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Tracking MODIS NDVI time series to estimate fuel accumulation

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Patterns of post-fire recovery in southern California chaparral shrublands are important for understanding fuel available for future fires. Satellite remote sensing provides an opportunity to examine these patterns over large spatial extents and at high temporal resolution. The relatively limited temporal range of satellite remote sensing products has previously constrained studies of post-fire recovery to chronosequence approaches, in which space is substituted for time, but the lengthening satellite data record is easing this limitation. In this study, we tracked vegetation recovery using a pixel-explicit approach from 2000 to 2013 using normalized difference vegetation index (NDVI) data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. We attempted to control for inter-annual precipitation variation and examined the influence of shrub cover on MODIS NDVI during the post-fire recovery process. We find strong variation in recovery trajectories associated with site differences, which would have been lost in a chronosequence approach. Shrub cover plays a larger role in explaining annual NDVI variation during the early stages of post-fire recovery, and is a less important factor in more mature stands.

1. Introduction

Patterns of chaparral biomass accumulation are important for understanding post-fire productivity, which is related to the fuel available for future fires and may be partially related to susceptibility of chaparral to massive fires (Riggan et al. 1988). Such fires have major societal and economic costs and have become increasingly common (Keeley et al. 2009). While chaparral is adapted to fire, the recovery can be disrupted by drought (Hope, Tague, and Clark 2007) and is spatially variable (Kinoshita and Hogue 2011). Typically shrub cover approaches pre-fire levels within 10–15 years; total aboveground biomass likely continues to accumulate over longer periods (McMichael et al. 2004; Riggan et al. 1988).

Satellite remote sensing has the potential for generating spatially explicit data on biomass accumulation in chaparral. Relatively frequent satellite observations enable tracking of vegetation greenness and fractional cover changes through seasons and over years. In particular, wide field-of-view polar orbiting satellites capture relatively coarse spatial resolution image data (e.g. National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), Système Pour l'Observation de la Terre (SPOT) Vegetation and Terra/Aqua MODIS) on a daily basis for most land areas. This enables fairly detailed tracking of vegetation growth and phenology, even after removing observations obscured by clouds, cloud shades or optically thick atmospheres. Image data and derived products from the Moderate Resolution

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Imaging Spectroradiometer (MODIS) sensors on National Aeronautics and Space Administration Terra and Aqua satellites are readily available for such applications. Spectral vegetation index (SVI) products are generated from radiometrically calibrated, atmospherically corrected and geometrically processed MODIS data for red and near infrared wavebands at the finest spatial resolution available for the system, 250 m. Specifically, normalized difference vegetation index (NDVI) and enhanced vegetation index products are generated from composites of single-date images for several time intervals. Here we utilize the NDVI 250 m, 16-day product because of its greater dynamic range (in space and time) for chaparral shrublands in southern California.

Several papers report results of multi-temporal satellite image analyses of chaparral growth following fire. Most of these have emphasized post-fire recovery dynamics and all are based on chronosequence approaches to sampling SVI values across landscapes (Hope, Tague, and Clark 2007; McMichael et al. 2004; Peterson and Stow 2003). For a chronosequence approach, space is substituted for time, such that SVI values are sampled from different age stands to create an SVI time trajectory. The benefit of this approach is that only one or a few well-processed images can be used to generate trajectories. A disadvantage is that the desired temporal trend is obscured by potentially large site-to-site variability.

A more promising and less tested approach is to generate SVI trajectories of individual pixels over time (Hope, Albers, and Bart 2012; Narasimhan and Stow 2010). Such tracking of SVIs for periods of around 14 years is now possible from the MODIS data archive (and has been possible for NOAA AVHRR NDVI data sets that are of lower geometric and radiometric fidelity and coarser spatial resolution). Pixel-based tracking is not as influenced by site variability and life history issues, though such factors can come into play if individual pixels trajectories are pooled.

The primary objective of this paper is to explore if pixel-explicit time series derived from the MODIS 250 m NDVI product contain signals of chaparral growth and biomass accumulation, and conversely, to consider what sources of noise serve to confound such signals. We also seek to understand the influence of shrub cover on MODIS NDVI values of chaparral shrublands and how such a relationship varies as a function of stand age. We meet these objectives through the exploitation of pixel-based tracking of NDVI trajectories, which should be less sensitive to site variability influences associated with trajectory analysis based on chronosequence sampling approaches.

2. Methods

2.1. Data

We compared the MODIS 250 m, 16-day NDVI (MOD13Q1) product to chaparral cover as estimated from digital orthoimagery for two study areas in San Diego County, California. MODIS products are available at a high level of radiometric and geometric processing from 2000 to the present. NDVI values are generated from red and near infrared apparent spectral reflectance values that are derived from radiometrically calibrated and atmospherically corrected spectral radiances. Compared with coarser resolution MODIS products, the 250 m product offers a smaller ground sampling distance (GSD) that reduces the likelihood of mixing with non-chaparral vegetation and land cover types. The high temporal resolution of MODIS data was an important consideration in the initial stage of the study.

We obtained airborne colour infrared (CIR) digital orthoimagery for 3 years within the time period of MODIS coverage. This includes July orthoimagery for 2000 (0.6 m GSD) derived from scanned CIR aerial photography from the San Diego Association of Governments (SANDAG), as well as June 2005 and May 2012 orthoimagery (both 1 m GSD), derived from ADS-40 digital line array sensor from the National Agriculture Imagery Program.

Two raster GIS layers are used for stratified sampling of image-derived SVI and vegetation cover data. A fire history layer from the Fire and Resource Assessment Program of the California Department of Forestry and Fire Protection (http://frap.fire.ca.gov, accessed 4 April 2014) was processed to create a layer depicting stand age since last burn. A vegetation community layer from SANDAG (generated in 1995 and updated quarterly by San Diego County Department of Planning and Land use) was the most currently available source for determining and stratifying by chaparral shrubland areas (http://www.sangis.org/, accessed 26 November 2013). Precipitation data were obtained from the Parameter Elevation Regressions on Independent Slopes Model Climate Group (http://prism.oregonstate.edu, accessed 4 April 2014) for the area central to each of the study regions.

2.2. Image processing

MODIS NDVI data for tile h08v05 were downloaded from the Land Processes Distributed Active Archive for dates starting February 2000 through 2013 for the MODIS orbital segment covering southern California. We initially applied a low-pass filter to the entire time series and calculated metrics of seasonal growth using Timesat time-series analysis software (Jönsson and Eklundh 2004). We found that seasonal metrics derived with Timesat software were not consistently indicative of annual plant growth and particularly sensitive to drought conditions, such that a single observation per year was more suitable. Based on this initial analysis, images for the first composite period of August for each year were selected. This period was selected based on the rationale that most of the foliar biomass at this time is associated with leaf production from the current growing season and because herbaceous vegetation has senesced, and therefore, does not contribute to NDVI. The annual MODIS NDVI image data were reprojected from Sinusoidal to Universal Transverse Mercator projections, then subset to an extent that includes shrubland areas of San Diego County, California, USA.

Two chaparral areas within the larger study extent were selected for growth form map generation and subsequent analyses of MODIS NDVI dynamics based on the vegetation community layer (Figure 1). Both areas come closest to matching the criteria of extensive homogenous chaparral community composition, and having been burned by multiple wildfires, particularly in the mid-1990s through the early 2000s period, with at least one portion of the study area remaining unburned for several decades. This time period allows us to focus on the early stages of post-fire recovery, and the oldest chaparral stands in both areas served as references to compare changes unrelated to the immediate post-fire recovery process.

One study area is located in northern San Diego County, and is mostly composed of Redshank (*Adenostoma sparsifolium* dominant) Chaparral community type. Different portions of this area most recently burned in 2003, 1999, 1995, and 1928. The other is located in southern San Diego County, near the border with Mexico and contains Granitic Southern Mixed Chaparral communities that most recently burned in 1999, 1995, and 1968. For the purposes of this study, we consider ‘stands’ to be the groups of pixels with a common vegetation type and recent burn history in each study area. Each stand contains between 20–54 MODIS pixels (each 250 m × 250 m) that entirely fit within the age and vegetation class of interest.

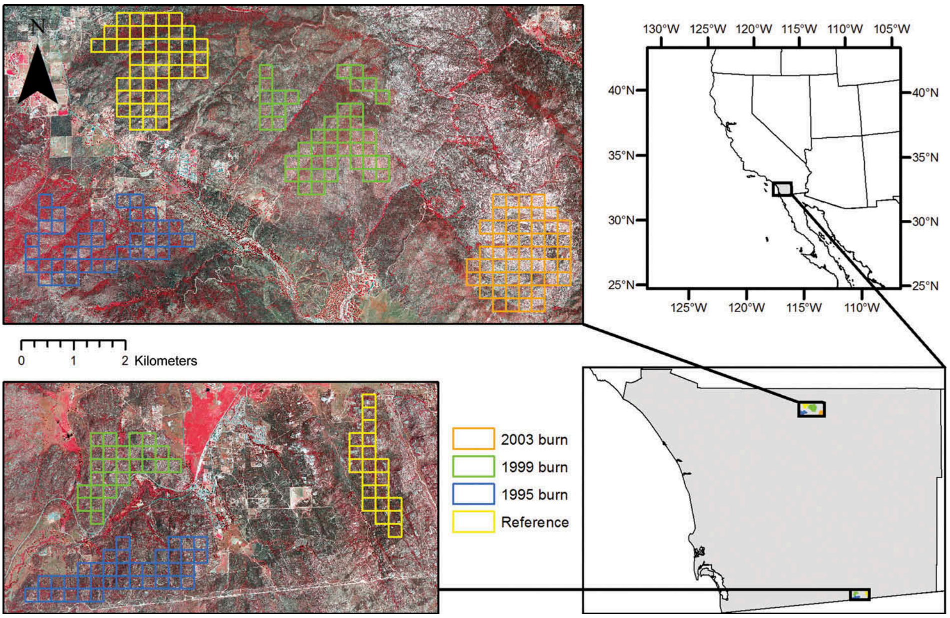

Figure 1. Map of study extent within San Diego County, California, USA, showing the two study areas and seven stands.

Table 1. The age of each recently burned stand in each calendar year, as well as the availability of colour infrared imagery (used for cover estimates) and MODIS imagery (used for NDVI).

	1999	2000	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	'13
1995 stand age	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1999 stand age	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2003 stand age	–	–	–	–	0	1	2	3	4	5	6	7	8	9	10
CIR imagery		x					x							x	
MODIS imagery		x	x	x	x	x	x	x	x	x	x	x	x	x	x

The two stands (in the north and south study areas) that burned in 1999 provide the longest and most complete single time series of post-fire recovery, with stand ages of 1–14 years covered by the MODIS imagery series (Table 1). The stands that burned in 1995 provide information on the slightly later stage of recovery, with ages 5–18 years covered. The stand that burned in 2003 (only in the northern study area) provides an additional time series of the earliest stage of recovery, with ages 1–10 years covered.

Image subsets for each stand were extracted for the three CIR orthoimage data sets from 2000, 2005 and 2012. Each image subset was co-registered and used as input to a per-pixel supervised image classification routine. Five training sites from each of four vegetation growth form categories (bare, herbaceous, open shrub, and dense shrub) were selected for each stand, starting with the 2000 image. These training sites are small, relatively homogenous areas approximately 100 m^2 each, and are used as input for the per-pixel supervised classification routine. After the 2000 image had been classified, the open and dense shrub categories were merged into a single ‘shrub’ category, and bare and herbaceous were combined as ‘non-shrub’. These shrub areas were masked out when classifying the 2005 image, and new shrub (open and dense shrub) training sites were selected from the areas remaining to be classified. This process was repeated for the 2012 image. This approach eliminated areas that had previously been classified as shrub from being classified as bare or herbaceous in later years, and was implemented based on the well-documented progression of shrub recovery (Keeley and Keeley 1981). We left the bare and herbaceous training sites unchanged in successive years whenever possible, but it was sometimes necessary to edit some of these training sites to account for co-registration errors. Separate training sites were selected to account for burned areas in the image subsets burned in 1999 and classified in 2000. Although there are some issues with differences in spatial resolution and co-registration in the three years of imagery, these errors are minor compared to the large changes in shrub cover that take place during the first several years of post-fire growth, as evidenced by the small change in shrub cover in the mature reference stands.

Shrub cover proportions were computed for nominal MODIS pixel boundaries. Using the years in which we had calculated shrub cover (2000, 2005, and 2012) and 3 years of most recent fire (2003, 1999, and 1995), we compared the relationship between NDVI and cover using regression analysis for each possible year in each study area (northern and southern). For example, for the stands that burned in 1995, we calculated the relationship at 5, 10, and 17 years after the fire (Table 1).

NDVI temporal trajectories for pixels from each stratum were derived for each 14-year series of annual August dates. Average trajectories for each stratum were calculated based on NDVI and a relative regeneration index (RRI), defined as recovering shrub NDVI divided by mature shrub NDVI (Hope, Albers, and Bart 2012). The linear slope for each pixel was calculated for the time periods matching the cover classification dates (2000–2005 and 2006–2012). Annual change in cover for each time period was calculated as the total change in cover divided by the number of years in that time period. We examined the relationship between NDVI slope and annual change in cover for each stand using regression analysis.

3. Results

Annual NDVI is responsive to changes in annual rainfall, regardless of burn history (Figure 2). This makes it difficult to isolate recovery trajectories. The RRI strongly

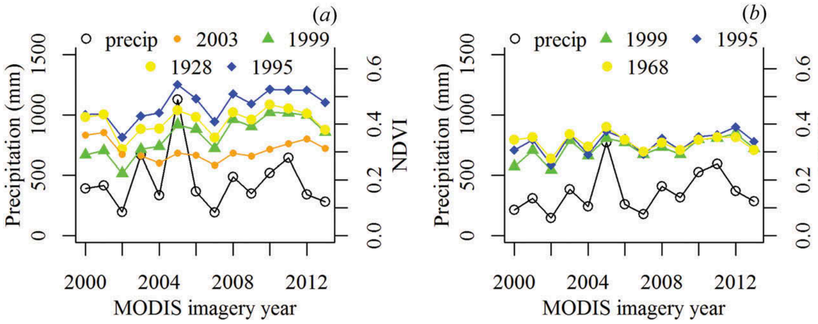

Figure 2. Average August NDVI trajectory and precipitation in the (*a*) northern stands (most recently burned in 2003, 1999, 1995, and 1928) and (*b*) southern stands (most recently burned in 1999, 1995, and 1968). Broken line in 2003 stand indicates pre- and post-fire NDVI. *N* values for each NDVI trajectory range from 20 to 54 pixels.

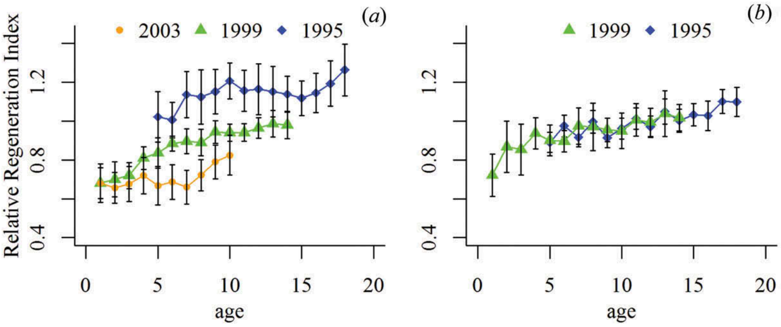

Figure 3. Average August NDVI relative to reference stand of mature chaparral (relative regeneration index) in (*a*) northern stands (most recently burned in 2003, 1999, and 1995) and (*b*) southern stands (most recently burned in 1999 and 1995). Error bars represent standard deviations. *N* values for each NDVI trajectory range from 20 to 54 pixels.

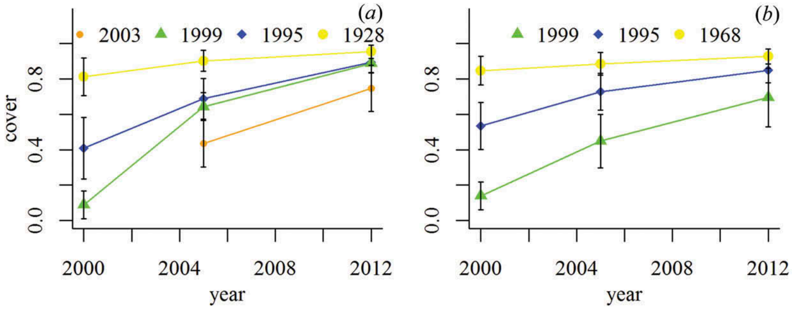

Figure 4. Average cover in the (*a*) northern stands and (*b*) southern stands. Error bars represent standard deviations. *N* values for each NDVI trajectory range from 20 to 54 pixels.

reduces the variation associated with differences in annual rainfall, although some precipitation-related variation is still evident (Figure 3). Visualizing the recovery in terms of post-fire stand age also reveals several substantial differences in post-fire growth in each of the stands. The first major difference is found in the distinct overall patterns in the two study areas. The two stands in the southern study area create a consistent chronosequence of post-fire recovery, with considerable overlap in RRI values during the time period from 5 to 14 years post-fire in which the recovery of both stands was recorded. The southern stands also recover to approximately the level of the mature reference stand. However, in the northern study area, the three stands (2003, 1999, and 1995) show three distinct recovery patterns, and the final recovery level is nearly 20% higher than the mature reference stand (Figure 3).

Each individual stand shows a unique pattern of recovery. For the 1995 south stand, recovery appears to continue throughout the entire time period recorded (5–18 years post-burn), while for the 1995 north stand the recovery trajectory appears to flatten out from about 10 to 15 years post-fire. Both of the 1999 recovery trajectories show continued recovery throughout the period recorded (1–14 years post-fire). The stand that burned in 2003 shows a delayed recovery trajectory that does not begin until around 8 years post-fire.

The trajectories of shrub cover recovery show patterns similar to the NDVI recovery trajectories (Figure 4). While only three dates were available for the cover trajectories

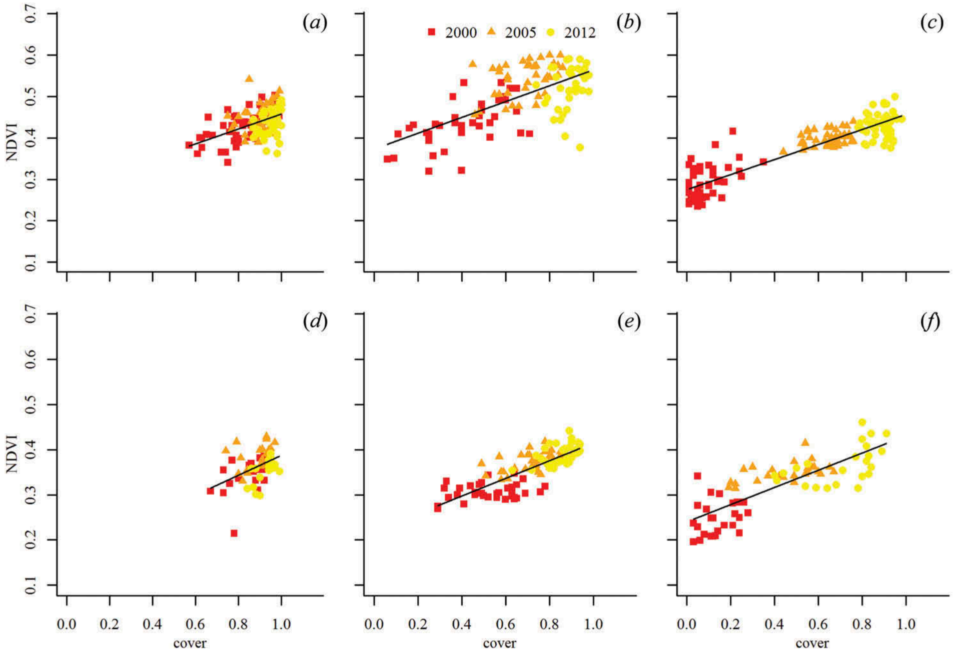

Figure 5. Relationship between NDVI and cover for each MODIS pixel and each year of high-resolution imagery (2000, 2005, and 2012) for the (*a*) 1928 north, (*b*) 1995 north, (*c*) 1999 north, (*d*) 1968 south, (*e*) 1995 south, and (*f*) 1999 south burn year stands.

(2000, 2005, and 2012), we still found a pattern of rapid recovery in the early stages of recovery in both the north and south 1999 stands.

We examined the relationship between NDVI and shrub cover for each of the 3 years in which cover estimates had been calculated (Figure 5). Although the relationship between NDVI and shrub cover is weak for the individual years, it is much stronger when the data from different burn years were pooled to create one data set representing all the NDVI/cover relationships for a given study area. In general, the stands that burned more recently (more of the early recovery sequence captured within the study time period) tend to have higher coefficient of determination (R^2) values (maximum $R^2 = 0.82$) as the greater range of values provided a better fit (Table 2).

Table 2. R^2 values for relationship between NDVI and cover for each MODIS pixel and each year of high-resolution imagery ($p < 0.001$ for all study areas).

Location	Burn year	R^2
North	2003	0.35
North	1999	0.82
North	1995	0.43
North	1928	0.23
South	1999	0.65
South	1995	0.62
South	1968	0.17

Table 3. R^2 values for the relationship between RRI slope and change in cover for each MODIS pixel and each time period, as defined by year of high-resolution imagery.

		2000–2005		2006–2012	
Location	Burn year	R^2	p	R^2	p
North	2003	–	–	0.1	0.02
North	1999	0.14	0.01	0.0	0.79
North	1995	0.0	0.91	0.15	0.02
South	1999	0.01	0.61	0.03	0.44
South	1995	0.17	0.02	0.04	0.24

The relationship between the RRI slope and change in shrub cover over the corresponding period is also weak, with a maximum R^2 value of 0.17 (Table 3).

4. Discussion and conclusions

If a signal of chaparral fuel accumulation (i.e. biomass growth) can be retrieved over time with reasonable fidelity on a per-pixel basis, then it should be possible to generate maps of post-fire biomass recovery and fuel development. Such spatially explicit information, even if restricted to portraying relative growth rates, would be tactically useful for fire managers to prioritize fire suppression and evacuation during fires and strategically useful for pre-fire fuel treatments. Most remote sensing research on chaparral recovery and fuel development has emphasized chronosequence approaches, which can be useful for capturing the generalized recovery trajectories, but cannot provide spatially explicit information in the way that uniquely tracking vegetation signals for each signal could.

In this study, we explored whether pixel-explicit time series contain signals of chaparral growth and biomass accumulation, and what sources of noise serve to confound such signals. We also examined how the relationship between shrub cover and NDVI varies as a function of stand age. We find that while the pixel-explicit time series approach does reveal signals of biomass accumulation, sources of noise include precipitation variability and site variability. Additionally, we find that while shrub cover can explain a large portion of the variance in NDVI over the full time period measured, changes in shrub cover are not necessarily related to changes in NDVI at the level of individual pixels.

The strongest signal in both the full temporal resolution (16-day composite) and annual early-August NDVI time series pertain to the vegetation greenness response to precipitation. In a chronosequence approach, fluctuations related to precipitation would not typically be obvious. The pixel-tracking approach allows for the separation of these precipitation-related fluctuations. It also allows for separation of site differences. Despite our efforts to carefully match stands based on vegetation type and proximity, comparison of the trajectories reveals substantial differences in recovery pattern for each unique burn history in the northern study area. The two study areas (northern San Diego County, composed of Redshank vegetation, and southern San Diego County, composed of Granitic Southern Mixed Chaparral) indicate even larger differences due to site location. This variation would have been lost in a chronosequence approach.

NDVI co-varies with both leaf area index and projected foliar cover of chaparral plants, which are indirectly related to foliar biomass and less strongly related to woody and total biomass. We found that from 17% to 82% of the variance in NDVI can be explained by the fraction of shrub cover for a MODIS pixel, when regressed over the full range of shrub cover over the stand and time period. The foliar:woody biomass ratio differs for different chaparral shrub species and as a function of stand age (Riggan et al. 1988). In addition, chaparral plants tend to have small leaves as an adaptation to seasonal and inter-annual droughts, which means that woody materials partially contribute to the remotely sensed spectral radiances. When chaparral canopies are not closed, such as for younger-age stands and those containing rock outcrops, exposed non-shrub vegetation, soil and rock also contribute to the remotely sensed radiance and therefore NDVI magnitude. These 'background noise effects' should be minimized by the pixel-tracking approach.

The primary factors that limit an evaluation of the potential of the NDVI pixel-tracking approach for estimating chaparral growth are a lack of comprehensive field data on chaparral biomass and growth in the study area, and a lack of spatially explicit and temporally varying data on chaparral stature (i.e. canopy heights). The best way to determine the strength of a chaparral growth signal would be to directly compare NDVI against chaparral fuel mass measurements over time, which are extremely difficult to make over large areas (chaparral is often impenetrable by humans on the ground) and are not available for the study area. Data on chaparral stature might be derived from light detection and ranging (lidar) data sets, but such data are not available for our study area and would be prohibitively expensive to generate over time to study changes in stature related to plant growth.

Our next research step towards the goal of generating spatially explicit information on chaparral growth will entail analyses of multiple SVIs derived from MODIS optical data products relative to estimates of chaparral growth rates based on measurements of shrub growth ring data, as a surrogate for biomass and its change. We will also explore new approaches to normalizing for inter-annual precipitation and background spatial variability on SVIs, and evaluate the potential of newly available Landsat surface reflectance products as an even finer spatial resolution source for tracking chaparral growth dynamics since the early 1980s.

Disclosure statement

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References

Hope, A. S., N. Albers, and R. Bart. 2012. "Characterizing Post-Fire Recovery of Fynbos Vegetation in the Western Cape Region of South Africa Using MODIS Data." *International Journal of Remote Sensing* 33 (4): 979–999. doi:10.1080/01431161.2010.543184.

Hope, A. S., C. Tague, and R. Clark. 2007. "Characterizing Post-Fire Vegetation Recovery of California Chaparral Using TM/ETM+ Time-Series Data." *International Journal of Remote Sensing* 28 (6): 1339–1354. doi:10.1080/01431160600908924.

Jönsson, P., and L. Eklundh. 2004. "TIMESAT – a Program for Analyzing Time-Series of Satellite Sensor Data." *Computers & Geosciences* 30 (8): 833–845. doi:10.1016/j.cageo.2004.05.006.

Keeley, J. E., and S. C. Keeley. 1981. "Post-Fire Regeneration of Southern California Chaparral." *American Journal of Botany* 68 (4): 524.

Keeley, J. E., H. Safford, C. J. Fotheringham, J. Franklin, and M. Moritz. 2009. "The 2007 Southern California Wildfires: Lessons in Complexity." *Journal of Forestry* 107 (6): 287–296.

Kinoshita, A. M., and T. S. Hogue. 2011. "Spatial and Temporal Controls on Post-Fire Hydrologic Recovery in Southern California Watersheds." *Catena* 87 (2): 240–252. doi:10.1016/j.catena.2011.06.005.

McMichael, C. E., A. S. Hope, D. A. Roberts, and M. R. Anaya. 2004. "Post-Fire Recovery of Leaf Area Index in California Chaparral: A Remote Sensing-Chronosequence Approach." *International Journal of Remote Sensing* 25 (21): 4743–4760. doi:10.1080/01431160410001726067.

Narasimhan, R., and D. A. Stow. 2010. "Daily MODIS Products for Analyzing Early Season Vegetation Dynamics across the North Slope of Alaska." *Remote Sensing of Environment* 114 (6): 1251–1262. doi:10.1016/j.rse.2010.01.017.

Peterson, S. H., and D. A. Stow. 2003. "Using Multiple Image Endmember Spectral Mixture Analysis to Study Chaparral Regrowth in Southern California." *International Journal of Remote Sensing* 24 (22): 4481–4504. doi:10.1080/0143116031000082415.

Riggan, P. J., S. Goode, P. M. Jacks, and R. N. Lockwood. 1988. "Interaction of Fire and Community Development in Chaparral of Southern California." *Ecological Monographs* 58 (3): 156–176.