Factors affecting California Wildfires: Ownership, Ecoregion, and Forest Types' Impacts on Forests and the likelihood of Wildfires

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ABSTRACT

In the face of changing climate, California and the Western United States are seeing increased occurrences and severity of wildfires. Previous authors investigated the factors contributing to wildfires, yet investigations into how ownership, ecoregion, forest type, and reserve status impacts fire probability are limited. California's diversity and roughly equal split between private and public ownership of California's forests allowed for a series of regression models to explore the impacts of different factors on wildfire occurrence. All of the linear regression models showed an increased probability of fire under publicly-owned lands. The relationship between ownership and fire probability changed depending on ecoregion and forest type.Ownership effects varied between California Conifer and Western Oak forests, relative to other forest types. There was also variation in fire probability across ownerships for California's different ecoregions. Reserved lands showed a lower probability of fire compared to unreserved lands. The decreased fire occurrence for private lands as well as reserved forests, calls for discussions about forest management strategies for public land and unreserved forests that are more vulnerable to fire.

KEYWORDS

forest management, linear regression, reserve status, fire occurrence, interaction

INTRODUCTION

Anthropogenic climate change impacts all parts of the world and California is not exempt from the effects of the changing climate. Between 2020 and 2021, there was an average of 8,741 fires that burned 4,304,379 and 2,568,948 acres respectively (CALFIRE 2020a, 2021b). Fires have been a part of Earth's ecosystem for over 400 million years ago and periodic fires are an integral part in the maintenance of the integrity and species composition of ecosystems (Syphard et al. 2007, Pausas and Keeley 2009). Although fires have been historically present, they are increasing in both number and severity causing current management practices to be insufficient for effectively managing land (Flannigan et al. 2013a). These increases in occurrence and severity of wildfires is more pronounced in the Western United States compared to the rest of the country (Westerling 2016). Fires are the result of many different factors, including nonhuman and human factors. Climate change, one of the major abiotic factors, isn't always the largest factor influencing the increase in fire (Syphard et al. 2007, Pausas and Keeley 2021). The common consensus concludes that weather and climate, fuels, ignition agents, and humans factor into forest fire frequency (Flannigan et al. 2005, Huang et al. 2015). Humans influence fires in areas of frequency and changes in fuel conditions through new ignition sources (such as setting off fireworks or burning campfires), as well as altering fuel conditions through fire suppression regimes or logging the area (Miller et al. 2012, Flannigan et al. 2013b). Much of the current literature looks at the climatic and other abiotic factors, leaving a gap about the influence of anthropogenic factors.

One anthropogenic factor looked at by Starrs et al. 2018 was land ownership. Land ownership of forests varies between different groups. Of California's 33 million acres of forestland, sixty percent is owned publicly (e.g. USDA Forest Service and National Parks Service) and the other forty percent is privately owned (USDA 2022a). Within the privately owned land, one third is under corporate private ownership and the other two thirds are owned by families, tribes, and individuals (non corporate ownership) (USDA 2022a). Each ownership type manages their land based on different priorities. The agriculture sector used the management differences to predict disturbances; in forested landscapes it has been shown that there were quantifiable differences in land use change along property boundaries (Turner et al. 1996, Lunt and Spooner 2005). Land ownership has been used to trace back legacies of logging and fire suppression that give insights on how forests behave today (Easterday et al. 2018). California's publicly owned land under the U.S. Forest Service is managed with high priority to "maintain and improve the health, diversity, and productivity of the nation's forests and grasslands to meet the needs of current and future generations. Forest management focuses on managing vegetation, restoring ecosystems, reducing hazards, and maintaining forest health" (US Forest Service 2021). While these goals may be a part of the practices within privately owned land, silvicultural differences occur, especially in the private forests under the corporate ownership. These discrepancies between priorities under different ownership groups provide an opportunity to investigate how land ownership factors into wildfire occurrence.

Human influence on fires should continue to be investigated, however to gain a fuller picture of what influences forest fire probability, the human factor should be looked at in conjunction with other abiotic factors. One important factor is the ecoregion. Ecoregions are mosaics of areas in which the biotic, abiotic, terrestrial, and aquatic ecosystems are similar (US EPA 2015). Ecoregions are arranged with the most fine details based on climates and precipitation, temperature, vegetation and land cover, and terrain features (USDA 2022b). Because of this fine detail, looking at ecoregion as a factor allows for a coverage of the climatic and vegetative features that could influence wildfire. Forest type, the dominant tree species in the overstory at a given location, is another factor that should be considered when determining influences on forest fire probability (Colorado State Forest Service 2022). California has nine dominant tree species: Douglas-fir, giant sequoia, Jeffrey pine, numerous oak species, pinyon pine, ponderosa pine, quaking aspen, redwood, and western juniper that make up its forests (US Department of the Interior n.d.). One last factor to look at is reserve status. Reserve status indicates whether a forest is excluded from commercially harvesting wood products in order to capture elements of biodiversity that can be missing from sustainably harvested sites (Massachusetts Executive Office of Environmental Affairs n.d.). The Forest Service was created in 1905 to manage the country's forest reserves and began to practice fire suppression soon thereafter in an effort to prove their qualifications (Berry 2007). However, this jump into suppressing all fires led to an increase in fuel sources, vegetation, and weakened trees from competition for water, nutrients, and light (Berry 2007). Due to the historic effort to put out every fire, reserved forests now have a higher fuel load and density of trees which lead these forests vulnerable to forest fires. Although the factors mentioned above have been investigated, their amalgamation with ownership has yet to be explicitly examined.

The current literature regarding forestland ownership and fire is limited, and the few sources who have looked into this topic have conflicting findings. One previously mentioned pieces of literature, Starrs et al. 2018, used CALFIRE’s Fire and Resource Assessment Program's (FRAP) 'FVEG' map, the United States Geological Survey's Protected Areas Database under the United States Gap Analysis Program (GAP) dataset, and the Direct Protection Area designation to examine how forest ownership, firefighting, and reserve status influence fire probability. They found that federal land plus firefighting under federal jurisdiction was associated with higher fire probability. Conversely, Levine 2022 and Zald and Dunn 2018 found that there was higher fire severity on private industrial land. While those papers were not examining the same things under the same conditions, the inconsistencies in findings about fires and land ownership lead to a need to further investigate land ownership and fire probability.

Using Forest Inventory and Analysis (FIA) data in conjunction with California Department of Forestry and Fire Protection (CALFIRE) data, I estimate correlations between land ownership and wildfire occurrence in California. This combination of datasets has yet to be explored in tandem and hopes to bring more conclusivity to the current findings. Using these datasets and ArcGIS, I quantified the impact of land ownership on the likelihood of wildfires, conditional on historical wildfire presence, through a statewide analysis of California. I also examined ownership effects on wildfire probability, vectored across ecoregion, forest type, and reserve status to see how the different factors affect forest fire probability as a whole. I hypothesize that ecoregion will play a statistically significant role in wildfire probability when connected to ownership because these areas have similar climates and vegetation, both variables have been proven to affect wildfire probability (Miller et al. 2012). I hypothesize forest types with large amounts of conifer trees will have the highest fire probability because of the conifer’s needles and large amounts of sap that burns quickly (“How Different Tree Species Impact the Spread of Wildfire” 2012). Finally, I predict that reserved FIA plots will have a higher wildfire probability due studies showing that a history of suppression leads to increased rates of high-severity burning (Steel et al. 2015).

METHODS

Study Area

The site I studied was the entire state of California. California has 33 million acres of forestland. I looked at 14,917 FIA plots within the state, so I was able to perform a large-scale analysis on fire probability, rather than looking at a single site. I looked at only accessible forestland, rather than also including non forest land, noncensus water, census water, and non sampled land. By looking at the entire state of California, I was able to examine a larger variety of ecoregions and forest types, to gain a better understanding of how fire, ownership, ecoregion, and forest type relate.

Data

To identify FIA plots, I used the United States Department of Agriculture (USDA), United States Forest Service's Forest Inventory and Analysis (FIA) data. I obtained the California FIA plots from FIA DataMart through a downloaded zip file. The FIA program has been monitoring the country's public and private forests since 1930 to create a dataset that "reports on status and trends in forest area and location; species, size, health of trees; in total tree growth, mortality, and removals by harvest; in wood production and utilization rates by various products; and in forest land ownership" (Burrill n.d.).

To determine whether ownership was public or private, I used the FIA dataset's Condition Table. Within the Condition Table were the Owner class code (OWNCD) and Owner group code (OWNGRPCD) variables. The variables indicate the ownership category of the forestland for each FIA plot (See FIA database documentation "2.5 Condition Table").

To determine whether a plot had experienced a wildfire, I used the California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP) Fire Perimeters database. This ESRI ArcGIS geodatabase shows historical fire perimeters dating back to the 1880s, but I decided to select dates beginning from 2011 because that is the date where my FIA data begins. Each recorded fire in this database has the year, state, agency, fire name, incident number, alarm date, containment date, cause, estimated area, GIS acres, collection method, objective, and fire number. There could be multiple fire perimeters associated with an area or FIA plot, if the location had burned twice since 2011. After the date restriction, the database had a total of 4083 FIA plot observations.

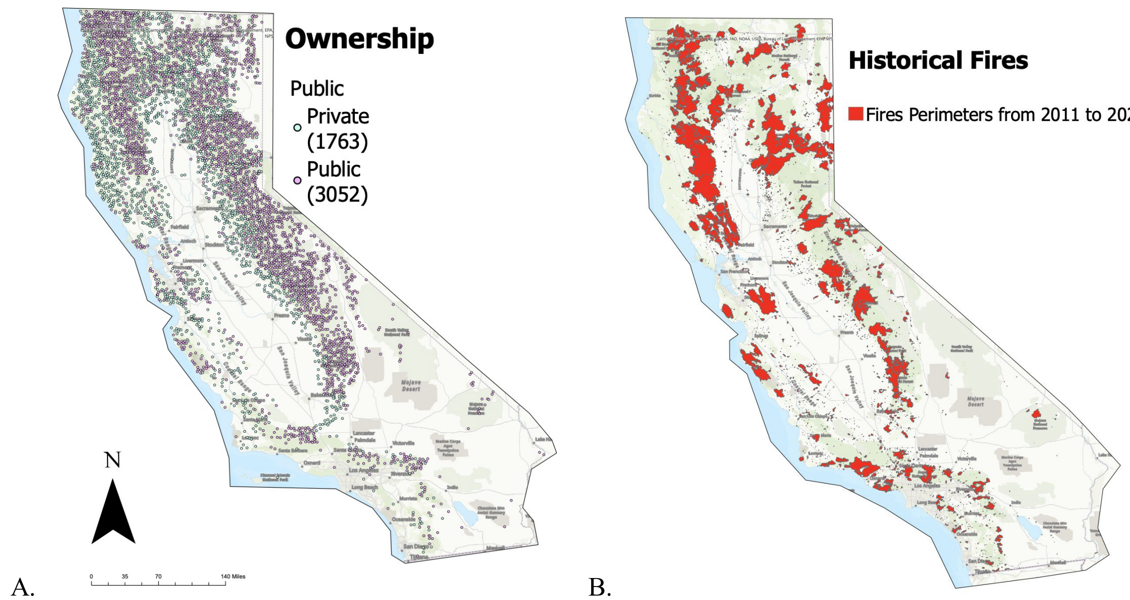

Figure 1. Spatial distribution of ownership and fire perimeters. (A) Shows the arrangement of FIA plots sampled from 2011 to 2021 and distinguishes public and private plots throughout the state of California. (B) Shows the fire perimeters across California from 2011 to 2021 for a total of 4074 fires.

To determine reserve status of publicly owned FIA plots, I used the Condition Table of the FIA dataset. The reserve status code (RESERVCD) gives a binary response about whether a plot is reserved or not reserved. A RESERVCD = 0 indicates "Not reserved" and a RESERVCD = 1 indicates "Reserved". Plots given the code of 1 are "permanently prohibited from being managed for the production of wood products through statute or agency mandate; the prohibition cannot be changed through the decision of the land manager. Logging may occur to meet protected area objectives. Examples include designated Federal wilderness areas, national parks and monuments, and most State parks. Private land cannot be reserved" (Burrill n.d.).

To identify ecoregion, I used the Plot Table's ecological subsection code (ECOSUBCD). These codes are given to plots with areas of similar surficial geology, lithology, geomorphic processes, soil grou[s, subregional climate, and potential natural communities. Subsection codes for the conterminous United States were developed as a part of the "Ecological Subregions: Sections and Subsections for the Conterminous United States (Brosofske et al. 2007).

To create the abridged FIA dataset, I merged a simplified Condition Table and Plot Table. I downloaded the zipped file into Rstudio. I then edited the Plot table to keep the variables: Sequence number, Latitude, Longitude, Elevation, Ecoregion, Inventory Year, Measurement Year, Ecological Unit, Topographic Position, Precipitation (For full list of Plot Table Variables, see FIA Documentation "2.4 Plot Table"). For the Condition Table I simplified the table so it only contained the variables: Plot Sequence Number, Reserve Status Code, Owner Class Code, Owner Group Code, Forest Type Code, Owner Subclass Code, Condition Proportion Unadjusted, Slope, Aspect, Condition Status Code, Physiographic Class Code (Table 2b). Because of the structure of the FIA data, I followed their instructions on how to merge the Plot and Condition tables. Based on the User Guide, I used the plot sequence number (PLT_CN) to link the Condition table to CN in the Plot table. I renamed PLT_CN using the rename() function in R and then used the left_join() function to merge the two tables by CN into a table called fia_plots. I then ran the write.csv() function to create a .csv file that could be imported into ArcGIS pro.

Spatially Matching FIA Plots to Historical Fires

To determine which FIA plots were affected by fire historically, I used ArcGIS Pro to spatially join the CALFIRE fire perimeters to the FIA dataset I created. I imported the CALFIRE geodatabase I downloaded from CALFIRE into ArcGIS pro and added the firep21_1 feature class (CALFIRE 2021). This resulted in 21,686 total fires from 1878; after filtering from the year of 2011, this left 4074 fires. I exported the selected results into a new layer called "wildfires_from_2011." I then imported the FIA csv file. Once the FIA table was imported into ArcGIS Pro, I right clicked on the table and chose the "Display XY Data" making the X Field the "LON", the Y field "LAT", and the Coordinate System "GCS_WGS_1984." This resulted in points marking where the FIA points are located. I projected the FIA points data layer to the "NAD_1983_California_Teale_Albers" which makes the Geographic Transformation WGS_1984 (ITRF00)_To_NAD_1983. I then filtered so that I was only looking at FIA plots where the sample date was 2011 to 2021 Finally, I used the "Add Spatial Join" tool to join the

FIA plots to the CALFIRE polygons. The target feature was the FIA points and the "Join feature" filtered fire data layer. I chose to keep all target features and selected the "Intersect" Match Option. My final output matched previous fire perimeters to FIA plots in a table that could be exported from ArcGIS Pro and imported into Rstudio.

To create the final dataset in which I ran my regression models, I created binary variables for Public land (Public = 1, Private = 0) and Fire (Fire = 1, No Fire = 0) so that I could use regression analyses. I then filtered out any duplicate plots (plots that were sampled more than once using function) in R so that I was not over-counting plots. To keep only unique plots, I grouped by the Sequence Number, used the slice() function on the which.max() function looking at the most recent Inventory Year. This left me with 4815 observations.

Estimating influence of Ownership, Forest Type, Ecoregion, and Reserve Status on Wildfire Probability

To estimate the influence of different factors, I used four different logit models. I first ran a naive regression on ownership. I then ran a preferred linear regression, matched linear regression, and interaction regression, each time changing an aspect of the graph to cast a wider coverage of the effects of different variables.

Estimating the influence of Ownership on Wildfire Probability

Naive linear regression. To estimate the influence of ownership on wildfire probability, I ran a naive linear regression by running a linear regression function in RStudio. My regression equation was $Fire = B_0 + B_1 * Public$ which predicts whether or not ownership affects the probability of forest fire occurrence.

Naive logistic linear regression. To further test the effect of ownership on wildfire probability, I ran a naive logistic regression. I used the same equation as the previous regression equation but this time I used RStudio to run a logistic regression function. By running a logistic regression, I looked into a classification of fire versus no fire.

Estimating the influence of Ecoregion and Ownership on Wildfire Probability

Naive linear regression. To estimate whether ownership and ecoregion impact the likelihood of wildfire, I ran a naive multiple linear regression in R Studio. The naive multiple linear regression was used to assess the association between ownership and forest type on my dependent fire variable. Using the equation: $Fire = B_0 + B_1 * Public + B_2 * Ecoregion$, I was able to calculate the expected value of fire (i.e. whether fire is expected to occur or not) but excluding the influence of other confounding variables.

Preferred linear regression. To estimate whether ownership and ecoregion impact the occurrence of wildfire, I ran a preferred multiple regression in R Studio. The preferred linear regression was used to determine whether or not adding confounding variables impacted the likelihood of fire across ownership type and forest type. I used the equation: $Fire = B_0 + B_1 * Public + B_2 * Ecoregion + B_3 * Slope + B_4 * Elevation + B_5 * Aspect + B_6 * Topographic\ position + B_7 * Stand\ stucture + B_8 * Site\ productivity + B_9 * Stand\ size + B_{10} * Ground\ land\ class + B_{11} * Stand\ origin$. Including the extra variables, allowed me to see how the control variables in this model impact ownership's effects on fire probability.

Matched linear regression. To examine whether owner and ecoregion impact wildfire occurrence, I ran a matched linear regression using a data frame with matched plots. By using the matched linear regression, I was able to compare the different regression models to see if my models had similar or different responses. My matched linear equation is the same as my naive linear model for ecoregion, except I used the matched dataset instead of my original data.

Interaction linear regression. To assess whether there was any interaction between ownership type and ecoregion in predicting fire, I used an interaction linear regression model in R Studio. I used the equation:

$$Fire = B_0 + B_1 * Public + B_2 * Ecoregion + B_3 * Public * Ecoregion$$

to see if the effect of ownership on fire occurrence differs as you change ecoregion.

Estimating the influence of Forest Type and Ownership on Wildfire Probability

To evaluate the effect of forest type and ownership on wildfire probability, I used the same four regression models as used for ecoregion. I replaced the ecoregion variable with forest type in each of the equations for this analysis.

Estimating the influence of Reserve Status on Wildfire Probability in Public Plots

To examine Reserve Status' influence on wildfire probability, I created a subset of data that included only public plots. I created this dataframe because reserve status can only be assigned to public land, so I needed to eliminate all of the private plots for an accurate regression. Using the filter() function in R, I kept only observations that were publicly owned. Then I used the rename() function to change "RESERVCD" to "Reserved" for reader clarity.

Naive linear regression. To look at the publicly owned forests and examine whether reserve status impacts fire occurrence, I used a naive linear regression with no other confounding variables. I used the base naive regression and the public dataset for this model. By excluding other possible confounding variables, I built a base model in which I can compare to my other models in order to gain a full understanding of how reserve status impacts wildfire.

Preferred linear regression. To run a preferred linear regression model on ownership and fire probability, I added confounding variables to my linear regression model to create a multiple linear regression model. My equation was the same as the equations used for ecoregion and forest type, but this time I used my subset of only public data.

Matched linear regression. To examine if confounding variables impact the outcome of fire occurrence for reserved versus unreserved land, I ran a matched linear regression using my "public_plots_matched_df." The matched linear regression equation I ran in Rstudio was: $Fire = B_0 + B_1 * Reserved.$

Identifying Control Plots

To find control plots, I used a matching algorithm in Rstudio. In my study, the treatment variable is Public because I want to see how Public versus Private Ownership affects the probability of wildfire. My confounding variables in this study include slope, aspect, topographic position, elevation, stand structure code, site class code, site productivity class, stand size, present ground land class, and stand origin. To produce a dataset with covariate balance and eliminate any bias, I used the "matchit" function (with nearest neighbor method) from the "MatchIt" package and matched on slope, elevation, aspect, topographic position, stand structure, site productivity, stand size, ground land class and method of stand regeneration which found FIA plots under the same ownership type that have the similar confounding variables. To create the matched dataset, I applied the match.data() function to my "matched_all_covariates" to produce the "matched_all_covariates_df" dataframe.

RESULTS

Effects of land ownership, ecoregion, and forest type on fire probability

I found that ownership type did impact forest fire probability. When looked at in isolation, forests under public ownership had a fire probability of 33% from 2011 to 2021. The naive linear regression output showed the shift from private to public resulted in a statistically significant ($p < 0.05$) increase in fire probability by 0.19 percentage points (Table 1). The naive logistic regression also resulted in a statistically significant outcome where public land had a higher likelihood of fire. The relationship between public ownership and higher fire probability held true when conditioned across ecoregion and forest type. When conditioning across ecoregion, all of the models showed an increase in fire probability for public ownership. With an estimated value of -0.287, the Intermountain Desert and Semi-Desert ecoregion had the greatest correlation to wildfire risk. Out of the seven ecological subregions, I found four statistically insignificant (p-value > 0.05) ecoregions with the Dry Steppe Ecoregion having the largest standard error at 0.099. Adding forest type to the models, resulted in a similar outcome to the ownership only models as well as the ecoregion models. The naive regression, preferred regression, and matched regression models all showed above a 20% fire probability (with statistical significance, $p < 0.05$) for public ownership when forest type was included in the model (Table 1). I found no trend for fire probability across the forest types as some had an increased fire probability compared to the Alder forests and some had a decreased fire probability. The preferred model for ecoregion and forest type had almost the same fire probability for public land. The ecoregion preferred model had a fire likelihood of 0.204 percentage points and the forest type preferred model had a fire probability of 0.207 percentage points (Table 1).

Table 1. Summary regression results of ownership on fire probability. Estimates (Top numbers) and standard errors (in parentheses) from the naive, preferred regression conditioned on forest type, and matched regression focusing on the effects of ownership and ecoregion.

	Dependent variable:		
	Fire		
	(Naive)	(Preferred Forest Type)	(Matched Ecoregion)
Public	0.190***	0.207***	0.164***
	(0.013)	(0.014)	(0.015)
Observations	4,815	4,815	3,526
R^2	0.043	0.149	0.063
Adjusted R^2	0.043	0.140	0.061
Residual Std. Error	0.430 (df = 4813)	0.407 (df = 4765)	0.402 (df = 3517)
F Statistic	217.696*** (df = 1; 4813)	16.994*** (df = 49; 4765)	29.725*** (df = 8; 3517)

*p<0.1; **p<0.05; ***p<0.01

Interaction linear regression on ecoregion

I found that there was no consistent trend between the results of the ecoregion interaction and the forest type interaction. I found that when ecoregion interacted with ownership, there was a significant positive fire probability on public forests. With a base case of the American Desert ecoregion, three of the seven interactions between ecoregion and ownership were significant (i.e. the error bar does not cross the intercept of 0) (Figure 2). However, when looking at the likelihood of fire on public land across ecoregions, the highest fire probability occurs under public ownership and with the Intermountain Semi-Desert ecoregion (Figure 3).

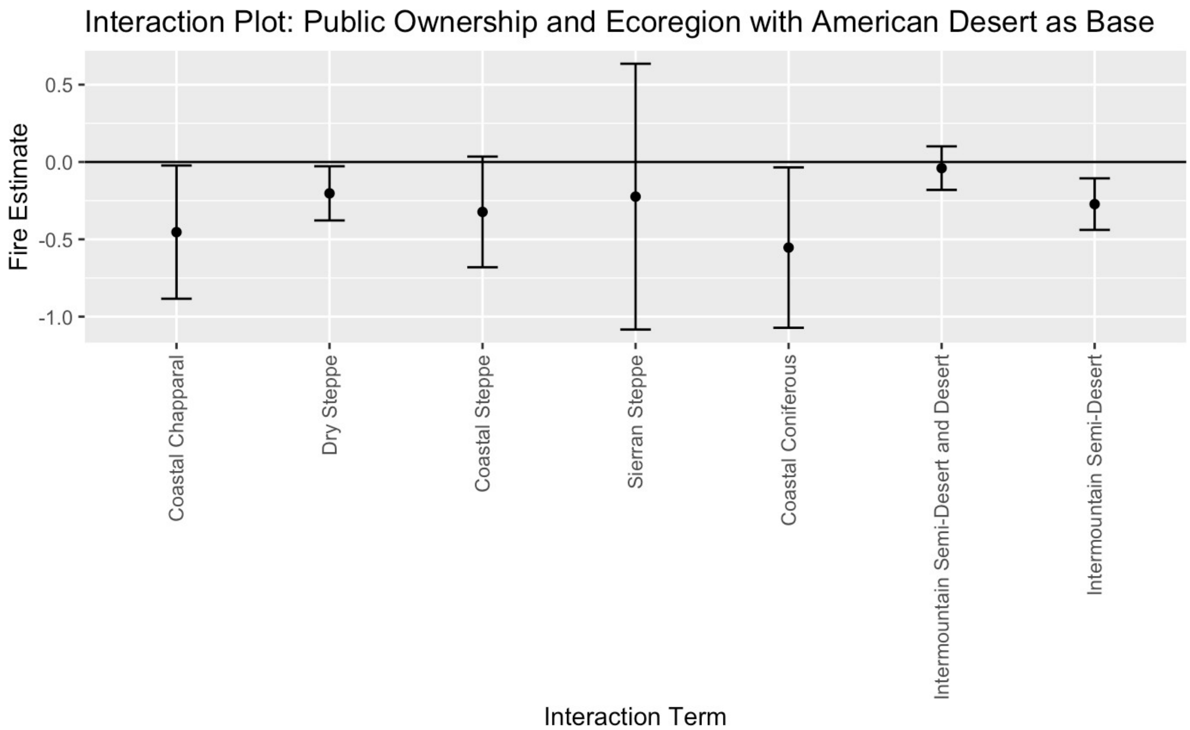

Figure 2. Interaction effects of ecoregion and public ownership on fire probability. Significant interaction effects for ecoregions that do not cross zero as it indicates there is a significant difference between the interaction of public ownership and ecoregion and the base interaction of public ownership and the American Desert Ecoregion.

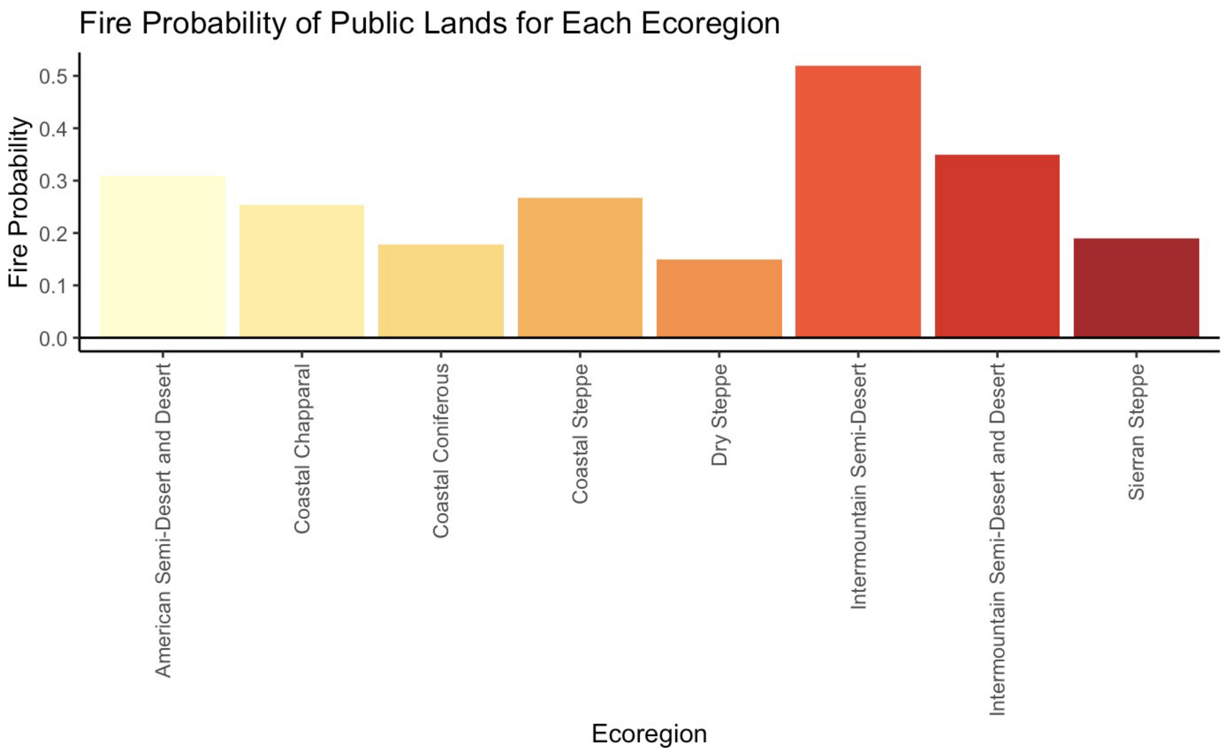

Figure 3. Fire probabilities of each ecoregion that is publicly owned. The highest fire probability occurs on publicly owned Intermount Semi-Desert ecoregions with a fire probability of 52%. The lowest probability of fire occurs on Dry Steppe with a probability of 0.15 from 2011 to 2021.

Interaction linear regression on forest type

The interaction regression model on forest type showed ownership's effect on fire probability did not change depending on forest type. When Alder forests were the base case, there were no significant interactions between forest type and ownership (Figure 4). However, when I ran the interaction regression with the California Conifer or Western Oak (the two forest types with the greatest number of observations) as the base cases, there were significant increases in wildfire probability on public land (Table 2). The regression results indicated there were significant interaction effects between ownership and forest type on fire probability. The interaction term between public ownership and the California Conifer forest type has a fire probability of 0.123 percentage points which is almost double that of the interaction term between public and the Western Oak at a fire probability of 0.062 (both have $p < 0.05$) (Table 2).

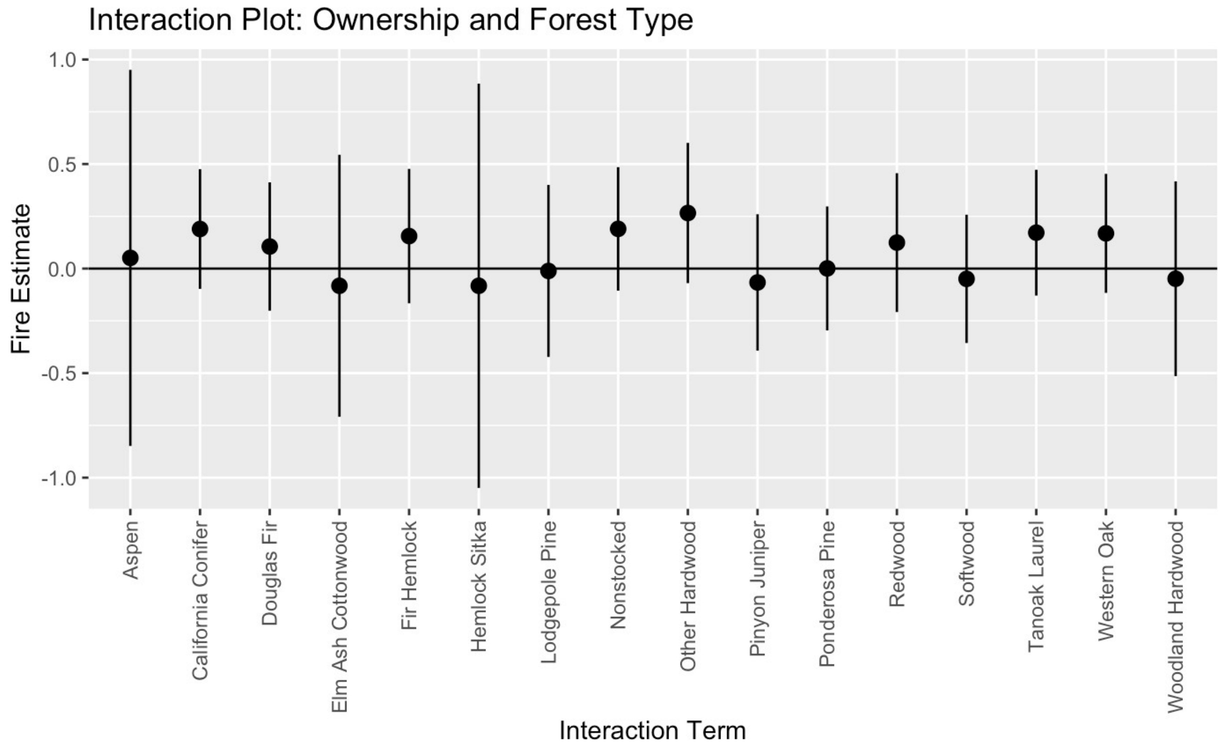

Figure 4. Interaction effects of forest type and public ownership on fire probability. Significant interaction occurs when lines do not cross intercept. None of these interactions are significant when compared to the base Alder forest.

Table 2. Interaction regression results for California Conifer and Western Oak. Table of two regression models for the two forest types with the most observations. Blank spaces indicate that the variable was not tested in the model. The constant represents the probability of fire on private forestland than is not the forest type being tested.

	Dependent variable:	
	Fire	
	(1)	(2)
Public	0.149***	0.189***
	(0.014)	(0.016)
CA Conifer	0.040	
	(0.027)	
Public CA Conifer Interaction	0.123***	
	(0.032)	
Western Oak		0.042**
		(0.021)
Public Western Oak Interaction		0.062**
		(0.029)
Constant	0.134***	0.124***
	(0.011)	(0.013)
Observations	4,815	4,815
R^2	0.062	0.049
Adjusted R^2	0.061	0.049
Residual Std. Error (df = 4811)	0.426	0.428
F Statistic (df = 3; 4811)	105.476***	82.804***

*p<0.1; **p<0.05; ***p<0.01

Effect of reserve status on fire probability

There is a significant difference in fire occurrence between reserved and unreserved plots. Linear regression showed that reserved plots negatively affected the chances of wildfire on public plots (Table 3). A significant p-value for reserve status indicates that reserved forest land has a lower likelihood of wildfire than unreserved land. I found a 5% decrease in likelihood of fire in the shift from unreserved land to reserved land (Table 3). I found that the reserve status did not significantly correlate with fire occurrence for the preferred linear regression ($p > 0.05$). It did follow the same trend as the naive linear regression–a decrease in fire probability for reserved lands (Table 3). Reserved plots had a decreased fire probability in the matched linear regression model. The p-value less than 0.05 indicates that the negative coefficient estimate significantly predicts a decrease in fire occurrence as you move from unreserved to reserved land (Table 8). I found an equation of $y = 0.36090 - 0.075\ x$ for the line of my matched linear regression which means there is a decreased fire probability on reserved lands compared to unreserved lands.

Table 3. Regression results for reserve status. Estimates of naive linear regression, preferred linear regression, and matched linear regression with standard errors below estimates.

	Dependent variable:		
	Fire		
	(Naive LM)	(Preferred LM)	(Matched LM)
Reserved	−0.054***	−0.028	−0.075***
	(0.018)	(0.018)	(0.021)
Observations	3,052	3,052	2,032
R^2	0.003	0.121	0.006
Adjusted R^2	0.003	0.112	0.006
Residual Std. Error	0.470 (df = 3050)	0.443 (df = 3020)	0.470 (df = 2030)
F Statistic	8.936*** (df = 1; 3050)	13.442*** (df = 31; 3020)	12.892*** (df = 1; 2030)

*p<0.1; **p<0.05; ***p<0.01

DISCUSSION

In looking at what is propelling the increase in fires in the western United States states, it is clear that a multitude of factors influence fire occurrence (Brosofske et al. 2007, Guo et al. 2016, Zhu et al. 2022). My results show that publicly and privately owned plots have different fire occurrences that can be attributed to ownership type. Furthermore, the trends I identified across ownership do affect fire occurrence when vectored across ecoregion and forest type. Within public forests, the unreserved lands are at a higher likelihood of fire.

The diversity of ecoregions in California leads to some ecoregions having a higher fire probability separate from ownership, based solely on climatic and vegetative factors. Some of these factors could include a dry and hot climate, or invasive grasses that act as an ideal fuel bed for fire. Given this, there may be stronger interactions between some ecoregions and public ownership and their influence on fire probability. Different forest types have different fire regimes meaning some are more likely to burn than others regardless of forest type, however my study's eighteen different forest types may be too granular for the amount of data available for analysis. When looking at the California Conifer and Western Oak, the two forest types with the most observations, a significant interaction with ownership type occurs. This could indicate the lack of data could be causing the insignificant results of the other forest types. The higher wildfire probability on unreserved lands may be due to increased human access which can lead to increased amounts of accidental fires due to human activities. Also reserved forests are often allowed to burn if the fire is caused by natural factors which could be reducing the amount of fuel and allowing the ecosystem to exist as it did before human interference.

Compared to existing literature surrounding public ownership and fire occurrence, my ownership results support the higher likelihood of fire on public lands found in Starrs et al. 2018. Given that the two papers use different datasets, a consistent result of higher fire probability on public lands indicates some aspect of public ownership contributes to an increased fire occurrence. A difference in results between this paper and the Starrs et al. 2018 paper exists within the reserve status results. I found a decrease in fire probability across reserved lands while they did not. Discrepancies between the two papers could have been attributed to differences in collection methods between the different datasets used. Because Starrs et al 2018 was using four different time periods, their study covers a much broader range of time in which the reserve status had more heavily changed management practices as public forest management strategies changed throughout that time period compared to the little change in the ten years of my study window. However, the answer to my main question regarding how public ownership affects wildfire probability shows consistency across the two papers and more evidence that publicly owned land is more likely to have a wildfire.

While my study was not identical in structure to the Levine et al. 2022 paper, our general results did not support the other: they found a higher occurrence of high severity fires owned by private industrial timber companies compared to other ownership types. As their high severity fire occurrence was conditional on fire occurrence, it can be said that my non-severity specific fire occurrence did not show the same trends across ownership type. This study only looked at a Yellow Pine and Mixed Conifer Forest, whereas my study looked at eighteen different forest types. Having different forest types could be one source of dissimilarity within the results as my analysis shows that some forest types are more prone to fire and others are less susceptible to burning. There was also a large difference within the study period as my study only covered ten years and the Levine study covered the years from 1985 to 2019. The large study time disparity between the two papers could have vastly different average climates or forest management changes which could have affected the fire probability results of each study. A faint similarity exists when looking at ecoregion and fire within both papers. The Eastern Cascade ecoregion experienced one of the lowest fire probabilities of [high severity] fire in both papers. Although the papers do not align with the general results, adding another analysis to a topic with uncertainty moves us in a positive direction.

Differences between fire probability in private and public forests may be due to land ownership objectives. Private forest owners may have a larger stake in the health of their forests. If economic motivations or the livelihood of a family drive management operations, there may be strategies in place that minimize the amount of fire, such as proper tree spacing to optimize water access allowing for healthy moisture content and not allowing the persistence of small vegetation to act as a fuel source. Management practices driven by incentives such as carbon credits where preventing fire is essential for an extra source of an income. In addition to private industrial timber companies and families, Native American tribes are under the private ownership class. Their rich historical understanding of fire has allowed them to continue fire regimes that benefit the forest ecosystem making it more resistant and resilient to wildfire. Native Americans used cultural burnings to keep forests less dense so trees did not fight for sunlight and water ("How the Indigenous practice of 'good fire' can help our forests thrive" 2022). The more sparsely populated forest acted as a reservoir for healthy and resilient trees rather than a pool of dead trees in which fire spreads rapidly.

Compared to private forests, public forest management underwent many changes throughout the course of history. The Northern Spotted Owl halted timber production in forests and brought a spotlight to the protection of wildlife in the forests. This resulted in the Northwest Forest Plan (1994) which restricted timber production in forests and turned toward conservation driven management of old-growth forests (Burnett and Roberts 2015). The government coupled this plan with the U.S. Forest Service's fire suppression strategy which resulted in densely packed forests whose trees are stressed and vulnerable to fire as they fight for water and sunlight. These forests became increasingly homogenous, filled with shade intolerant plants, and dry.

Collectively, the factors just mentioned created an ecosystem prone to fire, but not allowed to burn, despite the fact that fire aids in this ecosystem's health. Along with the forest management strategies leaving the forests at risk of massive wildfire, the publicly owned forests also have limited funds devoted to preventative measures against large wildfires. While the state of California now acknowledges the increasing need for fire prevention and forest management in the face of catastrophic wildfires by increasing the State's fire budget from $800 million in 2006 to $3.7 billion, this has previously been allocated primarily towards suppression instead of managing for prevention ("The 2022-23 Budget: Wildfire and Forest Resilience Package" n.d. p. 203). As you move from the state level to the federal level, the funding for wildfire prevention is even worse. Between 2016 and 2020, the federal government spent 2.5 billion dollars on wildfire suppression and the USDA Forest Service proposed a 2.97 billion dollar budget for wildland fire and hazardous fuels management, which included using 1.2 billion dollars allocated to wildfire suppression ("President's 2024 Budget Advances Efforts to Address the Nation's Wildfire Crisis through Workforce Reform and Other Investments in Wildland Fire Management Programs" n.d.). While the public sector's fire management plans made progress, much still needs to be done to create fire resistant and resilient forests after a history of forest management that created forest fire utopias.

As with any project, some limitations inhibited certain aspects of the study. Due to privacy reasons, the individual private owners were withheld from my dataset. This left me with only the broad umbrella of a privately owned FIA plot instead of knowing if a plot was owned by a family, Native Americans, or a private industrial company. Without this more detailed information, I was unable to perform an in depth analysis of the smaller groups within private ownership and so I could not determine if there were fire probability differences between the private owners. In addition to the restricted access to ownership type, there was no climate related data. Had there been a temperature or moisture record, I would have performed a regression analysis on climate data. As climate has a proven role in fire occurrence, I would have liked to see how my analysis of temperature and moisture fared against previous studies. The impact of ownership is still yet to be fully understood, which allows others to expand this study of ownership to be conditioned across more variables. Possible future directions include looking at how the impact of ownership on fire probability reacts when it is conditioned across variables such as proximity to roads, homes, and urban centers. An examination of socioeconomic status across ownership types and fire probability could provide information that has important planning and policy implications. Using the two datasets in this paper, one could examine if prescribed burns reduce the likelihood of wildfires or severity of wildfires across FIA plots using the disturbance codes from the FIA Condition Tables and the prescribed fire perimeters from the FRAP data to see if prescribed burns are a justifiable forest management strategy.

Fire is an undeniable aspect of California's forests. My results of higher fire probability on public forestlands compared to private forestlands indicate that investigations into differences in management practices are necessary to see if that is the driver behind the inconsistencies. Determining what is causing these discrepancies between public and private fire probabilities is one step in finding a way to adapt to a changing climate and possibly return to healthier and more resilient fires.

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