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Effect of Climate on Wildfire Size: A Cross-Scale Analysis

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Abstract

Theory predicts that wildfires will encounter spatial thresholds where different drivers may become the dominant influence on continued fire spread. Studying these thresholds, however, is limited by a lack of sufficiently detailed data sets. To address this problem, we searched for scale thresholds in data describing wildfire size at the Avon Park Air Force Range, south-central Florida. We used power-law statistics to describe the ''heavy-tail'' of the fire size distribution, and quantile regression to determine how the edges of data distributions of fire size were related to climate. Power-law statistics revealed a heavy-tail, a pattern consistent with scale threshold theory, which predicts that large fires will be rare because only fires that cross all thresholds will become large. Results from quantile regression suggested that different climate conditions served as critical thresholds, influencing wildfire size at different spatial scales. Modeling at higher quantiles (≥75th) implicated drought as driving the spread of larger fires, whereas modeling at lower quantiles (≤ 25th) implicated that wind governed the spread of smaller fires. Fires of intermediate size were negatively associated with relative humidity. Our results are consistent with the idea that fire spread involves scale thresholds, with the small-scale drivers allowing fires to spread after ignition, but with further spread only being possible when large-scale drivers are favorable. These results suggest that other data sets that have heavy-tailed distributions may contain patterns generated by scale thresholds, and that these patterns may be revealed using quantile regression.

Key words: wildfire size; cross-scale interactions; scale thresholds; quantile regression; power-law statistics; climate.

Introduction

Studies of ecological disturbances have indicated the importance of cross-scale interactions in determining how they grow in size or intensity (Allen 2007; Peters and others 2004, 2007). These studies have documented how disturbances are initially governed by processes operating at smaller scales, but as they grow in size or intensity they reach points where future growth is governed by different processes. These points are referred to as scale thresholds, and the changes in behavior associated with crossing these thresholds result in cross-scale interactions, that is, the change of the underlying process is associated with crossing a threshold from one scale to the next. Moreover, this pattern of changes can be non-linear because

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growth at a larger scale is not proportional to the processes operating at smaller scales. One analogy useful for understanding this concept is the relay race. The second runner cannot make any progress unless the first runner reaches her to pass the baton, but the speed of the second runner does not depend on the speed of the first runner. As such threshold processes have been implicated in catastrophes—not only with ecological disturbances but for a wide variety of phenomena—modeling these dynamics is of great interest to scientists, managers, and policy makers in numerous fields (Scheffer and Carpenter 2003).

Fire is one ecological disturbance that clearly appears to be governed by cross-scale interactions. As such, Peters and others (2004) use wildfire spread as a prominent example of their proposed general framework for how cross-scale interactions operate. In this framework, there are four stages of behavior and three scale thresholds (we reproduce this framework in Figure 1). The first stage is the ''initiation'' stage, for example, a lightning strike. The conditions that allow the strike to ignite a fire are specific (for example, characteristics of the strike, electrical-resistance of soil and fuels). For further fire spread, however, different conditions are required (that is, dry fine fuels). Thus, if both conditions are met, the fire can pass from the initiation stage and into the second stage of behavior, the ''within-patches'' stage. Similarly, as a fire spreads during the within-patches stage, the conditions driving it will not be the same as those that will allow it to spread into the third stage, the ''among-patches'' stage. For this to occur conditions must be favorable for the fire to burn into different fuel types.

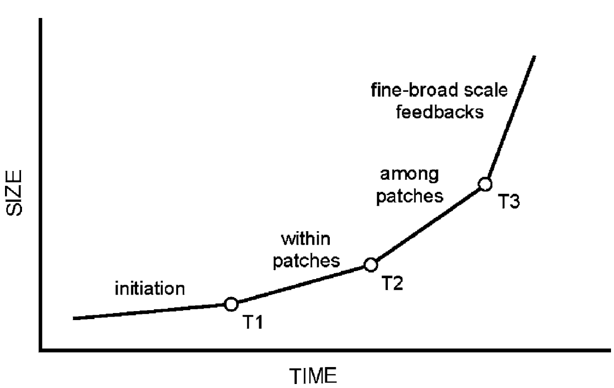


Figure 1. A reproduction of the framework of scale thresholds proposed by Peters and others (2004) (see their Figure 1). As a fire spreads it will go through four stages of behavior (*solid line segments*) and three thresholds (*points labeled* T1, T2, and T3).

Finally, the fourth stage is defined as having ''fine-broad scale feedbacks.'' This occurs when fires produce enough heat that they generate their own weather, allowing for the combustion of yet more fuel types as well as other types of fire behavior that promotes rapid fire spread (for example, spotting). Thus, in the framework outlined by Peters and others (2004), as each threshold is crossed, there is a leap in fire intensity and rate of spread accompanied by a new set of conditions governing the fire. Each step of the process represents a threshold because conditions in a previous stage are not related to those governing fire spread in the current stage.

Evidence supporting the proposed framework is difficult to obtain. Data sets that document fire spread with sufficient detail to reveal scale thresholds and their associated mechanisms are rare (for example, data that document hourly changes in fuels and weather as a fire burns) (Crimmins 2006). For example, Peters and others (2004) described two fires that experienced rapid leaps in rate of spread corresponding to the scale thresholds proposed, but the specific processes operating in each stage of behavior were not described. Rather, the processes operating in each stage are often inferred from direct observation; such examples are particularly common in the gray literature (for instance Wade and Ward 1973; Finney and others 2003; see examples in Crimmins 2006). Similarly, Falk and others (2007) point out that the processes involved in different stages can be inferred from empirical studies conducted at particular scales. For example, at small spatial scales (1–100 m^2) fires are governed by fuel type, moisture, and weather conditions, whereas at bioregional scales ($>10^5$ ha) fire regimes vary based on climate patterns with decadal or longer periodicity. Although these inferences regarding the properties within scale thresholds are useful in that they produce hypotheses regarding cross-scale interactions, these approaches do not examine data across scales.

We asked if there were relatively simple approaches for conducting cross-scale analyses of fire spread. We sought approaches that can exploit data sets that are of relatively low detail but that are more widely available than highly detailed data sets (such as those documenting hourly fire spread). In this article, we present an analysis of a data set of wildfire size and daily climate that meets these criteria. We reasoned that a cross-scale analysis of these data would be useful because climate is clearly a principal driver of fire spread, and fire size data represent the ''endpoints'' of fire spread. Moreover, these data are common and are a potentially rich source of information for revealing possible scale thresholds and mechanisms across a wide range of study sites. Finally, these data are almost always heterogeneous in that they contain an extreme positive skew, such that most of the total area burned in a given region is accounted for by just a handful of fires (Malamud and others 2005; Moritz and others 2005). Although this heterogeneity presents difficulties when employing standard statistical techniques (for example, ordinary least squares regression), examining them with analyses specifically designed for dealing with heterogeneity can reveal important trends.

In this article, we applied two analyses to a data set of wildfire size and climate at the Avon Park Air Force Range, south-central Florida, USA. These two analyses were as follows.

(1) *Power-law statistics.* As with many phenomena in nature, wildfire regimes are characterized as having frequent small events and less frequent large events. Complexity theory states that these distributions often follow a power-law distribution and that complex interactions may be involved (for example, self-organized criticality) (Malamud and others 2005; Moritz and others 2005; Newman 2005; Clauset and others 2009). This notion is consistent with the idea of cross-scale interactions, which predicts that large events will be infrequent because only those events that successfully pass through all of the thresholds will become large. In this article, we describe whether or not our data of fire size follows power-law behavior.

(2) *Quantile regression.* Quantile regression is well suited for problems regarding changes in scale because it measures how an explanatory variable (for example, a climate variable) relates to a response variable (fire size) when this response depends on a broad range of other, often unmeasured, conditions (Cade and others 1999; Cade and Noon 2003). Quantile regression accomplishes this by deriving linear functions that describe patterns at the edges of data distributions. As such quantile regression can suggest which processes are important at particular scales of observation, and can thereby reveal potential scale thresholds.

These two bodies of statistics are well developed, but to our knowledge have not been applied to the concept of scale thresholds in ecological systems. Here, we describe if they can extract useful information from a low-quality data set of fire size and daily climate, and if this information is consistent with the theory of scale thresholds.

Methods

Study Site

The Avon Park Air Force Range (APAFR) is a 42,000 ha military installation covering large parts of Polk and Highland Counties of south-central Florida (27°35′ N, 81°16′ W). The site has a subtropical climate, with a wet season that typically lasts from late May to early October and a dry season lasting from early October to late May. The wet season typically has twice the rainfall as the dry season (mean ± 1 SD: 89 ± 27 cm in the wet season versus 42 ± 15 cm in the dry season; M. G. Slocum, unpublished data; Chen and Gerber 1990). The range was established in World War II for practicing bombing, strafing, and related missions. It is still active, and numerous wildfires are started by ordnance as well as by lightning. To control fires the installation employs a fire crew which uses numerous fire breaks (for example, roads, disk lines) which delimit approximately 1400 ''containment units''. Some of these units are managed as pine plantations, pastures or as target sites, but most contain natural plant communities. These communities are arranged along elevation gradients that, although being of low-relief, clearly demark distinct plant communities of varying flammability and hydroperiod (Slocum and others 2003; Orzell and Bridges 2006a, b; Platt and others 2006). Pine savannas occur at higher elevations and are the most flammable community with the shortest hydroperiod; at mid-elevations lie dry prairies, which have a longer hydroperiod; and at the lowest elevations lie wet prairies and marshes, which are flooded for substantial parts of the year and are the least flammable.

Data

To obtain data on sizes of wildfires, we used the installation's records over 1997–2007. Except for a few large fires, all fires burned for 1 day or less.

To describe weather during fires, we collected mean daily data on air temperature, relative humidity, wind speed, and solar radiation. These variables are important drivers of fires and are often used in fire spread models (for example, Rothermel 1972). These data were obtained for a climate station (S65CW) located 20 km southeast of the installation using the DBHYDRO browser of the South Florida Water Management District (http://www.sfwmd.gov). In addition to these data, we collected data on a fifth variable describing drought. These data—mean daily soil moisture at 30–60 cm depth—were obtained from the Experimental

Surface Water Monitor (ESWM), a daily analysis of hydrologic conditions throughout the continental United States (www.hydro.washington.edu/forecast/monitor; Wood 2008). This project has 0.5° resolution, and we obtained data from a point (27.75° N × 81.25° W) located 10 km north of the APAFR. Drought was indicated when moisture in this soil layer was low. Note that we explored other drought indices measuring moisture at the soil surface (for example, the Keetch–Byram drought index), but these indices have not been found to be predictive of fire activity in this study or in other studies at the APAFR (Slocum and others unpublished data; McCallum and others unpublished data).

Data Analysis

Power-Law Statistics

Many phenomena in nature have frequency distributions that have an extreme positive skew and are said to be ''heavy-tailed.'' In some of these cases, the distributions follow what is called a power-law, meaning that the frequency of the event (for example, fires) varies as a power of some aspect of the event (for example, its size) (Newman 2005). Such phenomena are of interest because of their universality; for example, power-law distributions describe the intensity of wars and the frequency of usage of words in most languages. Power-laws have been used to describe fire size distributions across many regions whose regimes are otherwise of widely varying character (Malamud and others 2005). How such heavy-tailed distributions are generated is an active field of research (Newman 2005; Clauset and others 2009), and scale thresholds may be one such mechanism, as any phenomenon that has scale thresholds will naturally be constrained to having fewer events that are larger.

To make an initial determination if a distribution might follow a power-law is straightforward; all that is necessary is to plot the data versus their frequency (or rank) using logarithmic horizontal and vertical axes. If this distribution can be described using a straight line, it may follow a power-law (Newman 2005). Although many distributions contain such a pattern, in practice most do so only after reaching some minimum value or cut-off (Newman 2005; Clauset and others 2009). Such distributions, therefore, are said to have a ''power-law tail.''

To examine our distribution of fire size, we first plotted fire size versus rank size on a graph with log10/log10 scales. We then conducted three estimates, including: (1) an estimate of the minimum value ($\hat{x}_{\min}$) after which the slope of the distribution followed a power-law. This was done using techniques developed by Clauset and others (2009) and a computer program (plfit) written in R and available at: http://tuvalu.santafe.edu/~aaronc/powerlaws/. (2) An estimate of the slope of the distribution using the best fit of $\log[\dot{f}(A_F)] = -\beta \log[A_F] + \log \alpha$, where A_F is the area burned by a fire and $\dot{f}(A_F)$ is the size rank of the fire (Malamud and others 2005). (3) We fit an exponential function before $\hat{x}_{\min}$ using a linear regression after transforming fire size with a natural-log transformation (using the REG procedure of SAS release 9.1; SAS Inc., Cary, NC).

Quantile Regression

In contrast to more standard statistical techniques that model mean trends in data (for example, ordinary least squares regression), quantile regression estimates trends along edges of data distributions. It accomplishes this by modeling a function such that a fraction τ of the observations is below the estimated function and a fraction $1 - \tau$ is above it (Cade and others 1999; Cade and Noon 2003). For example, a regression quantile of 0.90 will produce a function such that 90% of the observations are below it, whereas a regression quantile of 0.10 will produce a function such that 10% of the observations are below it. This method is useful for describing data sets in which heterogeneity may be related to unknown or un-sampled environmental drivers. In particular, quantile regression has been successfully applied where organisms or other ecological phenomena follow the law of limiting factors (also known as Liebig's law of the minimum). This law describes how the growth, survival, or reproduction of an organism or phenomenon is governed by whichever factor is the least available among a number of important (and often unmeasured) factors. For example, Dunham and others (2002) found that trout grew to large sizes in narrower, deeper streams, but that in many streams body size was constrained by unknown factors. Thus, when depth/width ratio was plotted versus body size, the result was a data distribution in the shape of a triangle. The edge of this triangle was modeled effectively using a regression quantile of 0.95, which had a statistically significant negative slope and under which most of the data points fell. For reviews of quantile regression with ecological examples, see Cade and others (1999) and Cade and Noon (2003).

The capability of quantile regression to identify limiting factors is useful for exploring scale thresholds in fire size, as scale thresholds are likely to result from shifts in the environmental conditions limiting fire growth. For example, the theory of scale thresholds indicates that large fires will only be possible after a fire passes through a number of thresholds, and thus the occurrence of large fires will be limited by these thresholds. Accordingly, for our data of wildfire size and climate in south-central Florida, we expect that the climatic variables responsible for allowing fires to pass to the largest scale threshold should be most effectively modeled using larger regression quantiles. We also expect that the large-scale drivers should not be associated with the size of smaller fires, but should potentially represent the ''among-patches'' stage as described by Peters and others (2004) (Figure 1). Conversely, we expect that small fires should exhibit a tendency to grow under particular environmental conditions, but that further spread should be limited when the conditions are not favorable for moving through the next scale threshold. Therefore, we expected that the relationships between small fires and environmental drivers that operate at finer scales should be effectively modeled using lower regression quantiles. Moreover, the size of these fires should not be associated with the large-scale drivers. As such this data pattern should potentially represent the ''initiation'' or ''within-patch'' stages. Therefore, if we examine relationships between fire size and environmental variables at different regression quantiles, scale thresholds should be suggested at spatial scales where the statistical relationship with a given variable stops being important (or as important) and another relationship becomes important (or more important). On the other hand, if scale thresholds were not important for influencing fire spread, then the environmental drivers should be indicated as having no relationship with fire size, or should be indicated as having the same effect at any quantile examined. The latter result would indicate that the data could be just as effectively modeled using standard linear techniques (for example, ordinary least squares regression).

We investigated the relationships between climate and fire size using quantile regression. For each climate variable, we examined a large number of quantile regressions (every interval of 0.01 from τ = 0.01 to 0.99). For each regression, an equation with a y-intercept (b_0) and slope (b_1) was estimated, along with confidence intervals. We report results in figures showing how b_0 and b_1 change as the quantiles tested moved over the tested range (this is a standard technique as used in Cade and Noon (2003)). Quantile regressions were performed using the QUANTREG procedure of SAS using the simplex algorithm to estimate quantile functions. Confidence intervals were estimated using the RESAMPLING option. As quantile regression is not robust when there are data points with high influence, we examined the data using the DIAGNOSTICS option. We found no problems after transforming wildfire size with a natural-log transformation.

Results

Distribution of Fire Size

Over the 11 years from 1997 to 2007, 142 wildfires were recorded at the Avon Park Air Force Range (APAFR). Fires ranged from 0.5 to 2,130 ha and burned a total of 23,000 ha. The distribution of fire sizes had an extreme positive skew, with most of the fires being small and just a few being very large (Figure 2A). The data do not follow a power-law over their entire distribution, as a single straight line does not fit the data on a logarithmic scale (Figure 2B). Rather it appeared that there was a cut-off point somewhere around the middle of the distribution after which the distribution could be fit by a straight line. We tested for this cut-off using a method developed by Clauset and others (2009), which revealed it lay at 223 ha. After the cut-off we found that a power-law distribution fit the data with an R^2 score of 0.98 and had a slope (β) of 1.33 ± 0.04 (±1 standard error) (Figure 2D). Before the cut-off the distribution was well explained using an exponential function (R^2 score = 0.98; Figure 2C).

In addition to this ''dual distribution,'' the cumulative distribution of fire sizes had a set of three breakpoints, with one lying at around 10 ha, another at around 230 ha, and a third at 750–1,000 ha (Figure 2B). These breakpoints suggested that the distribution could be divided into different size stages, suggesting thresholds in fire behavior and environmental variables driving fire growth. Each stage progressively accounted for more area burned: stage 1 had 35 fires that accounted for just 0.4% of the total area burned, stage 2 had 73 fires that accounted for 17% of the total area burned, stage 3 had 29 fires that accounted for 47% of the area burned, and stage 4 had just five fires that accounted for 35% of the total area burned. The second breakpoint corresponded with our estimate of where the size distribution switched from being explained by an

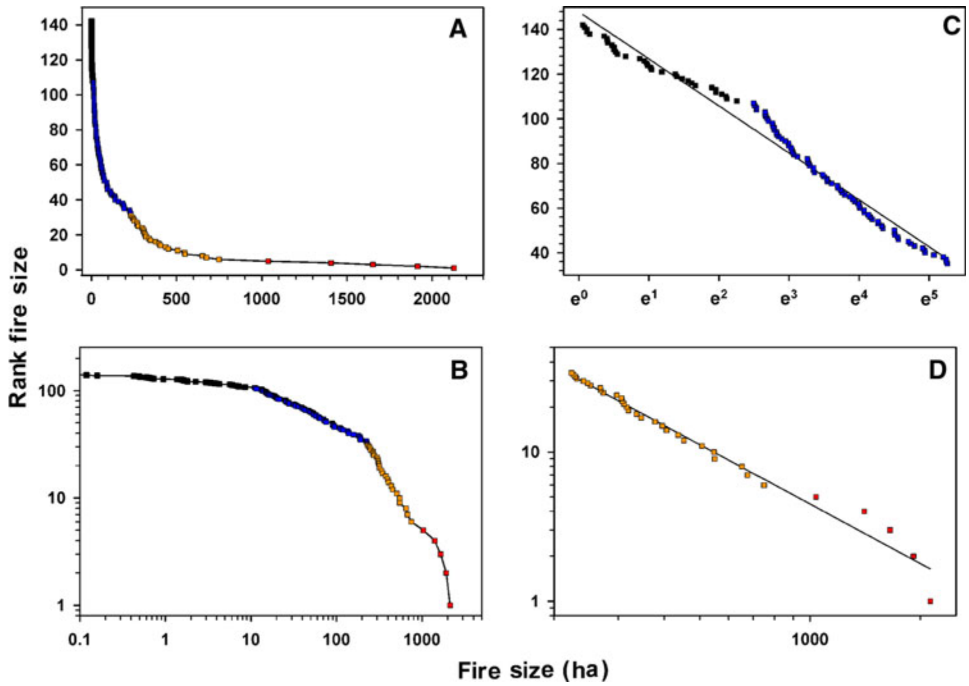


Figure 2. Cumulative distributions or rank/frequency plots describing the relationship between fire size and rank fire size for 142 wildfires at the Avon Park Air Force Range, south-central Florida, USA (1997–2007). Panel **A** shows the raw data, whereas panel **B** shows the same data plotted on logarithmic scales. Panel **B** had a pattern of breakpoints which roughly divided the data into four groups or stages, including a stage of very small fires (*black squares*, <10 ha), a stage of small to medium-sized fires (*blue squares*, 11 to ~200 ha), a large fire stage (*orange squares*, 200–800 ha), and a very large fire stage (red squares, >1,000 ha). An exponential function (panel **C**) was found to accurately fit the cumulative distribution below 230 ha (using a natural-log transformation of fire size; predicted line in black; $R^2 = 0.98$), whereas after 230 ha a power-law (panel **D**) was found to be a better fit ($R^2 = 0.98$).

exponential function to being explained by power-law behavior. The R^2 scores of the exponential and power-law functions were both high, but there was a lack of fit near the breakpoints. Finally, we noted that if we take Figure 2B and reverse the *y*-axis, the distribution looks remarkably like the scale thresholds and stages outlined by Peters and others (2004) and reproduced in our Figure 1. Therefore, these breakpoints appear consistent with the behavior expected for scale thresholds.

We examined how the fires within the four stages were associated with environmental gradients such as soil moisture (Figure 3). Most of the fires burned when soil moisture was low; in fact, half of the fires occurred when soil moisture was below 30 mm. However, patterns relating soil moisture to fire size were not effectively described using linear statistical techniques. For example, it was clear that stage 4 fires only occurred when soil moisture was very low (<8 mm) (Figure 3). However, a Pearson correlation between soil moisture and fire size within this stage suggested that soil moisture was *positively* related to fire size ($n = 5$, $r = 0.86$, $P = 0.06$). Moreover, it was also clear that stage 3 fires only occurred when soil moisture was below 30 mm, but a Pearson correlation using

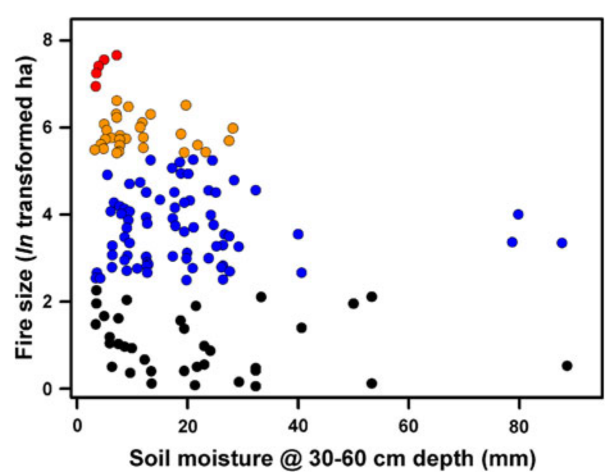


Figure 3. Plot of fire size versus soil moisture at 30–60 cm depth for 142 wildfires at the Avon Park Air Force Range, south-central Florida, USA (1997–2007). Colors of symbols (*filled circles*) refer to the stages suggested in Figure 2.

these fires was not statistically significant ($n = 29$, $r = -0.03$, $P = 0.89$). Similarly, when soil moisture was very high fires appeared to be constrained to be relatively small, but analyses within stages 1 and 2 where neither negative nor statistically significant (stage 1: $n = 35$, $r = -0.07$, $P = 0.67$; stage 2: $n = 73$, $r = -0.04$, $P = 0.76$). Similar results were found when we examined other environmental variables within the different stages. There were weak negative associations with relative humidity and temperature (for both climate variables: $n = 73$, $r = -0.26$ to -0.27, $P = 0.02$) within stage 2. A strong positive relationship was found between wind speed and fire size, however, within stage 1 ($n = 35$, $r = 0.50$, $P = 0.002$).

Climate/Fire Size Relationships Using Quantile Regression

In contrast to these results revealed by Pearson correlations, quantile regression revealed a series of strong associations between climate and fire size. First, wind speed was found to be associated with fire sizes at smaller scales. This was shown by significant quantile regressions at the 5th–25th quantiles (95% confidence intervals did not include zero at these quantiles; Figure 4). For example, the regression equation at the 10th quantile [ln(ha) = −0.95 + (0.36 × wind speed)] predicted that when wind speeds were 11 kph, 90% of the fires were at least 20 ha in size, but when winds were 2.5 kph, 90% of the fires were predicted to be greater than 1 ha (Figure 5A). Similarly, at the 25th quantile wind speeds of 11 and 2.5 kph were predicted to result in 75% of the fires being greater than 200 and 1 ha, respectively [ln(ha) = −0.86 + (0.56 × wind speed); Figure 5A]. Wind speed was generally not associated with fires at larger scales (confidence intervals generally contained zero at regression quantiles above 30th; Figure 4). For example, the predicted line at the 90th quantile clearly shows that fires did not tend to be larger when winds were faster (Figure 5A).

Relative humidity was found to be negatively related to fire size at the 20th–70th quantiles (Figure 4). For example, the 25th regression quantile predicted that 80% of the fires were larger than 33 ha 60%, but only larger than 1 ha when humidity was 90% [ln(ha) = 10.7 − (0.12 × humidity); Figures 4, 5B]. At the 70th quantile, these humidity levels were predicted to result in 30% of the fires being larger than 365 and 45 ha, respectively [ln(ha) = 10.1 – (0.07 × humidity); Figures 4, 5B]. The lack of an association of relative humidity with the smallest or largest fires was shown by confidence intervals that included zero at quantiles below 20th or above 70th (Figure 4); for example, at the 10th and 90th quantiles (Figure 5B). These results suggested that when fires burned under conditions of low relative humidity, they had a greater tendency to reach medium or moderately large sizes. Relative humidity, however, was not suggested to affect the size of the smallest or largest fires.

Air temperature had a pattern similar to that of relative humidity, but this trend was weaker and there was some inconsistency in it around the 30th quantile (Figure 4). For example, the function at the 40th quantile predicted that 60% of fires would be larger than 120 ha when air temperatures were 11°C, but would be larger than 12 ha when air temperatures were 30°C [regression equation: ln(ha) = 6.1 − (0.12 × temp.); Figures 4, 5C]. These results suggested that when fires burned under conditions of high air temperatures, they tended to be smaller. This counterintuitive result appears to be related to seasonality, and we explain why in the ''Discussion'' section.

Solar radiation was not found to be associated with fire size for any of the quantiles tested (Figures 4, 5D).

Soil moisture was strongly associated with the largest fires but not with medium or small fires. This was shown with non-zero relationships for quantiles greater than 75th (Figure 4). For example, the function at the 99th quantile predicted that 99% of the fires were 2070 ha or smaller when soil moisture was very low (3.5 mm), but were smaller than 45 ha when soil moisture was near its maximum (85 mm) [ln(ha) = 7.8 − (0.047 × soil moist.); Figures 4, 5E]. Similarly, the trend at the 95th quantile corresponded with the size of the stage 3 fires; at this quantile 95% of wildfires were predicted to be smaller than 1060 and 44 ha when soil moisture was 3.5 and 85 mm, respectively [ln(ha) = 7.1 − (0.039 × soil moist.); Figures 4, 5E]. As soil moisture indicated drought conditions when it was at low levels, this analysis suggested that the largest fires occurred when there were severe droughts. The size of smaller fires, however, did not appear to be associated with drought conditions as indicated by soil moisture.

Discussion

We explored a data set of wildfire size and daily climate for evidence of scale thresholds (using data from the Avon Park Air Force Range [APAFR] in south-central Florida). We used two lines of analysis: an examination for evidence of power-law

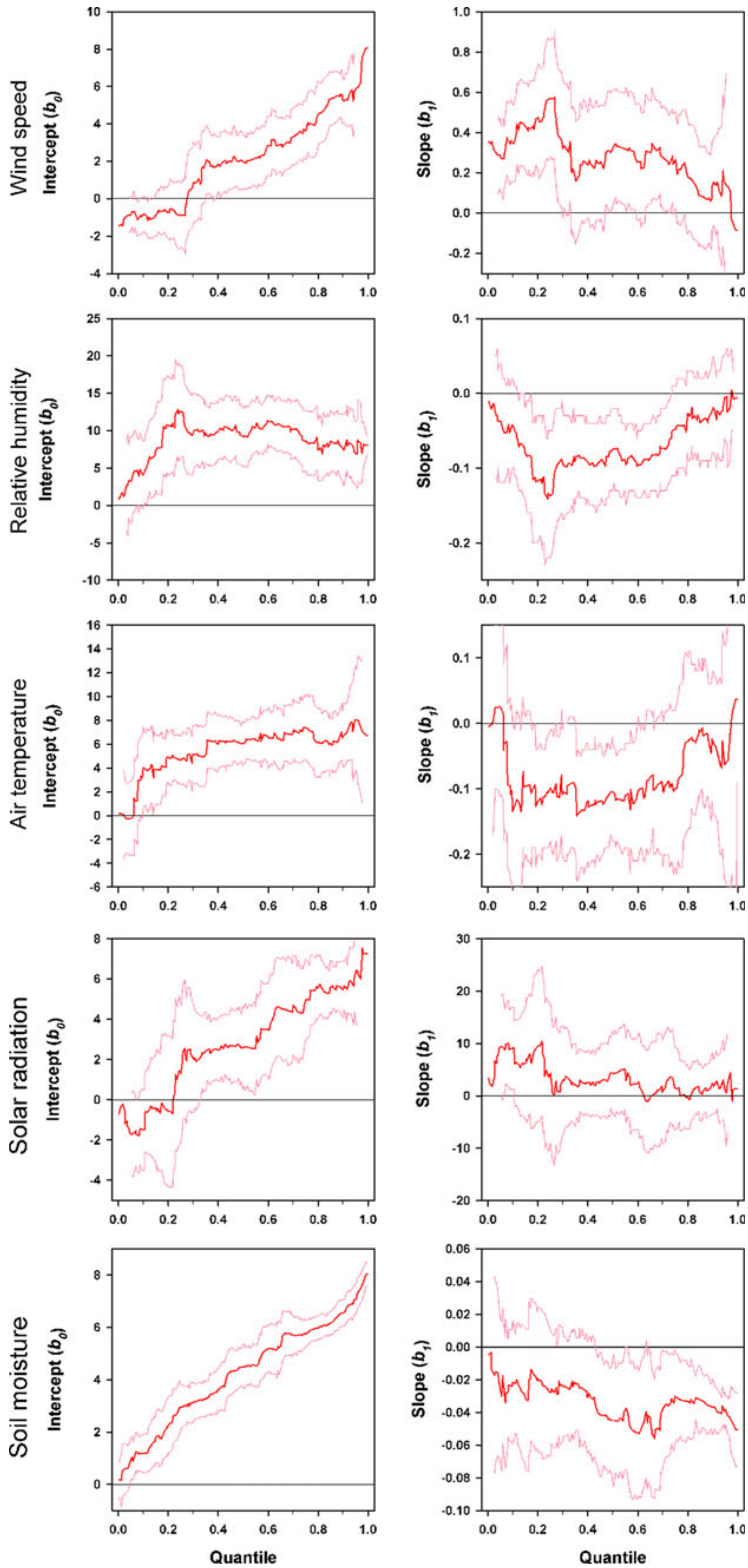
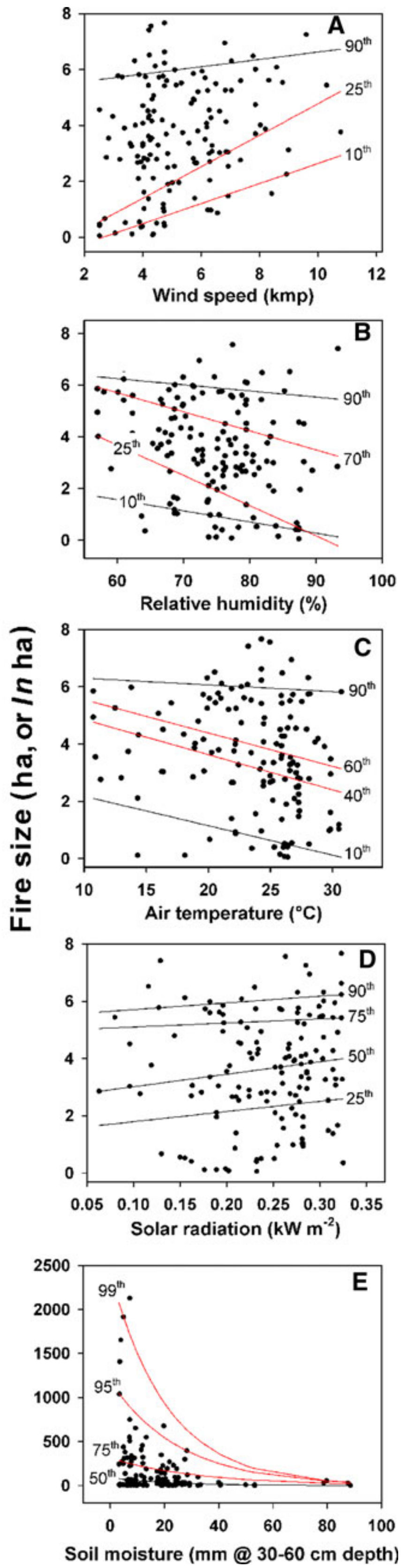


Figure 4. Results of quantile regressions in estimating fire size (natural-log transformed) as a function of wind speed, relative humidity, air temperature, solar radiation and soil moisture at 30–60 cm depth. The data used described environmental conditions and size of 142 wildfires at the Avon Park Air Force Range, south-central Florida, USA (1997–2007). Shown are estimates of y-intercepts (b_0, *first column*) and slopes (b_1, *second column*) at different quantiles (*dark red line*). 95% confidence intervals are shown with *lighter red lines*.



◀ **Figure 5.** Relationships between sizes of 142 wildfires at the Avon Park Air Force Range (south-central Florida, USA, 1997–2007) and five environmental variables (*black filled circles*), including **A** wind, **B** relative humidity, **C** air temperature, **D** solar radiation, and **E** soil moisture at 30–60 cm depth. *Labeled lines* represent trends predicted at different regression quantiles; the *y*-intercepts and slopes of these lines are shown in Figure 4 and in the text. *Red lines* indicated statistically significant slopes (at 95th confidence intervals), whereas *black lines* indicate slopes that are not significant. Fire size is natural-log transformed in all the panels except for in panel (**E**).

behavior, and an analysis of fire-size/environmental relationships using quantile regression. These analyses revealed patterns consistent with the idea that growth of fires was limited unless particular environmental thresholds were met. In this discussion, we first summarize these patterns with respect to behavior of wildfires in this region. We then propose a conceptual model of fire spread that synthesizes our results with previous studies. We conclude the discussion with some consideration of limitations of our approach, additional lines of investigation, and practical applications.

The distribution of fire size in our data set had a tail that followed a power-law, whereas the remainder of the distribution was described by an exponential function. Such bipartite distributions are commonly found for wildfires (Newman 2005), and the slope of our ''power-law tail'' ($\beta = 1.33$) lay toward the lower end of that found in other studies, for example, β for a number of regions worldwide varied from 1.1 to 1.8, and an analysis of different ecoregions in the United States found a range of 1.3 to 1.8 (see Malamud and others (2005) and sources therein). This indicated that the tendency for large fires to be much larger than small fires at our site was not quite as extreme as for many other regions. Malamud and others (2005) found that fire regimes in the Eastern United States tended to have β values around 1.8, a result not consistent with our findings. This is perhaps not surprising, however, given the uniqueness of the wildfire regime in southern Florida. Moreover, Malamud and others (2005) did not have data for southern Florida.

In our distribution of fire size, we found a series of breakpoints or thresholds that divided the distribution into four segments or stages (Figure 2B). Previous studies have noted that fire size distributions, as well as other distributions in nature, often have cut-off points or breakpoints where they can be better described using different mathematical functions (Moritz and others 2005; Newman 2005; Beckage and others 2007; Clauset and others 2009). Moreover, the fourth stage that we identified may reflect the small number of very large fires rather than a fourth stage distinct from our stage 3: the tail ends of distributions have been noted to often wander away from distributions that otherwise follow power-law behavior (Newman 2005). This pattern may simply reflect the rarity of large events, that is, there is a lack of sample size, and hence more error, when modeling the ends of such distributions. Finally, it is worth noting that an examination of a data set for Everglades National Park (just south of the APAFR) also displayed a pattern similar to the one we found for the APAFR (see Figure 2 in Slocum and others (2007)).

Overall, the universality of power-law behavior and of cut-offs for wildfires suggest common mechanisms for how fires spread. Some suggested mechanisms include self-organized criticality and highly optimized tolerance (Malamud and others 2005; Moritz and others 2005; Newman 2005). Our results indicate that environmentally driven scale thresholds may be an additional explanation for these patterns, as this mechanism would predict that most fires will burn under conditions that prevent them from crossing an environmental threshold limiting their growth. Thus, most fires will be constrained to be small, and only a few will cross all thresholds and become very large. Scale thresholds could thus explain the set of discontinuities that we found in our cumulative distribution of fire size (Figure 2B). Moreover, as previously mentioned, if we simply reverse the axes of Figure 2B we get a pattern that is strikingly similar to that described by Peters and others (2004) (see Figure 1).

This environmental threshold explanation of our fire size distribution is supported by results from our quantile regressions. This analysis indicated that the climatic processes governing wildfire spread appeared related to how large the fires ultimately became. A hierarchy of limiting conditions was implied, corresponding to stages in our fire size distribution with scale thresholds lying between these stages. In the first stage, the minimum size of fires was found to be positively associated with wind speed; in the second stage, larger fires were found to be negatively associated with relative humidity and to some extent with air temperature; whereas in the third and forth stages large fires were associated with drought conditions. Finally, we note that the environmental drivers associated with particular thresholds, and stages of the fire size distribution, were not found to do be associated within the other stages, that is, drought was not found to be associated with smaller fires, wind was not found to be associated with larger fires, and relative humidity was not associated with the smallest or largest fires.

We propose a simple conceptual model based on the results of our two analyses, together with previous studies of fire spread in the region. The key concept for this model is fuel connectivity over time and space. Natural spatial barriers for fire spread in the region primarily consist of different plant communities that vary in elevation, hydroperiod, and fuel moisture (Beckage and others 2003; Slocum and others 2003; Orzell and Bridges 2006a, b; Platt and others 2006). Given that all of our fires lasted at most a few days, the most important temporal barrier was likely simply day versus night, with daylight hours generally having lower relative humidity, higher temperatures, and surface heating by the sun, compared to nighttime hours. Scale thresholds appeared to be related to how climate alleviated or reinforced these barriers, doing so in a stepwise fashion, as follows: (1) Wind. All fires spread faster when winds were stronger, but fires driven primarily by wind would have been restricted to upland plant communities during the most favorable hours of the day (for example, pine savannas around noon). Therefore, these fires were not able to pass into the next scale threshold, and thus wind was associated with fires of small size. This corresponds to the 'initiation' stage of the framework proposed by Peters and others (2004; see Figure 1). (2) Relative humidity. Favorable conditions of humidity may have allowed fires to burn more habitat types, spreading from pine savanna into dry prairie, and also to burn during more hours of the day. Fires having only relative humidity as their main driver, however, would not have been able to spread into wet prairie or marshes and probably would not have burned or smoldered during the night. This corresponds to the ''within-patches'' stage of Figure 1. (3) Drought. Fires burning during droughts would have been able to cross from one upland community to another through lower elevation areas that would have otherwise acted as fire breaks. The two stages of fire size associated with drought may have been related to how dry the different plant communities became during droughts of varying intensity. The stage associated with ''large'' fires (200–800 ha) was indicated as occurring only during intense droughts, perhaps because such droughts allowed fires to burn in both dry and wet prairie, and to endure nighttime conditions by smoldering in logs and duff and then resuming when conditions changed. The ''very large'' stage (fires > 1000 ha) may have simply been a strengthening of this trend; it occurred only during the most severe droughts, and may have allowed fires to cross even the most stanch spatial barriers and to endure more than one night. These stages related to drought correspond to the ''among-patches'' stage proposed by Peters and others (2004) (Figure 1). Fires within our data set did not appear to enter into the proposed ''fine-broad scale feedback'' stage in Figure 1.

This conceptual model is supported by field observations and other studies in the region. During intense droughts we have observed fires moving rapidly and with relatively high intensity even in wet prairies and marshes at the APAFR, and we have also observed drought fires enduring nighttime conditions and rain by smoldering in duff, thick grasses, and course (100–1,000 h) fuels. Similarly, in the Everglades we have documented that prescribed fires tended to be more severe and less patchy in higher elevation communities (pine savanna) than in lower elevation communities (Slocum and others 2003). Moreover, the climate in the Everglades is clearly more favorable for intense/non-patchy fires during the dry/wet season transition, as it is during this period that water levels are the lowest and fuels are the most connected (Beckage and others 2003; Slocum and others 2003, 2007). This suggests that lower elevation communities naturally operate as barriers to fire (Gill and Allan 2008), and these barriers are lowered by droughts that generally occurred during the dry/wet season transition. Finally, field observations in the Everglades noted that large-scale fires (some close to two orders of magnitude greater than the fires at the APAFR) burned during droughts associated with the La Niña phase of the El Niño-Southern Oscillation (Synder 1991; Brenner 1991; Beckage and others 2003). These fires were often of long duration, some lasting more than 30 days. During most days conditions were not favorable, and the fires did not burn rapidly or intensely, but instead survived by smoldering in peat or other fuels. In many cases, they were thought to have been extinguished, only to resume when conditions improved (Slocum and others 2007). When conditions were particularly favorable, fires often had very high rates of spread (known to be common in grasslands [Gill and Allan 2008]), and during these periods wildfires could cross through the lowest-elevation plant communities, even stands of sawgrass (*Cladium jamaicense*) with standing water.

These observations from south Florida agree with more general observations from other parts of the world. For example, in a review about large fires and the fire-regime concept, Gill and Allan (2008) provide a number of reasons why fires may become large, including rapid rates of spread, long duration, and well connected fuels. Also, in modeling area burned in California chaparral, Schoenberg and others (2003) found that once certain thresholds in climate and fuel variables were attained, further changes in these variables did not predict fire spread. This agrees closely with our finding that fire size was not strongly associated with climate variables over their entire size range, but rather appeared to vary more-or-less randomly within particular size categories (Figure 3).

Although our conceptual model involves fire spread with respect to natural environmental variation, management also certainly played a prominent role in our study system. For example, we have observed that when a wildfire was initiated under favorable wind or humidity conditions, it often became intense and spread quickly, readily crossing roads and other barriers before fire fighters were able to respond. Similarly, some fires appeared to have become larger because of slow response times and a failure of initial containment, a factor that was listed by Gill and Allan (2008) as being another of the reasons that fires become large. For example, some fires occurred during the weekends, and thus fire fighters were not able to respond as quickly compared to when fires occurred during normal workdays.

The agreement between our conceptual model, analysis, and previous studies in this system is important because our study is, by its nature, observational. Our results, therefore, are correlative only and cannot be used to resolve the problem of determining which variables actually cause fire spread. Rather, our results and models should be thought of as contributing to a growing body of evidence about the mechanisms operating in the system (Anderson and others 2000; Burnham and Anderson 2002; Hobbs and Hilborn 2006; Murray and Conner 2009). Such approaches are critical when investigating problems where it is impractical to experimentally manipulate relevant variables.

One variable that did not agree with our a priori expectations was air temperature. Air temperature was expected to have a positive association with fire spread—as higher air temperatures lead to lower fuel moistures—but we found the opposite trend. We did not find this result surprising, however, because in exploratory analyses of wildfires in the region we have consistently found that daily air temperature negatively associates with wildfire size. The reason for this is simple: the smallest wildfires in the region tend to occur during the wet/summer season when air temperatures are warmer and fuel moisture is high. Thus, daily air temperature behaves as an index for seasonality in our models rather than as a driver affecting fire spread on smaller scales. This result highlights the fact that in many cases a variable may be predicted to have one statistical effect in a model—with this effect being based on what is known about behavior on one scale—but instead is found to have a different association because it has an effect at a different scale. A similar example involving scale dependence is shown with the role of wind. In Florida winds tend not to be a large-scale phenomenon, but rather tend to be gusty with higher overall speeds during particular hours of the day. Thus, in our study, wind behaved as a small-scale driver. However, in other regions, this is certainly not the case; for example, the Santa Ana winds of California operate at large spatial and temporal scales and act as the main driver of many of the largest wildfires there (Miller and Schlegel 2006; Keeley and others 2009).

Our detection of scale thresholds in fire spread indicates that scale thresholds in wildfire regimes can be revealed using commonly available data sets describing fire size and climate. The availability of these data contrasts with the more limited availability of the highly detailed data sets that are normally required to reveal thresholds (for example, maps of daily fire spread) (Crimmins 2006). As such, our analysis can be applied to numerous sites to potentially reveal site-specific scale thresholds in fire spread. As described by Peters and others (2004), the benefits of revealing scale thresholds on a site-by-site basis are numerous. On the applied side, managers can anticipate when fires are apt to experience a rapid, and often dangerous, ''blow up'' in intensity and fire spread (Byram 1954). They can then take actions before these events take place, for example, by thinning fuels or by adopting different fire-fighting tactics. Similarly, on the basic science side ecologists can study fire behavior and effects within particular thresholds, specifically incorporating them within experimental designs. They may also compare results across numerous sites, potentially providing a greater understanding of how the dynamics of fire spread vary from site to site. This will provide yet another estimate of how scale dictates fire behavior, and may lead to better models for understanding past fires and predicting future ones. Finally, we can take this one step further and suggest that—although heavy-tailed distributions in other systems are certainly generated by a variety of mechanisms—our results imply that one class of mechanisms are those involving scale thresholds.

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