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Mapping live fuel moisture with MODIS data: A multiple regression approach

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ABSTRACT

Live fuel moisture (LFM) is an important factor for ascertaining fire risk in shrublands located in Mediterranean climate regions. We examined empirical relationships between LFM and numerous vegetation indices calculated from MODIS composite data for two southern California shrub functional types, chaparral (evergreen) and coastal sage scrub (CSS, drought-deciduous). These relationships were assessed during the annual March–September dry down period for both individual sites, and sites pooled by functional type. The visible atmospherically resistant index (VARI) consistently had the strongest relationships for individual site regressions. An independent method of accuracy assessment, cross validation, was used to determine model robustness for pooled site regressions. Regression models were developed with $n-1$ datasets and tested on the dataset that was withheld. Additional variables were included in the regression models to account for site-specific and interannual differences in vegetation amount and condition. This allowed a single equation to be used for a given functional type. Multiple linear regression models based on pooled sites had slightly lower adjusted R^2 values compared with simple linear regression models for individual sites. The best regression models for chaparral and CSS were inverted, and LFM was mapped across Los Angeles County, California (LAC). The methods used in this research show promise for monitoring LFM in chaparral and may be applicable to other Mediterranean shrubland communities.

1. Introduction

Live fuel moisture (LFM), a measure of the water content of live vegetation, is a strong determinant of fire ignition, spread rate, and intensity (Countryman & Dean, 1979; Anderson, 1982). LFM is particularly important in the shrublands of southern California as a large proportion (55–75%) of the biomass available to fires is living, so fires will only propagate if LFM is low (Countryman & Dean, 1979; Dennison et al., 2008). Additionally, in fire-related research, plant moisture is important for predicting crown fire initiation in conifers (Agee et al., 2002) and burning efficiency (Chuvieco et al., 2004). Detecting water stress is also important for agricultural applications as it is a primary control on plant growth (Brix, 1962, Acevedo et al., 1971, Boyer, 1982).

Field measurement of LFM involves clipping live foliage, placing it in an airtight container, weighing it wet, drying the foliage, and then weighing it dry. The moisture content of the vegetation is expressed as a percentage of the dry weight (W_d):

$$\mathrm{LFM}(\%) = 100 \cdot (W_w - W_d)/W_d \tag{1}$$

where W_w is wet weight (Countryman & Dean, 1979). Weise et al. (1998) suggested that fire danger can be approximated using LFM, with low fire danger for LFM > 120%, moderate fire danger for 120% > LFM > 80%, high fire danger for 80% > LFM > 60%, and extreme fire danger for LFM < 60%. Dennison et al. (2008) examined relationships between LFM and fire history in the Santa Monica Mountains of Los Angeles County (LAC), and found that large fires only occurred when LFM dropped below 77%.

LFM varies temporally and spatially, primarily due to available soil moisture, and soil and air temperature (Countryman & Dean, 1979; Bowyer & Danson, 2004). However, because field surveys are expensive and time consuming, LFM is generally measured in the field at only a few discrete locations to determine the level of fire danger. For example, the field dataset used in this research involves 14 sampling locations within nearly 380,000 ha of chaparral (evergreen) and coastal sage scrub (CSS, drought deciduous) shrublands. Remotely sensed data provide the opportunity to study LFM over larger spatial extents and the use of remotely sensed data to map/monitor LFM is a developing research area.

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There are two main approaches to LFM estimation, empirical relations between vegetation indices (VIs) and LFM, and simulation methods using radiative transfer models (RTM). Yebra et al. (2008) compared the two methods for estimating LFM in Mediterranean grassland/shrubland in Spain. Regression results were superior for RTM when the same dataset was used to calibrate and test the models. However, when the datasets were split into separate calibration/validation datasets, the two techniques performed similarly. For grasslands, R^2 were 0.914 and 0.927, for the empirical and RTM approaches, respectively. For shrublands the R^2 were again similar, 0.723 and 0.703, however the predictions using the RTM deviated from the 1:1 line, so root mean squared error (RMSE) was much higher, 25.18 versus 16.01. Hence, as RTM are difficult to parameterize, and may not be superior to an empirical approach (Yebra et al., 2008), an empirical approach was utilized in this research.

Previous studies have examined correlations between VIs and LFM data. The normalized difference vegetation index (NDVI, Rouse et al., 1973) has most commonly been used in LFM research (e.g., Paltridge & Barber, 1988; Hardy & Burgan, 1999). Other VIs, such as normalized difference water index (NDWI, Gao, 1996), vegetation index green (VI_{green}) and visible atmospherically resistant index (VARI, Gitleson et al., 2002), and enhanced vegetation index (EVI, Huete et al., 1997) are being evaluated or reevaluated with the availability of Moderate Resolution Imaging Spectrometer (MODIS) data (Dennison et al., 2005, 2007; Stow et al., 2005, 2006; Roberts et al., 2006; Hao & Qu, 2007). Greenness indices (e.g., NDVI, VI_{green}, VARI, and EVI) are sensitive to changes in vegetation chlorophyll absorption and leaf area index (LAI), which co-occur with changes in water content (Hardy & Burgan 1999). Wetness indices (e.g., NDWI and normalized difference infrared index (NDII, Hardisky et al., 1983)) are more directly sensitive to changes in vegetation moisture content. The formulations of the indices, with respect to MODIS band numbers are listed in Table 1.

NDVI and LFM are highly correlated in grassland functional types (Paltridge & Barber, 1988; Hardy & Burgan, 1999). Paltridge and Barber (1988) studied grassland LFM in Australia, finding linear agreement up to about 200% LFM, at which point NDVI saturated. Hardy and Burgan (1999) used fine spatial resolution Airborne Data Acquisition and Registration (ADAR) data and similarly found that a western Montana grassland had a strong relation between LFM and NDVI (R^2 of 0.815), however, shrubland R^2 was lower at 0.539. Chuvieco et al. (2004) studied grassland and Mediterranean shrubland LFM in Spain with Advanced Very High Resolution Radiometer (AVHRR) data and found a similar pattern for the utility of NDVI. Pearson correlation (r) was 0.754 for grassland LFM and NDVI. For *Cistus ladanifer* and *Rosmarinus officinalis*, r was 0.474 and 0.529 for NDVI, but increased to 0.717 and 0.806 when an NDVI/surface temperature ratio was utilized. Hence, other indices beyond NDVI have been examined for LFM studies in shrublands.

The use of near infrared (NIR) and short wave infrared (SWIR) bands for estimating LFM was suggested by Tucker (1980) and papers cited therein. These bands have been used in various configurations by Hardisky et al. (1983), Hunt et al. (1987), and Hunt and Rock (1989). Chuvieco et al. (2002) used a time series of seven Landsat Thematic Mapper (TM) scenes to study LFM in a Mediterranean shrubland ecosystem. They evaluated correlations between LFM and the following indices: NDVI, NDII5 (using Landsat TM bands 4 and 5), NDII7 (TM bands 4 and 7), leaf water content index (LWCI), tasseled cap wetness, band integrals and derivatives, and NDVI relative greenness. The Pearson correlation coefficients (r) between grassland, shrubland, and *Quercus faginea* LFM and NDVI were 0.869, 0.486, and 0.091. NDII5 had the highest correlations on average, with values of 0.855, 0.753, and 0.808, demonstrating the utility of the use of SWIR bands for LFM estimation.

Table 1
Vegetation indices from MODIS data with their acronyms

Index	Formula
NDVI	$(\rho_2-\rho_1)/(\rho_2+\rho_1)$
EVI	$2.5*(\rho_2-\rho_1)/(1+\rho_2+6*\rho_1-7.5*\rho_3)$
VI_{green}	$(\rho_4-\rho_1)/(\rho_4+\rho_1)$
VARI	$(\rho_4-\rho_1)/(\rho_4+\rho_1-\rho_3)$
NDII6	$(\rho_2-\rho_6)/(\rho_2+\rho_6)$
NDII7	$(\rho_2-\rho_7)/(\rho_2+\rho_7)$
NDWI	$(\rho_2-\rho_5)/(\rho_2+\rho_5)$

MODIS samples seven spectral bands, centered at 469, 555, 645, 857, 1240, 1640, and 2130 nm at a spatial resolution of 500 m. The greater spectral dimensionality relative to AVHRR data provides a more diverse set of indices that can be correlated with LFM. Dennison et al. (2005) compared MODIS NDVI and NDWI for monitoring LFM of chaparral shrublands in LAC. They found that both indices correlated well with LFM at most sites, with R^2 values ranging from 0.25 to 0.60 for NDVI, and 0.39 to 0.80 for NDWI. NDWI showed better agreement at each site, though the difference was significant for only three of the 17 sites. Stow and colleagues studied LFM at 3 chaparral sites in San Diego County, California (Stow et al., 2005, 2006; Stow & Niphadkar 2007). Stow et al. (2005) compared VARI and NDWI from MODIS; for their three study sites R^2 values were 0.94, 0.74, and 0.75 for VARI and 0.91, 0.4, and 0.42 for NDWI. VARI was significantly higher than NDWI for the second and third sites. Regression equations were similar for all three sites, and the R^2 for VARI when the data from the three sites were pooled was 0.72. Stow et al. (2006) tested the temporal stability of the relationships by developing a regression model for each study site using 2001–2003 data and testing the models on 2004 data. They found a large, systematic bias in RMSE, predicted values of LFM were higher than measured values. Stow and Niphadkar (2007) used a longer time series of data which added a very wet and a very dry year. Pooled R^2 for VARI was again 0.72 and the regression coefficients were similar to those from the shorter Stow et al. (2005) timeseries. They also tested relative VIs, where the continuous VI variable for a pixel is normalized by the maximum and mean value of that VI in the timeseries (Burgan & Hartford 1993). Using normalized VARI improved the pooled R^2 slightly to 0.75, while normalized NDWI and NDII6 R^2 values improved more, to 0.74 and 0.75. Roberts et al. (2006) also investigated pooled site regressions. VARI was the best overall index, with an individual site average R^2 of 0.668. It outperformed NDVI, EVI, VI_{green}, NDII6, NDII7, NDWI, as well as endmember fractions (Adams et al., 1993). When all of the datasets were pooled together, irrespective of functional type, the R^2 decreased to 0.308. However, when grouping them by functional type, results were stronger. For CSS the average R^2 of the individual site regressions was 0.767, the pooled R^2 was 0.533. For chaparral the corresponding R^2 were 0.643 and 0.526. While there was a drop off in the amount of explained variance, the regressions pooled by functional type still showed a high degree of agreement.

This study seeks to model spatial and temporal variations in LFM by developing robust relationships between field and remotely sensed data which account for site-specific and interannual differences in sensor measured vegetation response. The research presented here is a significant advancement beyond relationships demonstrated in Roberts et al. (2006) and Stow and Niphadkar (2007). Roberts et al. (2006) stratified the study sites by functional type, but did not use multiple regression. Stow and Niphadkar (2007) used relative VIs to account for site differences. Relative VIs have a specific form, whereas the approach used in this research is not predetermined. We account for site-specific differences by including additional regression variables in a multiple regression (per-pixel minimum, maximum, range, mean, median VIs). These variables can affect the slope or the intercept in the regression equation, making their use more flexible than that of relative VIs. Additionally, we evaluate pooled regressions between LFM and vegetation indices using an independent measure of goodness-of-fit, cross-validated R^2 (Michaelsen, 1987). To our

Table 2
Sample size for the Los Angeles County LFM sites

Site	Functional type	Sampled species	# Dates	# Dates, dry down only	Years
Bitter Canyon 2	Chaparral	*Adenostema fasciculatum*	143	80	2000–2006
Bouquet Canyon	Chaparral	*Adenostema fasciculatum*	36	22	2000–2001
Clark Motorway	Chaparral	*Adenostema fasciculatum*	144	80	2000–2006
Clark Motorway	Chaparral	*Ceanothus megacarpus*	144	80	2000–2006
La Tuna Canyon	Chaparral	*Adenostema fasciculatum*	139	78	2000–2006
Laurel Canyon	Chaparral	*Adenostema fasciculatum*	139	79	2000–2006
Pico Canyon	Chaparral	*Adenostema fasciculatum*	82	45	2000–2003
Placerita Canyon	Chaparral	*Adenostema fasciculatum*	92	50	2000–2004
Scheuren Road	Chaparral	*Adenostema fasciculatum*	140	78	2000–2006
Sycamore Canyon	Chaparral	*Adenostema fasciculatum*	52	31	2000–2002
Sycamore Canyon	Chaparral	*Ceanothus crassifolius*	52	31	2000–2002
Trippet Ranch	Chaparral	*Adenostema fasciculatum*	144	80	2000–2006
Woolsey Canyon	Chaparral	*Adenostema fasciculatum*	118	67	2000–2005
Peach Fire Road	Chaparral	*Adenostema fasciculatum*	61	35	2004–2006
Glendora Canyon	Chaparral	*Adenostema fasciculatum*	72	38	2003–2006
Glendora Canyon	Chaparral	*Ceanothus crassifolius*	72	38	2003–2006
Bitter Canyon 1	Coastal sage scrub	*Artemisia californi*	143	80	2000–2006
Bitter Canyon 1	Coastal sage scrub	*Salvia leucophylla cophylla*	143	80	2000–2006
Bouquet Canyon	Coastal sage scrub	*Salvia mellifera*	36	22	2000–2001
Trippet Ranch	Coastal sage scrub	*Salvia mellifera*	143	79	2000–2006

knowledge, Yebra et al. (2008) is the only other study of LFM to use an independent validation dataset. These advances permit the first validated time series maps of LFM that could be used to monitor the spatial variation and temporal progression of LFM and fire risk.

2. Methods

2.1. Study sites and data

2.1.1. LFM data

This study uses the LAC LFM data used in Dennison et al. (2005), Roberts et al. (2006), and Dennison et al. (2007), with two modifications: additional years of data have been collected, and only the late March through September dry down period was considered. A study site map is provided in Roberts et al. (2006). The data were collected at 12 sites in 2000, however one site burned in late 2002 (Sycamore Canyon) and one in late 2003 (Pico Canyon) so two new sites were located (Glendora Ridge and Peach Motorway). The Bouquet Canyon site burned in 2001, but the new sampling location is still within the fire perimeter, so the useful sample period is quite short. Two other sites burned and their new sampling locations are also too close to burned areas to be useful for satellite remote sensing studies: Placerita Canyon burned in 2004 and Woolsey Canyon in 2005. Thus 14 sites were sampled (Table 2). The precise species composition of each site is not known, but 11 of the sites were dominated by evergreen chaparral species, one site by drought deciduous CSS species, and two by a mixture of evergreen and drought deciduous species.

LFM data have been gathered at approximately two week intervals since 1983 by the Los Angeles County Fire Department. The sampling protocol was designed by Countryman and Dean (1979). Samples were taken from at least three random shrubs for each dominant species within a 1–4 ha area at each sampling date. The samples consist of live leafy material as well as some woody stems. The samples were immediately sealed, then weighed wet, oven dried for 15 h at 104 °C, and weighed dry. LFM was calculated as per Eq. (1). LFM data from 2000 to 2006 were used in this research (MODIS data began in 2000). The field sampling dates were not coincident with the 16-day MODIS composite dates, so the LFM data were linearly interpolated to the middle of the 16 day MODIS compositing intervals.

LFM peaks in the spring, declines as the summer drought progresses, and remains low until the onset of growth in the following spring (Countryman & Dean 1979) (Fig. 1). The long-term mean annual trend in chaparral and CSS LFM for LAC (Fig. 1) was used to define the dry down period to be from day 81 (late March) until day 257 (middle September). Most remote sensing/LFM papers have also focused on

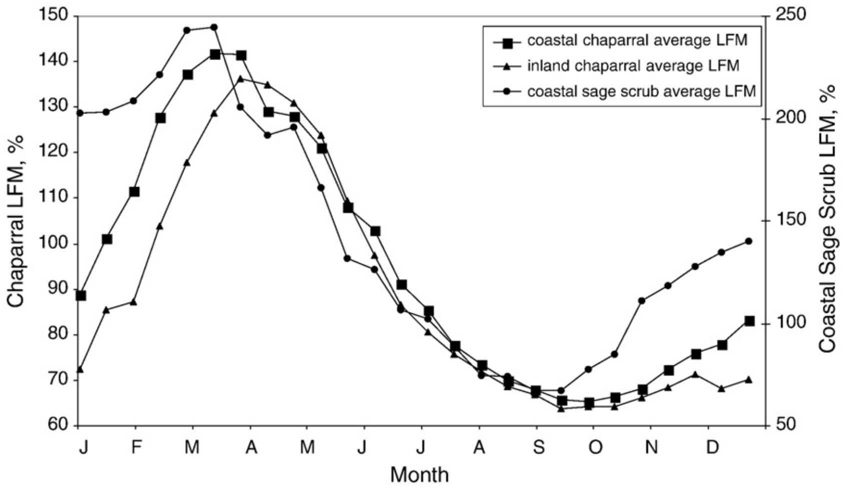

Fig. 1. Average LFM (1981–2007) for coastal and inland chaparral sites, and coastal sage scrub in Los Angeles County, California.

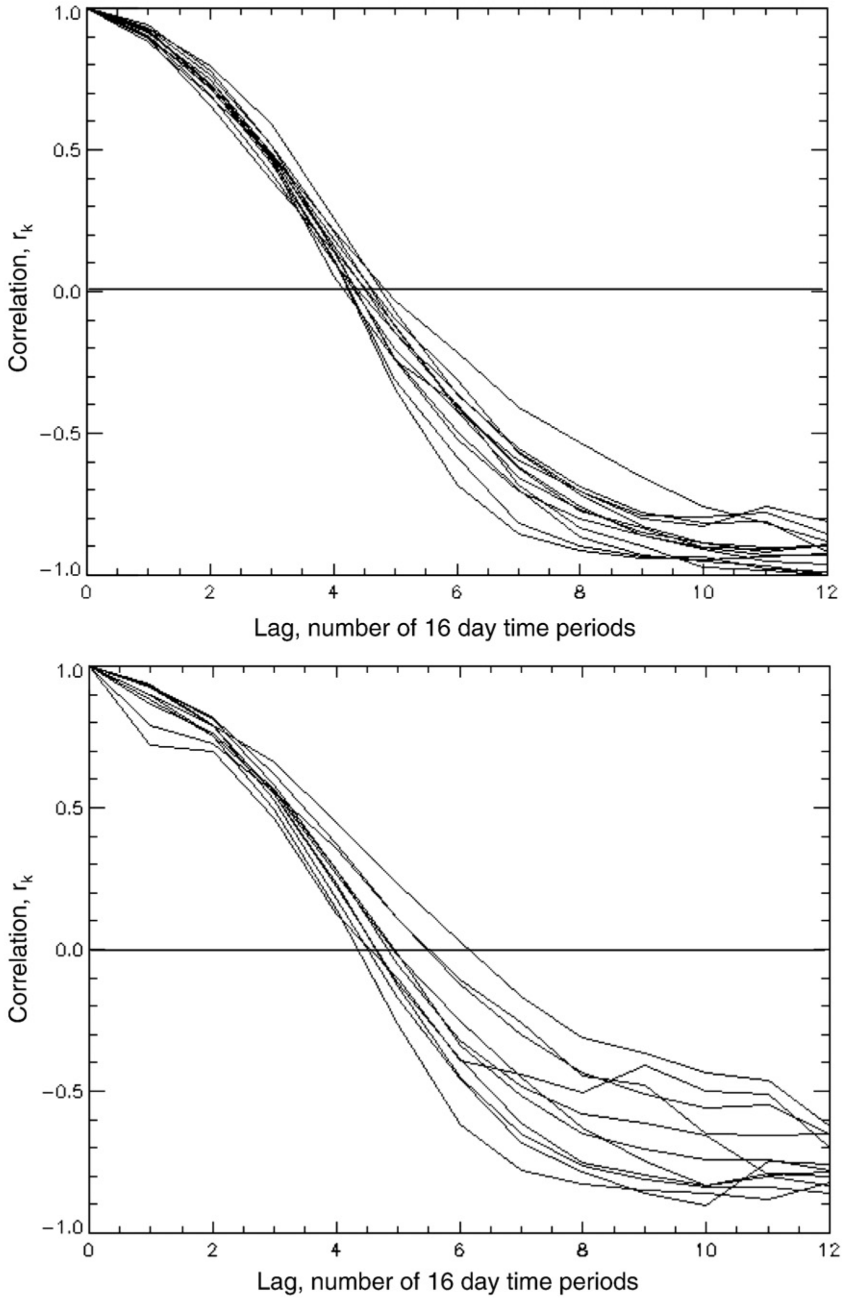

Fig. 2. Temporal correlograms for LFM (top) and VARI (bottom) for the 16 chaparral datasets.

the late spring through early fall dry down period only (e.g., Paltridge & Barber, 1988; Hardy & Burgan, 1999; Chuvieco et al., 2002; Stow et al., 2005, 2006), because LFM is more of a concern when vegetation is drying down/under increasing fire risk than when it is "greening up".

2.1.2. Remotely sensed data

Daily 500 m MODIS/Terra version 4 MOD09GHK surface reflectance data were used to construct 16-day composites from 2000 through 2006 (Dennison et al., 2007). These data were acquired from the Land Processes Distributed Active Archive Center (http://edcimswww.cr.usgs.gov/pub/imswelcome). The compositing algorithm screens for clouds using the MOD09GST 1 km cloud product, resampled to 500 m. Pixels are screened out if Bit 0–1 (cloud state) is not "clear", or if Bit 2 (cloud shadow) is not "no", or if Bit 8–9 (cirrus detected) is not "none". Off-nadir look angles are screened with a threshold of 45° applied to the MODMGGAD 1 km geolocation angles product. Off-nadir views can result in an effective ground sampling distance on the order of 2 km, resulting in blocks of 500 m pixels having the same values. After cloudy and off-nadir pixels are removed, a spectral shape compositing algorithm (described in Dennison et al., 2007) was used to select the most representative date for each pixel.

2.2. Analysis

The sampled vegetation stands were identified and boundaries were delineated on 1 m spatial resolution Digital Ortho Quarter Quads (DOQQs). These polygons were overlayed on a MODIS image in order to select a single MODIS pixel for each of the 14 sites. Timeseries were extracted from the MODIS composite data for 2000–2006.

Multiple regression was used to examine relationships between LFM and MODIS data. Potential predictors include the time series of seven VIs (NDVI, NDWI, NDII6, NDII7, VI_{green}, VARI, EVI) from a MODIS 16 day composite and summary statistics (minimum, maximum, mean, median, and range) of these seven VIs. Summary statistics of VIs have been used in global land cover classification schemes because different vegetation types have different phenologies (De Fries et al., 1998; Friedl et al., 1999). In this research, the goal is to account for phenological variability in the regressions in order to explain more variance in the time series VI/LFM relationships. Summary statistics involving two time periods, yearly and overall, were calculated for each site. The yearly summary statistics control for both interannual and intersite differences in the vegetation. Statistics were calculated for each year from 2000 to 2006. The overall summary statistics control for general differences in greenness across sites. Overall statistics were calculated from 2000–2001 data, the only period when all of the sites in this study were unburned. The values for the overall statistics were replicated seven times so that they could be used in the same manner as the yearly statistics. 35 yearly and 35 overall statistics were generated; the minimum, maximum, mean, median, and range of the seven VIs. Only one time series variable was included in the regressions to avoid possible multi-colinearity effects. Equations of the following form were fit:

$$\mathrm{LFM} = \beta_0 + \beta_1 \cdot \mathrm{VI} + \beta_2 \cdot \mathrm{ss_{add}} + \beta_3 \cdot \mathrm{VI} \cdot \mathrm{ss_{mult}} \tag{2}$$

where β_0 is the y-intercept; β_1, β_2, and β_3 are the parameters for the independent variables; VI is the continuous timeseries VI variable; ss_{add} is the additive VI summary statistic variable; and ss_{mult} is the multiplicative VI summary statistic variable.

As the number of variables under consideration was reasonable, the all possible regressions approach to multiple regression was implemented. Analyses were performed for individual sites, all evergreen chaparral sites pooled together, and all CSS sites pooled together — to determine the potential for mapping LFM across evergreen chaparral and CSS areas. For individual site regressions, the seven continuous variables were combined with 35 yearly VI summary statistic variables to determine the best single, two and three variable combinations. For pooled regressions across all sites, the seven continuous variables were combined with 70 VI summary statistic variables (35 yearly and 35 overall) to determine the best single, two and three variable combinations. The summary statistic variables control for interannual differences in LFM relationships at individual sites and interannual/intersite differences for the pooled analyses.

Adjusted R^2 values were utilized to assess goodness-of-fit for the individual sites. Adjusted R^2 reduces the effect of additional explanatory variables automatically inflating the R^2 metric. The generality of the LFM/image product models (i.e. potential for mapping) was assessed using cross-validated adjusted R^2 (Michaelsen, 1987) through leave-one-dataset-out cross validation for the pooled chaparral and CSS datasets. Leave-one-out cross validation involves developing a regression equation from $n-1$ datasets and testing the equation on the remaining dataset. The process is repeated n times, once for each dataset. For the CSS regressions there were only four LFM datasets, two of which came from the same site. Leave-one-out models were constructed so that only one LFM dataset from the Bitter Canyon site was included in each model.

The significance of differences in R^2 due to the addition of additional variables was tested using a sum of squared errors comparison test:

$$F_{obs} = \left[\left(R^2_{full} - R^2_{reduced}\right)/(p-k)\right] / \left[R^2_{full}/(n-p-1)\right] \tag{3}$$

where R^2_{full} is the R^2 of the full model, $R^2_{reduced}$ is the R^2 of the model with fewer predictor variables, p the number of variables in the full model, k the number of variables in the reduced model and n the number of samples. R^2 rather than adjusted R^2 is used in this equation. If F_{obs} is larger than $F_{critical}$ found from an F-distribution with a 0.05 significance level and $(p-k)$ and $(n-p)$ degrees of freedom, the difference is significant.

Temporal autocorrelation can inflate the significance of differences in F scores because all of the data points used in the regression are not independent. In order to reduce the effects of temporal autocorrelation, n was reduced when $F_{critical}$ and F_{obs} were calculated to $n/4$. The factor of 0.25 ($n/4$) was determined through inspection of temporal autocorrelograms for FMC and VARI for the first 12 16-day lags, corresponding to half of a year (Fig. 2). Temporal autocorrelograms are analogous to the more commonly used spatial semivariograms, with the lags referring to nearby time steps as opposed to nearby pixels. The data values of adjacent 16 day composites are highly correlated, with r on the order of 0.9 for a lag of one. At a lag of four

Table 3
Adjusted R^2 for individual site regressions

Site	NDVI	NDWI	NDII6	NDII7	VI_{green}	VARI	EVI	2_{add}	3
Bitter Cyn 2 Chamise	0.748	0.803	0.750	0.699	0.843	0.847	0.708	0.846	0.853
Bouquet Cyn Chamise	0.632	0.774	0.816	0.753	0.799	0.802	0.785	0.794	0.820
Clark Mtwy Chamise	0.652	0.481	0.748	0.699	0.708	0.714	0.419	0.713	0.742
Clark Mtwy Ceme	0.634	0.438	0.720	0.670	0.724	0.728	0.428	0.742	0.777
La Tuna Cyn Chamise	0.650	0.740	0.667	0.591	0.819	0.826	0.554	0.835	0.854
Laurel Cyn Chamise	0.448	0.548	0.609	0.570	0.671	0.678	0.351	0.698	0.742
Pico Cyn Chamise	0.626	0.767	0.725	0.679	0.786	0.789	0.546	0.792	0.784
Placerita Cyn Chamise	0.652	0.716	0.717	0.662	0.811	0.816	0.526	0.842	0.853
Schueren Rd Chamise	0.350	0.563	0.455	0.365	0.643	0.645	0.382	0.670	0.668
Sycamore Cyn Chamise	0.707	0.756	0.741	0.712	0.847	0.845	0.663	0.849	0.865
Sycamore Cyn Hoaryleaf Ceanothus	0.770	0.832	0.817	0.781	0.922	0.922	0.699	0.924	0.934
Trippet Ranch Chamise	0.679	0.684	0.696	0.640	0.777	0.790	0.362	0.795	0.792
Woolsey Cyn Chamise	0.675	0.739	0.682	0.624	0.816	0.822	0.611	0.820	0.865
Peach Motorway Chamise	0.935	0.902	0.899	0.888	0.909	0.914	0.683	0.913	0.943
Glendora Ridge Chamise	0.588	0.729	0.617	0.497	0.716	0.728	0.565	0.754	0.754
Glendora Ridge Hoaryleaf Ceanothus	0.537	0.746	0.592	0.428	0.673	0.683	0.635	0.747	0.811
Chaparral average	0.643	0.701	0.703	0.641	0.779	0.784	0.557	0.796	0.816
Bitter Cyn 1 California Sage	0.801	0.734	0.706	0.649	0.883	0.896	0.733	0.903	0.923
Bitter Cyn 1 Purple Sage	0.776	0.842	0.804	0.730	0.840	0.860	0.766	0.912	0.945
Bouquet Cyn Black Sage	0.749	0.900	0.891	0.852	0.935	0.939	0.781	0.940	0.942
Trippet Ranch Black Sage	0.662	0.616	0.645	0.592	0.798	0.799	0.271	0.807	0.829
CSS average	0.747	0.773	0.761	0.706	0.864	0.873	0.638	0.890	0.910

Significant differences ($p<0.05$) are underlined. The multivariate models used for chaparral are VARI and yearly EVI range and VARI, yearly NDWI minimum, and yearly VI_{green} median. The models used for CSS are VARI and yearly NDWI median and VARI, yearly VARI median, and yearly EVI maximum.

Table 4
Coefficients for the regression equations between VARI and LFM for chaparral and CSS sites

Site	Intercept	Slope
Bitter Cyn 2 Chamise	127.8	325.0
Bouquet Cyn Chamise	109.5	271.7
Clark Mtwy Chamise	90.6	322.6
Clark Mtwy Ceme	88.1	421.0
La Tuna Cyn Chamise	116.0	330.9
Laurel Cyn Chamise	101.3	687.8
Pico Cyn Chamise	107.3	352.0
Placerita Cyn Chamise	101.8	335.6
Schueren Rd Chamise	115.9	382.1
Sycamore Cyn Chamise	93.0	283.3
Sycamore Cyn Hoaryleaf Ceanothus	90.9	306.1
Trippet Ranch Chamise	75.0	373.0
Woolsey Cyn Chamise	110.7	285.3
Peach Motorway Chamise	97.3	296.7
Glendora Ridge Chamise	100.6	312.1
Glendora Ridge Hoaryleaf Ceanothus	93.4	311.2
Bitter Cyn 1 California Sage	225.7	787.4
Bitter Cyn 1 Purple Sage	237.3	828.9
Bouquet Cyn Black Sage	218.8	984.0
Trippet Ranch Black Sage	99.2	1112.5

the correlation approaches zero (implying independence) for both variables. Hence n was reduced to $n/4$ for use in Eq. (3).

The best overall three variable models for chaparral and CSS were inverted and applied to MODIS data of LAC. A vegetation map was acquired from the state of California Fire and Resource Assessment Program (FRAP) website (http://frap.cdf.ca.gov/) in the form of a 2003 fuel model map at 30 m spatial resolution. Fuel models (Anderson, 1982) are broad vegetation classes that are used in fire models such as Farsite (Finney, 1998) and HFire (Morais, 2001; Peterson et al., in review). The FRAP map delineates the extent of chaparral and CSS areas, as well as grasslands, forests, etc. Masks were generated for chaparral and CSS areas, and resampled to 500 m using a majority rule. Hence, the inverted three variable chaparral equation was applied to pixels classified as chaparral and the inverted CSS equation was applied to pixels classified as CSS.

3. Results

3.1. Individual site regressions

For individual datasets, one, two, and three variable models were considered. Table 3 presents the adjusted R^2 values for the 20 LAC (16 chaparral, four CSS) datasets. VARI and VI_{green} were the best single predictors on average, though NDWI was best for the two Glendora Ridge datasets and NDII6 was best for Bouquet Canyon Chamise and Clark Motorway Chamise. Adjusted R^2 values were high for all datasets, with an average value of 0.784 for chaparral sites and 0.873 for CSS sites.

The addition of summary statistic variables can help control for interannual variability at a given site. For chaparral, neither two nor three variable models led to significant increases in adjusted R^2, though the models with the highest average R^2 are listed in Table 3. For CSS, the best overall two variable model used VARI and the yearly median of NDWI as an additive term, and the Bitter Canyon Purple Sage dataset showed a significant increase in R^2. The addition of two summary statistic variables allows the intercept and the slope to vary on a yearly basis at each site. The best overall three variable model for CSS used VARI, the yearly median of NDWI for the additive term, and yearly maximum of EVI for the multiplicative term. The Bitter Canyon Purple Sage dataset again showed significant improvement with three variables.

3.2. Pooled site regressions

The slope and y-intercepts from the individual regressions of VARI with LFM show a wide range of values (Table 4). The y-intercepts varied from 75 to 128% LFM for chaparral datasets, and from 99 to 237% LFM for CSS. Slope varied from 272 to 688 for chaparral, and from 787 to 1113 for CSS. The Laurel Canyon site has a particularly steep slope due to a reduced range in VARI values, caused by adjacent urban areas which exhibit much less temporal variability in greenness than natural areas. Slopes are steeper for the CSS sites than the chaparral sites because there is a larger range in LFM values. The Trippet Ranch site has a much different regression equation than the other CSS sites, likely because the other sites are purely CSS whereas Trippet has a

Table 5
Cross-validated adjusted R^2 for pooled, cross-validated regressions

Site	NDVI	NDWI	NDII6	NDII7	VI_{green}	VARI	EVI	2_{add}	3
Bitter Cyn 2 Chamise	−0.55	−0.07	−1.14	−1.05	0.11	0.112	−0.09	0.814	0.782
Bouquet Cyn Chamise	−0.05	0.487	0.046	−0.11	0.655	0.64	0.18	0.664	0.603
Clark Mtwy Chamise	0.432	0.285	0.63	0.563	0.578	0.579	0.38	0.689	0.688
Clark Mtwy Ceme	0.367	0.303	0.515	0.452	0.55	0.549	0.336	0.673	0.684
La Tuna Cyn Chamise	0.547	0.636	0.621	0.541	0.625	0.631	0.517	0.824	0.846
Laurel Cyn Chamise	0.095	−0.05	0.321	0.343	0.394	0.403	0.259	0.448	0.507
Pico Cyn Chamise	0.492	0.612	0.572	0.491	0.716	0.72	0.49	0.763	0.740
Placerita Cyn Chamise	0.512	0.566	0.587	0.529	0.764	0.767	0.483	0.808	0.801
Schueren Rd Chamise	0.277	0.015	0.082	0.17	0.482	0.491	0.111	0.597	0.582
Sycamore Cyn Chamise	0.577	0.648	0.666	0.63	0.758	0.765	0.62	0.785	0.827
Sycamore Cyn Hoaryleaf Ceanothus	0.568	0.659	0.68	0.638	0.772	0.784	0.619	0.856	0.867
Trippet Ranch Chamise	−0.28	0.26	−0.05	−0.26	0.097	0.106	−0.29	0.657	0.664
Woolsey Cyn Chamise	0.571	0.525	0.484	0.471	0.711	0.71	0.561	0.774	0.771
Peach Motorway Chamise	0.741	0.43	0.568	0.527	0.881	0.881	0.478	0.893	0.921
Glendora Ridge Chamise	0.418	0.448	0.43	0.364	0.694	0.702	0.482	0.518	0.504
Glendora Ridge Hoaryleaf Ceanothus	0.371	0.508	0.458	0.347	0.629	0.632	0.515	0.632	0.648
Chaparral average	0.318	0.392	0.342	0.29	0.589	0.592	0.353	0.712	0.715
Bitter Cyn 1 California Sage	−0.3	−0.97	−0.82	−0.45	−0.57	−0.6	0.057	0.738	0.882
Bitter Cyn 1 Purple Sage	−0.38	−0.87	−0.79	−0.47	−0.63	−0.65	−0.01	0.766	0.856
Bouquet Cyn Black Sage	0.236	0.513	0.3	0.249	0.624	0.641	0.21	0.919	0.932
Trippet Ranch Black Sage	−3.9	−1.3	−3.29	−3.67	−1.06	−1.06	−4.32	0.737	0.785
CSS average	−1.08	−0.66	−1.15	−1.08	−0.41	−0.42	−1.02	0.790	0.864

Significant differences ($p<0.05$) are underlined. The multivariate models used for chaparral are VARI and VI_{green} overall mean and VARI, VI_{green} overall median, and VI_{green} yearly range. The models used for CSS are VI_{green} and VI_{green} overall median and VARI, NDII6 overall mean, and NDVI overall range.

mixture of chaparral and CSS. Additional predictor variables are clearly needed in order to account for the different slopes and intercepts when the data are pooled together.

Leave-one-dataset-out cross validation was performed once for each of the 16 LAC chaparral datasets and once for each of the four CSS datasets (Table 5). As expected, based on the different slopes and intercepts evident in Table 4, a single variable model was less than ideal for both functional types; the best average cross-validated adjusted R^2 was 0.592 (VARI) for chaparral and −0.42 (VI_{green}) for CSS. A negative value for cross-validated R^2 means the predicted values for LFM are worse than if the overall average LFM value had been assigned to each data point. Or, in statistical terms, the residual sum of squares is larger than the mean sum of squares. This can only happen when a model is developed on one dataset and tested on another. There is no lower limit on cross-validated R^2, however the upper limit is still 1.0.

The best overall two variable (additive variable added) models for the pooled analyses were VARI and overall median of VI_{green} for chaparral with an average cross-validated adjusted R^2 of 0.712, and VI_{green} and overall minimum of NDWI for CSS with an average cross-validated adjusted R^2 of 0.790. Most sites showed improvement in R^2, with six of the chaparral datasets and three of the CSS datasets showing significant improvement. Reduced sample sizes at the sites which burned (Bouquet Canyon, Pico Canyon, Peach Motorway, and Sycamore Canyon) make it more difficult for differences to be significant.

The best overall three variable model (additive and multiplicative variables added) for chaparral was VARI, overall median of VI_{green}, and yearly range of VI_{green} with an average R^2 of 0.715. No sites showed a significant improvement in R^2 compared to values from the two variable model. The best overall three variable model for CSS showed considerable improvement over the two variable model. VARI, overall mean of NDII6, and overall range of NDVI produced an average R^2 of 0.864. Two CSS datasets showed a significant increase in R^2 for three variable models. The Trippet Ranch dataset also shows a significant improvement when slope is included if the p-value threshold is 0.1 rather than 0.05.

3.3. Mapping LFM

The two plant functional type three variable models were inverted and applied across the landscape to map LFM. The equations are:

$$\mathrm{LFM_{chap}} = 97.8 + 471.6 \cdot \mathrm{VARI} - 293.9 \cdot omVI_{green} - 816.2 \cdot VARI \cdot yrVI_{green} \quad (4)$$

$$\mathrm{LFM_{CSS}} = 179.2 + 1413.9 \cdot \mathrm{VARI} - 450.5 \cdot omNDII6 - 1825.2 \cdot VARI \cdot orNDVI \quad (5)$$

where VARI is the time series of VARI, $omVI_{green}$ is the overall median of VI_{green}, $yrVI_{green}$ is the yearly range in VI_{green}, omNDII6 is the overall mean of NDII6, and orNDVI is the overall range of NDVI. Scatterplots of predicted versus observed LFM values are shown in Fig. 3. The regression lines show some deviation from the 1:1 lines for both functional types. However, there is more scatter for high LFM values than low values. The low values show good agreement between observed and predicted LFM values for both chaparral and CSS.

The maps of chaparral and CSS LFM for 2000–2006 show spatial and temporal patterns that reflect the topography and weather of LAC. Areas with LFM < 60% are highlighted in red, areas from 60%–77% are highlighted in yellow, and there is a color scale from 77% to 200% on Figs. 4, 6, 7 and 8. These threshold values follow thresholds suggested by Weise et al. (1998) and Dennison et al. (2008).

Starting with day 113 (23 April), early in the dry down portion of the year, only the driest year, 2002, showed large areas of chaparral LFM less than 77% (Fig. 4, Table 6). These areas are located on the desert side of the coastal mountain ranges which experience higher

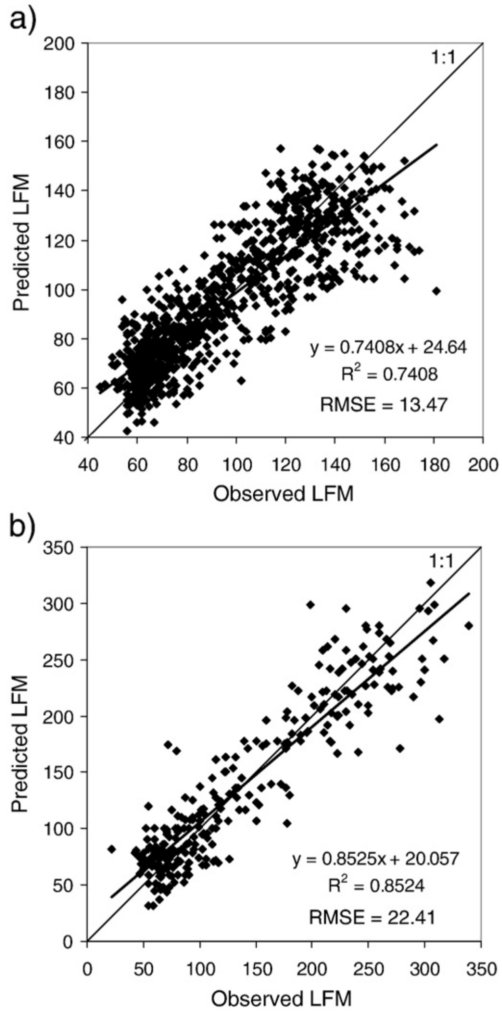

Fig. 3. Observed vs. predicted values of LFM for a) all chaparral and b) all CSS datasets.

summer air temperatures and lower winter precipitation, hence vegetation dries out earlier. Precipitation at the Saugus remote automated weather station (RAWS), centrally located relative to the LFM sampling sites, was well below average for the 2001–2002 water year (Fig. 5). This led to the early onset of dry conditions. The area of low LFM values in 2004 corresponds to the fire scar of the 2003 Simi Fire. Table 6 provides quantitative comparisons of the different years.

Drying progressed gradually through day 161 (10 June) (Fig. 6). By day 161, year 2004 also showed a coherent pattern of low LFM values, in similar areas as for 2002. Precipitation in the 2003–2004 water year was the second lowest of the study period (Fig. 5). Large areas of dangerous (LFM < 77%) levels of LFM by day 161 are almost entirely restricted to the two dry years, with two exceptions. First, the Simi Fire scar is visible in the central west portion of the 2004, 2005, and 2006 maps. Second, there is a small chaparral stand in the northern part of the county that had lower values in 2005 and 2006. This stand had low LFM values at the beginning of the dry down period in 2002, 2004, and 2005 (Fig. 4), so it appears to be susceptible to early onset of drying.

The period from day 177–241 (26 June 26–29 August) experienced the most rapid drop in LFM. The peak in dryness occurred on day 241 (Fig. 7). As with previous timesteps, 2002 and 2004 had the largest amount of low LFM areas on day 241, but all of the other years showed a large amount of pixels having LFM < 77%.

In contrast, the CSS maps showed a more limited amount of interannual variability. There were some differences early in the dry down period, with 2002 and 2004 drying out sooner than the other

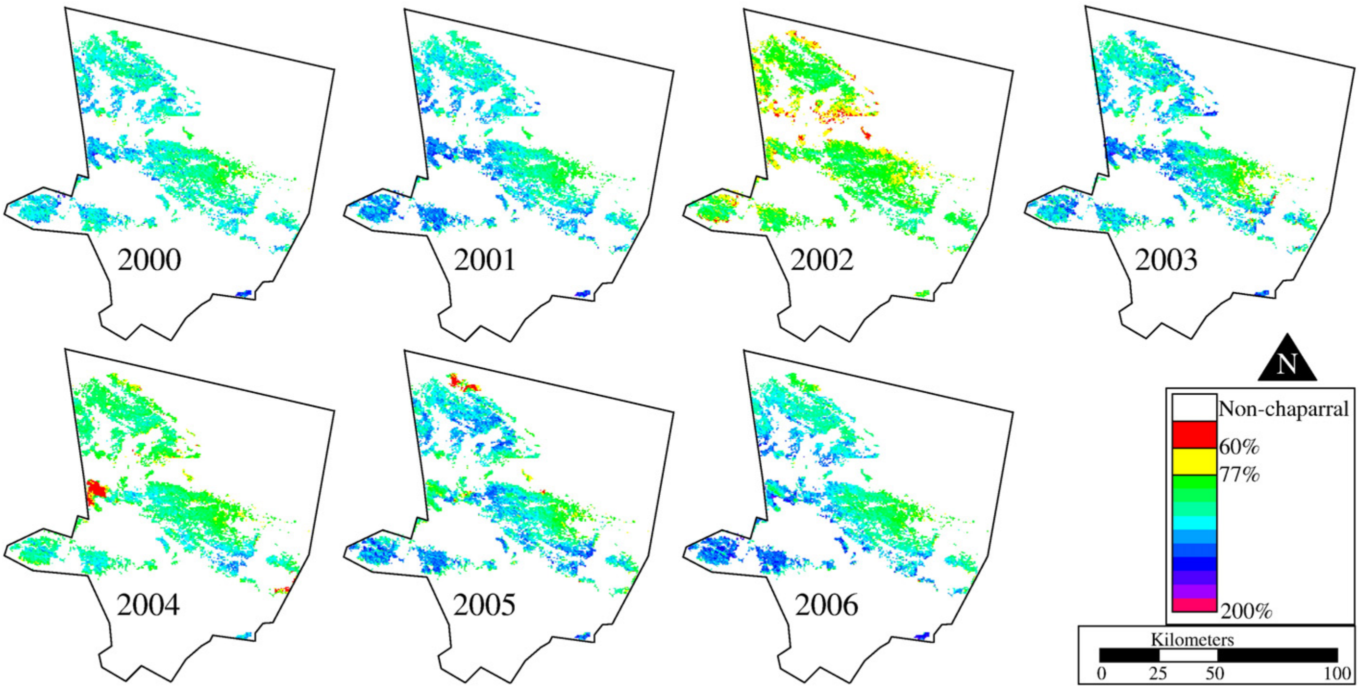

Fig. 4. Mapped LFM for Los Angeles County, California chaparral for day 113 (23 April) for 2000–2006. Values representing LFM<60% (extreme fire danger) are in red, values representing 60%<LFM<77% (high fire danger) are in yellow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

years, but from day 193 (mid July) on there are large areas of LFM<60% in all years (Fig. 8, Table 6). The earlier onset of low LFM values for CSS corresponds with the finding that soil moisture reaches seasonal low values two months earlier in the CSS than the chaparral (Miller and Poole, 1979). Areas of high LFM values at the CSS/urban margin are due to the FRAP fuels map mapping irrigated areas in the wildland urban interface as CSS. The irrigated landscaping retains high moisture values year-round.

Table 6
MODIS pixel counts in three live fuel moisture categories for Figs. 4, 6, 7 and 8

Day	Year	Functional type	Live fuel moisture categories			
			<60%	60%–77%	>77%	Total
113	2000	Chaparral	3	48	9211	9262
113	2001	Chaparral	1	14	9247	9262
113	2002	Chaparral	281	2285	6696	9262
113	2003	Chaparral	26	245	8990	9261
113	2004	Chaparral	228	491	8543	9262
113	2005	Chaparral	110	246	8903	9259
113	2006	Chaparral	3	97	9162	9262
161	2000	Chaparral	22	413	8827	9262
161	2001	Chaparral	13	260	8989	9262
161	2002	Chaparral	2086	5620	1556	9262
161	2003	Chaparral	58	343	8861	9262
161	2004	Chaparral	892	4152	4218	9262
161	2005	Chaparral	281	595	8386	9262
161	2006	Chaparral	149	297	8816	9262
241	2000	Chaparral	1584	5134	2544	9262
241	2001	Chaparral	1285	5227	2750	9262
241	2002	Chaparral	7629	1426	207	9262
241	2003	Chaparral	1125	5234	2903	9262
241	2004	Chaparral	6157	2741	364	9262
241	2005	Chaparral	1848	5644	1770	9262
241	2006	Chaparral	1280	5195	2787	9262
193	2000	Coastal sage scrub	1171	1727	4960	7858
193	2001	Coastal sage scrub	987	1453	5418	7858
193	2002	Coastal sage scrub	2779	2016	3063	7858
193	2003	Coastal sage scrub	1564	988	5306	7858
193	2004	Coastal sage scrub	2916	2084	2858	7858
193	2005	Coastal sage scrub	1943	1754	4161	7858
193	2006	Coastal sage scrub	1324	1594	4940	7858

4. Discussion and conclusions

For the individual site regressions for chaparral, models consisting solely of a VI time series predictor variable were generally preferable. Variables accounting for interannual variability did not significantly improve the chaparral models. In contrast, Roberts et al. (2006), utilizing the entire year, rather than the dry down period only, found that interannual variability did have an effect on LFM/VI regressions. Interannual variability in greenness should be greater for full year datasets which include the late winter/early spring time period when greenness is at a peak, hence it would have a larger effect on the regressions. However, variables accounting for interannual variability improved individual site regressions for the CSS datasets. CSS is shallower rooted than chaparral, so plant moisture is more dependent on annual precipitation (Hellmers et al., 1955). As total water year precipitation varied widely from 6 to 69 cm during the study period (Fig. 5), variables to account for interannual variability in greenness were needed.

In contrast, additional variables were utilized for both functional types in the pooled regressions. The variables selected for the additive term reflect the general greenness of the sites (median VI summary statistic variables were selected twice, mean and minimum once each). Using these variables acts to shift and better align the data clouds, controlling for intersite differences in greenness. Bitter Canyon 2 Chamise and Trippet Ranch Chamise show the largest increase in R^2 between one and two variable models for chaparral (Table 5). These two sites have the lowest and highest value for the y-intercept in Table 4, so including a variable which accounts for the intercept has the largest effect for these sites. A similar trend is found for the CSS sites. The Bitter Canyon 1 datasets and Trippet Ranch Black Sage show very large increases in R^2 (Table 5), and have the highest and lowest y-intercepts in Table 4.

The range between minimum and maximum VI value was selected for the multiplicative term for both pooled regressions. The range in

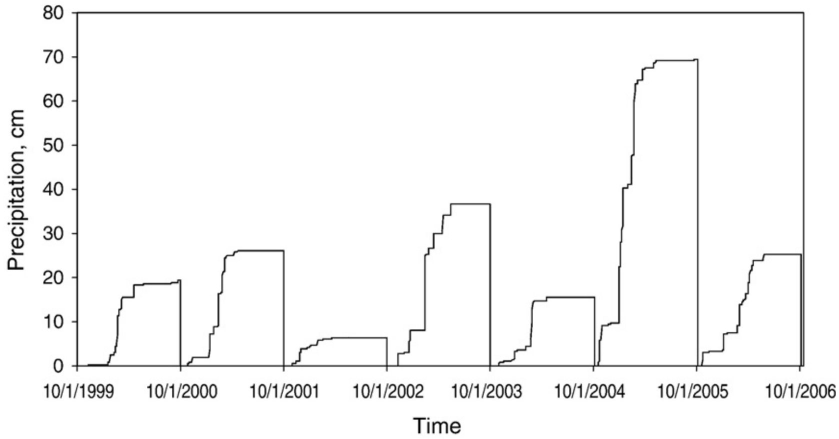

Fig. 5. Cumulative precipitation by water year (1 October–30 September) for the Saugus, CA RAWS station.

LFM is relatively consistent across sites, so the range in values of the VI dictates the slope of the regression line. Hence the multiplicative summary variable acts to adjust for differences in slope of the datasets. For CSS, the Bitter Canyon datasets show a significant improvement when a variable accounting for slope is included in the regression model.

The best three variable model when chaparral sites were pooled has an average adjusted R^2 that is 0.069 lower than that of the best single variable model for individual sites. This is a minimal decrease in predictive power considering the broader applicability of the cross-validated model. Four datasets show large departures between cross-validated and individual R^2 greater than 0.10. Two of these sites (Bouquet Canyon Chamise and Glendora Ridge Chamise) have smaller sample sizes so they may be more sensitive to poor predictions. The Laurel Canyon chaparral stand is approximately the size of 1 MODIS pixel, and is surrounded by housing with non-native, irrigated landscaping, which can influence the remotely sensed signal when dates having less vertical look angles (larger effective pixel sizes) are selected in the compositing process. Hence, it is not surprising that a model developed for chaparral does not work well for an area within the wildland urban interface. The Trippet Canyon Chamise dataset has the highest values for VARI of the chaparral sites (lowest value for y-intercept in Table 4) so it may be that the model developed at less green sites does not extrapolate well to the greenest site.

For CSS, the cross-validated three variable model provides a similar average R^2 as the best single variable individual model, 0.864 vs. 0.873. The similarity in R^2 between individual and pooled regressions suggests that the cross-validated regression equations are robust.

This research, as with the prior studies of LFM with MODIS data, found that VARI is the best index for predicting shrub LFM (Stow et al., 2005, 2006; Roberts et al., 2006). VARI is a greenness index, introduced by Gitelson in a study measuring vegetation fractional cover in wheat canopies (2002). It was found to retain a linear relationship with vegetation fraction for all values, whereas NDVI saturated at 50% cover. The proposed mechanism for the strength of the VARI/LFM relationships is that LFM co-varies with chlorophyll

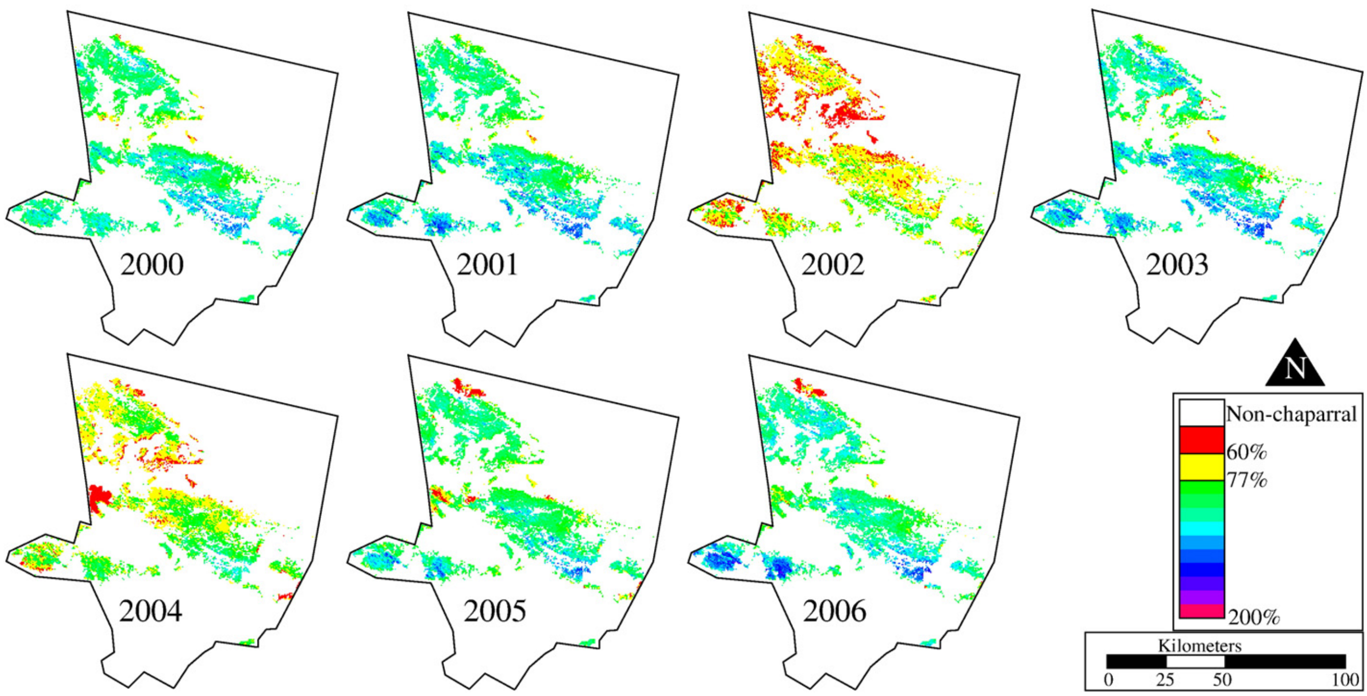

Fig. 6. Mapped LFM for Los Angeles County, California chaparral for day 161 (10 June) for 2000–2006. Values representing LFM<60% (extreme fire danger) are in red, values representing 60%<LFM<77% (high fire danger) are in yellow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

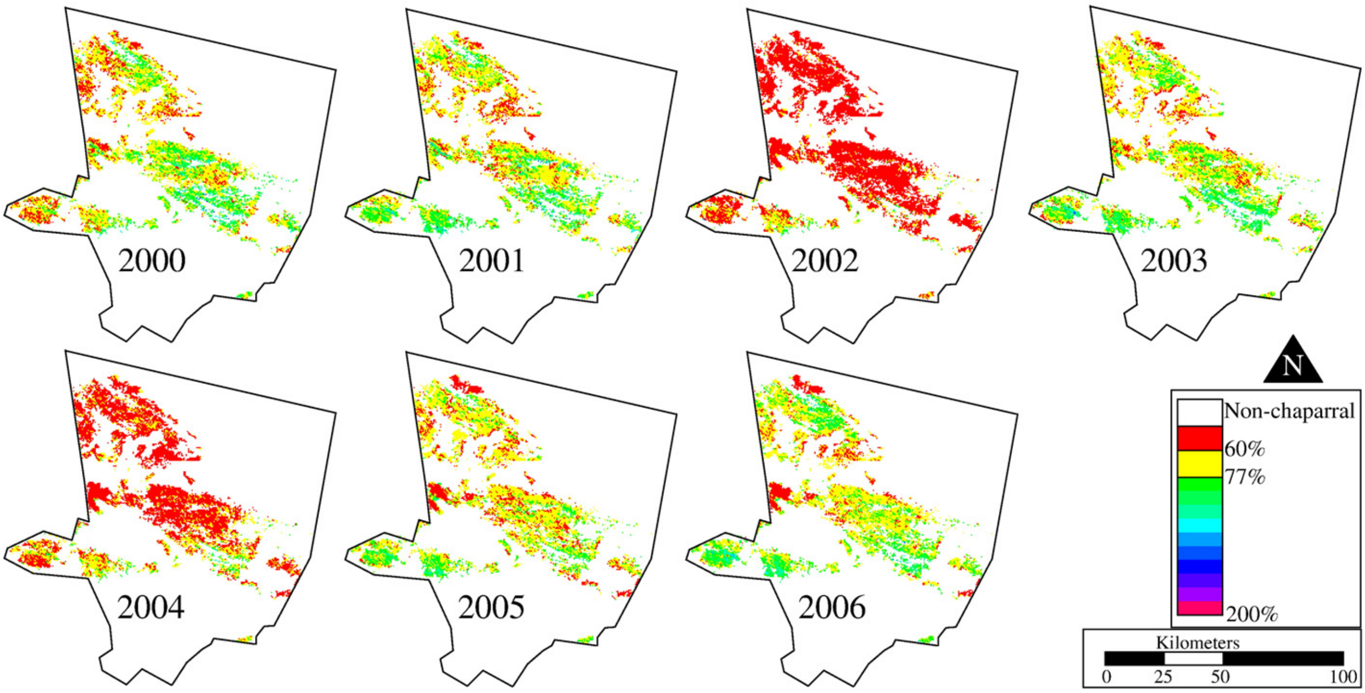

Fig. 7. Mapped LFM for Los Angeles County, California chaparral for day 241 (29 August) for 2000–2006. Values representing LFM<60% (extreme fire danger) are in red, values representing 60%<LFM<77% (high fire danger) are in yellow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

absorption and LAI. Chlorophyll content and water content co-vary in grassland functional types (Tucker, 1977), and this is the basis for studies of LFM in grasslands (Paltridge & Barber, 1988; Hardy & Burgan, 1999). A study by Harrison et al. (1971) also suggests a chlorophyll content–water content relationship for shrublands. They took cuttings from chaparral and CSS shrubs and measured rates of photosynthesis while lowering the water content of the leaves by placing them in a chamber and pumping in air of low relative humidity. A linear relationship was found for chaparral species and a piece-wise linear relationship was found for CSS species. LAI is sensitive to overall site water balance, interannual precipitation variability, and the progression of the summer drought for Ceanothus

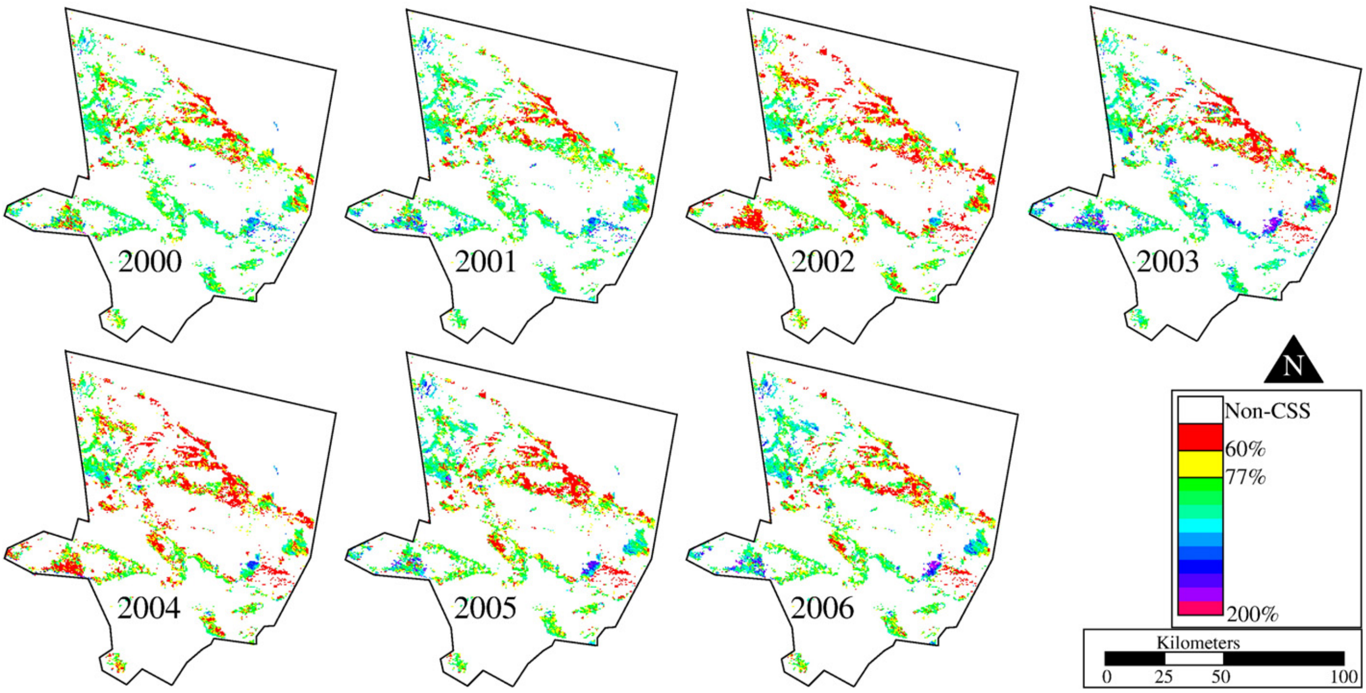

Fig. 8. Mapped LFM for Los Angeles County, California coastal sage scrub for day 193 (12 July) for 2000–2006. Values representing LFM<60% (extreme fire danger) are in red, values representing 60%<LFM<77% (high fire danger) are in yellow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

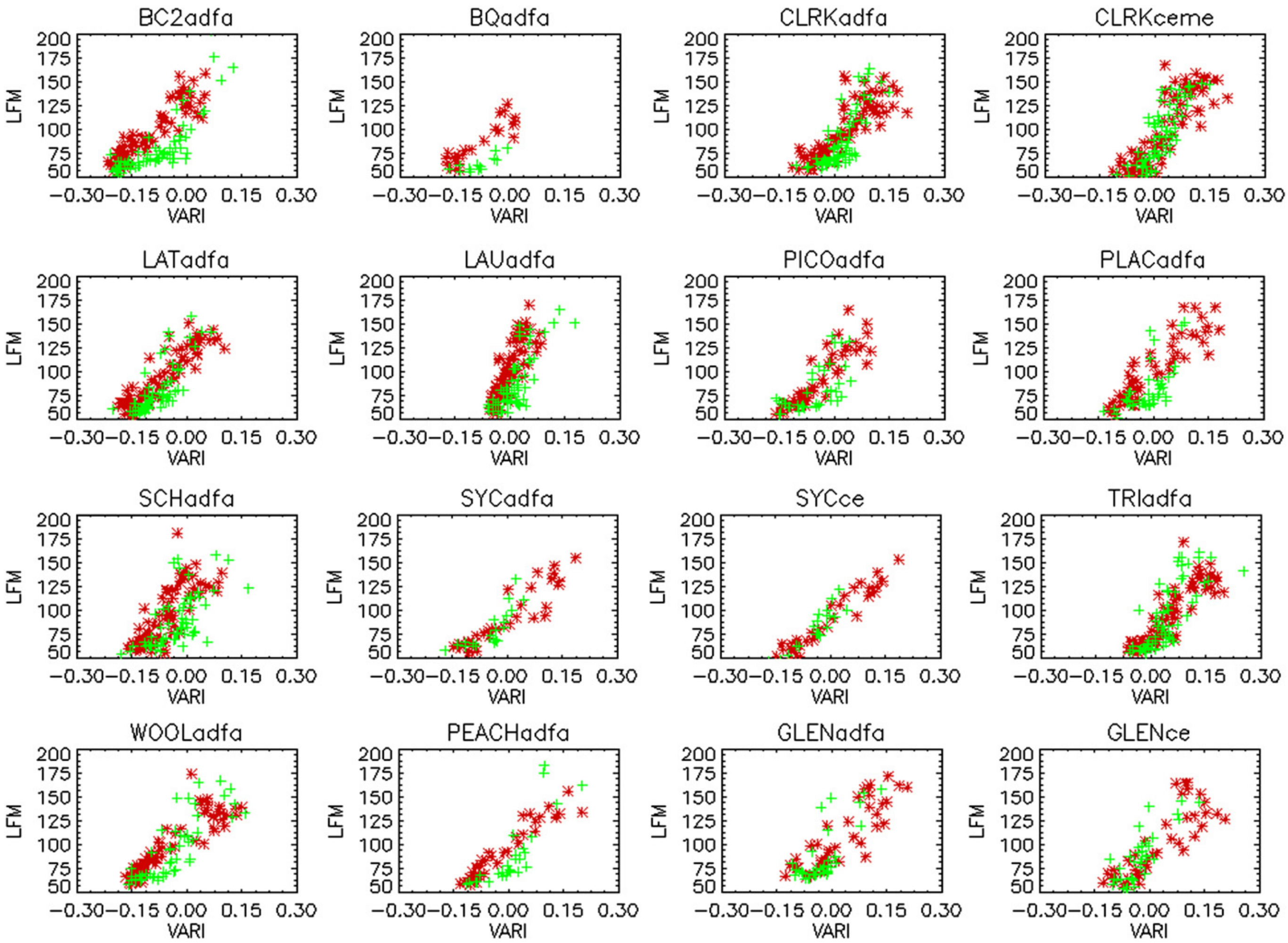

Fig. 9. Scatterplots of VARI and LFM for the 16 chaparral data sets with dry down period in red and green up period in green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

chaparral (Riggan et al., 1988). CSS species reduce leaf area during the summer drought through leaf shedding (Harrison et al., 1971) and leaf curling (Gill & Mahall, 1986).

The maps of LFM developed from the inverted equations show coherent temporal and spatial patterns, which serves to increase confidence in the validity of the cross-validated models. Drying begins

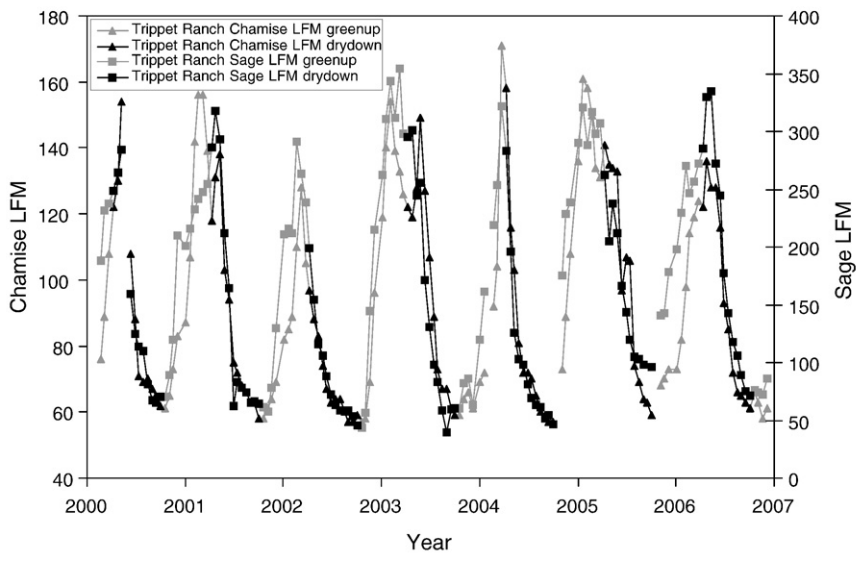

Fig. 10. Time series plot of greenup and dry down LFM for the Trippet Ranch LFM site, for a CSS and a chaparral species, for 2000–2006.

earliest for all years in areas which receive low annual precipitation: low elevation sites in the rain shadow of mountain ranges. The northern interior portion of the county was next to experience low values of LFM. The coastal mountains dry out last, with some pixels not showing LFM less than 77%.

Drying begins earlier in the two years having the lowest precipitation, 2002 and 2004. On average, expansive areas of low LFM values occur in the CSS starting around day 177 (late June) while the period of high fire risk begins around day 209 (late July) in the chaparral. The maps of LFM suggest that by the end of the dry down season, most of LAC is susceptible to burning. The end of September is also a time when the risk of Santa Ana wind events begins to increase, leading to very high fire risk (Keeley et al., 2004).

While the dry down period was utilized in this research, data for the full year were available, and were examined in detail. Fig. 9 shows scatterplots between VARI and LFM for all 16 chaparral datasets used in this research. The relationship between LFM and VARI is generally linear during the dry down and generally non-linear for the green up period, and the data clouds are distinct. An additional, separate equation would be needed for the green up period in order to model LFM year-round.

A possible explanation for the different behavior in the green up and dry down periods is that the remotely sensed signal during the green up is affected by other species present, but not sampled, at a site. The Trippet Ranch site is the only site where species from two functional types were sampled, chamise and black sage. Examining their phenological timing is instructive. It can be seen that the sage LFM increases earlier in the growing season than that of chamise during the 2000–2001, 2001–2002, and 2005–2006 winters (Fig. 10). The potential for earlier onset of growth for CSS species is well established in the literature (e.g., Gray, 1982; Gill & Mahall, 1986). The two functional types behave more similarly during the dry down period; this leads to more linear relationships during the dry down period as the mixture of species does not have a mixed effect on the remotely sensed signal.

A fundamental assumption in this work is that the sampled vegetation stands are homogeneous, and that averaging the LFM of three shrubs is representative of all of the shrubs within a MODIS pixel. The strength of the regressions, and lack of outliers in temporal trajectories of LFM (Fig. 10), suggest that this assumption is met, though future work is planned to quantify sub-MODIS pixel variability in LFM.

Measuring LFM in the field is costly and time consuming, so developing a reliable methodology that incorporates remote sensing is advantageous. This research has shown that there are strong relationships between LFM and VIs at individual study sites of chaparral and CSS functional types, and that by incorporating phenological metrics, regression equations can be generalized for use throughout the functional types with a minimal loss in explained variance. These equations were inverted, and maps of LFM reveal the progression of vegetation drying in LAC from internal valleys to internal mountains to coastal mountains. The methods used in this research should be portable to other vegetation communities where LFM is important in determining fire risk, such as Mediterranean shrub communities in Europe, Australia, South America, and southern Africa, though this has yet to be proven.

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