Interactions between antecedent climate and wildfire variability across south-eastern Arizona

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Abstract. Long-term antecedent climate conditions are often overlooked as important drivers of wildfire variability. Fuel moisture levels and fine-fuel productivity are controlled by variability in precipitation and temperature at long timescales (months to years) before wildfire events. This study examines relationships between wildfire statistics (total area burned and total number of fires) aggregated for south-eastern Arizona and antecedent climate conditions relative to 29 fire seasons (April–May–June) between 1973 and 2001. High and low elevation fires were examined separately to determine the influence of climate variability on dominant fuel types (low elevation grasslands with fine fuels *v.* high elevation forests with heavy fuels). Positive correlations between lagged precipitation and total area burned highlight the importance of climate in regulating fine fuel production for both high and low elevation fires. Surprisingly, no significant negative correlations between precipitation and seasonal wildfire statistics were found at any seasonal lag. Drought conditions were not associated with higher area burned or a greater number of fires. Larger low elevation fires were actually associated with wet antecedent conditions until just before the fire season. Larger high elevation fires were associated with wet conditions during seasons up to 3 years before the fire season.

Introduction

Fire plays a critical role in the maintenance of healthy grassland and forest ecosystems and is strongly regulated by climatic variability (Pyne 1984; Swetnam and Betancourt 1990). This fact is often overlooked, as historic fire suppression has limited humans' exposure to the natural fire cycle that is inherently regulated by local climate conditions. As public policy shifts towards more ecological land management techniques that include restoring natural fire ecologies, a better understanding of anthropogenic and environmental controls on fire regimes is necessary. Currently fire regimes are strongly governed by human land use management policies as well as long-term and short-term climate conditions preceding fire incidents. Efforts to restore ecosystems with fire rely heavily on understanding climate variables such as precipitation and temperature that regulate the flammability of fuels and an ecosystem's response to fire (Brown and Betancourt 1999). The mesoscale response of ecosystems to long and short-term climatic controls is an important but poorly understood moderator of fire regimes (Swetnam and Betancourt 1998).

Much research has been done to characterize fire weather, that is, the weather conditions on the order of days to weeks preceding fire events (Schroeder 1969; Bessie and Johnson 1995; Flannigan and Wotton 2001). Little work has been done to reveal how weather conditions before fire events fit into a larger spatial and temporal setting. Several days or weeks of above-normal temperatures and below-normal precipitation are not always the only important climatic factors that dictate the elevation of fire risk (Flannigan and Wotton 2001). Seasonal, annual, and interannual variability in climate can regulate fire risk by controlling the production and conditioning of fuels in ecosystems (Swetnam and Betancourt 1990; Westerling *et al*. 2002). These longer-term climate variations are often much more important than short-term fire weather conditions in arid climates, such as the desert South-west, where there is a seasonal climatology of favorable fire weather conditions that persist for several months every year. Large fire events in the desert South-west appear to be related to complex climatic signatures in antecedent conditions up to several years before the event (Rogers and Vint 1987; Swetnam and Betancourt 1998; Grissino-Mayer and

Swetnam 2000; Barton *et al.* 2001). The basin and range landscape of south-eastern Arizona possesses a unique diversity of ecological community types with unique fire regimes that may be influenced differently by antecedent climatic conditions.

The aim of this study is to identify the importance of antecedent climatic conditions to wildfire variability (total area burned and total number of fires) across south-eastern Arizona. A correlation analysis will help isolate relationships between wildfire and climate at specific lags while a regression analysis will be used to identify which combinations of lagged climate variables have the greatest power at predicting wildfire activity. Identification of lagged climate variables strongly related to wildfire variability helps to identify potential causal mechanisms and can be used in a predictive capacity to forecast wildfire activity.

Study area

The study area (Fig. 1) is defined by the boundary of Arizona climate division number seven. This climate division includes the south-eastern Arizona counties of Pima, Graham, Greenlee, Santa Cruz, and Cochise. A basin-and-range relief dominates most of the study area with elevations ranging from over 2800 m at the highest range to 200 m at western edge low desert locations. Climate in low desert locations is classified as arid with annual precipitation amounts rarely exceeding 200 mm. Annual precipitation amounts are bimodally distributed with most precipitation occurring in either the summer (JAS) monsoon season or winter (DJFM) season. Winter temperatures average around 10°C while summer maximum temperatures can often exceed 40°C at lower elevations. The highest elevations are subject to daily average temperatures ranging from 4°C to 25°C annually and precipitation amounts exceeding 1000 mm (SCAS 2003; WRCC 2003). The complex terrain produces high temperature and precipitation gradients over short distances. A rich diversity of community types is supported by the steep climatological gradients. Communities transition from desert scrub at lowest elevations up through desert grassland, open oak woodland, pine–oak woodland, pine–oak forest, pine forest, montane fir
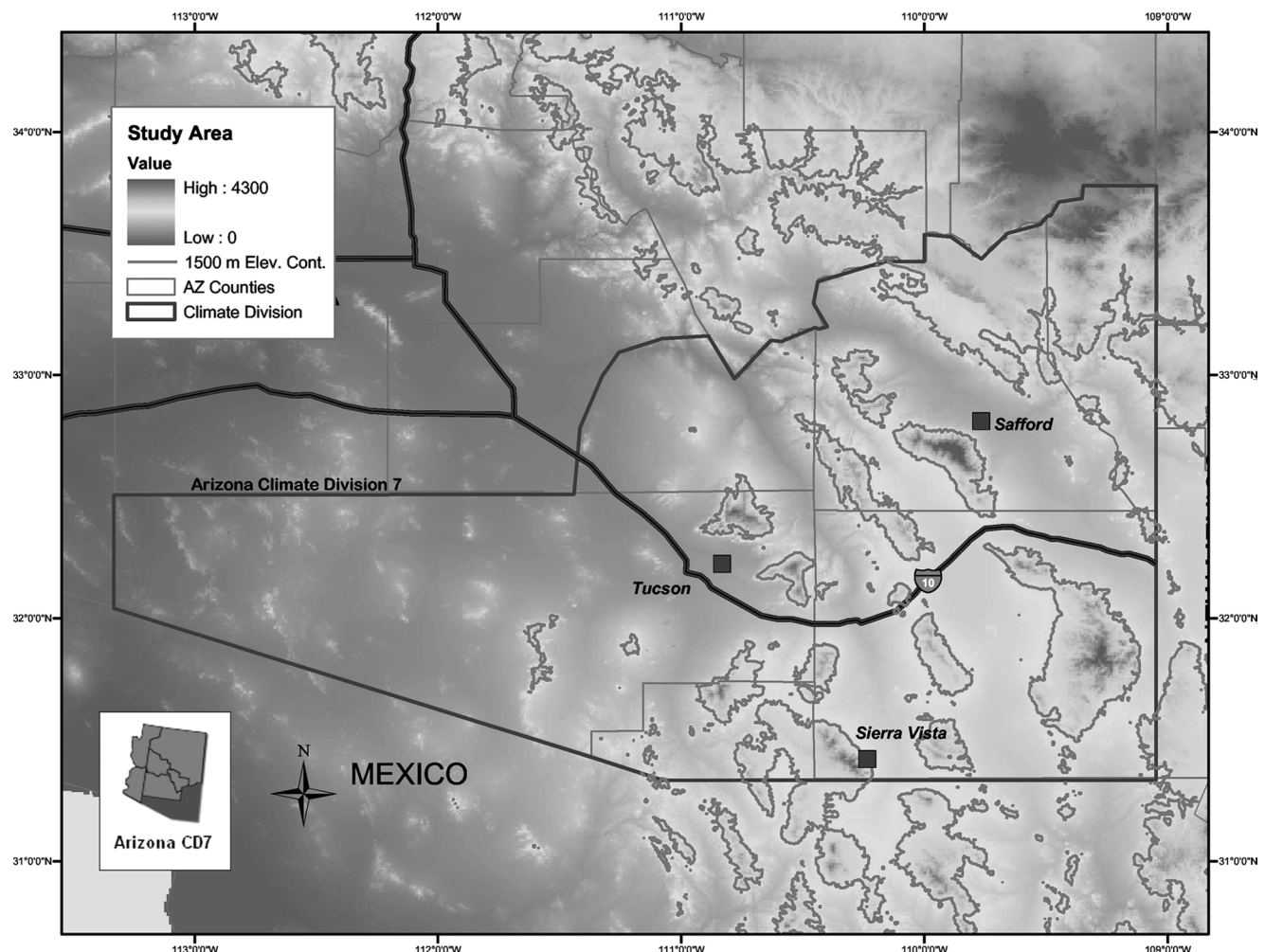

Fig. 1. Study area in south-eastern Arizona.

forest, to subalpine forest at highest elevations in the study area (Whittaker and Niering 1965).

Data and methods

The Laboratory of Tree Ring Research at the University of Arizona compiled the wildfire data used in this study from county, state and federal sources for the state of Arizona. The multi-agency dataset included information for all reported fires in Arizona for the period 1973–2001. Each record entry included the fire start date, end date, total area burned and specific location, if known, recorded by township, section, and range. All fires with locations were included in this study, regardless of ignition cause. This includes all lightning fires as well as human-caused ignitions. Prescribed fires were not part of the original compilation of the wildfire dataset and hence were not used in the analysis.

Many challenges exist when using multi-agency wildfire data. Under-reporting and accuracy of fire location are common problems in wildfire datasets (Brown *et al*. 2002; Westerling *et al*. 2003). Less than 5% of the total number of fires in the present wildfire dataset had to be excluded due to lack of fire location information. This does not contain every fire that occurred during the period of record, but is adequate at defining general trends and patterns at the regional scale.

The study area (Fig. 1) was purposely confined to the boundary of Arizona climate division seven (AZCD7) to facilitate the use of divisional data. Monthly values for temperature, temperature anomaly, precipitation, precipitation anomaly, Palmer Z index, and Palmer drought severity index (PDSI) were obtained for AZCD7 from the National Climatic Data Center. Climate division values are calculated by averaging many surface observations within a several-county area so that a single time series can be generated. This method is often inadequate in areas with complex topography and few weather stations and can produce divisional time series that fail to capture higher elevation climate variability. Time series data generated for AZCD7 most likely suffer from these problems; however, few upper elevation weather stations exist in this region for validation or to use in place of divisional data. Even with its limitations, the monthly divisional data is probably adequate at capturing the broader, regional variability in temperatures and precipitation amounts.

Reanalysis variables from the National Centers for Environmental Prediction (700 mb geopotential height, specific humidity, omega, zonal wind and meridional wind) were included in the original climatological dataset to investigate the importance of upper level circulation patterns and moisture levels on wildfire variability. Several time series of monthly average reanalysis variables were obtained from the Climate Diagnostics Center for the model grid point closest to the center of AZCD7. Time series data from surrounding grid points were highly correlated ($r > 0.9$) with the target grid point, demonstrating the insensitivity of data point choice.

Eight reanalysis time series from the target grid point were screened in the initial correlation analysis. These correlations between the wildfire statistics and Reanalysis variables were very similar to the surface variables (PDSI, Z-index, precip. anomaly and temp anomaly). They did not provide additional explanatory power and were ultimately excluded to simplify the presentation of results.

An important aim of this study is to explore the complex fire–climate relationships that exist along steep ecological gradients where fine and heavy fuel production and conditioning are dominated by climate variability. High elevation fire events that occur in heavy, woody fuels are most likely influenced by different antecedent climate conditions than low elevation fires in fine, grassy fuels. Elevation was used as a proxy for fuel type by splitting the original fire events dataset into a high elevation set and low elevation set. Whittaker and Niering (1965) conducted an extensive vegetation sampling study on several southern Arizona mountain ranges to characterize the general change in vegetation types along topographic gradients. They determined that, on most slopes, desert grasslands transitioned into oak woodlands at around 1500 m in elevation. This elevation was used as a breakpoint to separate low elevation grass fires from high elevation forest fires in the event dataset. Additional breakpoints at 1350 m and 1700 m were also used to evaluate the sensitivity of using elevation for data stratification. Slight differences in wildfire–climate correlations were observed depending on the breakpoint used, but results were generally similar. This study focuses on the results obtained using 1500 m elevation as the breakpoint between high and low elevations given the guidance provided by the Whittaker and Niering (1965) study. Misclassifications of high or low event fires are possible given the coarse township/range/section reporting of fire locations, but this is an unavoidable limitation of the data. Elevation in this dataset is a coarse approximation for fuel type and can only superficially represent the complex interaction between climate variability and different fuel types. Wildfire, climate and vegetation data at higher spatial resolution than currently available are needed to advance understanding of specific fire–climate relationships across a landscape of varying fuel types.

The high/low elevation wildfire events and monthly climate data were aggregated to a seasonal temporal resolution to aid in the interpretation of lagged relationships. Seasons were defined as winter (DJFM), spring (AMJ), summer (JAS), and fall (ON). These seasonal definitions stray from the convention of regular, 3-month seasons, but are more appropriate for the unique precipitation regime of southern Arizona. Precipitation is bimodal with more than 50% of the annual total occurring during the monsoon season (JAS) and 30% occurring during winter months (DJFM). Wildfire counts and total area burned were summed for each season between 1973 and 2001, while climate variables were converted into seasonal averages. AMJ was designated the

Table 1.   Mean, minimum, and maximum seasonal total area burned in acres and total number of fires for south-eastern Arizona for the period 1973–2001

Minimum and maximum values are shown in parentheses

Elevation group	Data type	DJFM	AMJ	JAS	ON
Upper elevation (>1500 m)	TAB	99 (0, 2156)	2953 (0, 41 376)	800 (0, 10 791)	20 (0, 157)
	TNF	0.9 (0, 7)	7 (0, 30)	3.5 (0, 18)	0.7 (0, 5)
Lower elevation (<1500 m)	TAB	655 (0, 4394)	7184 (0, 58 864)	2520 (0, 28 023)	48 (0, 283)
	TNF	16 (0, 89)	55 (0, 170)	28 (0, 99)	6 (0, 26)

AMJ, April–May–June; DJFM, December–January–February–March; JAS, June–August–September; ON, October–November; TAB, total area burned; TNF, total number of fires.

fire season because it experienced the highest levels of fire activity (Table 1).

Both upper and lower elevation datasets of seasonal total area burned (TAB) and total number of fires (TNF) were positively skewed and required transformations before calculating statistics with normality assumptions. This type of skew in the data distributions suggested the need for a logarithmic transformation. The skew was effectively removed from each through the use of a log_{10} transformation. Several seasons with zero TAB or TNF were more than two standard deviations from the mean of the transformed dataset. Given that these values are unlikely in reality and most likely attributable to poor fire records, they were removed as outliers to further improve the shape of the distributions. Each distribution passed the Shapiro-Wilks normality test after transformation and removal of outliers. Climate variables were also examined for normality. None were excessively skewed or possessed outliers that would require transformations.

A matrix of bivariate Pearson's r correlations between the fire and climate datasets was developed. Total area burned and TNF values were correlated with coincident seasonal climate data as well as lagged seasonal climate data. As an example, this means that April–May–June TAB values were correlated with April–May–June temperature anomaly values as a correlation with no lag. Seasonally aggregated data were used rather than monthly data to clarify and aid in the interpretation of long lag relationships. Additional lagged correlations were calculated where AMJ TAB was correlated with the prior season (DJFM) temperature anomaly, two seasons prior (ON), and so forth, back 16 seasonal lags (4 years). Several studies have found significant relationships between fire activity and antecedent climate conditions with fire lagging climate by over 3 years (Swetnam and Betancourt 1998; Barton et al. 2001). A window of 16 seasonal lags appears to be a long enough to capture the lagged relationships highlighted in these other studies. Auto-correlation functions (ACF) were calculated out to 20 lags for each of the climate variables to assess the potential impact of persistence or periodicity in the climate time series on the lagged correlations. The ACF fell to non-significant levels ($P < 0.05$) after just one season for temperature anomalies, precipitation anomalies and the Z-index values. Palmer drought severity index values have inherent persistence so it expectedly

had significant autocorrelation for the first three lags. This is an important consideration when interpreting the lagged correlations between PDSI values and wildfire statistics. No significant autocorrelations were detected past nine months in the PDSI dataset.

Ultimately 272 correlations were calculated between four variables at seasonal lags ranging from zero to 16 for four different datasets (upper TAB, lower TAB, upper TNF, and lower TNF). This exercise was done to evaluate the discrete relationship between antecedent seasonal climatic conditions and wildfire variability and to also identify variables that would be the strongest predictors in regression equations built to forecast wildfire activity. To reduce the pool of potential predictors, only significant correlations ($P < 0.1$) were considered as candidates for the regression models.

To further screen the variables and to guard against modeling with many collinear predictors, surface variables with significant correlations ($P < 0.1$) were subjected to a rotated principal components analysis. Five components captured most of the variance for each of the four predictor subsets (low elevation TAB, 88.8%; low elevation TNF, 67.4%; high elevation TAB, 85.6%; high elevation TNF, 78.7%). The highest loading variables on each of the components were identified and used to form the final pool of predictors.

All combinations of variables in the final pool of predictors were used to develop the final regression model using SPSS v. 11.0. Regression models were developed with discrete variable combinations entered into each model (stepwise method not used). Each of the final regression models had the simplest structure with the greatest explanatory power. Overall model significance, coefficient significance, and explained variance (R^2) were used to assess model performance. Residuals in the final models were examined and indicated no violations of the assumptions of normality or equal variance and absence of autocorrelation.

Results

Upper elevation fire–climate relationships

Significant ($P < 0.1$) positive correlations between total area burned (TAB) and moisture-related climate variables (Z-index, precipitation anomaly, and PDSI) were concentrated in the period eight to four seasons (AMJ[−2] to
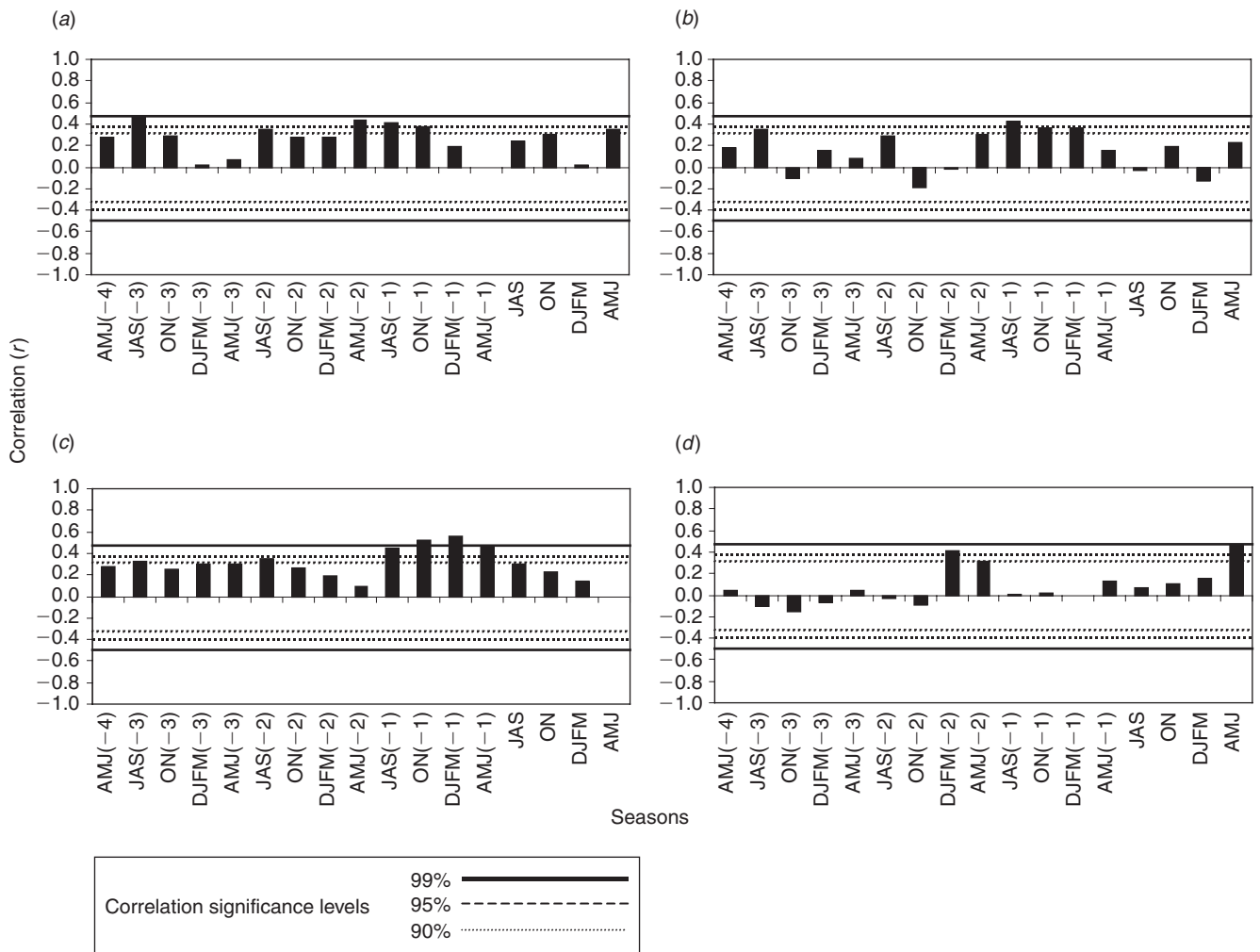
Fig. 2. Correlations between upper elevation total area burned (TAB) and climate variables ($n = 27$ seasons). Time moves from the left over 4 years up to the fire season in the right-most column. (*a*) Z-index, (*b*) climate division 7 precipitation anomaly, (*c*) Palmer drought severity index, and (*d*) climate division 7 temperature anomaly.

AMJ[−1]) before the zero lag AMJ season (AMJ[0]) (Fig. 2). This grouping of significant correlations was found during JAS[−1], ON[−1], and DJFM[−1] for precipitation anomaly and Z-index. Significant PDSI correlations occur during the same period plus an additional season (AMJ[−1]). An additional group of positive correlations between TAB and moisture-related climate variables was found at JAS[−3], the July–August–September monsoon season, 3 years before AMJ[0]. A significantly positive relationship between TAB and temperature anomaly occurs during AMJ[0] and the winter season 2 years prior (DJFM[−2]).

The TNF at upper elevations had a different pattern of correlation with climate variables than the TAB values (Fig. 3). Temperature anomaly had highly significant positive correlations with TNF at short seasonal lags (AMJ[0], DJFM[0], and ON[0]). PDSI and TNF were significantly related during seasons JAS[−1] and DJFM[−1] and at longer lags (DJFM[−3] through AMJ[−4]). Correlations between TNF

and all moisture-related climate variables were highly significant ($P < 0.05$) during JAS[−3] just as TAB correlations were at the same seasonal lag.

The regression model developed to predict upper elevation TAB used two predictor variables that explained 43% of the variance in AMJ total area burned. The precipitation anomaly for JAS[−3] and the average PDSI value for the winter season the year prior (DJFM[−1]) both entered into the final model. The lagged precipitation anomaly variable was the stronger predictor in the model with a standardized (β) coefficient of 0.46 over the PDSI β coefficient of 0.349. The model performed reasonably when cross-validated using the 'leave one observation out' method, producing a predicted residual sum of squares (PRESS) statistic of 0.354.

The upper elevation TNF regression model performed exceptionally well with two predictors entering into the final model and accounting for 75% of the variance in AMJ total number of fires. JAS[−3] precipitation anomalies were again
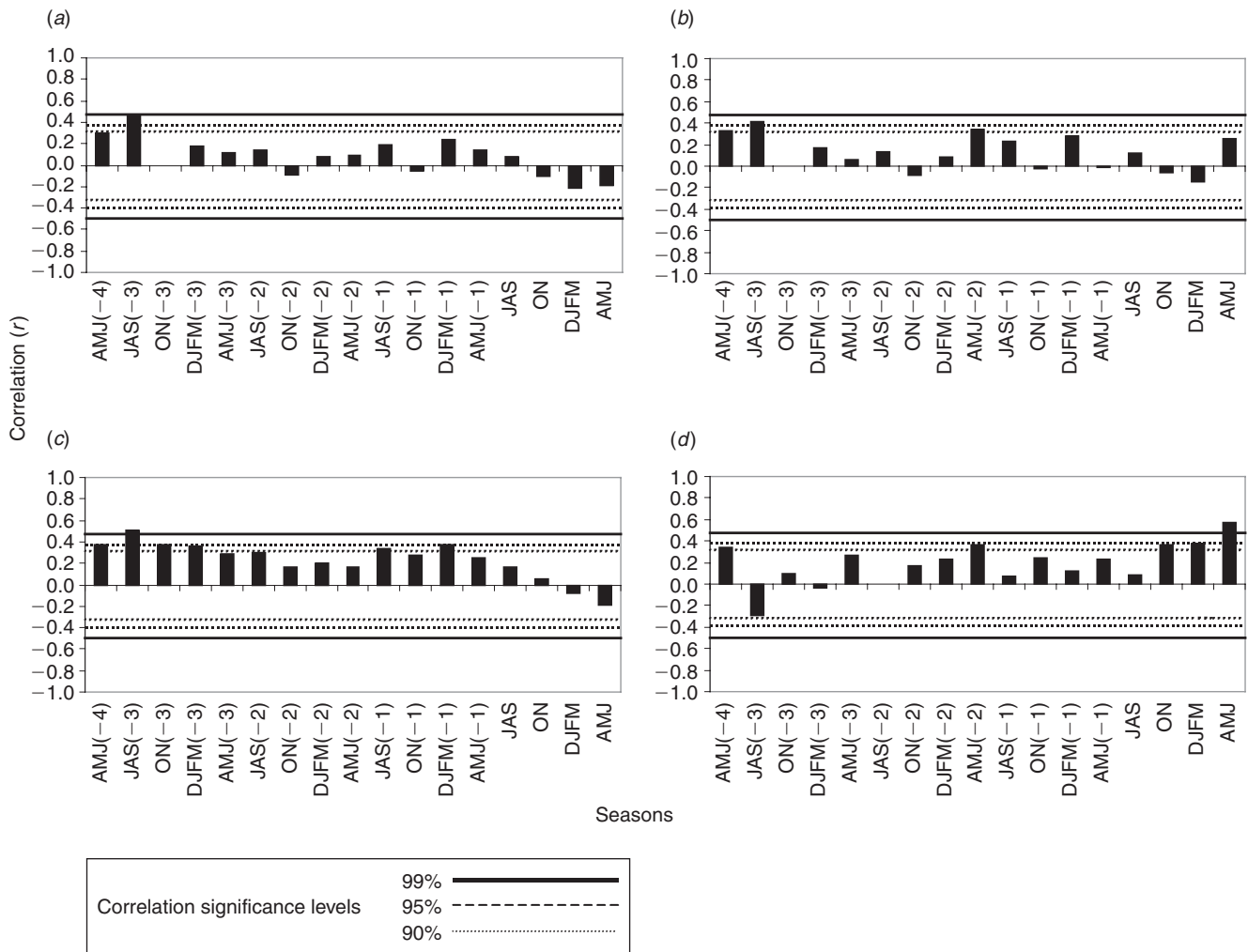
Fig. 3. Correlations between upper-elevation total number of fires (TNF) and climate variables ($n = 27$ seasons). Time moves from the left over 4 years up to the fire season in the right-most column. (*a*) Z-index, (*b*) climate division 7 precipitation anomaly, (*c*) Palmer drought severity index, and (*d*) climate division 7 temperature anomaly.

the most important predictor ($\beta = 0.615$) with the AMJ[0] temperature anomaly as the second predictor ($\beta = 0.478$). Model cross-validation produced a PRESS statistic value of 0.705. This value was comparable to the overall model R^2 of 0.75, demonstrating the stability of the regression equation with respect to individual observations.

Lower elevation fire–climate relationships

Most significant correlations between low elevation TAB and moisture-related variables were found during seasons of the concurrent year or year before AMJ[0] (Fig. 4). Precipitation anomaly and Z-index were significantly correlated with TAB during the seasons of DJFM[0], AMJ[−1], DJFM[−1], and also during the longer lag season of JAS[−2]. Z-index had an additional significant correlation during the AMJ[0] while precipitation anomaly did not. Palmer drought severity index was significantly correlated at all seasons from JAS[−3] to the AMJ[0] season. Seasonal temperature anomaly was

significantly correlated with TAB only during the AMJ[0] season.

No correlations between lower elevation TNF and either precipitation anomaly or Z-index were significant at any seasonal lag (Fig. 5). Only two seasons (JAS[−3] and AMJ[−4]) were significantly correlated for PDSI and TNF correlations. Significant correlations between temperature anomaly and TNF were found for nine of the 17 seasonal lags tested. Seasons with highly significant correlations ($P < 0.05$) include several spring seasons (AMJ[0], AMJ[−1], and AMJ[−4]) and one winter season (DJFM[−1]).

Three predictor variables were entered into the final lower elevation TAB regression model. The β values for DJFM[0] Z-index (0.676) and AMJ[0] temperature anomaly (0.637) were very similar, indicating that both variables weight equally important as predictors. The third variable was DJFM[−1] precipitation anomaly. With $\beta = 0.243$, this variable added a small amount of additional explanatory
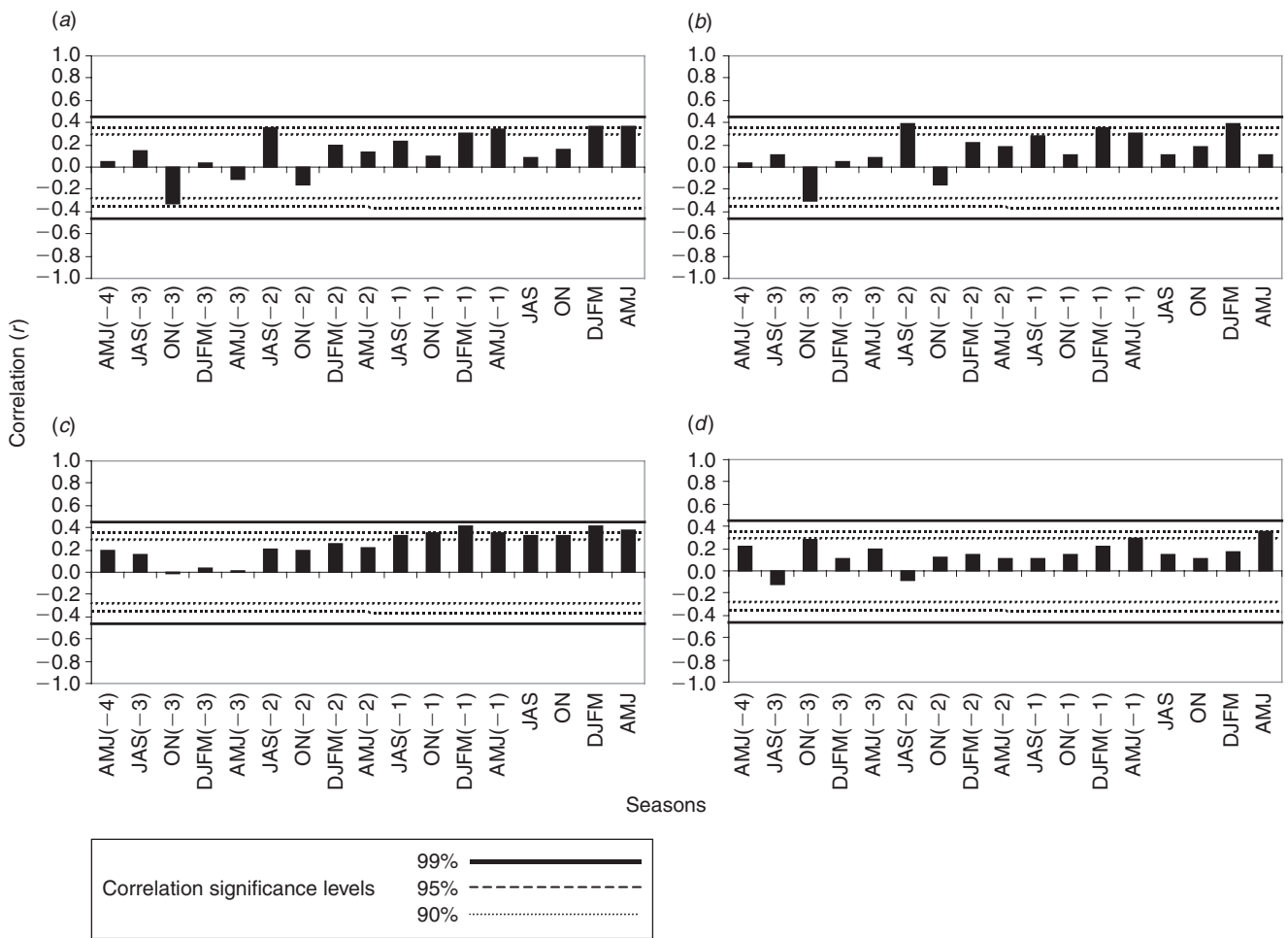
Fig. 4. Correlations between lower-elevation total area burned (TAB) and climate variables ($n = 28$ seasons). Time moves from the left over 4 years up to the fire season in the right-most column. (*a*) Z-index, (*b*) climate division 7 precipitation anomaly, (*c*) Palmer drought severity index, and (*d*) climate division 7 temperature anomaly.

power to the overall model R^2 of 0.354. Model cross-validation by the 'leave one out' method produced a PRESS statistic of 0.285.

Correlations were generally weak and non-significant between climate variables and lower elevation TNF. This limited the initial number of potential predictors considered in the regression model. The regression equation for lower elevation TAB included DJFM(0) Z-index suggesting that winter moisture was important factor in lower elevation fire size. Correlation patterns in the lower elevation TNF moisture-related variables were not significant for DJFM(0) but still indicated that a weak correlation may exist. This guided the inclusion of DJFM(0) Z-index, precipitation anomaly and PDSI into the final pool of predictors with AMJ(0) temperature anomaly. The combination of DJFM(0) precipitation anomaly and AMJ(0) temperature anomaly, produced a model R^2 of 0.505, which was better than any other combination of predictors from the final pool. When comparing β values, the temperature anomaly variable (0.645) was slightly higher than the precipitation anomaly variable

(0.538). Cross-validating the final regression model produced a PRESS statistic of 0.397.

Discussion

Short-term weather conditions have traditionally been viewed as the most important interaction between the atmosphere and wildfire variability (Schroeder 1969; Bessie and Johnson 1995; Skinner *et al*. 1999). Several studies have established that important relationships between wildfire variability and antecedent climate conditions exist across the western United States (Rogers and Vint 1987; Swetnam and Betancourt 1998; Grissino-Mayer and Swetnam 2000; Barton *et al*. 2001; Westerling *et al*. 2002). Variability in precipitation and temperature over a period of years can regulate the accumulation of fine fuels and dictate moisture levels in heavier fuels over large regions. Our study reveals that even more complex fire–climate relationships exist when upper and lower elevation fires are considered separately because of different dominant fuel types.
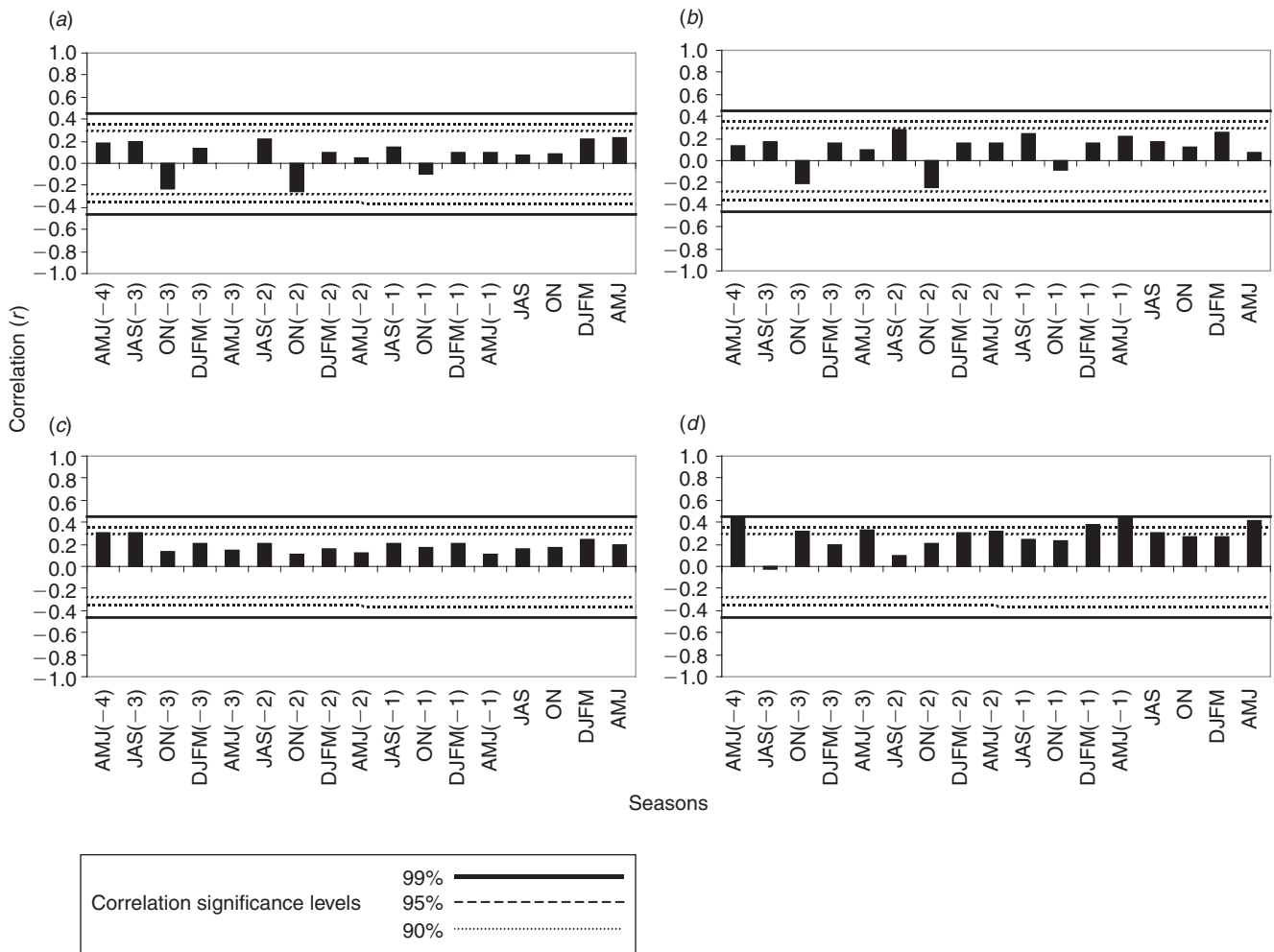
Fig. 5. Correlations between lower-elevation total number of fires (TNF) and climate variables ($n = 28$ seasons). Time moves from the left over 4 years up to the fire season in the right-most column. (*a*) Z-index, (*b*) climate division 7 precipitation anomaly, (*c*) Palmer drought severity index, and (*d*) climate division 7 temperature anomaly.

Correlations indicate that upper elevation TAB is significantly related to wet conditions during the year before larger fire events in the dataset. Perennial native grasses in south-eastern Arizona respond primarily to warm season precipitation (Neilson 2003) and may account for the positive correlation between TAB and moisture-related surface climate variables. Wetter monsoon conditions may spur on more perennial grass productivity, creating a greater continuity of fine fuels across the landscape that would support wildfire spread. This phenomenon is probably more important for fires occurring at the lower elevations (close to the 1500 m threshold) of the entire upper elevation dataset, where grasses are still strongly present as they are in the open oak community (Whittaker and Niering 1965).

Higher elevation forest communities are likely influenced by some combination of other climate-regulated fine fuel production mechanisms and the one described above. The wet conditions during all seasons of the year prior may be an indication that fine fuels are produced by different species in

different ways. The accumulation of leaf litter from deciduous trees may be more dependent on an autumn wet signal while conifers may drop more needles with higher snowfall amounts. Both would result in an accumulation of fine fuels available to carry fire in the following year.

'Wet' fire–climate correlations, linked to fuel production, occur during the year before the fire season (AMJ[0]), but not necessarily during the year of the current fire season. Neither wet (positive) nor dry (negative) correlations were observed between TAB and the three moisture-related surface variables (PDSI, Z-index, and precipitation anomaly). This suggests that dry conditions were not consistently a precursor to large upper elevation fire events. These results are counter-intuitive and contradict several fire history studies conducted in the desert South-west that found more large forest fires occurring during unusually dry years (Swetnam and Betancourt 1998; Grissino-Mayer and Swetnam 2000; Barton *et al*. 2001). This is most likely a product of the relatively short time span of the fire event data used in this
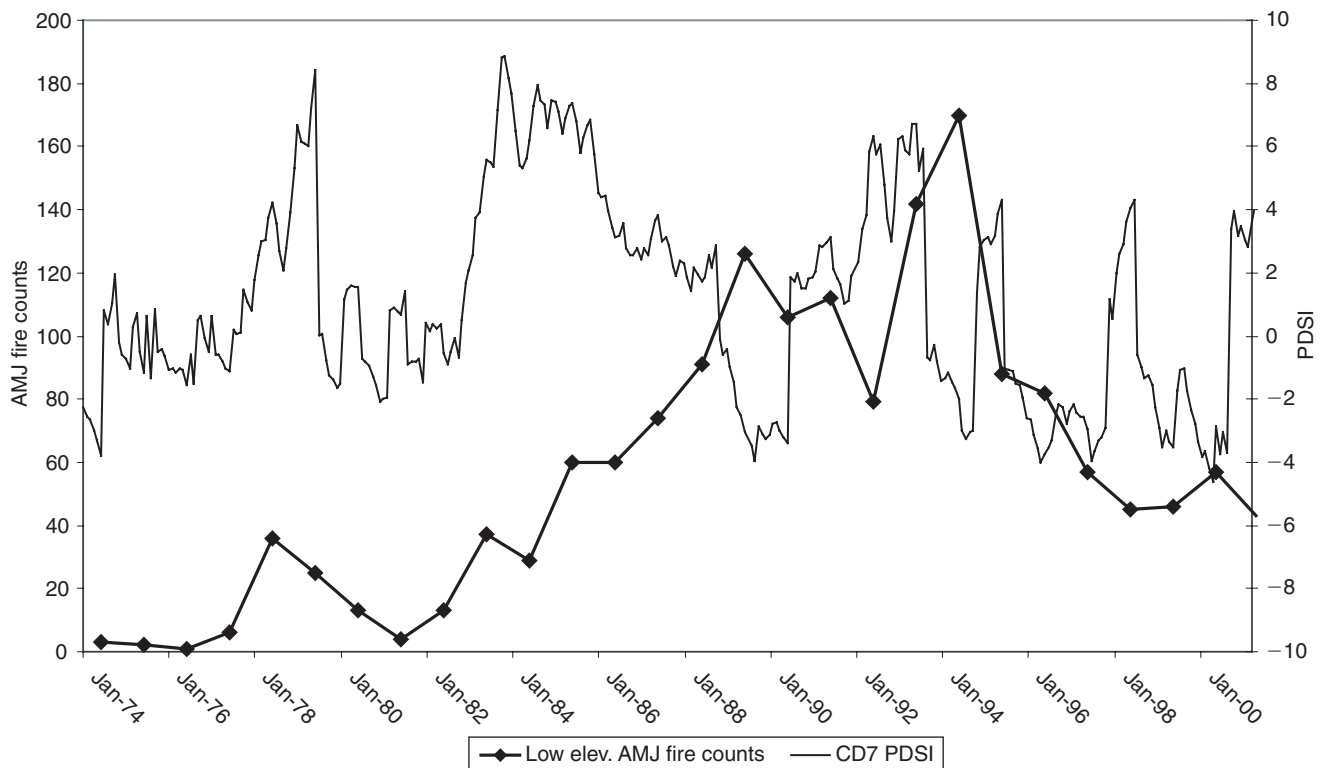
Fig. 6. Time series of lower-elevation total number of fires during the April–May–June (AMJ) season and monthly Palmer drought severity index (PDSI) for Arizona climate division 7 (CD7).

analysis. The period of record of the dataset is almost coincident with a period (1976–2001) known to be exceptionally wet with several El Niño events producing record amounts of winter precipitation across south-eastern Arizona. Palmer drought severity index values indicate that no long periods of moderate drought (PDSI < −2) occurred between 1973 and 2001 (Fig. 6). This lack of exceptionally dry conditions may have suppressed the signal of other fire–climate interactions important to seasonal wildfire activity across the study area (e.g. extended drought conditions and wildfire activity in upper-elevation forests).

Variables entering into the final upper elevation TAB regression equation include PDSI for DJFM(−1) and precipitation anomaly for JAS(−3). Both of these variables most likely represent long-lag, fuel production mechanisms and together provide a modest degree of explanatory power when predicting upper-elevation TAB values. It is unclear whether the 3-year lag on the precipitation anomaly variable is related to a fuel production and accumulation process that actually takes 3 years, or if it is an artifact of some areas not burning immediately after fine fuels are produced. The entire study area does not burn every year, so the lagged relationship may extend several years even though fuel production is occurring on a much shorter timescale. Wet seasons may actually induce conifer needles to drop prematurely and accumulate as fine fuels. Reich *et al.* (1994) found that needle lifespan was inversely proportional to water availability in most

major conifer species. Wet conditions may cause faster needle turnovers and higher fine fuel accumulation rates during this 3-year period between wet signal and TAB response. Needle accumulations would experience minimal decomposition over the 3-year period, especially in the ubiquitous *Pinus ponderosa* (ponderosa pine) stands found at upper elevations in the study area. Murphy *et al.* (1998) found that *P. ponderosa* needles decompose very slowly in semi-arid environments due to high lignin content. In their study, most sites retained over 70% of their original mass after 700 days.

Upper-elevation TNF was dominated by a short-lag, positive temperature correlation reflected in surface temperature anomalies and also a long-lag, positive moisture variable correlation at JAS[−3]. This short-term temperature and long-term moisture pattern enters the upper elevation TNF regression model as temperature anomaly from AMJ[0] and precipitation anomaly from JAS[−3]. Above-normal temperatures at short lags, from two seasons prior through the fire season, may be related to the drying of fuels. Most moisture-related climate variables were negatively correlated with TNF during these seasons, but not significantly. The long-lag precipitation anomaly, which is also present in the TAB correlations and regression, is most likely related to a fuel production process. Together, short-term drying and longer-term fuel production may boost the number of possible fires that become large enough to be reported. Analyses with TNF are particularly sensitive to reporting errors in the

original data. It is likely that many small fires from lightning ignitions were never observed and reported during the period of record. The fires captured in this analysis probably were large enough to be easily observed and, in turn, needed the fuel production mechanisms to achieve that minimum size.

Lower-elevation TAB has 'wet' correlations through seasons of the year prior that extend right up to the AMJ[0] fire season. This is different from the upper elevation fires in that fine fuel production may be occurring in the seasons just before AMJ[0] or during AMJ[0] itself. This is primarily reflected in the significantly positive (wet) correlations between PDSI and TAB at DJFM[−1] and DJFM[0]. These winter-time, wet correlations suggest that fine fuel production may be in the form of annuals rather than native perennial grasses which typically respond to warm season precipitation. Sonoran desert annuals are known to respond to winter precipitation and can provide a continuous source of fuel across the landscape in time for the fire season (Rogers and Vint 1987). Positive correlations at both DJFM[0] and DJFM[−1] also suggest that annuals may both accumulate as litter from previous years and quickly senesce to be available as fuel for AMJ[0] fire activity.

The non-native and invasive perennial grass *Eragrostis lehmanniana* (Lehmann lovegrass) has quickly spread across south-eastern Arizona after being introduced by the Soil Conservation Service in the early 1950s as a soil stabilization tool (Cox *et al*. 1984). *E. lehmanniana* has a distinct advantage over most native perennial grasses in that it is more productive with winter season precipitation, when other native grasses are dormant (Cable 1971). The abnormally wet winters attributed to increased El Niño activity over the past 30 years may have provided an opportunity for the species to spread at an unprecedented rate, quickly invading areas once dominated by native species. *E. lehmanniana* is known to produce more continuous fine fuels than native grass species and can do so even during dry years (Cable 1971). The litter is also highly lignified, meaning that it decomposes slowly, allowing fine fuels to accumulate over longer periods, which increases fuel loads (McPherson 1995). The 'wet' correlations in AMJ[0], DJFM[0], and DJFM[−1] may all be related to the increasing presence of *E. lehmanniana*, because of its ability to utilize precipitation during these seasons where other grasses are dormant.

Precipitation anomaly for DJFM[−1] and Z-index value for DJFM[0] both entered the lower elevation TAB regression equation and express the importance of fuel production, potentially by mechanisms discussed above. The third regression predictor, temperature anomaly at AMJ[0], likely represents the importance of fuel conditioning on lower-elevation grass fires. Very little precipitation typically falls during a normal April–May–June season in south-eastern Arizona, so a negative precipitation anomaly is not necessary to characterize dry conditions. The absence of a negative correlation between AMJ[0] TAB and precipitation is likely due

to conditions being climatologically dry during this period. Yet, above-normal temperatures could aid in the senescing and drying of grassy fuels needed to carry low elevation fires. This was also an important factor in predicting total number of fires, with temperature anomaly during AMJ[0] entering as the most important value for the lower elevation TNF regression model.

No significant positive correlations emerged between moisture-related climate variables and lower elevation TNF as would be expected if antecedent wet conditions and grassy fuels production were important to the number of fires. There does appear to be a relationship between the number of AMJ low elevation fires and soil moisture, but not a clear, linear one. Fire counts (shown in Fig. 6) did not fluctuate from year to year but steadily rose between 1982 and 1994 and then steadily decreased until the end of the record in 2001. The steady rise in fire counts after 1982 is strikingly coincident with the very wet period between 1983 and 1989 where two El Niño events (1982–1983 and 1985–1986) brought record amounts of precipitation to south-eastern Arizona. In addition, the 1994 peak in fire counts may be a lagged product of the above-normal precipitation associated with the 1991–1992 El Niño event. These unusually wet periods may have promoted high productivity in perennial and annual grasses, which in turn helped to overcome fuel continuity limitations usually present across the desert landscape. Areas with typically sparse vegetation would then have fine fuels to carry fires. The total area burned associated with these fires does not increase steadily over the same time period. This may be attributed to the wet conditions of the period, limiting the ability of fires to quickly spread. Also, many of the low-elevation fires were reported to have occurred close to major roads and highways. Road access may have aided firefighting, keeping fire sizes small.

Southern Arizona is especially sensitive to teleconnection patterns induced by strong El Niño events in the tropical Pacific (Redmond and Koch 1991). Strong El Niño events tend to alter winter storm tracks across the western United States, bringing above-normal precipitation amounts to southern Arizona (Sheppard *et al*. 2002). Five of the 10 strongest El Niño events of the last century occurred between 1973 and 2001 (Livezey *et al*. 1997; NCDC 1998) with Arizona experiencing some of its wettest winters on record during this period (NCDC 2003). There is some evidence that multi-decadal variability in ENSO may modulate the winter precipitation teleconnection pattern over southern Arizona (Gershunov and Barnett 1998; Gutzler *et al*. 2002; Brown and Comrie 2004). The Pacific Decadal Oscillation (PDO) appears to capture this low frequency variability in ENSO and can be useful in tracking large-scale regime shifts in Pacific Ocean sea surface temperature patterns (Mantua *et al*. 1997). A regime shift, as indicated by a change to positive PDO index values, occurred during the late 1970s which is coincident with the beginning of a period marked by strong El Niño

activity and above-normal winter precipitation in southern Arizona. This wet period may be ending with some indications of another regime shift in the Pacific Ocean during the late 1990s, which may change El Niño–winter precipitation relationships in the south-western USA. If conditions indeed tend toward below-normal or even average precipitation in the coming years, the statistical relationships developed between wildfire and climate, using data from the 1980s and 1990s, may experience diminished predictive ability. Drought conditions may then be more important in drying heavy fuels that drive large wildfires. The longer-term build-up of fine and medium size fuels spurred on by the wet conditions of the last several decades will only exacerbate conditions by ensuring fuel continuity across the landscape.

Conclusions

Wet antecedent conditions during seasons from 1 to 3 years before fire activity appear to be important in controlling fine fuel production. This relationship was observed in both the high elevation and low elevation datasets. Wet conditions most likely promote grass growth as fine fuels for lower elevation fires, but the mechanism related to upper-elevation fine fuel production is less clear. A complex interaction between different species producing different litter types (leaves, grasses, needles) further regulated by antecedent climate conditions may be occurring at upper-elevation sites.

Fuel conditioning did not appear to be as important as fuel production with respect to wildfire variability across our study area. No strong relationships between below-normal antecedent moisture levels and wildfire TAB or TNF were observed in either the high- or low-elevation datasets. Short-term drying of fine fuels is most likely facilitated by the hot and dry conditions normally experienced during the April–May–June fire season and may not show up as a strong negative correlation between wildfire and moisture variables. The exceptionally wet conditions of the study period may have also precluded strong dry signals (with respect to wildfire variability) from emerging in the analyses.

The quality of wildfire data strongly limits the inferences that can be drawn from analyses like the ones performed in this study. Lack of complete and detailed fire location information clouds potentially strong and insightful relationships between wildfire and climate. Knowing specifically where fires start and stop would help to characterize dominant fuel types that could then be related to antecedent climatic conditions. The ecosystem response through fuel production and conditioning to climate can only be weakly inferred using the current, poor quality of wildfire data.

Given these other factors, the importance of climate relative to wildfire variability will be different from location to location and through time, depending on the local land management history of the site. Fire–climate interactions are driven by processes through the continuum of climatic scales, but can be fundamentally understood only at the local scale after accounting for these non-climatic factors.

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