing data of Santa Cruz Island, vegetation maps that emphasize both distinct vegetation communities and gradations among them were produced. TWINSPAN (two-way indicator species analysis) was used to produce a classification of 93 field samples yielding eight major classes that are interpreted to represent: grassland, coastal sage scrub, fennel-invaded, mixed coastal sage scrub/grassland, mixed oak woodland/ island chaparral, island chaparral, Bishop pine forest, and oak woodland. These field data were used to assess classification accuracy for maps depicting locations and extent of the primary community types produced from a Bayesian and an iterative clustering classifier. Spectral mixture analysis was used to map the gradations within and between the vegetation communities on the island.

Results from both hard classification approaches were similar to the 89% cover of the dominant communities (oak-woodland, grassland, chaparral, and coastal sage scrub) reported by Minnich (1980). Combining the areal extent of the grassland, coastal sage scrub, fennel-invaded, coastal sage scrub, oak woodland, island chaparral and Bishop pine forest communities, the Bayesian classification yielded 88% cover and the map-guided classification yielded 84% cover. The low accuracies and inconsistent areal extents of the Bayesian and map-guided classification methods are not surprising in that a hard classification algorithm is based on classical set theory requiring pixels to be assigned to one or another class and these assignments are typically evaluated on a correct/incorrect basis. In addition, remote sensing data is not typically homogenous and the lack of distinct boundaries among vegetation communities only increases the difficulty of accurately mapping land-cover.

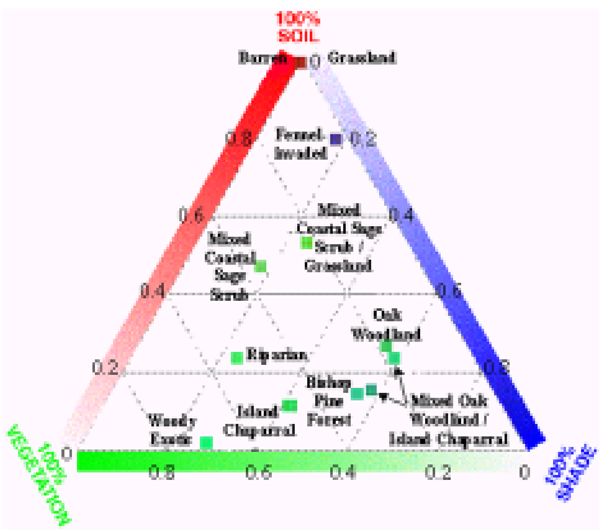

Figure 3. Ternary plot of fraction images from spectral mixture analysis.

It is not entirely surprising that a fuzzy accuracy assessment of the Bayesian and map-guided methods yielded only slightly improved results. However, the spectral mixture analysis, with the assumption of heterogeneous data, proves to be much more conducive to mapping naturally occurring phenomena. In terms of practical use of the SMA map in the field, an understanding of the premise of the method must be attained.

The following is a discussion of the eight TWINSPAN classes with respect to the SMA results. The TWINSPAN and SMA results were generally analogous for the grassland, fennel-invaded and coastal sage scrub field data. In fact, in the case of the coastal sage scrub classes, the SMA results proved to be more useful than those of TWINSPAN. Beginning with the grassland class, as one would expect from image data collected during the fall season, the grassland plot had little or no shade and was absent of healthy vegetation, and therefore yields a reddish-orange color on the SMA map. In terms of the TWINSPAN analysis, this is a relatively distinctive class from the other vegetation communities aside from barren areas. In the case of the fennel-invaded sample plot, the purple-bluish color from the SMA map corresponds well with the TWINSPAN results as the class has a distinct fraction combination (approximately 0.8 soil, 0.0 vegetation, 0.2 shade) from the other classes. Fennel (*Foeniculum vulgare*) flowers during the months of February through June and is a perennial herb measuring 1 to 2 m tall (Junak et al. 1995:80) resulting in a lack of healthy vegetation in fall and a modest degree of self-shading. The coastal sage scrub and mixed coastal sage scrub/grassland classes are yellowish-green colors on the SMA map. As yellow results from the additive mixture of red and green (Paine 1981:228, Plate 1), this yellowish-green color indicates a

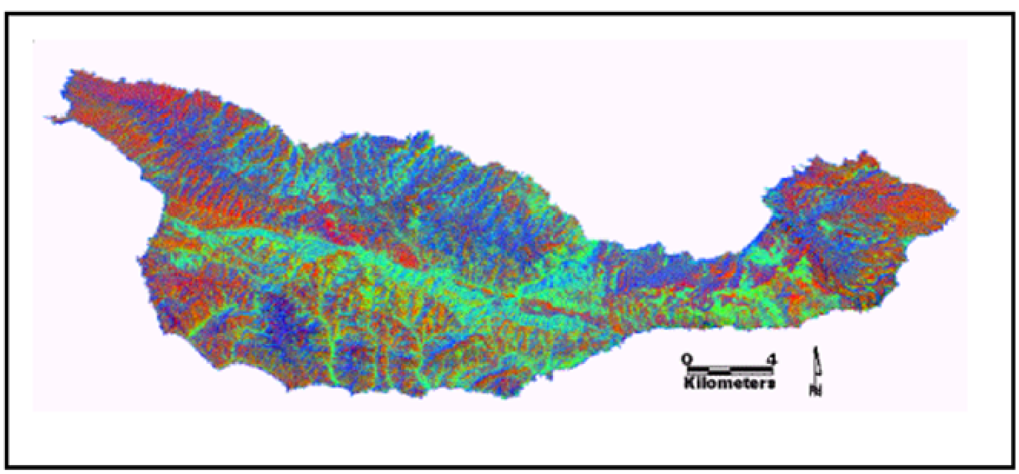

Figure 4. Color composite image of the soil (red), vegetation (green) and shade (blue) fraction images from the spectral mixture analysis.

higher fraction of healthy vegetation (0.3) along with the high fraction of soil (0.5) present in the grassland sample and some shade (0.2). Perhaps due to the fact that the TWINSPAN analysis is limited to the input data of presence/absence and relative dominance of species within the field plots, samples labeled as coastal sage scrub in the field were not easily distinguished from the grassland and fennel-invaded plots. However, the ternary plot illustrates the ability to identify the differences between grassland, fennel-invaded and coastal sage scrub communities through SMA.

As indicated by the mixed results from the TWINSPAN analysis of the oak woodland, island chaparral and Bishop pine forest field data, the SMA results were more subtle than for the grassland, fennel-invaded and coastal sage scrub classes. Although the fraction combinations for the woody classes are relatively distinguishable, their colors from the SMA map are similar, which creates difficulty in visual interpretation. In general, the variations in the amount of shade and vegetation for each of the classes coincide with field observations. For example, the fraction combination of 0.3 soil, 0.2 vegetation and 0.5 shade for the oak woodland class is consistent with a community which contains open space (soil), sparse vegetation and typically occurring on "north-facing slopes, [in] ravines, and [in] narrow canyons" (Junak et al. 1995:20) which explains the high fraction of shade. In the case of the island chaparral, the fraction combination of 0.1 soil, 0.5 vegetation and 0.4 shade is consistent with a more open woodland than mainland chaparral (Holland and Keil 1990) occurring on north-facing slopes. As the Bishop pine forest populations are recovering from the effects of grazing of feral sheep, one of the three populations on the island (Pelican Bay) is described as "primarily open, with scattered groves of mature pine" (Wehtje 1994:331) and another (Christy Pines) has a rich understory consisting of species such as *Adenostoma fasciculatum*, *Arctostaphylos insularis*, *Ceanothus arboreus*, which are dominants of the island chaparral community. Thus, the fraction combination of 0.15 soil, 0.3 vegetation and 0.55 shade can be construed as consistent with the Christy Pines population, but not as much with the more open, Pelican Bay population. Hence, we see the mixtures of the communities in the TWINSPAN results and the similarities in their colors on the SMA map.

In conclusion, although the SMA map does not yield measurements of areal extent for each vegetation community on the island, it does serve as a guide to the type of land-cover likely to be found at any location. Through the analysis of combinations of proportions of soil, vegetation and shade pixel by pixel, the distinct and subtle differences amongst and between the various vegetation communities are illuminated.

ACKNOWLEDGMENTS

Funding for this research was provided by the University of California Natural Reserve System and a California Space Grant fellowship to M. L. Cobb. For their valuable support and guidance, we thank Lyndal Laughrin and the staff of the University of California Natural Reserve System, Steve Junak of the Santa Barbara Botanic Garden, and Rob Klinger of The Nature Conservancy. Lastly, our sincere thanks for the tireless encouragement and assistance of Kevin Crooks.

LITERATURE CITED

Adams, J. B., D. E., Sabol, V. Kapos, R. F. Almeida, D. A. Roberts, M. O. Smith and A. R. Gillespie. 1994. Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. Remote Sensing of Environment 52:137-154.

Beatty, S. W. and D. L. Licari. 1992. Invasion of fennel (*Foeniculum vulgare*) into shrub communities on Santa Cruz Island, CA. Madroño 39:54-66.

Brenton, B. and R. Klinger. 1994. Modeling the expansion and control of fennel (*Foeniculum vulgare*) on the Channel Islands. Pages 497-504 *in* Halvorson, W. and G. Maender (eds.), The Fourth California Islands Symposium: Update on the Status of Resources. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Brumbaugh, R. W. 1980. Recent geomorphic and vegetation dynamics on Santa Cruz Island, California. Pages 139-158 *in* Power, D. M. (ed.), The California Islands: Proceedings of a Multidisciplinary Symposium. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Cobb, J. L. 1999. Mapping gradients on Santa Cruz Island, California from remotely sensed and ground sample data. Masters Thesis. University of California, Santa Barbara, CA.

Frew, J. E., Jr. 1990. The Image Processing Workbench. Ph.D. dissertation. University of California, Santa Barbara, CA.

Gopal, S. and C. Woodcock. 1994. Theory and methods for accuracy assessment of thematic maps using fuzzy sets. Photogrammetric Engineering & Remote Sensing 60:181-188.

Hickman, J. C. (Ed.). 1993. The Jepson Manual: Higher Plants of California. University of California Press. Berkeley and Los Angeles, CA.

Hill, M. O. 1979. TWINSPAN, a FORTRAN Program for Arranging Multivariate Data in Ordered Two-way Table by Classification of Individuals and Attributes. Cornell University. Ithaca, NY.

Hobbs, E. 1980. Effects of grazing on the northern populations of *Pinus muricata* on Santa Cruz Island, California. Pages 159-166 *in* Power, D. M. (ed.), The California Islands: Proceedings of a Multidisciplinary Symposium. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Holland, V. L. and D. J. Keil. 1990. California Vegetation. California Polytechnic State University, San Luis Obispo, CA.

Jensen, J. R. 1986. Introductory Digital Image Processing: A Remote Sensing Perspective. Prentice-Hall. NJ.

Jensen, J. R. 1996. Introductory Digital Image Processing: A Remote Sensing Perspective, 2nd Edition. Prentice-Hall. NJ.

Jones, J. A., S. A. Junak and R. J. Paul. 1993. Progress in mapping vegetation on Santa Cruz Island and preliminary analysis of relationships with environmental factors. Pages 97-104 *in* Hochberg, F. G. (ed.), Third California Islands Symposium: Recent Advances in California Islands Research. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Junak, S., T. Ayers, R. Scott, D. Wilken and D. Young. 1995. A Flora of Santa Cruz Island. Santa Barbara Botanic Garden and California Native Plant Society. Santa Barbara, CA.

Klinger, R., P. Schuyler and J. Sterner. 1994. Vegetation response to the removal of feral sheep from Santa Cruz Island. Pages 341-350 *in* Halvorson, W. and G. Maender (eds.), The Fourth California Islands Symposium: Update on the Status of Resources. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Mertes, L. A. K., M. O. Smith and J. B. Adams. 1993. Estimating suspended sediment concentrations in surface waters of the Amazon River Wetlands from Landsat Images. Remote Sensing of Environment 43:281-301.

Mertes, L. A. K., D. L. Daniel, J. M. Melack, B. Nelson, L. A. Martinelli and B. R. Forsberg. 1995. Spatial patterns of hydrology, geomorphology, and vegetation on the floodplain of the Amazon River in Brazil. Geomorphology 13: 215-232.

Minnich, R. A. 1980. Vegetation of Santa Cruz and Santa Catalina Islands, Pages 123-138 *in* Power, D. M. (ed.), The California Islands: proceedings of a Multidisciplinary Symposium. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Paine, David P. 1981. Aerial Photography and Image Interpretation for Resource Management. John Wiley and Sons, NY.

Philbrick, R. N. and J. R. Haller. 1977. The southern California Islands. Pages 893-906 *in* Barbour, M. G. and J. Major (ed.), Terrestrial Vegetation of California. John Wiley and Sons, NY.

Raven, P. H. 1967. The floristics of the California Islands. Pages 57-67 *in* Philbrick, R. N. (ed.), Proceedings of the Symposium on the Biology of the California Islands. Santa Barbara Botanic Garden, Santa Barbara, CA.

Richards, J. A. 1986. Remote Sensing Digital Image Analysis. Springer-Verlag, Berlin.

Schuyler, P. 1993. Control of feral sheep on Santa Cruz Island. Pages 443-452 *in* Hochberg, F. G. (ed.), Third California Islands Symposium: Recent Advances in California Islands Research. Santa Barbara Museum of Natural History, Santa Barbara, CA.

Smith, M. O., S. L. Ustin, J. B. Adams and A. R. Gillespie. 1990. Vegetation in deserts: I. A regional measure of abundance from multispectral images. Remote Sensing of Environment 31:1-26.

Stoms, D. M., M. J. Bueno, F. W. Davis, K. M. Cassidy, K. L. Driese and J. S. Kagan. 1998. Map-guided classification of regional land-cover with multi-temporal AVHRR data. Photogrammetric Engineering & Remote Sensing 64: 831-838.

Van Vuren, D. 1981. The feral sheep on Santa Cruz Island: Status, impacts, and management recommendations. Report to The Nature Conservancy, Arlington, VA.

Van Vuren, D. and B. E. Coblentz. 1987. Some ecological effects of feral sheep on Santa Cruz Island, California, USA. Biological Conservation 41:253-268.

Wehtje, W. 1994. Response of a bishop pine (*Pinus muricata*) population to removal of feral sheep on Santa Cruz Island, California. Pages 331-340 *in* Halvorson, W. and G. Maender (eds.), The Fourth California Islands Symposium: Update on the Status of Resources. Santa Barbara Museum of Natural History, Santa Barbara, CA.