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Land-cover change monitoring with classification trees using Landsat TM and ancillary data

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Land-Cover Change Monitoring with Classification Trees Using Landsat TM and Ancillary Data

John Rogan, Jennifer Miller, Doug Stow, Janet Franklin, Lisa Levien, and Chris Fischer

Abstract
We monitored land-cover change in San Diego County (1990–1996) using multitemporal Landsat TM data. Change vectors of Kauth Thomas features were combined with stable multitemporal Kauth Thomas features and a suite of ancillary variables within a classification tree classifier. A combination of aerial photointerpretation and field measurements yielded training and validation data. Maps of land-cover change were generated for three hierarchical levels of change classification of increasing detail: change vs. no-change; four classes representing broad increase and decrease classes; and nine classes distinguishing increases or decreases in tree canopy cover, shrub cover, and urban change. The multitemporal Kauth Thomas (both stable and change features representing brightness, greenness, and wetness) provided information for magnitude and direction of land-cover change. Overall accuracies of the land-cover change maps were high (72 to 92 percent). Ancillary variables representing elevation, fire history, and slope were most significant in mapping the most complicated level of land-cover change, contributing 15 percent to overall accuracy. Classification trees have not previously been used operationally with remotely sensed and ancillary data to map land-cover change at this level of thematic detail.

Introduction
Growing concern over the status of global and regional forest resources has led to the implementation of numerous multi-agency projects to establish long term operational systems for land-cover monitoring (Levien *et al.*, 1999; Hansen *et al.*, 2000). Land-cover change (i.e., location, extent, and cause) is identified as the most important and challenging research theme for many of the programs recently initiated by monitoring agencies (Gutman, 2002; Muchoney and Strahler, 2002). A key element in successfully addressing this theme is the involvement of regional management authorities (e.g., U.S. Geological Survey and U.S. Forest Service) to provide the necessary link between local/municipal and national/international land-cover monitoring projects (Loveland and Shaw, 1996; Ahern *et al.*, 1998). Increasingly, these projects are using complex mapping procedures that require the integration of remotely sensed data, state-of-the-art image processing approaches, ancillary spatial data, and georeferenced field validation data within a geographic information system (Gao, 2002).

To address the growing threat to forest and shrubland sustainability caused by rapid and widespread land-cover change in California, the U.S. Forest Service and the California Department of Forestry and Fire Protection are collaborating in the statewide Land Cover Mapping and Monitoring Program (LCMMP) to improve the quality and capability of monitoring data, and to minimize costs for statewide land-cover monitoring (Levien *et al.*, 2002). Changes in forest, shrub, and grassland cover types are the primary focus in this program, but changes in urban/suburban areas are also mapped. These change maps are required for regional interagency land-management planning, fire and timber management, and species habitat assessment, and for updating existing land-cover maps (Levien *et al.*, 1999).

The LCMMP requires an examination and comparison of the variety of remote sensing methods available, such as scene normalization, change feature extraction, classification, and accuracy assessment, in order to meet operational and standardization needs (Rogan *et al.*, 2001). Faced with this task, the monitoring program welcomed a research alliance with San Diego State University as a way to improve and automate change-monitoring procedures. Specifically, this involved testing techniques that minimize time-consuming human interpretation and maximize automated procedures for large-area retrospective monitoring of land-cover change. Thus, a classification tree approach was chosen for this task, given promising results derived from two previous studies conducted by the research team (Levien *et al.*, 1999; Rogan *et al.*, 2002a). These studies demonstrated the potential of classification tree algorithms to map land-cover change, in two relatively small study sites, based on acceptable change-map accuracy and interpretability of tree-structured classification rules. Therefore, the purpose of this paper is to use the large-area context of the LCMMP

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as a case study to examine the application of classification trees to multitemporal Landsat TM and ancillary data inputs in order to map three increasingly detailed thematic levels of land-cover change in southern California.

Remote Sensing of Land-Cover Change

Land-cover change results in alterations (increase or decrease) in the abundance, composition, and condition of remote sensing scene elements over various spatial and temporal scales (Stow *et al.*, 1990; Stow, 1995). To adequately assess these alterations, two specific techniques are used: post-classification comparison and pre-classification enhancement (Abuelgasim *et al.*, 1999). Post-classification comparison examines changes over time between suites of independently characterized thematic land-cover categories (e.g., forest, grassland, agriculture), advantageous when using different sensors, with different spatial and spectral resolutions, between image dates (Singh, 1989). Further, post-classification comparison permits the use of data with inter-date phenological differences and provides information on the types of land-cover transformations that have occurred (i.e., what it was and what it became). However, this approach has significant limitations because the comparison of classifications for different dates does not allow the detection of subtle, low-magnitude modifications within land-cover categories (Stow *et al.*, 1980). For example, a low intensity wildfire, or an onset of pest infestation may alter the condition and/or composition of a forest type, but not its overall abundance, thus preventing identification of temporal changes within land-cover change categories. Further, the propagation of error through post-classification comparison approaches has been documented (Stow *et al.*, 1980; Macleod and Congalton, 1998).

Land-cover modifications in condition and composition of vegetative cover are important aspects of change that need to be considered in current research (Skole and Tucker, 1993; Radeloff *et al.*, 2000). Indeed, land-cover modifications are currently considered more prevalent than land-cover type conversions (Lambin, 1998). Pre-classification enhancement approaches to land-cover change involve enhancing alterations in the concentration of some landscape attribute that can be continuously measured (e.g., spectral vegetation index) (Coppin *et al.*, 2001). Various methods have been developed to compare multitemporal signatures and are reviewed in Singh (1989) and Jensen (1996). Pre-classification enhancement may allow the detection of subtle changes in vegetative abundance, composition, and condition, depending on the task and spatial scale of the project. A pre-classification enhancement, therefore, appears more suitable than post-classification comparison for land-cover monitoring programs that require detailed regional estimates of forest-cover change and the associated causes of that change.

A standard overall accuracy for land-cover mapping studies has been set between 85 percent (Anderson *et al.*, 1976) and 90 percent (Lins and Kleckner, 1996). However, no standard currently exists for change-monitoring studies. A review of the change-detection literature, where map accuracy was reported (35 articles) revealed that the mean number of classes resolved in change-monitoring studies is seven. The mean overall map accuracy of these studies is approximately 76 percent. In light of these findings, we set a target overall accuracy goal of 80 percent for our land-cover change maps.

Use of Ancillary Data in Remote Sensing Studies

Traditional methods of change detection and identification have typically relied on image-derived variables, but evidence from unitemporal land-cover mapping studies indicates that including non-spectral variables may help to improve discrimination between land-cover change categories (Rogan *et al.*, 2002b). Digital ancillary (non-remote sensing) data sets are incorporated into multivariate classification of remotely sensed data because spectral-radiometric data cannot always discriminate land-cover classes in their entirety (Franklin, 1995). Therefore, ancillary data have been included in classifications to improve discrimination of classes of interest, which typically results in higher overall map accuracies (5 to 10 percent overall) than those produced using spectral-radiometric data alone (Trietz and Howarth, 2000). Ancillary data are incorporated in land-cover mapping in three ways: (1) pre-classification image stratification (Hutchinson, 1982; Vogelmann *et al.*, 1998), (2) post-classification image stratification (Hutchinson, 1982), and (3) direct inclusion in the classification process (Strahler *et al.*, 1981; Ricchetti, 2000). Typically, the use of ancillary data is dependent on the classification technique used (Brown *et al.*, 1993). Classification tree algorithms, used in this study, permit the direct inclusion of ancillary variables in land-cover change classification, which has not, to our knowledge, been attempted in previous change-detection studies.

Given the added data volume and increased complexity of the classification measurement space when non-spectral variables are included, researchers have employed non-parametric machine-learning classifiers, including classification trees (Lawrence and Wright, 2001) and artificial neural networks (Liu *et al.*, 2001). Machine learning is a branch of artificial intelligence that investigates how machines can be trained to recognize patterns from a given set of training examples (Malerba *et al.*, 2001). Machine learning classifiers have been used effectively in a variety of unitemporal land-cover mapping studies (Friedl and Brodley, 1997; Huang and Jensen, 1997; Friedl *et al.*, 1999; Borak *et al.*, 2000; DeFries and Chan, 2000). In almost all cases, these classifiers have proven superior to conventional classifiers (e.g., maximum likelihood), often recording overall accuracy improvements of 10 to 20 percent.

The success of machine learning classifiers in resolving land-cover and land-cover change classes from often complex measurement spaces can be attributed to several factors: (1) due to their non-parametric natures, they deal well with multi-modal, noisy, and missing data; (2) they can readily accommodate both categorical and continuous ancillary data; (3) they allow users to investigate the relative importance of input layers in contribution to classification accuracy; and (4) they are flexible and can be adapted to improve performance for particular problems.

Classification trees are a particular type of machine learning algorithm, which reveal information on the classification structure (DeFries and Chan, 2000). The classification tree approach is appealing because of the advantages mentioned above, but can have notable drawbacks. For example, tree models are adversely affected by outliers, which can cause very different tree results when they are included (Breiman *et al.*, 1984; Miller and Franklin, 2002). Other limitations are discussed later in the section on Classification and Evaluation. Machine learning classifiers have only recently been applied to land-cover change studies (Gopal and Woodcock, 1996; Roberts *et al.*, 1998; Levien *et al.*, 1999; Abuelgasim *et al.*, 1999: Rogan *et al.*, 2002a). We applied a classification tree approach to map land cover changes in this study.

Methods

Study Area

Western San Diego County was chosen as the study area (Figure 1). Desert areas were excluded from this analysis,

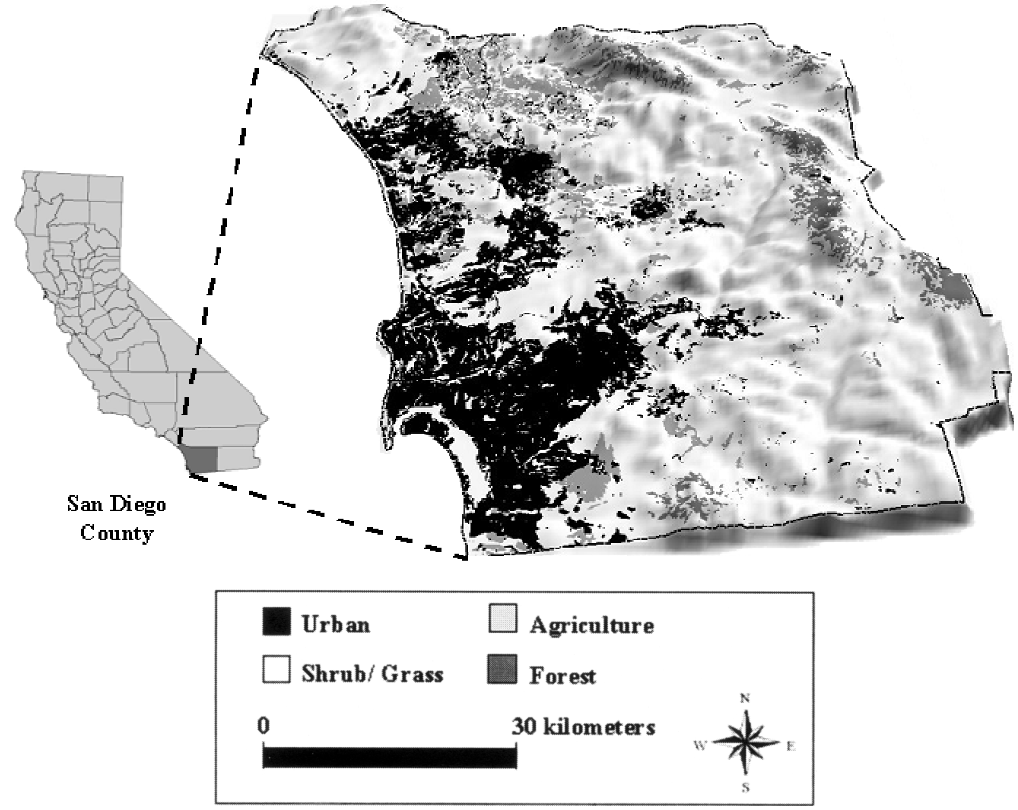

Figure 1. Maps of study area location, San Diego County, southern California. Generalized land-cover/land-use classes are portrayed on a shaded relief map.

because we were only interested in the area encompassed by California Coastal Chaparral Forest Shrub and California Coastal Range Open Woodland-Shrub-Coniferous Forest-Meadow Provinces (Stephenson and Calcarone, 1999). The study area is composed of a variety of land-cover types, including shrub-grassland (60 percent), conifer and hardwood forest (12 percent), agriculture (6 percent), and urban (18 percent). The area is currently undergoing accelerated and extensive land-cover change due to natural and anthropogenic disturbance. These spatially and temporally diverse disturbances result in land-cover changes ranging from dramatic (e.g., wildfire burn scars, land development) to very subtle (e.g., conifer pest infestation, post-fire regeneration).

Wildfire is the most prevalent ecological disturbance agent in the region (Stephenson and Calcarone, 1999). Indeed, in the last decade, more than 2700 fires burned at least 1100 km^2 (Rogan *et al.*, 2002b). Post-fire regeneration in shrub/grassland areas has also been a frequent cause of land-cover change (Riano *et al.*, 2002). Pest infestation is another, though less dramatic, disturbance agent. The fir engraver (*Scolytus ventralis*) was a factor in low level mortality on approximately 80 hectares of white fir (*Abies concolor*) in the mid-1990s. Outbreaks of fir engraver typically occur following periods of tree stress due to drought, as was the case in San Diego County at the time investigated in this study (Ferrell and Otrosina, 1996). Furthermore, non-metropolitan expansion of human settlements has increased dramatically in the last decade due to regional suburbanization, causing extensive alteration in land cover (e.g., grading, road and building construction) (Scott and Soja, 1998).

Satellite and Ancillary Data

Two Landsat TM 5 images acquired on 24 June 1990 and 08 June 1996 were geometrically registered to the UTM WGS84 projection with 41 ground control points (GCPs) at major road intersections. GCPs dispersed throughout the entire scene yielded less than a 0.45-pixel root-mean-square error. A nearest-neighbor algorithm was used to resample the images to a 30-m output grid. The two images were normalized for atmospherical illumination differences independently and converted to reflectance values using a dark-object subtraction approach described by Chavez (1989). Recent change-detection studies have found this method adequate for correction of atmospheric effects (Pax-Lenney *et al.*, 2001; Song *et al.*, 2001).

The Landsat TM Multitemporal Kauth Thomas (MKT) linear transformation was selected to spectrally enhance the radiometrically corrected data prior to classification. The MKT produces six features of interest: three features that represent change in brightness, change in greenness, and change in wetness, and three features that represent mean or stable brightness, greenness, and wetness, between image dates (Collins and Woodcock, 1996). The MKT approach is similar to multitemporal principal components analysis (PCA) in that major components are termed *stable components* and minor components are termed *change components*. However, recent studies have demonstrated the superiority of the MKT over multitemporal PCA (Rogan and Yool, 2001) due to the biophysically based features produced by the MKT versus the scene-dependent components derived by PCA. To date, few studies have examined the utility of stable MKT features in a change-detection study (Seto *et al.*, 2002).

Furthermore, Rogan *et al.* (2002a) compared the easily implemented MKT to the more complex process of multitemporal spectral mixture analysis and found that both were statistically comparable in emphasizing changes in forest and shrub cover in southern California.

Ancillary data layers were chosen based on our knowledge of land-cover changes in California (Rogan *et al.*, 2002b). We hypothesize that *elevation* is useful in discriminating land-cover change classes that occur in lowland coastal areas versus forested mountain ranges (e.g., urban change in coastal cities versus wildfire in montane forest). *Slope* is useful in reducing the effects of terrain shadowing on satellite imagery covering steep montane areas. *Aspect* is useful in identifying areas susceptible to severe wildfires (e.g., equator-facing aspects in Mediterranean ecosystems, such as San Diego County, are typically drier than others and are fire-prone). *Fire* can aid in the distinction between *change* and *nochange* areas. Finally, a *Vegetation*-type layer can help in the discrimination of change in vegetation type-specific change categories, where the specificity of land-cover change class is a defining characteristic (e.g., Shrub/grass decrease more than 15 percent and Shrub/grass increase less than 15 percent). These categories are described in the next section.

Twenty 7.5-minute, 30-m USGS digital elevation models (DEMs) were mosaicked and used to produce elevation, slope, and aspect layers for classification. In addition, fire perimeter data were subset to years including 1990 through 1996 for the study site, and converted to binary grid format. The minimum mapping unit (MMU) for this layer was 4 ha for U.S. Forest Service lands, 121 ha or greater for California Department of Forestry lands, and no MMU for Vegetation Management Program perimeters (California Department of Forestry, http://www.fire.ca.gov; last accessed July 2002). Finally, an existing vegetation land-cover map was obtained (MMU = 1 to 2 ha) and aggregated to nine categories (USFS, 2001). Descriptions of the layers used in the classification are shown in Table 1.

TABLE 1. REMOTE SENSING/ANCILLARY DATA VARIABLES USED AS INPUT TO CLASSIFICATION (30-METER RESOLUTION)

Variable	Variable Name	Data Range	Data Units
Δ Brightness	MKT1	0–255	Rescaled reflectance
Δ Greenness	MKT2	0–255	Rescaled reflectance
Δ Wetness	MKT3	0–255	Rescaled reflectance
Stable Brightness	MKT4	0–255	Rescaled reflectance
Stable Greenness	MKT5	0–255	Rescaled reflectance
Stable Wetness	MKT6	0–255	Rescaled reflectance
Elevation	Elevation	0–1991	Meters
Slope	Slope	0–66	Degrees
Aspect	Aspect	0–360	Degrees
Fire History	Fire	0–1 (0 = no fire; 1 = fire);	Binary
Existing Land Cover	Vegetation	Nine classes: shrub, hardwood, conifer, mixed, urban, herbaceous, barren, water, agriculture	Categorical

Land-Cover Change Categories and Reference Data Collection

A three-level hierarchical land-cover change classification scheme was used in this study and is shown in Table 2. Level 3 is the most detailed and describes three discrete categories of forest canopy cover decrease and two classes of canopy increase. Furthermore, a shrub cover increase and shrub decrease class is used, along with change in developed (urban) areas and no-change (±15 percent canopy change) categories. The ±15 percent change class was designed to reduce the confusion between phenological differences between image dates and post-disturbance change classes. This classification scheme was developed and is currently in statewide use by the LCMMP (Levien *et al.*, 1999; Levien *et al.*, 2002).

Figure 2 presents the processing flow of reference sample allocation and data collection for training the classifier and assessing map accuracy. The study site was stratified into preliminary change versus unchanged areas using the *change in greenness* feature and vegetation life-form categories (i.e., conifer, chaparral, hardwood, scrub, and non-forest) of an existing vegetation map (USFS, 2001). This ensured that an adequate number of samples could be acquired, employing random stratified sampling, and that these samples would be representative of the wide variety of land-cover types found in the study area. Plot size was based on a 60- by 60-m sample area, following recommendations of Justice and Townshend (1981). In this approach, the minimum dimensions of a sample area A should be estimated as $A = P(1 + 2L)$, where P is the ground sampling distance and L is the positional accuracy of the geometric registration in terms of pixels. In a multitemporal context, therefore, when at least two image dates are used, $A_{\text{multitemp}} = \bar{x}\,(A_{\text{time1}} + A_{\text{time2}})$, where $\bar{x}$ is the mean value between time periods.

Ground reference cover proportion data for July 1996 (second date) were estimated through dot grid sampling of tree canopy/shrub cover by interpretation of 1:15,840-scale (resolution better than 1 m) color-infrared imagery (digital images were captured using a DCS420 Kodak infrared camera), acquired over 250 selected sites. In addition, field visits facilitated the collection of 550 additional canopy-cover measurements (i.e., per-plot percentage tree and shrub canopy cover recorded using a densitometer), and the recording of additional site information (i.e., dominant vegetation species, slope, aspect, elevation, the probable cause of change, and GPS location). Ground reference land-cover and forest-cover data for July 1990 (first date) were acquired and interpreted using the same dot grid aerial photointerpretation approach based on 1:15,840-scale true-color forest resource photographs.

Once cover estimates were recorded for both dates,

TABLE 2. HIERARCHICAL LAND-COVER CHANGE CLASSIFICATION SCHEME USED IN THIS STUDY

Level 1	Level 2	Level 3
No Change	No change (*nochange*)	±15% canopy change (*1*)
Change	Decrease in vegetation (*decrease*)	−71 to −100% canopy change (*2*) −41 to −70% canopy change (*3*) −16 to 40% canopy change (*4*) Shrub/grass decrease > 15% (*5*)
	Increase in vegetation (*increase*)	+16 to +40% canopy change (*6*) +41 to 100% canopy change (*7*) Shrub/grass increase > 15% (*8*)
	Change in developed area (*changedev*)	Change in developed areas (*9*)

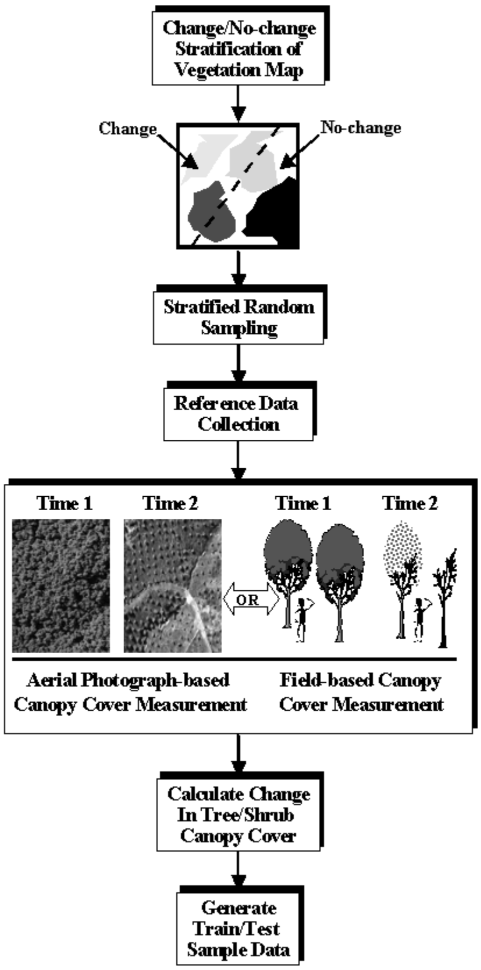

Figure 2. Flow diagram depicting stratification and ground reference data collection.

the 1990 percent cover estimates were subtracted from the 1996 percent cover estimates, producing sample values representing "percent change tree and shrub cover." These categorized "change" data were then randomly divided into train (70 percent) and test (30 percent) subsets. This provided 560 samples for training the classifier and 240 samples for testing the accuracy of the resultant classification map. These sample data were aggregated to each land-cover change level (Table 2) and a separate classifier was developed and assessed for each categorical level.

Classification trees are sensitive to large discrepancies in the number of training samples among individual classes, such that a class with a larger number of training pixels might have greater weight in the analysis (Borak and Strahler, 1999; McIver and Friedl, 2002). Therefore, the number of training samples per class was kept roughly equal (i.e., 80 samples per class) so that within-class variations did not overwhelm the among-class distinctions that are the primary interest of classification. Furthermore, map accuracy assessment was performed on subsets of 40 samples per class for each change level (1–3) to prevent bias in the accuracy statistics.

Classification and Evaluation

A classification tree algorithm was applied to the 11-variable set (Table 1) for each of the three sets of training data to produce rule sets for three separate maps of land-cover change. Classification trees were developed using S-plus statistical software (Clark and Pregibon, 1992). The univariate classification tree approach employs tree-structured rules that recursively divide the data into increasingly homogeneous subsets based on splitting criteria. At each split, the values of each explanatory variable are examined and the particular threshold value of a single variable that produces the largest reduction in a deviance measure (e.g., increase in subset homogeneity) is chosen to partition the data (Breiman *et al.*, 1984; Franklin, 1998). Explanatory variables that have already been used in the model may be reexamined and potentially reintroduced into the tree structure. As a result, hierarchical, non-linear relationships within the data are revealed (Borak and Strahler, 1999). However, classification trees can neither "look forward nor back," when divisively classifying a data set, regarding the decision about a variable selected for a particular split.

Classification trees were pruned to an optimum size based on cross-validation using ten independent subsets of the training data. This results in a parsimonious tree model that does not overfit the training data, thus leading to more generalizable results (i.e., how well will the algorithm classify new data?) (DeFries and Chan, 2000). Because the training observations were evenly distributed among classes, the class assignment at each terminal node was determined by the majority of per-class observations at that node (Breiman *et al.*, 1984). The three tree models were used to generate three land-cover change maps using the ERDAS Imagine Expert Classifier. A 3 by 3 "moving window" majority filter was applied to the final land-cover change maps to smooth the classification results (Bauer *et al.*, 1994) and achieve an effective minimum mapping unit (MMU) of 0.9 ha.

Accuracy assessment is an important aspect of land-cover change mapping as a guide to map quality, or fitness for use, and also in understanding map error and its likely implications (Congalton and Mead, 1983; Congalton, 1991). For each of the three levels of land-cover change, the effectiveness of the classifier was evaluated in the following ways:

- Change map accuracy was assessed with the training data used originally to generate the classification tree (resubstitution accuracy). This measure was used as a classification calibration metric because it is useful as a guide to the maximum possible accuracy that can be achieved.
- Change map accuracy was assessed with the independent set of testing data not yet encountered by the classification tree algorithm. This step is necessary because classifier accuracy and map accuracy are not always the same (Richards, 1996) and the end-user is normally more interested in the accuracy of the resulting thematic map rather than the performance of the classifier.

The set of accuracy parameters used to evaluate each approach were (1) Overall accuracy, (2) Producer's accuracy (omission error), and (3) User's accuracy (commission error).

Furthermore, the kappa statistic was used to examine the accuracy of the maps. The kappa statistic is based on the difference between the actual agreement in the error matrix (i.e., the agreement between the remotely sensed classification and the reference data as indicated by the major matrix diagonal) and the chance agreement which is indicated by the row and column totals (i.e., marginals) of the matrix (Fitzgerald and Lees, 1994). The kappa statistic describes agreement achieved beyond chance, as a proportion of that agreement which is possible beyond chance.

The kno statistic was also derived to compensate some of the shortcomings of the kappa, as kno is not a chance-corrected measure of agreement and does not make distinctions among various types and sources of disagreement (Pontius, 2000). Finally, the improvement in map accuracy attributed to the suite of ancillary data was assessed by classifying the sets of spectral and ancillary data independently, and then comparing the overall accuracy measure for resultant maps.

Results

Figure 3 illustrates the hierarchical structure of the pruned tree produced from the training data for Level 1. The path highlighted in Figure 3 can be translated as the following set of decision rules: "In the training data there were 14 observations where *change in greenness* falls between values of 6.1 and −5.0, *change in wetness* is greater than −3.4, and a fire occurred in the last six years. Of these 14 observations, 13 were *change* and 1 was *no change*." Classes with little variability, such as *nochange*, have few terminal nodes, whereas classes with high variability, such as *change*, have several terminal nodes. Three variables were selected from the original set of eleven (Table 3). *Change in greenness* was the first split, followed by *change in wetness*, discriminating *change* from *nochange*. *Change in greenness* was selected three times, demonstrating a strong influence throughout the tree. When two variables are equally suitable at a split, one is chosen arbitrarily, resulting in a tree whose subset of variables may produce similar accuracies to a tree with different variables.

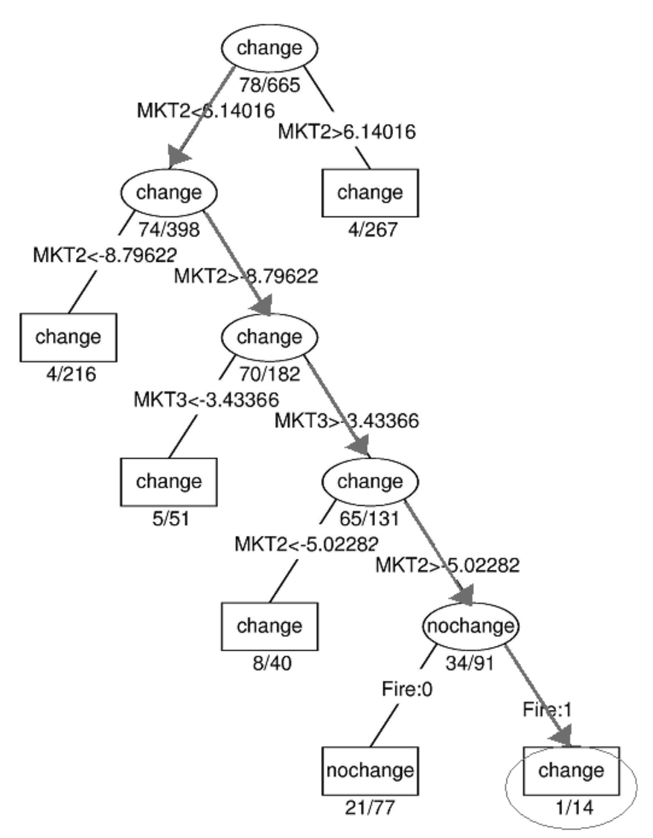

Figure 3. Classification tree used classify Level 1 change.

Table 3. Binary Classification Tree Response Variables for Land-Cover Change Classification Levels 1–3

Level 1 Response Variables	Level 2 Response Variables	Level 3 Response Variables
MKT2 (3)	MKT2 (3)	MKT2 (2)
MKT3 (1)	Elevation (1)	Elevation (5)
Fire (1)	MKT3 (1)	MKT3 (2)
	MKT6 (1)	MKT6 (2)
	MKT1 (2)	MKT5 (2)
	Fire (1)	MKT1 (2)
	Slope (3)	Slope (1)
	Vegetation (1)	Fire (1)
	MKT4 (1)	MKT4 (2)

Number of times that a variable was selected in the classification tree in parentheses.

Table 4. Training Accuracy Results for Land-Cover Change Levels 1–3.

	Level 1	Level 2	Level 3
Overall %	94	93	76
Kappa %	87	89	75
Kno %	87	91	74

Table 5. Error Matrix and Accuracy Statistics for Level 1 Land-Cover Change

		Reference Class		
Classified as		change	nochange	**Sites**
	change	38	4	42
	nochange	2	36	38
	Sites	40	40	80
Producer's Accuracy			**User's Accuracy**	
Class	%		Class	%
change	95.0		Change	90.4
nochange	90.0		nochange	94.7
Overall	**Kappa**	**Kno**		
92%	85%	85%		

The training accuracy for Level 1 was 94 percent, with kappa and kno at 87 percent (Table 4). The Level 1 change map produced by the splitting rules of the tree had an overall accuracy of 92 percent (40 samples for both classes), a kappa of 85 percent, and a kno of 85 percent, showing very little degradation of "best achievable accuracy" (Table 5). Results from independent classifications of spectral and ancillary data sets showed that the ancillary data contributed 2 percent overall to the final classification accuracy.

The tree generated for Level 2 is presented in Figure 4. The *nochange* and *changedev* classes had few terminal nodes, indicating little within-class variability. In contrast, *decrease* exhibited high variability, followed by *increase*. Nine variables were selected in this model (Table 3). *Change in greenness* was used again for the first split, followed by *elevation* and *change in wetness*. The left branch of the tree with lower magnitude *change in greenness* predominantly sorted *increase*, and *changedev* classes from *decrease* (right). *Elevation* was selected to split *changedev* from *increase*. This makes intuitive sense, because developed areas tend to be located at lower elevations in the study area (Figure 1). *Stable wetness* was then selected to further discriminate these two classes, indicating the utility of this variable in distinguishing urban areas from non-urban areas, where the abundance and type of vegetation is very different.

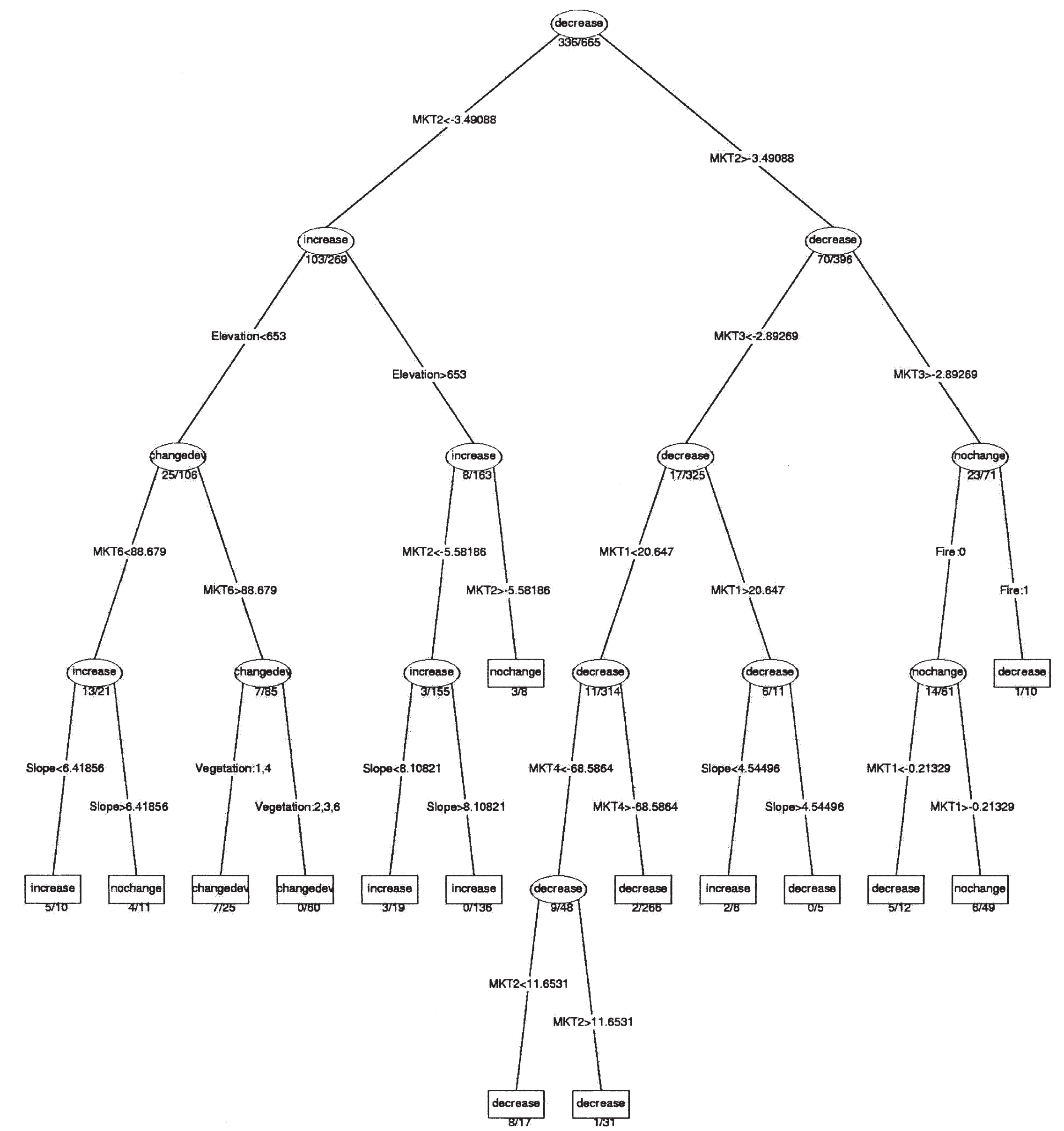

Figure 4. Classification tree used to classify Level 2 change.

Based on high magnitude *change in greenness*, the right branch of the tree predominantly sorted *decrease* and *nochange* classes (although *nochange* appeared on both branches). *Change in wetness* was selected to split *decrease* from *nochange*, indicating its ability to discriminate a wide variety of *decrease* from *increase* subclasses in the study area. The training accuracy was 93 percent overall, with a kappa of 89 percent and a kno of 91 percent (Table 4). The overall map accuracy was 91 percent, with a kappa of 89 percent and kno of 89 percent (Table 6). Omission and commission errors were low, with the most notable confusion occurring between *nochange* and *increase*. As for Level 1, the ancillary data set contributed only 2 percent overall to Level 2 classification accuracy.

Classification of Level 3 classes presented the most challenging task in this study. Figure 5 illustrates the tree model for Level 3. Nine variables were selected by the classification tree algorithm (Table 3). The selection of variables was similar to that of the Level 2 tree, with *change in greenness, elevation,* and *change in wetness* chosen for lead splits. The left and right branches also followed the structure of Level 2, by splitting *increase* classes (*6* through *8*) and *changedev*, right, and decrease classes (*2* through *5*) and *nochange*, left. Following the left branch, *elevation* split low-elevation shrub cover increase from the class representing subtle increases in tree canopy cover. Significantly, the stable MKT features, *stable wetness* and *stable brightness,* were used to separate the two classes representing tree-cover increase. Following the right branch, *elevation*, *change in brightness*, and *fire* were selected to distinguish the shrub cover decrease class (*5*) from the two lower-magnitude tree cover decrease classes (*3* and *4*), while *elevation* and *change in greenness* separated the two largest magnitude tree cover decrease classes (*2* and *3*). Unlike the left branch, which exhibited reasonable discrimination of the *increase*-related and *changedev* classes, the right branch

Table 6. Error Matrix and Accuracy Statistics for Level 2 Land-Cover Change.

Classified as	Reference Class: changedev	decrease	increase	nochange	Sites
changedev	39	2	1		42
decrease		37			37
increase	1		36	5	42
nochange		1	3	35	39
Sites	40	40	40	40	160

Producer's Accuracy Class	%	User's Accuracy Class	%
changedev	97.5	changedev	92.8
decrease	92.5	decrease	100.0
increase	90.0	increase	85.7
nochange	87.5	nochange	89.7

Overall	Kappa	Kno
91%	89%	89%

exhibited a large degree of heterogeneity and confusion within the three tree-cover decrease classes, and between these decrease classes and the shrub-cover decrease class.

The training accuracy for Level 3 was 76 percent overall, with a kappa of 75 percent and kno of 74 percent (Table 4). The overall map accuracy was 72 percent, with a kappa of 69 percent and kno of 71 percent (Table 7). This lower accuracy was caused by larger commission errors in the tree-cover decrease classes and by omission errors in the shrub decrease class.

The mapped area of the Level 3 land-cover change categories are presented in Table 7. By far, the largest class is ±15% *canopy change*, which is not surprising for a land-cover change study in such a large area. Among the change classes, however, shrub decrease and increase are largest, caused by wildfire and post-fire regeneration, respectively. *Change in developed areas* was the next largest class, followed by the largest-magnitude forest-cover decrease class. The smallest class was the lowest-magnitude forest-cover decrease class. This decrease was almost entirely caused by fir engraver infestation, mentioned earlier. Unlike the results of Levels 1 and 2, the ancillary data increased the overall accuracy of the Level 3 change map by 15 percent. Level 2 land-cover changes in the study area are shown in Plate 1.

Discussion and Conclusions

The results confirm the value of classification tree algorithms for mapping land-cover change. Spectral and ancillary variables were readily integrated and their contribution to map accuracy was revealed in the hierarchical structure of the tree, and in the increase in accuracy when ancillary data were included in the classification. The methods used in this study were successful for mapping discrete categories of land cover change at Levels 1 and 2. Overall change map accuracies were about 85 percent in both cases, falling within the target for studies of this nature. The Level 3 change map accuracy was less than the target, as the overall accuracy was 72 percent. Commission errors greater than 20 percent, caused by class confusion, are not generally acceptable in operational approaches. However, classes such as *changedev, nochange,* and the vegetation increase classes were successfully mapped.

The poorest result was the inability to discriminate among the forest-cover decrease classes. The three error matrices for Level 3 (Table 7), however, reveal that the majority of the misclassification errors are confusions with other forest-canopy decrease classes and are not mixed among vegetation increase classes, etc. There are several sources of error that may have contributed to the lower accuracy of these classes. It is possible that the canopy-cover change intervals used are not suitable for operational change-detection mapping. This issue will be investigated in future research.

Table 7. Error Matrix and Accuracy Statistics for Level 3 Land-Cover Change

Classified as	Reference Class: 1	2	3	4	5	6	7	8	9	Sites	% Area
1	35					2	1	6		44	96.90
2		28	7	2	1					38	0.422
3		6	25	9	3					43	0.077
4		4	5	24	9					42	0.048
5		2	3	5	27					37	0.820
6	1					30	8	2	2	43	0.390
7	1					5	28			34	0.083
8	3					3	3	32		41	0.690
9									38	38	0.570
Sites	40	40	40	40	40	40	40	40	40	360	

Class Name	Class Number	User's Accuracy (%)	Producer's Accuracy (%)
±−15% canopy change	1	87.5	79.5
−71 to −100% canopy change	2	70.0	73.6
−41 to −70% canopy change	3	62.5	58.1
−16 to 40% canopy change	4	60.0	57.1
Shrub/grass decrease > 15%	5	67.5	72.9
+16 to +40% canopy change	6	75.0	69.7
+41 to 100% canopy change	7	70.0	82.3
Shrub/grass increase > 15%	8	80.0	78.0
Change in developed areas	9	95.0	100.0

Overall	Kappa	Kno
72%	69%	71%

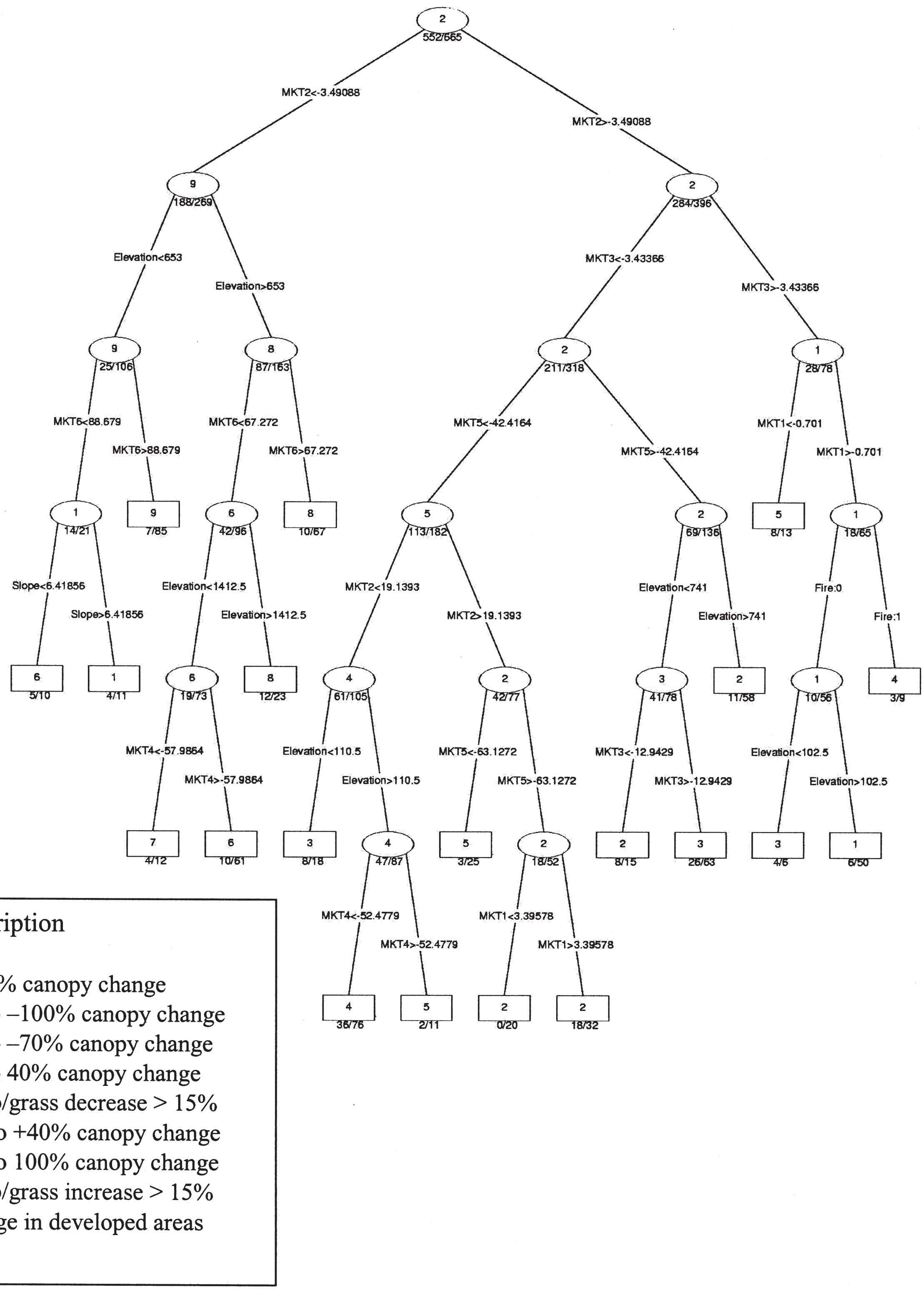

Figure 5. Classification tree used to classify Level 3 change.

Other sources of error were revealed when misclassified pixels were traced to their locations on the change maps and against the 11-variable set. For example, from on-screen inspection, training/test points that were observed in the field were determined to be locations where fires occurred, but located well outside the mapped perimeter of the fire database. This discrepancy caused misclassification of several samples in the classification and points to the li-

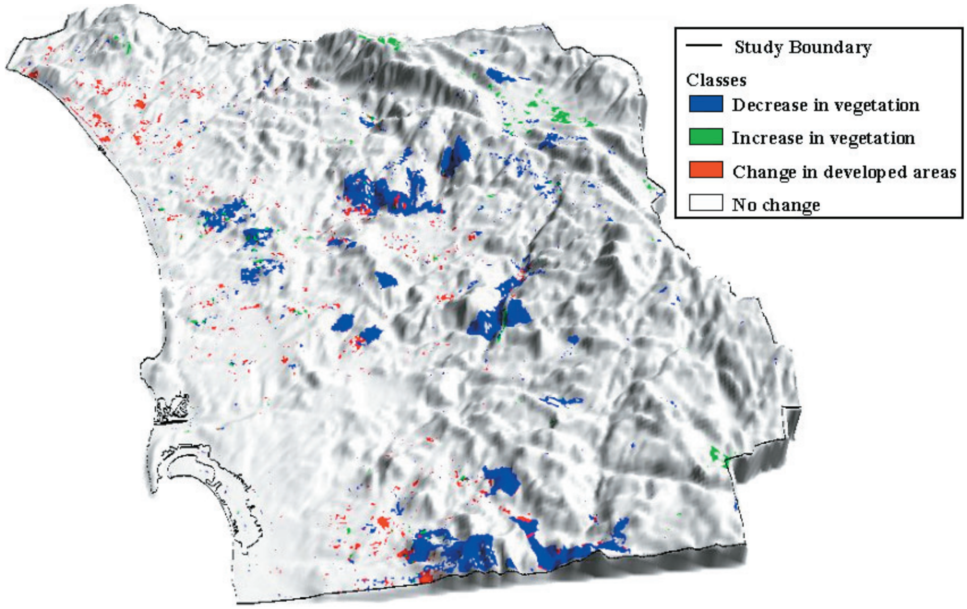

Plate 1. Level 2 land-cover changes in the study area.

abilities involved when using GIS layers of varying MMUs, scales, and origin.

As has been shown previously (Seto *et al.*, 2002), the MKT variables proved very useful for mapping land-cover changes. *Change in greenness* was selected as the lead split in all three classification trees and was used more than once in each case. *Change in wetness* was also useful in discriminating vegetation decrease classes. However, in this study discrimination among the more subtle change classes was often determined by the stable MKT features, such as *stable brightness* and *stable wetness*, rather than the MKT change components. We posit that an area undergoing decrease in hardwood cover is spectrally different from an area undergoing decrease in conifer cover, due to intrinsic differences in canopy structure. Therefore, the mean brightness, mean greenness, and mean wetness features were selected to discriminate subclasses (i.e., change in conifer vs. change in oak) of the same *decrease* category. Including stable or mean/average layers in the classification process, therefore, appears to be advantageous for change mapping studies because these layers provide important information on the "direction" of change between the two time periods.

Ancillary layers also proved discriminatory in this study. *Elevation* was often selected to distinguish between changes in urban areas and *increase* classes. *Slope* was typically associated with *increase* classes and was selected often to separate them from other classes. The fire perimeter layer was important in sorting between change and any other classes, owing to its binary nature. *Aspect* was not used in any of the classifications. This may be because slope and elevation layers have a greater physical influence on change processes than does aspect (i.e., related to fire severity, or location of new construction). The vegetation type layer was used only once, in the Level 2 tree. This suggests that *change in greenness* is such a strong discriminator of changes that categorical land-cover information was not needed. The ancillary data contributed little to change map accuracy in Levels 1 and 2 (i.e., 2 percent). This may be because these change levels are fairly simple, and spectral data alone provided enough discriminatory information to resolve the classes therein. However, at Level 3, the most complicated measurement space, ancillary data increased overall accuracy by 15 percent, demonstrating their importance in discriminating land-cover change with a large number of classes. This is because, as measurement space becomes increasingly complex, with an increased number of change classes, and given an adequate training sample and robust classifier, the addition of ancillary information increases dimensionality and can help separate these classes (Hughes, 1968).

Areal proportions (Table 7) reveal important information about the spatial arrangement of the land-cover change classes. Future work will investigate the use of prior probabilities to improve areal estimates of land-cover change classes derived from classification tree algorithms (McIver and Friedl, 2002). Furthermore, we note that the classification training and map accuracy assessment phases of this research were based on stratified random selection of field samples at the pixel level. Recent research has demonstrated the optimistic bias of pixel-level sampling approaches (Friedl *et al.*, 2000) and, therefore, our future research will address map accuracy at the site/patch level, in order to provide more realistic, unbiased estimates of change map accuracy.

Finally, this work presents a case study of the potential of classification trees for land-cover change monitoring. Future work will apply this methodology to other regions with different vegetation types and disturbance regimes (e.g., upland conifer and hardwood vegetation types in northern California, primarily disturbed by logging and wildfire). Our long-term goal is to provide information to resource managers in regions outside California (national and international) on how this approach could be adapted and applied in their management areas.

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