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Evaluating predictive models of critical live fuel moisture in the Santa Monica Mountains, California

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Abstract. Large wildfires in the Santa Monica Mountains of southern California occur when low levels of live and dead fuel moisture coincide with Santa Ana wind events. Declining live fuel moisture may reach a threshold that increases susceptibility to large wildfires. Live fuel moisture and fire history data for the Santa Monica Mountains from 1984 to 2005 were used to determine a potential critical live fuel moisture threshold, below which large fires become much more likely. The ability of live fuel moisture, remote sensing, and precipitation variables to predict the annual timing of 71 and 77% live fuel moisture thresholds was assessed. Spring precipitation, measured through the months of March, April, and May, was found to be strongly correlated with the annual timing of both live fuel moisture thresholds. Large fires in the Santa Monica Mountains only occurred after the 77% threshold was surpassed, although most large fires occurred after the less conservative 71% threshold. Spring precipitation has fluctuated widely over the past 70 years but does not show evidence of long-term trends. Predictive models of live fuel moisture threshold timing may improve planning for large fires in chaparral ecosystems.

Additional keywords: chamise, chaparral, precipitation, wildfire danger.

Introduction

Southern California possesses a Mediterranean climate characterised by variable winter and spring precipitation followed by drought during the summer and fall. Seasonal drought causes a decrease in available soil moisture, which can in turn produce senescence and a decrease in live vegetation water content. Evergreen chaparral shrublands dominate higher elevations in southern California's coastal mountain ranges, and the moisture content of live chaparral vegetation decreases as seasonal drought progresses (Miller and Poole 1979). Low moisture content in live chaparral vegetation and in dead litter, combined with Santa Ana winds (Schroeder *et al*. 1969), can result in intense wildfires that burn tens of thousands of hectares.

Moisture content in live chaparral biomass is typically measured as live fuel moisture (LFM). LFM is defined as the water content of live vegetation expressed as a percentage of the dry mass of vegetation (m_d):

$$\mathrm{LFM} = \frac{m_w - m_d}{m_d} \quad (1)$$

where m_w is the mass of the undried vegetation. LFM in southern California typically peaks in late spring and then declines through summer and fall until precipitation returns in late fall or winter. Fire behaviour varies dramatically with fuel moisture content, as the moisture contained within both live and dead fuels must be driven off before fuels can combust (Pyne *et al*. 1996). As LFM decreases, fires lose less heat to fuel dehydration and can propagate at higher spread rates. Several wildland fire agencies in southern California therefore routinely sample chaparral LFM as a measure of fire danger.

Previous research has proposed a variety of relationships between chaparral LFM and fire danger. Green (1981) and Weise *et al*. (1998) described gradually increasing fire danger as chaparral LFM decreases. Green (1981) proposed a three-class scale for fire intensity, with the highest intensity occurring below 60% LFM. Weise *et al*. (1998) used four fire danger classes, with high fire danger occurring between 60 and 80% and extreme fire danger occurring below 60%. Other studies have proposed that fire danger dramatically increases when LFM drops below a threshold. Pirsko and Green (1967) suggested that fire behaviour transitions at an LFM threshold of 70%. Schoenberg *et al*. (2003) investigated monthly chaparral LFM, stand age, temperature, and precipitation thresholds, and found that burned area increased at an LFM threshold of 90%. Below a monthly average of 90% LFM, average burned area did not change.

The present study examines the relationship between a time series of LFM and fire history data from the Santa Monica Mountains in southern California. We find two potential 'critical' LFM thresholds, below which large fires occur, by comparing LFM and area burned. LFM, remote sensing, and precipitation

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variables are examined for their ability to predict the timing of when these thresholds are exceeded annually. The best-fit predictive models are assessed using 'leave-one-out' cross-validation, and the thresholds are validated using long-term fire history data.

Background

Santa Ana winds are the primary driver of fire danger in southern California (Minnich 1983; Moritz 1997, 2003; Keeley *et al.* 1999; Keeley and Fotheringham 2001; Moritz *et al.* 2004). Although Santa Ana winds can occur in any month, they are most frequent from September through April, with the peak frequency occurring in December (Raphael 2003). Fuel moisture can limit fire danger during Santa Ana conditions. This limitation is evident in that large fires do not occur during late winter and spring Santa Ana wind events, when live and dead fuel moisture is typically high. Schoenberg *et al.* (2003) determined that total area burned in Los Angeles County peaks in September and October, caused by a combination of more frequent Santa Ana winds with low LFM.

Previous work has shown that accumulated precipitation influences the number of fires and area burned in southern California. Davis and Michaelsen (1995) examined the fire history of Los Padres National Forest. They found that precipitation for the months of March through May explained much of the variation in the area burned each year, and years with low spring precipitation possessed a disproportionately large percentage of the total area burned over a 77-year period. Average fire season LFM, as measured by the departure from monthly mean LFM for June through October, was found to be strongly correlated with spring precipitation (Davis and Michaelsen 1995). Keeley (2004) examined correlations between climate and the number of fires and area burned over a larger area of southern and central California. In contrast to Davis and Michaelsen (1995), Keeley (2004) found that same-year seasonal precipitation was not significantly correlated with the number of fires or area burned in southern California. Previous-year winter and growing season precipitation did have a weak positive correlation with the number of fires, however.

Chaparral LFM is traditionally assessed by destructive field sampling (Countryman and Dean 1979). As field sampling is manually intensive and may not capture spatial variation in LFM, remote sensing has been suggested as an alternative means for assessing chaparral LFM (Dennison *et al.* 2005). Several recent studies have evaluated the potential for remote sensing retrieval of southern California chaparral LFM. These studies have used regression analysis to compare the strengths of relationships between LFM and different remote sensing indices. Dennison *et al.* (2005) compared normalised difference vegetation index (NDVI) (Rouse *et al.* 1973) and normalised difference water index (NDWI) (Gao 1996) correlations, while Stow *et al.* (2005) compared correlations for NDWI and the visible atmospherically resistant index (VARI) (Gitelson *et al.* 2002). Roberts *et al.* (2006) and Dennison *et al.* (2007) compared correlations between LFM and seven different remote sensing indices. Stow *et al.* (2006) used relationships between LFM and remote sensing indices to map spatial changes in LFM. These studies have found that greenness indices using visible bands (e.g. VARI) have the strongest correlations with chaparral LFM, with r^2 values exceeding 0.9 for individual sites and 0.7 across multiple sites (Roberts *et al.* 2006; Stow *et al.* 2006; Dennison *et al.* 2007). These studies have been limited to LFM monitoring, and have not examined the ability of remote sensing indices to forecast chaparral LFM.

Study site

The Santa Monica Mountains are an east–west-trending mountain range west of Los Angeles, California (Fig. 1). Santa Ana winds and steep topography contribute to frequent wildfires in the Santa Monica Mountains. Ignitions in the Santa Monica Mountains are almost exclusively human-caused, either by accident or by arson (Radtke *et al.* 1982). Area burned in the Santa Monica Mountains peaks in October, when more frequent Santa Ana winds coincide with low fuel moisture conditions (Radtke *et al.* 1982; National Park Service 2005).

Elevations in the Santa Monica Mountains range from sea level to 948 m. Precipitation measured at the University of California Los Angeles (UCLA) meteorological station at the base of the Santa Monica Mountains (Fig. 1) averages 46 cm per year. On average, 94% of this precipitation falls during the months of November through May. This wet season is followed by a long summer drought with little or no precipitation. Precipitation ranges widely from year to year. The minimum water year (beginning 1 October) precipitation measured at the UCLA station over the 1934–2005 period was 16 cm, whereas the maximum water year precipitation over the same period was 110 cm. Precipitation also varies spatially, with the coastal side of the range and higher elevations receiving more precipitation, while the lee side and lower elevations receive less.

The 620 km^2 Santa Monica Mountains National Recreation Area (SMMNRA) encompasses a majority of the range and represents the world's largest urban national park. The SMMNRA is surrounded by and surrounds several communities, making it one of the major areas of wildland–urban interface and intermix in southern California. Lower elevations of the SMMNRA near the coast are dominated by sage scrub (~20% of total area (National Park Service 2005)), whereas lower elevations in the northern part of the park are dominated by introduced European grasses (e.g. *Bromus* spp.) and black mustard (*Brassica nigra*) (<5% of total area). Most of the remainder of the range is chaparral (54% of total area), characterised by dense shrubs ranging in height from 1 to 4 m. Chaparral dominant species in the Santa Monica Mountains include chamise (*Adenostoma fasciculatum*) and big pod ceanothus (*Ceanothus megacarpus*).

Methods

Live fuel moisture data

LFM values sampled at three sites in the Santa Monica Mountains (Fig. 1) were provided by the Los Angeles County Fire Department (LACFD). LACFD samples LFM approximately once every 3 weeks for sites across Los Angeles County. Sampling methods used by LACFD are described by Countryman and Dean (1979). Dates reported in the LACFD time series do not always reflect the actual day vegetation sampling occurred, but are accurate to within 7 days of the actual sampling date. At each site, one to three shrub species are sampled within an

Fig. 1. The locations of three live fuel moisture sampling sites and the University of California, Los Angeles (UCLA) meteorological station relative to the Santa Monica Mountains. 'C' is Clark Motorway, 'S' is Schueren Road, and 'T' is Trippet Ranch. The background image is a 2002 Landsat Enhanced Thematic Mapper+ image.

area of 0.4–1.2 ha (T. Bristow, pers. comm.). Chamise is sampled at most of the Los Angeles County sites, including three sites in the Santa Monica Mountains. LFM analysis was limited to chamise, one of two dominant species in the Santa Monica Mountains, to ensure consistent LFM response to precipitation and soil moisture conditions (Miller and Poole 1979).

The 3-week temporal resolution of the LACFD time series was insufficient for determining LFM during individual fire events, especially during periods of rapid drying. To estimate daily LFM, samples from the three sites were averaged and then linearly interpolated to daily temporal resolution. Chamise LFM from the Clark Motorway, Schueren Road, and Trippet Ranch sites (Fig. 1) were averaged for each date provided by LACFD from 1984 to 2005. Averaging the sites eliminated information on spatial differences in LFM values, but served to decrease noise in the temporal dimension caused by sampling error. Linear interpolation assumes a constant rate of LFM change between sampling dates. LFM was not sampled at the Schueren Road site from November 1993 to October 1998, so the average LFM only includes the Clark Motorway and Trippet Ranch sites during this period.

California Department of Forestry and Fire Protection (CDF) fire history data were used to determine an LFM threshold to be used in further analysis. This critical LFM threshold is the value below which large fires have occurred. Fires within the area of the Santa Monica Mountains were extracted from the statewide CDF fire history data. The subset fire history data includes 267 fires from 1933 to 2005, the date each fire was reported, and the area of each fire. Potential LFM threshold values were determined by comparing area burned and cumulative area burned with decreasing LFM to the interpolated LFM record for 59 fires from 1984 to 2005. The sequential day of year (1–365) that the interpolated LFM first dropped below the threshold was then found for each year.

Nine environmental and remote sensing variables were assessed for their ability to predict the date LFM dropped below the threshold value in each year (Table 1). Variables based on LFM or remote sensing data were designed to capture either the maximum value, the timing of the maximum value, or the value on a specific date. Three variables were calculated from the interpolated LFM time series. The maximum LFM was calculated as the maximum annual LFM, using the average of the three sampling sites. The day of year of the maximum LFM was also used as a variable. As the linearly interpolated LFM values cannot exceed the original non-interpolated values, the day of year of the maximum LFM possessed the same 3-week temporal resolution as the original LACFD LFM time series. A third LFM variable, the 1 June LFM, was extracted from the interpolated LFM time series. This date is after the end of the wet season, but typically before steep drops in LFM that occur in late June through August.

Remote sensing data

Ideally, remote sensing data used for the present analysis would possess weekly temporal resolution to allow observation of changing LFM over short time scales, and high spatial resolution to permit direct correlation of site-sampled LFM to remote sensing indices calculated from single pixels. Unfortunately, data that satisfied both temporal and spatial needs were not available. Correlations between 30-m spatial resolution Landsat Thematic Mapper (TM) data and LFM have been previously demonstrated (Chuvieco *et al*. 2002), but a limited number of TM scenes were available during each year of the study period. Although remote sensing indices calculated from 500-m spatial resolution

Table 1. Variables regressed against the day of year of the critical live fuel moisture (LFM) threshold
AVHRR, Advanced Very High Resolution Radiometer; NDVI, normalised difference vegetation index; UCLA, University of California, Los Angeles

Variable	Definition
Maximum LFM	Maximum averaged LFM for three sample sites
Max. LFM DOY	Day of each year that the maximum LFM occurred on
1 June LFM	LFM on 1 June of each year, based on interpolated average of three LFM sample sites
Maximum NDVI	Maximum mean NDVI calculated from 50 pixels extracted from AVHRR composite
Max. NDVI DOY	Central date of the composite for which the maximum mean NDVI was found
1 June NDVI	Mean NDVI calculated from 50 pixels extracted from composite period closest to 1 June
Wet Season Precip.	November–May total precipitation measured at the UCLA station
DJF Precip.	December–February total precipitation measured at the UCLA station
MAM Precip.	March–May total precipitation measured at the UCLA station

Moderate Resolution Imaging Spectrometer (MODIS) temporal composites have been shown to have strong correlations with chaparral LFM (Dennison *et al.* 2005, 2007; Stow *et al.* 2005, 2006; Roberts *et al.* 2006), MODIS data are only available since March 2000. Advanced Very High Resolution Radiometer (AVHRR) data have a long time series compared with MODIS data, but at the cost of reduced spectral dimensionality (2 bands) and spatial resolution (1.1 km). To provide the maximum temporal density and extent for comparison with the LFM time series data, AVHRR data were used. The United States Geological Survey 14-day 1-km AVHRR NDVI composite product was used to create a time series spanning 1989–2005. This composite was constructed using the maximum NDVI value for each pixel over a 14-day period (Holben 1986). Fifty-two composites were created for each year, with each composite overlapping the temporally adjacent composite by 1 week.

The AVHRR NDVI time series was compared with the LFM time series using the composites with a central date closest to each LACFD-reported LFM sampling date. The spatial extent of the composited NDVI pixels (1 by 1 km) presented a problem for determining a single NDVI value for each date. Each pixel contains multiple land cover types at this resolution, so correlations between NDVI and LFM were poor but significant ($r^2 < 0.2$, $P < 0.001$) at the pixel level. To enhance the predictive ability of the extracted NDVI values, 50 pixels in the Santa Monica Mountains with the strongest correlations with the LFM time series were averaged to produce a 'regional mean' NDVI. This method increased r^2 between NDVI and LFM to 0.58 ($P < 0.001$). Three variables were calculated from the regional mean NDVI time series. The maximum NDVI was found for each 1 November–1 June period. The day of year of this maximum NDVI was determined using the central date of the composite period possessing the maximum NDVI. Finally, the regional mean NDVI for the composite with a central date closest to 1 June was found.

Meteorological data

Three variables were calculated from precipitation records from the UCLA meteorological station (Fig. 1). For each water year, the total precipitation during the period between 1 November and 31 May was calculated as the 'wet season' precipitation. Wet season precipitation was further broken down into winter and spring precipitation. Winter precipitation was calculated as total precipitation during the months of December, January, and February (DJF). Spring precipitation was calculated as the total precipitation during the months of March, April, and May (MAM). For both the wet season and MAM precipitation variables, the end of the precipitation period coincides with the 1 June date used for calculating the third LFM and NDVI variables.

Data analysis

These nine variables (Table 1) were compared with the timing of the LFM critical threshold using linear regression. Regressions were calculated using the time period common to all of the time series, 1989–2005. Simple linear regression was used to calculate slope, intercept and r^2 values for each variable. Stepwise multiple linear regression was used to test whether combinations of variables were able to explain additional variation in the timing of the LFM critical threshold.

The best-fit predictive model, as assessed by r^2, was tested using leave-one-out cross-validation because of the relatively small number of years in the LFM time series. New regression models were calculated with 1 year left out of the regression in turn. The difference between the actual and predicted day of year that LFM dropped below the critical threshold was calculated for each left-out year. The LFM threshold was validated using 'backcasting'. The best-fit predictive model was used to calculate the day of year that LFM dropped below the threshold in previous years, for the 1933–2005 period of the CDF fire history. The dates of past fires were compared with the dates that the threshold was exceeded during the year of each fire. Large fires occurring before the date the threshold was exceeded might indicate that the threshold was invalid.

Results

Comparison of LFM and area burned showed that fires occurred across a wide range of LFM values, from 139 to 59% (Fig. 2). Most of the fires burned during lower LFM conditions, with 48 of the 59 fires occurring below an interpolated LFM value of 95%. A small number of fires accounted for most of the area burned. The seven largest fires, all with areas greater than 1000 ha, represented 90% of the total area burned from 1984 to 2005. Newspaper accounts describe all seven fires as wind-driven events, and specifically mention Santa Ana winds for six of the fires (Anon. 2007). Low LFM combined with high wind speeds allowed these fires to grow to large sizes.

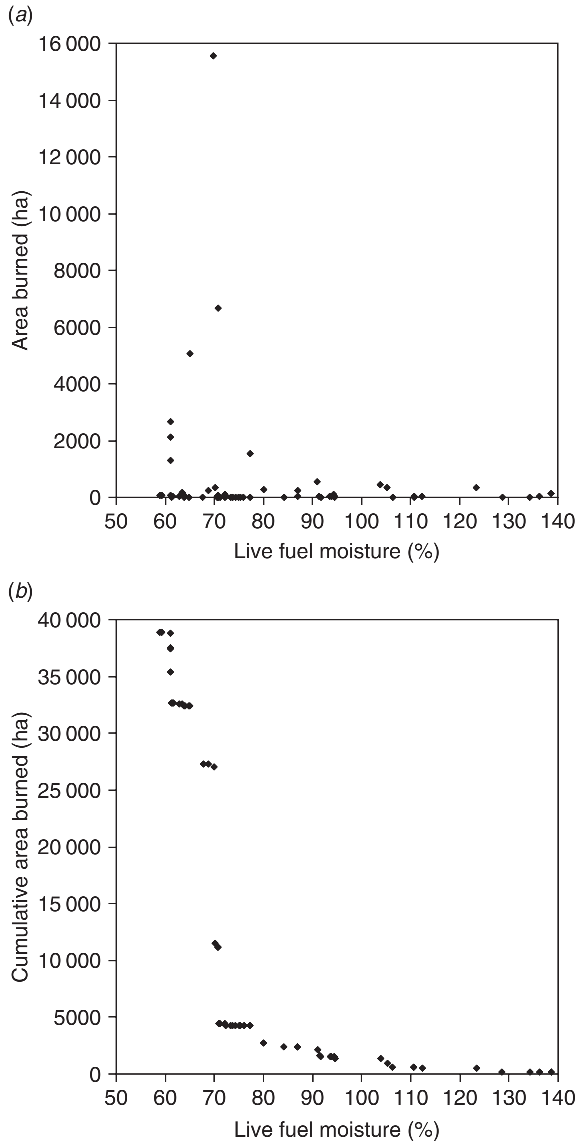

Fig. 2. (*a*) Live fuel moisture (LFM) *v.* area burned and (*b*) cumulative area burned with decreasing LFM for fires in the California Department of Forestry and Fire Protection fire history between 1984 and 2005.

The seven largest fires occurred between a maximum interpolated LFM value of 77% and a minimum interpolated LFM value of 61% (Table 2). With the exception of the 1985 Sherwood Fire, all of the large fires occurred when the interpolated LFM was below 71%. Unlike the other six large fires, the Sherwood Fire was an early-season fire that occurred during a period of rapidly changing LFM. For this reason, the interpolated LFM time series may have overestimated regional LFM during the Sherwood Fire. Regardless, the 77% interpolated LFM value for the Sherwood Fire complicates the selection of a single threshold. Eighty-nine percent of the area burned in the 1984–2005 period was burned at or below a 71% LFM threshold (Fig. 2). Yet the 77% LFM of the Sherwood Fire indicates that large fires may be possible at higher LFM values. Rather than select a single threshold based

Table 2. The seven largest fires in the Santa Monica Mountains between 1984 and 2005
LFM, live fuel moisture

Fire	Date	Area (ha)	LFM (%)
Green Meadows	26 October 1993	15 571	69.8
Topanga	2 November 1993	6664	70.7
Calabasas	21 October 1996	5063	65.0
Decker	14 October 1985	2658	61.1
Piuma	14 October 1985	2104	61.1
Sherwood	30 June 1985	1535	77.2
Pacific	29 October 1989	1287	61.0

Table 3. Linear regression coefficients, r^2 values, and significance for each variable regressed against the day of year live fuel moisture (LFM) dropped below 77%
Refer to Table 1 for definitions of variables

Variable	Slope	Intercept	r^2	*P*-value
MAM Precip. (cm)	3.40	174.15	0.78	<0.001
1 June LFM	1.16	85.68	0.39	0.007
Wet Season Precip. (cm)	0.62	179.67	0.38	0.008
1 June NDVI	258.08	98.36	0.32	0.019
DJF Precip. (cm)	0.59	189.95	0.24	0.049
Maximum NDVI	313.66	22.54	0.23	0.049
Max. NDVI DOY	0.22	192.82	0.06	0.348
Maximum LFM	0.24	173.43	0.03	0.532
Max. LFM DOY	0.04	207.11	0.00	0.867

on such a small number of large fires, we evaluated two potential critical thresholds at 71 and 77% LFM.

77% critical LFM threshold

The interpolated day of year that LFM dropped below the 77% threshold ranged from day 161 (10 June) in 2002 to day 269 (26 September) in 1995 and 1998. This is a range of approximately 3.5 months. Linear regression showed that three variables had significant ($P < 0.01$) correlations with the date of the 77% threshold (Table 3). Correlations were highest for MAM precipitation, with an r^2 of 0.78 and a significance greater than 99.9% (Table 3). Based on the best fit linear relationship between MAM precipitation and the day of year of the 77% threshold, the critical LFM threshold of 77% was passed on day 174 (23 June) during a year with no spring precipitation. For every centimetre of spring precipitation, the threshold was passed 3.4 days later. The 1 June LFM and total wet season precipitation had similar r^2 values of 0.39 and 0.38 respectively, and both correlations were significant at the 99% level. Because wet season precipitation includes MAM precipitation, the two variables are somewhat correlated ($r^2 = 0.34$, $P = 0.11$). Stepwise multiple linear regression found that no secondary variables were significant in addition to MAM precipitation, so multiple linear regression results are not shown.

As none of the NDVI variables were selected by simple or multiple linear regression, the relationship between MAM precipitation and the day of year LFM dropped below 77% was validated using the entire LFM time series, from 1984 to 2005. Leave-one-out cross-validation used 21 of the 22 years to find

Table 4. r^2 values, regression coefficients, and residuals for the leave-one-out cross-validation of March–May precipitation (MAM Precip.) regressed against the day of year live fuel moisture (LFM) dropped below 77%

Left-out year	MAM Precip. (cm)	r^2	Slope	Intercept	Predicted LFM <77% day of year	Actual – predicted (days)
None		0.78	3.68	170.36		
1984	1.88	0.77	3.57	172.14	179	−16
1985	5.41	0.78	3.65	171.09	191	−9
1986	14.30	0.78	3.66	170.30	223	6
1987	3.51	0.78	3.57	172.32	185	−20
1988	8.81	0.80	3.70	169.15	202	22
1989	3.35	0.77	3.69	170.22	183	1
1990	5.00	0.78	3.72	169.51	188	10
1991	16.87	0.78	3.71	170.30	233	−5
1992	18.06	0.77	3.70	170.29	237	−3
1993	7.49	0.82	3.74	168.43	196	30
1994	5.23	0.83	3.82	167.45	187	35
1995	25.07	0.73	3.57	171.04	261	8
1996	8.97	0.78	3.69	169.82	203	10
1997	0.00	0.77	3.73	169.53	170	6
1998	26.97	0.73	3.69	170.27	270	−1
1999	12.42	0.78	3.67	170.21	216	6
2000	12.34	0.81	3.73	170.99	217	−25
2001	9.50	0.79	3.68	171.09	206	−15
2002	1.27	0.77	3.57	172.21	177	−16
2003	17.91	0.79	3.79	170.00	238	−17
2004	2.18	0.77	3.61	171.50	179	−10
2005	11.10	0.78	3.68	170.37	211	0

the best fit linear relationship. The residuals between the best fit lines and the left-out years are shown in Table 4. Adding the 1984–88 LFM data produced steeper slopes and an earlier intercept. Slope and intercept values were stable across all of the left-out years.

The day of year LFM dropped below 77% was predicted within 1 week of the actual date in only 36% of years (Table 4). However, in 64% of years, the predicted threshold date was within 2 weeks of the actual threshold date. The largest residual occurred for 1994, when the actual date of the 77% threshold occurred more than a month after the predicted date. Negative residuals, indicating years in which the threshold was reached earlier than predicted, are potentially more dangerous than positive residuals. The largest negative residual was 25 days in 2000 (Table 4). The coarse resolution of the original LFM time series, uncertainty in the sampling date, and LFM measurement error may have influenced the size of the residuals.

The best fit linear regression equation for all years (1984–2005), shown in the first row of Table 4, was used to calculate the predicted day LFM dropped below 77% from the UCLA MAM precipitation data (1933–2005). Fires that occurred during the months of January, February, and March were excluded from the analysis, because these fires were likely influenced by moisture conditions during both the previous and current wet seasons. Fig. 3 shows the difference between the date each fire was reported and the date during that year that LFM was predicted to drop below 77%. Fires were recorded from 119 days before the threshold was reached to 161 days after the threshold was

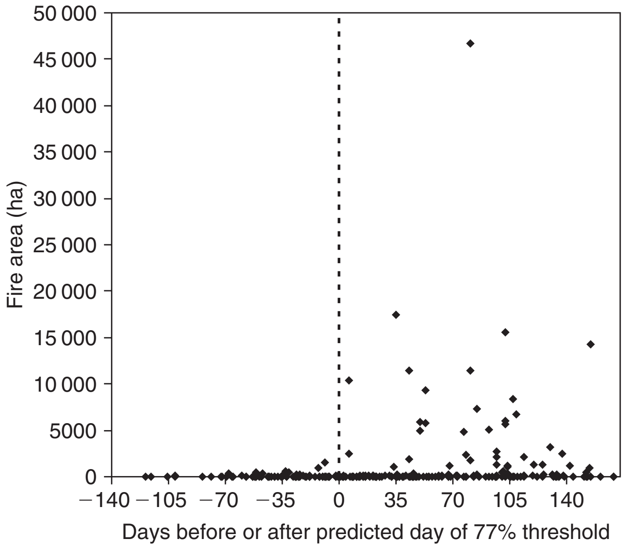

Fig. 3. The difference between the day of year each fire was reported and the day of year live fuel moisture was predicted to pass below 77%, for 256 fires in the Santa Monica Mountains (1933–2005). The dashed line indicates no difference between a fire date and the predicted threshold date.

Table 5. Linear regression coefficients, r^2 values, and significance for each variable regressed against the day of year live fuel moisture dropped below 71%

Refer to Table 1 for definitions of variables

Variable	Slope	Intercept	r^2	*P*-value
MAM Precip. (cm)	3.58	195.43	0.66	<0.001
1 June NDVI	356.13	78.83	0.46	0.003
Wet Season Precip. (cm)	0.77	195.05	0.45	0.003
DJF Precip. (cm)	0.81	205.42	0.34	0.015
Maximum NDVI	375.96	8.36	0.26	0.038
1 June LFM	1.06	119.85	0.25	0.042
Max. NDVI DOY	0.30	210.36	0.08	0.278
Maximum LFM	0.40	170.59	0.06	0.351
Max. LFM DOY	−0.02	235.64	0.00	0.955

reached. Ninety-seven percent of the total area burned between 1933 and 2005 was burned in fires that started after the predicted 77% LFM threshold date. The largest fire that burned before the predicted threshold date was the 1985 Sherwood Fire, which occurred 9 days before the predicted threshold date. Twenty-seven fires larger than the Sherwood Fire all burned on or after the predicted threshold date, including the 10 355 ha 1978 Kanan Fire that burned 6 days after the predicted threshold date.

71% critical LFM threshold

The interpolated day of year that LFM dropped below the 71% threshold ranged from day 173 (22 June) in 2003 to day 308 (4 November) in 1998. This is a range of approximately 4.5 months, and is 27 days longer than the range for the 77% threshold. Three variables were found to be significantly correlated ($P < 0.01$) with the date of the 71% threshold using linear regression (Table 5). Again, correlations were highest for MAM

Table 6. r^2 values, regression coefficients, and residuals for the leave-one-out cross-validation of March–May precipitation (MAM Precip.) regressed against the day of year live fuel moisture (LFM) dropped below 71%

Left-out year	MAM Precip. (cm)	r^2	Slope	Intercept	Predicted LFM <71% day of year	Actual – predicted (days)
None		0.68	3.89	189.48		
1984	1.88	0.67	3.90	189.33	197	1
1985	5.41	0.68	3.81	191.21	212	−21
1986	14.30	0.68	3.89	189.49	245	−1
1987	3.51	0.68	3.70	192.92	206	−35
1988	8.81	0.68	3.89	189.13	223	7
1989	3.35	0.67	3.88	189.65	203	−2
1990	5.00	0.68	3.88	189.57	209	−1
1991	16.87	0.69	4.00	189.25	257	−19
1992	18.06	0.66	3.85	189.61	259	6
1993	7.49	0.82	4.02	185.11	215	67
1994	5.23	0.72	4.02	186.68	208	33
1995	25.07	0.64	3.94	189.17	288	−4
1996	8.97	0.68	3.89	189.22	224	5
1997	0.00	0.68	4.04	187.21	187	18
1998	26.97	0.58	3.61	191.34	289	19
1999	12.42	0.68	3.87	189.32	237	7
2000	12.34	0.68	3.90	189.65	238	−7
2001	9.50	0.69	3.88	190.42	227	−19
2002	1.27	0.66	3.71	192.30	197	−24
2003	17.91	0.69	4.00	189.12	261	−17
2004	2.18	0.67	3.89	189.48	198	0
2005	11.10	0.68	3.90	189.88	233	−11

precipitation, with an r^2 of 0.66 and a significance greater that 99.9%. As expected, the intercept of the best fit line was higher, as the 71% threshold occurs later in the year than the 77% threshold. Based on the best fit linear relationship between MAM precipitation and the day of year of the 71% threshold, the 71% threshold should be passed on day 195 (14 July) during a year with no precipitation. For every centimetre of spring precipitation, the threshold should be passed 3.6 days later. This slope was slightly steeper than the best fit slope for the 77% threshold. Total wet season precipitation ($r^2 = 0.45$) was again found to be significant at the 99% level. The 1 June NDVI was also significantly correlated with date of the 71% threshold ($r^2 = 0.46$, $P = 0.003$). Stepwise multiple linear regression again showed that no secondary variables were significant in addition to MAM precipitation.

Leave-one-out cross-validation for the 71% threshold also used the entire LFM time series from 1984 to 2005 (Table 6). Adding the 1984–88 LFM data again produced steeper slopes and an earlier intercept. Using the 71% threshold increased the number of years in which the predicted threshold date was within a week of the actual threshold date. The predicted threshold date was within 2 days of the actual threshold date for 23% of the years, and within 1 week of the actual threshold date for 50% of the years. Although the residuals decreased in the best years for the 71% threshold, they increased in the worst years (Table 6). Three years had greater than 1 month difference between the predicted and actual threshold dates. The largest residual occurred

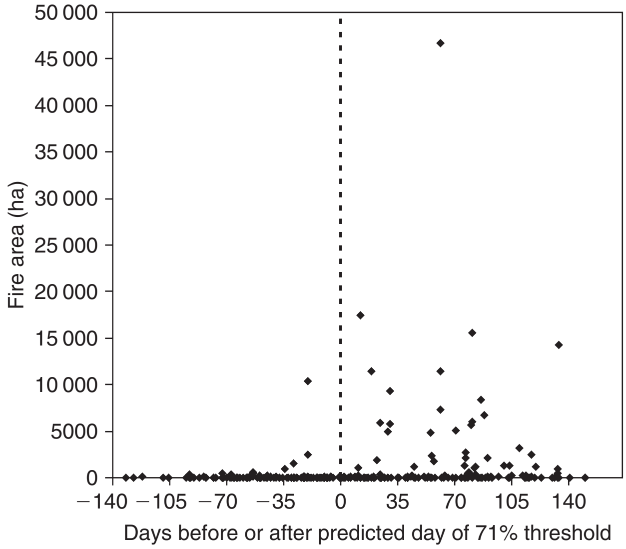

Fig. 4. The difference between the day of year each fire was reported and the day of year live fuel moisture was predicted to pass below 71%, for 256 fires in the Santa Monica Mountains (1933–2005). The dashed line indicates no difference between a fire date and the predicted threshold date.

for 1993, when the actual day of year of the 71% threshold occurred 67 days after the predicted day of year. A large negative residual of 35 days was found for 1987.

The best fit linear regression equation for all years (1984–2005) in the first row of Table 6 was used to calculate the predicted day LFM dropped below 71% for 1933–2005 (Fig. 4). Fires were recorded from 132 days before the threshold was reached to 150 days after the threshold was reached. Three fires larger than 1000 ha burned before the predicted threshold. The 1985 Sherwood Fire burned 29 days before the predicted 71% threshold date. The 1978 Kanan and Mandeville Fires burned 20 days before the predicted threshold date. Despite missing these three large fires, 92% of the total area burned between 1933 and 2005 was burned in fires that started after the predicted 71% threshold date.

Long-term trends in MAM precipitation

Westerling *et al.* (2006) found an earlier start to fire season across the Western United States linked to earlier spring snowmelt, driven largely by trends in temperature. It is unclear whether these findings also apply to fire regimes that typically receive little or no precipitation in the form of snow. Based on our findings, and supported by those of others in the region (Davis and Michaelsen 1995; Schoenberg *et al.* 2003), large wildfires in chaparral ecosystems appear to be dependent on low LFM coinciding with extreme fire weather conditions. In particular, the strong relationship between the timing of 77 and 71% LFM and large fire occurrence indicates that the beginning of fire season may be primarily controlled by the amount of spring precipitation. Spring precipitation thus provides a means for assessing whether the fire season is starting sooner in the Santa Monica Mountains, analogously to the temperature-based approach of Westerling *et al.* (2006) for higher elevation forest sites.

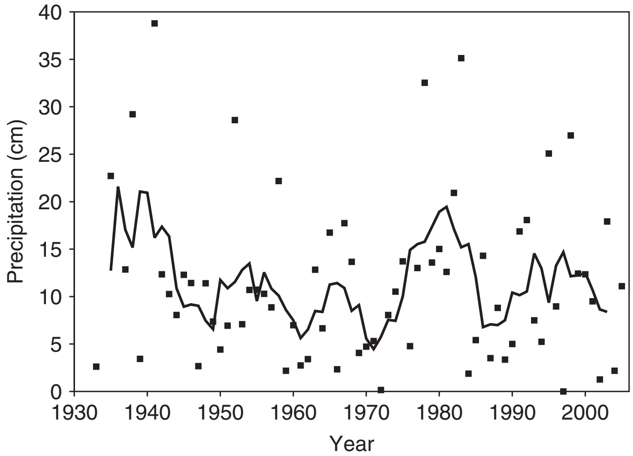

Fig. 5. March–May (MAM) precipitation for 1933–2005 measured at the University of California, Los Angeles meteorological station, and the 5-year running mean of MAM precipitation.

Annual MAM precipitation measured at the UCLA meteorological station between 1933 and 2005 is shown in Fig. 5. These data display high year-to-year variability characteristic of precipitation in southern California. A 5-year running mean of MAM precipitation was calculated to reveal decadal trends in MAM precipitation (Fig. 5). The 5-year running mean shows higher MAM precipitation during the late 1930s, early 1940s, late 1970s, and early 1980s. There are no statistically significant long-term trends in MAM precipitation, although minor long-term trends might be difficult to isolate given the annual- and decadal-scale variability in MAM precipitation. Unlike Westerling *et al.* (2006), no evidence for an earlier start to the fire season is seen in spring precipitation trends for the Santa Monica Mountains.

Previous studies have demonstrated that fire activity may be correlated with climate indices, including the Southern Oscillation Index (SOI), the Pacific Decadal Oscillation Index (PDOI), and the Atlantic Multidecadal Oscillation Index (AMOI) (Keeley 2004; Kitzberger *et al.* 2007). Yearly MAM precipitation was not significantly correlated with SOI, PDOI, or AMOI, but 5-year mean MAM precipitation was weakly correlated with 5-year mean PDOI ($r^2 = 0.35$, $P = 0.012$).

Discussion

Both 77 and 71% thresholds are within the 60–80% high fire danger class described by Weise *et al.* (1998), but below the 90% threshold found by Schoenberg *et al.* (2003). The 71% LFM threshold is similar to the 70% LFM threshold established by Pirsko and Green (1967). The 77% LFM threshold is more conservative than the 71% threshold, and appears to have several advantages over the 71% threshold. The date of the 77% threshold has a stronger correlation with MAM precipitation. The 77% threshold produced smaller negative residuals, and fires larger than 1000 ha occurred almost exclusively after the predicted date of the 77% threshold. Most of the large fires, however, occurred more than 5 weeks after the threshold was reached. This produces an apparent gap between the 77% threshold dates and the actual dates of most large fires. MAM precipitation may have been a poor predictor of the dates of LFM thresholds in 1978, the year of the Kanan and Mandeville Fires. The actual LFM during these fires may have been much closer to 71% than indicated by the relationships between MAM precipitation and the LFM thresholds. Alternatively, the gap may indicate that other conditions necessary for large fires, such as Santa Ana winds, are rarer when LFM is near 77% than when LFM is lower. A more extensive fire history will be needed to absolutely determine whether the actual chamise critical LFM threshold is closer to 77 or 71%. Until this analysis has been done, caution dictates use of the 77% threshold.

Despite the coarse temporal resolution of LFM sampling and uncertainty in the exact sampling date, a strong relationship exists between spring precipitation and the timing of LFM decline. Spring precipitation provides soil moisture during the early part of summer, delaying the onset of LFM decline. In contrast, winter precipitation has a relatively poor correlation with the timing of the 77 and 71% thresholds. Moderate winter precipitation followed by early onset of the summer drought does not appear to delay LFM decline. In one year, 1993, winter precipitation did appear to play a strong role in the large residual found for the 71% threshold model (Table 6). The year 1993 had the highest DJF precipitation (82.6 cm), but a below-average MAM precipitation (7.5 cm). The high winter precipitation provided enough soil moisture to delay the 71% threshold by almost 10 weeks past the predicted threshold date. Besides this one year, there is little apparent relationship between DJF precipitation and residuals from either the 71 or 77% threshold–MAM precipitation regressions, and DJF was not selected as an additional variable for stepwise multiple linear regression for either threshold. Surprisingly, maximum LFM and the day of year of maximum LFM are very poor predictors of when the critical LFM thresholds are surpassed. Higher maximum LFM values and later LFM maximum dates appear to have no influence on when the 77 and 71% thresholds are reached.

Although the LFM thresholds and extreme fire behaviour may be linked, LFM is certainly not the only factor producing large fires. The timing of decreasing LFM is correlated with Santa Ana frequency. Raphael (2003) determined that Santa Ana conditions occur with low frequency in the month of September but increase in frequency of occurrence through the month of December. Six of the seven large fires from 1984 to 2005 occurred in October or November (Table 2), months when Santa Ana wind events are relatively frequent. From 1933 to 2005, 30 out of 35 fires in excess of 1000 ha occurred in October, November or December. Dead fuel moisture, which responds to short-term meteorological conditions and is especially important for determining the success of ignitions, may also play a strong role in determining the occurrence of large fires. Fire suppression is another complicating factor. Suppression success will be enhanced by high live and dead fuel moisture and low wind speeds. Suppression likely amplifies the large increase in fire size that occurs at lower LFM.

Poor correlations between the dates of the LFM thresholds and remotely sensed variables were likely due in part to the type of remote sensing time series used. Previous studies, including Dennison *et al.* (2005), Roberts *et al.* (2006) and Dennison *et al.* (2007) have found NDVI to be inferior to other indices for LFM retrieval in chaparral. Dennison *et al.* (2007) also found that the compositing method used to create the AVHRR NDVI time series reduces index correlations with chaparral LFM. The predictive power of other indices calculated from a newer generation of sensors (e.g. MODIS) may be higher than NDVI as investigated here.

Conclusions

Based on a comparison of 22 years of chamise LFM data sampled at three sites with fire history data and precipitation records, we conclude the following:

(1) A chamise critical LFM threshold appears to exist in the range of 70–80%, although the exact value of this threshold cannot be determined using time series LFM and fire history date from the Santa Monica Mountains. More comprehensive data are needed to determine whether the 77 or 71% threshold is more appropriate and whether LFM directly controls fire size in chaparral.
(2) Spring precipitation is strongly correlated with the timing of chamise LFM decline in the Santa Monica Mountains.
(3) Spring precipitation does not provide evidence that the fire season is starting earlier in the Santa Monica Mountains over the past 70 years.

The present research did not investigate spatial variability of precipitation and spatial variability of LFM. Future research will focus on understanding relationships between spatial variation in precipitation and LFM decline over larger areas. The strength of precipitation correlations with LFM decline may be dependent on local differences in soil water availability and evapotranspiration. Understanding spatial variability caused by these factors may lead to an improved model of critical LFM timing. Further research will also explore correlations between precipitation and LFM thresholds in other important chaparral species, such as big pod ceanothus and sagebrush.

Predictive models of critical LFM threshold timing may allow planning for the potential occurrence of large fires. Predicted critical threshold dates could be used to improve allocation of fire protective resources, including personnel and equipment. Critical threshold dates could also allow wildland–urban interface residents to plan for increased fire and arson vigilance during periods of fire susceptibility.

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