Higher incidence of high-severity fire in and near industrially managed forests

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The increasing prevalence of high-severity wildfire in forests in the US state of California is connected to past forest management, but uncertainty remains regarding the differential effects of land ownership on these trends. To determine whether differing forest management regimes, inferred from land ownership, influence high-severity fire incidence, we assembled and analyzed a large dataset of 154 wildfires that burned a combined area of more than 971,000 ha in California. We found that where fires occurred, the odds of high-severity fire on "private industrial" lands were 1.8 times greater than on "public" lands and 1.9 times greater than on "other" lands (that is, remaining lands classified as neither private industrial nor public). Moreover, high-severity fire incidence was greater in areas adjacent to private industrial land, indicating this trend extends across ownership boundaries. Overall, these results indicate that prevailing forest management practices on private industrial timberland may increase high-severity fire occurrence, underscoring the need for cross-boundary cooperation to protect ecological and social systems.

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The increased incidence of high-severity wildfires in the state of California and western US forests over the past several decades threatens both ecological and social systems (Stevens *et al*. 2017; Steel *et al*. 2018; Hessburg *et al*. 2021). The complete or near-complete mortality of dominant vegetation associated with high-severity fire effects, and the unprecedented scale of these effects, is particularly concerning in certain forests – including many in California – where tree species lack direct mechanisms for recovery or regeneration from large, severe fires (Shive *et al*. 2018). These forests are highly fire prone and adapted to withstand low–moderate severity fires, which primarily spread on the forest floor but recover slowly (decades to centuries) from extensive high-severity crown fire (Coop *et al*. 2020). Trends in high-severity fire are associated with the broader pattern of increasingly extreme wildfire events that has resulted in the loss of human life, extensive property damage, carbon emissions, and long-lasting disruptions to ecosystem services and the communities that rely on them (Stephens *et al*. 2014; Stenzel *et al*. 2019). The effects of these fires on forest ecology are long-lasting and can facilitate conversion to non-forest ecosystem types, which has major negative implications for carbon storage and wildlife habitat (Coop *et al*. 2020).

There are discussions in the scientific, management, and political arenas about the causes of increased extreme fire effects, a conflict that has played out in forums ranging from presidential statements to high-profile court cases (Dixon 2018), scientific journals (Peery *et al*. 2019; Hagmann *et al*. 2021), and traditional news media. Much of this discussion focuses on the role of forest management or lack thereof in contributing to more extensive high-severity effects.

Disputes about the role of forest management in driving extreme wildfire effects frequently center on the differing management practices of industrial timber companies and public land agencies (Schwartz *et al*. 2020). Typically, industrial timber companies aim to maximize sustainable wood production while minimizing costs; consequently, intensive management practices such as plantation forestry, a highly efficient method of timber production (Sedjo 1999), are frequently applied. In contrast, forest management by public agencies in California, such as the National Park Service (NPS), the Bureau of Land Management (BLM), and the US Forest Service (USFS), tends to have a substantially smaller impact, as measured by standing biomass and removals (Stewart *et al*. 2016). This is largely due to the diverse set of objectives across public forests, ranging from resource conservation to recreation, lower consensus on management goals, and increased litigation and public scrutiny (Collins *et al*. 2017).

There is considerable scientific disagreement concerning how these different forest management approaches affect fire severity. On public lands, the combination of aggressive fire suppression with low rates of both restoration thinning and fuel treatments has resulted in dense stands with high fuel loads that contribute to extreme fire behavior (Starrs *et al*. 2018). Meanwhile, under intensive plantation management, the homogenous stand structure and high fuel continuity common in even-aged plantations can foster rapid fire spread (Zald and Dunn 2018; Koontz *et al*. 2020). The complex and intermixed pattern of ownership boundaries in the western US further complicates this debate (Zald and Dunn 2018). Given the "contagious" nature of wildfire, it might be expected

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that issues of adjacency, wherein the heightened incidence of high-severity effects associated with a given management practice spills over onto nearby land of differing ownership types, receive greater attention.

Empirical studies of the relationship between ownership and fire severity are limited and conflicting. Several have demonstrated reduced fire severity and area burned in industrially managed forests (Lyons-Tinsley and Peterson 2012; Starrs *et al*. 2018), whereas others have reported increased severity (Zald and Dunn 2018). Most of these studies examined only a single fire event, with very little work done at larger geographic scales on cross-boundary risk associated with ownership type or management approach (but see Downing *et al*. 2022). Here, our goal was to quantify the impact of land ownership on the incidence of high-severity fire, conditional on fire occurrence, through large-scale analyses of wildfires in California. We also examined whether ownership effects on high-severity fire are vectored across ownership boundaries, and we compared these outcomes to the effects of other important topographic, climatic, and meteorological drivers of fire severity.

Methods

Study area

We analyzed 154 wildfires that burned a combined area exceeding 971,000 ha in California from 1985 to 2019 (Figure 1a; WebTable 1). All fires occurred in predominantly yellow pine (ponderosa pine [*Pinus ponderosa*] and Jeffrey pine [*Pinus jeffreyi*]) and mixed-conifer (white fir [*Abies concolor*], Douglas-fir [*Pseudotsuga menziesii*], incense-cedar [*Calocedrus decurrens*], ponderosa pine, sugar pine [*Pinus lambertiana*], and black oak [*Quercus kelloggii*]) forests. We refer to these forest types collectively using the acronym YPMC (that is, yellow pine and mixed-conifer). Historically, YPMC forests were characterized by high-frequency, low-to-moderate-severity fire regimes until the forced cessation of Indigenous burning practices in the 19th century and a policy of fire suppression was adopted in the early 20th century (Anderson 2013; Stephens *et al*. 2014). We selected all fires from the California interagency fire perimeter database (https://frap.fire.ca.gov/frap-projects/fire-perimeters) that contained both private industrial and public lands in YPMC forests with at least 16.2 burned ha (40 acres) in each

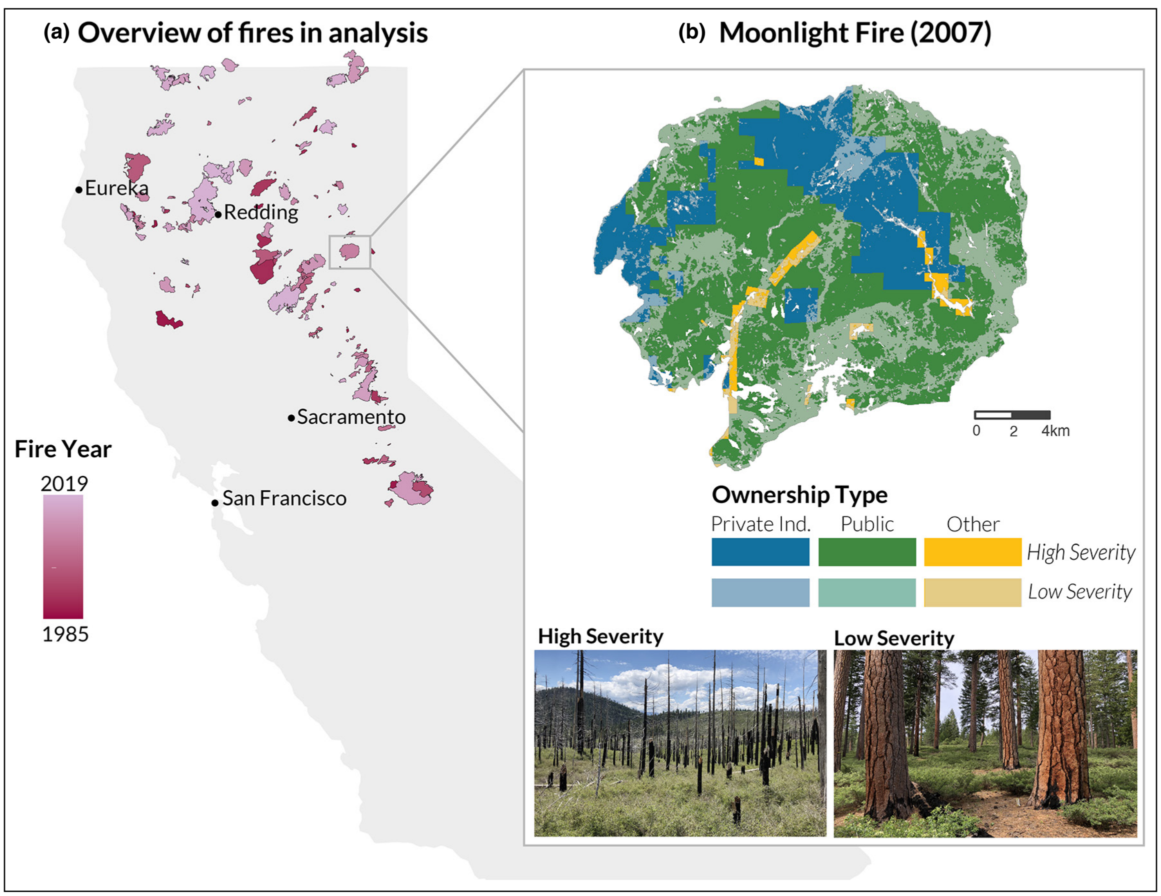

Figure 1. (a) Map of northern California, with the location of the 154 fires analyzed in the study. The year in which each fire burned is denoted by color, with lighter colors representing more recent fires. (b) Example of the ownership and severity patterns for one specific fire, the Moonlight Fire. Ownership is denoted by the three colors, with darker shades of each color representing areas that burned at high severity. Images were taken on public land (US Forest Service) within the Moonlight Fire perimeter in two locations, one that burned at high severity and another that burned at low severity, and depict the state of recovery 10 years after the fire; note high shrub density and lack of conifer regeneration in the high-severity location.

ownership category in order to partially control for ignition type and suppression response. We determined forest type using pre-settlement fire regime (PFR) groups from the California Fire Return Interval Departure (FRID) database (Safford and Van de Water 2014). We classified land ownership into three categories – "private industrial" (26%), "public" (64%), and "other" (10%) – using the Fire and Resource Assessment Program's (FRAP) ownership database (https://frap.fire.ca.gov/mapping/gis-data) and a database of industrially managed timberland (T Moody pers comm; for an example from a single fire, see Figure 1b). The public land category consisted of all government-owned land (primarily USFS: 82.1%; NPS: 8%; BLM: 6%; with the remaining ~4% largely under the jurisdiction of state and local government agencies), whereas the "other" category comprised land not classified as private industrial or public (primarily private nonindustrial ownership, such as small landowners, conservancies, and preserves).

We estimated fire severity in units of composite burn index (CBI) at a 30-m resolution using Landsat imagery (thematic mapper [TM] and operational land imager [OLI] sensors) and Google Earth Engine following Parks *et al.* (2019), which relied heavily on the relativized burn ratio spectral index. Severity was categorized as "high" or "low–moderate" using the CBI threshold determined empirically by Miller and Thode (2007) (eg Figure 1b). The CBI threshold for high severity (>2.25) has been shown to capture nearly complete overstory tree mortality (>95% live basal area loss) based on a robust pre- and post-fire field dataset (Lydersen *et al.* 2016). Although not a direct measure of fire severity, and despite reports of variation in the fire-effects observed for any given value, CBI's predictive accuracy of on-the-ground fire effects remains high, making it a useful metric for analyzing fire severity over large spatial extents (Miller and Thode 2007; Lydersen *et al.* 2016; Parks *et al.* 2019).

Analysis

To determine the effect of land ownership on high-severity fire probability we fit a binomial, generalized linear model (GLM) and used spatial block bootstrapping to account for autocorrelation in the data. We modeled the probability of each 30-m × 30-m pixel burning at high severity, conditional on fire occurrence, as a function of ownership type, ownership proximity, elevation, slope, topographic position index (TPI), heat load, ecoregion, and a categorical identifier for each fire (fire ID). Because we only considered pixels that actively burned, our assessment of the probability of high-severity fire was conditional on the occurrence of fire; however, for improved readability, we refer to this conditional probability simply as the probability of high-severity fire.

To assess whether ownership-related differences in the probability of burning at high severity extend to nearby pixels of different ownership type, we included the weighted average proximity to each ownership type as three variables in the model. P_{jt} (proximity of a pixel of ownership type j to ownership type t) was defined using the nearest pixel of type j, and was calculated as:

$$\begin{gathered} P_{jt} = e^{-qD}, t \neq j \\ P_{jt} = 0, t = j \end{gathered} \qquad \text{(Equation 1)},$$

where D is the distance in kilometers to the nearest pixel of ownership type j and q is a positive attenuating constant, fit by maximum likelihood, that decreases the weight given to pixels farther away as it increases. P_{jt} then is a variable bound between 0 and 1, where a value of 1 indicates that the pixel of type j is adjacent to a pixel of type t and a value close to 0 indicates that the pixel is far away from any pixel of type t. Ownership values equal to 0 are impossible, as all pixels are owned. Because a pixel may be close to pixels of both other ownership types, P_{jt} was defined as:

$$\eta_{jt} = P_{jt} \times \frac{P_{jt}}{\sum_{t=1}^{3} P_{jt}} \qquad \text{(Equation 2)}.$$

This yields two explanatory variables for ownership type j, one for each other ownership type. A positive estimated coefficient for η_{jt} indicates that the probability of a pixel burning at high severity increases as proximity to ownership type t increases.

We included elevation and ecoregion in the model to control for and assess potential climatic and environmental effects on fire severity, which has been demonstrated in previous studies (Steel *et al.* 2018; Zald and Dunn 2018). Topographic variables were calculated from the US National Elevation Dataset 30-m digital elevation model (Gesch *et al.* 2002), and ecoregions were classified from the US Geological Survey's Ecoregions of California database (WebFigure 1; Griffith *et al.* 2016); slope, TPI, and heat load are topographic indices known to affect fire behavior and severity. TPI describes the elevational position of a pixel in relation to its neighbors, thereby capturing the effects of local topography. We used a 300-m annuli to calculate TPI, because previous studies have shown effects on severity at this range and the relatively small scale help avoid collinearity with elevation (Zald and Dunn 2018). Heat load describes incident radiation as a function of slope, aspect, and latitude, and was calculated following McCune and Keon (2002). Canopy height was also considered to capture major differences in forest structure (ie mature versus young forests), but was excluded from the model due to limited data availability prior to 2000 and because preliminary analyses did not indicate a clear relationship to severity. All continuous topographic variables were normalized to standard units to aid model convergence and facilitate comparison of effect sizes. Correlations among model predictors were low (<0.2).

Fire ID was included to capture unmeasured fire-level effects such as suppression activity, local climate, ecology, and weather. Weather was not included as a covariate in the model due to its high correlation with fire ID. Instead, we performed a post-hoc analysis to determine its residual effect on severity. We considered maximum burning index (BI) during the first 7 days of each fire, a composite meteorological variable that integrates the effects of temperature, humidity, wind speed, and fuel moisture, and that has been linked to incidence of high-severity fire (Stevens *et al.* 2017; Zald and Dunn 2018). BI values were extracted from the GridMet dataset at a 4-km resolution (Abatzoglou 2013). We fit a linear, mixed-effects meta-analytic model with a fire's average maximum BI as a predictor of each fire's fitted coefficient, which represented the difference in high-severity rate from the comparison level (the Moonlight Fire) and a random effect of fire ID.

Accurate statistical analyses of spatial datasets are often hindered by spatial autocorrelation, as spatially autocorrelated data violate the assumption of independence required for valid statistical inference. If unaccounted for, spatial autocorrelation biases standard error estimates and can lead to Type I errors (Dormann *et al.* 2007; Lahiri 2018). However, most methods for dealing with spatially autocorrelated data are computationally cumbersome, often preventing consideration of large spatial datasets altogether (Dormann *et al.* 2007). Here, we used a relatively new and computationally efficient method known as spatial block bootstrapping to obtain accurate standard error estimates and to calculate confidence intervals (Lahiri 2018; Socolar *et al.* 2021). Nevertheless, we took a 25% random sample of pixels, stratified by fire ID, in order to reduce computing time (from >28 days to <3 days). The reduced dataset included 2.7 million pixels, covering an area of over 240,000 ha. Full descriptions of the modeling approach and spatial block bootstrapping method are presented in WebPanel 1, and the reproducible code is available on GitHub (https://doi.org/10.5281/zenodo.6338495).

Results

We found a clear, negative effect of both public and other ownership on the conditional probability of high-severity fire compared to industrial private ownership (public: −0.58 [−0.68, −0.47]; other: −0.68 [−0.73, −0.53]; 95% Wald confidence intervals [CIs] are shown in square brackets, and all effects are shown in log-odds). These effects indicate that the odds of a pixel burning at high severity on private industrial land were approximately 1.8 times higher than on public land and 1.9 times higher than on land categorized as other (calculated from odds ratio; Figure 2). In addition, we found a clear positive effect of proximity to private industrial land (0.33 [0.2, 0.46]), meaning that pixels near private industrial land are more likely to burn at high severity than those farther away. The odds of burning at high severity for a pixel adjacent to private industrial land were approximately 1.4 times higher than for a pixel 3 km away from private land when other covariates were held at their mean values. The odds of a pixel 1 km away from private industrial land burning at high severity were still 1.3 times higher than for a pixel 3 km away. There was, however, a negative effect of proximity to the other ownership category (ie small private) (−0.27 [−0.40, −0.14]). The effect of proximity to publicly owned land was also negative, although the 95% CI spans 0 (−0.096 [−0.25, 0.059]; Figure 2a).

TPI, slope, and heat load all exhibited clear, positive effects on the probability of high-severity fire, although the effect of TPI was much larger than the effects of slope or heat load (TPI: 0.22 [0.21, 0.23]; slope: 0.06 [0.04, 0.08]; heat load: 0.03 [0.01, 0.04]; Figure 3, a–c). The estimated effect of elevation was negative (−0.09 [−0.13, −0.05]; Figure 3d). Ecoregion effects varied, with the Klamath and Eastern Cascades experiencing the lowest probabilities of high-severity fire and the Basin and Range, Sierra Nevada, and Cascades experiencing the highest (Figure 3e). There was no evidence of a relationship between average maximum

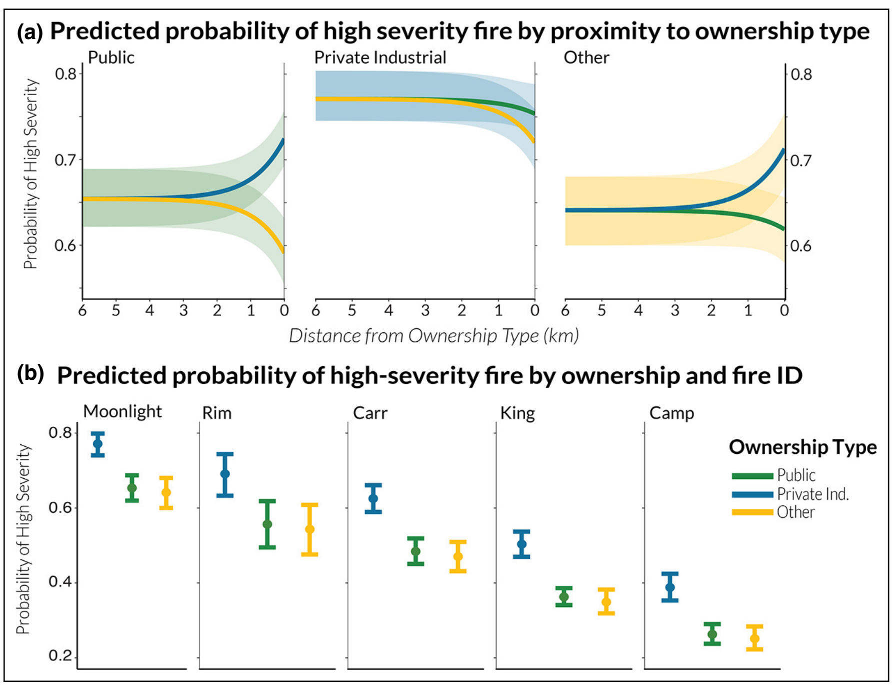

Figure 2. (a) Predicted mean probabilities of high-severity fire for each of the three ownership types as a function of distance to the other ownership types, along with 95% Wald confidence intervals (CIs). The color of the shaded regions indicates the true pixel type, whereas the color of the trend line indicates which ownership type is being approached as one moves left to right across each plot. All predictions are for the Moonlight Fire and the Sierra Nevada ecoregion. (b) Predicted mean probabilities of high-severity fire for each ownership type in five of the largest fires in the study. Points represent mean predictions, and error bars represent 95% Wald CIs.

BI and high-severity probability at the fire level (–0.005 [–0.02, 0.03]).

Discussion and conclusions

Land managed by private industrial timber companies is associated with a higher probability of high-severity fire than public land or land owned by individuals or entities other than industrial timber interests and the federal government, indicating that prevailing forest management practices on private industrial timberland are associated with increased occurrence of high-severity fire (Figure 2). The magnitude of this effect is substantial. The effect of a pixel's ownership classification being private industrial versus public is equivalent to the effect of increasing TPI by 2.6 standard deviations (SDs; 51 m) from the mean, slope by 9.5 SDs (88%), or heat load by more than 8 SDs (3.4 megajoules per centimeter per year), the latter two being outside the range of variation in the data. That the effect of ownership is large, even compared to the effects of topographic variables known to play major roles in controlling fire behavior, demonstrates the important role of land-ownership type in influencing fire severity.

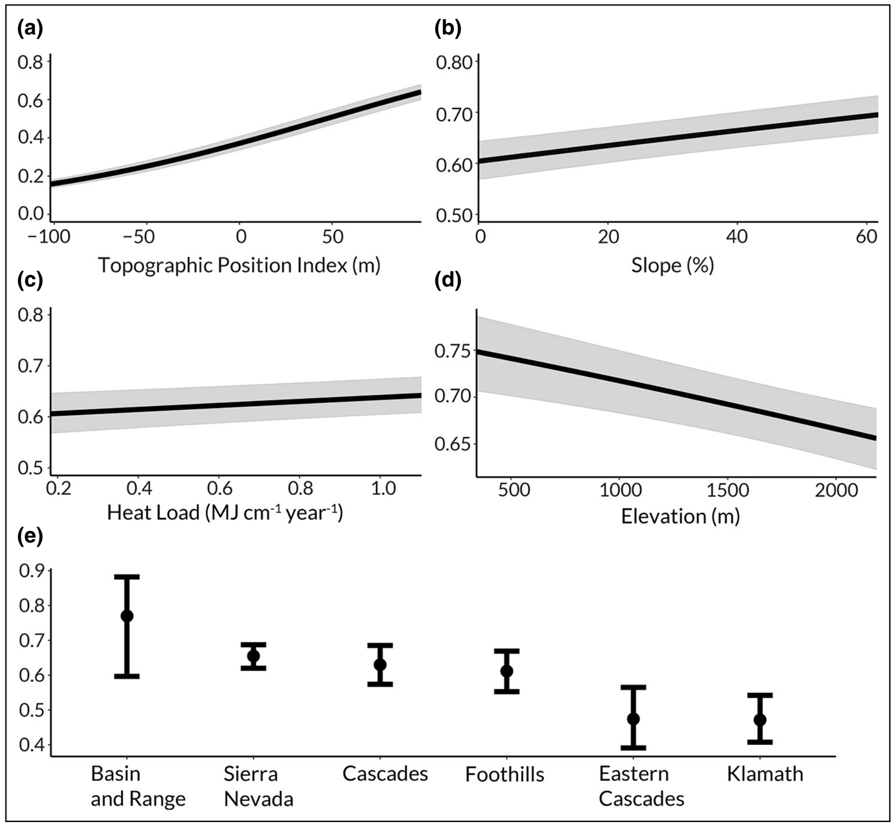

Figure 3. (a–d) Predicted mean probabilities of burning at high severity as a function of the topographic covariates: topographic position index, slope, heat load (in megajoules per centimeter per year), and elevation. The shaded regions represent 95% Wald CIs. (e) Predicted means and 95% Wald CIs for the six US Geological Survey ecoregions covered in the study (WebFigure 1).

Proximity to private industrial land is also clearly associated with increased probability of high-severity fire, indicating that high-severity effects may be vectored onto neighboring ownership types. This pattern informs the already fraught issue of cross-boundary fire management in the western US (Fischer *et al*. 2016). Over 250,000 ha of our study area (26%) was within 1 km of private industrial land, for which the odds of burning at high severity were estimated to be at least 1.3 times as high than for land 3 km away or further (260,000 ha, or 27% of the study area; Figure 2). Because wildfires often burn across a patchwork spatial arrangement of ownership types, effective risk mitigation requires cooperation across ownership boundaries, but groups with differing management priorities and philosophies often do not engage in cooperative management behavior (Fischer *et al*. 2016; Dunn *et al*. 2020). The finding that severity risk may be vectored across boundaries further emphasizes the importance of regional planning and cooperation.

The lack of a relationship between extreme fire weather (as captured by maximum BI) and the probability of high-severity fire (WebFigure 2) contrasts with the results of several previous analyses (eg Birch *et al*. 2015). Most likely, the correlation between fire weather and other covariates removed some of its association with fire severity, and therefore the absence of an observed relationship here should not be overinterpreted. We know from previous research that extreme weather is an important driver of fire severity, and that differences in forest structure and fuel load can be less important under extreme weather conditions (Coppoletta *et al*. 2016; Stevens *et al*. 2017).

The clear relationship between private forest management and increased high-severity fire suggests that forest management practices on private industrial land within our study area contribute to increased fire severity, possibly through the creation of continuous forest-fuel structures (eg younger, even-aged forests; Stephens and Moghaddas 2005). We can only connect ownership patterns to actual forest management practices by general association. Throughout our study area, even-aged silviculture is more prevalent in private industrial forests (Christensen *et al*. 2015). However, the mechanisms underlying the association between private industrial land and high-severity fire are complex. Private landowners are not monolithic. Indeed, uneven-aged forest management systems also occur on some privately owned lands. Perhaps future studies can more directly connect specific management practices with severity risk, independent of ownership, in order to better inform policy and management decisions.

The lower probability of high-severity fire occurrence on public forest lands should not be interpreted as a tacit endorsement of public agencies' dominant management practices. Concerning increases in high-severity fire incidence are prevalent on lands across California, regardless of ownership type (Stephens *et al*. 2014; Stevens *et al*. 2017; Steel *et al*. 2018). The relatively better performance of public land is not evidence that forest management there is combatting this trend. Regardless of ownership type, scientific evidence suggests that massive increases in prescribed fire, managed wildfire for resource benefit, and restoration thinning are necessary to mitigate fire severity across the state (LHC 2018).

We chose to analyze high-severity fire specifically because of its severe ecological and economic consequences, but previous studies have identified opposite ownership-related trends when considering other important dimensions of fire regimes, including ignitions, patch size and complexity, and area burned (eg Starrs *et al*. 2018). This indicates that the role of ownership in the more general pattern of increasingly extreme wildfire events is nuanced. For example, differences in post-fire outcomes are worth noting; more active management on private industrial land often results in more successful reforestation post-fire (Stephens *et al*. 2020). Additional research is needed to fully evaluate the effect of ownership on wildfire patterns throughout California forests.

Several other limitations exist. For one, CBI, while predictive of on-the-ground fire effects (Miller *et al*. 2009; Lydersen *et al*. 2016), is an indirect measure of fire severity. Because it is derived from satellite imagery, CBI is not always reliable for distinguishing between young stands that burned at high severity and old stands that burned at high severity – outcomes that are distinct in terms of carbon emissions and ecological effect. Additionally, small trees are more susceptible to death by fire than large trees. Possibly, the short rotation ages common in industrial forests contribute to the higher incidence of high-severity fire on those lands. However, canopy height as estimated from Landfire was not associated with fire severity in preliminary analyses. Finally, we used extended assessment severity estimates, which compare pre-fire imagery to imagery taken 1-year post-fire. In contrast, initial assessment estimates compare pre-fire imagery to imagery taken 1–3 months post-fire. While extended assessments are more accurate (Lydersen *et al*. 2016), they can be impacted by post-fire management (eg salvage harvesting), potentially leading to overestimation of high-severity effects (Safford *et al*. 2015). To investigate this potential bias, we examined the aforementioned 2007 Moonlight Fire, for which extensive salvage logging occurred on private industrial forestland. We found a slight increase in the probability of a pixel burning at high severity in the extended versus initial assessment: 0.017. However, this proportion was small relative to the observed difference between private industrial and public land throughout our entire dataset (0.017 versus 0.14) and fell within the reported classification error for the dataset (Miller *et al*. 2009; see WebPanel 2).

Fire is a complex natural process that occurs on land managed in diverse manners, for diverse objectives and in a wide array of socioeconomic and political contexts. Here, in investigating fire-severity patterns across major forest ownership classes, we discovered that the incidence of high-severity fire is clearly increased in and near private industrial forests. The heightened likelihood of high-severity fire both on and around industrially managed forests suggests that the predominant forest management practice on these lands (even-aged plantation forestry) may contribute to the broader pattern of increased high-severity fire incidence in California on land of all ownership types. This, together with the complex intermix of ownership types and evidence that high-severity fire effects may be spread across ownership boundaries, emphasizes the necessity of cross-ownership cooperation to reverse recent, concerning trends in extreme fire effects.

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Data Availability Statement

All data used in this study are freely available (accessible either through the publications cited below or within this article's Supporting Information) with the exception of the property boundaries of private industrial timber companies in California, which cannot be publicly posted due to issues of privacy and data ownership. Related queries should be directed to the corresponding author of this study. All code used in the processing and analysis of data in this paper can be found on Github (https://doi.org/10.5281/zenodo.6338495).

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Supporting Information

Additional, web-only material may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1002/fee.2499/suppinfo