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Article

The Influence of Socioeconomic Factors on Human Wildfire Ignitions in the Pacific Northwest, USA

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Abstract: Historical land and fire management practices coupled with climate change and modern human development pressures are contributing to larger, more frequent, and more severe wildfires across Western U.S. forests. Human ignitions are the predominant cause of wildfire throughout the United States, necessitating wildfire management strategies that consider both the causes of human ignitions and the factors that influence them. Using a dataset of over 104,000 ignitions from 1992 to 2018 for Oregon and Washington (U.S), we examine the major causes of wildfire ignitions and build regression models to evaluate the potential influence of both biophysical and socioeconomic factors on human and natural ignitions across distinct fire regimes west and east of the Cascade Range. Our results corroborate prior findings that socioeconomic factors such as income, employment, population density, and age demographics are significantly correlated with human ignitions. In the Pacific Northwest, we found that the importance of socioeconomic factors on human ignitions differs significantly between the west and east sides of the Cascade Range. We also found that most human ignitions are linked to escaped fires from recreation or debris and open burning activities, highlighting opportunities to tailor wildfire prevention efforts to better control higher risk activities and reduce accidental ignitions.

Keywords: wildfire occurrence; human ignitions; pacific northwest; social-ecological systems; wildfire policy; regression analysis

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1. Introduction

Historical land and fire management practices [1–3], coupled with anthropogenic climate change and modern human development pressures, are contributing to larger, more frequent, and more severe wildfires across the U.S., especially in western U.S. forests [4–8]. Humans directly and indirectly influence wildfire patterns and impacts through multiple avenues [9]. Not only have humans significantly altered the landscape, more than 90 percent of wildfires worldwide are linked to intentional and unintentional human actions [10]. This is also true in the U.S.: humans accounted for 84 percent of all wildfires across the country between 1992 and 2012 [5], and human ignitions are the dominant cause of wildfires in 98 percent of U.S. counties [11]. In addition, the rapid expansion of human communities into forested landscapes has both increased the number of human ignitions [6] and the number of communities exposed to wildfire risk [9,12,13].

Given the magnitude of human influence on ignitions nationally, programs that target the prevention of human ignitions may have significant potential to reduce overall wildfire risk. However, effective prevention programs need to be tailored to specific causal factors and community dynamics that drive human ignitions [11]. Although ignition itself is a biophysical process, the spatial and temporal patterns of wildfire ignitions are functions of both the biophysical environment and socioeconomic factors, such that both must be considered in wildfire policy and management [12,14,15]. Understanding regional ignition causes and socioeconomic factors associated with human ignitions is of growing policy and management interest, especially in regions where human–fire interactions may increase in frequency or severity with global climate shifts. Were we to find that socioeconomic factors are correlated with human ignitions, such relationships might point to a need for policy or programmatic interventions addressing socioeconomic contexts associated with human ignitions.

Studies examining the spatial and temporal influence of humans on ignition patterns have been conducted across many regions, including European Mediterranean environments, China, South America, Australia, and the United States (Table 1). Biophysical factors influencing ignitions (i.e., climate, vegetation, physiography) have been extensively studied and found to be important predictors in many regions [16]. Although the roles of socioeconomic factors (e.g., land use, wealth, education levels) in influencing ignitions are less well understood, studies have suggested that socioeconomic context can influence the patterns of wildfire occurrence, especially in regions dominated by human ignitions (Table 1).

Large fires are becoming more frequent in many regions, with more than half of the land area in the western U.S. experiencing extreme drought in 2021 [17,18]. Research suggests the Pacific Northwest will likely face more frequent and severe wildfires in the years to come because of warmer and drier conditions [19]. As human development expands onto fire-prone landscapes, the influence of human activities has been shown to override climate change in effecting when and where wildfires occur [5,6]. Recent expensive wildfire-related losses in the region highlight the need for wildfire management strategies that include consideration of both socioeconomic and biophysical factors that potentially influence human ignitions. Despite calls for greater integrated research addressing both the socioeconomic and biophysical conditions that influence human behavior and wildfire [20,21], few studies have examined the combined influence of these factors on human ignitions in the Pacific Northwest.

Table 1. Previous studies examining factors associated with wildfire occurrence, explanatory variables examined, relationships found, and analysis methods. The (+/−) denotes the direction of relationship for variables that were significant [1] at some level in each study; (~) denotes variables tested but not significant.

Study	Area	Dependent Variable	Socioeconomic Variables	Biophysical Variables	Analysis
[22]	U.S.: MN, WI, MI	All ignitions (most human-caused)	Seasonal housing units (−), Road density (+), Rail density (−), Ownership: state, Tribal, national forest (−), Population density (+), Distance to city (+), Distance to non-forest (−), Owner occupied units (−)	Mean march precipitation (+), Mean august max temperature (−), Land cover (sig. categorical var w/no sign), Lake density (−), Mean June precipitation (~)	Generalized linear regression (GLM) (negative binomial, Poisson regression, or logistic)
[23]	Spain	All ignitions (most human-caused)	Pop density (+), Rural exodus (+), Unemployment (+), Highway density (+), Rural road density(+), Conventional road density (+), WUI area (+), Dense built area (+)	Land cover type (all significant, relationships vary), Elevation (+), Slope range (−), Mean Temperature (+), Mean Precipitation (−)	GLM, negative binomial
[24]	Spain	All ignitions	Population over 64 years (+), Population density (−), Income per person (−), Ratio of men to women (+), Active population: ratio pop age 40–64 to age 15–39 (−), Livestock (~), Parcel value (−), Town debt (~), GDP (~), Foreign population (+)	N/A	Multiple linear regression

Table 1. *Cont.*

Study	Area	Dependent Variable	Socioeconomic Variables	Biophysical Variables	Analysis
[25]	Argentina	All ignitions in the WUI	Population density (+), Unemployment (+), Unoccupied teens (+), Educational attainment (−), Age (+), Poverty (~)	Slope (−), Aspect (+)	Principal component analysis and quantile regression
[26]	U.S.: MS	Human ignitions (major causes modeled separately)	Distance to road, distance to railroad, distance to city Population density, Income, Poverty, Unemployment (sig. vars reported, relationships varied by ignition causes)	Spring, Fall/Winter	Logistic Regression
[27]	China	All ignitions (95% human caused)	Distance to nearest road (+), Distance to nearest river (+), Distance to nearest settlement (+), Population density (+), Per capita GDP (+)	Elevation (−), Slope (−), Aspect (+), Daily max temperature (+), Daily min temperature (−), Daily max wind (−), Daily precipitation (−), Sunshine hours (+), Relative Humidity (−)	Logistic regression
[28]	Italy	All fire occurrence	Road length in total municipal area (+), Average per-capita disposable income (−), Commuting workers (+), Unemployment (+), Built up area (−), Non-native resident (−), Tourism facilities (+), Natural protected land in total municipal area (+), Public-owned land in total agricultural area (−), Inequality in personal income (−)	Coefficient of variation in landscape patch size (+), Pielou’s evenness index of landscape diversification (+)	OLS, interval regression, quantile regression, GLM (Gaussian, inverse, negative binomial, Poisson distributions)
[29]	Spain	All ignitions	Rural exodus (+), Density of human, settlements (+), Density of roads (+), Density of agricultural machinery (+), Rural aging: owners of agrarian holdings >55 years (+), Urban/forest interface density (+)	Mean annual precipitation (+), Agricultural land fragmentation (+), Mean elevation (−), Percentage of wildland area (+)	Linear regression (OLS), logistic regression (both geographically weighted)
[30]	U.S.: FL	All ignitions	Housing density (−), Unemployment (−), Poverty (−), Population (+), Police (−), Past prescribed burns (−)	Sea surface temperature anomalies El Nino (−), North Atlantic Oscillation (+)	Fixed effects, Poisson panel model
[31]	U.S.: WA	Human/ lightning ignitions modeled separately	Paved road density (+), Gravel road density (+), Distance to WUI (−)	Slope (−), Elevation (−), Brush fuel model (−)	Logistic regression
[32]	Portugal, Spain, France, Italy, Greece	All ignitions	Unemployment (−), Livestock density (+), Density of local roads (+), Density of highways (+), Low urban density area (+), Average pop density (−), WUI land cover (−)	Pre fire season precipitation (+), During fire season precipitation (−), soil moisture (+), Max temperature (−), Aspect (+), Relative humidity (−), Max temp (−)	Multiple linear regression and Random Forest model
[33]	Chile	All fire occurrence (most human-caused)	Pop density (+), Indigenous population (+), Unemployed (+), Road density (+)	Agriculture land (+), Exotic plantation land (+), Native forests (+)	Generalized additive models with a Poisson error structure
[34]	U.S.: FL	Arson ignitions	Police per capita (−), Poverty rate (+), Unemployment (~), Retail wage (−), Population (−)	Previous years wildfire extent (−), Previous years fuel treatments (−)	Fixed-effects panel, Poisson model (among other models)

Table 1. *Cont.*

Study	Area	Dependent Variable	Socioeconomic Variables	Biophysical Variables	Analysis
[35]	U.S.: CA	All ignitions (most human caused)	Distance to WUI (−), Level of WUI (+), Distance to roads (−), Distance to trails (−), Level of Development (+)	January temperature (−), Elevation (−), Slope (−), Southwestness (~), Vegetation type (results vary by cover type)	Logistic regression (fire ignitions) Poisson regression (fire frequency)
[36]	Australia	All ignitions	Distance to primary road (−), Distance to secondary road (−), Distance to railway (−), Distance to WUI (−)	Land cover (Forest, grassland, savannas, shrublands) (−), Permanent wetlands (~), Vegetation Index (+), Elevation (+), Northwestness (~)	Binary multiple logistic regression

[1] Significance and direction of the relationships is included but not strength of significance since magnitude is influenced by units of measure that varied among studies. Not all variables tested or model results for each study are listed; instead, the table prioritized listing variables and model results relevant to our study area.

We sought to address these research and policy needs, and build upon previous research, by examining the major causes of wildfire ignitions in the Pacific Northwest. What are the primary causes of ignition and what are the key socioeconomic and biophysical factors that drive ignitions? Specifically, our objectives were to examine ignitions data spanning years 1992–2018 in Oregon and Washington (U.S.) to (1) characterize patterns of ignition causes in the distinct fire environments west and east of the Cascade Range and (2) develop regression models describing the relationships between ignitions and socioeconomic and biophysical variables. Although our focus was on investigating factors associated with human ignition, we conducted a separate analysis of factors associated with natural ignitions for comparison.

2. Materials and Methods

2.1. Study Area

We examined wildfire ignitions in Oregon and Washington, two states that span 108 million acres and share similar environments, settlement histories, and socioeconomic characteristics (Figure 1). Both states can be broadly characterized as having two distinct climates and fire regimes separated by the Cascade Mountain range [37]. The landscape west of the Cascades range crest (the "westside") is temperate rainforest dominated by wetter conifer coastal and lower Cascades forests that have historically experienced higher severity, stand-replacing fires at an infrequent interval (35–200+ years) [38]. The westside receives higher annual and summer (June through August) precipitation, 1641 mm and 103 mm, respectively, and on average has lower mean summer (17 °C) and higher mean annual temperatures (10 °C) as compared to the eastern region (Figure 2). The region east of the Cascades range (the "eastside") is dominated by dry ponderosa pine or mixed conifer forests with less severe but more frequent fires occurring every 0–35 years [38]. Precipitation on the eastside averages 470 mm annually and 54 mm during the summer months, with an average summer temperature of 19 °C and an average annual temperature of 9 °C. To account for major difference in the fire environment, we separated our study area into two regions divided by the crest of the Cascade Range, which generally follows several county boundaries for analysis (Figure 1), a common practice among fire ecologists studying Pacific Northwest fire regimes [39]. Of note, the Klamath-Siskiyou region in southwestern Oregon ("Klamath Ecoregion" in Figure 1) has climate and fire regime characteristics intermediate between the eastside and westside, and we accounted for this in our analysis of the westside.

Some socioeconomic characteristics also differ between the westside and eastside (Figure 3). In 2018, the combined population of Oregon and Washington was 11.4 million, with most of the large population centers and 82 percent of the total population living on the westside. The eastside was more sparsely populated and had higher proportions of seasonal housing, lower median household income, and higher rates of poverty as compared to the westside.

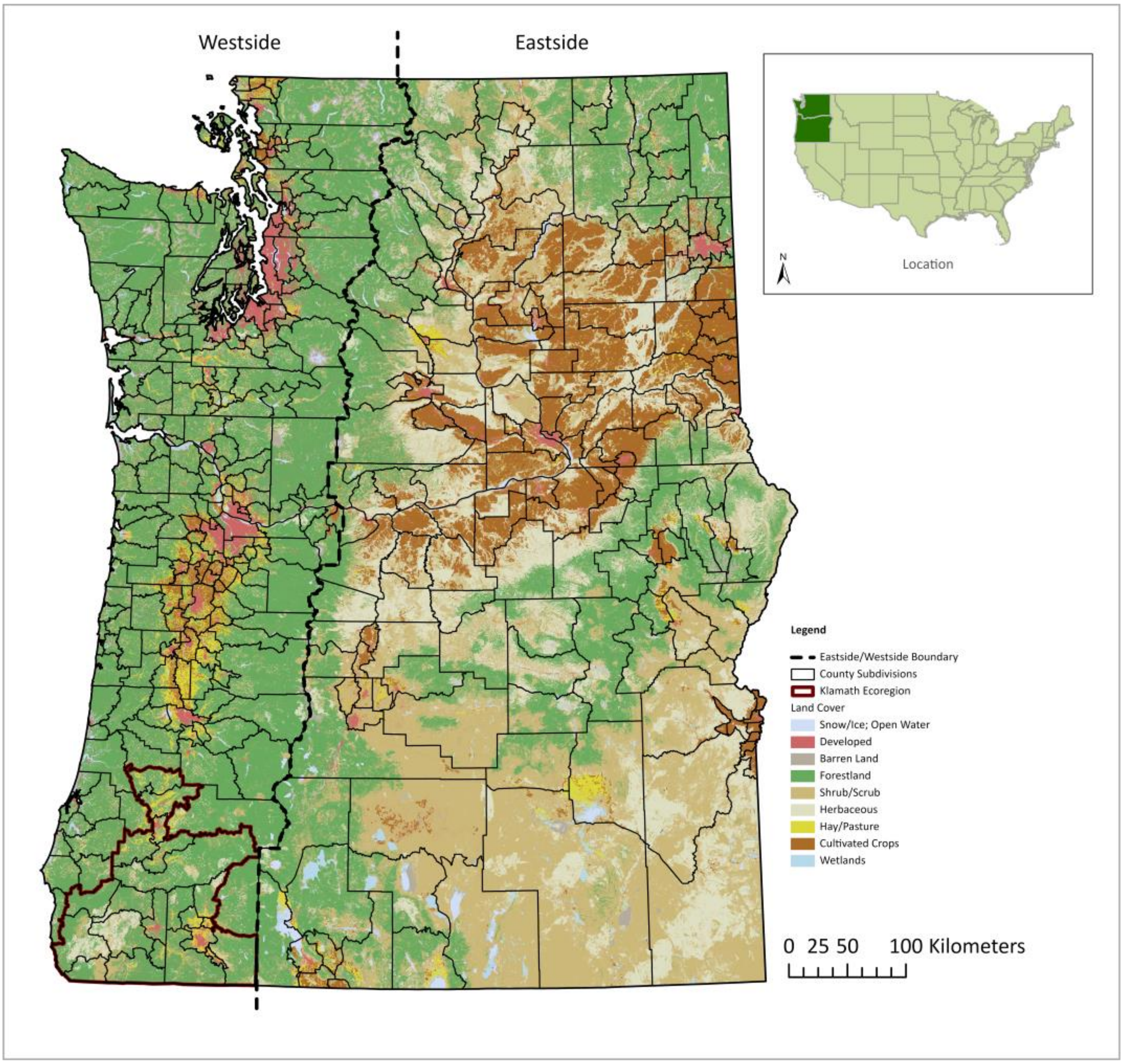

Figure 1. Map of the study area (Oregon and Washington) showing major landcover types and U.S. Census county subdivisions, the unit of analysis. Dashed black line demarcates the boundary between westside and eastside regions for analysis. Data: County subdivision lines from US Census Bureau 2018 TIGER/line files. Major landcover types from United States Geological Survey 2018 National Land Cover Database. Klamath Ecoregion boundary are authors calculations of county subdivisions 30 percent or more contained within "Klamath Mountains" ecoregion from the 2013 release of the Environmental Protection Agency Level III Ecoregion dataset.

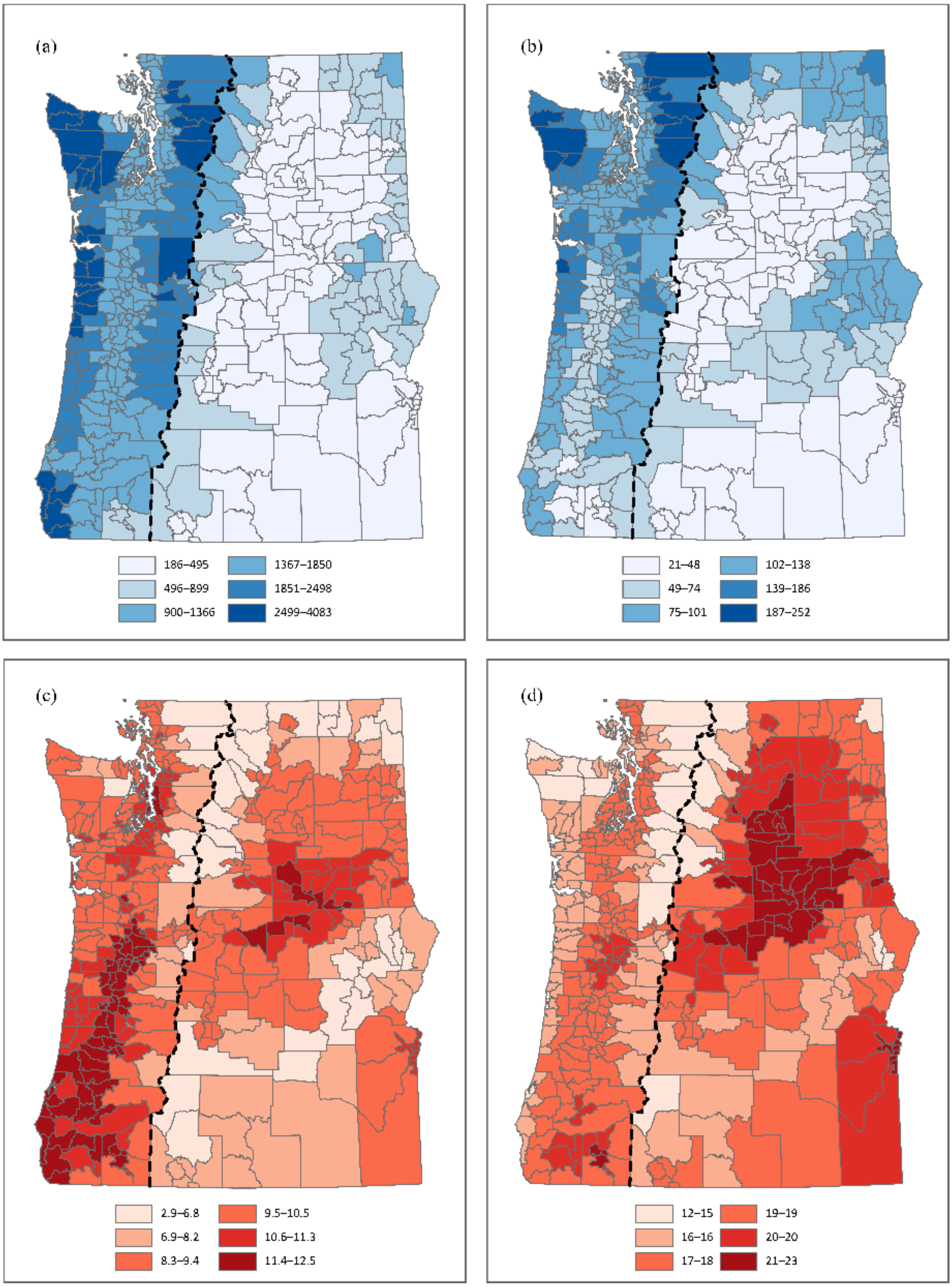

Figure 2. Mean (**a**) annual precipitation (mm), (**b**) summer (June–August) precipitation (mm), (**c**) Annual Temperature (°C), and (**d**) Summer (June–August) temperature (°C) between 1992–2018 by U.S. Census county subdivisions. Dashed black line demarcates the boundary between westside and eastside regions for analysis. Data: County subdivision lines from US Census Bureau 2018 TIGER/line files. Climate variables were author generated from the 2020 release of Parameter-elevation Relationships on Independent Slopes Model (PRISM) gridded climate data.

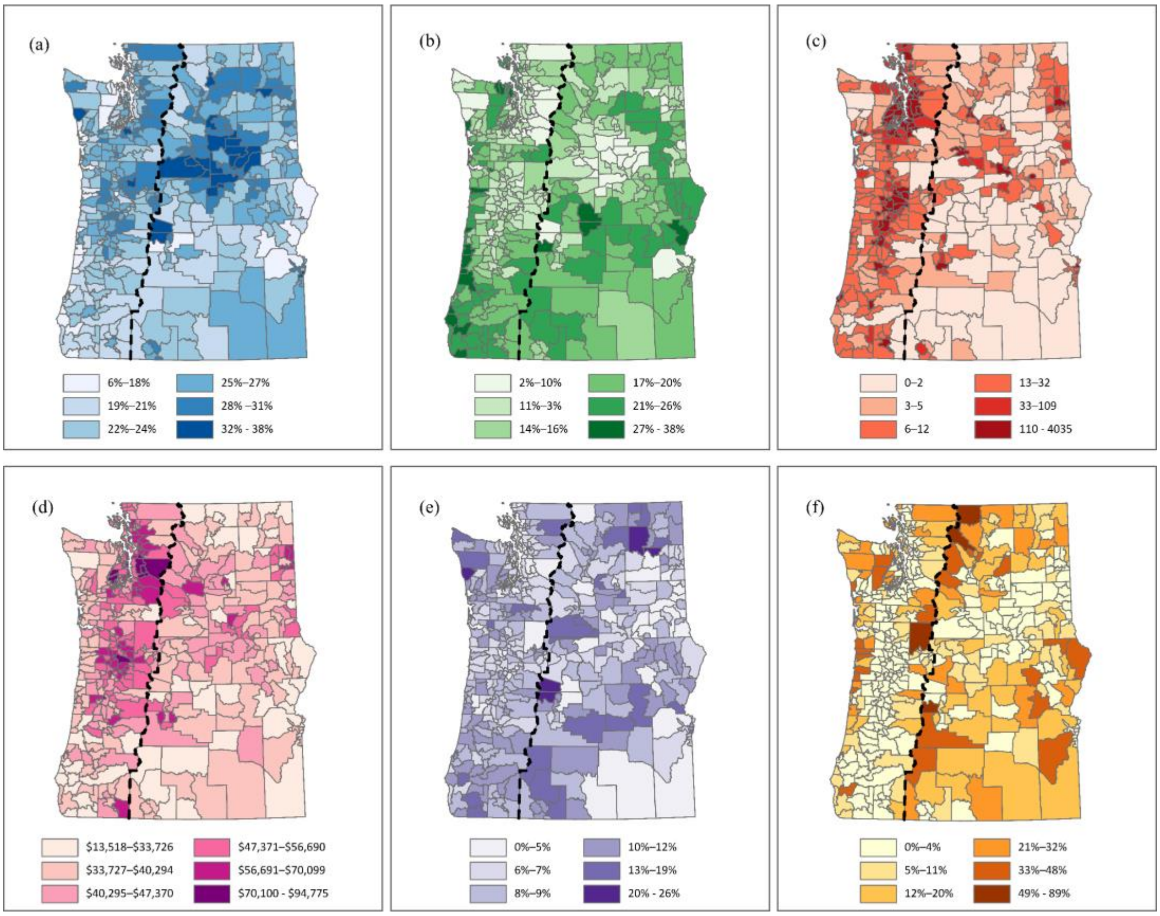

Figure 3. Select socioeconomic variables by U.S. Census county subdivisions: (**a**) population under 18 years, (**b**) population over 65 years, (**c**) population density (persons/km^2), (**d**) median household income, (**e**) percent unemployment, (**f**) percent of vacant housing for seasonal, recreation, or occasional use. Dashed black line demarcates the boundary between westside and eastside regions. Data: County subdivision lines from US Census Bureau 2018 TIGER/line files. Socioeconomic data from the U.S. Decennial Census and American Community Survey averaged over study period from 1992–2018.

2.2. Geographic Unit of Analysis

Our analysis of possible factors associated with human and natural wildfire ignitions required combining ignitions, biophysical, and socioeconomic data at a scale or unit of geography for which socioeconomic data were available. We acquired socioeconomic data from the U.S. Census, which provides statistics for multiple levels of census-defined and political geographies (e.g., blocks groups, tracts, county subdivisions, and counties). We chose to use Census County Divisions (CCDs) for our analysis—otherwise known as county subdivisions—because they are statistical entities designed to represent population centers or major land use areas with visible and easily described boundaries [40]. Unlike census tracts or block groups, which are designed to delineate geographies of similar population sizes such that they are larger in rural areas and smaller in urban areas, county subdivisions are designed to describe population centers regardless of their population sizes. They arguably represent a useful approximation of "communities" for social science analysis.

County subdivision boundaries can change in extent or in name before each decennial census. To ensure that a consistent set of geographies were used over our study period, we identified any changes over time in county subdivisions by comparing the unique 10-digit identifier ("GEOID") and the location of the boundary for each county subdivision across the census years 1990, 2000, and 2010 and then reconciled these to develop a consistent set of county subdivisions for each observation period. Where only name changes occurred, the 1990 and 2000 county subdivision names were re-coded to match the 2010 name. In some cases, county subdivisions were split or combined. For boundaries that had been split, we recombined those to the original for comparison across time, and, in one case, three county subdivisions in Washington that had been reconfigured completely were combined into one new unit across all census years and assigned an arbitrary GEOID and name to create an appropriate time series approximation. After accounting for boundary and name changes over time, we were left with a final set of 450 county subdivisions for Oregon and Washington that we used for our analysis.

2.3. Data Collection

We obtained wildfire ignition data from the USDA Forest Service Fire Program Analysis wildfire-occurrence database (FPA FOD), which provided a compilation of fire records from federal, state, and local fire organization reporting systems [41]. The data included discovery date, final fire size (acres), fire cause, and a point location at least as precise as Public Land Survey System section (1 square mile grid) [41]. The 2021 data release included all recorded fires between 1992–2018, a total of 104,946 ignitions in Oregon and Washington. We tabulated counts of human ignitions and natural ignitions by year and county subdivision, removing four misclassified ignition points that occurred outside of our study area (Appendix A). Natural ignitions were those caused by lightning, with all other known ignition causes attributed to humans. As county subdivisions vary in size (ranging from 3126 acres to 4.4 million acres in our study area), we divided the final counts of human and natural ignitions for each county subdivision and year by the area of the county subdivision to compute ignition density in number of human or natural ignitions per unit area.

Reporting on wildfire causes has long suffered from a lack of consistent cause categories and standardized cause determination protocols across local, state, and federal agencies [42]. The FPA FOD dataset transforms local, state, and federal fire reports to the standards of the National Wildfire Coordinating Group (NWCG), reconciling 27 years of data across numerous agencies with slightly different cause classifications to the NWCG general cause categories of "arson/incendiarism, debris and open burning, equipment and vehicle use, firearms and explosives use, fireworks, misuse of fire by a minor, power generation/transmission/distribution, railroad operations and maintenance, recreation and ceremony, smoking, other causes, or missing data/not specified/undetermined [41].

We developed a set of 24 biophysical and socioeconomic explanatory variables to consider for analysis of both human and natural wildfire ignitions based on their use in previous studies (Table 2). The time span of our explanatory variable data coincided with the 1992 to 2018 period, for which we had wildfire ignition data. All wildfire ignition, biophysical, and socioeconomic data were reorganized to conform to the final 450 county subdivisions using the 2018 boundary Tiger/line shapefiles from the U.S. Census Bureau and combined into a longitudinal panel structure in R for analysis using Generalized Linear Models (GLMs). Summary statistics for all variables by analysis regions are provided in Table 3.

Variation in climate and fuel was largely accounted for by separating the study area into regions eastside and westside of the Cascade Range for analysis. However, we included an additional variable to account for the unique fire environment of southwest Oregon. Specifically, we created a dummy variable identifying those county subdivisions comprising land 30 percent or more contained within the EPA level III Klamath Mountains ecoregion. Additional climate covariates were generated from the 2020 release of Parameter-elevation Relationships on Independent Slopes Model (PRISM) gridded climate data [43], available for the conterminous U.S. at a 30 arc-second spatial resolution (approximately 800 m). We calculated mean annual and mean summer (June–August) temperature and precipitation for each county subdivision for the period 1992–2018. Because we were modeling ignitions aggregated across communities, we did not include specific topographic variables (e.g., aspect, slope, elevation), since inclusion would require averaging or otherwise adjusting data across space into one value per county subdivision.

Except for road density, all socioeconomic data were derived from the U.S Census and retrieved from the National Historical Geographic Information System (NHGIS), which provided both single-year and time series tables that linked together comparable statistics from multiple census years at selected geographic levels [44]. Multiple socioeconomic variables were acquired for decennial census years 1990 and 2000 and 5-year American Community Survey (ACS) estimates for 2010 and 2018. We used these to build the panel dataset by interpolating values between survey years. Oregon and Washington both had extensive networks of logging roads, some of which conceivably influenced human ignitions. We used a road layer obtained through the USDA Forest Service that incorporated detailed network information from HERE Technologies and the U.S. Department of Homeland Security [45] to compute the density of publicly accessible roads and all roads as a proportion of land area (km of road/km^2) for each county subdivision.

Table 2. Independent variables considered in ignition occurrence models.

Variable	Description	Hypothesized Relationship to Human Ignitions	Data
Poverty Rate Near Poor Rate Household Income Per Capita Income	Population below the poverty level Population below 185% of the poverty level Median household income in previous year Per capita income in previous year	Human ignitions have been linked to areas with difficult economic conditions including high poverty in other studies [34]. Greater wealth also provides more opportunity and access to fire prevention resources [46,47]. Income is also linked with more leisure time which can increase human activities that carry risk of fire (i.e., recreation) [48].	[44]
Home Value	Median home value in previous year	Fire occurrence may decrease in areas with higher value homes as homeowners have more resources for fire prevention and fire wise activities (i.e., thinning and pruning).	[44]
Educational Attainment	Population over age 25 with at least a bachelor's degree	Higher education is correlated with higher income, potentially influencing access to resources. Education may also be linked to awareness of fire risk and valuation of natural resources, overall reducing human-caused fire occurrence.	[44]
Unemployment Rate Labor Force Participation Rate	Population over age 16 and under 65 in labor force and unemployed Population over age 16 and under 65 participating in the labor force.	Unemployment and labor force participation may be linked with social unrest and higher crime, which may increase arson fires but also may indicate high levels of idleness among members of the population, which could increase the number of human ignitions.	[44]
Seasonal Housing	Vacant housing units that are designated for seasonal, recreational, or occasional use	Second homes are linked with both amenity communities, wildland urban interface areas, and the presence of human activity. Areas with high percentages of second homes may decrease fire occurrence due to the presumed wealth associated with second homeownership and less frequent human activity or it may increase human fires due to the potential links to the wildland urban interface and fuels rich environments. Vacant or abandoned land has been linked to increased wildfire occurrence [24].	[44]
Elder (65+) Youth (0–18) Adults (18–24) Adults (18–39) Adults (40–64)	Population over 65 years Population under 18 years Population between 18–24 years Population between 18–39 years Population between 40–64 years	Age demographics influence patterns of development and land use and may be tied to certain types of human activities that carry a risk of fire (i.e., more youth may be associated with more misuse of fire or accidental fires related to risky behaviors and negligence, whereas more active adults may be associated with recreation activities or equipment use that may lead to accidental fire).	[44]
Rural Population Rural Housing Units Population Density	Population in US Census designated rural areas Housing units in US Census designated rural areas Population per area of land	Population density and urban/rural status can influence fire occurrence through fuel availability, presence of human activity, and through cultural activities associated with rural or urban areas (i.e., open burning of yard debris in rural areas with no organized garbage pick-up).	[44]
All Road Density Public Road Density	Kilometers of all public and private roads per area of land Kilometers of public access roads per area of land	Roads represent greater density of human settlements and regional access to forested areas. As in other studies, it is expected that more roads will increase human ignitions [22,31,33].	[45]
Klamath Ecoregion	1 indicates county subdivisions 30% or more contained in the EPA Klamath Mountains Ecoregion	The Klamath Ecoregion is a dummy variable accounting for the substantially different vegetation, climate, and fire regime in the southern portion of the "westside" of the study area.	[49]
Annual Precipitation Summer Precipitation Summer Temperature Annual Temperature	Mean annual precipitation Mean June–August precipitation Mean June–August temperature Mean annual temperature	Annual and summer precipitation influence the amount of vegetation available for ignition during the fire season. Annual and summer temperatures and precipitation are also related to fuel moisture and thus influence the likelihood of ignition.	[43]

Table 3. Summary statistics for dependent and independent variables for all county subdivisions across all years (1992–2018).

Variable	Western Region (N = 7128)				Eastern Region (N = 4968)			
	Mean	**St. Dev.**	**Min**	**Max**	**Mean**	**St. Dev.**	**Min**	**Max**
Natural Ignition Density (10,000 km^2)	11.9	40.4	0.0	790.0	36.5	58.6	0.0	805.0
Human Ignition Density (10,000 km^2)	91.8	137.3	0.0	1501.0	59.6	117.3	0.0	1872.0
All Road Density (km/km^2)	2.3	2.0	0.2	13.0	0.5	0.8	0.0	6.8
Public Road Density (km/km^2)	1.8	2.1	0.1	12.8	0.6	0.9	0.0	6.7
Rural Housing Units (%)	62.9	36.9	0.0	100.0	78.5	32.8	0.2	100.0
Rural Population (%)	62.7	36.8	0.0	100.0	77.6	33.2	0.1	100.0
Youth (0–18 years) (%)	23.5	4.7	0.0	41.3	25.2	5.6	0.0	44.0
Young Adults (18–24 years) (%)	11.7	3.0	0.0	32.3	12.3	4.9	0.0	50.6
Young Adults2 (18–39 years) (%)	25.2	6.0	0.0	63.4	24.8	7.0	0.0	68.3
Adult (39–64 years) (%)	35.3	5.2	0.0	55.9	34.0	6.0	0.0	55.3
Elder (65+ years) (%)	16.1	6.4	0.7	100.0	16.0	5.9	0.0	67.5
Seasonal Housing (%)	7.4	12.2	0.0	91.3	10.3	13.4	0.0	83.5
Educational Attainment (%)	21.0	10.4	0.0	70.5	18.4	9.0	0.0	85.7
Unemployment (%)	8.0	3.5	0.0	34.8	8.7	4.5	0.0	44.8
Labor Force Participation (%)	59.6	8.2	0.0	85.6	58.8	8.2	0.0	89.6
Household Income ($)	47,459.9	16,150.7	0.0	197,152.0	39,783.5	11,775.7	0.0	97,639.0
Per Capita Income ($)	23,159.0	8099.4	0.0	118,166.0	19,496.5	6431.8	0.0	68,229.0
Poverty (%)	12.3	5.2	0.0	44.4	15.5	7.1	0.0	53.7
Near Poor (%)	28.5	9.2	0.0	63.3	35.8	10.8	0.0	72.8
Home Value ($)	184,573.6	83,362.0	36,060.0	676,400.0	130,490.0	62,801.6	0.0	538,500.0
Population Density (km^2)	132.4	352.2	0.0	4621.2	26.9	77.6	0.0	696.2
Summer Temperature (°C)	17.0	1.6	10.4	23.4	18.6	2.4	9.3	24.7
Annual Temperature (°C)	10.4	1.4	4.1	14.1	8.8	1.8	1.6	13.5
Summer Precipitation (mm)	103.5	65.1	1.5	550.4	54.1	39.1	0.0	326.9
Annual Precipitation (mm)	1641.5	738.1	283.5	5268.5	470.3	265.2	85.1	2008.2

2.4. Data Analysis

We first conducted preliminary analyses to characterize spatial patterns of major ignition causes (human vs. natural) and specific human ignition causes across the area. We then estimated separate regression models to evaluate the influence of biophysical and socioeconomic factors on human ignitions and natural ignitions for each county subdivision and year (1992–2018). We modeled both human and natural ignitions for the westside and eastside regions separately to control for major differences in climate, vegetation, and fire regime. Independent models for ignition cause and region also enabled us to compare the influence of explanatory factors on human ignitions relative to natural ignitions and detect differences between the westside and eastside regions. To aid in later interpretation of regression results, we feel it is important to stress that the wildfire ignition data are a proxy for the true numbers of actual ignitions because they necessarily reflect ignitions that were both observed and reported by someone. Some ignitions may have gone unobserved and/or unreported. As such, any potential correlations between individual socioeconomic variables examined and ignitions could be owed to either an actual correlation with ignition, a correlation with observation and reporting of an ignition, or both.

Previous studies of ignition occurrence have tended to rely on generalized linear regression techniques, including multiple linear regression, logistic regression, or Poisson and negative binomial regressions, depending on whether response variables were constructed from continuous, discrete, or count data [16]. Our response variable represented counts of ignitions that were normalized by the area of each county subdivision to create a measure of ignition density that accounted for large variations in the sizes of the county subdivisions. Although commonly used for count data, the Poisson distribution was limited by the assumption that the sample mean was equal to the sample variance ("equi-dispersion"). Our data showed signs of overdispersion, where variance exceeded the mean, which is commonly found in fire occurrence datasets [23]. The negative binomial distribution was an alternative used to fit over-dispersed count data [50] that had been used in other fire occurrence studies [23,33,51], and we deemed this to be most appropriate for our data.

Our data included many zero observations (e.g., county subdivisions that did not record an ignition in a particular year). Zero-inflated models were developed to cope with data with a high occurrence of zeros. These models assume that zero observations originate from two different processes—"sampling" and "structural" [50]. "Sampling zeros" are those due to chance, whereas "structural zeros" are those due to some specific structure in the sampling procedures [51]. In our dataset, we assumed that we had both. Wildfire is a relatively rare event; thus, "sampling zero" observations occurred in some years and county subdivisions as a part of a negative binomial distribution that included both zero and non-zero counts, and some "structural zeros" occurred because of data collection methods (e.g., in sparsely populated rural areas ignitions may have occurred but not developed into a large enough fire to be observed or reported).

We chose to use a zero-inflated negative binomial (ZINB) regression, which belongs to the family of generalized linear models (GLMs) and estimates linear and non-linear effects of the covariates on ignitions [52]. We rescaled our dependent variable to reflect ignitions per 10,000 km^2 then rounded to the nearest integer to ensure that smallest density values were preserved (and not rounded to zero)—a similar approach to that used by Pozo et al. [33]. We evaluated our explanatory variables for potential multicollinearity using Pearson's correlation coefficients, ensuring that our estimated models did not include highly correlated explanatory variables, which we assumed were indicated by a Pearson's correlation coefficient greater than 0.60 (Appendix A). We used a stepwise selection process that utilized AIC (Akaike's Information Criterion) to determine the set of explanatory variables that best described human ignitions for our dataset. We also estimated models describing natural ignitions using the same covariates for comparison. All analyses were performed in R version 3.6.2 GUI 1.70, and models were run in the R package pscl [52].

We also tested zero-inflated GLMs with random effects (RE) for county subdivision and year to account for relationships across space and time and their influence on ignitions. Diagnostic plots of random effects models suggested that these alternative models were not superior to the zero-inflated negative binomial (ZINB) model estimated with fixed effects.

3. Results

3.1. Question 1: What Are the Patterns of Ignition Causes across the Pacific Northwest?

The historical wildfire data that we examined indicated that human ignitions were the predominant cause of wildfires on the westside from 1992 to 2018, accounting for 73 percent of all ignitions (28,711 ignitions). Natural causes (e.g., lightning) made up the remaining 26 percent (10,301 ignitions) (Figures 4 and 5). On the eastside, the proportions of human and natural ignitions were roughly even at 48 percent (49,516 ignitions) and 51 percent (33,727 ignitions). On both the eastside and the westside, the remaining roughly one percent of ignitions were classified as having missing or unknown causes. Across both regions, over half of all human ignitions with known causes were caused by either "recreation and ceremony" or "debris and open burning" (Figures 6 and 7). Human ignitions with unknown origins made up the third largest category for both regions followed by "equipment and vehicle use" at 9 percent (eastside) and 13 percent (westside) (Figure 6).

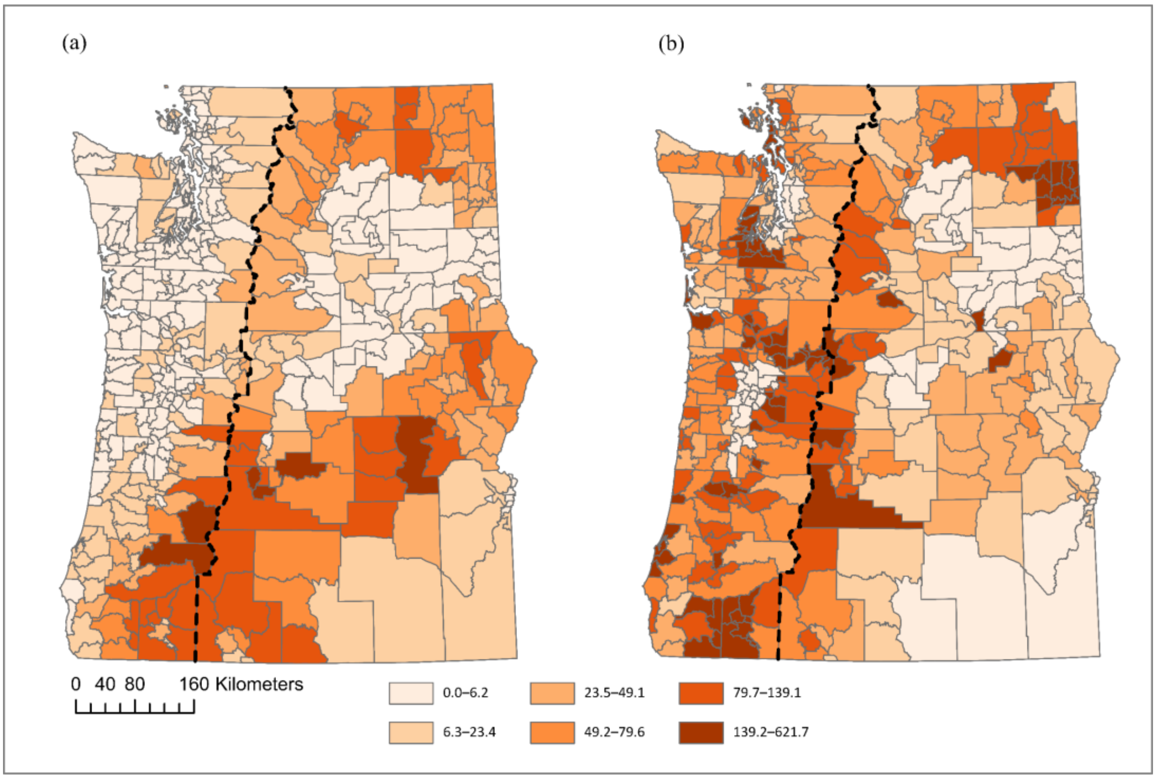

Figure 4. (**a**) Natural Ignition Density; (**b**) Human Ignition Density. Spatial patterns of average human and natural ignition density (ignitions per 10,000 km^2) from 1992–2018 by U.S. Census county subdivisions. Dashed black line demarcates the boundary between westside and eastside regions for analysis. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD). County subdivision lines from US Census Bureau 2018 TIGER/line files.

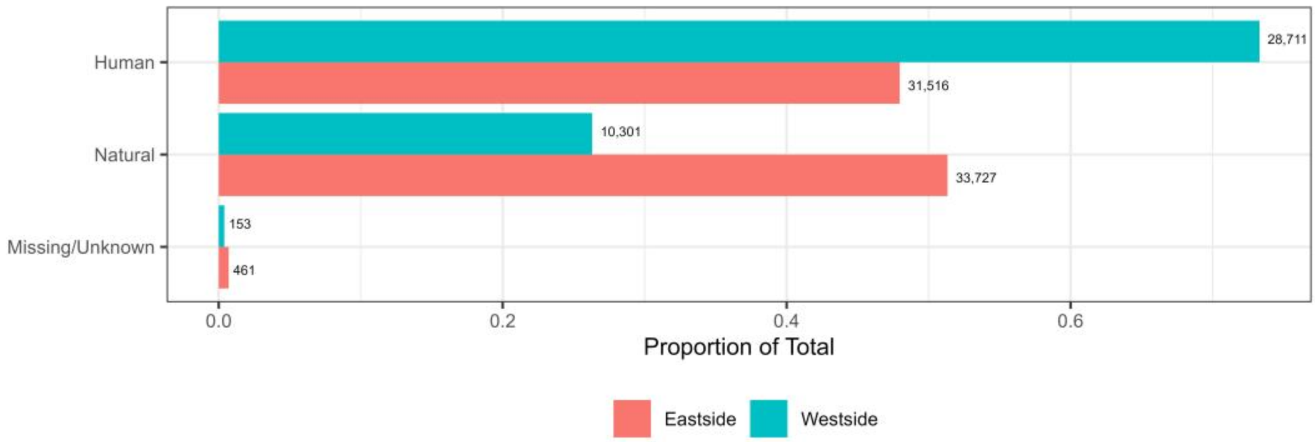

Figure 5. Proportion of human vs. natural ignitions between 1992–2018 by region. Numbers indicate total ignitions over the study period. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD).

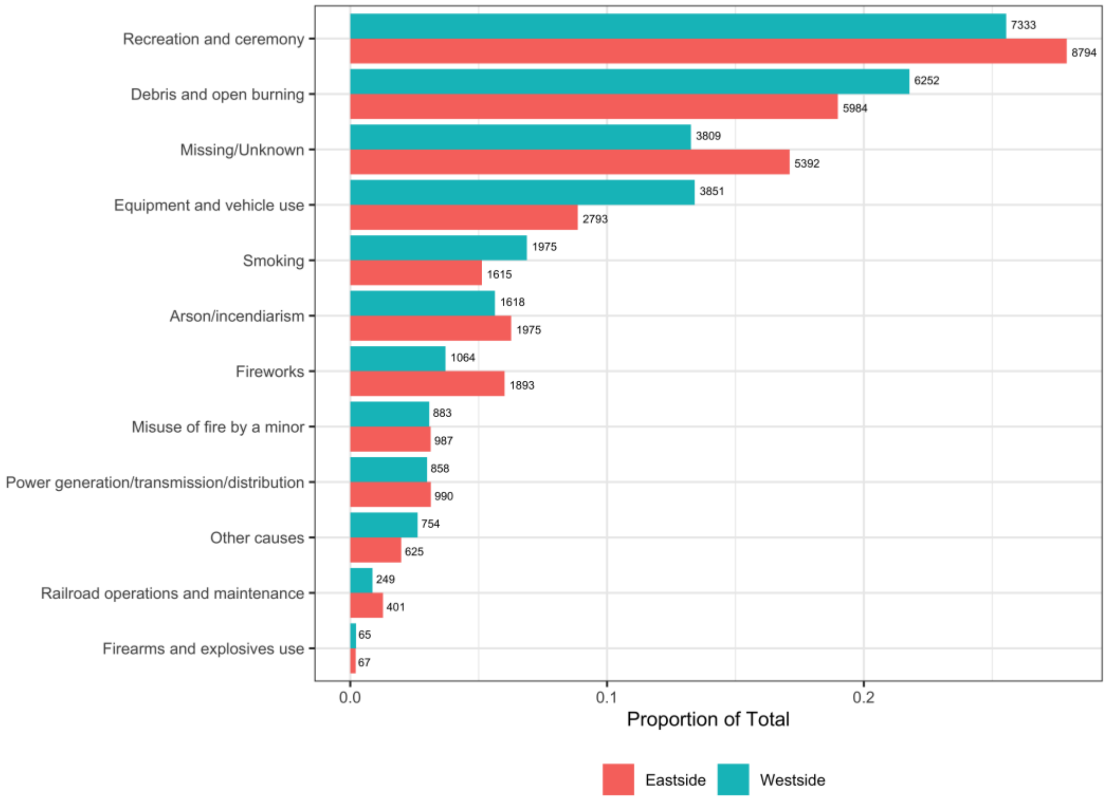

Figure 6. Proportion of ignitions attributed to specific human causes across Oregon and Washington between 1992–2018 by region. Numbers indicate total ignitions over the study period. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD).

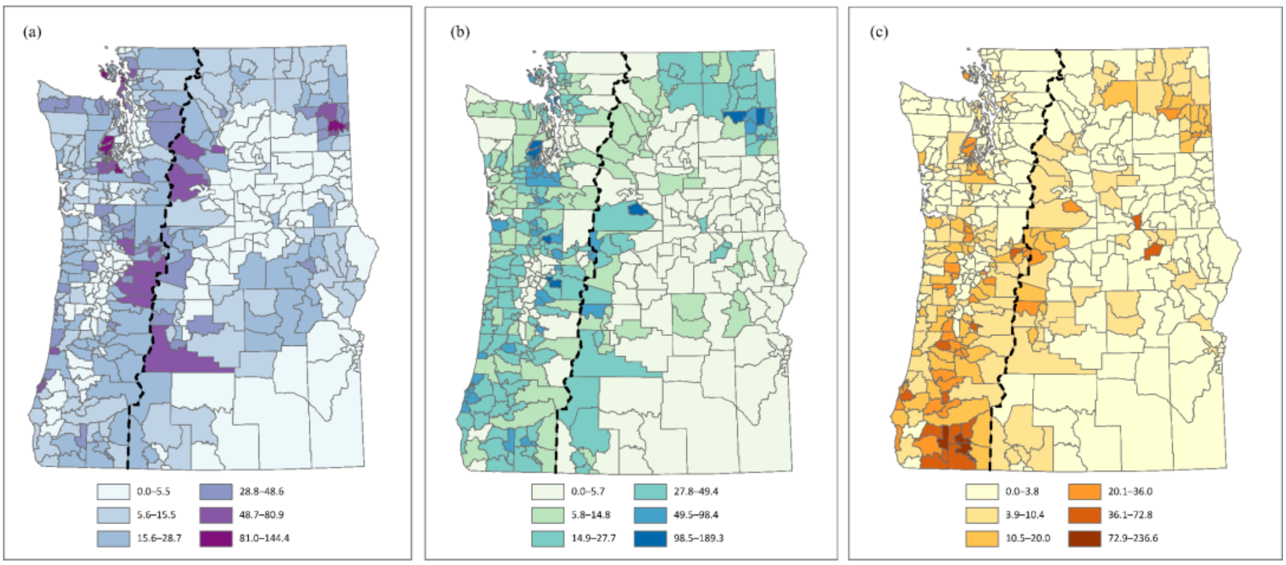

Figure 7. Top three known causes of human ignitions, 1992–2018, by U.S. Census county subdivisions: (**a**) recreation and ceremony, (**b**) debris and open burning, and (**c**) equipment and vehicle use. Values are shown as average ignitions per 10,000 km^2. Dashed black line demarcates the boundary between westside and eastside regions for analysis. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD). County subdivision lines from US Census Bureau 2018 TIGER/line files.

3.2. Question 2: How Might Socioeconomic and Biophsyical Factors Influence Wildfire Ignitions?

Our selected final regression models estimated relationships between human and natural ignition density for each county subdivision and year for westside and eastside regions and several socioeconomic and biophysical covariates:

$$Xit = \beta 0 + \beta 1it \text{ vacant seasonal housing} + \beta 2it \text{ elder} + \beta 3it \text{ household income} + \beta 4it \text{ population density} + \beta 5it \text{ unemployment} + \beta 6it \text{ summer precipitation} + \beta 7it \text{ summer temperature} + \beta 8it \text{ klamath ecoregion} + \in it$$

where Xit = Number of human or natural ignitions per square kilometer in county subdivision i in year t, i = 1. . .450, and t = 1992–2018.

Most explanatory variables for our models of human ignition density were significant at a 10 percent significance level or stronger (Table 4). Vacant seasonal housing was associated with increased human ignitions on the westside and fewer human ignitions on the eastside. Unemployment also had opposite relationships with human ignitions between the two regions, with higher unemployment correlated with fewer ignitions on the westside and increased human ignitions on the eastside. In both regions, an increased proportion of population over age 65 was associated with decreased human ignitions while higher median household income and population density was associated with increased human ignitions. The relationship between mean summer temperature was significant and positively correlated with human ignitions across both eastside and westside models, whereas mean summer precipitation was only significant in the westside model and associated with decreased ignitions.

Table 4. Regression results evaluating the relationships between biophysical and socioeconomic factors and human and natural ignition density across westside and eastside regions.

	Human Ignitions				Natural Ignitions			
	Westside		Eastside		Westside		Eastside	
Explanatory Variables	**Estimated Coefficients**	**Odds**	**Estimated Coefficients**	**Odds**	**Estimated Coefficients**	**Odds**	**Estimated Coefficients**	**Odds**
Intercept	3.499 ***	33.09	3.018 ***	20.46	3.847 ***	46.85	4.618 ***	101.27
Seasonal Housing	0.212 *	1.24	−0.541 ***	0.58	−0.491 **	0.61	0.079	1.08
Elder	−0.600 ***	0.55	−4.976 ***	0.01	1.238 **	3.45	0.215	1.24
Unemployment Rate	−1.041 ***	0.35	6.708 ***	818.54	−0.321	0.73	4.237 ***	69.23
Household Income	0.027 ***	1.03	0.308 ***	1.36	−0.072 ***	0.93	0.041 **	1.04
Population Density	0.001 ***	1.00	0.004 ***	1.00	0.000	1.00	0.002 ***	1.00
Summer Precipitation	−0.321 ***	0.73	0.094	1.10	−0.269 ***	0.76	0.091 *	1.09
Summer Temperature	0.095 ***	1.10	0.008 *	1.01	0.033 *	1.03	−0.067 ***	0.93
Klamath Ecoregion Dummy	0.079 *	1.08	NA	NA	0.177 **	1.19	NA	NA
AIC Value	64,727		40,561		20,131		33,445	

Notes: * $p < 0.1$ (10%), ** $p < 0.05$ (5%), *** $p < 0.01$ (1%); Westside (N = 7182), Eastside (N = 4968). Select variables were rescaled during analysis: Household Income ($10,000), Population Density (1000 persons/km^2), and Summer Precipitation (cm).

Some socioeconomic and biophysical factors were statistically significant ($p < 0.1$) in the natural ignition density model as well (Table 4). On the westside, median household income and vacant seasonal housing were associated with fewer natural ignitions, and elder population was associated with increased natural ignitions. On the eastside, unemployment, income, and population density were significant and associated with increased natural ignitions. Both mean summer precipitation and temperature variables were significant across both regions. Higher mean summer precipitation was associated with decreased natural ignitions on the westside and increased natural ignitions on the eastside. Higher mean summer temperature was associated with increased natural ignitions on the westside and decreased natural ignitions on the eastside.

A sensitivity analysis of the estimated coefficients for human ignitions indicated that summer precipitation and summer temperature had the greatest magnitudes of influence on human ignitions for the westside over the actual range of individual explanatory variable values (Table 5, Figure 8). Of the socioeconomic explanatory variables, sensitivity analysis indicated that the greatest magnitude of impact arose from the elder population and median household income variables (Table 5, Figure 8). For the eastside model, median household income, elder population, and unemployment had far greater influences on human ignitions than biophysical variables. By comparison, sensitivity analysis indicated natural ignitions models were most sensitive to mean summer precipitation and median household income on the westside, and to mean summer temperature and precipitation on the eastside (Table 5).

Table 5. Sensitivity analysis showing predicted values * of human ignition and natural ignitions (ignitions/10,000 km^2) when setting individual explanatory variables at their sample minimum, mean, and maximum values (see Table 3).

	Westside				**Eastside**			
	Explanatory Variables Held at:				**Explanatory Variables Held at:**			
Explanatory Variables	**Minimum**	**Mean**	**Maximum**	**Difference §**	**Minimum**	**Mean**	**Maximum**	**Difference §**
Human Ignitions predicted values †:								
Seasonal Housing	4.74	4.76	4.94	0.19	4.24	4.18	3.79	0.45
Elder	4.85	4.76	4.26	0.60	4.98	4.18	1.62	3.36
Unemployment Rate	4.84	4.76	4.48	0.36	3.60	4.18	6.60	3.00
Median Household Income	4.63	4.76	5.17	0.54	2.96	4.18	5.96	3.01
Population Density	4.76	4.76	4.77	0.01	4.18	4.18	4.18	0.00
Mean Summer Precipitation	5.09	4.76	3.33	1.76	5.00	4.18	4.44	0.56
Mean Summer Temperature	4.13	4.76	5.37	1.24	4.03	4.18	4.23	0.21
Klamath Ecoregion Dummy	4.75	4.76	4.83	0.08	NA	NA	NA	NA
Natural Ignitions predicted values †:								
Seasonal Housing	3.98	3.94	3.53	0.45	3.98	3.98	4.04	0.07
Elder	3.75	3.94	4.98	1.23	3.95	3.98	4.09	0.15
Unemployment Rate	3.97	3.94	3.85	0.11	3.62	3.98	5.51	1.90
Median Household Income	4.28	3.94	2.86	1.42	3.82	3.98	4.22	0.40
Population Density	3.94	3.94	3.94	0.00	3.98	3.98	3.99	0.00
Mean Summer Precipitation	4.21	3.94	2.74	1.48	4.78	3.98	4.23	0.54
Mean Summer Temperature	3.72	3.94	4.15	0.43	5.24	3.98	3.57	1.67
Klamath Ecoregion Dummy	3.92	3.94	4.10	0.18	NA	NA	NA	NA
Global minimum, mean, maximum predicted values ‡:								
Human Ignition Density	4.48	4.76	3.82	−0.66	3.89	4.18	5.74	1.85
Natural Ignition Density	4.19	3.94	2.58	1.62	4.62	5.13	6.63	2.01

Notes: Westside (N = 7182), eastside (N = 4968); * Predicted using the estimated coefficients in Table 4. † Predicted values computed by setting listed explanatory variables at their minimum, mean, and maximum value, respectively, and holding all other variables at their mean. ‡ Predicted by using the estimated coefficients and setting all explanatory values at their global mean, minimum, and maximum values. § Difference between the predicted value at the maximum vs. predicted value at the minimum.

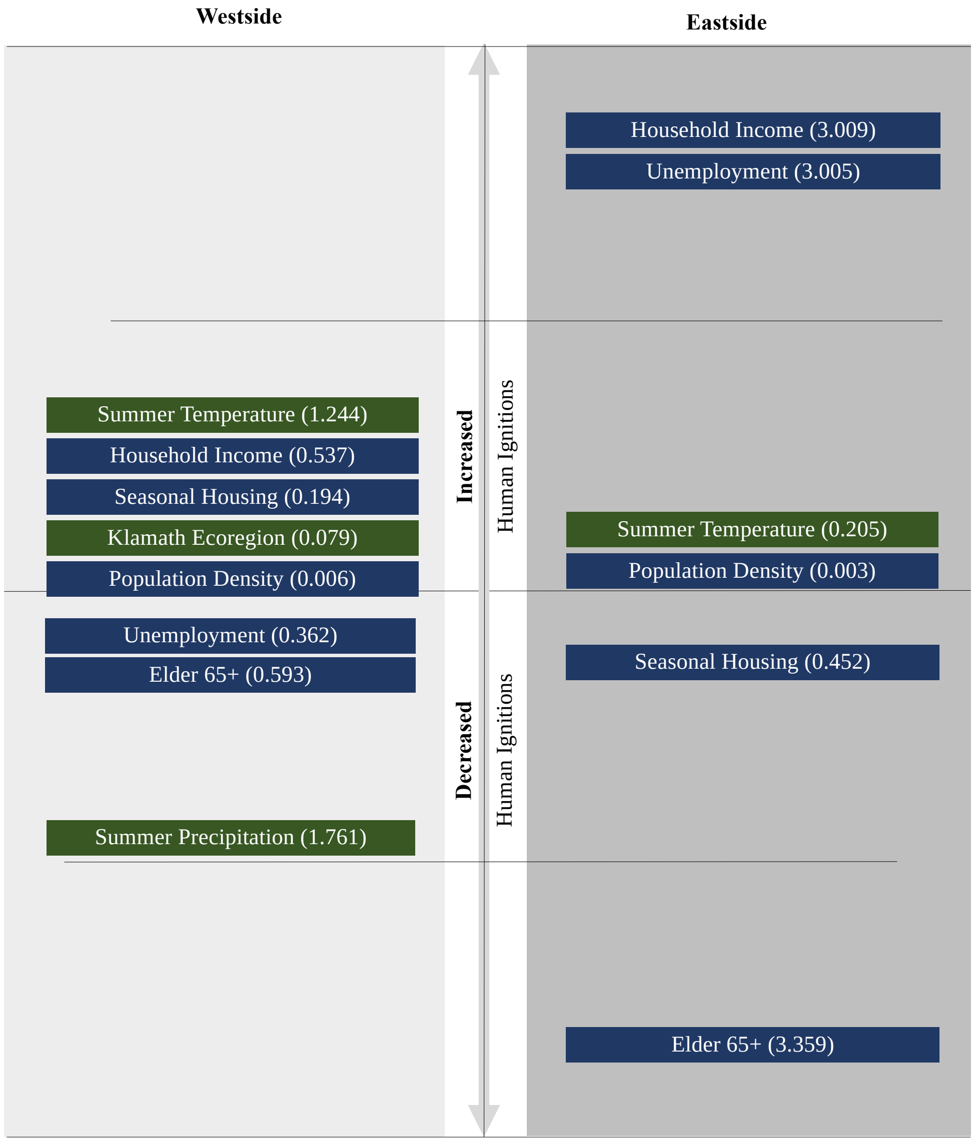

Figure 8. Summary of regression and sensitivity analysis results illustrating the relationships between significant ($p < 0.10$) socioeconomic (blue) and biophysical (green) factors and human ignitions only. Significant factors are shown by magnitude of impact based on sensitivity analysis in Table 5 (noted in parenthesis). Note that significance is not absolute and the choice to use a different significance cutoff would have resulted in a different graphical representation of results.

4. Discussion

Our results suggest that human ignitions in the Pacific Northwest are influenced by socioeconomic factors. Although many of our findings reinforce results of other studies that suggest that human ignitions are influenced by social, economic, and cultural contexts, we found that relationships between individual socioeconomic factors and human ignitions may be regionally specific. Moreover, the variation across regions in how socioeconomic factors might influence human ignitions may not always be intuitive. This was the case with results from our eastside and westside regions.

For example, the proportion of vacant seasonal housing was associated with fewer human ignitions on the eastside, a result also found by Cardille et al. [22] in the upper Midwest U.S., but increased human ignitions on the westside. This inverse relationship may indicate that there are differences in the characteristics of the seasonal housing across the westside and eastside regions. The negative relationship between seasonal housing and human ignitions on the eastside could involve a combination of greater fire awareness among eastside homeowners, where fire risk is higher, and an association between second homeownership and wealth, with individuals in locations having higher proportions of seasonal homes potentially having greater financial resources with which to invest in wildfire mitigation activities [47].

Estimated relationships between unemployment and human ignitions also varied between our westside and eastside regions. Unemployment was associated with increased human ignitions on the eastside and decreased human ignitions on the westside. Unemployment can be a proxy for the economic vitality of an area [23,32], which conceivably could influence ignition occurrence in several ways. The opposite effect of unemployment on the westside from the eastside suggests the characteristics of the unemployed populations differ between the two regions. For example, on the more densely populated westside, unemployment may be driven by urban populations, whereas unemployment may have more to do with a lack of employment opportunities in extensively rural areas on the eastside. Some analysts linked high unemployment and other measures of economic distress with increased social unrest and elevated accounts of arson [23]. Previous research literature has found varied results regarding relationships between human ignitions and unemployment, with many studies finding statistically significant positive correlations [23,28,35]. A positive relationship could suggest that investments in education and employment opportunities could lead to reductions in human ignitions over time.

We found that other socioeconomic factors, including elder population, median household income, and population density, had similar relationships with human ignitions across our westside and eastside regions, even as our results differed from other studies. For example, an increase in population over age 65 was associated with fewer human ignitions in the Pacific Northwest, whereas results from Spain found older adult populations had a positive relationship with human ignitions, potentially due to the associated cultural burning practices in the region [24]. Given that the largest subset of human ignitions in the Pacific Northwest was attributed to recreation, relationships between age demographics and human ignitions may have been related to patterns of recreation use (e.g., less overnight camping in the backcountry where campfire may escape more easily among adults over age 65). Unsurprisingly, population density was also associated with increased human ignitions in both regions, results found in numerous studies nationally and globally [23,25,53].

Interestingly, median household income was associated with increased human ignitions across in the Pacific Northwest, a somewhat counterintuitive finding given that studies in Italy and Spain have found higher incomes associated with decreased wildfire ignitions [24,28], and studies in the Southern United States have found higher poverty rates associated with increased human ignitions [26]. This inconsistency may be explained by the fact that higher income areas are often located in amenity-rich communities that interface with forestlands in the Pacific Northwest, providing greater opportunity for human ignitions. These differences highlight the importance of regional social and cultural contexts in influencing ignition patterns. Conceivably, there also may be a non-linear relationship between income and human ignitions, whereby income might be associated with increased ignitions up to a point but then lead to reductions in ignitions in the wealthiest locations. Testing for this possibility was beyond the scope of our analysis.

We also modeled natural ignitions as a function of both biophysical and socioeconomic factors for comparison. As expected, biophysical factors were significant predictors of both human and natural ignitions. On the westside, increased mean summer precipitation was associated with fewer human and natural ignitions, results found in numerous studies indicating additional summer rain can increase fuel moisture and lower ignition risk [23,27,32]. Mean summer temperature was associated with increased ignitions in both westside and eastside models of human ignitions and in the westside natural ignition model. Summer temperature's positive influence on human ignitions is well established [23,27] and is likely related to the fact that drier fuels present more opportunity for accidental ignitions or fire escape during permitted activities such as burning slash or logging.

We had expected to find that none or few of the socioeconomic factors were significant predictors of natural ignitions, given that humans and civil infrastructure are unlikely to directly influence where and when lightning strikes. Prior research has established lightning-caused ignitions to be primarily driven by biophysical factors such as elevation, fuel moisture, vegetation type, and local weather [54–56], with few studies explicitly addressing human influence on natural ignitions. However, unemployment, median income, and population density were statistically significant in our eastside model, and median income, seasonal housing, and elder population were statistically significant in our westside model. It is worth remembering that an ignition needed to be witnessed and reported by humans to be included in the FPA FOD. Thus, any correlation found between socioeconomic factors and natural ignitions likely arises either from spurious correlation between a particular factor and the propensity of lightening to strike a given location or from the correlation between a particular factor and its influence on facilitating the propagation or discovery of natural ignitions. For example, we speculate that more lightning ignitions on hills or ridgetops are reported than those in valleys obscured from view, and more lightning ignitions are reported near buildings and roads than in roadless areas. It also is conceivable that human presence may, in some way, influence the ignitability of forest fuel at the location of lightning strikes, either because of past forest management practices that alter fuel density, moisture content, stand age, species composition, or some other factor. In the Western U.S., where lighting fires are more common, both road density and recreational infrastructure have been shown to be correlated with increased natural ignitions [31,57]. Regardless of the reason, our results indicate that there can be a spatial correlation between reported natural ignitions and human communities. And, while we assume that the statistically significant relationships we found between natural ignitions and socioeconomic variables reflect an unknown relationship, more directly examining possible causes for correlation could yield useful insights regarding how best to interpret possible causation inherent in correlations found between socioeconomic and natural ignitions.

Our results demonstrate the potential influence of socioeconomic factors on human ignitions in the Pacific Northwest, but also underscores the role of human ignitions in overall wildfire risk in Oregon and Washington, where the vast majority of ignitions on the westside and nearly half of ignitions on the eastside were caused by humans over the past quarter century. A closer look at specific causes of human ignitions reveals nearly half of those human ignitions were caused by recreation or open burning, both of which are discretionary behaviors in that they are generally permitted activities involving directly ignited fires that escaped their intended purpose. Although they make up a smaller portion of ignitions, vehicle use, smoking, operating firearms, and fireworks also contribute to human ignitions, each of which are also discretionary human behaviors that carry an indirect risk of accidental ignition given the right conditions.

Maps of ignitions density (Figure 7) suggest that specific ignition causes exhibit unique spatial patterns. Higher densities of recreation caused ignitions were found along the westside of Cascade mountain range and outside of urban centers such as Portland, Oregon, and Seattle, Washington, where recreation use is high (Figure 7a), and concentrations of ignitions attributable to debris and open burning were clustered in more rural areas immediately surrounding major cities and in the northeast region of Washington (Figure 7b). Ignitions caused by equipment and vehicle use (Figure 7c) were concentrated in the southwest of Oregon, where forestry and agriculture activity intersected with the areas of higher wildfire hazard potential. These patterns were further explored with spatial hotspot analysis, which indicated that these clusters of county subdivisions with high human ignition density were statistically significant (Appendix B, Figures A1 and A2).

From a policy and management perspective, it may be useful to consider how interventions might be designed and deployed to address behaviors that lead to ignitions of unintended human-caused wildfires (Table 6). Given that discretionary direct behaviors (recreation and open burning) generated over half of the known causes of human ignitions (56 percent) in Oregon and Washington over the past quarter century, it may be prudent to develop more tailored information and outreach programs that guide risk assessment of these activities under high risk fire weather conditions geared towards recreationists or for those applying for burn permits and to target interventions to the most relevant areas. Similarly, the development of tailored information regarding wildfire risk of common discretionary indirect activities could help reduce the number of ignitions resulting from activities such as vehicle and equipment use, the third largest known cause of human ignitions in the region.

Table 6. The percentage of all human ignitions in Oregon and Washington between 1992–2018, grouped to highlight potential areas for policy intervention.

Discretionary Direct Behavior	
Recreation and ceremony	32%
Debris and open burning	24%
Total	56%
Discretionary Indirect Behavior	
Equipment and vehicle use	13%
Firearms and explosives use	0%
Fireworks	6%
Misuse of fire by a minor	4%
Smoking	7%
Total	30%
Institutional Behaviors	
Railroad operations and maintenance	1%
Power generation/transmission/distribution	4%
Total	5%

Notes: Arson and "other cause" make up 10%. Does not include missing or unknown causes that account for ~16% of human-caused ignitions. Discretionary direct are accidental ignitions that arise from human activities, in which individuals intend to light fires that escaped control; discretionary indirect are those accidental ignitions that arise indirectly from common human activities that carry a risk of wildfire in certain conditions; and institutional behaviors are those ignitions that arise from operation of human infrastructure.

Our study reinforces the findings of others: that socioeconomic contexts are associated with human wildfire occurrence. We demonstrate that vacant seasonal housing, age demographics, and economic factors such as income and unemployment significantly influence human ignition activity in Oregon and Washington, though their influences on human ignitions vary across the region. While wildfire managers cannot easily change the socioeconomic conditions that may lead to increased human ignitions, analysis of ignition data indicated 56 percent of human ignitions, for which we have known causes, were attributed to recreation or open burning, human behaviors that could be addressed through increased regulation, improved enforcement of current regulations, or more targeted education campaigns. A useful next step would be to use results from this study to design more in-depth analysis of circumstances that lead to specific human ignition causes and to investigate the effectiveness of current regulatory and fire prevention efforts in communities where human ignitions are particularly high. Fuel treatments and improved wildfire responses will play an important role in restoring fire resiliency to western landscapes and protecting communities, but understanding regional ignition causes and the social factors that influence human ignitions will also be imperative for tailoring wildfire prevention efforts to address the underlying human behaviors that drive unplanned human ignitions, especially given that human ignitions are more likely to occur near human communities putting homes and lives at risk.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request to corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Appendix Table

Table A1. Misclassified ignition points removed from Fire Program Analysis Fire Occurrence Database for Oregon and Washington prior to analysis. Data: (Short, 2021).

FOD ID	State	NWCG General Cause	Fire Year	Notes
400025889	OR	Arson/incendiarism	2017	In OK not OR, point dropped
400280014	WA	Missing data/not specified/undetermined	2010	In CA not WA, point dropped
400025885	OR	Arson/incendiarism	2017	In OK not OR, point dropped
1276308	WA	Natural	1994	In ID not WA, point dropped

Table A2. Correlation matrix of variables included in final models.

	Westside (N = 7128)							Eastside (N = 4968)						
Explanatory Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. Summer Temperature	1.0							1.0						
2. Summer Precipitation	−0.6	1.0						−0.5	1.0					
3. Elder (65+ years)	0.0	−0.2	1.0					−0.2	0.1	1.0				
4. Vacant Seasonal Housing	−0.4	0.2	0.4	1.0				−0.4	0.2	0.3	1.0			
5. Unemployment rate	0.0	0.0	0.1	0.0	1.0			−0.2	0.1	−0.1	0.0	1.0		
6. Household Income	0.2	−0.1	−0.2	−0.2	−0.2	1.0		0.2	−0.2	0.1	0.0	−0.3	1.0	
7. Population Density	0.2	−0.1	−0.2	−0.2	−0.1	0.3	1.0	0.2	−0.1	−0.2	−0.2	0.0	0.1	1.0

Appendix B. Hotspot Analysis

Hotspot analysis was performed in ArcGIS pro 2.9.5 using the Optimized Hot Spot Analysis tool for both human and natural ignitions (Figure A1) and for the top three known causes of human ignition (Figure A2). The tool calculated the Getis-Ord (Gi*) statistic for each feature. For our hotspot analysis, we used the mean ignition density for each county subdivision across the study period (1992 to 2018). The Gi* statistic returned a z-score for each feature in the dataset. For statistically significant positive z-scores, the larger the z-score was the more intense the clustering of high values ("hotspots" indicated in red). For statistically significant negative z-scores, the smaller the z-score was the more intense the clustering of low values ("coldspots" indicated in blue). The statistical significance reported was automatically adjusted for multiple testing and spatial dependence using the False Discovery Rate (FDR) correction method [58].

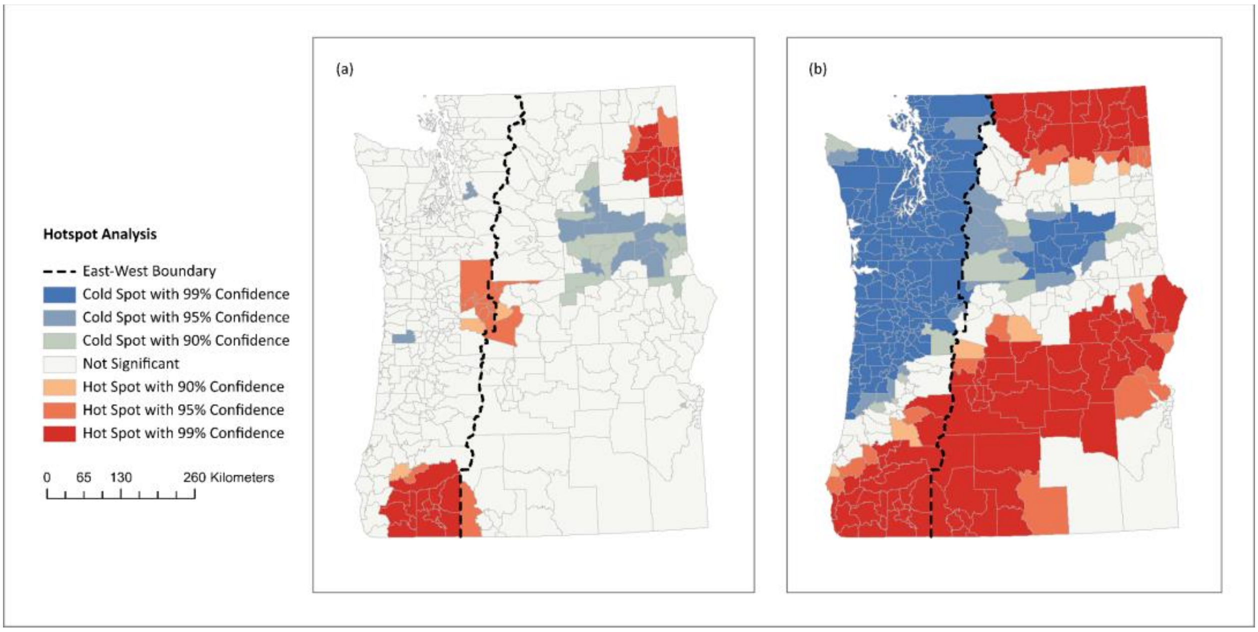

Figure A1. Hotspot analysis of average ignition density 1992–2018 for (**a**) all human and (**b**) all natural ignitions. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD). County subdivision lines from US Census Bureau 2018 TIGER/line files.

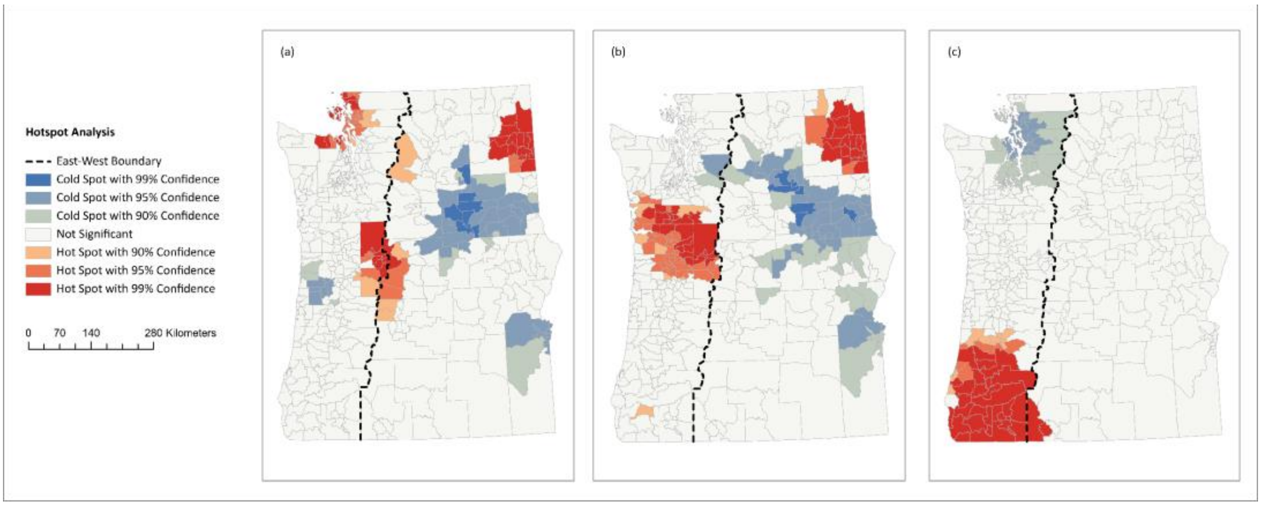

Figure A2. Hotspot analysis of average ignition density 1992–2018 for the top three known human ignition causes: (**a**) recreation and ceremony, (**b**) debris and open burning, and (**c**) equipment and vehicle use. Data: Ignitions data are from the 2021 release of the United States Forest Service Fire Program Fire Occurrence Database (FPAFOD). County subdivision lines from US Census Bureau 2018 TIGER/line files.

References

1. Bond, W.J.; Keeley, J.E. Fire as a Global 'Herbivore': The Ecology and Evolution of Flammable Ecosystems. *Trends Ecol. Evol.* **2005**, *20*, 387–394. [CrossRef] [PubMed]
2. Montegomery, C. Ch 11, Fire: An Agent and a Consequence of Land Use Change. In *The Oxford Handbook of Land Economics*; Duke, J.M., Wu, J., Eds.; Oxford University Press: Oxford, UK, 2014; pp. 281–301.
3. Pyne, S.J. *Fire: A Brief History*, 2nd ed.; University of Washington Press: Seattle, WA, USA, 2019; ISBN 978-0295746180.
4. Abatzoglou, J.T.; Williams, A.P. Impact of Anthropogenic Climate Change on Wildfire across Western US Forests. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 11770–11775. [CrossRef] [PubMed]

5. Balch, J.K.; Bradley, B.A.; Abatzoglou, J.T.; Nagy, R.C.; Fusco, E.J.; Mahood, A.L. Human-Started Wildfires Expand the Fire Niche across the United States. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 2946–2951. [CrossRef] [PubMed]
6. Cattau, M.E.; Wessman, C.; Mahood, A.; Balch, J.K. Anthropogenic and Lightning-started Fires Are Becoming Larger and More Frequent over a Longer Season Length in the U.S.A. *Glob. Ecol. Biogeogr.* **2020**, *29*, 668–681. [CrossRef]
7. Evers, C.; Holz, A.; Busby, S.; Nielsen-Pincus, M. Extreme Winds Alter Influence of Fuels and Topography on Megafire Burn Severity in Seasonal Temperate Rainforests under Record Fuel Aridity. *Fire* **2022**, *5*, 41. [CrossRef]
8. Parks, S.A.; Abatzoglou, J.T. Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017. *Geophys. Res. Lett.* **2020**, *47*, e2020GL089858. [CrossRef]
9. Radeloff, V.C.; Helmers, D.P.; Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Bar-Massada, A.; Butsic, V.; Hawbaker, T.J.; Martinuzzi, S.; Syphard, A.D.; et al. Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 3314–3319. [CrossRef]
10. Food and Agriculture Organization of the United Nations. *Fire Management Global Assessment: A Thematic Study Prepared in the Framework of the Global Forest Resources Assessment*; Electronic Publishing Policy and Support Branch: Rome, Italy, 2007.
11. National Science Analysis Team. The Science Analysis of The National Cohesive Wildland Fire Management Strategy. Available online: https://cohesivefire.nemac.org/challenges-opportunities (accessed on 22 August 2022).
12. Prestemon, J.P.; Hawbaker, T.J.; Bowden, M.; Carpenter, J.; Brooks, M.T.; Abt, K.L.; Sutphen, R.; Scranton, S. *Wildfire Ignitions: A Review of the Science and Recommendations for Empirical Modeling*; U.S. Department of Agriculture, Forest Service, Southern Research Station: Asheville, NC, USA, 2013; p. SRS-GTR-171.
13. Steelman, T.U.S. Wildfire Governance as Social-Ecological Problem. *Ecol. Soc.* **2016**, *21*. Available online: http://www.jstor.org/stable/26270036 (accessed on 15 July 2023). [CrossRef]
14. Ager, A.A.; Kline, J.D.; Fischer, A.P. Coupling the Biophysical and Social Dimensions of Wildfire Risk to Improve Wildfire Mitigation Planning: Coupling the Biophysical and Social Dimensions of Wildfire Risk. *Risk Anal.* **2015**, *35*, 1393–1406. [CrossRef]
15. McCaffrey, S.; Toman, E.; Stidham, M.; Shindler, B. Social Science Research Related to Wildfire Management: An Overview of Recent Findings and Future Research Needs. *Int. J. Wildland Fire* **2013**, *22*, 15. [CrossRef]
16. Costafreda-Aumedes, S.; Comas, C.; Vega-Garcia, C.; Costafreda-Aumedes, S.; Comas, C.; Vega-Garcia, C. Human-Caused Fire Occurrence Modelling in Perspective: A Review. *Int. J. Wildland Fire* **2017**, *26*, 983–998. [CrossRef]
17. Gillson, L.; Whitlock, C.; Humphrey, G. Greater Temperature and Precipitation Extremes Intensify Western U.S. Droughts, Wildfire Severity, and Sierra Nevada Tree Mortality. *Ecol. Soc.* **2019**, *24*, 14. [CrossRef]
18. Hrozencik, A. Drought in the Western United States. Available online: https://www.ers.usda.gov/newsroom/trending-topics/drought-in-the-western-united-states/ (accessed on 3 April 2022).
19. Halofsky, J.E.; Peterson, D.L.; Harvey, B.J. Changing Wildfire, Changing Forests: The Effects of Climate Change on Fire Regimes and Vegetation in the Pacific Northwest, USA. *Fire Ecol.* **2020**, *16*, 4. [CrossRef]
20. Fischer, A.P.; Spies, T.A.; Steelman, T.A.; Moseley, C.; Johnson, B.R.; Bailey, J.D.; Ager, A.A.; Bourgeron, P.; Charnley, S.; Collins, B.M.; et al. Wildfire Risk as a Socioecological Pathology. *Front. Ecol. Environ.* **2016**, *14*, 276–284. [CrossRef]
21. Kline, J.D.; White, E.M.; Fischer, A.P.; Steen-Adams, M.M.; Charnley, S.; Olsen, C.S.; Spies, T.A.; Bailey, J.D. Integrating Social Science into Empirical Models of Coupled Human and Natural Systems. *Ecol. Soc.* **2017**, *22*, art25. [CrossRef]
22. Cardille, J.A.; Ventura, S.J.; Turner, M.G. Environmental and Social Factors Influencing Wildfires in the Upper Midwest, United States. *Ecol. Appl.* **2001**, *11*, 111–127. [CrossRef]
23. Chas-Amil, M.L.; Prestemon, J.P.; McClean, C.J.; Touza, J. Human-Ignited Wildfire Patterns and Responses to Policy Shifts. *Appl. Geogr.* **2015**, *56*, 164–176. [CrossRef]
24. de Diego, J.; Rúa, A.; Fernández, M. Designing a Model to Display the Relation between Social Vulnerability and Anthropogenic Risk of Wildfires in Galicia, Spain. *Urban Sci.* **2019**, *3*, 32. [CrossRef]
25. Dondo Bühler, M.; de Torres Curth, M.; Garibaldi, L.A. Demography and Socioeconomic Vulnerability Influence Fire Occurrence in Bariloche (Argentina). *Landsc. Urban Plan.* **2013**, *110*, 64–73. [CrossRef]
26. Grala, K.; Grala, R.K.; Hussain, A.; Cooke, W.H.; Varner, J.M. Impact of Human Factors on Wildfire Occurrence in Mississippi, United States. *For. Policy Econ.* **2017**, *81*, 38–47. [CrossRef]
27. Guo, F.; Su, Z.; Wang, G.; Sun, L.; Lin, F.; Liu, A. Wildfire Ignition in the Forests of Southeast China: Identifying Drivers and Spatial Distribution to Predict Wildfire Likelihood. *Appl. Geogr.* **2016**, *66*, 12–21. [CrossRef]
28. Mancini, L.D.; Corona, P.; Salvati, L. Ranking the Importance of Wildfires' Human Drivers through a Multi-Model Regression Approach. *Environ. Impact Assess. Rev.* **2018**, *72*, 177–186. [CrossRef]
29. Martínez-Fernández, J.; Chuvieco, E.; Koutsias, N. Modelling Long-Term Fire Occurrence Factors in Spain by Accounting for Local Variations with Geographically Weighted Regression. *Nat. Hazards Earth Syst. Sci.* **2013**, *13*, 311–327. [CrossRef]
30. Mercer, D.E.; Prestemon, J.P. Comparing Production Function Models for Wildfire Risk Analysis in the Wildland–Urban Interface. *For. Policy Econ.* **2005**, *7*, 782–795. [CrossRef]
31. Narayanaraj, G.; Wimberly, M.C. Influences of Forest Roads on the Spatial Patterns of Human- and Lightning-Caused Wildfire Ignitions. *Appl. Geogr.* **2012**, *32*, 878–888. [CrossRef]
32. Oliveira, S.; Oehler, F.; San-Miguel-Ayanz, J.; Camia, A.; Pereira, J.M.C. Modeling Spatial Patterns of Fire Occurrence in Mediterranean Europe Using Multiple Regression and Random Forest. *For. Ecol. Manag.* **2012**, *275*, 117–129. [CrossRef]

33. Pozo, R.A.; Galleguillos, M.; González, M.E.; Vásquez, F.; Arriagada, R. Assessing the Socio-Economic and Land-Cover Drivers of Wildfire Activity and Its Spatiotemporal Distribution in South-Central Chile. *Sci. Total Environ.* **2022**, *810*, 152002. [CrossRef]
34. Prestemon, J.P.; Butry, D.T. Time to Burn: Modeling Wildland Arson as an Autoregressive Crime Function. *Am. J. Agric. Econ.* **2005**, *87*, 756–770. [CrossRef]
35. Syphard, A.D.; Radeloff, V.C.; Keuler, N.S.; Taylor, R.S.; Hawbaker, T.J.; Stewart, S.I.; Clayton, M.K. Predicting Spatial Patterns of Fire on a Southern California Landscape. *Int. J. Wildland Fire* **2008**, *17*, 602. [CrossRef]
36. Zhang, Y.; Lim, S.; Sharples, J.J. Modelling Spatial Patterns of Wildfire Occurrence in South-Eastern Australia. *Geomat. Nat. Hazards Risk* **2016**, *7*, 1800–1815. [CrossRef]
37. Agee, J.K. *Fire Ecology of Pacific Northwest Forests*; Island Press: Washington, DC, USA, 1996; ISBN 978-1-55963-230-0.
38. Haugo, R.D.; Kellogg, B.S.; Cansler, C.A.; Kolden, C.A.; Kemp, K.B.; Robertson, J.C.; Metlen, K.L.; Vaillant, N.M.; Restaino, C.M. The Missing Fire: Quantifying Human Exclusion of Wildfire in Pacific Northwest Forests, USA. *Ecosphere* **2019**, *10*, e02702. [CrossRef]
39. Reilly, M.J.; Zuspan, A.; Halofsky, J.S.; Raymond, C.; McEvoy, A.; Dye, A.W.; Donato, D.C.; Kim, J.B.; Potter, B.E.; Walker, N.; et al. Cascadia Burning: The Historic, but Not Historically Unprecedented, 2020 Wildfires in the Pacific Northwest, USA. *Ecosphere* **2022**, *13*, e4070. [CrossRef]
40. United States Census Bureau County Subdivisions, The Geographic Areas Reference Manual of the United States Census Bureau. Available online: https://www2.census.gov/geo/pdfs/reference/GARM/Ch8GARM.pdf (accessed on 18 July 2022).
41. Short, K.C. *Spatial Wildfire Occurrence Data for the United States, 1992–2018 [FPA_FOD_20210617]*, 5th ed.; USDA Forest Service Research Data Archive: Washington, DC, USA, 2021.
42. Donoghue, L. *Classifying Wildfire Causes in the USDA Forest Service: Problems and Alternatives*; U.S. Department of Agriculture, Forest Service, North Central Forest Experiment Station: St. Paul, MN, USA, 1982.
43. Daly, C.; Halbleib, M.; Smith, J.I.; Gibson, W.P.; Doggett, M.K.; Taylor, G.H.; Curtis, J.; Pasteris, P.P. Physiographically Sensitive Mapping of Climatological Temperature and Precipitation across the Conterminous United States. *Int. J. Climatol.* **2008**, *28*, 2031–2064. [CrossRef]
44. Manson, S.; Schroeder, J.; Van Riper, D.; Kugler, T.; Ruggles, S. *IPUMS National Historical Geographic Information System: Version 15.0*; University of Minnesota: Minneapolis, MN, USA, 2020. [CrossRef]
45. HERE Technologies; U.S. Department of Homeland Security Internal Road Layer from U.S. Forest Service. Internal dataset.
46. Brenkert-Smith, H.; Champ, P.A.; Flores, N. Trying Not to Get Burned: Understanding Homeowners' Wildfire Risk–Mitigation Behaviors. *Environ. Manag.* **2012**, *50*, 1139–1151. [CrossRef]
47. Collins, T.W. What Influences Hazard Mitigation? Household Decision Making about Wildfire Risks in Arizona's White Mountains. *Prof. Geogr.* **2008**, *60*, 508–526. [CrossRef]
48. Winter, P.L.; Crano, W.D.; Basáñez, T.; Lamb, C.S. Equity in Access to Outdoor Recreation—Informing a Sustainable Future. *Sustainability* **2020**, *12*, 124. [CrossRef]
49. Omernik, J.M.; Griffith, G.E. Ecoregions of the Conterminous United States: Evolution of a Hierarchical Spatial Framework. *Environ. Manag.* **2014**, *54*, 1249–1266. [CrossRef]
50. Hu, M.-C.; Pavlicova, M.; Nunes, E.V. Zero-Inflated and Hurdle Models of Count Data with Extra Zeros: Examples from an HIV-Risk Reduction Intervention Trial. *Am. J. Drug Alcohol Abuse* **2011**, *37*, 367–375. [CrossRef]
51. Su, Z.; Hu, H.; Tigabu, M.; Wang, G.; Zeng, A.; Guo, F. Geographically Weighted Negative Binomial Regression Model Predicts Wildfire Occurrence in the Great Xing'an Mountains Better than Negative Binomial Model. *Forests* **2019**, *10*, 377. [CrossRef]
52. Jackman, S. *Pscl: Classes and Methods for R Developed in the Political Science Computational Laboratory*; United States Studies Centre, University of Sydney: Sydney, NSW, Australia, 2020.
53. McWethy, D.B.; Pauchard, A.; García, R.A.; Holz, A.; González, M.E.; Veblen, T.T.; Stahl, J.; Currey, B. Landscape Drivers of Recent Fire Activity (2001–2017) in South-Central Chile. *PLoS ONE* **2018**, *13*, e0201195. [CrossRef]
54. Chen, B.; Jin, Y. Spatial Patterns and Drivers for Wildfire Ignitions in California. *Environ. Res. Lett.* **2022**, *17*, 055004. [CrossRef]
55. Dorph, A.; Marshall, E.; Parkins, K.A.; Penman, T.D. Modelling Ignition Probability for Human- and Lightning-Caused Wildfires in Victoria, Australia. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 3487–3499. [CrossRef]
56. Abatzoglou, J.T.; Kolden, C.A.; Balch, J.K.; Bradley, B.A. Controls on Interannual Variability in Lightning-Caused Fire Activity in the Western US. *Environ. Res. Lett.* **2016**, *11*, 045005. [CrossRef]
57. Benefield, A.; Chen, J. Does Human Accessibility Affect Lightning-Caused Wildfires? A Case Study of the Southern Rocky Mountains. *Fire Technol.* **2023**. [CrossRef]
58. Environmental Systems Research Institute. Optimized Hot Spot Analysis (Spatial Statistics)—ArcGIS Pro | Documentation. Available online: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/optimized-hot-spot-analysis.htm (accessed on 25 July 2023).