CHAPTER 17.

Forest Health Monitoring in Southern California: High-temporal Monitoring Using Advanced Image Analysis Techniques

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Carlos Ramirez
Shengli Huang
Kama Kennedy
Jeffrey Mallory

INTRODUCTION

Developing an adaptive management strategy to aid in the restoration of ecosystem function and health requires timely monitoring information. Although plot-based data provide critical detailed information on the status of the ecosystem, they are costly, time consuming to acquire, and do not provide wall-to-wall spatial coverage. The lack of spatial coverage can underestimate certain forest dynamics that exhibit clustered spatial patterns on the landscape. Additionally, the temporal resolution is generally low, especially relative to the frequency of earth observation systems. For this project, we accessed the ability of the Forest Inventory and Analysis (FIA) plot data coupled with 30-m imagery from the Landsat5 archive to provide timely indicators of ecosystem status. Annual assessments can be provided by combining ground-plot data with large-scale imagery. It should be noted that an initial exploratory assessment of the FIA plots was conducted to assess forest mortality since we had two measurements between 2000 and 2010. Only 3 of 195 plots showed a measurable amount of mortality, making it impossible to determine forest trends from the plot data alone.

The area of interest encompasses multiple National Forests (NFs) including San Bernardino, Cleveland, and the eastern portion of the Angeles National Forests and adjacent areas. A Mediterranean climate typifies the area's climate regime, with cool moist winters and hot dry summers. This bioregion frequently experiences prolonged drought conditions, frequent wildfires, and substantial areas of tree mortality due to a variety of biotic and nonbiotic factors. These processes produce a highly dynamic ecosystem that requires frequent temporal monitoring.

Existing automated classification methods have been deemed ineffective because of the lack of automation and low efficiency over a large area (Chen and others 2015). For this study, an automated land cover mapping algorithm called the Automatic UpdaTe On Land Cover Database (AutoLCD[1]) was developed to assess changes in land cover in the South Coast bioregion of California that experienced drought and high incidences of bark-beetle mortality from 2003 to 2005 (Walker and others 2006). Since many monitoring objectives quantify annual changes (Hansen and Loveland 2012), this algorithm

[1] Huang, S.; Ramirez, C.; Kennedy, K. [and others]. In preparation. AutoLCD: a potential tool to automatically update large-area land cover database from times series satellite data. Remote Sensing of Environment.

was developed to assess land cover changes across the project area in annual time steps. The automated nature of AutoLCD allowed for quick and efficient analysis of land cover changes to monitor the biophysical characteristics such as biomass, carbon storage, and leaf area index.

METHODS

The AutoLCD algorithm uses existing land cover baseline and disturbance information to select candidate training pixels to update land cover in each time step. As an example, if we have multiple years of Landsat data but we are interested in information on land cover changes for a particular year, the tool compares the Landsat data with the baseline land cover data and with other Landsat years to detect changed and unchanged areas. The land cover class for an unchanged area is inherited from the baseline classification for the year being assessed. However, pixels that have experienced disturbance are reclassified by identifying their "similar" pixels within the unchanged area of the baseline classification and then using the majority as a pixel's classification value (fig. 17.1). This process is repeated for every pixel in the changed area. This basic premise

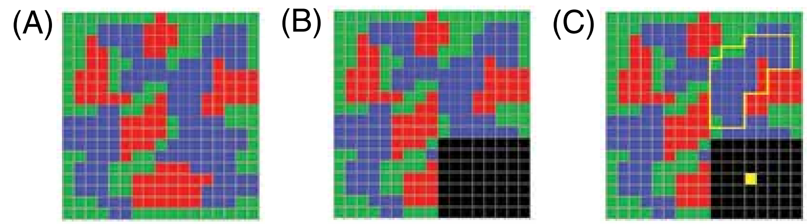

Figure 17.1—Basic concept of AutoLCD algorithm: (A) a baseline classification where red, green, and blue indicate different land cover values; (B) black areas indicate changed areas; the classification for unchanged areas are inherited from the baseline classification; (C) for one pixel within the change area (yellow pixel), its "similar" surrogates are enclosed by the yellow polygon. The majority of these "similar" pixels, which are blue in this case, are deemed as the land cover value for the yellow pixel.

that the majority classification relies on is a measure of similarity (Huang and others 2013) using several metrics derived from Landsat (e.g., reflectance, normalized difference vegetative index [NDVI], etc.), as well as physiographic and topographic variables (e.g., national forest boundaries, elevation zones, ecoregions, aspect). Expert rules (e.g., pixel categorized as "barren land" when NDVI is less than 0.02) were also incorporated into the AutoLCD processing chain. More detailed explanation of AutoLCD can be found in Huang and others (see footnote 1). For this project, the 2009 baseline classification has 10 land cover types determined from two known sources: (1) land cover classes in the national forests generated from Landsat data, and (2) land cover classes outside of national forests from the National Land Cover Database (Jin and others 2013).

We selected an annual times series of optimal Landsat images for the years 2002 to 2010. The images were selected near the yearly anniversary of a baseline set of images in order to minimize climatic and phenologic influences. The images used in the classification process are composed of surface-reflectance data from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) and derivative spectral indices [i.e., NDVI, normalized burn ratio (NBR)] (Masek and others 2006). We used AutoLCD to classify each year's Landsat data for all scenes spanning the project area.

After annual discrete land covers were produced with AutoLCD, we used a three pixel minimum patch size (2700 m^2) in eight directions and applied landscape metrics to five land cover classes: shrubland, conifer-hardwood mix, hardwood, conifer, and dry grass. These five land cover classes have experienced moderate and high severity fires since 2002. Subsequently, FRAGSTATS (McGarigal and others 2012) was used to quantify the spatial structure of the AutoLCD time series in terms of land cover composition and configuration within the landscape. To achieve this, various landscape metrics were selected: (1) total class area (CA), (2) number of patches (NP), (3) largest patch index (LPI), (4) average patch area (AREA_MN), (5) total area (TA), (6) total edge (TE), (7) interspersion and juxtaposition index (IJI), (8) Shannon's diversity index (SHDI), (9) Shannon's evenness index (SHEI), (10) contagion (CONTAG), (11) percentage of landscape (PLAND), (12) edge density (ED), and (13) patch density (PD). Using similar metrics, Linh and others (2012) suggested that certain changes to the spatial configuration of land cover types reduce ecological resilience at the landscape level.

RESULTS AND DISCUSSION

A detailed portion of an annual land cover map produced for the entire study area using the AutoLCD algorithm is shown in figure 17.2 (A-D). To evaluate the classification accuracy, 240 points were randomly selected for visual interpretation from National Agriculture Imagery Program (NAIP) imagery (USDA 2005) and compared with the 2005 AutoLCD classification results. The comparison showed an overall classification accuracy of 79 percent and an overall kappa coefficient of 0.76. Although we did not assess additional years, based on trends examined in the land cover time series, we expect a similar level of accuracy for each time step.

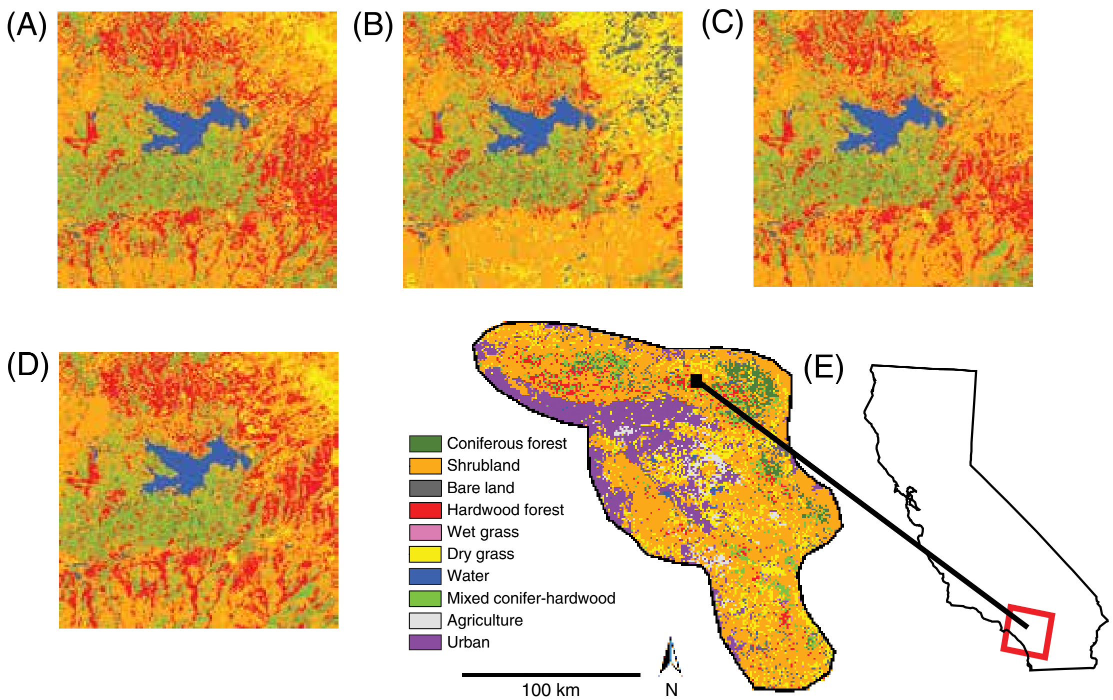

Figure 17.2—Land cover classes updated with the AutoLCD algorithm are shown for a small section (9 km x 9 km) of the entire study area for the years (A) 2003, (B) 2005, (C) 2007, and (D) 2010. The last panel (E) shows the general location in southern California and the magnified area as indicated by the black square.

Figure 17.3 illustrates the successional changes that occurred after moderate and high intensity fires moved through the project area. In 2003, approximately 303 515 ha (California Department of Forestry and Fire Protection 2003) burned, which contributed to the decline of tree and shrub cover and an increase of senesced grass in 2004. The 2006 Sawtooth Complex fire burned approximately 250 901 ha in San Bernardino County, which was dominated by shrub cover and is reflected in the downward trend in shrubland (fig. 17.3). In 2007, large fires (i.e., Zaca, Moonlight, and Angora) once again resulted in large changes in land cover. The area predominately affected was once chaparral-dominated communities, as seen in the continued decline of shrubland in year 2008. In 2009, the Station Fire consumed approximately 64 750 ha of the Angeles NF and reduced hardwood cover by 79 percent, reduced areas of conifer-hardwood mix by 13 percent, and reduced conifer cover by 8 percent. Despite these local decreases, shrubland areas across the entire study area continued to increase from 2002 to 2010.

Forest health is threatened when biotic and/or abiotic factors are severely disrupted and resiliency is compromised. Walker and others (2004) define ecological resilience as "the capacity of a system to absorb disturbance and reorganize while undergoing change so

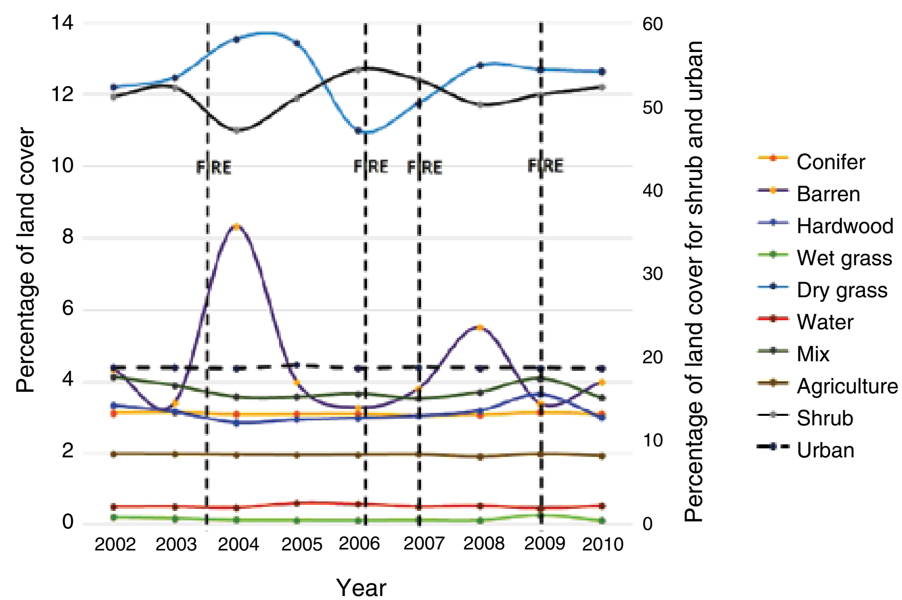

Figure 17.3—Land cover over time across all ownerships.

as to still retain essentially the same function, structure, identity, and feedbacks." Fire is one of the most influential processes that has changed the vegetation dynamics in the study area. The changes to the edge structure and land cover composition on the landscape influence the adjacent communities (Harper and others 2005). Successional trends following large moderate to high severity fires in southern California have been well documented (Franklin and others 2006, Franklin 2007, Goforth and Minnich 2008, Keeley 1998, Keeley and others 2004). Typical post-fire vegetation dynamics following major disturbances include a high intensity flush of herbaceous plants the first two years with their decline in the third year (Franklin 2007). Sprouting of heat resistant buds in shrubs and hardwoods along with sprouting of fire dependent obligate seeders from stored seed banks buried in the soil continue to expand cover and dominate the landscape in years after. Conifer and the conifer portion of the conifer-hardwood mix land covers are the least successful in recovery as seedling replacement and regeneration can be practically nonexistent, and in some high severity fires conifer can be completely extirpated from the landscape (Franklin 2007, Goforth and Minnich 2008). Pre-fire and post-fire heterogeneity, vegetation dynamics, life history traits, and successional trends show up as changing vegetation patterns (change) in the landscape. The gradients of change are quantifiable using landscape metrics. Spatial landscape metrics were computed for the 2002 and 2010 land cover classifications and are displayed in table 17.1.

Table 17.1—Spatial landscape metrics for selected classes, 2002 and 2010

Year	TYPE	CA	PLAND	NP	PD	LPI	TE	ED	AREA_MN
		ha	*%*	*number*	*number/ha*	*%*	*m*	*(m/ha)*	*ha*
2002	Conifer	68 940.99	3.1351	16,096	0.732	1.346	24 726 930	11.2446	4.2831
2002	Shrubland	1 126 861	51.2441	43,344	1.9711	39.4732	169 369 890	77.021	25.9981
2002	Hardwood	73 551.78	3.3448	32,641	1.4844	0.2817	34 188 900	15.5474	2.253
2002	Grassland	268 620.7	12.2155	62,396	2.8375	0.3856	94 526 490	42.986	4.3051
2002	Mix	90 955.62	4.1362	29,933	1.3612	0.1329	37 763 640	17.173	3.0386
2010	Conifer	68 195.61	3.1012	13,708	0.6234	1.4193	23 380 260	10.6322	4.9749
2010	Shrubland	1 151 373	52.3588	42,473	1.9315	40.5777	161 026 920	73.2271	27.1084
2010	Hardwood	65 951.1	2.9991	30,615	1.3922	0.2059	30 308 640	13.7829	2.1542
2010	Grassland	278 266.6	12.6542	63,562	2.8905	1.4723	92 987 850	42.2863	4.3779
2010	Mix	78 028.74	3.5484	28,301	1.287	0.1241	33 911 070	15.4211	2.7571

CA = total class area; PLAND = percentage of landscape; NP = number of patches; PD = patch density; LPI = largest patch index; TE = total edge; ED = edge density; AREA_MN = average patch area.

The conifer habitat exhibited a class area (CA) loss of 745 ha, a reduction in the number of patches (NP) by 2,388, but an increase in mean patch area (AREA_MN) of 0.7 ha. Conversely, the conifer-hardwood mix class exhibited a loss of 12 926 ha and a decrease in the number of patches by 1,632 with most loss due to conifers and not hardwood. The hardwood component of the mix typically resprouts whereas the conifer component has poor regeneration success as seen in the high severity Cedar Fire of 2003 (Franklin and others 2006, Goforth and Minnich 2008). The poor regeneration in conifer equates to a shift in vegetation dynamics and development of new ecotones that favor vegetation species with fire-adapted abilities to fulfill the niche once occupied by the conifer component. Not only will there be a shift in species composition but also a shift in structural attributes, particularly the percentage of cover and height. Where there is not a species compositional shift, a structural ecotone may be manifested on the landscape. Changes in species and structural attributes will lead to greater exposure to abiotic factors such as direct sunlight, temperature, and wind. The physical structure of vegetation within this time period has changed. Resiliency is apparent to some degree in hardwoods but not yet with conifer regeneration to a pre-fire ecosystem functional condition. As noted above, forest health issues are still apparent in this time period. The analysis for the hardwood land cover class shows a class area loss of 7601 ha, number of patches decreasing by 2,026, and patch area mean decreasing by 0.1 ha. In the earlier to middle part of the study, the hardwoods gradually increased with a portion of the loss due to the 2009 Station Fire on the Angeles NF. Since many of these hardwood species resprout, we expect that ecosystem resiliency will increase.

The shrubland experienced an increase in area by 24 512 ha, a decrease in patch number by 871, and an increase in the mean patch area by 1.1 ha. This combination of metrics suggests shrubland occurs as larger parcels that have decreased in number with an overall increase in shrubland occupancy. Shrubland appears to be resilient in this area as it recovers quickly from moderate to high severity fires due to its resprouting and obligate seeding capacities.

Dry grassland experienced an increase in total area by 9646 ha, an increase in the number of patches by 1,166, and an increase in the mean patch area of nearly 0.1 ha. Grasses respond very quickly under moderate to high fire conditions within the first 2 years and occupy a greater proportion of the fire landscape than does woody vegetation (fig. 17.3).

Analysis at the landscape level exhibited a decrease in the total number of patches across all class types to 5895 ha while the mean area patch increased by 0.22 ha (table 17.2). Shannon's diversity index (SHDI) is the amount of patch per class (McGarigal and others 2012) and Shannon's evenness index (SHEI) is expressed as the observed level of diversity divided by the maximum possible diversity for a given patch richness (McGarigal and others 2012). These indices decreased from 2002 to 2010, indicating that the patches of land cover types slightly declined in heterogeneity and evenness. Furthermore, the interspersion and juxtaposition index (IJI) decreased from about 64 percent to 61 percent, indicating a trend toward land cover types becoming less dispersed across the landscape.

Discrete land cover changes within specific categories produced with AutoLCD enable us to better understand ecosystem changes quickly and in an automated manner. In addition, monitoring the progression of trends of biophysical characteristics such as biomass, carbon storage, and leaf area index is also important. There are three basic steps to integrate the data:

1. Because the cycle of FIA single plot measurements spans 10 years and the plots undergo changes, a subset of the full complement of FIA plots is automatically selected for each individual year and the measurement (e.g., biomass increment) is accordingly adjusted for annual increase or decrease.

2. Since the number of FIA plots sampled in an individual year may be limited, the pixels that are "extremely similar" to the FIA plots (in terms of remote sensing metrics and abiotic factors such as elevation, precipitation, temperature, aspect, soil type, and drainage) are identified and the sampled FIA attributes are assigned to these pixels. The original FIA plots and these newly identified pixels are categorized as "expanded plots."

3. A comparable "similar" process as discussed above is used to identify the closely related pixels as a group. After identifying which "expanded plots" fall within this group, the weighted mean of field-derived parameters such as biomass is assigned to these pixels. The basic idea of this algorithm is comparable

Table 17.2—Landscape level metrics, 2002 and 2010

Year	TA	NP	LPI	AREA_MN	CONTAG	IJI	SHDI	SHEI
	ha	*number*	*%*	*ha*	*%*	*%*		
2002	2 199 008	243,249	39.4732	9.04	53.33	64.3	1.52	0.66
2010	2 199 008	237,354	40.5777	9.26	56.38	61.09	1.49	0.62

TA = total area; NP = number of patches; LPI = largest patch index; AREA_MN = average patch area; CONTAG = contagion; IJI = interspersion and juxtaposition index; SHDI = Shannon's diversity index; SHEI = Shannon's evenness index.

to the K-Nearest Neighbors-(K-NN) method (McRoberts and others 2007, McRoberts and Tomppo 2007).

Further explanation of the biomass estimation process and results may be found in an upcoming paper by Huang and others.[2]

CONCLUSIONS

There is a pressing need to develop robust, efficient, and accurate automated approaches for cost-effective monitoring of land cover changes at moderate spatial resolution scales. AutoLCD provides such a mechanism to automatically update regional, and potentially global, land cover changes from Landsat or Landsat-like imagery. The AutoLCD algorithm provides a mechanism for rapidly assessing the state of the ecosystem as a function of trends in land cover change. An additional strength of AutoLCD is that it can be easily adapted to work with other passive optical imagery, such as WorldView2/3, AVIRIS, and other sensors.

Major fires in southern California have contributed to the shaping of the landscape and ecosystem. The transition between successional stages influences the patch number, patch shape, mean patch size, and spatial pattern on the landscape for land cover classes. Over time, hardwoods, conifer-hardwood mix, and conifers in particular have been strongly influenced by these interactions. At the landscape level, evidence of fragmentation exists over the study period and the capacity for ecological resilience is in question. Structurally dependent species will experience habitat and continuity loss as their ecosystems become further stressed under issues such as climate change. However, we expect hardwood forests and woodlands to recover to an unknown extent. AutoLCD can be used to provide frequent temporal monitoring of land cover to better assess forest health, ecosystem resiliency, and/or fragmentation of landscapes.

CONTACT INFORMATION

Carlos Ramirez: carlosramirez@fs.fed.us.

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