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Climate change drives earlier wildfire season onset in California

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Abstract

Wildfires in California have become more frequent in recent decades, with increasingly devastating impacts. The fire season is also lengthening, with an earlier onset. This trend has been hypothesized to be driven by climate change, but it has yet to be quantitatively attributed to climate drivers. Using a comprehensive fire occurrence dataset, we analyze fire season onset and climate controls on its variability and change during 1992-2018 in California's forested ecoregions. Onset shows an advancing trend, by 14 days in Northern California and 17 days in Southern California. In Southern California, this trend is dominated by decreasing winter precipitation, possibly natural in origin. By contrast, in Northern California, the largest contributor to the advancing onset is a springtime temperature increase, driven to a large degree by climate change. No matter what the dominant contributor to the trend is, the influence of

climate-change-driven warming on onset has already emerged from the influence of natural temperature variability in both regions. Given inevitable future warming trends, this influence will continue to accelerate fire season onset and exacerbate wildfire risks in California in coming years.

Introduction

Wildfire damage in recent decades has caused billions of dollars' worth of property damage and numerous casualties in the United States (Doerr & Santín, 2016; Zhuang et al., 2017). The western US, particularly California, is a hotspot for disastrous wildfires (Bowman et al., 2017; Schoennagel et al., 2017). Total wildfire damages in 2018 within California are estimated to be about \$148.5 billion dollars (Wang et al., 2021). Climate change has the potential to change fire conditions directly through altering seasonal patterns of temperature, precipitation, wind, and other conditions relevant for fire-weather and fuel aridity, and indirectly through affecting the fuel availability (Scott et al., 2013). During recent decades, a significant increasing trend in annual total burned area has been observed in California with strong links to the climate change-driven warming in the region (Abatzoglou & Williams, 2016; Westerling, 2016; Williams et al., 2019). A consideration of various characteristics of wildfires and a robust understanding of their controlling factors is vital for understanding how climate change influences fire conditions (Bowman et al., 2020; Krawchuk & Moritz, 2014).

Fire season onset is a fire behavior characteristic with practical applications in fire risk outlooks (NICC, 2021). An earlier than usual onset is an indicator of a potentially longer fire season, and therefore more fire risk with a longer mean burning time (Westerling, 2016). Additionally, when the onset is earlier, the environment has more potential to become primed for

subsequent large fires (Khorshidi et al., 2020). Onset has been widely identified as when fire weather conditions first surpass a selected threshold (e.g., Jolly et al., 2015). For instance, examining Canadian forests, Wotton & Flannigan (1993) defined onset as when maximum daily temperature starts to exceed 12°C for three consecutive days. Such an emphasis on temperature in defining onset has naturally led to the conclusion that climate change has the potential to advance onset in many regions (e.g., Wotton & Flannigan, 1993; Strydom & Savage, 2017), including California (Abatzoglou & Kolden, 2011). While fire weather is indicative of the fire danger, fire occurrence also depends on the fuel availability and ignition (Moritz et al., 2012). Additionally, widely-used fire weather metrics may not represent complex hydrological processes such as snow influence (Abatzoglou & Williams, 2016), which also influences aridity and hence fuel flammability. This highlights the importance of investigating fire season onset using fire occurrence data to develop a robust understanding of its drivers, thereby identifying the influence of climate change (Williamson et al., 2016).

Fire-occurrence-based analysis of fire season onset has previously been constrained by the limitation of fire occurrence data (Williamson et al., 2016). The question of how much climate change and natural variability have contributed to the changes in historical fire season onset in California has yet to be answered (Westerling et al., 2006; Westerling, 2016). One major limitation of previous attempts (Westerling et al., 2006; Westerling, 2016, Dennison et al., 2014) is that they were restricted to large fire sizes (e.g., fire size > 405 ha). This reduced the sample size and made it more difficult to develop robust statistics. In addition, large fires may require the occurrence of multiple unique environmental stressors (Khorshidi et al., 2020), making causal interpretations difficult. Similarly, conditioning on fire size implicitly combines fires with distinct types of driving mechanisms (Jin et al., 2015). Offshore-wind-dominated large fires in

Southern California, in particular, are limited by human ignitions (Keeley et al., 2021). This stresses the need for assessing the onset using comprehensive fire records with a wide spectrum of fire sizes and an objective definition of onset.

In this study, we use an extensive record of fire occurrence data for 1992-2018 for ecoregions in Southern and Northern California (Supplementary Fig. 1). By analyzing the distribution of starting dates of all recorded fires, we define a physically interpretable fire season onset. We utilize high-resolution observational and dynamically-downscaled reanalysis climate data to identify mechanisms and main drivers of this onset. Through this mechanistic understanding, we quantify the influence of climate change and natural variability on observed changes in onset during recent decades.

Results

Fire occurrence record-based fire season onset

The probability distributions of the discovery dates of fires during each calendar month (Fig. 1a,d) show that each month from October to May produces fewer than 10% of total annual fires in both domains. The number of fires increases in summer. The peak occurs in July, with 18% and 26% of the annual fires in Southern California and Northern California, respectively. We define the mean discovery date of the year (i.e., Julian date) of all fires, regardless of their size or other characteristics, as the fire season onset (hereafter, onset). The mean onset from 1992-2018 is 205 (24th July) and 210 (29th July) for Southern and Northern California, respectively. Onset shows a considerable variability within July and August (standard deviation of 11.2 and 12.2 days for Southern and Northern California, respectively) (Fig. 1b,e). For

example, the wet year of 2011 in California (Goulden and Bales, 2019) exhibits the latest onset in Northern California and one of the latest in Southern California. But this was immediately followed by the 2012-2015 drought (Williams et al., 2015; Madakumbura et al., 2020), which brought consecutive years of exceptionally dry and warm conditions. During these years, the onset reached its earliest in the record for both regions. Despite the interannual variability, a negative trend can be seen over both regions. This trend has advanced the onset by about 17 days (90% CI 4 to 31 days) in Southern California and 14 days (90% CI -2 to 29 days) in Northern California.

Mean fire size during a particular year shows a significant negative correlation with the mean onset (Fig. 1c,f, Supplementary Fig. 2), indicating that an earlier onset leads to a greater average fire size. This could be due to fires having a longer mean burn time when onset is earlier (Westerling, 2016), along with a higher probability of large fires. Demonstrating the causal link between onset and size is beyond the scope of this study. However, this significant relationship, along with the variability of onset associated with dry and wet years, suggests the onset metric is a predictor of critical fire behavior later in the season. Furthermore, from June to July (i.e., when the onset approaches), cumulative burned area surges from 6.2% to 24.7% of the annual total in Southern California, and from 2.8% to 10% in Northern California (Supplementary Fig. 3). This steep increase in burned area during onset illustrates that our definition of onset is not an abstract quantity but rather represents a step change in the development of the fire season. The fact that onset is swiftly followed by a rapid increase in burned area is further evidence that a proper understanding of climate controls of onset can aid early warnings in fire outlooks.

Climate controls of fire season onset

By analyzing regions with abundant vegetation in this study (Methods), we assume that the fuel loading in these regions is abundant and only a small fraction of the region ever becomes fuel limited (e.g. Abatzoglou & Williams, 2016). We further assume that very few areas are ignition limited in these regions (e.g. Krawchuk et al., 2009; Thonicke et al., 2001). This allows us to control for fuel and ignition, and model the fire season onset as a function of fuel aridity, the remaining element of the classic fire triangle (Moritz et al., 2012). As temperature and precipitation are the main state variables that drive ecohydrological aridity (e.g., Stephenson, 1998; Lutz et al., 2011; Minnich, 2018), we hypothesize that onset can be modeled as a function of temperature and precipitation. To test this, we use a simple multivariate linear regression model that predicts onset as a linear combination of temperature and precipitation during different months (Figure 2). This model yields high R^2 values, with maximum values of 0.76 and 0.72 for Southern and Northern California, respectively. This strong relationship between climate and onset suggests that the above assumptions relating to fuel abundance and ignition saturation are justified.

There is a distinct seasonal dependence of this regression model. The optimal predictor months differ between the two regions, despite both having similar precipitation seasonality (Supplementary Fig. 4). In Southern California, the highest R^2 values result from using winter precipitation, with winter temperature providing secondary predictability. By contrast, for Northern California, spring conditions are the greatest predictor, with spring temperature and precipitation independently resulting in high R^2 values. Compared to Southern California, Northern California has a larger snowpack (Minnich, 2018), which could explain the above differing seasonal influences of precipitation and temperature for two domains. Based on these

results, we hypothesize that through surface and subsurface moisture buffers, winter to spring precipitation influence is being carried over to summer in Northern California, influencing onset.

To test the mechanism hypothesized above, through which winter-spring precipitation and temperature influence the summer fire season onset, we look at soil moisture profiles. Soil moisture can be considered as a direct estimate of the ecohydrological aridity (e.g., Greve et al., 2019). Depleting soil moisture during the summer in California contributes to plant desiccation and drying of dead fuels, and optimal fire conditions (van Wagtendonk et al., 2018). Univariate relationships between onset and temperature/precipitation (Fig. 3) reflect the multivariate relationship portrayed in Fig. 2. Temperature has a peak influence during late spring (April-July) for both domains (Fig. 3a). The influence is greater in Northern ($R^2=0.56$) than Southern California ($R^2=0.36$). The influence of precipitation (Fig. 3b) peaks in April-June for Northern California ($R^2=0.54$) and January-March in Southern California ($R^2=0.59$). The R^2 seasonality for soil moisture at the surface layer (0-10cm) parallels the R^2 for precipitation in both domains (Fig. 3c). At a given depth, the change in the R^2 value over the course of the season reflects the evolution of soil moisture in that layer, i.e., the seasonality of moisture fluxes into and out of the layer (Supplementary Fig. 4). The change of R^2 profile with depth for a given month, however, may reflect the relationship between moisture at that level and plant water uptake, which may depend on various vegetation traits and environmental factors (e.g., Fellows and Goulden, 2017). Next, we test this hypothesis for the two domains by looking at results from soil moisture at different depths.

In Northern California, when moving to deeper soil layers, the peak R^2 of soil moisture shifts to later months of the year (Fig. 3d-f). The deepest layer considered here (100-200m) shows the strongest relationship with onset ($R^2=0.74$) in JJA, i.e., coinciding with the onset. In

Northern California, soil moisture at 100-200cm varies considerably over the year, e.g., the correlation between NDJ and JJA soil moisture is 0.55 (Supplementary Fig. 5). This likely results from the large contribution of snow melt and increasing evaporative demand when proceeding from winter to summer (Supplementary Fig. 4), temperature-influenced processes that could produce a distinct soil moisture anomaly. For Southern California, the R^2 seasonality is less dependent on depth of soil moisture (peaking in JFM at 0-10cm and in FMA at 100-200 cm). At all depths from 10cm downward, there is a near constant sensitivity of onset to soil moisture from spring onward. In Southern CA, there is very little contribution from snow, and a near constant evapotranspiration and runoff during the spring and summer (Supplementary Fig. 4). This results in a very little inter-seasonal variability of soil moisture at 100-200cm after FMA, e.g., every 3-month average thereafter is correlated above 0.9 with that in JJA (Supplementary Fig. 5). This partially explains the 100-200cm soil moisture R^2 leveling off after the peak in February-April (Fig. 3f). Southern California forests also may be water-limited (Fellows and Goulden, 2017) and, therefore, soil moisture buffers have a larger sensitivity to the wet season precipitation. Our results are also consistent with previous studies that found a strong relationship between spring precipitation and the timing of live fuel moisture decline (Dennison et al., 2008; Dennison & Moritz, 2009).

In both domains, the shift in the peak R^2 with depth is approximately consistent with volumetric soil moisture (i.e., volume of water per unit volume of soil) declining below a certain threshold in each soil layer (Supplementary Fig. 4). This is consistent with plant water stress being triggered by soil moisture decreasing below a threshold corresponds to plant physiological effects, such as incipient stomatal closure (Rodriguez-Iturbe & Porporato, 2004). These results are indicative of how in Northern California, precipitation and temperature influence summer

aridity (hence fire season onset) through snow-related mechanisms, whereas for Southern California, onset is predominantly controlled by wet-season precipitation variability.

Causes of observed trend in onset

With the above mechanistic understanding of how precipitation and temperature control onset, we next try to decompose the influence of each variable on the observed onset trend. Here we select cases where both variables have statistically significant independent causal influence on onset (Methods) (Fig. 2, green rectangles). This allows us to treat temperature and precipitation in these models as independent variables (e.g. Kretschmer et al., 2016; Supplementary Fig. 6). We then separate each variable into natural-variability and climate-change-driven components (Methods). Only for temperature is there a significant influence from climate change for both domains (Supplementary Fig. 7-10), which is consistent with findings of Williams et al. (2019). This allows us to model onset as a function of temperature variability (Tv), precipitation variability (Pv) and the climate-change driven change in temperature (CC) (Methods).

The linear model of onset using Tv, Pv and CC adequately captures the observed onset (Fig. 4a,b). Inspecting the contribution of individual components allows us to understand their roles during extreme events (Fig. 4d,e). For instance, during the 2012-2015 extreme drought, the early onset in Southern California (Fig. 4a) is linked mainly to dry conditions (i.e., precipitation deficit) (Fig. 4d), whereas in Northern California (Fig. 4b), onset is regulated not only by the precipitation deficit, but also the warm conditions produced jointly by temperature variability (Tv) and climate change (CC). All three components contribute similarly to the onset anomaly (Fig. 4e). Decomposition of the linear trend of observed onset into individual components (Fig.

4c) shows that in Southern California, the dominating component is Pv, which accounts for -13 days (90% CI -25 to -3 days), with a moderate contribution from CC, which accounts for -3 days (90% CI -12 to 4 days), and negligible impact from Tv (90% CI -4 to 4 days). For Northern California, CC is the largest contributor, accounting for -7 days (90% CI -17 to 2 days), with smaller contributions from Pv (-4 days, 90% CI -13 to 2 days) and Tv (-2 days, 90% CI -9 to 4 days). We also find that in both regions, the contribution from CC to the onset trend during 1992-2018 has started to exceed the contribution from the mean variability in Tv. (The Tv contribution is ± 3 days (90% CI 1 to 4 days) in Southern California and ± 5 days (90% CI 1 to 8 days) in Northern California (Supplementary Fig. 11)). The above attribution of historical change in onset to its mechanistic drivers highlights how climate variability and climate change both influence onset, and how the latter can amplify the adverse effect of the former.

Discussion

Understanding how climate change influences fire season onset in California is of vital importance for disaster risk reduction efforts. Many previous analyses to understand onset in general were limited to fire-weather, not fire occurrence. Fire weather indices may be indicative of the atmospheric evaporative demand and near surface soil moisture, and therefore a proxy for fuel moisture. But they do not capture complex ecohydrological processes and feedbacks, and do not fully represent mechanisms relevant to fire-season onset (e.g., Holden et al., 2018). Our results based on fire occurrence data present an estimate of onset that is physically consistent with variations in surface and subsurface water budgets in two distinct climate regimes of California.

A larger sensitivity to temperature in Northern California stems from the higher influence of temperature on the water buffers through modulating the snow melting and evapotranspiration (Bales et al., 2006; 2011). Climate-change driven warming is therefore having a large influence on onset through earlier snow melting (Westerling et al., 2006) and larger evaporative demand (Goulden & Bales, 2014; 2019). In contrast, Southern California has a lower sensitivity to temperature, due to the much smaller amount of snow it receives (Minnich, 2018). Additionally, results show that the cumulative impact of climate-change-driven warming from 1992-2018 is larger than the influence of interannual temperature variability in both domains (Supplementary Fig. 11). This indicates a lasting shift of the distribution of the onset beyond the envelope of natural variability. In this study, we assumed that the climate change signal in precipitation for the two domains is small. There is a large natural variability in precipitation in California (Dettinger et al., 2011), and there is large uncertainty regarding the sign of the anthropogenic precipitation change (Langenbrunner & Neelin, 2017). This makes the detection and separation of the climate-change component very difficult (McKinnon & Deser, 2021). The decreasing precipitation trend that explains most of the advancing onset trend in Southern California reflects the drying trend in the western US during recent decades (Williams et al., 2020). More subtle changes in precipitation characteristics driven by climate change, such as a shortening of the wet season (Swain, 2021) and a decrease in the number of wetting rain days (Holden et al., 2018) could also influence statistics of aggregate fire behavior like onset. The model presented here for predicting onset could be modified to incorporate these other changes in precipitation characteristics.

The assumptions made regarding the fuel and ignition limitations could be relaxed to allow the research framework presented in this study to be applied in settings that are

considerably more fuel and/or ignition limited. Fuel characteristics can have interannual variability (e.g., Koontz et al., 2020). Wet years can increase vegetation density in forests (e.g., Goulden & Bales, 2019) as well as promote fuel growth in fuel-limited regions (Williams et al., 2019; Keeley & Syphard, 2019); meanwhile, drought leads to tree mortality, which can increase fire risk (Millar & Stephenson, 2015). Climate variability shapes fuel availability, ignition efficiency and fuel combustibility, irrespective of the ignition sources (Abatzoglou et al., 2016; Scott et al., 2013). However, human activities are constantly changing the ignition traits (Keeley & Syphard, 2018) and therefore the fire season characteristics (Balch et al., 2017). Natural ignitions also influence characteristics of fire seasons, such as the 2020 anomalous fire season that was boosted by unusual bursts of dry lightning (CALFIRE, 2020). Furthermore, ignition and fuel could have trends that are themselves influenced by temperature and precipitation. Fuel and ignition can be considered in an extended analysis, using additional variables and modeling approaches that can capture nonlinear interactions.

Our analysis provides a framework for understanding the mechanisms through which climate conditions control fire onset. Given that the temperature and precipitation predictors have lead times of several months, the model presented here could be adapted to a seasonal prediction system of fire season onset. Moreover, the climate change component in predicting onset is indicative of what is to come, as inevitable climate change-driven warming trends continue. Thus, our findings have major implications for wildfire disaster prevention and management strategies in coming seasons and years.

Methods

Fire occurrence and climate data

We use the 5th edition of the United States Forest Service Fire Program Analysis-Fire Occurrence Database (FPA-FOD) (Short, 2021). The dataset is quality controlled and comprehensive, with ~2.17 million wildfires that were recorded by United States federal, state, and local agencies during 1992-2018. We use the data attributes discovery date, fire size and the location (latitude and longitude) in the analysis.

To investigate the climate drivers of fire season onset, monthly mean temperature, precipitation, maximum vapor pressure deficit and minimum vapor pressure deficit data at 4 km spatial resolution are obtained from Parameter-elevation Relationships on Independent Slopes Model (PRISM; <http://prism.oregonstate.edu/recent/>). Monthly mean vapor pressure deficit is calculated as the mean of monthly minimum and maximum values. Data of surface and subsurface water budget are obtained from a recently developed dynamically downscaled ERA5 dataset using the Weather Research and Forecasting (WRF) model version 4.1.3 at 3 km spatial resolution (Rahimi et al., 2021). This dataset was created to physically resolve atmospheric processes (and their descriptive variables) not resolvable (and in some cases not observable) across data-sparse areas of California. It provides daily and hourly variables at high spatial resolution for land-surface modeling, hydrologic modeling, and wildfire process applications. We use variables snow water equivalent, surface latent heat flux, surface and subsurface runoff, and soil moisture at different depths. In contrast, many of the previous ecohydrological studies for California at comparatively high resolutions have been limited to a simple bucket type water balance model in investigating soil moisture conditions (Flint et al., 2013; Stephenson & Das, 2011; Dobrowski et al., 2013; Lutz et al., 2011; Fellows & Goulden, 2017). This only allows a

bulk assessment of total plant available moisture amount and often uses simple parameterizations for snow, evapotranspiration, and runoff, which may not realistically represent the real conditions (Dobrowski et al., 2013). In the downscaled ERA5 product, a land-surface model is coupled with the atmospheric model to yield more physically sophisticated water balance and soil moisture profiles.

Considering the two distinct climatic conditions (Swain et al., 2018; Norris et al., 2021; Minnich, 2018) and fire behavior (Williams et al., 2019; van Wagtendonk et al., 2018), we analyze Southern and Northern California separately in this study. Fire and climate data were first extracted for two montane ecoregions in California (ref., North et al., 2016) where fuel is abundant: Southern California mountains and Northern Californian Western Cordillera (Supplementary Fig. 1), based on United States Environmental Protection Agency's ecoregion classifications (Omernik & Griffith, 2014). California's Western Cordillera region includes sub ecoregions Eastern Cascades Slopes and Foothills, Sierra Nevada, Cascades, Klamath Mountains and California High North Coast. We hereafter refer to Southern California mountains and Western Cordillera as Southern and Northern California domains, respectively. Note that by considering regions with forests where fuel is abundant, we implicitly focus on so-called "fuel-dominated fires" that are occurring in summer (Jin et al., 2014; Keeley & Syphard, 2019). Off-shore wind driven fires (known as Santa Ana and Diablo winds in Southern and Northern California, respectively) also have a distinct seasonality, occurring during Autumn and Winter. These fires have mainly occurred closer to urban areas in the past in Southern California (Jin et al., 2015), in part because they are limited by human ignitions (Keeley et al., 2021), not by fuels (Keeley & Syphard, 2019).

Estimation of the influence of climate variability and climate change

To estimate the influence of climate variability and climate change, we first develop a simple causal network (Supplementary Fig. 6). We take temperature and precipitation as the main drivers of onset, based on the mechanism identified in this study, where antecedent precipitation and temperature influence is carried through to the summer through soil moisture buffers, influencing the fire season onset (Results). We adapted a simplified version of the causal effect network approach presented in Kretschmer et al. (2016).

As the first step, the correlation between the onset time series of each year and antecedent precipitation and temperature is calculated (Figure 3) and the significant ($p < 0.01$) cases are selected. This list of selected variables is called potential parents (P_0). As the second step, the P_0 are sorted based on the absolute value of the correlation above. Conditional independence tests are then carried out between each of the variables in P_0 and onset, first, by removing the influence of the variable with the highest correlation (say Z). This is done by calculating the partial correlation. If a variable X has a statistically significant ($p < 0.01$) partial correlation with onset, it is declared that X has an influence on onset independent of Z . If the partial correlation is not significant, the variable is removed. This way we objectively obtain a smaller subset of P_0 (say P_1). This is repeated by conditioning on the variable with the next highest absolute correlation with onset in P_1 . Finally, for Southern California, January-March average precipitation and March-May average temperature are obtained as the potential drivers of onset. For Northern California, April-June average precipitation and temperature are obtained (Figure 2). Repeating the above analysis using vapor pressure deficit, a fire weather metric that is highly correlated with historical burned area (e.g., Abatzoglou & Williams, 2016) does not show an independent influence from precipitation and temperature.

With the above selected drivers of onset, we proceed to quantify their influence on onset. First, we assume that climate change is influencing onset through temperature and precipitation (Supplementary Fig. 6). To isolate this influence from natural climate variability, we use a global mean surface temperature-based (GMST-based) method to extract the climate signal (Hawkins et al., 2020). Using this method, natural variability and climate change components are identified based on a longer time series (1880-2018) of PRISM temperature and precipitation. In this way, we can separate signal from noise in temperature and precipitation more robustly than when based on the shorter fire-occurrence data period (1992-2018). The target variable is regressed onto a smoothed GMST time series obtained by 41-year locally weighted scatterplot smoothing. The component explained by GMST is considered as the climate-change-driven change and the residual is taken as natural variability (Hawkins et al., 2020). GMST from GISS Surface Temperature Analysis version 4 (<https://data.giss.nasa.gov/gistemp/>; Lenssen et al., 2019) is used for this task. Our results show that only for temperature, a significant climate change influence can be seen for both domains (Supplementary Fig. 7-10). This is consistent with findings of Williams et al. (2019). Therefore, we model onset as a linear function of variability of temperature (T_v), variability of precipitation (P_v , which is equal to P in this study) and influence of climate change (CC), which is represented by the climate-change-driven change in temperature (Fig. 4). Based on this linear model, we estimate the influence of trends of each component on the observed linear trend of the onset. The linear regression model used is as follows,

$$\text{Onset} = \alpha T_v + \beta P_v + \gamma CC + \lambda + \varepsilon$$

where α , β and γ are the regression coefficients, λ is the intercept, and ε is the residual.

It should be noted that, we do not assess the uncertainty arising from the method used to separate the climate change-driven change in temperature and precipitation (e.g., Williams et al., 2015). Different techniques for this task exist (Deser et al., 2020) and they could be used to estimate this uncertainty.

Uncertainty estimation of the regression model

The uncertainty in regression coefficients is calculated by temporal bootstrap resampling of the time series. For each sample, we randomly select years with replacement 1000 times and create the regression model for each sample.

For the uncertainty in the trend estimates of observed onset, T_v , P_v and CC , we adopt the approach used in Davenport et al. (2021). We randomly select 80% of the years with replacement and calculate the trend of T_v , P_v and CC , for 1000 samples. To estimate the uncertainty of the attribution of observed trends in onset to trends in T_v , P_v and CC , we calculate the contribution of trends for each of the above-created 1000 regression models. This results in 1 million estimates for each variable. Empirical quantiles 0.05 and 0.95 of this distribution are calculated to obtain a 90% confidence interval.

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561 **Figure 1. Fire occurrence-based fire season onset during 1992-2018.**

562 **(a,d)** Percentage of annual fires started in each month, **(b,e)** time series of the onset date, defined
563 as the mean fire start date of the year, **(c,f)** relationship between the onset and the mean fire size
564 during each year. Results are shown for Southern California mountains **(a-c)** and Northern
565 California **(d-f)**. The box and whiskers in **(a,d)** represent the interquartile range and 5th-95th
566 percentiles, respectively, while the red horizontal line and blank circles represent the median and
567 outliers, respectively. Red lines in panels **(b,e)** and **(c,f)** show the linear trend and the best fit
568 line, respectively. Statistical significance of the linear trend was estimated using a modified
569 Mann-Kendall trend test (Hamed & Rao, 1998).

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Figure 2. Relationship between onset and temperature and precipitation

R^2 value from multiple linear regression of onset using temperature (T) and precipitation (P), for Southern California (**a**) and Northern California (**b**), for different combinations of preceding seasons. Green boxes indicate the cases where each variable has a statistically significant causal influence on onset, identified following Kretschmer et al. (2016) (Methods). In the regression equation, α , β and γ are the regression coefficients, λ is the intercept, and ε is the residual.

Figure 3. Relationship between antecedent climate variables and onset

R^2 for the linear regression between onset and (a) temperature (T), (b) precipitation (P), (c-f) soil moisture (SM) at depths 0-10cm (c), 10-40cm (d), 40-100cm (e) and 100-200cm (f). Blue crosses and red dots show results for Northern California (NC) and Southern California (SC), respectively

Figure 4. Influence of climate variability and climate change on observed trend in onset

Onset modeled using variability of temperature (Tv), variability of precipitation (Pv) and climate change component of temperature (CC). Months with an independent influence on onset by both T and P are used (Methods). These are marked by green rectangles in Figure 2. **(a,b)** Observed (black thick line) and modeled (blue shading for the 90% CI) onset. Multimodel mean is shown by the black dotted line. **(d-e)** Influence of individual variables Tv (blue), Pv (green) and CC (red). Mean is shown by a thick line. Shaded region shows the 90% CI. **(c)** Influence of the trend of individual variables and the full model (All) on onset, compared with the trend of observed onset (Obs), shown as the total number of days during 1992-2018. Circle indicates the mean and the error bars show the 90% CI. Crosses (X) shown under All indicate the sum of mean values of Tv, Pv and CC. Negative and positive values indicate a decrease and an increase of the Julian date of onset, respectively. Results for Northern California (NC) and Southern California (SC) are shown in blue and green in **(c)**, respectively.

Supplementary Figure 1. California's domains analyzed in this study.

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621 **Supplementary Figure 2. (a,b) Same as Fig. 1c,f, respectively, but with linear trend removed**
 622 **from both variables.**

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Supplementary Figure 3. Cumulative area burned each month.

The box and whiskers represent the interquartile range and 5th-95th percentiles, respectively, while the red horizontal line and blank circles represent the median and outliers, respectively.

Supplementary Figure 4. Climatology of climate variables

(a) temperature (T), (b) precipitation (P), (c) snow water equivalent (SWE), (d) surface latent heat flux (ET), (e) Surface (sfc) runoff, (f) Subsurface (subsfc) runoff, (g-j) soil moisture (SM) at depth ranges 0-10cm (g), 10-40cm (h), 40-100cm (i) and 100-200cm (j). Results for Northern California (NC) and Southern California (SC) are shown in blue and red, respectively. The error bars represent 0.5 standard deviations in each direction. Shading in (g-j) represents the volumetric SM value (y value) that corresponds to the peak R^2 value of the relationship with onset, shown in Figure 3c-f. Shading extends from NDJ to the period when the peak R^2 occurs.

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654 **Supplementary Figure 5. Lead correlation between 100-200 cm soil moisture in June-August**
655 **and preceding months.** Results for Northern California (NC) and Southern California (SC) are
656 shown in blue and red, respectively.

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A causal diagram for assessing the influence of T,P variability and climate change

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662 **Supplementary Figure 6. Causal diagram for assessing the influence of temperature and**
663 **precipitation on onset.**

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670 **Supplementary Figure 7. Separating the climate change signal of temperature (Southern**
671 **California)**

672 Standardized (with respect to 1992-2018) temperature (T) is regressed on smoothed global
673 mean surface temperature (GMST) time series obtained by 41-year locally weighted scatterplot
674 smoothing. Predicted T using GMST (orange line) is taken as the climate change component and
675 the residual is taken as the natural variability component. Red shaded region shows $\pm$ standard
676 deviation (SD). The year when the climate change component starts to exceed 1SD is shown in a
677 dashed vertical line. Results are shown for months **(a)** November-January (NDJ), **(b)** December-
678 February (DJF), **(c)** January-March (JFM), **(d)** February-April (FMA), **(e)** March-May (MAM), **(f)**
679 April-June (AMJ), **(g)** May-July (MJJ), **(h)** June-August (JJA).

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681 **Supplementary Figure 8. Separating the climate change signal of precipitation (Southern**
682 **California)**

683 Standardized (with respect to 1992-2018) precipitation (P) is regressed on smoothed global
684 mean surface temperature (GMST) time series obtained by 41-year locally weighted scatterplot
685 smoothing. Predicted P using GMST (orange line) is taken as the climate change component and
686 the residual is taken as the natural variability component. Red shaded region shows $\pm$ standard
687 deviation (SD). Results are shown for months **(a)** November-January (NDJ), **(b)** December-
688 February (DJF), **(c)** January-March (JFM), **(d)** February-April (FMA), **(e)** March-May (MAM), **(f)**
689 April-June (AMJ), **(g)** May-July (MJJ), **(h)** June-August (JJA). Note that compared to temperature
690 (Supplementary Fig.8), the climate change component does not exceed 1SD.

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693 **Supplementary Figure 9. Same as Supplementary Fig. 7, but for Northern California**

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697 **Supplementary Figure 10. Same as Supplementary Fig. 8, but for Northern California**

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Supplementary Figure 11. Influence of temperature and precipitation variability on onset

Mean variability is calculated as the standard deviation of each variable during 1992-2018.

Contribution of temperature variability, T(var) and precipitation variability, P(var) are shown, along with the cumulative influence by climate change driven warming (CC). CC effect is the same as that shown in Figure 4c. Results for Southern California (SC) and Northern California (NC) are shown in green and blue, respectively. For Southern California, the CC effect is -3.4 days (90% CI -11.8 to 3.9 days) and the T(var) effect is ± 2.6 days (90% CI 0.85 to 4.4 days). For Northern California, the CC effect is -7.1 days (90% CI -16.6 to 1.8 days), whereas the T(var) effect is ± 4.5 days (90% CI 0.6 to 8.3 days). Variability components are shown as negative values for a better comparison with the decreasing contribution of CC.