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The fate of working landscapes: Quantifying changes in social-ecological systems

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The fate of working landscapes: Quantifying changes in social-ecological systems

By

Katherine J. Siegel

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Committee in charge:

Professor Van Butsic, Chair
Professor Laurel Larsen
Professor Justin Brashares

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Abstract

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Working landscapes face intensifying pressures from global and local environmental, socioeconomic, and governance changes. These landscapes represent social-ecological systems composed of natural and anthropogenic ecosystems, the human communities that use them, and interactions between the components of the system and the wider world. Disentangling the drivers of change in these complex systems poses conceptual and methodological challenges, but improved understandings of these systems' interactions and feedbacks may enable humans to manage working landscapes to provide biodiversity conservation and sustainable livelihoods in the face of rapid environmental change. My dissertation integrates theories and methods from conservation science, land system science, and econometrics to identify and quantify drivers of change in three distinct social-ecological systems: fire-prone forests of the western US, California rangelands subject to livestock grazing and wildfire, and a protected area in Amazon Basin experiencing deforestation.

Across three chapters, my dissertation examines three main questions: 1) What is the effect of land ownership on wildfire probability in forests of the western US? 2) How does livestock grazing impact wildfire probability in California's rangelands? 3) How does integrating qualitative discourse analysis into land use change modeling affect model outcomes and predicted future forest loss? In the first chapter, I demonstrate that federally-owned forests are more likely to burn in wildfires than privately-owned forests and that these management effects are greater than some changes in climate variables. In my second chapter, I assess the impact of livestock grazing on wildfire probability in three regions of California and three different dominant land cover classes. I find that the impact of grazing on wildfire varies by region and vegetation type, but in some regions and land cover classes, grazing reduces wildfire probability. In my third chapter, I present a framework for integrating qualitative discourse analysis into quantitative land use change modeling and demonstrate the benefits of this methodological integration for understanding deforestation drivers and dynamics in Jamanxim National Forest, Brazil.

For Catherine Johannet, who is still teaching me every day to be kinder, braver, and more generous.

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Introduction

Working landscapes are under increasing pressure from local and global environmental, socioeconomic, and governance changes (Foley et al., 2005). These landscapes, composed of the cultivated land, rangelands, and forests that humans use to produce food, fuel, fiber, and other products, support ecological processes and provide essential ecosystem services (Huntsinger and Sayre, 2007; Kremen and Merenlender, 2018). In the absence of sustainable management, human use of working lands and the conversion of natural habitats to intensive human uses threatens biodiversity, freshwater resources, carbon storage, and other ecosystem services that support human well-being (Ellis et al., 2013; Foley et al., 2005). Working lands cover about 80% of the world's terrestrial surface, making their sustainable management a globally important issue (Ramankutty et al., 2018).

The social-ecological systems framework conceptualizes the complex interactions within coupled human and natural systems. These systems are characterized by non-linearities, feedbacks, time lags, heterogeneity, resilience, and unexpected outcomes (Berkes et al., 2003; Folke, 2006; Gunderson and Holling, 2002; Liu et al., 2007; Walker et al., 2006), and the social-ecological systems framework can aid in understanding the processes and interactions leading to sustainable or unsustainable management of natural resources within these systems (Ostrom, 2009, 2007). The framework conceptualizes natural resources as part of complex social-ecological systems comprised of biophysical, social, economic, and political subsystems, all interacting across multiple scales to produce system outcomes (McGinnis and Ostrom, 2014). In my dissertation, I position working landscapes as social-ecological systems composed of natural and anthropogenic ecosystems, the people who use and manage them, and the interactions between the components within the system and the wider world.

The social-ecological systems framework provides a useful tool for understanding the components of and interactions within complex systems. However, operationalizing the framework to disentangle drivers of change in these systems poses conceptual and methodological challenges (Leslie et al., 2015; Partelow, 2018; Virapongse et al., 2016). The complex interactions across scales, time lags, and nonlinearities inherent in social-ecological systems complicate efforts to determine causal relationships and predict outcomes. In my dissertation, I develop frameworks using causal inference methods to identify and quantify drivers of change in complex social-ecological systems, using three different social-ecological systems as case studies that span different geographies, ecosystems, and types of land use.

My first chapter looks at wildfires in the western United States as outcomes of complex interactions in a complex social-ecological system comprised of diverse forest ecosystems, climates, government and private landowners, and many actors and stakeholders with different objectives. In the context of this social-ecological system, I study the relative impacts of management and climate factors on wildfire probability, motivated by increases in wildfire activity in recent decades. I quantify the role of management in modifying wildfire probability by comparing annual fire frequency in federally-managed and privately-owned, unprotected forests, using these two ownership categories as proxies for the complex, diverse management approaches used across the eleven states of the western contiguous United States. I address the question of management impacts on wildfire probability using pre-regression matching and panel regression modeling, and I estimate marginal effects to compare the impact of management category to that of changing climate variables.

In my second chapter, I study privately-owned California rangelands as social-ecological systems composed of fire-adapted ecosystems interacting with human land uses. I focus on livestock grazing as a land use that influences wildfire activity in the system, motivated by recent calls in the popular media for increased livestock grazing as a tool to reduce wildfire activity following rangeland wildfires that have had significant impacts on human lives and well-being, such as the 2017 Tubbs and Thomas Fires. I build on the methods used in Chapter 1, adding further precision regarding the spatial distribution of and variation in land management through a telephone survey of large property owners that enabled the creation of a dataset of grazing levels across three social-ecological regions of California. I use pre-regression matching and panel regression modeling to assess the impact of varying levels of grazing intensity on wildfire probability in the three social-ecological regions and across three different dominant vegetation covers.

Chapter 3 models forest conversion to agriculture as an outcome in the social-ecological system in and around Brazil's Jamanxim National Forest. This system is composed of diverse human actors, including farmers, ranchers, miners, land speculators, and conservationists, who interact with environmental regulations, regional and global commodity chains, and a landscape of tropical rainforest ecosystems and anthropogenic land uses such as farmland, pastures, and settlements. This chapter is motivated by continued forest loss within Amazonian protected areas and the limitations of land use change models with regards to accounting for explanatory factors that are not easily quantified or made spatial. In this chapter, I use qualitative discourse analysis to identify themes related to deforestation in Jamanxim and integrate these themes into quantitative land use change modeling by converting them to quantitative, spatial proxy variables. I then assess the performance of four land use change models that use different combinations of variables derived from the discourse analysis and those identified through a review of the land use change literature in the region.

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CHAPTER 1

Quantifying drivers of change in social-ecological systems: land management impacts wildfire probability in forests of the western US

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Included as a dissertation chapter with permission from co-authors.

Abstract

Sustainable management of complex social-ecological systems depends on understanding the effects of different drivers of change, but disentangling these effects poses a challenge. We provide a framework for quantifying the relative contributions of different components of a social-ecological system to the system's outcomes, using forest fires in the western United States as a model. Specifically, we examine the difference in wildfire probability in similar forests under different management regimes (federally managed vs. privately owned) in eleven western states from 1989-2016 and compare the magnitude of the management effect to the effect of climate variables. We find a greater probability of wildfires in federally managed forests than in privately owned forests, with a 127% increase in the difference between the two management regimes over the 28-year time period. Furthermore, we find that the effect of the different management regimes is greater than the marginal (one-unit change) effect of most climate variables. Our results indicate that projections of future fire risk must account for both climate and management variables, while our methodology provides a framework for quantitatively comparing different drivers of change in complex social-ecological systems.

Introduction

Sustainable management of social-ecological systems requires an understanding of the impacts of multiple factors across spatial and temporal scales (Carpenter et al., 2009; Liu et al., 2007; Ostrom, 2009). It is difficult, however, to tease apart the varied influences that shape the trajectories of these systems due to complex interactions and feedbacks between the human and environmental components across multiple scales, as well as the presence of different initial endowments, non-linearities and thresholds, time lags, and unexpected outcomes (Ferraro et al., 2019; Holling et al., 1998; Ostrom, 2007). This complexity leads to both conceptual and methodological challenges in determining causal relationships and predicting outcomes, particularly in the context of rapid global environmental change (Lade et al., 2013; Scheffer et al., 2012; Schlüter et al., 2019). Overcoming these challenges will improve our ability to sustainably and adaptively manage social-ecological systems.

Wildfires offer a laboratory to study questions about the relative influences of different factors in driving outcomes for social-ecological systems because wildfire regimes are changing along with climate and forest management. Since the 1980s, forests in the western US have experienced increases in the frequency and size of large fires, with consequences for ecosystem functioning and human lives, health, and property (Abatzoglou and Williams, 2016; Dennison et al., 2014; Westerling et al., 2006). This trend mirrors current and projected increases in the area burned, fire season length, and fire severity in many regions around the world, including North American boreal forests (Doerr and Santin, 2016; Kasischke and Turetsky, 2006), the Mediterranean (Pausas and Fernández-Muñoz, 2012), southern Africa (Giglio et al., 2013), and Australia (Pitman et al., 2007). These fires represent the outcomes of complex interactions in a social-ecological system comprising forest ecosystems, climate, government and private landowners, and diverse actors, each with their own objectives and policy constraints (Fischer, 2018; Fischer et al., 2016; Moritz et al., 2014; Spies et al., 2018, 2014).

Climate change and forest management both affect the biophysical context of this social-ecological system and thus impact wildfires (Abatzoglou and Williams, 2016; Hurteau et al., 2014; Littell et al., 2009), with climate change acting as an external stressor while forest management mediates the relationship between actors and ecosystems within the system (Perry et al., 2010). Climate change is expected to exacerbate fire risks in some regions of the western US through earlier snowmelt, decreased precipitation, increased fuel aridity due to higher temperatures and vapor pressure deficit, longer fire seasons, and changes to species composition and productivity (Abatzoglou and Williams, 2016; Krawchuk et al., 2009; Westerling, 2016). Land management will simultaneously modify the effects of climate change on fire regimes, as management decisions influence forest structure, fuel quantities and connectivity, and fire suppression; management can enhance or dampen the effects of climate change on fire regimes (Bowman et al., 2011; Taylor et al., 2016). Understanding the impact of land management on fire risk is thus important in guiding responses to climate-induced changes in fire regimes in these complex systems.

Given their interacting influences, it is not surprising that there is ongoing debate about the attribution of increases in fire activity to climate variation as opposed to land management (Harvey, 2016; Starrs et al., 2018; Whitlock et al., 2003). Much of this debate stems from methodological difficulties in determining causal relationships in social-ecological systems. However recent advances in methods of causal inference (Butsic et al., 2017; Ferraro et al., 2019; Ferraro and Hanauer, 2014) and access to high-resolution data across large temporal and spatial scales give us the ability to re-examine these questions with greater precision. Here, we exploit spatial and temporal variation in climate, management, and wildfire to understand changes in social-ecological systems driven by local (management) and global (climate change) human influences, at broad spatial scales. Beyond informing our understanding of the effect of forest management on wildfire risk in the western US, our work represents a novel approach to quantifying the relative roles of governance and external climate drivers in shaping the outcomes of social-ecological systems in general.

To isolate the impact of forest management from climatic and biophysical drivers of wildfire, we compare federally-owned forests to privately-owned, unprotected forests, using these two categories of land ownership as proxies for the complex, diverse forest management approaches deployed in the western US. Federal agencies and private entities are the two largest forest owners in the western US, owning 64% and 30% of forested area, respectively (Figure 1); federal agencies manage 44-96% of forests in the eleven western states of the contiguous US, while private entities own 4-44% of forested land (Bansal et al., 2017; Christensen et al., 2016; Goeking and Menlove, 2017; Menlove et al., 2016, 2012; Palmer et al., 2019; Shaw et al., 2018; Thompson et al., 2017, 2005; Werstak Jr. et al., 2016; Witt et al., 2012). Federal and private landowners manage their forests for various objectives and are subject to different political and economic constraints and demands. Federal agencies must take into account objectives including conservation of protected species, access to recreation, and local timber sectors (Spies et al., 2010), while private landowners may manage their forests to maximize economic opportunities or for noncommercial uses, subject to state- and federal-level regulations such as the Endangered Species Act (Ager et al., 2017; Charnley et al., 2017; Christensen et al., 2016). These management decisions influence vegetation structure, which in turn influences fire risk; publicly owned forests typically have higher biomass levels than private forests, where periodic grazing and harvesting are more common (Heath et al., 2011; Hudiburg et al., 2009; Spies et al., 1994; Turner et al., 1996).

Furthermore, forest ownership affects perceptions of and responses to wildfires. Since the 1970s, federal agencies have moved slowly away from their historic focus on fire suppression due to increased recognition of the ecological role that fire plays in the forested ecosystems of the western US. Specific policy revisions highlight this paradigm shift, including the use of prescribed fires in national parks and wilderness areas, allowing fires with natural ignition sources to burn for management purposes, and an explicit requirement for ecosystem-based approaches to fire management (Steelman and McCaffrey, 2011; Stephens and Ruth, 2005). Meanwhile, aggressive fire suppression remains the norm on private land due to socio-political pressure and overarching goals of protecting human lives and property (Canton-Thompson et al., 2008; Liang et al., 2008; Office of the Inspector General, 2006).

Using data from forests in these two management categories in the eleven states of the contiguous western US, along with spatially-explicit data on fire occurrence, biophysical and climatic variables related to fire risk, and human activities, we use pre-regression matching and panel data analysis that accounts for time lags to answer the following questions: 1) Is there a difference in the probability of wildfire in federally managed forests as opposed to privately-owned, unprotected forests in the western US? 2) If so, has this difference changed over the past three decades? 3) Do this difference and any potential trends over time vary by state? 4) How does the magnitude of this difference compare to the effects of climate variables in modifying wildfire risk?

Materials and methods

Study area

Our study includes forests in the eleven western states of the continental US: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming (hereafter "western US"). We sampled points along a 1-kilometer grid across the eleven states, then selected all points that met our inclusion criteria (forested points located either on federally owned land or on private, unprotected land). For these points, we compiled data on fire activity and a suite of independent variables. We performed pre-regression matching and subsequent modeling at the state level, as states are the administrative scale at which variation in firefighting capacity, land use laws, and road maintenance operate (Starrs et al., 2018). We thus bound our social-ecological systems as encompassing the federally-managed and privately-owned forests in each individual state of the western US.

Data compilation

Vegetation: We identified forested points based on vegetation data from the 2001 National Land Cover Database (USGS, 2014) and LANDFIRE's Existing Vegetation Cover map for 2001 (Rollins, 2009). We included deciduous, evergreen, and mixed forest types from the NLCD and LANDFIRE classes with tree cover of greater than or equal to 20% to match the canopy cover cut-off used by the NLCD. We included all points classified as forest in either of the land cover maps (Berner et al., 2017; Hicke et al., 2015), using R, QGIS, and ArcGIS for our data compilation and subsequent modelling (ESRI, 2018; QGIS Development Team, 2019; R Core Team, 2019). For spatial analyses in R, we used the *raster*, *sf*, *lwgeom*, and *tidyverse* packages (Hijmans, 2019; Pebesma, 2019, 2018; Wickham, 2017).

Management status: We used the US Geological Survey's Protected Area Database (USGS, 2018) to classify the land management categories of forested land. This database includes all public, undeveloped land in the US, including land owned by federal, state, and local governments, regional agencies, and American Indian tribes. It also includes protected areas owned by NGOs or private entities. For our first management category, federally managed, we included all forest points that occurred on federal land in the database, regardless of GAP status code, which indicates the level of protection against land conversion. This includes land owned and managed by the US Forest Service, the Bureau of Land Management, the National Park Service, and other federal agencies. It excludes protected areas managed by other entities, including private land owners and state agencies. We included all protection categories for federal land so we could capture the effect of federal management across variation in management intensiveness and objectives. Our dataset thus includes strictly protected forests in national parks and wilderness areas, but very few of these points remained after we implemented the matching process (n = 1503, or 0.7% of sample points). For our second management category, private forest, we only included points that fell outside of the areas in the database. We recognize that this division of federal vs. private management is blunt and does not capture nuances between management by different federal agencies or for different objects, but it allowed us to analyze relationships at broad spatial scales.

Fires: We acquired fire perimeter data for all fires at least 1000 acres in size from the Monitoring Trends in Burn Severity database for the western US (Eidenshink et al., 2007; USFS and USGS, 2018). This database includes several categories of fires: prescribed fires (fires ignited for management purposes), wildfires, wildland fire use (fires with natural ignition sources that are allowed to burn to accomplish management goals), and fires classified as "unknown." For each sample point in each year from 1984-2016, we determined whether or not the point occurred within the perimeter of a wildfire. We did not include wildland fire use, prescribed fires, or uncategorized fires in our first set of analyses. We also calculated a lag variable for each point in each year, indicating whether or not the point had burned in any fire type in the previous year, in the previous two years, and in the previous five years, since recent fire history affects fire risk (Parks et al., 2016; Price et al., 2015); because we used these lag variables, our models began in 1989, rather than 1984. In a subsequent analysis, we included the occurrence of wildland fire use in our model (see *Model Robustness* section for details) to assess whether our results held for managed wildfires.

Lightning strikes: Lightning is an important wildfire ignition, especially in mountainous regions of the western US (Balch et al., 2017; Miller et al., 2012; Stephens, 2005). We used annual data on the number of lightning strikes per county for 1986-2014 (NCES, 2018) to assign a number of strikes per year for each sample point (i.e., every sample point in a county was assigned that county's tally of annual strikes). Because the lightning data were available only at a coarse spatial scale and for a limited time period, we used it as a covariate in our matching but not in the subsequent regression models.

Climate: We compiled a suite of climate variables for each sample point using TerraClimate, a dataset of monthly climate data at a 4-km resolution (Abatzoglou et al., 2018) that has been used for large-scale modeling of wildfires in the region (Davis et al., 2019). We used TerraClimate in lieu of a finer-scale dataset such as PRISM (Daly et al., 2008) because TerraClimate includes additional climate variables that are relevant to wildfire, including soil moisture and wind speeds. We selected climate variables related to fuel conditions, ignition probability, and subsequent fire behavior: wind speed, precipitation, maximum and minimum temperatures, soil moisture, and Palmer Drought Severity Index (Abatzoglou et al., 2017; Abatzoglou and Williams, 2016; Barbero et al., 2014; Dennison et al., 2014; Dillon et al., 2011; Krawchuk and Moritz, 2011; Littell et al., 2016, 2009; Miller et al., 2012; Westerling et al., 2006, 2003; Westerling, 2016; Whitlock et al., 2003). We summarized this data into seasonal climate variables in each year: winter (December of the previous year, January, and February), spring (March, April, and May), summer (June, July, and August), and fall (September, October, and November) average maximum wind speed (m/s), total precipitation (cm), average maximum and minimum temperatures (˚C), average soil moisture (mm), and average Palmer Drought Severity Index, a measure of long-term drought. We included these variables in all seasons since climate factors in seasons preceding the fire season are important predictors of fire risk in some regions, while fire season climate factors are most important in other regions (Littell et al., 2009; Syphard et al., 2017). We also used total precipitation in the previous water year (e.g. for 2015, precipitation accumulated from December 1, 2013-November 30, 2014 (Miller et al., 2012)) as an explanatory variable, as this is an important predictor of wildfire risk in some regions of the western US (Littell et al., 2009; Syphard et al., 2017).

Topography: We acquired elevation data at 30-m resolution from the National Elevation Dataset (USGS, 2013), then calculated slope and aspect in QGIS (QGIS Development Team, 2019), as topographic variables can impact fuel conditions, fire probability and behavior, land management, and responses to fires (Dillon et al., 2011; Hurteau et al., 2014; Littell et al., 2009).

Human activity: Human population density and remoteness (as measured by distance to roads) may impact frequency of anthropogenic fire ignitions and influence fire response decisions (Balch et al., 2017; Nagy et al., 2018; Syphard et al., 2017). We extracted census block-level population density data for each sample point in 1990, 2000, and 2010 from a database of population and housing density (Radeloff et al., 2018). We also calculated the Euclidean distance from each sample point to the nearest road (US Census Bureau, 2018).

Matching

Pre-regression matching techniques can improve causal inference by reducing the effects of confounding variables (Schleicher et al., 2020; Stuart, 2010). There are likely to be systematic differences between federally managed and private forests in some of the geographic and climatic factors related to fire risk (Joppa and Pfaff, 2011, 2009); to control for covariate differences by management category, we matched federally managed and private data points in each state using nearest neighbor propensity score matching with the *MatchIt* package and a caliper set to 0.1 (Ho et al., 2011; Stuart, 2010). For each federally owned site (the treated group) in the dataset, we identified the private and unprotected site (the control group) with the closest propensity score, then removed all unmatched treated and control sites. As causal inference in social-ecological systems requires that treated and control pairs be matched on both environmental and social variables (Ferraro et al., 2019), we matched our datasets for each state using the relevant continuous socioeconomic, topographic, and climatic data: slope; aspect; latitude; longitude; distance to roads; population density at three years in the time period (1990, 2000, 2010); seasonal averages of maximum wind speed, maximum temperature, minimum temperature, soil moisture, and PDSI, averaged over the first five years in the dataset (1984-1988); total seasonal precipitation (again averaged from 1984-1988); and the average number of lightning strikes annually for the period from 1984-1988. This yielded a matched dataset of federal and private points for each state, with a minimum matched dataset size of 1455 points per management class in Nevada and maximum of 24267 points per class in California (Table S1). The matched datasets reduced systematic differences in environmental and social variables between federally managed and private forests (Tables S2, S3).

Models

We used mixed effects models to account for unobservable factors that may have influenced the probability of a site burning, such as historical legacies of land use and forest management or fine-scale climatic and geographic factors. Using logistic regression, we modeled whether or not a given point burned in a given year. We fit a single model for all eleven states together, with a state fixed effect. From the suite of climate, geographic, and social variables used for matching, we dropped highly correlated explanatory variables (absolute value of Pearson's correlation coefficient ≥ 0.66, p-value < 0.05), yielding the following panel regression:

$BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*State + B_4*BPYone + B_5*BPYtwo + B_6*BPYfive + B_{7-18}*Controls + B_{19-22}*Interactions + u_i + e_{it}$

where *BN* was whether or not a point (i) burned in a given year (t); *Management* was either federally managed or private and unprotected; *Year* was year as a continuous variable; *State* was the state fixed effect; *BPYone*, *BPYtwo*, and *BPYfive* were the lag variables for whether the point had burned in the previous one, two, or five years, respectively; and *Controls* represented the list of covariates that we expected to influence the probability of a point burning: elevation (in 1000s of meters), slope (degrees), aspect, distance to the nearest road (km), population density in 1990 (people/km^2), average fall PDSI, average winter PDSI, average maximum fall temperature (°C), average maximum summer temperature (°C), average maximum summer wind speed (m/s), total precipitation in fall (cm), and total precipitation in summer (cm). *Interactions* includes all possible interactions between *Management*, *Year*, and *State* to allow the effect of management to vary over time and between states. u_i is the site-specific random effect and e_{it} is the error term for each point in each year. We used the R package *lme4* for our modelling (Bates et al., 2015).

It can be difficult to interpret the estimated coefficients for interacting variables in a logistic regression model. To better understand the effect of management and the change in this effect over time, we calculated the marginal effects of management (the difference in the probability of burning depending on the management type, holding all other variables constant) and the predicted probability of burning in a given management/year combination for the all-state and state-level models (described under *Robustness checks*) using the R packages *margins* (Leeper, 2018) and *ggeffects* (Ludecke, 2018). To understand the magnitude of the effect of management relative to the effect of climate variables, we also calculated the marginal effects of each climate variable used in the state-level models for the year 2016 and compared these values to the marginal effect of the management category in 2016.

Model robustness

We fit several additional models to our data to check for the robustness of our results against the effects of state-level trends, the type of wildfires included in the response variable, changes in forest cover over time, our treatment of our annual time steps as a continuous variable, temporal lags, and spatial trends. First, to assess whether our modeled patterns were robust for each state, we ran individual, state-level models for each of the eleven states. We then compared the patterns derived from each state-level model with the all-state model's predicted probability of burning for each state. The state-level models had the same response variable as the all-state model (whether or not a sample point burned in a wildfire in a given year). We dropped independent variables that were highly correlated (absolute value of Pearson's correlation coefficient ≥ 0.66, p-value < 0.05) in each state and categorical variables that perfectly predicted the outcome (e.g., *BPYone*), yielding slightly different sets of explanatory variables for each state (Table S4). For all of the state models, we included the management category (federally managed or private), year, and interactions between year and management category.

To determine whether our results were influenced by differences in the designation of fires as wildland fire use in the different management classes (USFS, 2009), we reproduced the all-state model using a response variable of whether a given point burned in either a wildfire or wildland fire use in a given year. The model otherwise used the same specification as the all-state model described above. See Table S5 and Figure S1 for results and predicted probabilities of burning, respectively. In addition, we fit the same model using only wildland fire use as the response variable (Table S6).

It is likely that the 2001 land cover data do not capture all sample points from our 1-km grid that were forested at some point between 1984-2016, as some points may have experienced forest loss between 1984 and 2001 through stand-removing disturbance events and chronic stressors, while others may have undergone post-disturbance succession post-2001 (Cohen et al., 2016; Coop et al., 2020; Yang and Mountrakis, 2017; Yang et al., 2005). To determine whether our results were robust to the inclusion of sample points that were forested during our time series but not forested in 2001, we assembled a second version of our dataset including all points from our 1-km sample grid that were forested in 1992, 2001, or 2016. While our time series begins in 1984, 1992 was the earliest year with standardized land cover data for our study region that is comparable to our later data, so we believe that it is an acceptable approximation of the distribution of forests at the beginning of the time period we studied. We identified these additional forested points from the retrofitted 1992 and 2016 National Land Cover Database (Fry et al., 2009; Yang et al., 2018) The 1992 land cover data had just one forest category, so we included all forested points from this dataset. For the 2016 land cover data, we included deciduous, evergreen, and mixed forest types, as we had done in our initial dataset of 2001 forested points. Using this expanded dataset of forested points, we assembled all other variables as previously described under *Data compilation*. In total, there were 26,489 additional forested points on federally managed or privately-owned, unprotected land when we included the 1992 and 2016 data. This represents a 3.5% increase in the number of sample points relative to when we only considered the 2001 forest data. We then re-ran the matching and modeling methods described in *Matching* and *Models* and calculated the coefficient estimates and predicted probabilities of burning for the all-state model to compare with our model that only included points that were forested in 2001 (Table S7).

We used logit models in order to calculate predicted probabilities, which allowed us to interpret the complex interaction effects. A drawback of this method is the inability to used unit-level fixed effects, which are often favored in causal analysis (Imbens and Wooldridge, 2009). Therefore, as a robustness check, we ran two linear probability models with fixed effects and lagged dependent variables for the state-level models: using the method suggested by Wooldridge (2002) (Woolridge, 2002) and using dynamic panel regressions with the Arellano-Bond estimator (Arellano and Bond, 1991) (Table S8). We implemented these models in Stata (Roodman, 2009; StataCorp, 2019). To ensure that our results were robust to our treatment of the time variable (*Year*) as continuous, we also ran each state-level logit model treating *Year* as a factor variable (Table S9) and an additional all-state model where we combined individual years into 5-year bins (Table S10).

Finally, to control for spatial autocorrelation, we ran a modified all-state model that included the X and Y coordinates of each sample point and their interactions as covariates. A comparison of the coefficient estimates and p-values of this spatially-explicit model (Table S11) with the non-spatial all-state model (Table S12) indicated that the addition of the X and Y coordinates and their interaction did not change the direction, magnitude, or significance of the other predictor variables, with the exception of elevation, which became a significant variable when latitude and longitude were added to the model. This indicated that spatial autocorrelation did not have a significant impact on the relationships between the outcome and the other response variables or the subsequent marginal effect of management (Schleicher et al., 2017). The X and Y coordinates and their interaction were significant predictors of wildfire probability, but the coefficient estimates had absolute values less than 0.0001.

Results

Model results

In the model that included all matched points from the 11 states (hereafter "all-state model"), slope, aspect, distance to roads, average winter PDSI, and maximum summer temperature and wind speeds had significant positive relationships with the probability of a point burning in a given year (Table 1): forests on steeper slopes, located further from roads, and with less drought in winter, hotter summers, and higher summer wind speeds were more likely to burn. There was also a significant positive trend in the probability of burning over time (over the time series, the probability of a point burning increased). Population density, average summer PDSI, maximum fall temperature, and precipitation in fall and summer had negative relationships with burn probability: forests in areas with lower human population density, greater levels of summer drought, lower fall maximum temperatures, and less rainfall in summer and fall were more likely to burn. Sites that burned in the previous year, previous two years, or previous five years were all less likely to burn in a given year. Full results of the logistic regression for this model are in Table S12.

The predicted probability of burning began at 0.0008 in federally managed forests and 0.0003 in privately owned forests and increased over time for both management categories. The predicted probability of burning increased more rapidly for federally managed forests than for private forests: in 2016, the predicted probability of burning was about 1.5 times higher in federally managed forests than private forests (0.0032 and 0.0021, respectively; Figure 2).

When we calculated the predicted probabilities of burning for forested points in each state separately using the all-state model, we found four general patterns of states. In the first pattern, observed in Arizona, Utah, and Washington, federally managed and private forests begin with the same predicted probability of burning. The predicted probability of burning increases over time for both management types but increases more rapidly for federally managed forests. Federally managed forests in states that demonstrate the second general pattern-- California, Colorado, Idaho, Montana, and Oregon-- begin the time series with a greater predicted probability of burning than privately-owned forests. The probability of burning increases over the time series for both forest types, but federally managed forests always have a greater probability of burning. Nevada is the sole example of the third pattern: the predicted probability of burning increases over time and does not differ significantly between the land management categories. New Mexico and Wyoming represent the fourth pattern: in these two states, federally managed forests have a greater predicted probability in 1989, and while their predicted probability of burning increases over time, the predicted probability of burning for private areas increases more rapidly; at the end of the time series, unprotected areas have a greater predicted probability of burning. The predicted probabilities for each forest type in each individual state, using the all-state model, tracked the patterns in predicted probability over time that resulted from the state-level models (Figure S2).

Model robustness

Our state-level regression models had different suites of geographic and climatic covariates (*Controls* in the regression specification), depending on which variables were highly correlated. Elevation was a significant predictor of wildfire probability in all eleven states, with a negative impact in every state except Idaho and Washington. Elevation in turn was strongly correlated with minimum and maximum temperatures in most states and most seasons. Slope had a positive relationship with wildfire probability in every state except Colorado, where there was no significant relationship. Additional variables that had significant effects in more than half of the state-level models included aspect, distance to roads, summer PDSI, fall wind speeds, precipitation in all seasons, and precipitation in the previous year. See Tables S13-23 for full regression results for each state and Table S24 for the model fits for each state. The patterns of predicted probabilities and marginal effects for each state's model reflected the patterns for that state in the all-state model (Figure S2). The state-level models that used *Year* as a factor variable yielded similar results to those that treated Year as a continuous variable (Table S9). Using 5-year bins did not change the patterns in predicted probability of fire over time in the 11 states, even though the last time period was only 3 years, not 5, which would potentially depress the burn probability in the final time step (Table S10). Similarly, using dynamic panel methods and fixed effects regression to account for time lags did not significantly alter our results at the mean (Table S8). Adding points that were forested in 1992 and 2016 did not change our findings either (Table S7).

Effects of management and climate

The average marginal effect of federal management was positive (i.e., associated with higher probability of burning) for five of the states across the entire time series, while for three additional states, the marginal effect was positive in all years but was only significant beginning in the mid-1990s. As in the all-state model results, Nevada, New Mexico, and Wyoming display a different pattern in the effect of federal management than the rest of the region (Table 2).

When we compared the marginal effect of the management category to that of the climate variables in the state-level models for 2016, we found that the effect on burn probability of federal management (when compared to privately owned forests) was greater than the effect of a one-unit change in the value of most climate variables (Figure 3). In California, Idaho, and Utah, the effect of federal management was greater than a one-unit change in any of the climate variables. Wind speed variables had greater marginal effects than federal management in the other eight states, as did summer precipitation in Nevada, summer PDSI in New Mexico, summer and fall maximum temperatures and winter PDSI in Washington, and spring precipitation in Wyoming, although several of these differences were within the standard error ranges.

Discussion

We find that over the last few decades, federally managed forests in the western US have had a higher probability of burning in wildfires than private forests, after controlling for systematic differences in geographic, climatic, and human factors that contribute to wildfire risk. While wildfire probability increased over time for forests in both management categories, federally managed forests experienced a greater increase. This pattern held true across the majority of states in the western US: in eight states, the marginal effect of being a federally managed forest was positive starting in the late 1990s at the latest (for five of these states, the marginal effect was positive and significant throughout the entire time series). Our results concur with those of a recent study looking at the effects of land management, protection status, and firefighting responsibility in California (Starrs et al., 2018). The generality of this pattern, and the increase in the divergence between federally managed and private forests, demonstrates the importance of forest management in shaping wildfire risk.

We also find that in most states, the effect of federal management on fire probability is greater than that of a one-unit change in many of the climate variables related to fire risk. For example, the effect of federal management on forest fire risk in Montana is more than eighteen times greater than that of a 1 cm increase in spring precipitation (0.0022 ± 0.0004 vs. 0.0001 ± 0.0001), while the state is projected to experience a 1.5-3 cm increase in spring precipitation by 2040-2069 (Whitlock et al., 2017). In Oregon, average summer temperatures are predicted to increase by 0.8˚C along the coast and 2.0˚C in the eastern part of the state by 2059 relative to 2019 observations (Mote et al., 2019); the effect of federal management is 1.4 times greater than that of a 1˚C increase in average maximum summer temperatures (0.0024 ± 0.0001 vs. 0.0017 ± 0.0002). These findings indicate that in the social-ecological systems of western US forests, management can have as large an impact as some aspects of climate change on the probability of wildfire as a system outcome.

Our finding that the probability of burning increased for both management types (federally managed and private) indicates that across management and ownership categories, fire risk is increasing in the western US. This mirrors previous regional studies that have found an increase in fire risk with climate change (Abatzoglou and Williams, 2016; Westerling, 2016) and suggests that as the western US continues to experience changing climate conditions, there may be limits in the ability of forest management to reduce fire risk. The upward trend that we found in burn probability over time may derive from an increase in the time since the last fire for each sample point (i.e. the year effect represents time since burning), reflect changing practices over time in both management categories, or capture the influence of climate variables that increased over the time period of our study but were not included as predictor variables. Nevertheless, our findings— that 1) federal forests have a greater probability of burning, 2) the difference in fire probability between federal and private forests has increased over time, and 3) the effect of federal management is greater than that of some changes in climate variables in increasing fire probability— demonstrate that forest management has a role to play in influencing fire activity and that projections of wildfire risk under climate change need to account for differences in land management.

Time lags and legacy effects are common features of social-ecological systems; different legacies of fire suppression and changing management goals may in part account for the observed increase in the probability of wildfires in federally managed forests relative to privately-owned forests. Decades of fire suppression on federal land and exclusion of fuel-removing activities (such as logging and grazing) have led to a build-up of fuels, setting the stage for increased fire activity (Noss et al., 2006). At the same time, in recent years, federal land management agencies have begun to recognize the ecological role of wildfires, leading to less rigid focus on fire exclusion and some efforts to approximate historic fire regimes (Steelman and McCaffrey, 2011; Stephens and Ruth, 2005), although our model accounts for this by excluding prescribed fires and wildland fire use. This combination of an accumulation of fuel following decades of fire suppression and more recent acceptance of the role of fire has primed federal lands for increased fire risk. We also accounted for time lags through our inclusion of three lag variables (whether or not a point had burned in the previous one, two, or five years) and use of dynamic panel modelling and fixed effects to incorporate time lags in the dependent variable. Across the western US, the fire probability decreases for at least five years following a fire, although this effect does not hold true in every state (Tables S13-23).

We found that Nevada, New Mexico, and Wyoming had different patterns of fire probability than the other eight states: in Nevada, the fire probability increased over time but there was no difference in risk between the two management categories; in New Mexico and Wyoming, federally managed forests had a greater probability of burning than private forests in the late 1980s, but this pattern had flipped by 2016. The different patterns in New Mexico and Wyoming may be in part attributable to trends in timber harvest on federal and private land in the last two decades: in both states, federal timber harvest increased from 2000 onward, overtaking harvest from private land, which declined during that time period (Hayes et al., 2018; McIver et al., 2017). This indicates greater fuel removal on federal than private land during the time period when the probability of burning for private forests began to exceed that of federally managed forests. However, Arizona did not display the same pattern in its fire probability, despite having a similar change in the relative dominance of timber harvests from federal versus private land (Figure S3) (Hayes et al., 2018). The patterns Nevada and New Mexico may also stem from ecological differences due to the dominant forest types present: over 50% of the forested points sampled in Nevada and New Mexico were pinyon-juniper woodland (62% and 53%, respectively); however, the only other state where the majority of sampled points were from pinyon-juniper woodlands was Arizona, which did not follow the same pattern as Nevada or New Mexico, thus complicating the relationship between dominant woodland species and fire probability (USGS, 2001).

Variable ignition rates are an important driver of differences in wildfire probability across space and time (Balch et al., 2017; Keeley and Syphard, 2017); we were unable to fully account for variation in ignitions due to a lack of data on lightning strikes and anthropogenic ignitions at fine spatial scales across the time period of our study. However, we expect increased rates of anthropogenic ignitions in areas with higher human population densities and closer to roads (Mann et al., 2016; Stephens and Ruth, 2005; Syphard et al., 2007). In our matched dataset, privately-owned forests were located in census blocks with higher population densities in all states, while private forests in four states were located closer to roads than federally managed forests (Table S3), suggesting that the privately-owned forests may experience higher rates of anthropogenic ignitions. Given this expected trend, the increased wildfire probability in federally managed forests, despite lower expected anthropogenic ignition rates, highlights the role of land management in influencing wildfire probability, as well as other factors associated with proximity to human population centers, such as probability of rapid detection of fires, firefighting resources, and preference for fire suppression (Syphard et al., 2007). In fact, in the all-state model and five of the state-level models, the probability of burning increased with distance from roads and at lower population densities (Tables 1, S14, S16, S17, S20, S22), suggesting that the effects of land management, detection, and firefighting response may swamp out the impact of more frequent human ignitions.

While our pre-regression matching methodology allowed us to control for potentially systematic geographic, climatic, and human differences between federally managed and private forests, it also limits the generalizability of our results. We can only apply our regression results to forested points that fall within the range of climatic, geographic, and human variables that were included in the matched dataset. This means that we cannot assume that our results would hold true for the most remote, high altitude forests in wilderness areas in the western US, for example, since our matching process discarded federally managed points that did not have a private forest point with similar geographic characteristics (elevation, distance to roads, and human population density, in this example). Notably, high elevation sites may experience above-average warming with climate change and be particularly sensitive to these changes (Diaz et al., 2003; Pepin et al., 2015; Rangwala et al., 2013).

In addition, by building state-specific models and including a state fixed effect in our overall model, we assume that there is an impact of state boundaries on fire probability. However, we think that this assumption is justified, as state-level policies constrain forest management and affect firefighting on private and federal land (Ager et al., 2017; Starrs et al., 2018). In addition, our model includes seasonal climate variables but does not account for shorter-term weather events that may have a large impact in the spread of individual fires (Finney et al., 2011). Finally, our model does not account for changes in forest cover in our study area over the time period, assuming instead that areas that were forested in 2001 had forest cover throughout our time series (Abatzoglou and Williams, 2016).

Our study represents an advance for understanding the impact of federal management of wildfires in the western US specifically and quantitative assessment of complex forcings in social-ecological systems broadly. Previous studies have assessed fire risk due to biophysical factors, but here we integrate the social component by disaggregating fire risk by management type. Using a high-resolution dataset on fire perimeters, climatic variables, and geographic factors over the last three decades, pre-regression matching, and logistic regression with mixed effects models, we provide a rigorous assessment of the effect of federal land management on wildfire risk and find that 1) federally managed forests have a greater probability of burning than private, unprotected forests; 2) this effect has increased over the last three decades; 3) this trend applies to eight of the eleven states in the region, despite the diversity of forest types and climates within the region; and 4) the effect of federal management on fire is greater than that of one-unit changes in many climate variables expected to impact fires. We also present a novel approach to quantifying the relative importance of different drivers of change in complex social-ecological systems, while accounting for the human-environment interactions and time lags that characterize these systems. Our method provides a potential framework for further research that seeks to untangle the roles of management, socioeconomic, and environmental factors in driving outcomes in social-ecological systems.

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Tables

Table 1. Regression model results of annual burn data across all eleven western states, showing coefficient estimates for climatic, topographic, and social variables and the interaction between time and management status. Standard errors are in parentheses beneath the corresponding coefficient estimate. See Table S12 for state effects and interactions between state effects, year, and federal management. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Variable	Coefficient
Intercept	-164.774*** (26.478)
Federally managed	-65.596* (33.322)
Elevation (thousand meters)	-0.037 (0.023)
Slope (˚)	0.023*** (0.001)
Aspect (˚)	0.000*** (0.000)
Distance to roads (km)	0.168*** (0.006)
Population density (1990)	-0.014*** (0.002)
Average PDSI, summer	-0.223*** (0.004)
Average PDSI, winter	0.072*** (0.004)
Average maximum temperature, fall (˚C)	-0.044*** (0.005)
Average maximum temperature, summer (˚C)	0.121*** (0.004)
Average maximum wind speed, summer (m/s)	0.181*** (0.015)
Total precipitation, fall (cm)	-0.022*** (0.001)
Total precipitation, summer (cm)	-0.103*** (0.003)
Year	0.078*** (0.013)
Burned in previous year	-2.839*** (0.243)
Burned in previous 2 years	-1.356*** (0.141)
Burned in previous 5 years	-0.738***

	(0.103)
Federally managed*Year	0.033* (0.017)

Table 2. Marginal effects (percentage point change in fire probability) of federal management for the state-level models. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Year	AZ	CA	CO	ID	MT	NV	NM	OR	UT	WA	WY
1989	0.02	0.12^{***}	0.05^{***}	0.09^{***}	0.13^{***}	0.05	0.24^{***}	0.17^{***}	0.01	0.01	0.09^{***}
1990	0.02	0.13^{***}	0.05^{***}	0.10^{***}	0.13^{***}	0.05	0.24^{***}	0.17^{***}	0.01	0.01	0.09^{***}
1991	0.03	0.14^{***}	0.05^{***}	0.10^{***}	0.14^{***}	0.05	0.24^{***}	0.17^{***}	0.01	0.01	0.10^{***}
1992	0.03	0.16^{***}	0.06^{***}	0.11^{***}	0.14^{***}	0.05	0.24^{***}	0.18^{***}	0.02	0.01	0.11^{***}
1993	0.04	0.17^{***}	0.06^{***}	0.11^{***}	0.15^{***}	0.06	0.24^{***}	0.18^{***}	0.02	0.01	0.12^{***}
1994	0.05	0.19^{***}	0.06^{***}	0.12^{***}	0.15^{***}	0.06	0.24^{***}	0.18^{***}	0.02	0.01	0.13^{***}
1995	0.05	0.20^{***}	0.07^{***}	0.13^{***}	0.15^{***}	0.06	0.24^{***}	0.19^{***}	0.02	0.01	0.14^{***}
1996	0.06	0.22^{***}	0.07^{***}	0.13^{***}	0.16^{***}	0.06	0.24^{***}	0.19^{***}	0.02	0.02	0.15^{***}
1997	0.07^{*}	0.24^{***}	0.08^{***}	0.14^{***}	0.16^{***}	0.06	0.24^{***}	0.19^{***}	0.03	0.02	0.16^{***}
1998	0.08^{*}	0.26^{***}	0.08^{***}	0.15^{***}	0.16^{***}	0.07	0.23^{***}	0.20^{***}	0.03	0.02	0.17^{***}
1999	0.10^{**}	0.28^{***}	0.08^{***}	0.15^{***}	0.17^{***}	0.07	0.23^{***}	0.20^{***}	0.03^{*}	0.02^{*}	0.18^{***}
2000	0.11^{**}	0.30^{***}	0.09^{***}	0.16^{***}	0.17^{***}	0.07	0.23^{***}	0.21^{***}	0.04^{*}	0.02^{*}	0.20^{***}
2001	0.12^{***}	0.32^{***}	0.10^{***}	0.17^{***}	0.17^{***}	0.07	0.22^{***}	0.21^{***}	0.04^{**}	0.03^{*}	0.21^{***}
2002	0.14^{***}	0.35^{***}	0.10^{***}	0.18^{***}	0.18^{***}	0.08	0.22^{***}	0.21^{***}	0.04^{**}	0.03^{*}	0.22^{***}
2003	0.15^{***}	0.37^{***}	0.11^{***}	0.19^{***}	0.18^{***}	0.08	0.21^{***}	0.22^{***}	0.05^{***}	0.03^{**}	0.23^{***}
2004	0.17^{***}	0.40^{***}	0.11^{***}	0.19^{***}	0.19^{***}	0.08	0.20^{***}	0.22^{***}	0.05^{***}	0.04^{**}	0.23^{***}
2005	0.19^{***}	0.43^{***}	0.12^{***}	0.20^{***}	0.19^{***}	0.08	0.19^{***}	0.22^{***}	0.06^{***}	0.04^{**}	0.24^{***}
2006	0.21^{***}	0.46^{***}	0.12^{***}	0.21^{***}	0.19^{***}	0.09	0.18^{***}	0.22^{***}	0.06^{***}	0.04^{**}	0.24^{***}
2007	0.24^{***}	0.49^{***}	0.13^{***}	0.22^{***}	0.20^{***}	0.09	0.17^{***}	0.23^{***}	0.07^{***}	0.05^{***}	0.24^{***}
2008	0.26^{***}	0.52^{***}	0.13^{***}	0.23^{***}	0.20^{***}	0.09	0.15^{***}	0.23^{***}	0.07^{***}	0.05^{***}	0.23^{***}
2009	0.29^{***}	0.56^{***}	0.14^{***}	0.24^{***}	0.20^{***}	0.10	0.13^{***}	0.23^{***}	0.08^{***}	0.06^{***}	0.22^{***}
2010	0.32^{***}	0.60^{***}	0.15^{***}	0.25^{***}	0.20^{***}	0.10	0.11^{***}	0.23^{***}	0.08^{***}	0.06^{***}	0.20^{***}
2011	0.35^{***}	0.64^{***}	0.15^{***}	0.26^{***}	0.21^{***}	0.10	0.08^{***}	0.24^{***}	0.09^{***}	0.07^{***}	0.16^{*}
2012	0.38^{***}	0.68^{***}	0.16^{***}	0.27^{***}	0.21^{***}	0.11	0.06^{*}	0.24^{***}	0.10^{***}	0.08^{***}	0.11
2013	0.42^{***}	0.73^{***}	0.16^{***}	0.29^{***}	0.21^{***}	0.11	0.02	0.24^{***}	0.10^{***}	0.09^{**}	0.05

2014	0.46***	0.77***	0.16***	0.30***	0.21***	0.11	-0.01	0.24***	0.11***	0.09**	-0.03
2015	0.51***	0.82***	0.17***	0.31***	0.22***	0.12	-0.05	0.24***	0.12***	0.10**	-0.14
2016	0.55***	0.88***	0.17***	0.32***	0.22***	0.12	-0.10*	0.24***	0.12***	0.11*	-0.28

Figures

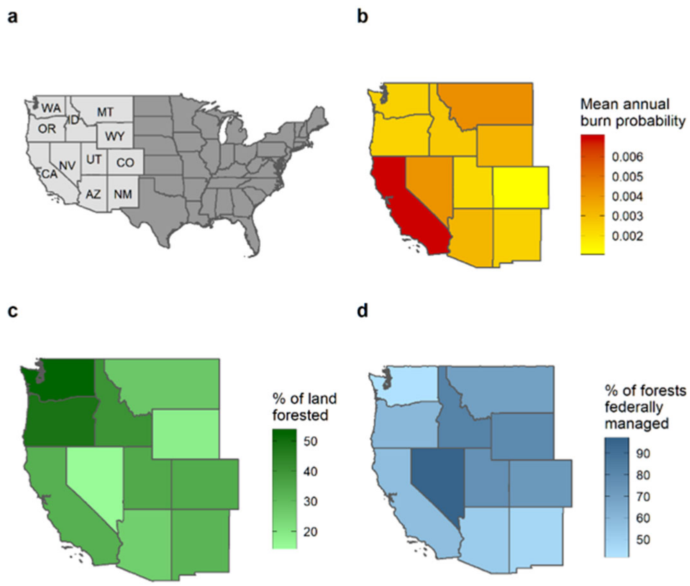


Figure 1. Map of the study area showing a) each state labeled with its postal code abbreviation; b) the annual probability of a given federally-managed or privately-owned forest burning, averaged from 1989-2016; c) the proportion of land area covered by forests; and d) the proportion of forests owned by the federal government.

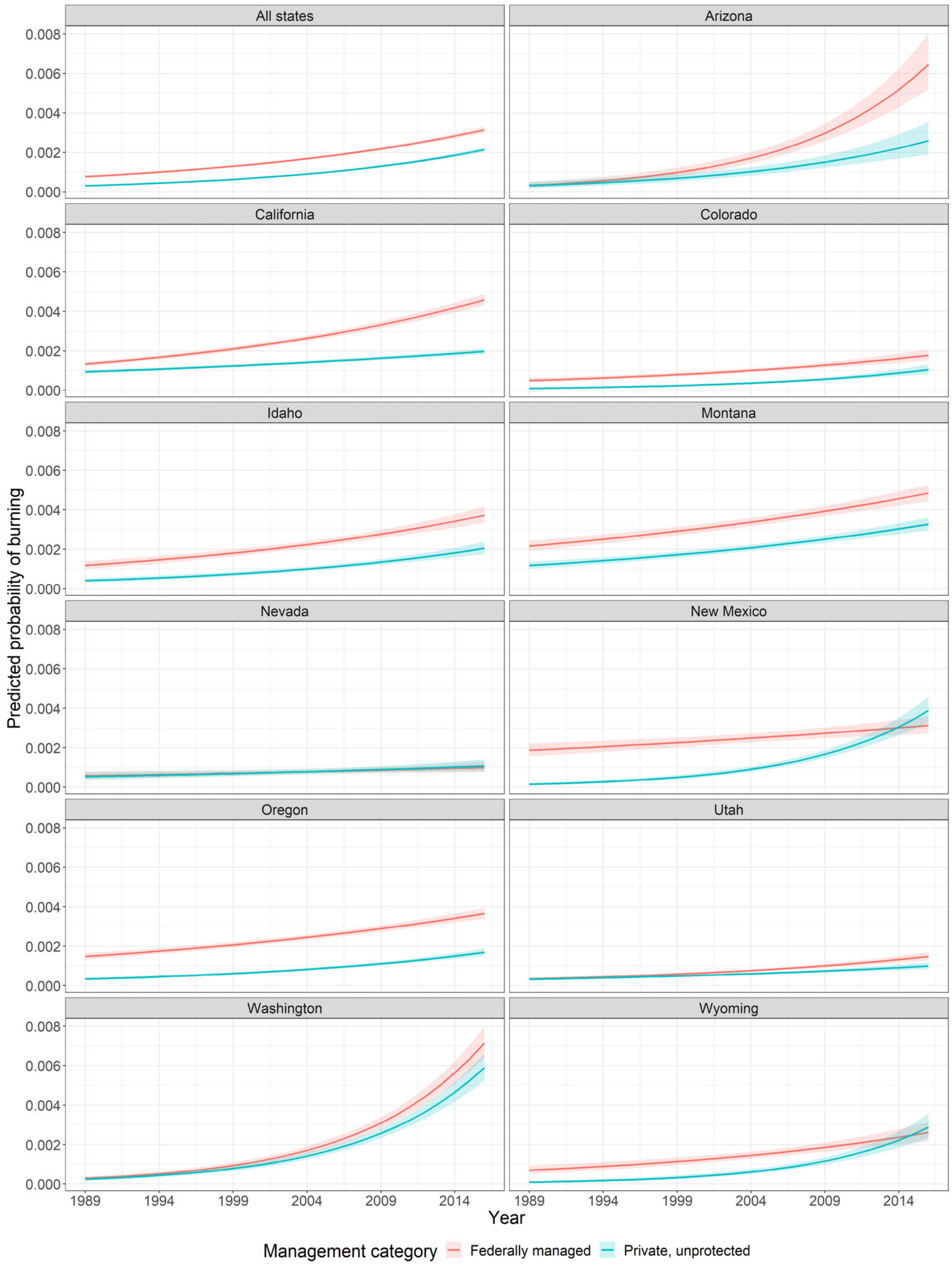
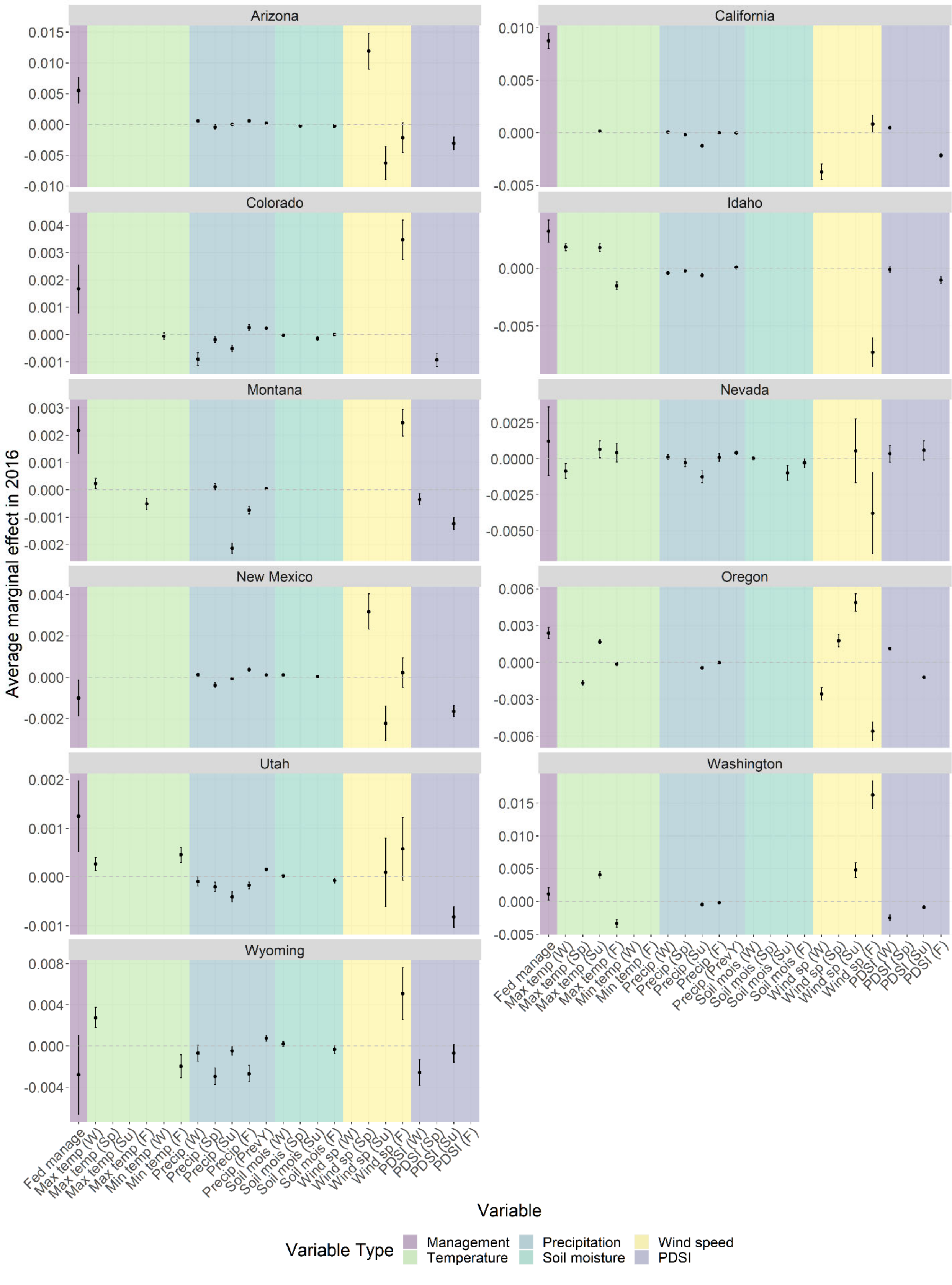


Figure 2. Predicted probability of fire in federally managed forests and private, unprotected forests using the all-state model, from 1989-2016, including 95% confidence intervals. The first panel shows the predicted probability across all states; the remaining panels show the predicted probability for each state within the all-state model.



Arizona
California
Colorado
Idaho
Montana
Nevada
New Mexico
Oregon
Utah
Washington
Wyoming
Average marginal effect in 2016
Variable
Fed manage
Max temp (W)
Max temp (Sp)
Max temp (Su)
Max temp (F)
Min temp (W)
Min temp (F)
Precip (W)
Precip (Sp)
Precip (Su)
Precip (F)
Precip (Prev Y)
Soil mois (W)
Soil mois (Sp)
Soil mois (Su)
Soil mois (F)
Wind sp (W)
Wind sp (Sp)
Wind sp (Su)
Wind sp (F)
PDSI (W)
PDSI (Sp)
PDSI (Su)
PDSI (F)
Variable Type
Management
Temperature
Precipitation
Soil moisture
Wind speed
PDSI

Figure 3. Comparison of the marginal effect of federal management (*Fed manage*) with a one-unit change in the value of the climate variables in each state's model in 2016: maximum temperature (*Max temp*, ˚C), minimum temperature (*Min temp*, ˚C), precipitation (*Precip*, cm), soil moisture (*Soil*, mm), wind speed (*Wind sp*, m/s), and PDSI in winter (*W*), spring (*Sp*), summer (*Su*), fall (*F*), and for precipitation in the previous year (*PrevY*, cm). Background colors indicate the type of variable. The y-axis ranges vary between states.

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Transition between Chapters 1 and 2

In Chapter 1, I used causal inference methods to assess the effect of land ownership on wildfire probability in forests of the western US. I found that federally-owned forests burned more frequently than privately-owned, unprotected forests from 1989-2016. I also found that the marginal effect of the different management types was greater than the effect of a one-unit change in most of the climate variables I assessed. These results may be due to varying levels of accumulated fuels in federally- vs. privately-owned forests stemming from different legacies of biomass removal, as well as variations in fire management. My results demonstrate that in this social-ecological system, management can have as large an impact as some aspects of climate change, highlighting the need to take both management and climate variables into account when projecting future wildfire activity. In Chapter 2, I again use pre-regression matching methods to assess the impact of different forms of land management on wildfire probability, this time looking at the impact of livestock grazing on wildfires in California rangelands. In this chapter, I was able to more precisely measure spatial variation in management than in Chapter 1: I use a novel dataset on the stocking levels of large-scale ranchers to analyze the impact of grazing and varying levels of grazing intensity on wildfire probability in three regions of California and three dominant vegetation types: grasslands, shrub/scrublands, and forests in the North Bay, Central Valley and Foothills, and Central Coast.

CHAPTER 2

Impacts of livestock grazing on wildfire probability across regions and vegetation types in California

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Included as a dissertation chapter with permission from co-authors.

Abstract

Wildfire activity has increased in California in recent decades, impacting ecosystem functioning and human well-being. California's rangelands are complex social-ecological systems composed of multiple ecosystems and the people who live and work in them. Livestock grazing has been proposed as a tool for reducing wildfire activity. Here, we explore how grazing affects wildfire at large spatial scales, assessing the likelihood of wildfires on rangelands subject to different levels of grazing. We collected data on grazing levels through a survey of 140 large private landowners (properties of at least 500 acres) in three social-ecological regions: California's North Bay, Central Coast, and Central Valley and Foothills. Using pre-regression matching methods and mixed effects regression models, we calculate the probability of wildfires occurring in a given year from 2001-2017 in each of the three social-ecological regions and three land cover types (grasslands, shrub/scrublands, and forests). We find that in the Central Coast and North Bay, wildfire probability decreases as stocking levels increase in all three vegetation types, with reductions ranging from 31.0-76.5%. In the Central Valley and Foothills, the relationship is less clear, with an increase in wildfire probability over some levels of grazing and large variations in the effect of higher stocking densities. Our results indicate that livestock grazing can effectively reduce annual burn probability in some regions and ecosystem types in California, providing the first large-scale assessment of this relationship and suggesting that expanded grazing on private and public land in California may reduce fire frequency in these social-ecological systems.

Introduction

Across the western United States, the severity and spatial extent of wildfires have increased over the past four decades (Abatzoglou and Williams, 2016; Dennison et al., 2014; Westerling et al., 2003), impacting ecosystems and human lives (Syphard et al., 2019a; Tubbesing et al., 2020). In California, the area burned each year has increased four-fold since 1972 (Williams et al., 2019), driven by interacting factors that include increased anthropogenic ignitions (Balch et al., 2017) and human development in wildland areas (Radeloff et al., 2018), climate change (Abatzoglou and Williams, 2016; Goss et al., 2020; Westerling, 2016; Williams et al., 2019), and the legacy of decades of aggressive fire suppression (Stephens and Ruth, 2005). While much of this increase in burned area has occurred in forested land, large areas of California's rangeland, especially grasslands and shrublands, have also burned in recent years (Syphard et al., 2007). As an example, the 2017 Tubbs and Thomas fires collectively burned over 150,000 acres of shrubland and 55,000 acres of grassland (over 64% of the total area burned in the two fires). In recent decades, California's rangelands have also experienced rapid human population growth, with a corresponding increase in the amount of wildland-urban interface present in the state (Radeloff et al., 2018; Syphard et al., 2019b). This pattern is also reflected globally, as 45.8% of temperate grasslands, savannas, and shrublands have been converted for human use, along with 41.4% of Mediterranean forests, woodland, and scrublands (Hoekstra et al., 2005).

California's rangelands represent complex social-ecological systems, with ranches, residential developments, and other human land use regimes interacting with diverse and fire-adapted ecosystems, including grasslands, oak savannas, chaparral and other shrublands, and woodlands (Cameron et al., 2014; *Forest and Rangeland Resources Assessment and Policy Act*, 1977). Historically, these landscapes burned periodically in lightning-ignited fires, and Indigenous groups used fire as a tool to manage the distribution and abundance of the resources they used (Anderson, 2005; Keeley, 2002; Stephens et al., 2007). Nineteenth century colonial policies prohibited Indigenous fire use, followed by widespread and intensive livestock grazing and other land use changes (Taylor et al., 2016). In the early twentieth century, California began practicing aggressive fire suppression, seeking to reduce loss of human lives and property (Pyne, 1982; Stephens and Sugihara, 2006). As a result of interactions between land management policies, land use change, and climate change, dry fuels have accumulated across California's landscapes, setting the stage for large and severe wildfires (Steel et al., 2015). These wildfires have the potential to disrupt ecological processes and force type conversions in vegetation communities such as forests in the Sierra Nevadas and Klamath mountains (Coop et al., 2020) and chaparral in coastal southern California (Syphard et al., 2019a).

In recent years, there have been calls in both the academic literature and popular media to use livestock grazing as a tool to mitigate the risk of large, high-severity fires in fire-prone ecosystems, both in the American West and elsewhere (Davies et al., 2016; Nelson, 2019; Williams et al., 2006). Grazing reduces the accumulation and connectivity of fuels, particularly fine (herbaceous) fuels: livestock directly consume potential fuels and trample vegetation, crushing fine fuels and reducing their flammability by mixing them in with the mineral soil while rearranging the spatial structure of fuels (Davies et al., 2010; Nader et al., 2007; Tsiouvaras et al., 1989).

Experimental and observational studies have shown that through these reductions in fuel accumulation and connectivity, grazing can reduce flame length, rate of spread, fire intensity and severity, and total area burned (Davies et al., 2016; Diamond et al., 2009; Launchbaugh et al., 2008; Leonard et al., 2010; Starns et al., 2019). Grazing and fire may also interact to create spatial heterogeneity in vegetation structure and composition (Fuhlendorf et al., 2009; McGranahan et al., 2012): in tallgrass prairies in the Great Plains, cattle and other large ungulates preferentially graze in recently-burned areas due to the higher nutritional value of regrowth forage, creating a heterogeneous landscape where recently-burned patches have low fuel accumulation due to grazing, while patches without recent fire have greater fuel accumulation, with implications for fire spread (Allred et al., 2011). This pattern is less clear but still present in arid shortgrass steppe (Augustine and Derner, 2014). Meanwhile, a study in southeastern Australia found no difference in fire probability between grazed and ungrazed sites in grasslands and shrublands (Williams et al., 2006). Overall, findings relating grazing to subsequent fires vary depending on vegetation type and the timing of grazing relative to both plant phenology and local fire seasons, and studies of this interaction in California's ecosystems are limited.

Questions remain about the relationship between livestock grazing and wildfire at broad spatial scales (Keeley et al., 2011). While information on trends in the extent and location of rangeland ecosystems (land cover) is widely available through satellite imagery, data on grazing levels (land use) are quite limited. The lack of spatially-explicit data on livestock grazing across broad areas is a major barrier to research on landscape-scale relationships between grazing and wildfire. Spatial data on rangelands as a land cover type do not typically include information on whether or not grazing is occurring, let alone stocking rates, which are key to driving grazing-fire interactions. As the impact of wildfire on rangeland social-ecological systems is mediated by human decisions regarding land management, a more complete understanding of the relationship between grazing and fire requires data on both land cover and land use.

Here, we assess the effect of grazing on fire probability in California, using data from three regions chosen for their variation in environmental and human land use factors. Combining a time series of fires from 2001-2017, grazing data from ranches across seven counties, and a suite of environmental and socioeconomic covariates, we use pre-regression matching and logistic mixed effects models to analyze whether 1) livestock grazing impacts the probability of fires in California, and 2) whether the effect of livestock grazing on fire probability varies by region and dominant vegetation type.

Methods

Study area

Our study area comprises three social-ecological regions in California, defined by both environmental and administrative boundaries (Bailey ecoprovinces (Bailey, 1995) and county borders, respectively): the Central Coast, Central Valley and Foothills, and the North Bay (Figure 1). Across the state, beef cattle make up the vast majority of livestock grazing on rangelands, and the cattle industry is composed of both cow-calf and stocker enterprises. Cow-calf operators maintain a breeding herd of mature females year-round and birth, rear, and sell calves annually. Stocker operations run mostly adolescent cattle seasonally, typically from October through May. Cattle production techniques are largely similar across the three study regions; however, due to seasonal precipitation patterns, the growing season is slightly longer in the North Bay. In the Central Valley and Foothills, the presence of artificially irrigated pastures allows for continued grazing in some areas during the summer months.

The Central Coast region contains the central portions of both the California Coastal Chaparral Forest and Shrub Province (hereafter "Coastal Chaparral"; Figure 1) and the California Coastal Range Open Woodland-Shrub-Coniferous Forest-Meadow Province (hereafter "Coastal Range"), located in Santa Barbara and Ventura counties. This region is characterized by a diverse mix of ecosystems, distributed along gradients of soil moisture and fire frequency (Keeley and Syphard, 2018). Historically, this region had frequent lightning-ignited fires that burned small areas and larger, wind-driven fires every 50-100 years (Keeley and Fotheringham, 2001). Prior to European contact, Indigenous Californians used fire to maintain grasslands and other resource-abundant vegetation communities (Keeley, 2002). The region has seen increased frequency of large fires in recent years as the human population has grown and ignitions coincide with Santa Ana winds (Keeley and Zedler, 2009). The region experienced a decline in cattle numbers from 1964-1997 (Andersen et al., 2002), with continued declines in cattle and the number of ranching operations from 2002-2017 (USDA-NASS, 2017, 2007).

The Central Valley and Foothills region, represented by San Joaquin, Merced, and Mariposa counties, is almost entirely part of the California Dry Steppe Province, as well as the lower-elevation western edge of the Sierran Steppe-Mixed Forest-Coniferous Forest-Alpine Meadow Province (hereafter "Sierran Steppe") and a small portion of the eastern edge of the Coastal Range ecoprovince. This region has had very high levels of land conversion for intensive human uses (Cameron et al., 2014) and little is known about its pre-colonization fire regime (Willis, 2018). In the latter half of the twentieth century, cattle numbers increased in the region (Andersen et al., 2002), with a relatively stable number of ranching operations and overall cattle since 2002 (USDA-NASS, 2017, 2007). In the Central Valley, rangeland livestock production systems are predominantly stocker systems in which beef cows are shipped in from other states, Northern California, or forest ecosystems in late October through early November and shipped out in late May through early June. Most ranchers ensure that when they ship out their livestock in late spring, they leave forage for the animals to come back to in early fall, before the new season's vegetation growth occurs. Ranchers in this region tend to have low levels of flexibility in adapting to interannual environmental variation, as they commit to the number and grazing period of cattle before the season begins.

The North Bay region includes most of Sonoma County and all of Napa County; most of the region falls within the southwestern portion of the Sierran Steppe ecoprovince, as well as the northernmost portion of the Coastal Chaparral ecoprovince. We omitted western Sonoma County from our study because it is located in the California Coastal Steppe-Mixed Forest-Redwood Forest Province and has a distinct fire regime and climate from the rest of the region (Stephens et al., 2018). The chaparral ecosystems in the North Bay are resilient to fire and historically had high-severity, stand-replacing fires every 30-100 years (Stephens et al., 2007). North Bay woodlands have experienced decades of fire suppression, leading to a greater density of fuels and more vertical fuel connectivity and thus increased risk of destructive crown fires (Stephens et al., 2018). Since 2002, the number of cattle in the North Bay has remained fairly stable (USDA-NASS, 2017, 2007).

Data

We collected data on grazing intensity levels through a telephone survey of large private landowners in the seven counties included in our study region (Sonoma, Napa, San Joaquin, Mariposa, Merced, Santa Barbara, and Ventura). We randomly sampled private landowners with properties of at least 500 acres, of which at least 250 acres were grassland or shrub/scrubland, until we obtained 20 responses per county. For each property, we asked the landowners whether or not they were actively grazing their land. For the grazed properties, we collected data on the number of animals grazed, the months of active grazing, and the acres grazed. The data provided represented long-term grazing levels, as the property owners reported relatively static trends in land use intensity. We used this data to calculate the animal units per year (AUY) per acre grazed, a measure of grazing intensity. In total, we collected data from 140 properties, 123 of which provided enough data for analysis. These 123 properties covered a total of 308,240 acres of rangeland (1247 km^2).

Within the boundaries of the surveyed properties, we sampled points along a 200-meter grid, using land cover data from the 2001 National Land Cover Database to restrict our samples to points that were in forests, grasslands, and shrub/scrubland. We excluded points located in water, wetlands, developed areas, and other land cover types unlikely to experience grazing (USGS, 2014). We used 2001 land cover data to capture the patterns of land cover at the beginning of our time series and assumed that the dominant land covers did not shift on our sampled properties from 2001-2017. For all sample points, we compiled data on fire history, climate, topography, and human variables related to fire occurrence.

We included all fires from 1996-2017 from the California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP) fire perimeter database that overlapped with the sampled points (CAL FIRE, 2020). FRAP is the most complete dataset available for California fire perimeters and it includes smaller fires that are omitted from national fire datasets. We determined whether or not each point burned in a wildfire in each year (2001-2017). In addition, to account for the legacy effects of past fires, we determined whether or not a point had burned in the previous five years (Parks et al., 2016; Price et al., 2015).

We calculated average seasonal climate variables for each point, using monthly climate data at a 4km resolution from TerraClimate (Abatzoglou et al., 2018). We used the TerraClimate dataset because it includes a wider range of fire-relevant climatic variables (e.g., Palmer Drought Severity Index, wind speeds, and soil moisture) than finer-scale datasets like PRISM (Daly et al., 2008). We included climate variables related to both fire probability (fuel conditions and probability of ignition) and fire behavior: seasonal average maximum wind speed (m/s), total precipitation (cm), average maximum and minimum temperatures (˚C), and average soil moisture (mm) and Palmer Drought Severity Index (Abatzoglou et al., 2017; Abatzoglou and Williams, 2016; Barbero et al., 2014; Dennison et al., 2014; Dillon et al., 2011; Krawchuk and Moritz, 2011; Littell et al., 2016, 2009; Westerling et al., 2003, 2006; Westerling, 2016). We defined winter as December of the previous year, January, and February, spring as March-May, summer as June-August, and fall as September-November. In addition to these seasonal variables, we calculated total accumulated precipitation from the previous water year (December-November) (Littell et al., 2009; Syphard et al., 2017).

To control for the effect of primary productivity on stocking levels and the amount of fuel left on the land at the end of the season (residual dry matter), we included the annual net primary productivity (NPP) of each sample point in our model. We extracted NPP data (in kg*C/m^2) from the MODIS/Terra Net Primary Production Gap-Filled Yearly Global 500m product (Running and Zhao, 2019), accessed through Google Earth Engine (Gorelick et al., 2017). This dataset estimates annual NPP at 500m resolution based on gross primary productivity and maintenance respiration. We used NPP to account for the effect that forage production may have on both grazing intensity and fire probability: an area with greater NPP can likely support higher grazing intensity and will also accumulate more biomass, and thus fuel, in the absence of grazing.

To account for the impact of human presence on anthropogenic ignitions and responses to fires made by relevant agencies (Balch et al., 2017; Nagy et al., 2018; Syphard et al., 2017), we included the population density (people/km^2) (Radeloff et al., 2018) and distance to the nearest road (in meters) for each point (US Census Bureau, 2018). We also included topographic variables in our model, since elevation, slope, and aspect may influence grazing levels, fuel conditions, fire probability, fire behavior, and management responses to fires (Dillon et al., 2011; Hurteau et al., 2014; Littell et al., 2009). We used 30km resolution elevation data from the National Elevation Dataset (USGS, 2013) and calculated slope and aspect in QGIS (QGIS Development Team, 2019). We converted aspect to the solar radiation aspect index, a linear scale that ranges from 0-1, where 0 indicates the lowest levels of solar radiation (Roberts and Cooper, 1989). Aside from the use of Google Earth Engine to extract NPP and QGIS to calculate slope and aspect, we performed all data compilation and calculations in R, using the *raster*, *sf*, *lwgeom*, and *tidyverse* packages (Hijmans, 2019; Pebesma, 2019, 2018; Wickham, 2017).

Matching

There may be fundamental geographic, climatic, or environmental differences between grazed and ungrazed properties. For example, we might expect property owners with steep terrain with very low net primary productivity to be less likely to graze livestock than property owners whose land has gentle terrain and abundant forage. The differences between grazed and ungrazed properties may also impact their fire probability, through differences in fuel accumulation, ignition probability, and fire spread. To control for these potential differences between grazed and ungrazed sites and improve our ability to make causal inferences, we used pre-regression matching techniques (Schleicher et al., 2020; Stuart, 2010). Using the *MatchIt* package in R (Ho et al., 2011), with the caliper set to 0.25 and the maximum ratio of grazed to ungrazed sample points set to 5, we matched sample points from the grazed and ungrazed properties along the suite of continuous covariates: population density in 2000 and 2010; distance to the nearest road; elevation; slope; aspect; seasonal averages of minimum and maximum temperatures, maximum wind speeds, soil moisture, and PDSI, averaged over the first five years of the dataset (2001-2005); average annual NPP from 2001-2005; and latitude and longitude. We assessed the match quality by comparing the standardized mean differences in variable values for grazed and ungrazed sample points in the matched and unmatched data and removed all unmatched sample points from our subsequent dataset (Table S1). We developed two matched datasets, one with only sample points on grasslands and shrub/scrublands, as these are the vegetation types where grazing occurs, and a second on points located in grasslands, shrub/scrublands, or forests (Table S2). The first matching procedure drew only from sample points in grassland or shrub/scrubland, while the second matching procedure drew from sample points in any of the three land cover types. This second matched dataset allowed us to explore whether the impact of grazing in grassland and shrub/scrublands might in turn affect the probability of wildfires spreading into forested land within the properties studied.

Of the 140 ranching properties surveyed, 123 had complete data on grazing intensity. We removed five properties from the dataset because they were located in the California Coastal Steppe-Mixed Forest-Redwood Forest province in Sonoma County. The remaining 118 properties in the dataset account for 301,649 acres (1220.73 km^2) of land across the three regions (Table 1). The matching process for grassland and shrub/scrublands points included sample points from all 118 properties, with a dataset of 78 grazed properties (12,184 grazed sample points) and 40 ungrazed properties (5020 ungrazed sample points). The standardized mean differences between the covariate values for the grazed and ungrazed points in the first matched dataset all had absolute values of less than 0.25 (and the majority had values of less than 0.10), which indicates that our matching procedure effectively reduced biases in the data (Table S1) (Schleicher et al., 2020). The matching process for grassland, shrub/scrublands, and forested points yielded a dataset with the same properties as the grassland and shrub/scrubland-only dataset, with 13,252 grazed sample points and 3992 ungrazed sample points. All variables in the this second matched dataset had standardized mean differences of less than 0.25 except for mean summer minimum temperatures (Table S2). On grazed properties, the level of grazing ranged from 0.012-0.424 AUY per grazed acre (equivalent to a range of 2.4-83.3 acres per animal unit per year).

Models

We estimated the effect of grazing on fire probability using logistic mixed effects models with cluster-robust standard errors. The mixed effects models allowed us to capture the effects of unobserved factors that may influence fire probability, such as land use legacies or fine-scale environmental factors that affect grazing levels or the production of forage (and thus fuel). We used cluster-robust standard errors to control for pseudoreplication and unobserved variables on individual ranch properties, since our dataset included multiple sample sites per property (Abadie et al., 2017; Cameron and Miller, 2015). We controlled for potential spatial autocorrelation by including the latitude and longitude coordinates of each sample point in the suite of covariates (Schleicher et al., 2017a).

We fit a logistic regression model to our first matched dataset (grassland and shrub/scrublands points), dropping the explanatory climate, geographic, and social variables from the matching process that were highly correlated (absolute value of Pearson's correlation coefficient ≥ 0.66, p-value < 0.05):

$$BN_{it} = B_0 + B_1*Grazed + B_2*YearFactor + B_3*AUYperGrazedAcre + B_4Region + B_5*Landcover + B_6*BPYone + B_7*BPYfive + B_{8\text{-}26}*Controls + B_{27\text{-}31}*Interactions + u_i + e_{it}$$

where *BN* represented whether or not point *i* burned in year *t*; *Grazed* was a binary variable indicating whether the point was in a grazed or ungrazed property; *Year* was a fixed effect for each year in the dataset; *AUYperGrazedAcre* was a continuous variable representing the animal units per year per grazed acre for each property; *Region* was a fixed effect for the region (Central Coast, Central Valley & Foothills, or North Bay); *Landcover* was a fixed effect for the dominant vegetation type present (grassland or shrub/scrub); *BPYone* and *BPYfive* were lag variables for whether the point had burned in the previous one or five years, respectively; and *Controls* was the list of covariates that may influence fire probability at each sample point: population density in 2000 (people/km^2), distance to roads (m), elevation (m), slope (˚), aspect, average fall PDSI, total precipitation in winter, spring, summer, fall, and the previous year (cm), average summer soil moisture (mm), average minimum and maximum fall temperatures (˚C), average maximum wind speeds in summer and fall (m/s), annual NPP (kg*C/m^2), latitude, and longitude. For *Interactions*, we included all possible interactions between *AUYperGrazedAcre*, *Region*, and *Landcover* to test for different responses to grazing levels across the different regions of California and dominant vegetation types. We also included the interaction of latitude and longitude as a control for spatial autocorrelation (Schleicher et al., 2017a). u_i is the site-specific random effect and e_{it} is the error term for each point in each year. The binary variable *Grazed* allowed us to capture unobserved differences between grazed and ungrazed properties for which the matching process did not control. To interpret the coefficients of the interacting variables, we calculated the predicted probability of burning across the range of grazing intensity (AUY per grazed acre) in the different combinations of regions and dominant land cover types. We performed our logistic regression models and estimated the predicted probabilities in Stata (StataCorp, 2019).

To assess whether grazing in grasslands and shrub/scrublands has an impact on fire probability in forests, we used our second matched dataset (which included sample points from all three vegetation types) to perform a logistic regression model using the same equation. For this model, the AUY per grazed acre was still a function of the animal units per year and the number of grassland and shrub/scrub acres on the property, as we assumed that no grazing was actually occurring in the forested points.

While our matching methods should provide comparable treatment and control datasets, as an additional robustness check, we ran the model using only the grazing properties and exploiting the variation in AUY per grazed acre to estimate the impact of grazing on fire in grasslands and shrub/scrublands. We again excluded highly correlated explanatory covariates and used cluster-robust standard errors:

$BN_{it} = B_0 + B_1*Year + B_3*AUYperGrazedAcre + B_4Region + B_5*Landcover + B_6*BPYone + B_7*BPYfive + B_{8\text{-}27}*Controls + B_{28\text{-}32}*Interactions + u_i + e_{it}$

where *Year* was again a fixed effect for each year in the dataset (with 2002 dropped because it perfectly predicted the model outcome); *BPYone* and BPY*five* were the lag variables for fires in previous years; and *Controls* included the covariates population density in 2000 (people/km^2), distance to roads (m), elevation (m), slope (˚), aspect, average fall PDSI, total precipitation in winter, spring, summer, fall, and the previous year (cm), average summer soil moisture (mm), average minimum and maximum fall temperatures (˚C), average maximum wind speeds in winter, summer, and fall (m/s), annual NPP (kg*C/m^2), latitude, and longitude. As before, the *Interactions* were all possible combinations of *AUYperGrazedAcre*, *Region*, and *Landcover* and the interaction of latitude and longitude. All other variables were the same as in the first model, and we again calculated the predicted probability of fires across the range of grazing intensity levels.

Results

In the Central Coast region, the predicted probability of burning in any given year decreased significantly as grazing levels increased in the grassland and shrub/scrublands matched dataset, even though the range of grazing levels in the region was low overall (Figure 2). In shrub/scrublands, this effect held across the observed levels of grazing, with a 31.0% decrease in fire probability as grazing increases to one AUY per 11 acres. At this level of grazing, the predicted probability of wildfires in shrub/scrublands was 0.020. In grasslands, the probability of fire decreased 43.8% as grazing levels increased to one AUY per 20 acres, without a significant continued decrease at higher levels of grazing intensity. At one AUY per 20 acres, the predicted probability of fires in grasslands was 0.025. In the absence of grazing, Central Coast grasslands had the highest overall fire probabilities (an annual burn probability of 0.045) of grasslands across the three regions.

Similarly, in the North Bay, fire probability declined as grazing intensity increased: in grasslands, we observed this trend when AUY per grazed acre ranged from 0-0.1, while in shrub/scrublands, this pattern held at AUY per grazed acre levels from 0-0.25 (Figure 2). Grassland fire probability decreased by over 50% (from 0.035 to 0.013) as grazing levels increased from no grazing to one AUY per 10 acres. In North Bay shrub/scrublands, fire probability decreased by 76.5% as grazing levels increased to one AUY per 4 acres, from an annual burn probability of 0.045 to 0.010. In the absence of grazing, North Bay shrub/scrublands had the highest likelihood of burning (0.045) out of shrub/scrublands in the three regions, but at one AUY per 4 acres, North Bay shrub/scrublands had lower fire probabilities than shrub/scrublands in the Central Coast at their maximum grazing intensity. At maximum levels of grazing, North Bay grasslands had slightly higher probabilities of burning than Central Coast grasslands at their highest observed level of grazing (0.015 vs. 0.017), even though grazing reached greater intensity levels in the North Bay than the Central Coast.

In contrast to the North Bay and Central Coast regions, grasslands and shrub/scrublands in the Central Valley and Foothills region showed an increase in fire probability when AUY per grazed acre increased from 0 to 0.3 and 0.2, respectively (Figure 2). From grazing levels of 0.2-0.3 AUY per grazed acre, grasslands showed an increase in fire probability from 0.015 to 0.029, but there was a lot of uncertainty around the predictions, as evidenced by the large confidence intervals. At higher levels of grazing, there was no significant trend for either land cover type. In the absence of grazing, the predicted probability of wildfires in these two landcover types was lower than in the other regions analyzed (0.003 for ungrazed grasslands and 0.005 for ungrazed shrub/scrublands). When grazing levels on grasslands increased to one AUY per 3.33 acres, the predicted probability of wildfires increased more than sevenfold. Shrub/scrubland fire probability more than doubled as grazing levels increased to one AUY per 5 acres, reaching a similar value as Central Coast shrub/scrublands under their maximum grazing levels.

In the grassland and shrub/scrubland matched dataset, points on steeper slopes, with more winter, summer, and fall precipitation, less spring precipitation and less total rainfall in the previous year, higher summer wind speeds, and lower annual NPP were more likely to burn in a given year (Table 2). Sample points that had burned in the previous year were much less likely to burn in a given year. Several years in the time series had significant effects on the probability of fires as well (2003, 2006, 2007, 2009, and 2016; Table S3). Across all three models, the coefficient estimates for latitude, longitude and the interaction between latitude and longitude had absolute values of less than 0.001, indicating that spatial autocorrelation had minimal impact on our estimates of wildfire probability (Schleicher et al., 2017b).

When we calculated the predicted probability of wildfire in the matched dataset that included grasslands, shrub/scrublands, and forests, we found that, similar to the grasslands and shrub/scrublands, forests in the Central Coast and North Bay regions showed decreases in the probability of burning as grazing levels increased (Figure 3). In the Central Coast, wildfire probability in forests declined by 48.4% as AUY per grazed acre increased from 0-0.05 (a decrease in the predicted probability of burning from 0.075 without grazing to 0.039 with 20 acres per AUY). In the North Bay, wildfire probability in forests decreased by 70.7% as grazing intensity increased from no livestock to 0.4 AUY per grazed acre (from a predicted probability of 0.042 to 0.012). Forests in the Central Valley and Foothills region, on the other hand, had a 18.7% increase in wildfire probability when AUY per grazed acre increased from 0.05-0.1, but there was no significant difference in wildfire probability at higher levels of grazing. Without grazing, Central Coast forests had the highest probability of burning in a given year. In the matched dataset that included grasslands, shrub/scrublands, and forests, points that were further from roads, on steeper slopes, and with more winter and fall precipitation were more likely to burn (Table 2). Sample points with higher annual NPP and that burned in the previous year were less likely to burn. Several years had positive effects on the probability of burning relative to the reference year of 2001: 2003, 2006, 2007, 2009, and 2016 (Table S3).

When we only included the grazed sample sites in our model, the patterns of predicted probability were broadly similar, with one exception (Figure 4). Again, the probability of burning decreased with increased grazing intensity for Central Coast shrub/scrublands and North Bay grasslands and shrub/scrublands while increasing for both vegetation types in the Central Valley and Foothills. In Central Coast grasslands, the predicted fire probability increased, from 0.018 at a negligible level of grazing (1000 acres per AUY) to 0.075 at the maximum grazing level observed in the region (11 acres per AUY), a result that runs contrary to the pattern observed in the matched dataset. Across the three regions and vegetation types, the marginal effect on fire probability of adding an additional acre per AUY was not significant (marginal effect = $-2.89*10^{-5}$, standard error = $8.49*10^{-5}$, $p > 0.05$).

When we considered only the grazed sample points, we found that the patterns in the relationship between burn probability and slope, fall, summer, and winter precipitation, annual NPP, and whether or not a point had burned in the previous year remained the same as in the matched dataset. Additional variables also had significant relationships with fire probability: sites with increased maximum fall temperatures and maximum winter wind speeds had an increased probability of burning, while increased maximum wind speeds in fall were associated with a decreased likelihood of burning. More years in the time series had significant positive effects on the probability of grazed points burning relative to the baseline of 2001 as well (2003-2007 and 2009-2016; Table S3).

Discussion

In fire-prone California landscapes, the impact of livestock grazing on fire probability varies across regions and dominant vegetation types. We find that an increase in grazing levels is related to reduced wildfire probability in the forests, grasslands, and shrub/scrublands in the North Bay and Central Coast regions (with Central Coast shrub/scrublands showing the smallest relative decline of the land cover types in these two regions). The sharp decreases in fire probability in these Central Coast ecosystems occur even with a small change in AUY per grazed acre (from no grazing to 1 AUY per 20 acres). In contrast, the three land cover types in the Central Valley and Foothills region showed increased fire probability over some of the range of grazing intensity values observed, but as grazing intensity increased, the trends were not significant.

The similar responses to increased grazing intensity in forests and grasslands in the North Bay and the Central Coast suggest that the relationship between grazing levels and fire probability may be generalizable across some ecological communities in California; in these communities, grazing is an effective form of fuel management that reduces the fuel availability and/or connectivity. Notably, this effect carries over into forested areas (where we assume that minimal grazing is occurring). In woodland areas of the Central Coast, nonnative grasses and forbs create flammable understories that can carry fires (Keeley and Syphard, 2018), while in the North Bay, decades of fire suppression have led to increased density of understory vegetation (Stephens et al., 2018). In both of these ecosystems, livestock grazing may reduce fire probability by removing fuel connectivity with adjacent grasslands and shrub/scrublands or by directly reducing understory biomass accumulation. Policies that reduce barriers to grazing on private and public lands adjacent to forests in both these regions may reduce the probability of high-severity wildfires (Sulak and Huntsinger, 2007; Wolf et al., 2017).

The different strengths of the shrubland response to grazing across the North Bay and Central Coast regions may reflect different climatic conditions. In the Central Coast, seasonal foëhn winds (known locally as Santa Ana winds or sundowners) spread fires over large areas in the fall. These strong winds may outweigh any effect of fuel quantity and connectivity in determining fires' extents (Keeley and Fotheringham, 2001). While our model accounts for seasonal wind speeds through the inclusion of mean maximum fall wind speeds, there may be effects at finer spatial scales than our data could capture. The Central Coast points we sampled were also drier on average than the North Bay sample points, which may correspond to greater fuel aridity and a dampened response to grazing.

The response to increased grazing intensity in grasslands was similar across the Central Coast and North Bay regions (a 44% decline in wildfire probability in the Central Coast and a 50% reduction in the North Bay). Non-native annual species dominate grasslands in both regions (Keeley and Syphard, 2018; Stephens et al., 2018), which may account for the similar observed responses to grazing. When we examined only the grazed sample points, our model indicated an increase in wildfire probability in Central Coast grasslands as grazing levels increased. This finding runs contrary to our results when we included both grazed and ungrazed points (the latter results support the claim that grazing reduces wildfire probability in California's rangelands). Because Central Coast grasslands show a decrease in wildfire probability with increasing grazing when the model included a binary grazed/not grazed dummy variable, we hypothesize that there are differences between lightly- and heavily-grazed grasslands in this region for which our model of grazed points does not control. The factors that underpin ranchers' decisions about stocking levels may also affect wildfire probability in these systems, complicating our results.

It is more difficult to draw conclusions about the link between grazing and fire in the Central Valley and Foothills. As previously noted, at lower stocking rates, the fire probability increases as grazing intensity increases. When stocking rates are moderate or high however, this effect is not significant and there is greater variation in wildfire responses. In this region, our dataset contained few sample points from shrub/scrublands or forests. In addition, this region had an overall lower fire frequency and proportion of area burned than the other two regions (Table 1), complicating comparisons. Large portions of this region have been converted to intensive human land uses, including agriculture and urban and residential developments, particularly in San Joaquin and Merced counties. Because many of the properties we surveyed are in close proximity to intensive agriculture and urban developments, these landscapes are likely to experience highly altered fire regimes, which may result in a changed relationship between grazing intensity and fire probability. In this highly-altered landscape, the geographic location of rangelands and their proximity to either wildlands or intensive agriculture—factors that our model did not control for—may be more important predictors of wildfire probability than grazing levels.

The relative abundance of native and non-native grasslands species in coastal regions of California as compared to inland regions may also play a role in the different effect of grazing on wildfire in the Central Valley and Foothills. While almost all of California's grasslands are dominated by non-native species (Seabloom et al., 2003), the abundance of non-natives annuals is higher in inland regions than on the coast (Hatch et al., 1999; Rayburn et al., 2016). It is possible then that in the coastal regions we studied, where grazing reduced fire probability, livestock grazing reduces the abundance of flammable shrubs and enhances native perennial species that are less flammable than the non-native annual plants without the same effect occurring in the more heavily-invaded Central Valley and Foothills region (Keeley, 2001).

While our data on grazing levels, collected through telephone surveys that directly reached ranchers, provided us with an unusually detailed breakdown of grazing intensity on private lands, our models still made several key assumptions about the grazing data. First, the theoretical link between grazing levels and fire probability is based on variation in fuel levels. We did not have data on the quantities of residual dry matter at the end of the season for each property; we used AUY per grazed acre as a proxy, assuming that as the grazing intensity (AUY per grazed acre) increased, the unconsumed forage (residual dry matter) would decrease. Second, we were not able to account for the seasonality of the grazing relative to the phenology of the dominant plant species, which is relevant for the amount of residual dry matter (Davies et al., 2016; Diamond et al., 2009; Launchbaugh et al., 2008; Nader et al., 2007). Finally, we assumed a uniform level of grazing across all grassland and shrub/scrubland areas within each property. In reality, cattle preferentially graze close to water sources, along fences, and in recently burned areas (Allred et al., 2011; Augustine and Derner, 2014), and some of the shrubland on grazed properties may be too dense for cattle to use. However, we did not have data on grazing intensity at spatial scales finer than the property level. In general, the impact of grazing on wildfire probability is also related to the livestock species used and the previous grazing experiences of the specific animals present (Nader et al., 2007). Our landscape-scale study does not seek to account for this level of interaction, although the majority of the properties we surveyed graze cattle exclusively.

Notably, we only assessed the impact of grazing levels on the probability of fires in a given location, not the severity of the fires that burned. Fire severity measures the ecosystem-level impact of a fire, accounting for vegetation mortality and biomass lost (Steel et al., 2015), with implications for recovery trajectories and subsequent community composition, as well as soil erosion and hydrological processes. However, the use of the concept of fire severity differs over ecosystems because of variation in how different vegetation types respond to fire (Moritz, 1997). In forest ecosystems, fire severity is commonly measured using satellite-derived indices that compare pre- and post-fire aboveground biomass on an annual basis (Eidenshink et al., 2007; Roy et al., 2006). However, chaparral shrublands tend to burn in high-intensity crown fires that result in nearly 100% mortality of aboveground biomass, so measuring fire severity using changes in aboveground biomass may not yield useful predictors of ecological responses to fires, especially since different functional types of chaparral vegetation respond differently to intense fires (Keeley et al., 2008; Meng et al., 2014). Further research to assess the impact of grazing levels on fire severity would need to account for these ecosystem-level differences in the measurement and significance of fire severity.

Along with its potential benefits for reducing fire probability, livestock grazing can have less desirable ecological effects, particularly at the stocking levels required to meaningfully reduce residual dry matter. These impacts include reductions in water quality, soil compaction, impacts on riparian vegetation, weed transmission, and disease interactions with wildlife (Nader et al., 2007). Land owners and land managers must balance these tradeoffs, along with the varying effects of grazing on fire probability based on vegetation type and region, when deciding if and where to use grazing as a tool to reduce fire probability. Targeted grazing, which focuses on patches that have not burned in recent years, may be especially effective in reducing fuel availability across rangeland landscapes (Diamond et al., 2009), potentially shifting the anticipated tradeoffs in the ecological effects of livestock grazing while sustaining a residual feed supply for fall grazing.

A key challenge for ranchers seeking to maximize the fuels reduction potential of their grazing will be interannual variation in the environmental factors that control forage production, as the ideal stocking level to leave the minimal amount of fuel at the end of the season is likely to vary from year to year (Bartolome et al., 2006). Variation in precipitation and other climatic factors may lead ranchers to use conservative stocking levels that are insufficient for reducing fuel levels. This may hold especially true in the Central Valley and Foothills region, where variability in weather drives vegetation dynamics due to the nonequilibrium dynamics of the rangeland system (Spiegal et al., 2016). Decisions about stocking levels can be further complicated under stocker operation agreements that limit flexibility in both livestock number and the dates of the grazing season. This highlights the uncertainties of land management in complex social-ecological systems like California's rangelands, where local ecology, varying climatic factors, and socioeconomic forces interact to shape the patterns of both livestock grazing and wildfires. While wildfire policies in California have typically focused on fire suppression and home hardening, our results show that working landscapes can also reduce fire probability. As California confronts the legacies of a century of fire suppression and the increasing impacts of climate change on fuel conditions and fire weather, grazing should be considered as one component of a multi-pronged approach to reducing wildfire probability.

Our findings indicate that livestock grazing can be an effective land management strategy to reduce wildfire probability in some regions and vegetation communities in California's rangelands. With grazing data from more than 100 ranchers, we demonstrate that the negative effect of grazing on wildfire probability, previously demonstrated only through small-scale experimental and observational studies, holds true across broad spatial scales (hundreds of square kilometers) and moderate temporal scales (17 years) in California's fire-prone landscapes. This result has implications for land managers seeking to reduce fire probability on both private and public lands, providing insights into which locations are most likely to benefit from fuel reduction via grazing and the stocking levels required to achieve these benefits.

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Tables

Table 1. Summary of the sizes, fire histories, land cover types, and select covariates of the properties in the grassland and shrub/scrublands matched dataset across the three regions.

	Central Coast		Central Valley & Foothills		North Bay	
	Ungrazed	Grazed	Ungrazed	Grazed	Ungrazed	Grazed
Number of properties	22	26	9	39	9	13
Mean property size (acres)	1634	3166	6267	2456	1132	1619
Mean area burned per year, 2001-2017 (acres)	879	2294	138	657	238	519
Forest area (acres)	4411	6016	2369	4698	4666	5624
Grassland area (acres)	2153	17555	20557	75647	947	4724
Shrub/scrubland area (acres)	24256	51727	2553	7930	4413	10212
Mean population density in 2000 (people/km^2)	7.1	1.1	1.0	0.7	2.8	2.4
Mean annual precipitation, 2001-2017 (cm)	38.5	40.1	39.9	45.2	95.0	81.8
Mean NPP, 2001-2017 (kg*C/m^2)	0.66	0.64	0.45	0.44	0.99	0.79

Table 2*.* Coefficient estimates for the logistic regression models of burn probability in the matched dataset of grasslands and shrub/scrublands (with grazed and ungrazed sample points), the grazed-only dataset (all grassland shrub/scrubland points with grazing), and the matched dataset of grasslands, shrub/scrublands, and forests. Cluster-robust standard errors are in parentheses below each coefficient estimate. The Central Coast serves as the reference region. For the datasets with grasslands and shrub/scrublands, grasslands are the reference land cover type. For datasets with grasslands, shrub/scrublands, and forests, forests are the reference. See Table S3 for complete table of coefficients, including the interactions between AUY per grazed acre, region, and landcover type and the effects of each year's fixed effect, latitude, longitude, and the covariates that were not significant in any of the models (population density, aspect, mean fall PDSI, mean summer soil moisture, mean minimum fall temperature, and whether or not the point had burned in the previous five years).
* $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Variable	**Coefficient estimates**		
	Matched dataset, grassland and shrub/scrubland	Grazed-only dataset, grassland and shrub/scrubland	Matched dataset, grassland, shrub/scrubland, and forest
Intercept	149.826 (70.041)	277.625** (92.748)	142.643* (69.307)
Grazed	0.978* (0.378)		0.802* (0.381)
AUY per grazed acre	-14.470 (10.431)	22.749 (12.846)	-18.406 (11.361)
Central Valley & Foothills Region	7.907* (3.653)	12.223** (3.418)	8.198* (3.507)
North Bay Region	11.186* (5.177)	9.968* (3.993)	11.936* (4.868)
Grassland			-0.958* (0.407)
Shrub/scrub	-0.577* (0.245)	0.926* (0.363)	-1.434*** (0.315)

Distance to roads (m)	$1.506 * 10^{-4}$ (0.000)	$-1.430*10^{-4}$ (0.000)	$2.770*10^{-4*}$ (0.000)
Elevation (m)	$1.529 * 10^{-4}$ (0.001)	0.001^{*} (0.001)	$-1.218*10^{-4}$ (0.001)
Slope (°)	0.033^{***} (0.007)	0.033^{**} (0.011)	0.035^{***} (0.008)
Total precipitation, fall (cm)	0.263^{***} (0.059)	0.303^{**} (0.114)	0.210^{***} (0.059)
Total precipitation, spring (cm)	-0.133^{*} (0.052)	-0.244 (0.136)	-0.095 (0.057)
Total precipitation, summer (cm)	0.824^{*} (0.415)	1.791^{***} (0.514)	0.615 (0.435)
Total precipitation, winter (cm)	0.181^{**} (0.058)	0.118^{*} (0.055)	0.117^{**} (0.041)
Maximum temp, fall (°C)	0.052 (0.225)	1.268^{**} (0.421)	-0.129 (0.204)
Max wind speed, summer (m/s)	0.568^{*} (1.248)	-0.244 (2.608)	0.959 (1.168)
Max wind speed, fall (m/s)	0.251 (1.127)	-5.609^{*} (2.489)	-0.958 (1.030)
Max wind speed, winter (m/s)		9.384^{***} (2.381)	
Previous year precipitation (cm)	-0.097^{*} (0.047)	-0.065 (0.034)	-0.049 (0.037)
NPP ($kg*C/m^2$)	-3.776^{***} (0.663)	-4.714^{***} (0.922)	-4.239^{***} (0.647)

Burned in previous year	-4.225*** (1.184)	-5.214*** (1.200)	-4.772*** (0.945)

Figures

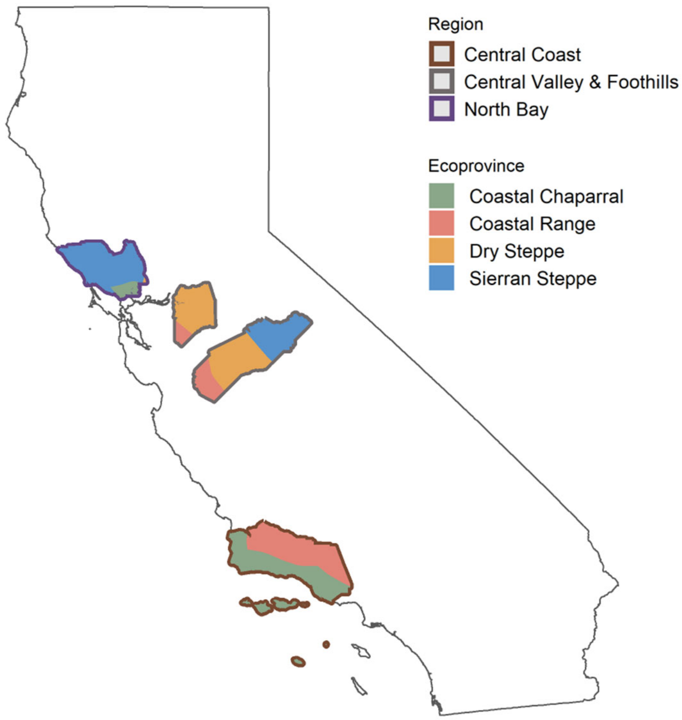

Figure 1. Map of the three social-ecological regions of California studied, with their component ecoprovinces denoted by color. The regions were defined by Bailey ecoprovinces and county boundaries.

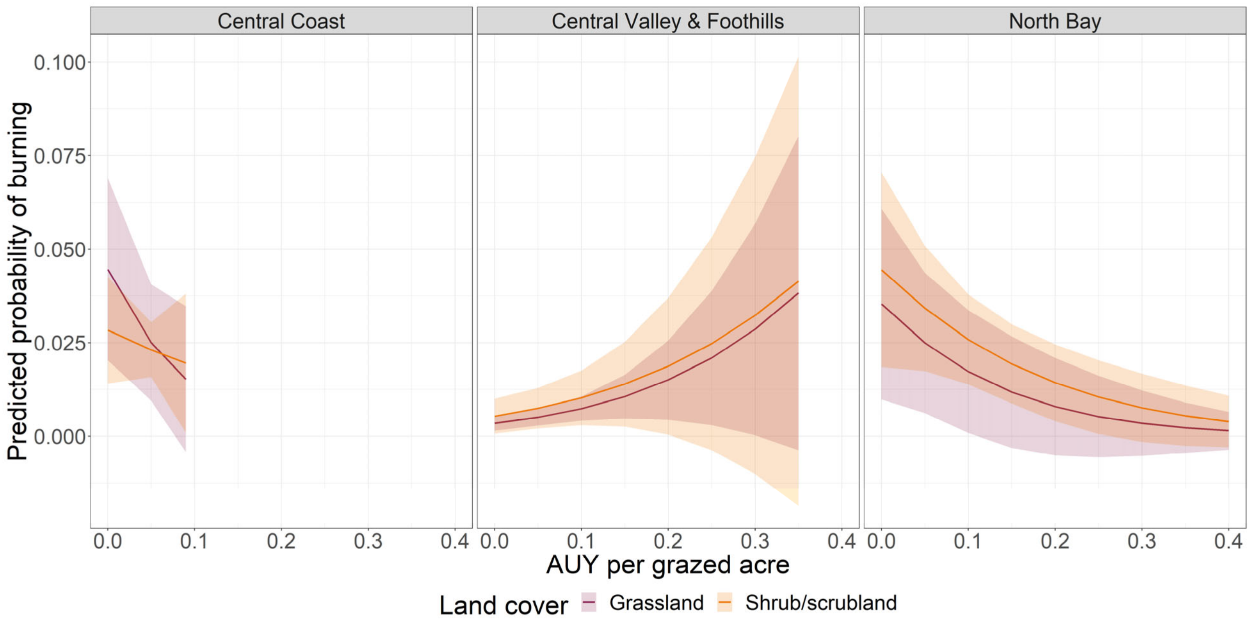

Figure 2. The predicted probabilities of burning in the three regions (Central Coast, Central Valley and Foothills, and North Bay), across the two dominant vegetation types using for grazing (grassland and shrub/scrubland) as AUY per grazed acre increases from 0 (ungrazed) in the matched dataset. The graphs extend across the range of AUY per grazed acre values observed in each region. The shaded regions represent the 95% confidence intervals.

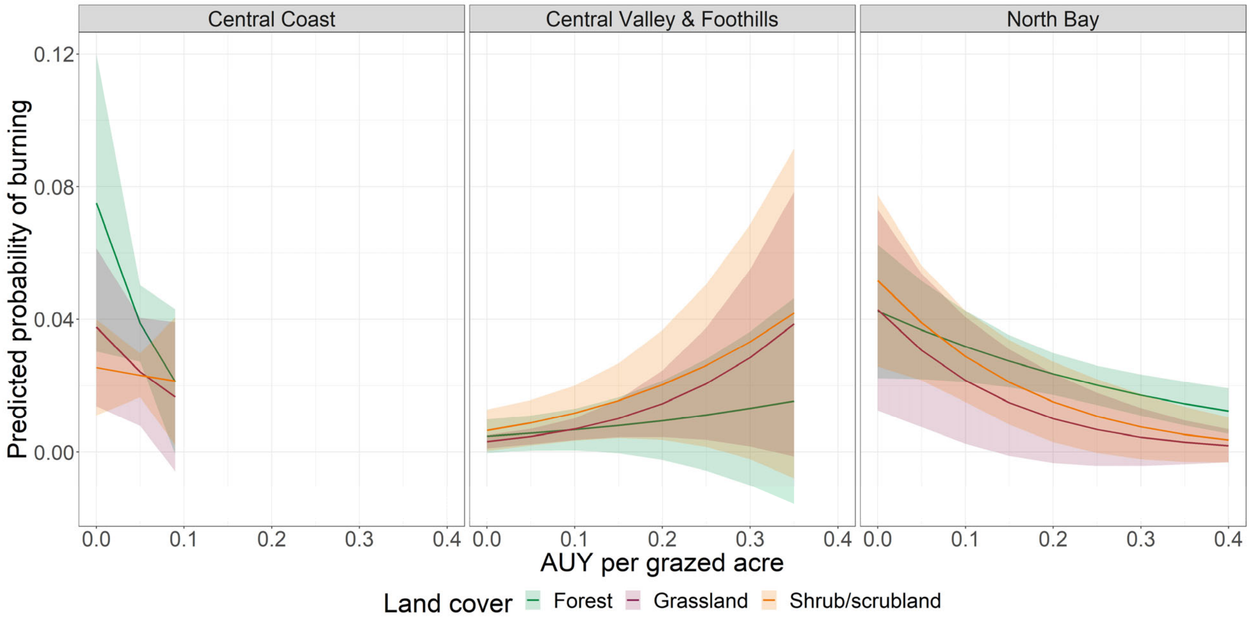

Figure 3. The predicted probabilities of burning in the three regions (Central Coast, Central Valley and Foothills, and North Bay), with matched data from across the three dominant vegetation types (forest, grassland, and shrub/scrubland) as AUY per grazed acre increases from 0. The graphs extend across the range of AUY per grazed acre values observed in each region. The shaded regions represent the 95% confidence intervals.

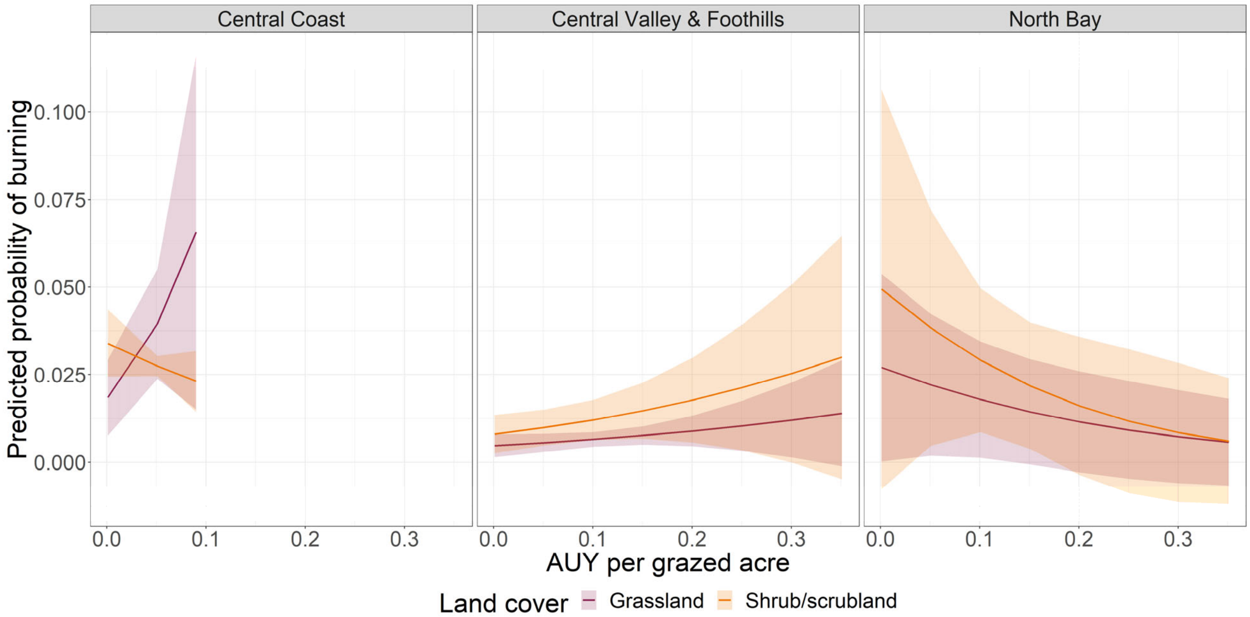

Figure 4. The predicted probabilities of burning in the three regions (Central Coast, Central Valley and Foothills, and North Bay), across the two dominant vegetation types used for grazing (grassland and shrub/scrubland) as AUY per grazed acre increases across all grazed points. Unlike the matched datasets, this dataset includes all sample points from grazed properties that were located in grasslands or shrub/scrublands. The graphs range from 0.001 AUY per grazed acre to the maximum grazing intensity value observed for each region. The shaded regions represent the 95% confidence intervals.

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Transition between Chapters 2 and 3

Chapter 2 used pre-regression matching and logistic regression to determine the influence of livestock grazing on wildfire probability in California's rangelands, focusing on grasslands, shrub/scrublands, and forests in the North Bay, Central Valley and Foothills, and Central Coast regions. My results showed that as grazing intensity increases, wildfire probability declines in all three vegetation types in the North Bay and Central Coast. The results for the Central Valley and Foothills are less straightforward, with an increase in wildfire probability as grazing levels increase from no grazing to low levels of grazing, followed by non-significant effects of grazing on wildfire at higher levels of grazing intensity. The different response in the Central Valley and Foothills as opposed to the North Bay and Central Coast may be due to the presence of highly modified, human-dominated landscapes in the Central Valley and Foothills region; neighboring land cover types may be more important than grazing levels in determining wildfire probability in this region than in the two other regions. In both Chapter 1 and Chapter 2, my models may not have accounted for important variables that are difficult to quantify spatially, a challenge in quantitative modeling that I address in my third chapter. In Chapter 3, I use logistic regression models to explore forest loss dynamics in Jamanxim National Forest, a protected area in the Brazilian Amazon. This chapter presents a framework for integrating qualitative and quantitative methods in land use change modeling, assessing how integration of qualitative discourse analysis into land use change modeling impacts our understanding of the drivers of deforestation and predictions of future forest conversion to agriculture.

CHAPTER 3

Integration of qualitative and quantitative methods improves land use change modeling in a protected area in an Amazonian deforestation frontier

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Included as a dissertation chapter with permission from co-authors.

Abstract

Deforestation threatens biodiversity, ecosystem functioning, and human communities across the Amazon Basin, including within protected areas. Development and implementation of effective management interventions depend in part on identifying the factors contributing to forest loss and areas at risk of future conversion, but traditional land use change modeling approaches may not fully capture contextual factors that are not easily quantified. To better understand forest loss and agricultural expansion in Amazonian protected areas, we combine quantitative land use change modelling with qualitative discourse analysis, using Brazil's Jamanxim National Forest as a case study. We model land use change from 2008-2018 and project deforestation through 2028 using variables identified from a review of studies modeling land use change in the Amazon and a critical discourse analysis examining documents produced by different actors at various spatial scales. We find that including variables identified as important in the qualitative discourse analysis alongside more traditional variables improves the predictive ability of these models. Our novel approach of integrating qualitative and quantitative methods in land use change modelling can provide a framework for future interdisciplinary work in land use change.

Introduction

Globally, forest loss threatens biodiversity, traditional land tenure and livelihoods, and ecosystem services (Baragwanath and Bayi, 2020; Haddad et al., 2015; Harris et al., 2012). Tropical forests in particular face rapid and widespread conversion to anthropogenic land uses, with consequences for species diversity, hydrology, and carbon emissions (Fearnside, 2005; Hansen et al., 2008; Lambin et al., 2003; Malhi et al., 2008). In response to persistent land use change and deforestation, governments throughout the tropics have pledged to set aside large amounts of their remaining forests in protected areas, and a global movement toward protecting 30% of Earth's area by 2030 ("30 by 30") has emerged (Baillie and Zhang, 2018; Buchanan et al., 2020; Dinerstein et al., 2019). The area of land designated as protected has increased over recent decades; by 2020, protected areas covered 15% of the world's land area, more than 29% of forests located in the tropics, and 10% of remnant forest in the tropical and subtropical moist broadleaf forest biome (Hansen et al., 2020; Morales-Hidalgo et al., 2015; UNEP-WCMC and IUCN, 2020). While protected areas have generally reduced the rate of deforestation within their boundaries (Andam et al., 2010; Joppa et al., 2008; Joppa and Pfaff, 2011; Laurance et al., 2012), forest loss nevertheless continues, with variation related to management objectives, location, existing land cover type, levels of enforcement, and other factors (Arima et al., 2014; Geldmann et al., 2019; Leberger et al., 2020; Nolte et al., 2013).

In the Amazon Basin, the Amazon rain forest represents a globally significant biodiversity hotspot that plays a role in global carbon and regional hydrological cycles (Arima et al., 2014; Fearnside, 2012; Hansen et al., 2020; Myers et al., 2000). The Amazon Basin includes land in nine countries across 6 million km^2, including more than 350 areas designated for conservation or sustainable resource management (CAMP, 2018). Across the region, rapid land use change has converted large swaths of forest to anthropogenic land uses over the last fifty years: forest cover has declined by about 15% (a loss of 900,000 km^2) since the 1970s (Amigo, 2020; Fearnside, 2005). Despite the establishment of protected areas throughout the region, protected forests are not immune to the pressures of timber harvesting, small- and industrial-scale livestock and agricultural expansion, infrastructure development, increases in human settlements, and mineral and fossil fuel extraction (Asner and Tupayachi, 2017; Curtis et al., 2018; Finer et al., 2008; Leisher et al., 2013; Soares-Filho et al., 2006; Viteri-Salazar and Toledo, 2020). As an example, protected areas in the Brazilian Amazon lost 0.05-0.1% of their forest cover annually from 2002-2016 (Cabral et al., 2018), and Brazilian protected areas in close proximity to roads or navigable rivers lost 10.9% of their forest cover from 2000-2006 (Barber et al., 2014). While overall deforestation rates in the Brazilian Amazon decreased after 2004, they have increased again in recent years (INPE, 2020).

Forest loss in Amazonian protected areas is part of a complex dynamic of environmental, political, and socioeconomic change, with both region-wide generalities and specific details relevant to each local context (Geist and Lambin, 2002; Rosa et al., 2014b). Developing policies and management responses that enhance the conservation of protected forests requires identifying the factors related to forest loss in specific locations (Ravikumar et al., 2017). Land use change modeling can improve our understanding of forest loss dynamics (Verburg et al., 2004). These models identify significant drivers of forest loss in the past and present, predict areas at risk of future land use conversion, simulate the impacts of different policy interventions, and explore future scenarios (Heilmayr et al., 2020; Piquer-Rodríguez et al., 2018; Rosa et al., 2014b, 2013; Soares-Filho et al., 2006; Turner et al., 2007; Veldkamp and Lambin, 2001; Verburg et al., 2004). They can contribute to debates about the drivers of and solutions to protected area deforestation and are thus tools for land use planning, conservation prioritization, and other management and policy interventions.

Despite the power of land use change models to explain and predict deforestation (Etter et al., 2006; Soares-Filho et al., 2004, 2006), they do not fully capture the discourses around forest loss. These discourses reflect how actors understand forest loss and thus influence proposed policy interventions, shaping future land use change (Ravikumar et al., 2017). Integrating qualitative discourse analysis with land use change modeling poses a methodological challenge, requiring synthesis of qualitative and quantitative methodologies and data (Kinnebrew et al., 2020). Many existing land use change models use a set of quantitative explanatory variables that have been previously related to the probability of forest loss, including distances to roads and urban areas, cropland suitability, and topography (Barber et al., 2014; Rosa et al., 2014a). While these variables are undeniably important for understanding the dynamics of land use change, they do not fully reflect discourses around the drivers of deforestation, such as land speculation and tenure issues, enforcement capacity, governance, and migration (Killeen et al., 2008; Martins et al., 2017; Pauquet et al., 2005; Valqui et al., 2014).

Here, we use a mixed methods approach to integrate qualitative discourse analysis with quantitative land use change modeling to analyze the factors related to deforestation in Amazonian protected areas and to project future deforestation, using Jamanxim National Forest in Brazil as a model system. We use a set of explanatory environmental, geographic, social, and management variables used in previous land use change models for the region, in addition to variables identified through a qualitative discourse analysis that identifies the narratives created and circulated by national, state-level, and local actors to explain and address forest loss in the protected area. This methodological integration facilitates a broader and deeper understanding of the role of different factors in contributing to or reducing the probability of deforestation (Kinnebrew et al., 2020; Ravikumar et al., 2017). We use this integrated approach to better understand deforestation in Jamanxim. We demonstrate the value of our approach by quantifying how the inclusion of the discourse analysis variables changes a) which variables are important, b) model performance, and c) the quantity and spatial patterns of predicted future deforestation.

Methods

1. Study site

We selected Brazil's Jamanxim National Forest (hereafter "Jamanxim") as a case study site because it has experienced high levels of deforestation relative to other Amazonian protected areas (Cabral et al., 2018; Pinheiro et al., 2016). Located in the state of Pará and with an area of 13,015 km^2, Jamanxim was established in 2006 as part of an initiative to limit deforestation associated with the construction of the BR-163 highway through the Amazon. As a national forest, Jamanxim is managed for sustainable use objectives, including watershed protection and sustainable logging and silviculture, although no logging concessions have been designated (Rylands and Brandon, 2005). The protected area has experienced significant deforestation through logging and land-clearing for ranching and agriculture. In the absence of a clear, well-enforced land tenure system, large- and small-scale farmers clear the forest to secure land claims and establish farming and ranching operations (Arima, 2016; Campbell, 2015; Fearnside, 2001). Large-scale landowners use deforestation as a form of land speculation: by clearing and "improving" the land, they increase its value (Fearnside, 2005; Torres, 2012, 2005). The national forest has also faced legal threats throughout its existence: a 2008 bill proposed to degazette the park to resolve competing land claims in favor of farmers and ranchers (de Marques and Peres, 2014), while in 2012, the president of Brazil temporarily reduced its size to allow for the construction of a hydropower dam (Fearnside, 2016). We modeled land use change within the boundaries of the national forest and in a 20km buffer around the protected area to capture land use dynamics directly outside the area of management (Figure 1).

2. Remote sensing

We generated land cover maps for 2008 and 2018 using supervised classifications of cloud-free composites of Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI) 30m Surface Reflectance (SR) datasets. We used dry season (May 15-October 15) data and masked clouds with the CFMask algorithm (Foga et al., 2017). To better distinguish between land cover types with seasonal variation, we integrated elevation data (SRTM Digital Elevation Data at 30m), Enhanced Vegetation Index (EVI), and the difference in seasonal EVI between wet and dry seasons (Liu and Huete, 1995), using methods described in Kinnebrew et al. in prep.

We developed our training data set using manual classifications of land cover in Geosurvey, which integrates 1m-resolution imagery from Bing Aerial, Google Hybrid, and Matchbox (QED, 2019). To classify the land cover types, we drew polygons for agriculture and pastures, forest, bare soil, built-up areas, wetlands, and water in 1000 randomly selected 250m x 250m windows. Each window could contain multiple polygons with different land cover types. In Google Earth Engine, we performed a supervised classification with random forest algorithms using our spectral imagery, training polygons, and additional elevation and EVI seasonal difference data (Belgiu and Drăguţ, 2016; Breiman, 2001). We used a 10 k-fold cross validation to validate the classification accuracy using the *dismo* package in R (Hijmans et al., 2017). Due to inaccurate classifications for the non-forest land cover types, we classified up to 100 more 250m x 250m polygons in the agriculture, bare soil, built-up, water, and wetland land covers. Including these additional polygons improved the accuracy of our classification.

3. Qualitative discourse analysis

We analyzed the discourse around the drivers and mediators of deforestation in Jamanxim National Forest using qualitative discourse analysis methods, sampling documents in English and Portuguese that discussed deforestation in the protected area (refer to Shoffner et al., in prep, for full details of sampling and coding methods). We sampled documents focused at the national, state, and park scale and included four document types: management (e.g., park management plans), policy (e.g., laws and decrees related to the protected areas and forest management), gray literature (e.g., reports from government agencies and NGOs), and advocacy (e.g., articles and other documents written by NGOs to promote their campaigns and initiatives or support certain arguments). We used a snowball sampling method to compile policy and management documents related to Jamanxim from the Brazilian government's legislative database (Federal Government of Brazil, 2019), using the name of the protected area (Jamanxim National Forest or *Floresta Nacional* do *Jamanxim) or the state where it is located (Pará), plus the word "deforestation" (desmatamento) or a closely related term as the inclusion criteria.* We sampled gray literature and advocacy documents by identifying all non-governmental and civil society organizations working in the area and locating their online publications. *We sampled to the* *point of saturation, including documents based on relevance and repetition (Shoffner et al., in prep.)* Our final sample consisted of 61 documents (five management, 12 policy, 23 gray literature, and 21 advocacy; Table S1).

We coded these documents in NVivo 12 (QSR International Pty Ltd., 2019) using predetermined themes as well as emergent themes derived through the process of open coding (Table S2). We developed the list of predetermined themes based on a literature review of variables used in Amazonian land use change modeling (Barber et al., 2014; Costa Roriz et al., 2017; Lambin et al., 2003; Molin et al., 2017; Müller et al., 2012; Pacheco, 2009; Pérez-Vega et al., 2012; Rosa et al., 2014b, 2013; Schielein and Börner, 2018; Soares-Filho et al., 2013, 2006; Viteri-Salazar and Toledo, 2020), while emergent themes arose during the process of coding the documents.

4. Land use change models

To better understand the role of the different types of variables in explaining trends in forest loss, we constructed four logistic regression models to explain and predict the conversion of forests to agriculture (Moulds et al., 2015; Rosa et al., 2014a). First, we built a model using variables derived from the land use change literature (LUC model). Our second model consisted of the variables identified through qualitative discourse analysis (DA Model; section 4.1). The third model included all the variables from the LUC model and DA Model (LUC & DA model), while the fourth model (Refined LUC & DA model) included the variables that were statistically significant in the LUC model and variables that were determined to be highly important through the qualitative discourse analysis. In constructing each model, we checked for correlations between the continuous variables and removed variables that were highly correlated (Pearson's correlation coefficient > 0.66, $p < 0.05$) prior to model runs. In all models, we sampled forested points in the case study areas along a 300 meter grid to control for spatial autocorrelation (Mets et al., 2017).

4.1 Variable selection

For the LUC model, we used a suite of variables that are frequently used in land use change models in the Amazon or that have been linked to deforestation risk in the region: distance to the nearest road, river, and city (proxies for accessibility and distance to markets); population density; elevation, slope, aspect, soil moisture, and precipitation (proxies for agricultural suitability); crop suitability; management status; poverty rate; distance to mining concessions; and the percentage of surrounding pixels that are a non-forest land cover type, to account for neighborhood effects (Barber et al., 2014; Costa Roriz et al., 2017; Lambin et al., 2003; Molin et al., 2017; Müller et al., 2012; Pacheco, 2009; Pérez-Vega et al., 2012; Rosa et al., 2014b, 2013; Schielein and Börner, 2018; Soares-Filho et al., 2013, 2006; Sonter et al., 2017; Viteri-Salazar and Toledo, 2020).

For the DA model, we used variables related to the dominant narratives around the drivers of and solutions to deforestation in Jamanxim National Forest, as identified through our qualitative discourse analysis. We identified themes and then determined quantitative spatial proxies for each theme for use in the land use change models. For example, an important theme was land grabbing (*grilagem*), which often occurs on publicly-owned land that has not yet been granted an official use type (e.g., logging concessions, protected area designation, etc.) (Campbell, 2015; Torres, 2012, 2005). Since there is no database of the locations where illegal clearing of public land has occurred, we used the percentage of non-allocated public land in the municipality as a spatial, quantitative proxy for the conditions that facilitate the process of land-grabbing. The availability of quantitative data that could be translated into a spatial layer limited our ability to include variables from the discourse analysis in our models. There were some factors identified as important through the discourse analysis, such as governance quality, that we could not represent spatially and quantitatively and thus had to omit from our models. This underscores a limitation of the quantitative, spatial modeling approach to understanding the causes of land use change. The number of themes identified was not pre-determined, but rather emerged through the coding process. After removing factors that we could not translate into spatial quantitative proxies, we had 10 variables: distances to existing agriculture, fires, proposed infrastructure developments (railroads and dams), and unauthorized mines; density of past fires; percent of non-allocated public land in the municipality; areas proposed for protected area downgrading, downsizing, and degazettement (PADDD); presence of agricultural reform settlements; and head of cattle per km^2 (Table 1). We then removed distance to proposed dams because it was highly correlated with distance to unauthorized mining sites.

The LUC & DA model included all variables from the LUC model and the DA model except for variables that were highly correlated: we dropped head of cattle per km^2 because it was highly correlated with population density (Pearson's correlation coefficient = -0.99, $p < 0.05$). The Refined LUC & DA model included nine variables from the LUC model (slope; elevation; distance to roads, cities, and mining concessions; crop suitability; soil moisture; protection status; and the percent of surrounding pixels of a different land cover type) and six variables from the DA model (distance to existing agriculture, fires, and proposed railroads, PADDD status, fire density, and agricultural reform settlements) (Table S3).

In all models, we included whether the forested point was located within the boundaries of the national forest, within a 10 km buffer around the national forest, or within a 20 km buffer. We included the buffer around the national forest because the presence of protected areas frequently impacts land use pressure in the surrounding area through processes like leakage (Ewers and Rodrigues, 2008) and we wanted to capture these dynamics as well as processes of agricultural encroachment from the buffer areas into the protected area itself. We used buffer sizes of 10 and 20 kilometers because these have been used in previous studies of land use change in and around protected areas (Bailey et al., 2016; De la Rosa-Velázquez et al., 2017; Tesfaw et al., 2018).

4.2 Data compilation

We compiled quantitative data on the relevant variables from local-, national-, regional- and global-scale sources (Table 2). Where possible, we matched the temporal scale of the data to the timeframe of our study (2008-2018). We converted all data sources to rasters with resolutions matching our land cover change maps (30m x 30m). We standardized the spatial data sets in QGIS and R, using the *raster*, *sf*, and *lwgeom* packages (Hijmans, 2019; Pebesma, 2019, 2018; QGIS Development Team, 2019).

4.3 Model performance

To compare how the models with different types of variables performed, we used ANOVA comparisons of model fit and McFadden's adjusted pseudo-R^2, which takes the number of explanatory variables into account (Hebbali, 2020).

4.3.1 Predicted 2018 deforestation

To assess the ability of the different models to accurately predict forest conversion to agriculture, we used each of the four logistic regression models to generate a raster layer with the predicted probability of conversion to agriculture for each forested pixel in 2008. We then used Monte Carlo simulations to generate 1000 projected landscapes for 2018 for each model, based on the predicted probability maps of forest conversion to agriculture. For all pixels with non-forest land cover types in 2008, we assumed no change in land cover type from 2008-2018. We calculated the mean area of forest loss across these simulations to assess the predicted deforestation rate for each model.

We also used these simulations to calculate the range of accuracy with which each model projected agricultural conversion. For each simulation in each model, we calculated the percent of correctly predicted agricultural conversions as the number of cells correctly predicted to have an agricultural conversion in 2018 divided by the total number of cells that converted from forest to agriculture from 2008-2018. We determined the number of cells that were correctly predicted to have converted from forest to agriculture by comparing each simulated landscape to the observed 2018 landscape. Similarly, we calculated the range of values for the percent of incorrectly predicted agricultural conversions for each model, where the percent of incorrectly predicted agricultural conversions is the number of cells that each simulation predicted as converting to agriculture that in reality remained forest, divided by the total number of cells that converted from forest to agriculture. Finally, we calculated the percentage of correctly predicted stable forest pixels, with stable forest pixels defined as those that were classified as forested in both 2008 and 2018.

4.4 Predicted future deforestation

To assess the predicted rates and spatial trends of deforestation of the different models, we used each model to generate a predicted probability of forest loss in 2028 by applying the models to the 2018 landscape. We used the same Monte Carlo simulation method as previously described to simulate 1000 landscapes for 2028 for each model, assuming static relationships between the explanatory variables and deforestation risk over time. For each model, we calculated the predicted rate of deforestation as the mean area converted across the simulations. We used the observed 2008-2018 deforestation rate to generate predicted land cover maps for 2028: with a set area of conversion, we spatially allocated forest loss to the pixels that converted in the highest number of simulations for each model until we reached the pre-determined area of forest loss. This yielded four predicted landscapes, one for each of the models.

4.5 Landscape connectivity
To quantify the different spatial distributions of the models' predicted deforestation, we calculated metrics of landscape connectivity and fragmentation for all observed and projected landscapes using the R package *landscapemetrics* (Hesselbarth et al., 2019). Our landscape metrics analyses focused on the class level, combining all forested patches, and we used eight-cell neighbor methods (Rosa et al., 2017). We selected metrics of connectivity and fragmentation related to overall forest area (class area), the fragmentation of contiguous forest area (patch area, number of patches, landscape division index), the amount of core forest area (core area index, core area as percentage of landscape, total core area), and patch complexity and edge effects (fractal dimension index, perimeter-area fractal dimension, perimeter:area ratio, total edge).

Results

Observed land use and land cover change

Our remote sensing yielded high accuracy rates, with an average producer's accuracy value of 94% and a user's accuracy rate of 91% (Table S4). We observed a 4.6% decline in forest cover from 2008 to 2018 in Jamanxim National Forest, for a total of 1164.81 km^2 of forest lost (Figure 2). Forested pixels in Jamanxim had a 5.0% probability of converting to agriculture during this time period (Table S5). Other land cover conversions with a relatively high probability of occurrence were agriculture to forest (18.1%, corresponding to 293.26 km^2), agriculture to bare soil (10.7%, or 172.87 km^2), bare soil to agriculture (68.0%, or 196.43 km^2), bare soil to forest (13.9%, or 40.14 km^2), built-up to agriculture (29.5%, or 5.16 km^2), built-up to bare soil (16.3%, or 2.86 km^2), and water to forest (10.8%, or 10.33 km^2). Jamanxim experienced a decrease in the mean area of forest patches from 2008-2018 and a corresponding increase in the number of forested patches. The mean of the core area index, or the percentage of each patch that is core area, also increased, while measures of patch complexity (mean fractal dimension index, perimeter-area fractal dimension, and perimeter:area ratio) did not change meaningfully. The total area of core forest decreased and the length of the total edges increased over time (Table 3).

Relationships between explanatory variables and deforestation probability

In the LUC model, elevation, slope, soil moisture, population density, and distances to roads and mining concessions all had negative relationships with the probability of forest conversion to agriculture (Table S3). Distance to cities, crop suitability, and the percent of non-forest neighboring pixels, as well as location within the buffer zone rather than the national forest, were all associated with a higher probability of forest conversion. This means that in this model, forested points at higher elevations and on steeper slopes with higher soil moisture and located further from roads and mining concessions were less likely to convert to agriculture, while forested points located outside the protected area boundary, further from cities, with greater agricultural suitability and more adjacent non-forest areas were more likely to convert. Aspect and distance to rivers did not have a significant relationship with the probability of forest loss for agriculture in this model.

The DA model indicated that the distance to unauthorized mining sites, existing agriculture, fires, and proposed railroads all had a negative relationship with the probability of forest conversion to agriculture, as did location within an area proposed for PADDD and the presence of agricultural reform settlements, the proxy variable for land tenure (Table S3). Fire density had a positive relationship with forest conversion probability, while the proportion of non-allocated public land (the proxy for land grabbing) had no significant relationship to deforestation. This means that forested points located further from areas of extractive and agricultural activity and proposed infrastructure had a reduced conversion probability, as did points located within agricultural reform settlements or areas proposed for PADDD, while areas with a greater density of fires were more likely to convert to agriculture.

In the LUC & DA and Refined LUC & DA models, elevation, slope, soil moisture, and distance to roads, cities, existing agriculture, and fires all had negative relationships with the probability of forest conversion to agriculture (Table S3). In the LUC & DA model, crop suitability also had a significant, negative relationship with forest loss, while the same was true for the proportion of non-allocated public land in the Refined LUC & DA model. In both models, the proportion of non-forest neighboring pixels, fire density, and location in the buffer, areas proposed for PADDD, and agricultural reform settlements had positive relationships with deforestation probability. This means that forest points with a higher percentage of non-forested neighbors were more likely to convert to agriculture, as were sites located outside of the national forest's boundaries, sites that have been proposed for PADDD, and forests located within agricultural reform settlements. In the LUC & DA model, distance to rivers also had a significant, positive relationship with deforestation, but this variable was not included in the Refined LUC & DA model because it was not a significant explanatory variable in the LUC model. The distances to the nearest mining concession and proposed railroad were insignificant in both models, as were aspect, population density, and the proportion of non-allocated public land in the LUC & DA model and crop suitability in the Refined LUC & DA model.

Differences in model performance

All four models predicted higher deforestation rates from 2008-2018 than we observed. The LUC model predicted the lowest rate of deforestation (1206.5 ± 0.9 km^2), while the DA model predicted the highest level of forest loss (1286.9 ± 0.9 km^2). The LUC & DA and Refined LUC & DA models had the highest level of accuracy in predicting the locations of pixels that converted from forest to agriculture from 2008-2018, correctly predicting the locations of an average of 34.6% and 34.4% of converted pixels, respectively (Figure 3). The LUC model had the highest percentage of incorrectly predicted agricultural conversions (for an average of 78.1% of the pixels where the simulations predicted a conversion of forest to agriculture, no conversion actually occurred), followed by the DA model (69.9% on average). The LUC & DA and Refined LUC & DA models also had the highest accuracy in predicting locations with stable forest cover from 2008-2018. Within each model, there was relatively little variation in the accuracy rate for predicting agricultural conversions and stable forest cover.

Based on ANOVA analysis, the Refined LUC & DA model had the best model fit ($p < 0.001$). The LUC & DA model also outperformed the LUC model and the DA model ($p < 0.001$). The LUC & DA and Refined LUC & DA models explained the greatest amount of variation in the observed forest conversion to agriculture from 2008-2018 (McFadden's adjusted pseudo R^2 values of 43.7% and 43.6%, respectively), while the DA model explained more of the variation than the LUC model (39.5% vs. 24.4%).

Projected deforestation

The four models predicted similar quantities of forest conversion to agriculture in the study area from 2018-2028, ranging from 1206.51 km^2 ± 0.91 for the LUC model to 1286.89 km^2 ± 0.93 for the DA model. The LUC & DA model and Refined LUC & DA model predicted 1279.31 km^2 ± 0.82 and 1274.77 km^2 ± 0.84 of forest loss, respectively. This represents a slight increase in the area deforested over the 2008-2018 time period (1164.81 km^2). Within the boundaries of the national forest itself, the models predicted 394.80-450.21 km^2 of forest conversion to agriculture, compared to an observed loss of 319.53 km^2 from 2008-2018. As in the case of overall forest conversion in the study area, the LUC model predicted the lowest level of deforestation, followed by the LUC & DA model, then the Refined LUC & DA model, while the DA model predicted the highest levels of forest loss.

While the observed number of forest patches increased from 2008-2018, all four models showed a decrease in the number of forest patches in 2028 relative to 2008 and an increase in the mean patch area. However, only the DA model predicted an increase in mean patch area and decrease in patch number relative to 2018. The LUC, LUC & DA, and Refined LUC & DA models displayed an increase in the mean of the core area index and the mean of core areas of all patches from 2018-2028, while the DA model showed the opposite trend (Table 3).

The spatial distribution of predicted deforestation varied between the models, but the four models' predictions had some overlap: 352.7 km^2 in the case study area, of which 75.6km^2 were within the national forest's boundaries (Figure 4). The areas where all four models predicted agricultural conversion by 2028 were mostly adjacent to areas with stable agriculture from 2008-2018, often forming thin perimeters around existing agriculture. There were also large contiguous blocks of projected conversion around the BR-163 highway and rivers in the eastern part of the buffer area. Three of the four models predicted a large area of contiguous forest conversion in the southern part of the national forest.

Discussion

Our findings demonstrate the value of integrating qualitative and quantitative research methods for studying land use change. The two models that included variables from both traditional land use change modeling approaches and discourse analysis had the best performance and predictive ability. Beyond providing a template for future efforts to combine qualitative and quantitative methods to understand land use change, our results indicate that the narratives about forest loss in protected areas, which emerge across scales and actors, are important sources of information for understanding and predicting deforestation processes. When attempts to understand and predict forest loss omit information from these narratives, they may overlook significant factors related to forest loss and have reduced ability to predict locations at risk of deforestation.

In terms of the effects of individual variables on deforestation probability, many of our results strengthen previous findings. For example, previous analyses of deforestation in the Brazilian Amazon have found that forested areas that are closer to roads and previously deforested areas are more likely to experience forest loss, while protected areas have lower rates of deforestation (Barber et al., 2014; Rosa et al., 2014b, 2013). Similarly, our finding that areas at higher elevation and with steeper slopes are less likely to experience deforestation is in accordance with results from elsewhere in the Amazon Basin (Muller et al., 2011), and our results linking fire activity to agricultural conversion align with observations that fire is a tool for land clearing in the region (Escobar, 2019).

The relationship between the proportion of non-allocated public land and deforestation probability did not match our expectations. There was notable discourse around land grabbing and illegal occupation of public land in the documents we analyzed (Abdala, 2015; Araújo et al., 2017; PPCDAm and PPCerrado, 2016), and we expected there to be less of this opportunistic land grabbing in areas where the tenure status of a greater percentage of public land had been resolved. However, we observed the opposite trend: areas with greater proportions of non-allocated public land experienced lower probabilities of deforestation. This may be the result of varying dynamics in the different municipalities included in the study area, since our data on non-allocated public land was at the municipality-level. Our study area included parts of three municipalities: Novo Progresso, Itaituba, and Altamira. Altamira has at least a five times greater proportion of non-allocated public land than the other two municipalities, but it is possible that other land use trends or underlying agricultural suitability in Altamira or the other municipalities are at play and affecting the role of land tenure in our models.

The DA model predicted the highest levels of forest conversion to agriculture, while the LUC model predicted the lowest rate of deforestation. The mean projected deforestation rate for all models was greater than the observed rate of forest loss from 2008-2018, highlighting the limitations of land use change models. However, the LUC model came closest to correctly estimating the area of forest converted to agriculture in that time period; the inclusion of variables from the discourse analysis led to higher estimates of forest loss. This implies that an understanding of deforestation trends rooted solely in the discourses surrounding forest loss might lead to disproportionate or poorly targeted management responses. While discourse analysis improves land use change modeling, management responses guided by discourses alone may not be effective.

The spatial distribution of predicted forest loss

In three other regions of Brazil's Amazon, agricultural expansion increased forest fragmentation and led to higher densities of forest edges (Rosa et al., 2017). While we observed a similar increase in fragmentation and forest edge density from 2008-2018, our models predicted a decrease in edge density from 2018-2028. We also did not observe or predict notable changes in patch complexity over time, in contrast to expectations that forest fragmentation will be accompanied by an increase in patch complexity (Wang et al., 2017). All the models that included LUC variables predicted an increase in mean forest patch area and decrease in number of forest patches from 2018-2028, indicating that these models project that small forest patches in 2018 will convert to agriculture. Notably, the DA model predicts an increase in mean patch area relative to 2018 (although still a decrease from 2008) and a concurrent decrease in the number of forested patches, contrary to the other three models. This implies that the inclusion of the LUC model variables is driving the previously-described pattern.

The different variables used for each model drove differences in the spatial distribution of projected future deforestation. In particular, the models that included fire density (the DA model, LUC & DA model, and Refined LUC & DA model) all predicted large clusters of deforestation in the southeast portion of the national forest and in the southeastern part of the buffer area. These clusters correspond to areas with high densities of fires from 2007-2018. Additional variables that are co-located with the areas of predicted deforestation in those three models are the presence of agricultural reform settlements in the southeastern region of the buffer and PADDD proposals along the eastern border of the national forest.

Further integration of discourse analysis and land use change modeling

Incorporating the discourse analysis into our methodology improved our models, but ideally, we would have even greater integration of variables identified in the discourse analysis into the models. The discourse analysis identified important themes that we were unable to include in the land use change models due to a lack of available data for spatial, quantitative proxies. This included themes such as state capacity, commodity traceability, inclusion and participation in the management process, enforcement capacity, and government accountability. We were also unable to include factors that did not vary spatially, such as state-level policies, as the values for these factors would be constant across the modeled landscape (although their implementation might not actually be uniform). These two categories of factors appeared frequently in the discourses around the drivers of and solutions to deforestation in Jamanxim National Forest, Pará, and Brazil at large and likely play an important role in shaping deforestation dynamics. Our inability to translate these themes into quantitative, spatial proxies for inclusion in land use change modeling highlights a limitation of our methodology in particular and quantitative modeling studies in general; these approaches cannot accommodate important variables that are not easily measured and incorporated into a GIS framework. This highlights the need for qualitative analyses in addition to quantitative analyses when considering complex socio-environmental change (Bennett et al., 2017; Kinnebrew et al., 2020; Palmer, 2012).

Our methodology, though more time-intensive than typical approaches to land use change modeling, can be an important tool for situations in which a higher degree of accuracy and localized nuance are needed for understanding and predicting land use trends. This may be the case in contexts where protected area managers seek to identify specific interventions to address the fundamental drivers of forest loss. Combining quantitative modeling with discourse analysis also has the potential to test the explanatory power of narratives around deforestation. Since the stories that actors use to explain deforestation shape the proposed solutions, assessing how they relate quantitatively to observed land use trends can potentially help to disrupt or shift narratives to better reflect observed changes.

The integration of qualitative discourse analysis methods into land use change modeling adds precision and nuance to our understanding of forest conversion in Jamanxim National Forest, a protected area located in a deforestation frontier in the Amazon. By converting themes identified through discourse analysis into spatial, quantitative variables for inclusion in land use change modeling, we are better able to explain observed deforestation dynamics and may be better able to predict future hotspots of forest loss. Despite the challenges and limitations of integrating qualitative and quantitative methodologies and data types, our results demonstrate the benefits that this approach provides for interdisciplinary conservation science.

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Tables

Table 1. Themes arising from the qualitative discourse analysis and their corresponding quantitative spatial proxies.

Theme	Proxy
Agriculture	Distance to existing agricultural land (m)
Fires	Distance to fires (2007-2018) (m); Fire density (2007-2018) (per km^2)
Unauthorized mining	Distance to unauthorized mining sites (m)
Legal threats to protected areas	Presence of PADDD proposals
Land grabbing	Proportion of non-allocated public land
Ranching	Head of cattle per km^2
Infrastructure development	Distance to proposed railroads (m); Distance to proposed dams (m)
Land tenure; settlements	Presence of agricultural reform settlements

Table 2. Table of variables and spatial proxies used in the models. “x” indicates that the variable was included in the model, while * indicates that it was excluded from the model due to correlation with another variable.

Variable	Justification	Original data resolution or format (processing method, where applicable)	Source	LUC Model	DA Model	LUC & DA Model	Refined LUC & DA Model
Elevation (m)	Used in LUC models; measure of suitability for alternative land uses	1 arc-second	Farr et al., 2007	x		x	x
Slope (˚)				x		x	x
Aspect (˚)				x		x	
Distance to nearest road (m)	Used in LUC models; measure of accessibility	Vector (Euclidean distance)	“Open Street Map,” 2019	x		x	x
Distance to nearest river (m)	Used in LUC models; measure of accessibility	Vector (Euclidean distance)	DIVA-GIS, 2019	x		x	
Distance to nearest city (m)	Used in LUC models; measure of accessibility	Vector (Euclidean distance)	IBGE, 2010	x		x	x
Population density (per km^2)	Used in LUC models; measure of	Vector at municipality scale	IBGE, 2010	x		x	

	pressure for land conversion						
Precipitation (mm)	Used in LUC models; proxy for agricultural suitability	0.05 arc degrees	Funk et al., 2015	*		*	
Surface soil moisture (mm)	Used in LUC models; proxy for agricultural suitability	0.25 arc degrees, 2016-2018 average	O'Neill et al., 2016	x		x	x
Crop suitability (metric integrating climate, topography, and soil properties)	Used in LUC models; index of agricultural suitability	30 arc-second	Zabel et al., 2014	x		x	x
Poverty rate	Used in LUC models; wealthier land owners may deforest more (Pacheco, 2009)	Vector at municipality scale	IBGE, 2003	*		*	
Distance to mining concessions (m)	Used in LUC models; measure of accessibility and localized human land use	Vector (Euclidean distance)	ANM, 2019	x		x	x
Protection status	Used in LUC models;	Vector	"Protected Planet: The	x		x	x

	presence of protected areas affects land use trends		World Database on Protected Areas (WDPA)," 2019				
Proportion of neighboring cells with a different land cover type	Used in LUC models; accounts for neighborhood effects and expansion of alternative land cover types	30m	Derived from land cover maps	x		x	x
Distance to existing agricultural land (m)	Discourse analysis: proximity to agriculture increases probability of deforestation	30m	Kinnebrew et al. unpublished data		x	x	x
Distance to fires (2007-2018) (m)	Discourse analysis: fire as part of land conversion process	Vector (Euclidean distance)	INPE, 2019		x	x	x
Fire density (2007-2018) (per km^2)	Discourse analysis: fire as part of land conversion process	Vector	INPE, 2019		x	x	x
Distance to unauthorized mining sites (m)	Discourse analysis: unauthorized mining as	Vector (Euclidean distance)	RAISG, n.d.		x	x	

	contributor to forest conversion and part of the land conversion process						
Presence of PADDD proposals	Discourse analysis: areas with proposed or implemented PADDD are at risk of deforestation	Vector (Euclidean distance)	Conservation International and World Wildlife Fund, 2019		x	x	x
Proportion of non-allocated public land	Discourse analysis: lack of an officially designated owner or land use type incentivizes forest conversion	Vector at municipality scale	Imaflora and GeoLab, 2018		x	x	x
Head of cattle per km^2	Discourse analysis: ranching as cause of deforestation	Vector at municipality scale	IBGE, 2017		*	*	
Distance to proposed railroads (m)	Discourse analysis: infrastructure development causes deforestation	Vector (Euclidean distance)	Ministério da Infraestrutura, 2019		x	x	x

Distance to proposed dams (m)	Discourse analysis: infrastructure development causes deforestation	Vector (Euclidean distance)	ANEE, n.d.		*	*	
Presence of agricultural reform settlements	Discourse analysis: secure land tenure as factor that reduces deforestation	Vector	INCRA, n.d.		x	x	x

Table 3. Landscape metrics for observed landscapes in 2008 and 2018, and projected landscapes in 2028 under the four different models. Standard deviations are in parentheses beneath mean values.

	2008	2018	2028			
Metric	Observed	Observed	LUC model	DA model	LUC & DA model	Refined LUC & DA model
Mean patch area (ha)	187.54 (15310.33)	134.32 (12770.25)	286.67 (18402.11)	166.44 (14028.57)	377.12 (21129.24)	375.57 (21077.05)
Number of patches	6696	9111	4151	7151	3156	3169
Class area (ha)	1255766.43	1223813.04	1189969.76	1190247.12	1190188.47	1190180.10
Mean of core area index	1.17 (5.24)	1.77 (6.79)	4.26 (11.22)	1.65 (6.78)	5.04 (12.12)	4.95 (12.15)
Mean of core areas of all patches (ha)	183.76 (15031.31)	131.19 (12512.43)	278.46 (17918.71)	162.45 (13724.26)	368.98 (20710.56)	367.47 (20659.93)
Core area as percentage of landscape	94.53	91.83	88.91	89.36	89.57	89.57
Landscape division index	0.07	0.12	0.17	0.17	0.17	0.17
Mean fractal dimension index	1.03 (0.05)	1.04 (0.05)	1.04 (0.05)	1.03 (0.05)	1.04 (0.05)	1.04 (0.05)
Perimeter-area fractal dimension	1.49	1.45	1.38	1.46	1.35	1.35
Mean perimeter:area ratio	0.11 (0.03)	0.11 (0.03)	0.10 (0.03)	0.11 (0.03)	0.09 (0.03)	0.09 (0.03)
Percentage of landscape forested	96.47	94.02	91.53	91.55	91.55	91.55
Total core area (ha)	1230444	1195300	1155876	1161696	1164510	1164509
Total edge (m)	12419796	14149824	12746011	11148707	8751671	8735984

Figures

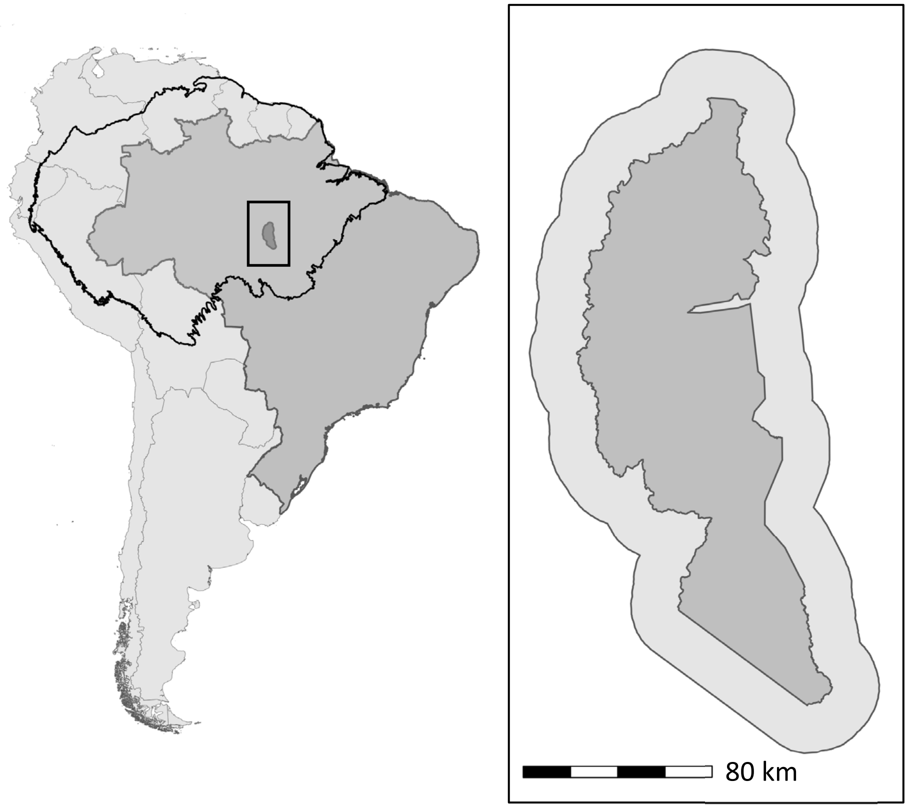

Figure 1. Map of the study site. The Amazon Basin is outlined in black and Brazil highlighted in gray. Jamanxim National Forest is in dark gray, with the 20-kilometer buffer around it in lighter gray.

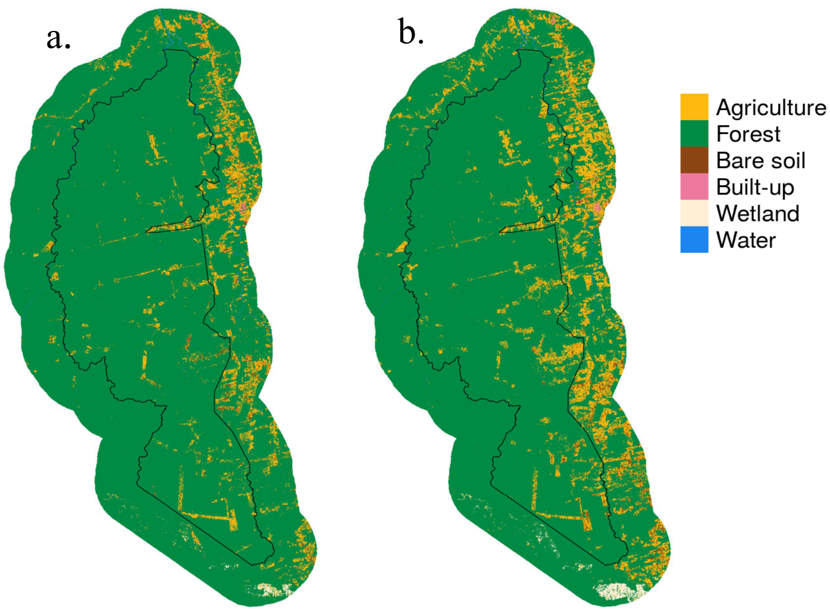

Figure 2. Map of land covers in a) 2008 and b) 2018 in Jamanxim National Forest and the 20-kilometer buffer area.

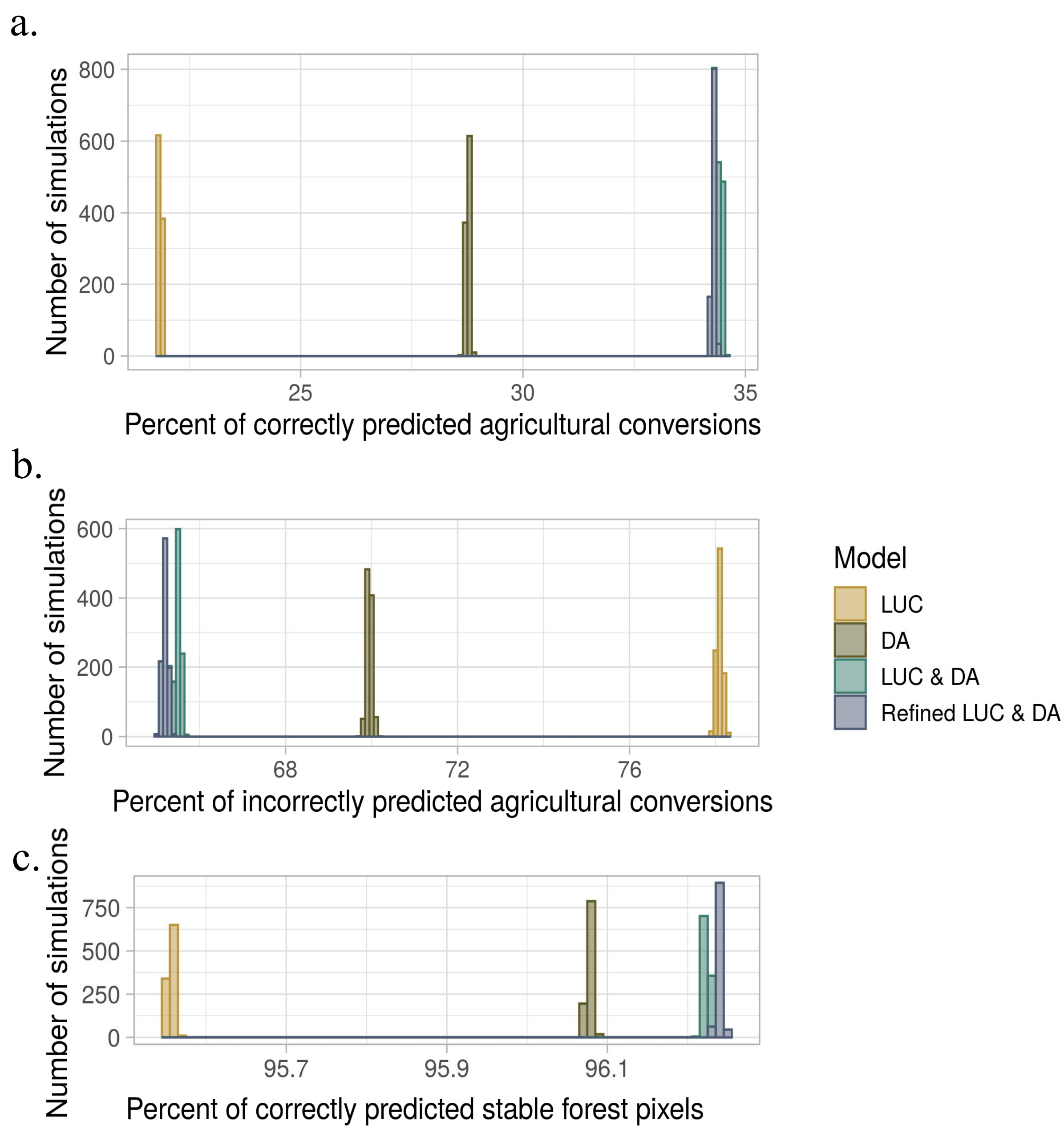

Figure 3. a) Histogram of the percentage of correctly predicted pixels with agricultural conversions from 1000 simulations for each model. We calculated this value as the number of pixels where the simulation correctly predicted a transition from forest to agriculture over the total number of pixels that experienced a forest to agriculture conversion in the observed 2008 and 2018 land cover maps. b) Histogram of the percentage of incorrectly predicted pixels with agricultural conversions from the 1000 simulations for each model. We defined incorrectly predicted pixels as those where the simulation predicted a transition from forest to agriculture that did not actually occur. We again divided this value by the total number of pixels that experienced a conversion from forest to agriculture. c)

Histogram of the percentage of correctly predicted stable forest pixels from the 1000 simulations for each model, where stable forest pixels are those that were classified as forest in both 2008 and 2018.

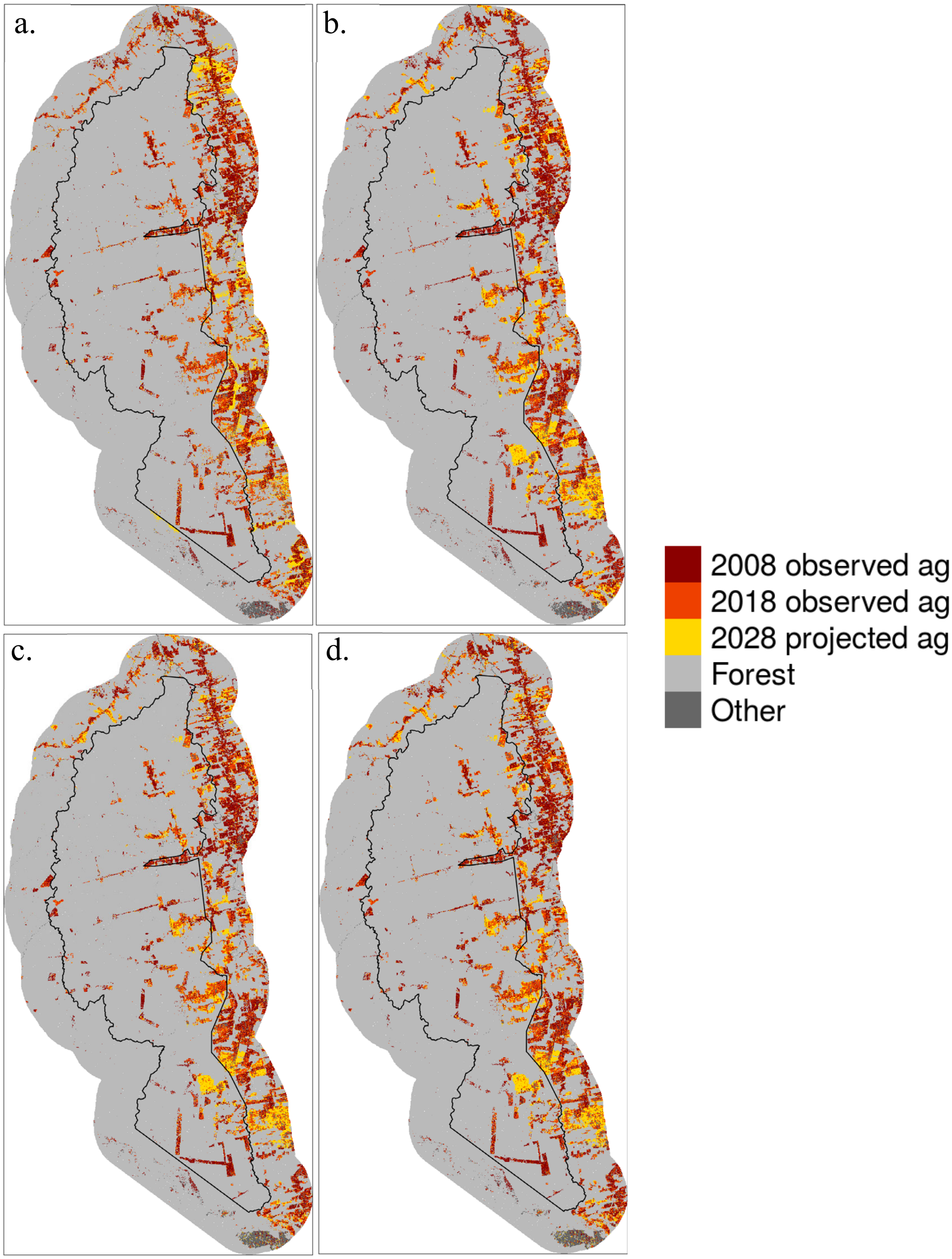

Figure 4. Maps comparing projected forest conversion to agriculture in 2028 using a) the LUC model, b) the DA model, c) the LUC & DA model, and d) the Refined LUC & DA model. Red represents agriculture observed in the 2008 land classifications, orange is 2018 agriculture, and yellow represents projected agriculture in 2028 under the different models.

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Conclusion

In my dissertation, I explored methods for identifying and quantifying the drivers of change in complex social-ecological systems and determining the impacts of different factors on system outcomes. I integrated methods from econometrics, land system science, and qualitative conservation science to understand the impacts of different land management practices on wildfire probability in the forests of the western United States and California rangelands and the factors related to deforestation in an Amazonian protected area. The results of my research can help to inform management responses in each of the three social-ecological systems in which I worked, while the methodologies I developed or refined can be broadly applied in the study of complex social-ecological systems.

In my first chapter, I demonstrated that federally-owned forests in the western United States had greater annual burn probabilities from 1989-2016 than privately-owned forests. I also demonstrated that the effect of federal forest ownership is greater than that of a one unit (1˚C, 1 mm, 1 cm, or 1 m/s, depending on the variable) increase in the majority of the climate variables assessed in most of the eleven western states. These findings have important management implications, and understanding the underlying mechanism driving the different fire probabilities on federal and private land will be important for crafting management responses. Notably, an increase in fire frequency on federal forest land relative to private forest land is not necessarily ecologically harmful, as decades of fire suppression reduced fire frequencies to well below their historic levels and restoring fire regimes to their pre-suppression characteristics may be a management goal in some contexts. However, the finding that federal management has a greater impact than a one unit increase in some of the climate variables projected to change with climate change emphasizes the importance of accounting for both climate change and forest management when projecting wildfire probability and creating management plans informed by these projections.

My second chapter showed that livestock grazing reduced wildfire probability in some regions and vegetation types in California rangelands from 2001-2017. In two of the regions studied, wildfire probability decreased as grazing intensity increased in grasslands, shrub/scrublands, and forests. In the third region, livestock grazing increased wildfire probability at low levels of stocking intensity, while there was no significant effect at higher levels of stocking intensity. These region- and vegetation type- specific results can guide land managers seeking to reduce the probability of wildfire on private and public land in a given year. Importantly, our finding that livestock grazing reduced wildfire frequency in North Bay and Central Coast forests indicates that the effects of livestock grazing on wildfire may extend beyond the boundaries of the locations with direct grazing impacts. Future research to understand why the impact of grazing on wildfire is different in the Central Valley and Foothills region than in the other regions could further guide land management by illuminating the conditions under which grazing does not reduce wildfire probability.

In my final chapter, I found that land use change models that include variables that are commonly used in land use change models and variables identified through qualitative discourse analysis methods performed better than models based on just one of the previously mentioned types of variables. These integrated models better explained agricultural expansion in Jamanxim National Forest from 2008-2018 than the model using only traditional land use change model variables or the model derived entirely from discourse analysis. This chapter's results quantify the relationships between deforestation probability and the explanatory variables and predict future deforestation hotspots in and around Jamanxim. The results can thus help to guide management responses to reduce forest conversion to agriculture within the protected area. The findings also suggest that discourses are important sources of information for understanding deforestation drivers but that management responses should not reflect discourses alone; combining knowledge derived from discourses around deforestation with land system science yields an improved understanding of the dynamics at play. Further research to assess whether this finding holds true for other protected areas or deforestation hotspots would help establish whether this pattern is specific to Jamanxim National Forest or generalizable to other contexts.

The methods developed in this dissertation represent advances for the study of complex social-ecological systems. The combination of pre-regression matching, panel regression that accounts for time lags, and estimation of marginal effects can be used to compare the relative impacts of different drivers of change in other social-ecological systems. This type of inquiry can inform management by improving our understanding of the role of different causal factors in generating desired or undesired outcomes. The integration of qualitative discourse analysis with quantitative land use change modeling, including the translation of qualitative themes into quantitative and spatial proxy variables, provides a methodology for developing land use change models that account for multi-scalar discourses, thus recognizing the impact of discourses in shaping land use change policies and decisions, as well as their role as sources of information about land use dynamics. Both methodologies can be used in a variety of contexts and will hopefully assist further efforts to quantitatively operationalize the social-ecological systems framework.

Further research can not only apply the methodological frameworks used and presented in this dissertation to other social-ecological systems, but can also advance the methods to improve our ability to disentangle causal relationships in complex systems. Methodological refinements could include integration of causal inference methods into the interdisciplinary land use change modeling framework presented in Chapter 3 to isolate the impacts of specific variables on forest loss, or methods to account for time lags in the discourse analysis, since there may be a delay between when a deforestation dynamic begins to occur and when it enters discourses at different spatial and administrative scales. Future work could also involve collaborations with government agencies, non-governmental organizations, and other stakeholder groups to translate the results of my three dissertation chapters into management responses, where appropriate, since an underlying goal of my research program is to inform sustainable management of social-ecological systems.

Chapter 1 Appendix

Table S1. Full and matched datasets for the eleven states.

State	Full dataset (# points)		Matched dataset (# points)	
	Private, unprotected	Federally managed	Private, unprotected	Federally managed
Arizona	2768	42194	1995	1995
California	47365	69183	24267	24267
Colorado	20733	58735	10691	10691
Idaho	11629	61088	8662	8662
Montana	19477	67227	13266	13266
Nevada	1455	31907	1455	1455
New Mexico	13563	38499	8465	8465
Oregon	38106	68024	21564	21564
Utah	10294	42848	7628	7628
Washington	31408	45922	10426	10426
Wyoming	5175	29288	2936	2936

Table S2. Reduction in bias in the matched dataset, as measured by the percentage improvement in the standardized mean difference between the matched and full dataset. The data were matched across the two management categories: 1) federally managed and 2) private and unprotected. For the matching, we used mean values for the first five years of the dataset for the climate variables, to reduce the effect of annual variation in climate. Negative values indicate that the matched dataset has reduced balance relative to the full dataset. All standardized mean differences in the matched dataset were < 0.25 for California, Idaho, New Mexico, Oregon, and Washington, indicating effective bias reduction (Schleicher et al. 2019). For Colorado and Montana, the maximum standardized mean differences were < 0.29, while the maximum values in Arizona, Utah, and Wyoming were all < 0.36. Nevada's matches were less effective at reducing bias, particularly for the population density variables. Part 1 has Arizona, California, Colorado, Idaho, Montana, and Nevada; Part 2 has New Mexico, Oregon, Utah, Washington, and Wyoming.

Table S2, Part 1

Variable	Arizona	California	Colorado	Idaho	Montana	Nevada
Longitude	84.4	99.2	87.2	94.2	91.8	67.4
Latitude	-1780.0	68.7	51.5	98.3	81.3	39.5
Lightning strikes	31.3	96.2	97.2	92.3	58.2	31.5
Elevation (1000 m)	79.1	99.3	94.8	99.0	96.5	36.9
Distance to roads (km)	95.4	97.2	95.7	93.0	95.2	32.6
Slope (degrees)	88.7	89.4	97.3	99.6	84.4	21.2
Aspect (degrees)	36.2	89.9	77.0	98.2	94.6	-108.1
Population density, 1990	86.6	92.9	93.8	71.2	75.8	2.3
Population density, 2000	88.4	94.2	94.0	79.2	74.3	2.4
Population density, 2010	89.5	93.9	92.7	77.9	74.7	0.8
Maximum wind speed, winter	22.0	97.6	-91.6	62.9	81.7	43.5
Maximum wind speed, spring	20.7	92.0	60.5	81.6	88.4	46.5

Maximum wind speed, summer	97.4	80.6	63.2	95.8	84.2	42.0
Maximum wind speed, fall	-174.4			89.4	-11.1	46.0
Total precipitation, winter	88.1	98.0	94.8	99.8	95.9	35.2
Total precipitation, spring	86.4	89.5	90.4	96.7	97.6	-47.7
Total precipitation, summer	70.0	95.9	58.2	88.6	98.2	41.0
Total precipitation, fall	90.5	81.9	98.9	95.7	97.8	-99.2
Average maximum temperature, winter	80.8	98.2	95.7	92.3	97.4	17.4
Average maximum temperature, spring	87.4	98.8	96.0	98.9	95.6	7.8
Average maximum temperature, summer	84.2	98.5	93.8	98.2	95.2	75.1
Average maximum temperature, fall	81.3			95.4	95.2	65.0
Average minimum temperature, winter	76.2	98.3	93.6	97.4	96.8	-19.8
Average minimum temperature, spring	81.9	98.5	96.1	98.8	96.5	96.1
Average minimum	72.2	97.3	94.8	98.5	95.2	21.2

temperature, summer						
Average minimum temperature, fall	57.4	97.0	94.2	98.0	97.0	-36.6
Average PDSI, winter	83.7	74.4	80.6	-2097.6	96.1	26.8
Average PDSI, summer	77.8	66.7	99.6	96.5	99.1	33.3
Average PDSI, fall	74.8	99.3	-81.6	85.5	95.8	30.3
Average soil moisture, winter	94.8	99.9	94.4	99.9	94.4	25.6
Average soil moisture, spring	95.9	99.8	94.7	98.4	92.4	2.0
Average soil moisture, summer	98.6	98.4	99.7	96.0	93.7	-3790.4
Average soil moisture, fall	94.4	99.3	99.7	97.0	95.5	22.1

Table S2, Part 2

Variable	New Mexico	Oregon	Utah	Washington	Wyoming
Longitude	98.9	94.7	76.5	99.8	97.8
Latitude	96.9	98.9	83.7	89.5	82.3
Lightning strikes	68.4	94.6	90.0	96.7	98.1
Elevation (1000 m)	93.4	96.3	91.8	99.3	99.3
Distance to roads (km)	96.2	98.8	97.3	95.1	94.3
Slope (degrees)	93.8	89.5	-1.0	98.8	93.8
Aspect (degrees)	81.4	92.8	86.8	71.7	82.4
Population density, 1990	77.0	96.2	93.0	86.0	73.1
Population density, 2000	78.6	97.0	93.4	84.6	76.5
Population density, 2010	78.2	96.9	93.8	85.8	73.7
Maximum wind speed, winter	96.0	98.4	84.3	87.9	96.8
Maximum wind speed, spring	96.0	98.7	74.5	89.8	98.1
Maximum wind speed, summer	99.3	94.2	59.8	91.2	98.4
Maximum wind speed, fall	99.3	95.6	83.8	61.2	96.1
Total precipitation, winter	95.0	97.9	88.0	-76.8	98.6
Total precipitation, spring	95.7	97.5	89.5	76.0	97.9
Total precipitation, summer	100.0	95.0	86.8	55.6	87.0

Total precipitation, fall	94.4	97.3	85.8	60.3	97.1
Average maximum temperature, winter	-546.0	96.9	87.1	99.1	96.3
Average maximum temperature, spring	73.3	95.1	76.4	99.1	98.1
Average maximum temperature, summer	88.4	92.7	65.5	95.4	98.7
Average maximum temperature, fall	61.0	96.2	83.0	98.8	98.3
Average minimum temperature, winter	-107.0	97.3	92.4	98.9	96.8
Average minimum temperature, spring	78.6	96.5	94.3	99.8	98.1
Average minimum temperature, summer	83.0	96.3	99.5	98.5	98.1
Average minimum temperature, fall	35.8	96.8	98.2	99.8	97.3
Average PDSI, winter	95.6	90.9	87.4	95.8	97.8
Average PDSI, summer	86.8	97.2	79.0	6.2	92.6
Average PDSI, fall	54.7	73.2	87.1	86.7	96.5

Average soil moisture, winter	97.5	98.8	89.7	96.6	99.5
Average soil moisture, spring	90.6	98.2	85.7	90.7	96.4
Average soil moisture, summer	93.6	97.9	78.3	87.5	98.1
Average soil moisture, fall	91.9	98.0	85.6	88.9	98.6

Table S3. Comparison of mean values of the variables in the full, unmatched dataset and the matched data. F indicates federally managed points, while P indicates points in privately-owned, unprotected forests. The table is divided into several parts: Part 1 includes values for Arizona, California, and Colorado; Part 2 has Idaho, Montana, and Nevada; Part 3 has New Mexico, Oregon, and Utah; and Part 4 has Washington, and Wyoming.

Table S3, Part 1

Variable	Match status	Arizona		California		Colorado	
		F	P	F	P	F	P
Longitude	Unmatched	510066.8	416622.6	-348596.0	-424869.3	842223.3	898058.8
	Matched	419148.1	433699.0	-399706.5	-400307.0	848758.2	841586.0
Latitude	Unmatched	3835280.0	3835605.4	4352337.0	4377648.6	4314256.2	4299124.1
	Matched	3830031.6	3823915.3	4413941.5	4421868.2	4318061.0	4325395.6
Lightning strikes	Unmatched	14772.3	15310.1	852.5	377.8	1656.2	1853.2
	Matched	15176.3	15545.7	539.7	521.8	1698.4	1703.9
Elevation (1000 m)	Unmatched	2.0	1.8	1.5	0.8	2.7	2.4
	Matched	1.8	1.8	1.1	1.1	2.5	2.5
Distance to roads (km)	Unmatched	0.9	0.6	1.4	0.4	1.2	0.5
	Matched	0.7	0.7	0.5	0.5	0.6	0.6
Slope (degrees)	Unmatched	11.8	9.2	18.9	15.7	15.9	12.8
	Matched	10.2	9.9	16.7	16.4	13.9	13.8
Aspect (degrees)	Unmatched	183.6	175.7	184.1	180.8	180.4	177.4
	Matched	175.0	180.0	180.2	180.5	179.8	180.5

Population density, 1990	Unmatched	0.3	12.0	0.3	14.0	0.1	6.5
	Matched	1.6	3.2	0.6	1.5	0.3	0.7
Population density, 2000	Unmatched	0.3	17.6	0.3	15.7	0.1	10.0
	Matched	2.1	4.1	0.7	1.6	0.5	1.1
Population density, 2010	Unmatched	0.3	23.0	0.3	16.8	0.1	11.2
	Matched	2.7	5.1	0.6	1.6	0.6	1.4
Maximum wind speed, winter	Unmatched	343.1	345.5	345.5	326.7	365.0	361.8
	Matched	344.8	346.6	322.4	321.9	341.5	335.4
Maximum wind speed, spring	Unmatched	436.9	433.8	380.0	362.9	418.8	433.8
	Matched	432.6	435.1	353.6	352.2	410.3	404.4
Maximum wind speed, summer	Unmatched	378.2	385.3	349.1	341.9	357.1	367.4
	Matched	383.7	383.9	330.0	328.6	351.4	347.6
Maximum wind speed, fall	Unmatched	363.0	362.3	323.8	292.9	373.8	374.1
	Matched	360.6	362.4	293.2	292.7	359.4	353.9
Total precipitation, winter	Unmatched	119.7	99.4	309.3	341.8	101.6	75.2
	Matched	99.7	102.2	331.6	332.2	84.1	82.7
Total precipitation, spring	Unmatched	78.4	65.3	168.8	179.8	127.0	116.2
	Matched	64.0	65.7	179.0	180.2	118.3	117.2
	Unmatched	186.8	173.8	32.5	20.7	164.2	159.2

Total precipitation, summer	Matched	173.1	177.0	27.5	28.0	156.0	153.9
Total precipitation, fall	Unmatched	149.5	127.8	233.5	242.8	148.0	123.4
	Matched	127.8	129.9	246.1	247.8	133.6	133.4
Average maximum temperature, winter	Unmatched	88.4	103.1	85.4	118.4	7.8	24.2
	Matched	106.2	103.4	101.8	101.2	15.1	15.8
Average maximum temperature, spring	Unmatched	173.6	191.9	145.2	181.3	96.3	121.3
	Matched	194.0	191.7	166.5	166.1	111.3	112.2
Average maximum temperature, summer	Unmatched	279.8	294.7	259.4	282.9	226.3	248.1
	Matched	296.5	294.1	277.7	277.3	240.9	242.2
Average maximum temperature, fall	Unmatched	189.8	204.0	177.4	207.3	120.6	139.8
	Matched	206.5	203.9	194.6	193.8	132.4	133.0
Average minimum temperature, winter	Unmatched	-58.6	-47.1	-33.6	0.4	-143.6	-129.9
	Matched	-43.7	-46.4	-18.7	-19.2	-138.1	-137.2
Average minimum	Unmatched	3.4	13.3	0.2	34.4	-58.3	-39.1
	Matched	16.5	14.7	16.0	15.5	-47.4	-46.6

temperature, spring							
Average minimum temperature, summer	Unmatched	109.3	117.5	83.0	104.6	53.2	69.2
	Matched	121.2	119.0	92.3	91.7	61.5	62.4
Average minimum temperature, fall	Unmatched	31.2	36.1	31.3	57.9	-31.1	-20.4
	Matched	39.9	37.8	41.3	40.5	-25.5	-24.9
Average PDSI, winter	Unmatched	217.1	197.9	27.7	19.2	313.9	301.4
	Matched	205.8	208.9	12.0	9.8	323.4	325.8
Average PDSI, spring	Unmatched	119.6	87.7	-53.3	-53.3	264.7	266.5
	Matched	93.7	100.0	-62.1	-63.7	280.9	281.4
Average PDSI, summer	Unmatched	137.3	115.4	-100.2	-98.2	226.1	232.4
	Matched	120.9	125.7	-104.9	-105.6	241.7	241.7
Average PDSI, fall	Unmatched	171.7	150.0	-98.4	-106.0	218.7	219.5
	Matched	154.8	160.2	-105.3	-105.2	228.9	230.4
Average soil moisture, winter	Unmatched	279.7	203.2	1704.0	2246.6	290.1	222.9
	Matched	205.8	209.8	1995.6	1995.3	256.4	260.2
	Unmatched	156.4	98.2	1576.6	1995.0	478.9	404.2

Average soil moisture, spring	Matched	100.7	103.1	1784.0	1784.9	469.0	473.0
Average soil moisture, summer	Unmatched	71.8	52.1	612.0	816.9	237.1	160.9
	Matched	54.7	54.4	696.7	693.5	192.3	192.1
Average soil moisture, fall	Unmatched	81.4	58.9	656.0	836.8	209.5	144.2
	Matched	61.5	60.3	749.9	751.1	171.0	171.2

Table S3, Part 2

Variable	Match status	Idaho		Montana		Nevada	
		F	P	F	P	F	P
Longitude	Unmatched	194164.2	137993.7	364775.7	499337.0	72412.1	22462.1
	Matched	147070.1	150353.4	473985.8	462920.1	38753.5	22462.1
Latitude	Unmatched	5032138.9	5139938.2	5201978.6	5189368.3	4323902.1	4449491.2
	Matched	5116066.8	5114223.6	5192093.6	5194446.9	4373491.2	4449491.2
Lightning strikes	Unmatched	938.9	493.1	764.5	815.7	9837.1	4445.4
	Matched	520.5	554.6	831.6	810.2	8139.5	4445.4
Elevation (1000 m)	Unmatched	1.8	1.2	1.8	1.3	2.2	2.0
	Matched	1.3	1.3	1.4	1.4	2.2	2.0
Distance to roads (km)	Unmatched	2.0	0.4	2.1	0.6	1.3	0.8
	Matched	0.6	0.4	0.7	0.6	1.1	0.8
	Unmatched	8.0	3.3	2.8	1.4	16.6	14.9

Slope (degrees)	Matched	4.1	4.1	2.0	1.8	16.2	14.9
Aspect (degrees)	Unmatched	149.3	77.6	89.2	114.1	181.5	180.2
	Matched	90.2	91.5	105.5	106.8	183.0	180.2
Population density, 1990	Unmatched	0.2	4.2	0.1	2.6	0.0	6.1
	Matched	1.0	2.2	0.5	1.1	0.2	6.1
Population density, 2000	Unmatched	0.2	5.4	0.1	3.2	0.0	7.0
	Matched	1.2	2.3	0.6	1.3	0.2	7.0
Population density, 2010	Unmatched	0.2	6.3	0.2	3.6	0.0	13.6
	Matched	1.3	2.6	0.6	1.5	0.1	13.6
Maximum wind speed, winter	Unmatched	261.2	258.5	384.6	394.7	414.2	382.0
	Matched	263.2	262.2	388.2	386.3	400.2	382.0
Maximum wind speed, spring	Unmatched	317.1	321.1	417.2	437.1	459.5	425.8
	Matched	323.8	323.1	431.4	429.1	443.9	425.8
Maximum wind speed, summer	Unmatched	290.5	280.7	357.5	367.9	425.1	391.4
	Matched	284.4	283.9	364.8	363.2	411.0	391.4
Maximum wind speed, fall	Unmatched	291.7	283.1	395.9	394.8	412.9	383.3
	Matched	287.4	286.5	391.4	390.2	399.3	383.3
Total precipitation, winter	Unmatched	125.0	162.5	88.1	59.9	63.5	73.4
	Matched	157.3	157.2	64.9	66.0	67.0	73.4

Total precipitation, spring	Unmatched	146.1	173.5	135.4	115.8	87.5	88.4
	Matched	169.5	170.4	118.3	118.8	89.7	88.4
Total precipitation, summer	Unmatched	101.6	97.2	128.4	119.9	77.9	58.9
	Matched	97.2	97.7	121.0	121.2	70.1	58.9
Total precipitation, fall	Unmatched	144.5	179.3	134.2	101.8	87.4	87.9
	Matched	175.1	176.6	106.9	107.6	89.0	87.9
Average maximum temperature, winter	Unmatched	0.8	7.1	0.3	15.4	45.5	38.9
	Matched	6.0	5.5	12.5	12.1	44.3	38.9
Average maximum temperature, spring	Unmatched	103.3	127.1	100.4	133.2	135.4	134.0
	Matched	123.6	123.4	128.0	126.5	135.2	134.0
Average maximum temperature, summer	Unmatched	236.2	256.0	230.6	263.3	270.4	273.0
	Matched	253.8	253.4	257.9	256.4	272.4	273.0
Average maximum temperature, fall	Unmatched	118.4	130.1	101.8	124.6	160.3	163.0
	Matched	129.2	128.6	120.7	119.6	162.1	163.0
Average minimum temperature, winter	Unmatched	-126.1	-88.8	-115.5	-103.7	-94.9	-97.9
	Matched	-93.5	-94.5	-105.9	-105.5	-94.3	-97.9

Average minimum temperature, spring	Unmatched	-45.5	-10.4	-39.8	-14.7	-23.6	-23.0
	Matched	-14.9	-15.3	-19.0	-19.9	-23.0	-23.0
Average minimum temperature, summer	Unmatched	35.8	66.5	46.6	79.2	81.1	77.7
	Matched	63.5	63.1	73.1	71.6	80.4	77.7
Average minimum temperature, fall	Unmatched	-36.6	-8.9	-35.3	-18.1	-4.4	-5.4
	Matched	-11.7	-12.2	-21.3	-21.8	-4.1	-5.4
Average PDSI, winter	Unmatched	24.1	24.2	-0.9	-30.8	158.4	131.4
	Matched	27.9	26.8	-25.7	-24.5	151.2	131.4
Average PDSI, spring	Unmatched	-37.7	-24.8	-74.4	-115.6	66.7	40.9
	Matched	-24.0	-26.2	-111.1	-109.9	60.6	40.9
Average PDSI, summer	Unmatched	-98.6	-77.6	-171.7	-195.3	13.2	-42.6
	Matched	-80.0	-80.8	-192.9	-192.7	-5.4	-42.6
Average PDSI, fall	Unmatched	-32.0	-20.0	-44.2	-70.7	25.9	-36.5
	Matched	-20.5	-22.2	-63.6	-62.5	7.0	-36.5
Average soil moisture, winter	Unmatched	675.6	1239.6	406.9	252.2	178.5	207.7
	Matched	1143.6	1143.1	269.5	278.1	186.0	207.7

Average soil moisture, spring	Unmatched	1214.1	1887.0	706.0	467.9	185.4	198.3
	Matched	1767.8	1778.8	508.5	526.7	185.6	198.3
Average soil moisture, summer	Unmatched	620.9	897.8	313.8	189.7	66.2	66.2
	Matched	844.1	855.2	205.9	213.8	64.7	66.2
Average soil moisture, fall	Unmatched	497.9	760.0	338.0	187.1	70.9	79.9
	Matched	715.1	722.9	204.8	211.5	72.9	79.9

Table S3, Part 3

Variable	Match status	New Mexico		Oregon		Utah	
		F	P	F	P	F	P
Longitude	Unmatched	845446.1	946463.6	-331733.1	-406624.5	461397.9	450184.6
	Matched	888468.4	887347.6	-370523.6	-366534.4	451037.4	448397.4
Latitude	Unmatched	3849814.8	3933635.2	4912184.3	4944304.1	4325452.8	4417602.2
	Matched	3895422.6	3898050.7	4916699.3	4916337.7	4400452.3	4385446.8
Lightning strikes	Unmatched	10651.0	9940.1	447.4	262.2	3888.2	2388.8
	Matched	10063.6	10288.6	396.6	386.6	2663.4	2814.0
Elevation (1000 m)	Unmatched	2.4	2.3	1.2	0.7	2.3	2.2
	Matched	2.3	2.3	0.9	0.9	2.3	2.3

Distance to roads (km)	Unmatched	1.2	0.6	0.6	0.3	0.9	0.5
	Matched	0.6	0.6	0.3	0.3	0.5	0.5
Slope (degrees)	Unmatched	13.6	10.7	7.1	5.1	16.2	15.8
	Matched	11.0	10.8	6.0	6.2	16.3	15.8
Aspect (degrees)	Unmatched	179.5	176.6	175.2	157.6	181.3	177.3
	Matched	179.6	179.1	172.1	173.4	178.2	177.7
Population density, 1990	Unmatched	0.3	2.9	0.1	7.5	0.0	2.3
	Matched	0.8	1.4	0.2	0.5	0.1	0.2
Population density, 2000	Unmatched	0.4	4.0	0.1	8.6	0.0	3.8
	Matched	1.0	1.8	0.3	0.5	0.1	0.3
Population density, 2010	Unmatched	0.4	4.3	0.1	9.3	0.0	4.6
	Matched	1.0	1.8	0.3	0.6	0.2	0.4
Maximum wind speed, winter	Unmatched	436.4	448.6	350.9	359.4	338.4	332.9
	Matched	436.8	436.3	354.4	354.3	336.8	337.7
Maximum wind speed, spring	Unmatched	521.4	527.4	357.0	353.9	415.7	408.9
	Matched	518.1	517.8	356.0	356.1	411.2	413.0
Maximum wind speed, summer	Unmatched	395.4	414.7	341.2	346.4	363.3	360.8
	Matched	398.2	398.3	343.9	343.6	361.6	362.6
Maximum wind speed, fall	Unmatched	430.1	444.8	339.9	339.0	367.5	362.3
	Matched	432.1	432.0	337.8	337.7	365.5	366.3

Total precipitation, winter	Unmatched	95.9	77.6	368.0	440.0	69.5	75.6
	Matched	88.6	89.5	396.3	394.8	75.5	74.8
Total precipitation, spring	Unmatched	79.6	92.2	242.3	296.2	98.3	109.9
	Matched	86.1	86.6	264.6	263.3	106.2	104.9
Total precipitation, summer	Unmatched	223.7	216.3	77.1	81.9	121.0	108.8
	Matched	213.1	213.1	77.1	76.8	113.9	115.5
Total precipitation, fall	Unmatched	139.6	127.0	316.4	378.3	102.6	113.1
	Matched	131.9	132.6	340.6	338.9	110.8	109.3
Average maximum temperature, winter	Unmatched	67.5	67.4	49.6	75.1	20.2	9.1
	Matched	64.5	63.8	65.6	64.8	10.2	11.6
Average maximum temperature, spring	Unmatched	157.8	160.8	123.0	144.8	123.2	120.2
	Matched	157.9	157.1	138.7	137.7	118.1	118.8
Average maximum temperature, summer	Unmatched	259.6	265.1	237.4	244.7	256.4	256.2
	Matched	262.6	262.0	245.3	244.8	253.8	253.9
Average maximum temperature, fall	Unmatched	171.5	173.0	147.9	164.1	143.7	139.8
	Matched	170.8	170.3	159.8	159.2	138.7	139.3

Average minimum temperature, winter	Unmatched	-94.2	-94.8	-48.5	-16.9	-110.6	-120.4
	Matched	-96.2	-97.6	-30.3	-31.1	-119.3	-118.6
Average minimum temperature, spring	Unmatched	-21.1	-14.9	-9.6	17.9	-26.4	-27.6
	Matched	-18.6	-19.9	6.8	5.9	-28.8	-28.8
Average minimum temperature, summer	Unmatched	83.0	90.7	55.6	76.4	84.2	80.3
	Matched	86.5	85.2	68.1	67.4	80.4	80.3
Average minimum temperature, fall	Unmatched	2.9	4.8	8.6	33.5	-3.7	-9.3
	Matched	3.1	1.9	22.8	22.0	-8.5	-8.4
Average PDSI, winter	Unmatched	267.3	254.3	34.9	21.7	231.3	256.4
	Matched	261.9	261.3	37.6	38.8	254.9	251.7
Average PDSI, spring	Unmatched	214.2	220.8	-8.8	-16.8	168.3	176.0
	Matched	214.0	213.4	-3.7	-3.1	180.5	179.8
Average PDSI, summer	Unmatched	278.6	286.7	-55.8	-39.6	161.3	142.4
	Matched	282.4	281.4	-40.3	-40.7	150.9	154.9
Average PDSI, fall	Unmatched	283.6	285.8	-45.4	-47.4	148.3	128.4
	Matched	284.7	283.7	-40.8	-41.3	137.3	139.8

Average soil moisture, winter	Unmatched	230.0	156.3	1625.9	2031.3	217.0	286.0
	Matched	187.5	189.4	1798.9	1793.9	271.4	264.3
Average soil moisture, spring	Unmatched	226.1	182.9	1673.9	1989.0	363.2	517.8
	Matched	212.9	217.0	1796.8	1791.2	491.4	469.3
Average soil moisture, summer	Unmatched	103.4	80.5	801.9	1024.7	152.0	200.8
	Matched	93.7	95.1	903.5	898.7	193.0	182.4
Average soil moisture, fall	Unmatched	104.0	77.2	904.4	1159.3	117.6	162.0
	Matched	92.8	95.0	1011.7	1006.6	153.2	146.9

Table S3, Part 4

Variable	Match status	Washington		Wyoming	
		F	P	F	P
Longitude	Unmatched	-241319.2	-303287.0	652082.6	886372.7
	Matched	-240891.3	-241037.3	835909.9	830683.4
Latitude	Unmatched	5331897.4	5298518.2	4820865.9	4809238.3
	Matched	5319507.9	5316011.3	4781297.0	4779241.2
Lightning strikes	Unmatched	54.6	40.4	1703.4	1396.5
	Matched	57.3	56.9	1544.9	1539.2
Elevation (1000 m)	Unmatched	1.1	0.4	2.5	1.8
	Matched	0.7	0.7	2.1	2.1

Distance to roads (km)	Unmatched	1.6	0.3	3.4	0.5
	Matched	0.4	0.4	0.8	0.6
Slope (degrees)	Unmatched	20.9	11.8	14.6	11.5
	Matched	15.2	15.3	12.9	12.7
Aspect (degrees)	Unmatched	4.1	2.4	183.4	176.5
	Matched	4.4	4.9	179.8	181.1
Population density, 1990	Unmatched	0.6	16.5	0.0	1.2
	Matched	2.3	4.5	0.2	0.5
Population density, 2000	Unmatched	0.7	21.7	0.1	1.6
	Matched	3.0	6.2	0.3	0.6
Population density, 2010	Unmatched	0.8	28.1	0.1	1.8
	Matched	3.4	7.3	0.4	0.8
Maximum wind speed, winter	Unmatched	279.7	297.5	421.7	482.5
	Matched	288.2	286.1	476.4	474.5
Maximum wind speed, spring	Unmatched	337.4	329.3	442.1	509.9
	Matched	340.3	339.5	497.2	495.9
Maximum wind speed, summer	Unmatched	326.6	316.6	391.1	419.2
	Matched	323.4	324.3	414.7	414.2
Maximum wind speed, fall	Unmatched	301.5	305.2	425.7	451.3
	Matched	306.7	305.2	451.4	450.4
	Unmatched	443.2	448.2	94.4	44.6

Total precipitation, winter	Matched	421.9	413.1	51.2	51.9
Total precipitation, spring	Unmatched	338.1	365.9	122.5	108.3
	Matched	340.4	333.7	107.8	108.1
Total precipitation, summer	Unmatched	106.2	103.8	121.4	117.3
	Matched	100.9	99.9	114.0	113.4
Total precipitation, fall	Unmatched	404.1	422.9	110.7	82.7
	Matched	391.9	384.4	84.4	85.2
Average maximum temperature, winter	Unmatched	11.8	53.0	-20.5	7.4
	Matched	30.8	30.4	-0.7	-1.8
Average maximum temperature, spring	Unmatched	97.1	135.9	75.4	122.3
	Matched	124.0	124.4	107.9	107.0
Average maximum temperature, summer	Unmatched	207.7	231.2	208.9	261.1
	Matched	228.8	229.9	245.6	244.9
Average maximum temperature, fall	Unmatched	110.9	142.6	92.4	128.5
	Matched	130.0	130.4	118.4	117.8

Average minimum temperature, winter	Unmatched	-59.4	-20.4	-152.7	-119.2
	Matched	-40.9	-41.3	-125.2	-126.3
Average minimum temperature, spring	Unmatched	-6.9	25.9	-69.8	-25.6
	Matched	12.6	12.6	-37.1	-38.0
Average minimum temperature, summer	Unmatched	65.8	88.1	32.3	85.4
	Matched	80.4	80.8	71.9	70.9
Average minimum temperature, fall	Unmatched	9.6	36.8	-52.4	-20.7
	Matched	22.8	22.7	-27.1	-28.0
Average PDSI, winter	Unmatched	-57.5	-80.6	87.7	122.6
	Matched	-55.7	-54.8	131.7	130.9
Average PDSI, spring	Unmatched	-50.5	-63.1	30.2	48.5
	Matched	-44.1	-43.7	46.5	45.6
Average PDSI, summer	Unmatched	-54.7	-53.7	-83.8	-63.8
	Matched	-50.7	-49.7	-70.8	-72.2
Average PDSI, fall	Unmatched	-65.0	-80.4	-76.5	-46.7
	Matched	-68.9	-66.8	-53.4	-54.4

Average soil moisture, winter	Unmatched	1370.9	1692.1	194.6	113.5
	Matched	1405.7	1394.8	114.3	114.7
Average soil moisture, spring	Unmatched	1572.7	1827.3	532.0	248.1
	Matched	1641.1	1617.3	271.8	282.1
Average soil moisture, summer	Unmatched	817.3	955.3	293.6	108.8
	Matched	823.0	805.7	122.4	126.0
Average soil moisture, fall	Unmatched	978.2	1138.7	169.8	85.3
	Matched	959.5	941.7	92.0	93.2

Table S4. Panel regression model for each state. *Management*, *Year*, *BPYone*, *BPYtwo*, *BPYfive*, u_i, and e_{it} are explained in the Methods section. *Interaction* is the interaction between *Year* and *Management*. *Controls* represents a list of covariates that influence the probability of burning. Units for the control variables are as follows: elevation (km), slope and aspect (°), distance to roads (km), soil moisture (mm) and precipitation (cm), minimum and maximum temperatures (°C), wind speed (m/s).

State	Model	Controls
Arizona	$BN_{it} = B_0 + B_1{*}Management + B_2{*}Year + B_3{*}BPYone + B_4{*}BPYtwo + B_5{*}BPYfive\ {*} + B_{6\text{-}21}{*}Controls + B_{22}{*}Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: summer • Average soil moisture: spring, fall • Maximum wind speed: spring, summer, fall • Total precipitation: winter, spring, summer, fall • Previous year precipitation
California	$BN_{it} = B_0 + B_1{*}Management + B_2{*}Year + B_3{*}BPYone + B_4{*}BPYtwo + B_5{*}BPYfive + B_{6\text{-}20}{*}Controls + B_{21}{*}Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, fall • Average maximum temperature: summer • Maximum wind speed: winter, fall • Total precipitation: winter, spring, summer, fall • Previous year precipitation
Colorado	$BN_{it} = B_0 + B_1{*}Management + B_2{*}Year + B_3{*}BPYfive + B_{4\text{-}19}{*}Controls + B_{20}{*}Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: spring • Average soil moisture: winter, summer, fall • Average minimum temperature: winter • Maximum wind speed: fall • Total precipitation: winter, spring, summer, fall

		• Previous year precipitation
Idaho	$BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYone + B_4*BPYtwo + B_5*BPYfive + B_{6\text{-}20}*Controls + B_{21}*Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, fall • Average maximum temperature: winter, summer, fall • Maximum wind speed: fall • Total precipitation: winter, spring, summer • Previous year precipitation
Montana	$BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYone + B_4*BPYtwo + B_5*BPYfive + B_{6\text{-}19}*Controls + B_{20}*Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, summer • Average maximum temperature: winter, fall • Maximum wind speed: fall • Total precipitation: spring, summer, fall • Previous year precipitation
Nevada	$BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYtwo + B_4*BPYfive + B_{5\text{-}24}*Controls + B_{25}*Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, summer • Average soil moisture: winter, summer, fall • Average maximum temperature: winter, summer, fall • Maximum wind speed: summer, fall • Total precipitation: winter, spring, summer, fall • Previous year precipitation
New Mexico	$BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYone + B_4*BPYtwo +$	• Elevation, slope, aspect • Distance to roads

	B_5*BPYfive + $B_{6\text{-}21}$*Controls + B_{22}*Interaction + u_i + e_{it}	• Population density (1990) • Average PDSI: summer • Average soil moisture: winter, summer • Maximum wind speed: spring, summer, fall • Total precipitation: winter, spring, summer, fall • Previous year precipitation
Oregon	BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYone + B_4*BPYtwo + B_5*BPYfive + $B_{6\text{-}21}$*Controls + B_{22}*Interaction + u_i + e_{it}	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, summer • Average maximum temperature: spring, summer, fall • Maximum wind speed: winter, spring, summer, fall • Total precipitation: summer, fall
Utah	BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYone + B_4*BPYtwo + B_5*BPYfive + $B_{6\text{-}20}$*Controls + B_{21}*Interaction + u_i + e_{it}	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: summer • Average soil moisture: winter, fall • Average minimum temperature: fall • Average maximum temperature: winter • Maximum wind speed: summer, fall • Total precipitation: winter, spring, summer, fall
Washington	BN_{it} = B_0 + B_1*Management + B_2*Year + B_3*BPYfive + $B_{4\text{-}16}$*Controls + B_{17}*Interaction + u_i + e_{it}	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, summer • Average maximum

		temperature: summer, fall • Maximum wind speed: summer, fall • Total precipitation: summer, fall
Wyoming	$BN_{it} = B_0 + B_1*Management + B_2*Year + B_{3\text{-}19}*Controls + B_{20}*Interaction + u_i + e_{it}$	• Elevation, slope, aspect • Distance to roads • Population density (1990) • Average PDSI: winter, summer • Average soil moisture: winter, fall • Average minimum temperature: fall • Average maximum temperature: winter • Maximum wind speed: fall • Total precipitation: winter, spring, summer, fall • Previous year precipitation

Table S5. Logistic regression results for model including points for all 11 states, where the response variable is whether or not a given point burned in either a wildfire or a wildland fire use in a given year.

Variable	Estimate	Standard error	z value	p-value
Intercept	-164.558	26.465	-6.218	< 0.001
Federally managed	-61.943	33.146	-1.869	0.062
Elevation (km)	-0.030	0.023	-1.261	0.207
Slope	0.022	0.001	29.810	< 0.001
Aspect	$4.40*10^{-4}$	0.000	7.081	< 0.001
Distance to roads (km)	0.175	0.006	28.123	< 0.001
Population density (1990)	-0.014	0.002	-6.178	< 0.001
Average PDSI, summer	-0.002	0.000	-59.207	< 0.001
Average PDSI, winter	0.001	0.000	19.144	< 0.001
Average maximum temperature, fall	-0.004	0.000	-9.039	< 0.001
Average maximum temperature, summer	0.012	0.000	32.935	< 0.001
Average maximum wind speed, summer	0.002	0.000	11.917	< 0.001
Total precipitation, fall	-0.002	0.000	-26.807	< 0.001
Total precipitation, summer	-0.010	0.000	-38.433	< 0.001
Year	0.078	0.013	5.893	< 0.001

Burned in previous year	-2.845	0.243	-11.712	< 0.001
Burned in previous 2 years	-1.364	0.141	-9.692	< 0.001
Burned in previous 5 years	-0.746	0.103	-7.208	< 0.001
California	100.622	26.873	3.744	< 0.001
Colorado	-21.278	34.262	-0.621	0.535
Idaho	35.693	29.651	1.204	0.229
Montana	80.476	27.583	2.918	0.004
Nevada	102.705	33.320	3.082	0.002
New Mexico	-84.858	32.187	-2.6367	0.008
Oregon	34.701	28.261	1.228	0.219
Utah	71.194	29.399	2.422	0.015
Washington	-81.929	29.598	-2.768	0.006
Wyoming	-102.794	37.406	-2.748	0.006
Federally managed:Year	0.031	0.017	1.888	0.059
Federally managed:California	26.029	33.639	0.774	0.439
Federally managed:Colorado	145.694	41.509	3.510	< 0.001
Federally managed:Idaho	97.760	36.750	2.660	0.008
Federally managed:Montana	78.993	34.565	2.285	0.022
Federally managed:Nevada	73.810	43.309	1.704	0.088

Federally managed:New Mexico	265.135	38.992	6.800	< 0.001
Federally managed:Oregon	116.408	35.050	3.321	< 0.001
Federally managed:Utah	35.541	37.274	0.954	0.340
Federally managed:Washington	60.213	37.704	1.597	0.110
Federally managed:Wyoming	223.098	45.117	4.945	< 0.001
Year:California	-0.050	0.013	-3.737	< 0.001
Year:Colorado	0.010	0.017	0.592	0.554
Year:Idaho	-0.018	0.015	-1.206	0.228
Year:Montana	-0.040	0.014	-2.895	0.004
Year:Nevada	-0.051	0.017	-3.093	0.002
Year:New Mexico	0.042	0.016	2.638	0.008
Year:Oregon	-0.017	0.014	-1.237	0.216
Year:Utah	-0.0358	0.015	-2.443	0.015
Year:Washington	0.041	0.015	2.784	0.005
Year:Wyoming	0.051	0.019	2.740	0.006
Federally managed:Year:California	-0.013	0.017	-0.772	0.440
Federally managed:Year:Colorado	-0.072	0.021	-3.504	< 0.001
Federally managed:Year:Idaho	-0.049	0.018	-2.657	0.008

Federally managed:Year:Montana	-0.039	0.017	-2.290	0.022
Federally managed:Year:Nevada	-0.037	0.022	-1.719	0.086
Federally managed:Year:New Mexico	-0.132	0.019	-6.799	< 0.001
Federally managed:Year:Oregon	-0.058	0.017	-3.311	0.001
Federally managed:Year:Utah	-0.018	0.019	-0.962	0.336
Federally managed:Year:Washington	-0.030	0.019	-1.610	0.107
Federally managed:Year:Wyoming	-0.111	0.022	-4.948	< 0.001

Figure S1. Predicted probabilities of burning in a wildfire or wildland fire use, calculated using the all-state model with state as a fixed effect. The red lines indicate the predicted probability of burning for federally managed forests, while the blue lines represent private, unprotected forests. 95% confidence intervals are displayed.

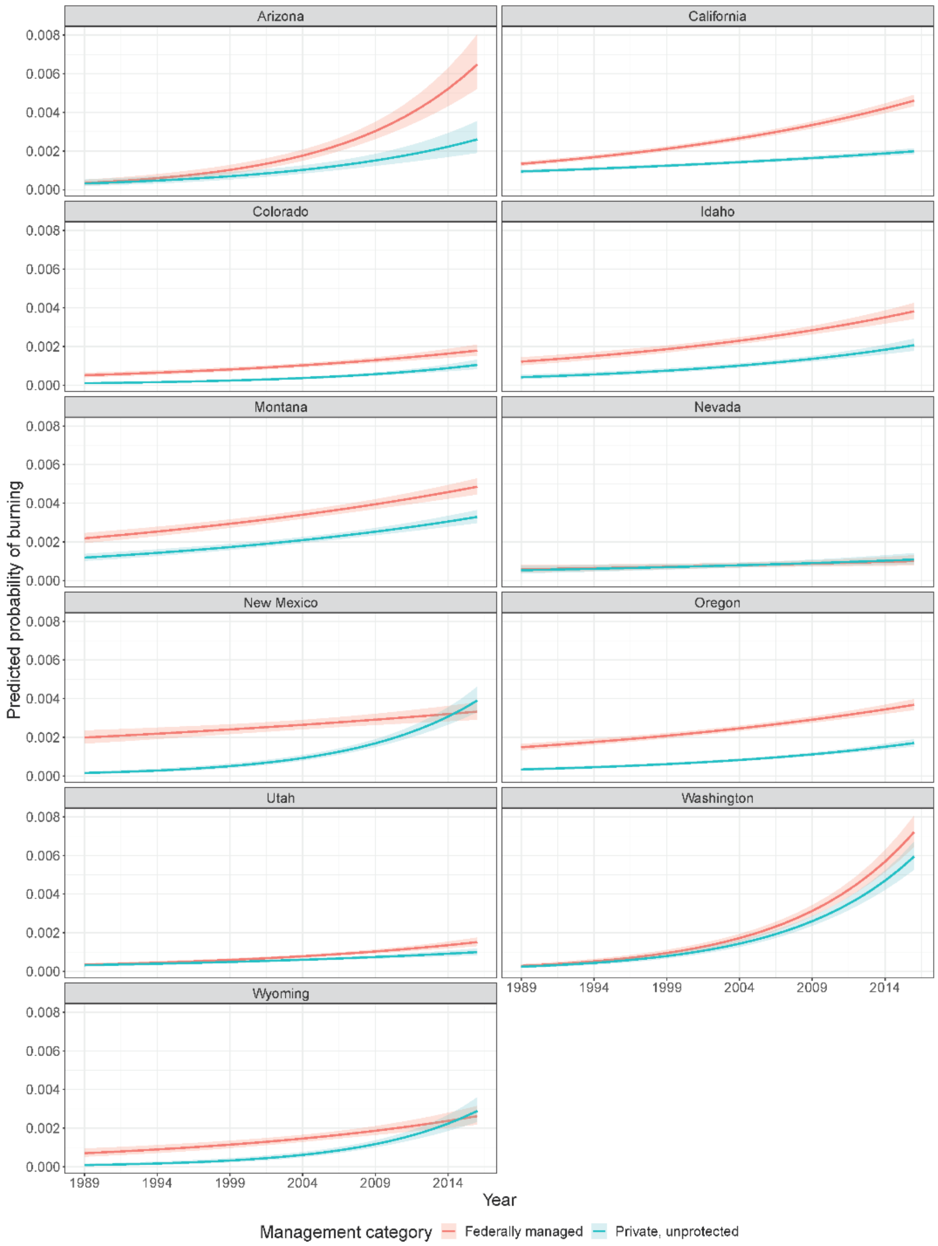


Table S6. Logistic regression model for all states, where the response variable is whether or not a given point burned in a wildland fire use in a given year. The high p-values and standard errors for many of the variables reflect the rarity of wildland fire use events in the dataset (there were 114 points that burned in Wildland Fire Use events across all years in the matched dataset, contrasted with 22,441 points that burned in Wildfires).

Variable	Estimate	Standard error	z value	p-value
Intercept	-106.793	652201	0.000	1.000
Federally managed	40.041	652201	0.000	1.000
Elevation (km)	1.755	0.418	4.194	< 0.001
Slope	-0.036	0.012	-2.898	0.004
Aspect	-0.003	0.001	-3.104	0.002
Distance to roads (km)	0.336	0.027	12.407	< 0.001
Population density (1990)	-0.276	0.265	-1.043	0.297
Average PDSI, summer	-0.001	0.001	-1.274	0.203
Average PDSI, winter	0.002	0.001	2.972	0.003
Average maximum temperature, fall	0.024	0.007	3.282	0.001
Average maximum temperature, summer	-0.023	0.007	-3.184	0.001
Average maximum wind speed, summer	-0.004	0.002	-1.884	0.060

Total precipitation, fall	0.003	0.002	1.880	0.060
Total precipitation, summer	-0.018	0.003	-6.764	< 0.001
Year	0.041	326	0.000	1.000
Burned in previous year	-16.979	3017	-0.006	0.996
Burned in previous 2 years	-17.193	2996	-0.006	0.995
Burned in previous 5 years	-17.172	3423	-0.005	0.996
California	96.221	674957	0.000	1.000
Colorado	120.785	694253	0.000	1.000
Idaho	-3.382	652201	0.000	1.000
Montana	129.242	684517	0.000	1.000
Nevada	95.415	941398	0.000	1.000
New Mexico	-3.567	652201	0.000	1.000
Oregon	101.108	678871	0.000	1.000
Utah	98.2461	718488	0.000	1.000
Washington	143.890	704385	0.000	1.000
Wyoming	139.259	783384	0.000	1.000
Federally managed:Year	-0.011	326	0.000	1.000
Federally managed:California	-37.079	674957	0.000	1.000

Federally managed:Colorado	-69.469	694253	0.000	1.000
Federally managed:Idaho	-26.191	652201	0.000	1.000
Federally managed:Montana	-4.282	684517	0.000	1.000
Federally managed:Nevada	-147.383	941398	0.000	1.000
Federally managed:New Mexico	-14.214	652201	0.000	1.000
Federally managed:Oregon	-40.380	704379	0.000	1.000
Federally managed:Utah	-144.014	718488	0.000	1.000
Federally managed:Washington	-16.014	752273	0.000	1.000
Federally managed:Wyoming	-16.795	871996	0.000	1.000
Year:California	-0.0487	337	0.000	1.000
Year:Colorado	-0.061	347	0.000	1.000
Year:Idaho	0.009	326	0.000	1.000
Year:Montana	-0.064	342	0.000	1.000
Year:Nevada	-0.048	470	0.000	1.000
Year:New Mexico	0.010	326	0.000	1.000
Year:Oregon	-0.051	339	0.000	1.000
Year:Utah	-0.050	359	0.000	1.000

Year:Washington	-0.072	352	0.000	1.000
Year:Wyoming	-0.070	391	0.000	1.000
Federally managed:Year:California	0.018	337	0.000	1.000
Federally managed:Year:Colorado	0.034	34	0.000	1.000
Federally managed:Year:Idaho	0.006	326	0.000	1.000
Federally managed:Year:Montana	0.001	342	0.000	1.000
Federally managed:Year:Nevada	0.073	470	0.000	1.000
Federally managed:Year:New Mexico	-0.001	326	0.000	1.000
Federally managed:Year:Oregon	0.011	352	0.000	1.000
Federally managed:Year:Utah	0.072	359	0.000	1.000
Federally managed:Year:Washington	-0.001	376	0.000	1.000
Federally managed:Year:Wyoming	-0.001	435	0.000	1.000

Table S7. Logistic regression model for all states, using the matched dataset derived from the set of points that were forested in 1992, 2001, or 2016.

Variable	Estimate	Standard error	z value	p-value
Intercept	-189.754	25.155	-7.54	< 0.001
Federally managed	-65.275	29.892	-2.18	0.029
Elevation (km)	0.035	0.023	1.53	0.126
Slope	0.025	0.001	33.84	< 0.001
Aspect	$3.946*10^{-4}$	0.000	6.46	< 0.001
Distance to roads (km)	0.154	0.006	24.38	< 0.001
Population density (1990)	-0.014	0.002	-6.42	< 0.001
Average PDSI, fall	-0.247	0.004	-61.81	< 0.001
Average PDSI, winter	0.031	0.003	9.14	< 0.001
Average maximum temperature, fall	-0.073	0.005	-15.85	< 0.001
Average maximum temperature, summer	0.164	0.004	44.38	< 0.001
Average maximum wind speed, summer	0.294	0.015	20.04	< 0.001
Total precipitation, fall	-0.014	0.001	-17.55	< 0.001
Total precipitation, summer	-0.084	0.003	-32.22	< 0.001
Year	0.089	0.013	7.12	< 0.001
Burned in previous year	-2.718	0.220	-12.36	< 0.001
Burned in previous 2 years	-1.412	0.139	-10.19	< 0.001
Burned in previous 5 years	-0.800	0.105	-7.63	< 0.001
California	122.815	25.584	4.8	< 0.001
Colorado	60.333	31.768	1.9	0.058
Idaho	45.494	28.554	1.59	0.111
Montana	89.969	26.350	3.41	0.001
Nevada	140.406	31.832	4.41	< 0.001
New Mexico	-28.937	30.797	-0.94	0.347
Oregon	69.135	26.836	2.58	0.010
Utah	106.847	27.898	3.83	< 0.001
Washington	-88.910	28.436	-3.13	0.002
Wyoming	-94.780	36.331	-2.61	0.009
Federally managed:Year	0.033	0.015	2.22	0.027
Federally managed:California	28.857	30.437	0.95	0.343

Federally managed:Colorado	129.980	37.326	3.48	< 0.001
Federally managed:Idaho	104.645	33.949	3.08	0.002
Federally managed:Montana	82.913	31.461	2.64	0.008
Federally managed:Nevada	82.977	39.674	2.09	0.036
Federally managed:New Mexico	262.320	35.835	7.32	< 0.001
Federally managed:Oregon	107.982	31.783	3.4	0.001
Federally managed:Utah	45.914	33.807	1.36	0.174
Federally managed:Washington	97.207	34.710	2.8	0.005
Federally managed:Wyoming	241.705	42.345	5.71	< 0.001
Year:California	-0.061	0.013	-4.78	< 0.001
Year:Colorado	-0.030	0.016	-1.92	0.054
Year:Idaho	-0.023	0.014	-1.59	0.113
Year:Montana	-0.044	0.013	-3.38	0.001
Year:Nevada	-0.070	0.016	-4.41	< 0.001
Year:New Mexico	0.014	0.015	0.94	0.346
Year:Oregon	-0.034	0.013	-2.57	0.010
Year:Utah	-0.053	0.014	-3.84	< 0.001
Year:Washington	0.045	0.014	3.15	0.002
Year:Wyoming	0.047	0.018	2.6	0.009
Federally managed:Year:California	-0.015	0.015	-0.96	0.337
Federally managed:Year:Colorado	-0.065	0.019	-3.49	< 0.001
Federally managed:Year:Idaho	-0.052	0.017	-3.09	0.002
Federally managed:Year:Montana	-0.042	0.016	-2.65	0.008
Federally managed:Year:Nevada	-0.042	0.020	-2.11	0.035
Federally managed:Year:New Mexico	-0.131	0.018	-7.33	< 0.001
Federally managed:Year:Oregon	-0.054	0.016	-3.4	0.001
Federally managed:Year:Utah	-0.023	0.017	-1.38	0.168
Federally managed:Year:Washington	-0.049	0.017	-2.83	0.005
Federally managed:Year:Wyoming	-0.121	0.021	-5.72	< 0.001

Table S8. Coefficient estimates for year and the interaction between year and federal management, using dynamic panel (Arellano-Bond estimator) and fixed effect regression to account for time lags. Estimates presented are for the state-level models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

State	Model	Variable	
		Year	Federal management * Year
Arizona	Fixed effects	0.0002^{***} (0.0000)	0.0003^{***} (0.0000)
	Dynamic panels	-0.0003^{***} (0.0001)	0.0002^{**} (0.0001)
California	Fixed effects	0.0001^{***} (0.0000)	0.0004^{***} (0.0000)
	Dynamic panels	$1.88*10^{-5}$ (0.0000)	0.0006^{***} (0.0000)
Colorado	Fixed effects	0.0001^{***} (0.0000)	$6.30*10^{-5***}$ (0.0000)
	Dynamic panels	$2.03*10^{-5}$ (0.0000)	0.0001^{**} (0.0000)
Idaho	Fixed effects	0.0001^{***} ($1.40*10^{-5}$)	0.0001^{***} ($1.85*10^{-5}$)
	Dynamic panels	0.0001^{***} ($3.77*10^{-5}$)	$-1.76*10^{-5}$ ($4.79*10^{-5}$)
Montana	Fixed effects	0.0002^{***} ($1.41*10^{-5}$)	$9.86*10^{-5***}$ ($1.88*10^{-5}$)
	Dynamic panels	0.0004^{***} ($3.95*10^{-5}$)	$2.79*10^{-5}$ (5.02e-05)
Nevada	Fixed effects	0.0002^{***} ($4.58*10^{-5}$)	$-1.44*10^{-5}$ ($5.61*10^{-5}$)
	Dynamic panels	$-6.32*10^{-5}$ (0.000123)	0.0003^{**} (0.000148)
New Mexico	Fixed effects	0.0002^{***} ($1.34*10^{-5}$)	$-4.46*10^{-5**}$ ($1.78*10^{-5}$)
	Dynamic panels	$1.31*10^{-5}$ ($3.50*10^{-5}$)	$1.78*10^{-5}$ ($4.69*10^{-5}$)
Oregon	Fixed effects	$6.73*10^{-5***}$ ($8.89*10^{-6}$)	0.0001^{***} ($1.10*10^{-5}$)
	Dynamic panels	0.0001^{***} ($2.14*10^{-5}$)	$1.04*10^{-5}$ ($2.92*10^{-5}$)
Utah	Fixed effects	0.0001^{***} ($1.37*10^{-5}$)	$6.76*10^{-5***}$ ($1.78*10^{-5}$)
	Dynamic panels	0.0001^{***} ($3.84*10^{-5}$)	$8.61*10^{-5*}$ ($4.75*10^{-5}$)
Washington	Fixed effects	0.0002^{***}	$5.43*10^{-5***}$

		($1.18*10^{-5}$)	($1.60*10^{-5}$)
	Dynamic panels	0.0002^{***} ($3.22*10^{-5}$)	0.0001^{***} ($4.30*10^{-5}$)
Wyoming	Fixed effects	0.0003^{***} ($2.59*10^{-5}$)	$1.63*10^{-5}$ ($3.48*10^{-5}$)
	Dynamic panels	0.0008^{***} ($7.37*10^{-5}$)	-0.0002^{*} ($9.28*10^{-5}$)

Table S9. Regression results for state-level models, using year as a categorical variable. The estimated coefficient for each variable is each state is listed, with the standard error below the estimate in parenthesis and the level of significance (p-value) indicated with an asterisk: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Part 1 includes Arizona, California, Colorado, Idaho, Montana, and Nevada; Part 2 includes New Mexico, Oregon, Utah, Washington, and Wyoming.

Table S9, Part 1

Variable	Arizona	California	Colorado	Idaho	Montana	Nevada
Intercept	-12.576*** (1.016)	-4.702*** (0.297)	-7.742*** (1.051)	-2.147* (0.984)	-23.484 (622.691)	-16.389*** (2.578)
Federally managed	-0.044 (0.818)	0.906*** (0.223)	1.721 (1.081)	0.024 (0.342)	14.805 (622.691)	0.227 (1.417)
Elevation (km)	-0.891** (0.339)	-0.120*** (0.027)	-1.350*** (0.171)	0.917*** (0.134)	-0.234** (0.085)	-0.524 (0.357)
Slope	0.028*** (0.006)	0.026*** (0.001)	0.006 (0.004)	0.009* (0.004)	0.027*** (0.003)	0.016* (0.006)
Aspect	0.000 (0.000)	0.000** (0.000)	-0.001 (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.000 (0.000)
Distance to roads (km)	-0.003 (0.066)	0.138*** (0.012)	-0.052 (0.051)	0.149*** (0.016)	0.096*** (0.015)	0.136* (0.056)
Population density (1990)	-0.005 (0.006)	-0.005* (0.002)	-0.008 (0.007)	-0.041* (0.016)	-0.107*** (0.018)	-0.048 (0.029)
Average PDSI, winter		0.020 (0.012)		-0.168*** (0.027)	0.189*** (0.026)	-0.056 (0.069)
Average PDSI, spring			-0.191*** (0.036)			
Average PDSI, summer	-0.606*** (0.101)				-0.326*** (0.026)	0.173 (0.095)
Average PDSI, fall		-0.095*** (0.013)		-0.152*** (0.040)		
Maximum temperature, winter				0.465*** (0.043)	-0.141*** (0.019)	-0.392*** (0.082)
Maximum temperature, spring						

Maximum temperature, summer		-0.010* (0.005)		0.271*** (0.051)		0.014 (0.089)
Maximum temperature, fall				-0.387*** (0.069)	0.209*** (0.023)	0.602*** (0.136)
Minimum temperature, winter			0.043 (0.023)			
Minimum temperature, spring						
Minimum temperature, summer						
Minimum temperature, fall						
Average soil moisture, winter			-0.009 (0.006)			0.011 (0.009)
Average soil moisture, spring	-0.031 (0.017)					
Average soil moisture, summer			-0.044*** (0.011)			-0.203*** (0.042)
Average soil moisture, fall	-0.013 (0.018)		0.000 (0.008)			-0.020 (0.027)
Maximum wind speed, winter		-0.806*** (0.040)				
Maximum wind speed, spring (m/s)	2.429*** (0.270)					
Maximum wind speed, summer (m/s)	-1.985*** (0.333)					-0.676 (0.346)
Maximum wind speed, fall (m/s)	0.112 (0.318)	0.440*** (0.043)	0.396*** (0.094)	-1.562*** (0.110)	0.241*** (0.042)	0.637 (0.351)
Total precipitation, winter (cm)	0.076** (0.023)	0.008*** (0.001)	-0.230*** (0.025)	-0.066*** (0.011)		0.058** (0.020)
Total precipitation, spring (cm)	0.023 (0.053)	-0.041*** (0.002)	0.056** (0.019)	-0.010 (0.015)	-0.043*** (0.011)	-0.118*** (0.032)
Total precipitation, summer (cm)	0.001 (0.021)	-0.098*** (0.009)	0.016 (0.020)	-0.141*** (0.021)	-0.205*** (0.013)	-0.184*** (0.039)

Total precipitation, fall (cm)	0.012 (0.026)	0.009*** (0.002)	0.023 (0.018)		0.017 (0.010)	0.177*** (0.041)
Total precipitation, previous year (cm)	0.053*** (0.010)	-0.001	0.069***	0.000 (0.005)	-0.003 (0.003)	0.052*** (0.011)
Year 1990	0.571 (1.013)	1.389*** (0.208)	-17.156 (2007.487)	-18.735 (703.471)	14.614 (622.690)	-15.825 (3109.443)
Year 1991	-0.684 (0.952)	-0.588 (0.339)	-17.852 (1848.166)	-19.337 (705.937)	16.810 (622.690)	-15.935 (3075.089)
Year 1992	-13.334 (2708.172)	1.934*** (0.204)	-17.295 (1935.897)	-3.275*** (0.462)	14.870 (622.691)	-15.314 (3107.336)
Year 1993	-17.004 (2475.488)	0.479 (0.255)	-15.662 (1800.829)	-15.833 (800.062)	2.642 (871.468)	-16.959 (3018.144)
Year 1994	0.188 (0.788)	-0.377 (0.233)	-1.396 (1.430)	-4.434*** (0.563)	14.267 (622.690)	1.867 (1.411)
Year 1995	-17.611 (2583.673)	0.339 (0.408)	-17.129 (1787.295)	-16.556 (751.226)	1.648 (879.052)	1.609 (1.511)
Year 1996	-19.571 (2758.674)	0.789*** (0.224)	-1.542 (1.422)	-3.228*** (0.817)	15.377 (622.690)	1.458 (1.267)
Year 1997	-17.402 (2619.699)	-0.956** (0.305)	-16.221 (1833.184)	-14.605 (732.041)	0.863 (875.177)	-16.950 (3031.365)
Year 1998	-15.487 (2702.774)	-1.175* (0.539)	-17.253 (1936.023)	-17.343 (747.532)	17.422 (622.690)	1.326 (1.378)
Year 1999	-18.132 (2634.975)	1.199*** (0.220)	-17.585 (1888.627)	-16.984 (746.278)	15.063 (622.690)	2.627* (1.127)
Year 2000	-1.119 (0.967)	-0.253 (0.274)	0.702 (1.061)	-3.032*** (0.533)	17.432 (622.690)	5.886*** (1.211)
Year 2001	-17.102 (2815.329)	0.184 (0.230)	-16.761 (1975.060)	-2.370*** (0.576)	15.842 (622.690)	2.919** (1.055)
Year 2002	1.511* (0.678)	-0.875** (0.259)	2.753** (1.025)	-19.987 (761.266)	15.601 (622.690)	-16.062 (3208.687)
Year 2003	-0.148 (0.800)	2.313*** (0.207)	1.363 (1.107)	-3.292*** (0.470)	18.022 (622.690)	-14.391 (3085.848)
Year 2004	-18.106 (2777.324)	-0.224 (0.229)	0.174 (1.236)	-18.450 (765.276)	14.777 (622.690)	1.586 (1.205)
Year 2005	0.922	-1.070**	0.965	-3.417***	16.828	0.541

	(0.939)	(0.387)	(1.109)	(0.429)	(622.690)	(1.463)
Year 2006	-1.886 (1.195)	1.381*** (0.232)	-0.499 (1.135)	-1.399** (0.519)	17.710 (622.690)	2.728* (1.218)
Year 2007	0.166 (0.952)	1.103*** (0.209)	-16.425 (1945.101)	-1.648*** (0.394)	16.704 (622.690)	3.101** (1.140)
Year 2008	-0.965 (1.216)	1.370*** (0.204)	1.888 (1.159)	-2.780*** (0.514)	15.739 (622.690)	-16.934 (3193.309)
Year 2009	-2.697* (1.210)	0.380 (0.230)	0.110 (1.232)	-2.618** (0.770)	15.649 (622.690)	-15.179 (3101.530)
Year 2010	-17.344 (2747.685)	-1.187** (0.370)	0.403 (1.234)	-2.592** (0.773)	16.435 (622.690)	-17.514 (3145.919)
Year 2011	1.343* (0.682)	0.663* (0.258)	0.932 (1.101)	0.910 (0.476)	17.281 (622.690)	3.682** (1.106)
Year 2012	1.745* (0.709)	2.077*** (0.203)	3.168** (1.023)	-0.793* (0.357)	17.056 (622.690)	3.467** (1.101)
Year 2013	-0.209 (0.875)	0.642** (0.211)	3.015** (1.057)	-1.096** (0.395)	16.780 (622.690)	2.442* (1.134)
Year 2014	-18.204 (2742.056)	1.769*** (0.200)	-16.364 (1859.093)	-0.693 (0.355)	0.235 (896.281)	0.805 (1.447)
Year 2015	2.040* (0.973)	1.031*** (0.206)	-16.348 (1882.772)	-1.615*** (0.442)	14.148 (622.690)	-15.721 (3136.094)
Year 2016	-1.534 (0.951)	1.706*** (0.205)	1.948 (1.048)	-3.889*** (0.598)	15.591 (622.690)	0.809 (1.175)
Burned in previous year	0.248 (0.627)	-2.832*** (0.379)	-19.573 (7155.970)	-3.104** (1.005)	-3.208** (1.002)	-20.447 (6498.204)
Burned in previous 2 years	-1.502 (1.029)	-1.605*** (0.237)	-19.576 (6975.360)	-1.630** (0.586)	-0.855 (0.452)	-1.296 (1.017)
Burned in previous 5 years	0.228 (0.485)	-0.999*** (0.157)	-0.462 (1.016)	-1.259* (0.513)	-0.228 (0.341)	0.089 (0.522)
Federally managed * 1990	-17.347 (2612.305)	-0.983*** (0.251)	15.181 (2007.487)	-0.107 (998.240)	-15.086 (622.691)	-0.119 (4367.860)
Federally managed * 1991	-17.808 (2547.950)	-1.904** (0.572)	-1.815 (2598.631)	15.682 (705.937)	-15.517 (622.691)	0.012 (4336.177)
Federally managed * 1992	-0.054 (3790.496)	-1.962*** (0.255)	-1.737 (2726.555)	1.133** (0.421)	-14.835 (622.691)	17.451 (3107.336)

Federally managed * 1993	16.495 (2475.489)	-0.891** (0.310)	-1.850 (2524.824)	-0.044 (1126.584)	-14.983 (1063.631)	-0.362 (4164.149)
Federally managed * 1994	0.058 (0.941)	-0.047 (0.269)	0.029 (1.529)	2.065*** (0.550)	-13.318 (622.691)	-0.864 (1.874)
Federally managed * 1995	17.360 (2583.673)	0.464 (0.453)	-1.843 (2526.048)	-0.079 (1061.496)	-14.774 (1079.554)	0.433 (1.878)
Federally managed * 1996	18.531 (2758.674)	0.471 (0.254)	0.164 (1.515)	1.156 (0.872)	-15.220 (622.691)	0.146 (1.612)
Federally managed * 1997	0.057 (3664.000)	-0.022 (0.344)	-1.814 (2573.346)	-0.087 (1039.039)	-14.867 (1067.716)	-0.003 (4259.923)
Federally managed * 1998	-0.032 (3798.311)	0.100 (0.625)	-1.773 (2724.182)	14.164 (747.533)	-14.157 (622.691)	-0.853 (1.875)
Federally managed * 1999	16.766 (2634.975)	0.210 (0.245)	-1.802 (2651.731)	15.325 (746.279)	-17.117 (622.692)	0.395 (1.451)
Federally managed * 2000	0.816 (1.192)	0.057 (0.321)	-1.050 (1.141)	0.462 (0.399)	-14.045 (622.691)	-0.380 (1.447)
Federally managed * 2001	17.552 (2815.329)	-0.029 (0.268)	16.198 (1975.060)	0.661 (0.702)	-14.949 (622.691)	0.076 (1.452)
Federally managed * 2002	0.342 (0.878)	0.453 (0.295)	-0.512 (1.091)	-0.009 (1081.408)	-12.932 (622.691)	18.646 (3208.687)
Federally managed * 2003	0.750 (0.986)	-1.117*** (0.246)	-1.917 (1.273)	0.997* (0.450)	-14.416 (622.691)	-0.110 (4333.221)
Federally managed * 2004	18.440 (2777.324)	-0.601* (0.269)	-0.120 (1.330)	-0.024 (1085.687)	-14.345 (622.691)	0.115 (1.537)
Federally managed * 2005	0.676 (1.086)	1.036* (0.420)	-0.086 (1.187)	0.814 (0.451)	-14.044 (622.691)	2.544 (1.757)
Federally managed * 2006	1.897 (1.356)	-0.075 (0.261)	-19.247 (1930.032)	1.169* (0.513)	-14.759 (622.691)	0.160 (1.505)
Federally managed * 2007	0.810 (1.192)	-0.616* (0.242)	15.759 (1945.102)	1.087** (0.373)	-13.814 (622.691)	-0.471 (1.486)
Federally managed * 2008	2.014 (1.347)	0.254 (0.231)	0.225 (1.245)	-0.312 (0.731)	-15.587 (622.691)	17.941 (3193.309)
Federally managed * 2009	2.469 (1.328)	0.475 (0.264)	-0.001 (1.324)	-14.955 (774.900)	-15.296 (622.691)	16.536 (3101.531)

Federally managed * 2010	16.934 (2747.685)	-0.113 (0.442)	0.299 (1.316)	0.324 (0.975)	-13.241 (622.691)	0.064 (4411.855)
Federally managed * 2011	0.772 (0.839)	-1.304*** (0.347)	-1.314 (1.223)	-0.579 (0.655)	-13.342 (622.691)	-2.075 (1.516)
Federally managed * 2012	-1.433 (1.140)	-0.443 (0.238)	-1.273 (1.094)	0.678 (0.390)	-14.703 (622.691)	-0.203 (1.465)
Federally managed * 2013	1.443 (1.047)	0.164 (0.243)	-1.288 (1.130)	-0.133 (0.390)	-16.315 (622.691)	-0.539 (1.508)
Federally managed * 2014	18.636 (2742.056)	-0.801** (0.235)	-1.863 (2609.718)	0.819 (0.435)	-0.254 (896.282)	1.138 (1.829)
Federally managed * 2015	0.702 (0.961)	0.141 (0.237)	-1.770 (2636.079)	0.854 (0.370)	-13.514 (622.691)	-0.156 (4390.391)
Federally managed * 2016	1.852 (1.120)	-0.183 (0.240)	-1.209 (1.114)	1.782 (0.640)	-14.650 (622.691)	1.422 (1.491)

Table S9, Part 2

Variable	New Mexico	Oregon	Utah	Washington	Wyoming
Intercept	-26.226 (784.770)	-11.802*** (0.838)	-8.657*** (0.645)	-39.042 (991.169)	-22.887 (1380.616)
Federally managed	16.731 (784.770)	-0.287 (0.466)	0.340 (0.528)	0.378 (1389.035)	-0.015 (1950.785)
Elevation (km)	-0.876*** (0.166)	-0.667*** (0.114)	-0.437** (0.160)	0.994*** (0.189)	0.164 (0.229)
Slope	0.007* (0.004)	0.017*** (0.003)	0.012** (0.004)	0.020*** (0.003)	0.033*** (0.005)
Aspect	-0.001* (0.000)	0.000* (0.000)	0.000 (0.000)	0.004*** (0.001)	-0.001 (0.000)
Distance to roads (km)	0.197*** (0.018)	0.517*** (0.031)	0.010 (0.058)	0.244*** (0.043)	0.164*** (0.032)
Population density (1990)	-0.012 (0.008)	-0.065** (0.022)	-0.031 (0.036)	-0.024* (0.011)	-0.014 (0.033)
Average PDSI, winter		0.599*** (0.023)		-0.773*** (0.041)	-0.220*** (0.056)
Average PDSI, spring					
Average PDSI, summer	-0.473*** (0.042)	-0.449*** (0.023)	-0.391*** (0.046)	-0.143*** (0.040)	0.040 (0.057)
Average PDSI, fall					
Maximum temperature, winter			-0.013 (0.037)		0.244*** (0.048)
Maximum temperature, spring		-0.527*** (0.046)			
Maximum temperature, summer		0.586*** (0.031)		0.881*** (0.059)	
Maximum temperature, fall		-0.021 (0.037)		-1.138*** (0.073)	
Minimum temperature, winter					

Minimum temperature, spring					
Minimum temperature, summer					
Minimum temperature, fall			0.339*** (0.035)		0.016 (0.062)
Average soil moisture, winter	0.028*** (0.003)		0.001 (0.004)		0.030* (0.012)
Average soil moisture, spring					
Average soil moisture, summer	0.008 (0.007)				
Average soil moisture, fall			-0.027** (0.009)		0.008 (0.019)
Maximum wind speed, winter		0.022 (0.119)			
Maximum wind speed, spring (m/s)	0.949*** (0.161)	-0.655*** (0.129)			
Maximum wind speed, summer (m/s)	-1.023*** (0.163)	1.477*** (0.121)	-0.197 (0.234)	1.362*** (0.123)	
Maximum wind speed, fall (m/s)	-0.379* (0.170)	-0.724*** (0.150)	0.408* (0.187)	1.744*** (0.179)	0.099 (0.132)
Total precipitation, winter (cm)	0.031* (0.013)		0.030 (0.019)		-0.111** (0.040)
Total precipitation, spring (cm)	-0.090*** (0.019)		0.059** (0.020)		-0.273*** (0.027)
Total precipitation, summer (cm)	0.146*** (0.014)	-0.220*** (0.016)	-0.008 (0.017)	-0.308*** (0.028)	0.106*** (0.024)
Total precipitation, fall (cm)	-0.022 (0.015)	-0.003 (0.003)	-0.036 (0.020)	-0.028*** (0.009)	-0.133*** (0.033)
Total precipitation, previous year (cm)	0.034*** (0.005)		0.011 (0.007)		0.037* (0.014)
Year 1990	2.013 (1138.571)	-2.509* (1.053)	-1.765* (0.832)	14.702 (991.168)	-0.292 (1947.819)
Year 1991	-0.106	-14.687	-14.799	1.445	0.372

	(1070.241)	(298.242)	(513.712)	(1359.905)	(1923.403)
Year 1992	2.995 (1112.117)	-0.502 (0.455)	0.016 (0.624)	-2.011 (1414.970)	-2.660 (1914.322)
Year 1993	15.859 (784.770)	-11.411 (277.929)	0.454 (1.131)	4.224 (1427.686)	0.287 (1914.280)
Year 1994	17.223 (784.770)	-2.805*** (0.440)	0.976 (0.537)	15.433 (991.168)	-0.406 (1960.838)
Year 1995	1.282 (1127.264)	0.479 (0.663)	1.623* (0.653)	3.190 (1413.304)	0.793 (1967.470)
Year 1996	13.066 (784.770)	-3.737*** (0.493)	1.486** (0.523)	0.900 (1435.885)	17.131 (1380.616)
Year 1997	16.554 (784.770)	-16.199 (291.898)	1.752** (0.584)	21.091 (991.168)	-0.129 (1947.328)
Year 1998	17.262 (784.770)	-16.711 (309.879)	0.311 (1.121)	20.861 (991.168)	-0.832 (1965.247)
Year 1999	15.069 (784.770)	-4.609*** (0.691)	0.912 (0.707)	3.883 (1393.897)	15.461 (1380.616)
Year 2000	17.999 (784.770)	-2.072*** (0.431)	1.574** (0.520)	11.533 (991.168)	15.938 (1380.616)
Year 2001	16.009 (784.770)	-1.290** (0.421)	0.672 (0.506)	15.758 (991.168)	16.824 (1380.615)
Year 2002	18.403 (784.770)	0.054 (0.349)	1.723** (0.501)	13.947 (991.168)	16.193 (1380.615)
Year 2003	16.503 (784.770)	-3.049*** (0.567)	0.191 (0.580)	12.007 (991.168)	-0.513 (1968.861)
Year 2004	18.980 (784.770)	-2.661*** (0.670)	0.621 (0.599)	14.378 (991.168)	15.152 (1380.616)
Year 2005	2.834 (1126.788)	-0.987* (0.460)	1.715** (0.623)	13.564 (991.168)	15.417 (1380.616)
Year 2006	14.601 (784.770)	-1.326** (0.419)	2.401*** (0.512)	19.210 (991.168)	17.646 (1380.615)
Year 2007	17.413 (784.770)	-1.270** (0.386)	2.047*** (0.440)	15.967 (991.168)	16.542 (1380.615)
Year 2008	17.230 (784.770)	-2.864*** (0.425)	-14.891 (522.610)	17.063 (991.168)	1.070 (1952.345)

Year 2009	0.828 (1137.631)	-1.782** (0.661)	0.859 (0.547)	13.054 (991.168)	14.143 (1380.616)
Year 2010	1.503 (1125.163)	1.199** (0.394)	-0.199 (0.721)	-0.002 (1424.234)	17.535 (1380.616)
Year 2011	19.234 (784.770)	-2.940*** (0.790)	0.024 (1.116)	20.544 (991.168)	18.005 (1380.616)
Year 2012	18.563 (784.770)	0.372 (0.375)	2.447*** (0.467)	19.155 (991.168)	19.156 (1380.615)
Year 2013	18.831 (784.770)	-1.225** (0.361)	0.548 (0.550)	16.583 (991.168)	1.218 (1968.005)
Year 2014	15.051 (784.770)	1.392*** (0.336)	-0.533 (0.714)	17.614 (991.168)	-0.149 (1972.621)
Year 2015	1.879 (1130.562)	-1.488*** (0.363)	-15.699 (499.340)	16.466 (991.168)	16.223 (1380.616)
Year 2016	17.908 (784.770)	-1.597** (0.476)	-0.334 (0.551)	16.367 (991.168)	18.395 (1380.615)
Burned in previous year	-18.495 (1884.342)	-3.056*** (0.711)	-0.704 (0.589)	-20.529 (2836.608)	-18.859 (2609.595)
Burned in previous 2 years	0.116 (0.291)	-2.443*** (0.582)	-0.385 (0.587)	-1.003 (0.511)	-17.269 (2758.820)
Burned in previous 5 years	-0.717 (0.513)	-0.123 (0.225)	-1.287 (0.714)	-18.700 (4363.025)	-18.622 (3597.360)
Federally managed * 1990	-1.680 (1138.571)	2.816* (1.135)	-0.027 (1.054)	-15.066 (1688.436)	-0.142 (2747.514)
Federally managed * 1991	-2.445 (1070.241)	14.409 (298.242)	-0.316 (726.088)	16.307 (1672.229)	0.060 (2725.115)
Federally managed * 1992	-1.255 (1112.117)	1.741** (0.560)	-1.975 (1.216)	15.595 (1717.307)	15.298 (2358.832)
Federally managed * 1993	-14.612 (784.770)	0.299 (394.583)	-13.852 (516.184)	-0.224 (2006.295)	-0.069 (2698.201)
Federally managed * 1994	-14.885 (784.770)	0.650 (0.562)	-0.691 (0.641)	-0.080 (1389.035)	16.771 (2396.737)
Federally managed * 1995	-0.682 (1127.264)	-13.051 (285.131)	-0.690 (0.788)	-0.796 (1981.313)	-0.048 (2773.367)

Federally managed * 1996	-13.351 (784.770)	3.180*** (0.579)	-0.346 (0.595)	16.558 (1734.581)	1.038 (1950.785)
Federally managed * 1997	-16.749 (784.771)	12.665 (291.900)	-2.488* (1.184)	-14.402 (1629.667)	16.814 (2385.697)
Federally managed * 1998	-15.563 (784.770)	12.697 (309.880)	-13.857 (510.351)	-2.056 (1389.035)	-0.048 (2773.244)
Federally managed * 1999	-15.663 (784.770)	1.948* (0.783)	-1.139 (1.014)	15.244 (1699.987)	-0.724 (1950.785)
Federally managed * 2000	-15.246 (784.770)	2.016*** (0.548)	-0.092 (0.601)	1.900 (1389.036)	2.495 (1950.785)
Federally managed * 2001	-14.516 (784.770)	0.777 (0.568)	-0.231 (0.650)	0.539 (1389.035)	0.491 (1950.785)
Federally managed * 2002	-15.687 (784.770)	1.138* (0.474)	0.415 (0.575)	-0.619 (1389.035)	1.074 (1950.785)
Federally managed * 2003	-13.778 (784.770)	2.818*** (0.658)	0.912 (0.661)	0.728 (1389.035)	18.625 (2403.305)
Federally managed * 2004	-14.971 (784.770)	3.041*** (0.756)	0.662 (0.689)	0.024 (1389.035)	-16.140 (2386.338)
Federally managed * 2005	-1.664 (1126.788)	2.025** (0.589)	0.519 (0.693)	1.044 (1389.035)	0.914 (1950.785)
Federally managed * 2006	-17.075 (784.770)	0.755 (0.526)	-0.736 (0.597)	-1.164 (1389.035)	0.698 (1950.785)
Federally managed * 2007	-16.075 (784.770)	1.954*** (0.503)	-0.597 (0.558)	0.711 (1389.035)	0.447 (1950.785)
Federally managed * 2008	-16.393 (784.770)	-0.034 (0.591)	14.237 (522.611)	0.417 (1389.035)	17.912 (2389.793)
Federally managed * 2009	0.444 (1137.631)	2.426** (0.766)	1.276* (0.623)	-1.307 (1389.036)	-15.499 (2395.051)
Federally managed * 2010	-0.371 (1125.163)	0.516 (0.551)	0.872 (0.839)	15.883 (1724.949)	0.033 (1950.785)
Federally managed * 2011	-16.625 (784.770)	3.901*** (0.855)	0.382 (1.334)	-17.047 (1730.858)	2.212 (1950.785)
Federally managed * 2012	-16.475 (784.770)	2.024*** (0.513)	-0.251 (0.544)	-0.203 (1389.035)	0.103 (1950.785)

Federally managed * 2013	-17.837 (784.770)	0.394 (0.484)	0.283 (0.667)	0.159 (1389.035)	15.449 (2402.604)
Federally managed * 2014	-15.208 (784.770)	0.761 (0.482)	-0.385 (0.972)	-0.484 (1389.035)	-0.041 (2775.419)
Federally managed * 2015	-0.085 (1130.562)	1.048* (0.478)	14.042	-0.106 (1389.035)	-15.476 (2369.186)
Federally managed * 2016	-16.833 (784.770)	0.252 (0.674)	0.371	1.441 (1389.035)	-1.145 (1950.785)

Table S10. Regression results for all-state model, using 5-year bins rather than annual data.

Variable	Estimate	Standard error	z value	p-value
Intercept	-6.007	0.349	-17.233	< 0.001
Federally managed	-0.047	0.398	-0.117	0.907
Elevation (km)	-0.102	0.025	-4.058	< 0.001
Slope	0.024	0.001	31.539	< 0.001
Aspect	0.001	0.000	8.990	< 0.001
Distance to roads (km)	0.164	0.006	25.528	< 0.001
Population density (1990)	-0.015	0.002	-6.658	< 0.001
Average PDSI, summer	-0.001	0.000	-22.120	< 0.001
Average maximum temperature, fall	0.005	0.000	11.166	< 0.001
Average maximum wind speed, summer	-0.001	0.000	-2.955	0.003
Total precipitation, fall	-0.004	0.000	-38.142	0
Total precipitation, summer	-0.005	0.000	-15.883	< 0.001
Year (bin)	0.237	0.059	4.028	< 0.001
Burned in previous 5-year bin	-0.463	0.043	-10.887	< 0.001

California	1.143	0.320	3.570	< 0.001
Colorado	-1.052	0.405	-2.600	0.009
Idaho	0.309	0.359	0.860	0.390
Montana	1.588	0.330	4.810	< 0.001
Nevada	0.809	0.398	2.032	0.042
New Mexico	-0.744	0.379	-1.962	0.050
Oregon	-0.162	0.340	-0.476	0.634
Utah	0.542	0.350	1.549	0.121
Washington	-1.015	0.369	-2.747	0.006
Wyoming	-0.965	0.446	-2.162	0.031
Federally managed:Year	0.135	0.073	1.848	0.065
Federally managed:California	0.332	0.404	0.823	0.410
Federally managed:Colorado	1.717	0.494	3.476	0.001
Federally managed:Idaho	1.156	0.447	2.588	0.010
Federally managed:Montana	0.642	0.415	1.548	0.122
Federally managed:Nevada	0.117	0.520	0.226	0.821
Federally managed:New Mexico	2.519	0.466	5.409	< 0.001
Federally managed:Oregon	1.658	0.423	3.918	< 0.001

Federally managed:Utah	-0.017	0.447	-0.037	0.970
Federally managed:Washington	0.218	0.471	0.463	0.644
Federally managed:Wyoming	2.185	0.541	4.040	< 0.001
Year:California	-0.149	0.060	-2.501	0.012
Year:Colorado	0.076	0.075	1.015	0.310
Year:Idaho	-0.018	0.066	-0.275	0.783
Year:Montana	-0.113	0.062	-1.840	0.066
Year:Nevada	-0.139	0.075	-1.848	0.065
Year:New Mexico	0.177	0.069	2.553	0.011
Year:Oregon	0.016	0.063	0.256	0.798
Year:Utah	-0.140	0.066	-2.129	0.033
Year:Washington	0.327	0.066	4.934	< 0.001
Year:Wyoming	0.263	0.080	3.293	0.001
Federally managed:Year:California	-0.053	0.074	-0.717	0.473
Federally managed:Year:Colorado	-0.287	0.091	-3.144	0.002
Federally managed:Year:Idaho	-0.201	0.082	-2.453	0.014
Federally managed:Year:Montana	-0.157	0.077	-2.048	0.041

Federally managed:Year:Nevada	-0.150	0.098	-1.534	0.125
Federally managed:Year:New Mexico	-0.485	0.085	-5.704	< 0.001
Federally managed:Year:Oregon	-0.248	0.078	-3.185	0.001
Federally managed:Year:Utah	-0.064	0.083	-0.768	0.442
Federally managed:Year:Washington	-0.136	0.084	-1.610	0.107
Federally managed:Year:Wyoming	-0.438	0.098	-4.485	< 0.001

Table S11. Regression model results of annual burn data across all eleven western states, with the x and y coordinates each sample point included as potential predictor variables. Longitude was not included as a predictor variable because it was highly correlated with elevation (Pearson's correlation coefficient = 0.74).

Variable	Coefficient	Standard error	z value	p value
Intercept	-163.754	26.491	-6.181	< 0.001
Federally managed	-65.845	33.320	-1.976	0.048
Elevation (km)	-0.130	0.025	-5.229	< 0.001
Slope	0.022	0.001	28.566	< 0.001
Aspect	0.000	0.00	6.921	< 0.001
Distance to roads (km)	0.168	0.006	26.510	< 0.001
Population density (1990)	-0.015	0.002	-6.460	< 0.001
Average PDSI, summer	-0.224	0.004	-59.507	< 0.001
Average PDSI, winter	0.075	0.004	19.594	< 0.001
Average maximum temperature, fall (˚C)	-0.082	0.006	-14.191	< 0.001
Average maximum temperature, summer (˚C)	0.137	0.004	35.369	< 0.001
Average maximum wind speed, summer (m/s)	0.124	0.016	7.863	< 0.001
Total precipitation, fall (cm)	-0.020	0.001	-24.596	< 0.001
Total precipitation, summer (cm)	-0.096	0.003	-35.382	< 0.001
Latitude	$-5.713*10^{-7}$	0.00	-11.557	< 0.001
Year	0.079	0.013	5.965	< 0.001
Burned in previous year	-2.839	0.243	-11.688	< 0.001
Burned in previous 2 years	-1.366	0.141	-9.706	< 0.001
Burned in previous 5 years	-0.755	0.103	-7.294	< 0.001
California	101.370	26.903	3.768	< 0.001
Colorado	-30.216	34.431	-0.878	0.380

Idaho	33.612	29.708	1.131	0.258
Montana	78.974	27.625	2.859	0.004
Nevada	102.463	33.390	3.069	0.002
New Mexico	-91.152	32.267	-2.825	0.005
Oregon	36.046	28.290	1.274	0.203
Utah	67.969	29.477	2.306	0.021
Washington	-79.436	29.627	-2.681	0.007
Wyoming	-113.404	37.623	-3.014	0.003
Federally managed:Year	0.033	0.017	1.995	0.046
Federally managed:California	29.241	33.816	0.865	0.387
Federally managed:Colorado	150.655	41.849	3.600	< 0.001
Federally managed:Idaho	102.240	36.966	2.766	0.006
Federally managed:Montana	83.083	34.756	2.390	0.017
Federally managed:Nevada	77.791	43.540	1.787	0.074
Federally managed:New Mexico	271.575	39.267	6.916	< 0.001
Federally managed:Oregon	120.514	35.220	3.422	0.001
Federally managed:Utah	39.020	37.534	1.040	0.299
Federally managed:Washington	64.188	37.863	1.695	0.090
Federally managed:Wyoming	230.874	45.470	5.078	< 0.001
Year:California	-0.050	0.013	-3.752	< 0.001
Year:Colorado	0.015	0.017	0.853	0.394
Year:Idaho	-0.017	0.015	-1.122	0.262
Year:Montana	-0.039	0.014	-2.821	0.005
Year:Nevada	-0.051	0.017	-3.071	0.002
Year:New Mexico	0.045	0.016	2.826	0.005
Year:Oregon	-0.018	0.014	-1.270	0.204
Year:Utah	-0.034	0.015	-2.321	0.020
Year:Washington	0.040	0.015	2.713	0.007

Year:Wyoming	0.056	0.019	3.016	0.003
Federally managed:Year:California	-0.015	0.017	-0.863	0.388
Federally managed:Year:Colorado	-0.075	0.021	-3.594	< 0.001
Federally managed:Year:Idaho	-0.051	0.018	-2.762	0.006
Federally managed:Year:Montana	-0.041	0.017	-2.395	0.017
Federally managed:Year:Nevada	-0.039	0.022	-1.802	0.072
Federally managed:Year:New Mexico	-0.135	0.020	-6.916	< 0.001
Federally managed:Year:Oregon	-0.060	0.018	-3.411	< 0.001
Federally managed:Year:Utah	-0.020	0.019	-1.049	0.294
Federally managed:Year:Washington	-0.032	0.019	-1.708	0.088
Federally managed:Year:Wyoming	-0.115	0.023	-5.080	< 0.001

Table S12. Regression model results of annual burn data across all eleven western states.

Variable	Coefficient	Standard error	z value	p-value
Intercept	-164.774	26.478	-6.223	< 0.001
Federally managed	-65.596	33.322	-1.969	0.049
Elevation (km)	-0.037	0.023	-1.569	0.117
Slope	0.023	0.001	30.088	< 0.001
Aspect	0.000	0.000	7.311	< 0.001
Distance to roads (km)	0.168	0.006	26.494	< 0.001
Population density (1990)	-0.014	0.002	-6.173	< 0.001
Average PDSI, summer	-0.223	0.004	-59.224	< 0.001
Average PDSI, winter	0.072	0.004	18.830	< 0.001
Average maximum temperature, fall (˚C)	-0.044	0.005	-9.282	< 0.001
Average maximum temperature, summer (˚C)	0.121	0.004	33.302	< 0.001
Average maximum wind speed, summer (m/s)	0.181	0.015	12.041	< 0.001
Total precipitation, fall (cm)	-0.022	0.001	-26.825	< 0.001
Total precipitation, summer (cm)	-0.103	0.003	-38.185	< 0.001
Year	0.078	0.013	5.898	< 0.001
Burned in previous year	-2.839	0.243	-11.687	< 0.001
Burned in previous 2 years	-1.356	0.141	-9.630	< 0.001
Burned in previous 5 years	-0.738	0.103	-7.131	< 0.001
California	101.153	26.885	3.762	< 0.001
Colorado	-21.508	34.285	-0.627	0.530
Idaho	35.675	29.671	1.202	0.229
Montana	80.546	27.597	2.919	0.004
Nevada	102.953	33.332	3.089	0.002

New Mexico	-87.233	32.318	-2.699	0.007
Oregon	35.107	28.272	1.242	0.214
Utah	71.152	29.411	2.419	0.016
Washington	-81.452	29.608	-2.751	0.006
Wyoming	-103.212	37.440	-2.757	0.006
Federally managed:Year	0.033	0.017	1.987	0.047
Federally managed:California	29.416	33.812	0.870	0.384
Federally managed:Colorado	148.514	41.697	3.562	< 0.001
Federally managed:Idaho	101.534	36.938	2.749	0.006
Federally managed:Montana	82.458	34.738	2.374	0.018
Federally managed:Nevada	77.704	43.469	1.788	0.074
Federally managed:New Mexico	271.312	39.310	6.902	< 0.001
Federally managed:Oregon	120.021	35.216	3.408	0.001
Federally managed:Utah	39.414	37.462	1.052	0.293
Federally managed:Washington	63.901	37.857	1.688	0.091
Federally managed:Wyoming	227.126	45.273	5.017	< 0.001
Year:California	-0.050	0.013	-3.755	< 0.001
Year:Colorado	0.010	0.017	0.598	0.550
Year:Idaho	-0.018	0.015	-1.205	0.228
Year:Montana	-0.040	0.014	-2.897	0.004
Year:Nevada	-0.052	0.017	-3.100	0.002
Year:New Mexico	0.043	0.016	2.700	0.007
Year:Oregon	-0.018	0.014	-1.251	0.211
Year:Utah	-0.036	0.015	-2.440	0.015
Year:Washington	0.041	0.015	2.767	0.006
Year:Wyoming	0.051	0.019	2.749	0.006
Federally managed:Year:California	-0.015	0.017	-0.868	0.385

Federally managed:Year:Colorado	-0.074	0.021	-3.555	< 0.001
Federally managed:Year:Idaho	-0.051	0.018	-2.745	0.006
Federally managed:Year:Montana	-0.041	0.017	-2.378	0.017
Federally managed:Year:Nevada	-0.039	0.022	-1.802	0.072
Federally managed:Year:New Mexico	-0.135	0.020	-6.901	< 0.001
Federally managed:Year:Oregon	-0.060	0.018	-3.397	0.001
Federally managed:Year:Utah	-0.020	0.019	-1.061	0.289
Federally managed:Year:Washington	-0.032	0.019	-1.700	0.089
Federally managed:Year:Wyoming	-0.113	0.023	-5.019	< 0.001

Figure S2. Predicted probability of burning for federally managed and private, unprotected forests in each state, using state-level regression models. Note that the y-axis ranges differ across the plots.

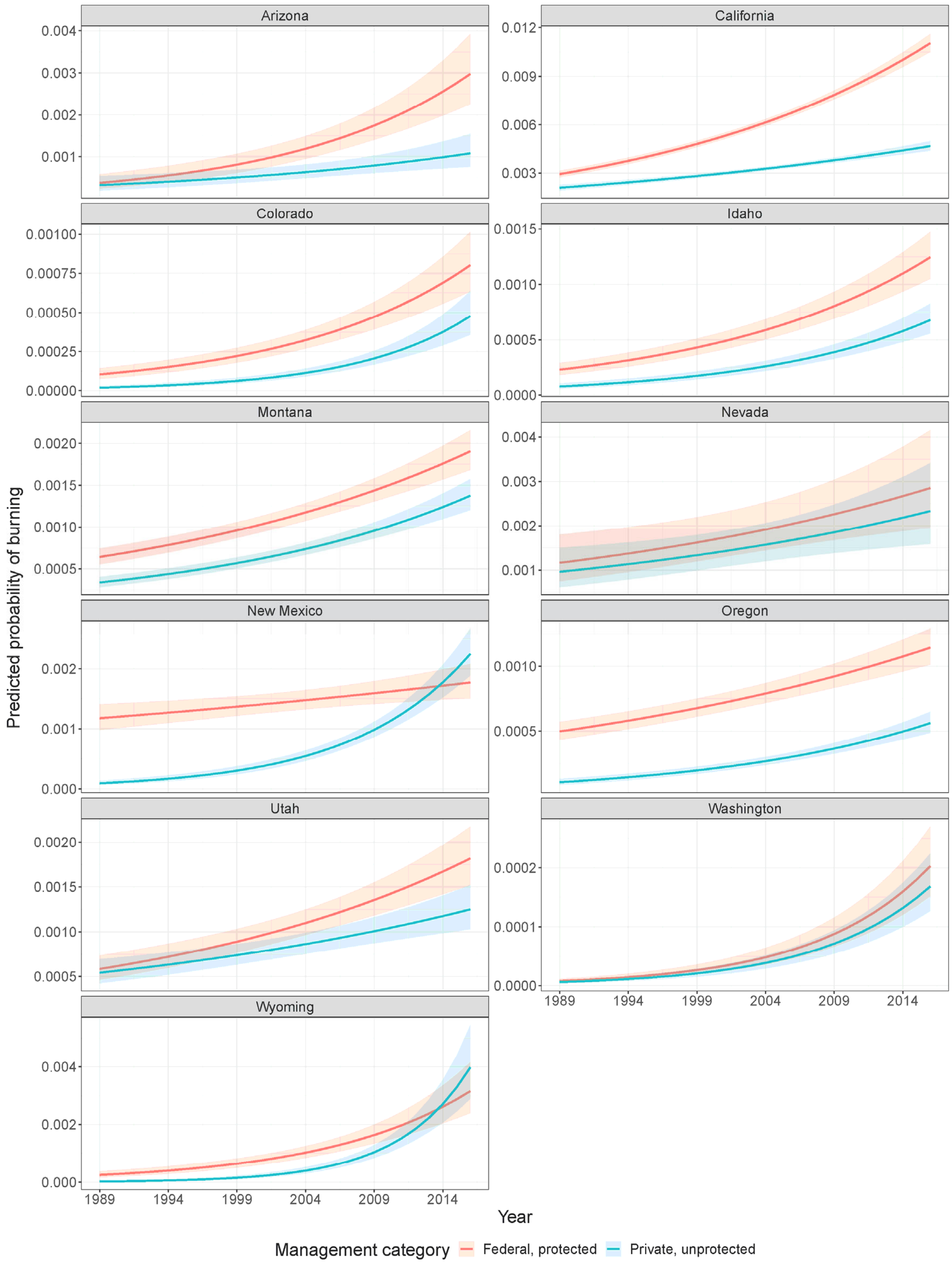


Table S13. Logistic regression model results for the Arizona model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-102.587	26.696	-3.843	< 0.001
Federally managed	-63.149	32.875	-1.921	0.055
Elevation (km)	-0.684	0.309	-2.210	0.027
Slope	0.034	0.006	5.985	< 0.001
Aspect	0.000	0.000	0.700	0.484
Distance to roads (km)	-0.022	0.066	-0.338	0.735
Population density (1990)	-0.006	0.006	-1.059	0.289
Average PDSI, summer	-0.536	0.073	-7.307	< 0.001
Average soil moisture, fall (mm)	-0.042	0.014	-2.918	0.004
Average soil moisture, spring (mm)	-0.037	0.015	-2.364	0.018
Maximum wind speed, fall (m/s)	-0.372	0.210	-1.775	0.076
Maximum wind speed, spring (m/s)	2.062	0.189	10.935	< 0.001
Maximum wind speed, summer (m/s)	-1.084	0.206	-5.249	< 0.001
Total precipitation, fall (cm)	0.102	0.014	7.452	< 0.001
Total precipitation, spring (cm)	-0.074	0.034	-2.164	0.030
Total precipitation, summer (cm)	0.006	0.015	0.425	0.671
Total precipitation, winter (cm)	0.099	0.013	7.581	< 0.001
Total precipitation, previous year (cm)	0.036	0.005	7.772	< 0.001

Year	0.045	0.013	3.353	0.001
Burned in previous year	0.423	0.605	0.699	0.485
Burned in previous 2 years	-1.761	1.011	-1.743	0.081
Burned in previous 5 years	-0.148	0.434	-0.341	0.733
Federally managed:Year	0.032	0.016	1.943	0.052

Table S14. Logistic regression model results for the California model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-64.782	4.902	-13.216	< 0.001
Federally managed	-38.419	5.881	-6.532	< 0.001
Elevation (km)	-0.090	0.026	-3.517	< 0.001
Slope	0.026	0.001	22.881	< 0.001
Aspect	0.000	0.000	2.487	0.013
Distance to roads (km)	0.143	0.012	12.339	< 0.001
Population density (1990)	-0.005	0.002	-2.548	0.011
Average PDSI, fall	-0.201	0.008	-23.995	< 0.001
Average PDSI, winter	0.045	0.008	5.915	< 0.001
Maximum temperature, summer (˚C)	0.014	0.004	3.164	0.002
Maximum wind speed, fall (m/s)	0.079	0.038	2.090	0.037
Maximum wind speed, winter (m/s)	-0.348	0.035	-10.011	< 0.001
Total precipitation, fall (cm)	-0.001	0.001	-0.859	0.390
Total precipitation, spring (cm)	-0.016	0.001	-12.577	< 0.001
Total precipitation, summer (cm)	-0.117	0.007	-15.875	< 0.001
Total precipitation, winter (cm)	0.006	0.001	9.504	< 0.001
Total precipitation, previous year (cm)	-0.003	0.000	-6.174	< 0.001
Burned in previous year	-2.911	0.378	-7.692	< 0.001
Burned in previous 2 years	-1.649	0.237	-6.968	< 0.001

Burned in previous 5 years	-1.059	0.156	-6.793	< 0.001
Year	0.030	0.002	12.199	< 0.001
Federally managed:Year	0.019	0.003	6.647	< 0.001

Table S15. Logistic regression model results for the Colorado model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-248.201	25.360	-9.787	< 0.001
Federally managed	89.754	26.548	3.381	0.001
Elevation (km)	-1.460	0.161	-9.046	< 0.001
Slope	0.007	0.004	1.715	0.086
Aspect	-0.001	0.000	-1.859	0.063
Distance to roads (km)	-0.108	0.051	-2.131	0.033
Population density (1990)	-0.005	0.007	-0.734	0.463
Average PDSI, spring	-0.282	0.026	-10.995	< 0.001
Average soil moisture, fall (mm)	0.001	0.008	0.179	0.858
Average soil moisture, summer (mm)	-0.044	0.011	-3.943	< 0.001
Average soil moisture, winter (mm)	-0.006	0.006	-1.124	0.261
Minimum temperature, winter (°C)	-0.018	0.019	-0.922	0.356
Maximum wind speed, fall (m/s)	1.059	0.078	13.656	< 0.001
Total precipitation, fall (cm)	0.080	0.012	6.551	< 0.001
Total precipitation, spring (cm)	-0.057	0.017	-3.410	0.001
Total precipitation, summer (cm)	-0.156	0.011	-13.889	< 0.001
Total precipitation, winter (cm)	-0.274	0.020	-13.483	< 0.001
Total precipitation, previous year (cm)	0.072	0.005	15.869	< 0.001

Year	0.120	0.013	9.536	< 0.001
Burned in previous 5 years	-0.180	1.024	-0.176	0.860
Federally managed:Year	-0.044	0.013	-3.347	0.001

Table S16. Logistic regression model results for the Idaho model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-168.654	14.169	-11.903	< 0.001
Federally managed	35.460	16.115	2.200	0.028
Elevation (km)	1.064	0.121	8.761	< 0.001
Slope	0.007	0.003	1.973	0.048
Aspect	0.002	0.000	7.960	< 0.001
Distance to roads (km)	0.166	0.016	10.627	< 0.001
Population density (1990)	-0.042	0.016	-2.606	0.009
Average PDSI, fall	-0.191	0.027	-7.085	< 0.001
Average PDSI, winter	-0.019	0.020	-0.950	0.342
Maximum temperature, fall (˚C)	-0.281	0.025	-11.396	< 0.001
Maximum temperature, summer (˚C)	0.328	0.027	12.173	< 0.001
Maximum temperature, winter (˚C)	0.337	0.021	15.703	< 0.001
Maximum wind speed, fall (m/s)	-1.339	0.097	-13.806	< 0.001
Total precipitation, spring (cm)	-0.042	0.009	-4.848	< 0.001
Total precipitation, summer (cm)	-0.115	0.013	-8.579	< 0.001
Total precipitation, winter (cm)	-0.076	0.005	-13.895	< 0.001
Total precipitation, previous year (cm)	0.015	0.003	5.281	< 0.001
Year	0.080	0.007	11.321	< 0.001
Burned in previous year	-3.094	1.003	-3.083	0.002

Burned in previous 2 years	-1.768	0.582	-3.038	0.002
Burned in previous 5 years	-1.059	0.508	-2.084	0.037
Federally managed:Year	-0.017	0.008	-2.153	0.031

Table S17. Logistic regression model results for the Montana model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-105.978	9.348	-11.337	< 0.001
Federally managed	23.876	10.719	2.227	0.026
Elevation (km)	-0.978	0.071	-13.844	< 0.001
Slope	0.041	0.003	14.891	< 0.001
Aspect	0.001	0.000	5.676	< 0.001
Distance to roads (km)	0.107	0.015	7.012	< 0.001
Population density (1990)	-0.112	0.018	-6.106	< 0.001
Average PDSI, winter	-0.051	0.015	-3.476	0.001
Average PDSI, summer	-0.182	0.017	-10.591	< 0.001
Maximum temperature, fall (˚C)	-0.076	0.014	-5.313	< 0.001
Maximum temperature, winter (˚C)	0.034	0.014	2.430	0.015
Maximum wind speed, fall (m/s)	0.363	0.033	10.954	< 0.001
Total precipitation, fall (cm)	-0.110	0.008	-14.294	< 0.001
Total precipitation, spring (cm)	0.017	0.009	2.002	0.045
Total precipitation, summer (cm)	-0.316	0.009	-37.016	< 0.001
Total precipitation, previous year (cm)	0.006	0.003	1.953	0.051
Year	0.052	0.005	11.103	< 0.001
Burned in previous year	-3.268	1.001	-3.263	0.001
Burned in previous 2 years	-1.230	0.450	-2.736	0.006

Burned in previous 5 years	-0.150	0.339	-0.444	0.657
Federally managed:Year	-0.012	0.005	-2.186	0.029

Table S18. Logistic regression model results for the Nevada model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-71.676	23.515	-3.048	0.002
Federally managed	-0.647	29.466	-0.022	0.982
Elevation (km)	-0.936	0.338	-2.769	0.006
Slope	0.017	0.006	2.728	0.006
Aspect	0.000	0.000	1.022	0.307
Distance to roads (km)	0.154	0.054	2.827	0.005
Population density (1990)	-0.058	0.032	-1.848	0.065
Average PDSI, winter	0.058	0.048	1.201	0.230
Average PDSI, summer	0.097	0.051	1.900	0.057
Average soil moisture, fall (mm)	-0.047	0.028	-1.697	0.090
Average soil moisture, summer (mm)	-0.162	0.038	-4.298	< 0.001
Average soil moisture, winter (mm)	0.004	0.007	0.593	0.553
Maximum temperature, fall (˚C)	0.071	0.055	1.298	0.194
Maximum temperature, winter (˚C)	-0.141	0.041	-3.433	0.001
Maximum temperature, summer (˚C)	0.109	0.048	2.276	0.023
Maximum wind speed, fall (m/s)	-0.624	0.220	-2.833	0.005
Maximum wind speed, summer (m/s)	0.091	0.186	0.490	0.624
Total precipitation, fall (cm)	0.016	0.025	0.639	0.523

Total precipitation, spring (cm)	-0.044	0.021	-2.128	0.033
Total precipitation, summer (cm)	-0.203	0.028	-7.332	< 0.001
Total precipitation, winter (cm)	0.020	0.013	1.535	0.125
Total precipitation, previous year (cm)	0.067	0.006	10.524	< 0.001
Year	0.033	0.012	2.770	0.006
Burned in previous 2 years	-0.655	1.007	-0.650	0.516
Burned in previous 5 years	0.004	0.516	0.008	0.993
Federally managed:Year	0.000	0.015	0.029	0.977

Table S19. Logistic regression model results for the New Mexico model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-246.735	18.194	-13.561	< 0.001
Federally managed	207.636	20.515	10.121	< 0.001
Elevation (km)	-0.896	0.146	-6.152	< 0.001
Slope	0.012	0.004	3.148	0.002
Aspect	-0.001	0.000	-2.205	0.027
Distance to roads (km)	0.195	0.018	10.834	< 0.001
Population density (1990)	-0.008	0.007	-1.154	0.248
Average PDSI, summer	-0.386	0.028	-13.820	< 0.001
Average soil moisture, summer (mm)	0.007	0.007	1.044	0.297
Average soil moisture, winter (mm)	0.028	0.003	8.969	< 0.001
Maximum wind speed, fall (m/s)	0.054	0.086	0.629	0.530
Maximum wind speed, summer (m/s)	-0.525	0.094	-5.605	< 0.001
Maximum wind speed, spring (m/s)	0.751	0.092	8.181	< 0.001
Total precipitation, fall (cm)	0.088	0.009	10.133	< 0.001
Total precipitation, spring (cm)	-0.090	0.015	-5.865	< 0.001
Total precipitation, summer (cm)	-0.017	0.008	-2.204	0.028
Total precipitation, winter (cm)	0.030	0.009	3.287	0.001
Total precipitation, previous year (cm)	0.027	0.003	9.544	< 0.001

Year	0.118	0.009	13.073	< 0.001
Burned in previous year	-14.187	264.427	-0.054	0.957
Burned in previous 2 years	0.073	0.298	0.245	0.807
Burned in previous 5 years	-0.636	0.514	-1.238	0.216
Federally managed:Year	-0.103	0.010	-10.096	< 0.001

Table S20. Logistic regression model results for the Oregon model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-133.519	10.828	-12.331	< 0.001
Federally managed	62.988	12.018	5.241	< 0.001
Elevation (km)	-0.672	0.082	-8.201	< 0.001
Slope	0.022	0.002	9.003	< 0.001
Aspect	0.000	0.000	-2.129	0.033
Distance to roads (km)	0.506	0.030	16.711	< 0.001
Population density (1990)	-0.049	0.020	-2.442	0.015
Average PDSI, winter	0.319	0.013	24.423	< 0.001
Average PDSI, summer	-0.346	0.015	-23.772	< 0.001
Maximum temperature, fall (˚C)	-0.034	0.018	-1.925	0.054
Maximum temperature, spring (˚C)	-0.472	0.022	-21.581	< 0.001
Maximum temperature, summer (˚C)	0.478	0.021	22.456	< 0.001
Maximum wind speed, fall (m/s)	-1.586	0.094	-16.796	< 0.001
Maximum wind speed, spring (m/s)	0.503	0.073	6.905	< 0.001
Maximum wind speed, summer (m/s)	1.379	0.089	15.510	< 0.001
Maximum wind speed, winter (m/s)	-0.722	0.066	-10.872	< 0.001
Total precipitation, fall (cm)	-0.005	0.003	-2.120	0.034
Total precipitation, summer (cm)	-0.121	0.011	-10.897	< 0.001
Year	0.062	0.005	11.370	< 0.001

Burned in previous year	-3.424	0.710	-4.823	< 0.001
Burned in previous 2 years	-2.547	0.580	-4.391	< 0.001
Burned in previous 5 years	0.174	0.216	0.803	0.422
Federally managed:Year	-0.031	0.006	-5.160	< 0.001

Table S21. Logistic regression model results for the Utah model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-68.151	13.230	-5.151	< 0.001
Federally managed	-22.023	16.628	-1.324	0.185
Elevation (km)	-0.661	0.149	-4.440	< 0.001
Slope	0.014	0.004	3.952	< 0.001
Aspect	0.000	0.000	1.509	0.131
Distance to roads (km)	0.055	0.057	0.959	0.337
Population density (1990)	-0.032	0.038	-0.844	0.399
Average PDSI, summer	-0.242	0.029	-8.374	< 0.001
Average soil moisture, fall (mm)	-0.022	0.008	-2.725	0.006
Average soil moisture, winter (mm)	0.007	0.003	2.244	0.025
Minimum temperature, fall (˚C)	0.134	0.025	5.392	< 0.001
Maximum temperature, winter (˚C)	0.077	0.019	4.082	< 0.001
Maximum wind speed, fall (m/s)	0.171	0.097	1.755	0.079
Maximum wind speed, summer (m/s)	0.028	0.106	0.262	0.794
Total precipitation, fall (cm)	-0.052	0.011	-4.769	< 0.001
Total precipitation, spring (cm)	-0.059	0.014	-4.082	< 0.001
Total precipitation, winter (cm)	-0.028	0.014	-2.038	0.042
Total precipitation, summer (cm)	-0.120	0.013	-9.008	< 0.001

Total precipitation, previous year (cm)	0.045	0.004	11.540	< 0.001
Year	0.031	0.007	4.685	< 0.001
Burned in previous year	-0.258	0.584	-0.441	0.659
Burned in previous 2 years	-0.281	0.584	-0.482	0.630
Burned in previous 5 years	-1.006	0.712	-1.414	0.158
Federally managed:Year	0.011	0.008	1.340	0.180

Table S22. Logistic regression model results for the Washington model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-272.874	14.655	-18.620	< 0.001
Federally managed	6.040	18.223	0.331	0.740
Elevation (km)	1.449	0.166	8.728	< 0.001
Slope	0.020	0.003	7.456	< 0.001
Aspect	0.003	0.000	7.011	< 0.001
Distance to roads (km)	0.195	0.041	4.799	< 0.001
Population density (1990)	-0.021	0.010	-2.097	0.036
Average PDSI, summer	-0.142	0.020	-7.028	< 0.001
Average PDSI, winter	-0.407	0.027	-15.245	< 0.001
Maximum temperature, fall (˚C)	-0.543	0.038	-14.230	< 0.001
Maximum temperature, summer (˚C)	0.654	0.032	20.397	< 0.001
Maximum wind speed, fall (m/s)	2.632	0.121	21.755	< 0.001
Maximum wind speed, summer (m/s)	0.770	0.088	8.752	< 0.001
Total precipitation, fall (cm)	-0.029	0.005	-6.093	< 0.001
Total precipitation, summer (cm)	-0.076	0.014	-5.635	< 0.001
Year	0.122	0.007	16.677	< 0.001
Burned in previous 5 years	-13.759	362.285	-0.038	0.970
Federally managed:Year	-0.003	0.009	-0.320	0.749

Table S23. Logistic regression model results for the Wyoming model. The response variable is whether or not a point burned in a wildfire in a given year; years are treated as a continuous variable.

Variable	Estimate	Standard error	z value	p-value
Intercept	-392.554	35.566	-11.037	< 0.001
Federally managed	198.496	35.265	5.629	< 0.001
Elevation (km)	-0.436	0.183	-2.384	0.017
Slope	0.030	0.005	6.094	< 0.001
Aspect	0.000	0.000	-1.236	0.217
Distance to roads (km)	0.147	0.030	4.845	< 0.001
Population density (1990)	-0.014	0.033	-0.408	0.683
Average PDSI, summer	-0.059	0.037	-1.609	0.108
Average PDSI, winter	-0.215	0.041	-5.207	< 0.001
Average soil moisture, fall (mm)	-0.027	0.016	-1.651	0.099
Average soil moisture, winter (mm)	0.017	0.010	1.769	0.077
Minimum temperature, fall (˚C)	-0.164	0.038	-4.301	< 0.001
Maximum temperature, winter (˚C)	0.233	0.031	7.385	< 0.001
Maximum wind speed, fall (m/s)	0.426	0.101	4.238	< 0.001
Total precipitation, fall (cm)	-0.226	0.023	-9.639	< 0.001
Total precipitation, spring (cm)	-0.246	0.022	-11.387	< 0.001
Total precipitation, summer (cm)	-0.058	0.032	-1.817	0.069
Total precipitation, winter (cm)	-0.040	0.018	-2.209	0.027

Total precipitation, previous year (cm)	0.064	0.010	6.264	< 0.001
Year	0.193	0.018	10.893	< 0.001
Federally managed:Year	-0.099	0.018	-5.616	< 0.001

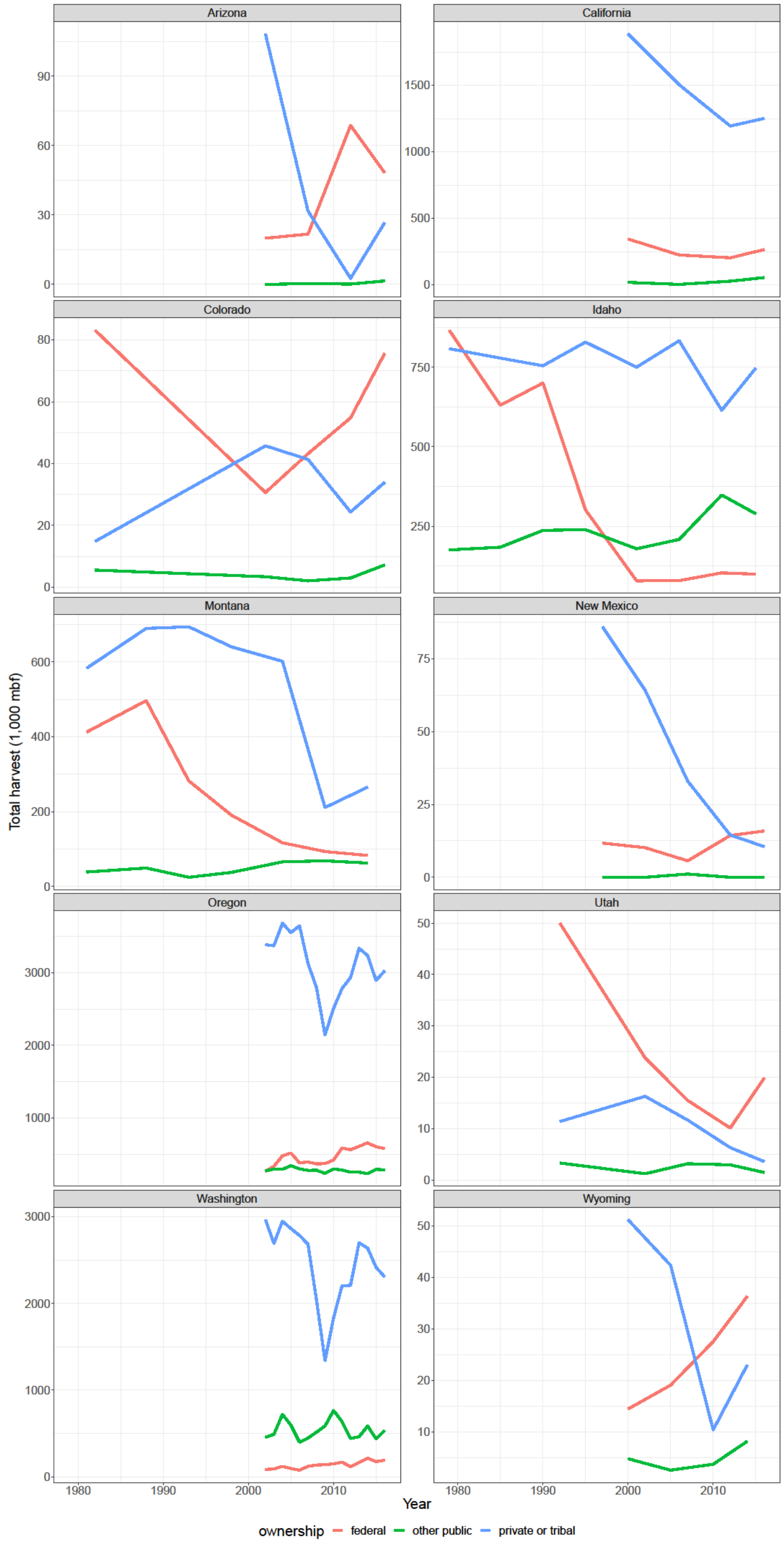
Table S24. Summaries of model fits for binomial regression models. Pseudo-R^2 values calculated for each model using the delta method with the *piecewiseSEM* package in R (Lefcheck 2016). The marginal pseudo-R^2 includes the variance of the fixed effects, while the conditional pseudo-R^2 includes the variance of both the fixed and random effects.

Model	Marginal pseudo-R^2	Conditional pseudo-R^2
Arizona	0.02	0.02
California	0.01	0.01
Colorado	0.01	0.01
Idaho	0.61	0.63
Montana	0.02	0.02
Nevada	0.04	0.04
New Mexico	0.40	0.41
Oregon	0.33	0.38
Utah	0.17	0.19
Washington	0.78	0.78
Wyoming	0.03	0.04
All-state	0.01	0.02

Figure S3. Timber harvest on federal, non-federal public, and private or tribal land in the states of the western US, in thousands of MBF (thousand metric board feet). All data from the Bureau of Business & Economic Research (BBER 2016a; BBER 2016b; Hayes & Morgan 2016; McIver et al. 2017; Simons & Morgan 2017; Hayes et al. 2018; Marcile 2019).

To understand the patterns in burn probability in the context of temporal trends in land management, we assembled data on timber harvests on federal and private land in the western US. We looked at timber harvest because it is a common form of vegetation management that influences fuel availability and forest structure and composition. We compiled timber harvest data from the University of Montana's Bureau of Business and Economic Research (BBER) for each state except for Nevada, which did not have data available through BBER (BBER 2016a; BBER 2016b; Hayes & Morgan 2016; McIver et al. 2017; Simons & Morgan 2017; Hayes et al. 2018; Marcile 2019). In Nevada, there is very little industrial timber harvest (Menlove et al. 2016), so we did not include Nevada in our analysis of timber harvest. The limitations of the BBER timber harvest data include variations in the years of data available and the groupings of ownership types. The time series of timber harvest data available varied from state to state, beginning in 1979 for Idaho and not until 2002 for Oregon and Washington. For many of the states, timber harvests on private and tribal land are grouped together, while our data includes private forests but not forests on tribal land.

We looked at timber harvest in ten of the eleven states to see if there were patterns in the harvest trends on federal and private land that might explain the different trends in wildfire probability across the states. In Wyoming, New Mexico, and Arizona, timber harvest on federal land increased from 2000-2014, while timber harvest on private and tribal land decreased. At the beginning of the time series, private and tribal timber harvest was greater than federal harvest, but federal harvest exceeded private by the end of the time series (Figure 3). In Montana and California, despite declines in harvests from private and tribal land, private and tribal harvests are still much greater than federal harvest. Oregon and Washington have similar patterns of decline and then recovery of private and tribal harvest in the last fifteen years, with much less harvest from federal lands, while in Colorado, federal harvest declined from the 1980s to the mid-2000s, but has since recovered. Idaho's timber harvest on private and tribal land has remained relatively stable since 1979, while federal harvest dropped off sharply after 1990. In Utah, both federal and private/tribal harvests have declined, but there is more harvest on federal land.


Arizona
California
Colorado
Idaho
Montana
New Mexico
Oregon
Utah
Washington
Wyoming
Total harvest (1,000 mbf)
Year
ownership
federal
other public
private or tribal

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Chapter 2 Appendix

Table S1. Reduction in bias in the matched dataset, as indicated by the standardized mean difference before and after matching. We matched grassland and shrub/scrubland sample points from grazed and ungrazed properties using the mean values from 2001-2005. The absolute values of the standardized mean differences for the matched dataset were all < 0.25, indicating effective bias reduction (Schleicher et al., 2020).

Variable	Mean values, ungrazed	Mean values, grazed	Standardized mean differences, unmatched	Standardized mean differences, matched
Population density, 2010 (people/km^2)	5.790	1.427	0.106	0.102
Population density, 2000 (people/km^2)	4.026	1.293	0.109	0.097
Elevation (m)	314.043	344.228	-0.170	-0.160
Slope (˚)	13.733	12.084	0.268	0.187
Aspect	0.549	0.567	0.025	-0.051
Distance to roads (m)	426.212	458.904	-0.357	-0.078
Mean maximum fall wind speed (m/s)	2.838	2.843	0.148	-0.017
Mean maximum winter wind speed (m/s)	2.830	2.879	0.114	-0.097
Mean maximum spring wind speed (m/s)	3.579	3.627	0.045	-0.145
Mean maximum summer wind speed (m/s)	3.548	3.542	-0.064	0.036
Total fall precipitation (cm)	9.286	9.830	-0.153	-0.161
Total winter precipitation (cm)	28.965	28.496	0.006	0.040
Total spring precipitation (cm)	9.949	10.679	-0.264	-0.203
Total summer precipitation (cm)	0.261	0.262	-0.265	-0.004
Mean maximum fall temperature (˚C)	24.107	24.017	-0.203	0.073
Mean maximum winter temperature (˚C)	15.486	15.178	0.381	0.144

Mean maximum spring temperature (˚C)	20.765	20.571	-0.151	0.118
Mean maximum summer temperature (˚C)	29.227	29.537	-0.410	-0.079
Mean minimum fall temperature (˚C)	10.503	10.483	0.090	0.021
Mean minimum winter temperature (˚C)	4.528	4.413	0.311	0.083
Mean minimum spring temperature (˚C)	7.847	7.791	0.047	0.048
Mean minimum summer temperature (˚C)	14.105	14.438	-0.474	-0.207
Mean fall PDSI	0.317	0.373	0.235	-0.114
Mean winter PDSI	0.732	0.662	0.197	0.233
Mean spring PDSI	0.485	0.464	0.365	0.049
Mean summer PDSI	0.558	0.510	0.412	0.125
Mean fall soil moisture (mm)	28.953	30.247	-0.154	-0.061
Mean winter soil moisture (mm)	110.714	112.965	-0.128	-0.034
Mean spring soil moisture (mm)	87.029	90.522	-0.119	-0.052
Mean summer soil moisture (mm)	34.281	35.615	-0.135	-0.052
Mean annual NPP (kg*C/m^2)	0.633	0.621	0.242	0.049
Latitude	-2146328	-2139514	-0.085	-0.114
Longitude	1717422	1705850	-0.218	0.060

Table S2. Reduction in bias in the matched dataset, as indicated by the standardized mean difference before and after matching. We matched grassland, shrub/scrubland, and forest sample points from grazed and ungrazed properties using the mean values from 2001-2005. The absolute values of the standardized mean differences for the matched dataset were all < 0.25, with the exception of average minimum summer temperature, indicating effective bias reduction (Schleicher et al., 2020).

Variable	Mean values, ungrazed	Mean values, grazed	Standardized mean differences, unmatched	Standardized mean differences, matched
Population density, 2010 (people/km^2)	3.670	1.927	0.109	0.045
Population density, 2000 (people/km^2)	2.909	1.755	0.115	0.045
Elevation (m)	352.482	359.807	-0.133	-0.038
Slope (˚)	14.227	11.968	0.335	0.247
Aspect	0.530	0.518	-0.025	0.031
Distance to roads (m)	452.593	487.723	-0.210	-0.074
Mean maximum fall wind speed (m/s)	2.839	2.807	0.171	0.098
Mean maximum winter wind speed (m/s)	2.872	2.802	0.176	0.137
Mean maximum spring wind speed (m/s)	3.590	3.576	0.053	0.040
Mean maximum summer wind speed (m/s)	3.570	3.604	-0.005	-0.174
Total fall precipitation (cm)	10.495	10.663	-0.024	-0.042
Total winter precipitation (cm)	32.191	32.369	0.106	-0.013
Total spring precipitation (cm)	11.278	11.681	-0.129	-0.100
Total summer precipitation (cm)	0.315	0.364	-0.136	-0.195
Mean maximum fall temperature (˚C)	23.951	24.084	-0.252	-0.109
Mean maximum winter temperature (˚C)	15.156	14.713	0.358	0.210

Mean maximum spring temperature (˚C)	20.469	20.746	-0.216	-0.168
Mean maximum summer temperature (˚C)	29.363	30.212	-0.428	-0.223
Mean minimum fall temperature (˚C)	10.225	10.222	-0.014	0.003
Mean minimum winter temperature (˚C)	4.283	4.116	0.268	0.120
Mean minimum spring temperature (˚C)	7.500	7.590	-0.058	-0.073
Mean minimum summer temperature (˚C)	13.964	14.411	-0.536	-0.274
Mean fall PDSI	0.296	0.191	0.217	0.208
Mean winter PDSI	0.726	0.723	0.211	0.012
Mean spring PDSI	0.409	0.303	0.307	0.244
Mean summer PDSI	0.533	0.442	0.427	0.246
Mean fall soil moisture (mm)	35.357	36.086	-0.035	-0.029
Mean winter soil moisture (mm)	129.480	129.732	-0.016	-0.003
Mean spring soil moisture (mm)	106.201	105.058	-0.005	0.015
Mean summer soil moisture (mm)	40.837	40.231	-0.027	0.021
Mean annual NPP ($kg*C/m^2$)	0.681	0.644	0.323	0.133
Latitude	-2153551	-2156053	-0.155	0.038
Longitude	1743934	1780135	-0.149	-0.177

Table S3. Full table of coefficient estimates for the logistic regression models from Table 1. The models estimate burn probability in the matched dataset of grasslands and shrub/scrublands (with grazed and ungrazed sample points), the grazed-only dataset (all grassland shrub/scrubland points with grazing), and the matched dataset of grasslands, shrub/scrublands, and forests. Cluster-robust standard errors are in parentheses below each coefficient estimate. The Central Coast serves as the reference region. For the datasets with grasslands and shrub/scrublands, grasslands are the reference land cover type. For datasets with grasslands, shrub/scrublands, and forests, forests are the reference.
* p<0.05, ** p<0.01, *** p<0.001.

	Coefficient estimates		
Variable	Matched dataset, grassland and shrub/scrubland	Grazed-only dataset, grassland and shrub/scrubland	Matched dataset, grassland, shrub/scrubland, and forest
Intercept	149.826 (70.041)	277.625** (92.748)	142.643* (69.307)
Grazed	0.978* (0.378)		0.802* (0.381)
AUY per grazed acre	-14.470 (10.431)	22.749 (12.846)	-18.406 (11.361)
Central Valley & Foothills Region	7.907* (3.653)	12.223** (3.418)	8.198* (3.507)
North Bay Region	11.186* (5.177)	9.968* (3.993)	11.936* (4.868)
AUY per grazed acre: Central Valley & Foothills	22.686* (10.156)	-19.130 (13.302)	22.188 (11.956)
AUY per grazed acre: North Bay	5.739 (11.243)	-27.783* (12.057)	14.577 (11.086)
Grassland			-0.958* (0.407)
Shrub/scrub	-0.577* (0.245)	0.926* (0.363)	-1.434*** (0.315)
AUY per grazed acre: Grassland			7.555 (11.549)
AUY per grazed acre: Shrub/scrub	9.583 (10.024)	-29.266** (10.688)	16.096* (7.294)
Central Valley & Foothills: Grassland			0.511 (0.720)
Central Valley & Foothills: Shrub/scrub	1.051* (0.488)	-0.326 (0.577)	1.781** (0.581)
North Bay: Grassland			0.971 (0.567)
North Bay: Shrub/scrub	0.882* (0.385)	-0.108 (0.683)	1.714*** (0.351)

AUY per grazed acre: Central Valley & Foothills: Grassland			-2.818 (12.112)
AUY per grazed acre: Central Valley & Foothills: Shrub/scrub	-10.603 (9.791)	30.524** (11.617)	-13.278 (7.757)
AUY per grazed acre: North Bay: Grassland			-12.599 (12.224)
AUY per grazed acre: North Bay: Shrub/scrub	-7.830 (10.660)	-0.108 (0.683)	-20.130* (7.851)
Population density in 2000 (people/km^2)	-0.003 (0.004)	0.002 (0.001)	-0.001 (0.003)
Distance to roads (m)	$1.506 * 10^{-4}$ (0.000)	$-1.430*10^{-4}$ (0.000)	$2.770*10^{-4*}$ (0.000)
Elevation (m)	$1.529 * 10^{-4}$ (0.001)	0.001* (0.001)	$-1.218*10^{-4}$ (0.001)
Slope (˚)	0.033*** (0.007)	0.033** (0.011)	0.035*** (0.008)
Aspect (SRAI)	-0.019 (0.202)	-0.260 (0.174)	0.001 (0.177)
PDSI, fall	0.018 (0.315)	-0.254 (0.289)	-0.242 (0.277)
Total precipitation, fall (cm)	0.263*** (0.059)	0.303** (0.114)	0.210*** (0.059)
Total precipitation, spring (cm)	-0.133* (0.052)	-0.244 (0.136)	-0.095 (0.057)
Total precipitation, summer (cm)	0.824* (0.415)	1.791*** (0.514)	0.615 (0.435)
Total precipitation, winter (cm)	0.181** (0.058)	0.118* (0.055)	0.117** (0.041)
Soil moisture, summer (mm)	-0.005 (0.014)	$3.596*10^{-4}$ (0.021)	0.009 (0.012)
Minimum temp, fall (˚C)	-0.098 (0.247)	-1.005 (0.572)	0.073 (0.251)
Maximum temp, fall (˚C)	0.052 (0.225)	1.268** (0.421)	-0.129 (0.204)
Max wind speed, summer (m/s)	0.568* (1.248)	-0.244 (2.608)	0.959 (1.168)
Max wind speed, fall (m/s)	0.251 (1.127)	-5.609* (2.489)	-0.958 (1.030)

Max wind speed, winter (m/s)		9.384*** (2.381)	
Previous year precipitation (cm)	-0.097* (0.047)	-0.065 (0.034)	-0.049 (0.037)
NPP (kg*C/m^2)	-3.776*** (0.663)	-4.714*** (0.922)	-4.239*** (0.647)
Latitude	4.780*10^{-5} (0.000)	1.257*10^{-4}** (0.000)	3.970*10^{-5} (0.000)
Longitude	-1.285*10^{-4}** (0.000)	-2.300*10^{-4}*** (0.000)	-1.223*10^{-4}** (0.000)
Latitude: Longitude	-4.250*10^{-11}* (0.000)	-9.040*10^{-11}** (0.000)	-3.830 *10^{-11}* (0.000)
Burned in previous year	-4.225*** (1.184)	-5.214*** (1.200)	-4.772*** (0.945)
Burned in previous 5 years	-0.912 (0.962)	-2.462 (1.400)	-1.431 (1.041)
2002	2.535 (2.400)		0.167 (1.729)
2003	5.673** (1.658)	13.678*** (3.334)	5.554** (1.701)
2004	3.161 (1.925)	13.145** (3.790)	2.916 (1.906)
2005	-3.837 (2.961)	10.797* (5.444)	-0.350 (2.735)
2006	4.483* (2.067)	15.239*** (4.110)	4.739* (2.076)
2007	6.671** (2.235)	15.436*** (2.753)	4.904** (1.662)
2008	-2.301 (2.281)	2.273 (4.343)	-0.861 (2.405)
2009	5.737* (2.490)	13.122*** (3.696)	5.024* (2.068)
2010	-1.556 (1.872)	12.203** (3.831)	0.181 (2.017)
2011	1.637 (1.509)	12.043*** (3.411)	1.886 (1.630)
2012	4.494 (3.273)	10.343** (3.170)	1.448 (2.438)
2013	3.391 (2.491)	12.230*** (3.256)	2.394 (2.236)
2014	0.438 (2.850)	8.393* (3.446)	-0.192 (2.270)
2015	1.355 (2.620)	8.788* (4.220)	1.064 (2.459)
2016	4.911**	8.812**	4.583**

	(1.597)	(2.821)	(1.415)
2017	0.035 (1.917)	7.981 (4.772)	2.444 (2.068)

Chapter 3 Appendix

Table S1. Documents assessed in the discourse analysis.

Scale	Management	Policy	Gray Literature	Advocacy
Local (Jamanxim National Forest)	2	4	1	9
State (Pará)	0	1	3	7
National (Brazil)	3	7	19	5

Table S2. Themes and variables from the discourse analysis.

Theme	Variables
Accessibility	- Distance to roads - Elevation, slope, aspect - Distance to navigable rivers - Distance to cities (markets)
Agricultural/livestock expansion	- Mechanized agriculture - Small-scale agriculture - Cattle grazing
Infrastructure development	- Proposed dams - Proposed railroads - Transmission lines
Population pressure	- Migration - Population growth - Settlements
Physical suitability for agriculture/livestock	- Climate - Soil quality
Economic development	- Poverty rate
Forest degradation	- Fires
Globalization	- Lack of commodity traceability
Land tenure	- Agrobusiness expropriation - Indigenous land titling - Land titling - Land grabbing - Pre-existing land claims in the protected area - Smallholder occupation
Non-state governance	- Level of local participation - NGO project interventions - Environmental education and public outreach
Protected area downgrading, downsizing, and degazettement	- Proposed PADDD events - Implemented PADDD events

Resource extraction	- Illegal logging - Logging - Mining
Urbanization	- Urbanization rate
State governance	- Enforcement - Monitoring - Lack of state capacity - Regulatory jurisdiction - Territorial planning - Governance quality
Economic incentives for forest conservation	- Boycotts - Carbon markets - Payments for ecosystem services - REDD+
Government policies	- Agricultural policies - Climate change policy - Forestry policies - Land use policies

Table S3. Coefficient estimates for all models, with standard deviations in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Variable	LUC model	DA model	LUC & DA model	Refined LUC & DA model
Intercept	11.358*** (0.559)	-0.795*** (0.044)	8.504*** (0.924)	6.723*** (0.825)
Aspect (°)	1.390×10^{-4} (0.000)		2.063×10^{-4} (0.000)	
Slope (°)	-0.048*** (0.003)		-0.055*** (0.003)	-0.055*** (0.003)
Elevation (m)	-0.003*** (0.000)		-0.002*** (0.000)	-0.002*** (0.000)
Distance to roads (m)	-0.009*** (0.000)		-0.001** (0.000)	-0.001** (0.000)
Distance to rivers (m)	-2.703×10^{-7} (0.000)		1.601×10^{-5}*** (0.000)	
Distance to mining concessions (m)	-0.003*** (0.000)		-2.901×10^{-4} (0.000)	-8.972×10^{-5} (0.000)
Distance to cities (m)	1.259×10^{-6}*** (0.000)		-5.114×10^{-6}*** (0.000)	-3.436×10^{-6}*** (0.000)
Crop suitability	0.020*** (0.004)		-0.009* (0.004)	-0.007 (0.004)
Population density (per km^2)	-0.872*** (0.046)		0.452 (0.639)	
Soil moisture (mm)	-0.706*** (0.028)		-0.423*** (0.042)	-0.334*** (0.041)
Proportion of non-forest neighboring pixels	0.059*** (0.001)		0.041*** (0.001)	0.041*** (0.001)
10 km buffer	0.796*** (0.026)		0.477*** (0.051)	0.427*** (0.050)
20 km buffer	0.799*** (0.029)		0.344*** (0.057)	0.307*** (0.057)
PADDD proposal		-0.079** (0.026)	0.274*** (0.046)	0.250*** (0.045)
Proportion of non-allocated public land		-0.118 (0.162)	-3.718 (2.265)	-1.524*** (0.217)
Distance to unauthorized		-2.386×10^{-6}*** (0.000)	5.729×10^{-6}*** (0.000)	

mining sites (m)				
Distance to existing agriculture (m)		-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Distance to fires (m)		-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Fire density (per km^2)		0.047*** (0.001)	0.049*** (0.001)	0.049*** (0.001)
Distance to proposed railroads (m)		$-1.183*10^{-5***}$ (0.000)	$2.006*10^{-6}$ (0.000)	$-1.871*10^{-6}$ (0.000)
Presence of agricultural reform settlements		-0.121** (0.042)	0.125** (0.046)	0.105* (0.045)

Table S4. Remote sensing accuracy assessment.

Type of accuracy	Ag	Forest	Bare soil	Built-up	Wetland	Water	Mean
Producer's	0.87	0.98	0.92	0.95	0.94	0.97	0.94
User's	0.94	0.97	0.78	0.84	0.95	0.95	0.91

Table S5. Transition probability matrix.

		2018 Land cover class					
		Ag	Forest	Bare soil	Built-up	Wetland	Water
2008 Land cover class	Ag	0.698	0.181	0.107	0.005	0.009	0.000
	Forest	0.050	0.940	0.007	0.000	0.003	0.000
	Bare soil	0.680	0.139	0.165	0.014	0.002	0.000
	Built-up	0.296	0.044	0.163	0.496	0.000	0.000
	Wetland	0.057	0.065	0.000	0.000	0.877	0.000
	Water	0.004	0.108	0.000	0.000	0.000	0.888