THESIS

COMMUNITY CAPACITY AND COLLABORATIVE WILDFIRE PLANNING: THE ROLE OF CAPACITY IN ACQUIRING FEDERAL MITIGATION GRANT FUNDING

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Benjamin Ryan

Department of Political Science

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Master's Committee:

Advisor: Ryan Scott

Iasmin Goes
Jesse Burkhardt

ABSTRACT

COMMUNITY CAPACITY AND COLLABORATIVE WILDFIRE PLANNING: THE ROLE OF CAPACITY IN ACQUIRING FEDERAL MITIGATION GRANT FUNDING

Since the passage of the Healthy Forests Restoration Act two decades ago, Community Wildfire Protection Plans (CWPPs) have become the predominant planning tool for community preparedness, risk mitigation, and response; improving coordination between governments, natural resource management agencies, and residents; give communities the ability access federal grant funding programs in the Western United States. Research on CWPPs has mainly been the focus of case studies, with relatively few large-scale studies to understand how a community's biophysical, socio-economic, vulnerability, and social conditions account for the variation in federal grant allocation. This study includes over 1,000 CWPPs in 11 states to evaluate the conditions that precipitate the allocation of grant funds for risk mitigation and community resilience. Through the estimation of a Binomial Integrated Nested Laplace Approximation Model to estimate the probability of winning grant funds based on the included indicators. Findings indicate that grant winnings are closely correlated with biophysical risk, financial capacity, and CWPP Update status, while socially vulnerable communities were more likely not to receive grant funds. However, we fail to find evidence that social capital affects the likelihood of winning grant funds. These findings suggest a need for a more equitable distribution of federal grant funds to mitigate wildfire risk properly.

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Chapter 1: Introduction

In the Western United States, wildfires have been increasing in frequency and intensity due to a variety of human causes factors such as the settlement of Euro-Americans and century of intense fire suppression in forests, climate change, and a rapid increase in the residential development within the wildland-urban interface (WUI), or where area when homes and vegetation intermix (Steelman & Burke 2007; Ojeiro et al. 2011; Little et al. 2016). Fire suppression in arid Western forests has led to an increase in fuel loads and other factors that have increased wildfire size and severity (Ojeiro et al. 2011; Littell et al. 2016). Climate change has increased tree mortality and prolonged droughts in parts of the U.S. West, contributing to wildfires (Littell et al. 2016). From 1990 to 2010, the WUI became the fastest growing land type in the United States with a 41% increase in new homes and a 33% increase in the total land area, posing a greater risk for more wildfire ignitions and both lives and property (Radeloff et al. 2018).

The combination of these factors has resulted in a rapidly increasing annual fire suppression financial burden on land management institutions (Ojeiro et al. 2011; Campbell 2022). From 2016 to 2020, the average annual federal spending on fire suppression increased to a total of $2.5 billion, with over 80% of the fire suppression costs for the same period originating with the U.S. Forest Service (Campbell 2022). Federal spending has increased across agencies responsible for managing wildfires, with the five-year moving average for federal wildfire spending more than tripling from 1985 to 2020 (Campbell 2022). Between December and May, the number of acres burned due to wildfire has more than doubled between 2001 and 2017, limiting both the labor force and time available to undergo pre- fire mitigation work (Campbell 2022).

Due to the burdens that wildfire poses to communities, federal wildfire management institutions are tasked with working collaboratively with local communities to better manage social-ecological systems and mitigate and respond to wildfire incidents. These collaborative programs are aimed at increasing resilience and the capacity of communities through a process of adaptive management. As a result, communities, stakeholders, and management officials have collaborated to create community protection plans aimed at mitigating wildfire hazards, creating a better assessment of risks posed, improving both community and land manager response to wildfire incidents, and making additional federal funding available to state, local, and tribal fire agencies to fill in the shortage of time and labor within federal land management agencies to wildfires.

To establish a better understanding of these community protection plans and the factors that influence the distribution of federal resources. In this paper, we will address two questions. First, how does the financial capacity of an area with a CWPP affect the distribution of Cooperative Forestry Assistance grants? Second, how does social capital affect the likelihood of receiving federal funding through the Cooperative Forestry Assistance program? In addition, we explore if there is any variation in the spatial and temporal features of a CWPP that affects the distribution of federal funding for wildfire mitigation and planning actions.

This paper begins with a background and literature review to provide context for relevant forest and community management policies surrounding wildfire planning. We then draw upon collaborative and network governance literature to understand how involvement within the CWPP planning process should evolve. This is followed by a discussion on outside factors that may influence the development of a CWPP over time, drawing upon literature on fiscal and social capital, as well as social vulnerability and wildfire preparedness planning. Next, I describe the data collection and analytical approach to text mining to classify actors named within a CWPP and how stakeholder involvement in the CWPP planning process changed over time. I then specify the model used to examine the social, geographical, and financial resources of a CWPP planning group that affects the likelihood of receiving pre-wildfire hazard grant funding – a key component in helping communities better plan and mitigate against wildland fire - and present the results. We find that measured social capital involved in the creation of CWPPs in the Western United States does not affect the likelihood of receiving federal grant assistance; rather, other variables – such as wildfire hazard potential, area of public land, and financial resources are significant factors for receiving federal grant funds. Finally, we conclude with a discussion of this work's broader theoretical and methodological implications.

Chapter 2: Background & Literature Review

2.1 The Evolution of Wildfire Management Policies

In 1905, Congress passed the Forest Transfer Act that transferred federally owned forests from the Department of the Interior (DOI) to the United States Department of Agriculture (USDA) (Busenberg 2004). To manage the newly transferred forests, the USDA created the United States Forest Service (USFS) and designated the new agency as the primary manager of national forests and grasslands (Busenberg 2004; USFS 2023c). For much of the agency's history, the USFS pursued a strategy of "coordinated, centrally directed decisions" aimed at protecting damages to timber production, water quality, and other natural resources from wildfire through suppression (Busenberg 2004; USFS 2023c).

In the 1960s and 1970s, shifting public concerns on the environment increased, leading to several key environmental legislations (USDA 2022). Key environmental legislation such as the Clean Water Act of 1972 (CWA), the Clean Air Act of 1973 (CAA), the Endangered Species Act of 1973 (ESA), the National Environmental Policy Act (NEPA) of 1969, the National Forest Management (NFMA) of 1976, and the Federal Land Policy and Management Act of 1976 (FLPMA), created and formalized the concept of management federal land for "multiple uses" and shifted USFS management decisions to include additional uses and benefits of timber, forage, water, and recreation national forests (USDA 2022).

While the USFS manages roughly much of the forest in the United States, nearly 60% of forests are owned by private landowners (Kouarti 2018). The large dispersion of private forests throughout the U.S. has created complex issues in balancing private property rights and public resources. Across the U.S., common concerns around private forest management revolved around water quality, and the passage of the CWA in 1972 left the primary rights and responsibility to control waterway pollution to the states (Kelly & Crandell, 2022). In the West, private forest management was directed under a science-regulatory approach, where private forest management is regulated through state-enforced rules and regulations (Kelly & Crandell, 2022). However, due to the increasing threat to forests by wildfire, insects, and diseases, as well as the rapid conversion of forests for residential development and expansion of the wildland-urban interface (WUI), Congress passed the Cooperative Forestry Assistance Act of 1978 (Kouarti 2018). The Cooperative Forestry Assistance Act allowed the USFS to partner with state forestry agencies to provide technical and financial assistance to landowners to mitigate these threats (Kouarti 2018; USDA 2022c).

Finally, the emergence of social forestry in the early 2000s "(re-)localized decision-making via participatory networks of local and regional actors (Kelly & Crandell 2022). One key piece of legislation, The Healthy Forest Restoration Act of 2003 (HFRA), is referred to as the "culmination of nearly a decade of wildland fire policy reforms designed to improve the capacities of land-management agencies in the U.S. Departments of Agriculture and Interior to protect communities, watersheds, and other at-risk lands from catastrophic wildland fires (U.S. Congress 2003; Jakes et al. 2011; Steelman 2008). A key purpose of the HFRA is aimed to reduce wildfire risk to at-risk communities, municipal water supplies, and other at-risk federal and non-federal lands through a collaborative process of planning, prioritizing, and implementing hazardous fuel reduction projects" (U.S. Congress 2003). The HFRA blended traditional science-based and social regulatory approaches for public and private forests to improve forest land management for multiple uses and address growing risks associated with wildland fire.

To encourage effective collaboration, the HFRA requires the involvement of stakeholders, such as federal land management agencies, state agencies responsible for forest management, and local fire authorities, in the development of a Community Wildfire Protection Plan (CWPP). Focusing on protecting at-risk communities and both federal and non-federal lands from catastrophic wildfires through a "a collaborative process of planning, prioritizing, and implementing hazardous fuel reduction projects' (U.S. Congress 2003; Jakes et al. 2007). In addition, the HFRA requires that a CWPP must be agreed upon by associated local governments, such as city and county governments. Since 2003, CWPPs have been praised as "one of the most successful tools" for addressing the rising costs and risk of wildland fires within the wildland-urban interface (WUI) through a collaborative process (Jakes et al. 2011; CWPP Task Force 2008).

2.2 Polycentricity, Collaborative Institutions, and CWPPs

The passage of the HFRA started shifting forest management structures from a traditional, top-down model to a more collaborative approach between federal agencies and local communities. Polycentric governance systems are characterized by "multiple and diverse actors at different scales operating in coordination with one another under an overarching set of rules" (Kelly & Crandell, 2022). These types of systems are based around "multiple centers of semi-autonomous decision-making, power, and authority over a public domain that can promote or hinder the adaptiveness of a governance arrangement" (Chang & Dale 2020; Tiernan et al., 2019; Lubell 2013; Kelly et al., 2019).

Collaborative wildfire management can be considered a form of polycentric governance as it comprises multiple levels of federal, state, and local governments with differing levels and can be linked with Ostrom's concept of "nested institutions at multiple scales" (Lubell 2013). Each level of government (federal, state, and local) has distinct responsibilities and authority over its jurisdiction but is interconnected and operates within the broader American federalist system. Ranging from operational rules governing resource decisions to collective choice rules to constitutional rules (Lubell 2013; Ostrom 1990), as well as integrating policy decisions to include many policy actors and issues across spatial and temporal boundaries (Lubell 2013).

CWPPs are created through a relatively autonomous planning process within each jurisdiction; plans may be interdependent upon one another due to the involvement of multiple actors in multiple CWPP planning processes (Hamilton et al., 2023). Interdependence provides a mechanism for information and resource transfer between CWPP jurisdictions (Lubell 2013; Hamilton et al. 2023). For example, actors whose dominions span geographical boundaries (such as federal land management agencies or state-level natural resources departments) participate in multiple planning processes because management jurisdictions overlap (Hamilton et al., 2023). Additionally, interdependence may be formed by shared wildfire risk across jurisdictions. Although CWPPs focus on risk mitigation within a particular jurisdiction, they may be linked to other CWPPs in a variety of ways. For example, wildfire risk may originate outside a CWPP jurisdictional boundary, "creating risk interdependence between multiple CWPPs" (Hamilton et al., 2023). Additionally, the spread of wildfires within or across CWPP boundaries and actions taken within on jurisdiction may affect the risk exposure of overlapping or nearby jurisdictions' (Hamilton et al., 2023; Ager et al., 2017).

Actors involved in one CWPP planning process can gain experience from the lessons and experiences of actors who participate in other CWPPs and contribute to risk mitigation planning at a larger scale (Hamilton et al., 2023). Therefore, CWPPs can be conceptualized as polycentric systems because they are composed within multiple scales of operational rules for wildfire mitigation with decisions that are interdependent due to overlapping risk and “social/policy interaction” (Hamilton et al. 2023; Lubell 2013; Berardo 2014).

Lubell’s previous work on polycentric institutions and collective problems suggests that “the very existence of fragmentation can create an evolutionary niche for institutions to ameliorate negative institutional externalities and capitalize on positive ones” (Lubell 2013; Kelly et al. 2019). Fragmentation across multiple institutions also provides redundancy in a policy system due to negative institutional factors such as budget cuts, personnel turnover, political ideology, or difficulties in information transmission (Landau 1969; Lubell 2013; Tiebout, 2009). Due to CWPP often being created across jurisdictional boundaries and with funding requirements in mind, fragmentation of institutional authority can provide redundancy to mitigate against negative externalities and internal forces while capitalizing on both positive internal and external factors.

Collaboration within wildfire management refers to the cooperative process involving multiple stakeholders, such as governments, organizations, and community members, together to assess wildfire risks, develop mitigation strategies, and create a comprehensive plan to protect communities from the threat of wildfires. Previous research on collaborative planning can be effective for wildland fire management, as the collaborative process can help build consensus between public and private stakeholders to mitigate wildfire risk (Sturtevant et al. 2005; Jakes et al. 2007; Sturtevant and Jakes 2008). In addition, working collaboratively may strengthen communication and relationships in a community that can offset limitations due to a lack of sufficient management incentives, increase institutional and social capacity, and provide opportunities for innovation, adaptation, and resilience (Kelly et al., 2019; Jakes et al. 2011; Emery & Flora 2006; Erikson & Simon 2017). Overall, collaboration within the CWPP planning process fosters a sense of shared responsibility through diverse stakeholder involvement, information and resource sharing, consensus building, and public engagement to create effective wildfire mitigation strategies and enhance community resilience.

2.3 Community Capacity: Social Capital & Fiscal Capacity

Due to the fragmented nature of the American federal system, a wide range of self-organizing mechanisms to informally coordinate the actions of multiple actors, both governmental and non-governmental, have evolved in different policy arenas (Berardo & Scholz 2010). These informal organizing mechanisms arise to manage collective action dilemmas at central and local levels of governance, forming self-organized social networks that are decentralized and dynamic (Berardo & Schulz 2010). In the context of local wildfire management, governmental and non-governmental entities engage in policy interactions (Berardo & Schulz 2010), and the network framework undergoes a continuous transformation. This transformation arises from uncoordinated choices made by actors who consistently seek new connections while editing previous ones to address sudden challenges, often referred to as social capital (Berardo & Schulz 2010). Over time, the connections that actors create shape the evolving structure of the social networks and, in turn influence the behaviors of both individuals and institutions (Berardo & Schulz 2010).

Social capital was originally identified by Louis Hanifan (1916) as “goodwill, fellowship, mutual sympathy, and social intercourse among a group of communities and families who make up a social unit" (Aldrich & Meyer, 2015). Since then, the concept of social capital has been broadened to identify how involvement and participation in groups can benefit individuals and communities (Aldrich & Meyer 2015). Measurements of the level of social capital within communities have been the level of trust between community members and the behaviors of individuals in their communities, such as volunteering, membership in community political organizations, and involvement in public meetings, political events, or community projects (Aldrich & Meyer 2015). Carmen et al. (2022) identified four broad interpretations within the literature of social capital: (i) social capital, (ii) social networks and outcomes, (iii) social networks, trust, and norms of reciprocity, and (iv) social networks and socio-cultural dimensions. Scholars focusing on social capital have now separated social capital and networks into either "strong or weak ties," often further defined into three distinctive separations: bonding, bridging, and linking social capital (Aldrich & Meyer 2015; Carmen et al. 2022).

Bonding social capital focuses on connections between individuals and communities who are close and results in tight bonds created within that group. This type of social capital is usually characterized by homogeneous groups that share high levels of similarities (Aldrich & Meyer 2015; Carmen et al. 2022). In the context of disaster management, bonding social capital can provide communities with social support and personal assistance. Communities with higher levels of bonded social capital allow for individuals to be better prepared for the consequences of natural disasters pre- and post-event as it allows for the social infrastructure to receive warnings, undertake preparations, locate shelters and supplies, and receive aid or recovery assistance (Aldrich & Meyer, 2015). This can reduce the likelihood of seeking formal aid from organizations after a disaster and increase the likelihood of social action by individuals or communities immediately after a disaster to respond to the needs of individuals (Aldrich & Meyer 2015).

Bridging social capital refers to the loose connections between individuals and communities that span social groups. These social ties usually include the involvement of individuals in community groups, political organizations, civic organizations, and other interest groups (Aldrich & Meyer 2015, Carmen et al. 2022). These groups often show more demographic diversity than situations of bonded social capital and provide resources for individuals to better prepare or respond to natural disasters.

Linking social capital refers to the ability of individuals and communities to connect with those in power. This social network type is the underlying norms of respect and trust between individuals acting across "explicit, formal, or institutionalized power or authority gradients in society" (Aldrich & Meyer 2015). For example, the relationships that residents have with rangers, forest managers, first responders, or other authority figures that would be of assistance in the situations of a wildfire or flood disaster, and the ability to receive immediate aid or assistance pre- or post-event.

These categorizations of social capital are closely linked to the prevalence, strength, and size of social connections between individuals and their communities or across local communities. These social connections are often framed or defined as networks at the community level. Social networks are analyzed by the way they provide a utilitarian resource for communities, as in the ability to manage risks and challenges (Carmen et al., 2022). Carmen et al. (2022) further defined the relationship between social capital, social networks, and community resilience as focusing on social networks and the outcomes of social actions, the importance of norms of reciprocity and trust, and the interplay of socio-cultural dimensions in shaping social networks.

Given that community, resilience is often conceptualized to come from the way individuals and groups can organize (Carmen et al., 2022). Social capital is often assumed to be a core mechanism of community resilience, as social networks can be closely linked with a community's ability to deal with unpredictability, uncertainty, and change in responding to natural disasters (Carmen et al. 2022; Aldrich & Meyer 2015). Because of this, community resilience is often linked to economic development and normative aspects, such as values and human agency, that shape individual and community goals and social actions (Carmen et al., 2022).

In terms of disaster management and mitigation, adaptive management and community resilience are based on the conception of replacing traditional, top-down methods of management with a more distributive, bottom-up approach. Socialization of responsibility often refers to the decentralization of both disaster risk and response through collaborative partnerships with local institutions and communities. Within the concept of polycentricity, social connections between individuals and organizations within a community dictate the ability for decision-making to be delegated away from a traditional command and control governance structure. These connections are based on the concept of capacity, or the ability to build social capital, or the level of trust between individuals within a community, individuals and governance institutions, norms of reciprocity, and the cultural connections within a social-ecological system (Carmen et al. 2022; Clarke & Meyer 2017).

Two main components are important to communities' capacity to prepare and mitigate catastrophic wildfires. These components are the institutional and financial capacities of communities and stakeholders consolidated in creating these collaborative plans. Previous literature has combined institutional and financial capacities when analyzing community capacity (Kelly at al. 2019; Jakes et al. 2011). Therefore, institutional capacity can be separated from the financial capacity of a collaborative policy system, such as CWPPs, derived from the people involved in the planning process. Institutional capacity can be defined as the cooperation, distribution, and learning by policy actors within the CWPP planning process (Lubell 2013). The interactions between the people and institutions within the policy process and the financial resources they can draw upon form the basis of community capacity. Community capacity is critical to better understand the ability of communities to plan and respond to immediate crises, such as wildfires, and result in more catastrophic outcomes than to surrounding communities.

2.4 Social Vulnerability

Vulnerability to wildfire is often recognized as being spatially distributed based on the geographic conditions that determine the probability of exposure (Coughlin et al., 2019). In the case of vulnerability to wildfire, much of the focus is on the Wildfire Urban Interface (WUI), where population areas are intermixed with flammable wildland vegetation, placing higher exposure to wildfire compared to more dense urban population centers (Coughlin et al., 2019). This intermix of humans and forested landscapes creates complex problems between the built environment, residents' values and preferences, biophysical conditions created by the proximity of wildland fuels, and management policies and practices at the federal, state, and local levels (Collins 2005; Coughlin et al. 2019). Yet within the WUI, when wildfire exposure risks are held constant, not all people or communities are more susceptible to wildfire events or their impacts. The inequitable distribution of wildfire susceptibility is due to the "social, economic, and cultural attributes that confer or limit access to material and informational resources, compounding simple exposure to [wildfire] hazards" (Coughlin et al., 2019).

Over the past few decades, a growing body of research on natural disasters has demonstrated that social circumstances affect the risks that individuals and communities face from natural disasters (Cutter et al. 2000). Social vulnerability originated in the 1970s from disaster and risk scholarship and by the 1990s two approaches emerged (Coughlin et al. 2019). One approach focus on aggregating socio-economic characteristics at the county level and comparing it to another county within a given region or national level, or generally referred to as the "hazards-of-place" approach (Coughlin et al. 2019). The "community vulnerability" approach compares the socio-economic characteristics of communities, either at the census block or city level (Coughlin et al. 2019; Ojeiro et al. 2011). Both the hazards-of-place and community vulnerability literature link social vulnerability to disparities between groups within the WUI, resulting in the inequitable allocation of resources to the more economically privileged through private and public avenues such as private insurance and fuel management and federal and state grant funding (Coughlin et al. 2019; Ojeiro et al. 2011).

Previous literature has expanded on viewing the WUI as often used to describe generally "communities at risk of wildfire" or "fire-prone communities" (Coughlin et al. 2019), thus attributing the term WUI to communities outside of suburban areas in proximity to wildlands and considered generally more prone to wildfire events (Flint & Luloff 2005; Bihari & Ryan 2012; Abrams et al. 2015). Within these studies, vulnerability is viewed as a community-level property tied to its overall resilience and adaptive capacity for wildfire hazards, often referred to as the "community resilience approach (Abrams et al. 2015; Coughlin et al. 2019). In terms of the hazards and social vulnerability literature, adaptive capacity refers to the ability of a household or community to respond to hazards by mitigating risks, learning from past experiences, and recovering from hazard events. Adaptive capacity involves the ability to direct material and social resources to reduce the potential impacts of wildfire events, both in the short and long term (Paveglio et al., 2012; Coughlin et al., 2019). Additionally, adaptive capacity is closely linked to social vulnerability through the unequal access to financial, material, and informational resources required to prepare, mitigate, and recover from wildfire events (Collins 2008).

Resilience relates to adaptive capacity and social vulnerability as it relates to the ability of residents, property owners, and land managers collective ability to recover from natural hazard events, such as wildland fires. In other words, resilience is often considered as the outcome of a community's "adaptive pathways collectively taken by community members following a wildfire event. While adaptive capacity and resilience may not affect direct wildfire exposure, these concepts are linked to social vulnerability, as increases in adaptive capacity and resilience cause decreasing social vulnerability and vice-versa (Coughlin et al. 2019; Maru et al. 2014).

2.5 Community Capacity & Federal Grant Allocation

Critical components of CWPPs are the improvement of community resilience and adaptive capacity in response to increasingly destructive climate threats (Houghteling & Scott, 2023; Davidson et al., 2019; Jakes & Sturtevant, 2012). Improving community resilience and adaptive capacity to wildland fire is built by the foundation of physical capital, such as equipment, personnel, and infrastructure, crucial to mitigation and response to wildfire events (Cutter, 2016; Houghteling & Scott, 2023). However, acquiring physical capital requires allocating additional financial resources, often acquired through debt issuance, which is more difficult for low-resourced communities (Scott et al., 2017; Houghteling et al., 2023).

Additionally, resilience and adaptive capacity relies on the continuous process of creating plans and monitoring programs to prepare for, prevent, respond to, and adapt to complex problems such as wildfire. These elements of capacity are more difficult to fund via annual community budgets, especially in lower-capacity communities. Instead, federal grant funding is crucial for communities to improve resiliency and undergo planning and adaptation efforts (Houghteling et al., 2023).

Research on federal grantmaking highlights the importance of capacity in determining who receives federal grant funds (Houghteling & Scott, 2023). Allocation of federal grants via competition is often efficient but not necessarily equitable (Collins & Gerber 2006; Houghteling & Scott 2023; Ojeiro et al. 2011). Some issues may garner more attention, while government agencies possess varying capabilities in navigating diverse funding landscapes (Houghteling & Scott, 2023; Howlett et al., 2009; Lubell et al., 2014). Therefore, the capacity of both government and individuals is limited, and tradeoffs exist between prioritizing other objectives over winning grants (Houghteling & Scott, 2023).

Sharing capacity between governmental agencies and individuals is especially relevant for wildfire management. Governments can individually prepare and respond to wildfire events, producing either positive or negative externalities for neighboring communities based on previous preparation efforts (Houghteling & Scott, 2023). Under HFRA requirements, local governments are required to coordinate wildfire preparation and response, creating a common goal to mitigate wildfire risks through the cooperative pursuit of grant funds or pooling resources for community benefit. Therefore, creating a common strategy via the creation of a CWPP can allow communities to access resources crucial to improving community resiliency and adaptive capacity.

However, sharing physical and administrative assets relies on a community's social capital, particularly bridging capital, and the capacity to pursue grant funding strategies. Communities with robust social networks, especially bridges to other jurisdictions, may have access to outside governments with the capacity to pursue grant opportunities and "facilitate resilience through a government that otherwise may be unable to pursue resilience" (Houghteling et al., 2023) via grant funds. Thus, we can hypothesize that (H1) *increased social capital within a CWPP region will be associated with an improved likelihood of winning federal wildfire mitigation grant funding.* Additionally, communities that already have high capacity or access to additional resources may be able to pursue grant funding opportunities independently without robust social capital. Therefore, we can hypothesize that (H2) *CWPP regions with access to more financial resources increase the* *likelihood of receiving federal wildfire mitigation grant funding*. If this hypothesis is validated, we should expect results consistent with an inverse response between a community's financial resources and winning grants.

In this study, we ran one model estimating the likelihood of communities with a CWPP winning federal grant funding for wildfire mitigation. In our model, we estimate the likelihood of areas with a CWPP of receiving federal wildfire mitigation grant funds based on several fixed effects, such as wildfire hazard potential, social vulnerability, financial capacity, the percentage of public land per CWPP jurisdiction boundary, social network density of entities named within 5% of the total document length from each other, and a dummy variable for whether a CWPP is an update or revision, and several spatial and temporal random effects.

Chapter 3: Data

Our empirical analysis is based on a variety of datasets that are available both privately and publicly online: Community Wildfire Protection Plans were retrieved from Dr. Matt Hamilton and team on a previous publication regarding actor engagement within each CWPP and updates, revisions, or addendums (Palsa et al. 2022). The data consisted of a compiled dataset of all published CWPPs and updates in the U.S. Mountain and West regions until 2021, including shapefiles for each CWPP jurisdictional boundary. CWPP boundary shapefiles were utilized to derive multiple variables included in this dataset, including social capital measures, and CWPP boundary shapefiles to link spatial data included in this study to each CWPP jurisdiction.

In this study, we approached our analysis by considering each version of a CWPP as the unit of analysis, focusing on assessing whether a CWPP secures a grant during its effective timeframe. As such the dataset is constructed as cross-sectional, rather than as a panel dataset. Within this framework, we assumed our covariates remain static throughout the entirity of a plan's implementation period.

This approach was deliberatively chosen due to it being the simpliest and most-conservative method of characterizing the effects of a CWPP. By treating each CWPP verision as an independent case, we create a straightforward model that assumes covariate values remain constant, rather than changing over the period in which a indiivudal CWPP is in effect. Additionaly, we have introduced a random effect for the year in which a CWPP was published to account for unobserved variations over time, providing a mechanism to control for time-related factors.

It is important to note, we did not opt to stucture our data as a panel dataset for several reasons. One key considerations is that, apart from whether a CWPP has secured a grant, we do not see and any variation in our covariates over time. As such, contructing our data as a panel dataset may inadvertantly reduce standard errors for our covariates without an actual increase in the number of observations. Therefore, our cross-sectional approach, with the inclusion of a random effect for the CWPP publication year, aligns with available data and the objectives of our study.

3.1 Community Wildfire Protection Plan Data

Included in this research are 1056 CWPPs published between 2001 and 2022 at three distinct jurisdiction levels: County (482), Community (481), and Fire Protection District (93) (Figure x). These CWPPs are those included in Palsa et al.'s dataset of CWPP plans, intended for evaluating CWPP development over time (CWPP Boundaries 2023; Palsa et al. 2021). The dataset included shapefiles, CWPP documents, Year Published, and Jurisdiction type for each wildfire mitigation plan published in the Western United States. Plan development varied significantly over time (Figure 3.1). Generally, CWPP publications peaked during the mid-to late-2000s, following the passage of the HFRA in 2003.

Of the 1,056 CWPPs included in this research, there are 851 original CWPPs and 205 updates, revisions, or addendums at the County (151), Community (46), and Fire Protection District (8) levels (Figure 3.1).

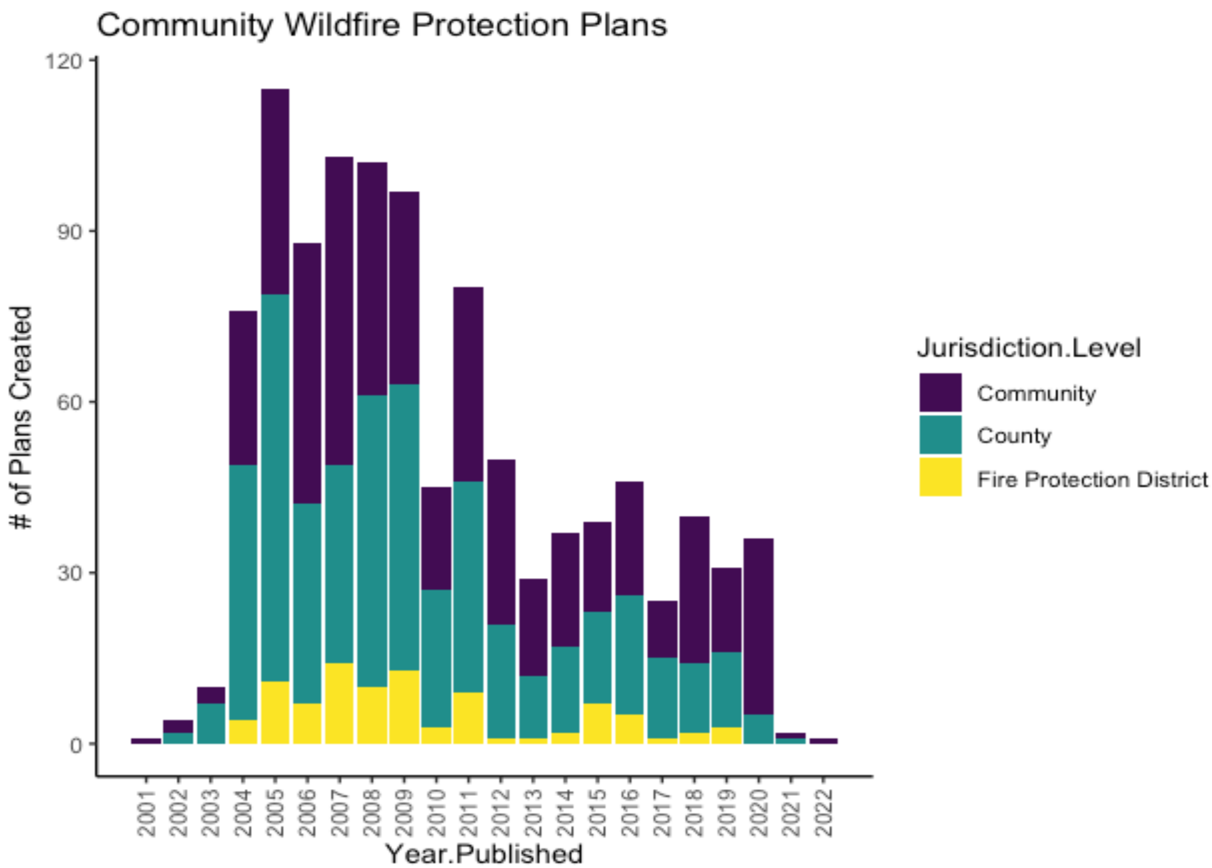

Figure 3.1: Bar plot of number of Community Wildfire Protection Plans (CWPP) published by year. Published CWPPs are split by jurisdictional level.

When separating the total number of CWPPs published by whether there has been an update, we see that subsequent plans published reached their peak in 2009, and most updates are to county-level plans. Figure 3.2 depicts the frequency of CWPP updates published by year over each jurisdiction type (Figure 3.2). Figure 3.2 shows a pulse of CWPP updates published in 2009, followed by a secondary pulse in the mid-to-late- 2010s.

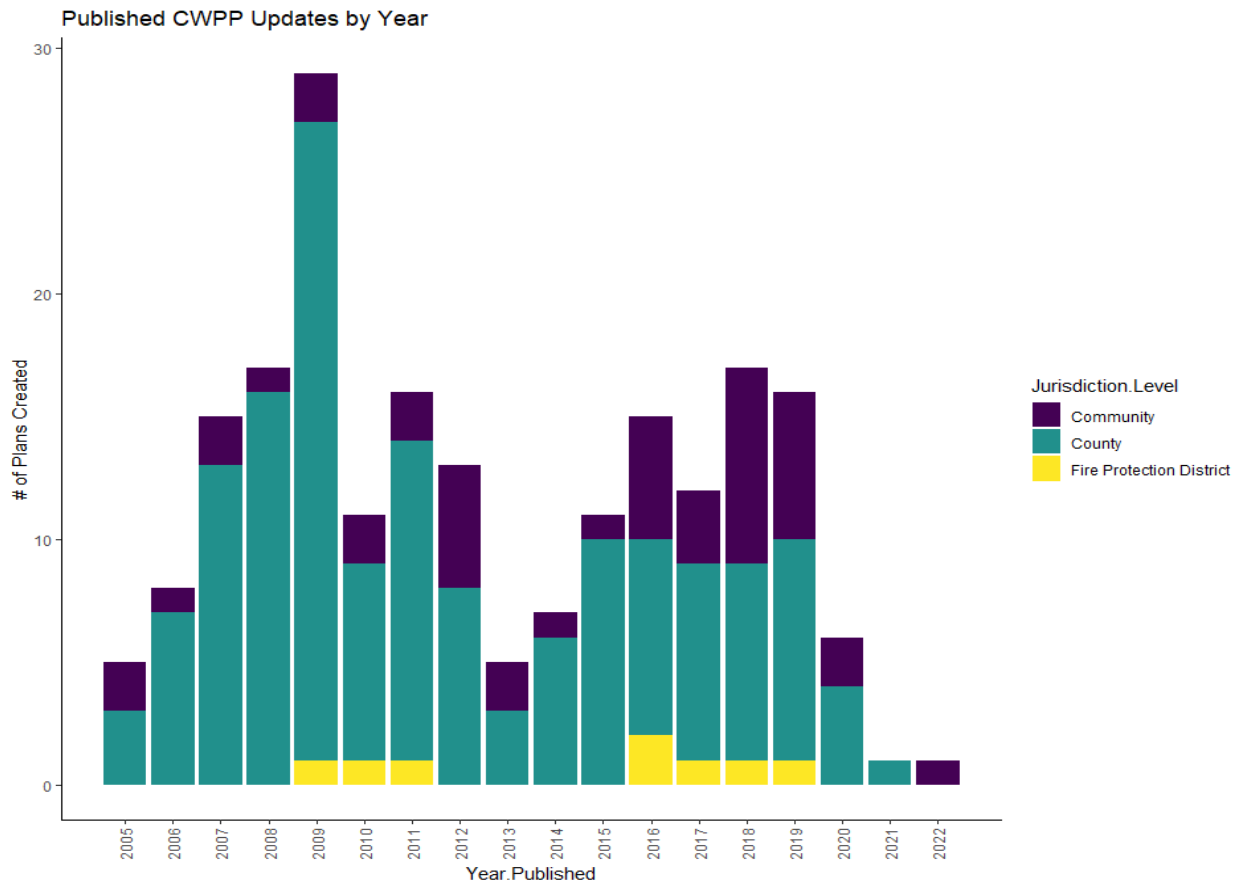

Figure 3.2: Bar plot of number of Updated Community Wildfire Protection Plans (CWPP) published by year. Published CWPP updates are split by jurisdictional level.

3.2 Measuring Social Capital

Due to time and personnel constraints, social capital is often difficult to measure without on-ground interviews or surveys. Previous research has used automated coding to track stakeholder involvement attendance and actions within collaborative governance processes (Scott et al., 2018; Baudoin et al., 2023; Ulibarri et al., 2019), as well as topic modeling and content analysis (Bell & Scott, 2020). These studies focused on analyzing stakeholder involvement and how it changed collaborative governance processes (Scott et al., 2018; Ulibarri et al., 2020; Heikkila & Gerlak, 2016; Bell & Scott, 2020) and affected public participation in environmental planning (Ulibarri et al., 2019). Prior findings have shown that there is a decrease in stakeholder engagement and communication decrease over time (Heikkila & Gerlak, 2016;

Hui et al., 2020; Scott et al., 2020), and collaboration is not guaranteed to be successful (Ulibarri et al., 2020). However, scarce literature exists using automated coding methods to obtain measures of social capital within collaborative governance processes.

This study uses a similar approach to Scott et al. (2020) to measure social capital via CWPP documents by extracting observations using Natural Language Processing (NLP) techniques, specifically the spaCyr tool for the automated processing of spoken and written language (Honnibal & Montani, 2017; Manning & Schütze 1999; Scott et al. 2020). To identify actors within each CWPP, we converted each document PDF into a readable PDF, which was then processed through the spaCyr tool. This approach involved the extraction of named entities within each CWPP, focusing on noun phrase recognition that represented involved entities by type (e.g., person, location, organization). For this study, we were mainly concerned with organizations mentioned within a document. Each document was processed format extracted entities for consistency, which included lowercasing, removing special characters and punctuation, and squishing multiple spaces together. This method was chosen due to the high involvement and participation of state and local governmental agencies and departments, fire organizations, homeowners associations, and other private stakeholders in the CWPP planning process (Palsa et al. 2021).

Subsequently, following the extraction of all of the named actors, we encountered instances where the spaCyr software produced errors and inaccuracies in identifying and coding entities within the CWPPs (Honnibal & Montani, 2017). To address these issues, a thorough review was conducted comparing each document to the list of named entities to reduce any errors introduced by the spaCyr tool. Following recoding the list of entities to reduce any errors, we assigned a unique identification number for each entity detected. We then re-analyzed each document and replaced the original entity identified in each document with the corresponding unique identification number to easily detect named entities within a document and any possible cross-boundary coordination between CWPPs.

To measure how entities were connected within each CWPP, we identified the sentence number that each unique entity occurred for each document and calculated the distance between the sentences that each unique entity mentioned for each document. Sentence level distances between each named entity were stored in a matrix for each CWPP. Using these matrices, we converted each matrix into a graph, using the 'igraph' tool in R (Nepusz et al. 2023), plotting unique entity numbers to the edges to represent the network structure based on the associated matrix for each document. Finally, we calculated our social capital measure by calculating the edge density, the ratio of actually connected entities to the number of possible connected entities within each document, to quantify how connected a network is for each CWPP. For each document and its' associated update or revision, we created an overall density score for 5%, 50%, and 100% cutoff parameters to scale documents based on total length. These parameters refer to the number of entities that lie within the percentage of the total document length for each document. For example, at the 5% cutoff parameter, we are measuring the number of entities mentioned within 5% of the total document distance and comparing it to the total length of each document. Figure 3.3 depicts matrices for Maricopa County's original and updated CWPP in Arizona. Moving from Maricopa County's CWPP in 2010 to the update in 2014, we see that entities are located closer to each other, as well as an increase in the number of entities detected in the updated CWPP.

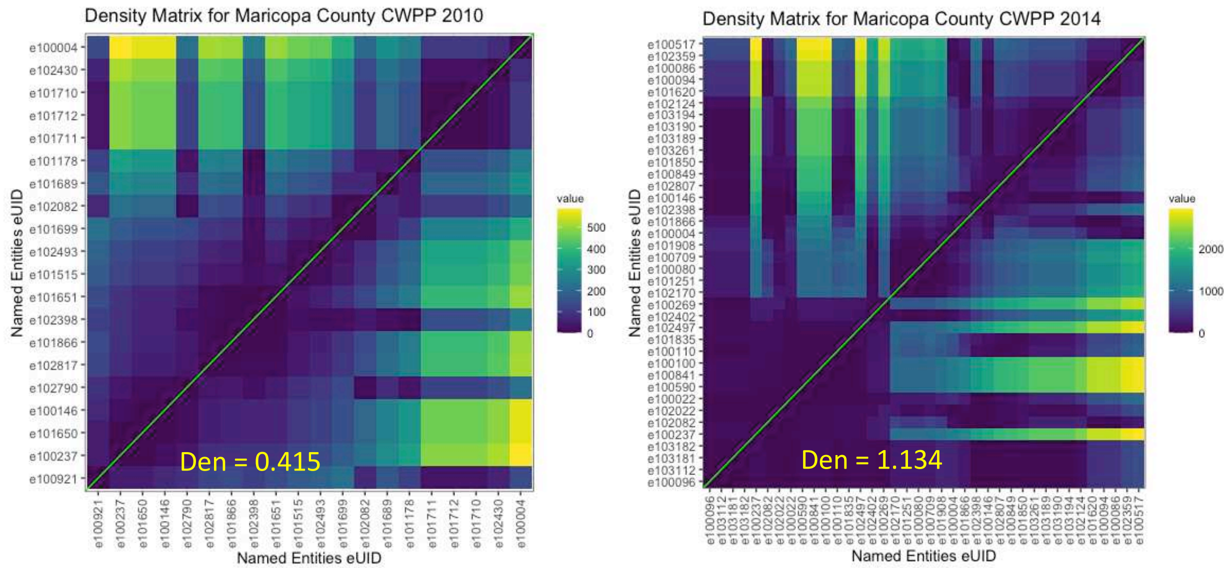

Figure 3.3: Tile plot of the total distance between each named entity within each Community Wildfire Protection, depicting social capital measures at the 100% cutoff parameter in Arizona's Maricopa County.

Figure 3.4 shows the change in entity density scores for updated CWPPs in Idaho, with each point representing the publishing date of each CWPP. From Figure 3.4, our network density results suggest considerable variation between the density of named entities between wildfire protection plans and their subsequent plan updates in Idaho. Similar variation is observed between CWPPs and their updates in other states included in this study.

As proof of concept for the measure, we evaluated two counties in Idaho where changes to social capital varied over time (Figure 3.5). Looking at each county's fire mitigation plan and its updates, we find evidence our social capital measures are consistent with our rationale. For example, in Blaine County, we see the addition of new actors in the CWPP planning process, such as Mid-Snake Resource Conservation and Development Council Inc., in the following 2009 Blaine County CWPP Addendum. In Cassia County, we see that from the original CWPP

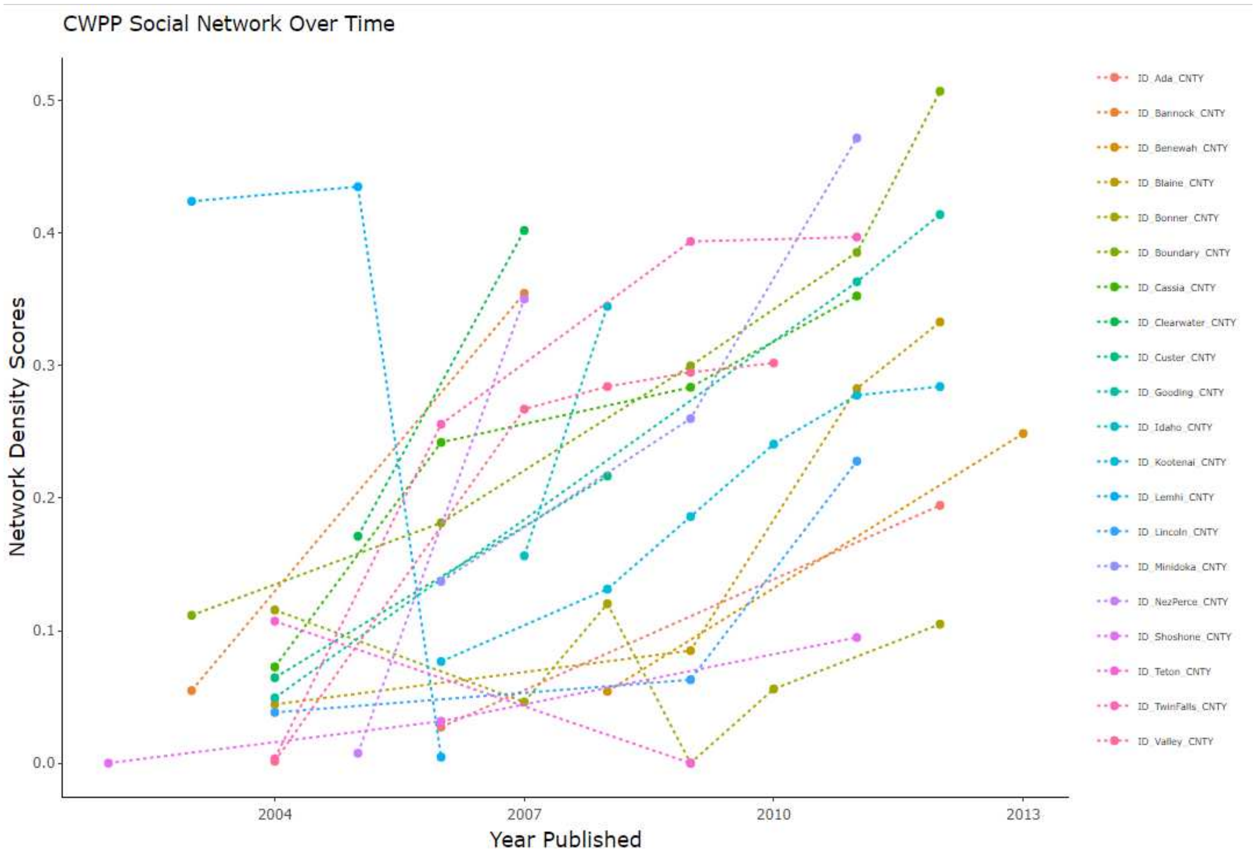

Figure 3.4: Line plot showing the change in density scores of named entities for all CWPP plans in Idaho over time.

published in 2004 to an update in 2006. Additionally, we also see the growth of named actors from existing institutions within wildfire protections, such as an increase in the number of participants from federal, state, and local land management agencies and fire officials. Looking at each plan for Cassia County, we see two interesting patterns emerge. While we see a general increase in organizations involved within the planning process, there is variation between actors involved within the initial CWPP planning process and subsequent updates or amendments to the Cassia County mitigation plans. For example, from the original CWPP to the following updates, we see the addition of new actors into the planning process, such as the Mid-Snake Resource, Conservation, and Development Inc., initially into the Cassia County 2006 update and subsequent plans.

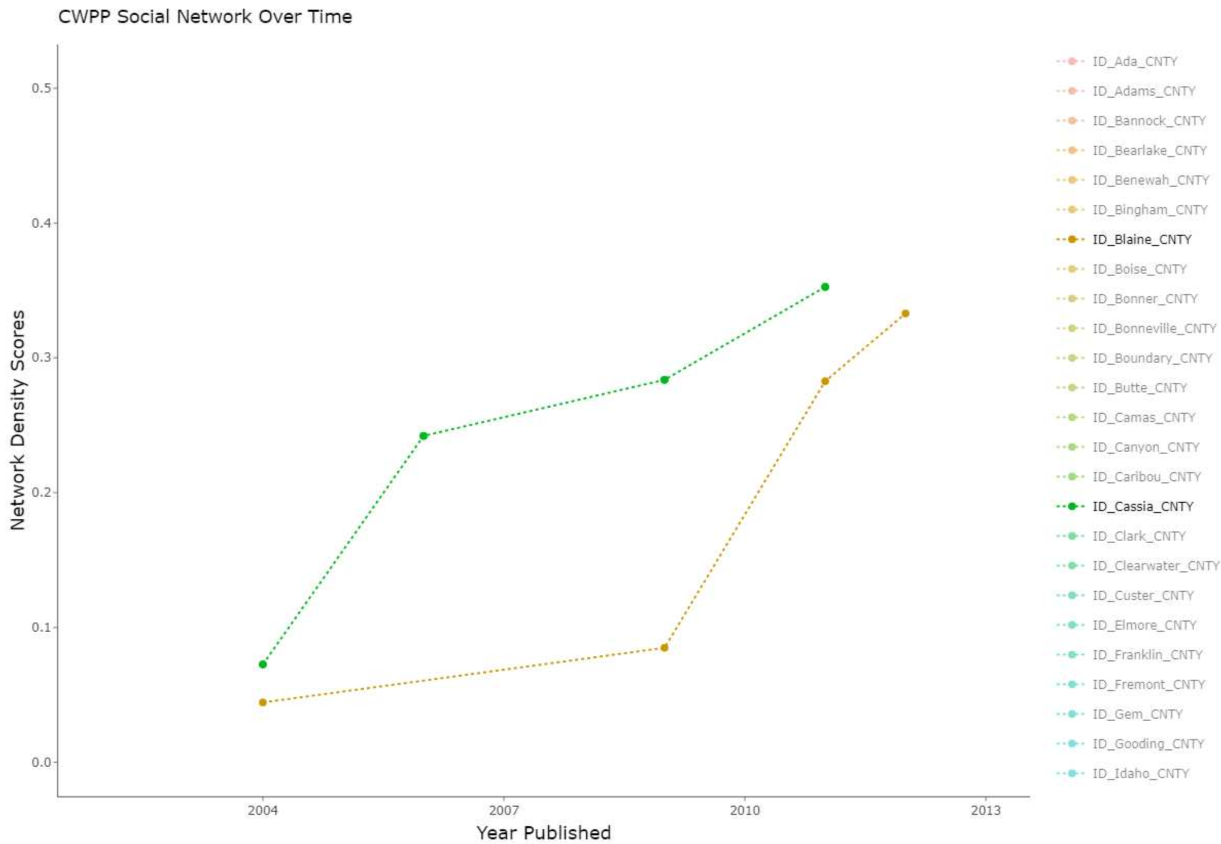

Figure 3.5: Line plot showing the change in density scores of named entities for Blaine and Cassia counties.

Another notable observation found in both Blaine and Cassia CWPPs is the increase of mutual aid agreements between fire departments or fire protection districts in case of wildfire events. For example, in the case of the Blaine County CWPP, a consolidation study was conducted of fire departments within Blaine County for rural or volunteer fire departments to access additional resources or training for preparedness or mitigation of future wildfire events. The increase in mutual aid agreements or consolidations of fire departments within a CWPP may increase entity density scores due to how named entities were observed for each CWPP, showing named entities becoming more connected, thereby increasing social capital within a CWPP jurisdiction area. In addition, we find that in Cassia County's protection plans, we see the addition of fire protection districts and emergency services from neighboring Minidoka County into the planning process, such as the involvement of the Minidoka East End FPD and the Minidoka County FPD in the original Cassia County CWPP in 2004, and the Minidoka-Cassia Local Emergency Planning Committee (LEPC) in the 2011 Cassia County CWPP update.

While Blaine County does experience an increase in network density scores, there are substantial differences in the observed changes between the original CWPP and subsequent plan updates. In Cassia County's CWPP updates, we observe additional fuel treatments or other mitigation projects conducted from CWPP update to update, the inclusion of actors into the planning process from outside the planning jurisdiction, as well as the addition of new organizations into the planning process and an increase in personnel from key federal, state, and local agencies critical to the creation of each CWPP. We also see that there are substantially fewer actions outlined in subsequent CWPP updates in Blaine County outlining fire officials undertaking additional prevention actions within the planning jurisdiction area or the expansion of mutual aid agreements or consolidation studies of fire districts or departments within Blaine County. However, in both Blaine and Cassia counties, we see that from the original mitigation plan to subsequent updates, increases in network density scores originate from the inclusion of new entities into the CWPP planning process, additional fuels, and hazard mitigation projects, or the expansion of mutual aid agreements between fire protection districts over time.

Table 3.1: Table depicts the observed changes between Blaine and Cassia County network density scores.

Blaine County CWPP	# of Actors	Notable Changes	Cassia County CWPP	# of Actors	Notable Changes
2004*	17		2004*	15	
2009	10	Decrease in total actors involved in the plan, but increase in fuels mitigation, education, firefighter training, and other mitigation projects being done by each department in the surrounding communities.	2006	17	Addition of multiple new actors into planning process, such as Mid-Snake RC &D, Mayors of Malta, Albion, and Oakley, and Cassia County Public Lands and Emergency Services Department Mutual Aid Agreement between ACE Fire Protection District and Box Elder County, Utah Firefighter Training of multiple fire protection districts with the Twin Falls BLM District, Southern Idaho Fire Academy, and Idaho Fire Service
2011	18	Increase in total actors, including a new organization (Mid-Snake RC&D), as well as additional personnel from Sun Valley FPD, Twin Falls BLM District, Sawtooth NF. Blaine County Consolidation Study between fire departments completed and expansion of mutual aid agreements between Blaine County Fire Departments	2009	14	Reduction of entities involved in addendum process. Additional fuels mitigation projects on federal and non-federal lands by relevant actors outlined
2012	18	Increase in fuels mitigation projects on federal and non-federal lands. Coordination of existing mitigation projects between Fire Departments in Blaine County (ex. Beaver Creek Treatments transferred from West Magic Rural Fire Dept. to Smiley Creek Fire Dept.	2011	20	Addition of new entities within the addendum process, such as Mini-Cassia LEPC, South Central Public Health, Idaho Dept. of Homeland Security. Cross-Boundary collaboration between Minidoka and Cassia counties in fire mitigation planning (ex. Minidoka-Cassia Local Emergency Planning Commission) Additional fuels treatment projects on federal and non-federal lands, as well as collaboration between both federal and non-federal agencies

When density scores are separated by the average change over all CWPP updates within each state, we also see differences between states. Figure 3.6 depicts the average change between all original CWPPs and subsequent updates for each state within our study area, with the range of the average change in density scores for each state denoted by the red lines. Montana was dropped due to the state's lack of updates or revisions to CWPPs. We calculated the average change in network density scores by state by finding the average change in network density

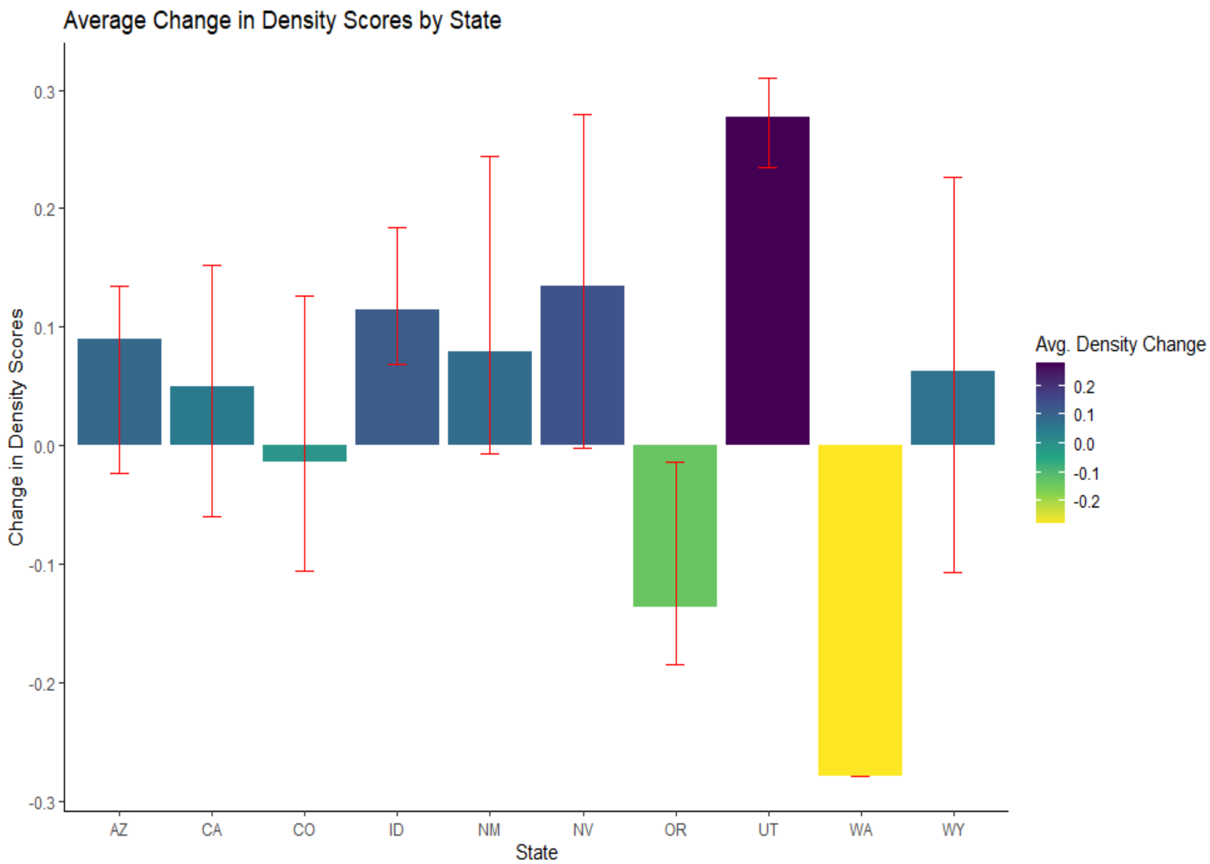

Figure 3.6: Bar Plot showing the average change in network density scores between all CWPPs with published updates by state.

scores for each CWPP and then calculating the average change for each state in our study. Throughout our study area, most states experience an average increase in social capital for all plans. However, we do find that Colorado, Oregon, and Washington show an average decrease in network density scores for all published CWPPs and updates. In Washington, we do see a more considerable reduction of average network density scores for all CWPPs and updates within the state due to the limited number of observations (n = 2) included in our study.

However, when calculating the average change of our density scores between all CWPPs within our study area at their jurisdiction level across states, we find that the change in density scores for each jurisdiction level is positive, with the highest rate of change at the county level CWPP and the lowest at the fire protection district level (Figure 3.7). Average network density change per jurisdiction was calculated similarly to Figure 3.6. Within the fire protection district level, we removed two community protection plans for the Vista Fire Protection District in California due to the original and updated CWPP being duplicated in our dataset.

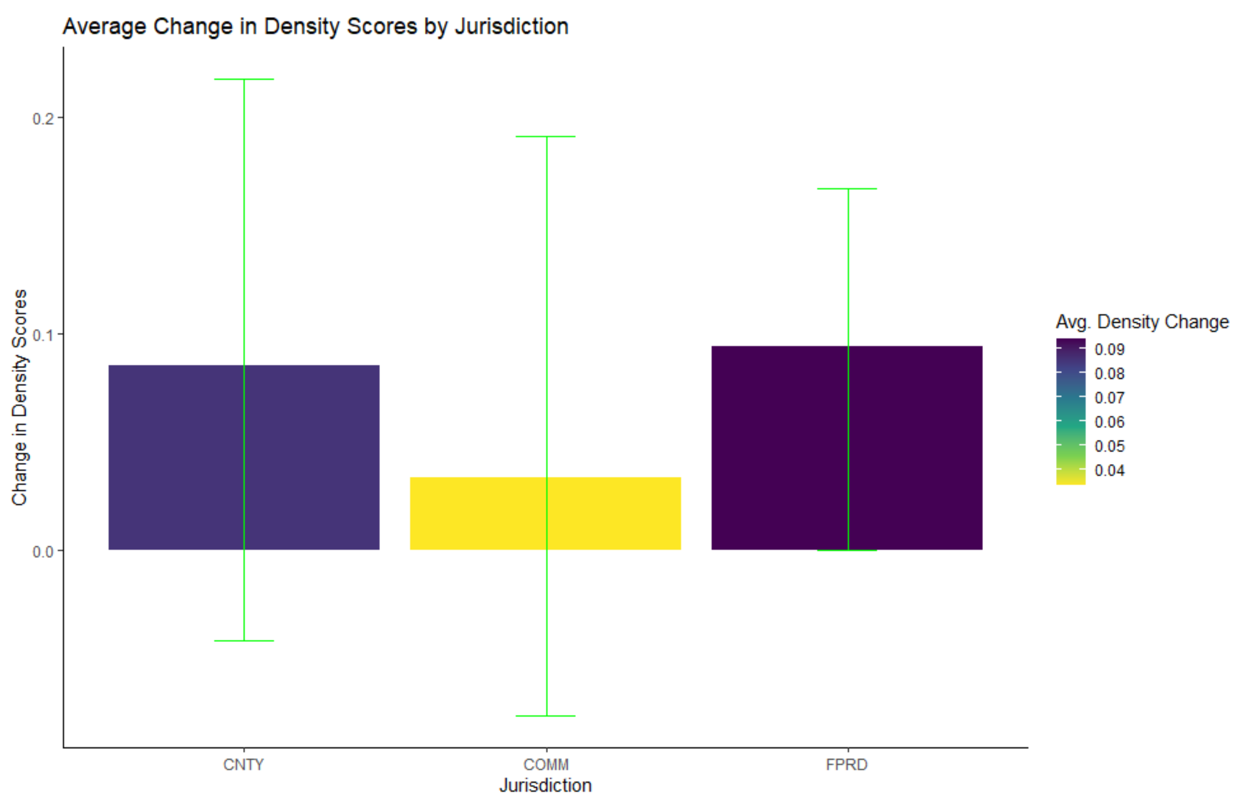

Figure 3.7: Bar Plot showing the average change in network density scores between all CWPPs with published updates by jurisdiction level.

3.2 Wildfire Hazard Potential

Wildfire Risk was gathered from the Wildfire Hazard Potential (WHP) raster dataset (Dillon 2015). The WHP dataset was built on spatial estimates of wildfire likelihood and intensity from the Large Fire Simulation system (Fsim), as well as fuels and vegetation data from LANDFIRE 2010 and the point location of fire occurrence from the Fire Program Analysis system for the contiguous United States (Dillon 2015). Each pixel contains WHP classes: 1) very low, 2) low, 3) moderate, 4) high, 5) very high, 6) non-burnable lands, and 7) water.

To retrieve the WHP score for each CWPP plan boundary, we masked the WHP raster layer by each boundary shapefile by jurisdiction level. After masking the WHP raster layer, we

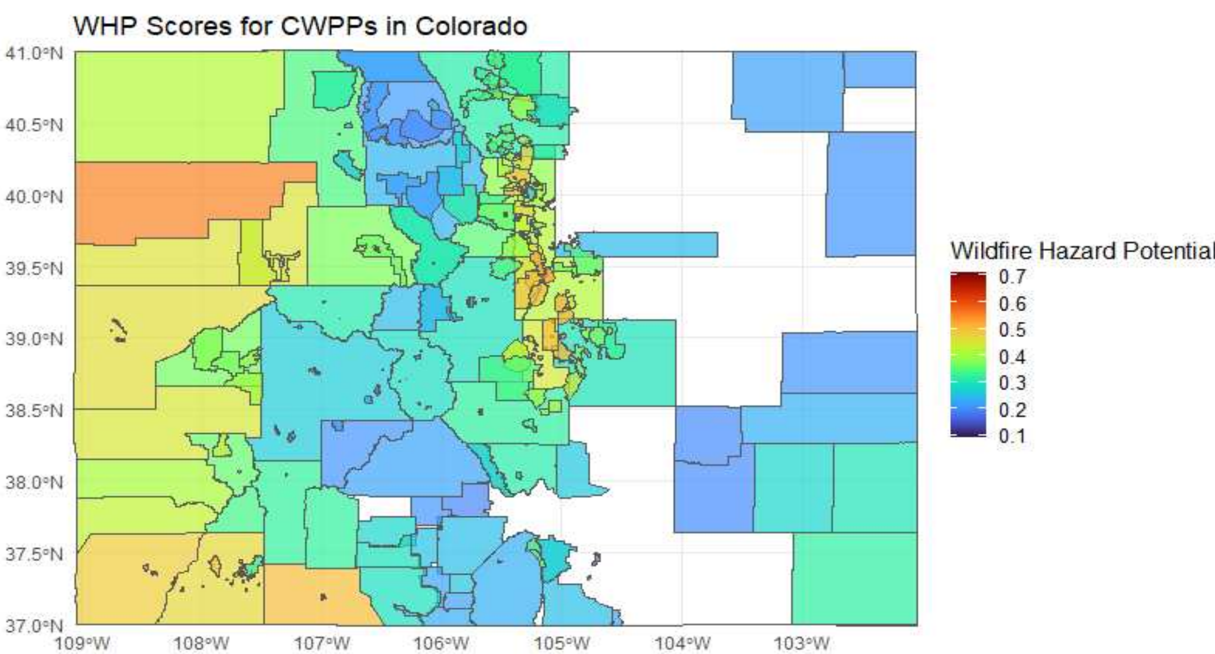

Figure 3.8: Distribution of Wildfire Hazard Potential (WHP) scores of each CWPP within Colorado

averaged the pixel values within each CWPP plan boundary. To avoid skewing each plan boundary's average wildfire hazard potential, pixel values originally classified as non-burnable lands (6) and water (7) were recorded as zero. After retrieving the average WHP value for each CWPP plan boundary, scores were standardized from zero to one scale in line with Palsa et al. (Palsa et al., 2021). Figure 3.7 depicts the distribution of WHP scores for each CWPP boundary area within Colorado.

3.3 Social Vulnerability

Social Vulnerability data was gathered from the 2020 CDC/ATSDR Social Vulnerability Index at the census tract level (CDC/ATSDR 2020). The CDC/ATSDR database includes a variety of community variables from the 2016 to 2020 American Community Survey (ACS), and measured at a percentile rank for each vulnerability theme. These themes include socio-economic status, household characteristics, racial & minority status, and household type and Transportation (Figure 3.8).

For the overall tract SVI score, each SVI theme was summed, ordered by tract, and an overall percentile ranking was calculated (CDC/ATSDR 2020). For this research, we were only concerned with the overall SVI percentile score across the four themes for each census tract and county within our study area. Measures for overall social vulnerability were calculated by SVI percentiles to better capture a community's vulnerability based on a variety of socio-demographic variables. SVI percentile scores are scaled from 0 to 1 within the CDC/ATSDR,

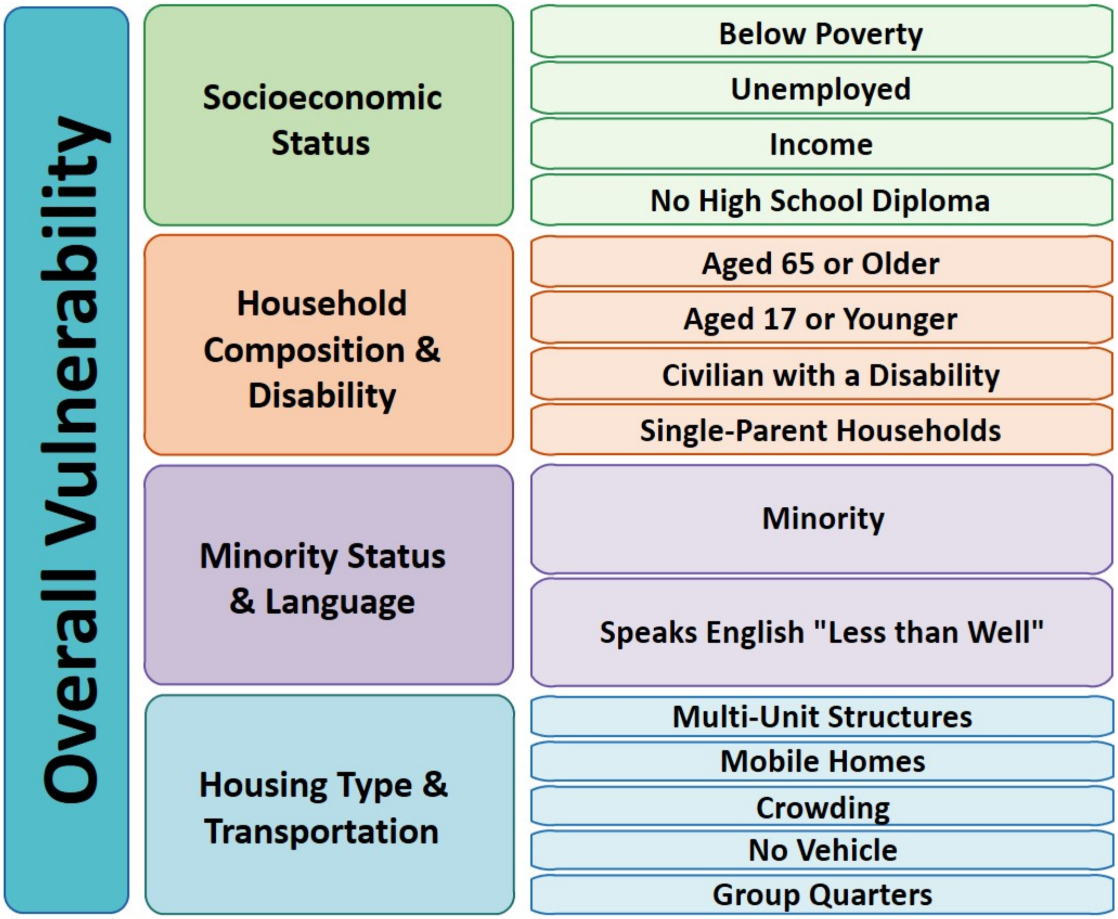

Figure 3.9: Individual measurements CDC/ADSTR SVI score and how they are compiled (taken from CDC/ADSTR 2023)

meaning tracts with scores of 1 are categorized as the most vulnerable and vice versa (CDC/ATSDR 2020).

SVI scores measured at the tract level were used to retrieve the SVI score for each CWPP at each jurisdiction level. Using the CDC/ATSDR and CWPP shapefiles, we intersected CDC/ATSDR SVI tract level and CWPP jurisdiction level shapefiles and calculated the weighted area of census tracts with each CWPP boundary based on each shapefile's geometry. After intersecting the SVI and CWPP datasets, we removed all missing census tract SVI scores that may skew each CWPP boundary SVI score. In order to optimize the fit of our model, SVI scores for plan jurisdictions were manipulated into four categories; "Low," "Low-Medium," Medium-High," and "High" based on SVI categorization within the CDC/ADSTR database. Each class was separated by one-quarter of the SVI percentile range. Figure 3.9 shows the distribution of SVI scores for each CWPP boundary area within Colorado.

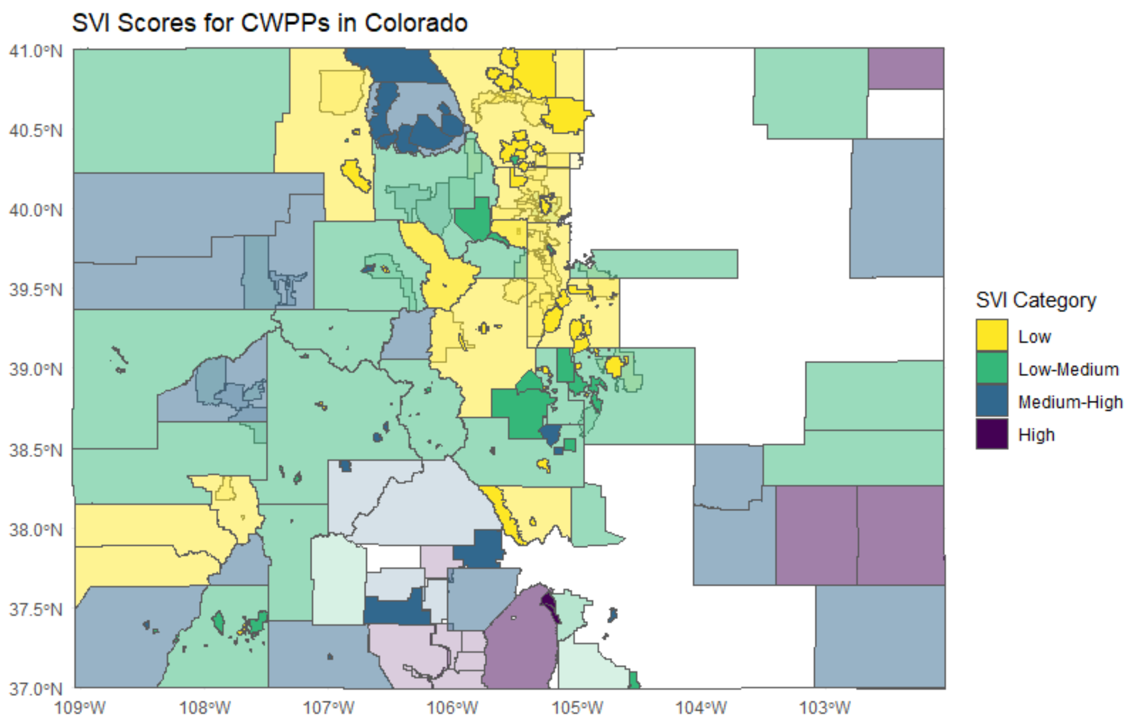

Figure 3.10: Distribution of Social Vulnerability Index (SVI) scores of each CWPP within Colorado

3.4 Financial Capacity

Financial capacity is integral in investigating the factors contributing to a CWPP's likelihood of receiving federal wildfire mitigation and planning funding. A community's financial capacity can be used to determine the ability to consolidate and collaborate to create and implement collaborative wildfire plans (Jakes et al. 2011). Data for financial capital was retrieved from the American Community Survey (ACS) 5-year dataset from 2015 to 2019 conducted by the U.S. Census Bureau of the aggregate real estate taxes by census tract (U.S. Census Bureau, 2019). We used real estate taxes in order as a measure of financial capacity for each CWPP. Property tax revenues for each CWPP area represent the funds that government authorities can draw upon for wildfire planning operations and project implementation, as well as give an insight into the values at risk of a CWPP area (Palaiologou et al. 2019; Coughlin et al. 2019).

To assign financial capacities to each CWPP boundary, we again intersected the ACS 2019 and each CWPP boundary for each jurisdiction. After intersecting the ACS 2019 and CWPP data, we grouped each census tract by CWPP name and calculated the average real estate

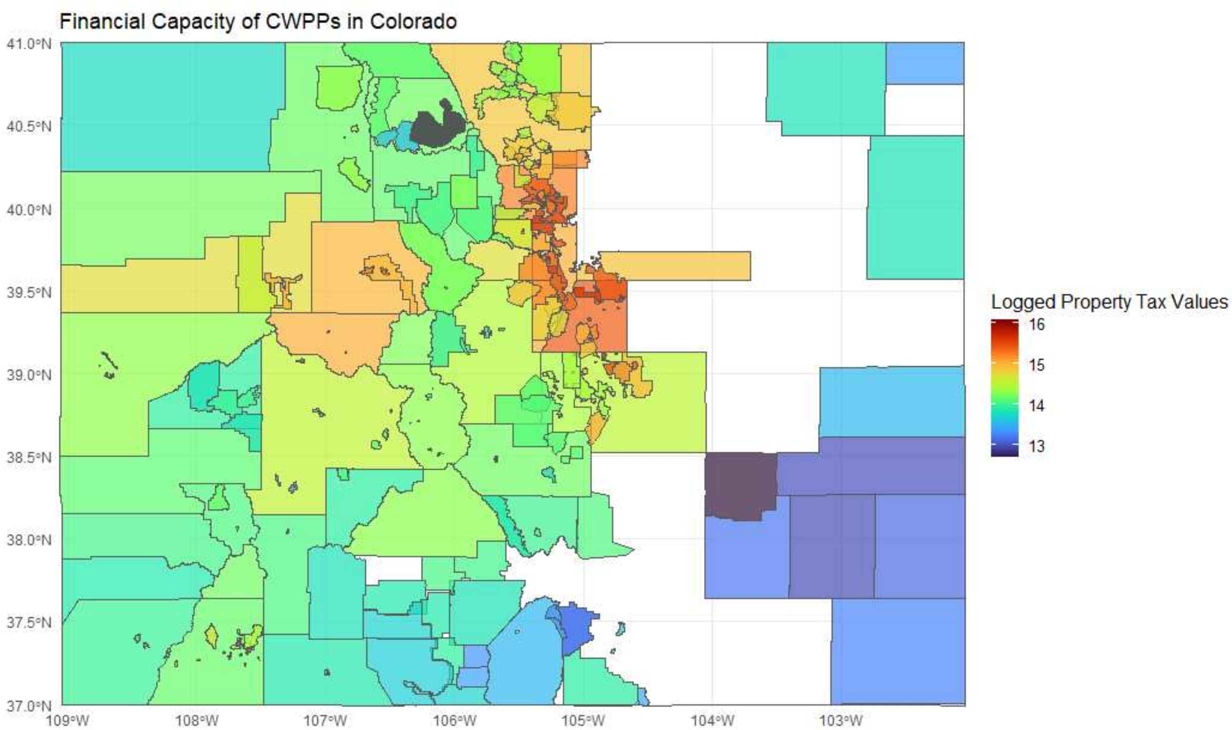

Figure 3.11: Distribution of Natural Logged Property Tax Revenues in dollars of each CWPP within Colorado

tax between census tracts within each CWPP boundary area. Average property tax revenues were calculated by adding the total real estate tax for each census tract within a CWPP boundary area and dividing by the total number of census tracts. Figure 3.10 depicts the spatial distribution of natural logged property tax values plus one for CWPPs within Colorado.

3.5 Public Land

Public Land data was retrieved from the USGS Protected Areas Databases of the United States (PAD-US) (USGS 2023). Protected areas data is used to calculate the percentage of public land within each CWPP area. From the PAD-US, we collected shapefiles for each state in the U.S. West Region included in our study. We then combined each state individual's shapefile and filtered out by federal, district, local, and state ownership types.

Once we had all the public land areas within each state, we intersected the PAD-US shapefiles with our CWPP county, fire protection district, and community jurisdiction levels. After intersecting the PAD-US data with our CWPP boundaries, we calculated the total area of all the PAD-US polygons within our CWPP boundaries at each jurisdiction level. We then aggregated the area of our PAD-US data within each CWPP boundary to get the total area of public lands within each CWPP. Followed by dividing the total public land area by the total area of each CWPP to derive the proportion of public land area to the total area for each CWPP in our study. Finally, we multiplied our proportion of public land area to the total extent of each CWPP boundary by one hundred to get the percentage of public land per CWPP. Figure 3.12 shows the spatial distribution of the percentage of public land for each CWPP jurisdiction within Colorado.

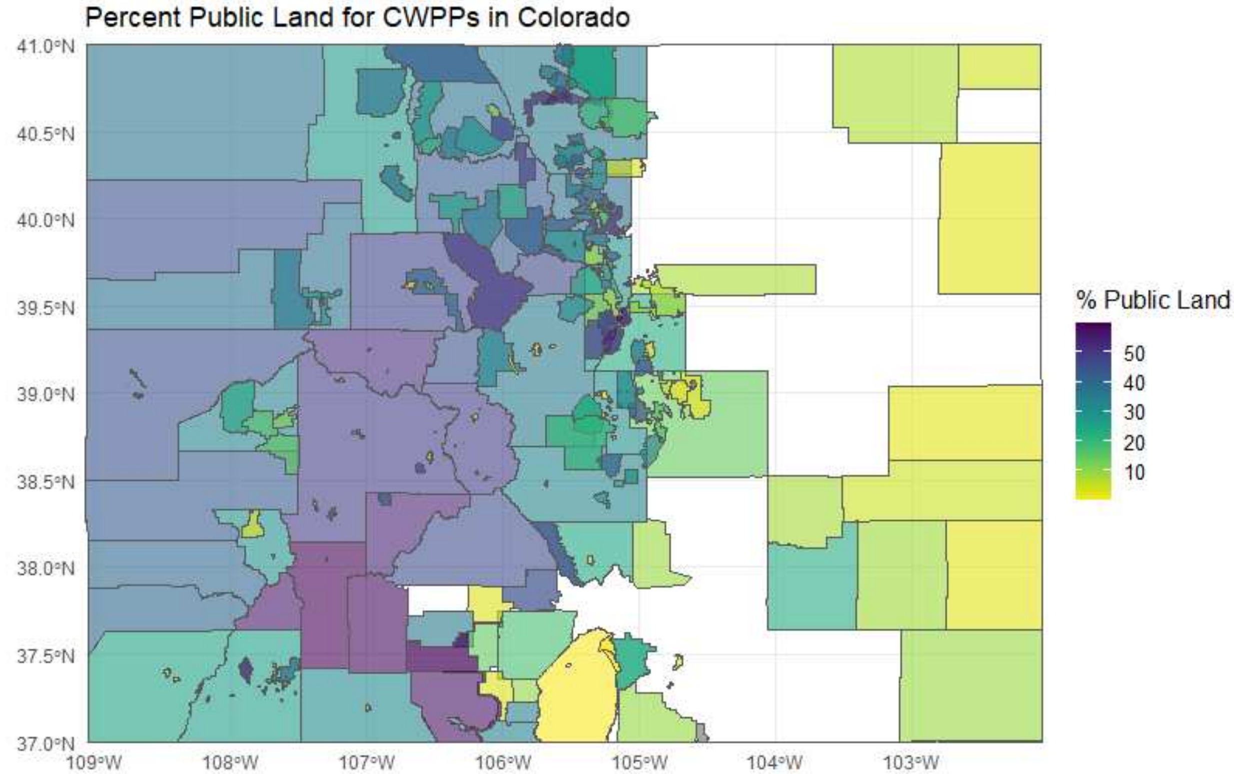

Figure 3.12: Distribution of the Percentage of Public Land by Total CWPP jurisdiction area of each CWPP within Colorado

3.6 Cooperative Forestry Assistance Grants

Cooperative Forestry Assistance grants were chosen for this study due to the program being a competitive consolidated payment grant from the Forest Service . This program encompasses multiple different competitive grant programs such as the State Fire Assistance (SFA), Forest Health, Forest Stewardship, Urban and Community Forestry, and Volunteer Fire Assistance programs (USFS 2023). Previous research on federal grant distribution has been done on the SFA grant program (Ojeiro et al. 2011). However, we included all grants within the Cooperative Forestry Assistance program to capture all proposed projects outlined within the scope of a CWPP.

Cooperative Forestry Assistance grant data was retrieved from USAspending.gov for FY2007 – FY2022. Included in the grant data were the prime and sub-award recipients for each grant distributed from FY2077 to FY2022. In total, we had 1,024 sub-awards for our study area of the 11 states within the Western United States.

Included within the Cooperative Forestry Assistance grant information was the sub-awardee information, including the sub-awardee name, address, organization type, and the sub-award primary place of performance: city, state, and grant description. To attribute whether a grant was distributed to a CWPP, we could not use the sub-awardee organization and sub-award description to connect CWPP and a grant distributed. Due to inconsistencies in reporting for the sub-award purpose, there was insufficient information to correctly link CWPPs with the associated sub-award. In addition, inconsistencies with the sub-awardee organization name made linking actors within CWPPs to a Cooperative Forestry Assistance grant improbable due to time constraints.

To link Cooperative Forestry Assistance sub-award funds to related CWPPs, we assumed that the sub-award project place of performance would benefit the associated CWPP if it were to lie within an associated CWPP jurisdictional boundary. Therefore, each sub-award primary place of performance locations was geocoded to retrieve the latitude and longitude for the city centroid location[1]. This is followed by intersecting each primary place of performance points with CWPP boundary shapefiles to link an associated CWPP with a sub-award based on the jurisdictional area.

[1] Due to the inconsistencies in documenting the precise location for each sub-award within the sub-award description in our dataset, to link grants with their respective allocatees based on the primary place of performance. Within the dataset we combined the primary place of performance address, state, and zip code. These addresses were then geocoded locations as points and joined with corresponding CWPP shapefiles that overlapped the primary place of performance geocoded points.

To correctly attribute each Cooperative Forestry Assistance grant to the correct CWPP, we created a sequence for CWPPs that had received federal grant funding each year from when the CWPP was published to the present year. This sequence consisted of annual increments from the year a CWPP was published to the last year of our Cooperative Forestry Assistance grant data for 2022. For plans with associated updates or revisions, we created a sequence of each year from the published year of the original plan to the previous year an update was published, and a similar process was used from update to update if a plan had multiple updates or revisions. Using this sequence, we then dropped all observations in which a CWPP was awarded grant funding

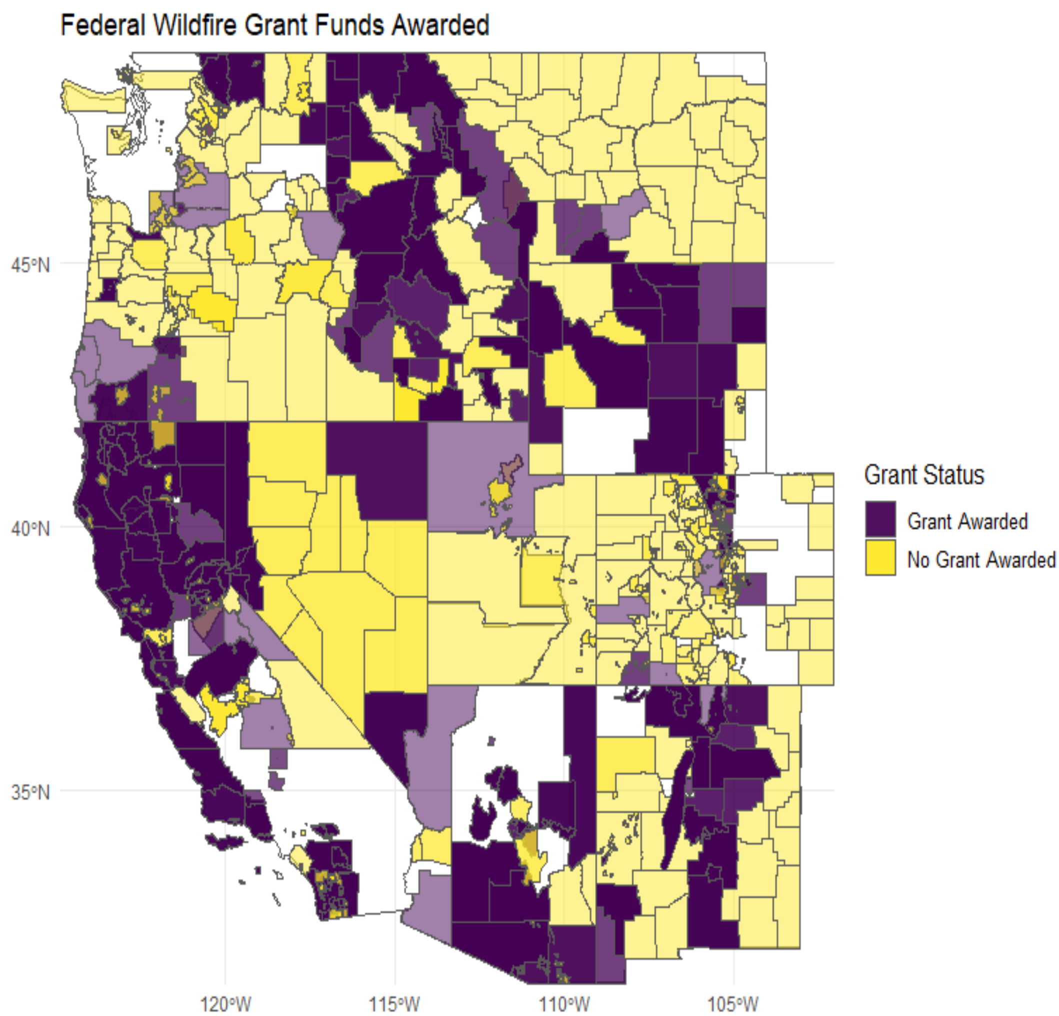

Figure 3.13: Spatial Distribution of Cooperative Forestry Assistance Grants awarded by CWPP jurisdiction for our study area.

before a CWPP was published, thus removing observations that were incorrectly coded as receiving federal funds. Figure 3.12 shows the spatial distribution of Cooperative Forestry Assistance funds to CWPPs throughout the study area. In Figure 3.13, we see a closer look within Colorado at the spatial distribution of federal grant funds allocated to existing CWPPs.

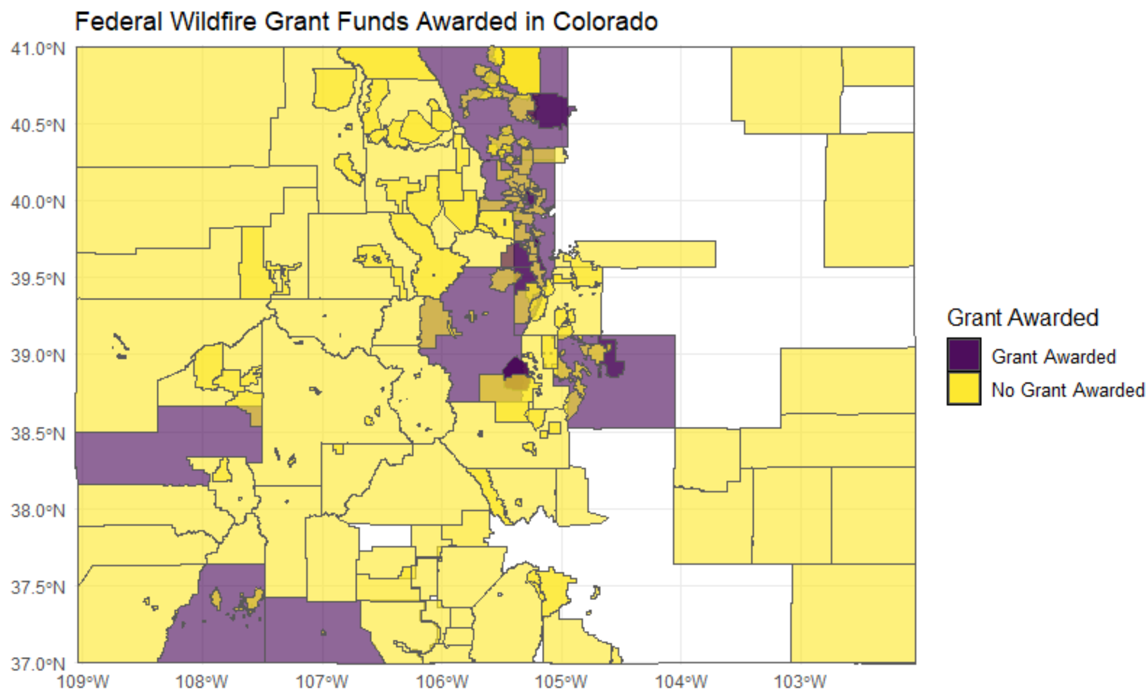

Figure 3.15: Spatial Distribution of Cooperative Forestry Assistance Grants awarded by CWPP with Colorado

Figure 3.14 shows the distribution of Cooperative Forestry Assistance grants by CWPP update status within our study area. This figure shows the frequency of updated CWPPs that have won federal grant funds compared to those that have not won federal funding from 2011 to 2022.

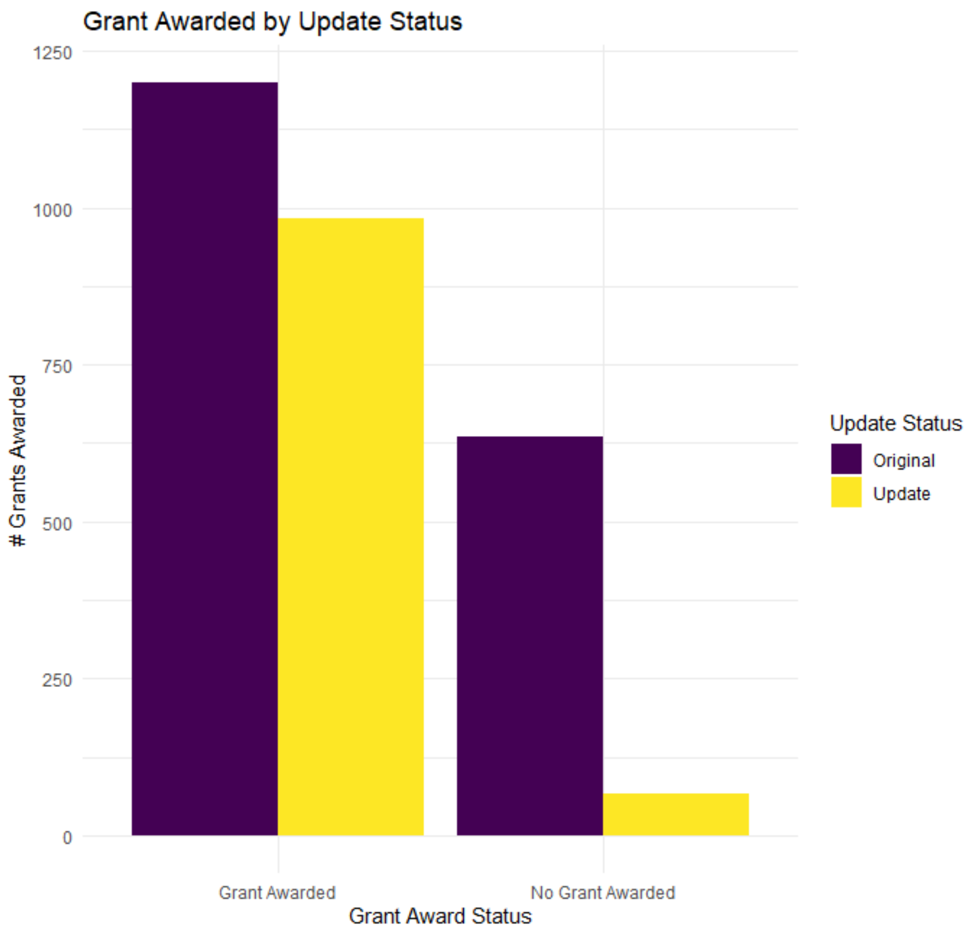

Figure 3.16: Bar Plot depicting the distribution of Cooperative Forestry Assistance Grants awarded by update status.

Chapter 4: Model

To estimate how biophysical, socio-economic, and community social capital impact the likelihood of winning federal wildfire mitigation or planning grant funding over time, we used a logistic Bayesian hierarchical approach using an Integrated Nested Laplace Approximation (INLA) method (Rue et al., 2009). Our model used scaled biophysical, socio-economic, and wildfire protection plan cross-sectional fixed effects and independent random effects for the state and year published for each CWPP. [2] Both fixed and random effects included in this model are structured as cross-sectional as they represent individual CWPP characteristics during a specific time.

Our base model is specified as follows:

$$Y_i \sim Binomial(p, n)$$

where Y represents our binomial likelihood for t variable, or whether a CWPP jurisdiction area has won grant funding, p represents the probability of winning grant funding, and n is the total number of observations in our model. Within our binomial model, the equation for our probability function is as follows:

$$logit(Y_i) = \beta_0 + \beta_{SVI}X_{i,SVI} + \beta_{WHP}X_{i,WHP} + \beta_{FC}log\,(X_{i,FC} + 1) + \beta_{SC}X_{i,SC} + \beta_{PL}X_{i,PL} + \beta_{UP}X_{i,UP} + \mu_{i,CWPP} + \mu_{i,state} + \mu_{i,Year} + \epsilon_i$$

[2] Variables included in the model were scaled by dividing each observation by the standard deviation meaning that change in one standard deviation results in a change of each variable's posterior parameters (further discussed in the Chapter 5). Our variables were scaled in order to optimize the fit of the model.

where FC_i= financial capacity; SC_i= document density scores for named entities at the 5% cutoff parameter[3]; SVI_i= social vulnerability scores; WHP_i= wildfire hazard potential scores; UP_i= binary variable of whether the CWPP is an update to a previous plan; PL_i= percentage of public land per CWPP jurisdiction area; and ε_i= the random error term. Each of our β terms represents the mean intercepts for each covariate parameter within our model.

In addition, we incorporated Gaussian random effects into our model to capture unexplained variability within our model that our fixed effects cannot explain. These covariates were included as random effects to provide an additional dimension to our analysis, capturing year-specific, state-specific, and individual CWPP-specific influences that affect the likelihood of winning federal grant funding. These random effects allow us to account for variations in our outcome variable (probability of winning federal grant funding) specific to different levels within our dataset beyond what can be explained by our fixed effects, such as community plan-level covariates.

For the random effects for states included in this model, we capture variation in grant funding outcomes associated with different states in our study area. For instance, some states exhibit higher or lower success rates in securing wildfire mitigation assistance funding, even after accounting for all other factors in our model. The notation signifies that these random effects are assumed to follow a normal distribution with a mean of 0, indicating that, on average, states do not have a higher or lower advantage or disadvantage in securing federal grant funding, as well as the estimated variance of our state random effect representing the degree of state-level variability contributing to the overall variation in our outcome variable.

[3] Rather than estimating three models for each of our measurements of social network density within each CWPP and their subsequent updates, we found similar outcomes at the 50% and 100% cutoff parameter based on the percentage of document length.

Additionally, the random effect for CWPP publication years accounts for variations in grant funding outcomes over different CWPP publication years across our study period. Including this random effect allows us to capture unobserved temporal dynamics and variation associated with when these plans were published. Changes in funding success rates across years, even after considering fixed effects, can be attributed to these random effects.

Our Bayesian hierarchical model estimates posterior parameter densities based on a function of prior expectations and our observed data. However, there are no empirical priors for fitting our model for the Western United States. Due to the lack of previous empirical priors, we implement penalized complexity priors (P.C. priors) on our model hyperparameters that provide a weakly informative estimation of our prior expectations (Simpson et al. 2017; Fuglstad et al. 2018). P.C. priors penalize deviations from the base model, thereby regulating model flexibility, reducing over-fitting, and improving predictive performance (Moraga, 2019). The estimated posterior density estimates measure each parameter value by the estimated probability of a given value based on our observed data. Results from our model are shown as a 95% credible interval by identifying quantile values at 0.025 and 0.975 of each of our posterior parameters' densities. Credible intervals give a range of values predicted to contain the true parameter estimate with a 95% probability.

Chapter 5: Results and Discussion

The following section discusses the results of our three models testing biophysical, socio-economic, and three levels measuring social network densities within published CWPP and updates. This model's results show these factors' effects on the probability of receiving Cooperative Forestry Assistance grant funding for wildfire mitigation projects.

Our model estimates the likelihood of communities with a CWPP-in-place receiving federal wildfire mitigation funding based on our fixed and random effects. The estimated posterior parameter β_x indicates that a one-unit change in variable X predicts an β_x increase in the natural log of the federal wildfire mitigation grant funds won. We can then exponentiate our posterior parameter to give the predictive change of our outcome variable (federal wildfire mitigation grant funding).

5.1 Discussion of the first hypothesis

Figure 5.1 plots the posterior means and credible intervals representing 95% of our posterior distribution for all model variables. Variables that do not span zero can be considered "statistically significant." From this model, we find evidence to support that *communities that have more financial resources to draw upon will win more federal grants* (H2). We find that an increase in the financial capacity of a community with a CWPP increases the likelihood of receiving federal wildfire mitigation grant funding. Table 5.1 shows a positive and significant relationship between a community's financial capacity and winning federal grant funds. From these results, we see evidence that as a community's financial capacity, or as a community's average real estate property taxes, increases, there is an increase in the probability of winning federal grant assistance to mitigate the effects of wildland fire. Our results show that federal grant funds are more likely to be allocated to wealthier communities with more resources than poorer communities. These findings suggest that an inverse response relationship exists between the government's financial resources, or the financial capacity of a community, and the

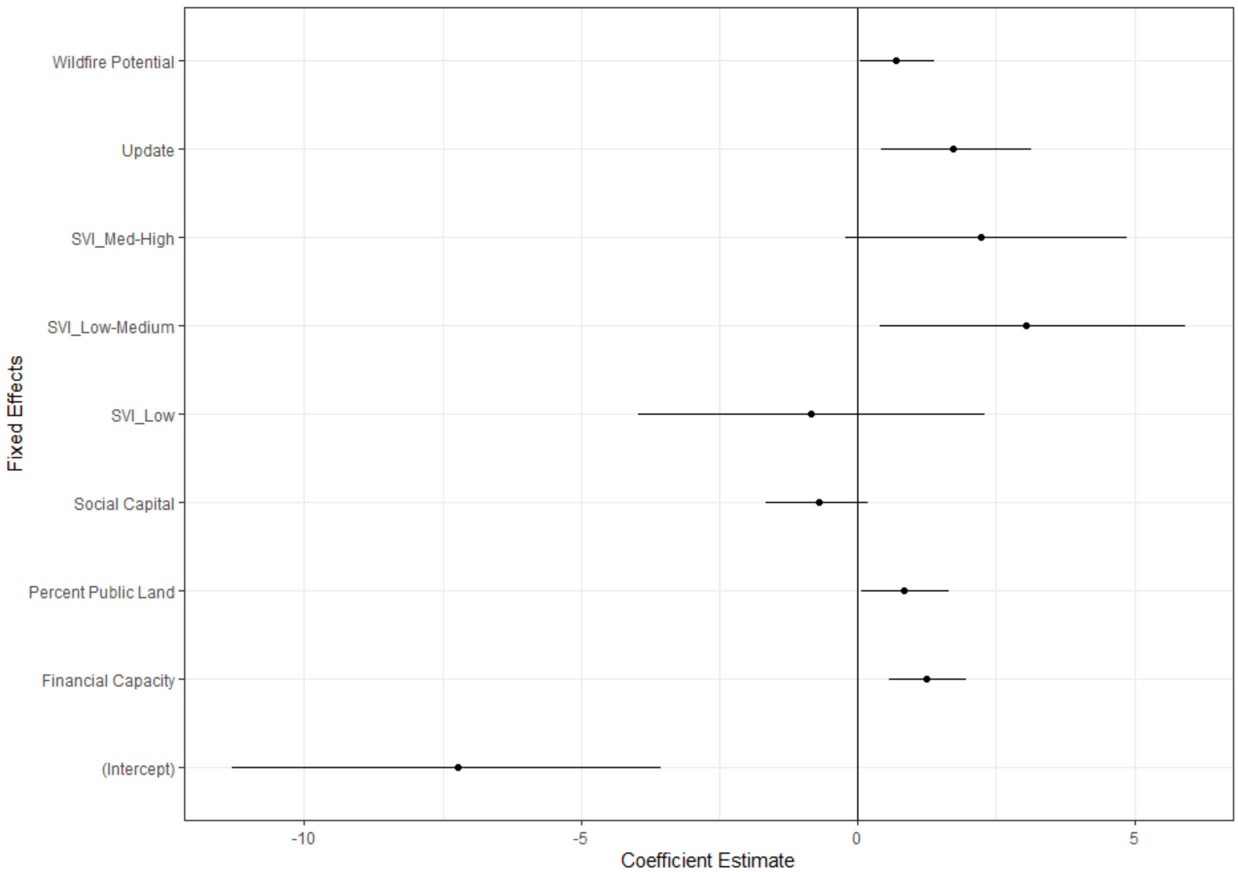

Figure 5.1: depicts of the 95% credible intervals for posterior distributions with the mean of our credible intervals represented by the dots.

allocation of federal grant funds. Specifically, wealthier communities with access to more resources are more likely to receive wildfire mitigation grant funds than poorer communities. Meaning that federal grant funds may be allocated to communities with the resources rather than considering socio-economic conditions when allocating wildfire mitigation funds.

In addition to a community's financial capacity, our results suggest a significant and positive relationship between a community's social vulnerability score and the probability of winning federal grant funding. While we do not have a statistically significant coefficient between social vulnerability scores within the Low or Medium-High percentile categories, we find the inverse for communities within the Low-Medium percentile range (SVI Scores with a range of 0.25 – 0.50). Our results do show consistency with existing literature, as communities with a Low-Medium social vulnerability score are more likely to receive federal wildfire assistance funds than communities that are more vulnerable to the effects of wildland fire (Ojeiro et al. 2011).

Of our biophysical and plan-based variables, we find that wildfire hazard potential ($\mu = 0.692$), the percentage of public land within a CWPP boundary ($\mu = 1.236$), and whether a CWPP has a published update or revisions ($\mu = 1.711$) are significant predictors of winning federal grant funding. All of these variables are shown to substantially impact the likelihood of receiving wildfire mitigation grant funding from the USFS. However, within our posterior parameters, we find a wide distribution of effects between the lower and upper bounds of our posterior distributions for wildfire hazard potential (0.040, 1.377), percentage of public land (0.570, 1.966), and update status variables (0.426, 3.143).

Table 5.1: Posterior and Hyperparameter distributions for the model including number of observations, mean, standard deviation, and lower and upper bounds of the credible intervals for each variable

Variables	*N*	*mean*	*sd*	*LowerCI*	*UpperCI*
(Intercept)	N =2884	-7.237	1.968	-11.306	-3.559
SVI_Low	N = 426	-0.843	1.597	-3.973	2.305
SVI_Low-Med	N = 1131	3.040	1.405	0.406	5.927
SVI_Med-High	N = 1126	2.221	1.294	-0.211	4.876
Wildfire Potential	N = 2884	0.692	0.340	0.040	1.377
% Public Land	N = 2829	1.236	0.355	0.570	1.966
Social Capital	N = 1471	-0.695	0.466	-1.650	0.184
Financial Capacity	N = 2878	0.835	0.398	0.076	1.641
Update	N = 2884	1.711	0.691	0.426	3.143
Random Effects					
State	N = 2884	0.071	0.030	0.029	0.146
CWPP Name	N = 2884	0.022	0.004	0.015	0.031
Year Published	N = 2884	12.610	13.588	1.977	47.841

5.2 Discussion of the second hypothesis

We fail to find evidence from our results that measured social capital affects the likelihood of winning federal wildfire mitigation grant funding. While social capital appears to have a negative relationship with our dependent variable, since the bounds of the confidence interval span zero, we cannot confidently say that it is correlated with federal grant funding distribution. Our posterior parameters suggest having a negative relationship between the likelihood of winning federal grant funds and named entity density within a CWPP.

In our model, we incorporated three random effects to capture variability in the allocation of federal grant funds: Year CWPP was Published, State, and observations for each CWPP nested within each CWPP name. The precision values for our random effects represent the inverse in the variance and indicate the level of shrinkage applied to the random effects. Higher precision values indicate less shrinkage, allowing random effects to considerably impact the model more. In contrast, lower precision values imply stronger shrinkage and reduce the influence of random effects on our model. These random effects allow us to account for unexplained heterogeneity at different spatial and temporal levels.

The year a CWPP was published random effect represents the variability associated with different years in which CWPPs and respective updates or revisions were published. This random variable captures the temporal variations in factors influencing the likelihood of communities receiving wildfire mitigation project funding. The estimated hyperparameter provides insight into the average level of variability among allocated federal grant funds across different years and based on when a particular CWPP was published. In Table 5.1, our results for the Year Published random effect show a high amount of variability in grants distributed across different years. Since our Year CWPP Published random effect has a higher mean, we see less variability, suggesting that the year a CWPP was published has a more concentrated and narrow impact on the likelihood of receiving federal grant funds. However, the width of our confidence interval (1.977, 47.841) and the magnitude of our random effect standard deviation (13.588) within our random effect of Year Published suggests that the year a CWPP was published has a high level of uncertainty and that our Year Published random effect is not significantly influencing our model (Figure 5.2).

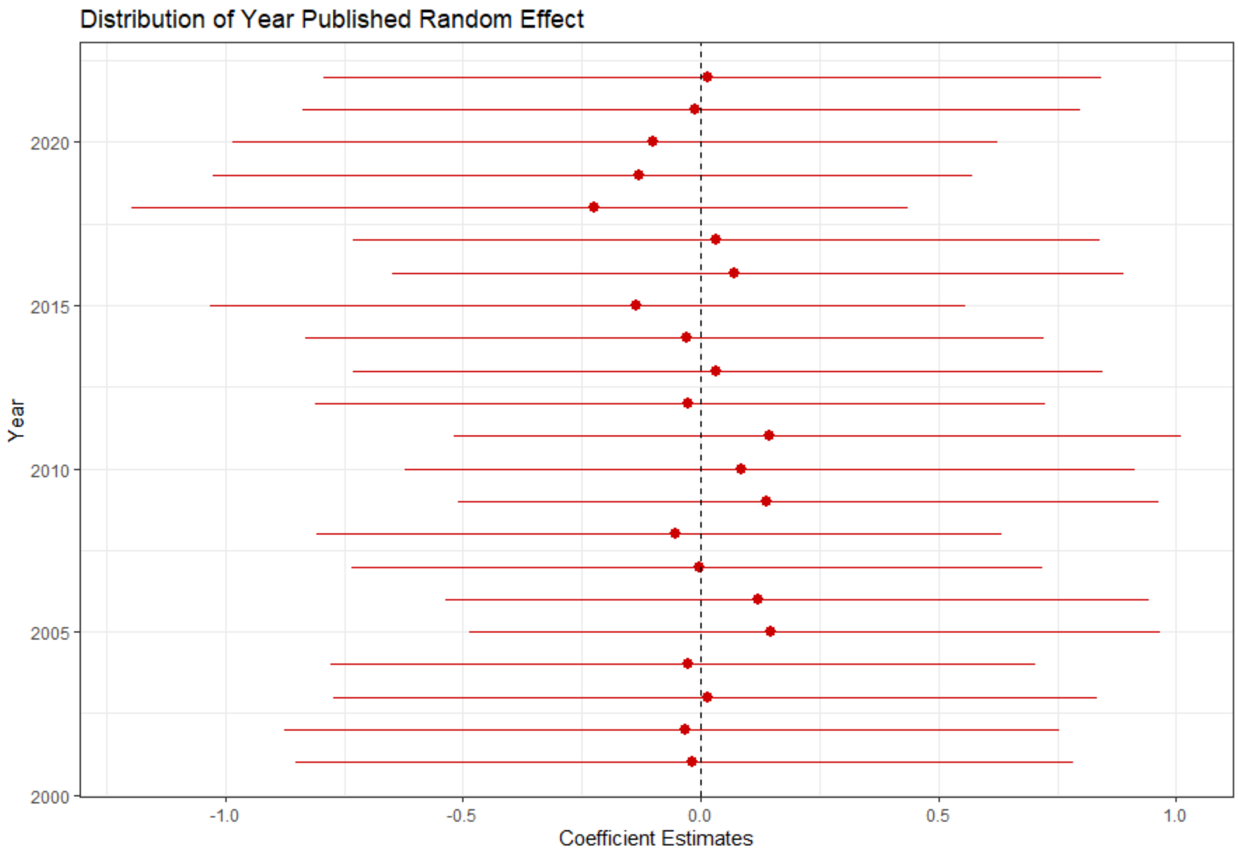

Figure 5.2: Depicts of the overall distribution of our Year Published random effect estimate. Coefficient estimates are represented by dots with the 95% confidence interval represented by lines.

Our State random effect captures the differences in our dependent variable due to the spatial differences between the locations of published CWPPs. The estimated hyperparameter associated with our State variable informs us of the average level of variability for our dependent variables across states. Table 5.1 shows the coefficient estimate (0.095) and standard deviation (0.030) confidence interval (0.049, 0.169) for our State random effect. From the results found in Table 5.1, we can see that we observe a moderate variability in the likelihood of receiving federal wildfire mitigation grant funds across states in our model. The overall distribution of our State random effect is visualized in Figure 5.3.

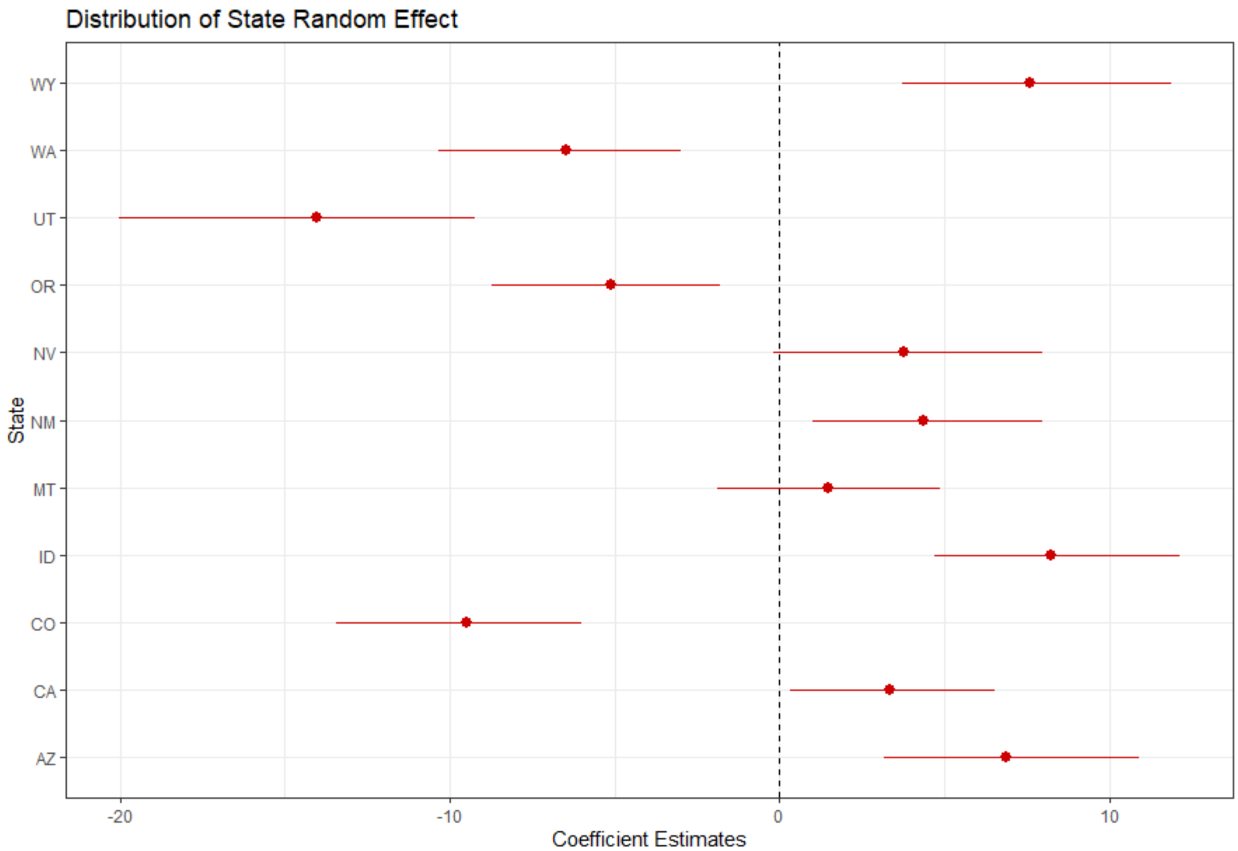

Figure 5.3: depicts of the overall distribution of our State random effect estimate. Coefficient estimates are represented by dots with the 95% confidence interval represented by lines.

Within our model, we included a random effect variable for individual CWPPs included within the model. Cooperative Forestry Assistance grants included in this study were distributed from 2011 to 2022. Table 5.1 shows the coefficient estimate (0.025), standard deviation (0.004), and lower and upper bounds of our confidence interval (0.018, 0.035). Based on the results from Table 5.1, our random effect for individual CWPPs suggests a high level of precision and a low level of variability within our hyperparameter due to the small mean and standard deviation values. From Table 5.1, we see that our CWPP and State random effects have a smaller precision value, suggesting that it is influencing the model, while the Year Published random effect has a larger precision value, meaning it is not influencing the model.

To control the complexity of our model and improve its performance, we employed penalized complexity priors for our precision parameters. Since we only have limited information based on the strength, magnitude, and variability from prior research (Ojeiro et al. 2011), we choose to structure our priors around a more diffuse prior distribution and a narrow scale of our prior distribution. The selection of our priors means that our model allows for a broader range of possible values for our precision parameters and structuring our model for more robust regularization for our parameter scale to account for previous findings. The diffuse shape and small scale for our prior parameters allow for a more reasonable range of values and control for more precise estimates for our hyperparameters.

The results from this model provide evidence consistent with previous literature that biophysical risk factors (wildfire hazard potential) are a significant predictor of receiving federal wildfire grant funding. We find a positive relationship between wildfire hazard potential for CWPP areas and the likelihood of receiving grant funding, or as wildfire risk increases, so does the probability of receiving grant funding. Related to wildfire hazard potential, we see a significant positive relationship between the percentage of public land within a CWPP jurisdiction area and increases in the odds of winning federal grant funding for wildfire mitigation projects. Our results suggest that the more public land within a CWPP jurisdiction area may bond public and private interests regarding wildfire mitigation and planning in the area and may lead to more federal resources implemented to protect communities against the impacts of catastrophic wildfire events.

In addition, we find evidence in our model that communities more vulnerable to wildfire events are less likely to receive federal grant funds. Our model finds a positive significant relationship between communities within the "Low-Medium" SVI percentile category and the likelihood of winning federal wildfire mitigation funding. These findings are consistent with previous literature on federal grant allocation for wildfire mitigation. They may be explained by the limited involvement of more vulnerable communities in the Cooperative Forestry Assistance grant program or potentially pursuing other external funding sources at the federal, state, or local levels. Additionally, we see that there is both a negative relationship with communities in the Low SVI category, as well as, on average, a positive relationship with communities in the Medium-High SVI category. However, we do not find a statistically significant relationship between these categories and winning federal grant funds.

In addition to our model findings that less vulnerable communities receive additional federal financial support than more vulnerable communities, the financial resources a community can draw upon (e.g., financial capacity) have a positive and significant relationship with the odds of winning federal grant funding. Evidence from our model shows that as a community's average real estate property tax revenues increase, it also increases the odds of winning federal grant funds over time. The relationship between financial capacity and federal grant funding allocation provides evidence to support H1 (*communities that have more financial resources to draw upon will win more federal grants*).

Of our CWPP-based variables (social capital & plan update status), we find mixed results for variables. For measures of social capital within each CWPP with subsequent updates and revisions, we do not find evidence to support H2 (*communities with higher social capital will win more federal grants*). Since our credible intervals for social capital measures for named entities with 5% of the total document length span zero, we cannot determine if there is any significant relationship between social capital and the likelihood of winning federal wildfire mitigation project funding. Interestingly, we find that trend towards a negative relationship with the odds of winning federal grant funding. One possible explanation may be due to the nature of the Cooperative Forestry Assistance grant data. This grant program was initially created to access and support forestry and fire departments in rural areas. These areas may have less diverse and expansive social capital, which may explain the evidence provided by our model.

To summarize, the biophysical characteristics of a CWPP area are significant predictors of winning Cooperative Forestry Assistance grant funding. Specifically, wildfire hazard potential was positively associated with winning federal grant funds over our study period. In addition, we do see that when controlling for geographic make-up, specifically the percentage of public land within a CWPP planning jurisdiction, we see a significant positive result of winning grant funding for wildfire mitigation and planning activities. Our socio-economic control variables have a statistically significant and positive relationship with winning grant funding, suggesting that communities with more resources can leverage their financial capacity to pursue and win grant funds. In contrast, we do find some evidence that socially vulnerable communities within the Low-Medium category are more likely to win grant funding, consistent with existing literature (Ojerio et al. 2011). Social capital was found to have a negative relationship with the likelihood of receiving wildfire mitigation grant funding, but the effect was not statistically significant. These results may be due to how we measured social capital from each CWPP. Another possible explanation may be due to the geographic composition of some communities, as differences between social networks may exist between urban and rural communities.

However, our model shows that CWPP jurisdiction areas that have created updates, revisions, or new CWPPs are more likely to win federal grant funding. Evidence from our model suggests that continued support for existing CWPPs around the Western United States increases the likelihood of winning federal grant funding even if social capital is not strengthened between CWPP updates over time. Further research should expand upon the relationship between social capital in communities and updates or revisions to existing CWPPs to better understand the interaction between these two variables and their effects on wildfire mitigation and planning over time.

5.3 Limitations

Using text scraping and natural language processing approaches, we observe named entities within an individual mitigation plan for all original and updated CWPPs throughout the Western United States. By measuring the number of named entities and their relative distance within a document to others, we capture a broad overview of the network structure within an individual CWPP. However, there are limitations to our methodological approach centered around how social capital was measured for this study.

First, it is essential to note the considerable error resulting from our named entity recognition methods. While hand-coding efforts were conducted to address and minimize that amount of from named-entity recognition within each CWPP, it is difficult to conclude that error in our observations no longer exists due to the large number of observations. Second, our methods to measure social capital centered around the number of entities mentioned between each other for each CWPP; therefore, our social capital measure is dependent on the total length of each document. Since a large portion of CWPP updates included are short addendums or appendices to original fire mitigation plans, the shorter length of these updates may influence the changes in social capital scores we observe. In addition, since these measures focus mainly on named entities and their position within each document, we may only capture the number of entities within the planning process or project implementation rather than the structure of social connections between stakeholders involved within a CWPP planning process. This means we may be only capturing stakeholder involvement throughout individual CWPP planning processes rather than measures of collaboration necessary to get an accurate estimate of social capital. In addition, we mainly focused on the outcomes of these collaborative planning processes through a completed and published CWPP. Further research on CWPPs can benefit from the addition of meeting minutes during the planning process to gain insight into the roles of particular stakeholders in shaping content during the creation or update process of a CWPP.

Future research should focus on refining our document analysis methodology to better capture and quantitatively measure social capital via document analysis. Additionally, qualitative methods to measure social capital, such as surveys or interviews, may be beneficial to better capture the drivers and interactions behind stakeholder involvement and network structures within collaborative wildfire planning. Most research on collaborative governance and social capital has relied upon survey-based approaches (Ingold and Leifeld 2016; Henry et al. 2011; Scott et al. 2018). Theoretical concepts understood to be critical factors in social network structures and social capital, such as trust, stakeholder reputation, norms, and reciprocity, are likely not observed from the methodology used in this study (Berardo & Scholz, 2010; Scott et al., 2018). Instead, using survey-based approaches provides many benefits to studying the drivers of collaboration and social capital that test-based methods cannot replace. Surveys and other instruments can provide insight into assessing stakeholders' perspectives involved in a complex planning process. Surveys also collect background data about participating stakeholders not found within a completed wildfire mitigation plan. Pairing text-mining methods to capture stakeholder involvement with survey-based assessments appears beneficial for future analysis. For example, wildfire mitigation plans and meeting minutes can be mined to observe stakeholder participation in the planning process. At the same time, surveys or interviews can be utilized to collect additional data on social networks within a CWPP area that may not be observable or provide meaningful context to observations found through text mining.

Chapter 6: Conclusion

This research adds to the growing body of literature analyzing the relationship between biophysical, socio-economic, and social capital variables on the distribution of USFS grant funds. Through the interaction between USFS sub-award grant funds and CWPP data, we explore the several variables influencing federal wildfire mitigation grant allocation to at-risk communities. We find a significant positive relationship between a community's financial capacity and the likelihood of winning federal grant funds over time. In addition, we find that communities with published updates or revisions to previous CWPPs have increased odds of receiving federal wildfire mitigation grant funding over time. Furthermore, strong evidence suggests that continued collaborative wildfire planning and more significant financial resources that community officials can draw upon increase the likelihood of winning federal grant funding for wildfire mitigation projects to improve community protection. These results contribute to the expanding body of literature on collaborative wildfire planning and federal grant allocation and provide insight into the potential impacts on communities at risk of wildfire events.

This study supports previous literature on collaborative wildfire planning and federal grant allocation decision-making. Within collaborative community wildfire plans, we find evidence that wildfire hazard potential scores have a significant relationship with the odds of winning federal grant funding. In addition, communities within the “Low-Medium” SVI percentile range have increased odds of winning federal grant funding. Such evidence supports previous literature, such as Ojeiro et al., 2011, suggesting that communities more vulnerable to wildfire events are not receiving federal support for wildfire mitigation or community protection and preparedness. Instead of community vulnerability to wildfire events being significant predictors of receiving federal grant funding, the land’s physical attributes may govern grant allocation decisions. However, this may be due to communities with higher levels of vulnerability pursuing external funding from other sources, such as other federal or state grant opportunities, or not seeking external funding due to budget or personnel constraints (Ojerio et al., 2011).

Again, we fail to find a statistically significant relationship between social capital and winning wildfire mitigation grant funding and validate H1. With additional money and time, this research could be improved or expanded to better measure social capital within communities with a CWPP or other federal grant programs. Future research could benefit from the inclusion of additional methods, including on-the-ground surveys, interviews, or community meetings, to measure social capital better quantitatively in these communities. Additionally, further research may be needed to refine the methodology for measuring social capital via automated coding procedures.

Insights provided in this study may be helpful to better inform federal agencies that provide grant opportunities, such as the USFS, to better reach low-income and vulnerable communities with resources for wildfire mitigation and planning projects. Because a community's financial resources and CWPP update status increase the odds of receiving federal project funding, and socio-economic and demographic factors may decrease the odds of federal funding, in the future, the USFS and other federal agencies may create additional grant programs targeting low-income and vulnerable communities and or altering existing grant programs to provide a more equitable distribution of funds to improve wildfire mitigation and community protection in the Western United States. Understanding the conditions that underlie the distribution of federal grant funds is essential due to the growing risks posed to Western communities by climate change and how continuous, collaborative planning processes may mitigate future destruction from wildfire events.

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