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Critical live fuel moisture in chaparral ecosystems: a threshold for fire activity and its relationship to antecedent precipitation

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Abstract. Large wildfires in southern California typically occur during periods of reduced live fuel moisture (LFM) and high winds. Previous work has found evidence that a LFM threshold may determine when large fires can occur. Using a LFM time series and a fire history for Los Angeles County, California, we found strong evidence for a LFM threshold near 79%. Monthly and 3-month total precipitation data were used to show that the timing of this threshold during the fire season is strongly correlated with antecedent rainfall. Spring precipitation, particularly in the month of March, was found to be the primary driver of the timing of LFM decline, although regression tree analysis revealed that high winter precipitation may delay the timing of the threshold in some years. This work further establishes relationships between precipitation and fire potential that may prove important for anticipating shifts in fire regimes under climate-change scenarios.

Introduction

Research has shown that the timing and amount of precipitation each year can have a strong influence on subsequent fire activity (e.g. Grissino-Mayer and Swetnam 2000; Veblen *et al.* 2000; Westerling *et al.* 2003), usually attributed to the accumulation and drying patterns of herbaceous fine fuels that can propagate fires in forests. In chaparral-dominated ecosystems, such as the widespread shrubland landscapes of southern California, fires are intense, stand-replacing, and relatively unaffected by herbaceous fuel characteristics. As such, research on the fire regime of chaparral shrublands has emphasized the influence of the age and spatial arrangement of shrub stands on the landscape *v.* fire weather patterns (e.g. Minnich 1983; Keeley *et al.* 1999; Moritz 2003). This Mediterranean-climate region is subject to Santa Anas, multiday episodes of hot, dry, and intense winds considered the worst fire weather in the world (Schroeder *et al.* 1969). Owing to the fact that large fires occur predominantly during Santa Ana events – and despite the fact that chaparral-dominated shrublands consist mostly of evergreen species – live fuel moisture (LFM) has received relatively little attention as a control on large fire occurrence. LFM is the water content of living vegetation, calculated as a percentage of dry mass. Previous work has shown that area burned tends to increase as LFM decreases (Davis and Michaelsen 1995; Schoenberg *et al.* 2003), a trend that is observed each year as soil moisture is gradually depleted during the summer–fall drought period. The amount of precipitation in months before the fire season has also been shown to correlate with area burned and LFM drying trends in a particular year (Davis and Michaelsen 1995).

Dennison *et al*. (2008) modeled LFM trends in the Santa Monica Mountains National Recreation Area, near Los Angeles, California. Comparisons of LFM decline and fire history data revealed a potential LFM threshold in the 70–80% range. Seven large fires with areas in excess of 1000 ha only occurred when LFM was below this threshold. Dennison *et al*. (2008) also examined whether the timing of LFM thresholds could be predicted using precipitation, satellite-derived greenness, or LFM variables. Spring precipitation, received in the months of March, April, and May, was most strongly correlated with how early in the fire season the LFM threshold was reached.

Dennison *et al*. (2008) examined a relatively small number of fires over a limited area. As a result, two potential LFM thresholds at 72 and 77% were investigated, but a definitive threshold could not be determined owing to the small sample size. In addition, only three precipitation variables were used to model the timing of the LFM threshold. The present paper improves on the previous effort by using statistical methods designed for detecting a LFM threshold and modeling how this threshold is driven by antecedent precipitation patterns. To determine a more precise LFM threshold, we examined historical trends in LFM over a period of 26 years within Los Angeles County, California. To better evaluate precipitation controls on the LFM threshold, we evaluated a total of 10 monthly and 3-month precipitation variables for their ability to predict the timing of the LFM threshold.

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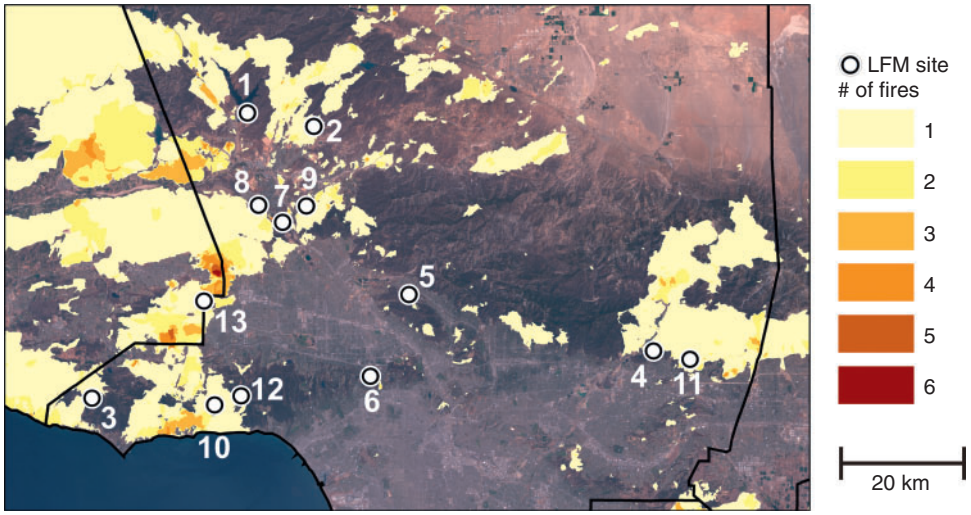

Fig. 1. The Los Angeles County, California, study area showing the locations of the live fuel moisture (LFM) measurement sites and number of fires for 1981–2006. The number closest to each point references the site numbers in Table 1. Fire perimeters were provided by the California Department of Forestry and Fire Protection.

Methods

Live fuel moisture data

Chamise (*Adenostoma fasciculatum*) is one of the most common shrub species found in southern California chaparral communities. Chamise is evergreen, but it is sensitive to seasonal drought. During southern California's long dry season, chamise leaf moisture content drops as soil water availability declines (Dennison and Roberts 2003). Because chamise is an important fuel component frequently found in proximity to residential development in the wildland–urban interface, chamise LFM is commonly used as a general indicator of wildfire danger in southern California. LFM is an also important variable in fire behavior and fire spread models (e.g. Andrews 1986; Finney 1998; Peterson *et al.* 2009), and is a factor in the US National Fire Danger Rating System (NFDRS; Deeming *et al.* 1972; Burgan 1988).

Los Angeles County possesses what is perhaps the longest-running continuous record of LFM in the United States. Since 1981, LFM has been manually sampled at multiple sites once every 2–3 weeks by the Los Angeles County Fire Department (LACFD). This time series has been used in analyses of how various environmental factors relate to area burned (Schoenberg *et al.* 2003) and to measure correlations between LFM and remote-sensing variables (Dennison *et al.* 2005, 2007; Roberts *et al.* 2006; Peterson *et al.* 2008). Chamise LFM measurements made by LACFD from 1981 through 2006 at 13 sites were used for the present analysis (Fig. 1; Table 1). Measurements were made on average every 16 days, although the actual sampling interval varied by site and through time. Sampling methodology used by LACFD is described by Countryman and Dean (1979). The length of time LFM was measured at each site ranged from 3 to 25 years, and 10 sites had records covering 20 years or longer (Table 1).

The accuracy of LFM sample data is an important source of uncertainty in the current study. Weise *et al.* (1998) examined confidence intervals associated with LFM sample data, including chamise sites in Los Angeles County. They found that confidence intervals were generally in the range of ±20%, and at the Bouquet Canyon chamise site, they found confidence intervals ranging from ±5% to as high as ±100%. Another source of uncertainty in analysis of long-term LFM trends is that the exact locations of the sampling sites have changed over time. LFM values from different periods in the time series may be sampled from adjacent, not overlapping, plots. Changes in plot locations may reduce the strength of correlations between the LFM time series and other variables.

A critical LFM threshold for chamise was determined by comparing the LFM time series with fire history data. While the temporal resolution of the time series was sufficient for capturing the slow decline of LFM during fire season (Countryman and Dean 1979), it was insufficient for comparison with individual fire events. To increase the temporal resolution of the LFM time series, the data were linearly interpolated to a daily resolution at each site. This linear interpolation assumed a constant

Table 1. Names and temporal coverage for the 13 live fuel moisture (LFM) sampling sites in Los Angeles County

Site no. (Fig. 1)	Site name	No. of years	Years covered
1	Bitter Canyon	25	1982–2006
2	Bouquet Canyon	24	1982–2001, 2003–06
3	Clark Motorway	24	1983–2006
4	Glendora Ridge	4	2003–06
5	La Tuna Canyon	23	1984–2006
6	Laurel Canyon	24	1981, 1984–2006
7	Peach Motorway	3	2004–06
8	Pico Canyon	20	1982, 1984–97, 1999–2003
9	Placerita Canyon	24	1981, 1984–2006
10	Schueren Road	21	1981–93, 1999–2006
11	Sycamore Canyon	14	1989–2002
12	Trippet Ranch	24	1982, 1984–2006
13	Woolsey Canyon	22	1985–2006

rate of LFM change between sampling dates, and did not provide actual data below the original 2–3 week temporal resolution of the LFM time series.

Critical LFM threshold

The interpolated LFM time series was compared with a fire history compiled by the California Department of Forestry and Fire Protection. This fire history includes fire perimeters, area, and the date of ignition. Fuel types burned in each fire were not examined, although chaparral is the most prevalent fuel type within the county. The distance between the centroid of each fire and the closest LFM measurement site operational during the year of the fire was determined. As the distance between the LFM sites and fire centroids increased, the LFM measurements were less likely to be representative of the LFM conditions in the fire. However, relatively few fires occurred in immediate proximity to the LFM sites (Fig. 1), so increasing the maximum allowed distance between sites and fire centroids also increases the number of fires available for analysis. Rather than arbitrarily select a single maximum allowable distance between fire centroids and LFM sites, four distances were chosen for comparison: 5, 10, 15, and 20 km. Fires with centroids within these maximum distances to the closest LFM site were selected for threshold analysis. A total of 78, 229, 324, and 383 fires were selected within maximum distances of 5, 10, 15, and 20 km respectively.

The interpolated LFM value on the date of ignition from the closest sampling site to each selected fire centroid was assigned to each fire. Potential critical thresholds necessary for large fires to develop were then determined using two different methods. For the first method, 'large' fires were defined as fires with areas in excess of 1000 ha (Dennison *et al.* 2008). The distributions of fire size with LFM were compared, and a threshold was selected based on the large fires with the highest LFM values. For the second method, the cumulative area burned with decreasing LFM was calculated, and piecewise or 'broken stick' regression (Toms and Lesperance 2003) was then used to optimally fit multiple lines at threshold breakpoints in data. Because our data displayed a clear linear fit on either side of a single critical LFM threshold, we used the technique appropriate for a sharp-transition model (Bacon and Watts 1971).

Predictability of the threshold using precipitation data

Once a critical LFM threshold was identified, the timing (day of year (DOY)) of the threshold during seasonal dry-down was calculated for all years for each LFM site. Continuous, directly measured precipitation records within the study area were found to be poorly located relative to the LFM sites, so a gridded precipitation product was used to examine the correlations between seasonal precipitation and the timing of the LFM threshold. Gridded monthly precipitation data with a spatial resolution of 4 km was obtained for 1981–2006 from the Oregon State University PRISM Group (www.prismclimate.org, accessed 22 November 2009). PRISM (the Parameter-elevation Regressions on Independent Slopes Model) interpolates point precipitation measurements using topographic, rain-shadow, and coastal effects (Daly *et al.* 1994). PRISM-estimated precipitation values are averages over 4-km grid cells, and do not account for topographic variation at higher spatial resolution. Monthly precipitation values were extracted from the 4-km cells containing LFM sites. Monthly precipitation values from the December through May wet season before LFM decline were used as stand-alone variables. Monthly precipitation values were also summed in 3-month intervals, including December, January, and February (DJF); January, February, and March (JFM); February, March, and April (FMA); and March, April, and May (MAM).

Regression models were used to test relationships between precipitation variables and annual timing of the LFM threshold. Precipitation variables were regressed against the DOY of the LFM threshold for 11 of the 13 individual sites using simple linear regression. Two sites had too few (3 or 4) years of LFM measurements to produce reliable regressions. All other sites possessed at least 14 years of LFM measurements (Table 1). The DOY of the LFM threshold from a pooled dataset containing all 13 sites and a total of 252 data points was modeled using both simple linear regression and multivariate linear regression. Multivariate regression was used to test whether adding additional precipitation variables could significantly improve prediction of the timing of the LFM threshold. Once a variable was selected by the multivariate regression, related variables were excluded from the model to avoid collinearity. For example, if MAM precipitation was selected as the first variable, variables containing March, April, and May precipitation were prohibited from being selected as a subsequent variable.

Linear regression assumes that model residuals are normally distributed. Precipitation variables are prone to outliers that produce non-normal distributions, which can potentially lead to non-normally distributed residuals in the regression model. Non-normally distributed residuals indicate that outlying data points may be introducing bias into the regression model. We tested the normality of model residuals using the Shapiro–Wilk test (Shapiro and Wilk 1965).

To capture any non-linear threshold responses that may exist between LFM and precipitation, as well as interactions that monthly precipitation variables could have on LFM, we used tree-based statistical models (Breiman *et al.* 1984). We followed a similar logic for variable selection to that described for the multivariate regressions. Analyses were performed with the recursive partitioning library (RPART) (Therneau and Atkinson 1997) in the open-source statistical package R (Ihaka and Gentleman 1996). Tree-based models are created by recursively dividing a dataset, based on the value of a single predictor variable at each split that results in the two most homogeneous subsets of the response variable (Therneau and Atkinson 1997). This statistical approach is well suited to complex biophysical relationships and interactions among variables, and graphical representation of tree-based output facilitates the interpretation of models (De'eath and Fabricius 2000). Very large (i.e. overfitted) trees are usually built by exhaustively partitioning the dataset in question, and then the trees can be pruned back to a smaller size according to several different rules. To prune back our model to an appropriate size, we used a cost-complexity penalty rule and 10-fold cross-validation as described by Breiman *et al*. (1984) and Therneau and Atkinson (1997).

Results

A total of 29 large fires with areas greater than 1000 ha had centroids within 20 km of any of the LFM measurement sites.

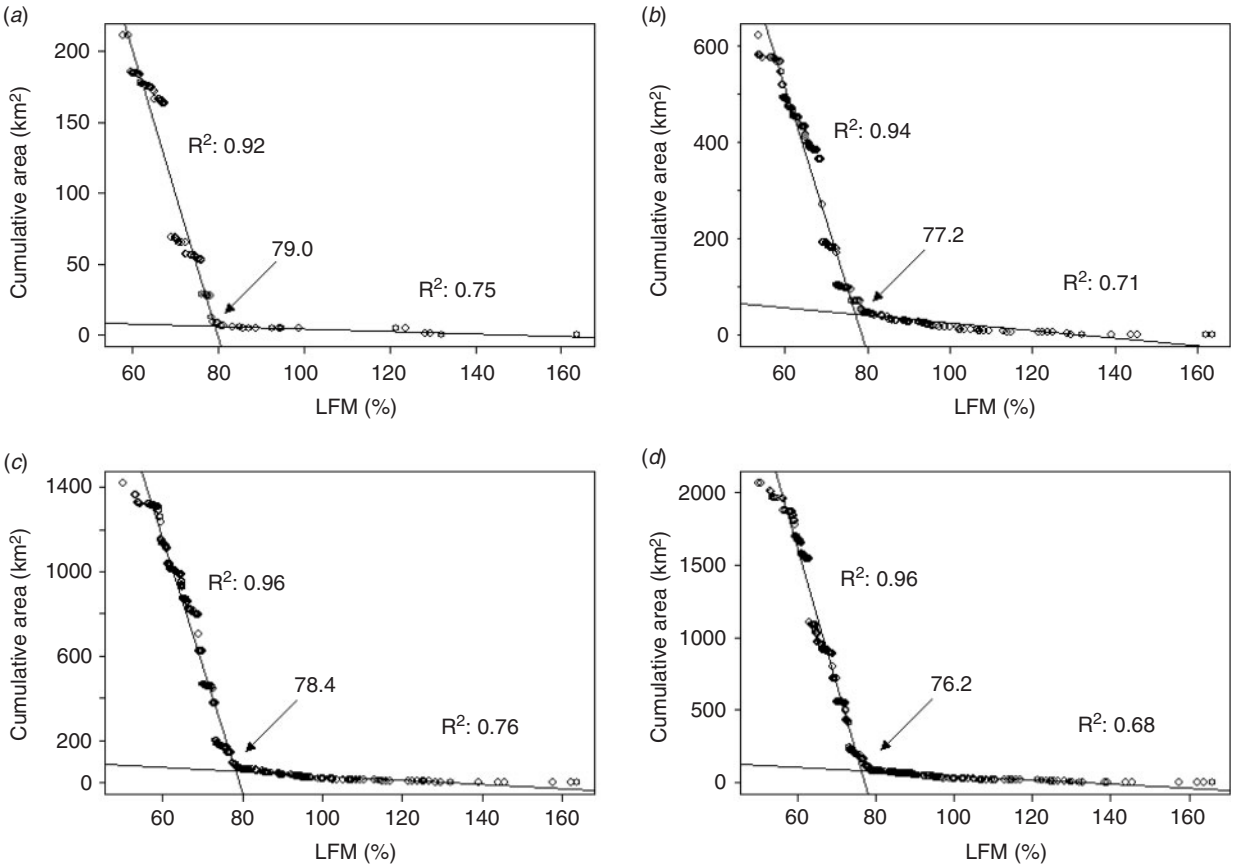

Fig. 2. Piecewise regression results for live fuel moisture (LFM) *v.* cumulative area burned for fires with centroids within 5 km (*a*), 10 km (*b*), 15 km (*c*), and 20 km (*d*) of LFM sites.

Surprisingly, only 14 of these fires occurred in October or November, when fire danger is typically highest in southern California owing to more frequent Santa Ana winds (Schroeder *et al.* 1969; Raphael 2003). Several large fires occurred much earlier in the year, with one large fire in May, two large fires in June, and four large fires in July. Large fires occurred over a wide range of closest interpolated LFM values, with a maximum LFM of 78.5% and a minimum LFM of 53.2%. There were no significant linear correlations between large fire size and either DOY or LFM.

Cumulative distributions for area burned in fires meeting the four distance criteria showed clear relationships between fire activity and LFM, revealing sharp breakpoints (Fig. 2). Large fires were responsible for the rapid increase in cumulative area burned at LFMs below the apparent threshold. At LFMs above the apparent threshold, the slope was much shallower owing to a lack of large fires adding to the cumulative area burned (Fig. 2). The threshold was also relatively consistent across all four distances, spanning an order of magnitude increase in area burned between the 5- and 20-km distances. The piecewise regression results demonstrated that a breakpoint for LFM exists in the relatively narrow 76–79% range. Piecewise linear fits were consistently stronger for LFM values below the breakpoint (multiple $R^2 = 0.92$–0.96) than for above (multiple $R^2 = 0.68$–0.76). Based on the maximum LFM threshold of ~79% found in both analyses, this threshold was chosen for subsequent predictability analysis.

The 79% LFM threshold occurred over a wide range of DOY values in the interpolated LFM time series (Table 2). The earliest threshold DOY was 131 (11 May), which occurred in the Placerita Canyon time series in 1987 and in the Trippet Ranch time series in 2002. The latest threshold DOY was 295 (22 October), which occurred in the Pico Canyon time series in 1995 and the Placerita Canyon times series in 1998. The difference between the minimum and maximum DOY was 164 days, or more than 5 months. The two most interior sites, Bitter Canyon and Bouquet Canyon, had earlier mean and median threshold DOY values. However, Schueren Road, one of the most coastal sites, also had earlier mean and median threshold DOY values.

MAM precipitation was most strongly correlated with the DOY timing of the 79% LFM threshold. Table 3 shows R^2 values for the simple linear regression models. For individual sites, MAM precipitation was significantly correlated ($P < 0.01$) with the timing of the 79% threshold for all sites with more than 4 years of LFM records, with R^2 values ranging between 0.49 and 0.79. All of these relationships were positive, meaning that more spring precipitation resulted in a later DOY for crossing the LFM threshold. Only three out of the total 110 single-site regressions were found to have significantly non-normal residual distributions ($\alpha = 0.05$). The average R^2 for all sites was highest

Table 2. The minimum, maximum, mean, and median day-of-year (DOY) for the 79% threshold in the interpolated live fuel moisture (LFM) time series, for each site

Site name	Years covered	Minimum DOY (Year)	Maximum DOY (Year)	Mean DOY	Median DOY
Bitter Canyon	25	141 (1997)	266 (1998)	193	187
Bouquet Canyon	24	133 (1999)	262 (1998)	190	190
Clark Motorway	24	160 (2002)	268 (1983)	212	214.5
Glendora Ridge	4	196 (2004)	253 (2005)	233	241.5
La Tuna Canyon	23	137 (2002)	256 (1995)	201	200
Laurel Canyon	24	134 (2002)	277 (2000)	208	212
Peach Motorway	3	156 (2004)	218 (2005)	196	214
Pico Canyon	20	134 (2002)	295 (1995)	209	203.5
Placerita Canyon	24	131 (1987)	295 (1998)	210	209.5
Schueren Road	21	157 (1984)	259 (1983)	194	193
Sycamore Canyon	14	141 (1997)	282 (1995)	209	202
Trippet Ranch	24	131 (2002)	274 (1998)	208	202
Woolsey Canyon	22	151 (1987)	259 (1998)	199	195.5

Table 3. R^2 values for linear regressions between monthly and 3-month precipitation variables and the timing of the 79% live fuel moisture (LFM) threshold

R^2 values with an asterisk (*) indicate models that were found to have significantly non-normal residuals. DJF, December, January, and February; JFM, January, February, and March; FMA, February, March, and April; MAM, March, April, and May

Period	Site average R^2	Pooled data R^2
MAM	0.62	0.48
FMA	0.54	0.44*
JFM	0.53	0.44
Mar	0.53	0.42
DJF	0.29	0.24
February	0.24	0.20*
January	0.22	0.19
April	0.14	0.08*
May	0.11	0.09
December	0.02	0.02*

for MAM precipitation, followed by FMA, JFM, and March precipitation (Table 3). All of these variables contain March precipitation, indicating the importance of March precipitation for determining LFM decline.

Pooling the site data resulted in lower R^2 values, likely owing to variability in site response to precipitation and to differences between actual site precipitation and PRISM-modeled precipitation. The pooled R^2 was again highest for MAM precipitation, closely followed by the three other variables containing March precipitation. The best fit multiple variable model for the pooled data used both MAM and DJF precipitation. This model moderately increased the adjusted R^2 value from 0.48 to 0.56. Unlike the single-site regressions, normality of residuals was an issue for the pooled data regressions. The four R^2 values marked with asterisks in Table 3 resulted from models with residuals that were found to be significantly non-normal by the Shapiro–Wilk test.

Consistent with the regression analysis (Table 3), MAM precipitation was the most important variable (i.e. top split) in the regression tree results; we therefore restricted additional precipitation information to that contained in the DJF precipitation variable. Our tree-based analyses produced only slightly stronger models for pooled site data, with the proportion of variation explained being ~0.58 for the appropriately sized tree. The primary advantage of tree-based models, however, is in their flexibility and interpretability. The pruned regression tree for the timing of the 79% critical LFM threshold (Fig. 3*a*) demonstrates the importance of spring precipitation, but also the importance of winter precipitation in certain years. Boxplots showing the range of typical rainfall amounts among stations are also provided (Fig. 3*b*) for context. With a much drier than average spring (i.e. MAM < 7.5 cm precipitation), winter rainfall of that year does not have a significant influence on the DOY threshold timing, which can occur as early as mid-June or early July. On the other extreme, during years with very high spring rainfall (i.e. MAM ≥ 25.4 cm precipitation), the DOY threshold is not crossed until early September and again winter precipitation is not significant. Between these extremes of low and high spring rainfall in a given year, we see that an unusually wet winter (i.e. DJF > 42.3 cm precipitation) can extend the DOY threshold date into mid-August; however, if that winter was not particularly wet, spring precipitation is again the driver of the critical LFM threshold (i.e. DOY from mid-July to early August).

Discussion and conclusions

Based on our findings from multiple decades of LFM, fire history, and climate records for a relatively large chaparral-dominated region, there is compelling evidence for a relatively sharp LFM threshold near 79%, above which large fires did not occur. The date that this critical LFM threshold is crossed is most strongly correlated with the amount of spring precipitation in that year, although there may be more complex interactions with winter rainfall amounts in certain years. Although the R^2 values for single-month precipitation variables never exceeded the R^2 values for MAM precipitation, March precipitation appears to be most important for determining the timing of the LFM threshold.

Interestingly, tree-based models that explicitly incorporated spatial variation in LFM and a variety of local environmental

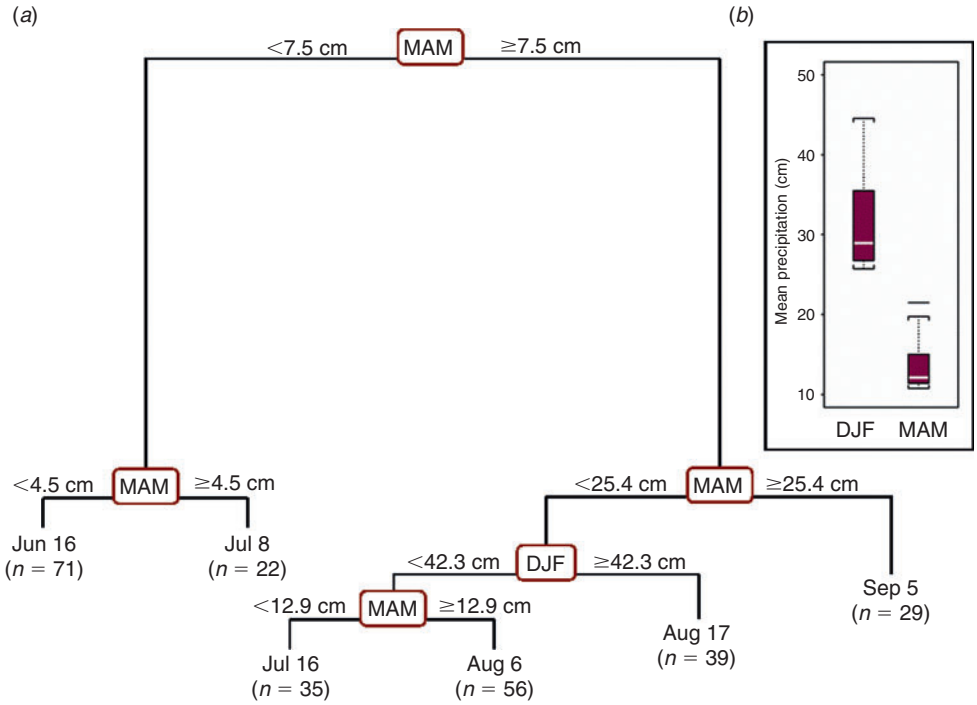

Fig. 3. Regression tree results for the day of year of the 79% live fuel moisture (LFM) threshold modeled using antecedent December–January–February (DJF) and March–April–May (MAM) precipitation (*a*), measured in centimetres. Numbers below each date in the terminal nodes refer to the number of observations (i.e. sampling sites in different years). The height of branches is scaled to the variation explained at each split, demonstrating the overall importance of a dry spring. Boxplots show the distribution of DJF and MAM average site precipitation for the 13 LFM stations (*b*). The median (center lines), quartiles (bounds of boxes), and outlier ranges (outer whiskers show the furthest data point within 1.5 times the interquartile range) are indicated.

factors, such as station-specific precipitation anomalies, topographic aspect, elevation, and distance from coast (data not shown), did not perform markedly better than models using only absolute precipitation amounts in winter and spring. This does not indicate that spatial variation in environmental factors is unimportant to vegetation characteristics at the scale of our study. Instead, it appears that the strong connection between LFM drying patterns and absolute precipitation allows for a relatively clear and parsimonious set of rules for when the critical LFM will be reached.

The uncertainty bracketing the 79% threshold could not be quantified owing to the unknown uncertainty of the original LFM measurements. Although threshold uncertainty was not estimated, the 79% threshold should still be a useful guideline for determining when elevated fire danger may occur. Future work should assess and reduce uncertainty associated with LFM sampling and attempt to provide higher-temporal-resolution estimates of LFM, especially during the transition period from high to low LFM. Results from this paper and from Dennison *et al.* (2008) demonstrate that multiple potential LFM threshold values within this transition zone are likely to be predictable based on antecedent precipitation.

Decreasing LFM coincides with increasing Santa Ana frequency later in the fire season. As both factors are present in most large fires in southern California, it is difficult to distinguish the relative importance of each. However, evidence from the 2007 Zaca Fire near Santa Barbara shows that LFM alone may be a dominant factor in some fires. The Zaca Fire burned throughout most of the fire season and became one of the largest shrubland fires on record in California (~970 km^2), and it was not a typical Santa Ana-driven fire. Instead, record low spring precipitation levels in 2007 and low LFM early in the fire season appear to have been driving factors in this event. At the opposite extreme, large fires may still be possible at higher LFM and very high wind speeds. The recent 2009 Jesusita Fire, also near Santa Barbara, appears to have occurred at a LFM well above 80%. Regardless, it is clear that for most fires in southern California chaparral, precipitation patterns play an important and somewhat underappreciated role in dictating fire activity. Further research is needed on how large fires depend on the combination of low LFM and extreme weather events, and how these factors interact with the age of fuels (Moritz *et al.* 2004).

Understanding climatic influences on fire patterns is crucial, especially in the face of climate change. Westerling *et al.* (2006) found increased fire activity in western US forests and attributed it to warmer spring temperatures and earlier snowmelt. In contrast to this temperature-related signal, large-fire occurrence in chaparral may be more directly dependent on precipitation variability. This dependence may apply to other ecosystems with extended hot and dry fire seasons. The timing and patterns of both temperature and precipitation should be factored into realistic scenarios of future fire activity in a warming world.

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