Assessing postfire recovery of chamise chaparral using multi-temporal spectral vegetation index trajectories derived from Landsat imagery

Emanuel A. Storey^{a*}, Douglas A. Stow^a, John F. O'Leary^a

^a *Department of Geography, San Diego State University, San Diego, CA 92182, USA*

* Corresponding author. Department of Geography, San Diego State University, 5500

Campanile Drive, San Diego, CA 92182, USA. *E-mail address:* estorey@mail.sdsu.edu

Keywords: chamise chaparral, fire ecology, remote sensing, postfire resilience, type conversion, postfire recovery metrics, Landsat time series, growth form classification, land management.

Abstract

Land managers and ecologists working in Mediterranean-type ecosystems require information on postfire recovery of shrublands as a means of identifying long-term changes in these sensitive systems. This study evaluates the utility of postfire regrowth trajectories, derived from multi-temporal Landsat satellite surface reflectance imagery, as a basis for estimating postfire recovery of chamise chaparral in southern California. Postfire recovery metrics are applied to time series trajectories of spectral vegetation indices (SVIs) including NDVI, EVI, SAVI, MSAVI, NBR, and NBR2. Shrub fractional cover changes following postfire recovery are estimated at 74 plots using multi-date high spatial resolution orthoimagery, enabling stratification of the recovery outcomes. The sensitivity of Landsat-based regrowth trajectories to postfire shrub recovery is assessed by ANOVA statistical testing based on the stratified recovery outcomes. We evaluate several combinations of postfire recovery metrics and SVIs as postfire recovery indicators. We compare SVI trends extending 19 to 29 years postfire with field-collected data on postfire recovery trends reported in previous studies, in order to assess the sensitivity of the SVIs to short- and long-term phases of regrowth. The utility and necessity of normalizing SVI time series based on unburned control plots to reduce moisture effects is also evaluated.

A primary finding is that the Scaled Recovery Metric (SRM), a variant of the Regeneration Index which incorporates the pixel-specific SVI value immediately after fire, is a particularly useful indicator of postfire recovery based on time-sequential SVI trajectories and facilitates inter-site comparisons. Time series of several SVIs (especially NDVI and NBR2) provide statistically significant ($p < 0.05$) indications of postfire recovery outcomes when postfire recovery metrics are applied; NDVI and NBR2 are also sensitive to the gradual regrowth of chamise up to 12 and 19 years postfire, respectively. Normalization by unburned control plots reduces the correlation of Landsat SVIs with annual precipitation by 25 to 70% and enhances recovery signals, but locating suitable control plots was difficult in many parts of our study area. NBR2 is useful for postfire recovery assessment without normalizing by control plots. This study provides an overview of some advantages, limitations, and technical considerations for using postfire regrowth trajectories from Landsat imagery to assess long-term impacts of fire on chamise chaparral.

1. Introduction

Assessing rates and spatial patterns of vegetation recovery following wildland fire events is important for shrubland communities that may risk degradation or type conversion under certain fire and disturbance regimes (Viedma et al. 2006; Chuvieco & Kasischke 2007). Chamise chaparral is a shrub community widely distributed in Alta and Baja California and dominated by chamise (*Adenostoma fasciculatum*), a shrub species observed to be non-resilient from fire in some areas (Zedler et al. 1983; Haidinger & Keeley 1993; Lippitt et al. 2013). Type conversion of chamise to other community types dominated by subshrub and herbaceous growth forms may be linked to frequent burning (Zedler et al. 1983; Haidinger & Keeley 1993; Lippitt et al. 2013), and exacerbated by drought during early regrowth years and invasion by non-native plants

(Keeley et al. 2009; Keeley & Brennan 2012). More information on the spatial extent and magnitude of type conversion in chamise would aid in understanding its causes more clearly.

Field-plot sampling is not ideal for large-scale study of postfire vegetation dynamics due to issues of limited spatial coverage and representativeness, difficulty of site accessibility, labor costs, and the requirement that fire occurs in areas where prefire vegetation was surveyed. Assessing postfire vegetation recovery based on high spatial resolution aerial imagery may be cost prohibitive and challenging due to limited availability of prefire and postfire images (Wing et al. 2014). Multi-temporal Landsat imagery of southern California has been collected since 1984 by Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) sensors. The Landsat image archive is potentially useful for assessing rates and large-scale spatial patterns of postfire recovery in chamise chaparral, due to its multi-spectral coverage (visible, near infrared, shortwave infrared, and thermal infrared wavebands), and 30 m nominal spatial resolution (60 or 90 m for thermal infrared). The 30 m spatial scale is consistent with that of most localized vegetation changes (Skole & Tucker 1993; Tucker & Townshend 2000; Wulder et al. 2008; Masek et al. 2013). Landsat satellite systems have ~16-day revisit intervals, providing greater temporal coverage than aerial image archives (Masek et al. 2008; Hansen et al. 2010). Landsat surface reflectance data generated by the United States Geologic Survey (USGS) enhances the comparability of multi-temporal observations which support land change research. The USGS provides the following spectral vegetation indices based on Landsat surface reflectance imagery: Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), Enhanced Vegetation Index (EVI) (Huete et al. 1999), Soil-Adjusted Vegetation Index (SAVI) (Huete 1988), Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) (Qi et al. 1994),

Normalized Difference Moisture Index (NDMI) (Hardisky et al. 1983), Normalized Burn Ratio (NBR) (Key & Benson 1999), and Normalized Burn Ratio 2 (NBR2) (Key & Benson 2006).

A useful approach for assessing postfire vegetation recovery using multi-temporal satellite imagery is to derive time-sequential regrowth trajectories based on SVIs (Viedma et al. 1997; Riaño et al. 2002; Quayle et al. 2005; Hope et al. 2007; van Leeuwen et al. 2010). This approach provides more reliable estimates of the timing and magnitude of vegetation changes than two-date image differencing (Fraser et al. 2011). High spatial resolution orthoimagery represents a source of reference data for assessing the sensitivity of time-sequential Landsat SVI trajectories (and applied recovery metrics) to shrub cover change and type conversion. Fractional cover of shrubs is a key metric in classifying chaparral communities and can be used to assess ecological health and postfire recovery; reduction of shrub cover and increase of herbaceous or subshrub cover represents type conversion and degradation (Zedler et al. 1983; Haidinger & Keeley 1993; Keeley & Brennan 2012; Lippitt et al. 2013). Such type conversions have occurred in San Diego County, California in recent decades (Keeley & Brennan 2012; Lippitt et al. 2013).

In order to assess postfire recovery of a Mediterranean shrubland based on Landsat imagery, Roder et al. (2008) fit piece-wise linear and polynomial regression models to the time series trajectories of each pixel, which supported comparison of prefire to postfire vegetation covers. A pixel-tracking approach is preferable because it reduces effects of inter-site differences in vegetation composition, substrate, and differential controls on vegetation growth (Hope et al. 2007; Narasimhan & Stow 2010), compared to a chronosequence approach (Peterson & Stow 2003; McMichael et al. 2004). In addition to vegetation recovery signals, Landsat SVI trajectories may capture changes in soil and plant-available moisture and plant phenology (Diaz-Delgado et al. 1998). To reduce the contribution of herbaceous plants (which are typically

admixed in Mediterranean-type shrublands) to modulating SVI values, researchers commonly select images from dry months when herbaceous vegetation is senescent (Henry & Hope 1998; McMichael et al. 2004; Hope et al. 2007). Normalization based on control plots of the same vegetation type that are mature and remain unburned during a study period has proven useful to suppress inter-annual precipitation effects on plant and soil moisture, for the purpose of postfire regrowth analysis (Diaz-Delgado et al. 1998; Riaño et al. 2002; Diaz-Delgado et al. 2002; Idris et al. 2005; Li et al. 2008). This approach is expressed computationally as the Regeneration Index (RI) normalization, which has the following form:

$$RI = \frac{SVI_{recovering}}{SVI_{control}} \quad (\text{Equation 1})$$

where $SVI_{recovering}$ is the spectral vegetation index (SVI) value of a pixel during postfire regrowth, and $SVI_{control}$ is the SVI value of a control plot, extracted from each image of a time series (Diaz-Delgado et al. 1998). Broad-scale application of this index is limited by the difficulty of selecting relevant control plots (Gitas et al. 2012). In addition, chaparral can exhibit different spatial patterns of NDVI during dry versus moist periods (Hope et al. 2007), which may introduce uncertainty in RI values and resultant trajectories. Applicability of RI normalization may be limited at burned sites (near the middle of large fire scars) that lack unburned neighbor sites, and by land cover differences or heterogeneity in the unburned landscape matrix (Gitas et al. 2012). This use of control-plot normalization represents an additional variable and potential constraint to postfire recovery assessments of chaparral based on time-sequential satellite imagery.

The main goal of this study is to assess the utility of Landsat SVI time series for detecting signals of differing postfire recovery trajectories in chamise chaparral. Our objectives are: 1) to assess the sensitivity of several SVIs and metrics of postfire recovery, relative to changes in

shrub cover estimated from high spatial resolution orthoimagery, 2) to determine how trajectories based on Landsat SVIs differ in short-term and long-term phases of postfire recovery, and 3) to assess the utility and feasibility of normalizing the SVI time series based on control plots to obtain clearer postfire recovery signals. This study addresses the following research questions in the context of chamise chaparral in southern California and its recovery 4 to 20 years after burning in wildland fires:

1. Which SVIs and regrowth trajectory metrics are most effective for distinguishing postfire recovery outcomes of chamise in a categorical manner (e.g. *recovered*, *moderately degraded*, and *severely degraded*)?
2. How do Landsat SVIs differ in sensitivity to the rapid, short-term (1 to 7 years) and gradual, long-term (10 to 20 years) postfire recovery phases of chamise?
3. To what extent is normalization for inter-annual moisture effects on SVI trajectories (using unburned control plots) beneficial, necessary, and feasible for postfire recovery assessment of chamise chaparral?

2. Methods

2.1. Overview of research approach

The main component of this study is to characterize temporal trajectories of Landsat SVIs for selected chamise sites of known fire histories and various levels of postfire shrub recovery, in order to evaluate the utility of the time series and applied metrics for detecting postfire recovery and partial type conversion. The general workflow of this study is illustrated by Figure 1.

High spatial resolution orthoimagery is used to estimate prefire and postfire differences in growth form cover types, with an emphasis on true shrubs, in order to determine if differences between prefire and postfire Landsat SVI values relate to differences in shrub cover. We evaluate several SVIs and metrics applied to the Landsat SVI time series. Analysis of variance (ANOVA) tests and scatterplots are used to determine which time series metrics and SVIs are most capable of distinguishing recovered, moderately degraded, and severely degraded sites (addressing

research Question 1). We also assess the accuracy of the prefire and postfire growth form maps based on orthoimagery, which are a key part of this study. The analytical component described above is termed the regrowth trajectory sensitivity analysis.

The second component of this study is based on SVI time series of sites which last burned between 1984 and 1994, enabling assessment of longer-term SVI trajectories. We refer to published, field-based data on postfire height and fractional cover increase in chamise, in order to explain differences observed in the long-term SVI trajectories. This component is termed the long-term change analysis and addresses Question 2. Postfire SVI time series of each site are derived *with* and *without* normalization based on unburned control plots. We empirically evaluate the utility of RI normalization by testing correlation with inter-annual precipitation, and explore whether recovery assessments are possible without normalization (addressing Question 3) by comparing results from each of the SVIs.

Figure 1. Workflow diagram depicting the data processing and general analytical framework of this study. Items with dashed-line perimeters represent the key research outcomes and analytical components.

2.2. Study area

The study area is located in a central, north-south trending region of San Diego County, California (USA) which is largely rural and contains variable topographic features. It is covered by approximately 740 km² of chamise chaparral, which occurs mainly on xeric, south- and west-facing slopes in low-elevation (100 m ASL) to mid-elevation (1250 m ASL) areas within a patch mosaic of other chaparral and vegetation types. Mean annual precipitation in the study area ranges from 250 mm at lower-elevation sites to 650 mm at higher-elevation sites. Approximately 93% of the mean annual precipitation occurs between October and April, which is followed by a protracted, dry summer season, typical of Mediterranean-type climate zones such as this.

2.3. Data

We obtained a 30-year (1984-2014) Landsat image time series of WRS path 40/row 37 through the USGS Land Surface Reflectance Climate Data Record (LSRCDR) (<http://espa.cr.usgs.gov/>). These image products are in surface reflectance form, based on Level-1 Landsat 5 TM and Landsat 7 ETM+ images using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) and Landsat 8 OLI images (using the L8SR algorithm) through radiometric calibration and correction for atmospheric effects and seasonal variations in illumination. Topographic and bi-directional reflectance distribution effects are not corrected in the LEDAPS and L8SR processes. Landsat 4-5 TM images are the only satellite image data that were used for the period 1984 to 2011, in order to maximize sensor consistency. Landsat 7 ETM+ images were only used for 2012, as they contain no-data pixels from the scan line corrector offset malfunction after 2003 (cf. Storey et al. 2005). Landsat 8 OLI images were used for 2013 and 2014.

We used annual single-date Landsat SVI images acquired during late August or early September for every year in the study period, as is consistent with similar studies on postfire

recovery of chaparral (Henry and Hope 1998; McMichael et al. 2004; Hope et al. 2007). Landsat datasets obtained through the LSRCRDR site also include nominal cloud-masking images derived from the *Fmask* software algorithm (Zhu & Woodcock 2012), which were used to remove cloud-affected pixels from five of the Landsat images (the other 25 images were cloud-free in the areas of interest). We used SVI datasets provided by USGS LSRCRDR, which are described in Table 1.

Table 1. Formulae and band wavelength ranges of spectral vegetation indices produced by USGS based on Landsat surface reflectance imagery.

$NDVI = \frac{NIR - Red}{NIR + Red}$	$NDMI = \frac{NIR - SWIR1}{NIR + SWIR1}$	Spectral band properties		
		<u>Sensor:</u>	TM,	OLI
$EVI = \frac{NIR - Red}{NIR + 6.0 * Red - 7.5 * Blue + 1.0}$	$NBR = \frac{NIR - SWIR2}{NIR + SWIR2}$	<u>Band</u>	<u>Wavelength range (μm)</u>	
		Blue	0.45 - 0.52	0.45 - 0.51
$SAVI = \frac{(NIR - Red) * 1.5}{(NIR + Red + 0.5)}$	$NBR2 = \frac{SWIR1 - SWIR2}{SWIR2 + SWIR2}$	Red	0.63 - 0.69	0.64 - 0.67
		NIR	0.77 - 0.90	0.85 - 0.88
$MSAVI2 = \frac{2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - Red)}}{2}$		SWIR1	1.55 - 1.75	1.57 - 1.65
		SWIR2	2.09 - 2.35	2.11 - 2.29

We used high spatial resolution orthoimagery from USGS (earthexplorer.usgs.gov) to map prefire and postfire growth form covers (classification procedures described below); site-level fractional cover changes were estimated from these maps. A set of 1 m spatial resolution, three band (G-R-NIR) color infrared (CIR) scanned aerial photographs (acquired September 1996) which had been orthorectified, enabled prefire vegetation cover classification, while 0.5 m spatial resolution, four band (B-G-R-NIR) digital orthoimage tiles (acquired May 2012) enabled recent (postfire) vegetation cover to be classified and quantified. We used vegetation community type maps (produced in 1995), which follow the Holland (1986) classification code, to identify chamise chaparral sites (<http://sandag.org>). We obtained historic fire perimeter maps from California Fire Resource and Protection (<http://frap.cdf.ca.gov>), which we combined with the vegetation community type maps in order to delineate even-age chamise chaparral stands.

2.4. Study site selection procedures

As a basis for the regrowth trajectory sensitivity analysis, we selected 74 areas of interest (AOIs) from chamise chaparral stands within the 2003 fire perimeters which include a range of shrub recovery levels. Fifty-five of these AOIs appeared to be partially type-converted based on visual comparison of the 1996 and 2012 orthoimages; 19 AOIs that appeared recovered were selected from areas near the degraded sites. The AOIs were delineated as 90 m x 90 m (~0.8 ha) plots which coincide with 3 x 3 30 m Landsat pixel blocks, from which SVI time series were later derived. Annual SVI values of the Landsat pixel elements were averaged at each site in order to reduce effects of geometric misregistration on the time series (cp. Hope et al. 2007). Subsets of the orthoimages corresponding to the AOIs were extracted to support prefire and postfire assessment of growth form cover. We selected areas that were fire-free during the period 1986-1996, to assure that prefire shrub cover assessments based on the 1996 orthoimages represented mature canopy states. Potential AOIs were constrained to areas that burned after the 1996 imagery was acquired, which are mainly in the extensive 2003 fire perimeters shown in Figure 2.

Figure 2. Location of the study sites, 2003 fire perimeters, and chamise chaparral patches in the study area (San Diego County, CA, USA). Long-term change analysis and regrowth trajectory sensitivity analysis sites are shown, along with the non-burned control sites used to normalize for inter-annual precipitation effects. The Landsat 8 (OLI) true-color image (acquired in November 2015) in the background provides geographic context.

As a basis for the long-term recovery analysis, we selected an entirely different set of 90 m x 90 m AOIs (hereafter referred to as sites) from chamise stands which underwent 19 to 29 years of postfire recovery during the study period. We ensured that these sites had not burned within a decade prior to 1984, when the first Landsat TM images were acquired. Although differences in prefire and postfire shrub cover were not estimated for this long-term change analysis, shrub cover at these sites appeared healthy and well recovered based on the 2012 orthoimagery. Unburned control plots were selected for the purpose of normalizing both sets of study sites, as outlined in Figure 1 and mapped in Figure 2. Control plots consisted of 3 x 3

blocks of Landsat pixels in older chamise stands which are proximal to the burned sites. Other factors for selecting control sites included stand size, shrub canopy homogeneity, and similarity of prefire Landsat NDVI values relative to the study sites.

2.5. Postfire recovery metrics applied to the Landsat time series

Two different Landsat time series were derived for each 0.8 ha study site, one based on the original SVI values and the other upon values that were normalized using the unburned control plots. For the regrowth trajectory sensitivity analysis, it was necessary to compute summary statistics which represent the prefire SVI levels and postfire trajectories according to their 10-year asymptotes. Median SVI values from the period 1998 to 2003 were used to represent prefire levels. From SVI vs. time plots, we derived ordinary least squares (OLS) best-fit lines for each regrowth trajectory, following the observation that the postfire trends are characteristically linear between 4 and 10 years. We excluded from the OLS regressions the first four postfire data points, because postfire annual and suffrutescent plants are often dominant during this period and introduce spurious noise to the signal of chamise chaparral recovery (Keeley 2000; McMichael et al. 2004; Hope et al. 2007). Hence, the early postfire years were deemed less appropriate and useful than the later years for estimating recovery. We used maxima of the OLS best-fit lines applied to the trends between 2008 and 2014 as postfire recovery asymptotes. We also derived averages of years 2009-2011 and 2012-2014 as alternative postfire asymptotes, because declines related to drought-like conditions were observed in the trajectories from 2012 to 2014. An example of a trajectory as captured by statistics and OLS regression is shown in Figure 3.

Figure 3. Schematic depiction of regrowth trajectory metrics. A prefire growth and postfire regrowth trajectory based on the Regeneration Index (computed from NDVI) is shown for one of the regrowth trajectory sensitivity analysis sites. The prefire median, the first postfire observation, and the postfire asymptote (maximum of a best-fit regression line derived for years 2008-2013) are separated respectively by double-arrows (a), (b), and (c).

Several postfire recovery metrics were tested on the Landsat SVI time series. Index values based on the SVI and plot-normalized SVI values are both represented as I for the sake of simplicity. We implemented the Difference Recovery Metric (DRM) and the Ratio Recovery Metric (RRM), which are both based on prefire median index values (I_{prefire}) and postfire asymptote index values ($I_{\text{recovering}}$) (cp. Diaz-Delgado et al. 1998):

$$\text{DRM} = I_{\text{recovering}} - I_{\text{prefire}} \quad (\text{Equation 2})$$

$$\text{RRM} = I_{\text{recovering}} / I_{\text{prefire}} \quad (\text{Equation 3})$$

The DRM and RRM represent the arithmetical difference and ratio of a postfire asymptote and a prefire median value, respectively, as represented by the variable c in shown in Figure 3.

Two factors may limit the consistency and comparability of trajectories based on the DRM and RRM: 1) variability in the baseline (first-year postfire) index values (I_{burned}) which mainly represent the soil background and senescent vegetation, and 2) variation in the ranges between I_{burned} and I_{prefire} values. To account or normalize for these differences, we formulated and evaluated a scaled version of the RRM, termed the Scaled Recovery Metric (SRM):

$$\text{SRM} = \frac{I_{\text{recovering}} - I_{\text{burned}}}{I_{\text{prefire}} - I_{\text{burned}}} \quad (\text{Equation 4})$$

The SRM is potentially less sensitive than the DRM and the RRM to differences in the spectral properties of shrub canopy backgrounds, and may provide a means of normalizing regrowth trajectories for inter-site differences in vegetation abundance (cp. Miller & Thode 2007). This metric represents fractional return from the SVI (or plot-normalized SVI) level under de-vegetated postfire conditions to the prefire level, across a range of values which is specific to each site.

2.6. Stratification of recovery outcomes based on orthoimagery

We estimated changes in the fractional cover of true shrubs (primarily chamise) at the 74 regrowth trajectory sensitivity analysis sites based on prefire (1996) and postfire (2012) aerial orthoimagery. Fractional cover of the following growth form classes was mapped: true shrub, subshrub (including *Artemisia californica*, *Salvia mellifera*, *S. apiana*, and *Eriogonum fasciculatum*), and herbaceous (mainly the grasses *Bromus madritensis* and *Vulpia octoflora*). Subshrub and herbaceous cover were combined into a single class because: 1) these growth form types are difficult to separate based on CIR orthoimagery of 1 m spatial resolution, and 2) substantial changes in cover from true shrub into subshrub and/or herbaceous growth forms typically represents a type conversion. Exposed soil/rock was represented as a third class, because substantial increase of bare soil and rock can also represent a lack of postfire recovery.

We conducted pixel-level classification of NDVI images derived from the high spatial resolution orthoimages. We classified the images into the three classes described above, by applying two different histogram cut-off thresholds that were determined independently for each site. This technique proved to be accurate and more efficient than conventional unsupervised and

supervised image classification techniques, based on several pilot studies. The rationale for this approach is based on the finding that areas covered by true shrubs (e.g. chamise) exhibit distinctly higher NDVI values than patches or stands of subshrubs and herbaceous plants, and that exposed rock and soil exhibit distinctly lower NDVI values than plant growth forms. We chose the NDVI thresholds used for each site by interactive sampling of NDVI values, while overlaying the CIR orthoimages to visually assess the spatial arrangement of vegetation types. We performed classifications iteratively until close agreement between the classification products and visual interpretations was achieved.

Thematic images resulting from this process provided estimates of shrub fractional cover change (SFCC) between 1996 and 2012, which are represented as absolute rather than relative percentages of change. We defined equal-interval postfire SFCC ranges in order to categorize the recovery outcomes, as follows: *recovered* (+7.5% to -7.5% SFCC), *moderately degraded* (-7.5% to -22.5% SFCC), and *severely degraded* (-22.5% to -37.5% SFCC). We randomly selected 10 of the study sites for accuracy assessment of the 1996 and 2012 growth form maps. We generated 40 points in a random spatial distribution within each of these sites. A growth form class was then assigned to each of the points, based on visual interpretation of the orthoimages in CIR display. We then extracted thematic values of the growth form maps to the same points and compared the results numerically.

2.7. Statistical analysis and interpretation

We derived a total of 126 recovery metric values from time series of seven different Landsat SVIs (Table 1), with and without control-plot normalization, using three metrics (DRR, RRM, and SRM), and three postfire trajectory asymptote measures. In order to assess correspondence between the recovery metric values and levels of shrub recovery, we first compared SFCC values

with the recovery metric values using X-Y regressions plots. This preliminary assessment suggested that eight of the 126 potential datasets co-varied closely with SFCC. For these eight dataset types, we conducted a one-way analysis of variance (ANOVA) to assess whether the Landsat SVI-based postfire recovery metric values are statistically different between the three recovery classes. The X-Y scatter plots of SFCC versus the recovery metric datasets which also showed high statistical significance (based on ANOVA tests) are included as results, providing an alternate basis for assessing the sensitivity and reliability of these recovery metrics.

To support the long-term change analysis, we compared the SVI trajectories with published field data showing rates of vertical and horizontal postfire regrowth of chamise, in a descriptive manner. In order to evaluate the effectiveness of RI normalization, we computed coefficients of correlation between annual precipitation and the prefire (1998-2003) and postfire (2008-2014) time series, based on annual averages among the 74 regrowth trajectory sensitivity analysis sites. These coefficients of correlation were computed using the original SVI data and SVI values that were normalized based on control plots. In order to account for variability in the time series related to regrowth, annual postfire values were normalized relative to the best-fit regressions lines derived for the period 2008 to 2014.

3. Results

3.1. Accuracy and results obtained from growth form maps

Accuracy assessment of growth form maps associated with 10 of the 74 regrowth trajectory sensitivity analysis sites indicates that classification accuracy was reasonable, and generally higher for the 2012 maps (88.8%) than for the 1996 maps (76.3%). This accuracy is based on the median number of points which were mapped correctly among the sites (Table 2). Error rates are highest in the subshrub/herbaceous class, followed by the true shrub class for both map sets.

These growth form map accuracies are acceptable the purpose of categorizing three postfire recovery classes. Errors of commission and omission in each class (not reported) are nearly equivalent, so there is no need to adjust these site-level estimates of true shrub cover.

Table 2. Results of accuracy assessment on the growth form maps. Statistics are associated with 1996 and 2012 growth form classifications of ten regrowth trajectory sensitivity analysis sites.

2012	<u>Accuracy statistics</u>		<u>Errors per growth form class (%)</u>			1996	<u>Accuracy statistics</u>		<u>Errors per growth form class (%)</u>		
Site ID	Number of sample points correct (of 40 total)	Percent correct	Soil/rock	Subshrub/herbaceous	True shrub	Site ID	Number of sample points correct (of 40 total)	Percent correct	Soil/rock	Subshrub/herbaceous	True shrub
1-A	36	90.0	0.0	5.0	5.0	1-A	26	65.0	5.0	20.0	7.5
2-A	34	85.0	0.0	10.0	5.0	2-A	35	87.5	2.5	10.0	0.0
3-A	37	92.5	0.0	0.0	7.5	3-A	35	87.5	0.0	12.5	0.0
4-A	37	92.5	0.0	5.0	2.5	4-A	27	67.5	2.5	20.0	10.0
5-A	34	85.0	2.5	7.5	5.0	5-A	32	80.0	5.0	12.5	2.5
6-A	33	82.5	15.0	2.5	0.0	6-A	32	80.0	7.5	7.5	5.0
7-A	35	87.5	0.0	12.5	0.0	7-A	29	72.5	2.5	17.5	7.5
8-A	38	95.0	2.5	2.5	0.0	8-A	29	72.5	2.5	12.5	12.5
9-A	36	90.0	2.5	5.0	2.5	9-A	32	80.0	0.0	15.0	5.0
10-A	35	87.5	5.0	2.5	5.0	10-A	27	67.5	12.5	12.5	7.5
Median:		88.8	1.25	4.5	4.5	Median:		76.3	2.5	12.5	6.3
Mean:		88.8	2.8	5.0	3.3	Mean:		76.0	4.0	14.0	5.8
Maximum:		95.0	15.0	12.5	7.5	Maximum:		87.5	12.5	20	12.5

Based on the growth form classification products, we differentiated portions of the shrub canopy matrix which recovered following fire from portions which changed to subshrub/herbaceous cover or soil/rock. Postfire shrub fractional cover change (SFCC) at approximately half of the study sites is between -10% (negative values indicate postfire decrease) and +10%, and therefore shows a general pattern of recovery at the 2003 fire sites, as shown in Figure 4. Twenty-seven of the sites exhibit -10% to -30% SFCC, while seven of the most severely degraded sites exhibit -30% to -40% SFCC. True shrub cover generally converted to subshrub/herbaceous cover at sites that were degraded. The subshrub/herbaceous growth form class shows more frequent postfire increases and fewer decreases in cover than the true shrub class. Postfire increase of the soil/rock class is the most prevalent, and generally between +10%

and +20%, as shown in Figure 4. An example of a growth form classification based on high spatial resolution NDVI images is given in Figure 5.

Figure 4. Bar chart of postfire fractional cover change magnitudes and frequencies, in units of absolute percent. This is based on two-date (1996 and 2012) growth form classifications derived from high spatial resolution orthoimagery for the 74 regrowth trajectory sensitivity analysis sites. Negative values represent postfire decline in cover.

Figure 5. Example of NDVI and growth form classification products. Frames (a) and (c) are NDVI images based on the 1996 and 2012 orthoimages, respectively. Frames (b) and (d) display growth form maps for 1996 and 2012, respectively. Postfire true shrub cover decrease is 5%, and increase of soil/rock cover is 4% at this regrowth trajectory sensitivity analysis site.

3.2. Sensitivity of Landsat SVI time series and metrics to postfire recovery

Results of ANOVA tests were used to determine if the Landsat SVI trajectory metric datasets (unique configurations of postfire recovery metric, asymptote type, SVI, and RI normalization) are statistically significant indicators of postfire recovery, and are presented in Table 3. All except two of the recovery metric datasets based on NDVI yielded p -values of less than 0.05, which suggests that these Landsat NDVI time series recovery metric values enable differentiation of the postfire recovery classes. The ANOVA test results for other SVIs indicated statistical significance for only one dataset based on NBR and NDMI, and three datasets based on NBR2. Based on the p -values ($Pr > F$) and R^2 values, the datasets which are the strongest indicators of recovery status are plot-normalized NDVI, NBR2 and plot-normalized NBR2, each based on the SRM (Table 3).

Scatterplots of the SRM datasets based on NDVI and NBR2 (shown in Figure 6) indicate co-variability with SFCC. The recovery estimates based on plot-normalized NDVI appear to distinguish SFCC differences of 15% or greater with moderate reliability. Because postfire fractional cover changes in the *subshrub/herbaceous* growth form class (whether positive or negative) may also contribute to changes in Landsat SVI values, fractional cover change estimates for this class were summed with the *true shrub* change estimates as a test. Applying a multiplier coefficient of 0.63 for contribution of the subshrub/herbaceous change values (a value which produced the most linear trend based on iterative testing), this combined estimate of fractional cover change co-varies with the SRM values (especially those based on plot-normalized NDVI) more closely than the SFCC data alone (Figure 6-d).

Table 3. Analysis of variance (ANOVA) results. Table shows the results for several SVIs based on selected postfire metrics/sample types relative to three postfire recovery classes, with a 95% confidence level and 65 degrees of freedom ($n = 65$). All results for NDVI are shown, and for other SVIs where ($Pr > F$) < 0.05 (in bold font).

Input dataset characteristics:			Goodness-of-fit:			ANOVA summary:				Model parameters:		
Dataset Basis	Postfire asymptote type	Recovery Metric	R^2	Adj. R^2	RMSE	Sum of Squares	Mean Squares	F	$Pr > F$	Standard Error	t	$Pr > t $
NDVI	2009-2011 average	SRM	0.16	0.16	0.20	0.33	0.11	2.88	0.046	0.14	6.94	< 0.0001
NDVI	2008-2013 RL* max.	SRM	0.17	0.12	0.17	0.27	0.09	3.13	0.035	0.12	6.42	< 0.0001
NDVI	2008-2013 RL max	DRM	0.07	0.01	0.31	0.35	0.12	1.20	0.320	0.22	7.86	< 0.0001
NDVI-RI	2009-2011 average	DRM	0.22	0.17	0.10	0.13	0.04	4.19	0.011	0.07	-1.31	0.1970
NDVI-RI	2008-2013 RL max.	DRM	0.22	0.17	0.10	0.12	0.04	4.28	0.010	0.07	-2.06	0.0454
NDVI-RI	2009-2011 average	SRM	0.16	0.16	0.19	0.32	0.11	2.90	0.045	0.14	5.10	< 0.0001
NDVI-RI	2012-2014 average	SRM	0.25	0.20	0.16	0.37	0.12	5.05	0.004	0.11	4.50	< 0.0001
NDVI-RI	2008-2013 RL max.	SRM	0.15	0.09	0.18	0.24	0.08	2.60	0.063	0.12	4.31	< 0.0001
NBR-RI	2009-2011 average	DRM	0.17	0.11	0.06	0.03	0.01	3.04	0.038	0.04	0.18	0.8597
NBR2	2009-2011 average	SRM	0.27	0.22	0.26	1.16	0.39	5.59	0.002	0.19	4.88	< 0.0001
NBR2	2008-2013 RL max.	SRM	0.25	0.20	0.29	1.22	0.41	4.96	0.005	0.20	4.15	0.0001
NBR2-RI	2009-2011 average	DRM	0.17	0.11	0.06	0.03	0.01	3.04	0.038	0.04	0.18	0.8597
NBR2-RI	2012-2014 average	SRM	0.19	0.16	0.31	1.56	0.78	8.07	0.001	0.17	3.05	0.0033
NDMI-RI	2009-2011 average	DRM	0.17	0.11	0.06	0.03	0.01	3.04	0.038	0.04	0.18	0.8597

* RL refers to best-fit regression lines derived from SVI or RI values (2008-2013).

Postfire *regrowth trajectories* were derived based on the SRM values of each postfire year; the SRM was previously applied only to postfire *asymptote values*. The SRM was applied to trajectories of NDVI, plot-normalized NDVI, NBR2, and plot-normalized NBR2 which were grouped according to recovery class, as displayed in Figure 7. The separability of the recovery classes based on the SRM is comparable between NDVI and plot-normalized NDVI during the last few years of the postfire monitoring period. However, NDVI appears to be more sensitive to inter-annual moisture availability than NBR2, and thus may result in less reliable estimates of postfire recovery.

The NBR2 trajectories are more similar to their control-plot normalized counterparts than those based on NDVI. The degree of separation between the *recovered* and *severely degraded* classes based on the SRM is comparable for NDVI and NBR2, and for their plot-normalized counterparts, respectively. Although plot-normalized NDVI exhibits a trend with fewer outliers in relation to SFCC than NBR2 (Figure 6), the higher R^2 value for NBR2 (Table 3) is likely a

result of its ability to better separate pixels belonging to the *recovered* category from those associated with the *moderately degraded* category (Figure 7). The plot-normalized NBR2 trajectories based on the SRM provide the clearest distinction between the three recovery categories overall, as shown in Figure 7.

Figure 6. Scatter plots depicting the SRM recovery metric based on NDVI-RI and NBR2 relative to fractional cover changes at the regrowth trajectory sensitivity analysis sites. Plots (a) and (b) show fractional cover change of true shrub, while (c) and (d) show a combination of *true shrub* + 0.63 *X* *subshrub/herbaceous* on the X-axes.

Figure 7. Regrowth trajectories according to recovery class derived from NDVI and NBR2. Regrowth trajectories represent mean scaled recovery metric values and (1.0) standard deviations bars for the regrowth trajectory sensitivity analysis sites within each of the recovery classes, derived from (a) NDVI, (b) NBR2, (c) NDVI-RI, and (d) NBR2-RI. These trajectories are extracted from sites which burned in 2003.

3.3. Longer-term vegetation changes and comparison of SVI sensitivities

We extracted Landsat SVI data to represent the regrowth trajectories of 14 chamise chaparral sites which burned during the period 1984-1994 and which were undisturbed by fire through 2014. For each SVI, the annual median value of 14 plot-normalized SVI trajectories relative to the final three years in each trajectory is shown in Figure 8.

Figure 8. Regrowth trajectories and field-based estimates of postfire recovery from: (a) NDVI, NBR, NBR2, NDMI, EVI, SAVI, and MSAVI based on median values from 14 sites during 19 to 29 years postfire. Regeneration Index values are relative to the mean of the final three years of each trajectory. Labelled arrows indicate times that trajectories reach 100%. (b) Field data of (absolute) surface cover increase rates of *A. fasciculatum*, averaged for 16 sites in San Diego County (from Keeley & Keeley 1981). (c) Field data showing rates of postfire height increase for *A. fasciculatum*, based on repeated measurements of one or two seedlings and resprouts over 25 years (from Horton & Kraebel 1955).

Rates of postfire surface cover and height increase of chamise based on published field data

are also shown in Figure 8. The time series trends suggest that NDVI, NBR, and NBR2 are more sensitive to the gradual, long-term growth of chamise associated with postfire recovery than the other SVIs. The EVI, SAVI, MSAVI, and NDMI trajectories show relatively steep, positive slopes in the first four postfire years. Based on the published field data, vertical regrowth of chamise continues well beyond four years (Figure 8-c), suggesting that the former SVIs are insensitive to gradual, long-term recovery. Based on a four-year observation period, Figure 8-b suggests that horizontal expansion of chamise begins to slow after three years

postfire. Hence, much of the observed increase in EVI, SAVI, MSAVI, and NDMI may be related to horizontal rather than vertical regrowth. NDVI, NBR, and NBR2 appear sensitive to short-term as well as long-term vertical and horizontal regrowth, and may thus be the most useful for postfire recovery assessment.

3.4. Utility of normalizing for precipitation variability based on unburned control plots

Annual precipitation and regrowth trajectories of several of the regrowth trajectory sensitivity analysis sites, based on NDVI and plot-normalized NDVI time series, are shown in Figure 9. The NDVI trajectories follow declining trends in annual precipitation from 1998 to 2002 and from 2012 to 2014, and exhibit a peak during the wetter years (2010 and 2011) of the postfire recovery period. Plot-normalized NDVI trajectories appear less affected by precipitation and more consistent with the expected pattern of vegetation regrowth, characterized by substantial and incremental increases in the first five years and gradual changes in subsequent years (Horton & Kraebel 1955). Plot-normalized NDVI also declines from 2011 to 2014, which may suggest that the recovering sites were more impacted by the dry conditions than their respective control sites during that period (Figure 9).

Figure 9. Co-variation of annual precipitation with selected NDVI time series per recovery categories (indicated by color in the legend). These trajectories from the same sites are based on (a) original NDVI values and (b) control-plot normalized values. (c) Annual precipitation by water year from NWS station at Lake Cuyamaca (1998-2014) illustrate inter-annual co-variation with NDVI.

In order to evaluate the utility of control-plot normalization for reducing the effects of precipitation on the Landsat SVI trends, we show coefficients of correlation between annual precipitation and annual SVI and plot-normalized SVI values in Table 4. Low coefficients of correlation signify low influence of precipitation variability on the SVI time series and more distinct trajectories, which are beneficial for estimating postfire recovery. The coefficients of correlation are lowered by 0.26 to 0.38 for NDVI, EVI, SAVI, and MSAVI as a result of RI normalization in the prefire period, and by 0.13 to 0.20 in the postfire period.

The NDMI exhibits negative correlation with annual precipitation, and correlation coefficients are not significantly reduced when RI normalization is used on NDMI. Coefficients of correlation based on NBR2 exhibit the greatest reduction (0.58) following RI normalization in

the prefire period, while the lowest overall coefficient of correlation (-0.07) during the postfire period is also associated with NBR2. In addition, the NBR2 shows the least correlation (0.31) with precipitation without the use of RI normalization (during the postfire period).

Table 4. Coefficients of correlation between annual precipitation and Landsat SVIs, using surface reflectance values without use of control plots ('no') and control-plot normalized ('yes') values in prefire and postfire periods.

Spectral vegetation index														
NDVI		EVI		SAVI		MSAVI		NDMI		NBR		NBR2		
Prefire period (1998-2003)														
Control-plot normalized														
no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	
Coefficient of correlation														
0.79	0.53	0.84	0.46	0.81	0.49	0.81	0.50	-0.83	0.77	0.83	0.65	0.80	0.22	
Postfire period (2008-2014)														
Control-plot normalized														
no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	
Coefficient of correlation														
0.69	0.50	0.88	0.71	0.86	0.73	0.88	0.75	-0.89	-0.25	0.90	-0.17	0.31	-0.07	
Ratio of 'original SVI' to 'control-plot normalized SVI' coefficients of correlation														
Prefire	1.49		1.83		1.65		1.60		-1.08		1.27		3.68	
Postfire	1.40		1.24		1.17		1.17		3.51		-5.35		-4.29	

4. Discussion and Conclusions

The primary objective of this study is to assess how well several metrics, applied to trajectories derived from Landsat SVI time series, capture postfire recovery and possible type conversion of chamise chaparral. ANOVA tests reveal that several of the Landsat-derived recovery indicators distinguish between recovering, moderately degraded, and severely degraded sites. Evaluation of several combinations of SVIs and postfire recovery metrics revealed that NDVI and NBR2 (and to a lesser degree, NDMI and NBR) trajectories are significantly correlated with postfire recovery outcomes, especially based on the Scaled Recovery Metric (SRM) but also the Difference Recovery Metric (DRM). Recovery estimates based on the SRM were most robust when control-plot normalization for precipitation effects was used. The soil-adjusted type of SVIs (e.g. SAVI, MSAVI and EVI) yielded regrowth trajectories that were less sensitive to

recovery. This finding reflects those of other studies which suggest that SAVI and SAVI-like indices are less sensitive than NDVI to changes in Mediterranean-type shrublands (Baret and Guyot 1991; Clemente et al. 2009; Vila and Barbosa 2010).

The moderate co-variability between the Landsat recovery metric datasets and the orthoimage-based shrub fractional cover change (SFCC) estimates, however, suggests some limitation in how reliably type conversion can be detected using Landsat SVI time series. Only type-converted chamise chaparral sites that underwent postfire shrub cover decline of 15% or greater were distinguishable from well-recovered sites, using the SRM. Most of the sites that were classified as *severely degraded* underwent substantial, negative postfire SFCC of 20-30%. It is likely that more severe postfire degradation occurs at chamise chaparral sites that experience frequent burning (cf. Lippitt et al. 2013), which would be detectible using a Landsat SVI time series and recovery trajectory metric approach. Using Landsat data to directly infer levels of type conversion in a particular landscape, however, would require calibration and empirical relationship based on detailed estimates of shrub cover change from orthoimagery and/or field measurements.

Long-term (19 to 29 year) postfire regrowth trajectories suggest that NBR2 is more sensitive to gradual growth of chamise during postfire recovery than the other SVIs which we examined (cp. Carreiras et al. 2006; Chen et al. 2011), followed by NDVI. The effectiveness of NBR2 reflects the sensitivity of the SWIR1 (1.55-1.75 μm) and SWIR2 (2.09-2.35 μm) spectral band combination to the postfire regrowth dynamics of chamise chaparral. In contrast, NBR and NDMI utilize the NIR spectral band, and are less sensitive to long-term recovery than NBR2. Although NBR2 showed sensitivity to subtle changes of chamise chaparral 12 to 19 years postfire, more than 95% of the postfire regrowth (as detected by NBR2 and NDVI) occurs within

ten years postfire. This finding is consistent with previous studies (Horton & Kraebel 1955; Keeley & Keeley 1981; Hope et al. 2007), though more substantive analysis of SVI trends during postfire recovery would require field data from the same site and study period.

The use of control-plot normalization proved effective for reducing the inter-annual variability (‘noise’) in the Landsat SVI time series that tends to co-vary with annual precipitation (cf. Diaz-Delgado et al. 1998; Diaz-Delgado et al. 2002; Idris et al. 2005; Li et al. 2008). In effect, this normalization yielded trajectories with clearer trends of regrowth and provided better estimates of recovery based on the Landsat time series and metrics. However, this method of normalization requires selection of a sufficient number of unburned control sites, which should be similar in terms of micro-climate and vegetation cover to the burned sites. These requirements posed a major challenge in our study area due to the fragmented spatial distribution of chamise chaparral patches, dissimilarity of vegetation cover and micro-climate between sites, and inaccuracies in the historic fire perimeter data. Reasonable estimates of recovery were obtained without normalization based on the scaled recovery metric and NBR2, potentially eliminating the requirement of control plots for differentiation of relative postfire recovery outcomes.

The Landsat SVI trajectory-based approaches explored here are intended to facilitate comparative, inter-site assessments of environmental and fire regime effects on postfire recovery of chamise chaparral. Differences in shrub cover heterogeneity, soil background, and general abundance of vegetation across the climatic gradient of our study area represent the main difficulties for inter-site comparison of postfire recovery patterns based on Landsat SVI time series. The findings of this study suggest that the scaled recovery metric and the NBR2 (which is useful without control-site normalization) would facilitate broad-scale, inter-site-comparative recovery assessment of geographically fragmented chamise chaparral stands. Other studies

underscore the utility in spatially explicit (i.e. per-pixel rather than pixel-group aggregated) assessment of postfire effects to elucidate relationships or feedbacks between fire regime, fuel development, and vegetation community structure, which may change through time (Finney & Ryan 1995; Chuvieco 1999; Henry & Yool 2002; Lloret et al. 2002; Roder et al. 2008; van Leeuwen et al. 2010). Our study represents an advancement toward this goal with regard to chaparral of southern California, and this exploratory framework may also prove applicable to other structurally heterogeneous vegetation types. In future studies it could be instructive to compare postfire recovery patterns of chamise chaparral within stands of various fire histories, landscape positions, and time periods in order to determine how fire regime, micro-climate, and drought are related to postfire recovery.

Acknowledgements

This research was supported by the USDA Forest Service through American Recovery and Reinvestment Act Agreement No. 10-JV-11279701-10: Airborne remote sensing to enable hazardous fuels reduction, forest health protection, rehabilitation, and hazard mitigation activities on Federal lands, and by San Diego State University Department of Geography.

References

- Baret, F., & Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*, 35(2), 161–173.
- Carreiras, J., Pereira, J., & Pereira, J. (2006). Estimation of tree canopy cover in evergreen oak woodlands using remote sensing. *Forest Ecology and Management*, 223(1), 45–53.
- Chen, X., Vogelmann, J., Rollins, M., Ohlen, D., & Key, C. (2011). Detecting post-fire burn severity and vegetation recovery using multitemporal remote sensing spectral indices and

552 field-collected composite burn index data in a ponderosa pine forest. *International*
553 *Journal of Remote Sensing*, 32(23), 7905–7927.

554 Chuvieco, E., & Kasischke, E.S. (2007). Remote sensing information for fire management and
555 fire effects assessment, 112(G1), DOI: 10.1029/2006JG000230.

556 Clemente, R., Navarro-Cerrillo, R., & Gitas, I. (2009). Monitoring post-fire regeneration in
557 Mediterranean ecosystems by employing multitemporal satellite imagery. *International*
558 *Journal of Wildland Fire*, 18(6), 648–658.

559 Diaz-Delgado, R., Lloret, F., Pons, X., & Terradas, J. (2002). Satellite evidence of decreasing
560 resilience in Mediterranean plant communities after recurrent wildfires. *Ecology*, 83(8),
561 2293–2303.

562 Diaz-Delgado, R., Salvador, R., & Pons, X. (1998). Monitoring of plant regeneration after fire by
563 remote sensing. *Fire management and landscape ecology*, 315–326.

564 Diaz-Delgado, R., Lloret, F., & Pons, X. (2003). Influence of fire severity on plant regeneration
565 by means of remote sensing. *International Journal of Remote Sensing*, 24(8), 1751–1763.

566 Finney, M. A., & Ryan, K. C. (1995, May). Use of the FARSITE fire growth model for fire
567 prediction in US National Parks. In *International emergency management and*
568 *engineering conference, edited by JD Sullivan, JL Wybo, and L. Buisson. Paris, France:*
569 *International Emergency Management and Engineering Society.*

570 Fraser, R., Olthof, I., Carrière, M., Deschamps, A., & Pouliot, D. (2011). Detecting long-term
571 changes to vegetation in northern Canada using the Landsat satellite image
572 archive. *Environmental Research. Letters*, 6(4), 045502.

573 Gitas, I., Mitri, G., Veraverbeke, S., & Polychronaki, A. (2012). Advances in remote sensing of
574 post-fire vegetation recovery monitoring—a review. INTECH Open Access Publisher.

575 Haidinger, T., & Keeley, J. (1993). Role of high fire frequency in destruction of mixed chaparral.
576 *Madroño*, 40, 141–147.

577 Hansen, M., Stehman, S., & Potapov, P. (2010). Quantification of global gross forest cover loss.
578 *Proceedings of the National Academy of Sciences*, 107(19), 8650–8655.

579 Hardisky, M., Klemas, V., & Smart, R. (1983). The Influences of Soil Salinity, Growth Form,
580 and Leaf Moisture on the Spectral Reflectance of *Spartina Alterniflora*
581 Canopies. *Photogrammetric Engineering and Remote Sensing*, 49, 77–83.

582 Henry, M., & Hope, A. (1998). Monitoring post-burn recovery of chaparral vegetation in
583 southern California using SPOT XS data. *International Journal of Remote*
584 *Sensing*, 19(16), 3097–3107.

585 Henry, M. C., & Yool, S. R. (2002). Characterizing fire-related spatial patterns in the Arizona
586 Sky Islands using Landsat TM data. *Photogrammetric Engineering and Remote Sensing*,
587 68(10), 1011-1020.

588 Holland, R. F. (1986). Preliminary descriptions of the terrestrial natural communities of
589 California.

590 Hope, A., Tague, C., & Clark, R. (2007). Characterizing post-fire vegetation recovery of
591 California chaparral using TM/ETM+ time series data. *International Journal of Remote*
592 *Sensing*, 28(6), 1339–1354.

593 Horton, J., & Kraebel, C. (1955). Development of vegetation after fire in the chamise chaparral
594 of southern California. *Ecology*, 36(2), 244–262.

595 Huete, A. (1988). A Soil-Adjusted Vegetation Index (SAVI). *Remote Sensing of Environment*,
596 25, 295–309.

- Huete, A., Justice, C., & van Leeuwen, W. (1999). MODIS Vegetation Index (MOD13) Algorithm Theoretical Basis Document (NASA Goddard Space Flight Center). Retrieved from http://modis.gsfc.nasa.gov/data/atbd/atbd_mod13.pdf.
- Idris, M., Kuraji, K., & Suzuki, M. (2005). Evaluating vegetation recovery following large scale forest fires in Borneo and northeastern China using multi-temporal NOAA/AVHRR images. *Journal of Forest Research*, 10(2), 101–111.
- Keeley, J. (2000). Chaparral. In Barbour, M., & Billings, W. (Eds.) *North American Terrestrial Vegetation* (pp. 204–253). Cambridge, UK: Cambridge University Press.
- Keeley, J., & Brennan, T. (2012). Fire-driven alien invasion in a fire-adapted ecosystem. *Oecologia*, 169(4), 1043–1052.
- Keeley, J., & Keeley, S. (1981). Post-fire regeneration of southern California chaparral. *American Journal of Botany*, 68, 524–530.
- Keeley, S.C., Keeley, J.E., Hutchinson, S.M., and A.W. Johnson. 1981. Postfire succession of the herbaceous flora in southern California chaparral. *Ecology* 62:1608-1621.
- Keeley, J., Safford, H., Fotheringham, C., Franklin, J., & Moritz, M. (2009). The 2007 southern California wildfires: lessons in complexity. *Journal of Forestry*, 107(6), 287–296.
- Key, C. H., & Benson, N. C. (1999). Measuring and remote sensing of burn severity: the CBI and NBR. Poster abstract. In Neuenschwander, L., & Ryan, K (Eds.), *Proceedings Joint Fire Science Conference and Workshop, Vol. II*. Boise, ID: University of Idaho and International Association of Wildland Fire.
- Key, C. H., & Benson, N. C. (2006). Landscape assessment (LA). *FIREMON: Fire effects monitoring and inventory system*. Gen. Tech. Rep. RMRS-GTR-164-CD, Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

620 Lhermitte, S., Verbesselt, J., Verstraeten, W., Veraverbeke, S., & Coppin, P. (2010). Assessing
 621 intra-annual vegetation regrowth after fire using the pixel based regeneration index.
 622 *ISPRS Journal of Photogrammetry and Remote Sensing*, 66, 17–27.

623 Li, M., Qu, J., & Hao, X. (2008). Detecting vegetation change with satellite remote sensing over
 624 2007 Georgia wildfire regions. *Journal of Applied Remote Sensing*, 2(1), 021505-021505.

625 Lippitt, C., Stow, D., O'Leary, J., & Franklin, J. (2013). Influence of short-interval fire
 626 occurrence on post-fire recovery of fire-prone shrublands in California, USA.
 627 *International Journal of Wildland Fire*, 22(2), 184–193.

628 Lloret, F., Calvo, E., Pons, X., & Díaz-Delgado, R. (2002). Wildfires and landscape patterns in
 629 the Eastern Iberian Peninsula. *Landscape Ecology*, 17(8), 745-759.

630 Masek, J., Goward, S., Kennedy, R., Cohen, W., Moisen, G., Schleeweis, K., & Huang, C.
 631 (2013). United States Forest Disturbance Trends Observed Using Landsat Time
 632 Series. *Ecosystems*, 16(6), 1087–1104. DOI: 10.1007/s10021-013-9669-9

633 Masek, J., Huang, C., Wolfe, R., Cohen, W., Hall, F., Kutler, J., & Nelson, P. (2008). North
 634 American forest disturbance mapped from a decadal Landsat record. *Remote Sensing of*
 635 *Environment*, 112(6), 2914–2926.

636 McMichael, C., Hope, A., Roberts, D., & Anaya, M. (2004). Post-fire recovery of leaf area index
 637 in California chaparral: A remote sensing-chronosequence approach. *International*
 638 *Journal of Remote Sensing*, 25(21), 4743–4760.

639 Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape
 640 with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of*
 641 *Environment*, 109(1), 66-80.

642 Narasimhan, R., & Stow, D. (2010). Daily MODIS Products for Analyzing Early Season
643 Vegetation Dynamics across the North Slope of Alaska. *Remote Sensing of Environment*,
644 114(6), 1251–1262.

645 Peterson, S., & Stow, D. (2003). Using multiple image endmember spectral mixture analysis to
646 study chaparral regrowth in southern California. *International Journal of Remote*
647 *Sensing*, 24(22), 4481–4504.

648 Qi, J., Kerr Y., & Chehbouni, A. (1994). External factor consideration in vegetation index
649 development. *Proceedings of Physical Measurements and Signatures in Remote Sensing*,
650 ISPRS, Val d'Isere, France.

651 Quayle, B., Brewer, K., & Williams, K. (2005, October 23–27). Monitoring post-fire vegetation
652 recovery of wildland fire areas in the western United States using MODIS data.
653 Proceedings of Pecora 16: Global Priorities in Land Remote Sensing, Sioux Falls, South
654 Dakota, USA. American Society for Photogrammetry and Remote Sensing.

655 Riaño, D., Chuvieco, E., Ustin, S., Zomer, R., Dennison, P., Roberts, D., & Salas, J. (2002).
656 Assessment of vegetation regeneration after fire through multitemporal analysis of
657 AVIRIS images in the Santa Monica Mountains. *Remote Sensing of Environment*, 79(1),
658 60–71.

659 Roder, A., Hill, J., Duguy, B., Alloza, J., & Vallejo, R. (2008). Using long time series of Landsat
660 data to monitor fire events and post-fire dynamics and identify driving factors. A case
661 study in the Ayora region (eastern Spain). *Remote Sensing of Environment*, 112(1), 259–
662 273.

663 Rouse, J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in
664 the Great Plains with ERTS. *NASA special publication*, 351, 309-317.

665 Schleeweis, K., Goward, S., Chengquan, H., Masek, J., & Moisen, G. (2012). Understanding
 666 trends in observations of forest disturbance and their underlying causal processes.
 667 *Proceedings of Forest inventory and analysis symposium 2012: Moving from status to*
 668 *trends* (pp. 131–136). Newtown Square, PA, USA.

669 Skole, D., & Tucker, C. (1993). Tropical deforestation and habitat fragmentation in the Amazon:
 670 satellite data from 1978 to 1988. *Science*, 260(5116), 1905–1910.

671 Storey, J., Scaramuzza, G., & Schmidt, J. (2005, October 23–27). Landsat-7 Scan Line
 672 Corrector-off gap filled product development. *Proceedings of Pecora 16: Global*
 673 *Priorities in Land Remote Sensing*. Sioux Falls, South Dakota, USA. American Society
 674 for Photogrammetry and Remote Sensing.

675 Tucker, C., & Townshend, J. (2000). Strategies for monitoring tropical deforestation using
 676 satellite data. *International Journal of Remote Sensing*, 21(6-7), 1461–1471.

677 van Leeuwen, W., Casady, G., Neary, D., Bautista, S., Alloza, J., Carmel, Y., Wittenberg, L.,
 678 Malkinson, D., & Orr, B. (2010). Monitoring post-wildfire vegetation response with
 679 remotely sensed time series data in Spain, USA and Israel. *International Journal of*
 680 *Wildland Fire*, 19(1), 75–93.

681 Viedma, O., Melia, J., Segarra, D., & García-Haro, J. (1997). Modeling rates of ecosystem
 682 recovery after fires by using Landsat TM data. *Remote Sensing of Environment*, 61(3),
 683 383–398.

684 Viedma, O., Moreno, J. M., & Rieiro, I. (2006). Interactions between land use/land cover
 685 change, forest fires and landscape structure in Sierra de Gredos (Central Spain).
 686 *Environmental Conservation*, 33(3), 212–222.

687 Vila, G., & Barbosa, P. (2010). Post-fire vegetation regrowth detection in the Deiva Marina
688 region (Liguria-Italy) using Landsat TM and ETM+ data. *Ecological Modelling*, 221(1),
689 75–84.

690 Wing, M., Burnett, J., & Sessions, J. (2014). Remote sensing and unmanned aerial system
691 technology for monitoring and quantifying forest fire impacts. *International Journal of*
692 *Remote Sensing Applications*, 4(1), 18–35.

693 Wulder, M., White, J., Cranny, M., Hall, R., Luther, J., Beaudoin, A., Goodenough, D., &
694 Dechka, J. (2008). Monitoring Canada’s forests. Part 1: completion of the EOSD land
695 cover project. *Canadian Journal of Remote Sensing*, 34(6), 549–562.

696 Zedler, P., Gautier, C., & McMaster, G. (1983). Vegetation Change in Response to Extreme
697 Events: The Effect of a Short Interval between Fires in California Chaparral and Coastal
698 Scrub. *Ecology*, 64(4), 809–818.

699 Zhu, Z., & Woodcock, C. (2012). Object-based cloud and cloud shadow detection in Landsat
700 imagery. *Remote Sensing of Environment*, 118(15), 83–94.