Accurate Quantification of Seasonal Rainfall and Associated Climate–Wildfire Relationships

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ABSTRACT

Wildfires are often governed by rapid changes in seasonal rainfall. Therefore, measuring seasonal rainfall on a temporally finescale should facilitate the prediction of wildfire regimes. To explore this hypothesis, daily rainfall data over a 58-yr period (1950–2007) in south-central Florida were transformed into cumulative rainfall anomalies (CRAs). This transformation allowed precise estimation of onset dates and durations of the dry and wet seasons, as well as a number of other variables characterizing seasonal rainfall. These variables were compared with parameters that describe ENSO and a wildfire regime in the region (at the Avon Park Air Force Range). Onset dates and durations were found to be highly variable among years, with standard deviations ranging from 27 to 41 days. Rainfall during the two seasons was distinctive, with the dry season having half as much as the wet season despite being nearly 2 times as long. The precise quantification of seasonal rainfall led to strong statistical models describing linkages between climate and wildfires: a multiple-regression technique relating the area burned with the seasonal rainfall characteristics had an R^2_{adj} of 0.61, and a similar analysis examining the number of wildfires had an R^2_{adj} of 0.56. Moreover, the CRA approach was effective in outlining how seasonal rainfall was associated with ENSO, particularly during the strongest and most unusual events (e.g., El Niño of 1997/98). Overall, the results presented here show that using CRAs helped to define the linkages among seasonality, ENSO, and wildfires in south-central Florida, and they suggest that this approach can be used in other fire-prone ecosystems.

1. Introduction

Fire is a pivotal disturbance process influencing ecosystems over much of the world's terrestrial surface (Chapin et al. 2002). How fire does this is fundamentally linked to climate cycles. For example, in seasonal environments large natural wildfires occur during the transitions between the dry and wet seasons, with the former desiccating and connecting fuels, and the latter producing lightning ignitions (Johnson 1992; Chu et al. 2002; Beckage et al. 2003; Riaño et al. 2007a; Slocum et al. 2007). Superimposed on these seasonal cycles are cycles of longer periodicity generated by climatic teleconnections. One of the most important teleconnections for fire is El Niño–Southern Oscillation (ENSO), whose effects on wildfires are conveyed by accentuating or diminishing the effects of seasonal climate (Williams and Karoly 1999; Chu et al. 2002; Le Page et al. 2008). In south Florida, for example, the cool La Niña phase of ENSO intensifies drought during the dry season, resulting in greater fuel connectivity and wildfire activity (Brenner 1991; Beckage et al. 2003). Thus, the current understanding of fire–climate relationships suggests that models that address both interannual and seasonal cycles will be more useful than models that address just one type of cycle.

To create such models, it is important for fire ecologists to use the most recent advances of climatologists.

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Such an approach has been conducted with a high degree of success for interannual cycles. For instance, in many regions it has been found that wildfires occur with a semiregular periodicity that corresponds with cycles of ENSO (e.g., Beckage et al. 2003). This understanding of the coupling of ENSO–wildfire cycles has been made possible by the development by climatologists and mathematicians of sophisticated models that address the formidable nonlinear dynamics involved [e.g., advances in spectral analysis; Ghil et al. (2002)]. This understanding has also depended on the collection of accurate and well-tested datasets describing ENSO (Philander 2004). Similarly, the in-depth study of ENSO has spurred the discovery of other teleconnections, and these have been used to predict wildfires in a wide variety of regions [e.g., the Pacific decadal oscillation in Alaska, the Arctic Oscillation in Siberia, and the Indian Ocean dipole in the tropics; see sources in Riaño et al. (2007b) and Le Page et al. (2008)]. Other investigations have shown that teleconnections can interact to influence wildfire regimes (Kitzberger et al. 2007).

In parallel with these advances involving interannual cycles, climatologists have also made notable advances with the modeling of seasonal cycles. These models use a broad range of climate parameters (e.g., rainfall, shifts in the intertropical convergence zone) and high-resolution temporal data to estimate when seasons start, end, and peak, as well as their duration (Camberlin and Diop 2003; Stewart et al. 2005; Slocum et al. 2007; also see sources in Lima and Lall 2009). Further, some studies have examined how seasonal onset dates are associated with teleconnections (e.g., Lima and Lall 2009). Because all of these recent efforts have estimated precise timing of shifts in seasonal climate, they may be useful for improving models that examine wildfires. However, these advances in understanding seasonal cycles have rarely been incorporated into studies of fire ecology [but see Westerling et al. (2006) for a notable exception].

In this manuscript we present a case study in which we relate the results of a high-resolution seasonal analysis to descriptors of a wildfire regime. Our study took place at the Avon Park Air Force Range (APAFR) in south-central Florida, a region that has dry and wet seasons that are generally, but not always, well defined in terms of rainfall (Chen and Gerber 1990). Lack of rainfall during the dry season produces well-connected fuels and allows for landscape-level wildfires, especially during droughts induced by La Niña (Beckage et al. 2003). Understanding how ENSO relates to patterns in rainfall is essential, therefore, for prediction of fires in this region. The approach we selected to investigate this system was developed by Camberlin and Diop (2003), and uses cumulative rainfall anomalies (CRAs) to delimit seasonal onset dates and durations. We asked the following questions:

1) How variable are seasonal onset dates and durations at the study site? How distinct are the wet and dry seasons in terms of characteristics of rainfall?
2) How does ENSO influence seasonal rainfall? Does ENSO appear to be associated with the durations of the dry and wet seasons and their onset dates? Do these associations appear to affect rainfall amounts or other seasonal rainfall characteristics?
3) Does the precise estimation of the durations of seasons and rainfall facilitate the development of statistical models describing wildfire activity at the APAFR?
4) How does the CRA approach compare to that of a more traditional approach that uses standardized seasonal spans to understand wildfire regimes? Does the CRA approach produce additional and valuable insights into the relationships between seasonal climate, ENSO, and wildfires in the region?

This manuscript is organized as follows. In section 2, we present our data and methods, including a description of the APAFR, how rainfall data were converted to CRAs, and how the resultant patterns in seasonal rainfall were statistically related to ENSO and the APAFR's wildfire regime. In section 3 we present the results of these analyses, and we interpret these results in section 4. We conclude the manuscript in section 5 with some assertions of why accurate quantification of rainfall is important for understanding the connections among seasonal climate, ENSO, and wildfires.

2. Data and methods

a. Study site

The APAFR is a 42 000-ha military installation covering large parts of Polk and Highland counties in south-central Florida (27°35′N, 81°16′W) (Fig. 1). The installation, despite being generally low in elevation, has subtle elevation gradients that demark distinct plant communities of varying flammability and hydroperiod (Orzell and Bridges 2006; Platt et al. 2006). Pine savannas and dry prairie occur at upper elevations and are highly flammable communities with short hydroperiods. At lower elevations lie wet prairie and marshes, which are flooded for substantial parts of the year and are the least flammable.

The installation was established in World War II for the purpose of practicing bombing, strafing, and related missions. It is still active, and given favorable weather conditions, numerous wildfires are started by ordnance as well as by lightning. Wildfires generally occur from

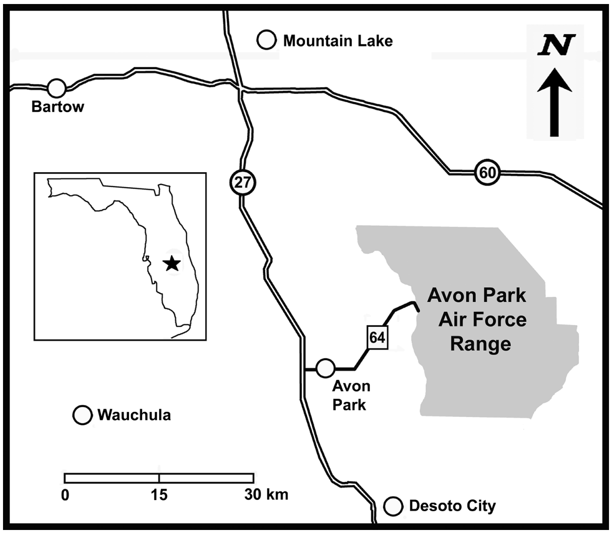

FIG. 1. Location of the Avon Park Air Force Range in south-central Florida in relationship to five rainfall stations (labeled with white filled circles) and major highways. The star in the insert shows the location of the installation within the state of Florida.

January to August, but the largest fires occur during the transition between the dry and wet seasons (Slocum et al. 2007; APAFR fire records). The reason that large fires occur at this time is because fuels tend to be very dry and well connected during this period (Slocum et al. 2003, 2010; Beckage et al. 2005). Smaller ordnance fires tend to occur earlier in the dry season (January–April), while smaller lightning fires tend to occur later in the wet season as this period has frequent lightning strikes but moist and disconnected fuels (Duncan et al. 2010).

b. Seasonal characteristics of rainfall

Camberlin and Diop (2003) developed the CRA approach to identifying wet-season onset dates in Senegal, where such information is useful for agriculture. The approach converts rainfall data into a waveform, thereby allowing investigators to easily visualize onset dates and durations of seasons within any given year. Useful parameters describing rainfall can then be estimated accurately within each precisely defined season. We tailored Camberlin and Diop's (2003) approach so that it delimited the spans of the dry season, something of obvious importance for describing linkages with ENSO and wildfires in southern Florida (Beckage et al. 2003; Slocum et al. 2007). The specific steps we took were as follow:

1) We collected daily rainfall data over 58 yr (1950–2007) from five rainfall stations within 60 km of the APAFR (Fig. 1). Five stations were used, rather than one, to address the spatial variation in the precipitation. Pearson correlations among the stations over the period of study varied from 0.35 to 0.60. These correlations were weakest during summer–wet-season months, when convective thunderstorms resulted in rainfall at some stations but not others. The stations were all part of the cooperative network operated by the National Oceanic and Atmospheric Admission. Data were obtained from the National Climatic Data Center (information online at http://cdo.ncdc.noaa.gov/CDO/dataproduct; station names were Avon Park 2, Bartow, Desoto City, Mountain Lake, and Wauchula).
2) The time series from these stations had <1% missing data. Missing data were filled in by the following process: (a) for a given station, missing values on days when all other stations had no rain were assigned a 0, and (b) if other stations had rain, we gave the station an estimate of the rainfall derived from multiple imputation [MI procedure, SAS release 9.1, SAS Inc., Cary, North Carolina; Rubin (1996)].
3) For each day of rainfall, we took the natural-log transformation of the mean of the five stations. This transformation emphasized the influence of frequent and smaller amounts of rainfall in data interpretation and decreased the influence of infrequent, large rainstorms (Camberlin and Diop 2003). This emphasis on steady rainfall is important because such rainfall is more likely to influence wildfires in the region than large rainstorms, as soils have limited ability to absorb rain, and excess water from large storms results in surface runoff (Albertson et al. 2009). The transformation did not deemphasize large storms to the extent that the patterns they generated became difficult to identify.
4) We took the mean of the log-transformed daily rainfall over the entire time series. We then subtracted this value from each record, producing rainfall anomalies. Next, we added these anomalies consecutively, starting with the first day of the time series, producing daily values of CRAs.
5) Using CRAs, changes in rainfall and the onset dates of the seasons could be readily visualized, as depicted in Fig. 2a. In any given year the dry season was characterized by a consistent decrease in CRAs, the result of consecutively adding negative rainfall anomalies. Conversely, the wet season was characterized by a consistent increase in CRAs, the result of adding positive anomalies. Where these upward and downward trends met within a given year was at the CRA minimum for that year, and this minimum was used to define the onset of the wet season (as per Camberlin and Diop 2003) This method produced reliable estimates

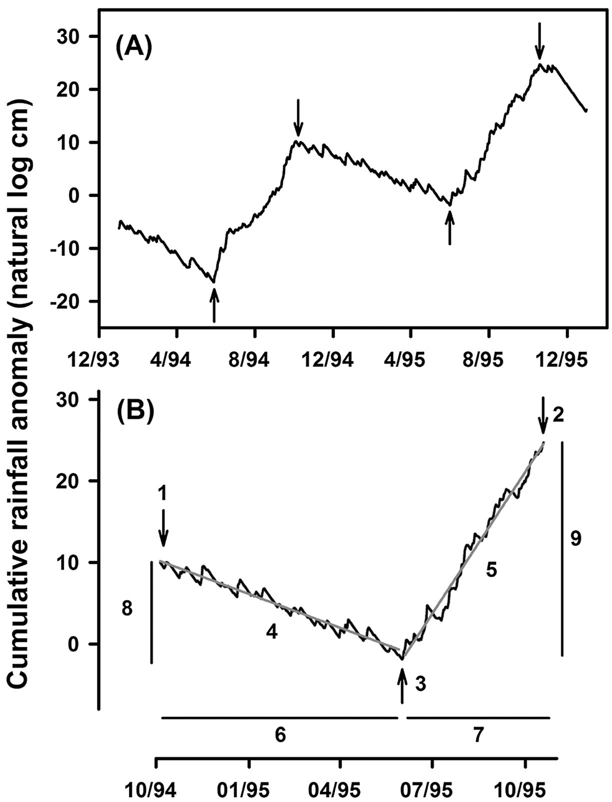

FIG. 2. Examples of CRAs (black jagged lines). (a) CRAs for 1994 and 1995. Upward arrows indicate onset dates of the wet season and downward arrows indicate onset dates of the dry season. (b) Seasonal characteristics of the fire year of 1995, with the fire year being defined as lasting from the beginning of the dry season of 1994 (arrow 1) to the end of the wet season of 1995 (arrow 2). Onset date of the wet season is estimated as the minimum CRA within the fire year (arrow 3). Onset dates defined seasonal spans and allowed other parameters describing seasonality to be estimated within them. These included rainfall accumulation rates (ΔCRA day^{-1}; black segments 4 and 5, estimated using linear regression), durations (in days; black segments 6 and 7), and total rainfall (ΔCRA; black segments 8 and 9). The R^2 scores from regressions were used to estimate the consistency of the drying trend in the dry season and of the moistening trend in the wet season.

for most years, as most years had a unimodal rainfall pattern (e.g., Fig. 2a). Some years, however, were bimodal and therefore had two CRA minima. For each of these years we selected the second minimum to denote the onset, as this minimum occurred immediately before the upward trend denoting the wet season. This second minimum also more closely corresponded with the timing of the minima found in unimodal years.

6) The onset date of the dry season was estimated where the upward trend of the wet season met the downward trend of the dry season (i.e., at annual CRA maxima). There were no problematic values for any year in the time series for estimating this variable.
7) We used onset dates to define ‘‘fire years,’’ periods spanning from the start of the dry season of one calendar year until the end of the wet season of the next calendar year. Fire years thus incorporated full fire seasons, which generally extended from January to August at the study site. This incorporation of fire seasons within fire years resulted in a straightforward interpretation of patterns (cf. Beckage et al. 2003).
8) Once seasonal spans were defined, we derived four additional characteristics describing rainfall during each season. Two of these characteristics were season duration and total rainfall (Fig. 2b). The third characteristic was rainfall accumulation rate (ΔCRA day^{-1}), which was obtained using the slope (parameter estimate) obtained from a linear regression using day of the fire year as the independent variable and CRA as the dependent variable (Fig. 2b). The fourth characteristic was ‘‘trend consistency,’’ which described how consistent the drying and moistening trends were during the dry and wet seasons, respectively. Trend consistency was estimated using the R^2 scores from the regressions used to estimate rainfall accumulation rates. For example, if the downward trend in CRAs during the dry season was smooth, then that dry season had a high R^2 score, but if the season was interrupted by periodic rainfall, its score fell. Likewise, during the wet season, trend consistency was high when there was a smooth upward trajectory of CRAs but fell if the trend was interrupted by ‘‘dry spells.’’

The characterization of seasonality based on the CRA approach was compared to that of a commonly used approach that uses standardized monthly spans. We call this latter technique the monthly approach. In this method the spans of the two seasons are estimated using mean monthly rainfall. These means were calculated by first summing the daily rainfall for each month of each year, and then by taking the mean of these sums for each month over the 58 yr of the time series. The seasons were then defined based on which months clearly had more or less average rainfall; for example, if August and September were found to have half the average rainfall as the rest of the months, then these months were assigned to the dry season and the rest of the months to the wet season. The resultant seasons were standardized in the sense that they had fixed durations for every year, as well as onset dates that were fixed to occur on the first day of the first month of each season. The total rainfall for each season of each year was calculated by summing the daily rainfall over the standardized spans.

c. Relationships between ENSO and seasonal characteristics

ENSO was described using the Niño-3.4 index. This index has been used in several studies describing climate in the region (Enfield et al. 2001; Schmidt et al. 2001), and we chose it over other ENSO indices because we found it to be more predictive of rainfall. The index is derived from anomalies in sea surface temperatures in the equatorial Pacific Ocean at 5°N–5°S and 120°–170°W. Monthly values from January 1950 to December 2007 were obtained from the National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (information online at http:\\www.cpc.ncep.noaa.gov\data\indices). ENSO was described by taking the mean of the Niño-3.4 values over the CRA-defined spans of each season. Because these spans started and ended within months, we adjusted the calculations so that incomplete months were proportionately weighted. For example, if a dry season was found to span from 1 March to 12 June, then the Niño-3.4 values of March, April, and May would be fully weighted in the calculation, but only 12/30th of the value for June would be used (i.e., 12 out of the 30 days in June).

We used linear regressions to compare ENSO with seasonal rainfall characteristics. For these regressions the normality of the residuals was examined using box and scatterplots, and when necessary transformations were applied to improve the normality and to linearize the models. In some cases data distributions were highly negatively skewed, so we first reflected the distribution before applying a transformation (Howell 1987). We paid close attention to outliers in the distributions, as they proved to be important for understanding the role of ENSO. All regressions were done using the REG procedure of SAS release 9.1.

The results revealed using regressions were further described using graphs of CRAs during fire years undergoing different ENSO phases. We assessed which seasons were undergoing particular phases based on the criteria of NOAA's Climate Prediction Center (information online at http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml). This criterion uses the oceanic Niño index (ONI), which is the 3-month running mean of Niño-3.4. El Niño events are indicated when there are five consecutive months with ONI values $\geq$0.5°C, and La Niña events are indicated when there are five consecutive months with values ≤ -0.5°C. All other periods are considered ENSO neutral. See Kousky and Higgins (2007) for more detail.

We compared the results of the CRA approach with those of the "monthly approach." For this latter approach, ENSO during the dry season was estimated using the mean of the monthly Niño-3.4 values over December–February. This technique is a standard way of estimating the intensity of ENSO, as anomalies in sea surface temperatures generally reach their highest levels in the equatorial Pacific during these months (Swetnam and Betancourt 1990). ENSO during the wet season was estimated using the mean of Niño-3.4 over the months determined to constitute the wet season. Estimates of ENSO were compared to rainfall amounts using linear regression.

d. Relationships between seasonal characteristics and wildfires

We described the wildfire regime at the study site by summing the number of wildfires and the total area burned for each fire year. Data were obtained by using the APAFR's fire records (1978–2007). To examine how the number of fires and the area burned related to climate, we conducted multiple regressions using an information-theoretic approach (Burnham and Anderson 2002). This approach is especially appropriate for observational studies where it is not feasible to control explanatory variables. In this approach, numerous models are produced that describe the associations between wildfire activity and seasonal rainfall. For each model statistics are produced describing "model uncertainty," that is, the likelihood that the model is the most predictive of the set of models tested. Uncertainty in parameter estimates is also addressed by examining how they vary over the models; this is done using a procedure called model averaging. Model averaging results in parameter estimates with improved precision and reduced bias when compared to estimates produced by approaches where a single "best" model is produced (e.g., stepwise regression) (Anderson et al. 2000). Our goal was to build predictive, hypothesis-generating models for the wildfire regime at the APAFR. The specific steps we took are as follow:

1) In exploratory analyses we found that wildfire activity during a given fire year was mostly associated with two seasons: the dry season within the current fire year and the wet season preceding the fire year. We therefore constructed models using seasonal rainfall characteristics of these two seasons, yielding a total of eight independent variables (rainfall, trend consistency, onset date, and duration of both the current dry season and previous wet season).
2) We used multiple regression to examine how these eight variables were related to the area burned and the number of wildfires. We limited the number of seasonal characteristics included in any one model to four, producing a total of 165 models for each dependent variable. For the sake of parsimony we did not include

several variables in these models. One variable not included was rainfall accumulation rate, as this variable is essentially a transform of season duration and total rainfall. We also did not include variables describing ENSO, as ENSO is a higher-order phenomenon whose contribution to the variation of the wildfire parameters was already adequately ''represented'' by rainfall variables or combinations of rainfall variables. (Such relationships would be more adequately modeled using a structural equation model, which is beyond the scope of this study.)

3) For each model produced, we determined its second-order Akaike information criterion (AIC_c), which is designed for datasets with small sample sizes (Akaike 1973). We addressed the uncertainty in our model selection by calculating Akaike weights (w_i) for each model. This statistic varies from 0 to 1 and represents the chance for a given model to be the ''best approximating model'' among the 165 models tested.
4) We used model averaging to address uncertainty in parameter estimates. In this technique, each parameter estimate of each model is multiplied by the Akaike weight of that model. These weighted parameter estimates are then summed over all models to produce model-averaged parameter estimates. Standard errors and 95th confidence intervals around each model-averaged estimate were also derived to provide estimates of effect size [i.e., the strength, precision, and potential significance of an independent variable; see formulas in Burnham and Anderson (2002)].
5) We also determined the ''relative importance'' [$w_+(j)$] of each seasonal characteristic, that is, the importance of a given characteristic relative to the other characteristics included in the full set of models. Relative importance was calculated as the sum of the Akaike weights over all the models in which the characteristic occurred.
6) A characteristic of seasonal rainfall was considered to be important when it had a high relative importance value and a 95th confidence interval that did not include 0 (Burnham and Anderson 2002). Once we determined which variables were important, we further examined them by adding them together into a multiple-regression model. We report the adjusted R^2 scores of these models.
7) We compared these R^2 scores to the scores produced by the monthly approach. This latter set of scores was derived from linear regressions comparing the area burned and the number of wildfires to rainfall amounts of the current dry season and previous wet season (as estimated within standardized seasonal spans).
8) For some analyses it was important to address results that were generated by strong leverage points–outliers associated with ENSO. In these cases it was sometimes necessary to remove the associated fire years to demonstrate trends. We explain these special cases in detail.

3 Results

a. *Seasonal characteristics of rainfall*

The CRA approach described the average wet season as lasting from 21 May to 1 October (a duration of 134 days), and the average dry season as lasting from 2 October to 20 May (a duration of 230 days) (Table 1). The average fire year therefore lasted from 2 October of one year to 1 October of the next year. The variation in the onset dates and seasonal durations was considerable, with onset dates having standard deviations of almost a month and seasonal durations having standard deviations of more than a month (Table 1). Moreover, the influence of statistical outliers related to ENSO was important. For example, one fire year (1997) was associated with an El Niño episode that is sometimes referred to as the ''Super El Niño'' (Philander 2004). When we removed this fire year from the time series, the standard deviation of the dry-season onset date dropped from 27 to 14 days (Table 1).

We estimated rainfall within these precisely delimited seasons. Average rainfall during the dry season was estimated to be about half that during the wet season (Table 1). Over successive years there were sharp differences in dry-season and wet-season rainfall, with some years being particularly striking (e.g., during the Super El Niño) (Fig. 3a). There were just a few years when the rainfall during the two seasons was found to be similar (e.g., 1973). Rainfall accumulation rates were less pronounced for the dry season than the wet season, indicating that desiccation during the dry season was more gradual than moistening during the wet season. These trends of desiccation and of moistening were highly consistent, as indicated with trend consistency estimates (R^2 scores) that were >0.90 for both seasons (Table 1). The drying trend, however, tended by be more readily interrupted by ''wet spells'' than the wet season was interrupted by ''dry spells''; this result was shown by a higher standard deviation for dry-season trend consistency than the standard deviation for wet-season trend consistency (Table 1). Many of the dry seasons that had wet spells were undergoing strong ENSO episodes that were associated with statistical outliers (Table 1). These outliers are explained in more detail in section 3b.

We contrasted this description of seasonal rainfall produced by the CRA approach with one produced by the monthly approach (i.e., an approach that is based on standardized monthly spans). To determine these standardized spans, we took the average rainfall per month

TABLE 1. Means and standard deviations (SD) of five parameters describing dry-season and wet-season rainfall. Fire years falling outside of normal distributions (outliers) are also indicated, and estimates without these fire years are shown in parentheses.

Seasonal characteristics	Dry season Mean	Dry season SD	Dry season Outliers	Wet season Mean	Wet season SD	Wet season Outliers
Onset date (day of year)	275* (272)	27 (14)	97	141* (144)	24 (18)	57, 59
Duration (days)	230 (232)	35 (30)	98	134 (131)	41 (30)	97
Total rainfall (cm)	42	15		89 (88)	27 (22)	97
Accumulation rate (ΔCRA day^{-1})	−0.10	0.04		0.18	0.05	
Trend consistency (R^2)**	0.91 (0.94)	0.16 (0.08)	58, 83	0.93	0.06	

* Day of year 275 = 2 Oct and day 141 = 21 May.
** The R^2 score of a linear regression using day of fire year to predict CRAs for each season.

over the time series. Rainfall was found to average >17 cm for 4 months (June–September) and to average <10 cm for the remaining 8 months. The approach therefore designated the wet season as lasting from 1 June to 30 September, a duration of 122 days, and the dry season as lasting from 1 October to 30 May, a duration of 243 days (Table 1).

When we compared these seasonal spans to the average spans estimated by the CRA approach, we did not find much difference. The monthly approach's estimate of the average onset date of the dry season was 1 day earlier (1 versus 2 October) and its estimate of the average onset date of the wet season was 11 days later (1 June versus 21 May; Table 1). These differences translated into a wet season that was 12 days shorter and a dry season that was 12 days longer (on average) when compared to the CRA approach's estimates.

While these differences were small, the considerable variation in onset dates and durations indicated by the CRA approach meant that the two approaches assigned many days to different seasons. When we examined this ''difference in assignment'' directly, we found that it averaged 33 ± 35 days [±1 standard deviation (SD)] per fire year, and ranged from 0 days in 1967 and 1986 to 222 days during the Super El Niño (1997). These differences in assignment resulted in the monthly approach not accentuating the contrast between wet and dry seasons as much as the CRA approach. The monthly approach described the dry season as having, on average, 74% of the rainfall as the wet season; this number, however, was only 47%

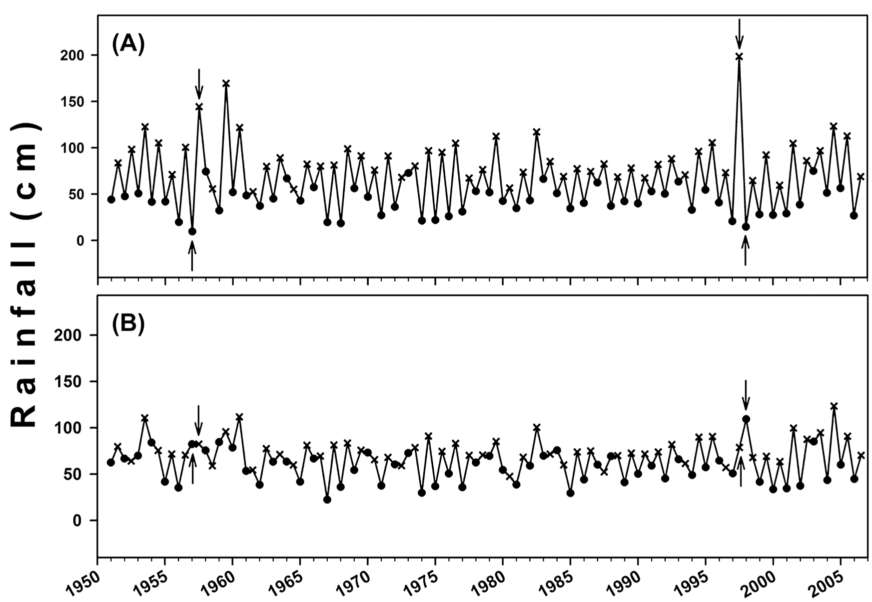

FIG. 3. Seasonal rainfall estimated using the (a) CRA and (b) the monthly approaches. Dry-season rainfall (solid filled circles) was usually, but not always, indicated with dips in rainfall, while wet-season rainfall (exes) was usually indicated with peaks. Arrows point to seasons that the CRA approach described as having unusual durations that coincided with strong El Niño events.

when using the CRA approach (Table 1). Also, compared to the CRA approach the monthly approach described many dry seasons as having just as much rainfall, or even more rainfall, as the wet season; the most prominent examples of this occurred during the fire years 1957, 1997, and 1998 (Fig. 3b). Rainfall during these unusual fire years turned out to have important relationships with ENSO; this relationship is covered in the next subsection.

b. Relationships between ENSO and seasonal rainfall

ENSO had a strong influence on rainfall during the dry season. As the Niño-3.4 index increased, the rainfall amount and accumulation rates increased, and the consistency of rainfall decreased (Table 2). This finding meant that more moisture arrived in the dry season during El Niño events and drier conditions were produced during La Niña events. More information about this result was obtained by examining graphs of CRAs during different ENSO phases. These graphs revealed that dry seasons undergoing El Niño conditions had peaks of rainfall that interrupted the drying trend, thereby increasing the total rainfall and lowering the trend consistency (e.g., 1987; Fig. 4). During stronger El Niño episodes, these peaks blended together to create an additional ''hump'' of rainfall in the middle of the dry season, thereby producing a bimodal rainfall pattern (e.g., 1983; Fig. 4). These bimodal fire years explained a number of the statistical outliers detailed in Table 1 (1958, 1959, and 1983), and they contrasted markedly with the unimodal pattern typical of ENSO neutral years, during which peaks in CRAs were reduced in number and strength (e.g., 1990; Fig. 4). When the dry season was undergoing La Niña conditions, rainfall was much reduced, resulting in steeply falling CRAs and a further reduction in the number and strength of the peaks in rainfall (e.g., 1989; Fig. 4).

In contrast with the dry season, ENSO was not strongly associated with characteristics of the wet season (Table 2). There was a slight indication that El Niño conditions produced a greater tendency for the wet season to have inconsistent rainfall (Table 2).

We also examined the relationships between ENSO and seasonal onset dates and durations. In examining these relationships we reasoned that if ENSO was associated with the duration of a season, then the upcoming season would have a correspondingly longer or shorter season to compensate, along with a shift in its onset date. No statistically significant relationships emerged that suggested that ENSO produced these effects (Table 2). In performing these analyses, however, we found that there did appear to be important relationships between ENSO and the onset dates and durations during the fire years already mentioned as being unusual (1958, 1997, and 1998). These effects appeared to be generated when strong El Niño conditions produced heavy rainfall during the dry season in such a way that it blended in with rainfall of the prior or subsequent wet season. For example, in 1957 heavy rainfall arrived during a strong El Niño in April–May, and this rainfall blended in with rainfall arriving in June–October (Fig. 4). The CRA approach therefore generated an early onset date of the wet season for this fire year, as well as a shortened dry season (see outliers in Table 1). A second, more important, example involved the Super El Niño of 1997/98. Starting in the wet season of 1997, this event resulted in heavy rainfall that did not end in October as in typical years, but instead persisted until March of the next year (Fig. 4). This event therefore produced the longest and moistest wet season during the period of record (Table 1; Fig. 3a). It also ''squeezed'' the ensuing dry season (of 1998) such that it was the shortest on record (lasting 102 days compared to a mean of 230 days; see Table 1 and Fig. 4).

TABLE 2. Results of linear regression comparing the intensity of ENSO during the dry and wet seasons with rainfall characteristics of those seasons. Shown are R^2 scores and p values. Signs of the R^2 scores indicate positive and negative associations. Here, ln indicates data normalized using a natural-log transformation, N.S. indicates not significant, r indicates data normalized by being reflected and then natural-log transformed (see text, section 2c), s indicates data normalized using a square root transformation, and ^2 indicates data squared to adjust for negative skew.

	Dry season		Wet season	
Seasonal characteristics	R^2	p value	R^2	p value
Total rainfall	+0.42	≤0.0001	+0.10 (ln)	≤0.05
Accumulation rate	+0.54	≤0.0001	−0.01	N.S.
Trend consistency	−0.51 (r)	≤0.0001	−0.20 (r)	≤0.001
Onset date	−0.00	N.S.	−0.02 (s)	N.S.
Duration	+0.02 (^2)	N.S.	+0.07 (ln)	N.S.

We compared these statistical relationships between ENSO and seasonal rainfall, as generated by the CRA approach, with the relationships revealed when a more traditional monthly approach was used. For the dry season, this approach described ENSO using the average of the Niño-3.4 index over December–February. We found that these averaged values were positively related to dry-season rainfall ($R^2 = 0.36$). For the wet season we estimated ENSO using the mean of the Niño-3.4 values over the months of June–September. These averages were not found to be associated with wet-season rainfall ($R^2 = 0.03$). Overall these R^2 scores were similar to those produced by the CRA approach (Table 2), and thus the monthly approach described similar associations between ENSO and seasonal rainfall amounts.

However, when we examined how the monthly approach described rainfall patterns during the unusual

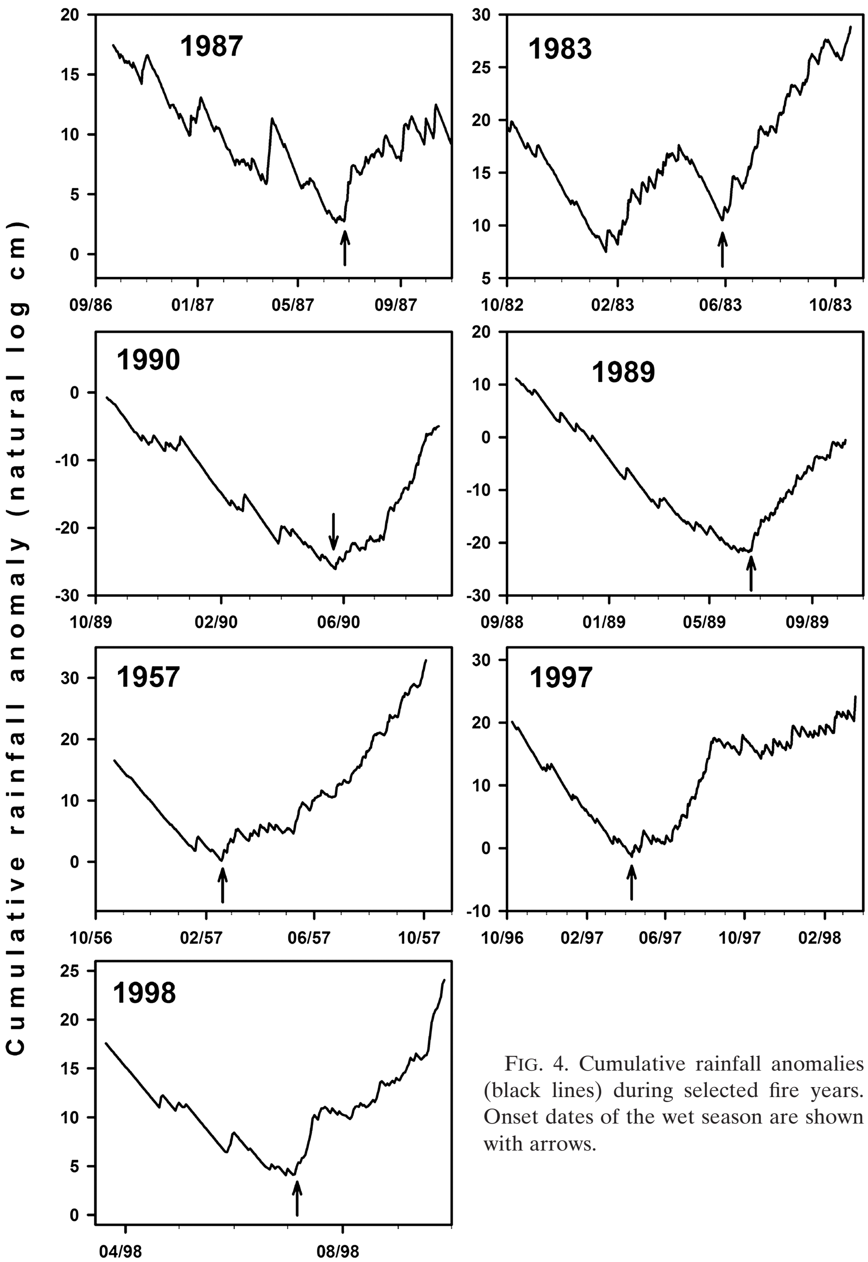

FIG. 4. Cumulative rainfall anomalies (black lines) during selected fire years. Onset dates of the wet season are shown with arrows.

fire years, we found that it revealed patterns that were the opposite of those revealed by the CRA approach. For example, the monthly approach described the dry season of 1998 as having intense El Niño conditions, with a sea surface temperature anomaly in the Niño-3.4 region of 2.01°C, the second highest value over the period of study. These conditions corresponded with record levels of rainfall over the standardized dry season (October 1997–May 1998) (Fig. 3b). The CRA approach, on the other hand, estimated the dry season of 1998 as spanning a much different period, from the end of March 1998 to the end of June 1998. ENSO during this period was in a neutral phase (0.41°C) and rainfall was very low (Fig. 3a). Similar opposing patterns between the monthly and CRA approaches were found for 1957 (cf. Figs. 3a and 3b). It was therefore clear that it was during the more unusual episodes of ENSO that the two approaches differed in how they described rainfall.

c. *Associations between seasonal rainfall and the wildfire regime*

We described the wildfire regime at the APAFR by summing the area burned and the number of wildfires within fire years. This description of the wildfire regime

TABLE 3. Results of model averaging of multiple-regression analyses describing how the area burned (top section) and number of fires (bottom section) were associated with seasonal rainfall characteristics. Seasonal characteristics found to be important are set in boldface. Here, $w_+(j)$ = relative importance, $\widehat{\overline{\beta}}_j$ = the model-averaged parameter estimate, $\widehat{\text{se}}$ = the unconditional standard errors, CI = confidence interval, pws = the wet season preceding the fire season, cds = dry season that occurs within the current fire season, s = data normalized using a square root transformation, ln = data normalized using a natural-log transformation, ^2 = data squared to adjust for negative skew, and r = data reflected and then natural-log transformed to adjust for negative skew (see text, section 2c).

Seasonal characteristic (j)	$w_+(j)$	$\widehat{\overline{\beta}}_j$	$\widehat{\text{se}}$	95% CI	
		Area burned (s)			
Consistency (pws) (r)	**0.98**	**−12.7**	**3.8**	**−5.3**	**−20.2**
Rainfall (cds)	**0.96**	**−0.91**	**0.24**	**−0.43**	**−1.39**
Duration (cds) (^2)	**0.73**	**0.0005**	**0.0002**	**0.0010**	**0.0001**
Rainfall (pws)	0.19	10	12	34	−14
Consistency (cds) (r)	0.17	0.31	5.5	11.0	−10.4
Duration (pws)	0.15	2.5	18	38	−33
Onset (pws)	0.14	−0.0004	0.0005	0.0006	−0.0014
Onset (cds) (ln)	0.10	2.4	54	108	−103
		No. of wildfires (s)			
Consistency (pws) (r)	**0.98**	**−1.02**	**0.27**	**−0.49**	**−1.55**
Onset (pws)	**0.98**	**-1.6×10^{-4}**	**4.4×10^{-5}**	**-7.4×10^{-5}**	**-2.5×10^{-4}**
Duration (pws)	**0.74**	**−3.2**	**1.1**	**−1.0**	**−5.3**
Rainfall (cds)	**0.57**	**−0.033**	**0.015**	**−0.003**	**−0.063**
Rainfall (pws)	0.26	−2.23	0.96	0.34	−4.11
Duration (cds) (^2)	0.11	-1.8×10^{-5}	3.3×10^{-5}	4.6×10^{-5}	-8.2×10^{-5}
Consistency (cds) (r)	0.07	−0.05	0.29	0.53	−0.62
Onset (cds) (ln)	0.05	0.21	4.01	8.07	−7.65

was then statistically compared to the CRA approach's characterization of seasonal rainfall using multiple regression and an information-theoretic approach. For the area burned, this analysis found that three seasonal rainfall characteristics—dry-season rainfall, dry-season duration, and consistency of rainfall in the previous wet season—had high relative importance values and strong effect sizes [i.e., $w_+(j)$ values ≥0.73 and 95th confidence intervals that did not include 0; see top section of Table 3]. The analysis therefore suggested that more area burned when the dry season was longer and had less rainfall, as well as when rainfall during the previous wet season was inconsistent. The other seasonal rainfall characteristics did not appear important, having relative importance values ≤0.19 and confidence intervals that included 0 (top half of Table 3). The area burned, therefore, did not appear to be associated with the consistency of the drying trend, or to when the seasons started and ended, or with how much rainfall arrived during the previous wet season.

Based on this information, we examined the results of a multiple regression examining how the area burned was associated with the three seasonal characteristics designated as important. This model explained a large proportion of the total variance in the data ($R^2_{\text{adj}} = 0.61$). The bulk of the explained variance was attributed to dry-season rainfall (partial $R^2_{\text{adj}} = 0.41$; see Fig. 5a), and smaller proportions were attributed to the consistency of moistening in the previous wet season (partial $R^2_{\text{adj}} = 0.12$) and dry-season duration (partial $R^2_{\text{adj}} = 0.07$).

In examining the number of wildfires, we found that four seasonal rainfall characteristics were important. These included three characteristics of the previous wet season (rainfall consistency, onset date, and duration) and one characteristic of the dry season (rainfall amount) [$w_+(j)$ values ≥0.56 and 95th confidence intervals that did not include 0; see bottom section of Table 3]. This result indicated that more wildfires occurred after wet seasons that were shorter, started earlier in the year, and had inconsistent rainfall, and when the dry season had less rainfall. The other four seasonal characteristics were not found to be important (relative importance values <0.27; see bottom half of Table 3). When we included the four important seasonal characteristics in a multiple-regression model, we found that the model explained about half the variation in the data ($R^2_{\text{adj}} = 0.56$). The consistency of rainfall during the previous wet season accounted for about half of this explained variation (partial $R^2_{\text{adj}} = 0.24$). The other three seasonal characteristics collectively accounted for the other half (onset of the previous wet season, partial $R^2_{\text{adj}} = 0.09$; previous wet-season duration, partial $R^2_{\text{adj}} = 0.13$; dry-season rainfall, partial $R^2_{\text{adj}} = 0.09$).

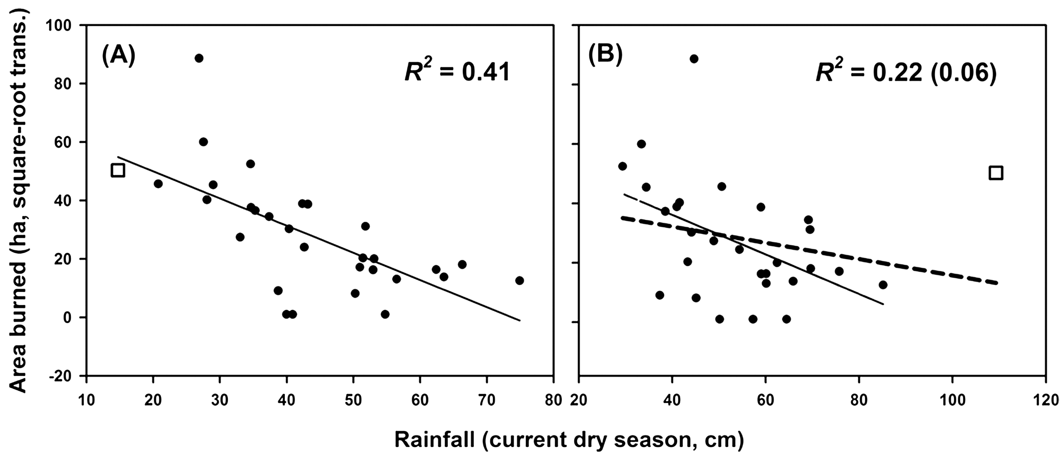

FIG. 5. Relationships between the area burned and the dry season rainfall when using the (a) CRA and (b) monthly approaches. Data for individual fire years are shown as black filled circles, and predicted values produced by linear regression are shown with black lines. The area burned during the fire season associated with the Super El Niño of 1997/98 is shown with a square symbol. In (b), the black dashed line shows predicted values when the Super El Niño is included in the dataset. The R^2 scores of the linear regressions are also reported, with the score of the dashed line shown in parentheses.

To demonstrate the effectiveness of the CRA approach in describing climate–wildfire relationships, we compared its results to those generated by the monthly approach. This latter approach found that less area burned when the dry season and the previous wet season had more moisture (previous wet-season rainfall, $R^2 = 0.14$; dry-season rainfall, $R^2 = 0.22$; see Fig. 5b). The statistical comparison with dry-season rainfall, however, was only predictive when the fire season associated with the Super El Niño was removed from the dataset. For the number of fires, the monthly approach found a slight negative effect of previous wet-season rainfall ($R^2 = 0.15$), and no effect for dry-season rainfall ($R^2 = 0.003$).

4. Discussion

a. *Relationships between wildfires and seasonal rainfall*

The use of CRAs (Camberlin and Diop 2003) to describe seasonal rainfall resulted in improved understanding of how climate affected the wildfire regime of our study site (APAFR) in south-central Florida. The approach generated a number of variables that precisely described the seasonality of rainfall, and when these variables were incorporated into statistical models, they accounted for roughly half of the variation in the data describing the area burned and the number of wildfires. This is a considerable proportion of the total ''explained'' variation considering the large number of other factors that drive wildfires in the region (e.g., fuel loads, management effects, and differences in ignition sources).

Why did the CRA approach result in effective predictive models? Because the approach is specifically designed to identify onset dates for each year of study, it tended to accurately assign wetter days to the wet season and drier days to the dry season. In south Florida this fine-tuning of assignment of days to seasons is important because the timing of the largest wildfires is also fine-tuned, being clustered around the onset of the wet season. For example, a study examining the wildfires in the Everglades (just south of the APAFR) found that 53% of the total area burned by lightning fires was by fires starting within a week of wet-season onset (Slocum et al. 2007). Fires starting 7–21 days after onset burned an additional 36% of the total area burned. Wildfires burn large areas during this short time period for a number of reasons. First, compared to the rest of year, this period is more likely to have favorable fire weather, such as combinations of low relative humidity and intense levels of solar radiation (M. G. Slocum et al. 2010, unpublished data). This period is also more likely to have available fuels, the result of cumulative desiccation and the lowering of water levels over the dry season (Slocum et al. 2003, 2007; Beckage et al. 2005). Finally, this period also has thunderstorms that produce lightning ignitions. These thunderstorms, however, can also produce deluges that end favorable fire conditions in just a matter of days, thereby severely constraining the ''window of opportunity'' for large wildfires. Because of the importance of the period around onset, and the fact that the timing of this period varies considerably from year to year, it is clearly important to estimate the onset date precisely for each year of study in the region.

A second reason for the effectiveness of the CRA approach was that it provided a full description of the seasonal rainfall, including estimates of rainfall consistency, onset dates, and durations. This full description proved to be important for generating possible explanations for why wildfire activity varied among years. For example, more area burned when dry seasons were longer, probably because longer dry seasons provided more time for ignitions to occur and for fuels to become dry and well connected (Westerling et al. 2006; Gill and Allan 2008). Similarly, we found that wildfire ignitions occurred less frequently after wet seasons that had consistent rainfall, were longer, and started later in the year. The reason for this effect is unknown, but we suggest that it depends on how dry and connected fuels were during military training missions. These missions tend to be conducted more frequently in January and afterward (after holiday break), and their ability to ignite fires may be reduced after wet seasons that end with particularly moist fuel conditions.

Our results are similar to other studies that examined how wildfire regimes were related to seasonal spans. For example, in a study in the northern Rocky Mountains, Westerling et al. (2006) found that fire seasons tended to be longer and have more large fires when snow melted earlier in the year. Flannigan et al. (2009) assert that accurate modeling of seasonal duration is important for forecasting the effects of global warming.

We further tested the CRA approach by comparing its results with those of a more commonly used technique that uses seasons of standardized monthly spans, something we have termed the monthly approach. This comparison was useful because the monthly approach demonstrates what occurs when a method is used that does not emphasize precise estimates of seasonal transitions. The monthly approach effectively designated a fixed onset date of the wet season (1 June) for each year of study. Because the actual dates for onset tended to be highly variable, this fixed date generally fell some time before or after the actual onset date of any given year. Therefore, the monthly approach tended to assign dry periods to the wet season or wet periods to the dry season, resulting in a ‘‘dilution’’ of how seasonality was described. As a result, statistical models using the monthly approach had much less predictive power than models generated using the CRA approach [models with R^2 scores of $\sim$(0.14–0.22) versus models with R^2 scores of 0.56–0.61]. Overall, the comparison between the two approaches made it clear that gaining insight into climate–wildfire relationships in the region depends on the accuracy with which seasonal transitions are modeled.

b. Relationship of ENSO with seasonal rainfall and wildfires

We sought to determine if ENSO was related to onset dates and durations of the dry and wet seasons, and if these relationships appeared to have effects on wildfires. In this examination we found that the years studied could be divided into two groups. The first group constituted the bulk of the years, and for this group there did not appear to be relationships between ENSO and season durations or onset dates. In this group ENSO cycled consistently, with sea surface temperatures that peaked in winter months and that gradually declined during succeeding months. This gradual decline allowed typical patterns of seasonal rainfall to assert themselves by late spring–early summer. Years with strong ENSO conditions were therefore not followed by unusual onset dates or season durations compared to years with ENSO neutral conditions. This result contrasted with a study by Lima and Lall (2009) that found that wet seasons in southern Brazil tended to start later in the year under El Niño conditions.

This first group was also characterized by wildfires that were influenced by how ENSO regulated dry-season rainfall. There were fewer wildfires and less area was burned during El Niño events because these events produced low pressure over the Florida peninsula, allowing the jet stream to move farther south and to frequently push strong storm fronts through the region (Hardy and Henderson 2003). This pattern was effectively illustrated by peaks in CRAs (e.g., 1987 in Fig. 4). During some El Niño episodes, sufficient rainfall was generated in the winter–spring to produce a bimodal rainfall pattern, such as occurred in 1983 (Fig. 4). Such bimodal patterns are unusual in the region, and are normally found >300 km to the north where the jet stream has a more consistent influence (Chen and Gerber 1990; Olson and Platt 1995; Huffman 2005). Conversely, La Niña episodes produced high pressure over the region, steering the jet stream north and resulting in less frequent and weaker storm fronts. This pattern was illustrated with trajectories of CRAs that were relatively flat and steeply declining (e.g., 1989 in Fig. 4). Consequently, there were more intense droughts during the dry season and more wildfire activity. Our results regarding ENSO, rainfall, and wildfires were similar to those of other studies conducted in south Florida (Brenner 1991; Beckage et al. 2003). Similar associations are produced by ENSO worldwide, but often in reverse, with El Niño events inducing drought and greater wildfire activity, and with La Niña events producing more moisture (e.g., in parts of Asia and south America) (Siegert et al. 2001; Le Page et al. 2008).

The second set of years constituted only two cycles of ENSO during our study: one in 1956/57 and the other in 1997/98. Despite being few in number, these cycles proved to be important for understanding the overall character of ENSO and how it affected rainfall and wildfires at the study site. During these years, ENSO conditions in winter months were followed by rapid shifts to the opposite phase, and they therefore produced abnormal rainfall patterns with associated changes in onset dates and season durations. For example, the winter months of 1956/57 were undergoing the tail end of a La Niña, but these conditions quickly cycled into a strong El Niño phase starting in April 1957. This cycling coincided with a strong increase in rainfall, and accordingly the CRA approach assigned an early date (6 April) for wet-season onset for this fire year (Fig. 4). Similarly, El Niño of 1997/98, commonly referred to as the Super El Niño (Philander 2004), featured rapid shifts in phase and unusual seasonal lengths. It started in the wet season of 1997 and continued until April of 1998, and over this time rainfall amounts typical of the wet season persisted until March 1998, well past the date when the wet season normally ended (around the beginning of October). Afterward, ENSO rapidly cycled through a neutral period and into a La Niña phase by July, and during this time rainfall was particularly unpredictable, with very little arriving during April–June. The CRA approach therefore described the dry season of 1998 as being abnormally short and very dry (Fig. 4), a description that corresponded accurately with the frequency and area burned by wildfires during this season.

Therefore, our analysis suggested that the use of flexible seasonal spans was important for describing ENSO's particularly stochastic episodes and how they related to rainfall and wildfires. This importance of flexible seasonal spans was further highlighted when we compared our results to those based on a monthly approach that estimated the intensity of ENSO over winter months. This approach worked well when examining relationships in the first group of years, but it was ineffective for the second group. For example, during the Super El Niño the approach estimated a dry season that was very wet (Fig. 3b), and it therefore predicted a wildfire season of particularly low intensity. This low estimate was the opposite of the actual result, and the lack of accuracy for this fire year was very apparent while performing statistical analyses (see outlier in Fig. 5b).

Our finding that particularly strong ENSO episodes produced unusual patterns in rainfall and wildfires agrees with other studies worldwide (Siegert et al. 2001; Lima and Lall 2009; see sources in Ghil et al. 2002). Thus, we postulate that for many regions the relationships between ENSO and wildfires may be modeled more effectively using the CRA approach or a similar ''fine-tuned'' approach. Moreover, in the future even more unusual ENSO episodes may occur under global warming. Some climatologists predict that global warming will constrain the equatorial Pacific to El Niño conditions, but that these conditions will be occasionally punctuated by strong La Niña episodes (Timmermann et al. 1999; Tsonis et al. 2003). Developing methods to describe the seasonality of the more unusual years, therefore, may be critical.

5. Conclusions

In south Florida, the largest and most important wildfires occur with precise seasonal timing, that is, around the onset of the wet season (Slocum et al. 2007). As a result, to effectively model climate–fire relationships in this region, it is important to describe the wet and dry seasons in a flexible manner and to employ a finescale unit of time (i.e., days rather than months). Moreover, ENSO plays a central role in governing wildfires in the region. In most years ENSO tended not to be strongly associated with the onset and cessation of seasons, but in some years there appeared to be important relationships. Because of the temporal resolution involved in this system of ENSO, wildfire, and seasons, it is important to use an approach—such as the CRA approach—that precisely delimits seasonal spans and thereby allows in-depth examination and modeling of the data.

Based on our results, we propose that the CRA approach or similar ''fine tuned'' approach should prove useful for modeling seasonal wildfire regimes in many regions. We make this assertion because seasonal climate plays a central role in governing most, if not all, fire-prone ecosystems. Moreover, studies examining various aspects of seasonal climate reveal that seasonal transitions tend to be highly variable (Stewart et al. 2005; Slocum et al. 2007; see sources in Camberlin and Diop 2003 and in Lima and Lall 2009). This assertion is also supported by other studies demonstrating the importance of describing seasonality in a way that is congruous with how wildfires propagate and spread. For example, in mountainous regions fuel availability is regulated by snowmelt, and it is therefore important to precisely define when snowmelt peaks in order to predict wildfire activity (Stewart et al. 2005; Westerling et al. 2006). Based on this evidence, we advocate using advances in quantifying seasonality, combined with advances in modeling teleconnections, to produce new wildfire models of substantially improved accuracy. These new models may include those that examine how teleconnections interact to influence climate and wildfires (e.g., Heyerdahl et al. 2008), those that examine spatial patterns of climate and wildfires, and those that predict–forecast wildfires stemming from different ignition sources (e.g., lightning fires versus anthropogenic wildfires such as those ignited by ordnance). All of these models may help land managers and policy makers control wildfires, as well as more effectively use them to maintain ecosystems that are naturally reliant on fire.

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