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Integrated wildfire risk management: Measuring risk perceptions, simulating fire severity maps, and visualizing fire risk in the California Wildland-Urban Interface

A dissertation submitted in partial satisfaction of the requirements for the degree of
Doctor of Philosophy

in

Environmental Systems

by

Samrajya Bikram Thapa

Committee in charge:

Jeffrey S. Jenkins, Chair
Professor Anthony LeRoy Westerling, Major Advisor
Spencer Castro

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University of California, Merced
2024

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Abstract of the Dissertation

Integrated wildfire risk management: Measuring risk perceptions, simulating fire severity maps, and visualizing fire risk in the California Wildland-Urban Interface

By

Samrajya Bikram Thapa

Doctor of Philosophy, Environmental Systems Program
University of California, Merced, 2024
Dr. Anthony LeRoy Westerling, Graduate Advisor

The escalating frequency and severity of wildfires in California have precipitated substantial economic losses and social strains, underscoring the imperative to comprehend the dimensions of wildfire management. This dissertation amalgamates three pivotal research endeavors focusing on different dimensions of wildfire risk: perceptions among wildland-urban interface residents, predictions of wildfire burn severity, and visualization of uncertainty. The surge in wildfires, coupled with the increasing population moving to Wildland-Urban Interface (WUI) areas, highlights the urgency of understanding both the physical and human dimensions of wildfire risk management. While various management practices involving communities have emerged as favored solutions, barriers to their implementation persist. Understanding public attitudes and perceptions regarding these practices is essential for successful fire management efforts.

Furthermore, the warming climate and increasing fuel loads due to fire exclusion, compounded by climate change and drought, have led to more frequent, extensive, and severe wildfires. Burn severity, a metric that measures the ecological impact of fire on vegetation, is crucial for post-fire management. The Composite Burn Index (CBI) emerges as a preferred method of characterizing fire effects due to its comprehensive approach, offering a systematic and visually intuitive estimation of ecological impacts following a fire.

Effective wildfire severity and risk information to stakeholders is paramount for enhancing understanding and promoting resilience. However, conveying complex information poses significant challenges. Visualization techniques play a vital role in conveying risk information and aiding comprehension of complex wildfire-related information. This research introduces a scalable visualization model for a use in predicting and managing the complex dynamics of wildfire occurrences.

This dissertation advances our understanding of wildfire management by elucidating the complex interplay between public perceptions, burn severity estimation, and risk visualization. By integrating social perspectives with empirical modeling and visualization techniques, it offers multifaceted approach to addressing the challenges posed by wildfires in California. The insights garnered from this dissertation are crucial for informing policy decisions, guiding mitigation efforts, and fostering community resilience in the face of escalating wildfire threats.

Keywords: wildfire management, burn severity, risk communication, uncertainty, visualization, decision-making

Chapter 1

Dissertation Introduction

Recent wildfires in the California have led to substantial economic losses and social stresses (Mell et al. 2010; Schoennagel et al. 2017). This surge in wildfires highlight the need for understanding the dimension of wildfire management (Absher et al. 2012) especially for policies and programs that affect property losses in the WUI. With more people moving to the WUI every year, there is a confluence of people and property located adjacent to or within areas of extreme wildfire risk. The continuing encroachment of human settlements into fire-prone areas and extreme fire seasons in recent years make it urgent that we better understand both the physical and human dimensions of managing the risk from wildfires.

Since local people usually have the most at stake in the event of a major fire, they should clearly be involved in mitigation efforts (Treue and Nathan, 2007). Numerous management practices such as prescribed fire, mechanical fuel reduction, defensible space, etc. are being practiced that directly involve communities (Blanchard and Ryan, 2007; Fischer 2011; Jarrett et al. 2009; Kreuter et al. 2008). Although acceptance of these practices has emerged as a favored solution and has increased across diverse geographic regions, various barriers to implement these actions remain (Fischer 2011; Kobziar et al. 2015; McCaffrey et al. 2012). Community members may not perform these risk reduction activities due to various key components lacking, such as common goals and shared vision, relationships and trust, place attachment, information sharing, and community outreach and education (McCaffrey and Olsen 2012; McCaffrey et al. 2013; Shindler 2007; Vaske et al. 2007; Winter et al. 2004). Therefore, to develop successful fire management efforts, it is necessary to understand public attitudes, perceptions, and beliefs about implementing different practices (Bright and Burtz 2006; Gunderson and Watson 2007; Holmes et al. 2007). Given the increased attention to wildfire risk, a significant body of work from the social science perspectives has examined wildfire mitigation behaviors by vulnerable community members (Brenkert et al. 2012; Stidham et al. 2011; McCaffrey and Winter, 2011). While published studies have documented fire management practices to reduce impacts of wildfire (McCaffrey and Olsen 2012; Toman et al. 2011) limited research has addressed public attitudes and behaviors regarding those management practices to conserve ecosystems and protect communities. Limited quantitative exploration of the influence of community members beliefs and characteristics on wildfire mitigation behaviors have been found in published literature. This study seeks to fill that gap. Such an examination is essential because residents and communities make important decisions based on their perceptions and locations within a local landscape. Wildfire social science research often finds risk perception correlated with risk mitigation behavior but relationships among these and related variables are complex.

Adding to this complexity are a warming climate compounded by increasing fuel loads as a result of fire exclusion, together with climate change and drought, the frequency, extent, and severity of the wildfires are surging ((Westerling et al. 2006; Westerling 2016; Abatzoglou and Williams, 2016). After wildfire occurrence, a number of key ecological processes (e.g., tree and vegetation mortality, regeneration by seeds and resprouts) gets affected to different degrees, depending on the extent and the severity of the fire (Spracklen et al., 2009; Cansler and McKenzie, 2014; Hurteau et al., 2014). Understanding the severity of fire is especially important for post-fire management. One metric that provides context for the biophysical disturbance of vegetation, as well as socio-economic impact of fire, is burn severity.

Burn severity, synonymous with fire severity, measures the ecological impact of fire on vegetation, considering the physical changes resulting from combustion and heating (Ryan, 2002; Gauthier et al., 2009). Factors influencing burn severity include topography (elevation, aspect, slope), weather (wind, temperature, fuel moisture), and fuels (stand structure, fuel loads, forest species composition) (Alexander et al., 2006; Miller et al., 2012; Prichard and Kennedy, 2014; Preisler and Westerling, 2007; Westerling et al., 2009). Climate during the fire year significantly influences burn severity occurrence and extent (Keyser and Westerling, 2017; Keyser and Westerling, 2019). Topography affects burn severity by modifying biophysical gradients like solar radiation and topographic moisture, thereby altering fuel characteristics (Birch et al., 2015; Holden et al., 2009; Parks et al., 2018). Fuel properties, including composition and availability, also play a crucial role in determining burn severity patterns (Finney, 2001; Cumming, 2001). Additionally, factors like landscape arrangement and tree size influence burn severity at different scales (Odion et al., 2004; Roman-Cuesta, 2002).

The Normalized Burn Ratio (NBR) is the most commonly used index for measuring burn severity (Eidenshink et al. 2007; French et al. 2008; Parsons 2003), a spectral index obtained from the ratio between near infrared and short-wave infrared measurements, which are sensitive to vegetation and exposed soil cover (Key and Benson 2006). However, the Composite Burn Index (CBI) is preferred over the Differenced Normalized Burn Ratio (dNBR) method due to its comprehensive approach in characterizing fire effects. CBI integrates multiple environmental variables to provide a holistic assessment of burn severity at point locations, making it suitable for diverse ecosystems and regions. Unlike dNBR, which relies solely on spectral indices and may lack standardized threshold values, CBI offers a systematic and visually intuitive estimation of ecological impacts following a fire. Additionally, CBI's ability to tabulate severity measurements within specific plots allows for a more precise and localized analysis of burn severity, particularly beneficial for mapping potential severity in complex landscapes such as urban and wildland-urban interface environments. This comprehensive approach enhances the sensitivity of burn severity metrics, facilitating better understanding and management of fire risks, vulnerability assessments, and resource planning.

Effective communication of wildfire severity or wildfire risk maps or information to various stakeholders/audience is essential for enhancing the understanding and promoting resilience in the face of wildfires. However, conveying complex information about wildfire severity and risk, particularly uncertainty associated with these assessments, poses significant challenges.

Visualization techniques including static and animated forms, are crucial in wildfire risk communication for several reasons. Static visualizations provide a snapshot of data, such as maps delineating high-risk areas, which are essential for planning and preparedness by illustrating potential impact zones and facilitating strategic decision-making. Animated visualizations add a temporal dimension, showing the progression of a wildfire over time, which is invaluable for emergency response and public information as it allows for the visualization of fire spread and evolution, aiding in situational awareness and the anticipation of future developments. Both static and animated forms play a pivotal role in making complex data comprehensible, helping stakeholders and communities to understand and respond to the risks of wildfires effectively. These visualization tools not only support informed decision-making but also promote engagement and proactive measures by vividly illustrating potential risks and the dynamic nature of wildfire events.

Chapter 1 here is an overall introduction to the dissertation. This dissertation synthesizes three distinct research projects focusing on wildfire risk: perception among California wildland-urban interface (WUI) residents, prediction of wildfire burn severity, and visualization of uncertainty. Integrating these aspects fosters a holistic approach to wildfire management. Public perceptions inform policy formulation, while accurate burn severity estimation guides mitigation efforts. Effective risk communication enhances public awareness and preparedness, ultimately contributing to more resilient communities and ecosystems.

Chapter 2 delves into the perceptions of wildfire management practices, employing both qualitative and quantitative methods to gauge community attitudes and support for mitigation strategies. The findings from this study provided insights into community members' perceptions of wildfire risk; knowledge and support for the use of wildfire management practices; and opinions about their role in wildfire management planning. These findings have been documented in a research paper titled "**Perceptions of wildfire management practices in California wildland-urban interface (WUI)**" which has been published in "***Environmental Advances***" journal.

Chapter 3 introduces a novel methodology for mapping burn severity, utilizing empirical modeling and simulation to predict fire outcomes under varying scenarios. Through the development of statistical methodology, this study not only estimates the probability of various burn severity levels but also identifies key variables influencing these probabilities within the wildland-urban interface (WUI) region of northern California. Factors such as vegetation type, topography, and weather conditions area analyzed to elucidate their roles in shaping burn severity outcomes. This comprehension investigation contributes valuable insights to wildfire risk assessment and mitigation strategies, aiding in the effective allocation of resources and implementation of targeted measures to reduce the impact of wildfire on communities and ecosystem.

Chapter 4 systematically utilizes data visualization, integrating historical and predictive data to construct static and animated maps that reveal the progression and potential future patterns or risk of wildfires. By employing models to simulate fire presence, absence, and size, this study aims to generate robust visual tools to better inform stakeholders, aiding in decision-making processes. The study seeks to enhance preparedness and resilience against the increasing threat of wildfires in California, with methodologies that could be adapted to diverse ecological and climatic contexts.

Chapter 5 gives overall conclusion of the dissertation.

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Chapter 2
Perceptions of wildfire management practices In a California wildland-urban interface

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Abstract

Wildland-urban interface (WUI) regions are exposed to increasing wildfire risk due to the effects of accelerating climate change on fuel flammability, as well as a legacy of fire exclusion that promoted fuel accumulations in seasonally dry forests of western US. State and Federal land management agencies are evolving policies and directing new resources to reduce the effects on homes and infrastructure in the WUI through fuel reductions and enhanced fire management measures. A widely supported strategy is to involve homeowners and their communities in efforts to reduce their exposure to wildfire risk by changing the structure and amount of unwanted vegetation around vulnerable structures, among other practices. Although these practices can reduce vulnerability to wildfires, people are hesitant to implement them for a variety of reasons broadly related to the issues of capacity and access to information. Based on Theory of Planned Behavior (TPB) conceptual framework, this study identifies salient factors impeding individual actions to reduce wildfire risks, and how those factors influenced willingness to participate in wildfire mitigation behaviors. This study examined intention to use prescribed fire and defensible space among community members as a wildfire management tool. Results from this study suggest intentions to undertake these wildfire management practices are positively associated socio-economic characteristics, along with knowledge regarding best practices, some perceived reasons, or hindrances to implementation, and ability to collaborate with others. These research findings have implications for designing and implementing policy instruments and improving community members' decision-making regarding practices to mitigate fire risk.

Keywords: Collaboration, Defensible space, Prescribed fire, Theory of planned behavior, Wildfire.

1. Introduction

Wildfire is undoubtedly one of the most significant and widespread natural disturbance agents in the Western United States, especially in California. Anthropogenic climate change has contributed to higher temperatures, drier conditions, and earlier snowmelt in California, which in turn has increased the risk of wildfire. Along with climate change and severe drought, the frequency and extent of wildfires and the area burning at high severity are surging (Abatzoglou and Williams 2016; Westerling et al. 2006; Sam et al. 2022; Xu et al. 2022). Increasing fuel loads resulting from fire exclusion and other management activities, and expansion of human settlements into fire-prone vegetation driven by population growth and sprawling development patterns, have both contributed to more frequent and costlier large wildfires in recent years (Radeloff et al. 2005; Sam et al. 2021; Theobald and Romne, 2007). The occurrence of large, devastating wildfires emphasizes the need to comprehend all of their components, particularly in the wildland-urban interface (WUI), where houses are next to or mixed in with wildland vegetation (Radeloff et al. 2005). With more people relocating to the WUI each year, there is a growing concentration of people and property next to or inside regions of high wildfire danger (Radeloff et al. 2018; Mockrin et al. 2022). As the WUI continues to grow, there is a need to develop an understanding of how residents of the WUI can reduce their vulnerability to wildfires. Engaging local communities in mitigation measures is one of the best ways to control disastrous fires (Fischer 2011; Kreuter et al. 2008; Roberts et al. 2019)). Local residents, who generally have the most to lose in the case of a large fire, can positively impact mitigation activities in their communities.

By employing efficient mitigation practices, wildfires can be reduced in intensity and severity. Examples of mitigation measures include implementing prescribed fire and mechanical fuel reduction (thinning), and creating and maintaining defensible space, in ways that directly engage communities (Blanchard and Ryan 2007; Winter et al. 2009). These actions alter the kind and amount of undesirable vegetation and are regarded as the most effective measures to reduce wildfire severity and its risk to property (Stephens et al. 2012; Syphard et al. 2014; Shi et al. 2022). Numerous studies indicate communities in fire-prone WUI areas comprehend the risk of wildfires in their area and, as a response, implement at least some risk-mitigation efforts (Brenkert-Smith et al. 2006; Dickinson et al. 2015; Kyle et al. 2010; Larsen et al. 2021; Nelson et al. 2004). Although these techniques are becoming more widely accepted, there are still a number of obstacles to overcome before they can be implemented broadly enough to address the scale of current and projected vulnerability to wildfire risks (Fischer 2011; Kobziar et al. 2015; McCaffrey et al. 2013).

Despite the recognized benefits of prescribed fire for wildfire management, there is hesitancy among landowners and stakeholders in California to adopt it. The complex regulatory framework requires permits from the California Department of Forestry and Fire Protection (CAL FIRE), approval from local air quality boards, and confirmation of safe weather conditions. Limited access to permits and recognition of local expertise contribute to confusion and barriers. Concerns about fire escape, smoke impacts, and liability further contribute to hesitancy. Additionally, the lack of resources and expertise, including equipment and training, hinders widespread adoption of prescribed fire. Defensible space regulations in many jurisdictions provide specific guidelines for vegetation management and fire-resistant construction. They require homeowners to maintain appropriate distances between trees and structures and clear dead vegetation. Adequate access, visible addresses, and water availability are also mandated. These rules create hesitancy due to the time, effort, and cost involved, as well as the perceived interference with property rights.

While published studies have demonstrated the effectiveness of fire control strategies to mitigate wildfire damage (McCaffrey and Olsen 2012; Toman et al. 2011), there have been limited studies on public attitudes and actions toward such management practices to safeguard ecosystems and populations. A growing body of social science research has explored the wildfire mitigation actions of vulnerable community members (Brenkert et al. 2012; Stidham et al. 2014; Alcasena et al. 2019). Decisions on reducing the risk of wildfires are often influenced by a variety of factors in addition to risk assessments. According to past research, a number of crucial factors, including shared goals and a similar vision, relationships and trust, a place attachment, information sharing, and community outreach and education, may influence whether residents take part in these risk reduction activities (Winter and Fried 2000; Vaske and Kobrin 2001; McGee 2007; Alam 2011; McCaffrey and Olsen 2012; McCaffrey et al. 2013; Paveglio et al. 2015; Stasiewicz and Paveglio 2022). As a result, understanding public attitudes, perceptions, and opinions about different approaches is critical to developing successful fire management measures (Bright and Burtz 2006; Gunderson and Watson 2007). This research employs a conceptual framework to identify key factors that influence willingness to participate in wildfire mitigation behavior. To our knowledge, there have been limited research to predict future behavioral trends in wildfire mitigation. This gap is noteworthy given the large number of resources dedicated to mitigating effects of wildfires over the last several decades. Considering the fact that communities and individuals base significant decisions on their perceptions and placements within a local landscape, such an examination is essential. Theoretical studies have provided a variety of viewpoints, but the discipline has yet to agree on a single theory or collection of ideas to explain the phenomena. The Theory of Planned Behavior (TPB) (Ajzen 1991) provides a useful context to examine individual-level components to understand the dynamics of mitigation activities, with a growing focus on measuring beliefs, attitudes, and intentions.

1.1. Theoretical framework

This study utilized TPB for predicting public attitudes toward fire management decisions. TPB asserts that behavior is influenced by the intention to perform specific behaviors. These intentions in turn are influenced by attitudes, subjective norms, and perceived behavioral control (Ajzen 1991, Wang and Ritchie 2010). The main idea is, whether one actually implements management activities around their residence in WUI depends on their intention to do so. While the literature is relatively limited, the TPB is being used to measure and identify some factors associated with wildfire mitigation behavior. Homeowners' attitudes, subjective standards, and perceived behavioral control were used by Bates et al. (2009) to explain why people intended to protect their houses and the environment from wildfires. The same framework has been applied in the wildfire mitigation field to understanding landowners' acceptance and intentions to approve fuel management practices, government policies focused on mitigation behaviors (Winter et al. 2002; Winter et al. 2009), and how knowledge predicts homeowners' attitudes, subjective norms, and perceived behavioral control in the context of protecting the environment and home against wildfires (Bates et al. 2009). Previous studies have found that individual socio-demographic variables such as age, gender, education, income, past experience with wildfires significantly influence perceptions and behavioral intentions regarding wildfire management practices (Joshi and Arano 2009, Thapa 2023). However, to the best of our knowledge, TPB has not been applied extensively to predict behavior in use of wildfire management practices. In trying to map behavioral intentions, the TPB can be used as a basis for predicting public attitudes towards wildfire management decisions.

The first part of the TPB model (Figure 1) emphasizes the significance of individual, sociodemographic, and informational background factors in shaping an individual's beliefs (behavioral, normative, and control), which in turn influence three predictors of behavioral intention (attitude toward the behavior, subjective norm, and perceived behavioral control) (Fishbein and Ajzen 2010). Individuals' opinions about the potential benefits or drawbacks of engaging in the behavior are known as behavioral beliefs. An individuals' attitude toward engaging in an action is determined by their behavioral beliefs. In context of wildfire practices, attitudes can include beliefs about the importance of taking steps to prevent or manage wildfires, as well as perceived benefits and costs of doing so. For example, if an individual has positive attitude toward wildfire prevention, they may be more likely to take action to reduce the risk of wildfires.

Individuals who hold normative beliefs consider that the opinions of important figures in their lives would determine whether they participate in a certain behavior or not. The subjective norm, or social pressure, to engage in or refrain from engaging in an action, is determined by normative beliefs (Fishbein and Ajzen 2010). This may include the beliefs and expectations of family members or community about the importance of taking action to prevent or manage wildfires. For example, if an individual's social network believes that wildfire prevention is important, they may feel more pressure to engage in those practices themselves.

Control beliefs are beliefs about individual's attempts to engage in the behavior. Perceived behavioral control is based on control beliefs, which take into account any barriers that may need to be overcome as well as the availability of knowledge, skills, opportunities, and other resources needed to carry out the behavior (Fishbein and Ajzen 2010). For example, if an individual feels that they have the knowledge and resources necessary to implement management practices, they may be more likely to engage on those behaviors.

Together, attitudes, subjective norms, and perceived behavioral control can help explain and predict an individual's behavior related to wildfire management practices. Interventions and strategies aimed at promoting these practices may target one or more of these factors, such as by providing education and resources to increase perceived behavioral control, or by using social norms to promote positive attitudes and subjective norms related to wildfire prevention and management. The framework used here can assist community residents, other stakeholders, including wildfire and natural resource professionals in understanding collective action to address wildfire risks.

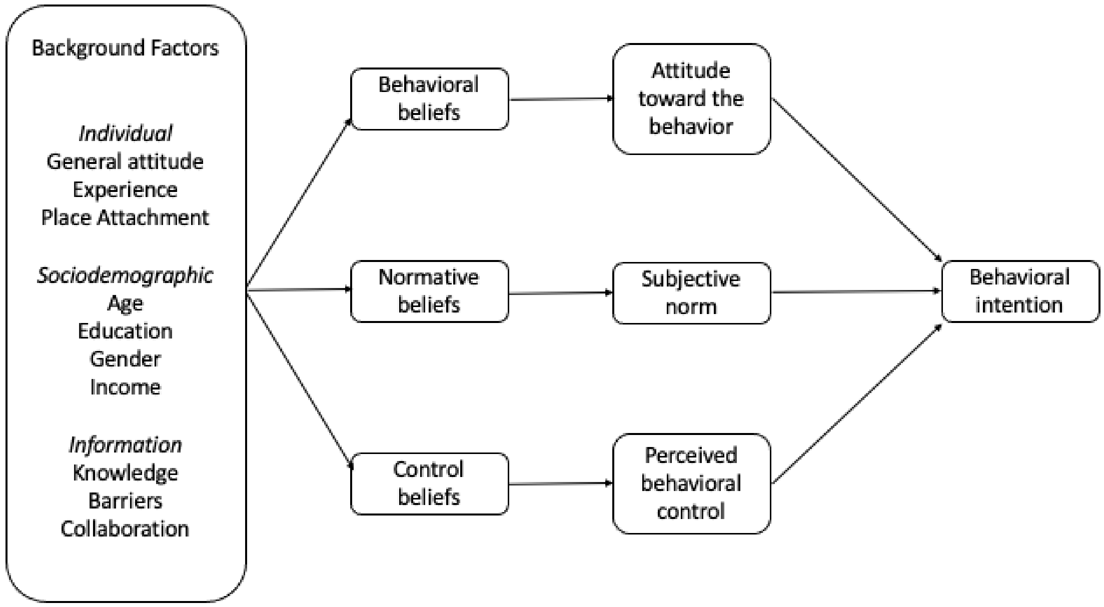

Figure 1: Conceptual framework regarding implementation of fire management practices

In this study we propose the following objectives: to assess community members' (1) perceptions of wildfire risk; (2) knowledge and support for the use of wildfire management practices; and (3) opinions about their role in wildfire management planning in the wildland-urban interface. To assess model stability, we hypothesize that:

1. H_1: There is a significant interest in usage of wildfire management practices
2. H_2: Intent to apply wildfire management practices depends on sociodemographic characteristics, place attachment, potential for collaboration, reasons for not implementing (barriers), and relevant knowledge.

2. Methods

2.1. Participants and procedures

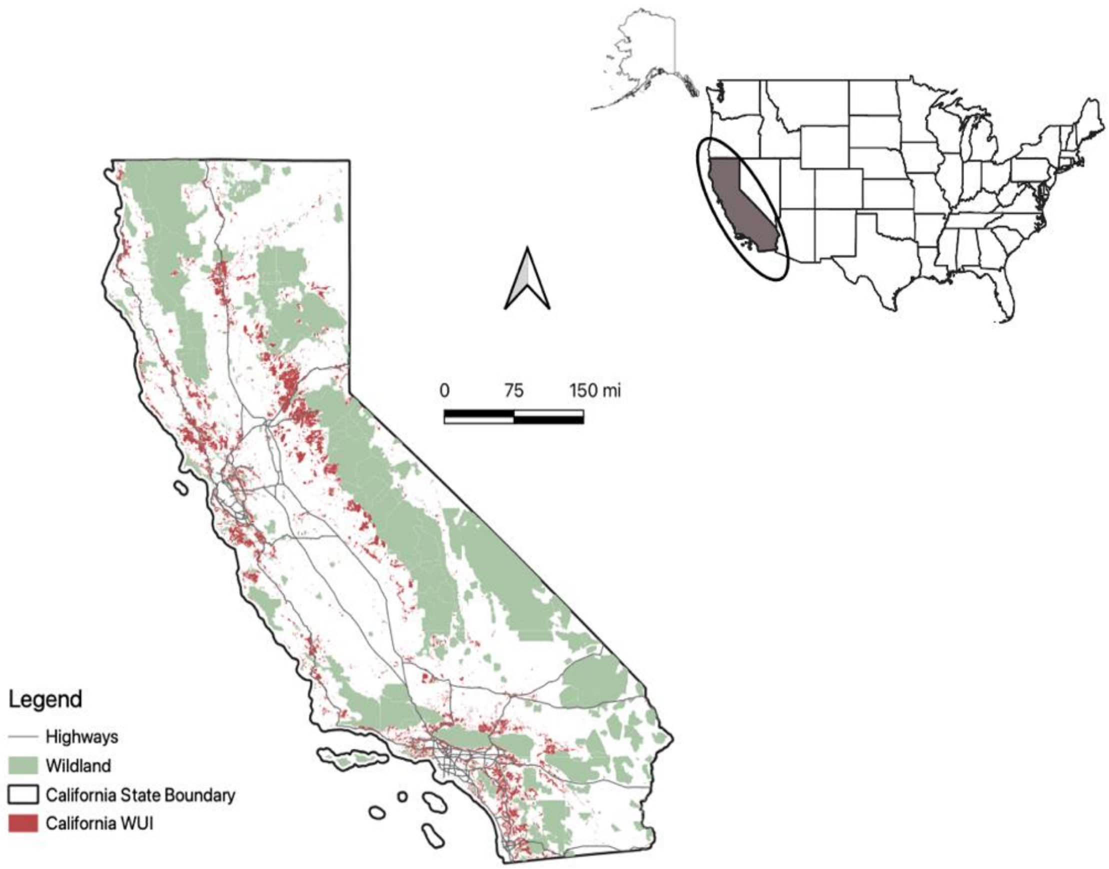

Figure 2 California Wildland Urban Interface

(generated with data available from http://silvis.forest.wisc.edu/data/wui-change/)

This study integrated multi-method forms of primary data collection. Data collection initially started with key informant interviews (KIs) in Mariposa County, California (Appendix 1). The goal of KIs was to gather data from a diverse group (District Supervisors, Fire Safe Council, CalFire) who represented various interest groups. Ten on-site KIs were conducted in the study area. Data was collected until saturation was achieved (i.e., when subsequent interviews supplied recurring information without contributing new knowledge to existing information). This led the foundation to the development of a multi-page standard survey questionnaire (Appendix 2) which was reviewed and approved by the University of California Institutional Review Board (IRB). Web-based survey was employed to gather information about wildfire knowledge, different management practices, along with attitudes, normative influences, and perceived behavioral controls regarding wildfire mitigation efforts. The responses qualified for this analysis were collected from residents who identified themselves as homeowners/landowners in the WUI from different parts of California. While debates on the definition and implications of the term WUI exist (Stewart et al. 2007; Caggiano et al. 2020; Carslon et al. 2021), we define WUI as an area where human settlements and natural vegetation meet each other, and because of this the risk to community life and property from fire and associated hazards is collective, without making a distinction between the intermix and interface zones. The state's expansive area includes wide range of geographical and climatic attributes. With valleys, cliffs, and steep ridges, the area has terrain that can increase the intensity of wildfires. Wildfire is a concern throughout the state, often incurring millions of dollars in containment and suppression costs annually. The survey was open statewide because of these inherent risks and the associated opportunities for studying wildfire mitigation behaviors. This provides the ability to examine behaviors across differing community dynamics.

Sampling assured that gender, age, education, and income characteristics were included and represented. To check for potential bias, respondents were asked compared with general population. For the most part, the demographic profile of respondents was similar to that of California's population (CPS 2020). These data show that, overall, survey respondents were older than the general population. This study purposefully sampled respondents over 18 years of age or over. Median annual income of survey respondents was approximately similar to that of general population. Survey respondents tended to have less education than general population. In terms of gender, proportion of survey respondents were slightly higher to that of the general population.

Table 1: Mean values for population and sample

Variable	Population	Sample
Age (years)	37	46
Gender		
Male	50%	55.7%
Female	50%	44.3%
Annual household income	$78,672	$82,500

The survey originally recorded 247 responses, of which only 183 were qualified, excluding partial responses. General survey questions include: (1) attitudes of residents toward wildfire; (2) behaviors and attitudes toward wildfire risk management practices; (3) residents meanings associated with local landscapes; (4) various constraints to the use of different practices; and (5) interest in participating in collaborative fire management arrangements.

2.2. Relevant variables

The conceptual model was operationalized to measure knowledge, attitudes, place attachment, and barriers to the use of management practices, as well as to account for socioeconomic characteristics. Measured socioeconomic characteristics consisted of age, gender, education, and annual household income. 'Age' was the age of the respondents as a continuous variable in years. 'Gender' referred to the respondent's gender (0, female; 1, male). 'Education' referred to respondents' level of education, originally with five categories, however, 'Education' was recoded as a dummy variable (0, all others; 1, more than high school graduate) to check whether advance education impacted the dependent variable. 'All others' included 'Less than high school', 'high school (or equivalent) graduate', or 'other'. 'Income' originally had six different categories ranging from less than $25,000 to more than $150,000. Responses were recoded to a dummy variable (0, less than $75,000; 1, more than $75,000). Respondents were asked if they were familiar with the concepts of prescribed fire (PF Knowledge) and defensible space (DS Knowledge). These responses were coded to a binary format: 0, no (never heard of it); and 1, yes. Following measurement of PF and DS knowledge, respondents were asked to what extent they were interested in implementation of prescribed fire and defensible space (PF and DS Interest), the dependent variable in the analysis. A four-point scale (not at all, not much, some, a lot) was recoded to a dummy variable: 0 (not at all, not much) and 1 (some, a lot). Respondents were asked about their level of attachment to the place where they live. The scale included six emotional attachment measures and four functional measures (Williams and Vaske 2003). Responses were recorded in five-point Likert scales (1, strongly disagree; 2, disagree; 3, agree; 4, somewhat agree; and 5, strongly agree). A summative scale (Place Attachment) was created from items by averaging the 10 measures to measure agreement (Williams and Vaske 2003). Similarly, respondents were asked for their reasons for not implementing prescribed fire or defensible space. The scale included six measures (liability issues, costs, parcel size, coordination, technical knowledge). Responses were recorded in five-point Likert scales (1, strongly disagree; 2, disagree; 3, agree; 4, somewhat agree; and 5, strongly agree). A summative scale (Barriers) was created from these items by averaging 5 measures (as described above) to measure agreement with reasons for not implementing wildfire management practices. Also, respondents were asked if they were interested in coordinating (Collaboration) with individuals, private organizations, and government entities to implement management practices. Responses were based on 5 five-point Likert scale (1, strongly unlikely; 2, unlikely; 3, likely; 4, somewhat likely; and 5, strongly likely). Responses were recoded to 0 (strongly unlikely, unlikely) and 1 (likely, somewhat likely, strongly likely).

2.3. Analysis

A Chi-square test was used to test the first hypothesis i.e., to determine if there were significant associations between pairs of categorical variables. Chi-square tests provided a picture of the association between two variables. If the proportion of individuals in the different columns varied significantly, the two variables were dependent (i.e., there is contingency). If there was no contingency, the two variables were considered independent. To explore the other hypothesis, a binomial logistic regression model based on our conceptual framework was used. Based on one or more continuous or categorical independent variables, this model was used to estimate the likelihood that an observation would fall into one of the two categories of a dichotomous dependent variable. A positive coefficient for an independent variable meant the independent variable had a positive impact on the likelihood that the dependent variable would occur, whereas a negative coefficient meant the independent variable had a negative impact. Reflecting the components of the conceptual model, the set of indicators were entered in successive stages to observe changes in the model.

There are some limitations of this research. Findings are based on small sample along the California wildland urban interface. A higher response rate could boost our confidence in extrapolating beyond the study population. Despite this limitation, the results of this survey should provide useful insights for land use managers and planners in WUI areas. Future studies might employ a different method to scale up to a larger population over the range of the fire prone WUI in California. Studies such as these aid in the development and implementation of successful regional policies to increase community engagement in wildfire risk mitigation.

3. Results

3.1. Interest in fire management practices

More than half of the respondents were familiar with the term defensible space (68%) and prescribed fire (60%). Of the respondents supportive of one or more of these practices, 77% of the respondents had an interest in defensible space practices. A Chi-squared test revealed association between 'Gender' and 'DS Knowledge' variables with an interest in defensible space. Male were 19% more interested in defensible space practice than female respondents ($p=0.001$). Respondents with higher defensible space knowledge were 22% more interested in defensible space practice than respondents with a lower level of knowledge ($p=0.003$). Similarly, 72% of the respondents had an interest in prescribed fire. A Chi-square result revealed association between 'Gender' and 'PF Knowledge' variables with an interest in prescribed fire. Male respondents were 16% more interested in prescribed fire than female respondents ($p=0.018$). Respondents with greater knowledge regarding prescribed fire were 21% more interested in prescribed fire practice than respondents with a lower level of knowledge ($p=0.001$). Results are in line with what we had initially anticipated in terms of the increased interest in using various fire management techniques (hypothesis 1). Despite an increase in interest in wildfire management practices, results also highlight different reasons for not implementing different practices. Sixty-nine percent of participants collectively reported liability to be the primary reason. Concern about costs was recognized as another reason by 62% of respondents. Fifty-six percent reported technical capacity/knowledge as other reason followed by coordination (51%).

3.2. Intent to apply fire management practices.

3.2.1. Intent to practice prescribed fire.

A logistic regression model was employed where variables were entered in successive stages as predictors of support for use of prescribed fire. Model I with only 'Socio-economic' characteristics explained only 13% of the variance in support of prescribed fire. Three of the four predictive variables in model I were significant: Age, Gender, and Income. Model II introduced PF Knowledge which together with socio-economic characteristics explained 29% of the variance in support for prescribed fire. Place Attachment was introduced in model III which resulted in model explaining more of the variance in the dependent variable ($R^2 = 0.32$). Model IV included the 'Barriers' variable, which increased the explained variance to 37%. The final model (Table 1) introduced 'Collaboration' which increased the variance explained in the dependent variable higher to 43% for the full model. All models were statistically significant. Four of the eight predictive variables in our final models were significant: Age, PF Knowledge, Barriers, and Collaboration. Young age respondents are 31% more interested in implementing prescribed fire than their counterparts ($p=0.025$). Similarly, respondents with higher knowledge regarding prescribed fire are almost three times more interested in applying prescribed fire than those without knowledge ($p=0.018$). In addition, as the 'Barriers' score increased, respondents are 34% less likely to prefer prescribed fire ($p=0.028$). Finally, respondents who are interested in collaboration with others are 70% more interested in applying prescribed fire in comparison to the respondents who were not interested in collaboration ($p=0.001$). Variables such as Education, Gender, Income, and Place Attachment were not found statistically significant in the analysis.

Table 2: Exp(B) value and Odds Ratio derived from logistic regression for Prescribed Fire final model.

Variable	Intent to apply Prescribed Fire		
	B	Odds Ratio	P-value
Socio-economic			
Age	-0.013	1.312	0.025*
Education	0.239	1.737	0.602
Gender	-0.093	0.497	0.801
Income	0.294	1.218	0.440
PF Knowledge	0.667	2.765	0.018*
Place Attachment	0.143	1.152	0.532
Barriers	0.443	0.661	0.028*
Collaboration	0.529	1.708	0.001*
Nagelkerke R^2	0.43		

* Significant at p <0.05

3.2.2. Intent to practice defensible space.

Predictive variables were entered in successive stages to predict intention to practice defensible space. Model I with only 'Socio-economic' characteristics explained only 17% of the variance in interest in defensible space implementation. Model II introduced 'DS Knowledge' as a predictor variable which increase variance explained to 36%. 'Place Attachment' was added in Model III which explained 40% of the variance in the dependent variable. Adding 'Barriers' resulted in Model IV explaining slightly more of the variance (R^2 = 0.43) in support of defensible space. The final Model (Table 2) added 'Collaboration' which increased the variance explained in the dependent variable slightly to 49%. All models were statistically significant with models improving most after inclusion of DS Knowledge (Model II). The final model (Table 2) had five significant predictive variables: Age, Income, DS Knowledge, Barriers, and Collaboration. Younger respondents are 46.7% more interested in practicing defensible space than their counterparts (p=0.005). Household with higher income are 44.2% more interested in applying defensible space (p=0.021). Respondents with more knowledge of defensible space are more than three times more interested in using it as a management practice than those with little or no knowledge (p= 0.003). As the 'Barriers' score increases, respondents are 24% less likely to favor defensible space (p=0.028). Finally, individuals who are interested in collaborating with others are more than two times as interested in using defensible space than those who are not (p=0.001). Variables such as Education, Gender, and Place Attachment were found to have no significant correlation in the analysis.

Results from this study suggest intent towards PF and DS would be positively influenced by age and income, along with knowledge regarding both practices, some perceived reasons for not implementing those practices, and collaboration with others (hypothesis 2). These findings were fairly consistent with our initial expectations. Results support the hypothesis of a causal chain between variables of our conceptual model.

Table 3: Exp(B) value and Odds Ratio derived from logistic regression for Defensible Space final model.

Variable	Intent to apply Defensible Space		
	B	Odds Ratio	P-value
Socio-economic			
Age	-0.117	1.467	0.005*
Education	0.332	1.411	0.186
Gender	0.293	1.329	0.218
Income	0.417	1.442	0.021*
DS Knowledge	0.722	3.469	0.003*
Place Attachment	-0.235	1.126	0.232
Barriers	0.344	0.766	0.011*
Collaboration	0.566	2.114	0.001*
Nagelkerke R^2	0.49		

* Significant at $p < 0.05$

4. Discussion

The TPB provides a useful framework for understanding the role of collective actions in shaping intentions to apply adaptive management practices in the context of wildfires. Collective actions can build on an adaptive approach to wildfire management practices by influencing attitudes, subjective norms, and perceived behavioral control, which in turn can increase intentions to apply adaptive management practices. By working together, communities can create a supportive environment that encourages the adoption of these practices, ultimately leading to more effective and sustainable wildfire management. While the models guided prediction of intentions to implement fire management practices, the inclusion of additional factors enriches the conceptual framework of beliefs, attitudes and intentions. The results suggest that respondents were interested in using prescribed fire and defensible space as a management tool as explained by age, annual income, knowledge of prescribed fire and defensible space, barriers, and collaboration. This increased interest might be attributed to the idea that some of the distinctive qualities of defensible space and prescribed fire make them preferable to other methods. In terms of demographic characteristics, age was negatively significant in both regression models. Younger respondents were more interested and were more likely to implement prescribed fire or defensible space practices. This finding is similar to other studies that have found a negative association between age and acceptance of forest management practices (Joshi and Arano 2009). Surprisingly, education and gender were not significant predictors of mitigation practices despite their importance in wildfire management in previous research.

Results from this study are in line with studies that have shown that understanding the role of prescribed fire and defensible space is crucial for reducing the effects of wildfires (Kreuter et al. 2008; Morton et al. 2010; Piatek et al. 2010; Ryan 2012; Thapa 2019) and can be an important determinant for risk perception and mitigation. This study suggests that educational efforts to increase knowledge can significantly raise interest and support for management programs. An increased level of knowledge contributes to understanding of risk and benefits of the practice required in management efforts. Prior research claimed knowledge gained from experts was favorably related to both structural and vegetation mitigation behaviors (Sharp et al. 2013; Dickinson et al. 2015). Other studies have supported this claim with associations between fire-related information and mitigation behavior (Brenkert-Smith et al. 2012; Champ et al. 2013; Hall and Slothower 2009).

In general, the attachments that individuals have to a place is important for public acceptance of management practices. Previous studies have illustrated how the relationships people have with a particular place influence environmental attitudes and interest in using management practices (Alam 2011; Gobster et al. 2022; Stedman 2003, Williams and Vaske 2003). Contrary to other results, however, this study did not find place attachment to be a statistically significant indicator of intention and support for wildfire management practices. For one possible explanation, Paton et al. (2006) discovered that persons with high environmental values and a sense of attachment to the environment did not favor mitigation strategies like prescribed fire that affected the ecosystem, regardless of how they felt about safety. This may be the situation because individuals are concerned about changing the landscape and altering the environment when mitigation requires modifying the area's surroundings. (Absher et al. 2009; Brenkert-Smith et al. 2006). Another explanation could be individuals might have experienced large and damaging wildfires, and because of place attachment's temporal quality, it is possible to feel less attached to place or environment and not develop an emotional connection. However, further study is required to determine how to make use of WUI inhabitants' place attachment to promote better mitigation and planning.

Implementation of prescribed fire and defensible space is challenging. This research identified multiple factors such as 'liability', 'technical capacity', 'costs', and 'coordination' as the major reasons for not implementing management practices. Literature has documented liability as a major reason for not using either prescribed fire or defensible space (Bailey et al. 2019; Kobziar et al. 2015; Kreuter et al. 2008; Morton et al. 2010). This earlier research revealed significant worries among landowners and organizations over litigation resulting from an escaped fire or smoke issue. Also, another reason may be inability to dispose of excess vegetation material which may produce highly flammable litter generated from creating and maintaining defensible spaces. Results also highlight technical capacity as an important reason, which is similar to lack of technical knowledge and 'need for assistance' as reported by Jarrett et al. (2009) and Kreuter et al. (2008). According to the findings, demand for defensible space and prescribed fire is rising but technological capability is not. This is due to a lack of technical service providers and burn specialists available in the area. Cost is often considered to be a critical reason for not implementing practices. This finding was consistent with results from Fischer (2011), Kobziar et al. (2015) and Thapa (2022), which found management costs at a regular interval were higher than that what homeowners preferred. Lack of financing from nonprofit organizations and government agencies for projects like prescribed fire or defensible space might be one contributing factor for this. Another factor that might be influenced by variations in risk perceptions is the cost-benefit analysis done by homeowners. Homeowners balance the expected benefits of their greater protection against the anticipated costs of mitigating (in terms of time and money), and they only decide to do so if the expected benefits outweigh the anticipated costs.

Intent towards applying different fire management practices was also influenced by interest in collaboration with various entities, a result which is consistent with previous studies (Kobziar et al 2015; Kreuter et al. 2008; McCaffrey and Olsen 2012; Gan et al. 2015; Thapa et al. 2018). This study suggest collaboration with peers may influence perceptions regarding prescribed fire and defensible space use. Collaboration can vary from information sharing, coordinating services, and sharing of services between homeowners and landowners as well as agencies and organizations. Numerous potential advantages of collaborative planning have been reported in prior research, including decreased conflict, the discovery of innovative solutions, increased agreement among varied interests, and increased capability to achieve goals (Bihari and Ryan 2012; Brummel et al. 2010; Reams et al. 2005). One reason could be that collaboration works toward educating the public, local communities, and decision-makers about the benefits of practices, and enhances communication between officials, fire-managers, and homeowners

(Ryan and Hamin 2006). Additionally, if participants are dedicated to continuing their engagement throughout the completion of the plan, project, or activity, collaboration produces long-term advantages. Social support from peers to engage in fire risk mitigation activities may contribute to the willingness to see projects through to completion.

5. Conclusions

This study verified the applicability of using the conceptual model to assess respondent intentions and behaviors towards wildfire mitigation using prescribed fire and defensible space. The results are in line with our initial predictions regarding the increased interest in wildfire management practices. According to the results, some demographic characteristics, knowledge regarding management practices, some perceived reasons for not implementing prescribed fire or defensible space, and collaboration with other homeowners, local organizations, or non-profit organizations, all influence intentions to use prescribed fire and defensible space practices. The findings from this study add to our deeper understanding of the factors that influence decision-making and suggest a need for future research to further understand other factors. The findings of this study have implications for designing and implementing policy instruments as well as enhancing community members' decision-making regarding practices to reduce fire risk. This research suggests implementing a range of measures, such as establishing a framework or a law for wildfire response and recovery that includes provisions for mutual aid agreements between local governments and increased funding for firefighting resources, aimed at improving wildfire prevention and response. This research also suggests, future research should consider additional factors such as prior experience, professional trust, incentive programs, environmental concerns, and the accuracy of individuals' assessment of their exposure to and vulnerability to wildfire risk, all of which could influence individuals' intention to apply risk mitigation practices. The findings suggest that additional efforts should be made to increase public awareness and knowledge of prescribed fire and defensible space in order to expand the use of these strategies for wildland fire management. These findings should be tested and expanded upon in future studies, with a focus on how the public perceives fire management practices.

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Chapter 3
A methodology for estimating burn severity in Northern California's Wildland-Urban Interface

Abstract

This study introduces a novel methodology for simulating wildfire burn severity maps at a 30-meter resolution across Northern California, leveraging empirical data and probabilistic modeling to assess the influence of key environmental factors. By applying conditional binomial logistic regressions within a generalized additive model (GAM) framework, this research evaluates the contributions of biomass, climate variables, and topography to estimate burn severity probabilities. Notably, this study utilized the composite burned index (CBI) for more accurate severity measurement and circumvents traditional method limitations. Through a series of iterative convolutions and the incorporation of a wind-distance weighting metric, this study adeptly simulates the spatial clustering of high-severity wildfire patches, mirroring the contagious nature of wildfire.

Key findings underscore the significant impact of both live and dead biomass, alongside climate and topographic factors, on burn severity. The analysis leveraged Akaike Information Criterion (AIC) scores to refine model accuracy, demonstrating that the inclusion of the wind-distance metric significantly improved model fit, as evidenced by substantial reductions in AIC scores across all models. Additionally, this study applied FRAGSTATS metric to evaluate the spatial clustering and distribution of high severity patches. Results confirmed that the simulation approach effectively replicated observed spatial patterns of burn severity, with specific iterations of the model producing high-severity patch distributions remarkably similar to historical data. This alignment between simulated and observed spatial patterns of burn severity underscores the effectiveness of the methodology in capturing the true nature of wildfire impacts. The approach demonstrated in this study provides a robust framework for generating realistic burn severity maps, facilitating the exploration of future wildfire scenarios and their potential impacts on landscapes and communities.

Keyword: Burn severity, Simulation methodology, GAM, CBI, Wind-distance weight metric, AIC, FRAGSTATS

1. Introduction

In the western United States, wildfire is undoubtedly one of the most important and extensive natural disturbance causes. Wildfires in California are becoming more frequent, as well as larger and more severe, because of climate change and drought (Westerling et al. 2006, Abatzoglou and Williams 2016, Westerling 2016). So too are the ecological, social, and economic consequences. Increasing fuel loads due to fire exclusion and other management actions, arson ignitions, and population growth-driven spread of human settlements into fire-prone vegetation have resulted in increasingly frequent and costly wildfires (Graham 2003, Radeloff et al 2005, Theobald and Romme, 2007, Abatzoglou and Williams 2016, Goss et al 2020). This has raised the risk of massive destructive flames wreaking havoc on human settlements and ecosystems. Depending on the length and severity of the wildfire, a variety of essential ecological processes (e.g., tree and vegetation mortality) are impacted to varying degrees (Spracklen et al 2009, Cansler and McKenzie 2014, Hurteau et al 2014). As a result, several areas are paying more attention to post-fire management (Ferreira et al 2015, Lasanta et al 2018). For post-fire management, it is extremely important to know how severe a fire is. Burn severity is one metric that helps put biophysical disruption of vegetation, as well as the socioeconomic consequences of fire, into context.

Burn severity is defined as the magnitude of ecological impacts of fire on vegetation (amount of physical change), through combustion and heating (Ryan 2002, Gauthier et al 2009). The differenced Normalized Burn Ratio (dNBR) is the most used index for measuring burn severity (Eidenshink et al 2007, French et al 2008, Parsons 2003). The dNBR is a spectral index obtained from the ratio between near infrared and short-wave infrared measurements, which are sensitive to vegetation and exposed soil cover (Key and Benson 2006). Most burn severity mapping applications to date have subtracted a post-fire NBR image from a pre-fire NBR image in an absolute change detection methodology to derive the dNBR. However, several problems make burn severity identification difficult using dNBR. Some limitations are: there are no defined dNBR threshold values by severity class, resulting in a wide range of burn severity interpretations (Kolden et al 2015); furthermore, burned vegetation patches are frequently mistaken for non-vegetated surfaces in terms of spectral appearance (e.g., rocks and bright soils). Recognizing the need for a systematic approach that could be used across several ecosystems and regions, the composite burn index (CBI) was developed as a method to visually estimate the ecological impacts of fire (Key and Benson 2006). In this study, we used a burn severity metric that incorporates CBI field measurements to map potential burn severity within northern California (Xu et al 2022).

The extent of burn severities depends on various factors namely topography (elevation, aspect, slope), weather (wind, temperature, fuel moisture), and fuels (stand structure, fuel loads, forest species composition) (Ryan 2002, Alexander et al 2006, Miller et al 2012, Prichard and Kennedy 2014, Preisler and Westerling 2007, Westerling et al 2009). Keyser and Westerling (2017 and 2019) found that fire year climate is important to estimating burn severity and area burned. Topography affects biophysical gradients such as solar radiation and topographic moisture, changing the composition and availability of fuel (Birch et al 2015, Holden et al 2009, Parks et al 2018). A body of studies have identified the role of fuels and their influence on burn severity patterns. On the one hand, some factors may have a positive influence on one component while having a negative impact on another. When climatic circumstances are not extreme, topographic, physiographic, and fuel characteristics, for example, may have a substantial influence on the severity, but when they are extreme, there may be disagreement (Bigler et al 2005, Bradstock et al 2010, Parks et al 2011). The distribution of burn severity, on the other hand, is non-linear function of the different factors that influence fire regimes (Parisien et al 2005, Salis et al 2014). The system's non-linearity may enhance certain influences while dampening others.

In this study, we introduce a methodology that combines empirical modeling and simulation to aid in the mapping of burn severity for future projections of fire under different scenarios. Previous wildfire models have used a process-based approach to simulate the effects of different factors on fire spread and its effect (Finney 2001, Lasslop et al. 2014, Hurteau et al. 2019). However, such an approach requires high resolution data and can be computationally costly, limiting its use for regional assessments of climate change impacts that explore many scenarios. This paper proposes a more efficient, probabilistic simulation technique that uses empirical modeling to iteratively cluster high severity patches and create burn severity maps. Our simulation process aims to capture the randomness of burn severity while also accounting for the contagious properties of high severity patches. Burn severity maps are the result of a complex combination of factors such as weather, climate, topography, and biomass. Thus, this study aims to address what variables influence probabilities of burn severity in a wildland urban interface region in northern California. This study also aims to identify how biomass simulated at different spatial scales influences burn severity classifications. In this study, we describe models to conditionally estimate probabilities of burn severity at 30 meters, which will better inform management decisions and better aid fire management. The methodology described here will build on the framework developed for application in California's 5th Climate Assessment for simulating long-term statistical forecasts of wildfire.

2. Methods

2.1. Data collection

Our study area covered interior northern California, excluding the northern Sierras and the Northern Coast (Klamath and Mendocino Forests) (Figure 3). Wildfire burn severity was obtained from the Wildfire Burn Severity Emissions (WBSE) dataset. WBSE transforms dNBR values to CBI categories to overcome known issues from classified product of Monitoring Trends in Burn Severity (MTBS) (Kolden et al 2015, Picotte et al 2020). CBI values were converted from dNBR values using the linear and Sigmoid B regression models developed by Picotte et al (2021) at a 30-meter scale and operationalized by Xu et al (2022). CBI values were classified into five severity classes; unburned, low, moderate, high, and grass burned. Unburned and grass burned categories were grouped together. WBSE data were obtained for all fires from 1984 to 2020 at 30 meters. To efficiently test our model, we randomly sampled roughly 10% of the entire WBSE dataset in our desired region at 30 m, giving us n = 4790478 pixels in our modeling dataset.

High spatial resolution (30 m) gridded climate data were retrieved from colleagues at Scripps institution of Oceanography, developed for California's State Climate Assessment. The work presented here is intended to be used with the Fifth California State Climate Assesment.

For this study, we used biomass products generated through simulations using the LUCAS (Land-use and Carbon Scenario Simulator) models. The LUCAS model is a simulation model that predicts changes in land use and land cover classes. It incorporates a stock and flow model to simulate carbon dynamics within a scenario-based framework. The simulated data represents standing carbon stocks in different vegetation pools. Three biomass products simulated via the LUCAS model were used in this study. Firstly, biomass data was obtained from the United States Geological Survey (USGS) (Sleeter et al 2017), which was simulated at a spatial resolution of 1km. To align with our modeling goals, we used a nearest neighbor approach to rescale it from 1km to 30m. Secondly, biomass data that was simulated at 30 m spatial resolution was obtained from the First Street Foundation as a byproduct of Research and Development is not used in their annualized Fire Factor (FF) Product. This biomass dataset employed the 2016 vintage of the canonical U.S. Forest Service (USFS) LANDFIRE fuels dataset (version 2.0) at a 30-meter resolution to assess combustible fuels sustaining wildfires throughout the United States. It also involved the refinement of the v2.0 LANDFIRE dataset (2014) through the incorporation of disturbances spanning from 2011-2023. Additionally, this dataset addresses the transformation of fuel classifications within the WUI specifically focusing on conversion of non-burnable classes to burnable classes (First Street Foundation 2023). These two biomass layers are a snapshot of tons of aboveground carbon per hectare and are a static measure of the amount of biomass in a given location. Thirdly, data from an annualized biomass simulation was used, which characterizes carbon annually in aboveground biomass pools. It takes into account changes in vegetation growth and mortality (including fire and beetle kill events) over time, providing a more dynamic measure of biomass in a given location. Biomass layers consist of both live and dead organic pools, which were aggregated during model construction. Aboveground biomass was aggregated into two classes: 'Live Heavy '(merchantable wood and other wood) and 'Dead Heavy '(snag branch, snag stem, leaf litter, decomposed litter, down branches, and down stems). All three biomass products were tested to identify if differences in spatial resolution of simulated vegetation would affect fire severity model fit and fire severity simulation outcomes.

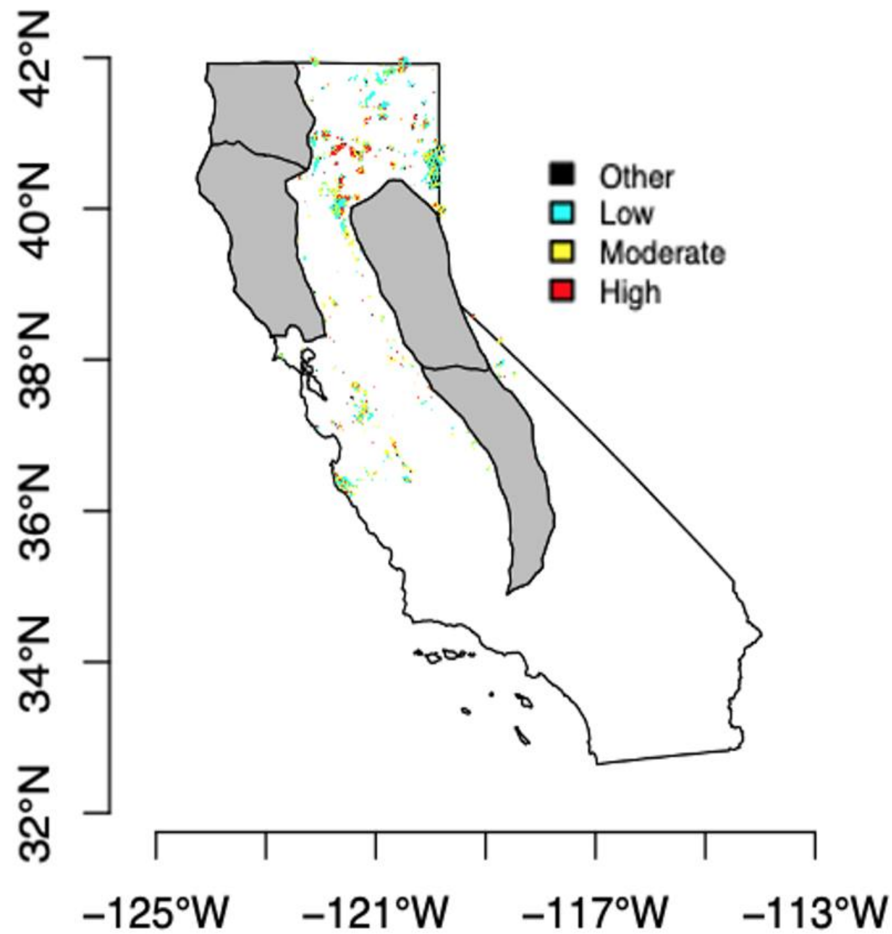

Figure 3: Northern California study region with burn severity maps between 1984 to 2020

[Northern California study region with burn severity maps between 1984 to 2020. The entire study site had 320 fires. Shaded area are forested regions (Sierra, Klamath and Mendocino)]

Topographic data which include elevation, slope, and aspect were downloaded from the USDA Forest Service project LANDFIRE. A‘ northness ’variable was calculated from aspect. Aspect is the direction that a slope is facing and ranges from 0 to 360 degrees, with 0 degrees being due north. To calculate ‘northness’, the aspect value was first converted to radians, then the cosine of that angle was taken. The result was a value between -1 and 1, with values of 1 indicating cells that face due north and values of -1 indicating cells that face due south. Existing vegetation type (EVT) was also downloaded from LANDFIRE. ‘EVT ’is a classification of land cover and vegetation types based on LANDFIRE biophysical settings.

We also used a metric called WindDist (Di) developed by Sam et al. (2022) to better understand the clustering of high severity in wildfires. This variable captures the inverse distance between pixel of interest, and neighboring high severity pixels in response to wind direction. Di is calculated using an inverse-distance wind-weighted approach that considers neighboring 30-meter pixels that were burned at high severity, up to ten pixels away in all directions and as close as 5 pixels away in all directions.

The Di metric was used in simulations by first generating a random selection from a joint probability model without Di to create a raster of pixel predictions of high severity burn patches for a given fire. Di was then calculated for all pixels based on a set of high severity candidate pixels, and a new raster generated those accounts for proximity to these pixels and wind direction. The simulation included three iterations of clustering, each increasing the clustering of high severity pixels into patches. At each step, binary rasters were generated from estimated probabilities, and convolution was used to smooth the images by applying a weighted smoothing kernel based on distance from a given pixel and the mean monthly wind direction at the time of the fire. A threshold was set on the continuous raster of 0 to 1 pixel to match a desired fraction in an observed burn severity class. Convolution occurred at each step, and tolerance limits were tested for precision in matching observed severity fractions of and computational costs when simulating burn severity pixels.

2.2. Statistical Model Development and Simulation

We investigated the relationship between various factors on burn severity using conditional binomial logistic regressions in the form of a generalized additive model (GAM) framework to estimate the probabilities of burn severity at 30m. GAMs are useful in identifying non-linear relationships and do not require a priori knowledge of the shape of smoothed functions of the predictor variables, which can identify the types of effects and non-linear relationship between variables (Wood 2001). We estimated probabilities of any given 30 m pixel burning in one of four severity classes: low, moderate, high, and unchanged (grass and unburned). We used a stepwise approach to determine the model with the optimal set of covariates, based on the lowest Akaike Information Criterion (AIC) (Akaike 1974). We used a stepwise method of adding smooth functions to variables to capture best fit while removing variables or smooth functions that caused high degrees of collinearity. This approach aimed to reduce overfitting and develop the most predictive models for each severity classification. The models with lowest AIC scores were considered. In this study, all the analyses were performed in the R computing environment, with GAM regression using the package "mgcv".

The models developed in this study follow three steps (Table 1). The first model estimates the probability of a pixel burning at low, moderate, high, or not at all; the second model estimates the probability of a pixel burning at moderate or high, given that it did in fact burn; and the third model estimates the probability of high severity, given that it was not moderate or low burned area. We employed interactions to add finer specificity of the biomass variables. Multiple iterations were required to simulate 30 m burn severity maps. The first iteration of these models uses climatic, biomass, and topographic data as explanatory variables. The first iteration then uses the severity probabilities to apply a first pass and create a raster of all pixels of fire. The second and third iteration adds a calculated Di from high severity neighbor variable which is dependent on the outcomes of the first iteration of models. The simulation had three iterations (iteration 0 to iteration 2) of clustering, where each additional iteration increased clustering of high severity pixels into patches.

Table 4: Explanatory variables that were selected for each of the individual models.

	Predictors
Northern California	
Presence of any Severity (LMH)	(Elevation, LiveHeavy) + (Slope, northness) + thousand-hour dead fuel moisture + (LiveHeavy, EVT)
Given it burned, M or H (MH)	(Elevation, Liveheavy) + (Slope, northness) + (LiveHeavy, EVT) + (DeadHeavy, EVT) + Temperature
Given it was M or H, H (H)	(Slope, northness) + (Elevation, LiveHeavy) + (LiveHeavy, EVT) + (DeadHeavy, EVT) + thousand-hour dead fuel moisture
Successive Iterations*	*Added IDwW variable*
LMH model	*Yes*
MH model	*Yes*
H model	*Yes*

To simulate high severity pixels, we followed a multistep approach. First, we estimated probabilities and generated binary rasters with values of 0 or 1 for each step within every iteration. To achieve smoother images, we employed a technique known as convolution. This involved applying a weighted smoothing kernel to the binary raster, converting it to a continuous raster with values ranging from 0 to 1. The smoothing kernel was defined by the distance from a given pixel and the mean monthly wind direction at the time of the fire event, summed across neighboring pixels at different focal windows. We tested focal window size of 5 x 5 pixels to observe the effects of smoothing on neighboring pixels. Through this process, we were able to selectively choose non-random pixels, setting a threshold on the raster with continuous values ranging from 0-1, that matched a desired proportion of observed burn severity class. The convolution process was repeated for each step of the simulation.

We also conducted tests to determine the tolerance limit of thresholding, which refers to the level of precision required for the convolution output to match the predicted severity fractions of the simulated fire map. To test the tolerance limit, we used two-percent tolerance when simulating burn severity pixels. Level of tolerance affects the degree of clustering of pixel of any given severity. We chose two-percent tolerance level as an acceptable due to evidence of strong levels of spatial dependence in burn severity in our analyses (after Sam et al 2022). That is, areas close together were more likely to burn at similar levels of burn severity than those at distant. Also, when running simulation, the tolerance level has significant implications for both accuracy with which we match the predicted severity fractions of the simulated fire map and the computational resources required for the simulations. This decision is particularly crucial when a large number of simulations are required. Therefore, it is essential to carefully choose an appropriate tolerance level to ensure both accuracy and efficiency in the simulation process.

2.3. Simulation testing

In order to evaluate the effectiveness of the smoothing iterations and the focal window size, we calculated the following metrics: Ripley's reduced second moment function K(r) (K function) for multivariate spatial patterns using the 'spatstat' package in R (Baddeley et al. 2016, R Core Team 2021), and FRAGSTATS metrics of patch size distributions (McGarigal and Marks 1995) using the 'landscapemetrics' package in R (Hesselbarth et al. 2019, R Core Team 2021). Here, we specifically compared the K(r) calculated from the observed image to the K(r) calculated from iterated simulations to ensure that we were capturing similar levels of observed high severity clustering. Additionally, we also calculated a high severity patch metric (patch count) for the observed burn severity map and for each iteration of simulation. Comparing patch statistics between the observed map and our simulated maps allowed us to test the size of our focal window and the number of iterations of smoothing in our simulation technique.

3. Results:

We incorporated data from over 320 fires to describe and explain the probability of burn severity. For the burn severity models, we tested for a total of 45 variables. Results from burn severity models show that certain annual climatic variables, along with biomass and topographic variables influence probabilities of burn severity. All the models were statistically significant. The results showed both, the independent and combined effects of the variables, note that even where certain variables were not explicitly included in a given severity model, they still affect a model that relied on a prior modeling step incorporating the variable. Model specifications varied between each severity class, and important drivers of each specific model changed (Table 1). The low severity model is conditioned on estimating high and moderate severity whereas moderate severity is conditioned on estimating high burn severity. Our results highlight substantial variation across models with spatially different biomass variables. Inclusion of Di in model increased performance and improved AIC scores (Table 5).

Table 5: AIC scores for each model with and without Di metric.

Model	AIC without Di	AIC with Di	Change in AIC
LUCAS 1 km			
LMH model	58151	55380	-2771
MH model	242179	193051	-49128
H model	117779	56408	-61371
FF 30 m			
LMH model	52739	51770	-969
MH model	232129	189309	-42820
H model	109138	54635	-54503
LUCAS Annual			
LMH model	56602	55353	-1249
MH model	241964	192793	-49171
H model	119783	56702	-63081

Negative change in AIC score represents improved model fit.

In this study, the number of convolution iterations involved was determined by a visual comparison of the simulated fire severity maps with the observed maps. Clustering was evaluated using Ripley's K statistics and the FRAGSTATS patch metric. For our analysis, a focal window size of 5x5 was used, and high severity patch counts were compared. This focal window was chosen because it yielded patch counts similar to historical observations when combined with a single iteration of smoothing (Table 6).

Table 6: High severity patch count with 5x5 focal window

5 x 5 Focal Window	Observed	Iteration 0	Iteration 1	Iteration 2
LUCAS 1 km	263194	762177	310223	139532
FF 30 m	263194	697453	264435	135140
LUCAS Annual	263194	645428	255715	113845

High severity patch counts with 5x5 focal window and iterations of clustering technique. A high severity patch count is counted as two or more contiguous high severity pixels.

Across all three sets of empirical models, we see that the FF 30 m and LUCAS annual fit models led to more overall clustering of patches as we see a decrease in patch number per simulation iteration. In both cases one iteration of smoothing yielded similar patch numbers with a focal window of five.

During simulations using different biomass datasets, we observed that our method could adequately replicate the high burn severity for all sets of biomass models. However, FF 30 m model came closest (Figure 4). In most scenarios, either iteration one or two captured an appropriate amount of clustering. To test the visual acuity and explore Ripley's K further, we only used the FF 30 m set of simulations for the rest of the study. By limiting the analysis to this dataset, we were able to evaluate severity across all classes and ensure that the evaluation was consistent across the different simulations.

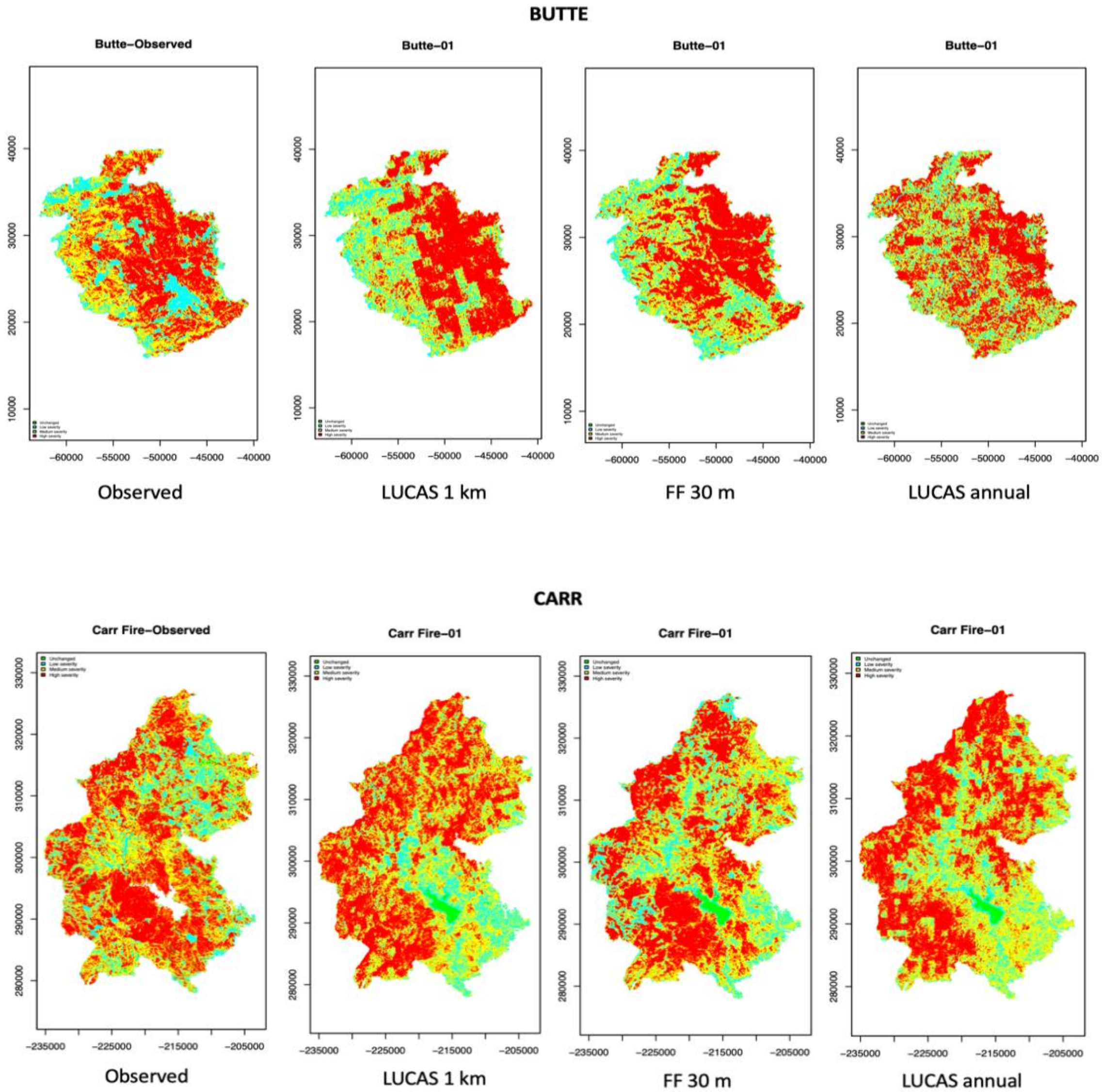

Figure 4: Spatial maps of observed vs predicted burn severity classes (Iteration 01) of each biomass model.

To assess the performance of our modeling approach, we utilized Ripley's K-function to compare the point pattern distributions of high severity clustering across all sets of models and iterations. By evaluating the K-statistics at each iterative step, on average we found, iteration one produced the most comparable results to observed burn severity maps (Figure 5). To further evaluate the accuracy of iteration one, we assessed the distance r of K(r) at four different distances (3km, 6km, 12km, and 21km), allowing for comprehensive comparisons across our simulated maps. Figure 5 illustrates that for all four tested distances, iterations one was found to be closer to historical fire severity maps, indicating that our approach can effectively replicate areas of high burn severity.

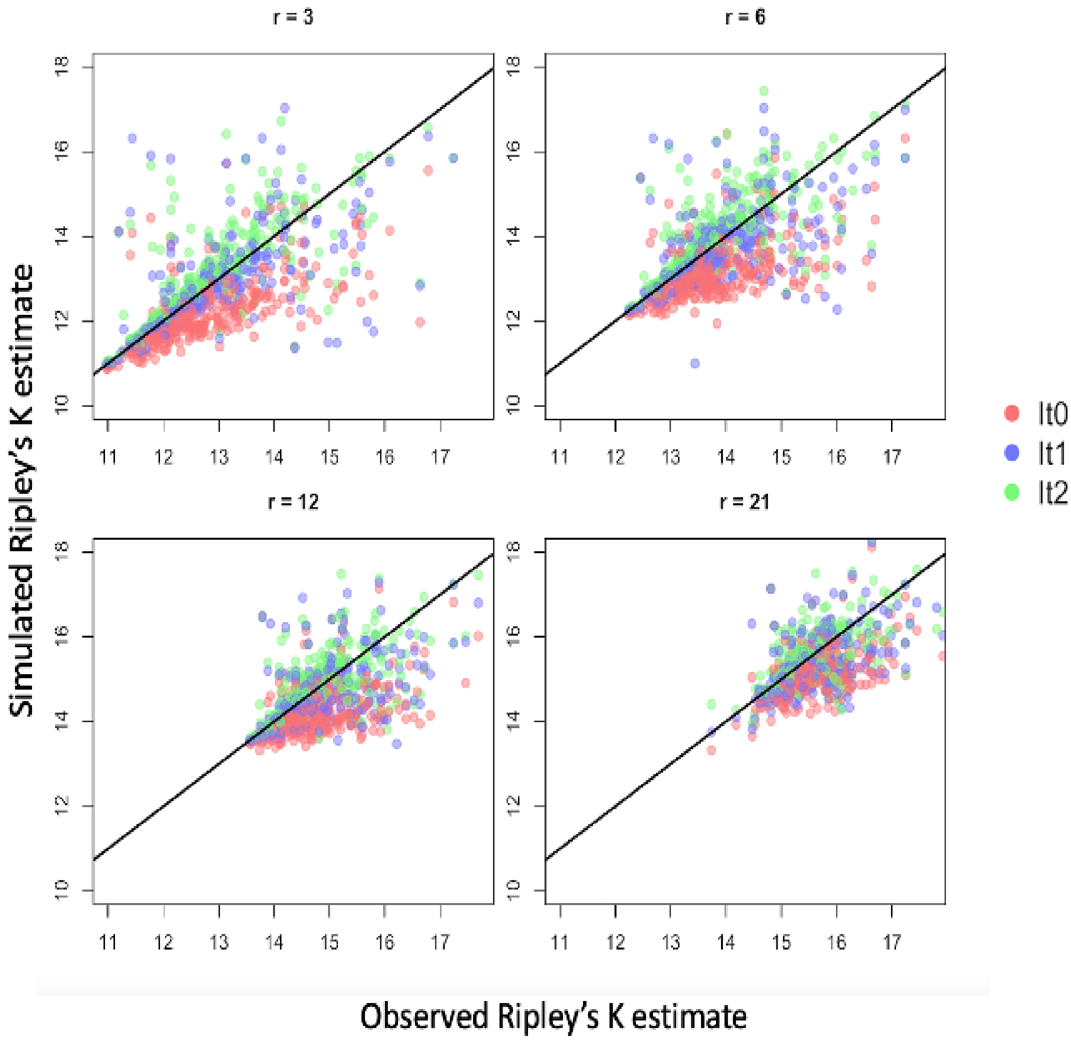

Figure 5: Log-log scale of Ripley's K (observed) x-axis and K(Iteration) y-axis

Figure 5: Log-log scale of Ripley's K (observed) x-axis and K(Iteration) y-axis where the different colored points correspond to different iterations (Iteration 0, red; Iteration 1, blue, Iteration 2, green). Equality line shown in black. Each image represents k(r) at different distances, the top left image r = 3km, top right r =6km, bottom left r = 12km, bottom left r = 21 km. (FF 30-m model)

We simulated burn severity maps (Figures 6 and 7) and visually assessed the results. Our observations revealed that iteration 1 and iteration 2 provided similar maps to the historical ly observed ones. Additionally, the application of Ripley's K function plots to each sample fire captured the desired clustering amount via one or two iterations of convolution. We found that iteration 1 provided the closest approximation on average to the historical clustering of high severity patches. Here in this study, Di metric was incorporated after iteration 0 into the empirical models, resulting in improved clustering performance. This increase in performance was observed in iteration 1 and is reflected in tables 5 and 6 as well as in Figures 6 and 7.

(a) BUTTE

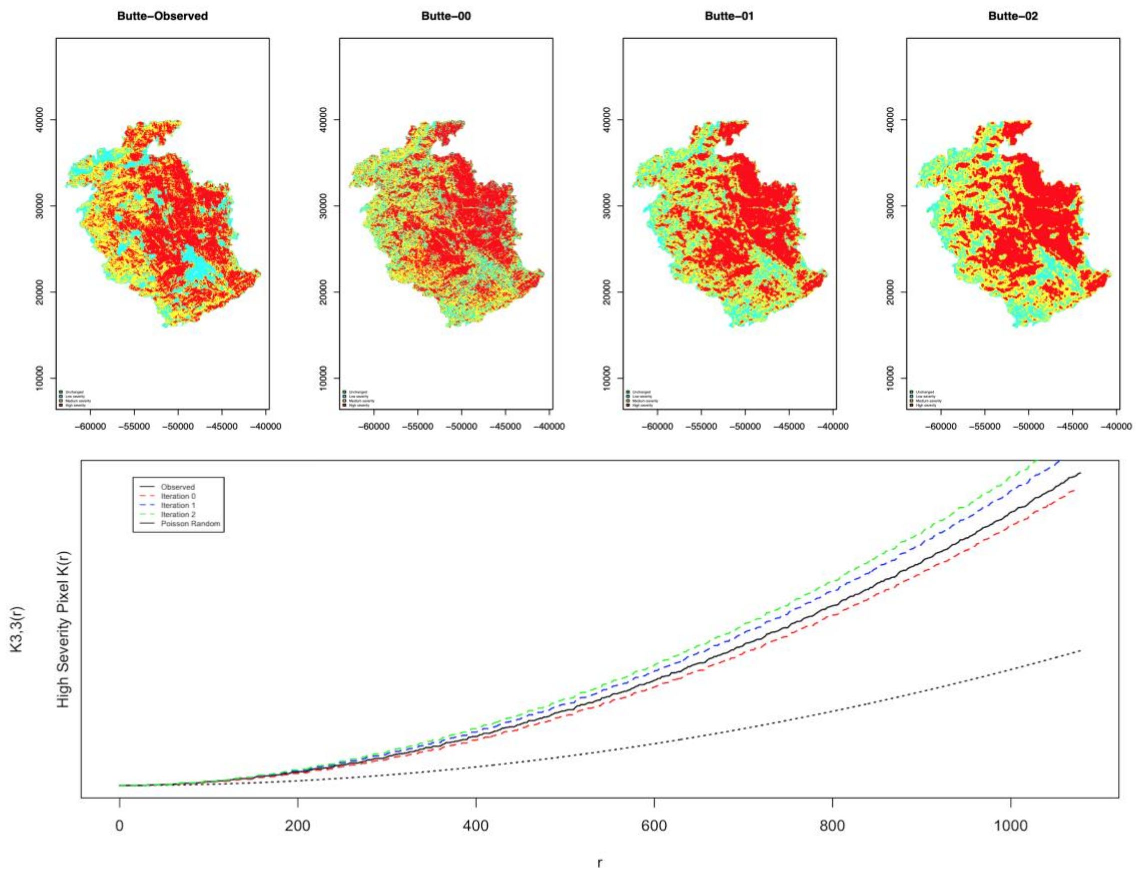

Figure 6: Analysis of the 2015 Butte Fire burn severity shows clustering patterns across iterations, closely mirroring the observed data as compared to Random Poisson Model

Figure 6: The Butte fire in 2015 saw large amount of high severity patches. Burn severity maps from left to right are observed, iteration 0, iteration 1, iteration 2. The bottom plot is a K(r) plot where solid black line is the observed function, and dotted line represents different iterations. Dotted black line is a random Poisson function for comparison. As the dashed lines match the solid (observed) line, at difference distances r, we observe similar levels of clustering to the observed burn severity map.

(b) CARR

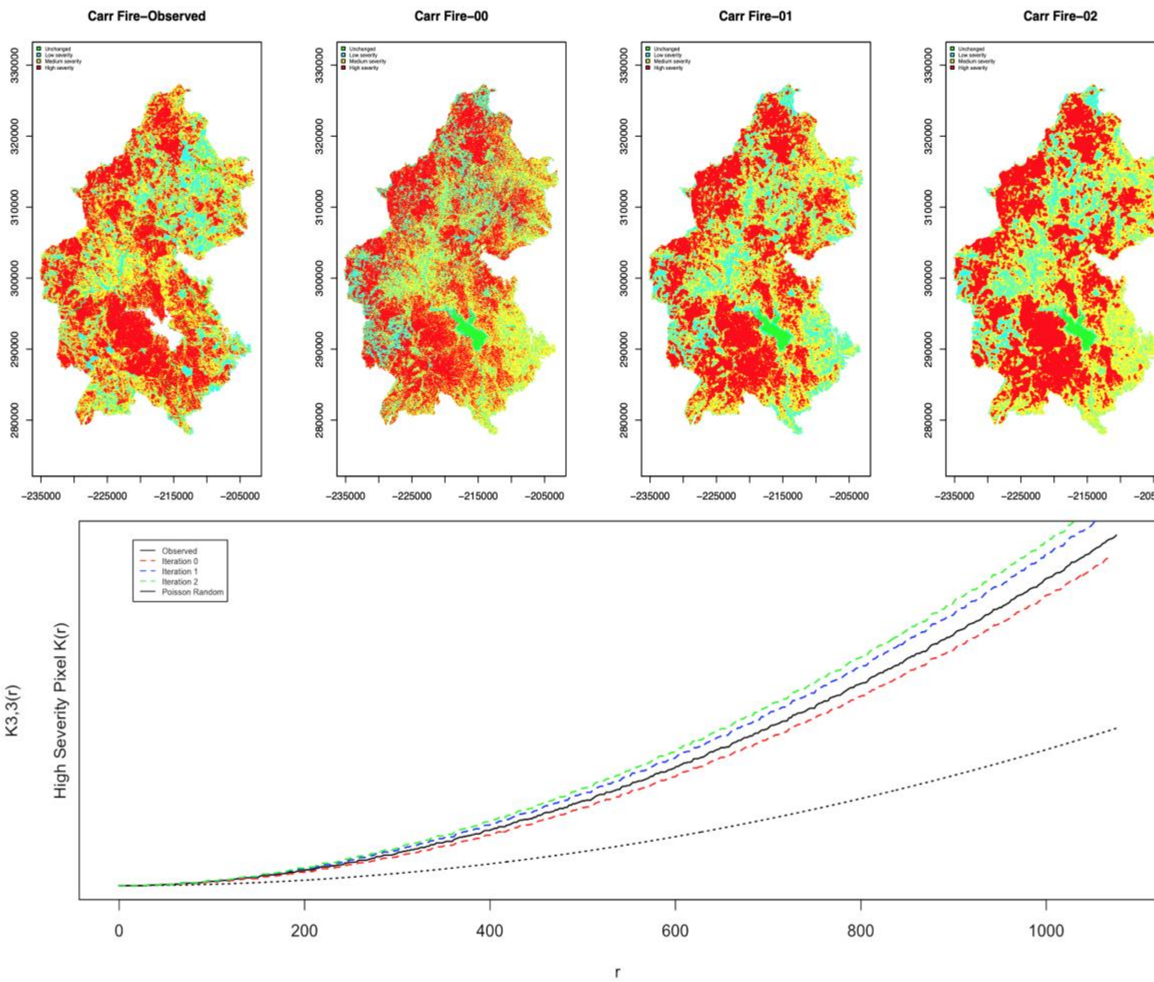

Figure 7: The Carr fire in 2018 saw large amount of high severity patches. Same as Figure 6.

4. Discussions

Our approach to simulating burn severity maps involved utilizing empirical data to inform probabilistic modeling of burn severity and clustering of high severity patches. Our analyses provided strong evidence that the probability of various burn severities was influenced by a combination of biomass (live and dead biomass), weather and topographic variables. Previous studies have demonstrated the significance of biomass and vegetation type in relation to fire frequency (Cumming 2001) and burn severity (Collins et al. 2007, Hall et al. 2008, Boucher et al. 2016) in the wildland urban interface (WUI).

Our results highlight those aggregates of live and dead biomass had a stronger influence than individual carbon pools in high severity classification. Including dead biomass in our model backs up previous research that has shown fuel load to be the most critical variable in determining burn severity (Birch et al 2015, Fang et al 2015, Estes et al 2017, Parks et al 2018). The association between greater biomass (i.e., both live and dead), and high burn severity is a straightforward interpretation. Greater biomass is related to higher total surface fuel loads (van Wagtendonk 2006, Lydersen et al 2015), potentially contributing to higher fire intensity and perhaps severity, and simulated accumulations of dead biomass from bark beetle and drought induced tree mortality (Wayman and Safford 2021) lead to increases in simulated large, severe fires. Dead biomass also was influential for moderate burn severity. For low burn severity, live biomass had a significant influence and dead biomass had an indirect effect. These relationships can be explained by vegetation characteristics. Fire severity is connected to how quickly fuels can regenerate, accumulate and desiccate, and as droughts become more intense as a result of climate change (Keyser and Westerling 2017, Robins et al 2021), increased mortality and more rapid desiccation increase the probability of high severity patches.

In California, there is a projected decrease in fuel moisture due to a drying trend caused by temperature increase, which is expected to affect all types of fuel. Our study found that thousand-hour dead fuel moisture, which represents the overall dryness of available dead biomass at the time of the fire, had impact on high burn severity. A decrease in thousand-hour deal fuel moisture may increase likelihood of frequent and severe wildfires. This result aligns with previous research in the western US, suggesting that hot and dry climatic conditions can decrease fuel moisture, leading to severe fire conditions. One explanation for this may be that heavy fuels might not ignite easily, but when they dry out significantly and start to burn, they release a lot of heat and contribute to severe fire conditions.

Studies in the western US revealed that high temperature exacerbates droughts, leading to increased water deficit and higher burn severity (Williams et al 2014, Abatzoglou et al 2017, Crockett and Westerling 2018). Williams et al. (2014) and Abatzoglou et al. (2017) predicted a continued exponential rise in vapor pressure deficit due to rising temperatures. Crockett and Westerling (2018) linked increased burned area and high severity burned area to drought and beetle induced mortality, with drought exacerbated by increasing temperatures and precipitation variability. Our results also support a link between burn severity and temperature. Higher temperatures directly impact the flammability of fuels, making them more susceptible to ignition in hot and dry conditions.

Topography, particularly elevation and aspect, played crucial roles in determining burn severity probabilities. Our study found that higher elevations were associated with lower burn severity, while low to mid elevations had a greater amount of moderate and high burn severity. This may be due to deeper soils and greater water holding capacity at lower elevations, which support higher densities of biomass. Aspect (northness) was also influential, with south-facing slopes being more exposed to fire risk due to receiving more solar radiation and having less moisture availability, resulting in drier vegetation.

Our approach to simulating burn severity maps improved upon previous methods that rely on process-based fire simulations (Finney 2001, Lasslop et al. 2014, Hurteau et al. 2019), and extend work done by Sam et al (2022) from the montane forests for which they modeled fire severity, to the lower, drier elevations with more varied vegetation and significant wild land-urban interface development that characterize our study area. We demonstrate a computationally efficient technique that utilizes empirical modeling of burn severity and incorporates the Di wind-distance weighting metric to cluster high severity patches in large fires. Taking into consideration the contagious characteristics of high severity fires, our simulation method can generate contiguous high severity clusters that exhibit a remarkable similarity to actual burn severity maps. This demonstrates substantial progress in our capacity to simulate fire severity at high spatial resolutions across various severity classifications using statistical models.

5. Management Implications:

This study can be used to make rapid estimates of severity and its statewide impacts and be used to inform management decisions. We suggest that the modeling framework used in this study will help researchers and managers to understand the relationship between burn severity and environmental variables and predict areas most at risk of high severity fire, allowing for proper mitigation and restoration strategies that reduce the negative effects of fire. Based on our results, strategically targeting fuel reductions can lead to less severe fire effects when fire does occur, especially on lower and warmer landscape and in dry forests that experienced frequent fire historically. Simulating realistic burn severity maps helps managers to explore the effects that fires can have on the landscape and allow to better understand potential changes to ecosystem function and services caused by fire. By creating realistic burn severity maps in the wildland urban interface that consider environmental factors and their relationship to burn severity, we gain insight into factors driving more severe impacts from fires, and provide a tool that allows managers to explore large numbers of both scenarios (climate, fuels, development footprint) and potential outcomes for each scenario (because many monte carlo simulations can be repeated at low cost).

6. Conclusions :

In this study we utilized a conditional wildfire burn severity modeling framework to simulate wildfire burn severity maps at 30 m resolution. Through the use of conditional binomial general additive models and iterative convolutions, we identified key factors that influence historical burn severity classes at 30 m, including biomass, climatic variables, and topographic variables. This approach enabled us to explore drivers of all severity classes and generate realistic burn severity maps comparable to historically observed maps. This technique applied is computationally efficient and provides valuable insights for planning and mitigating wildfire hazards in the future.

Differences in the temporal and spatial resolution of simulated biomass influenced simulated wildfire severity. The FF 30-meter LUCAS snapshot and the LUCAS 1 km annually resolved biomass both improved the AIC scores compared to models using LUCAS 1 km snapshot biomass and produced burn severity maps more statistically and visually similar to historical severity maps. These models performed well even when applied to reconstruct fires outside of the estimation sample. As a result, we expect that a single statewide severity mapping model framework could be developed for California with similar skill to subregional models such as that presented here or by Sam et al (2023).

This study will help better inform monitoring and management of potential high burn severity risks in urban and wildland-urban interface regions, which are subject to fast biophysical changes under climate and anthropogenic factors. The methodology used in this study aims to add a more detailed representation of statistical wildfire for simulations under different scenarios. Estimation from this study will aid in the development of fire risk maps, vulnerability assessments, and resource planning. The findings of this study will aid fire managers in identifying areas of concern based on burn severity data, that can then be incorporated into management procedures to assist, minimize, and reduce wildfire's negative consequences.

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Chapter 4
Developing effective wildfire risk visuals: A comparative study of static maps and animated simulations.

Abstract

This study explores the application of advanced visualization techniques to enhance understanding and management of wildfire risks exacerbated by climate change. As wildfires increase in frequency, size, and severity due to shifting climate conditions, effective risk communication becomes crucial. Utilizing static and animated visualization methods, this study integrates historical data and projections to develop a comprehensive wildfire susceptibility map and dynamic temporal progressions of wildfire incidence.

The methodology combines Fire Presence/Absence Model and Fire Size Model with high resolution data from the LUCAS and Global Climate Model (GCM), assessing fire risk across five California counties. The integration of these models facilitates robust simulations of wildfire scenarios, contributing to detailed static and animated visualizations that depict the spatial and temporal dynamics of fire spread.

Results indicate a significant risk in wildfire risk and its coverage, projected to worsen by 2041-2050. These findings highlight the critical influence of climate factors such as temperature, drought conditions, and vegetation changes on wildfire behavior or spread. The study's visual tool successfully conveys complex data. This research underscores the necessity of advanced visual communication strategies in managing increasing wildfire risks, proposing a model that could be adapted for global application in diverse ecological and climatic contexts.

1. Introduction

Climate change and drought conditions are leading to an increase in frequency, size, and severity of wildfires (Westerling et al. 2006; Abatzoglou and Williams 2016; Westerling 2016). Climate-ecosystem interactions are inherently dynamic systems characterized by complex interactions between various atmospheric and environmental factors (Raymond 2020; Abbass et al. 2022). These interactions give rise to intricate feedback loops and nonlinear behaviors, making it challenging to predict with absolute certainty how they evolve over time. Climate change further complicates these dynamics, altering temperature patterns, precipitation levels, and atmospheric conditions (Bonebrake and Mastrandrea 2010; Ebi et al. 2021; Clarke et al. 2022). As a result, wildfire behavior and its predictions become unavoidably uncertain. Factors such as changing vegetation dynamics, shifting wind patterns, and varying moisture levels greatly influence wildfire behavior, making it difficult to precisely predict their occurrence, intensity, and spread (Stephens et al. 2007; Miller and Safford 2012; Billmire et al. 2014; Keyser and Westerling 2019; Sam et al. 2022; Garner and Kovacik 2023). Understanding and managing wildfire risks in the modern context necessitate advanced technological tools that can communicate complex data effectively and efficiently.

Effective risk communication is vital for fostering public understanding, preparedness, and resilience in the face of escalating wildfire occurrences (Bradley et al. 2014; Cheong et al. 2016; Ma et al. 2023). Therefore, it is imperative to employ advanced visualization techniques that transparently convey the wildfire risk information to stakeholders and the public, facilitating informed decision-making and adaptive response strategies. Data visualization plays a crucial role in modern scientific research as a methodological approach for visually representing intricate datasets, thereby enhancing comprehension and facilitating decision-making processes (Aerts 2003; Platts and Tan 2004; Padilla et al. 2015; Padilla et al. 2018; Perdana et al. 2018; Li 2020; Vazquez-Ingelmo 2024). Through the utilization of images, diagrams, and animations, data visualization effectively converts both abstract and concrete data into comprehensible formats, thereby aiding in the exploration, management, and interpretation of extensive datasets. A common finding in the literature is that different visual representations of the same information can lead to performance differences for a wide variety of tasks (Dull and Tegrden 1999; Aerts 2003; Dong and Hayes 2012; Ajayi 2014; Dambacher et al. 2016; Alhadad 2018; Casenti et al. 2019). Furthermore, empirical studies have demonstrated that different visual representations of the same dataset can yield performance variations across diverse tasks, highlighting the impact of visualization techniques on cognitive processes and decision-making (Heer and Bostock 2010; Cheong 2016; Abdul-Rahman et al. 2019; Eberhard 2021). The growing interest in data visualizations has given rise to two main areas of study: first, exploring the trends and elements that contribute to the success of these visualizations (Ojo and Heravi, 2018, and second, examining how data visualizations affect the way readers learn and perceive information (Oh et al. 2018).

Effective data visualization not only enhances data comprehension but also promotes informed decision-making by conveying complex information in a comprehensible manner. Visualizations, which are external visual representations systematically linked to the information they convey (Bertin, 1988; Stenning & Oberlander, 1995), play a crucial role in conveying information. In recent times, there has been a growing interest in conceptualizing and addressing risk using various visualization techniques. Visualization techniques encompass a variety of methods, including textual, static, and dynamic visualizations, which enable stakeholders to comprehend complex data and information more intuitively (Pang et al. 1997; Aerts et al. 2003; Thomson et al. 2005; Sanyal et al. 2009, Hullman et al. 2019; Padilla et al. 2020; Kamal et al. 2021). By transforming raw data into graphical representations, visualization techniques facilitate the identification of patterns, trends, and relationships with datasets, empowering decision-makers to make timely and well-informed choices. Effective risk visualization plays a pivotal role in minimizing the adverse consequences of natural disasters (Bradley et al. 2014; Hanson et al. 2020; Heydari et al. 2021; Khumairoh et al. 2021). The unique characteristics of wildfires, including their rapid escalation, unpredictability, and potential for long-term ecological impact, necessitate visual communication approaches that go beyond traditional methods. Visual communication, with its ability to convey complex information quickly and intuitively, emerges as a promising avenue for enhancing public understanding of wildfire risks.

While several studies have assessed the impact of different types of visualizations on decision making, relatively few have systematically compared visualizations to other representations, such as numerical or verbal representations. In one of the few studies to do so, Cheong et al. (2016) compared visual and numerical representations of uncertainty. In this study, participants were given a wildfire evacuation task in which they saw maps or numerical probabilities indicating the likelihood that their house would be in the burn zone of a wildfire. They found that participants were more likely to evacuate when shown the numerical information, making the correct decisions more often. However, when participants had to make decisions under time pressure, their performance was significantly worse for the numerical information than for the visualization.

A wildfire mapping is a form of risk communication that relies upon imminent danger and fear of injury or loss of property as the primary motivations for protective action during a crisis situation (Lundgren and McMakin 2009). The process of receiving and understanding risk communication messages and making a decision to take protective action is quite complex. While risk is conceptualized in various ways in the physical and social sciences, its definition in risk and hazards research often involves at least two basic components: the probability that a hazardous event will occur and the probability of consequences or impacts stemming from that event (Bostrom et al. 2008; Haimes 2009).

Static visuals play a vital role in wildfire risk visualization providing clear and actionable information to both decision-makers and the public. They are essential tools for mapping areas where wildfires pose significant risks to structures and other developments, guiding emergency responses and informing preventive strategies (Joslyn and LeClerc 2013). These maps integrate spatial data to delineate the fire risk areas which is critical for effective wildfire risk assessment (Liu et al. 2020; Chuvieco et al. 2023). Moreover, static maps aid in communicating complex information such as current and projected risk conditions in an understandable format, enhancing risk map comprehension (Lindell 2020). Through simplification of complex geographical and climatic data, static maps ensure that vital wildfire risk information is accessible and utilizable by a broad audience (Wood 2021).

Similarly, animated maps serve as a dynamic tool in wildfire risk visualization, enhancing the comprehension and utility of geographic information. These maps provide animated sequences that depict the progression of wildfires over time offering an invaluable resource for both emergency responders and public information. By integrating data on fire size, fire severity, spread patterns, and hazard conditions, animated maps facilitate a more interactive and engaging approach to understand wildfire dynamics (Harrower and Fabrikant 2008; Cinnamon et al. 2009; Shipley et al. 2013). This visualization method improves situational awareness and decision-making by visualizing changes as they occur, allowing for timely and effective responses. For instance, the use of map animation enhances the ability to track wildfire risk and predict future risks based on current and forecasted conditions, thereby supporting protective action planning and risk communication (Harrower and Fabrikant 2008; Lindell 2020). Furthermore, animated maps can be tailored to show specific elements to such as fire size and burned area, making them a versatile tool in risk management (Ghorbanzadeh et al. 2019; Engeset et al. 2022; Li et al. 2022).

Previous research on wildfire risk and susceptibility mapping has made significant strides in understanding and predicting wildfire risk using static and dynamic models. However, there are several gaps that this research aims to address more comprehensively. Previous studies such as those by Malik et al. (2021) and Brown et al. (2021) have developed wildfire risk maps based on various parameters like coarser vegetation, terrain, and climate date. However, there is a need for deeper integration of datasets, with finer spatial scales. This study intends to employ newer, more robust climate models and integrate them with finer spatial scales variables to refine the predictive accuracy of wildfire risks. While static maps only provide snapshots of susceptibility, they often lack the dynamic progression essential for understanding the temporal trends. This study not only explore susceptibility mapping but also extend the models into dynamic visualizations. By developing animated visualizations of wildfire incidences, this study not only provide the risk representation of fire but also project future trends of wildfire risk.

By addressing these gaps, this study not only enhance the understanding of wildfire risks through more advanced statistical modeling techniques but also improve the utility of data produced. The ultimate goal is to create visual tools that are not just reflective of current conditions but are also predictive, helping to mitigate future wildfire risks. To achieve this goal, this research has following objectives:

Objective 1: Create a comprehensive static wildfire susceptibility map, comparing historical wildfire data with projected, to assess changes in wildfire risk over time.

Objective 2: Develop a dynamic temporal progression of wildfire incidence through animated visualizations, to elucidate temporal patterns and trends in wildfire risk.

By addressing these objectives, the study aims to enhance understanding of how wildfire risks are evolving due to changes in climate patterns and vegetation dynamics, by integrating historical data with future projections. This comprehensive mapping will allow policymakers and communities to better prepare for and mitigate the impacts of wildfires. This study will provide a visual tool that can dynamically represent changes in wildfire risks over time, aiding in more effective communication of risk to stakeholders and enable more informed decision-making processes.

2. Methods:

2.1.Site Selection:

Five counties of California (Figure 8) were selected for this study, several factors were carefully considered to ensure a comprehensive and representative examination of wildfire risk. Specifically, the selected counties were chosen based on their similar levels of wildfire risk, historical incidences of wildfires, and population density of the west slope of southern Sierra Nevada foothills.

Figure 8: Study area with 5 counties

2.2.Data overview

This study utilizes a comprehensive set of data from multiple sources to assess fire risk and simulate wildfire scenarios accurately.

For this study, biomass products were generated using the Land-use and Carbon Scenario Simulator (LUCAS) models. LUCAS is designed to forecasts shifts in land use and cover categories and employs a stock and flow model to simulate carbon dynamics under various scenario frameworks. The output from these simulations provides data on the standing carbon stocks in various vegetation types. This dataset provides detailed records of vegetation from 1985-2020. For projections post-2020, data from the year 2020 are extrapolated to remain static, serving as a baseline for future simulations.

Topographic data were downloaded from project LANDFIRE which includes elevation, slope, and aspect for understanding the geographical factors that influence the fire behavior.

Climatic data were sourced from UCLA and bias-corrected by Scripps, this dataset is integrated using the EC-Earth3-Veg Global Climate Model (GCM). The data was aligned to a 3km Teale Albers grid and includes semimonthly aggregates of climate variables.

2.3.Simulation

This study employed a comprehensive methodology for simulating wildfire scenarios (creating fire lists), integrating two primary models: the Fire Presence/Absence Model and Fire Size Model. The Fire Presence/Absence Model utilizes variables such as dead fuel moisture content (fm1000, fm100), minimum relative humidity (rh_min), maximum 10-meter windspeed (wspd10mean), wet/dry status, mean elevation, summed southwest aspect (SWAspect), and mean slope percentage logarithm (SlopePercentLog). Conversely, the Fire Size Model focuses on variables critical for predicting the extent and severity of fire, including minimum wind speed (wspd10mean), mean precipitation (precip), and mean of the maximum daily temperature (tmax).

Data from these models were aggregated by location, year, and iteration, spanning over 2000 simulation/iterations to ensure the robustness of the results. The spatial allocation of fire data employed a circular fire expansion model, with each fire grown algorithmically from its centroid. This was visualized through raster layers for each simulated year, which compile all fire instances to depict the comprehensive impact and potential reoccurrence of fires across susceptible landscapes. Fire lists were then integrated with the EC-Earth3-Veg climate model to provide both historical and projected climate data, which were treated as projections to maintain consistency with future scenarios.

2.4. Analysis and visualization

2.4.1. Static Visualization

Maps were created using geospatial analysis techniques in R environment. The data comprised of raster images obtained from series of simulations conducted. Each raster layer corresponds to a single layer from 2011-2020 and 2041-2050. These raster layers were converted into data frames, allowing for manipulation and aggregation of data. The values in each raster layer represented the burned area in hectares for each pixel, covering entire state of California. The data frames were then merged based on the coordinates (x,y) to create a comprehensive dataset covering the entire study area. From this merged dataset, new variables were derived, total sum of burned area, the sum was then divided by 2000 (number of iterations), and then again by 10 (number of years), to create a decadal average. These variables provided insights into the spatial and temporal patterns of wildfire occurrences over desired two decades. To visualize the decadal average of burned areas, the merged dataset was transformed into a raster layer using ‘rasterFromXYZ’ function, with a specified coordinate reference system (CRS). This raster layer was then masked to the study area boundary using the ‘mask’ function to focus the analysis on the relevant geographic extent (Figure 9 and Figure 10). In the final step, the raster layer was plotted alongside the study area, providing spatial context to the data.

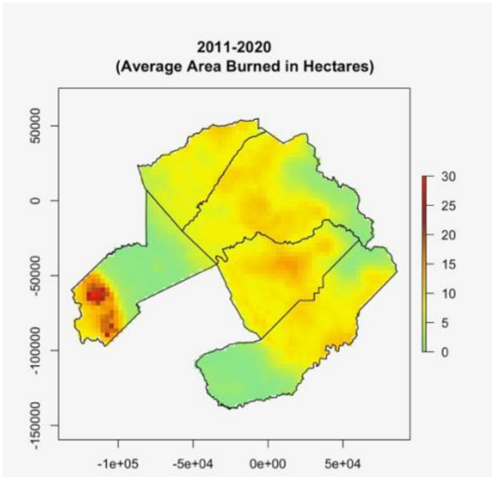
2.4.2. Animated Visualization

Animations were created by leveraging the functionalities of the 'magick' and 'raster' packages in R environment. The process of generating the wildfire animation involved several key steps. Initially, a color palette was established to visually encode the wildfires, with shades of grey representing historical wildfires and red denoting current wildfire (Figure 11 and Figure 12), to provide clear visual differentiation and aid in the interpretation of the animation. Spatiotemporal wildfire data (generated by series of simulations) was retrieved and organized, resulting in a series of raster images corresponding to different time points. A custom plotting function was then defined to sequentially render these images into geographical backdrop. Nested loops were then employed to overlay each raster image onto the background map to manage the temporal progression of the animation. Fine-tuning of temporal dynamics, including adjustments to parameters such as frame duration to ensure smooth transitions between frames and maintain consistency throughout the animation. Additionally, the spatial extent and resolution of the animation were carefully considered to balance detail with comprehensibility. Finally, the 'saveGIF' function was utilized to export the animated visualization, encapsulating the spatiotemporal evolution of wildfire.

3. Results and Discussions:

Each mapped visuals showed different likelihood of being impacted by a fire across study region. Figure 9 and Figure 10 are the visual output from a complex wildfire simulation. The comparative analysis of the average area burned by wildfires over two distinct periods, 2011-2020 and 2041-2050, reveals significant changes in the wildfire patterns and risk. The first period (2011-2020) shows concentrated areas of high burned area, particularly in the Southwest of Stanislaus County where coloration indicates an average area burned exceeding 25-30 hectares. The rest of the region displays a moderate burned area, with average ranging from 5-15 hectares, as depicted by yellow to orange gradient.

In contrast, the projections for the period 2041-2050 indicate an alarming increase in intensity of wildfires and its burned area. The region that previously exhibited the highest burned area now shows an even greater average burned area, suggesting that wildfire events have become more severe over time. Additionally, the overall distribution of burned area has expanded, with a more extensive spread into previously moderate zones. This change is evident by the broadening of the red coloration and the enlargement of areas shaded orange, indicating and increase in the average area burned across the landscape. These results suggest that not only have wildfire occurrences increased, but the severity, as measured by area burned, has also intensified, which could be indicative of the broader impacts of climate change on wildfire behavior and ecosystem vulnerability.



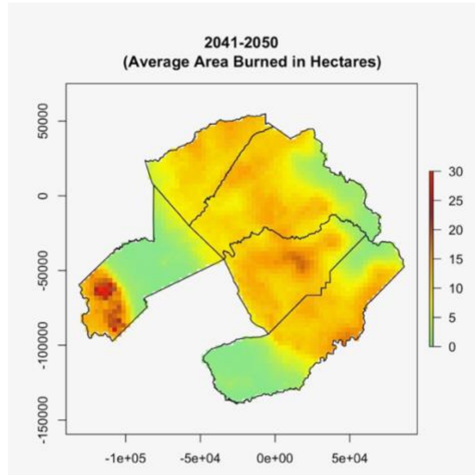


Figure 9: Average area burned in the year 2011-2020

Figure 10: Average area burned in the year 2041-2050

Figure 11 and Figure 12 serves as a dynamic visual aid to illustrate the progression and spatial distribution of wildfire incidences over two distinct periods, 2011-2020 and 2041-2050. The animations are presented in a simple two-dimensional color scheme, with boundaries representing specific geographical region. The animations show accumulative points of wildfire incidents in two different categories: “All previous year Fire” indicated by greyscale and “Current Year Fire” marked by color red. In the first decade, 2011-2020, the occurrence of wildfires was relatively sparse and localized, as indicated by minimal wildfire footprints. Conversely, the projection for the decade 2041-2050 illustrates a significant increase in large wildfires. The large footprints of the wildfires indicate a more aggressive fire regime, with a notable concentration of wildfires occurring within the central region of the mapped area. This intensification aligns with predictions of increased wildfire activity under changing climate conditions, underscoring the influence of temperature, elevations, dryer conditions, and potential shifts in vegetation patterns.

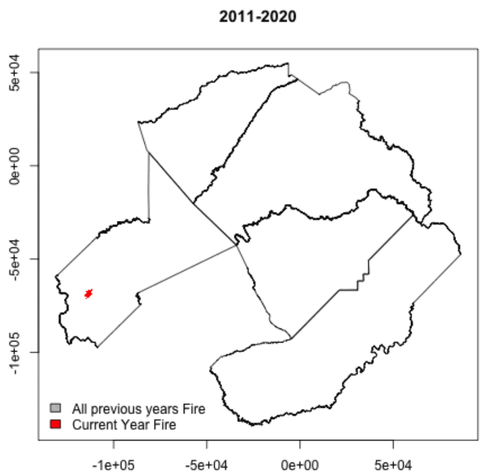


Figure 11: Temporal progression of wildfire incidence from 2011-2020.

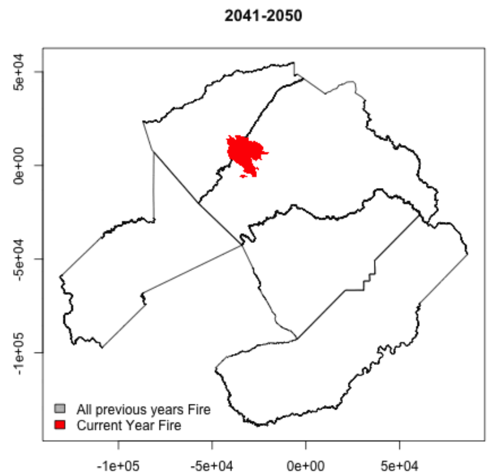


Figure 12: Temporal progression of wildfire incidence from 2041-2050.

The findings from this study underscore significant transformation in wildfire risk across the designated region between two distinct periods, 2011-2020 and 2041-2050. These transformations reveal not only an intensification in wildfire risk but also an expansion of affected areas, indicating a profound shift in fire ecology possibly driven by climate changes. The findings of this study resonate with and are supported by a wealth of research in the fields of wildfire modeling and risk management.

Firstly, the increasing wildfire risk and severity are closely linked to climate change. According to a study by Vilar et al. (2018), their models predict a rising trend in wildfire occurrences across different regions, emphasizing the need for robust predictive tools that incorporate regional climate variabilities. Similarly, a report by Environmental Protection Agency (EPA) (2022) highlights that climate change has not only lengthened the wildfire season but also increased the frequency and total area burned, corroborating our observations of escalating wildfire risks from our models. Moreover, the study by Gutierrez (2021) specifically examined the response of wildfire incidents to changing daily temperature extremes, projecting an increase in fire number by the 2040s due to rising summer temperatures. This is particularly relevant to our projections for 2041-2040, where we observe an increase in size of wildfires, signaling a shift towards more aggressive fire regimes as global temperatures continue to climb.

Collectively, these studies offer a robust scientific foundation supporting our analysis and projections. By integrating historical data with predictive modeling, this study contributes to the deeper understanding of how wildfire risks are evolving and underscores the importance of policymaking to safeguard both natural ecosystems and human communities from the impending increase in wildfire occurrences.

4. Future research

The findings from this study lay a solid foundation for future research in the field of risk communication, particularly concerning natural disasters like wildfires. Future investigations could expand on the comparative analysis of static and animated visuals to assess their potential in enhancing risk perception and decision-making processes. Future studies should consider diversifying the demographic and geographic scope of participants to include a wider range of socio-economic backgrounds, educational levels, and cultural contexts. This expansion would provide a more comprehensive understanding of how different communities perceive and react to wildfire risks, potentially uncovering unique challenges and needs that could inform more tailored communication strategies.

The results from this study will be used (second phase) (Appendix 3 and Appendix 4) to investigate the effectiveness of two distinct visualization techniques in communicating wildfire risk information and explore their impact on risk perception. This study will utilize static image representations and dynamic animations to convey wildfire risk data. To measure effectiveness, further study will focus on: Comparative effectiveness; Risk perception and decision making; Accuracy of understanding. Specifically, future study will; 1) assess how well static and animated visuals convey wildfire risk information; 2) determine the impact of communication methods on stakeholders' risk perception and decision-making; and 3) identify possible misunderstanding/misinterpretation using different risk communication forms.

5. Conclusions

This study has addressed wildfire risks through the application of advanced visualization techniques and data analysis methods. By comparing historical wildfire data with projected trends, this study has created a static wildfire susceptibility map and developed animated visualizations to dynamically represent wildfire progression. These tools have enhanced the understanding of temporal and spatial patterns in wildfire activity or patterns, as demonstrated by the results.

The study findings indicate an increase in the frequency, intensity, and geographical spread of wildfires over time, especially projecting a severe rise in these parameters by 2041-2050. This transformation underscores the profound impact of climate change on wildfire dynamics and emphasizes the critical need for innovative strategies in risk communication and management. The combination of static and animated mapping techniques not only improve situational awareness but also facilitate a more interactive approach to understand and manage wildfire risks. In conclusion, by advancing the methodologies for visualizing and analyzing wildfire risks, this study contributes significantly to the field of wildfire science. This study offers a promising pathway for enhancing the resilience of societies to the growing threat of wildfires, ensuring that communities can better prepare for, respond to, and recover from these increasingly frequent and natural disasters.

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Chapter 5
Dissertation Conclusion

The escalating threats posed by wildfires, exacerbated by climate change and the expansion of the WUI, necessitate an integrated approach to wildfire management, combining community involvement, advanced modeling, and effective risk communication. The study presented in this dissertation illuminate the multifaceted nature of wildfire risks and the crucial elements required to foster a comprehensive wildfire management strategy.

The study underscores the significance of understanding community perceptions and attitudes towards wildfire management practices. Findings reveal a general interest in adopting wildfire management practices, such as defensible space and prescribed burning, contingent on socioeconomic characteristics, knowledge level and perceived barriers. These insights highlight the need for targeted education programs and policy interventions to enhance community engagement in wildfire mitigation efforts, addressing barriers and leveraging collaborative opportunities.

The development of novel methodology in this dissertation for estimating burn severity in Northern California's WUI represents a significant advancement in our ability to predict wildfire outcomes. By incorporating factors such as biomass, topography, and weather conditions, this approach enables a more precise analysis of burn severity patterns, facilitating improved resource allocation and mitigation strategies. The methodological innovation underscores the importance of empirical modeling and simulation in enhancing our understanding of wildfire dynamics and informing post-fire management decisions.

Other study of this dissertation represented a significant step forward in wildfire risk management by integrating advanced visualization techniques with comprehensive data analysis. The development of static and animated visualizations has allowed for a deeper understanding of wildfire risks, illuminating the increasing threat posed by climate change. These visualization tools have proven to be crucial in improving situational awareness and facilitating proactive wildfire management. As the frequency and intensity of wildfires are projected to escalate, particularly by 2041-2050, this research underscores the urgency of adopting innovative communication and management strategies.

The convergence of social, scientific, and communicative aspects of wildfire management within these studies advocates for an integrated approach to addressing wildfire risks. By combining insights into community perceptions, advancing burn severity prediction methodologies, and utilizing effective risk visualization techniques, we can foster a more informed, prepared, and resilient response to wildfire threats. This integrated strategy not only enhances our understanding of wildfire dynamics but also empowers communities and policymakers to implement effective mitigation and preparedness measures.

In conclusion, the insights gleaned from these comprehensive studies provide a robust foundation for advancing wildfire management practices. By fostering an integrated approach that encompasses community engagement, scientific innovation, and effective visualization, we can enhance our collective resilience to the escalating threat of wildfires. Future efforts should focus on bridging the gap between research findings and practical applications, ensuring that the insights gained from these studies inform policy decisions, community practices, and communication strategies aimed at mitigating wildfire risks and enhancing public safety.

Appendix

APPENDIX 1: KEY INFORMANT INTERVIEW QUESTIONS (Chapter 2)

Name:
Title:
Time in position: ________ years
Length of time in community: ______ years
State and County:
Email:

A. Opening Questions

- Please tell us your name and, and how long you have been a resident here.
- Please tell us if you have personally experienced an emergency situation involving wildfire.

B. Introductory Questions (Framing the wildfire issue/Problem Issue)

i. When you think of wildfires, what comes to mind?
ii. What have your experiences been with wildfires?
iii. In your experiences, what do you think are the impacts of a wildfire, broadly?
   - Impacts forest ecosystems
   - Impacts human health
   - Impacts human safety
   - Impacts private property
   - Impacts public property
   - Impacts local economy
   - Impacts communities
   - Impact water quality
   - Impact air quality
   - Impact wildlife

iv. Were you impacted by the 2018 Ferguson Fire? How were you impacted?
   - How was the community impacted

   (For example: House was burnt, roads were closed, schools were closed, etc.)

C. Key Questions

1. Do you see wildfire as a problem?
2. How do various groups in your community view the wildfire problem-issue?
3. To whom do people attribute responsibility for the wildfire problem-issue and/or possible measures to reduce risk or threats, as they see them?

4. Do you think community members are actively managing the fuels/vegetation?
    b. How common is it for community members to get involved in fire and fuel management practices? What kind of practices?
    c. Has the use of different management practices increased or decreased?

5. Motivations to apply different practices (these questions are general or too broad/ make these questions specific to one practice)

i. What conditions would need to exist in your community, in order for you and others to develop a productive dialog on wildfire issues and/or any actions to reduce community risks? [Example: sense of participation for productive outcomes, access to information or knowledge, etc. (There could be many other types of conditions)].

ii. What would it take to get community involved in applying different practices?

iii. Should the community members have more protection from liabilities associated with those practices? Why or why not?

iv. How well do community get along with government agencies?
- What have government agencies done to promote fire management practices? If nothing has been done, why do you think so?

v. Would one community be interested in working with a nearby community with similar effects from wildfire?
- What would be the benefits/ challenges to this?

6. Fire Education Needs and Preferences

i. Are you aware of any educational programs for community about wildfire and management practices to mitigate the effect of wildfires? [what kind of awareness programs]

ii. What do members of your community need to know to begin talk productively about the wildfire issues and potential measures to improve community safety?

iii. Where do people prefer to obtain information about community issues of this nature? (Radio, TV, newspaper, workshops, etc.)

iv. Are you, or others you know, willing to be a part of a monitoring group that would visit sites where efforts are being made to reduce wildfire risks in your community as a part of a learning dialogue?

D. Ending Questions

- Moderator will provide a summary of the comments regarding the key questions.
    - o Are there any other important points that we might have missed? And would you like to add any other significant points?
    - o Are there any other factors that you think are important in terms of preparing a community for emergency like wildfire?

APPENDIX 2: SURVEY INSTRUMENT (Chapter 2)

Thank you for your participation in this survey. The study is being conducted by faculty and researchers at the University of California, Merced Department of Environmental Systems. Your participation is essential to ensure that opinions and actions of community members are represented. For the study to be valid, we need to know about the full range of opinions and situations of the respective community. While your participation is voluntary, you can help us very much by sharing your experiences and opinions.

GENERAL QUESTIONS

1. Do you own, lease and/or manage home and land?
   ☐ Yes
   (i) Own (ii) Lease (iii) Rent

   ☐ No
   If your answer is no, please stop here and you can exit the survey. Thank you for your time.

2. Please indicate the approximate total number of acres you own, lease and/or manage:
   ☐ Less than 1 acre
   ☐ 1-5 acres
   ☐ 6-10 acres
   ☐ 11-25 acres
   ☐ 26- 50 acres
   ☐ 51- 100 acres
   ☐ More than 100 acres

3. How long have you owned, leased and/or managed this land?
   ☐ Less than 5 years
   ☐ 6- 10 years
   ☐ 11-15 years
   ☐ 16- 30 years
   ☐ More than 30 years

4. What is the primary uses and goals for this land?
   (**Please check all that apply)**
   ☐ Office site
   ☐ Primary Residence (Zip code: ___________)
   ☐ Secondary Residence
   ☐ Recreation
   ☐ Other – Please specify:
   ____
   ☐ Hunting
   ☐ Timber production
   ☐ Wildlife habitat
   ☐ Not currently in use

5. What management techniques have you employed in your land?
(**Please check all that apply)**
☐ Landscape improvement ☐ Timber
harvesting/removal
☐ Bush-hogging/mowing ☐ Prescribed burning
☐ Defensible space ☐ Trail improvement
☐ Timber stand improvement ☐ Other – Specify:
____

WILDFIRE QUESTIONS

Specific to this survey, "WILDFIRE" is defined as a fire that occurs naturally (e.g., lightning strike), fire that was set for management purposes that becomes uncontrolled, fire set with malicious intent (e.g., arson) or fire due to negligence/accident.

1. In what extent are you familiar with the term "Wildfire"?
(i) Not at all (ii) Not much (iii) Some (iv) A lot

2. In your opinion, how would you rate the level of risk from wildfire on this land?
(i) Very Low (ii) Low (iii) Average
(iv) High (v) Very high (vi) Don't know

3. What factors influenced how you rated your wildfire danger?
(Please check all that apply)
☐ Number of trees, grass or other fuels located on the property
☐ Proximity of trees and/or fine fuels to structures located on the property
☐ Proximity to local fire suppression units/fire stations
☐ Proximity to local bodies of water such as ponds, lakes, streams, and water bodies
☐ Other – please specify in the space provided here:
____

____

4. Regarding wildfire damage, what are your specific concerns?
(Please check all that apply)
☐ Loss of human life ☐ Damage to structures
☐ Loss of wildlife ☐ Loss of timber
☐ Loss of wildlife habitat ☐ Damage to soils (e.g. Erosion)
☐ Loss of land – related income from timber sales and/or business (e.g. tourism)
☐ Other – Please specify:
____

5. Have you ever experienced wildfire on or nearby this land?
   - ☐ Yes
   - ☐ No

6. If you answered Yes to question 5, what was the source of wildfire(s)? **(Please check all that apply)**
   - ☐ Lighting strike
   - ☐ Brush pile or leaf burns that became uncontrollable
   - ☐ Prescribed burn that became uncontrolled
   - ☐ Negligence (e.g. campfire left unattended)
   - ☐ Other – Please indicate: ____
   - ☐ Arson
   - ☐ Unknown

7. Since owning this land, what is the closest a fire has come to it?
   - ☐ On the property
   - ☐ Up to the property line
   - ☐ Within 1 mile
   - ☐ Between 1 and 5 miles
   - ☐ Between 5 and 10 miles
   - ☐ Not sure

8. Since owning this land, have you noticed changes nearby in "**number of fires**"?
   ☐ Yes ☐ No ☐ Not sure
   If Yes is it increasing or decreasing? __________________

9. Since owning this land, have you noticed changes nearby in **"the size of fires"**?
   ☐ Yes ☐ No ☐ Not sure
   If Yes is it increasing or decreasing? __________________

10. Since owning this land, have you noticed changes nearby in **"accumulation of flammable weeds, brush, and other fuel loads"**?
    ☐ Yes ☐ No ☐ Not sure
    If Yes is it increasing or decreasing? __________________

11. Since owning this land, have you noticed changes nearby in **"risk of fire to houses in community"?**
    ☐ Yes ☐ No ☐ Not sure
    If Yes is it increasing or decreasing? __________________

12. Experience with Fire (**Please check all that apply)**

Experience with fire	This year	1 year ago	2 Years ago	3-5 years ago	Over 5 years ago	Never
Have you ever been evacuated from house due to wildfires?	☐	☐	☐	☐	☐	☐
Has your property ever been damaged by wildfire?	☐	☐	☐	☐	☐	☐
Have you ever been evacuated from a previous home due to wildfire?	☐	☐	☐	☐	☐	☐
Has wildfire ever damaged a previous home of yours?	☐	☐	☐	☐	☐	☐

13. Future chance of Wildfire

What is your best guess about the chance of wildfire happening in the next 5 years?	Very unlikely to happen	Unlikely to happen	Likely to happen	Very likely to happen	Certain to happen	Not sure
A wildfire will occur in your community	☐	☐	☐	☐	☐	☐
A wildfire in your community will reach your property	☐	☐	☐	☐	☐	☐
A wildfire in your property will reach your house	☐	☐	☐	☐	☐	☐
A wildfire that reaches your house damages it	☐	☐	☐	☐	☐	☐
A wildfire that damages your house will destroy it	☐	☐	☐	☐	☐	☐

PRESCRIBED FIRE QUESTIONS

“Prescribed Fire” is the specific use of fire to accomplish a management objective under low risk environmental conditions. In contrast, wildfire can occur under any set of conditions and carries a high risk of causing property damage.

1. To what extent are you familiar with the term “Prescribed Fire”?
   (i) Not at all (ii) Not Much (iii) Some (iv) A lot

2. To the best of your knowledge, what is your level of agreement on the effects of prescribed fire? SCALE – (**1) Strongly Disagree (2) Disagree (3) Somewhat Agree (4) Agree (5) Strongly Agree (9) Don’t know/ No opinion**

Effects of Prescribed Fire	1	2	3	4	5	Don’t know
(1) Endangers wildlife/ human life						
(2) Removes accumulated material on the ground to prevent wildfire						
(3) Maintains natural balance in the ecosystems						
(4) Easily gets out of control and becomes wildfire						
(5) Improves access to forested lands						

3. What is your perception of the manageability of prescribed fire? SCALE – (**1) Strongly Disagree (2) Disagree (3) Somewhat Agree (4) Agree (5) Strongly Agree (9) Don’t know/ No opinion**

Prescribed fire	1	2	3	4	5	Don’t know
(1) Rarely burn at the intensity planned						
(2) Rarely harm desirable timber when properly executed						
(3) Rarely stay confined to the targeted area						
(4) Are not really “controlled” at all, and successful burns are merely good luck						
(5) Are fast and efficient methods for achieving a variety of land management goals						

4. Have you or your neighbors used prescribed fire on your respective land? **(Please check all that apply)**
   - ☐ Yes, I have
   - ☐ No, I have not.
   - ☐ Yes, my neighbors have.
   - ☐ No, my neighbors have not.
   - ☐ Don't know

5. If you answered YES to previous question, did the prescribed fire have the desired management outcome?
   (i) Yes, prescribed fire went as planned
   (ii) No, at least one prescribed fire produced undesirable result
   Please explain briefly:
   ____
   (iii) Don't know

6. Are you aware of any laws in your state regarding the use of prescribed fire?
   (i) Yes (ii) No

7. Of the following who do you trust to implement a prescribed fire on private property.
   (i) The property owner who is not a state-certified prescribed burn manager
   (ii) The property owner who is a state-certified prescribed burn manager
   (iii) A public forester who conducts the burn as part of a wildfire fuel reduction program
   (iv) A forester who is a state-certified prescribed burn manager.

8. In your opinion, who should be responsible for conducting prescribed fire? **(Please check all that apply)**
   - ☐ The landowner
   - ☐ State of California
   - ☐ Private land management consultants
   - ☐ Local government
   - ☐ The Federal Government
   - ☐ Other (specify)

9. To the best of your knowledge, how would you describe the degree of legal responsibility of people who conduct prescribed fire?
   (i) Insufficient (needs to be stricter)
   (ii) Sufficient
   (iii) Too strict (limits the amount of burning needed)
   (iv) Don't know

10. How important are the following factors in your decision NOT to implement a prescribed fire? Please indicate if each of the following issues are **(1) Very unimportant, (2) Unimportant, (3) Somewhat important, (4) Important, (5) Very important, and (9) Don't know**

Factors	1	2	3	4	5		Don't know
(1) Property size not big enough	☐	☐	☐	☐	☐		☐
(2) Lack of technical knowledge/assistance/equipment	☐	☐	☐	☐	☐		☐
(3) Prefer to use herbicides	☐	☐	☐	☐	☐		☐
(4) Use mechanical methods only	☐	☐	☐	☐	☐		☐
(5) Issues with smoke	☐	☐	☐	☐	☐		☐
(6) Potential liability	☐	☐	☐	☐	☐		☐
(7) Cost-related issues	☐	☐	☐	☐	☐		☐

DEFENSIBLE SPACE QUESTIONS

A "defensible space" is an area around a building in which vegetation, debris, and other types of combustible fuels have been treated, cleared, or reduced to slow the spread of fire to and from the building.

In what follows, the inner zone includes the house and 30 feet around it.

The outer zone extends from the 30-foot inner zone to 100 feet from the house.

1. To what extent are you familiar with the term "defensible space"?
   (i) Not at all (ii) Not Much (iii) Some (iv) A lot

2. Is there good road access to your house so that fire engines could easily pass other vehicles?
   (i) Yes (ii) No (iii) Don't know

3. Do you have water supply for fire (hydrant, tank, pond, ditch) within 30 feet of your house?
   (i) Yes (ii) No (iii) Don't know

4. About maintaining defensible space. SCALE – (**1) Strongly Disagree (2) Disagree (3) Somewhat Agree (4) Agree (5) Strongly Agree (9) Don't know/ No opinion**

	1	2	3	4	5	Don't know
I am (or could be) good at doing defensible space actions	☐	☐	☐	☐	☐	☐
I am (or could be) good at hiring competent people to do them for me	☐	☐	☐	☐	☐	☐
I do most defensible space actions as part of my routine	☐	☐	☐	☐	☐	☐

Defensible space in inner zone (the house and 30 feet around it)

5. Does your house have?

Q. Does your house have?	Yes	No	Don't know	Does not apply		If No, do you plan to? (Yes/No)
Fire Resistant Roof (tile, cement, asphalt)	☐	☐	☐	☐		
Fire-resistant sliding (cement fiberboard, brick)	☐	☐	☐	☐		
Sparks arrester or chimneys	☐	☐	☐	☐		
Vents covered with mesh						

6. Did you spend money during 2017 and 2018 on your house specifically to reduce fire risk?

☐ Yes ☐ No If Yes, How much: $______________

7. What is in the inner zone around your house?

	None	Little	Some	Most	Lots	All
Green lawn	☐	☐	☐	☐	☐	☐
Rock/sand/other non-flammable landscaping materials	☐	☐	☐	☐	☐	☐
Invasive species and weeds	☐	☐	☐	☐	☐	☐
Leafy trees	☐	☐	☐	☐	☐	☐
Bushes	☐	☐	☐	☐	☐	☐
Shrubs	☐	☐	☐	☐	☐	☐

8. When have you done the following in your inner zone?
(**Please check all that apply)**

	2019	2018	2017	2016	Earlier	Don't plan to	Plan to
Clear brush and pruned overgrown shrubs and trees	☐	☐	☐	☐	☐	☐	☐
Clear leaves and needles from rood and gutters	☐	☐	☐	☐	☐	☐	☐
Clear out grass and invasive species	☐	☐	☐	☐	☐	☐	☐
Clear wood piles and other scrap wood	☐	☐	☐	☐	☐	☐	☐
Maintain a green lawn	☐	☐	☐	☐	☐	☐	☐
Prune low hanging branches	☐	☐	☐	☐	☐	☐	☐

Defensible Space in the Outer Zone (30 feet to 100 feet beyond house)

9. During 2017 and 2018 wildfire did your outer zone include…

During 2017 and 2018 wildfires did your outer zone include …	None	Little	Some	Most	Lots	All
Green lawn	☐	☐	☐	☐	☐	☐
Rock/sand/other non-flammable landscaping materials	☐	☐	☐	☐	☐	☐
Dead trees and shrubs	☐	☐	☐	☐	☐	☐
Leafy trees	☐	☐	☐	☐	☐	☐
Heavily overgrown bushes	☐	☐	☐	☐	☐	☐
Shrubs	☐	☐	☐	☐	☐	☐

10. When have you done these in your outer zone?
(**Please check all that apply)**

	2019	2018	2017	2016	Earlier	Don't plan to	Plan to
Clear dead trees and shrubs from this area	☐	☐	☐	☐	☐	☐	☐
Prune or trim trees, shrubs and plants	☐	☐	☐	☐	☐	☐	☐
Clear brush and dead grasses	☐	☐	☐	☐	☐	☐	☐
Maintain a green and well-watered landscape	☐	☐	☐	☐	☐	☐	☐
Install fire-resistant landscaping (rock, sand)	☐	☐	☐	☐	☐	☐	☐

11. About "defensible space", why not do more to your house or property? **SCALE – (1) Strongly disagree, (2) Disagree, (3) Somewhat Agree, (4) Agree, (5) Strongly Agree, (9) Don't know/No opinion**

	1	2	3	4	5		Don't know
(1) Already done enough to the house	☐	☐	☐	☐	☐		☐
(2) My **inner zone** already protects the house well	☐	☐	☐	☐	☐		☐
(3) My **outer zone** already protects the house well enough	☐	☐	☐	☐	☐		☐
(4) Defensible space on nearby properties is enough to protect my house	☐	☐	☐	☐	☐		☐
(5) Would be pointless, risk is too high from surrounding properties	☐	☐	☐	☐	☐		☐
(6) It would cost more than I could gain	☐	☐	☐	☐	☐		☐
(7) The **outer zone** around my house is not in my property	☐	☐	☐	☐	☐		☐

12. Does any of the following factors affect your choice to do more defensible space practices? Please indicate if each of the following issues are **(1) Very unimportant, (2) Unimportant, (3) Somewhat important, (4) Important, (5) Very important, and (9) Don't know**

Factors	1	2	3	4	5		Don't know
(1) Expense or cost	☐	☐	☐	☐	☐		☐
(2) Too little time	☐	☐	☐	☐	☐		☐
(3) Don't tend to think about the risk of wildfire damage very much	☐	☐	☐	☐	☐		☐
(4) Don't want to make my house less attractive	☐	☐	☐	☐	☐		☐
(5) Don't want to make my landscape less attractive	☐	☐	☐	☐	☐		☐
(6) Changing landscape may reducing my privacy	☐	☐	☐	☐	☐		☐
(7) Concern about wildlife habitat	☐	☐	☐	☐	☐		☐

13. Would you be more likely to work on defensible space if?
SCALE – (**1) Very unlikely (2) Unlikely (3) Somewhat likely (4) Likely (5) Very likely (9) Don't know/ No opinion**

	1	2	3	4	5		Don't know
(1) Your nearest neighbor does	☐	☐	☐	☐	☐		☐
(2) Other neighbors do	☐	☐	☐	☐	☐		☐
(3) Respected community members do	☐	☐	☐	☐	☐		☐
(4) Insurance rates are low to maintain	☐	☐	☐	☐	☐		☐
(5) You knew where to start	☐	☐	☐	☐	☐		☐
(6) You knew which actions would be most effective for you	☐	☐	☐	☐	☐		☐

Attitudes about wildfire management

1. Indicate your level of agreement.
   SCALE – **(1) Strongly Disagree (2) Disagree (3) Somewhat Agree (4) Agree (5) Strongly Agree (9) Don't know/ No opinion**

Factors	**1**	**2**	**3**	**4**	**5**		**Don't know**
(1) Risks of an escaped fire associated with prescribed fire are negligible if fire managers follow established guidelines	☐	☐	☐	☐	☐		☐
(2) Benefits of prescribed fire outweigh the potential harm of an escaped prescribed fire	☐	☐	☐	☐	☐		☐
(3) A large commitment [agency] to reduce heavy fuels would help reduce the need for aggressive fire suppression in the future	☐	☐	☐	☐	☐		☐
(4) When fire threatens homes and other private property, managers should only try to protect those structures when the probability of success is high	☐	☐	☐	☐	☐		☐
(5) Whether or not a fire management strategy achieve its objectives is largely determined by the actions of managers and fire crews.	☐	☐	☐	☐	☐		☐
(6) Letting a fire burn, rather than aggressively suppressing a fire, is a good	☐	☐	☐	☐	☐		☐

way to reduce the costs of managing wildland fires.							
(7) Limiting the amount of resources used to suppress a fire is likely to increase a fire's potential damage	☐	☐	☐	☐	☐		☐
(8) Limiting the amount of resources used to suppress a fire is likely to reduce the risks of injury or fatalities for firefighters	☐	☐	☐	☐	☐		☐
(9) It is the responsibility of individual private landowners to take actions that reduce the risk of fire on their property, like creating "defensible space"	☐	☐	☐	☐	☐		☐
(10) It is the responsibility of the Forest Service to invest in large-scale suppression efforts to protect private property within fire-prone areas.	☐	☐	☐	☐	☐		☐

2. How important are the following factors when deciding how to manage a fire? SCALE- **(1) Very unimportant, (2) Unimportant, (3) Somewhat important, (4) Important, (5) Very important, and (9) Don't know**

Factors	**1**	**2**	**3**	**4**	**5**		**Don't know**
(1) Reducing heavy fuel loads	☐	☐	☐	☐	☐		☐
(2) Encouraging beneficial effects of fire for wildlife habitat, plant life, and ecological values	☐	☐	☐	☐	☐		☐
(3) Minimizing damage to ecological values	☐	☐	☐	☐	☐		☐
(4) Protecting private property	☐	☐	☐	☐	☐		☐
(5) Ensuring the safety of firefighting personnel	☐	☐	☐	☐	☐		☐
(6) Total cost of suppression efforts	☐	☐	☐	☐	☐		☐

PLACE ATTACHMENT

"Sense of Place" Items	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree	Not sure

(1) I would rather live somewhere else	☐	☐	☐	☐	☐	☐
(2) I have no particular feeling [love] for this place	☐	☐	☐	☐	☐	☐
(3) I do not really feel like I am from this place	☐	☐	☐	☐	☐	☐
(4) I (always) feel like I belong here	☐	☐	☐	☐	☐	☐
(5) I am emotionally attached to this place	☐	☐	☐	☐	☐	☐
(6) I wouldn't substitute any other place for doing what I do here	☐	☐	☐	☐	☐	☐
(7) I identify with the goals of this (community)	☐	☐	☐	☐	☐	☐
(8) I identify with the lifestyle and values of the people who live here	☐	☐	☐	☐	☐	☐
(9) I have (am willing to) invest(ed) my heart and soul in this place	☐	☐	☐	☐	☐	☐
(10) I would make (have made) personal sacrifices to save/ protect/ preserve/ maintain this place.	☐	☐	☐	☐	☐	☐

SOCIODEMOGRAPHICS

1. In what year were you born? _____ (year)

2. Gender?
   (i) Male
   (ii) Female
   (iii) I do not wish to say

3. What is your race/ethnicity?
   (i) African American
   (ii) Caucasian
   (iii) Asian
   (iv) Hispanic/ Latino
   (v) Native American
   (vi) Other (Specify)
   (vii) I do not wish to say
4. What was the last level of education that you completed?
   (i) Less than High School
   (ii) High School (or equivalent) Graduate
   (iii) Some College or Post-High School Trade School
   (iv) College Graduate
   (v) Graduate School or other Post College Degree
   (vi) Other (Specify)
   (vii) I do not wish to say

5. Including yourself, how many individuals live in your household who are:
   (i) 18 years of age or less? ________
   (ii) 19 to 59 years of age? ________
   (iii) 60 years of age and older? ________

6. How long have you owned or rented your property in the community? ______ years

7. What kind of home do you live in?
   (i) Single family home
   (ii) Mobile home/trailer
   (iii) Townhouse/duplex
   (iv) Apartment
   (v) Other (specify)

8. How do you describe yourself politically? Would you say you are?
   (i) Liberal
   (ii) Moderate Liberal
   (iii) Conservative
   (iv) Moderate Conservative
   (v) Refused

(vi) Don't know

9. What was your total household income (before taxes) in 2018? Would you say:
    (i) Less than $15,000
    (ii) $15,000 but less than $25,000
    (iii) $25,000 but less than $50,000
    (iv) $50,000 but less than $75,000
    (v) $75,000 but less than $100,000
    (vi) $100,000 but less than $150,000
    (vii) $150,000 or more

APPENDIX 3: STATIC VISUALIZATON SURVEY INSTRUMENT (Chapter 4)

BLOCK 1

Important Information about the survey – PLEASE READ!

Welcome to our research survey. We are exploring perceptions of wildfire risk across five counties of California State, as shown in the map. The purpose of this survey is to better understand whether people like you would benefit from new types of information in wildfire risk. This study uses modeling techniques to predict wildfire risks and examines how visual representation of this data might influence public perception. Specifically, the survey focuses on wildfire maps that shows historical and future fire risk. It may be costly to develop new information, and we want to make sure it is worthwhile to do so.

You do not need any special knowledge about wildfire and its risk to respond to any of the questions. We want to learn about how you interpret and use wildfire risk information, and what are your opinions about the presented information.

Two scenarios will be presented for your consideration: First reflects the historical wildfire risk simulation from year 2011-2020; and second reflects the projected wildfire risk simulation in near future (2041-2050).

We will use your responses to guide future research related to wildfire risk communication to provide better information for you, so your responses are very important for us. All your responses will remain anonymous. None of the information or opinions you provide can be linked back to you, so please respond as honestly as you can.

Thank you for taking the time to complete the survey!

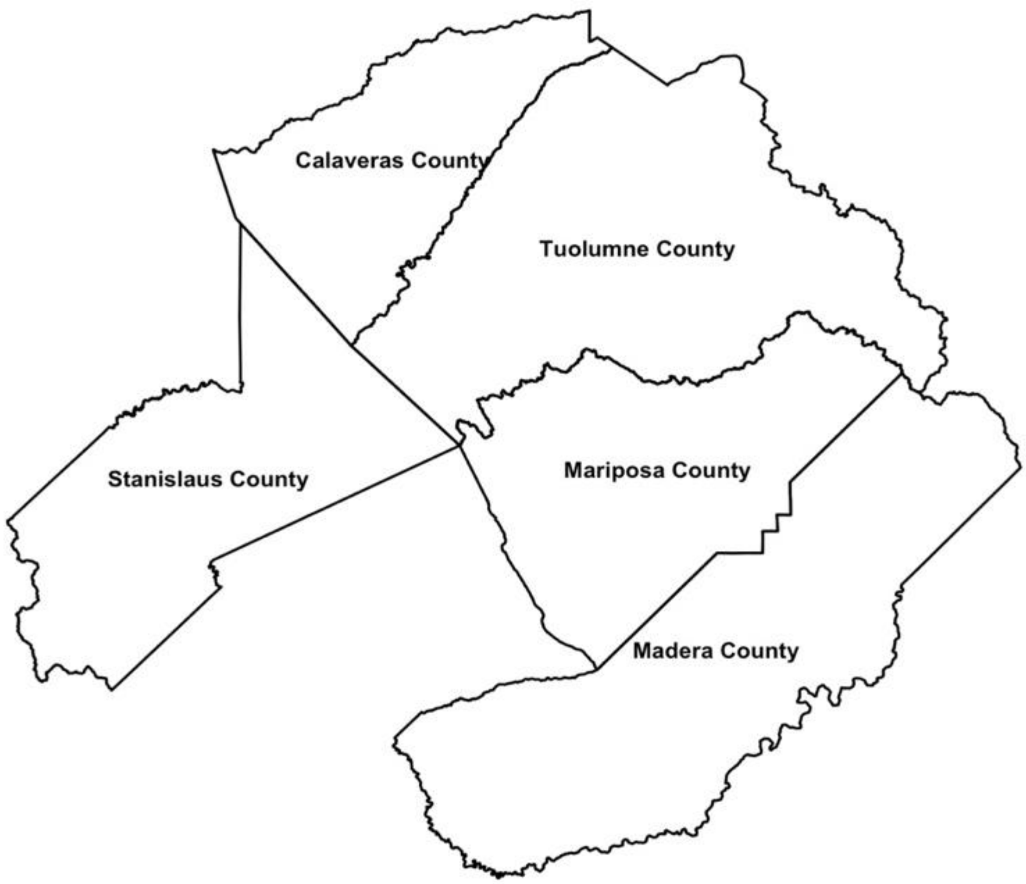


Figure showing the 5 counties selected to create various maps to include in survey

In this study, you will be randomly assigned with different scenarios depicting wildfire risk and communication method. Your task is to provide feedback on how well the presented method communicates the uncertainty and severity of wildfire risk. Your participation will play a crucial role in enhancing wildfire risk communication strategies, ultimately contributing to better preparedness and safety measures for communities like yours.

BLOCK 2

General Information

1. In what year were you born? _____ (year)

2. Gender:
   a. Male
   b. Female
   c. Non-binary
   d. Prefer not to say

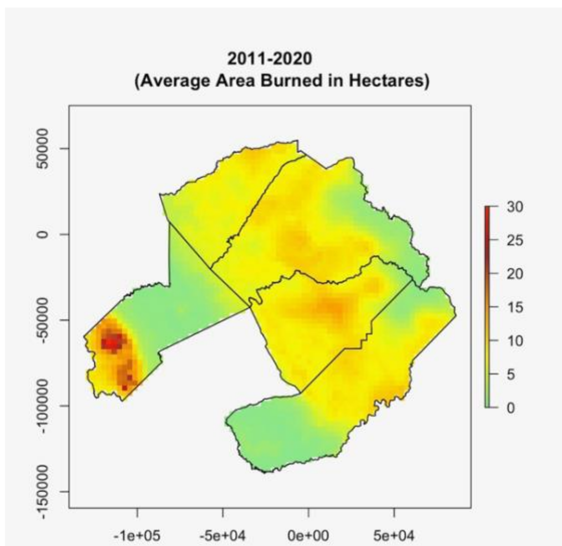
3. What is the highest level of education you completed?
   a. Some high school
   b. High school graduate
   c. Some college
   d. College graduate
   e. Postgraduate

4. How often do you use maps or visual data in your daily life or profession?
   a. Never
   b. Rarely
   c. Occasionally
   d. Frequently
   e. Always

5. How would you assess your ability to read and interpret digital maps?
   a. Very poor
   b. Fair
   c. Good
   d. Very Good
   e. Excellent

Block 3
Scenario (Static Image)
Part A

Description:
The image provided here showcases information regarding the average area burned due to wildfires from the year 2011 to 2020. The area represented here are measured in hectares. This image incorporates a color scale to represent different ranges of hectares burned. The scale ranges from 0 to 30, with colors transitioning from Green, Light-green, Yellow, Brown, and finally Red. Each color represents a specific range of hectares burned. The map creation process involved simulating historical fire occurrences over 2000 times. These simulations considered various factors contributing to wildfires. After simulation, the average burned area was calculated based on these 2000 simulations, providing a comprehensive overview of wildfire impact over the specified period.



1. Did the visual representation increase your concern about wildfires? (Hypothesis 1.1)
    a. Yes
    b. No
    c. Unsure

2. Did your perception of wildfire risk change after viewing the visual? (Hypothesis 1.1)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.
    e. Increased significantly.

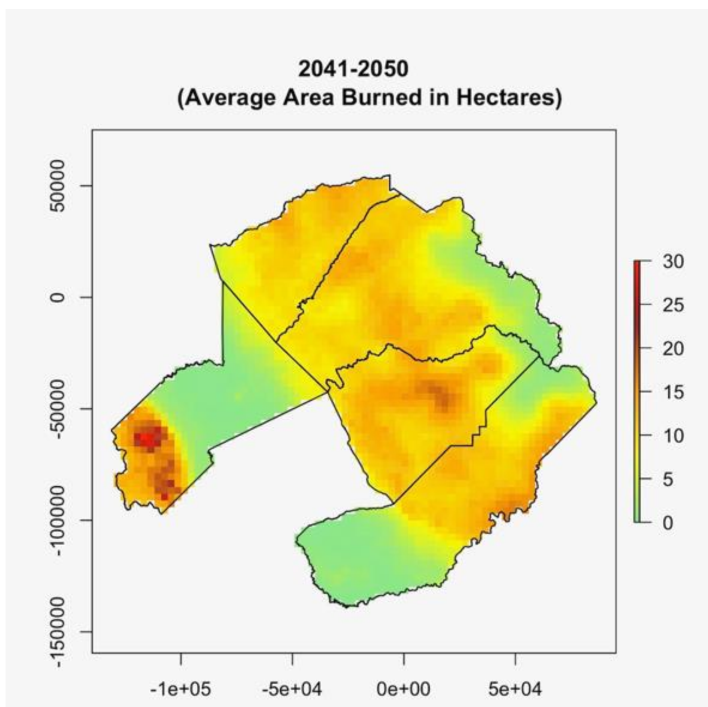
3. In your opinion, how severe do you perceive the risk of wildfire to be after viewing the visual? (Hypothesis 1.1)
    a. Not severe
    b. Slightly severe
    c. Moderately severe
    d. Quite severe
    e. Extremely severe

4. Did the visuals make you feel that wildfire risks are an urgent issue? (Hypothesis 1.2)
    a. Yes
    b. No
    c. Unsure

5. How urgent do you feel it is to prepare for wildfires after viewing the visuals? (Hypothesis 1.2)
    a. Not urgent at all
    b. Slightly urgent
    c. Moderately urgent
    d. Very urgent
    e. Extremely urgent

Block 4
Scenario (Static Image)
Part B

Description:
The image provided here showcases information regarding the projected average area burned due to wildfires from the year 2041 to 2050. The area represented here are measured in hectares. This image incorporates a color scale to represent different ranges of hectares burned. The scale ranges from 0 to 30, with colors transitioning from Green, Light-green, Yellow, Brown, and finally Red. Each color represents a specific range of hectares burned. The map creation process involved using climate model future projections to simulate wildfire occurrences. These simulations were conducted 2000 times to account for variability. These simulations considered various factors contributing to wildfires. After simulation, the average burned area was calculated based on these 2000 simulations, providing a comprehensive overview of wildfire impact over the specified period.



1. Did the new visual representation increase your concern about wildfires? (Hypothesis 1.1)
    a. Yes
    b. No
    c. Unsure

2. In your opinion, how severe do you perceive the risk of wildfire to be after viewing the new visual? (Hypothesis 1.1)
    a. Not severe
    b. Slightly severe
    c. Moderately severe
    d. Quite severe
    e. Extremely severe

3. Did your perception of wildfire risk change after viewing the new visual? (Hypothesis 1.1)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.
    e. Increased significantly.

4. Did the new visuals make you feel that wildfire risks are an urgent issue? (Hypothesis 1.2)
    a. Yes
    b. No
    c. Unsure

5. After viewing new visual, how urgent do you feel it is to prepare for wildfires?
   (Hypothesis 1.2)
    a. Not urgent at all
    b. Slightly urgent
    c. Moderately urgent
    d. Very urgent
    e. Extremely urgent

6. Did the new visual affect your perception of the need for immediate action? (Hypothesis 1.2)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.
    e. Increased significantly.

BLOCK 5

1. How easy was it to interpret the visual? (Hypothesis 2.1)
a. Very difficult
b. Difficult
c. Easy
d. Very easy
e. Extremely easy

2. How clear is the information presented in visual? (Hypothesis 2.1)
a. The information was very complex, and I did not understand it all.
b. The information was somewhat complex, and I had some difficulty understanding it.
c. The information was moderately complex, and I mostly understood it.
d. The information was simple, and I understood it without any difficulty.
e. The information was very simple, and I completely understood it.

3. How effectively do you think the visuals communicated the risk information? (Hypothesis 2.1)
a. Not effective at all
b. Slightly effective
c. Moderately effective
d. Very effective
e. Extremely effective

4. How confident are you that you correctly understood the risk levels shown in the visuals? (Hypothesis 3.1)
a. Not very confident
b. Slightly confident
c. Moderately confident
d. Very confident
e. Extremely confident

5. How would you rate the understandability of wildfire risk information? (Hypothesis 3.1)
a. Least understandable
b. Somewhat understandable
c. Moderately understandable
d. Very understandable
e. Extremely understandable

APPENDIX 4: DYNAMIC VISUALIZATON SURVEY INSTRUMENT (Chapter 4)

BLOCK 1

Important Information about the survey – PLEASE READ!

Welcome to our research survey. We are exploring perceptions of wildfire risk across five counties of California State, as shown in the map. The purpose of this survey is to better understand whether people like you would benefit from new types of information in wildfire risk. This study uses modeling techniques to predict wildfire risks and examines how visual representation of this data might influence public perception. Specifically, the survey focuses on wildfire maps that shows historical and future fire risk. It may be costly to develop new information, and we want to make sure it is worthwhile to do so.

You do not need any special knowledge about wildfire and its risk to respond to any of the questions. We want to learn about how you interpret and use wildfire risk information, and what are your opinions about the presented information.

Two scenarios will be presented for your consideration: First reflects the historical wildfire risk simulation from year 2011-2020; and second reflects the projected wildfire risk simulation in near future (2041-2050).

We will use your responses to guide future research related to wildfire risk communication to provide better information for you, so your responses are very important for us. All your responses will remain anonymous. None of the information or opinions you provide can be linked back to you, so please respond as honestly as you can.

Thank you for taking the time to complete the survey!

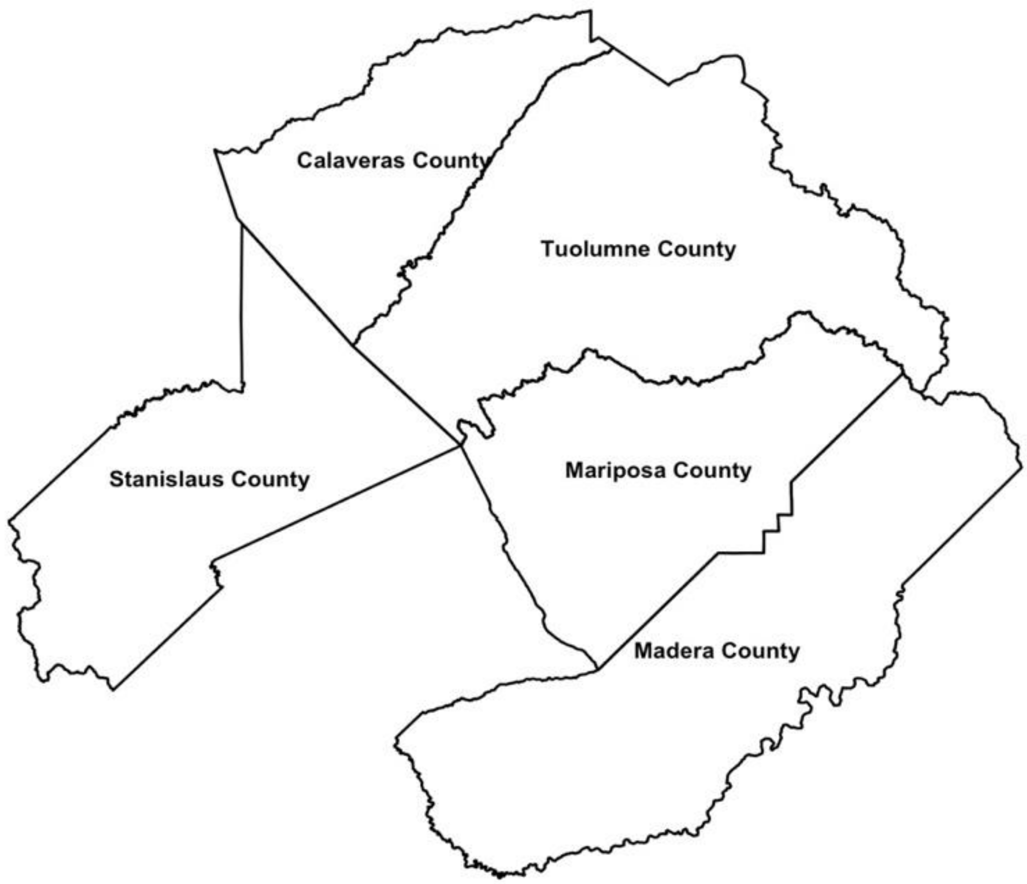


Figure showing the 5 counties selected to create various maps to include in survey

In this study, you will be randomly assigned with different scenarios depicting wildfire risk and communication method. Your task is to provide feedback on how well the presented method communicates the uncertainty and severity of wildfire risk. Your participation will play a crucial role in enhancing wildfire risk communication strategies, ultimately contributing to better preparedness and safety measures for communities like yours.

BLOCK 2

General Information

6. In what year were you born? _____ (year)

7. Gender:
   a. Male
   b. Female
   c. Non-binary
   d. Prefer not to say

8. What is the highest level of education you completed?
   a. Some high school
   b. High school graduate
   c. Some college
   d. College graduate
   e. Postgraduate

9. How often do you use maps or visual data in your daily life or profession?
   a. Never
   b. Rarely
   c. Occasionally
   d. Frequently
   e. Always

10. How would you assess your ability to read and interpret digital maps?
    a. Very poor
    b. Fair
    c. Good
    d. Very Good
    e. Excellent

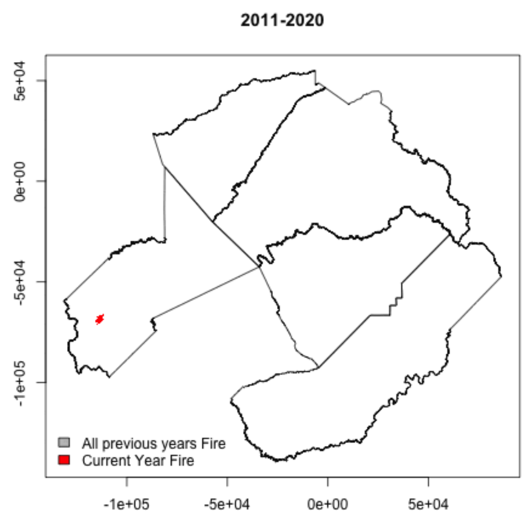
Block 3

Scenario (Animated Visual)

Part A

Description:

The animation provided here showcases information regarding wildfire risk in the study region between the years 2011 to 2020. Each sequential frame within the animation delineates a distinct fire perimeter, with subsequent frames overlapping the preceding ones. The utilization of distinct colors in animation serves to signify the current and preceded frames. The creation of the animated map involved simulating historical fire incidents numerous times, wherein a multitude of contributing factors to wildfire occurrence were carefully considered. Following these simulations, the resultant fire perimeters were generated, providing an all-encompassing depiction of the wildfire landscape over the specified time period.



6. Did the visual representation increase your concern about wildfires? (Hypothesis 1.1)
    a. Yes
    b. No
    c. Unsure

7. Did your perception of wildfire risk change after viewing the animation? (Hypothesis 1.1)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.

    e. Increased significantly.

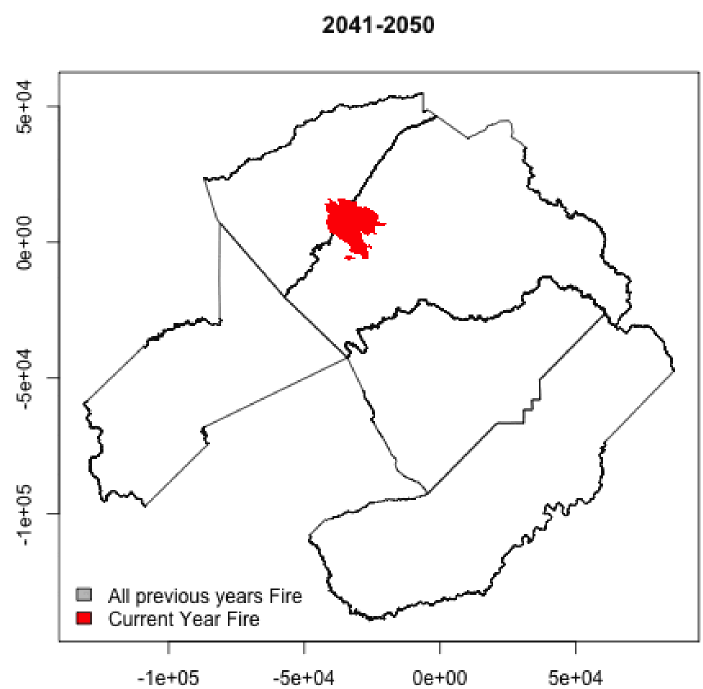
8. In your opinion, how severe do you perceive the risk of wildfire to be after viewing the visual? (Hypothesis 1.1)
    a. Not severe
    b. Slightly severe
    c. Moderately severe
    d. Quite severe
    e. Extremely severe

9. Did the visuals make you feel that wildfire risks are an urgent issue? (Hypothesis 1.2)
    a. Yes
    b. No
    c. Unsure

10. How urgent do you feel it is to prepare for wildfires after viewing the visuals? (Hypothesis 1.2)
    a. Not urgent at all
    b. Slightly urgent
    c. Moderately urgent
    d. Very urgent
    e. Extremely urgent

Block 4
Scenario (Animated Visual)
Part B

Description:
The animation presented here offers a comprehensive portrayal of wildfires spanning from 2041 to 2050. Similar to the previous timeframe, each frame depicts a distinct fire perimeter, overlapping with subsequent frames for continuity. Unique colors in the animation signify different frames (current and previous all other frames), aiding in visual comprehension. To simulate future wildfires, advanced wildfire statistical models were employed, incorporating various environmental, topographical, and vegetation factors influencing fire occurrence. These models project potential fire occurrences based on anticipated climate conditions. Through these projections, simulated fire perimeters for the specified timeframe were generated, providing insights into the potential wildfire landscape in the future.



7. Did the new visual representation increase your concern about wildfires? (Hypothesis 1.1)
    a. Yes
    b. No
    c. Unsure

8. In your opinion, how severe do you perceive the risk of wildfire to be after viewing the new visual? (Hypothesis 1.1)
    a. Not severe
    b. Slightly severe
    c. Moderately severe
    d. Quite severe
    e. Extremely severe

9. Did your perception of wildfire risk change after viewing the new visual? (Hypothesis 1.1)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.
    e. Increased significantly.

10. Did the new visuals make you feel that wildfire risks are an urgent issue? (Hypothesis 1.2)
    a. Yes
    b. No
    c. Unsure

11. After viewing new visual, how urgent do you feel it is to prepare for wildfires? (Hypothesis 1.2)
    a. Not urgent at all
    b. Slightly urgent
    c. Moderately urgent
    d. Very urgent
    e. Extremely urgent

12. Did the new visual affect your perception of the need for immediate action? (Hypothesis 1.2)
    a. Decreased significantly.
    b. Decreased slightly.
    c. No change.
    d. Increased slightly.
    e. Increased significantly.

BLOCK 5

6. How easy was it to interpret the visual? (Hypothesis 2.1)
    f. Very difficult
    g. Difficult
    h. Easy
    i. Very easy
    j. Extremely easy

7. How clear is the information presented in visual? (Hypothesis 2.1)
    a. The information was very complex, and I did not understand it all.
    b. The information was somewhat complex, and I had some difficulty understanding it.
    c. The information was moderately complex, and I mostly understood it.
    d. The information was simple, and I understood it without any difficulty.
    e. The information was very simple, and I completely understood it.

8. How effectively do you think the visuals communicated the risk information? (Hypothesis 2.1)
    a. Not effective at all
    b. Slightly effective
    c. Moderately effective
    d. Very effective
    e. Extremely effective

9. How confident are you that you correctly understood the risk levels shown in the visuals? (Hypothesis 3.1)
    a. Not very confident
    b. Slightly confident
    c. Moderately confident
    d. Very confident
    e. Extremely confident

10. How would you rate the understandability of wildfire risk information? (Hypothesis 3.1)
    a. Least understandable
    b. Somewhat understandable
    c. Moderately understandable
    d. Very understandable
    e. Extremely understandable