CSIRO PUBLISHING

International Journal of Wildland Fire **2016**, *25*, 657–668
http://dx.doi.org/10.1071/WF15104

Concurrent and antecedent soil moisture relate positively or negatively to probability of large wildfires depending on season

Erik S. Krueger[A,E], *Tyson E. Ochsner*[A], *J. D. Carlson*[B], *David M. Engle*[C], *Dirac Twidwell*[C,D] *and Samuel D. Fuhlendorf*[C]

[A]Department of Plant and Soil Sciences, 371 Agricultural Hall, Oklahoma State University, Stillwater, OK 74078, USA.
[B]Department of Biosystems and Agricultural Engineering, 111 Agricultural Hall, Oklahoma State University, Stillwater, OK 74078, USA.
[C]Department of Natural Resource Ecology and Management, 011 Agricultural Hall, Oklahoma State University, Stillwater, OK 74078, USA.
[D]Department of Agronomy and Horticulture, 202 Keim Hall, University of Nebraska-Lincoln, Lincoln, NE 68588, USA.
[E]Corresponding author. Email: erik.krueger@okstate.edu

Abstract. Measured soil moisture data may improve wildfire probability assessments because soil moisture is physically linked to fuel production and live fuel moisture, yet models characterising soil moisture–wildfire relationships have not been developed. We therefore described the relationships between measured soil moisture (concurrent and antecedent), as fraction of available water capacity (FAW), and large (≥405 ha) wildfire occurrence during the growing (May–October) and dormant (November–April) seasons from 2000 to 2012 in Oklahoma, USA. Wildfires were predominantly grass and brush fires but occurred across multiple fuel types including forests. Below-average FAW coincided with high wildfire occurrence each season. Wildfire probability during the growing season was 0.18 when concurrent FAW was 0.5 (a threshold for plant water stress) but was 0.60 when concurrent FAW was 0.2 (extreme drought). Dormant season wildfire probability was influenced not only by concurrent but also by antecedent FAW. Dormant season wildfire probability was 0.29 and 0.09 when FAW during the previous growing season was 0.9 (near ideal for plant growth) and 0.2, respectively. Therefore, although a wet growing season coincided with reduced wildfire probability that season, it also coincided with increased wildfire probability the following dormant season, suggesting that the mechanisms by which soil moisture influences wildfire probability are seasonally dependent.

Manuscript received 28 May 2015, accepted 3 February 2016, published online 27 April 2016

Introduction

The ongoing proliferation of large-scale soil moisture monitoring networks (e.g. Oklahoma Mesonet, McPherson *et al.* 2007) and the advent of dedicated soil moisture satellites (e.g. SMAP, Entekhabi *et al.* 2010) have created the opportunity to develop innovative wildfire danger assessments that incorporate soil moisture data. Improved assessments have the potential to increase wildfire preparedness and reduce the negative effects that wildfires have on humans. Wildfire suppression costs in the US have approached US$2 billion annually (NIFC 2013), and in 2012, losses due to wildfires reached US$1 billion (Sutley 2014). Furthermore, recent changes in climate have resulted in increased wildfire danger in North America (Jolly *et al.* 2015), and the eight years in which wildfires were most widespread in the US all occurred since 2000 (NIFC 2013). These recent increases in wildfire danger highlight the need to refine current wildfire danger assessments.

Wildfire danger rating systems such as OK–FIRE in Oklahoma in the US (Carlson 2010; JFSP 2011) and the US National Fire Danger Rating System (NFDRS) (Bradshaw *et al.* 1983) rely on a variety of environmental variables including air temperature, relative humidity, wind speed, and precipitation to assess fire danger. These variables have been used to estimate live fuel moisture (LFM), a key influence on fire behaviour (Yebra *et al.* 2013). In the 1978 NFDRS, for example, herbaceous and woody LFM estimates are used directly in model calculations, and they also are involved in the transfer of fuel between live and dead categories (Bradshaw *et al.* 1983). Typically, LFM is estimated using weather data (Bradshaw *et al.* 1983; Forestry Canada Fire Danger Group 1992; Viegas *et al.* 2001; Castro *et al.* 2003; Dennison *et al.* 2008; Matthews 2014), using weather-derived soil moisture metrics (Dimitrakopoulos and Bemmerzouk 2003; Pellizzaro *et al.* 2007; Yebra *et al.* 2013) or satellite remote sensing techniques (Chuvieco *et al.* 2002; Caccamo *et al.* 2012;

Jurdao *et al.* 2012). In the absence of measured LFM, these indirect estimates have been critical for assessing wildfire danger in operational fire danger rating systems.

However, wildfire danger assessments informed by measured soil moisture may be an improvement over existing techniques because soil moisture directly influences the amount and rate of water that can be supplied to growing vegetation. Plant–water interactions are driven by the water potential gradient between plants and soil, and when water demand by the plant exceeds the rate at which water can be supplied by the soil, water potential within the plant (and by extension LFM) decreases (Hillel 1998). Pellizzaro *et al.* (2007) provided evidence for the potential benefits of using measured soil moisture in wildfire danger assessments when they reported that it was more highly correlated with LFM than weather variables or drought indices in shallow-rooted perennial shrubs. Similarly, Qi *et al.* (2012) found that *in situ* soil moisture measurements were more strongly correlated with LFM in shrubs and deciduous trees than were several remote sensing proxies that they investigated.

With continued advances in soil moisture monitoring, soil moisture data are becoming widely available (Ochsner *et al.* 2013), but the link between measured soil moisture and wildfire occurrence has only recently been studied. Our preliminary work found that soil moisture expressed as fraction of available water capacity (FAW) was among the strongest environmental drivers of growing-season wildfire size in Oklahoma (Krueger *et al.* 2015), a region where grass and brush fires account for the majority of wildfires. Values of FAW typically range between 0 (no soil moisture available to plants) and 1 (maximum available soil moisture). Values of FAW less than ~0.5 indicate conditions of plant water stress (Allen *et al.* 1998), and values less than 0.2 indicate extreme drought (Sridhar *et al.* 2008). Krueger *et al.* (2015) found that 91% of growing-season fires $\geq$121 ha occurred at FAW $<$0.5 and 77% occurred at FAW $<$0.2, a clear indication of the effect of soil moisture on wildfire occurrence in the growing season. Measured soil moisture is often expressed as an index such as FAW because soil moisture *per se* does not account for the control that soil physical properties have on moisture available to plants, or plant available water (PAW). Maximum PAW varies greatly across soils depending on their physical properties. This maximum is referred to as available water capacity (AWC), and FAW is the ratio of PAW to AWC. By normalising soil moisture as FAW, comparisons across sites of varying soil properties can be made.

Both concurrent and antecedent soil moisture are likely to affect wildfire occurrence and extent but, in previous studies, soil moisture has necessarily been estimated from weather-derived soil moisture surrogates such as the Palmer Drought Severity Index (PDSI), accumulated precipitation, and Z-index (Westerling *et al.* 2003; Crimmins and Comrie 2004; Collins *et al.* 2006; Mondal and Sukumar 2014). In the North American Great Plains, for example, accumulated rainfall and PDSI were negatively related to wildfire area during the year of fire, whereas lags of up to 2 years generally had positive relationships with wildfire area (Littell *et al.* 2009). Likewise, large grass fires in the western US occurred more regularly when soil moisture estimated using the Z-index was near normal or wetter the previous year (Knapp 1998). These results highlight the effect that soil moisture can have on wildfire extent and suggest a mechanism behind the effect. In the short term, low soil moisture reduces LFM of existing fuels, potentially resulting in the curing of herbaceous and deciduous woody fuels if drought conditions are severe. The long-term mechanism includes increased fuel production during times of high soil moisture followed by decreased fuel moisture induced by low soil moisture or phenological processes.

The research focus on the relationships between surrogates of soil moisture and wildfire occurrence has been necessary because measured soil moisture data were lacking on operational scales of time and space. Now, such data are increasingly common and underutilised. We aimed to identify the effect of concurrent and antecedent FAW on the occurrence of large wildfires in Oklahoma and to develop statistical models describing these relationships. We hypothesise that the effect of FAW differs by season, with FAW being more important in temperate climates during the growing season than during the dormant season when most plants have senesced or are dormant. Our objectives were (1) to assess the monthly and seasonal trends in FAW and wildfire occurrence, (2) to develop regression models that describe the relationship of FAW and important weather variables with daily wildfire occurrence for two seasons of contrasting fuel conditions, and (3) to investigate the temporal autocorrelation, or persistence, of important wildfire predictors. We used logistic regression to produce daily wildfire probability models based on FAW and weather variables at lags of up to 2 years for large ($\geq$405 ha) wildfires during the growing season and during the dormant season in Oklahoma. We used autocorrelation analysis of daily time series FAW and weather data to investigate their persistence during each season.

Materials and methods

Study area

Oklahoma was chosen for this study because of the availability of soil moisture and weather data, which are intensely monitored throughout the state. Soil moisture and weather data are recorded by the Oklahoma Mesonet, a state-wide meteorological monitoring network with a data record spanning over 20 years (McPherson *et al.* 2007). Beginning in 1999, soil moisture was recorded at 101 sites across the state (McPherson *et al.* 2007), a number that increased to ~110 sites by 2012 (Ochsner *et al.* 2013). Soil moisture measurements cover 184 900 km^2, making the Oklahoma Mesonet one of the largest and most densely monitored soil moisture networks in the world (Ochsner *et al.* 2013).

The climate of Oklahoma is primarily temperate with state-wide average monthly air temperatures ranging from 3°C in January to 27°C in July. More precipitation occurs during the growing season from May to October (573 mm) than during the dormant season from November to April (369 mm) (SCIPP 2014). Mean annual temperature and precipitation also vary geographically, with both increasing from the north-west to the south-east. Precipitation ranges from 432 mm in the arid north-west to 1422 mm in the humid south-east, and average annual temperature ranges from 13°C to 17°C from north-west to south-east (OCS 2014). Annual precipitation can vary greatly, and drought lasting from months to years is a recurring characteristic of Oklahoma's climate (Stockton and Meko 1983). Approximately 72% of Oklahoma's vegetated land cover is made up of

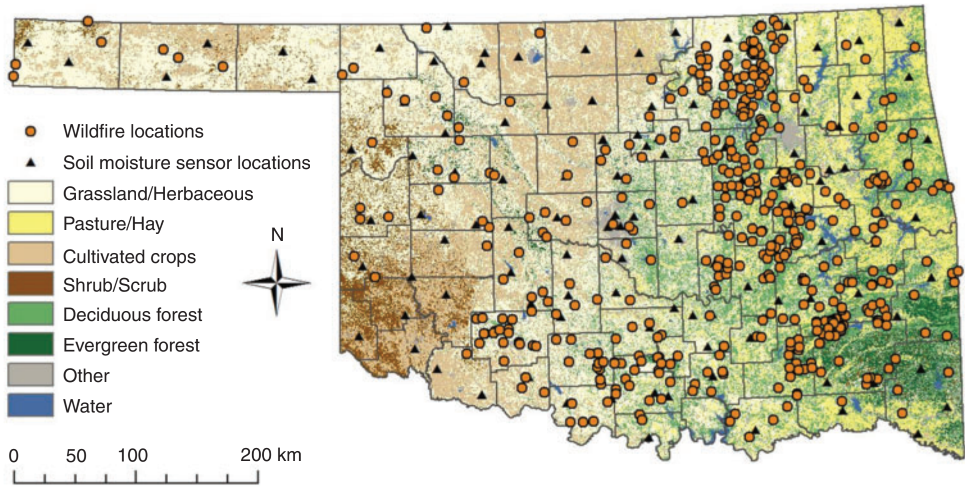

Fig. 1. Oklahoma land cover (Homer *et al.* 2015), locations of Oklahoma Mesonet soil moisture sensors used for the calculation of fraction of available water capacity (FAW), and locations of 501 wildfires ≥405 ha from 2000 to 2012. (For colour figure, see online version available at http://www.publish.csiro.au/nid/17.htm.)

herbaceous plants, which includes grassland (40% of vegetated area), cultivated crops (20%), and pasture/hay (12%), with 23% of the vegetated area forest and 5% shrub/scrub (Fig. 1) **(**Homer *et al.* 2015)**.**

Wildfires

We studied 501 Oklahoma wildfires ≥405 ha that occurred from 2000 to 2012 (Fig. 1). Wildfire data, excluding prescribed fires, were compiled primarily from two sources. Our principal source was the Fire Program Analysis Fire Occurrence Database (FPA FOD) compiled by the USDA Forest Service and consists of both federally and state reported fires (Short 2014*b*). This database is unique in that it contains standardised data that have been compiled from disparate databases, and the data are readily accessible online. Of the 501 fires in our study, 389 came from the FPA FOD. The FPA FOD data include date of fire ignition, final area burned, and origin (latitude and longitude).

Our second source of data was the Oklahoma State Fire Marshal's office, which maintains an annual record of reported wildfires in Oklahoma. This database contained 251 wildfires ≥405 ha from 2000 to 2012. With the assistance of the USDA Forest Service (K.C. Short, pers. comm., March 2014), these fires and several from other available sources were examined, and those deemed valid yet not in the FPA FOD (112 fires) were added to our final database. Of the additional fires, 109 were from the Fire Marshal database, with the remaining three from the Stillwater, Oklahoma Fire Department and Oklahoma Forestry Services. It is likely that these 112 fires were excluded from the FPA FOD because they were not recorded in the databases used to compile it, or they were intentionally excluded from the FPA FOD because they were missing one or more of the required core data elements (Short 2014*a*). The data obtained from the Oklahoma Fire Marshal did not contain specific location descriptions, but the name of the responding fire department was recorded for each fire. We assigned approximate latitude and longitude to each of the 112 additional fires according to the US Postal Service ZIP code of the responding fire department (Fig. 1).

Because the soil moisture and weather conditions that promote wildfire occurrence are not the same throughout the year (Krueger *et al.* 2015), growing season and dormant season fires were analysed separately. The dormant season was defined as the months of November through April, which corresponds approximately with the period after vegetation has senesced and before completion of spring regrowth (Senay and Elliott 2000). The growing season was defined as the months of May through October.

Vegetation descriptions were not included for fires in the FPA FOD, so it was impossible to develop separate analyses by vegetation type (i.e. fuel type). However, descriptions of vegetation type were available for some of the wildfires (2008–2012) in the Fire Marshal dataset. Of the 165 fires ≥405 ha from 2008 to 2012, 39% were classified as 'brush or brush/grass fire', 30% as 'grass fire', and 20% as 'forest, woods, or wildland fire', with the remaining fires classified as 'natural vegetation fire, other' (5%), 'fire, other' (5%), and 'cultivated vegetation, crop fire, other' (1%). Based on the vegetation types for these fires and visual assessment of distribution of wildfires across vegetation types in Oklahoma (Fig. 1), it is likely that the results of our analyses are primarily applicable to brush and grass fires, but forest fires were also part of our dataset. Furthermore, the spatial variability of vegetation in Oklahoma (Fig. 1) suggests that large fires typically burn across multiple fuel types and cannot be neatly categorised by a single vegetation type.

Soil moisture

Soil moisture from 1997 to 2012 was calculated based on the output of heat dissipation sensors (Model 229, Campbell Scientific Inc., Logan, Utah) installed at depths of 5 and 25 cm beneath warm season grasses at weather stations maintained by the Oklahoma Mesonet (McPherson *et al.* 2007) (Fig. 1). Raw data (temperature difference after application of a brief heat pulse) were recorded every 30 min, normalised, and used to compute daily average reference temperature difference, which was then converted to soil matric potential using a calibration function (Illston *et al.* 2008). Reliable data were not available when soil was frozen (Illston *et al.* 2008); however, frozen soil conditions occur only infrequently in Oklahoma, the depth of freezing is limited, and the duration of freezing is brief (OCS 2014). Soil volumetric water content (θ) was calculated from soil matric potential using a database of soil water retention properties for the Mesonet stations (Scott *et al.* 2013).

At a given volumetric water content, soils vary in the amount of water available to growing plants. Therefore, soil moisture alone does not provide a complete description of soil water status. Instead, soil moisture conditions are better described by plant available water (PAW):

$$\mathrm{PAW} = (\theta - \theta_{WP})d \tag{1}$$

where θ is measured volumetric water content, θ_{WP} is the volumetric water content at the permanent wilting point, and d is the thickness (mm) of the layer represented by the measurement. To normalise PAW across sites, the ratio of PAW to maximum possible PAW, or available water capacity (AWC), was calculated to get FAW:

$$\mathrm{FAW} = (\theta - \theta_{WP})/(\theta_{FC} - \theta_{WP}) \tag{2}$$

where θ_{FC} is volumetric water content at field capacity. In this study, FAW was calculated for the 0–10-cm layer using the data from the soil moisture sensor at 5 cm and for the 10–40-cm layer using the data from the soil moisture sensor at 25 cm. Then the depth-weighted average FAW for the 0–40-cm layer was calculated using FAW from 0–10 cm and 10–40-cm layers weighted 0.25 and 0.75, respectively. Daily state-wide average FAW was calculated using data from each Mesonet site. Although this averaging obscures any spatial information in the dataset, it was necessary because our analysis was designed to model the daily probability of a large wildfire occurring somewhere in the state. The average daily standard deviation for FAW measurements across the state was 0.24 and 0.19 during the growing and dormant seasons, respectively.

We chose the 0–40-cm depth because only 76 Oklahoma Mesonet sites record soil moisture at deeper depths (McPherson *et al.* 2007). Soil moisture in the 0–40-cm layer is well suited for our analysis because most root biomass in grasslands, shrub lands and forests – the primary vegetation types in our study – is within 30 cm of the soil surface (Jackson *et al.* 1996). However, we recognise that most vegetation types have rooting depths that extend below 40 cm. Therefore, to identify differences in near surface and subsurface soil moisture, we calculated FAW from 0 to 80 cm for sites with available data. We found that state-wide average FAW in the 0–40-cm layer was significantly correlated with FAW in the 0–80-cm layer (Pearson correlation coefficient, $r = 0.97$, $P < 0.001$), which suggests that FAW in the 0–40-cm layer is indicative of soil moisture conditions deeper in the soil profile.

Permanent wilting point, the water content at which plants cannot remove additional water from the soil profile, was defined as the volumetric water content corresponding to a matric potential of −1500 kPa (Scott *et al.* 2013). Based on visual inspection of matric potential data, field capacity, the water content at which drainage of water from the soil becomes negligible, was defined as the water content corresponding to a matric potential of −10 kPa. Mesonet sites vary greatly in AWC (i.e. $(\theta_{FC} - \theta_{WP})d$), with values for the top 400 mm of the soil profile ranging from 20 mm for a sandy loam to 113 mm for a silt loam.

Long-term (1997–2012) average monthly FAW was calculated from daily state-wide average values and compared with the total number of wildfires for each month. Seasonal FAW anomaly was calculated from daily state-wide average values for each growing season and dormant season and compared with the number of wildfires for each season from 2000 to 2012. To calculate FAW anomaly, state-wide average FAW was first calculated for each day of the year from 1 to 365, and this average was smoothed using the central moving average method with a window of 19 days (Dente *et al.* 2013). The smoothed average was then subtracted from state-wide daily average FAW for each day from 2000 to 2012 to obtain daily FAW anomaly. Finally, seasonal FAW anomaly was calculated from daily FAW anomaly.

Weather

Daily weather data were obtained for each Oklahoma Mesonet station from 1995 to 2012. Weather data included maximum air temperature, minimum relative humidity, maximum wind speed (measured at 10-m height) and precipitation. At each Mesonet site, air temperature, relative humidity, and wind speed were measured continuously, and 5-min averages were recorded. In our analysis, maximum air temperature, minimum relative humidity, and maximum wind speed were respective maximum and minimum 5-min averages for each day. Precipitation was the daily total. These variables were chosen because they have previously been shown to be related to the occurrence of large wildfires in Oklahoma (Reid *et al.* 2010; Krueger *et al.* 2015). Daily state-wide averages for each variable were calculated from data from each Mesonet site.

Logistic regression model

The relationship between wildfire occurrence probability (hereafter referred to simply as probability) and environmental variables (FAW and weather) was examined using stepwise multiple logistic regression. Our use of the term ‘occurrence’ encompasses both the wildfire behaviour (i.e. spread and energy release components) and occurrence (i.e. ignition component) portions of the NFDRS because ‘occurrence’ in our study requires both that a fire occur and that it be large. Logistic regression is a commonly used technique in wildfire research (Preisler *et al.* 2004; Mermoz *et al.* 2005; Catry *et al.* 2009; Martínez *et al.* 2009; Magnussen and Taylor 2012; Mondal and Sukumar 2014) and is appropriate for studies with a dichotomous response variable and continuous predictor variables, such as the presence or absence of a wildfire related to environmental conditions. In the case of multiple regression, the logistic equation has the form:

$$P_w = \frac{e^{\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_{k-1}x_{k-1}+\beta_kx_k}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_{k-1}x_{k-1}+\beta_kx_k}} \tag{3}$$

where P_w is the probability of an outcome (wildfire occurrence) and ranges from 0 to 1, β is the modelled regression coefficient of each independent variable, x, and k is the number of independent variables.

The logistic regression model was designed to represent the probability of a large wildfire occurring in Oklahoma for each day from 2000 to 2012. Our spatial scale was chosen to avoid zero inflation caused by an increased number of days without fires at smaller spatial scales (Magnussen and Taylor 2012). The analysis was subdivided by season, with 2392 and 2357 days during the growing and dormant seasons, respectively. Candidate input variables were chosen based on earlier research. Large wildfires in Oklahoma tend to occur under conditions of low FAW, high maximum air temperature, low minimum relative humidity, high maximum wind speed, and low precipitation (Reid *et al.* 2010; Krueger *et al.* 2015). Values of these variables for each day as well as their values at lags of 7, 14, 21, 30, 60, 90, 180, 270, 365, 455, 545, 635, and 730 days (before the present day) were entered into the regression, resulting in 70 possible predictors. Lags were chosen to examine the influence of antecedent environmental conditions at short term, seasonal and annual time scales.

Variables retained in the final model were selected using the stepwise approach outlined by Shtatland *et al.* (2001) using the LOGISTIC procedure of SAS software ver. 9.2 of the SAS System for windows (SAS Institute Inc., Cary, NC). In this method, the significance levels for a variable to be entered and retained in the initial model were each set to $P = 1.0$. At each step, the variable with the greatest value of the Score χ^2-statistic was added to the initial model, and the process was repeated until all 70 possible predictors had been entered and retained. The Schwarz Criterion (SC) was determined at each step, and the variables for the final models were identified by those in the model at the step at which the SC was minimised. An advantage of using SC for variable selection instead of the commonly used Akaike Information Criteria (AIC) is that SC results in a model with simpler explanatory equations because the SC is more restrictive than AIC. The SC is also preferable when the model is intended for description and interpretation rather than prediction (Shtatland *et al.* 2001), as was the case with our study. In our analysis, final models had corresponding entry significance levels of $P < 0.001$ and $P < 0.007$ for the growing and dormant seasons, respectively.

We tested for collinearity among independent variables in the final model using the variance inflation factor (VIF). The VIF was determined by conducting a multiple linear regression of each independent variable against all other independent variables and was calculated as:

$$\mathrm{VIF} = \frac{1}{1 - R^2} \tag{4}$$

where R^2 is the coefficient of determination of the regression (O'brien 2007). A VIF of 1 represents no collinearity, values >5 indicate collinearity may be present, and values >10 are strong evidence of the presence of collinearity (Menard 2001). In our study, the variables in the final growing and dormant season models had VIF values <1.5 and <3, respectively, and we therefore concluded that collinearity was not a problem.

When reporting results of logistic regression, the information included must be sufficient to (1) evaluate the overall model, (2) assess model goodness of fit, (3) determine the significance of individual predictors, and (4) validate predicted probabilities (Peng *et al.* 2002). Model performance and goodness of fit were assessed using the likelihood ratio χ^2 statistic and the McFadden pseudo-R^2, respectively (Menard 2001). Although pseudo-R^2 is analogous to R^2 in linear regression, its values tend to be lower than those in linear regression, with pseudo-R^2 values in the range of 0.2–0.4 indicating excellent fit (McFadden 1979). The significance of individual predictors was assessed using the Wald χ^2 statistic (Menard 2001).

Validation of the model's predicted probabilities was done using the 2×2 classification table and the c-statistic (Swets 1988; Peng *et al.* 2002). With these techniques, the wildfire probabilities generated by the logistic regression models (P_w) were converted to dichotomous values representing the presence or absence of wildfire for each day. The first step in the dichotomisation was to determine the cut-off value of P_w that would indicate that a wildfire occurred. When there is an equal probability of each outcome, the cut-off value is 0.5, but this was not the case with our study because the number of days without fires greatly outnumbered days with fires. The cut-off values were instead calculated for each season as the fraction of days with fires from the total number of days within each season (Cramer 1999). The calculated cut-off values were 0.034 and 0.088 for the growing season and dormant season, respectively. Therefore, when the modelled probability was dichotomised for growing-season fire days, for example, $P_w \geq 0.034$ indicated that a fire occurred. The 2×2 classification table is an account of the number of days with and without fires that were correctly and incorrectly classified after dichotomisation. The c-statistic was also reported because it describes the model predictive performance in a single value ranging from 0.5 (prediction accuracy equal to that of random category assignment) to 1 (perfect category prediction). Accurate models generally have c-statistic values greater than 0.7 and highly accurate models have values greater than 0.9 (Swets 1988).

Sensitivity of wildfire probability to fraction of available water capacity

For illustrative purposes, wildfire probability for varying levels of FAW, minimum relative humidity and maximum wind speed was determined for the growing season and dormant season using the final logistic regression model for each season. In this analysis, minimum relative humidity and maximum wind speed were held constant at moderate, high and extreme levels, while FAW was varied across its entire range, and other significant variables were held constant at their median values. Moderate levels of minimum relative humidity and maximum wind speed corresponded to their median daily values for a given season for observations from 2000 to 2012. High levels were intended to represent conditions more favourable to the occurrence of large wildfires than moderate conditions, and were defined as minimum relative humidity equal to its 25th-percentile value and maximum wind speed equal to its 75th-percentile value. During the growing season, minimum relative humidity values corresponding to the 50th and 25th percentiles were 40% and 31%, respectively, while the 50th and 25th percentiles were 39% and 29% in the dormant season. For maximum wind speed, the growing-season 50th and 75th-percentile values were 7.3 and

8.7 m s^{-1}, respectively, with corresponding dormant season 50th and 75th-percentile values of 8.1 and 9.7 m s^{-1}.

Extreme levels of minimum relative humidity and maximum wind speed were chosen to approximate the US National Weather Service (NWS) criteria for red flag warning (i.e. fire weather warning) for central and western Oklahoma, which include relative humidity ≤20% and wind speed (measured at 6-m height) ≥8.9 m s^{-1}. The 6-m NWS wind speed criterion was adjusted to 10 m by multiplying by 1.15 (Turner and Lawson 1978). Extreme levels were thus defined as minimum relative humidity of 20% and maximum wind speed of 10.3 m s^{-1}. During the growing season, extreme minimum relative humidity and maximum wind speed were their 3rd and 93rd-percentiles values, respectively, while during the dormant season, these values were in the 6th and 82nd percentiles.

Autocorrelation analysis

Successive observations of climatological variables (WMO 2011) and soil moisture tend to be similar (De Lannoy *et al.* 2006; Dente *et al.* 2013). Variables that are significant predictors of fire occurrence and that exhibit strong persistence, or autocorrelation, may be particularly useful for assessing wildfire danger because they can be better anticipated. For example, the period over which soil moisture is predictable is closely related to its period of autocorrelation (Schlosser and Milly 2002). Therefore, we calculated autocorrelation functions of FAW and weather variables for each season for lags up to 90 days as:

$$r = \frac{\sum_{t=k+1}^{n}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{n}(y_t - \bar{y})^2} \quad (5)$$

where r is the autocorrelation coefficient at lag k, n is the number of observations, y_t is the data value at time t, and $\bar{y}$ is the average of all observations. The significance of autocorrelation is generally assessed as $\pm 2/\sqrt{n}$, where n is sample size (Dente *et al.* 2013). As the sample size for each season in our study was large, the correlation coefficient corresponding to significant autocorrelation was small (0.04). Although autocorrelation values at this level are unlikely to be of practical importance, values as low as 0.2–0.5 may be useful for anticipating future conditions (Walsh *et al.* 2005). We conducted the VIF and autocorrelation analyses with Matlab R2012a (The MathWorks, Inc., Natick, MA).

Results and discussion

Seasonal characteristics of fraction of available water capacity (FAW) and wildfire occurrence

Measured soil moisture is a strong candidate variable for wildfire probability assessments because it is physically linked to fuel production and LFM and thereby wildfire occurrence. We aimed to assess the monthly and seasonal trends in FAW and wildfire occurrence in Oklahoma and found that during the growing season, the months of greatest wildfire occurrence coincided with the months of lowest average FAW (Fig. 2). Average monthly FAW reached its minimum by mid to late summer (August), and it was recharged throughout the fall and winter before reaching its maximum in February and March. The pattern of wildfire occurrence was bimodal, peaking in March and again in August. Few fires occurred during the growing-season months of May, June and October when average monthly FAW ranged from 0.56 to 0.68; whereas FAW averaged 0.41 from July to September. In contrast, during the dormant season, most wildfires occurred during the months when average FAW was high (Fig. 2), and the dormant season months of greatest wildfire occurrence coincided with high FAW. Furthermore, more fires occurred during the dormant (382) than the growing season (119) even though average monthly FAW was higher during all dormant season months than at any time during the growing season. A cursory inspection of these results could lead to the false conclusion that soil moisture conditions are not an important influence on dormant season wildfire occurrence in Oklahoma.

However, when analysed seasonally from 2000 to 2012, negative FAW anomalies were associated with high wildfire occurrence during both the growing and dormant seasons (Fig. 3). The four growing seasons when FAW anomaly was at its lowest (2000, 2006, 2011, and 2012) corresponded with the four growing seasons of greatest wildfire occurrence. Growing seasons with positive FAW anomalies averaged only 2 wildfires per season, whereas those with negative FAW anomalies averaged 18. An apparent exception to the pattern occurred during the 2000 growing season when FAW anomaly was only slightly negative (−0.05), yet wildfire occurrence was the third highest for any growing season in the study. Upon closer inspection, we discovered that each of the 24 growing-season wildfires in 2000 occurred from August to October when the FAW anomaly averaged −0.20 and 17 occurred during September when the FAW anomaly was −0.32. Thus, the pattern of low FAW associated with large wildfire occurrence was also present in 2000.

Similar to the pattern observed in the growing season, the three dormant seasons when FAW anomaly was at its lowest (2005–2006, 2008–2009, and 2010–2011) corresponded with the three dormant seasons of greatest wildfire occurrence. Notably, the FAW anomaly during the 2005–2006 dormant season was far lower than at any other point in the study, and this

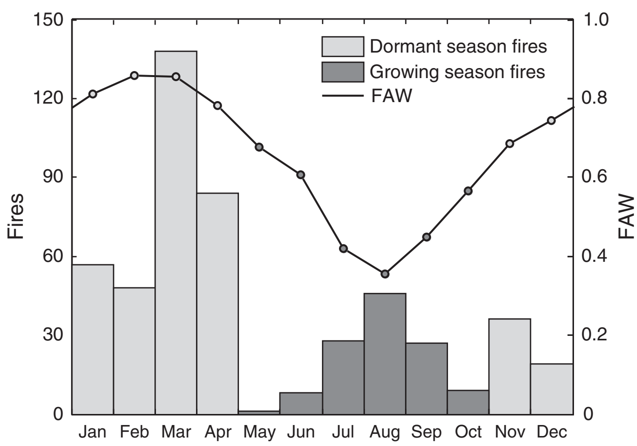

Fig. 2. State-wide average monthly fraction of available water capacity (FAW) and monthly distribution of 501 wildfires ≥405 ha in Oklahoma from 2000 to 2012.

period corresponded with extreme wildfire outbreaks throughout Oklahoma. Unlike the growing season, however, dormant season wildfire occurrence was relatively high in some seasons when the FAW anomaly was positive (2002–2003, 2007–2008 and 2009–2010).

A lag effect of FAW on dormant season wildfire occurrence was apparent, with above-average FAW for a year or more before a given dormant season corresponding with increased wildfire occurrence. Each of the four dormant seasons when wildfire occurrence was greatest (2005–2006, 2007–2008, 2008–2009, and 2010–2011) occurred after a period of near or above-average FAW (Fig. 3). For example, the wildfires during the outbreak of the 2005–2006 dormant season occurred after a 3-year period when FAW was near or above average, and wildfires during the 2008–2009 dormant season occurred after a period of 2 years with above average FAW. A similar trend was not observed for the growing season, with the growing seasons of highest wildfire occurrence occurring after dormant seasons of above- (2012) and below-average (2011) FAW.

This distinction likely arises from key seasonal differences in the underlying mechanisms behind the soil moisture–wildfire occurrence relationship. During the growing season, we found evidence of a direct effect of FAW on growing vegetation. The months of greatest wildfire occurrence (July, August, and September) each had average monthly FAW <0.5 (Fig. 2), a threshold below which moisture stress in plants typically occurs (Allen *et al.* 1998). Under conditions of moisture stress, LFM decreases in grasses (Wittich 2011), annual herbaceous vegetation (Dimitrakopoulos and Bemmerzouk 2003), shallow- and deep-rooted perennial shrubs (Pellizzaro *et al.* 2007), and evergreen trees (Engle *et al.* 1987), thereby increasing the likelihood of wildfire occurrence. During the dormant season, wildfire occurrence was likely influenced by multiple factors in addition to FAW, and the apparent lag effect suggested that fuel accumulation during wetter periods helps drive dormant season wildfires after vegetation has senesced. These trends support previous findings where individual wildfires ≥405 ha occurred exclusively at low FAW during the growing season

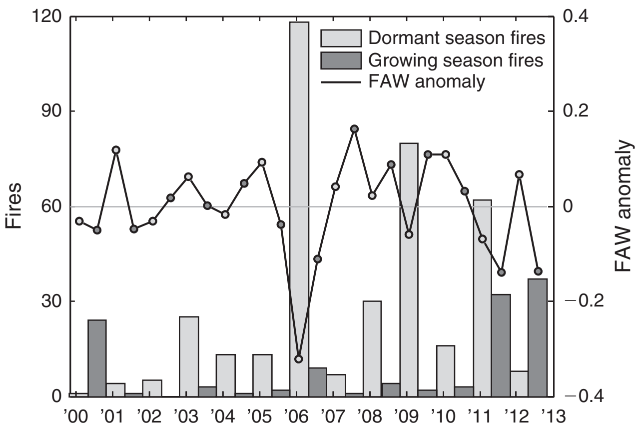

Fig. 3. State-wide average seasonal fraction of available water capacity (FAW) anomaly and growing (May–October) and dormant season (November–April) wildfires ≥405 ha in Oklahoma from 2000 to 2012. Year labels are positioned at the first day of each year (1 January).

and at all levels of FAW during the dormant season (Krueger *et al.* 2015).

Fraction of available water capacity (FAW) and wildfire probability

To further investigate the relationships between FAW and wildfires, we developed seasonal models to describe the relationships between environmental conditions and wildfire probability. Logistic regression models incorporating FAW and weather variables were significantly related to wildfire probability during both growing and dormant seasons. Concurrent FAW was significant during both growing and dormant seasons, with lagged FAW also being significantly related to dormant season wildfire probability.

Growing season

During the growing season, wildfire probability was negatively related to FAW and minimum relative humidity, and positively related to maximum wind speed (Table 1). The final logistic regression model was highly significant (likelihood ratio $\chi^2 = 261$, $P < 0.0001$), and the high McFadden R^2 of 0.37 indicated excellent fit. Remarkably, of the 70 possible predictor variables, only three were retained in the final model. Temperature and precipitation were not retained, and all lagged variables were insignificant. The model had a *c*-value of 0.92, indicating a high degree of accuracy (Swets 1988), with 89% of days with fires and 83% of days without fires being correctly classified (Table 2).

Under conditions of extreme relative humidity and wind, wildfire probability increased more than three-fold, from 0.18 to 0.60, as FAW decreased from 0.5 to 0.2 (Fig. 4). Extreme conditions approximated the criteria for fire weather warnings

Table 1. Growing-season logistic regression model for 119 wildfires ≥405 ha in Oklahoma 2000–2012

The likelihood ratio χ^2-statistic for the final model was 260.8 ($df = 3$, $P < 0.001$). The McFadden R^2 was 0.37, with values in the range of 0.2–0.4 indicating excellent fit (McFadden 1979)

Variable	*df*	Coefficient	Standard error	Wald χ^2	*P* value
FAW	1	−6.42	1.038	38.2	<0.0001
Maximum wind speed	1	0.25	0.036	47.6	<0.0001
Minimum relative humidity	1	−0.13	0.019	46.0	<0.0001
Intercept	1	−1.41	0.652	4.6	0.0312

Table 2. Observed and predicted frequency for days with and without fire for 2392 growing-season days in Oklahoma 2000–2012

The cut-off value was 0.034. The *c*-value for the model was 0.92, with highly accurate models generally having values >0.9 (Swets 1988)

	Predicted		
Observed	Fire	No fire	% correct
Fire	72	9	88.9
No fire	402	1909	82.6
Correctly classified			82.8

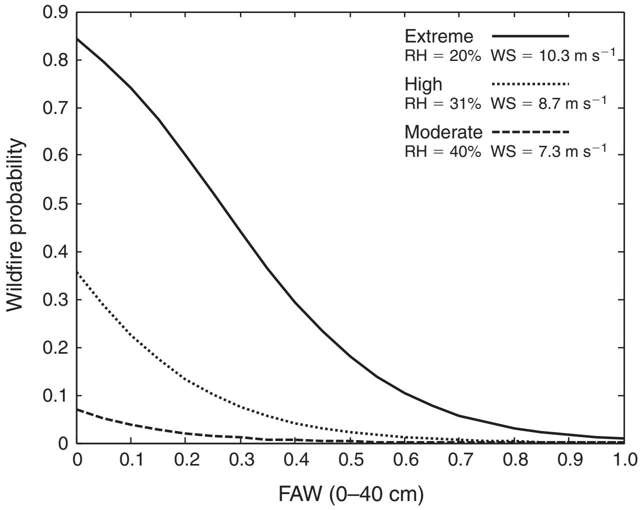

Fig. 4. Daily probability of wildfire occurrence during the growing season as a function of fraction of available water capacity (FAW) and three levels of wildfire conditions (extreme, high, and moderate). Data are based on 119 growing-season wildfires ≥405 ha in Oklahoma from 2000 to 2012. Under 'extreme' wildfire conditions, minimum relative humidity (RH) and maximum wind speed (WS) approximate criteria for the US National Weather Service fire weather warnings in central and western Oklahoma. Under 'high' wildfire conditions, RH and WS corresponded to their respective 25th (low) and 75th (high) percentile values, and moderate RH and WS were their medians over the 13-year period. Daily wildfire probability markedly increased for FAW <0.5, the threshold for water stress in plants.

issued by the NWS, with minimum relative humidity of 20% and maximum wind speed of 10.3 m s^{-1}. In contrast, when FAW was higher than the 0.5 threshold for water stress in plants, wildfire probability was relatively low even when relative humidity and wind speed were extreme. This result suggests that fire weather warning criteria might be improved by the inclusion of soil moisture information. Wildfire probability under high conditions, where daily minimum relative humidity and maximum wind speed were 31% and 8.7 m s^{-1}, respectively, was lower than under extreme conditions, as expected, with probabilities of only 0.02 for FAW = 0.5 and 0.13 for FAW = 0.2. When minimum relative humidity and maximum wind speed conditions were moderate (minimum relative humidity = 40% and maximum wind speed = 7.3 m s^{-1}), wildfire probability was only 0.02 even with FAW = 0.2.

Our results suggest that low FAW, low minimum relative humidity and high maximum wind speed worked in concert to create conditions under which the probability of large wildfire occurrence during the growing season was great. When soil was moist during the growing season, a condition that would support high LFM in shrubs (Pellizzaro *et al.* 2007), evergreen trees (Engle *et al.* 1987) and herbaceous vegetation (Dimitrakopoulos and Bemmerzouk 2003; Wittich 2011), wildfire probability was low even under extreme relative humidity and wind speed conditions. Conversely, when soil was dry, a condition that could lead to low LFM, wildfire probability was high only when minimum relative humidity and maximum wind speed were sufficient to support large fires. Each of the studied variables may explain a portion of the mechanism behind growing-season wildfire danger. According to the NFDRS, high wildfire danger

Table 3. Dormant season logistic regression model for 382 wildfires ≥405 ha in Oklahoma 2000–2012

The likelihood ratio χ^2-statistic for the final model was 387.0 ($df = 9$, $P < 0.001$). The McFadden R^2 was 0.28, with values in the range of 0.2–0.4 indicating excellent fit (McFadden 1979)

Variable	*df*	Coefficient	Standard error	Wald χ^2	*P* value
FAW	1	−2.28	0.563	16.4	<0.0001
FAW −270d	1	2.08	0.479	18.8	<0.0001
FAW −635d	1	2.31	0.475	23.6	<0.0001
Maximum temperature	1	0.04	0.008	24.5	<0.0001
Maximum temperature −90d	1	−0.03	0.007	27.0	<0.0001
Maximum temperature −455d	1	−0.03	0.007	15.3	<0.0001
Maximum wind speed	1	0.10	0.016	35.6	<0.0001
Minimum relative humidity	1	−0.06	0.008	67.1	<0.0001
Minimum relative humidity −360d	1	−0.02	0.005	9.2	0.0024
Intercept	1	−1.45	1.074	1.8	0.1783

is associated with environmental conditions that support wildfire ignition, spread, and energy release (Bradshaw *et al.* 1983). Moisture content of live fuels declines as soil moisture declines, which results in an increased rate of wildfire spread and energy release. If soil drying persists, vegetation can transition from live to dead. Low relative humidity, and therefore low dead fuel moisture, increases the likelihood of wildfire ignition, rate of spread and energy release, and wildfire spread is driven by increased wind speed.

Dormant season

During the dormant season, the final logistic regression model was highly significant (likelihood ratio $\chi^2 = 387$, $P < 0.0001$) (Table 3) and was well fitted to the data, with a McFadden $R^2 = 0.28$. Nine of 70 possible predictors remained in the final model, including all concurrent variables except precipitation. The directions of the relationships were as expected for all concurrent variables, with FAW and minimum relative humidity being negatively related to wildfire probability, and maximum temperature and wind speed being positively related. Several lagged variables were also significant, including positive relationships for FAW −270d and FAW −635d. These two variables represent lag times of 9 and 21 months, respectively, and are 1 year apart. The dormant season model correctly classified 77% of days with fires and 76% of days without fires and had a *c*-value of 0.86 (Table 4).

The positive influence of lagged FAW on dormant season wildfire probability is apparent from the wildfire probability sensitivity analysis (Fig. 5). Here, FAW −270d was varied across its range whereas minimum relative humidity and maximum wind speed were held at extreme, high, and moderate values, with all other significant variables being held constant at their medians. Under extreme conditions, wildfire probability was 0.09, 0.15, and 0.29 when FAW −270d was 0.2, 0.5, and 0.9, respectively. The greater than three-fold increase in wildfire probability occurred as FAW −270d ranged from extreme drought (FAW = 0.2) (Sridhar *et al.* 2008) to the threshold for

Table 4. Observed and predicted frequency for days with and without fires for 2357 dormant season days in Oklahoma 2000–2012

The cut-off value was 0.088. The *c*-value for the model was 0.86, with accurate models generally having values >0.7 (Swets 1988)

	Predicted		
Observed	Fire	No fire	% correct
Fire	161	47	77.4
No fire	508	1641	76.4
Correctly classified			76.5

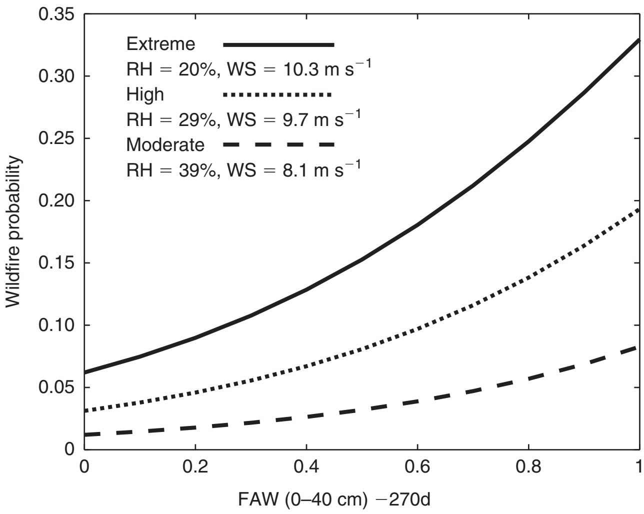

Fig. 5. Daily probability of wildfire occurrence during the dormant season as a function of fraction of available water capacity (FAW) −270d and three levels of wildfire conditions (extreme, high, and moderate). Data are based on 382 dormant season wildfires ≥405 ha in Oklahoma from 2000 to 2012. Under 'extreme' wildfire conditions, minimum relative humidity (RH) and maximum wind speed (WS) approximate criteria for the US National Weather Service fire weather warnings in central and western Oklahoma. Under 'high' wildfire conditions, RH and WS corresponded to their respective 25th (low) and 75th (high) percentile values, and moderate RH and WS were their medians over the 13-year period. Daily wildfire probability markedly increased for FAW −270d >0.5, the threshold for water stress in plants.

water stress in plants (FAW = 0.5) to conditions near optimum for plant growth (FAW = 0.9). For fires during the peak dormant season wildfire months of March and April, the −270d lag corresponds to soil moisture conditions the previous June and July, suggesting that moist conditions at the beginning and middle of the growing season increased wildfire probability in the subsequent dormant season. Similar correlations with FAW −635d suggest conditions during the growing season 2 years prior are also linked to increased fire probability.

We expected that the dormant season variables related to the occurrence of large wildfires would be those that dictate moisture of dead fuels (temperature, relative humidity and precipitation) and wildfire spread (wind speed) (Bradshaw *et al.* 1983; Nelson 2000; Carlson *et al.* 2007), with FAW being less important because of the relatively low proportion of live fuels during the dormant season. The monthly analysis (Fig. 2) suggested a weaker link between FAW and wildfire occurrence during the dormant season than during the growing season, and large dormant season wildfires are known to occur across a range of FAW (Krueger *et al.* 2015). Nonetheless, FAW was significantly related to dormant season wildfire probability (Table 3). It is likely that the importance of FAW during the dormant season was partially a result of our definition of dormant season (November–April). Although vegetation in Oklahoma does not reach peak greenness until after 1 May, the onset of spring growth begins in March (Senay and Elliott 2000). Low FAW during the transition from dormant to growing seasons could inhibit spring growth, resulting in a lower proportion of live fuels and increased wildfire probability. The moisture of long-lag-time dead fuels (i.e. 100-h and 1000-h fuels) also decreases under drought conditions (Bradshaw *et al.* 1983). Finally, low dormant season soil moisture may reduce leaf moisture content of live fuels during the dormant season (Engle *et al.* 1987), increasing their flammability (Weir and Scasta 2014) and contributing to increased wildfire probability (Ursino and Rulli 2011).

The foreshadowing of elevated dormant season wildfire probability by high FAW the previous growing seasons has also been reported for moisture-limited grass and shrublands (Knapp 1998; Westerling *et al.* 2003) and in the Great Plains in the US (Littell *et al.* 2009). Unlike during the growing season when the probability of large fires is constrained by the moisture content and level of curing of live fuels, which is driven by concurrent soil moisture, the probability of large dormant season wildfire occurrence is driven in part by low within-season soil moisture and high soil moisture during previous growing seasons. Therefore, we conclude that the mechanisms behind the influence of FAW on wildfire occurrence are seasonally dependent. Decreased moisture content and curing of live fuels induced by low FAW increased wildfire occurrence during both dormant and growing seasons, and fuel accumulation under high moisture conditions during previous growing seasons also increased dormant season wildfire probability.

Persistence of fraction of available water capacity (FAW) and weather variables

The persistence of FAW and weather variables in the final logistic regression models was assessed using autocorrelation for the growing and dormant seasons. We found that FAW was more persistent than the other variables, with the autocorrelation coefficient (r) for FAW remaining above 0.5 for a lag of 22 days during the growing season (Fig. 6). For minimum relative humidity and maximum wind speed, the other significant growing-season variables, r was >0.5 for only 2 and 0 days, respectively. Similarly, for FAW during the dormant season, r remained above 0.5 for a lag of 54 days, compared with only 2, 1, and 0 days for maximum temperature, minimum relative humidity, and maximum wind speed, respectively (Fig. 7). At a lag of 7 days, FAW had autocorrelation coefficients of 0.80 and 0.94 during the growing and dormant seasons. At a lag of 3 days, FAW had $r = 0.93$ during the growing season and 0.97 during the dormant season, respectively. No other significant variable had r >0.5 after 2 days.

The persistence of FAW suggests strong potential for its use in short-term wildfire danger forecasts. For example, the NWS Storm Prediction Center prepares wildfire weather outlooks at 1, 2, and 3–8 day increments based on weather forecasts and fuels

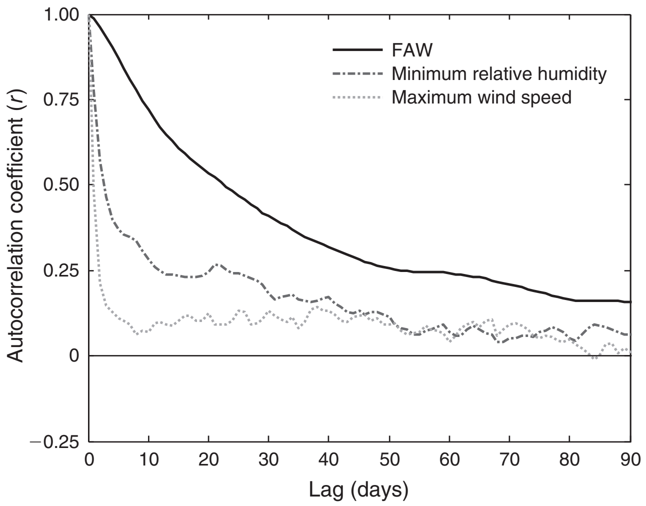

Fig. 6. Growing-season correlogram for fraction of available water capacity (FAW) and weather variables for daily observations as a function of lagged days in Oklahoma from 2000 to 2012.

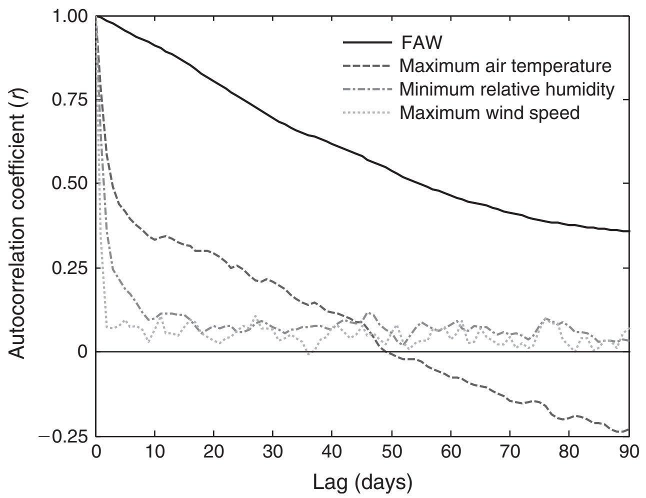

Fig. 7. Dormant season correlogram for fraction of available water capacity (FAW) and weather variables for daily observations as a function of lagged days in Oklahoma from 2000 to 2012.

information (NWS 2015). Likewise, the National Interagency Coordination Center produces 7-day fire potential outlooks as part of its Predictive Services Program. This service has demonstrated skill in predicting large wildfire occurrence, although wildfire probability on moist and dry fuel days could not be differentiated (Riley *et al.* 2014). Given the strong relationship between FAW and wildfire occurrence and the persistence of FAW, it may provide a simple and effective supplement to weather and fuels data in these wildfire danger forecasts.

Conclusion

Wildfire occurrence was found to be dependent on soil moisture, expressed as FAW, during both the growing and dormant seasons, but the mechanisms by which FAW influenced wildfire occurrence were seasonally dependent. For the growing season, wildfire probability increased when FAW was low, whereas dormant season wildfire probability was increased by high FAW the previous growing season and low FAW during the current season. Our results demonstrate that soil moisture and weather work in concert to support high wildfire probability, with each variable explaining a portion of the mechanism behind occurrence of large wildfires. During the growing season, low FAW decreases LFM and may cause herbaceous and deciduous woody fuels to transition from live to dead, low relative humidity lowers dead fuel moisture, and high wind speed drives fire spread. Low FAW and extreme weather were both required for wildfire probability to be high. Dormant season wildfire probability was increased by low concurrent FAW and high lagged FAW, indicating that fuel accumulation from previous growing seasons supports dormant season wildfire. Relative to rapidly fluctuating weather variables, FAW also exhibits considerable persistence and may therefore improve wildfire danger forecasts.

No wildfire danger models currently incorporate soil moisture because the necessary data have been lacking at operational scales. The increasing availability of soil moisture data makes its inclusion in wildfire danger assessments more feasible, and our results can guide wildfire managers on how to use this information when assessing wildfire danger. In light of our finding that soil moisture is significantly related to wildfire probability during both the growing and dormant seasons, we recommend that concurrent and lagged soil moisture be included in wildfire danger assessments in Oklahoma and other regions across the world with similar climates and vegetation types.

Acknowledgements

The authors would like to thank Karen Short of the USDA Forest Service for her assistance in compiling and vetting wildfire data. We thank the Oklahoma State Fire Marshal's office, and especially Madelyn Brandon for providing wildfire data, and the Oklahoma Mesonet for providing daily weather and soil moisture data. We also thank Angela Reid, Tall Timbers Research Station and Land Conservancy, Tallahassee, Florida and John Weir, Oklahoma State University, Stillwater, Oklahoma for their assistance with preparation of wildfire data. We thank Mark Gregory, Oklahoma State University for assistance in preparing the map included in this manuscript. Funding for the project was provided by the Joint Fire Science Program (JFSP 11–1-2–19) and the Oklahoma Agricultural Experiment Station.

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