THESIS

ASSESSING WILDFIRE RISK REDUCTION THROUGH FUEL TREATMENTS AND EDUCATIONAL ACTIVITIES

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ABSTRACT

ASSESSING WILDFIRE RISK REDUCTION THROUGH FUEL TREATMENTS AND EDUCATIONAL ACTIVITIES

Hazardous forest fuel reduction and prevention education are key strategies for reducing wildfire risk. While fuel reduction efforts have become a shared goal of many agencies, the cost of implementing them remains a significant challenge. Increasing biomass utilization can be a strategy for reducing these costs. Yet little is known about the impact of wood manufacturing facilities on fuel treatment activities. Additionally, human activities cause nearly 84% of wildfires, often leading to rapid spread and severe impacts, including health issues, environmental damage, suppression expenditures, degraded air and water quality. As such, evaluating the effectiveness of educational prevention activities is crucial at reducing undesirable human-caused ignitions and enhancing cost-effectiveness of wildfire management. This study examines two interrelated research objectives related to wildfire risk reduction: (1) the impacts of forest market proximity on fuel treatment activities in National Forests (USFS) and Bureau of Land Management (BLM) lands in Colorado, and (2) the effectiveness of wildfire prevention education (WPE) in reducing undesirable human-caused ignitions on tribal lands in the U.S. To address objective 1, we developed a mixed linear model using fuel treatment data (n = 779 BLM sites and n = 9,709 USFS sites), the location of active wood manufacturing facilities, and climatic variables from 2012 to 2020. We found that proximity to facilities significantly impacts treatment activities, with sites relatively closer in proximity treating more acres and utilizing more biomass than those further away, in both BLM and USFS lands. Additionally, we identified a threshold of 70 minutes beyond which proximity had no significant effect on fuel treatment on both lands. To address objective 2, we employed Poisson regression by using seven categories of monthly WPE activities (mass media coverage, signage placements, programs/events, individual/key-personnel contacts, community contacts, brochures, hazard assessments), wildfire ignitions, acres burned, and climatic factors across 35 U.S. tribal units from 2012 to 2020. After controlling for potential endogeneity biases, the Poisson model revealed that certain WPE activities, such as community contacts, significantly reduced ignitions caused by debris and open burning, fireworks, fire misuse by minors, power generation, recreation/ceremony, firearms/explosives and smoking. Hazard assessments were marginally significant, whereas individual/key-personnel contacts, informational brochures, and programs/events were negatively related to fire ignitions. In contrast, media coverage and signage had no significant effect, although the lagged six-month aggregates showed a significant and negative effect on the number of ignitions. Our findings underscore the role of strategic planning of well-distributed wood-processing facilities for optimizing fuel treatment costs and the importance of continued WPE efforts to reduce human-caused ignitions.

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1.1 Introduction

Colorado's (CO) forests and diverse topography, ranging from the Rocky Mountains to the High Plains, represent instrumental ecological, economic, and recreational assets fundamental to the state's well-being. However, these landscapes are increasingly threatened by wildfires, which have become a significant and recurring issue due to their escalating intensity and severity. Multiple factors like fuel accumulation, prolonged drought conditions, warming climate, and expansion of the Wildland-Urban Interface (WUI) increase the risk of wildfires (Synolakis & Karagiannis, 2024). The accumulation of dead trees, dry leaves, and other organic matter provides ample fuel for fire ignition. The increased grass fuel loading and continuity create a fuel bed susceptible to rapid fire spread in CO (National Interagency Fire Center, 2024). Climate change is another significant factor that raises temperatures and prolongs droughts, which dries out vegetation and makes it more susceptible to ignition. Furthermore, it exacerbates other disturbances like insect outbreaks and diseases, weakening trees and making forests more vulnerable to fires (Halofsky et al., 2020). Additionally, the expansion of the WUI further intensifies the wildfire problem. The proximity of the wildlands to residential areas increases human presence, which leads to more activities igniting fires, such as campfires, barbecues, and the use of machinery. Increased development in areas where urban environments meet wildlands has also heightened the risk and impact of wildfires (Markus & Penny, 2021; Synolakis & Karagiannis, 2024).

In recent decades, the frequency and expenses associated with devastating wildfires have increased significantly in the US West (USDA Forest Service, 2022). For example, the cost of wildfire suppression nationwide has increased from $200 million in 1994 to over $400 million in 2018 (U.S. DOI, 2020). Reduction of hazardous forest fuels is one of the forest management strategies to reduce the overall wildfire risk and associated costs of battling ignitions. Integrating fuel treatments like mechanical with fire such as prescribed burns has been the most effective strategy for reducing fuel hazard and promoting future fire-resilient forests (Jain et al., 2021). These treatment decisions on public lands are primarily managed by federal agencies such as the Bureau of Land Management (BLM) and United States Forest Service (USFS).

BLM and USFS use a collaborative decision-making process for hazardous fuel treatments where the line officer is responsible for signing the decision, but it varies by project size. District rangers sign smaller projects, while larger ones require approval from the forest supervisor, regional forester, or chief of the USFS. Except in emergencies, vegetation treatments are open to public comment during the National Environmental Policy Act (NEPA) process, including input from state and local governments, federal agencies, industry, and tribes. For the treatment project, USFS raises awareness through legal notices, websites, social media, and public meetings. The choice of treatment method, whether prescribed burning, mechanical thinning, or other strategies depends on factors such as forest type, stand conditions, ecological goals, and available resources. Further, fire behavior models and climate projections help guide treatment decisions, where local knowledge and factors like risk values and infrastructure also play key roles in determining treatment areas (Sierzega, 2025). The USFS aims to treat an additional 20 million acres on National Forest System lands in the West and up to 30 million acres on other federal, state, tribal, and private lands over the next decade (Weseman, 2022). Despite these efforts, there is a need for a breakthrough in treating hazardous fuels, with estimates suggesting that it would take $20 billion over a decade to adequately address the challenge (Gabbert, 2022). Factors such as labor costs, fuel prices, market conditions, contractor supply, equipment, regulatory changes, and forest management practices present unique challenges for efficient forestry practices and cost management (Watson et al., 1987; Belli et al., 1993; Dubois et al., 1999; Callaghan et al., 2019).

In states such as CO, where over 2.4 million acres of forests are currently in need of restoration, treatment of hazardous fuels is critical (CSFS, 2021). However, the structure and fuel loads in CO's forests are changing due to heavy insect infestations and changing climate (Vorster et al., 2017; Woodward et al., 2018), thereby influencing the cost and efficacy of fuel treatments. In recent years, large-scale pest outbreaks, like the mountain pine and spruce beetles have led to widespread tree mortality which has increased the wildfire risk and complications of treatment efforts (USFS, 2023). Additionally, extended fire seasons and increased droughts, and the expanding WUI adds complexity and cost to treatment efforts (CSFS, 2025). The lengthy planning processes, often extending beyond a year due to regulations like the NEPA exacerbate treatment implementation delays, causing difficulties in cost management of treatment efforts (Hunter et al., 2007). Further, the existence of several small towns tucked away in or close to forested areas increases the risk and possible expenses associated with wildfires (Lynch & Mackes, 2002). Specified treatments like thinning and pruning can be costly, and the financial burden varies depending on the scale and specific forest environment. In CO, the average cost of mechanical thinning ranges from $500 to $2,000 per acre, while prescribed burns can cost between $50 and $500 per acre (Mueller & Caggiano, 2022). Implementation costs of treatment, which include overhead and administration, can add an additional 35% to 51% to the total cost (CSFS, 2020). The costs are even higher in the WUI, where residential and commercial development meets undeveloped wildlands. This is due to the additional precautions and measures that need to be taken to ensure the safety of nearby structures and people.

The USFS and BLM, which manage a large proportion of forests in CO, operate under budget constraints, and the high costs associated with forest management practices strain their limited financial resources (CSFS, 2020). In addition, the accurate cost estimation for fuel treatments remains limited due to unreliable cost data, which complicates budgeting and prioritization of treatment activities even more (Calkin & Gebert, 2006; Rummer, 2008). Despite the recognized need for hazardous fuels reduction work, funding limitations restrict efforts. In a recent 2023-2024 round of Forest Restoration and Wildfire Risk Mitigation grant cycle, many projects requesting over $11 million out of $18 million remained unfunded, leaving 4,890 acres untreated (CSFS, 2024a). Such increasing numbers underscore the escalating costs and challenges associated with conducting fuel treatment activities. Whilst assessing the viability of any fuel treatment, it is crucial to consider both the net treatment costs and the decrease in fire risk (Hartsough et al., 2008). Kline (2004) also emphasized the importance of considering the long-term costs and benefits of fuel treatments within a broader analytical context that includes wildfire suppression and postfire restoration. With the rise of catastrophic wildfires in CO, avoided cost assessments are becoming increasingly necessary (CSFS, 2020).

Given the challenges of fuel treatment and associated costs, a key strategy is to create viable markets for forest removals that come out of treatment activities. This could involve developing local markets for small-diameter trees and other unique forest products, which would not only offset treatment costs but also contribute to local economies (Lynch & Mackes, 2002). Often, small-diameter trees that are removed have no commercial value. They are either left scattered on-site or burned in piles, increasing the fuel loads and overall emissions from treatments (Han et al., 2004). The thinning activities produce significant amounts of woody material, encompassing smaller trees, limbs, and other woody biomass. Utilization of woody biomass contributes to healthy ecosystem, reduces wildfire risk and increased use of local wood products by industries. Implementing substantial biomass removals could potentially lead to a nearly twofold increase in timber output in many fire-prone areas of the West (Abt & Prestemon, 2006). Consistent policies for woody biomass utilization and collecting comminuted biomass can help reduce costs of treatments and enhance overall efficiency (Stephens et al., 2012). Policies and financial incentives further promote biomass utilization by subsidizing the establishment of new wood-based facilities, thereby offsetting treatment costs and encouraging the use of small-diameter wood and biomass. The effectiveness of biomass utilization centers on the presence of markets capable of processing low-value wood. For instance, the National Renewable Energy Lab in Golden, CO utilize wood chip boilers for energy, demonstrating the practical applications of biomass utilization (CSFS, 2024b). Without such markets, the financial feasibility of biomass-based treatments becomes limited.

The implementation and success of fuel treatments are intrinsically linked to the complex interplay between forest market dynamics and management decisions (Houtman et al., 2016). The forest products market exerts profound influence on forest management decisions, shaping the economic viability of fuel treatments and timber harvesting activities (Wear, 2024). Forest management agencies typically do not own the equipment necessary for harvesting and removing materials from fuels reduction projects. Instead, they facilitate material removal through contracts or agreements with wood manufacturing facilities. Notably, all resources extracted from public lands are regarded as public assets. Therefore, payment for these resources must be completed by the forest facilities before any residual materials can be removed. In certain instances, the value of the products removed can help offset the costs of other services agreed within these contracts or agreements, further aligning the economic feasibility of fuel treatments with the broader goals of forest management. This interplay is further complicated by the factors influencing treatment costs, such as the volume of the materials, the terrain and prevailing weather conditions, size of the treatment area and its closeness to residential or other developed areas (Fight & Barbour, 2005).

Additionally, transportation costs complicate matters, especially in remote areas where hauling low-value materials long distances is financially impractical (Daugherty & Fried, 2007). The transportation costs associated with moving biomass such as the need for high-quality roads to accommodate chip trucks can often exceed the revenue generated from its sales, making it economically unfeasible to transport. These high costs are compounded by the fact that the material's value is typically lower than other forest products like logs, which are more easily sold to processing facilities. As a result, biomass often becomes a financial burden rather than a valuable resource, and the decision to remove it is influenced by the economic feasibility of transport. When the cost of treatment and transportation exceeds the material's appraised value, the agencies may choose not to remove the material. In the process of appraising forest materials, the total value of the harvested product is first determined based on what processing facilities are willing to pay for it. From this total value, the costs associated with treatment (getting the material from the stump to a landing) and transportation (such as road improvements and hauling) are deducted. If these costs approach or exceed the total value, the material is deemed to have a negative value and is often left in place (Sierzega, 2025). This interplay between treatment costs, transportation costs, and the value of residual materials is crucial in shaping the decisions regarding which areas are treated, and which materials are removed.

The decision to leave low-value materials behind rather than remove them adds complexity to the overall cost-effectiveness of hazardous fuel reduction efforts. Becker et al. (2009) underscored that decreasing the distance between markets and treatment locations is essential for cost-effective hazardous fuels reduction. Traditional wood product markets often don't provide enough financial offset for treatment costs, especially when factoring in transportation expenses in CO's vast landscapes. A significant portion of the volume slated for removal can be effectively used in traditional forest products processing facilities, if there are economically feasible transportation options to markets (USDA, 2005). CO has a significant amount of wood waste and residues that could be utilized for energy production. However, the recovery and transportation costs present barriers to their use. Understanding the geographic limits of market influence can help optimize the use of these resources, supporting both economic development and environmental sustainability (Ward et al., 2004). Building upon the work by Pincus et al. (2013), our study extends the research to CO, incorporating more recent data from 2012 to 2020 and including lands managed by both the BLM and USFS. Furthermore, this study considers additional climatic variables which will enhance model precision and reliability. Prior studies suggested transportation costs could be a barrier, but the specific distance at which market influence diminishes is still not established in CO. The concept of threshold distance is yet to be tested and provide metrics for forest managers to understand the geographic limits of market impact. This study aims to address the research gaps by focusing on two main following research questions: (1) Does the proximity of wood-based facilities influence fuel reduction activities in BLM and USFS lands in CO? and (2) Is there a threshold beyond which proximity to facilities has no influence on fuel treatments?

This study makes important contributions to literature. First, it provides some new insights into the role of wood product markets in accomplishing fuel treatments in CO, where the need for managing fuel loads is critical. Second, it expands the research on treatment activities across federal forestlands managed by various agencies within the state. Third, it utilizes data covering a period from 2012 to 2020, allowing for thorough analysis and providing a more comprehensive picture of market impacts. Overall, the findings from this study will help inform efficient planning and implementation of forest management activities. Further, it is expected to improve policy designs for cost-effective fuel management and operation of wood processing facilities in the future.

1.2 Materials and Methods

1.2.1 Study Area

We focused on the impact of wood products markets on hazardous fuel reduction activities in the BLM and USFS lands in CO. BLM oversees 4.2 million acres of forest land in CO, distributed across 34 counties (CSFS, 2025), with more than 2.5 million acres classified as woodlands dominated by oak, juniper, and pinon, while the remaining forested acres consist of traditional commercial tree species such as ponderosa pine, lodgepole pine, and Douglas fir (U.S. DOI, 2024). Most BLM-managed public lands fall within the western slope, with semi-arid regions and deserts that include unique ecosystems such as sagebrush steppe and pinon-juniper woodlands. These are often noted for sparse vegetation and low fuel loads. Despite their lower fuel loads, these ecosystems still experience fast-moving fires due to the dry conditions. USFS is the primary land manager with 11 national forests and 2 national grasslands that encompass approximately 11.3 million acres of forested region distributed across 42 counties of CO. Around 75% of the state's high-elevation species, such as spruce-fir, lodgepole pine, and aspen, thrive on lands managed by the USFS (U.S. DOI, 2024). These lands include significant portions of the Rocky Mountains, characterized by rugged terrain, high peaks, and deep valleys (National Park Service, 2004), leading to substantial fuel accumulation in the forests. Riparian zones generally have higher moisture levels, which help reduce fire intensity, but they can become susceptible to wildfire during extreme fire weather conditions (Dwire & Kauffman, 2003; Hunsaker & Long, 2014). Besides, this agency manages grasslands like the Pawnee National Grassland, which preserves CO's natural prairie landscape.

The CO wood processing industry plays a critical role in meeting forest management and timber harvesting needs for the improvement of forest health and rural economies. However, major sawmills processing aspen, pine, spruce, and fir are at risk of collapse due to weather and contract issues, threatening jobs, and forest management efforts to clear beetle-killed trees (Markus, 2011). The number of sawmills decreased by 10 from 2016 to 2020, highlighting the industry's ongoing struggles (Irey et al., 2023). Additionally, workforce shortages have become a critical issue, with many sawmills struggling to attract and retain skilled labor. The forestry sector faces serious challenges, such as the absence of an effective monitoring tool for the logging industry, a persistent shortage of logging labor, and increasing operating costs (He et al., 2021). Although the forest industry has declined considerably due to the reduced value of timber resulting from wildfires and insect damage, there has been some recent expansion of sawmills, like those in San Luis Valley, and biomass facilities, such as those in Gypsum, in the southern part of the state (CO Forest Action Plan, 2020). In addition, a total of 9 new facilities in CO have received wood innovation grants to advance innovation in wood products and wood energy economies in 2023 (US Forest Service, 2024). Some of them include Rocky Mountain Timber, which aims to optimize and expand their sawmill operations; PHX LLC, which focuses on sustainable woody biomass management in Southwest Colorado; and Mountain Pine Manufacturing, which seeks to develop a waste-wood system to utilize wood strands for various products (U.S. Forest Service, 2024). CO's timber harvest and average lumber production per sawmill have seen a notable increase with 64 and 43 percent higher in 2020 than 2016 respectively (Irey et al., 2023). Despite the challenges, the recent increase in timber harvests, average lumber production, and expansion of new wood-based facilities could impact the spatial dynamics of hazardous fuel reduction activities. The proximity of these facilities may enhance the efficiency and effectiveness of fuel management efforts, making it crucial to evaluate how location affects hazardous fuel treatments in relation to these expanding industry opportunities.

1.2.2 Data

Data for the analysis was collected from various sources. We gathered geospatial data on hazardous fuel reduction activities in BLM and USFS lands from 2012 to 2020 from the Colorado Forest Restoration Institute (Mueller & Caggiano, 2022). CFRI's data collection process involved soliciting spatial data on forest management activities from various land management agencies, both public and private, across the state. The database primarily focused on activities that physically altered or removed woody vegetation through mechanical cutting, prescribed fire, or other means, excluding activities like herbicidal spraying or grazing (Mueller & Caggiano, 2022). Treatment attributes common across all organizations included treatment shape and extent, size, dates of treatment, and treatment type. We compiled and cleaned this data by addressing issues with overlapping treatments, out-of-state boundary treatments, and variations in data completeness and quality. Within treatments in BLM, 13 located in neighboring states Utah and Wyoming were dropped. BLM and USFS lands had a total of 779 and 9,709 treatment locations, respectively.

Treatment data within the WUI were collected separately from the real-time online website and key personnel from CFRI, as the treatment data didn't have distinct information for WUI.

We collected data on the geographic locations of wood manufacturing facilities from the Bureau of Business and Economic Research (Irey et al., 2023), and Colorado State Forest Service (CSFS, 2023a). This data included a comprehensive list of active wood manufacturing facilities in 11 western states, their status from 2012 to the present time, types of operation, geographic locations, state, county, and input size class. We extracted all the industry data for CO and filtered them based on the active status of the facilities. After filtering, we had 70 facilities that were actively operating. We cross-checked this list of facilities with the CSFS industry database and added one wood manufacturing facility, Todd Enterprises, which was missing in the BBER database (CSFS, 2023a). The types of facilities included sawmill, biomass/energy, firewood, fuel pellet, log furniture, log home, plywood, post/pole/piling, and other primary manufacturers. In the Rocky Mountain Region, there are 96 entities holding contracts with the USFS to remove wood products from federal lands. These facilities produce a variety of goods, including dimensional lumber, mine timbers, biochar, biofuels, Oriented Strand Board (OSB), and Medium Density Fiberboard (MDF), among others (Sierzega, 2025). These primary wood processors handle wood from the treatment activities in accordance with contracts established by the managing agencies. We then created a geographic dataset of the facilities using the geographic coordinates information, which then served as a representation of markets for wood products and wood-based fuels. This information was later imported and mapped in ArcGIS Pro to visualize and analyze the proximity of wood product facilities to treatment locations. We also collected annual data on climatic variables (maximum temperature and precipitation) from the National Oceanic and Atmospheric Administration (NOAA, 2024). Our sample size focused on the period 2012 to 2020 to match the hazardous fuel reduction activities (treatment) data from CFRI. Besides, we had access to Arc GIS online road layers which were used as network datasets (ESRI, n.d.-a).

1.2.3 Data Analysis

Network Analysis

We used the Network analysis tool in ArcGIS Pro 3.1 to identify the closest travel time distance from fuel treatment locations to wood manufacturing facilities (ESRI, n.d.-b). The tool uses the Dijkstra algorithm that solves the single source, shortest-path problem on the weighted graph and finds the shortest path from a starting point (for instance, treatment location) to a destination location (for instance, forest facility location) (Kai et al., 2014; ESRI, n.d.-c). To run the network analysis, all the treatment and facility locations with their closest point in the road network were associated with the online road network usage provided by ESRI. We followed the approach outlined by Attreya et al. (2024), which used the ArcGIS online roads layer as the network dataset to find the shortest route from the harvest sites to mills. The average speed of the highways and roads was used as per the default precise calculations made by online road network usage. The closest facility was used to establish the nearest point between treatment locations and wood manufacturing facilities. In the closest facility layer, we imported geographic coordinates of wood facility locations in the input feature 'facilities' and all treatment locations for BLM and USFS in the input feature 'incidents'. As the treatment limit for the analysis was 5,000 incident observations, we separated USFS treatments equally in two different files. Then, we ran the network analysis that generated different attributes, including routes, point barriers, line barriers, and polygon barriers. Using the route, we created a file with the shortest travel time route between each treatment location and wood manufacturing facility along with their details on geographic locations and treatment types.

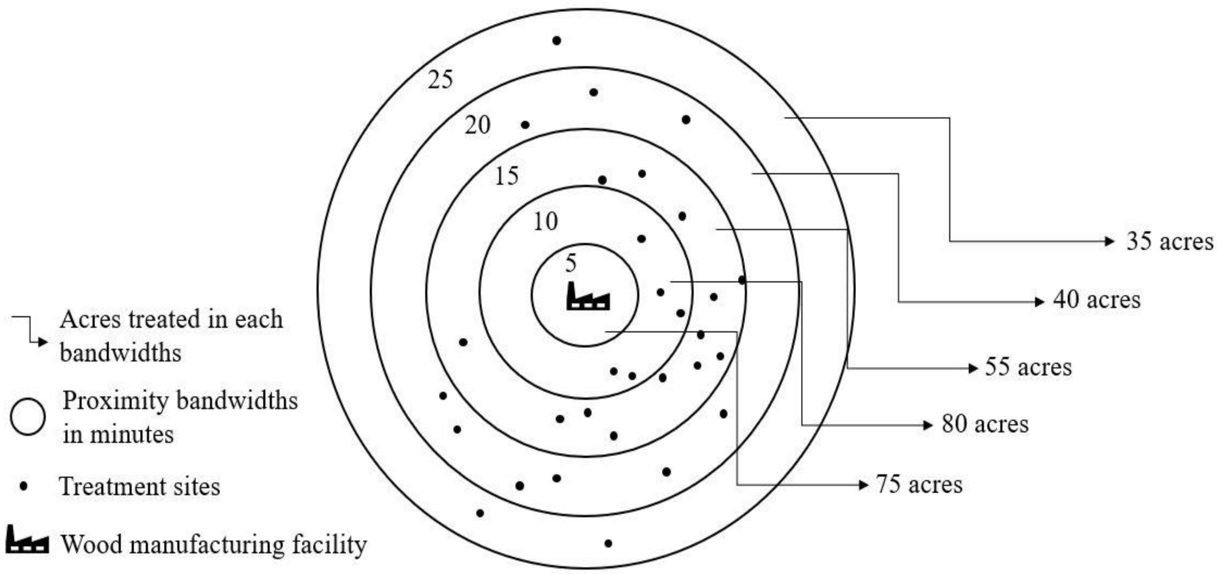

Figure 1.1. Conceptual diagram showing the total acres of treatment in each proximity bandwidth, denoting the closest distance to nearest wood manufacturing facilities.

We defined the travel time generated by the network analysis for each treatment location as ‘proximity’. The travel time was divided into 5-minute proximity bandwidths, meaning that each proximity bandwidth denoted the total number of acres treated within that time interval in each county in each year (Figure 1.1). We used 5-minute bandwidth specifically to examine how very short travel times might have directly affected decision-making for hazardous fuel treatments. This measure helped detect immediate effects that might have been diluted in larger bandwidths. Additionally, 5-minute intervals are a standard choice in spatial analysis for creating manageable and interpretable data categories, making it easier to compare different treatment locations and their proximity to facilities. Carpita et al. (2024) also used 5-minute intervals to track and analyze the traffic flows between different areas, ensuring accurate flow analysis. We do not imply that materials produced from hazardous fuel treatments necessarily travel these specific routes or even leave the treatment locations. Instead, we used the acreage treated within the defined proximity bands to represent the general influence of industry infrastructure on hazardous fuel treatments. We estimated how the presence of wood manufacturing facilities might impact the scale and distribution of treatment activities, without assuming the actual movement of materials along these routes. Further, the service area facility tool under network analysis was used to visualize the wood manufacturing facility points and treatment locations with the associated closest travel distance. We applied a cutoff increment of 5 minutes to the facility points. We then created polygons of the surface by buffering the route lines, which symbolized the travel time for each treatment location in both BLM and USFS land to reach the nearest wood manufacturing facility (Figure 1.2).

Mixed linear model regression

Prior to model specification, we summarized the total number of treatments, total acres of treatments, acres treated per treatment type, acres treated from which biomass was used, and treatment proximity to wood manufacturing facilities from 2012 to 2020 in BLM and USFS lands. Then, we divided the counties with treatments into two groups to compare treatment locations based on their proximity to forest facilities. With this grouping, we analyzed whether treatment locations closer to the forest facilities conducted more hazardous fuel treatments and utilized more biomass than those farther away. We divided the groups based on the medians of travel time between treatment locations and wood manufacturing facilities: counties with an average proximity of treatments to facilities less than the median and counties with an average proximity equal to or greater than the median. The median observed for BLM and USFS land was 54 and 48 minutes, respectively. We used median to represent the central tendency of the travel times between hazardous fuel treatment locations and wood-processing facilities. We then calculated the total acres treated within each divided group of counties.

Following Pincus et al. (2013), a mixed model was used to examine the relationship between treated acres and acres from which biomass was utilized with proximity to the locations of wood manufacturing facilities. This model was used for unobserved heterogeneity and correlations within individual treatment by including both fixed and random effects terms. Fixed effects quantified the systematic influence of the explanatory variables (such as proximity to facilities, WUI acres, and climatic factors) on the treated acres, assuming these effects are constant across counties. Random effects, on the other hand, captured county-specific deviations from the average treatment level, allowing for variability in treatment practices across counties. Mixed model accounted for the hierarchical nature of our data, and variability at multiple levels, such as treatments within each proximity bandwidth, different counties, and years. It also addressed variability both within individual treatment groups (within-subject) and between different counties and years (between-subject), providing a more nuanced understanding of the relationships between the variables. We created two regression models (total acres treated model and biomass utilization model) with two dependent variables:

$$y_{ijk} = \beta_0 + \beta_1 x_{1ijk} + \cdots + \beta_m x_{mijk} + \gamma_j + \varepsilon_{ijk} \tag{1}$$

where, y_{ijk} is the acres treated (total and acres from which biomass was used) in proximity band i, county *j,* and land ownership *k,* β_0 is the average intercept across all counties, $\beta_1 \ldots \beta_m$ is the set of m slope coefficients for fixed effects $x_{1ijk} \ldots x_{mijk}$, and γ_j and ε_{ijk} are uncorrelated random error terms. γ_j is also the random intercept coefficient. Our main interest in independent variables was proximity bandwidth value. We also included covariates: acres treated in WUI, and climatic variables (maximum temperature and precipitation). These covariates were included to specify the significance of proximity independently. The model controlled for the influence of WUI area and climatic variables, isolating the impact of proximity to wood manufacturing facilities on the total acres treated. We expected the counties with treatment locations closer to the forest facilities would have positive intercept values while counties with treatment locations farther from forest facilities would have negative intercept values.

Threshold Analysis

Lastly, we conducted separate and multiple iterations of the regression model (1) with different subsets of data to identify a potential threshold beyond which wood manufacturing facilities no longer impacted hazardous fuel treatments in both BLM and USFS lands. For this, we first analyzed counties with an average proximity of over 20 minutes. We used a 20-minute threshold based on the idea that it represented a practical boundary where the relationship between proximity and treatment likelihood was most pronounced. It seemed reasonable maximum distance within which facilities were considered accessible for planning and executing fuel treatments. In the context of forest management, this threshold reflected logistical considerations and operational efficiency. Besides, for average proximities less than 20 minutes, the general estimates with all counties didn't differ. Then, we repeatedly ran the regressions by gradually increasing the minimum average proximity by 10-minute intervals; 30, 40, 50, 60, and 70 minutes. For each proximity threshold, we ran separate regressions, and in each iteration, we adjusted the minimum average proximity threshold. With this, we identified the distance at which the effect of proximity on hazardous fuel treatments became negligible.

1.3 Results

Figure 1.2 shows a spatial overview of the relationships between fuel treatments and wood-processing facilities within CO from 2012 to 2020. The points in grey and black are treatments in BLM and USFS lands, respectively, and the points in green are the locations of the 70 wood manufacturing facilities that were in operation during the study period. The network of roads and highways illustrates the proximity and travel routes between treatment locations and wood processing facilities. The surface of the map demonstrates different colors denoting proximity bandwidth intervals, which are displayed by the index. With each proximity bandwidth value, the index shows the travel time distance between treatment locations and the closest forest facilities. We found the maximum travel time was up to 260 minutes, with a total of 52 proximity bandwidths.

1.3.1 Summary of fuel treatments

Table 1.1 provides a detailed summary of fuel treatment activities from 2012 to 2020 on BLM lands. We found that a total of 214,693 acres were treated across 779 treatment locations in 34 counties. Of these, 23,326 were treated in WUI areas. We found mechanical treatments to be the most common type of treatment activity conducted at 463 locations covering 109,694 acres, followed by fire treatments at 218 locations covering 72,527 acres. Treatments within closer market proximity based on median of (< 54 min) covered 62,354 acres across 390 locations, while those beyond this timeframe (≥ 54 min) accounted for 152,339 acres across 389 locations. Annual treatment data showed variability across the years. For instance, in 2016, the BLM treated 44,093 acres, whereas in 2013, they treated only 6,009 acres.

Table 1.2 provides a detailed summary of fuel treatment activities from 2012 to 2020 on USFS lands. We observed a total of 9,709 fuel treatments, covering 578,889 acres. We found that biomass removal accounted for the majority, covering 3,754 treatments and 162,970 acres, followed by mechanical treatments covering 3,633 locations and 162,462 acres. Treatments conducted within less than median of 48 minutes proximity to markets spanned over 4,865 locations, with 299,553 acres. On the contrary, treatments beyond this timeframe (48 minutes or more) amounted to 4,844 locations, covering 279,336 acres. The number of treatments and acres treated was higher within closer market proximity than for treatments conducted beyond the 48-minute timeframe. The total number of treatments fluctuated over the years. There was a notable increase from 49,925 acres in 2012 to a peak of 94,720 acres in 2015. However, this was followed by a decrease to 53,599 acres in 2020.

1.3.2 Mixed model results

The first panel (Panel A) of Table 1.3 shows the impact of the proximity of wood manufacturing facilities on fuel treatments within BLM lands. In the total acres treated model, proximity exhibited a negative and statistically significant relationship at the 0.1% level. This indicates that as the distance from manufacturing facilities increased, significantly fewer acres were treated. Acres treated within the WUI was significant and positively correlated (0.99) with the total acres treated. The maximum temperature revealed an insignificant negative coefficient, indicating that the increase in temperature decreased the total acres treated. Similarly, precipitation also showed a negative coefficient implying that as the precipitation increased, the total acres treated decreased. Similarly, proximity had a significant negative impact on treated acres from which biomass was utilized. That is, when the distance of facilities to treatment locations increased, the biomass utilization decreased by 0.005 units, all else being equal. WUI had a negligible negative relationship with biomass used (-0.000014). Maximum temperature had a negative relationship with the total biomass used from the treated acres, while precipitation showed a positive relationship with biomass used.

For USFS, the mixed model regression analysis revealed a significant association between the variables of interest in our study (Table 1.4, Panel A). We observed a significant negative coefficient of -3.83 for proximity at 0.1% level, suggesting that an increase in distance of forest facilities to treatment locations corresponded to a significant decrease in acres treated. With a significant coefficient of 0.087, an increase in the acres treated in WUI area positively correlated with a rise in the total acres treated. Maximum temperature and precipitation both revealed an insignificant negative association with the total acres treated. Likewise, in the biomass utilization model, proximity had a significant negative relationship with biomass used (-1.02) at the 0.1 % level. WUI showed an insignificant positive relationship with biomass used (0.02). Both maximum temperature and precipitation revealed negative relationships with biomass used, but these were not statistically significant.

1.3.3 Threshold analysis results

The second panel (Panel B) of Table 1.3 shows how average proximity to wood processing facilities affected acres treated across different time intervals in BLM lands. We observed a significant negative association between the increased proximity and total acres treated across differing time thresholds. The coefficients for the thresholds of 20, 30, 40, 50, 60, and 70 minutes were -1.20, -1.30, -1.18, -1.24, -1.37, and -1.75, which indicated the negative effect of increased distance on acres treated within each time range. At a proximity threshold of >20 min, an increase in average proximity was associated with a decrease in acres treated. Similarly, at the >70 min threshold, the effect was even more pronounced, indicating that an increase in proximity led to a greater decrease in acres treated. However, beyond the threshold of 70 minutes, the proximity didn't show any significance. For the biomass used, the coefficients for different proximity thresholds (-0.003, -0.004, -0.0009, -0.001, -0.0005 and -0.0007) revealed an insignificant negative effect of increased distance. These results suggest consistent negative relation between increased average proximity (distance to treatment site) and acres treated across various time thresholds.

In USFS land, the results consistently indicated a significant negative association between increased distance and acres treated across different time intervals (Table 1.4, Panel B). The coefficients for the thresholds of 20, 30, 40, 50, 60 and 70 minutes were -3.81, -3.87, -3.98, -2.46, -1.54, and -1.74, which indicated a significant negative effect of increased average proximity on acres treated within each time range. At a proximity threshold of >20 min, an increase in average proximity was associated with a decrease in acres treated. Similar to the BLM results, the effect of proximity didn't show any significance beyond the threshold of 70 minutes. The coefficients for the thresholds (-1.05, -1.07, -1.19, -0.77, -0.47, and -0.51) revealed a significant negative effect of the increased average distance on biomass used within each time range. The result was similar to proximity effect for the total acres treated, meaning that the utilization of biomass was not significant beyond a distance of 70 minutes.

1.4 Discussion and Conclusions

This study examined the impact of market proximity on fuel treatment activities conducted within BLM and USFS lands in CO from 2012 to 2020. We observed that mechanical treatments followed by fires were carried out the most in BLM lands. In USFS managed forests, biomass removal followed by mechanical treatment and prescribed burn were the most common treatment types. Prescribed burning and mechanical thinning are key fuel management practices used in ponderosa pine forests of CO to reduce fire risks, lower fire intensity, and enhance suppression efforts (Hunter et al., 2007; Vaillant & Reinhardt, 2017). Mechanical treatments reduce the incidence of high severity fire, and are beneficial for economic outcomes due to their positive financial return on investment (Furniss et al., 2024). Within the BLM lands, a total of 62,354 acres of treatments were in close proximity (<54 minutes), whereas 152,339 acres of treatments were farther away from the wood processing facilities. While we detected an unusual spike in treated acres around the proximity bandwidth of 140 to 145 minutes, the outlier did not show a huge effect on the results. The lower total treated acres in closer proximity could be due to the funding placement, land management policies, and ecological factors that are not accounted for in our analysis. Inconsistent and fluctuating funding for fuel treatments have hindered long-term planning, execution, and upkeep of the treatments (Hunter et al., 2007; Reiner et al., 2014), and the effectiveness is influenced by landscape heterogeneity (Urza et al., 2023). For instance, the implementation of the Public Lands Rule emphasizes the protection and restoration of specific public lands that require urgent attention (Pilliod, 2015). Areas with higher wildfire risks or those that are ecologically sensitive may also receive more attention and resources (Thompson et al., 2013). In addition, the average treated acres by proximity level confirmed our result since it was decreasing at farther proximity, except for one spike at 140 minutes (Figure 1.3). As for biomass removal, we found a relatively higher number of biomasses removed from closer proximity. Within the USFS lands, both the total acres treated, and biomass utilized were greater in close proximity (< 48 minutes). Further, the average treated acres by proximity level validated our findings for USFS since the treatments were higher in closer proximity (Figure 1.4).

Our findings indicate that the proximity of wood manufacturing facilities to treatment locations has a highly significant impact on managing hazardous fuels and utilizing biomass in the forests nearby in both BLM and USFS lands. The coefficient was higher in USFS, which may be attributed to the total acres treated which were larger in USFS as the land types differ in terms of size, diversity, risks of fires and priority of treatments. This could also mean that there is higher infrastructure availability and better access to forest facilities in USFS, making it more economically viable to treat larger areas near the facilities. The USFS treated 900 acres near Silverthorne as part of a larger effort to reduce fire risks in high-priority areas, saving $913 million in homes and infrastructure. Further, USFS had invested $33 million in treatments across 70,000 acres through partnerships like 'From Forests to Faucets' with Denver Water, showing the value of infrastructure in forest management (Krake, 2018). The negative significant coefficient for proximity implies that counties with treatment locations closer to facilities are more likely to conduct more treatments and use more biomass. This finding corroborates with Wu et al. (2011), who noted that the influence of forest markets on hazardous fuel treatment decreases with distance. Along the same lines, Pincus et al. (2013) found that proximity to sawmills and biomass facilities in Oregon and Washington significantly affects fuel reductions on national forest lands and within the WUI. When facilities are nearby, the cost of transporting biomass could be lower, making it more economically viable to use the raw forest materials. Thus, the strategic placement of processing facilities is important for reducing the overall cost of fuel treatments (Becker et al., 2009). When treatment locations are in close proximity to manufacturing facilities, coordinating and managing operations could be easier, leading to more effective and timely treatments (Evans & Finkral, 2009). Such practices may also add value to the economic side by creating additional revenue from the biomass, supporting the development of value-added forest products, such as bioenergy or wood products, which can further incentivize fuel treatment efforts (Becker et al., 2009). The appraisal process conducted by the federal agencies considers the value of the material and transportation costs, which directly impacts whether low-value materials like biomass are economically viable for removal. The high costs of transporting biomass, especially given the need for higher-quality roads and increased hauling costs reinforces the critical role of economic threshold. To address such complexities, our findings emphasize the consideration of the influence of distance of wood manufacturing facilities in managing the cost effectiveness of hazardous fuel reduction treatments.

The significant positive coefficient for the WUI in both BLM and USFS land suggests that as the acres treated within the WUI increase, the total acreage of treatments also tends to increase. This suggests that forest managers are prioritizing treatments in WUI areas due to their significance in wildfire risk reduction and community protection. This could be due to the increased risk of wildfires in these areas, necessitating more treatments (Evans et al., 2015). CO's WUI areas are highly vulnerable to severe wildfires due to dense forests and accumulated fuel over the past century (CSFS, 2023b). Factors like wind gusts, fire line arrangement, and distance from fire ignition are key factors influencing the likelihood of a wildfire reaching the WUI (Wei et al., 2023). However, WUI areas are relatively more conducive to treatment due to lower transportation costs, as they are in proximity to roads (Wear et al., 2023). We observed very negligible negative WUI coefficient in the biomass model for BLM lands. This could be because of the relatively small sample size with only 453 acres biomass utilization out of 214,693 acres of treatment. The utilization of biomass is also influenced by the production capacity of nearby mills, a factor that was not available at the individual mill level for our study. Without specific data on the mills' capacities, it was difficult to assess the direct impact of mill proximity on biomass utilization. This limitation suggests that the utilization of biomass may not be significantly influenced by whether the hazardous fuel treatment takes place within the WUI or in non-WUI areas.

The influence of forest facilities on hazardous fuel treatments was less significant as we looked at father proximity and not at all significant beyond 70 minutes in both BLM and USFS lands. This suggests that beyond a certain threshold, other factors may become more influential in determining the number of acres treated. A similar threshold effect of 40 minutes was observed by Pincus et al. (2013) in Oregon and Washinton in USFS managed lands. Wu et al. (2011) also found that optimized woody biomass handling with some logging system could produce economically viable biomass utilization equal at haul distances of up to about 70 km, (approximately 70 minutes). This could align with the concept of a ‘distance decay’ effect, where the influence of a factor decreases with increasing distance (Thompson et al., 2013). Beyond a certain distance, the logistical challenges and costs associated with transporting resources for treatments may outweigh the benefits leading to a decrease in the number of acres treated. Alternatively, other factors, such as the availability of resources, local regulations, or ecological considerations, may become more influential in determining the number of acres treated beyond this threshold (Hood et al., 2022). This indicates that similar threshold effects may be common in land management decisions. This could also suggest that more accessible areas are at greater risk or more frequently treated. The changes in sawtimber prices, influenced by factors like wood product demand and policy interventions may affect the supply of treatable land. Combining treatments with saw timber harvest practices may have an impact on the availability of land suitable for treatment (Wear et al., 2023). Moreover, the economic feasibility of fuel treatments is also influenced by the variety of products produced by wood processors in the region, such as biochar, biofuel, and plywood. Since these products are market-dependent, fluctuations in demand can impact the economic appeal of removing certain materials (Sierzega, 2025). Thus, before establishing new facilities, a cost-benefit analysis should be conducted to determine the most economically viable locations, considering the threshold distance of 70 minutes.

Regarding the climatic variables, the positive and negative influences were similar on both BLM and USFS. Maximum temperature and precipitation seemed to have a negative relationship with the total acres treated. As the temperature increased, the number of acres treated seemed to decline. The temperature can influence the number of acres treated, as extreme temperatures can exacerbate wildfire conditions, potentially making treatments more challenging or less effective. BLM oversees numerous resources that could be significantly affected by climate change, such as drought, severe fires, shifts in precipitation, and extreme weather events (Gonzalez et al., 2018). Higher temperatures, and longer periods of 'fire weather' have contributed to the increased number, extent, and cost of wildfires over the last several decades (Vaillant & Reinhardt, 2017). In the biomass utilization model in both BLM and USFS land, we observed negative coefficient for maximum temperature, while being insignificant. We also found a negative relationship between precipitation and the number of acres treated in USFS land. This could be because heavy rainfall can make certain treatments less effective or more difficult to apply. Fuel treatments were not designed for and were not effective in extreme conditions such as record low live fuel moistures or extreme fire behavior (Henson, 2007). However, precipitation had a small positive coefficient for biomass utilization model in BLM land, which again could be because of the low number of biomass utilization in BLM lands.

Enhancing the scope of fuel treatments could involve implementing policies that involve private sectors and improving the economic viability and market appeal of treatments. The establishment of wood products and biomass energy markets in a well-distributed network across forest-based communities and the efficient utilization of treatment byproducts is critical (Powell

& Lenton, 2012; Pincus et al., 2013). In our analysis, we couldn't locate any facilities on the northwest side of the state, which is mostly dominated by pinon-juniper, ponderosa pine, and aspen (Figure 1.2). Creating a demand for small-diameter materials through the advancement of technologies like biochar or mass timber enables more efficient utilization of such materials (Wear et al., 2023). According to Abt and Prestemon (2006), implementing substantial and rapid biomass removal programs can lead to a decrease in prices, negatively impacting private producers while benefiting wood product manufacturers (timber consumers). Woody biomass for energy has the potential to offset the costs associated with forest management and fuel treatment. For instance, the CSFS's Wood to Energy program highlights how using woody biomass can lead to healthier forests and stronger rural communities by treatment costs (CSFS, 2024). In 2013, the biobased products sector in the state supported 11,500 direct jobs (21,800 in total) and contributed $635 million in direct value of $1.53 billion in total value (U.S. DOE, 2017). Gypsum biomass plant generates 11.5 MW of electricity by using waste wood as fuel (CSFS, 2024). Similarly, Xcel Energy's 19 MW biomass power plant in CO will use forest waste and pine beetle kill wood as sustainable biofuel and employ local community workers (Voegele, 2023). However, the feasibility of biomass removal sales, even in areas where the removals are more valuable, is hindered by high harvest and transportation costs. This emphasizes the spatial variability of market potential both among regions and within a specific region (Hunter & Taylor, 2022). It is also important to consider that market demand significantly influences biomass utilization practices (Nicholls et al., 2008).

This study has several limitations. Data regarding the volumes of biomass removed from treated acres as well as the mill-level processing capacity of manufacturing facilities were unavailable at the time of this analysis. In addition, our study focused on the timeframe 2012-2020, which may not fully capture recent changes in fuel treatment activities. Significant developments have occurred since 2020 that could drastically alter the landscape of fuel management. For instance, in 2022, the USFS announced a 10-year strategy to significantly increase the scale of forest health treatments (Gabbert, 2022). This initiative aims to treat 50 million acres over the next decade, representing a substantial increase in fuel treatment activities (Housewright, 2022). However, the constantly evolving policies and funding situations may likely have a profound impact on the pace and scale of expected fuel treatment activities across the country. Further, this study did not incorporate data on other factors like stewardship contracts and administrative information that could influence the management of treatment activities in CO. To fully understand the dynamics of fuel treatments on federal lands, future studies could explore other potential influential factors such as funding allocations, regulatory frameworks, and community engagement. Future studies could also explore the economic feasibility of utilizing treatment removals for the production of forest products like biochar and mass timber.

In summary, our study indicates that the proximity of treatment locations to forest facilities significantly impacts the management of hazardous fuels and the utilization of biomass in CO. A proximity threshold effect of 70 minutes exists, beyond which the proximity of forest facilities has no significant impact on fuel treatment activities. This highlights the importance of considering such thresholds when planning new facility locations, particularly biomass facilities, which could offer long-term cost benefits. As land management agencies plan and implement fuel treatments, it is critical to consider factors such as market proximity and forest resource availability. These elements are crucial to optimizing the effectiveness and efficiency of these operations. Overall, this study will contribute to the development of more resilient forest ecosystems by informing forest management strategies that align economic and environmental objectives, ultimately supporting effective and lasting policy decisions.

Table 1.1. Summary of hazardous fuel treatment activities from fiscal year 2012 to 2020 in BLM land of Colorado reported by Colorado Forest Restoration Institute, 2022.

	Treatment Locations	Total Treatments (Area in Acres)	WUI Treatments	Mechanical Treatments	Market Proximity	
					<54 min	≥54 min
Total	779	214,693	23,326	109,694	62,354	152,339
Fiscal Years						
2012	58	11,559	332	4,939	2,989	8,570
2013	56	6,009	592	3,170	2,374	3,635
2014	89	9,417	246	4,642	5,173	4,244
2015	81	9,839	212	4,764	4,892	4,947
2016	87	44,093	20,528	32,249	10,738	33,355
2017	93	25,504	-	13,052	6,827	18,677
2018	112	43,225	1,015	21,203	8,407	34,818
2019	98	37,463	222	13,855	10,647	26,816
2020	105	27,584	179	11,820	10,307	17,277
Treatment Types						
Biomass Removal	7	453	-		439	14
Prescribed Fire	218	72,527	452		21,584	50,943
Mechanical	463	109,694	22,874		32,199	77,495
Other	91	32,019	-		8,132	23,887
Market Proximity						
<54 min	390	62,354	2,539	32,199	62,354	-
≥54 min	389	152,339	20,787	77,495	-	152,339

<54 min includes total acres of treatments within median of travel time less than 54 minutes and ≥54 min includes total acres of treatments within median of travel time equal to or greater than 54 minutes.

Note: BLM, Bureau of Land Management; CFRI, Colorado Forest Restoration Institute; WUI, Wildland-Urban Interface.

Table 1.2. Summary of hazardous fuel treatment activities from fiscal year 2012 to 2020 in USFS land of Colorado reported by Colorado Forest Restoration Institute, 2022.

	Treatment Locations	Total Treatments (Area in Acres)	WUI Treatments	Mechanical Treatments	Market Proximity	
					<48 min	≥48 min
Total	9,709	578,889	42,739	323,759	299,553	279,336
Fiscal Years						
2012	1,045	49,925	2,313	38,329	31,631	18,294
2013	1,211	54,490	2,752	40,027	31,957	22,533
2014	1,122	60,689	1,647	38,026	39,407	21,282
2015	1,179	94,720	30,062	30,364	30,557	64,163
2016	1,246	59,055	1,962	43,431	33,080	25,975
2017	871	36,963	1,040	22,670	17,351	19,612
2018	961	89,262	708	38,844	50,671	38,591
2019	1,081	80,186	1,181	31,299	37,662	42,524
2020	993	53,599	1,074	40,769	27,236	26,363
Treatment Types						
Biomass Removal	3,754	162,970	1,497		92,582	70,389
Mechanical	3,633	162,462	7,557		89,287	73,175
Other Fire	1,311	110,949	2,977		73,883	37,066
Prescribed Burn	861	131,227	30,564		38,566	92,661
Other	150	11,280	145		5,235	6,045
Market Proximity						
<48 min	4,865	299,553	35,038	89,287	299,553	-
≥48 min	4,844	279,336	7,702	73,175	-	279,336

<48 min includes total acres of treatments within median of travel time less than 48 minutes and ≥48 min includes total acres of treatments within median of travel time equal to or greater than 48 minutes.

Note: USFS, United States Forest Service, CFRI, Colorado Forest Restoration Institute, WUI, Wildland-Urban Interface.

Table 1.3. Mixed model regression results of proximity on dependent variables (total and treated from biomass used) controlling for Wildland-Urban Interface (WUI) treatments, temperature, and precipitation with random intercept summary by county (Panel A) and subset regressions showing diminished significance of proximity for acres treated and biomass utilization in counties where average travel time exceeds 70 minutes to a wood manufacturing facility (Panel B) for BLM.

Independent variables	Dependent variables	
	Acres Treated	Biomass used from acres treated
Panel A: Parameters Coefficient		
Intercept	481.17	3.39
Proximity[1]	-0.99***	-0.005**
WUI	0.99***	-0.000012
Maximum Temperature	-1.36	-0.04
Precipitation	-8.84	0.01
R^2	0.51	0.01
Panel B: Proximity Coefficient		
Average proximity		
(Number of counties)		
>20 min (n = 25)	-1.20***	-0.003
>30 min (n = 21)	-1.30***	-0.004
>40 min (n = 14)	-1.18***	-0.0009
>50 min (n = 11)	-1.24**	-0.001
>60 min (n = 9)	-1.37*	-0.0005
>70 min (n = 7)	-1.75*	-0.0007

*p<0.05, **p<0.01, ***p<0.001

[1]Proximity is the travel time in minutes from treatment locations to the closest forest facilities. The negative coefficients denote that the treatment locations farther from forest facilities resulted in fewer acres treated.

Note: BLM, Bureau of Land Management

Table 1.4. Mixed model regression results of proximity on dependent variables (total and treated from biomass used) controlling for Wildland-Urban Interface (WUI) treatments, temperature, and precipitation with random intercept summary by county (Panel A) and subset regressions showing diminished significance of proximity for acres treated and biomass utilization in counties where average travel time exceeds 70 minutes to a wood manufacturing facility (Panel B) for USFS.

Independent variables	Dependent variables	
	Acres Treated	Biomass used from acres treated
Panel A: Parameters Coefficient		
Intercept	1470.77	604.632
Proximity[1]	-3.83***	-1.02***
WUI	0.087*	0.02
Maximum Temperature	-11.28	-6.86
Precipitation	-2.76	-0.33
R^2	0.12	0.10
Panel B: Proximity Coefficient		
Average proximity (Number of counties)		
>20 min (n = 41)	-3.81***	-1.05***
>30 min (n = 40)	-3.87***	-1.07***
>40 min (n = 33)	-3.98***	-1.19***
>50 min (n = 20)	-2.46***	-0.77***
>60 min (n = 13)	-1.54***	-0.47***
>70 min (n = 10)	-1.74***	-0.51***

*p<0.05, **p<0.01, ***p<0.001

[1]Proximity is the travel time in minutes from treatment locations to the closest forest facilities. The negative coefficients denote that the treatment locations farther from forest facilities resulted in fewer acres treated.

Note: USFS, United States Forest Service

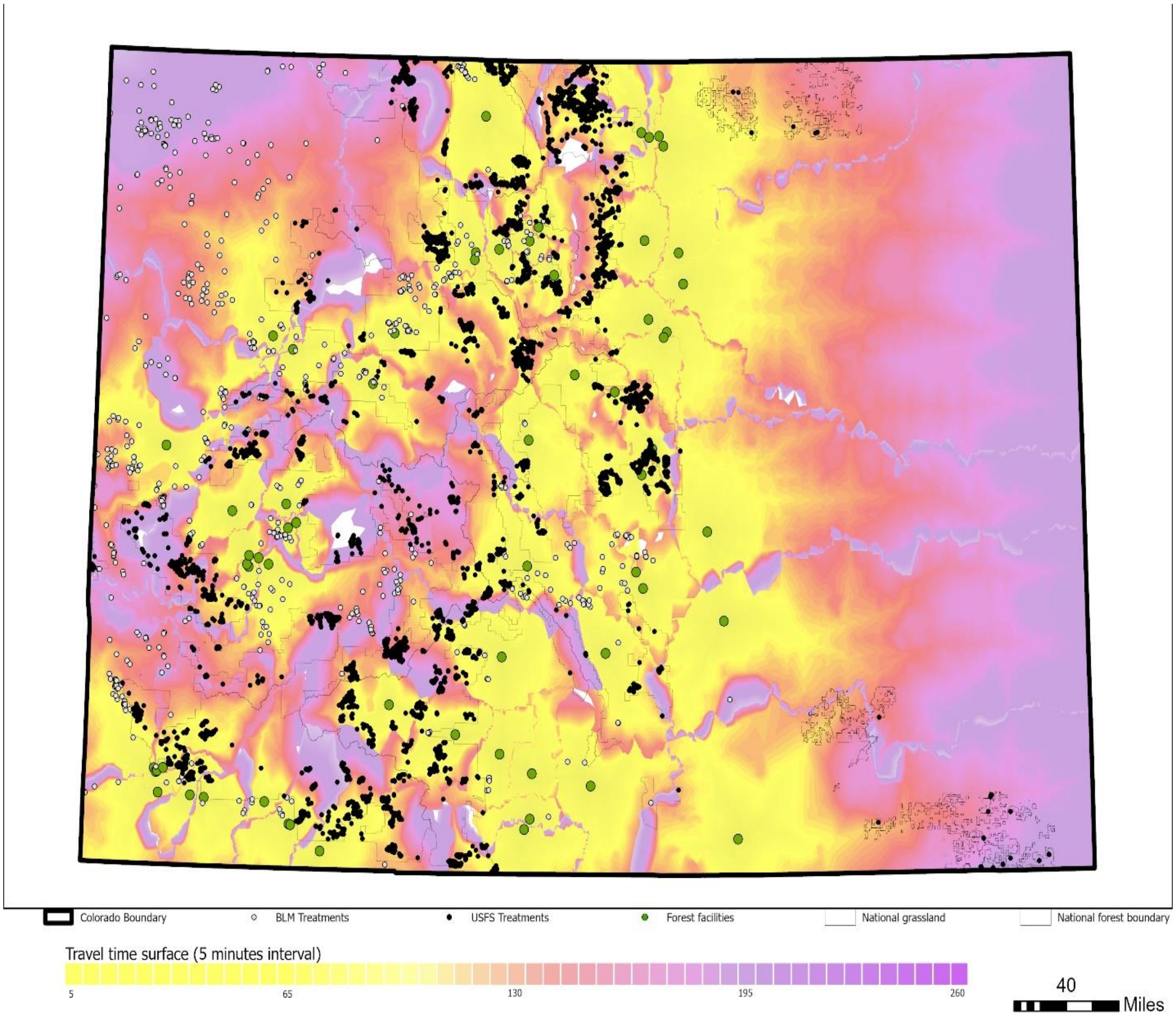

Figure 1.2. Travel time surface for hazardous fuel treatments (grey circles for BLM and black circles for USFS) and forest facilities (green circles) in Colorado. Travel time surface illustrates the closest estimated time to reach the forest facilities from treatment sites using different road networks, as shown in the index with closer proximity denoting dark yellow to farther proximity denoting dark purple. National forest and grassland boundaries are traced in black and grey, respectively.

Note: BLM, Bureau of Land Management; USFS, United States Forest Service

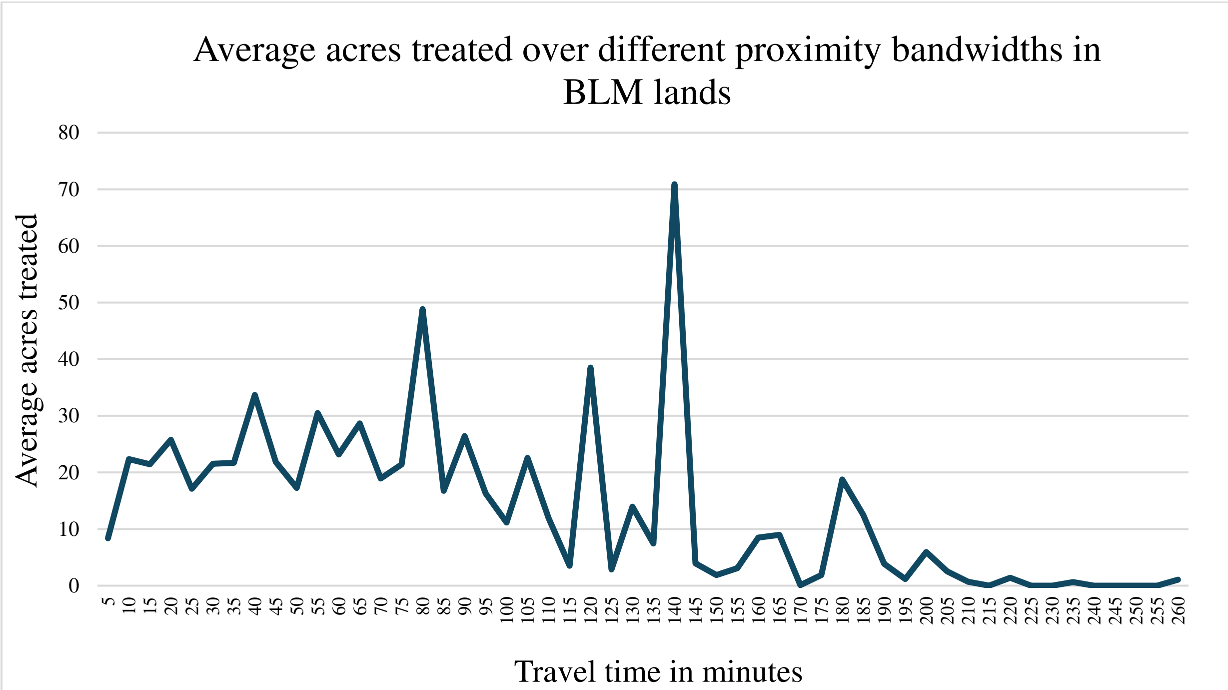

Figure 1.3. Line chart showing the average acres treated per proximity bandwidth in Bureau of Land Management (BLM) lands.

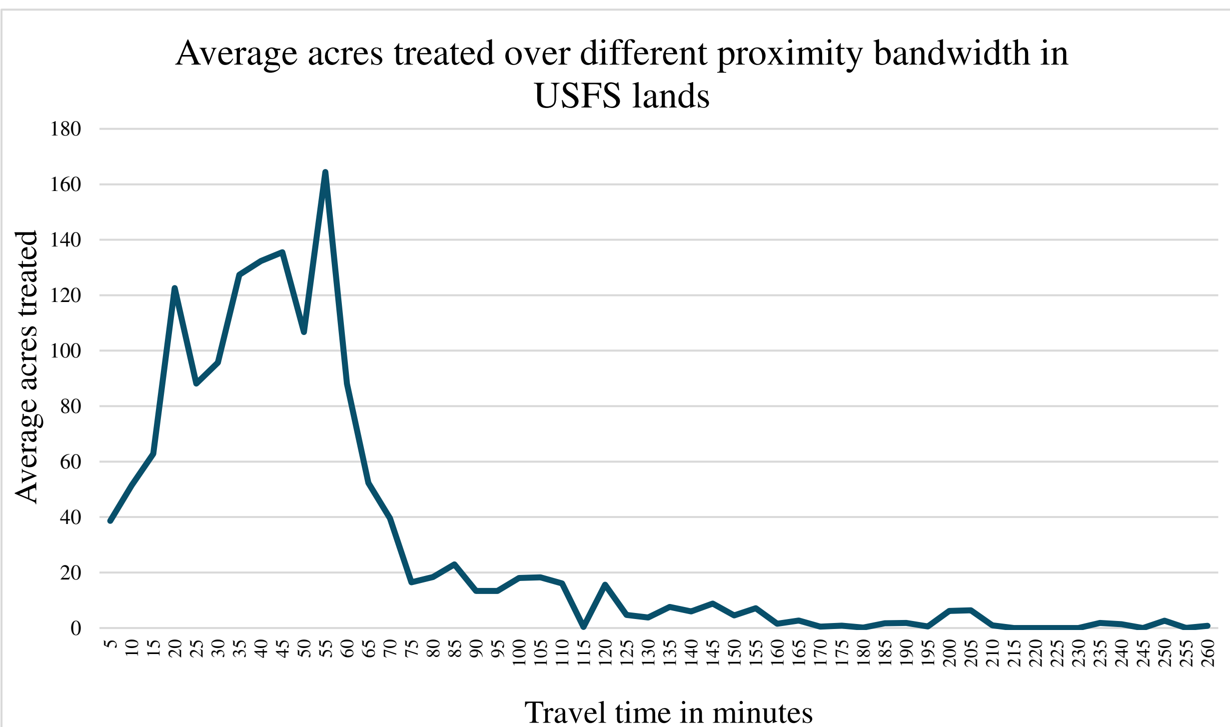

Figure 1.4. Line chart showing the average acres treated per proximity bandwidth in United States Forest Service (USFS) lands.

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CHAPTER 2: EFFECT OF WILDFIRE PREVENTION EDUCATION ACTIVITIES ON UNDESIRABLE HUMAN-CAUSED WILDFIRES ACROSS TRIBAL NATIONS IN THE U.S.

2.1 Introduction

Wildfires have been a significant threat to ecosystems, property, and human lives, particularly in regions with dense vegetation and dry climates. Over the years, the number of wildfires and the extent of their damage have been intense in the United States (U.S.). In the last five years, there have been around 308,400 wildfires in the U.S., including 276,292 human-caused fires, resulting in a five-year average loss of $2,989.05 million (National Interagency Coordination Center, 2024). Human activities (accidental and intentional) have become a leading cause of wildfires, accounting for nearly 84 % of ignitions (Balch et al., 2017; NPS, 2022). Climate and vegetation collectively create an environment conducive to wildfires. Human activities interact with the preconditioned landscapes created by these factors, increasing the risk and occurrence of wildfires. Ninety percent of fires occur due to human clearing at forest margins with more fires occurring deeper in the forest, indicating increased anthropogenic burning (Xu et al., 2021). The increased frequency of human-caused ignitions resulting from both direct activities and indirect causes such as infrastructure damage significantly boosts the likelihood of fires during extreme weather events (Hantson et al., 2022). Moreover, rising population levels and the expansion of areas within the Wildland-Urban Interface (WUI) have increased fire occurrences and broadened the range of climate conditions in which fires can take place (Balch et al., 2017). Modern human activities, such as clearing forests, promoting grazing, dispersing plants, altering ignition patterns, and actively suppressing fires, increase or decrease natural fire activity, leading to significant ecosystem changes and a loss of biodiversity (Bowman et al., 2011). Such wildfires have severe impacts, including health issues from smoke inhalation, environmental damage, economic costs, and degraded air quality due to increased particulate matter. Additionally, the health impacts from prolonged exposure to wildfire smoke include respiratory and cardiovascular issues, as well as mental health challenges for affected communities (Reid et al., 2016; Fann et al., 2018; East et al., 2023; Farid et al., 2024). The yearly economic impact of wildfires is estimated to range from $71.1 billion to $347.8 billion ($2016). The annual costs are projected to fall between $7.6 billion and $62.8 billion, while annual losses are expected to range from $63.5 billion to $285.0 billion (Thomas et al., 2017). Between 2017 and 2021, the extent of the destruction caused by wildfires rose to $81.6 billion, almost a tenfold increase when compared with the $8.6 billion in damage documented from 2012 to 2016 (NOAA National Centers for Environmental Information, 2024).

Human-caused ignitions are the leading cause of wildfires in the Indian Country, accounting for more than 80% of total annual wildfires on average destroy nearly 190 structures annually (BIA, 2022). Census tracts with majority Native American populations experience approximately 50% greater wildfire vulnerability compared to other tracts (Davies et al., 2018). The impacts of wildfires are more pronounced in the indigenous communities due to several factors, including socioeconomic vulnerabilities, geographical locations, limited resources, and unique cultural practices (Kohler, 2021). Indigenous communities experience disparate impacts due to longstanding inequities, rural living conditions, and insufficient inclusion in policymaking (Jhaveri, 2024). Over the past decade, increasingly severe wildfires have significantly impacted tribal lands and communities. Wildfires burned nearly 400,000 acres of federal Indian reservation lands, with even more acreage affected on state reservations and other tribal lands (Mcduff, 2021). For instance, the Navajo Nation has been exposed to high fire danger due to extreme temperatures and inadequate precipitation, for which they implemented Stage 1 Fire Restrictions as a preventive measure (Navajo Nation, 2024). Additionally, the Slide Ranch Fire near White Swan on the Yakama Indian Reservation burned 3,054 acres and destroyed several residential properties (Metcalf, 2024).

Historically, tribal communities have managed and reduced fire risks by relying on traditional ecological knowledge and practices. However, the increasing frequency and intensity of wildfires necessitate the integration of modern wildfire management activities (Stoof & Kettridge, 2022). This approach has been further highlighted in the U.S. Forest Service's comprehensive 10-year Wildfire Crisis Strategy (USDA Forest Service, 2022). The strategy combines fuel management, active suppression, community protection, and landscape-scale treatments, all supported by extensive collaboration with states, tribes, and other stakeholders. The current approaches to wildfire management recognize the need to balance the ecological benefits of fire for community protection and adaptive management strategies including enhanced public education (Schoennagel et al., 2017; Colavito, 2021). The role of public education in wildfire prevention has been more critical for raising awareness, altering behaviors, and ultimately decreasing the occurrence of unintentional human-caused wildfires (Murphy, 2022). These efforts aim not only to combat wildfires more effectively but also to foster ecosystem health and community resilience in fire-prone areas (Kolden, 2019). Educational programs help communities understand the risks associated with wildfires and the importance of preventive measures while encouraging responsible behavior. From an economic lens, investing in wildfire prevention activities can lead to substantial economic savings. For example, in Florida, a small investment in prevention education saved millions in fire suppression costs and prevented significant property losses (USDA Forest Service, 2022). Educational efforts can also influence policy by encouraging the adoption of fire-safe regulations and building codes. The community wildfire protection plan underscores the importance of collaboration between government agencies, local communities, and educational institutions can create a more unified and effective approach to wildfire prevention (Communities Committee, National Association of Counties, National Association of State Foresters, Society of American Foresters, & Western Governors' Association, 2004). Wildfire education programs for youth across the U.S. offer a valuable chance to explore how contemporary science, interdisciplinary teaching methods, and place-based learning are applied in the field of environmental education (Ballard et al., 2012). Having in-person communications with the locals is the most effective way to raise risk awareness and participate in risk reduction initiatives (Madsen et al., 2018). They also found strong support for fire departments in educating the public about daily fire danger and wildfire risks.

On the tribal lands, the Bureau of Indian Affairs (BIA) has been active in addressing undesired human-caused wildfires through its wildfire prevention program by implementing educational outreach, engaging communities, enforcing regulations, and conducting activities such as school programs, public events, media campaigns, patrols, and inspections. They also conduct investigations to identify wildfire causes, particularly in cases of arson (U.S. DOI Indian Affairs, 2024). Examples of prevention educational management practices include mass media coverage (radio, television, print, internet), public engagement (presentations, fairs, school programs, community meetings), and fire prevention materials (brochures, fire danger ratings, risk assessments). The importance of wildfire prevention has been recognized more than ever in the present time. A few studies have investigated the effectiveness of Wildfire Prevention Education (WPE) activities in reducing the number of wildfires caused by debris burning, campfire escapes, smoking, and children. Butry et al. (2010) examined the economic optimization of wildfire intervention activities in Florida and found that WPE primarily reduces human-caused ignitions.

In addition, Prestemon et al. (2010) found that WPE efforts, such as public service announcements and community outreach, have significantly reduced wildfires ignited by debris burning, campfire escapes, smoking, and children. Their study also indicated that the marginal benefits of WPE exceed the marginal costs by an average of 35-fold statewide. Another study by Abt et al. (2015) focused on tribal lands and found that prevention activities led to significant reductions in human-caused wildfires, with partial benefit-cost ratios of greater than 4.5 for all BIA Affairs regions for the continuation of the prevention program. By educating the public on simple, yet effective prevention measures, such as properly extinguishing campfires and maintaining vehicles to prevent sparks, the incidence of wildfires can be significantly reduced (Thurston, n.d.). In fact, the Indian Country have experienced a significant reduction in unintentional human-caused wildfires, indicating the positive impact of the prevention programs (U.S. DOI Indian Affairs, 2024). Educating young people about wildfires can have a direct impact on community preparedness, as they may engage in discussions with their parents, participate in service projects, and give presentations. Indirectly, these education programs prepare them to be informed homeowners and land managers in the future (Ballard et al., 2012). Many jurisdictions actively use education campaigns and public service announcements to share knowledge and promote practices that can help reduce the risk of wildfire ignitions (Hesseln, 2018). Despite these efforts, the unique challenges faced by tribal communities, such as limited resources and socio-economic vulnerabilities, necessitate continuous improvement and adaptation of wildfire prevention strategies (Avitt, 2021).

Regardless of the recognized importance of WPE activities in addressing wildfire threats, there is a significant gap in the literature regarding their specific impact on tribal nations, especially in recent years, specific causal categories of wildfire ignitions successfully reduced by WPE activities are not addressed. In our study, we consider the causal categories impacted by WPE as described in previous studies (Prestemon et al., 2010; Butry & Prestemon, 2019), which will represent the primary human-related ignition sources that can be significantly influenced by prevention programs. While previous studies, such as Abt et al. (2015), have analyzed the effect of wildfire prevention programs and law enforcement, their analysis was limited by data constraints, including a small number (17 BIA tribal units) and inconsistent information on education and outreach. Their study spanned from 1996 to 2011, which provides a significant temporal perspective but may not capture the most recent trends in wildfire causes. Previous studies have not specifically examined the impact of WPE efforts or their monthly timing on human-caused wildfires, using primary causal categories, on tribal lands. Besides, they lacked more comprehensive data of WPE on tribal lands. By addressing these research gaps, this study seeks to quantify the effects of WPE programs on the occurrence of human-caused wildfires across the 35 tribal nations in U.S., providing critical insights for optimizing resource allocation and shaping more effective wildfire prevention policies. We now have approximately 9 recent years of data from 2012 to 2020 covering 35 tribal nations (BIA agencies and tribes), allowing us to provide updated estimates on the impact of WPE programs.

This study makes valuable contributions to the implications of WPE on tribal lands. First, it will provide evidence-based insights into the impact of WPE programs on human-caused wildfires, empowering tribal communities with the knowledge and best practices to prevent human-caused wildfires, thereby protecting their lands, resources, and cultural heritage. Second, our findings will benefit tribal nations make informed decisions regarding timely investments in WPE efforts, ultimately reducing fire hazards and improving community safety. Third, this study will identify effective educational practices, offering practical recommendations that can be applied on the ground while contributing to the broader scientific community. Fourth, the inclusion of an increased number of tribes (35 tribal nations) and the new causal categories will provide a broader and better understanding of wildfire prevention needs and strategies. Lastly, our study aims to examine overlooked factors that affect the costs of wildfire suppression which will help improve cost models to ensure more efficient use of wildfire suppression and rehabilitation resources. Additionally, land-use planning agencies like the BIA will benefit from insights into how cross-jurisdictional pre-fire planning affects fire management. These contributions will enhance and update software application tools like the WPSAPS (Wildfire Prevention Spatial Analysis and Planning Strategies), optimizing decision-making and planning for tribal stakeholders and interagency fire managers. Improving this tool will have direct impacts for efficient assessment, planning, and accomplishment reporting of wildfire prevention programs. Overall, our research aims to improve understanding of how different WPE efforts can be used effectively to minimize spread of wildfire ignition across different areas, helping agencies identify optimal practices for prevention.

2.2 Methodology

2.2.1 Data

We gathered several sets of data to quantify the timing effects of prevention education activities on undesirable human-caused wildfire ignitions. Data on WPE conducted within the tribal units was collected from the BIA (BIA, 2022). While the prevention programs were instituted in the mid-2000s (Abt et al., 2015), we focused our analysis on the period from 2012 to 2020 as consistent data became available for more tribal units in the U.S. We collected monthly educational prevention activities for a total of 42 tribes and agencies. Monthly activities in many tribal units were either not reported or missing. To account for this, we removed seven units that had more than 3 years of missing information. Table B.1 shows the list of included 35 tribal units, their corresponding agencies' full names, states, total wildfire count, total burned acres from wildfire, percentage of wildfire count, and percentage of acres burned. The data covers 14 states, including Arizona, California, Idaho, Kansas, Minnesota, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Washington, and Wyoming. Over the years, the same type of WPE was observed across the tribal units. We focused specifically on the WPE actions aimed at educating communities and raising awareness about wildfire risks. Out of a total of 109 actions, we identified a total of 57 prevention actions that were related to educational efforts and grouped them into seven categories: mass media coverage, signage placement, individual/key personnel contacts, community contacts, programs/events, informational brochures, and hazard assessments. Examples include mass media coverage (radio, television, print, internet), public engagement (presentations, fairs, school programs, community meetings), and fire prevention materials (brochures, fire danger ratings, risk assessments). Other specific initiatives included volunteer training, interagency campaigns, stakeholder meetings, and mitigation training. The full list of all 57 actions is listed in Appendix B (Table B.3).

The wildfire data was collected from the USDA Forest Service (Short, 2023). The raw wildfire dataset was provided in Microsoft Access database format. We filtered the data based on reporting agencies and ownership, selecting only BIA and tribal entities, and narrowed the reporting unit names to include tribal nations in our dataset. Additionally, we focused on data from the years 2012 to 2020 and filtered the broad cause classification to include only human-caused ignitions. Further, the general cause classifications were refined to focus specifically on human-caused ignitions resulting from debris and open burning, fireworks, fire misuse by minors, power generation/transmission/distribution, recreational and ceremonial activities, and smoking. These causes were specifically selected based on the understanding that human-caused wildfires, particularly undesirable ones, can be significantly reduced through WPE efforts (Prestemon et al., 2010; Butry & Prestemon, 2019). After extracting and cleaning the data, we identified a total of 9,117 stances of wildfire with different fire sizes in 35 tribal nations for the defined study period (Figure 2.1). As for the demographic information, we gathered the population estimates of each tribal unit for each year from the U.S. Census Bureau (U.S. Census Bureau, 2024). We took the five-year estimates for each year and summed up the population for the agencies covering multiple tribes.

Data on most of the climatic variables were collected from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NOAA, 2024). Climatic variables included average monthly maximum temperature, average monthly palmer drought severity index, number of days with precipitation per month, and average relative humidity. For tribes covering multiple counties, we summed up the values for each tribe. For the relative humidity, we correlated airport stations with the nearest counties and averaged hourly relative humidity values in percentage, from the local climatological dataset. For those stations that didn't have any record, we used the next nearest station's data. We also included Canadian fire weather index (FWI) data, which was collected from Copernicus Climate Change Service, Climate Data Store (Copernicus Climate Change Service, 2019). By combining temperature, humidity, rain, wind, fire spread and key fuel moisture metrics such as fine fuel moisture, duff moisture, and drought code, FWI captures the critical variables and quantify the meteorological conditions that can lead to fire ignition (Figure B.13). FWI is a robust tool for predicting fire risk and understanding environmental and anthropogenic factors contributing to wildfire intensity and behavior (Van Wagner, 1974; Natural Resources Canada, n.d.). Building upon this framework, we downloaded the Copernicus FWI data and addressed issues with the latitude and longitude coordinates by converting the projections from '0–360' degrees to '-180–180' degrees. Using R, we filtered the data, which was in Network Common Data Form (NetCDF4) experimental format, to include only U.S. points and merged it with tribal boundaries. This allowed us to assign the closest FWI points to each observation, resulting in over 40 million entries. Finally, we calculated the daily average FWI for each agency each year, offering a complete dataset to assess fire risk and behavior across multiple tribal regions. Finally, we merged all the climatic variables with the WPE efforts in 35 tribal units.

2.2.2 Data Analysis

Linear Interpolation and Extrapolation

We used linear interpolation to estimate the number of WPE activities that were missing for some of the tribes for some years. Equation (1) was used to estimate the missing values by following the methods and derivation discussed in Chapra and Canale (2010):

$$f_1(x) = f(x_0) + \frac{f(x_1)-f(x_0)}{x_1-x_0} + (x - x_0) \tag{1}$$

where, $f(x_0)$ is the value at the start year x_0, $f(x_1)$ is value at the end year x_1, $f_1(x)$ is the first-order interpolating polynomial, $[f(x_1) - f(x_0)]$ / $(x_1 - x_0)$ is the slope of the line linking the two known data points, and x is the year for which we want to estimate the missing value. When data at the beginning or end of the study period was missing, we used extrapolation by applying the same formula to extend the linear relationship beyond the available data range.

Model quantifying WPE effects

Before estimating the effect of WPE on wildfire ignitions, we checked for potential endogeneity between these variables by creating a set of auxiliary regressions for seven categories of WPE activities (mass media coverage, signage placement, individual contacts, community contacts, educational programs/events, informational brochures, hazard assessments), where each of these was regressed with a vector of instruments (Equation 2). Instrument variables included all the previous (lagged) wildfire ignitions, and the exogenous variables included lagged WPE efforts, lagged burned acres, lagged climatic variables, current month climatic variables, population, tribal units, season, year, and time trend to control for external influences. Following Prestemon et al. (2010), we used the control function approach to check for endogeneity:

$$WPE_{k,l,t} = \gamma'_{k,t}\, h_{k,c,t} + e_{k,c,t} \tag{2}$$

where, $h_{k,c,t}$ is a vector of WPE instruments that are orthogonal to $\varepsilon_{c,l,t}$, $\gamma_{k,t}$ contains parameters associated with a constant and the instruments, and $e_{k,l,t}$ is the error term or normally distributed disturbance term, which is also orthogonal to $h_{k,c,t}$ and contains all unobserved heterogeneity that causes the correlation between WPE effort and ignition rates, 'k' is an index for different types of WPE interventions, 'l' is the specific location or tribal nations, 't' is the specific month when WPE was carried out, 'c' is the specific cause of wildfire, $\hat{e}_{k,l,t}$ serves as an estimated disturbance term that captures unobserved heterogeneity affecting the relationship between WPE efforts and the ignition rates of wildfires. The residuals from this first-stage regression for each model were saved and included as additional regressors in the Poisson model. Significant residuals were included in the final model to control for any omitted variable bias that could arise from endogeneity.

In the second step, we estimated the effects of WPE on wildfire ignitions using the Poisson processes. The number of wildfire ignitions of cause *c* in location *l* and time t, which is a function of WPE activities and other variables, can be described as a Poisson or negative binomial process:

$$I_{c,l,t} = \exp\left(\boldsymbol{\beta}'_{c,l}\boldsymbol{Y}_{c,l,t} + \varepsilon_{c,l,t}\right) \quad (3)$$

where, $I_{c,l,t}$ represents the count of wildfire events at tribal locations *l* in month *t* by cause *c*, exp is the exponential function that ensures the predicted count is positive, $\boldsymbol{\beta}'_{c,l}$ contains the coefficients associated with the predictors $\boldsymbol{Y}_{c,l,t}$, including WPE activities and other influencing factors, and $\varepsilon_{c,l,t}$ is the random error that follows a gamma distribution $\left(\frac{1}{\alpha}, a\right)$. Poisson distribution is used for count data, assuming that the variance is equal to the mean under the assumption of equidispersion. This approach has been used in several previous studies for predicting forest fire occurrences (Prestemon et al., 2010; Xiao et al., 2015).

The empirical model assumed a fixed-effects panel of Equation 3, estimated across the various tribal locations '*l*' reporting WPE efforts. In this model, we assumed that the parameter $\beta_{c,l}$=β_c is constant for all tribal locations '*l*'. Following Prestemon et al. (2010), we used maximum likelihood estimation that maximizes the log-likelihood based on a Poisson distribution:

$$ln\ L = \Sigma_{c=1}^{C}\Sigma_{l=1}^{L}\Sigma_{t=1}^{T} - exp\left(\boldsymbol{\beta}'_{c,l}\boldsymbol{Y}_{c,l,t}\right) + \boldsymbol{\beta}'_{c,l}\boldsymbol{Y}_{c,l,t}I_{c,l,t} - \ln(I_{c,l,t}!) \quad (4)$$

where, $\boldsymbol{Y}_{c,l,t} = (1, \boldsymbol{x}_{c,k,l,t-p}, \boldsymbol{z}_{c,l,t})'$, $\boldsymbol{x}_{c,k,l,t-p}$ is a vector including the WPE variables for the current and previous months p and $\boldsymbol{z}_{c,l,t}$ are other potential factors influencing wildfire ignitions in month '*t*' at location '*l*'. The independent variables in the model included current month WPE activities across seven categories media, signage, individual contacts, community contacts, programs/events, brochures, and hazard assessments, lagged WPE (aggregated/sum of actions in the previous 6 months), lagged acres burned by wildfires, climatic variables (maximum temperatures, drought index, daily precipitation, mean fire weather index and relative humidity), and residuals from the first-stage regression for the endogenous variables. The lagged acres burned were included to capture the delayed effects of previous wildfires on current wildfire risk. This also accounted for the impacts of past fire activity on fuel availability and fire behavior. The lagged climatic variable was considered because wildfire ignition and spread are influenced not only by current weather conditions but also by past climatic patterns that affect fuel moisture, vegetation growth, and overall fire susceptibility (Halofsky et al., 2020). We also created dummy variables for years to capture year-specific effects or differences that could influence wildfire occurrences. Seasonal dummies were also included to account for the seasonal variations where the fall season was in the intercept as a baseline reference for the season. We also included dummies for tribal nations to capture differences between tribal nations as different tribal nations might experience varying levels of risk or have different WPE activities based on geographical or cultural factors. Finally, we included a trend variable to account for any broader, long-term patterns or changes that are not captured by other variables. Incorporating time trend variables and lagged data into predictive models is advised to enhance the accuracy of statistical models for wildfire ignitions (Prestemon et al., 2013).

After fitting the Poisson regression, we checked for overdispersion by calculating the dispersion ratio, defined as the deviance divided by the residual degrees of freedom. Overdispersion occurs when the observed variance exceeds the mean, indicated by a ratio significantly greater than 1. In our analysis, the dispersion ratio was found to be greater than 1 (2.85), suggesting the presence of overdispersion. As a result, a Negative Binomial model was fitted, which introduced an additional parameter to account for the extra variability not captured by the Poisson model.

2.3 Results

2.3.1 Wildfire Prevention Education Activities

Table 2.1 and Figure 2.5 summarize the WPE measures across seven different activity categories from 2012 to 2020. Individual (key person) contacts were the most frequently conducted activity, with a total of 66,552.5 actions, followed by hazard assessments that included around 16,435 actions. Other actions included a total of 12,714 programs/events, 6,164.5 mass media activities, and 5,214 informational brochure distribution. Of all categories, signage placement and community contacts were least carried out with 4,814 and 3,615 actions, respectively. The minimum action of zero indicates that the tribal units may not have been engaged in WPE activities in all months of the year.

2.3.2 Undesirable Human Caused Ignitions

Table 2.2 and Figure 2.2 summarize the causal categories of human-caused wildfires across 35 tribal units (2012-2020) in terms of total ignitions and acres burned. Debris and open burning was the leading cause of wildfire ignitions, accounting for 50% (4,558 ignitions) of the total ignitions that burned 230,217 acres. Fireworks caused 21.45% (1,956) of total ignitions but only burned 6,373.7 acres (1.4% of the total). The misuse of fire by minors caused 15.83% (1,443) of ignitions and burned 3.35% (15,285.2 acres). Recreational and ceremonial activities resulted in 6.92% (631) of ignitions and burned 7.31% (33,326.3 acres). Further, power generation, transmission, or distribution accounted for only 3.61% (329) of total ignitions but were responsible for a substantial 24.12% (109,928 acres) of the total acres burned. Smoking, in particular, caused only 2% (182) of ignitions, but had a disproportionate impact on acreage burned, contributing to 13.24% (60,352.1 acres) of the total acres burned. Lastly, use of firearms and explosives caused only 0.2% (18) of ignitions and burned 357.5 acres. As per distribution of ignitions over different regions, we found that most wildfire ignitions were recorded from the Great plains region and Midwest region with a peak in the year 2012 and 2017 (Figure 2.3). Looking at the trend, we observed that the debris and open burning, fireworks, and misuse of fire by minors were consistently the major cause of ignitions through the years 2012 to 2020 (Figure 2.4).

2.3.3 Control Function Results

We estimated seven sets of auxiliary regressions for the WPE efforts mass media coverage, signage placement, individual contacts, community contacts, programs/events, informational brochures, and hazard assessments to address potential endogeneity and isolate the individual impact of WPE on wildfire ignitions. The control function models showed a moderate proportion of the variation in preventable wildfires, explaining 17.84% to 37.24% of the variation (Table 2.3). The residuals of six models, including media coverage, signage, individual contacts, community contacts, hazard assessments, and informational brochures, were significant at the 0.1% level, except for the residuals of programs/events. Six significant residuals were included in the Poisson model (Equation 4), which indicated overdispersion with a value of 2.85 (>1). To address overdispersion, we used a negative binomial model that provided a more appropriate fit for the data.

2.3.4 Poisson Regression Results

Regression results showed varying effects of WPE on human-caused wildfire ignitions (Table 2.4). The 6-month lagged aggregates of prevention educational activities showed a negative effect for the signage at 5%, and media at 10% significance level. The lagged effect of community contacts, individual contacts, programs/events, brochures and hazard assessments were insignificant. WPE activities from the present month were negatively related to the number of preventable wildfires for programs/events, brochures, hazards, individual contacts and community contacts. Specifically, community contacts and hazard assessments were significant at the 5% and 10% levels, respectively. Surprisingly, mass media coverage and signage placement were found to be relatively ineffective in reducing wildfire ignitions. As expected, the control variables for brochures, hazards, individual contacts and community contacts were positive and significant for hazards and community contacts, which implies that it was important to consider the residuals as it would have given biased estimates. Conversely, the control variables for signage and mass media were negative and significant.

The climatic variable such as maximum temperature was positively correlated with preventable wildfire counts, though the relationship was not statistically significant. The palmer drought severity index was negatively correlated with preventable wildfires, but the effect was not significant. It is important to note that the higher values signify wetter conditions. As drought values increased, wildfire ignitions seemed to decrease, as expected. On the other hand, relative humidity was negatively and significantly related to preventable wildfire ignitions, suggesting that higher humidity levels are associated with fewer ignitions. Further, the fire weather index showed a highly significant positive association with the fire ignitions. Similarly, higher number of days with precipitation had a negative correlation with preventable wildfire counts, with a 10% level significance, indicating that wetter conditions might reduce ignitions. The acres of land burned by wildfire, lagged by 3, 4, and 5 years, were negatively related to wildfire ignitions, with a significant effect of 4 year lagged acres burned. Except for the winter season, both the spring and summer seasons were significantly associated with higher wildfire ignitions compared to the fall season, which aligns with our expectations. In contrast, the winter season showed lower ignitions than the fall season. Wildfire ignitions were significantly higher in each year from 2013 to 2020 compared to the baseline year (2012). The coefficients for all years were all statistically significant at the 0.1% level, indicating a steady increase in wildfire ignitions over this period. Surprisingly, population size was negatively associated with wildfire ignitions, though this relationship was not statistically significant. Only the Navajo region had significantly higher wildfire ignitions than the reference tribal nation Anadarko Agency. Except for 9 tribal nations, all the others had significantly lower ignitions than the agency in reference. We also observed that the trend variable had a statistically significant negative relationship with wildfire ignitions. As time progresses, the frequency of wildfires tends to decrease, with an approximate reduction of 0.059 for each unit increase in the trend variable. The variables included in the negative binomial model explained 69.31% of the variation in the preventable wildfire ignitions.

Table 2.5 presents the elasticity values, which measures the percentage change in the dependent variable resulting from a percent change in the independent variable, calculated at their mean values. The current month's effect of community contacts with an elasticity of -4.263, indicates that a 10% increase in community contacts leads to a 42.63% significant decrease in the wildfire ignitions. Hazard also had a negative elasticity of -0.125, meaning that a 10% increase in hazard assessments lead to a 1.25% decrease in the fire ignitions, and was marginally significant. Educational variables like individual contacts and programs/events showed negative elasticities of

-0.014 and -0.00075, respectively, meaning that a 10% increase resulted in a decrease in the wildfire ignitions (0.14% for individual contacts and 0.0075% for programs/events), but neither was statistically significant. Similarly, brochures had a negative elasticity of -0.069, indicating a 0.69% insignificant decrease in the wildfire ignitions. In contrast, the mass media and signage had a positive elasticity of 3.005 and 0.965, respectively.

Regarding the lagged 6-month aggregate effects, we found mixed results. Lagged aggregated media and signage had negative elasticity of 0.074 and 1.145 at 10% and 5% significance level, respectively. However, except for hazard assessments, programs/events, brochures, individual contacts, and community contacts do not appear to have significant associations with wildfire ignitions. The combined effects of six-month aggregate and current-month activities of community contacts, signage, and individual contacts were -4.05, -0.18, and -0.01, respectively, representing the highest elasticities among all the WPE variables. These elasticities indicate that a 10% increase in community contacts, signage, and individual contacts over the past seven months would result in a 40.5%, 1.8%, and 0.1% decrease in preventable wildfire ignitions due to these respective activities. Overall, the elasticities associated with the significant current-month WPE variables are greater than those of the significant six-month WPE effort aggregates. This suggests that activities conducted within a more recent time frame appear to have a stronger and more immediate effect on reducing preventable wildfire ignitions compared to those conducted over the preceding months.

2.4 Discussion and Conclusions

This study examined the effectiveness of seven categories of WPE efforts, media, signage, community contacts, individual contacts, programs/events, brochures, and hazard, on preventing the number of undesirable human-caused wildfire by various causal categories, including debris and open burning, firearms and explosives use, fireworks, misuse of fire by a minor, power generation/transmission/distribution, recreational and ceremonial activities, and smoking. The use of control models proved to be crucial in addressing the endogeneity problem, thereby ensuring that the estimates are unbiased and reliable. Significant residuals from the control models for media, signage, individual contacts, community contacts, hazard assessments, and brochures were included in the Poisson model estimation to control unobserved factors that might have influenced both the endogenous variables and the number of ignitions. Due to overdispersion, a negative binomial model was used to better capture the effects of underlying factors of wildfire prevention. The negative binomial model was used that accounted for 69.31% of the variation in preventable ignition rates.

Our findings showed variation in the effectiveness of WPE activities in reducing the number of human-caused wildfire ignitions. Individual contacts had a negative effect on preventable ignitions. Of all the WPE activities, individual contacts were the most recorded, involving any individual with authority or influence to deliver fire prevention messages (e.g., tribal officials, agency employees, and regional or state officials) (BIA, 2019). While the number of community contacts was relatively lower, it showed a statistically significant negative association with wildfire ignitions. These findings are supported by Ballard et al. (2012) and Hesseln (2018), that found face-to-face and interactive communication to be effective ways for increasing risk awareness, engaging in risk reduction, and potentially influencing peoples' attitudes and beliefs regarding fire prevention. Other WPE efforts, including hazard assessment, programs/events, and brochures also exhibited negative correlations with the number of ignitions. However, only hazard assessment was statistically significant at the 10% level. Such efforts included fire danger ratings, community firewise assessments, risk assessments, residential structural ignitability assessments, and wildfire threat notifications. Concentrating these kinds of activities in priority areas has been shown to have the potential to reduce and prevent large-scale wildfires (Palsa et al., 2022). Educational programs and events, including presentations, fairs, parades, and campaigns, could be highly effective in communicating prevention messages to specific groups such as children, youths, community members, and local organizations for preparedness through increased knowledge and active participation (Prestemon et al., 2010; Synolakis & Karagiannis, 2024). However, their reach may be more limited than that of individual or key personnel contacts, which could explain a weaker correlation with wildfire ignitions. Along the same lines, informational brochures can be helpful for disseminating ideas and basic knowledge about wildfire prevention, but the way public processes, understands, and interprets the information may differ from what is actually conveyed (Toman et al., 2006; McCaffrey et al., 2012).

Other WPE variables, media and signage, had unexpected correlations with wildfire ignitions. Land management agencies together with local communities depend on strategic planning strategies to prepare for wildfires (Remenick, 2018) and they require effective communication channels between government agencies and residents for successful implementation of reduction activities (Brenkert-Smith et al., 2013; McCaffrey et al., 2013). Thus, media campaigns may need to be less broad and more individualized, outlining specific preventive steps, continuing follow-up, and establishing multifaceted community-centered prevention programs. In our study, a total of 4,814 signage activities on tribal lands are significantly lower than most other WPE activities, indicating that signs may not be as commonly used or engaging as more direct activities like individual contacts or programs/events. They might still be placed in high-risk areas where human activity is more common, increasing the potential for ignitions. If signage placement is not accompanied by adequate education or enforcement, the increased activity around these signs could lead to more human-caused ignitions.

Elasticities of WPE variables showed that media and signage efforts over the last 6-month period seem to influence wildfire occurrences in the present times. Other, aggregated variables, including community contacts, hazard assessments, programs/events, brochures and individual contacts, seem to not have a lasting influence on wildfire occurrence beyond their immediate time frame. This suggests that their long-term impact on behavioral change appears minimal, emphasizing the need for sustained or repeated interventions. However, it is important to note that the inclusion of aggregated WPE improved the explanatory variation in the control models. Opposite to our findings, Prestemon et al. (2010) found that 6-months aggregated WPE efforts, except for home contacts had statistically negative effects on the wildfire ignitions in Florida. Our study raises the question of longevity of WPE efforts and whether there is requirement of frequent wildfire prevention activities which can lead to sustained behavior change in people in tribal nations. While WPE activities are beneficial, their effectiveness can be limited by factors such as wildfire risk public perception and engagement levels, which is affected by cognitive biases and uncertainty. This leads to a skewed understanding among officials and residents (Eiser et al., 2012; Hutchison, 2020). While residents are generally aware of wildfire risks, many may not implement the necessary mitigation measures (Gakavian et al., 2024). This highlights the challenges of translating awareness into action, particularly among certain demographic groups, and underscores the need for continuous evaluation and improvement of wildfire mitigation strategies to ensure greater public participation and effectiveness.

Climatic variables had a significant effect on wildfire ignitions. Relative humidity showed a highly significant negative effect, indicating that higher humidity levels reduce wildfire occurrences, aligning with our expectations. Extended periods of low humidity during a month typically result in the drying of all forest fuels to a hazardous degree. Just a couple of days of low humidity can heighten the chances of brush and forest fires (Xiao et al., 2015). Similarly, FWI also revealed a highly significant positive association with wildfire ignitions. Strong winds are positively correlated with rapid wildfire propagation, a relationship reflected in fire weather indices like Canadian Fire Weather Index, where wind speed increases the fire weather index (Wagner, 1974; Shmuel & Heifetz, 2023). Furthermore, maximum temperature was positively correlated with preventable wildfire counts, although the effect was not significant. This could be due to wildfire management initiatives, along with other local environmental factors collectively overshadowing temperature-related impacts. If a region has an active number of wildfire prevention programs with well managed natural fuel woods, the influence of temperature may not be that strong. The number of days with precipitation was a marginally significant predictor and negatively associated with wildfire ignitions. This implies that as the number of days with precipitation increases, the number of wildfire ignitions tends to decrease. Our findings corroborate with that of Xepapadeas et al. (2024), who found that the primary causes of wildfire incidents overall are summer temperature and summer and spring precipitation. The palmer drought severity index's negative coefficient confirmed that drier conditions are conducive to more wildfires. Drought is expected to increase fire risk due to drier conditions and more easily ignitable vegetation. The timing of WPE actions is vital because they show excellence during periods that consider weather conditions and current wildfire activity (Butry et al., 2010).

Acres burned by wildfire in the last 3, 4, and 5 years were negatively correlated with wildfire ignitions, suggesting that the past wildfire activity may alter vegetation and fuel availability, leading to decreased susceptibility to current wildfires (Stevens-Rumann et al., 2016). Analysis of past global wildfire incidents can educate residents and local officials about local wildfire risks and mitigation strategies (Hutchison, 2020). Interestingly, population had a small positive effect on wildfire ignitions. As population grows, land development, urban sprawl, and deforestation can lead to reduced vegetation, which in turn could affect the occurrence of wildfires. This shift in the landscape may reduce fuel availability, potentially explaining the observed relationship (Prestemon et al., 2010). Regarding regional variation, the Navajo region had significantly higher wildfire ignitions compared to the reference tribal nation, Anadarko Agency. In addition, the Okmulgee Agency also showed higher ignitions, but this difference was not statistically significant. This result reflects differences in local fire management practices, access to resources, or even cultural differences in fire prevention strategies. With the exception of 9 tribal nations, all other tribal nations had significantly fewer ignitions compared to the reference agency. This highlights the importance of adapting WPE efforts to local conditions and ensuring that resources are allocated to regions with the highest need. The statistically significant negative relationship between the trend variable and wildfire ignitions suggests that wildfire prevention efforts may have a cumulative positive effect. As time progresses, wildfire ignitions seem to decrease. This aligns with the notion that fire management activities contribute to a downward trend in wildfire occurrences. However, the reduction could also be attributed to other factors such as firefighting resource and technology, changes in fire regulations, even the land use change patterns, climatic patterns, and socioeconomic factors.

Vulnerability to wildfire may vary by geography and community, with some communities facing significantly higher risk. Communities that have higher social capital tend to join wildfire preparedness programs and frequently implement strategies to reduce wildfire risks (Agrawal & Monroe, 2006). However, those with lower social capital may have different attitudes towards fire risk due to differences in local cultures. For instance, some view fire as natural and beneficial, which leads to failure in the applications of WPE efforts. Community partnerships between agencies and citizens are crucial for implementing effective, place-based solutions to reduce wildfire vulnerability (Kolden & Henson, 2019). It may be wise to create more specialized information and outreach programs that guide risk assessment of these activities under high-risk weather conditions. The sustainability of wildfire prevention efforts is a critical challenge. McCaffrey (2015) suggested that no single outreach or policy approach will work universally, given the varied responses to wildfire risks and the importance of local context and community connections. The provision of brief educational activities serves as an initial information source about wildfire risk yet insufficient to generate enduring behavioral changes among community members. According to Reilley et al. (2023), the current situation demands intensive strategies towards understanding human-induced ignition behaviors that stem from recreational practices and open burning activities. Educational efforts and their impacts can sometimes fade from people's minds over time, leading to a decrease in their interest or engagement with certain behaviors. Therefore, consistent engagement with the local communities is necessary. One approach to this could be integrating WPE practice within the local government policies and school curriculums. Extending support through long-term reinforcement strategies such as continuous education programs together with regular climatic risk evaluation updates and monitoring programs could address this concern.

Despite the efforts, our study had some limitations. Although we included a relatively larger number of tribal units, missing data on WPE for certain years prevented us from including all the tribal units. We also did not examine the individual impact of WPE on ignitions of different causes or considered potential confounding variables, such as socioeconomic characteristics, land use patterns, law enforcement practices, police per capita, and prescribed fire permits issued. Additionally, we were unable to include prevention data from recent years due to the lack of updated wildfire data. Further, some WPE data were limited to agency levels, not accounting for the activities in specific tribes within those agencies, which may have overlooked finer spatial variations in WPE needs and effectiveness. Moreover, better specific instrumental variables like funding allocations, law enforcement and regulatory changes for each WPE activity could have provided more precise estimates. By aligning specific instrumental variables with the characteristics and influencing factors of each WPE activity, future studies can improve the validity of statistical models and adjust for potential endogeneity issues related to those activities. Since we didn't account for the proportion of different ignition causes, our study may overlook other dynamics that influence the overall effectiveness of WPE. Regardless of the limitations, the findings offer several important implications. Community contacts and hazard assessments appear to function as important actions for timely implementation. However, inconsistent results for media and signage reveal the need for a refined method in WPE program design and execution. Additional attention needs to be directed at evaluating the unintended effects of mass media coverage and signage because higher public awareness may result in escalated reported ignitions. Consequently, the findings could be useful for enhancing and updating software application tools like the WPSAPS (Wildfire Prevention Spatial Analysis and Planning Strategies), optimizing decision-making, and planning for tribal stakeholders and interagency fire managers. Improving this tool will have direct impacts for efficient assessment, cost-effective planning, and accomplishment reporting of wildfire prevention programs.

Overall, this study quantifies that WPE efforts like community contacts, hazard assessments, individual or key person contacts, information brochures, and programs/events have the potential to reduce human-caused wildfires on the tribal lands. We also highlight that while some WPE activities provide immediate benefits, their long-term effectiveness is limited without continuous reinforcement. Further, our findings suggest that climatic factors, regional variations, and seasonal patterns can play significant roles in wildfire ignitions. Lastly, we identify that previous wildfires and certain WPE activities could have a lasting impact on current ignitions, emphasizing the importance of sustained educational efforts. In conclusion, this study underscores the need for continuous and context-specific WPE efforts, along with further research to refine strategies for long-term impact and enhance community engagement in wildfire reduction. Future research can investigate the effectiveness of specific WPE strategies by causal categories of wildfires. Further, future studies can examine the effects of other 52 prevention actions like patrols, inspections, law and permits on the fire ignitions and see how that differs from educational activities. In addition, prospective research could conduct thorough economic assessments of various WPE activities quantifying both direct costs and indirect benefits such as reduced property damage and lower firefighting expenses, to provide a complete cost-benefit analysis. Besides, studies could also assess how media messages resonate differently with distinct demographic groups in tribal nations, and how the content of these messages (e.g., fear-based versus empowerment-based messages) influences behavior change. Further, whether the behaviors instilled by these WPE programs are maintained across generations, or if communities experience a "fade" in engagement and preparedness after a few years remains a critical question.

Table 2.1. Summary of Wildfire Prevention Education (WPE) activities across 35 tribal nations in the U.S., 2012-2020 (BIA, 2022).

WPE Activities	Sum	Average	Count	Maximum	Minimum
Media Coverage	6164.5	1.63	3780	100	0
Signage Placement	4814	1.27	3780	38	0
Individual Contacts	66552.5	17.61	3780	2522	0
Community Contacts	3615	0.96	3780	300	0
Programs/Events	12714	3.36	3780	2626	0
Informational Brochures	5214	1.38	3780	2413	0
Hazard Assessments	16435.75	4.35	3780	301	0

Table 2.2. Total and percentage distribution of human-caused wildfires across 35 tribal nations, 2012–2020 (USDA, 2022).

Human Cause of Wildfire	Total Ignition	Total Acres Burned	Percentage of Total Ignitions	Percentage of Total Acres Burned
Debris and open burning	4558	230217.22	50	50.5
Firearms and explosives use	18	357.5	0.2	0.08
Fireworks	1956	6373.7	21.45	1.4
Misuse of fire by minors	1443	15285.2	15.83	3.35
Power generation/transmission/distribution	329	109928.04	3.61	24.12
Recreation and ceremony	631	33326.25	6.92	7.31
Smoking	182	60352.05	2	13.24

Table 2.3. Estimates from the control function equation for the seven wildfire prevention education variables.

	Estimates						
Predictors	Media	Signage	Community Contacts	Individual Contacts	Programs /Events	Brochures	Hazard
L_WC_1	-0.010	0.008	0.0005	-0.137	-0.191	-0.158	0.011
L_WC_2	-0.026 **	0.004	-0.007	0.053	0.05	-0.046	-0.026
L_WC_3	0.004	-0.009	-0.002	-0.083	-0.001	-0.04	0.009
L_WC_4	-0.001	0.001	-0.006	0.1	0.054	-0.052	0.034
L_WC_5	-0.004	-0.004	0.004	-0.037	0.04	-0.048	-0.011
L_WC_6	-0.005	0.004	-0.012	0.603 **	0.024	0.031	0.004

L_WC_7	-0.005	-0.008	-0.046***	-0.057	0.033	0.02	0.012
L_WC_8	0.000	0.002	0.007	-0.114	-0.019	-0.063	-0.021
L_WC_9	-0.008	0.001	-0.002	0.083	-0.015	0.024	0.054**
L_MaxT	0.029	0.005	0.084	0.189	-0.75	1.049*	-0.052
L_D	0.039	-0.017	0.034	1.085	0.218	0.128	-0.119
L_RH	0.013	0.009	0.011	0.117	-0.215**	0.025	0.107
L_FWI	0.002	-0.001	0.0002	-0.409***	0.051	0.005	0.009
MaxT	0.138**	-0.035	0.119	-0.224	0.935	-0.886	0.209*
D	-0.018	0.018	0.08	-0.166	0.597	-0.353	0.004
RH	-0.030**	-0.001	-0.001	-0.065	0.04	-0.071	-0.021
PPT	-0.008**	-0.002	-0.009*	0.023	0.02	-0.007	-0.021***
FWI	-0.014	0.003	0.006	-0.047	0.062	-0.054	-0.006
L_WA_1	-0.0002	0.00006	-0.00004	0.0002	0.0002	0.000005	-0.000004
L_WA_2	0.00004	-0.00002	-0.00002	-0.001	0.00008	0.00002	0.00004
L_WA_3	-0.00006	-0.00001	0.00002	0.001	-0.00006	0.0001	0.00003
L_WA_4	0.00006	-0.00001	-0.00005	0.0007	-0.00002	0.00005	-0.0001
L_WA_5	0.00003	-0.00001	-0.00003	-0.0003	0.00009	0.0002	0.0001
L_WA_6	-0.000002	-0.00002	0.00002	-0.0003	-0.00004	-0.00002	0.00001
L_WA_7	0.000005	-0.000002	0.0017***	0.0017*	0.00002	0.00003	0.00006
L_WA_8	-0.00002	-0.00001	-0.000004	0.0002	0.0001	0.00008	-0.000008
L_WA_9	-0.00002	-0.00001	-0.000002	-0.0002	0.0002	-0.00004	-0.000002
Spring	0.106	0.09	0.5	-1.603	-0.631	0.772	0.387
Summer	0.13	0.106	0.226	2.427	-1.659	0.768	0.789
Winter	-0.149	-0.027	0.161	-3.319	1.339	0.098	-0.38
Pop	0.00007*	0.00002	-0.00001	0.00005	-0.00001	0.0001	-0.0001*
2013	-0.056	-1.529	1.669	13.626	40.137	-24.012	4.034
2014	-0.02	-3.052	3.299	31.377	79.349	-47.187	8.251

2015	-0.852	-4.459	4.524	47.94	118.772	-71.293	11.719
2016	-1.392	-5.876	5.576	61.747	157.358	-94.613	15.21
2017	-1.628	-7.312	7.121	79.788	197.168	-118.795	19.14
2018	-1.744	-8.824	8.535	96.889	237.523	-142.577	23.018
2019	-1.903	-10.361	10.494	109.294	275.938	-165.593	27.424
2020	-2.561	-11.783	11.743	130.02	314.732	-189.308	30.936
Trend	0.0008	0.003	-0.003	-0.039	-0.094	0.056	-0.009
Agg_M	0.161***	-0.004	0.004	-0.158	-0.032	-0.001	-0.007
Agg_S	0.0007	0.165***	0.001	-0.044	-0.036	0.132	0.005
Agg_C	-0.002	0.001	0.138	-0.026	-0.0004	-0.014	-0.006
Agg_I	0.0005	-0.0002	0.0002	0.167***	0.0008	-0.001	-0.0004
Agg_P	-0.0002	0.00004	0.0001	-0.003	0.167***	-0.0007	-0.0002
Agg_B	-0.000006	-0.0009*	0.0001	0.0007	-0.001	0.167***	0.000006
Agg_H	-0.005	-0.0006	0.005	0.164**	0.013	-0.015	0.169***
Intercept	-24.712	-2.639	-11.15	14.06	4.774	-28.05	16.159
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
R^2	0.318	0.302	0.359	0.219	0.18	0.178	0.372

*p<0.05, **p<0.01, ***p<0.001

Notes: Region-specific variables for tribal units were included in the model to control for as dummy variables, but their coefficients are not shown for clarity. FWI (Fire Weather Index), D (Palmer Drought Severity Index), MaxT (Maximum Temperature), RH (Relative Humidity), PPT(Days with Precipitation), Pop(Tribal population), L_WC (Lagged wildfire counts or ignitions for each year), L_WA (Lagged wildfire acres for each year), M (Mass media coverage), S (Signage placements), C (Community Contacts), I (Individual Contacts), H (Hazard assessments), B (Informational Brochures), P(Programs/Events), Agg(Six-month aggregates or sum of prevention education activities).

Table 2.4. Estimates of preventable wildfire ignitions using a Poisson model for the study period, 2012-2020.

	Estimate	Standard Error	z value	Pr(>|z|)
MaxT	0.007	0.035	0.209	0.835
D	-0.0001	0.018	-0.006	0.995
RH	-0.044	0.007	-6.51	<0.0001
PPT	-0.003	0.002	-1.67	0.095
FWI	0.016	0.004	3.67	0.0002
L_WA_1	0.00004	0.00003	1.28	0.202
L_WA_2	0.00004	0.00002	2.53	0.012

L_WA_3	-0.00001	0.00004	-0.352	0.725
L_WA_4	-0.0001	0.00003	-2.18	0.029
L_WA_5	-0.00004	0.00002	-1.69	0.09
L_WA_6	0.00003	0.00002	1.6	0.109
L_WA_7	0.0005	0.0002	2.43	0.015
L_WA_8	0.00002	0.00002	0.954	0.34
L_WA_9	0.00003	0.00001	1.75	0.08
Spring	0.819	0.116	7.03	<0.0001
Summer	0.589	0.097	6.09	<0.0001
Winter	-0.185	0.129	-1.43	0.153
Population	-0.00004	0.00002	-1.44	0.148
2013	24.5	5.94	4.12	0.00004
2014	49.3	11.9	4.16	0.00003
2015	74.3	17.8	4.18	0.00003
2016	98.9	23.7	4.17	0.00003
2017	123	29.6	4.16	0.00003
2018	148	35.5	4.16	0.00003
2019	173	41.5	4.16	0.00003
2020	197	47.4	4.16	0.00003
Trend	-0.059	0.014	-4.17	0.00003
Agg_M	-0.053	0.028	-1.89	0.059
Agg_H	0.021	0.008	2.57	0.01
Agg_S	-0.116	0.051	-2.27	0.023
Agg_P	0.0003	0.0003	1.01	0.314
Agg_C	0.026	0.015	1.71	0.087
Agg_I	0.001	0.001	0.935	0.35
Agg_B	0.004	0.003	1.44	0.149
Media	0.359	0.18	2	0.046
Hazard	-0.076	0.041	-1.85	0.064
Signage	0.752	0.309	2.43	0.015
Programs/Events	-0.001	0.001	-0.986	0.324
Community Contacts	-0.254	0.111	-2.28	0.022
Individual Contacts	-0.003	0.005	-0.695	0.487
Brochures	-0.020	0.015	-1.34	0.182
M_resid	-0.344	0.18	-1.91	0.056
H_resid	0.098	0.041	2.4	0.016
S_resid	-0.761	0.31	-2.46	0.014
C_resid	0.261	0.111	2.34	0.019
I_resid	0.004	0.005	0.929	0.353
B_resid	0.021	0.015	1.37	0.17
Intercept	29.5	7.28	4.05	<0.0001
Log-likelihood	-5073.646			
AIC	10313			
Pseudo-R^2	0.6931			

Notes: Region-specific variables for tribal units were included in the model to control for as dummy variables, but their coefficients are not shown for clarity. FWI (Fire Weather Index), D (Palmer Drought Severity Index), MaxT (Maximum Temperature), RH (Relative Humidity), PPT(Days with Precipitation), L_WC (Lagged wildfire counts or ignitions for each year), L_WA (Lgged wildfire acres for each year), M (Mass media coverage), S (Signage placements), C (Community Contacts), I (Individual Contacts), H (Hazard assessments), B (Informational Brochures), P(Programs/Events), Agg(Six-month aggregates or sum of prevention education activities).

Table 2.5. Elasticities of the preventable wildfire count in response to prevention education variables, computed at the mean values of the data.

	Elasticity	Standard Error	z_Value	P_value
Media	3.005	1.505	1.997	0.046
Signage	0.965	0.397	2.431	0.015
Community Contacts	-4.263	1.866	-2.284	0.022
Individual Contacts	-0.014	0.02	-0.695	0.487
Hazard	-0.125	0.067	-1.853	0.064
Programs/Events	-0.001	0.001	-0.986	0.324
Brochures	-0.069	0.052	-1.335	0.182
Aggregated Media	-0.074	0.039	-1.89	0.059
Aggregated Signage	-1.145	0.504	-2.272	0.023
Aggregated Community Contacts	0.203	0.119	1.711	0.087
Aggregated Individual Contacts	0.004	0.004	0.935	0.35
Aggregated Hazard Assessments	0.423	0.164	2.571	0.01
Aggregated Programs/Events	0.026	0.026	1.007	0.314
Aggregated Brochures	0.097	0.067	1.444	0.149

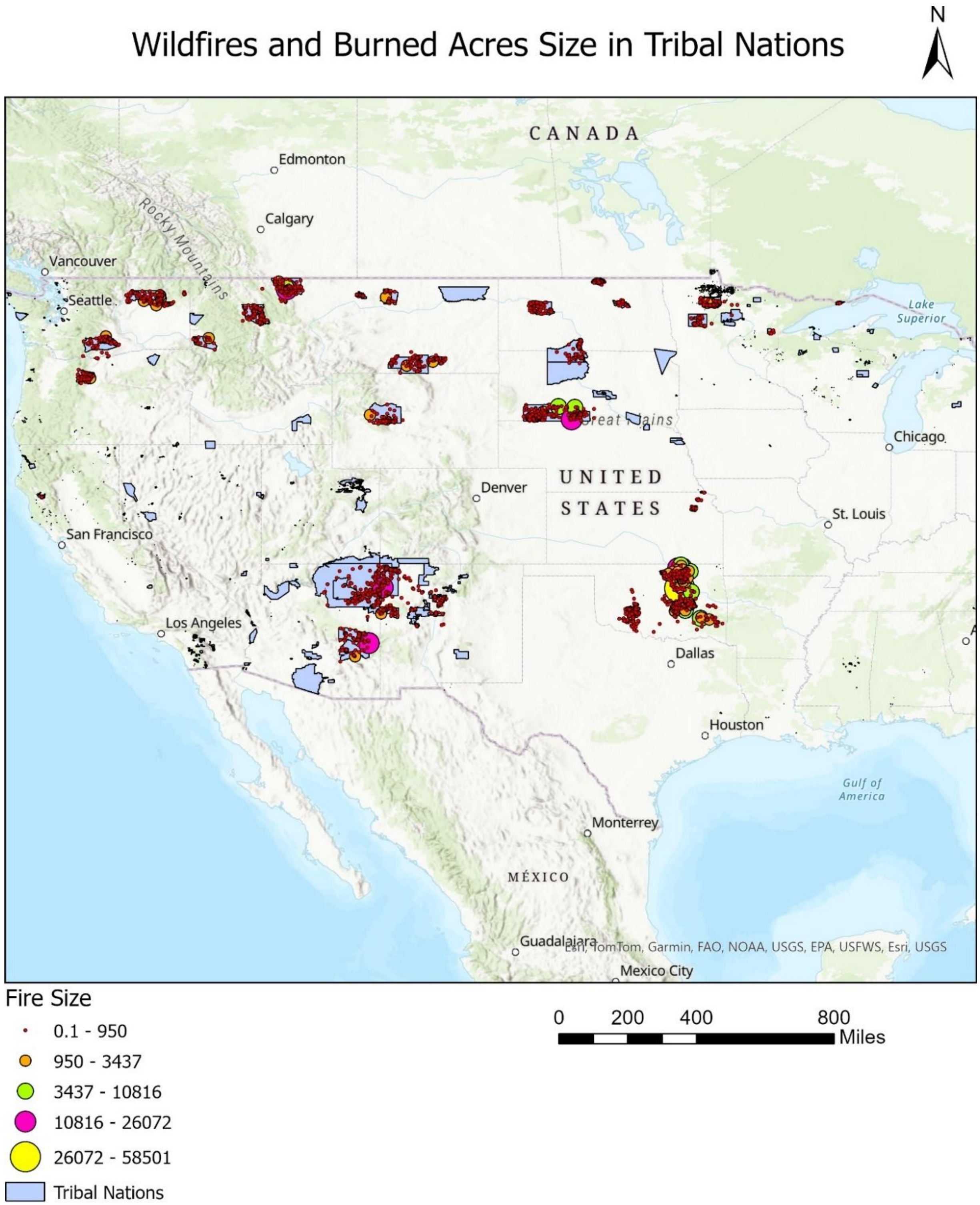

Figure 2.1. Map showing wildfires and burned acres size in tribal nations from our study area.

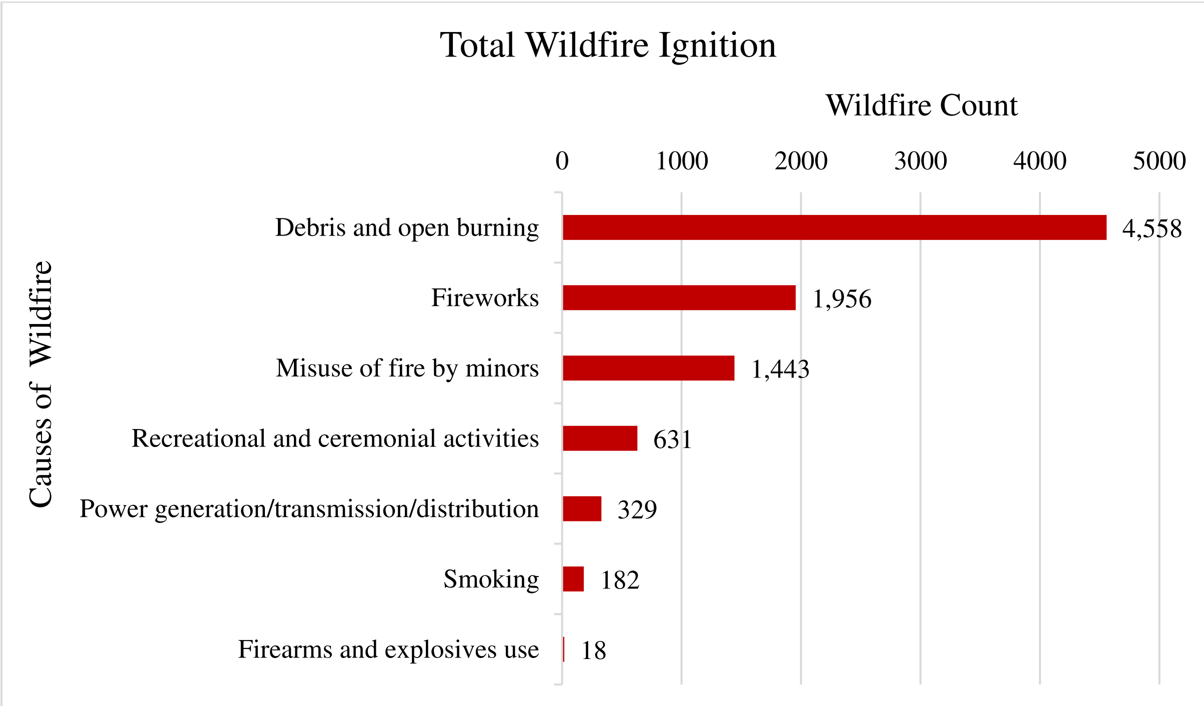

Figure 2.2. Bar graph showing the total wildfire ignitions by human causes of wildfire over the years, 2012-2020.

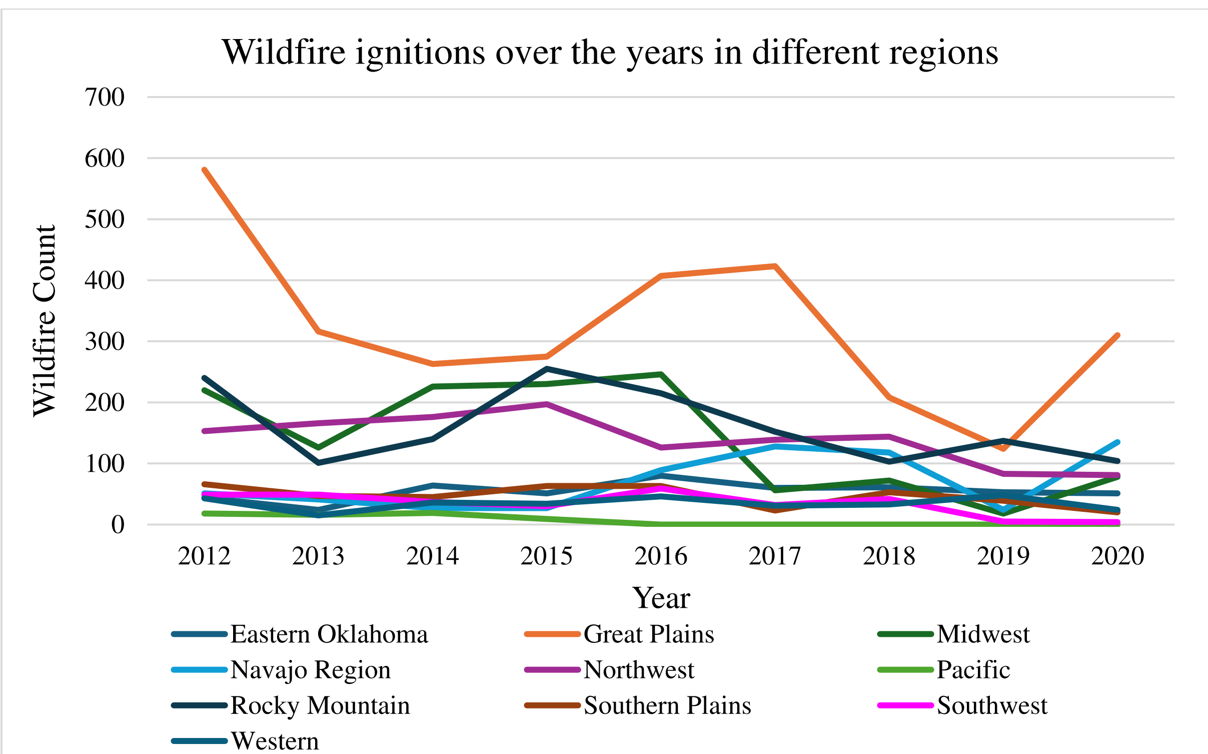

Figure 2.3. Line chart showing wildfire ignitions over the years in different regions, 2012-2020.

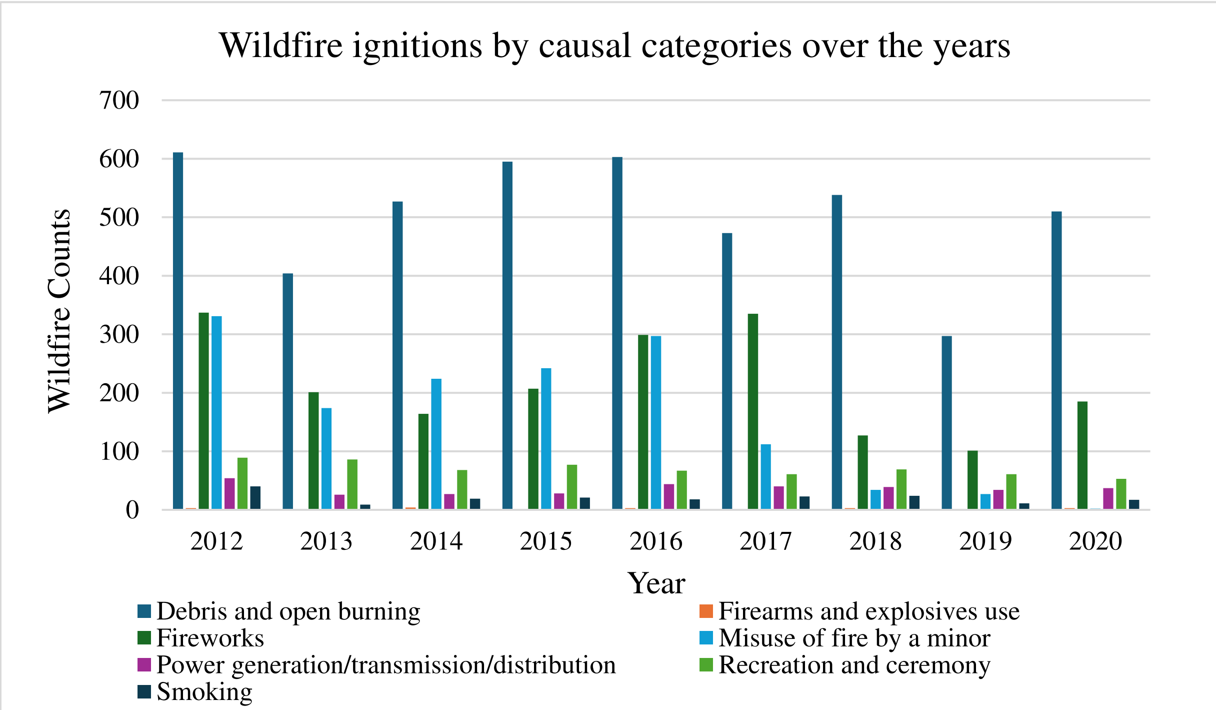

Figure 2.4. Bar graph showing the total wildfire ignitions by causal categories over the years, 2012-2020.

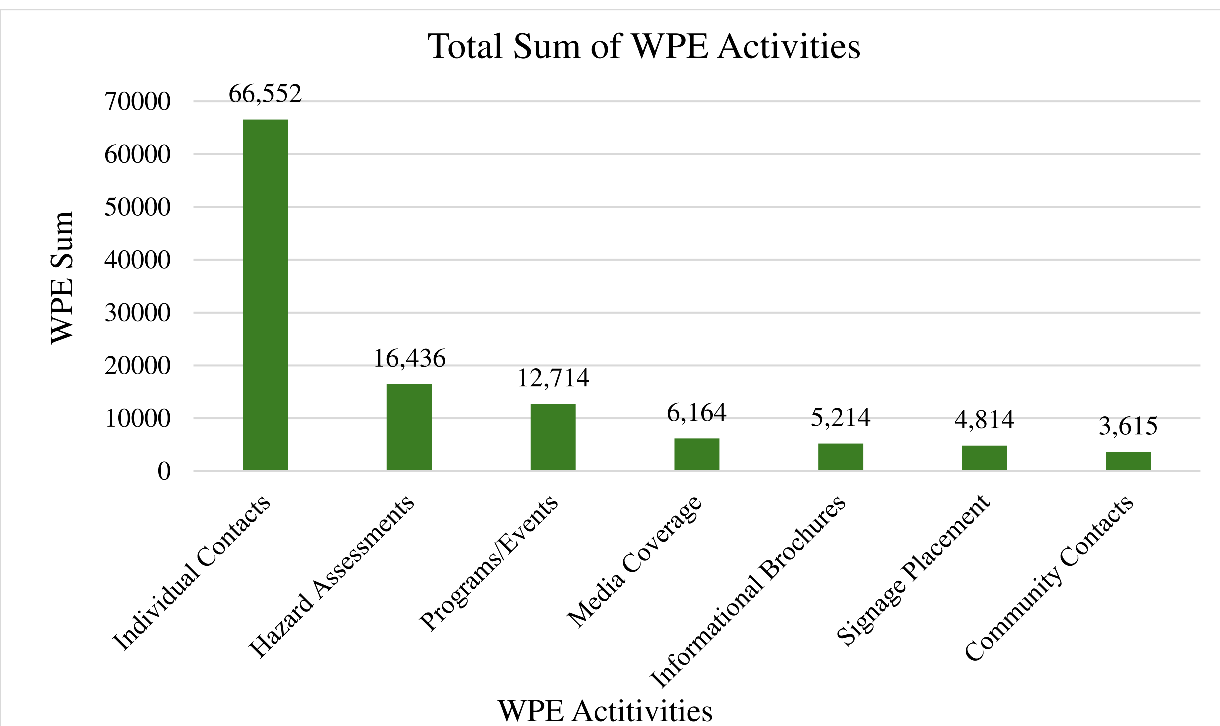

Figure 2.5. Bar graph showing the total wildfire prevention education (WPE) activities over the years, 2012-2020.

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APPENDICES

Appendix A: Supplementary Materials for Chapter 1

Table A.1. List of generalized canopy and surface treatment types, as reported by Colorado Forest Restoration Institute, 2022.

Database Treatment Field	Treatment Type
Canopy Treatment	Broadcast Burn Hand Thin Mechanical Thin Other Thin Patch/Stand Clearcut None (surface only)
Surface Treatment	Biomass Removal Broadcast Burn Chip/Haul Lop and Scatter Machine Pile Mastication Manage Pile Burn None (canopy only)

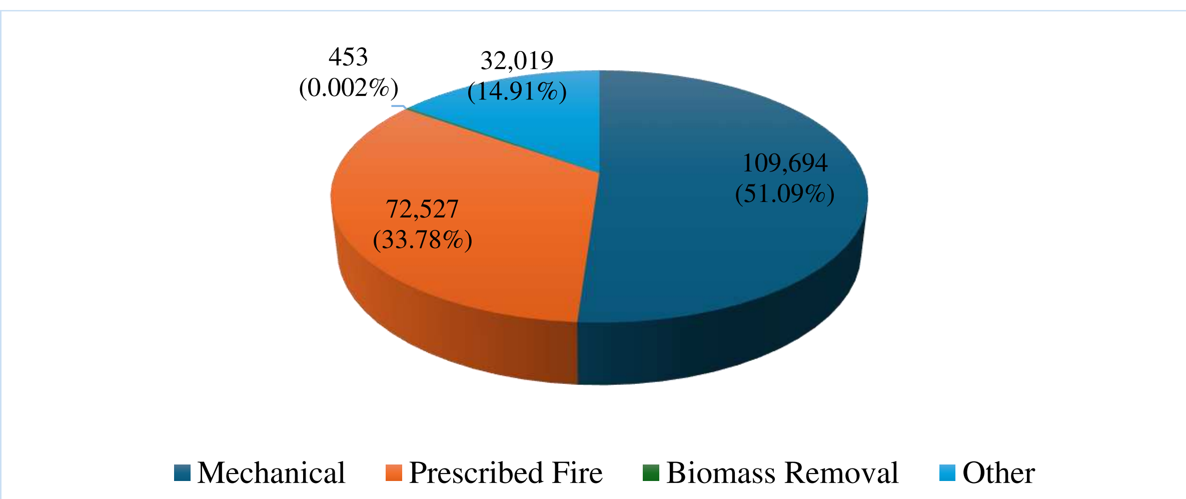

Figure A.1. Summary of acres treated per treatment type in Bureau of Land Management (BLM) lands in Colorado from 2012-2020.

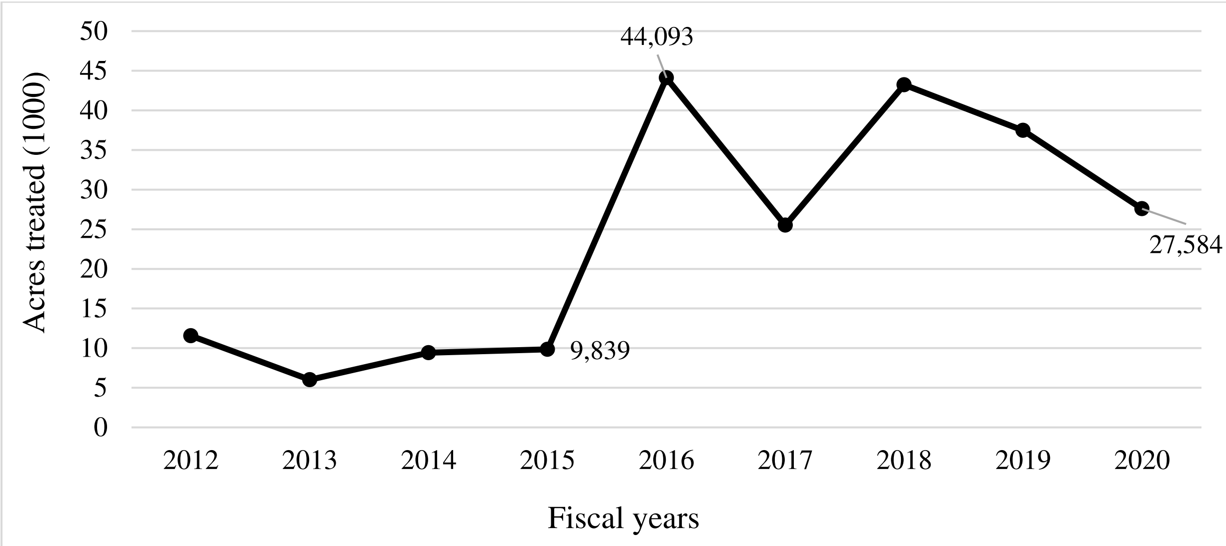

Figure A.2. Summary of acres treated over the fiscal years '2012-2020' in Bureau of Land Management lands (BLM) in Colorado.

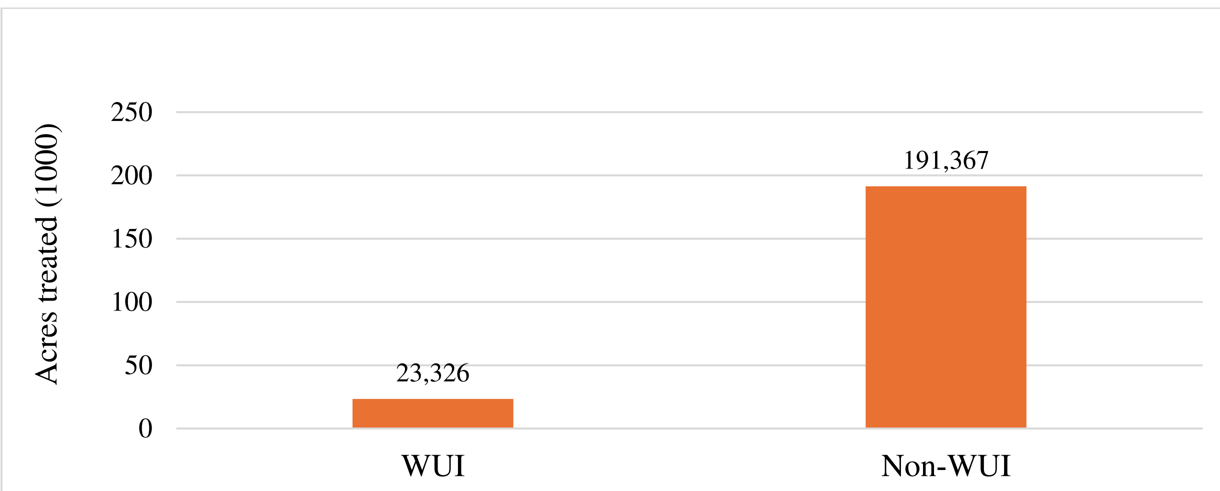

Figure A.3. Summary of acres treated in Wildland Urban Interface (WUI) vs Non-Wildland Urban Interface (Non-WUI) area over the fiscal years '2012-2020' in Bureau of Land Management (BLM) lands in Colorado.

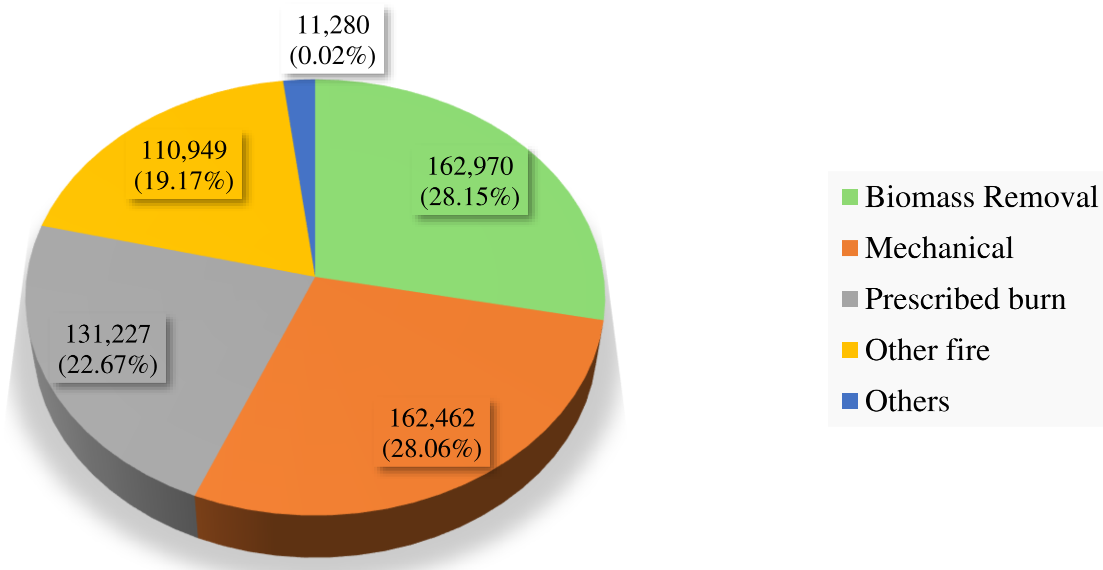

Figure A.4. Summary of acres treated per treatment type over the fiscal years ‘2012-2020’ in United States Forest Service (USFS) lands in Colorado.

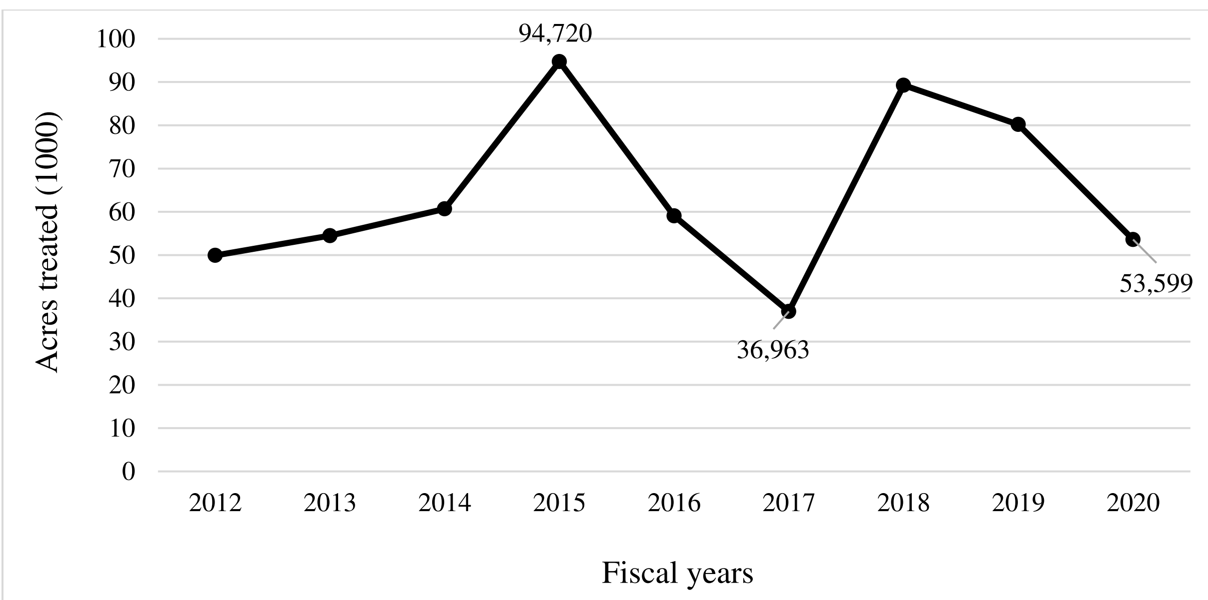

Figure A.5. Summary of acres treated over the fiscal years over the fiscal years ‘2012-2020’ in United States Forest Service (USFS) lands in Colorado.

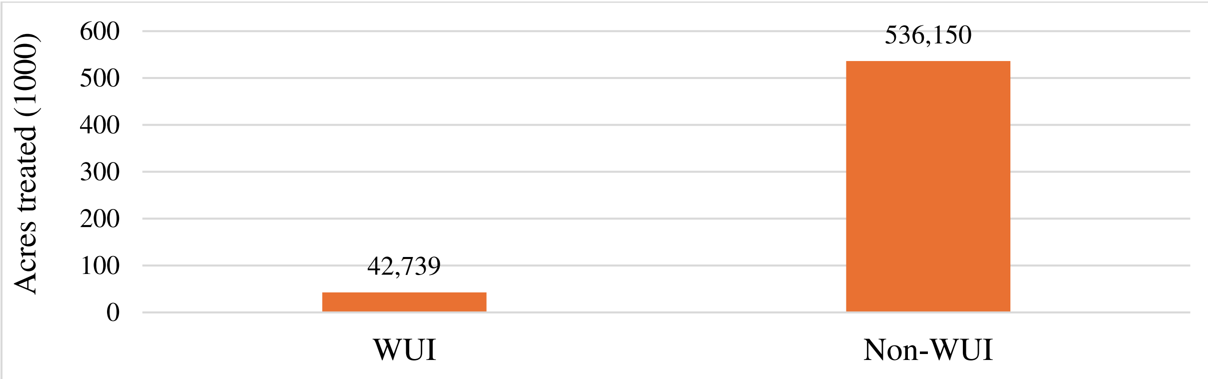

Figure A.6. Summary of acres treated in Wildland Urban Interface (WUI) vs Non-Wildland Urban Interface (WUI) area over the fiscal years '2012-2020' in United States Forest Service (USFS) lands in Colorado.

Appendix B: Supplementary Materials for Chapter 2

Table B.1. Summary of wildfire size and counts in 35 tribal units across the years, 2012-2020.

Tribal units	Agencies Full Name	State	Total Wildfire Count	Total Wildfire Acres	Percentage Wildfire Count	Percentage Acres Burned
ADA	Anadarko Agency	Oklahoma	242	2597.4	2.65	0.57
BLF	Blackfeet	Montana	524	22050.5	5.75	4.84
CCT	Colville Confederated Tribes	Washington	229	11635.29	2.51	2.55
CHA	Chickasaw Agency	Oklahoma	6	438.7	0.07	0.1
COA	Concho or Coahuitecan	Oklahoma	35	2893.6	0.38	0.63
CSKT	Confederated Salish and Kootenai Tribes	Montana	174	1248.2	1.91	0.27
CWA	Crow Agency	Montana	317	3998.75	3.48	0.88
FAA	Fort Apache Agency	Arizona	153	26493.3	1.68	5.81
FDL	Fond Du Lac	Minnesota	16	16.6	0.18	0
FTB	Fort Belknap	Montana	78	1823.7	0.86	0.4
GPA	Grand Portage	Minnesota	6	5.1	0.07	0
HNA	Horton Agency	Kansas and Nebraska	79	4079.4	0.87	0.89
LLR	Leech Lake	Minnesota	0	0	0	0

NCY	Northern Cheyenne Agency	Montana	118	2070	1.29	0.45
NDA	Great Plains North Dakota	North Dakota	974	6034.4	10.68	1.32
NR	Navajo Region	New Mexico, Utah and Arizona	640	20313.6	7.02	4.46
NZP	Nez Perce	Idaho	55	1881.9	0.6	0.41
OMA	Okmulgee Agency	Oklahoma	121	97776.4	1.33	21.45
OSA	Osage Agency	Oklahoma	210	170001.5	2.3	37.29
PRA	Pine Ridge Agency	South Dakota	1135	12116.1	12.45	2.66
RBA	Rosebud Agency	South Dakota	428	20136.3	4.69	4.42
RBC	Rocky Boy's Chippewa Cree	Montana	90	231.3	0.99	0.05
RL	Red Lake	Minnesota	1250	6342.1	13.71	1.39
RVT	Round Valley Tribe	California	62	40.2	0.68	0.01
SFO	Shawnee/ Pawnee	Oklahoma	63	2630.9	0.69	0.58
SK	Spokane Agency	Washington	64	540.71	0.7	0.12
SLA	San Carlos Agency	Arizona	157	3819.18	1.72	0.84
SPA	Southern Pueblos Agency	New Mexico	307	1151.8	3.37	0.25
SRA	Standing Rock Agency	North Dakota and South Dakota	370	2045.125	4.06	0.45
TLA	Choctaw Nation	Oklahoma	48	10294	0.53	2.26
WDR	Wind River Agency	Wyoming	320	2874.1	3.51	0.63
WE	White Earth	Minnesota	0	0	0	0
WEA	Wewoka	Oklahoma	103	10845.3	1.13	2.38
WSP	Warm Springs Agency	Oregon	212	3077.7	2.33	0.68
YKA	Yakama	Washington	531	4336.8	5.82	0.95

Table B.2. Summary of Wildfire Prevention Education (WPE) activities in 35 tribal units per year, 2012-2020.

Year	M	S	IC	CC	P/E	B	H	Total
2012	407	436	18802.5	1156	1169	334	1796.5	24101
2013	775.5	538	8892	344	1281	412	2148	14390.5
2014	864	436	4707	362	3731	409	1539	12048
2015	807	540	6606	277	1038	305	1342.75	10915.75
2016	465	408	5032	216	1122	267	2013	9523
2017	795	666	6174	283	1129	2694	2129.5	13870.5
2018	896	621	5375	314	1278	300	1765	10549
2019	646	649	7053	392	1241	336	2100	12417
2020	509	520	3911	271	725	157	1602	7695

Note: M; Mass media coverage, S; Signage placements, IC; Individual contacts, CC; Community contacts, P/E; Programs/Events, B; Informational brochures, H; Hazard assessments

Table B.3. Grouped categories of wildfire prevention education activities from general actions (GA), specific action (SA) and community actions (CA), as per data by Bureau of Indian Affairs.

Mass Media Coverage	Signage Placement	Community Contacts	Individual Contacts	Programs/ Events	Brochures	Hazard Assessments
GA-4 Mass Media	GA-1 Signs	SA-12 Group Contacts	SA-13 Key Person Contacts	GA-11 Wilderness Train/ Equip	GA-23 Fire Education Materials	GA-3 Fire Danger Rating
GA-5 Mass Media-Radio	GA-2 Signs	CA-12 Community Contact - Homeowner Groups	SA-11 Individual Contacts	GA-12 Public Education	GA-24 Printed Material-Other	CA-14 Community Firewise Assessment - Structure Vulnerability
GA-6 Mass Media-Written	SA-2 Maintenance	GA-28 Public Contact-Group	GA-29 Public Contact-Key Persons	GA-13 Interagency Campaigns (Plans Prepared)	CA-10 Printed Material - Designed	CA-22 Community Protection Plan - Risk Assessment
GA-7 Mass Media-Television	SA-3 Construct-ion	CA-21 Community Protection Plan - Community Involvement	CA-13 Communi-ty Contact - Key Person	GA-14 Interagency Campaigns Implemen-ted	CA-9 Fire Education Materials Ordered	CA-16 Wildfire Threat Notification/ Procedures

GA-8 Mass Media-WWW	CA-15 Participate in Community Stakeholder Meetings	GA-15 Specific Campaign Development	CA-11 Exhibits	CA-18 Residential Assessment
CA-1 Mass Contacts - WUI	CA-17 Community Partnership Development	GA-16 Programs-Bilingual	GA-25 Exhibits	
	GA-9 Volunteers	GA-17 Cause Specific Childrens' Programs		
	CA-20 Community Protection Mitigation Plans	GA-18 Level 1 School Program		
	CA-23 Prevention Programs in Place	GA-19 Level 2 School Program		
	CA-2 Volunteer Plans	GA-20 Parade		
		GA-21 Fair		
		GA-22 Sports Activity		
		GA-26 Character Appearance		
		GA-27 Poster Contest		
		GA-10 Volunteer Fire Departments		

CA-3
Volunteer
Fire
Department
Mitigation
Training
CA-5
Communi-
ty
Mitigation
Campaign
Plans
CA-8
School
Program
Presentatio
ns
CA-6
Communi-
ty
Mitigation
Campaigns
- Lvl 1
CA-7
Communi-
ty
Mitigation
Campaigns
- Lvl 2
CA-4
Communi-
ty
Education -
Mitigation
Programs
CA-23
Prevention
Programs
in Place

Table B.4. Human causes of wildfire (USDA Forest Service, 2022).

Human Cause of Wildfire	Description
Debris and open burning	Burn piles, burn barrels, yard debris burning, ditch/fence line burning, pest control, open trash burning, land clearing, and other controlled burns that escape.
Firearms and explosives use	Firearms projectiles, including various types of ammunition (such as steel core, tracer, incendiary, and black powder), as well as exploding targets and flares.
Fireworks	Fireworks, including ground-based, aerial, and explosive types, can easily ignite wildfires due to the high temperatures they burn at, especially airborne fireworks and sparklers, which emit hot particles capable of igniting flammable vegetation.
Misuse of fire by a minor	Fires caused by minors, particularly children (12 and younger) and adolescents (13-17), are often due to curiosity or anger. Younger children tend to "play with matches" or use other ignition devices like lighters and fireworks, while adolescents may start fires out of frustration, anger, or a desire for destruction.
Power generation/transmission/distribution	Caused by power lines, including factors like arcing, equipment failure, vegetation or wildlife/human contact, and high winds. Other sources include wind turbines and oil/gas recovery. Wildfires can occur when electrical equipment, such as power lines or transformers, comes into contact with dry vegetation, sparks, or molten metal.
Recreation and ceremony	Campfires improperly constructed, unattended, improperly extinguished, or abandoned; barbeque/smokers; bonfires; ceremonial fires; gas cookers, warming and lighting devices; luminary (sky lanterns); and outdoor furnaces, oven, fireplace, or metal fire ring.
Smoking	Generated from discarded unextinguished cigarettes, matches, cigarettes, cigars, pipes, electronic cigarettes (vape heads), and drug paraphernalia.

Description Source: National Interagency Fire Center

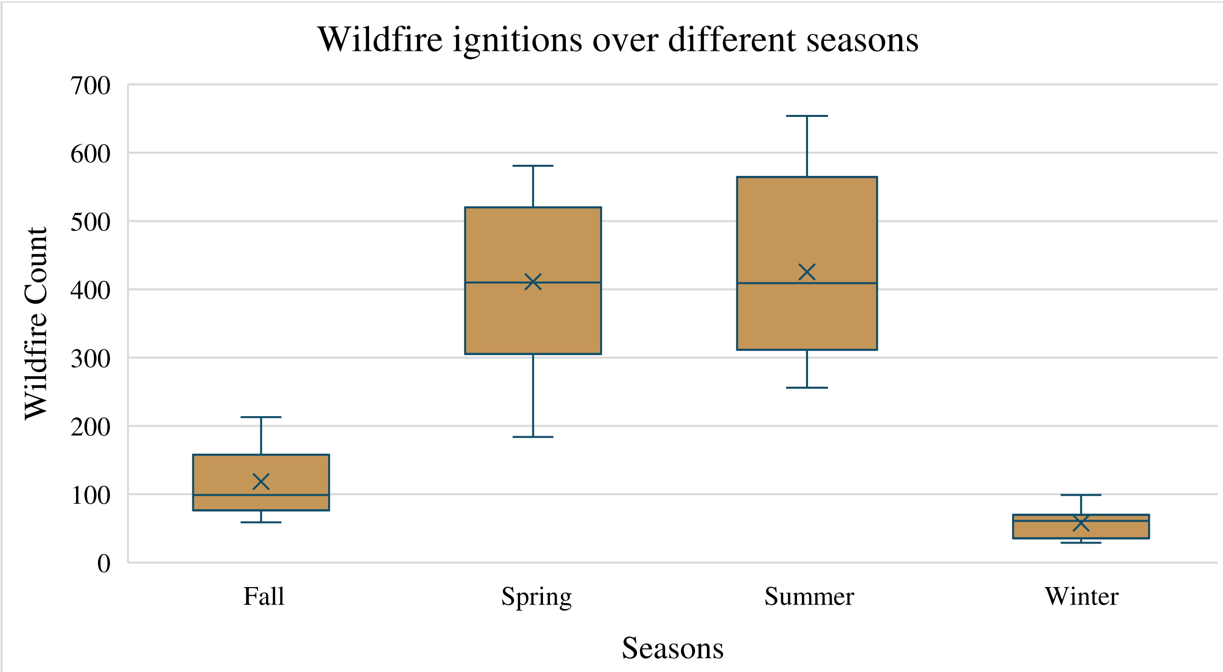

Figure B.1. Boxplot illustrating the frequency of wildfire ignitions across different seasons.

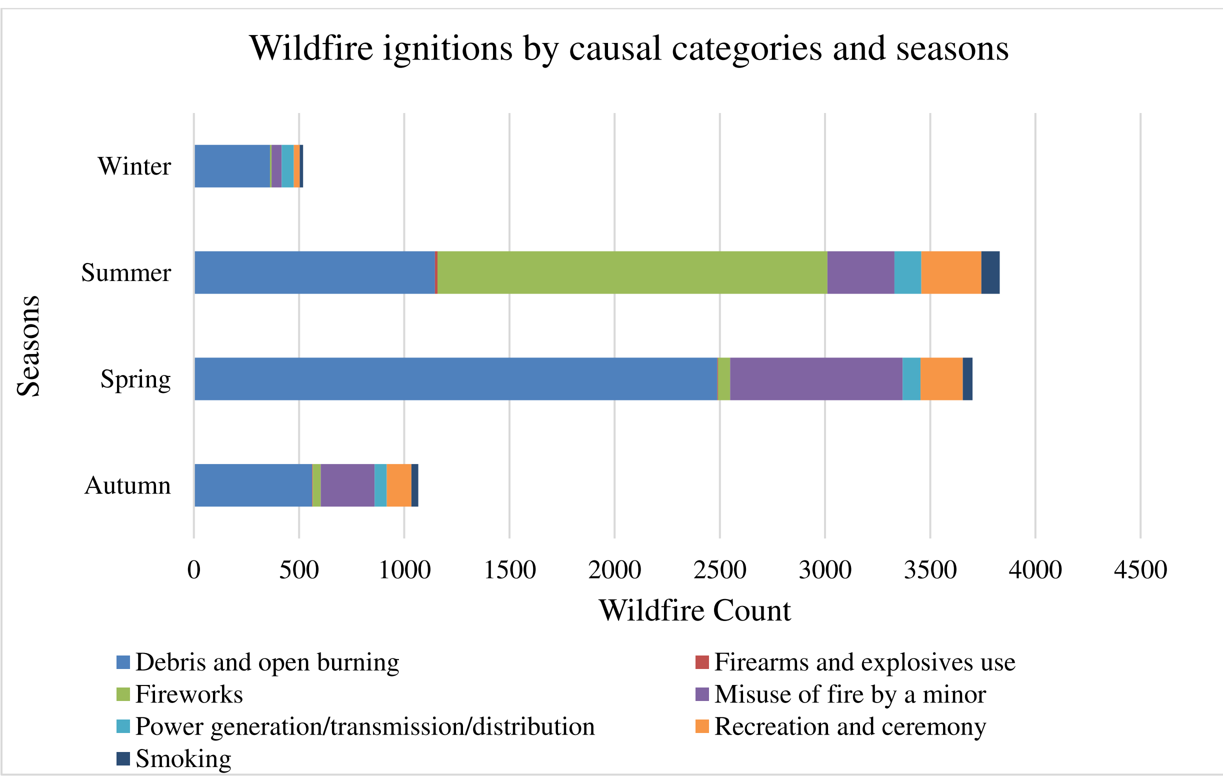

Figure B.2. Stacked bar graph showing total wildfire ignitions by causal categories and seasons throughout the years, 2012-2020.

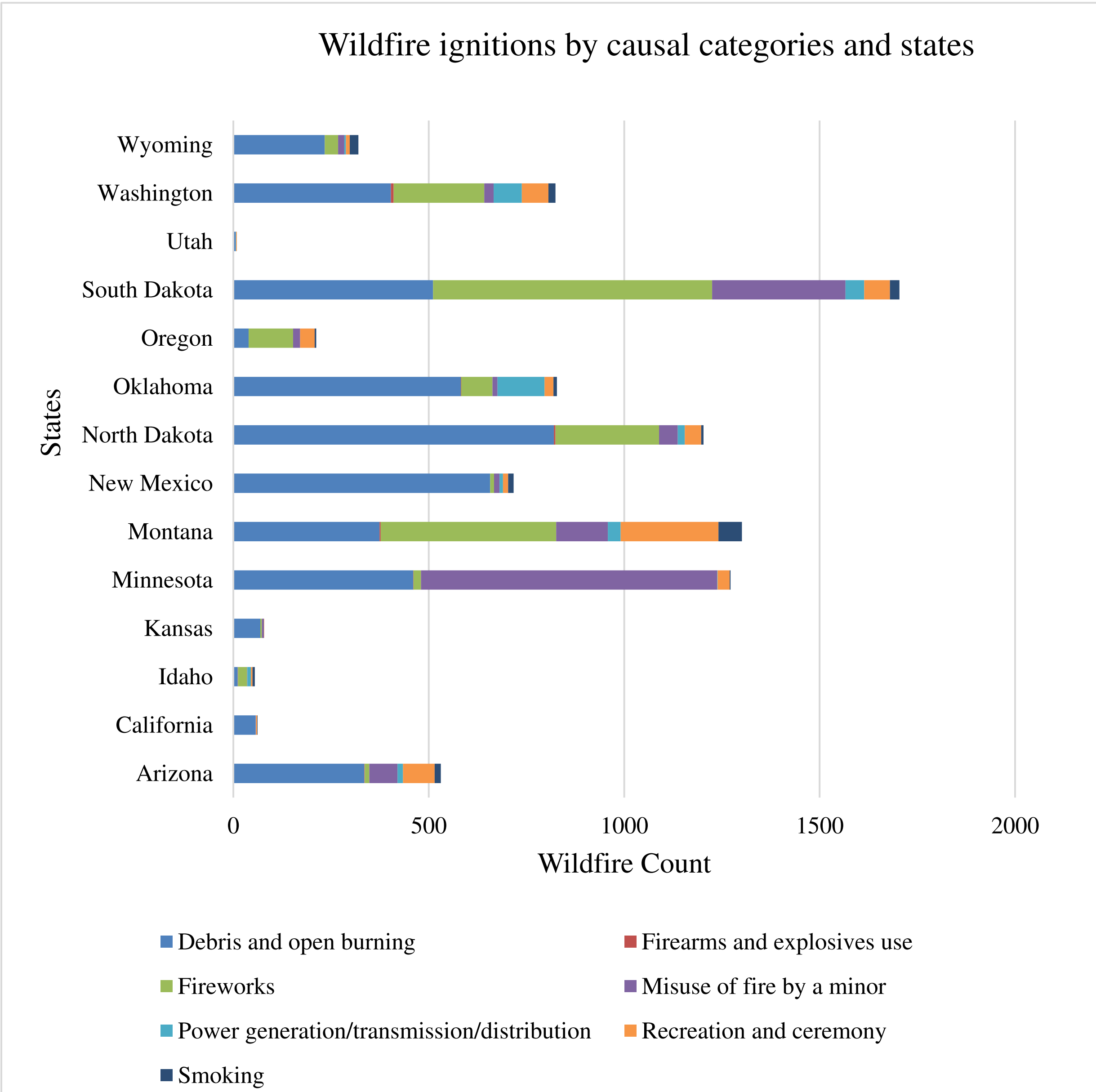

Figure B.3. Stacked bar graph showing total wildfire ignitions by causal categories and states throughout the years, 2012-2020.

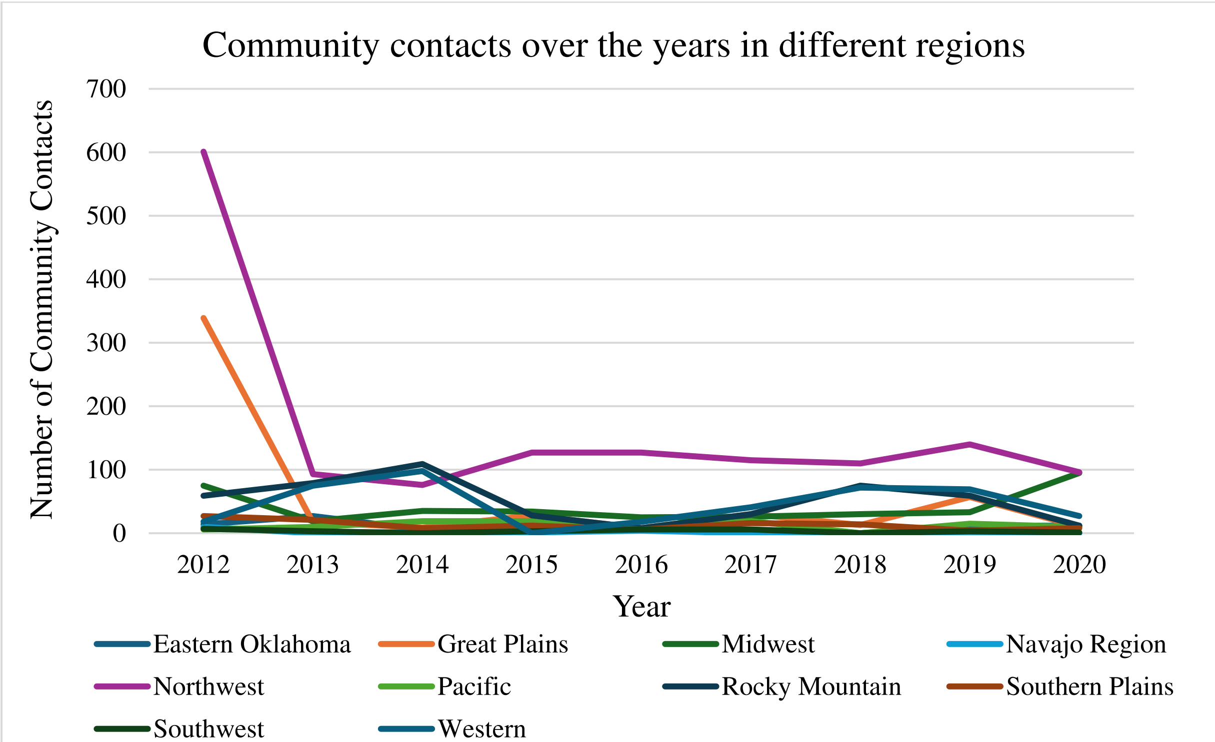

Figure B.4. Community contacts made over the years in different regions, 2012-2020.

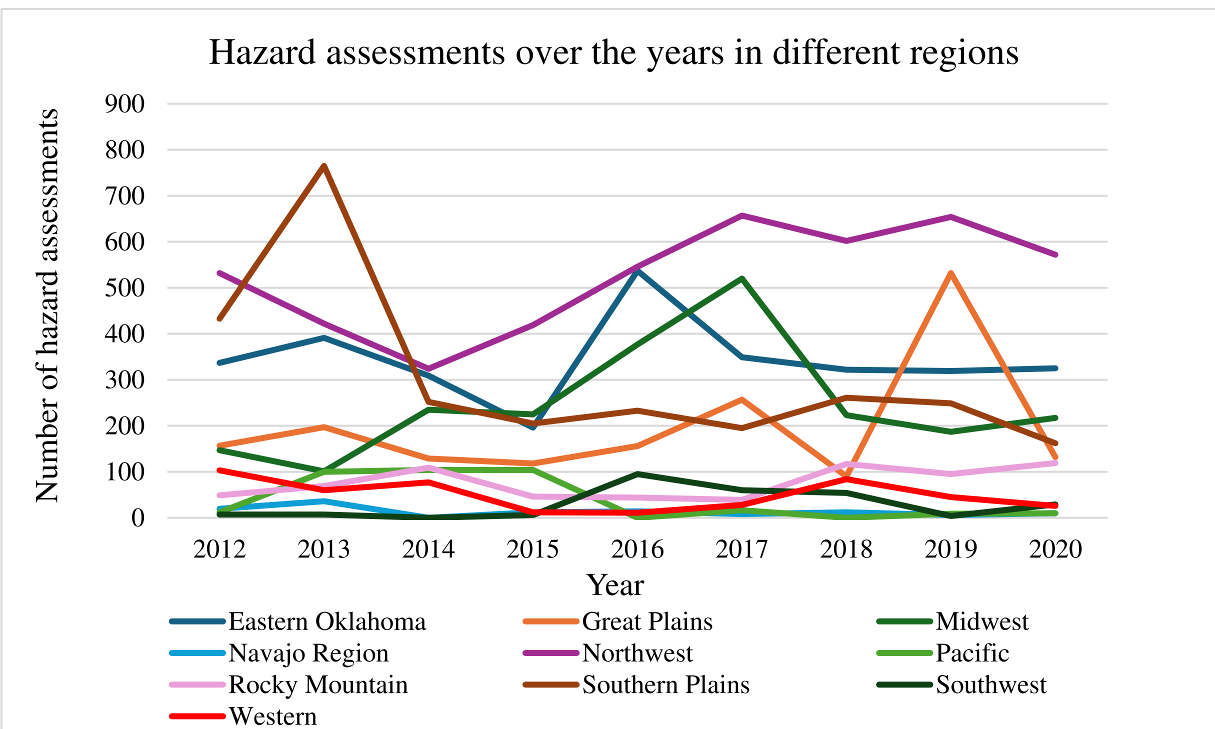

Figure B.5. Hazard assessments over the years in different regions, 2012-2020.

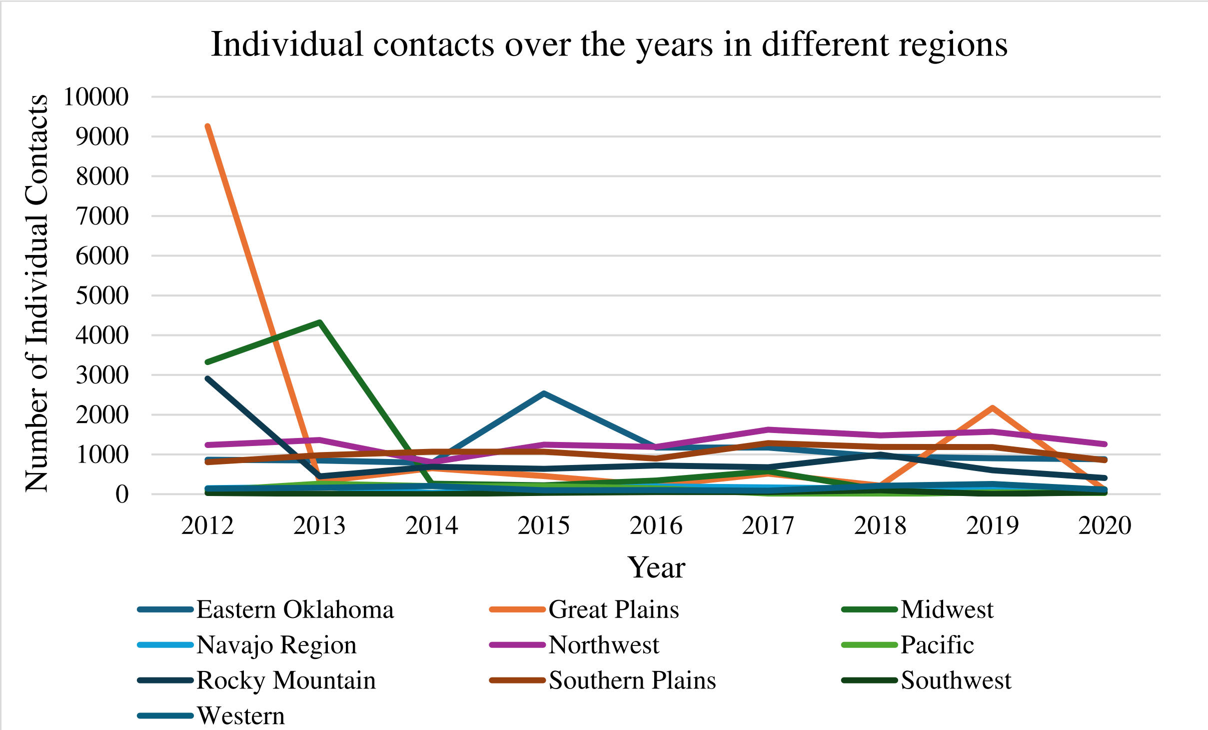

Figure B.6. Individual contacts made over the years in different regions, 2012-2020.

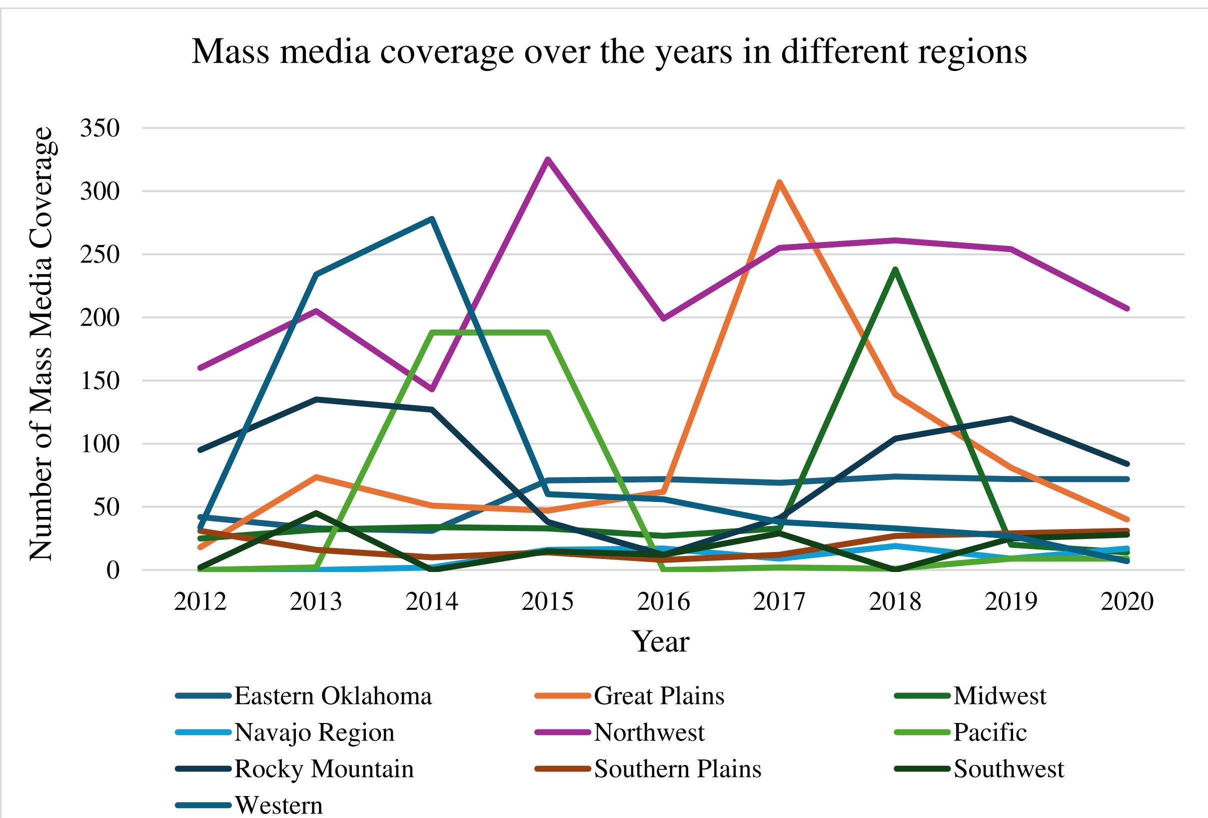

Figure B.7. Mass media coverage over the years in different regions, 2012-2020.

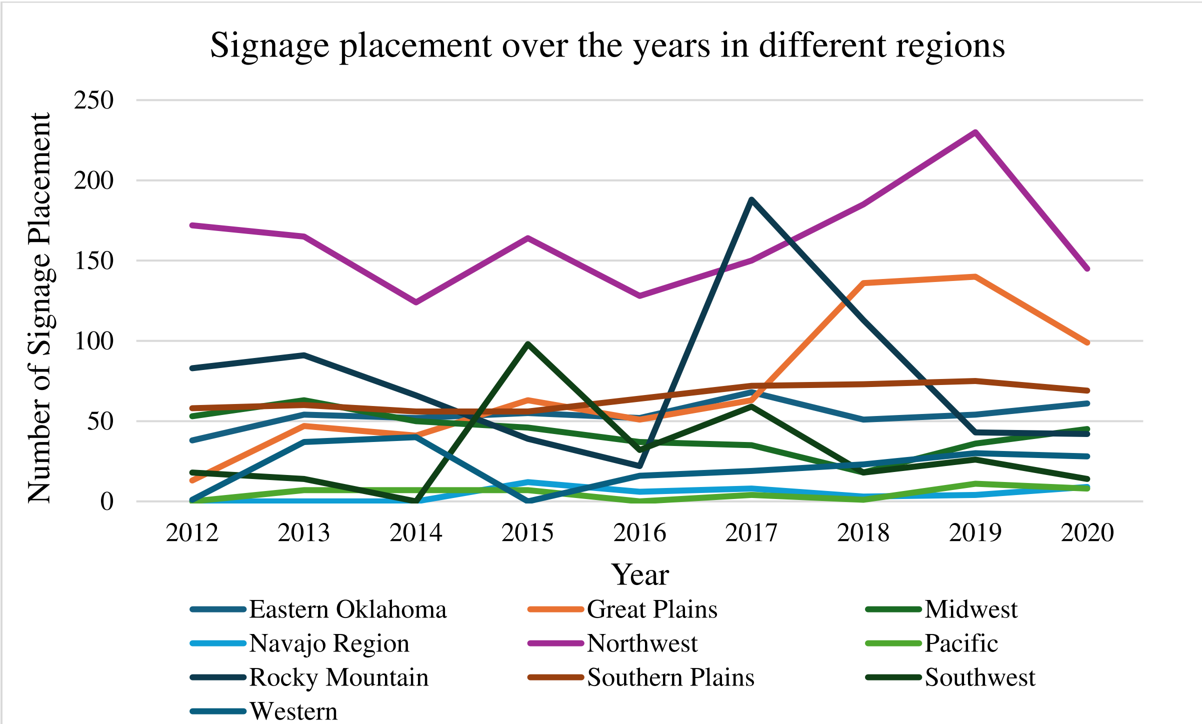

Figure B.8. Signage placement over the years in different regions, 2012-2020.

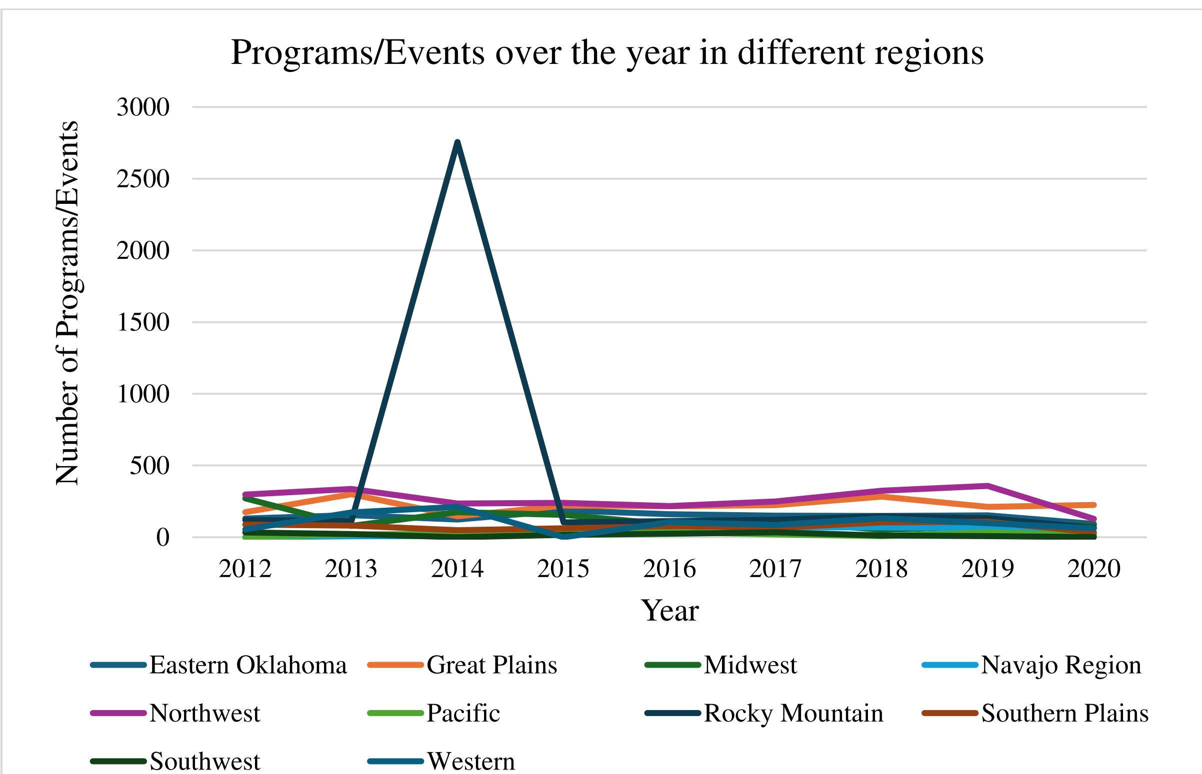

Figure B.9. Programs/Events over the years in different regions, 2012-2020.

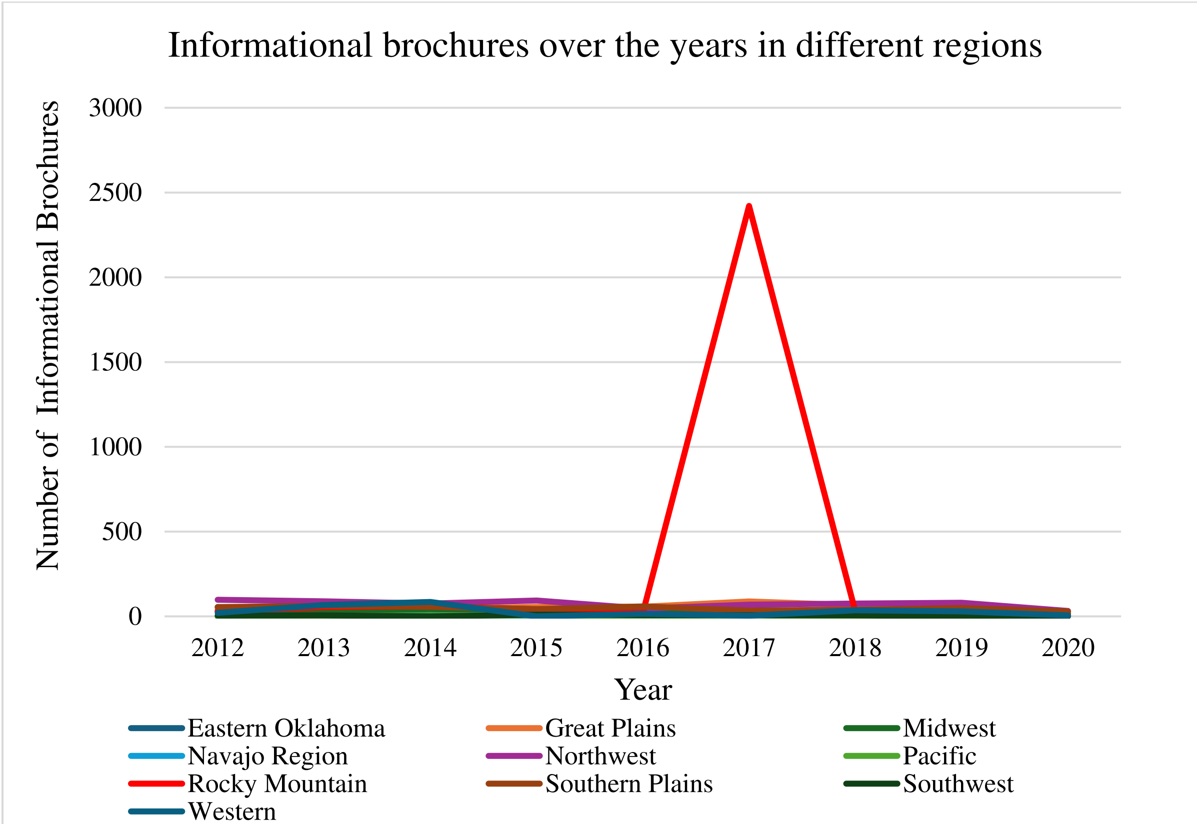

Figure B.10. Informational brochures distribution over the years in different regions, 2012-2020.

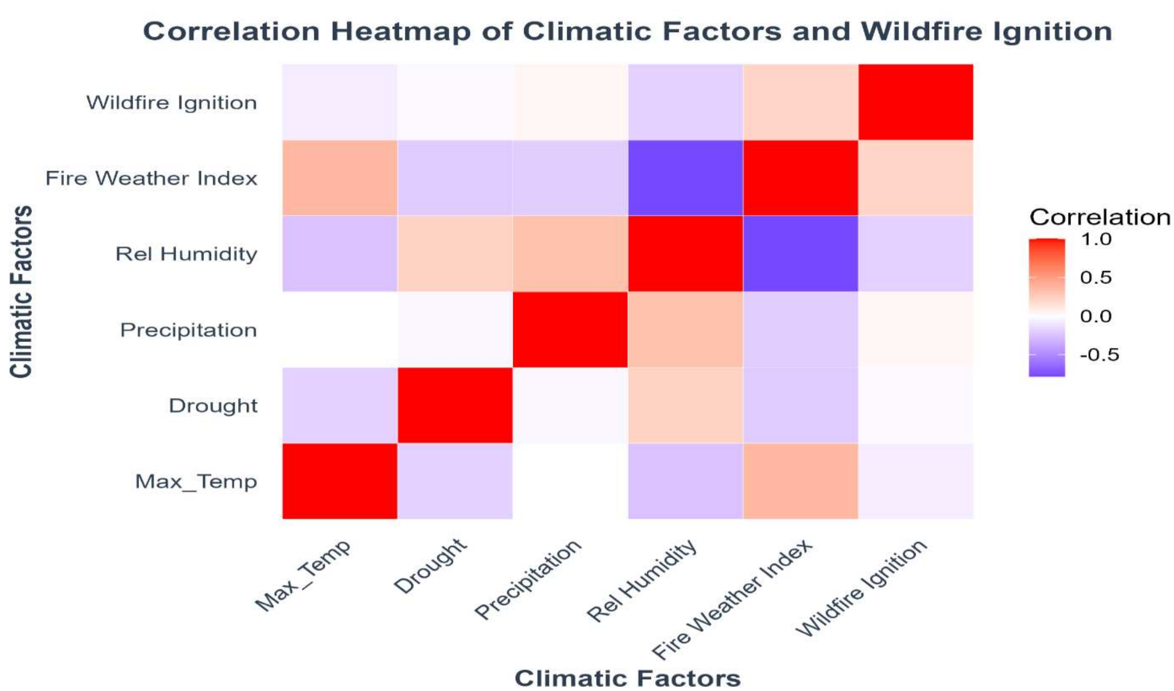

Figure B.11. Correlation heatmap showing relation of climatic factors with wildfire ignitions.

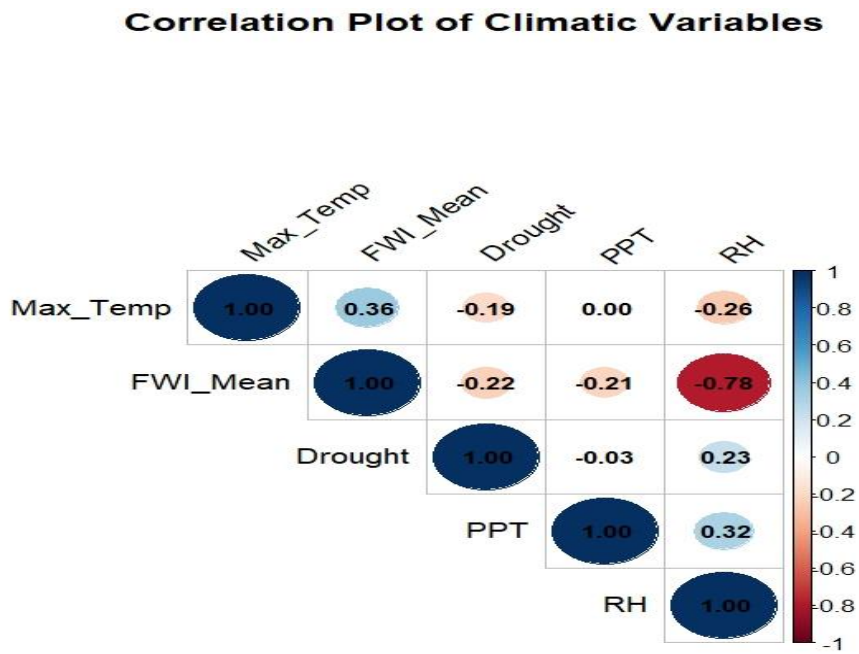

Figure B.12. Correlation plot of climatic variables (Maximum Temperature, Mean Fire Weather Index, Daily Precipitation, Relative Humidity and Palmer Drought Severity Index)

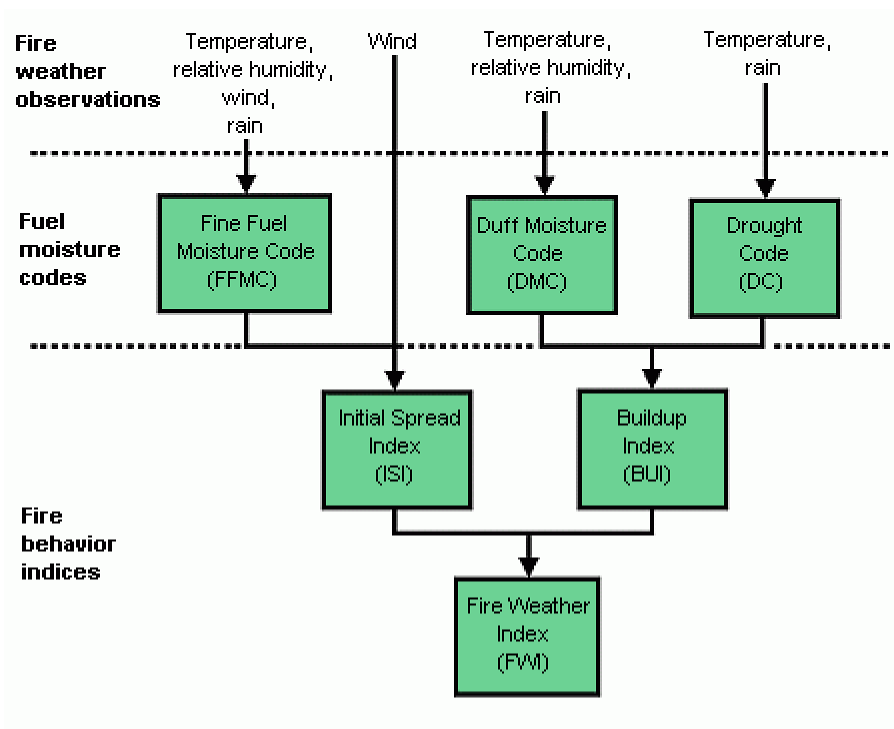

Figure B.13. Diagram illustrating the components of the Fire Weather Index System (Source: Natural Resources Canada)

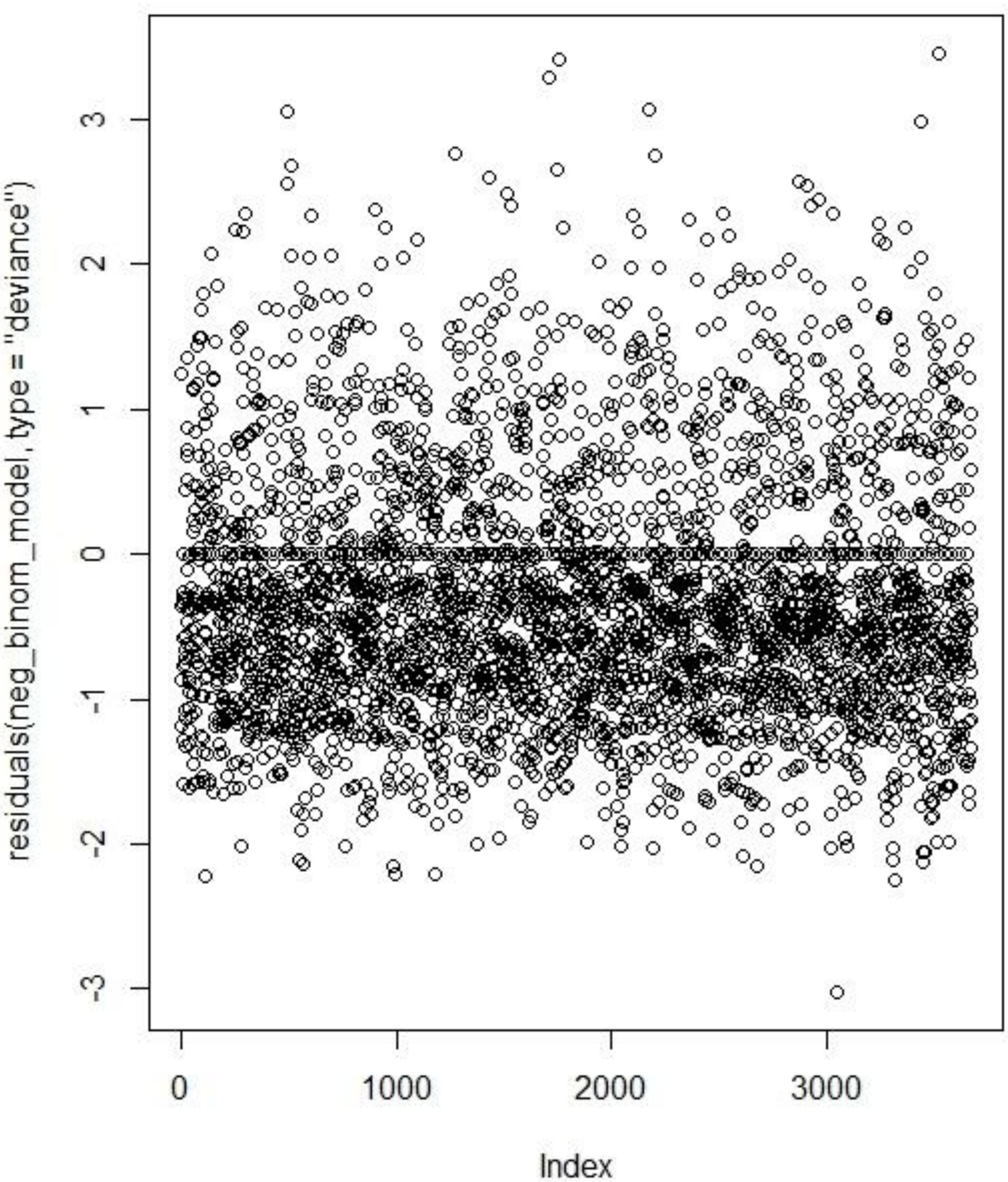

Figure B.14. Deviance Residuals vs. Index for the Negative Binomial Model of Wildfire Counts, Demonstrating the Random Scatter of Residuals