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ORIGINAL PAPER

Quantifying increased fire risk in California in response to different levels of warming and drying

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Abstract

Warming temperatures and severe droughts have contributed to increasing fire activity in California. Decadal average summer temperature in California has increased by 0.8 °C during 1984–2014, while the decadal total size of large fires has expanded by a factor of 2.5. This study proposes a multivariate probabilistic approach for quantifying changes to fire risk given different climatic conditions. Our results indicate that the risk of large fires in California increases substantially in response to unit degree changes in summer temperature. The probability of annual mean fire size exceeding its long-term average increases by 30% when summer temperature anomaly increases by 1 °C (from −0.5 °C to + 0.5 °C). Furthermore, the probability of annual average fire size exceeding its long-term average doubles when the annual precipitation decreases from the 75th (wet) to the 25th (dry) percentile. The proposed model can help manage fire-prone regions where fire activity is expected to intensify under projected global warming.

Keywords Wildfire · Drought · Global warming · Copula

1 Introduction

Wildfire activity in the western United States is strongly associated with precedent regional climate conditions (Westerling et al. 2006; Keeley 2004). Frequent droughts and increasing seasonal and annual temperatures (Abatzoglou and Williams 2016) in the past few decades have contributed to the increasing frequency and size of wildfires in the region (Littell et al. 2009; Miller et al. 2009; Abatzoglou et al. 2020; Goss et al. 2020), resulting in substantial repercussions on ecosystems (Thompson et al. 2011) and human health (Bowman and Johnston 2005). Fire size and burn area are two terminologies closely related to one another that have been frequently used in the literature; latter (burn area) refers to exterior boundaries of the area burned and might include islands of unburned land, whereas former (fire size) refers to the area that experienced fire and does not include unburned islands (Dennison et al. 2014). In the western United States, the number of fires larger than 4 km^2 has grown at a rate of seven fires per year (Eidenshink et al. 2007) and the cumulative large fire area has expanded at a rate of 355 km^2 per year between 1984 and 2011 (Dennison et al. 2014). Due to global warming, this upward trend is expected to continue in areas with available fuel, underscoring the need for reliable estimates of future fire statistics (Turco et al. 2014; Jin et al. 2015). Accurate projections are vital for improving fire management, decision-making, and long-term adaptation and mitigation planning (Miller and Ager 2013).

To address the growing impacts of wildfires, experts have developed many wildfire risk models in both natural (e.g. Trigo et al. 2016; Zhijun et al. 2009; Zhang et al. 2015) and built (Nishino 2019) environments. Generally, available fire risk models represent fire likelihoods as either ignition probability based on statistical models (Elia et al. 2019) or burn area probability based on fire simulation

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models (Moghaddas et al. 2010; Finney et al. 2011). Statistical models use historical fire occurrences to predict ignition probability, whereas fire simulation models consider fire growth mechanisms unique to each region, accounting for fuel, weather, and topography (Keane et al. 2010; Koutsias et al. 2013). Fire simulation models are computationally demanding and typically involve simplifying assumptions about weather and fuel conditions (Finney 2007; Cruz and Alexander 2010) and fire spread mechanisms (Salis et al. 2010). These assumptions add uncertainty to fire risk simulations, limiting their applicability in fire management (Thompson and Calkin 2011). Moreover, fire risk models are often run on daily or weekly time scales (Preisler et al. 2004; Keane et al. 2010), which are not applicable for longer-term seasonal and annual planning and management (Miller et al. 2008; Chen et al. 2011).

Although available risk models provide useful information about wildfires, they often only produce a single distribution function for all possible climate conditions (Cumming 2001; Pausas 2004; Turco et al. 2013). There are also existing models that offer annual fire size probability distributions based on observed or simulated climate conditions (Westerling et al. 2011a; b). However, these models require sufficient fire data in each year to fit the data to the distribution function. Focus of this study is on changes of annual fire size distribution given a one-degree Celsius increase in summer temperature or deficit in annual precipitation, as examples of valuable information for risk assessment and planning. We present a statistical model that builds a conditional probability distribution function of fire size for a given expected climatic condition. This model provides a wide range of distribution functions and calculates the probability of exceeding critical thresholds for different precipitation and temperature conditions.

The proposed model's simple and flexible structure avoids the complexity and data requirements of fire models available in the literature. In addition, the model can be applied to any fire-prone region. The focus of this study is California, which has suffered from severe droughts, high temperatures (AghaKouchak et al. 2014; Shukla et al. 2015) and large, costly fires in recent decades (Keeley et al. 2009; Miller and Safford 2012). The proposed model evaluates the growing risk of large wildfires in response to increasing temperatures and drought severity in the region. Although there is a consensus on the increasing trends of fire frequency and severity in most areas within the state (Miller and Safford 2012; Miller et al. 2012), only few studies have explored changes in fire risk under highly likely and specific future climate conditions (Westerling et al. 2011b; Bryant and Westerling 2014). Current fire risk models assume stationary weather conditions (Finney 2007) or an average estimate of probable weather conditions (Ager et al. 2010). Our proposed risk model, however, provides critical information on fire likelihood given expected climate conditions anticipated by seasonal predictions. Next section provides details of the proposed methodology, and Sects. 3 and 4 present results of conclusions of this paper.

2 Materials and methodology

We examined all Californian wildfires larger than 1000 acres (405 ha) reported by the Monitoring Trends in Burn Severity (MTBS) Project during 1984–2014 (Eidenshink 2007). MTBS uses satellite remote sensing data to determine burn area of wildfires in the U.S. and hence provide a record of all fires occurred on all public and private lands. Selection of MTBS data stems from our preference of higher consistency and better coverage in the study area over longer, less complete data sources limited to administrative boundaries and management units (Dennison et al. 2014; Abatzoglou and Kolden 2013; Hart et al. 2015). All large fires used in this study are "non-prescribed" events with "high" confidence in fire area boundaries, as described in the MTBS database. The "fire area" used in this study is the area inside the fire boundary minus area categorized as "unburned to low" by MTBS.

We acknowledge that a variety of fire regimes exist across California and fires within some specific regions may exhibit behavior not captured in our state analysis (Keeley and Syphard 2017). The application of the proposed model on a combined dataset of California's eco-regions (with different fire regimes) is presented in the *Supplementary Materials* (see Figure S1). We have explored both eco-region and state-wide statistics of climate and fire condition. In the main manuscript, we focus on statewide statistics to track the general impacts of climate (temperature and precipitation) variability on the state's wildfires. In supplementary materials, we present the same results based on climate data and the corresponding wildfires from different eco-regions.

We retrieved monthly temperature and precipitation from the CRU TS v3.23 gridded climate dataset (Harris et al. 2014) supported by the U.K. Natural Environment Research Council (NERC) and the U.S. Department of Energy (https://crudata.uea.ac.uk/cru/data/hrg/). The data covers the world's land areas excluding Antarctica at 0.5-degree resolution during the period 1901–2014.

2.1 Fire risk model

This study describes a fire risk model that estimates the probability distribution of the cumulative size of all large fires in the state of California, given projected climate conditions preceding or during the fire season. The model uses copula functions (Nelsen 2013) to integrate climate information, e.g. summer temperature or annual precipitation, with the total fire size in the corresponding year. Copula functions describe the dependence among variables, which is an essential step in connecting climate information to wildfire occurrences. The joint distribution of the two variables X (climate variable) and Y (fire size) with cumulative marginal distribution functions $F_X(x)$ and $F_Y(y)$ is expressed by copula functions as:

$$F_{XY}(x,y) = C[F_X(x), F_Y(y)] \tag{1}$$

where C is the cumulative distribution function (CDF) of the copula function. Note that C joins the marginal distributions of X and Y (i.e. $F_X(x)$ and $F_Y(y)$), while F_{XY} joins the original variables (i.e. x and y). This is a unique feature of copula functions, where multiple variables are joined through their marginal distribution instead of their original values. Copulas are also flexible in the type of marginal distributions used and do not require the input variables to share similar distributions, unlike other multivariate distributions (Kelly and Krzysztofowicz 1997; Sharma 2000; Yue et al. 2001).

We have explored two main copula families including elliptical and Archimedean (Embrechts et al. 2003; Nelsen 2013): with *t*- and Gaussian from elliptical copulas, and Clayton (Clayton 1978) and Frank (Frank 1979) from Archimedean copulas (e.g. Shiau 2006; Salvadori et al. 2011; Madadgar and Moradkhani 2015). We applied the parametric bootstrapping goodness-of-fit test (Genest and Rémillard 2008) to select the best copula function for historical fires and climate conditions. Table 1 shows the distribution parameter and the p-value for all tested copula functions. The table also lists the test statistics for parametric bootstrapping goodness-of-fit test, called Sn (Genest and Rémillard 2008). The copula function with greatest *p*-value and smallest Sn is selected as the best fit (shown in bold font). The test did not converge for Clay copula function for precipitation-fire copula distribution. We determined Gaussian (*p*-value = 0.86) and t-copula (*p*value = 0.94) to be the best-fitted functions to join fire size with summer temperature and annual precipitation, respectively. Note that these copula models are selected specific to this region, and data from other regions might be associated with other copula families. The goodness-of-fit statistical tests (p-value and Sn test) can inform such decision (Genest and Rémillard 2008). For more information on copula fitting and parameter estimation, as well as uncertainty quantification, we refer the reader to the Copula Analysis Toolbox (MvCAT; Sadegh et al. 2017, 2018; Mallakpour et al. 2019; Shojaeezadeh et al. 2018, 2020).

In this study, the fire risk model is defined as the conditional probability of fire size given a specific climate condition (e.g., temperature or precipitation amount). Statistically speaking, we are interested in the probability of fire size, Y, exceeding a certain threshold, y, at the climate condition, X, denoted as x; i.e. $F_{Y|X}(Y > y|X = x)$.

The conditional probability density function $f_{Y|X}(y|x)$ is defined as follows:

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} \tag{2}$$

where $f_{XY}(x,y)$ is the joint density function of the original data (x,y), and $f_X(x)$ is the density function of the marginal distribution of x. The joint density function $f_{XY}(x,y)$ can be written as:

$$fXY(x,y) = c[F_X(x), F_Y(y)] \cdot f_X(x) \cdot f_Y(y) \tag{3}$$

where $c[F_X(x), F_Y(y)]$ is the probability density function of the continuous copula function $C[F_X(x), F_Y(y)]$; and $f_X(x)$ and $f_Y(y)$ are the density functions of the marginal distributions of x and y, respectively.

Hence, the conditional probability density function $f_{Y|X}(y|x)$ can be rewritten as (Madadgar and Moradkhani 2014):

$$\begin{aligned} f_{Y|X}(y|x) &= \frac{c[F_X(x), F_Y(y)] \cdot f_X(x) \cdot f_Y(y)}{f_X(x)} \\ &= c[F_X(x), F_Y(y)] \cdot f_Y(y) \end{aligned} \tag{4}$$

Table 1 Parameter, *p*-value, and test statistics (Sn) for all tested copula functions for joining average fire size and annual precipitation or summer temperature

		Copula function			
Variable	Test statistics	*t*	Gaussian	Clay	Frank
Precipitation	Parameter	Rho = **−0.6270** nu = **1.30e + 7**	−0.5093	1.45E−06	−3.9497
	Sn	**0.0276**	0.0358	–	0.03
	p-Value	**0.9371**	0.7754	–	0.8493
Temperature	Parameter	Rho = 0.7143 nu = 1.23e + 7	**0.5841**	1.8762	4.7807
	Sn	0.0257	**0.0194**	0.0389	0.0259
	p-Value	0.5978	**0.8593**	0.2625	0.7295

The conditional probability of $F_{Y|X}(Y > y|X = x)$ is then obtained from the area under $f_{Y|X}(y|x)$ in the domain of $Y > y$.

3 Results

This study analyzes the impacts of summer (May–September) temperature (see Fig. S5) and annual water-year precipitation (October-September; see Fig. S5) on wildfire risk in California. High summer temperatures result in dry vegetation and increase the risk of spreading wildfires. Annual precipitation implicitly indicates fuel availability and aridity by merging winter precipitation and summer precipitation. Winter precipitation is required for vegetation growth and summer precipitation defines vegetation dryness during fire season.

Average summer temperature shows an increasing trend in several past decades (see Fig. S5c). The 10-year moving averages of summer temperatures and annual temperatures and the 10-year total number of large wildfires (greater than 405 ha) exhibit strong positive trends in California during 1984–2014 (Fig. 1a). The number of large fires (greater than 405 ha) has increased at a rate of 4.7 events per decade. Increasing trends of temperature and fire activity is not limited to California and is observed across most of the western U.S. (Dennison et al. 2014; Westerling 2016), and are expected to worsen with projected rising temperatures in the region (Moritz et al. 2012).

Figure 1b illustrates 10-year total fire size—only including large fires (> 405 ha)—and average summer temperatures in three consecutive decadal periods, i.e. 1985–1994, 1995–2004, and 2005–2014. The figure shows that the 10-year total fire size increased from approximately 700,000 ha in 1985–1994 to 1,800,000 ha in 2005–2014, indicating over 2.5 times increase in decadal fire size across three decades. Over the same period, the average summer temperature increased from 20.9 °C to 21.7 °C, a 0.8 °C increase in three decades. These observations highlight the need to explore the increasing risk of large fires given a warming climate.

Using the fire risk model developed in this study, we developed fire size distributions for a range of summer temperatures in California. We use the term "fire size" as the average size of all large fires occurring in a given spatial region in each year (e.g., California, eco-regions). Figure 2 shows the conditional distributions of fire size given 'cool' or 'warm' summer temperature anomalies (i.e. $Pr(Fire > F|Temp = T)$. The shaded areas in the distributions convey the probability of exceeding the long-term

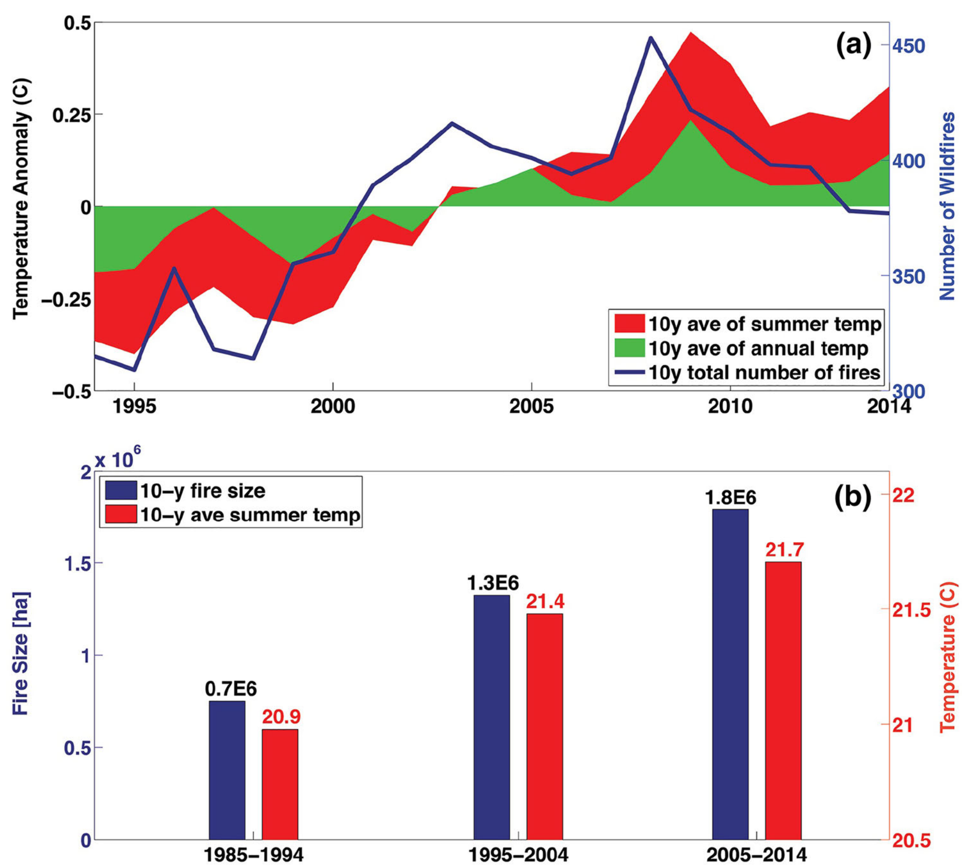


Fig. 1 Comparison of **a** anomalies in a rolling decadal average of annual and summer temperatures, and the corresponding number of fires in 1984–2014; and **b** average summer temperature and total fire size in three consecutive decades: 1985–1994, 1995–2004, and 2005–2014

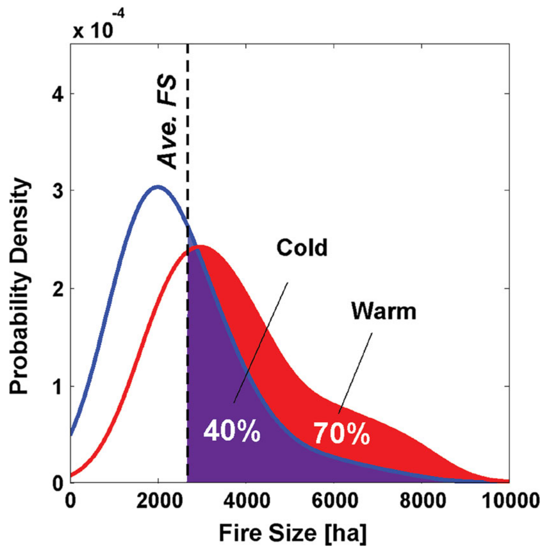


Fig. 2 Conditional probability distribution of annual average fire size in cool and warm summers. We define cold and warm summers as −0.5 °C versus + 0.5°C temperature anomalies, respectively. The shaded area indicates the probability of exceeding the average fire size in California (i.e. 2700 ha)—shown by the dash line

(1984–2014) average fire size, 2700 [ha] for the state of California, in cool (temperature anomaly = − 0.5 °C) or warm (temperature anomaly = + 0.5 °C) summers. From the conditional distributions, the probability of fires burning an area larger than 2,700 [ha] is 40% at T = − 0.5 °C and 70% at T = + 0.5 °C. This implies that a 1 °C increase in summer temperature increases the risk of fires exceeding the average size in the state by 30%. For marginal and joint probability density functions of fire size and summer temperature refer to Figure S6. We also estimated the proposed model's probability of correctly exceeding (non-exceeding) California's average fire size (i.e. 2700 [ha]) and compared them with probabilities from a simple logistic regression model (see Fig. S3 in *Supplementary Materials*). In both scenarios, the proposed risk model outperformed the logistic regression model in capturing the observations (Fig. S3).

Low annual precipitation can also increase the chance of wildfires (Dennison et al. 2014) by making dry vegetation widely available to burn (Westerling et al. 2006). Figure 3 shows California's annual average and total precipitation against annual average fire size in 1984–2014. Although large fires generally occurred in dry years, not all dry years experienced large fires. That is, low precipitation contributes to large fires but is not the only driver. Previous studies have shown that the key instigators of large wildfires are ignition sources, sufficiently available dry vegetation, high wind speed, and low humidity (Aldersley et al. 2011; Miller and Ager 2013). In general, large wildfires occur after a period of wet years followed by a dry year, during which fuel accumulates and dries out (Littell et al. 2009). As seen in Fig. 3, large fires in California generally occur within 2–3 years following a relatively long period of wet years.

The existing relationship between precipitation and fire activity in the region is clearly shown in Fig. 4a. The box-and-whisker plots depict the variation in annual average fire size for years with given precipitation conditions. The horizontal red lines indicate the average fire size in each box. From the figure, we observe a 40% decline in average fire size (from 3844 to 2307 [ha]) from below-normal to above-normal precipitation conditions.

Such a relationship between precipitation and wildfires lends to a fire risk model as discussed in the Materials and Methodology section. Figure 4b displays conditional probability density functions (PDFs) for 25th and 75th percentile of annual precipitation. The figure shows the results from integrating annual precipitation with the proposed fire risk model, displaying the effect of annual precipitation on fire size distribution in California. Clearly, annual precipitation strongly influences fire size distribution. In California, the incidence probability of fires larger than the long-term average is significantly lower in wet years compared to dry years (71% in dry years as opposed to 35% in wet). The study's precipitation scenarios are arbitrary selections to show the impact of annual precipitation on wildfire risk. Similar analyses using precipitation percentiles relevant to decision makers can provide useful information concerning the conditional distribution of wildfires. For marginal and joint probability density functions of fire size and annual precipitation refer to Fig. S7.

The herein outlined fire risk model can improve fire management by providing simple fire thresholds to help prepare and manage resources. The model offers distribution functions for climate conditions predicted by meteorological forecast models, which can be used to extract the likely corresponding fire size distributions for the upcoming fire season. Such risk analyses provide additional information on fire distributions in a variety of climate conditions and may allow seasonal forecasts to better inform wildfire resource and response decision-making. We note that precipitation and temperature have feedback on each other (AghaKouchak et al. 2014). Ideally, we need to explore the compounding effects of changes in both temperature and precipitation on fire hazard using a multi-hazard concept (e.g., using a three dimensional copula). However, at this point, we do not have sufficiently long-records for developing a similar multi-hazard model for the case study presented, although the copula framework is general and can address this topic. We hope that future research in this area provides opportunities to consider not only the impact of climate warming and drying on fires, but

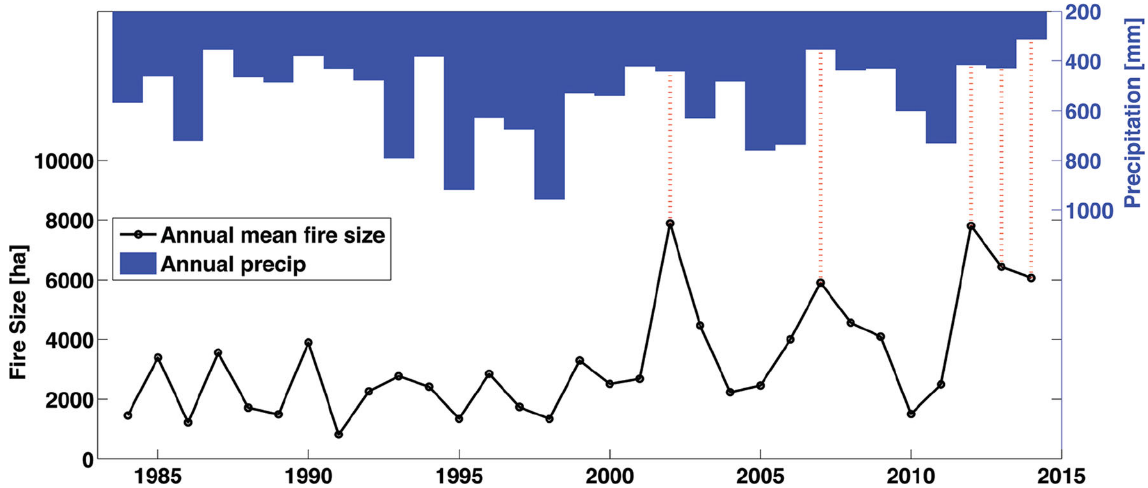
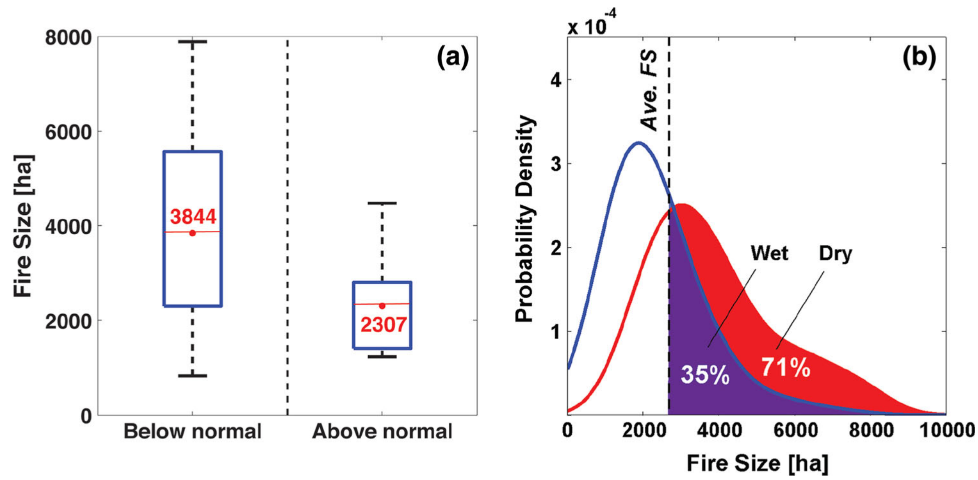


Fig. 3 Variation of annual precipitation versus annual average fire size during 1984–2014. The vertical dashed lines associate the largest fires with annual precipitation

Fig. 4 **a** Variation of annual fire size in years with below-normal (box on the left) and above-normal (box on the right) precipitation; **b** conditional probability distribution of annual average fire size in dry and wet years. We define dry and wet years as 25th and 75th percentile of annual precipitation, respectively. The shaded area indicates the probability of exceeding the average fire size in California (i.e. 2700 ha)—shown by the dashed line



also the compounding effects of both on changes in fire risk.

4 Concluding remarks

Warming temperature and severe droughts in the western US have helped increase frequency and size of wildfires during the past few decades. Historical observations for California show that the decadal total fire size increased by a factor of 2.5 between 1984 and 2014, and number of large wildfire events has increased significantly during the same period. At the same time, the average summer temperature increased from 20.9 °C during 1985–1994 to 21.7 °C during 2005–2014, i.e. 0.8 °C increase in three decades. Owing to likely hotter and drier future conditions in the region, the increasing trend of fire activity is expected to continue and even worsen. This study outlines a fire risk framework that describes the relationship between fire size and climate conditions, specifically summer temperature and annual precipitation. The model develops the fire-size distribution for different climate conditions using conditional probability.

Our analysis on historical observations during 1985–2014 indicates that the fire risk in the study region of California is strongly sensitive to the summer temperature and substantially increases in response to 1 °C increase in summer temperature anomaly. Unlike the current fire risk models, the proposed model offers the fire size distribution under different temperature conditions (e.g. −0.5 °C and + 0.5 °C anomaly). This model offers a distribution function (similar to Fig. 2) for a wide range of temperatures. This means that summer temperatures, predicted by seasonal forecast models, can be used to extract the corresponding fire size distributions for the upcoming fire season.

This study also analyzes fire activity under different precipitation scenarios. Based on the historical records, significantly large fires in California usually occur during dry years, especially after a long period of wet years with sufficient growth of fine fuel. Our analysis indicates that the average fire size declines by 40% (from 3844 to 2307 [ha]) from below-normal to above-normal precipitation years. The proposed model estimates a 71% probability of average fire size above long-term average (i.e. 2700 [ha]) under dry condition (25th percentile precipitation) versus a 35% probability under wet condition (75th percentile precipitation).

This multivariate model provides probabilistic information to support risk assessment and decision-making, and can be augmented by crowd-sourced near real-time hazard assessment frameworks for operational purposes (Wang et al. 2016; Yue et al. 2019). Such risk analyses provide additional information on fire distribution in different climate conditions and may allow for seasonal forecasts to better inform wildfire resource and response decision-making, especially in those fire-prone regions where future climate will lead to more favorable fire conditions.

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Author contributions AA and SM conceived the study. SM and MS developed the code. SM led the data analysis with inputs from AA and ER. SM, AA and FC prepared the first draft. All authors reviewed the paper and contributed to the discussions.

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