Increasing concurrence of wildfire drivers tripled megafire critical danger days in Southern California between1982 and 2018

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Increasing concurrence of wildfire drivers tripled megafire critical danger days in Southern California between 1982 and 2018

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Abstract

Wildfire danger is often ascribed to increased temperature, decreased humidity, drier fuels, or higher wind speed. However, the concurrence of drivers—defined as climate, meteorological and biophysical factors that enable fire growth—is rarely tested for commonly used fire danger indices or climate change studies. Treating causal factors as independent additive influences can lead to inaccurate inferences about shifting hazards if the factors interact as a series of switches that collectively modulate fire growth. As evidence, we show that in Southern California very large fires and 'megafires' are more strongly associated with *multiple* drivers exceeding *moderate* thresholds concurrently, rather than direct relationships with *extreme* magnitudes of *individual* drivers or additive combinations of those drivers. Days with concurrent fire drivers exceeding thresholds have increased more rapidly over the past four decades than individual drivers, leading to a tripling of annual 'megafire critical danger days'. Assessments of changing wildfire risks should explicitly address concurrence of fire drivers to provide a more precise assessment of this hazard in the face of a changing climate.

1. Introduction

The idea that climate change can push extremes even further than expected shifts in averages has been well explored, in both causes and consequences [1]. In the literature, this concept has been applied with respect to wildfire, capitalizing chiefly on air temperature changes and their consequences for snowpack, vapour pressure deficit (VPD), or potential evapotranspiration [2–4] with ever stronger extremes in these values correlated to ever greater wildfire extent. This is partly because in the context of ascription of fire trends to underlying drivers, it is difficult to go past single variables driven by temperature change because model disagreement for other variables can be high for the short historical record [5]. This can create a difficulty in interpretation for outcomes like wildfire, which are inherently driven by multiple variables [6]. In particular, where interacting variables with limiting impacts on wildfire outcomes exist, setting aside the influence of some variables can be consequential to any capacity for generalization or projection [7]. Furthermore, disregarding interactions of multiple relatively common stressors can lead to unintentional consequences and maladaptation, as compounding effects of multiple non-extreme stressors can lead to an extreme impact.

In contrast, the application of concurrence, coincidence, synchrony, or coordination of events that are not extreme individually but produce extreme outcomes or events, has received substantially less attention in the context of ascription of fire trends in a changing climate [8, 9]. As an example of concurrence of drivers in a hazard context, the most extreme floods

often occur when rain falls on an existing snowpack [10], and it is the combination of the two drivers together that 'precipitates' the extreme event. Similarly, for fire, most field practitioners note that the greatest growth in fire size occurs on hot, dry, AND windy days. If any one of these factors is missing, the fire may grow, but the most dangerous fire events require all three [11]. This explains why in Southern California, annual area burned is only moderately correlated with the magnitude of climate variables [12]. Importantly, it is not simply multivariate analysis that is needed to address concurrence since linear multivariate regression uses linear combinations that represent additive interactions. Rather, a hazard framework that accounts for collective impact of switch-type (on-off) interactions among drivers on fire growth—a binary multiplicative framework—needs to be adopted, which is not practiced in the great majority of studies examining relationships between variables and fire [4, 6, 12]. Traditional approaches like those described in table S1 (available-online at stacks.iop.org/ERL/15/104002/mmedia) typically examine the correlation between the magnitude of a small number of drivers and fire size.

In this manuscript, we approach the concept of concurrence as an alternative framework for understanding the probability of very large fires and 'megafires'. We use this framework to examine two central questions: (1) Is the concurrence of drivers exceeding moderate thresholds (i.e. acting as on-off 'switches') more important than the magnitude of individual drivers? and (2) Is concurrence of drivers exceeding moderate thresholds changing at a rate faster than that of individual drivers? We explore these questions in coastal Southern California, an area with extreme vulnerability to wildfires given its large population (19 million people) and extensive wildland urban interface (WUI; zone of transition between wildland and human development) and WUI growth [13]. This region also has unique seasonality and weather patterns around its largest fires that set it somewhat apart from the Western U.S. context employed in many papers on fire [14]. Nevertheless, some general principles can be drawn from this one well-sampled example.

2. Methods

The intersection of seven southern California counties and the boundaries of Omernik ecoregions 8 and 85 [15] defines our study area (figure S1). Chaparral and grassland are the dominant vegetation types in the studied region (figures S1 and S2). The U.S. Forest Service Fire Program Analysis Fire-Occurrence Database (FPA FOD [16]) was used to obtain records of all wildfires in this region between 1992 and 2015. FPA FOD contains 35 916 wildfires between 1992 and 2015 within the study region, with a minimum and maximum fire size of 0.004 and 113 336 ha, respectively. Since the study region is extensively populated, the discovery date was assumed to represent the fire start date.

We investigated eight different drivers of individual fire size based on climatic, meteorological, and biophysical variables: live fuel moisture (LFM), wind speed, Standardized Heatwave Index (SHI3), 100 and 1000 h dead Fuel Moisture (FM100, FM1000), energy release component (ERC), burning index (BI), and VPD. Definitions of these variables are provided in sections S1.1–S1.5 in supplementary information, SI. These variables were selected due to their previously established correlation with fire sizes in the study area, and importantly because they are widely used in the fire literature and among practitioners. All eight variables were estimated at the location and discovery day of each wildfire between 1992 and 2015 (see section S1 in SI).

Four fire size thresholds were used for this analysis. A 0 ha threshold includes all fires. 'Large' fires were defined as fires in excess of 405 ha (1000 acres), and 'very large' fires were defined as fires in excess of 2025 ha (5000 acres) [6]. 'Megafires' were defined as fires in excess of 27 000 ha (66 700 acres), corresponding to the 99.98th percentile of fire size within the study area. This value coincides with the 99th percentile of fires larger than 40 ha (100 acres).

We examined correlations between the eight individual drivers and all fire, large fire, and very large fire sizes. We also examined the redundant information among the eight drivers to ensure that one variable cannot be fully predicted by the others. We used a normalized variant of mutual information named redundancy measure, which adopts a value of zero when two vectors are fully independent and a value of one when one variable is completely redundant. The redundancy measures of each pairwise combination of these eight variables, demonstrating that none of the combinations are redundant, are provided in table S2.

We then followed Dennison and Moritz [17] to determine critical values for each driver resulting in a steep increase in cumulative area burned. We examined the cumulative fire sizes against ascending (positive correlation) or descending (negative correlation) order of drivers' values. Then, using piecewise linear regression, we determined the change-points for each driver. The first change point that corresponded with rapidly increasing cumulative fire size was designated as a critical threshold for that driver.

Using the concurrence framework, we subsequently investigated the number of drivers meeting or exceeding the critical condition for each fire, based on populations of all fires, large fires, very large fires, and megafires. Each driver having its critical threshold exceeded can be thought of as a switch that has been flipped to the 'on' position [18, 19].

Thresholds exceeded for multiple drivers could lead to increased probability of fires, large fires, very large fires, or megafires. Conversely, a switch in the 'off' position could limit fire spread even if other drivers are at extreme values. Accordingly, we determined the percentage of fires that were associated with 1, 2, 3,…, 8 critical drivers in each category of fire size. Moreover, we investigated unique combinations of concurring critical drivers that contributed to fire sizes of various categories (all fires, and >25th, >50th, >75th, >95th, >99th percentiles).

We then used kernel smoothing function estimation to obtain smooth probability density functions for large and very large fires in response to values of LFM, wind, SHI3, FM100, FM1000, ERC, BI, and VPD. We further expanded this analysis and estimated the probability of large and very large fires in response to critical values of various drivers given critical combinations of other drivers.

Finally, to investigate the spatial and temporal trends in the critical state of each driver and their concurrence in the region during the study period, we downscaled NARR's wind data to 4 km resolution and generated a gridded dataset of LFM at 4 km resolution to make them consistent with GridMET and PRISM datasets. To downscale wind data, we used Gaussian process regression models (GPR) at a daily resolution. We extended this analysis to 1982–2018 to provide a better picture of trends in various drivers of fire. For each calendar day during 1982 to 2018, we fitted a GPR model to average daily wind speed calculated via NARR's 3-hourly wind speed data for the entire study region. For LFM, we used support vector regression models to generate gridded daily time-series of LFM during 1982 to 2018. We determined that weekly precipitation and average weekly temperature and relative humidity during the 21 weeks prior to the LFM measurement yields the most accurate model of LFM. We eliminated outlier data from the 9680 records of Chamise (*Adenostoma fasciculatum*) LFM during 1983 to 2017, and randomly selected 75% of the retained LFM data for training and 25% (out-of-sample) for testing. We used the coefficient of determination (R^2) and mean absolute relative error (MARE) to evaluate model performance for train and test stages. The final product is associated with $R^2 = 0.85$ and MARE = 0.07 for training and $R^2 = 0.8$ and MARE = 0.066 for test stages (also see figure S3). This LFM model is only used for spatial analysis. LFM values associated with each fire are estimated through temporal interpolation (see section S1.1 in SI).

Using the modelled, downscaled and other gridded data at 4 km resolution, we determined whether or not each driver was critical in each day and each grid cell between 1982 and 2018, which was then used to determine the number of megafire critical danger days per year per grid cell. We spatially averaged the annual number of critical days for each driver and concurrence of all drivers to determine a mean number of critical days per year for the entire region. This provided a time series of annual critical days for each driver and concurrence of all drivers to analyse their temporal trends. We also determine the spatial distribution of critical conditions by averaging the number of critical days for each and all of the drivers between 1982 and 2018 for each grid cell.

3. Results

3.1. Critical conditions for wildfires in Southern California

Figures 1(a)–(c) shows linear correlation coefficients between eight climatic, meteorological and biophysical variables and individual fire sizes. Expectedly, some of these variables can be correlated; however, there exists non-overlapping information among them that can inform our analysis (see table S2). All eight drivers showed statistically significant linear correlations (p-value < 0.05) with individual fire sizes (figure 1(a)). Stronger correlations were found between all the drivers and size of large fires (>405 ha; figure 1(b)). However, for very large fires (>2025 ha), only wind, ERC, and FM100 were significantly correlated (p-value < 0.05) with fire size (figure 1(c)). Further analysis will demonstrate that the reduced number of variables that are significantly correlated with very large fire size is partially due to the importance of concurrence of critical conditions of multiple drivers, rather than the magnitude of each individual driver. Critical thresholds for various wildfire drivers are listed in table 1 (also see figures 1(d)–(k)).

3.2. Compounding effects of various drivers enlarge fire sizes

Fire drivers exceeding their critical thresholds promote larger fires compared to fire drivers below their critical thresholds, even though these thresholds were found at relatively moderate values (figure 2). Critical values of wind (>2.3 m s^{-1}), for example, are associated with large (>405 ha) and very large (>2025 ha) fire probability of 0.37 (figure 2(a); orange line) and 0.17 (figure 2(b); orange line), respectively, whereas these probabilities plummet to 0.2 and 0.05 (figures 2(a) and (b); blue line) if the wind speed is not critical. Similar behaviour is observed for all drivers of fire with the most pronounced impacts associated with wind and VPD for large fires, and wind, BI, ERC, FM100, FM1000, VPD and SHI3 for very large fires (figure S4). However, the concurrence of critical conditions for multiple drivers can grow fire sizes even larger than the critical state of each driver individually. For example, if LFM and SHI3 are in their critical states, a critical level of wind speed prompts large and very large fire probabilities of 0.45 and 0.21 (figures 2(a) and (b); red line), respectively, which are 22% and 25% higher than the state where

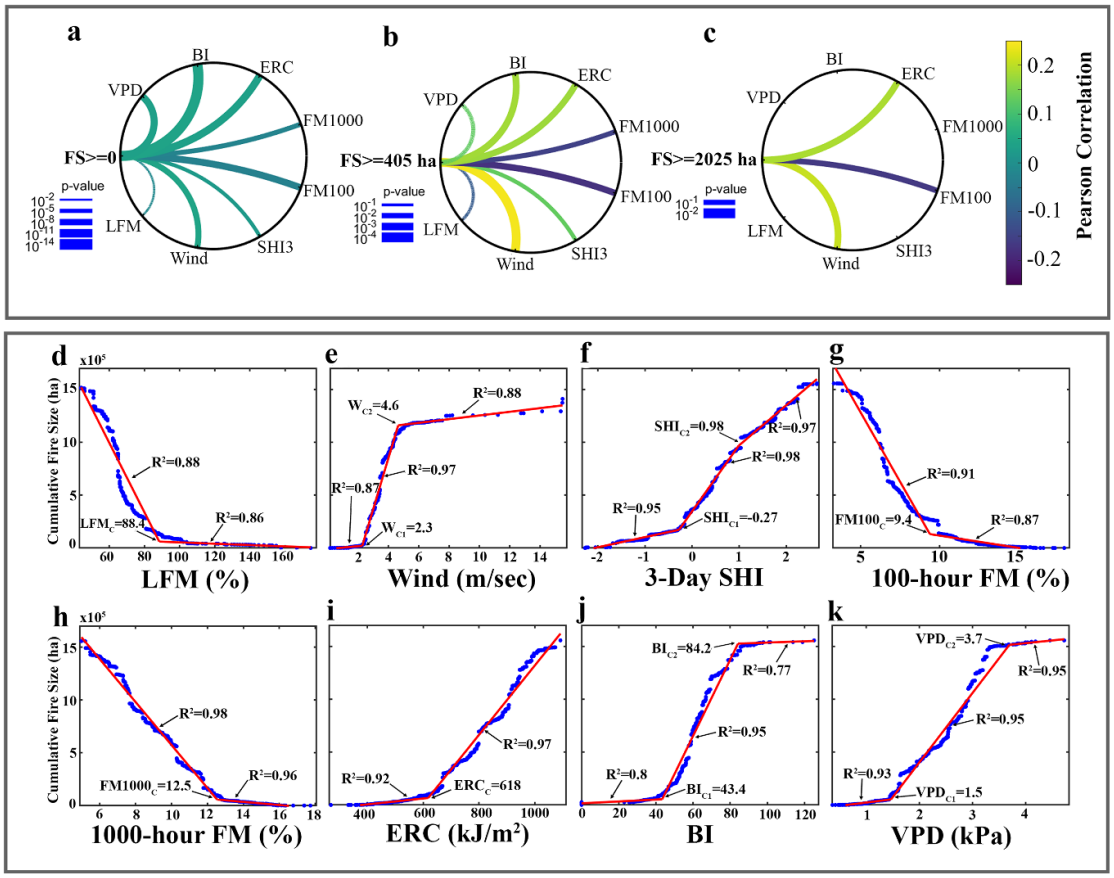

Figure 1. Fire-climate/weather relationship and critical threshold for each fire driver. Pearson correlation coefficient (color-coded) between individual fire sizes (FS) and various climatic, meteorological and biophysical drivers for (a) FS $\geq$ 0 ha (all fires), (b) FS $\geq$ 405 ha (large fires), and (c) FS $\geq$ 2025 ha (very large fires). Depicted correlation coefficients (a), (b), (c) are significant at the 5% level with the line widths signifying p-values (also see tables S3–5). Critical thresholds for (d) live fuel moisture (LFM), (e) wind, (f) 3 d standardized heatwave index (SHI3), (g) 100 h dead fuel moisture (FM100), (h) 1000 h dead fuel moisture (FM1000), (i) energy release component (ERC), (j) burning index (BI), and (k) vapour pressure deficit (VPD) derived through piecewise linear regression analysis against cumulative fire size for each driver.

Table 1. Critical thresholds for wildfire drivers.

Driver:	LFM	Wind	SHI3	FM100	FM1000	ERC	BI	VPD
Threshold:	88.4%	2.3 m s^{-1} (10 m above ground)	−0.27	9.4%	12.5%	618 kJ m^{-2}	43.3	1.5 kPa

the constraint of being critical ('concurrence') is not imposed upon LFM and SHI3 (figures 2(a) and (b); orange line). Put more simply, LFM and SHI3 switches already being 'on' increase the probability of large and very large fires when the variables shown in figure 2 exceed their thresholds. Further, table S6 lists ten example fires with driver values that are not individually extreme, but their concurrence corresponded with large fires. The Aliso (971 ha; March 2002) and Antonio (596 ha; May 2002) fires are clear examples of wildfires with multiple non-extreme drivers (below 70th percentile when driver is positively correlated with fire size, or above 30th percentile when driver is negatively correlated). Not a single driver for either of these two fires was extreme, however, the compounding effects of multiple non-extreme but critical drivers permitted their growth.

3.3. Megafires are strictly multi-driver events

Although megafires are infrequent, they constitute a large portion of the total area burned in the Western U.S. Total area consumed by the 9 megafires (>27 000 ha) from nearly 36 000 fires in our study region accounts for more than 36% of the total area burned in the period of 1992–2015. All of the megafires in our study area occurred when at least seven drivers were critical, and one third occurred when all eight drivers were critical (figure 3(a)). As smaller fire sizes are included in the analysis, wildfires with lower number of critical drivers emerge (figures 3(a) and S5). For example, while the concurrence of 7–8 drivers remains the most frequent descriptor for large and very large fire sizes, there are few instances of very large fires with only one critical driver (figure 3(a)). Smaller size fires can be impelled by any combination of one to eight critical drivers (figure 3(a)). Figure S5

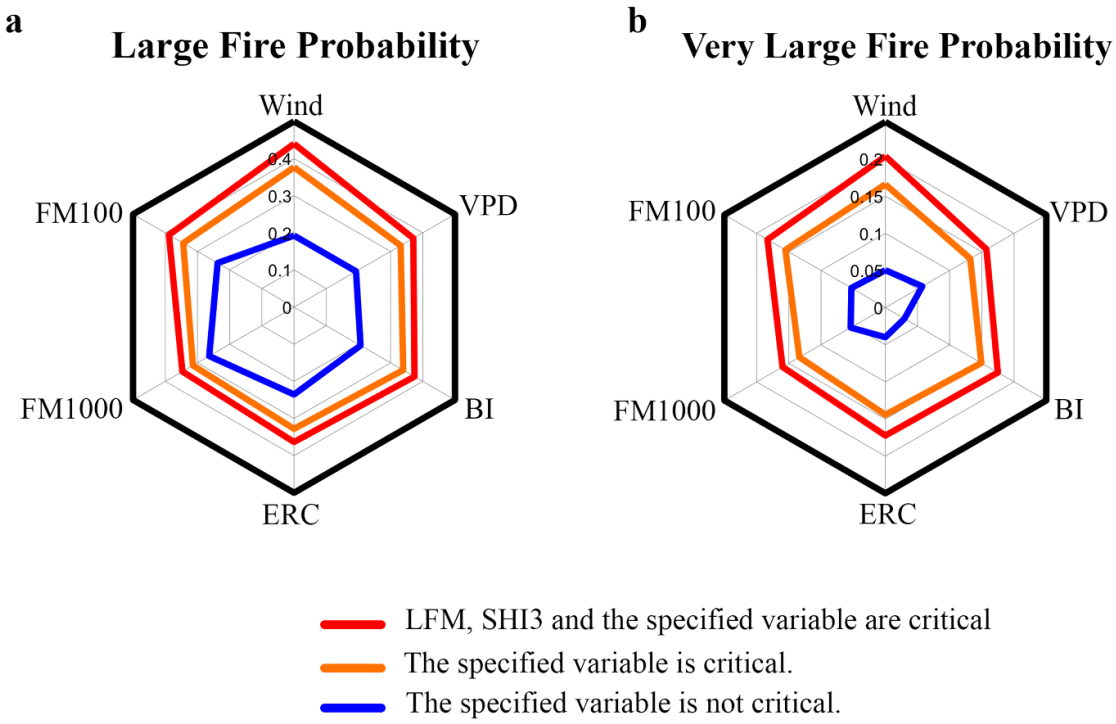

Figure 2. Compounding effects of multiple drivers grow fire sizes. Probabilities of observing (a) large (>405 ha) and (b) very large (>2025 ha) fires when various drivers are not critical (blue line), are critical (beyond thresholds; orange line), and are critical when LFM and SHI3 are also critical (red line). Fires of >40 ha are used in this analysis. Black hexagons show the borders of each figure.

shows the top 7 combinations of concurring critical drivers for different fire size categories.

The 2003 Cedar fire (∼113 336 ha) is a vivid example of multi-driver compound megafire events (figures 3(b)–(j)). Fuelled by extremely dry vegetation and expanded rapidly by high wind speeds to a growth rate of 1000–1500 ha per hour [20], the Cedar fire destroyed 2800 structures and claimed 14 lives [21]. Concurrence of critical conditions for all eight drivers at the start date of fire contributed to the rapid growth of this fire (figures 3(c)–(j)). Close examination depicts that BI, ERC, FM100 and wind were oscillating between critical and non-critical conditions from late June to late October 2003 and VPD, LFM, SHI3 and FM1000 predominantly remained at the critical level in the same period; but at the start date of the fire, all variables concurrently became critical (figures 3(c)–(j)). By the containment date, 11 d after the fire started, many of the driving variables (BI, VPD, wind, SHI3, FM100, FM1000 and ERC) retreated from critical conditions (figures 3(d)–(j)). The Thomas fire in December 2017 (∼114 000 ha; outside of our study period) was also the result of compounding effects of low fuel moisture (LFM = 54%, FM1000 = 9.6%), heatwave (temperatures of 1.3 standard deviation above normal, SHI3 = 1.3), extreme biophysical variables (ERC = 744 KJ m^{-2} and BI = 66), and most importantly extreme Santa Ana winds (wind = 6.6 m s^{-1}).

Although many of the examined drivers are highly correlated, detailed information-theoretical analysis using the concepts of entropy, mutual information and redundancy shows that each driver provides a certain level of unique information that can help further resolve fire-climate/weather relationships (table S2). Normalized redundancy—defined by mutual information of two variables divided by their joint entropy—ranging between 0 (no redundancy) and 1 (full redundancy) is an appropriate index to measure the relative dependency of each two drivers. The lowest levels of relative redundancy are observed between BI and LFM (0.32), wind (0.33) and SHI3 (0.35). Maximum relative redundancy occurs between ERC and FM1000 (0.51) and FM100 (0.48), which is expected given the direct dependence of the ERC formulation on these two measures [22]. While there is a high level of redundancy between ERC and dead fuel moisture indices, there is still some level of unique information that can help refine critical conditions. The various time scales of fuel moistures can become synchronized during extended dry spells, but occasional summer wetting would cause desynchronization of the fuel moistures for different fuel sizes, leading to, for example, low fuel moisture in fine fuels while coarse fuels are still slightly damp.

3.4. Megafire critical danger days tripled in four decades

In the early 1980s, concurrence of critical conditions of all eight studied drivers occurred roughly 15 d per year in our study region, which has escalated to

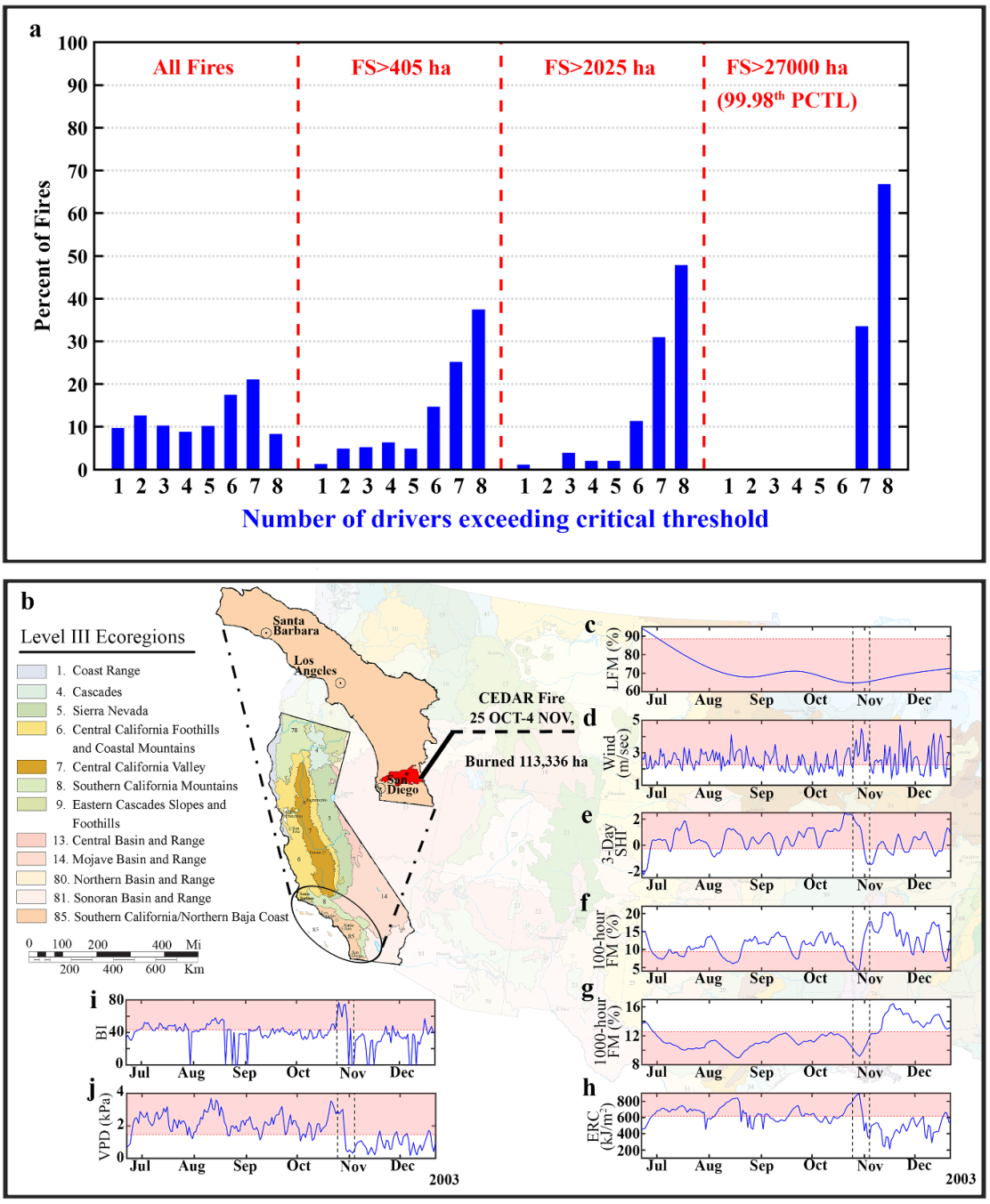

Figure 3. Large fires are multi-driver events. (a) Number of critical drivers for fires of various sizes. (b) Map of the Cedar Fire, and daily time series of (c) LFM, (d) wind, (e) SHI3, (f) FM100, (g) FM1000, (h) ERC, (i) BI, and (j) VPD during summer and fall of 2003. All drivers had become critical (red zone) before the start of the Cedar Fire (vertical dashed line).

more than 50 d in the late 2010s (figure 4(b)). This marks a more than tripling of the number of megafire critical danger days in coastal Southern California between 1982 and 2018. Frequency of annual critical days for each individual driver of fire, except for wind speed, also shows an increasing trend in the studied region (figures 4(c)–(j)), which collectively contributed to tripling the megafire critical danger days. Most importantly, the rate of increase in the number of all variables being synchronously critical (figure 4(b)) is higher than the rate of increase for each individual driver (figures 4(c)–(j)).

4. Discussion

Through a detailed quantitative analysis of nearly 36 000 individual fires in Southern California, we show that that fire-climate/weather studies should consider various climatic, meteorological and biophysical variables simultaneously within a concurrence framework that accounts for synchronization of multiple variables. We already know that megafires are the result of the compounding effect of many drivers (see table S1), but 'additive' statistical models that are used in the literature to relate fire sizes to

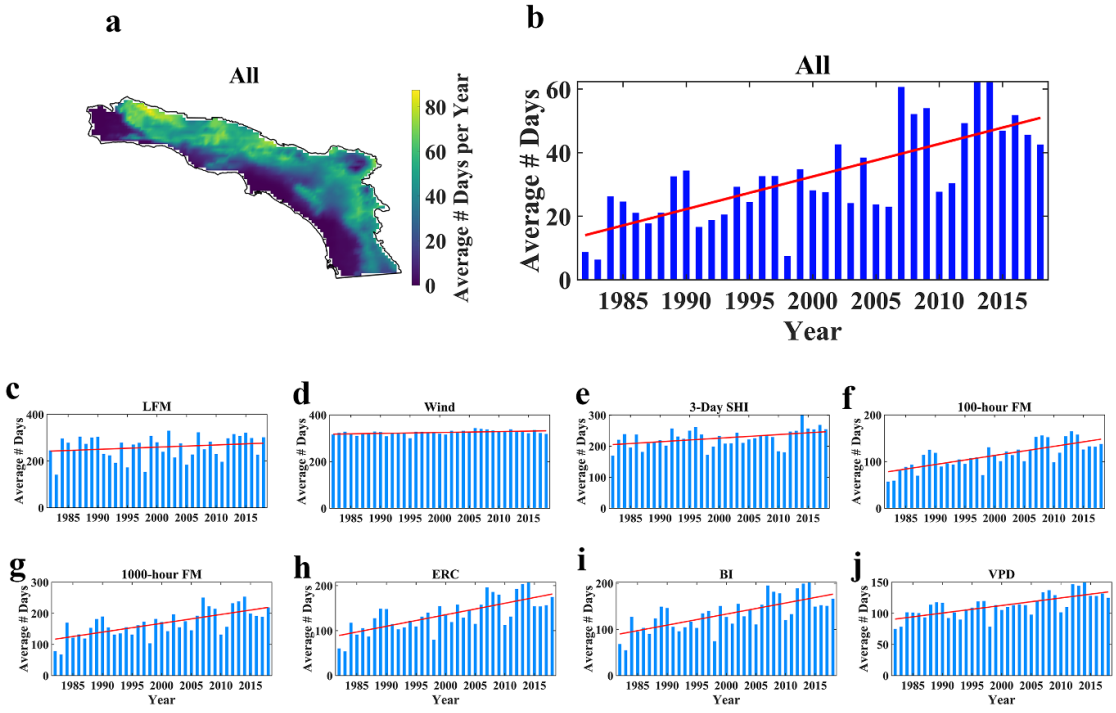

Figure 4. Megafire season in Southern California tripled in four decades. (a) Spatial distribution of annual number of days averaged over the period of 1982–2018 that all eight drivers exceeded critical thresholds in the study region. Spatially averaged number of days in each year that values of (b) all eight drivers, (c) LFM, (d) wind, (f) SHI3, (h) FM100, (j) FM1000, (l) ERC, (n) BI, and (p) VPD exceeded critical thresholds in the study region.

the driver magnitudes do not reflect this knowledge. With additive regression models, extreme magnitudes of one variable can compensate for low values of another. A concurrence framework, however, ensures that synchronous impacts of critical states of all drivers is factored into the analysis. Hot-Dry-Windy Index ([19]); is an important step towards formulating the synchronous impacts of multiple fire drivers. However, this index is a multiplicative function of only weather variables (not directly including fuel moisture), and does not address critical thresholds of drivers. Machine learning-based approaches may provide an alternative means for studying concurrence in fire-climate/weather relationships [23].

As climate change shifts precipitation patterns, adds background warming to the system, and fosters concurrence of multiple extremes [24], a paradigm shift to incorporate multiple drivers in a concurrence framework for modelling future fire activity is urgently needed. This paradigm shift is particularly important for Southern California, as projected future precipitation in this region is associated with wetter winters and drier spring-summer-fall seasons [25]. Shift of precipitation timing is particularly significant as it extends the dry season to late fall and early winter when hot and intense downslope Santa Ana winds peak. Although katabatic winds' overall activity in this region is projected to decrease in early fall and late spring, their intensity and frequency is not projected to change significantly during November–January, which coincides with a potentially extended dry season to increase the probability of concurrence of critical conditions of multiple fire drivers [26]. Anthropogenic warming only adds to the complexity of this phenomenon through enhancing the likelihood that warmer temperatures co-occur with precipitation deficit and other fire drivers, and through escalating the probability that precipitation deficit causes drought in California [27, 28].

Climate change will not only change probabilities of weather and fuel synchrony, it will likely also change the nature of the fuels themselves, with potential vegetation type changes resulting from more frequent fire disturbance and shifted weather during reestablishment [29]. Interactions between fire, climate, and introduced species could further complicate such changes [30]. Climate volatility [31]—rapid shifts between dry and wet conditions—for example, fosters growth of annual grasses and potentially invasive species, which grow quickly in the presence of abundant moisture in winter and early spring and provide ample dry fine fuels in summer and fall. While coastal Southern California fire regimes are currently flammability limited [32], changes in fuels could result in changes to both driver critical thresholds and concurrence.

Neglecting the multi-driver nature of wildfires and their synchronous interactions will underestimate the risks and costs associated with changes in fire activity resulting from climate change [33]. An increasing climatic risk for fire, however, does not

necessarily lead to an actual trend in the area burned nor does it lead to actual fires (figure S6). Indeed, the total area burned in the study region does not show an increasing trend (figure S7). Total area burned depends on various factors including ignition, fuel availability, climatic and weather drivers, and human controls, among others. Nonetheless, increasing critical megafire danger days is associated with grave socioeconomical implications even in the absence of fire. For example, the Fall 2019 intentional blackouts in California that impacted millions of people for several days were used to avoid fire ignitions by power transmission lines during high fire danger periods.

Through consideration of concurrence, we quantitatively show how probability of large, very large, and megafires can be explained as drivers acting as 'switches' as they exceed critical thresholds, rather than simply to the magnitude of drivers. Current metrics used for operational assessment of fire danger (e.g. ERC, BI, and LFM) either do not account for increased fire danger due to the concurrence of multiple critical drivers or do not have well-defined critical conditions that capture this concurrence (e.g. 'red flag warnings' issued by the National Weather Service forecast office). Concurrence of drivers can be assimilated into operational fire danger indices, but should be tailored to individual regions based on specific fuel, climate, and weather characteristics.

Data availability statement

The data that support the findings of this study are openly available at the following DOI: https://doi.org/10.2737/RDS-2013-0009.4.

Author contribution

MSK, PED and MS conceived the study and together with CHL wrote the first draft of the paper. MSK conducted the analysis. All authors contributed to the analysis and final draft of the paper.

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