WILL OAKLAND BURN AGAIN:
UNDERSTANDING THE FIRE HAZARD IN AN URBAN PARK SYSTEM

A Thesis

presented to

the Faculty of California Polytechnic State University,

San Luis Obispo

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in Forestry Sciences

by

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May 2021

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ABSTRACT

Will Oakland Burn Again:
Understanding the Fire Hazard in an Urban Park System

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Though almost thirty years have passed since the 1991 Tunnel Fire, the wildfire hazard is still present in the Oakland Hills. This study was conducted to determine if the vegetation in the Oakland Hills had reverted back to fuel conditions that contributed to the Tunnel Fire, examine how the fire hazard has changed since 1991, and evaluate planned wildfire mitigation. The goal was to determine how fuel conditions have changed since 1991 and compare potential fire behavior to that of the Tunnel Fire. Additionally, the study examined the effectiveness of the mitigation actions described in the East Bay Regional Park District's Wildfire Hazard Reduction and Resource Management Plan on lowering extreme fire behavior. Through the use of remote sensing, historical aerial imagery, satellite imagery, and Landsat imagery the 1991 and 2018 fuel conditions were analyzed. ArcGIS Pro and FlamMap 6 were used to compare hectares of fuel and changed in fire behavior between the two year. Mitigation actions were modeled with FlamMap 6 and ArcGIS Pro and fire behavior was compared between untreated conditions and post treatment conditions. The vegetation in the Oakland Hills, in the absence of fire, returned to a mature state, similar to the 1991 conditions. However, there was a reduction in the overall hectares of fuel model 147 in 2018. Modeled fire behavior indicated an overall reduction in extreme fire behavior when comparing 1991 to 2018. This reduction varied on a park level with each park performing differently. When modeled, mitigation was able to lower extreme fire behavior across the landscape but success varied on an individual park basis. In conclusion, should ignition occur presently, under foehn wind conditions, a fire would still exhibit very extreme behavior with a high potential for catastrophic loss, and implantation of planned mitigation measures may be able to lower the degree of extreme fire behavior.

Keywords: [Oakland Hills, fire hazard, wildland fire hazard, WUI fire, fire mitigation]

ACKNOWLEDGMENTS

Throughout the thesis process I have received generous amounts of support and guidance from various sources. I would first like to thank my advisor and project supervisor Dr. Chris A. Dicus for guiding me through the thesis process and supporting my endeavors to create my own research project. Your support allowed me the freedom to chose a subject I was passionate about and genuinely interested in. Thank you for all the opportunities I was given to further my research, funding opportunities, and for helping my grow my network.

I would also like to extend my thanks to my committee member Russ White, for his GIS expertise and input. You were invaluable part of the methodology process. It was with your help that I was able to overcome many project hurdles. Thank you for taking the time to help me learn GIS and discover new ways of creating and analyzing data. I would also like to give my thanks to my committee member Dr. Bill Henricks for taking time to meet with me and help me shape my project ideas. Your advice helped me find necessary background research and helped me shape the design of my project. I would also like to thank you for your editorial input.

Thank you to the Cal Poly Statistical Consulting for assisting me with the data analysis process. In particular I would like to thank Dr. John Walker, Dr Soma Roy, and especially Dr. Ulric Lund. Your assistance and efforts were invaluable to my data analysis process I could not have done it without you . Thank you all for your patience, kindness, and support.

Thank you to the Natural Resources Management and Environmental Sciences (NRES) department for providing me with resources necessary to complete my thesis, such as the graduate research room and funding to attend and present at conferances. I would especially like to thank the late Dr. Greg Brown, Dan Turner, and Walter Ruzzo for advice, support, and input. I would also like to thank Lisa Wallravin and Dr. Chiu for helping me support my research through my employment as a department ISA.

I would like to extend my gratitude to my family, my partner, and my friends. Their support kept me grounded throughout this process. They were my sound boards, my confidants, my editors, and my biggest fans. Thank you all for not only staying by my side through these years but for taking the time to attend my defense.

Finally, I would like to take this opportunity to thank the WUI Fire Institute at Cal Poly. Their generous donation helped me finishes the final aspects of my thesis and alleviated some of the burden of graduate school.

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CHAPTER 1: INTRODUCTION

In 1991 a fire in the Oakland Hills of California changed the traditional view of fire hazards. The 1991 Tunnel Fire ushered in the current era of catastrophic fires in the wildland-urban interface (WUI). The fire remains one of the most destructive and one of the deadliest fires in California history (CAL FIRE, 2020; California Office of Emergency Services, 1992). Nevertheless, a comparison of current wildfire hazard conditions to those that caused the Tunnel Fire event is largely unknown. Understanding how past fire events compare to current fire hazards may help in shaping wildfire management. There is a need to understand similarities and differences to the fire hazard in 1991 and to determine the potential effect of fuel mitigation.

The Tunnel Fire originally started as a small grass fire by the Temescal Tunnel in the East Bay Regional Park District (EBRPD) in Oakland, California on October 19, 1991. The following day, a spike in Diablo wind conditions caused the small fire to rekindle, flare up and rapidly move down the ridgeline spreading from EBRPD lands into residential areas (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; U.S Fire Adiministration, 1991). Within an hour the fire was considered to be out of control (U.S Fire Adiministration, 1991). The main factors that drove extreme fire behavior were 48-110 kph winds, dense accumulation of fuels such as eucalyptus, and the layout of homes (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; U.S Fire Adiministration, 1991). Many homes in the area were made with wood shingle roofs, set into vegetation, and difficult to access by road (California Office of Emergency Services, 1992; U.S Fire Adiministration, 1991). In less than ten hours, 25 lives were lost and over 2,000 homes were destroyed (California Office of Emergency Services, 1992; U.S Fire Adiministration, 1991).

Almost thirty years have passed since the original fire and in that time the fire hazard in the Oakland Hills seems to have returned to a high level (CAL FIRE, 2008). The local area has had a significant fire history with wildfires occurring in 1923, 1970, and 1980 (California Office of Emergency Services, 1992; U.S Fire Adiministration, 1991). It is not unreasonable to expect the area to burn again. Both then and now, thousands of homes exist in the WUI of the area, many at the top of the EBRPD western border (California Office of Emergency Services, 1992; U.S Fire Adiministration, 1991). Furthermore, since the Tunnel Fire, vegetation within the parks has regrown, matured, and changed in composition, influencing the fire hazard in the region.

The EBRPD parklands were last assessed between 2007-2010 by the EBRPD for the Wildfire Hazard Reduction and Resource Management Plan. The mitigation plan outlined a fuel modification action plan for reducing wildfire hazards within the park system (LSA Associates Inc. & East Bay Regional Park District, 2010a). The plan largely focused on reducing hazardous fuels within close proximity to neighborhoods, removing and thinning Blue Gum Eucalyptus (*Eucalyptus globulus),* and creating firefighter safety zones (LSA Associates Inc. & East Bay Regional Park District, 2010a). A common challenge to fuel mitigation in large areas is conflicts between management objectives and public expectations (Ager, Vaillant, & Finney, 2010), this is why large-scale mitigation has yet to be fully implemented in the EBRPD. Furthermore, the delay between the wildfire assessment and mitigation implementation means that it is unclear if the recommended treatments would be effective on the present-day fire hazard

Understanding the current fire hazard provides a starting point for wildfire management and hazard mitigation in a given locality. But it is not often that current fire hazards are extensively compared to historical ones. To effectively manage wildfire, the specific factors that influence fire hazards, especially in WUI areas, need to be understood (Syphard *et al.*, 2007; Bründl *et al.*, 2009, Brenkert-Smith *et al.*, 2012; Ager *et al.*, 2015). One of these factors is how a fire hazard on a landscape has changed. Which is why it is important to go beyond simply modeling the present by hazard but to also model historical fire events. In areas with a significant fire history, examining how the current fire hazard compares to the historical one on a fire behavior level can not only shed light on how the landscape has altered but also contextualize how a fire might behave today. Thus, allowing for this hazard to be more readily understood and prepared for. While, the Oakland hills area was previously assessed by the EBRPD there was no extensive comparison to the historical conditions in 1991, which was due in part to a lack of historical fuels data at the time. However, to best determine how a potential fire could burn locally and the mitigation steps necessary to reduce the hazard, it is imperative to compare known current fuel conditions and fire behavior that occurred in the 1991 Tunnel Fire with current physical conditions.

For this project, there were two main objectives. The first was to quantify and compare how the present-day fire hazard to the fire hazard that existed at the time of the 1991 Tunnel Fire in order to better understand how fire might behave on the landscape. The second objective was to evaluate how the EBRPD mitigation plan affects the occurrence of extreme fire behavior based on the present-day fire hazard. To that end, via remote sensing, I compared (i) the hectares of fuel in 1991 vs. 2018 in the EBRPD, (ii) fuel composition for 1991 vs. 2018, (iii) simulated and compared potential wildfire behavior under average conditions and extreme conditions for 1991 and 2018, and (iv) determined how potential mitigation actions may lower extreme fire behavior in the EBRPD.

CHAPTER 2: LITERATURE REVIEW

THE MULTIFACED NATURE OF FIRE: LOOKING BEYOND THE BIOPHYSICAL HAZARD

2.1 Introduction

In California, fires are a frequent and powerful disturbance. Their prevalence is exacerbated by the state's climatic system and native vegetation (Steinberg, 2002). Summer and early fall are especially fire-prone due to high temperatures and offshore wind events (Holmes et al., 2008). This dries out fuels and drives the potential for extreme fire behavior (Holmes et al., 2008). However, as more people move into the Wildland Urban Interface (WUI), the challenge and threat of fire have become more complex (Calkin, Thompson, & Finney, 2015; Olsen et al., 2017; Syphard et al., 2007). The result is an increase in human-caused ignitions (Cardille, Ventura, & Turner, 2008; T. W. Collins, 2005; Dennison, Brewer, Arnold, & Moritz, 2014) extreme fire behavior, and home loss (Calkin et al., 2015; Marlon et al., 2012). The wildfire problem in California goes beyond the biophysical realm and it is increasingly costly to manage (Kramer, Mockrin, Alexandre, & Radeloff, 2019). To understand the wildfire problem not only does the biophysical hazard need to be considered, but wildfire mitigation measures and social dimensions of fire must be assessed as well.

2.1.1 Biophysical Fire Hazard Components

The biophysical fire hazard is the basis for fire management, fire risk assessment, and people's relationship with fire. It cannot be ignored when doing anything related to fire. The fire hazard reflects the condition of the forest and the condition of the fuels within it (Calkin et al., 2015). Currently, our fire systems are under great stress, and the fire hazard in many locations is quite high (Calkin et al., 2015). We have affected fire and fuels in both very intentional and unintentional ways (Safford, Schmidt, & Carlson, 2009). Policy decisions regarding suppression, consequences of climate change, and where we build our homes have changed how fire returns to the landscape (Dombeck, Williams, & Wood, 2004; Safford et al., 2009).

2.1.1.1 Wildland Areas Fire Hazard

One of the biggest deliberate effects we have had on the fire system is the legacy of suppression. Large scale suppression activities started in the 1920s and by the 1940s the effects of those decisions were evident (Stephens, 2005). While the intention was to make the wildlands safer, removing fire has only increased the hazard and the danger.

The fire problem we are currently facing is increased frequency, increased severity, and a positive feedback loop (T. W. Collins, 2005; Marlon et al., 2012). Suppression policies have caused the fire hazard to worsen over time and management decisions are still contributing to the problem. In the Western U.S, long-term exclusion and suppression have changed the fuel composition by increasing fuel density and fuel homogeneity (Calkin et al., 2015; Snider, Daugherty, & Wood, 2006). The changes in fuel structure have resulted in fires shifting from surface fires to crown fires (Calkin et al., 2015; Snider et al., 2006). Despite efforts to remove fire from the landscape fire cannot be suppressed, it will always return (Calkin et al., 2015). However, as fire returns it may no longer fit the management goals of that landscape. The longer that fire has been excluded from a system the more it shifts towards extremes, increasing wildfire hazards and changing fire behavior (Calkin et al., 2015). Our deliberate choices to remove fire have made the landscape more hazardous than ever before.

As the system moves toward extremes, fires are happening more often and the area burned is increasing (Olsen et al., 2017). Dennison *et al.* (2014) found that this positive trend occurs in areas with a high history of suppression (Figure 1-1) (Dennison et al., 2014). Across all high suppression areas fire increased at a rate of seven large fires per year (Figure 1-1). Within California, except in the Mediterranean region where fire has remained relatively constant, all other regions had a positive trend with fire increasing from 1984-2011 (Figure 1-1). However, the Mediterranean region had the highest frequency of large fires overall (Dennison et al., 2014). They also found that in all nine ecoregions total fire area increased by a rate of 355 km^2 per year. The positive feedback loop contributes to more large fires which in turn results in more suppression. This illustrates that as we keep trying to remove fire from the landscape it continuously returns at a greater level than before.

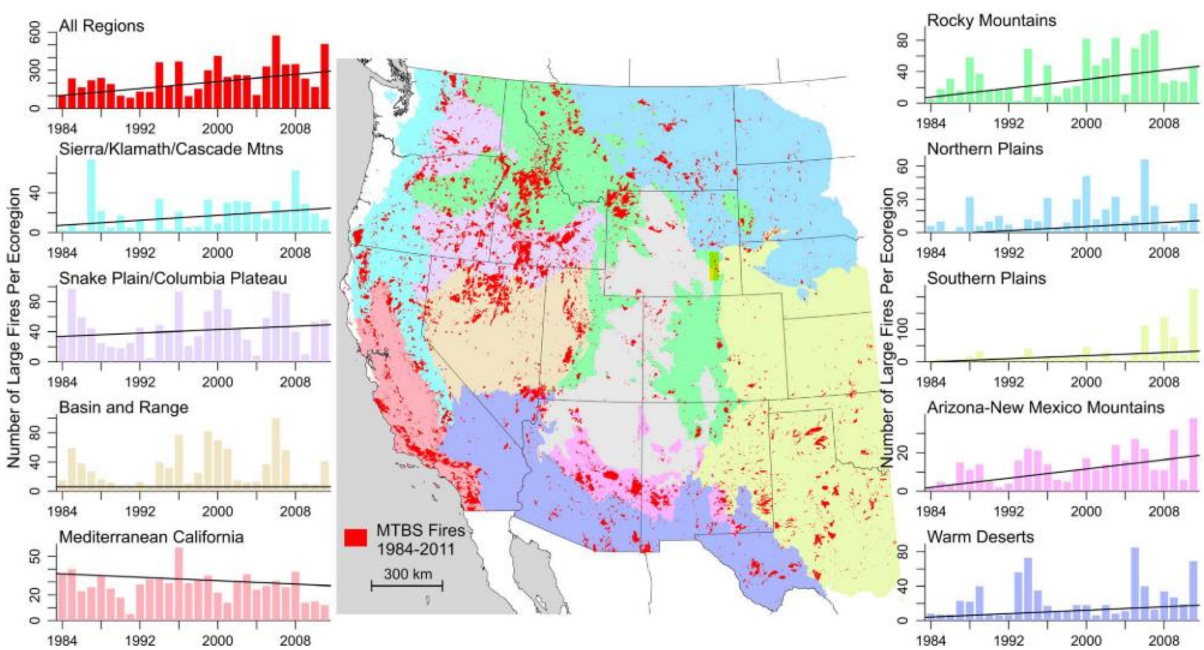

Fig. 2-1: Trends of the number of large fires across the Western U.S. from 1984-2011. The black line indicates the trend for each ecoregion. Large fires are classified by a burned area of greater than 1000 acres. Reprinted from "Large wildfire tends in the western United States, 1984-2011" by P.E. Dennison et al, 2014, AGU, 41(8), p.2929, Copyright 2014 by American Geophysical Union. Reprinted with permission.

While suppression was an intentional decision we made, other choices have unintentionally affected the fire hazard as well. Climate change is altering the aspects of the natural environment daily. Our choices regarding it have had an unintentional effect on fire. How climate change is altering fire is still in the process of being understood, but it cannot be ignored. One of the most evident effects of climate change is the lengthening of the fire season (Westerling, Hidalgo, Cayan, & Swetnam, 2006). Since 1980, the fire season has been increasing by the delay of winter and the advancement of spring (Westerling et al., 2006). Overall, the fire season is 78 days longer than before and will continue to grow (Westerling et al., 2006). This means fuels will be drier, the opportunities for ignitions will increase, and extreme fire behavior will be more common (Schulte & Miller, 2010). This effect will likely continue in the future, making containment even more difficult (Schulte & Miller, 2010).

Climate change also affects moisture variability (Westerling *et al.*, 2006). This can cause an increase in the fluctuation between wet/dry conditions, promoting a period of biomass growth followed by a period of higher dry fuel availability (Westerling et al., 2006). Northern California has been greatly affected by climate change (Westerling et al., 2006). The advancing spring and delayed rains have created moisture deficits and increased the number of high fire risk days (Schulte & Miller, 2010; Westerling et al., 2006). Drier fuels and increased red flags days could result in more catastrophic wildfires in Northern California and beyond. Increased fuel may result in higher fire frequency and severity than current vegetation types are accustomed to (Calkin et al., 2015; Russell & McBride, 2003). Therefore, there is a need to better understand the fire hazard as it relates to the region it affects.

With a history of large-scale fire suppression and worsening of climate change, the wildland fire hazard has grown (Calkin et al., 2015; Marlon et al., 2012; Schulte & Miller, 2010). Removing fire from a system has had an opposite effect by increasing the level of fuels and extremity of fire behavior (Calkin et al., 2015; Snider et al., 2006). We need to understand what this effect will mean for the future of fire management. However, fire does not exist exclusively in wildland systems. Not only do we have to consider the consequences we have had on the ecological system, but we also must consider that where we choose to live greatly effects the wildfire hazard. This intersection is becoming increasingly important and crucial to study and understand.

2.1.1.2 Wildland Urban Interface Fire Hazard

Wildfire is strongly influenced by where people choose to build their homes and the actions they take on their property (Cardille et al., 2008). In the wildland urban interface (WUI), fires can start in either wildland areas and burn into residential areas or vice versa (Mell, Manzello, Maranghides, Butry, & Rehm, 2010). A WUI fire will consume both home and wildland fuels and is very difficult to suppress. California, Arizona, and Colorado have the highest percentages of WUI residential areas (Schoennagel, Nelson, Theobald, Carnwath, & Chapman, 2009). These states also have some of the highest suppression areas (Dennison et al., 2014). An unintentional effect of historical suppression is that it allowed for people to move further into the wildlands, increasing the area of the WUI (S. McCaffrey, 2004). As the WUI grows, ignitions in these regions increase and are more likely to be human-caused (Marlon et al., 2012; Safford et al., 2009). In California, the rise in human-caused ignitions is most evident in chaparral and coastal scrub communities where the population is increasing (Syphard et al., 2007). Syphard et al. (2007) found that the number of fires is highest in WUI areas with shorter distances to the intermix or interface, (Figure 1-2). However, this trend starts to level off when the distance to the WUI area reaches 9-10km for intermix and 14-15 km for interface (Figure 1-2) (Syphard et al., 2007). The trend illustrates that the closer people live to wildland areas the more likely WUI fires are to occur. This results in a different fire hazard with a high percentage of assets at risk. The consequences of WUI growth need to be considered in fire hazard assessment.

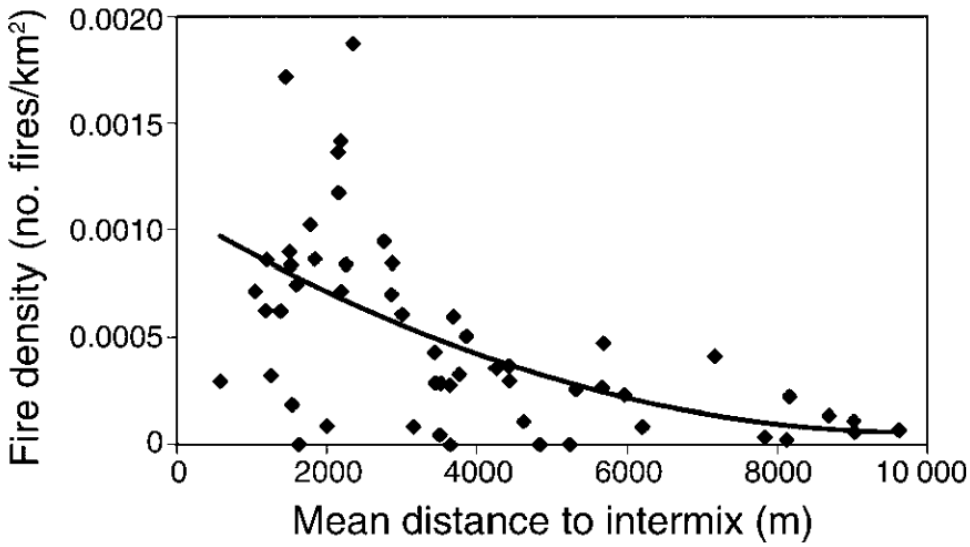

Fig. 2-2: The proportion of the number of fires and the mean distance to the WUI intermix. Reprinted from "Human Influence on California Fire Regimes," by A. D. Syphard et al, 2007, Ecological Society of America, 17(5), p.1395, Copyright 2007 by Ecological Society of America. Reprinted with permission.

WUI areas are also where the most destructive fires tend to occur (Kramer et al., 2019). WUI fires are highly destructive due to the relatively short distances between homes and fuels (Kramer et al., 2019). These types of fires comparatively need minimal wildland fuel to cause extensive damage versus fires that occur exclusively in wildland fuels (Kramer et al., 2019). Once a fire transitions into the WUI, home to home spread makes devastation high and containment difficult. In the 1991 Oakland Firestorm, the quick transition from wildland fuels to residential structures resulted in over 2,000 homes being lost in a few hours (Kemper, Blonski, & Honeycutt, 2001; Pagni, 1993; U.S Fire Adiministration, 1991). 75% of structures lost during wildfires exist in areas classified as WUI (T. W. Collins, 2005). In terms of home distribution, most homes tend to be in the WUI interface but the WUI intermix is generally more widespread (Kramer et al., 2019). One-third of these homes are built in areas where ignitions are more likely to occur (T. W. Collins, 2005), leaving a high proportion of homes potentially at risk. From 1996 to 2016 approximately over 1,449 residence were destroyed annually in WUI fires alone (Mockrin, Fishler, & Stewart, 2018). Every fire season this number continues to increase.

Structure loss in WUI areas is due to a combination of weather, wind, home ignitability, and suppression (Ager et al., 2010). The attributes and characteristics of a house drive its home ignitability potential (T. W. Collins, 2005; Meldrum et al., 2015). Home ignitability is also be affected by wildland conditions (P. A. Champ, Donovan, & Barth, 2013) and surrounding property characteristics (Meldrum et al., 2015). The complexity of multiple driving factors can make reducing ignitability a serious challenge.

Because so many factors can influence structure loss and WUI fires, this issue is incredibly difficult to manage. WUI fires are complex and have a high potential for damage. This also means that the WUI hazard is unique to each community in which it is being evaluated (Brenkert, Champ, & Flores, 2005). There is a need to understand how fire hazards apply to the specific community it will affect. As the WUI grows, fire management cannot have a one-size-fits-all approach; it must be appropriate to the setting and the scale of the hazard that exists (Brenkert et al., 2005).

2.1.2 Wildfire Mitigation Measures

Suppression, climate change, and population densities have made wildfire management more complex and dangerous than ever before (Kramer et al., 2019). Our suppression system on average costs 1 billion dollars each year and this total is expected to rise (Ager, Kline, & Fischer, 2015; Calkin et al., 2015). The cost of suppression also pulls from land management and is an inappropriate substitution for mitigation (Calkin et al., 2015; T. W. Collins, 2005; Steelman & Burke, 2007). Just as our actions can increase the wildfire hazard, we can also intentionally reduce the wildfire hazard. Mitigation reduces the potential effect or damages the hazard may inflict (Godschalk, 2003). Within fire management, there are two main types of mitigation, wildland mitigation, and property mitigation (Toman, Stidham, Shindler, & Mccaffrey, 2011). These factors do not exist independently and must be considered in conjunction when mitigating for fire (Cohen & Jack, 2008; T. W. Collins, 2005).

2.1.2.1 Wildland Fuels Mitigation Measures

Management decisions can directly reduce or increase a wildfire hazard (P. A. Champ et al., 2013). Effectively managing a landscape requires first understanding the way the historical fire regime was altered (Syphard et al., 2007). The current fire regime and the desired fire regime outcome will influence the type of wildfire mitigation undertaken. Often wildfire mitigation falls to local government agencies (Kramer et al., 2019). They can provide expertise regarding their area and more freedom in management. Large scale forest managers often are not fully supported by their institutions (P. A. Champ et al., 2013). The longer a manager is in an agency, the more susceptible they are to the status quo; typically defaulting to suppression (Wilson, Winter, Maguire, &

Ascher, 2011). However, support for fuels management is growing, likely due to increased awareness (Toman et al., 2011). In 1970, prescribed fire was reintroduced as a tool for the National Park System and the U.S. Forest Service (Wilson et al., 2011). This marked the start of considering alternate management options for mitigating wildfire.

One of the biggest questions regarding fuel treatments is its long-term effectiveness. Although treatments are often implemented, they are not always monitored (B. M. Collins, Stephens, Moghaddas, & Battles, 2010). The long-term effects of fuels mitigation depend on the rate of treatment and the type of application (M. A. Cochrane et al., 2011). This can vary greatly; a treatment rate of 1-30% of the area can last from one year to two decades (B. M. Collins et al., 2010; Finney et al., 2007). Part of this variance is due to differences in treatment types and the rate treatments degrade overtime (M. A. Cochrane et al., 2011; Vaillant, Noonan-Wright, Dailey, Ewell, & Reiner, 2013). To maintain effectiveness, mitigation is an ongoing process rather than a one-time application.

In general, treatments will be either mechanical based or fire-based (Vaillant et al., 2013). Mechanical treatments initially increase 1-100 hour fuels before reducing fuel loads for up to eight years (Mark A Cochrane et al., 2011; Vaillant et al., 2013). Adding prescribed fire to mechanical treatment can reduce the initial spike in fuels (Mark A Cochrane et al., 2011; Safford et al., 2009; Vaillant et al., 2013). Fuel loads post fire-based treatment generally will have an initial sharp decrease and then increase over time (Safford et al., 2009; Vaillant et al., 2013). Fire-based treatments can reduce fuels by 75% for about eight to ten years; before returning to previous levels (Mark A Cochrane et al., 2011; T. W. Collins, 2005; Vaillant et al., 2013). Properly prescribed treatment can effectively reduce surface fuels and crown fire behavior, resulting in lower severity (Safford et al., 2009; Vaillant et al., 2013). However, while prescribed fire can be an effective mitigation tool, it requires extensive risk (Wilson et al., 2011) and smoke management (Mark A Cochrane et al., 2011). This makes the implementation of prescribed fire very difficult and is why it has largely been eclipsed (Wilson et al., 2011).

In California, most mitigation efforts occur near WUI areas (Safford et al., 2009). The goal is to reduce the spread and potential impact of fire from wildlands to residential areas. In Northern California, prescribed fire is the most effective fuel treatments, reducing severity for up to ten years (Mark A Cochrane et al., 2011). Attitudes towards prescribed fire and jurisdictional restrictions can make implementation difficult. Mechanical treatments are generally used in the place of prescribed fire. However, in Northern California mechanical treatments such as mastication may have a detrimental effect on fire hazard reduction (Mark A Cochrane et al., 2011). There is a need to increase our understanding of how fuel treatments affect potential fire behavior.

2.1.2.2 Property-Based Mitigation Measures

Home attributes can drive ignitability (T. W. Collins, 2005) and ignitability is determined by the materials used and the level of exposure (Mell et al., 2010). However, properties that are defended during a fire have a 77% survival rate (Handmer, Van der Merwe, & O'Neill, 2019). Measures like defensible space give fire personnel room to defend properties from flames. For a home to be effectively defended mitigation needs to be in place. Property mitigation can come in a variety of forms. The main issues property mitigation tries to adress are community adaptation, structural materials, and exposure to fuels (McGee, 2011) Whether or not homeowners implement mitigation on their property is the primary factor in the likelihood of property loss (J. G. Champ et al., 2012; Olsen et al., 2017). Active mitigation can be the difference between catastrophic home loss and property damage.

Local governments or the individual property owners are typically the responsible for property mitigation (Mockrin et al., 2018). Measures can take the form of codes, ordinances, programmatic measures, or voluntary compliance (Kramer et al., 2019). Neighborhood and community-based mitigation programs may effectively reduce property fire hazards (Olsen et al., 2017). However, Olsen et al., (2017) only found this to be true in areas where a strong community relationship was in place before implementing a program (Olsen et al., 2017).

The goal of the National Fire Plan, Firewise program, and other fire-safe programs is to encourage wildfire adaptation through mitigation and stewardship (McGee, 2011). Fire adapted communities acknowledge the risk of wildfires and can withstand wildfires without the loss of life or property (Mockrin, Stewart, Radeloff, Hammer, & Alexandre, 2015). The Healthy Forest Restoration Act facilitates the Community Wildfire Protection Plan program (CWPP), to attempt to foster residential based fire adaptations. A CWPP can help communities build capacity to solve and leverage fire problems (Jakes & Sturtevant, 2013). In communities with active CWPPs that later experienced a fire, the residents cited that the CWPP helped them prepare, recover, and change for the future (Jakes & Sturtevant, 2013). Many residents felt that without the CWPP the fire could have been worse (Jakes & Sturtevant, 2013).The local context of mitigation programs drives its level of success. Having mitigation measures tailored to the local community is crucial (Brenkert et al., 2005). Programs need to consider people and the environment but also feasibility, willingness to participate, and local culture (Brenkert et al., 2005). Wildfire mitigation programs that include local context rather than a generalized approach are more likely to succeed (Brenkert et al., 2005).

The main forms of homeowner mitigation measures are structural materials, landscaping, and property maintenance (McGee, 2011). The overall goal is to reduce the likelihood of property ignition. These actions can be carried out independently or programmatically. One of the most well-known actions is defensible space (McCaffrey, Stidham, Toman, & Shindler, 2011). A study by McCaffrey found that most homeowners undertake activities related to landscaping, thinning, lawn maintenance, and self-exclusion (McCaffrey et al., 2011). This was found to be consistent across five different WUI communities (McCaffrey et al., 2011). Often these actions were carried out only when fire protection also satisfied aesthetic values or other property values (McCaffrey et al., 2011). When mitigation is carried out, the community fire-related behaviors are fairly consistent year to year (Table 1-1) (Wolters, Steel, Weston, & Brunson, 2017). At least 40% of property owners continuously engaged in property protection activities, landscaping maintenance, and materials selection in regards to fire risk reduction, (Table 1-1) (Wolters et al., 2017)

Table 2-1: Percent participation by residents in firewise based activities across three survey years in Central Oregon. Reprinted from "Determinants of residential Firewise behaviors in Centeral Oregon," E. A. Walters et al, 2017, The Social Science Journal, 54(2), p. 173. Copyright 2017 by Wester Social Science Association. Reprinted with permission.

	Percentage participating			
	2011	2012	2013	Combined years
General planning				
Prepare an evacuation plan in case of wildfire	33.3%	36.5%	34.6%	34.7%
Plan recreational activities that involve fire (e.g., campfires, fireworks) around weather service reports	62.1%	66.0%	61.9%	63.5%
Community activities				
Attend community-based meetings related to wildfire	19.3%	20.0%	19.1%	19.5%
Obtain information from a land management, community group or firefighting agency on how to prepare for wildfire	40.7%	42.9%	41.8%	42.0%
Volunteer within the community to help clear and remove combustible material (e.g., brush, litter)	24.6%	24.5%	24.3%	24.6%
Help organize community education programs related to wildfire	9.1%	8.9%	8.0%	9.0%
Property protection activities				
Plant fire-resistant plants	46.8%	47.1%	46.0%	46.7%
Plant trees and shrubs at least 15 feet apart	47.6%	47.8%	46.8%	47.6%
Prune the branches of all trees within 85 feet of your house to a height of 10 feet above the ground	49.0%	49.6%	48.2%	49.1%
Reduce the density of trees within 100 feet of your home	41.4%	41.5%	41.0%	41.3%
Home protection activities				
Clean roof surfaces/gutters and surrounding vegetation to avoid accumulation of needles, leaves and dead plants	80.2%	79.9%	79.8%	79.9%
Stack firewood/lumber at least 30 feet from house	52.4%	52.7%	52.3%	52.5%
Use nonflammable building materials such as tile, slate, stone, etc.	49.9%	50.1%	48.7%	49.8%
N range	696–705	666–675	643–654	2,666–2,701
Mean number of activities	5.66	5.58	5.59	5.65
s.d.	3.54	3.51	3.52	3.53

However, the activities undertaken are those that already have a relationship to property maintenance or property values. There is a need to identify what actions homeowners are likely to engage with automatically and those that may require additional agency support. These factors need to be considered when designing a mitigation plan for a community.

2.1.3. Social Dimensions of Fire

Hazards cannot be understood nor prevented without consideration of humans (Eiser et al., 2012). The threat to human lives and values is often what makes hazards so important. A large portion of California communities exists in WUI areas, leaving a high proportion of lives and assets at risk (Schoennagel et al., 2009). However, to effectively evaluate hazards social factors need to be considered in conjunction with biophysical factors (Ager et al., 2015). Both elements greatly influence each other and in turn, influence the potential for loss. How people perceive the risk from a fire hazard can differ greatly from the physical hazard condition. But someone's belief in the fire hazard is no guarantee that mitigation will be undertaken (Olsen et al., 2017; Eiser et al., 2012).

2.1.3.1 Risk Perceptions of Fire Hazards

Measuring fire risk involves judging the likelihood that a fire hazard will result in ignition with the potential for damage and personal consequences (McGee, 2011). People who live in hazardous areas often view hazard-related risks differently. Residents judge the risk from fire based on social and cultural learning, which will vary community to community (Wachinger, Renn, Begg, & Kuhlicke, 2013). People in high risk areas also tend to evaluate the fire risk based on the level of controllability, the voluntariness of mitigation, catastrophic potential, and the degree of outcome certainty (W. E. Martin, Martin, & Kent, 2009). How residents view and respond to the fire problem can be very different from the expectations of fire professionals. Understanding these gaps may lend insights into the role of how communities view and deal with the fire hazard problem.

Risk perception influences the decisions people make to live and remain in a hazardous area (P. A. Champ et al., 2013). Many residents do understand the fire hazard but respond differently (P. A. Champ et al., 2013). In general, the fire risk in the wildlands is viewed as greater than the fire risk to personal property (Olsen et al., 2017). A study by Martin et al. (2009) looked at how subjective knowledge of fire, fire experience, responsibility, and self-efficacy affect risk perception (W. E. Martin et al., 2009). They also examined how risk perceptions changed based on full time versus part-time resident status (W. E. Martin et al., 2009). There was a significant effect between the subjective knowledge of fire, self- efficacy, and residential status on risk perceptions,

(Table 1-2) (W. E. Martin et al., 2009). Despite what many believe, direct experience with fire was not found to have a significant impact on risk perceptions, (Table 1-2) (W. E. Martin et al., 2009).These factors can either raise or lower risk perceptions depending on the resident (I. M. Martin, Bender, & Raish, 2007). This is why it is important to understand what people believe they know about fire (W. E. Martin et al., 2009) and how people view their ability to take action (Brenkert-Smith, Champ, & Flores, 2012; W. E. Martin et al., 2009).

Table 2-2: The relationship between independent variables and risk perception. Location is a dummy variable. FT represents full-time status. As excerpted from Reprinted from "The role of W. E. Martin et al, 2009, Journal of Environmental Management, 91(2), p. 495. Copyright 2009 by Elsevier Ltd. Reprinted with permission.

Variable	Mean	Beta coefficient	Standard error	*t*-Value	*p*-Value
Subjective knowledge	5.84	0.307	0.077	3.98	0.0001
Fire experience	2.36	0.024	0.304	0.08	0.936
Self-efficacy	4.88	−0.096	0.053	−1.86	0.065
Responsibility	6.58	−0.061	0.084	0.73	0.467
FT/seasonal[a,b]	0.50	−1.317	0.127	−10.45	.0001
Location1[a]		−0.519	0.169	−3.08	0.002
Location 2[a]		−0.633	0.181	−3.49	0.001
Risk perceptions: 5.24 (1.22)					

Perceptions of fire will differ from community to community but also within the community as well (Alexandre, Mockrin B, Stewart, Hammer, & Radeloff, 2015). There are four community archetypes within WUI communities: (1) Formalized Suburban Communities, (2) High-Amenity High Resource Communities, (3) Rural Lifestyle Communities, and (4) Working Landscape/Resource Dependent Communities (Paveglio et al., 2015). These communities differed in their attitudes towards the fire problem and who has the main responsibility for it. Archetype 1 felt that the fire problem was largely a fuel issue and should be handled through formal programs (Paveglio et al., 2015). Whereas, archetype 2 viewed fire as an ecosystem issue and had mixed opinions but ultimately favored programmatic implementation (Paveglio et al., 2015). Both archetypes 3 and 4 agreed that the fire problem was a forest health and fuel reduction issue, but archetype 3 favored grassroots efforts while archetype 4 favored individual resident responsibility (Paveglio et al., 2015). Community make-up can greatly influence how fire is understood and residents' willingness to participate. There is a wide variety of WUI communities in California, and managers need to consider community dynamics when discussing fire hazards, fire-related risk, and potential mitigation efforts.

Risk perception is often coupled with the perceived capacity to respond (Brenkert-Smith et al., 2012). If people feel they have the means and skill to respond to the fire hazard, they will evaluate their risk as lower. A common assumption is that if people experience fire they will view it differently; however, experience does not significantly influence homeowners' decisions regarding risk (W. E. Martin et al., 2009; S. McCaffrey, 2004). Understanding this relationship can shed light on areas in which managers can influence resident risk perceptions of fire.

Another challenge is that the risk perception of the fire hazard by homeowners is not always aligned with experts (Meldrum et al., 2015). Often this is due to homeowners emphasizing different factors in their risk assessment process (Meldrum et al., 2015). For experts it is often very clear how to evaluate the risk from a fire hazard; there are set criteria. However, for homeowners, many competing factors in their daily lives influence how they view the fire. When experts and homeowners aggregate individual risk differently gaps occur in fire management (Meldrum et al., 2015). Understanding the divergence between the two groups is necessary to move forward in fire hazard reduction. Many residents do perceive the risk from fire in some way and will engage to a certain degree, but predominantly when implementation cost is low and is associated with existing property maintenance (Wolters et al., 2017). It is not guaranteed that the way they are viewing the fire hazard and taking action is within the expectation of experts. Risk perception gaps demonstrate where residents understand the risk, where they do not, and what actions they are willing to undertake (Wolters et al., 2017). While a high-risk perception of fire is necessary for mitigation it is not sufficient (T. W. Collins, 2005; S. McCaffrey, 2004; Wolters et al., 2017).

Fire cannot be considered outside the realm of society. Societal factors need to be considered in California. How residents of the WUI measure the fire hazard and measure risk is a key component of reducing fire hazards. Gaps in fire perception illustrate differences in how residents and how experts think of fire. Taking into consideration community dynamics when designing mitigation efforts may help maximize the likelihood of participation. Moving forward, there is a need to understand how residents measure fire hazard and fire risk in comparison to experts.

2.1.3.2 Motivations and Hurdles to Wildfire Mitigation

Two main categories influence people's relationships with natural hazards such as wildfire (S. McCaffrey, 2004). First are factors that affect their awareness and perception, and second are factors that drive how people turn knowledge of hazards into action (McCaffery, 2004). A multitude of social components affects the likelihood that residents will implement mitigation measures around their homes. A common assumption is that education and knowledge are all that is needed to get people to mitigate (McCaffery, 2004; S. M. McCaffrey et al., 2011). However understanding risk, while necessary, does not guarantee mitigations actions are taken (Olsen et al., 2017). Understanding what hurdles prevent people from mitigating and what motivates them to take action may be the key to solving the wildfire problem.

Property owners are more likely to mitigate when the perceived risk of fire is high and the mitigation actions do not compromise their landscape preferences (McGee, 2011). This combination is difficult to achieve. Wildfire mitigation is often viewed by homeowners as a trade-off between desirable attributes on their property and the benefit of risk reduction (McFarlane, McGee, & Faulkner, 2011). WUI residents tend to place high values on nature and privacy; it is often why they within the WUI. Commonly, mitigation creates more open space or changes the physical composition of the surrounding vegetation. The conflict between potential mitigation actions and desired property values can be a direct barrier to mitigation (Wolters et al., 2017). Residents, not only consider the trade-offs between mitigation and resource availability in their decision making, but also potential conflicts of interest, personal values, and beliefs about nearby wildlands (S. McCaffrey, Wilson, & Konar, 2018). If the comprise is too great it is unlikely that mitigation will be carried out fully or at all. People need to believe that the actions will work without major sacrifices. Mitigation plans and mangers need to acknowledge these conflicts and provide solutions for residents.

Mitigation is not as simple as implementing a program or educating the public (McCaffery, 2004). Factors of everyday life influence the likelihood that mitigation will be undertaken. Self-efficacy and response-efficacy are crucial and can either help or hinder mitigation efforts (Brenkert-Smith et al., 2012; Bubeck, Botzen, & Aerts, 2012; I. M. Martin et al., 2007; W. E. Martin et al., 2009). Self-efficacy deals with people's ability to carry out mitigation actions and response-efficacy deals with their beliefs in the action’s worth (Brenkert-Smith et al., 2012; Bubeck et al., 2012; I. M. Martin et al., 2007). For people to mitigate both types of efficacies must be high (I. M. Martin et al., 2007). This affects the type of mitigation behaviors people are willing to engage with, (W. E. Martin et al., 2009), which can be a major problem for mitigation plans. More complex mitigation actions will only be carried out by those who feel they have the means to accomplish it. Communities do not always have the level of ability or financial resources available to carry out necessary mitigation actions (Kunreuther, 2001). Within the four WUI archetypes, efficacy differs (Paveglio et al., 2015). Archetypes 1 and 2, suburban-based WUI communities, have the lowest level of local efficacy whereas, archetypes 3 and 4, rural-based WUI communities, have the highest levels of local efficacy (Paveglio et al., 2015). This may be because rural WUI communities are often more self-reliant that suburban WUI communities. Mitigation plans need to consider ways to raise residents’ level of efficacy and their belief in the effectiveness of the action. Without belief in the action and belief in themselves, it is unlikely that mitigation will be carried out (W. E. Martin et al., 2009; McGee, 2011).

It is easy to think that if people experience a wildfire they will change and implement future mitigation measures, especially in California where wildfires are frequent (Dennison et al., 2014). However, direct experience with wildfire guarantees nothing (I. M. Martin et al., 2007; McGee, 2011; Wachinger et al., 2013). The effect is inconsistent and can result in a positive or negative outcome (I. M. Martin et al., 2007; McGee, 2011; Wachinger et al., 2013). If experience increases awareness it may only be a temporary effect that fades over time (S. McCaffrey, 2004). In Oakland, California after the 1991 Tunnel Fire a property tax was created to fund fuel management activities;

however six years after the fire the tax was removed (S. McCaffrey, 2004). Fading awareness or interest can be attributed to the concept of disaster subculture (S. McCaffrey, 2004). This is a phenomenon where people get so accustomed to a natural hazard that it feels inevitable and mitigation seems pointless (S. McCaffrey, 2004).

Mockrin et al. (2018) studied how experience with fire changes community behavior. They looked at how local government and community-level wildfire response changed after experiencing wildfire across eight different WUI communities (Mockrin et al., 2018). They found that changes were most common in emergency response or suppression based activities followed by revision of planning documents (Figure 1-3) (Mockrin et al., 2018). Alterations in fire education and outreach only occurred at half the sites and were in areas where some level of education existed before the fire (Figure 1-3) (Mockrin et al., 2018). At the neighborhood level, changes in mitigation were informal, modest, and only if they were considered non-controversial to the resident (Mockrin et al., 2018). None of the sites enacted WUI regulations that focused on homes (Mockrin et al., 2018). Overall, the effect of experience with fire was inconsistent, and changes predominantly occurred in the public sector or programmatic level rather than at the homeowner level (Mockrin et al., 2018). It is not reliable nor enough to assume that experience with catastrophic wildfire will change human behavior.

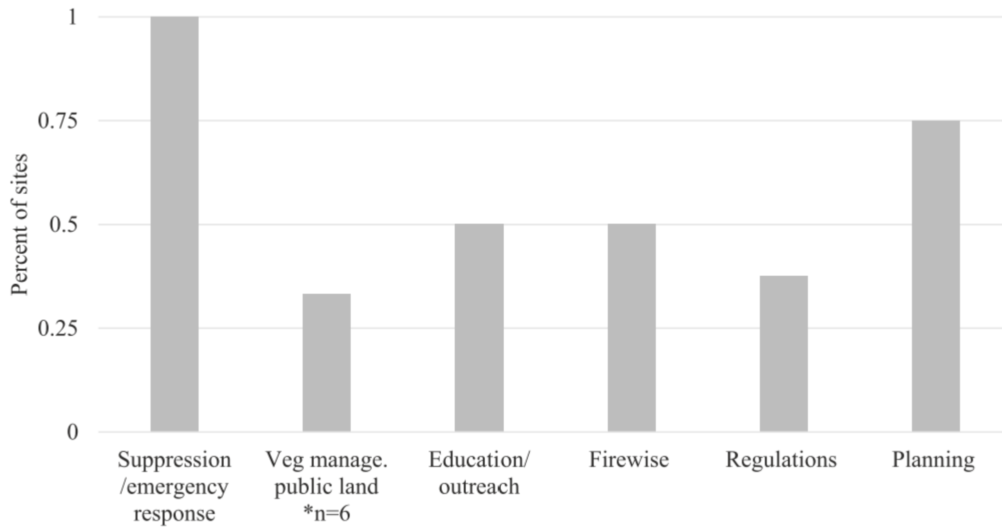

Fig. 2-3: Percent of study sites reporting community-level changes in regards to wildfire mitigation. For vegetation management on public lands, this only applied to six of the communities in the study. The categories were based on areas where denominate actions were undertaken. Reprinted from "Does Wildfire Open a Policy Window? Local Government and Community Adaptation After Fire in the United States," by Mockrin et al, 2018, Environmental Management, 62, p. 219. Copyright 2018 by Springer Science+Business Media LLC. Reprinted with permission.

Finally, the level of trust a community has within itself and outside agencies can define the level of motivation people have for mitigation. Communities tend to support fuel management on adjacent public lands (Toman et al., 2011). However, they can be reluctant to support fuel management on their properties (Paveglio et al., 2015). A lack of trust not only in a public agency but the disaster management system as a whole can be a significant barrier to mitigation (Richard Eiser et al., 2012). As repeated catastrophic wildfire events demonstrate how this system has failed. Trust and community relations will vary based on the community but is an important aspect of mitigation to consider (Toman et al., 2011). Trust can reduce uncertainty and overcome judgments surrounding mitigation measures (Wachinger et al., 2013). Building trust can also help build the resiliency of a community and increase the likelihood that residents carry out mitigation actions (Brenkert et al., 2005).

The lack of emphasis on the sociopolitical setting has resulted in an inadequate integration of social-based risk into the biophysical setting (Ager et al., 2015). While efforts have been made in fuel reduction and mitigation measures, we have failed to understand the role of residents. Disregarding what motivates people and what prevents people from undertaking mitigation leaves our systems vulnerable and disconnected (Ager et al., 2015). We need to build up the capacity of communities so that mitigation goes beyond general information (Wolters et al., 2017). This starts by trying to not only understand how people view hazards but also how they are motivated to take action.

2.2 Conclusions

Fire in California is an inevitable (Steinberg, 2002) challenge that has increased in complexity over the years (Calkin et al., 2015; Olsen et al., 2017; Syphard et al., 2007). We are seeing changes in the frequency and severity of fire due to suppression activities (T. W. Collins, 2005; Dennison et al., 2014; Marlon et al., 2012), climate change (Westerling et al., 2006), and the growing WUI (Cardille et al., 2008; Syphard et al., 2007). Suppression has resulted in fire returning to the landscape in a more extreme form than before (Calkin et al., 2015; Dennison et al., 2014). The effects of climate change are something we are still determining and areas such as Northern California are already seeing an increased number of high fire risk days (Schulte & Miller, 2010; Westerling et al., 2006). Wildfires are also driven by where people live and the WUI is growing (Cardille et al., 2008). We can reduce the wildfire hazard with mitigation actions in the wildlands and around homes (Safford et al., 2009; Vaillant et al., 2013). But there is a need to further study how mitigation affects potential fire behavior. Additionally, hazard assessment and mitigation plans often fail to emphasize social factors (Ager et al., 2015).

This results in a lack of understanding of how people view risk and their decisions regarding mitigation (Olsen et al., 2017). Wildfire cannot be analyzed in a vacuum. Biophysical factors, mitigation, and social drivers need to be integrated when determining how a wildfire will affect an area. Moving forward there is a need to undertake hazard assessments within the local context of a community and look beyond the biophysical setting.

CHAPTER 3: METHDOLOGY

3.1 STUDY AREA

The project area consisted of four parks, totaling 1337.21 hectares within the Oakland Hills in Oakland, California (Figure 3- 1), including Claremont Canyon Regional Preserve (CC), Sibley Volcanic Regional Preserve, Huckleberry Botanic Regional Preserve, and Reinhardt Redwood Regional Preserve (RED). For the purpose of this study, Sibley Volcanic Regional Preserve and Huckleberry Botanic Regional Preserve were grouped for modeling and collectively referred to as Sibley Volcanic Preserve (SIB), as Huckleberry Preserve bisected Sibley Preserve with no physical boundary and the vegetation existed continuously between the two areas. All parks were managed by the East Bay Regional Park District (EBRPD), a multijurisdictional park system for both Alameda County and Contra Costa County. The terrain varied in topography ranging from steep canyons to flat meadows.

The dominant vegetation communities differ in each park. Claremont Canyon consists predominantly of coastal scrub and chaparral (LSA Associates Inc. & East Bay Regional Park District, 2010d). Sibley Volcanic Preserve is dominated by a mixture of Oak-Bay Woodlands and California Annual Grassland (LSA Associates Inc. & East Bay Regional Park District, 2010d). Finally, Redwood Preserve is mostly Oak-Bay Woodland and Redwood forest (LSA Associates Inc. & East Bay Regional Park District, 2010d) (Figure 3-2).

The parks varied in size; Claremont Canyon Preserve was 88.9 hectares; Sibley Preserve was 471.88 hectares, and Redwood Preserve was 770.37 hectares. Of the total park area, 207.69 hectares were designated by EBRPD as proposed wildfire mitigation treatment areas (LSA Associates Inc. & East Bay Regional Park District, 2008, 2010c) (Figure 3-3).

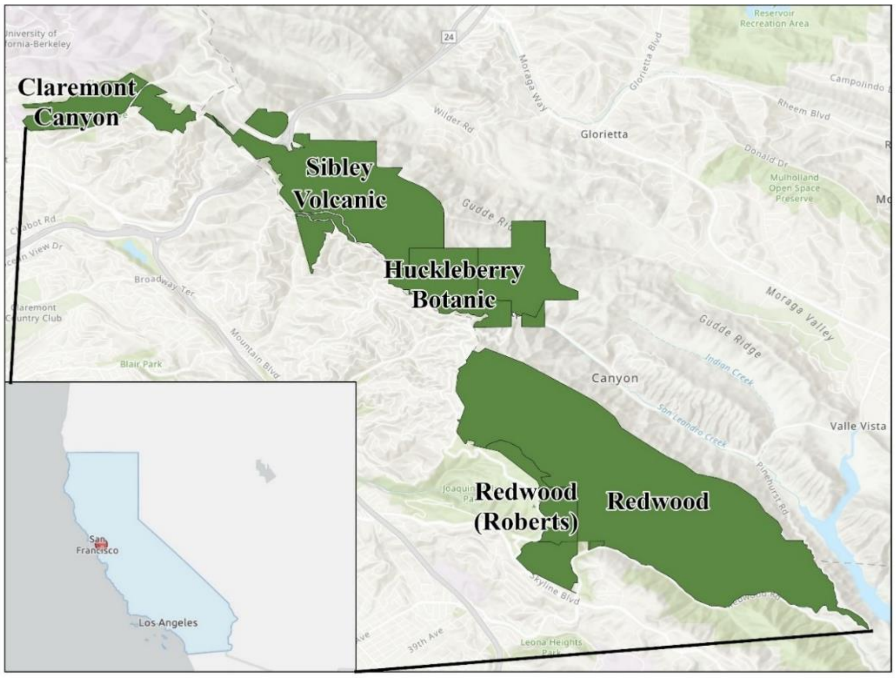

Fig. 3-1: Map of study area displaying the four parks in the EBRPD. These parks are located in the Oakland Hills of Oakland, California.

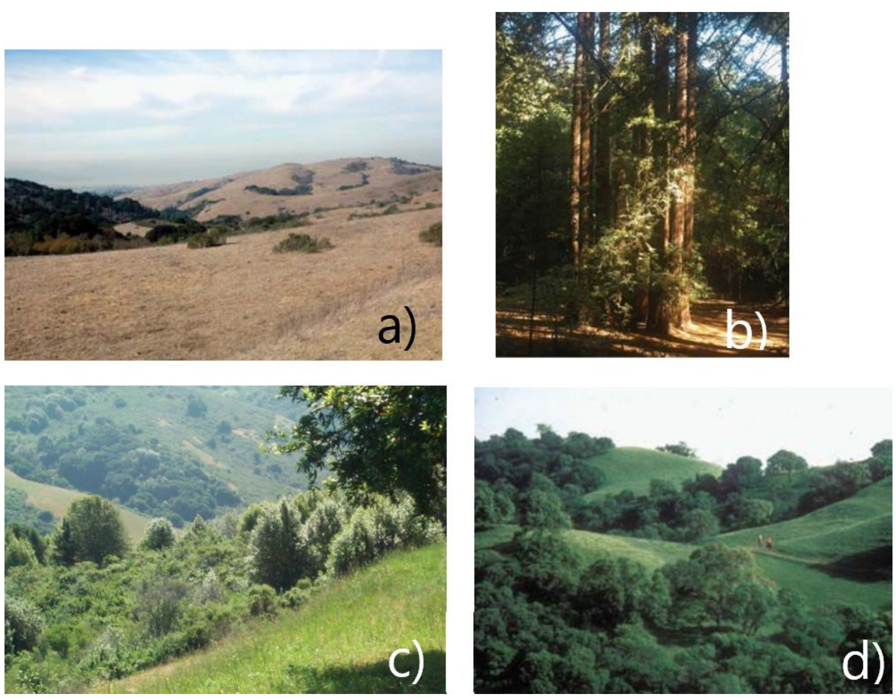

Fig. 3-2: a) California annual grassland, b) Redwood forest, c) coastal scrub/chaparral, and d) oak woodland

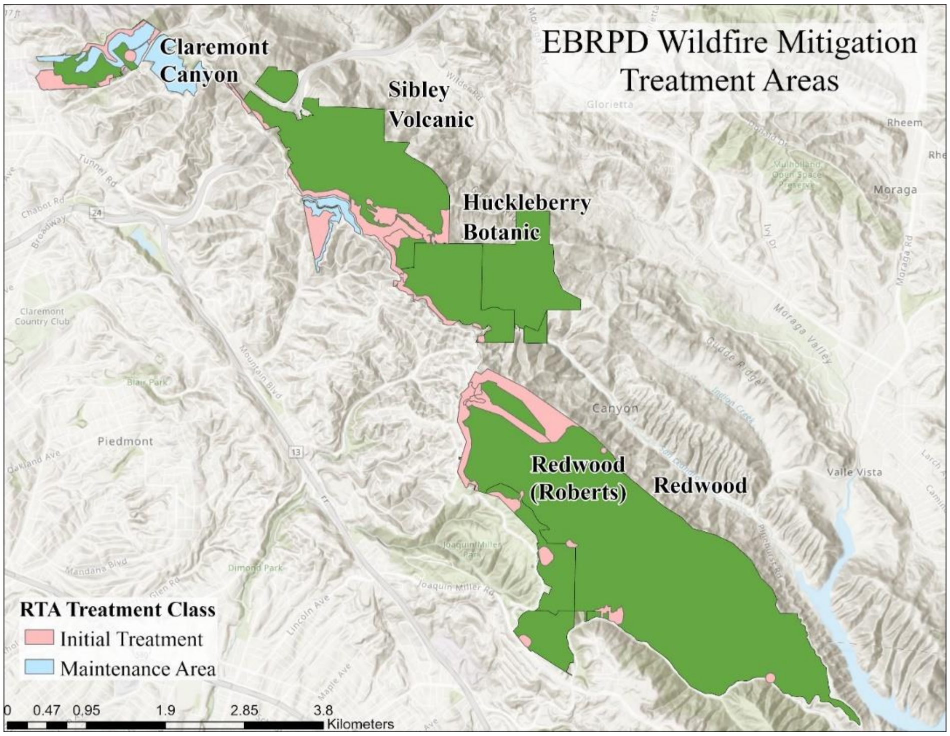

Fig. 3-3: Map of RTA within the project boundaries. Treatment areas are divided into initial treatments and maintenance treatments. Initial treatments are priority areas.

3.2 DATA SOURCES

In order to establish baseline vegetation composition, I used vegetation classification shapefiles, created by the EBRPD for their Wildfire Hazard Reduction and Resource Management Plan (LSA Associates Inc. & East Bay Regional Park District, 2010e). The 1991 Tunnel Fire fuel reconstruction required both an aerial mosaic from June 1991 and a 30-m resolution Landsat 5 image from October 13, 1991 (Keane, Burgan, & van Wagtendonk, 2002; Mitsopoulos, Mallinis, & Arianoutsou, 2014; Xiao-rui, McRae, Li-fu, & Ming-yu, 2008), courtesy of the U.S. Geological Survey, which was captured seven days before the start date of the 1991 Tunnel Fire.

To determine the 2018 fuel composition, I analyzed an ESRI Wayback image at 0.5-m resolution from September 8, 2018, and a Landsat 8 image from October 7, 2018 courtesy of the U.S Geological Survey (Keane et al., 2002; Mitsopoulos et al., 2014;

Xiao-rui et al., 2008). To create the fuel models for the untreated landscape and the treated landscape I used a combination of vegetation shapefiles from the EBRPD Wildfire Mitigation and Resource Management Plan (WMRMP) and the vegetation-to-fuels crosswalk from the EBRPD wildfire assessment (LSA Associates Inc. & East Bay Regional Park District, 2008, 2010c). Details regarding mitigation actions and desired vegetation outcomes were obtained from the EBRPD Wildfire Mitigation and Resource Management Plan, the Recommended Treatment (RTA) area map, as wells as supplementary resource mitigation assessment documents (East Bay Regional Park District, 2018; LSA Associates Inc. & East Bay Regional Park District, 2008).

Topographic data for fire behavior simulations were provided by LANDFIRE at a 30-m resolution. Weather conditions and wind velocities for fire behavior simulation runs were acquired from the Remote Automated Weather Station (RAWS), Oakland North, on Grizzly Peak in Oakland, California .

3.3 METHDOLOGY

3.3.1.1991 vs. 2018 Fire Hazard Assessment

3.3.1.1 Fuel Modeling Methodology

To determine how the 2018 fuel conditions and potential fire behavior compared to the 1991 Tunnel Fire conditions, fuel models were created for both years within ArcGIS Pro (Keane et al., 2002; Xiao-rui et al., 2008) and modeled fire scenarios using FlamMap 6 during average and extreme weather conditions (Mitsopoulos et al., 2014). The EBRPD vegetation shapefiles served as a starting point for reconstructing the 1991 pre-fire conditions (LSA Associates Inc. & East Bay Regional Park District, 2010e). This data was used due to the lack of fuel data for the 1991 Tunnel Fire and because it was created from a park wide-field survey (LSA Associates Inc. & East Bay Regional Park District, 2010e). It was assumed, due to this being a managed park system, there would not be major conversions in vegetation type, rather, there would only be changes in existing area and extent. In order to convert the vegetation map into a fuel model, the vegetation to fuels crosswalk created by the EBRPD was used (LSA Associates Inc. & East Bay Regional Park District, 2008) and the Scott & Burgan Standard Fire Behavior fuel models (Scott & Burgan, 2005). This base fuel model was overlaid on the 1991 aerial mosaic of the Oakland Hills and zoomed in to a ratio of 1:3000 within ArcGIS Pro. To reconstruct the pre-fire conditions, direct mapping was used to assign fuel characteristics and modify polygons based on the visible extent of fuel within the image (Keane et al., 2002; Xiao-rui et al., 2008). The fuel model was converted and stored as a raster with 30-m resolution for modeling and analysis.

Using the 1991 fuel model, the fuel conditions for 2018 were constructed. The 1991 fuel model was overlayed onto the ESRI Wayback image from October 7th, 2018.The assumptions were for this procedure remained the same. The same methodology was used for creating the 1991 fuel model to create the 2018 fuel model (Keane et al., 2002; Xiao-rui et al., 2008). The fuel model was converted and stored as a raster with 30-m resolution for modeling and analysis.

3.3.1.2 Canopy Coverage Modeling Methodology

An important component of fire modeling is a canopy coverage layer that matches the fuel model (Polinova, Wittenberg, Kutiel, & Brook, 2019). Custom canopy coverage files were created (a required input for FlamMap 6 simulations) from the Landsat images rather than depending on LANDFIRE data because the LANDFIRE canopy files only existed for 2018. Landsat images can be used to create a canopy layer when LANDFIRE data is unavailable or insufficient (Brandis & Jacobson, 2003; Gitelson, Stark, & Rundquist, 2002; Polinova et al., 2019). This allowed for canopy coverage information to be consistent between the two years. Further, Landsat imagery can provide the vegetation and canopy coverage needed for fire modeling (Brandis & Jacobson, 2003). Thus, canopy coverage can be estimated from Landsat images using the Visible Atmospheric Reflection Index (VARI) (Eq. 1.) (Gitelson et al., 2002; Polinova et al., 2019).

$$\text{Eq. 1 VARI} = \text{Green-Red} / \text{Green} + \text{Red Blue}$$

VARI uses the visible color spectrum to assess the level of "greenness" and estimate vegetation characteristic of for fuel parameters (Gitelson et al., 2002; Polinova et al., 2019). Each output was created at 30-m resolution raster that matched the extent of the respective fuel model. The results were then calibrated using the FlamMap 6 canopy coverage classes. This procedure was done with both the Landsat 5 image for 1991 and with the Landsat 8 image for 2018.

3.3.1.3 Fire Behavior Modeling Methodology

In order to model fire in FlamMap 6, I made landscape models for 1991 and 2018. FlamMap 6 composites elevation, aspect, slope, fuel, and canopy coverage files into one landscape that can be used to simulate fire behavior. The same elevation, slope, and aspect layers from LANDFIRE were inputted for both 1991 and 2018. The topographic inputs remained constant for the 1991 and 2018 models. However, fuel and canopy coverage inputs changed in accordance with the fuels that were present during each specific time period, to ensure that changes in fire behavior resulted solely from changes in fuels between the two time periods.

Fire behavior scenarios were created for average weather conditions and extreme (i.e. 97th percentile) weather conditions from August through October, which is considered fire season in the region (Mitsopoulos et al., 2014). 1991 and 2018 fire model used the same calculated weather scenarios to model potential fire behavior. RAWS data from 1995 to 2018 were summarized and used to calculate average weather conditions and 97th percentile weather conditions (Table 3-1). For the 97th percentile, the weather conditions recorded during the 1991 Tunnel Fire were used to calibrate RAWS values (California Office of Emergency Services, 1992; Radke, 1995; U.S Fire Adiministration, 1991). Because the Oakland North weather station did not exist until 1995, RAWS data did not exist on the day of the 1991 Tunnel. Fire. However, incident reports from the fire contained did contain limited weather data. In areas, where this was appropriate such as temperature and wind speed, these data points were substituted for calculated weather data values for the 97th percentile weather scenario (U.S Fire Administration, 1991; California Office of Emergency Services, 1992; Radke, 1995). The purpose was to have the 97th percentile scenario more closely reflect the conditions that occurred on the day on the actual fire event (U.S Fire Administration, 1991; California Office of Emergency Services, 1992; Radke, 1995). Each model, 1991 and 2018, used the same weather files for fire behavior simulation, allowing for comparability between the results of both models. Fuel moistures for fire simulation were generated for both scenarios using standard fuel moisture conditions, with respect to each weather scenario (Scott & Burgan, 2005) (Table 3-1).

Table 3-1: Weather inputs for FlamMap 6 for average conditions and 97th percentile conditions.

WEATHER INPUTS	**AVERAGE CONDITIONS**	**97^{TH} PERCENTILE**
Month	10	10
Day	19-23	19-23
Precipitation (mm)	00	00
Time of lowest temp	600	600
Time of highest temp	1500	1500
Low temp c°	11.7°	22.8°
High temp c°	16.7°	33.3°
Low rh (%)	73	18
High rh (%)	68	10
Elevation (m)	457.2	457.2
WIND CONDITIONS		
Month	10	10
Day	19-23	19-23
Km hr	16	48
Wind direction (from north)	194	329
% Cloud cover	0	0
FUEL MOISTURE		
1-hr	9	3
10-hr	10	4
100-hr	11	5
Live herbaceous	90	30
Live woody	120	60

Each fire behavior run produced 3 outputs: average flame length (m), rate of spread (m/min), and fireline intensity (kW/m) (Mitsopoulos et al., 2014). The outputs are contained within grid ASCII files at 30-m resolution and with over 140,000 individual cells. For the purpose of this study, canopy-based outputs were excluded due to insufficient canopy data. While canopy coverage was available for each year, other canopy data, with base height and canopy height, were not available and therefore were insufficient to model fire behavior. As a result, there was not enough data to model spotting. However, spotting was assumed to be a likely fire behavior due to historical conditions of the 1991 Tunnel Fire and identified spotting areas in the EBRPD vegetation management plan (U.S Fire Administration, 1991; California Office of Emergency Services, 1992; LSA Associates & East Bay Regional Park District, 2010). The outputs from each year were uploaded to ArcGIS Pro the six standard fire behavior classes for flame length (FL), rate of spread (ROS), and fireline intensity (FLI) were then used to classify and organize the results into classes 1-6 for each fire behavior output (Khakzad, 2018; Scott, Thompson, & Calkin, 2013))(Table 3-2). Fire behavior between classes 1 and 3 is considered low to moderate whereas fire behavior that falls between classes 4 and 6 is considered a highly vigorous fire to a conflagration (Khakzad, 2018; Scott et al., 2013). Each scenario was uploaded into ArcGIS Pro and converted into 30-m resolution raster files.

Table 3-2: Fire intensity classes for the three fire behavior outputs flame length, rate of spread, and fireline intensity.

FIRE INTENSITY CLASS	FLAME LENGTH (M)	RATE OF SPREAD (M/MIN)	FIRELINE INTENSITY (KW/M)
1	0-0.6	0-1	0-10
2	0.6-1.2	1-3	10-100
3	1.2-1.8	3-10	100-1,000
4	1.8-3.7	10-18	1,000-10,000
5	3.7-15	18-25	10,000-30,000
6	>15	>25	>30,000

3.3.2 Wildfire Mitigation Assessment

3.3.2.1 Fuel Modeling Methodology

To assess the effectiveness of the proposed wildfire mitigation, fuel models were created for the untreated landscape and the treated landscape. These models were based on 2018 fuel conditions and modeled using direct mapping in ArcGIS Pro (Keane et al., 2002; Xiao-rui et al., 2008). The 2018 fuel model represented the untreated fuel conditions, as no fuel mitigation from the plan has yet to be implemented on the project areas (East Bay Regional Park District, 2018). The EBRPD vegetation files and map served as the base fuel model for both scenarios. The same assumptions about fuel were made as in the fuel models for the 1991 vs. 2018 fire hazard assessment.

The EBRPD Wildfire Mitigation and Resource Management Plan (WMRM) detailed specific locations and actions to reduce wildfire within the RTA (LSA Associates Inc. & East Bay Regional Park District, 2010b). Actions were divided into two phases, the initial treatment phase and maintenance phase (LSA Associates Inc. & East Bay Regional Park District, 2010c). Initial treatments were defined as priority treatments that will progress into maintenance treatments. The best-case scenario occurs when all mitigation has been completed, is in the maintenance phase, and operating at maximum effectiveness on the landscape (M A Cochrane et al., 2012). The treated models used here represented the best-case scenario for wildfire mitigation in the EBRPD.

To model mitigation, first a table was created detailing treatment location, treatment methods, current vegetation, current fuel, vegetation goal, and fuel goal (LSA Associates Inc. & East Bay Regional Park District, 2008) (Appendix I). Mitigation information was obtained from the WMRM and the RTA shapefile provided by EBRPD (LSA Associates Inc. & East Bay Regional Park District, 2008). Using the vegetation-to-fuel crosswalk and standard fuel models, the current vegetation and vegetation goals were converted into standard fuel models (LSA Associates Inc. & East Bay Regional Park District, 2008; Scott & Burgan, 2005). The table was then uploaded into ArcGIS Pro and added to the RTA shapefile. The RTA layer was then combined with the 2018 fuel model, as they occurred in the same geographic location. The purpose was to have the 2018 fuel map served as a base layer because the RTA file only contained areas where treatment was being proposed rather than the full park extent. This ensured that it would encompass the total project area and create comparable outputs when modeling fire behavior. Furthermore, by including the total park area in this procedure it more accurately reflects how mitigation may affect fire behavior, since mitigation in one area can affect the entirety of a landscape (M A Cochrane et al., 2012; B. M. Collins et al., 2010; Finney et al., 2007; Vaillant et al., 2013). Fuels in the RTA areas were altered from the base layer to reflect the fuel treatment goals, while fuels outside treatment areas remained the same (B. M. Collins et al., 2010; LSA Associates Inc. & East Bay Regional Park District, 2008) (Appendix I). The treated landscape fuel map was converted and stored as a 30-m raster.

3.3.2.2 Canopy Coverage Modeling Methodology

The 2018 canopy layer was used for the untreated canopy coverage layer, which was calibrated with FlamMap 6 Canopy Coverage Classes and stored as a 30-m raster. Because fuel models in the treated landscape reflected theoretical fuel conditions, there was no corresponding Landsat image available. To overcome this issue, the untreated canopy coverage layer served as a basis for the treated canopy coverage layer. ArcGISPro to calculate the majority count of each canopy class for each fuel model in the untreated canopy coverage layer, and then designated which canopy coverage class occurred most often for each fuel model. Based on this information, I estimated which canopy coverage class would coordinate with the new fuels on the treated landscape. For fuels that were not part of the RTA, the originally assigned canopy coverage classes from VARI were used. The file was converted and stored as a 30-m raster.

3.3.2.3 Fire Behavior Modeling Methodology

To model differences in potential fire behavior, the same procedure as in the 1991 vs. 2018 hazard assessment was followed. The LCP file for 2018 represented the untreated constions and a new LCP was made for the treated scenario that incorporated the relevant raster layers of fuel models, canopy coverage, and topography information (i.e. elevation, slope, and aspect) (Mitsopoulos et al., 2014; Scott et al., 2013). Fuel models and canopy coverage files, for both scenarios, were created in ArcGIS Pro, and topography files were downloaded from LANDFIRE.

Fire behavior for the mitigation assessment was only modeled under extreme weather conditions on the untreated and treated landscape. This was because the main goal of the EBRPD mitigation plan was to reduce extreme wildfire behavior under 97th percentile weather conditions (B. M. Collins et al., 2010; LSA Associates Inc. & East Bay Regional Park District, 2010c). The 97th percentile weather conditions were based on RAWS weather data from 1995 to 2018 and conditions recorded during the 1991 Tunnel Fire (California, 1991; California Office of Emergency Services, 1992) (Table 3-1). Fuel moisture conditions for fire modeling were generated using standard fuel moisture (Scott & Burgan, 2005) (Table 3-1).

Fire behavior modeling was performed on the untreated LCP and on the treated LCP, which resulted in three outputs for each scenario: flame length (m), rate of spread (m/min), and fireline intensity (kW/m) (Mitsopoulos et al., 2014; Scott et al., 2013). The fire behavior outputs for scenario were also organized and reclassified into classes 1-6 based on six standard fire for each output (Khakzad, 2018; Scott et al., 2013) (Table 3-2). As with the fire hazard assessment, fire behavior between categories 1 and 3 is considered low to moderate whereas fire behavior that falls between categories 4 and 6 is considered a highly vigorous fire to a conflagration (Khakzad, 2018; Scott et al., 2013). These files were uploaded into ArcGIS Pro and converted into a 30-m raster with over 140,000 cells.

CHAPTER 4: RESULTS

4.1 FIRE HAZARD FUEL RESULTS

4.1.1 1991 vs. 2018 Fuel Analysis

ArcGIS Pro and remote sensing were used to model differences in the hectares of twenty-one fuel models in 1991 versus 2018 (Figure 4-1). In 1991 there were 18 of the 21 fuel models present with a total area of 1352.52 hectares. In 2018 all 21 fuel models were present and had an area of 1334.25 hectares. Fuel model 147 had the most evident change in hectares (Figure 4-1).

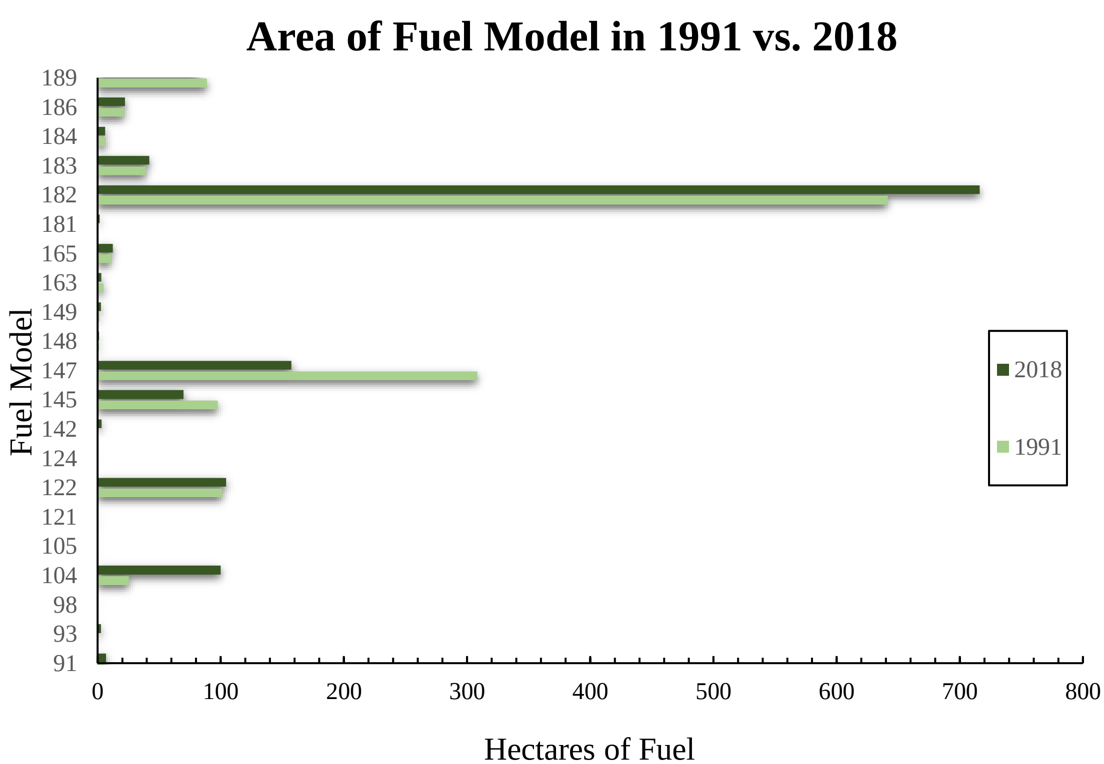

Fig. 4-1: Plot of the areas (hectares) of the 21 fuel models within the project area in 1991 vs. 2018.

The change in hectares of fuel model from 1991 to 2018 was analyzed with a two-way ANOVA. The response variable was the computed change in hectares of fuel model. The effects were location (CC, SIB, RED) and fuel model. For location there was 2 levels and 20 levels for fuel models. There was no two-way interaction between location and fuel model because there was only one observation per fuel model per location. The effects test found that the difference in fuel models based on location was not significant (p = 0.985) (Table 4-1). However, there was a highly significant difference (p = 0.001) in the average change in hectares based on the individual fuel models.

Table 4-1: Effects test for two-way ANOVA on Fuel Results

SOURCE	*N*	*df*	*F*	*p*
Location	2	2	0.01	0.989
Fuel Model	20	20	3.15	0.001*

*Significant at $p \leq .05$ level

An estimated model calculated the average change in hectares of fuel for each fuel model with 95% confidence (Figure 4-2). All fuel model, except for 147, had confidence intervals that included zero (Figure 4-2). These average changes were not significantly different from zero and therefore not considered significant (Figure 4-1) For fuel model 147 the confidence interval did not contain zero, indicating the average change was significant (Figure 4-2). The estimated average change for fuel model 147 was 86.73 hectares of fuel and significant at a p-value level of less than 0.05 (Table 4-2). Positive average change indicated that there was a reduction in hectares of fuel from 1991 to 2018 for fuel model 147.

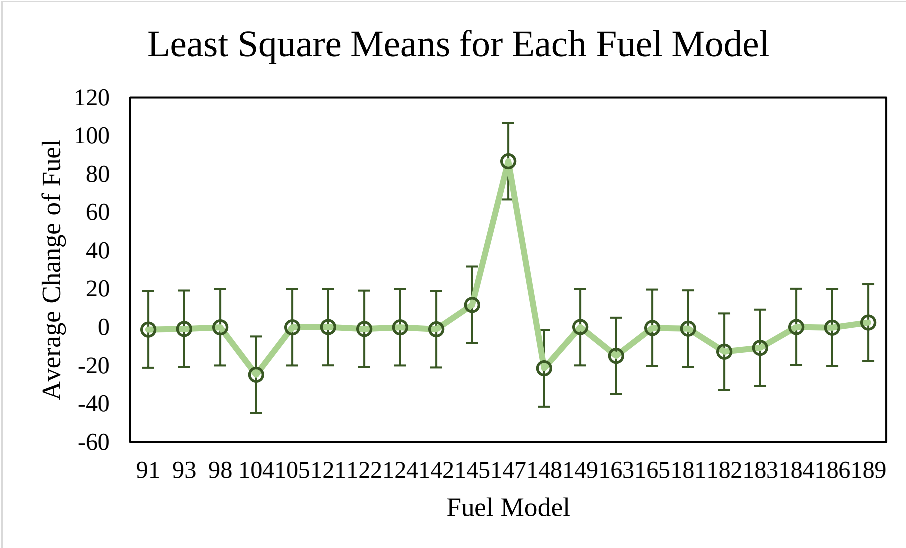

Fig. 4-2: The average change (open circle) for each fuel model in response to changes in hectares of fuel from 1991 vs 2018. The bars indicate 95% confidence intervals. Confidence intervals containing zero were considered not significantly different from zero.

Table 4-2: Least square means table for fuel model showing the estimated average change of each fuel model from 1991 to 2018 with a 95% confidence interval. Intervals without zero were considered significant. Negative estimates indicated an increase in hectares whereas a positive estimate indicated a reduction in hectares from 1991 to 2018.

SOURCE	*Estimate*	*Std Error*	*N*	*Lower 95%*	*Upper 95%*
91	-1.17	12.11	3	-25.65	23.31
93	-0.84	12.11	3	-25.31	23.64
98	-1.44e-15	12.11	3	-24.48	24.48
104	-24.84	12.11	3	-49.32	-0.37
105	-5.55e-16	12.11	3	-24.48	24.48
121	0.06	12.11	3	-24.42	24.54
122	-0.87	12.11	3	-25.35	23.61
124	-1.44e-15	12.11	3	-24.48	24.48
142	-1.05	12.11	3	-25.53	23.43
145	11.70	12.11	3	-12.78	36.18
147*	86.73	12.11	3	62.25	111.21
148	-21.54	12.11	3	-46.02	2.94
149	0.03	12.11	3	-24.45	24.51
163	-15.03	12.11	3	-39.51	9.45
165	-0.33	12.11	3	-24.81	24.15
181	-0.75	12.11	3	-25.23	23.73
182	-12.81	12.11	3	-37.29	11.67
183	-10.83	12.11	3	-35.31	13.65
184	0.12	12.11	3	-24.36	24.59
186	-0.18	12.11	3	-24.66	24.29
189	2.43	12.11	3	-22.05	26.91

*Significant at $p \leq 0.05$ level

4.2 1991 VS. 2018 FIRE BEHAVIOR RESULTS

FlamMap 6 produced twelve maps that were separated into four maps per fire behavior output: flame length, rate of spread, and fireline intensity. The maps were further divided based on year and weather scenario. The outputs were then classified based on the six standard fire intensity classes for each output (Khakzad, 2018; Scott et al., 2013) and then lumped into two categories, category 1-3 and category 4-6. Category 1-3 represented classes 1-3 or low to moderate fire behavior. Category 4-6 was composed of classes 4-6 or high to extreme fire behavior.

Two nominal logistic regressions analyzed the differences in fire behavior. The first nominal logistic regression modeled for the likelihood of fire behavior falling in category 4-6 over category 1-3. The second nominal logistic regression was used to estimate differences in the percentage of category 4-6 based on the three-way interaction. The response variable for the first regression was category 4-6 and the output was binary. Whereas for the second regression the response variable was count which represented the number of fire behavior instances that fell in category 4-6; the outcome was also binary. Both models had three main effects park location (CC, SIB, RED), year (1991 and 2018), and weather scenario (average and extreme). The two-way interactions consisted of park * weather, year * weather, and year * park. Finally, there was a three-way interaction between year * park * weather. The estimates from the first model were interpreted using odds ratios of category 4-6 versus category 1-3 with 95% confidence intervals. Odds ratios that were greater than one were considered more likely to occur. The second logistic regression interpreted these estimates using pairwise comparison and Bonferroni adjusted *p*-values.

4.2.1 Flame Length (m) 1991 vs. 2018 Results

When comparing flame lengths under average conditions for 1991 versus 2018, in 1991 there were more instances where flame lengths were class 4 or higher (Figure 4-3). For flame lengths in the extreme weather scenario, the two years were fairly similar with some reduction in flame lengths in the upper classes in 2018 (Figure 4-4).

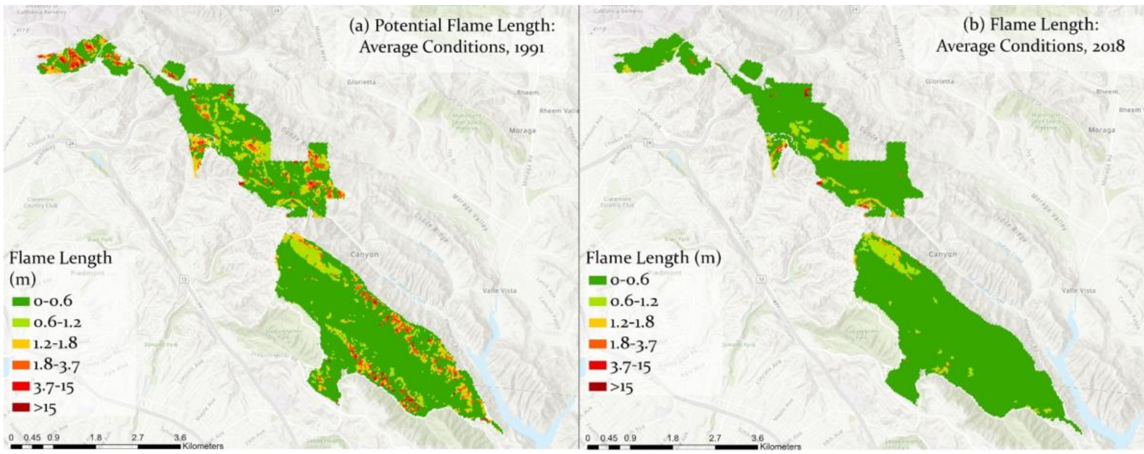

Fig. 4-3: Modeled flame lengths under average weather conditions in 1991 (a) and 2018 (b). Flame lengths were classified based on the six standard flame length classes.

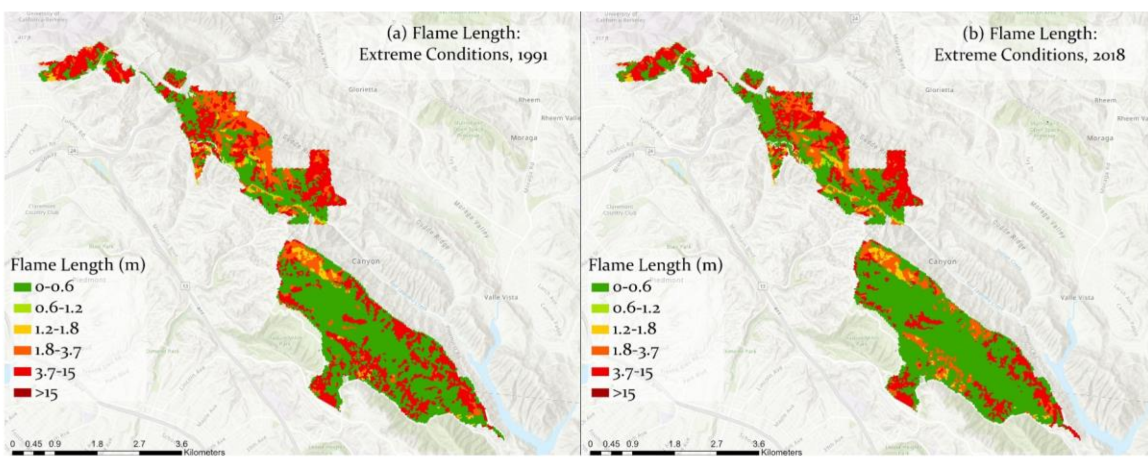

Fig. 4-4: Modeled flame lengths under extreme weather condition s from 1991 (a) and 2018 (b). Flame length instances were classified based on the six fire intensity classes for flame length.

<u>4.2.1.1 Nominal Logistic Regression for Likelihood</u>

The effects test showed the three main effects were significant ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$) and therefore affected the likelihood of category 4-6 (Table 4-3). All three two-way interactions were significant as well ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$). For year * park the effect year has on the likelihood of category 4-6 varied by park location. Park * weather was significant so the effect of park location was dependent on the weather scenario. Year * weather was significant as well and the effect year had on category 4-6 varied based on the weather scenario (Table 4-3). However, for flame length, the three-way interaction between year, park, and the weather was not significant and therefore dropped from the model (Table 4-3).

Table 4-4: Effects for nominal logistic regression for the likelihood of flame length categories in 1991 vs. 2018

SOURCE	*df*	*L-R* χ^2	*p*
Park	2	922.55	<.0001*
Year	1	626.93	<.0001*
Year * Park	2	1106.88	<.0001*
Weather	1	8229.52	<.0001*
Park * Weather	2	102.33	<.0001*
Year * Weather	1	1187.75	<.0001*

*Significant at $p \leq .05$ level

The odds ratios found that CC was more likely to produce category 4-6 flame lengths than RED and SIB (Table 3-6) ($p \leq .0001$). The odds between SIB and RED were also significant, with SIB having a higher likelihood for category 4-6 flame lengths ($p \leq .0001$). Between 1991 and 2018, 1991 was three times more likely than 2018 was to have category 4-6 flame lengths ($p \leq .0001$). Extreme weather had a twenty-seven-time stronger likelihood than average weather to produce category 4-6 flame lengths ($p \leq .0001$) (Table 4-5).

Table 4-5: Odds ratio details for flame length categories with odds of 4-6 vs. 1-3 for 1991 vs. 2018. Odds ratios that are greater than one meant that the level 1 effect was more likely to have category 4-6 flame lengths.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.21	<.0001*	0.19	0.23
SIB	CC	0.44	<.0001*	0.39	0.45
SIB	RED	2.13	<.0001*	1.97	2.29
CC	RED	4.79	<.0001*	4.31	5.32
CC	SIB	2.25	<.0001*	2.02	2.51
RED	SIB	0.47	<.0001*	0.44	0.51
Odds Ratios for Year					
2018	1991	0.30	<.0001*	0.27	0.3
1991	2018	3.32	<.0001*	2.98	3.71
Odds Ratios for Weather					
AVG	EX	0.04	<.0001*	0.03	0.04
EX	AVG	27.70	<.0001*	24.83	30.91

*Significant at $p \leq .05$ level

4.2.1.2 Nominal Logistic Regression for Percentage

The three main effects park, year, and weather were significant ($p \leq .0001$) (Table 4-6). The two-way interactions year * park, park * weather, and year * weather were significant ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$). The three-way interaction between year, park, and the weather was not significant ($p = 0.58$). However, in this scenario it was kept in the model because when it was removed the outcomes were not affected. Keeping the interaction, the model also allowed it to remain consistent with the other regressions for percentage (Table 4-6).

Table 4-6: Nominal logistic regression effects test for the estimated percentage of flame lengths in category 4-6 for 1991 vs. 2018.

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	243.46	<.0001*
Year	1	286.21	<.0001*
Weather	1	2107.54	<.0001*
Year * Park	2	263.15	<.0001*
Park * Weather	2	48.29	<.0001*
Year * Weather	2	424.52	<.0001*
Year * Park*Weather	2	1.09	0.58

*Significant at $p \leq .05$ level

The pairwise analysis showed that all parks except for SIB followed a similar trend of a reduction in the percentage for category 4-6 in 2018 (Figure 4-5). There was a notable reduction in percentage from 1991 to 2018 for CC AVG (Figure 4-5). The rate of decline for CC EX and RED EX were similar. Under the average weather scenario, the percentage of category 4-6 flame lengths in CC decreased by 22.97% ($p \leq .0001$), and under extreme weather it only decreased by 7.32% ($p = 0.0039$). RED the average scenario dropped by 4.69% ($p \leq .0001$) and by 7.69% in the extreme scenario ($p \leq .0001$) (Table 4-7). However, SIB EX deviated from the group by increasing in percentage 4-6 flame lengths in 2018 (Figure 4-5). For SIB, in the average weather scenario category 4-6 decreased by 5.14% ($p \leq .0001$). But, under the extreme weather scenario, the percentage increased from 23.27% in 1991 to 57.51% in 2018 for park SIB ($p \leq .0001$).

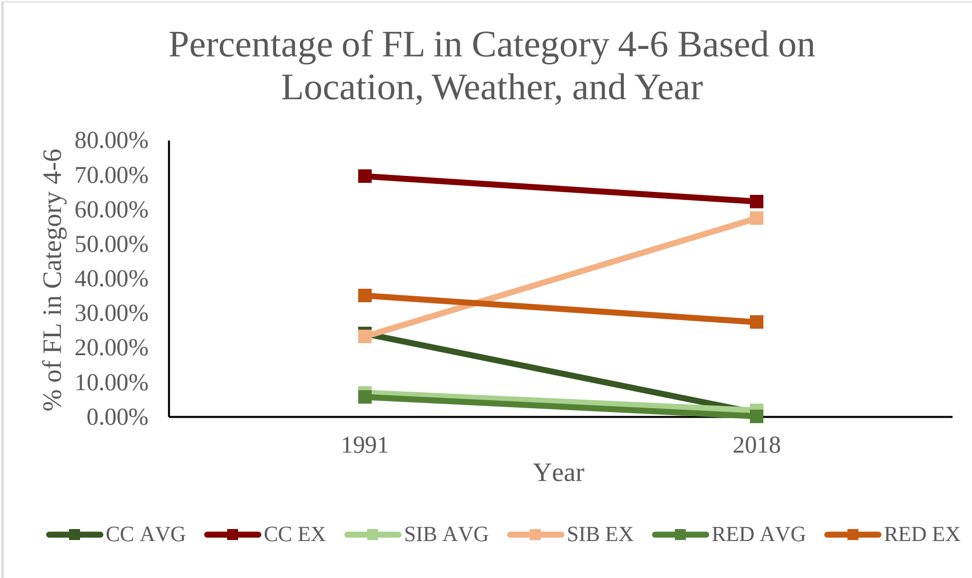

Fig. 4-5: The percent of modeled flame lengths in category 4-6, ≥ 1.8m, for 1991 vs. 2018 based on the park location and weather scenario.

Table 4-7: The estimated percentage of modeled flame lengths in category 4-6 for 1991 vs. 2018 based on the park location and weather scenario with Bonferroni adjusted p-values.

EFFECT	*Estimated % 1991*	*Estimated % 2018*	*Adj p*
CC * AVG	24.11%	1.14%	<.0001*
CC * EX	69.68%	62.36%	0.0039*
SIB * AVG	7.00%	1.86%	<.0001*
SIB * EX	23.27%	57.51%	<.0001*
RED * AVG	5.76%	0.18%	<.0001*
RED * EX	35.12%	27.43%	<.0001*

*Significant at p ≤ 0.05 level

4.2.2 Rate of Spread (m/min) 1991 vs. 2018 Results

The 1991 average weather scenario had more instances of rate of spreads being class four or higher than in 2018 (Figure 4-6). For the extreme weather scenario, both years showed an increase in class 6 (Figure 4-7). Rate of spreads were faster in CC and SIB in 1991 and 2018 under extreme weather (Figure 4-7).

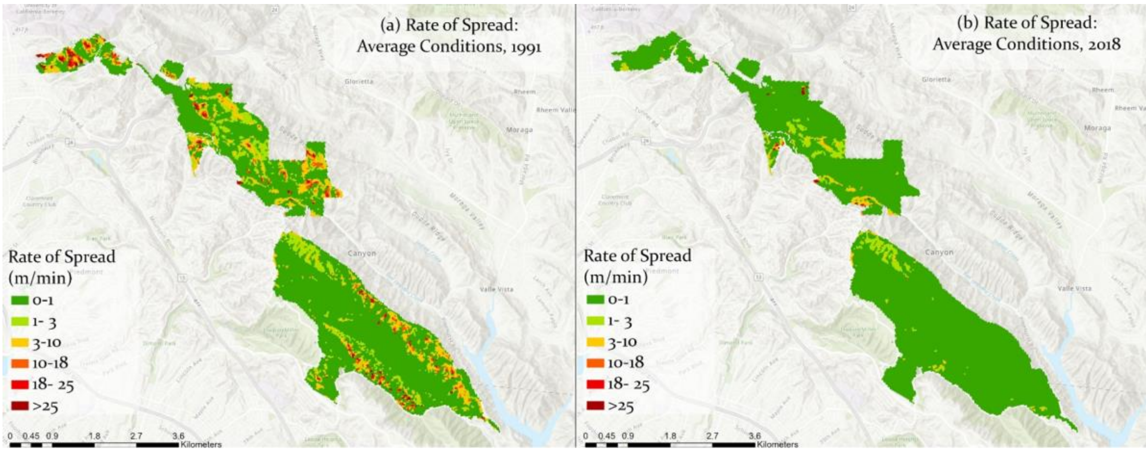

Fig. 4-6: Modeled rate of spread instances under average weather scenario for 1991 (a) and 2018 (b). The rate of spread instances was classified based on the six standard fire intensity classes for the rate of spread.

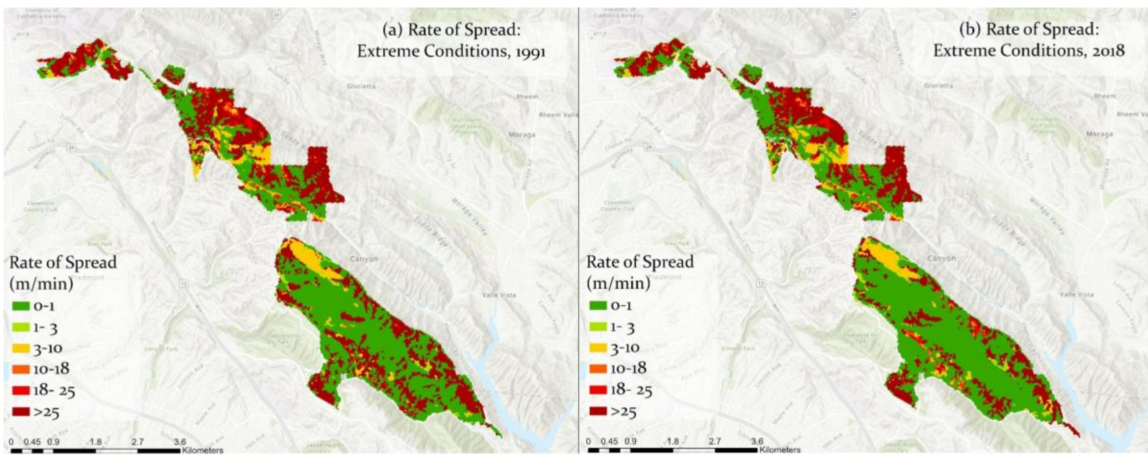

Fig. 4-7: Modeled rate for spread instances under the extreme weather scenario for 1991 (a) and 2018 (b). The rate of spread instances was classified based on the six fire intensity classes for the rate of spread.

<u>4.2.2.1 Nominal Logistic Regression for Likelihood</u>

The main effects were all significant ($p \leq .0001$, $p \leq .0001$) (Table 4-8). All two-way interactions were significant as well ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$). In the rate of spread model, the three-way interaction of year*park*weather was significant ($p \leq .0001$). The likelihood of category 4-6 rate of spread was affected by year but this effect was not only dependent on park location but on weather scenario as well (Table 4-8).

Table 4-8: Effects for nominal logistic regression for the likelihood of rate of spread categories for 1991 vs. 2018.

SOURCE	*df*	*L-R* χ^2	*p*
Park	2	280.51	<.0001*
Year	1	899.32	<.0001*
Year*Park	2	72.79	<.0001*
Weather	1	9031.89	<.0001*
Park*Weather	2	22.31	<.0001*
Year*Weather	1	548.42	<.0001*
Year*Park*Weather	2	60.50	<.0001*

*Significant at $p \leq .05$

The odds ratios found that CC and SIB were more likely to produce a category 4-6 rate of spreads than RED ($p \leq .0001$, $p \leq .0001$) (Table 4-9). The difference in the likelihood of the category 4-6 rate of spreads between CC and SIB was insignificant ($p = 0.2645$). Between 1991 and 2018, 1991 had the higher likelihood for category 4-6 rate of spread instances ($p \leq .0001$). The extreme scenario was more likely to produce a category 4-6 rate of spreads that the average weather scenario; this was highly significant ($p \leq .0001$) (Table 4-9).

Table 4-9: Odds ratio details for the rate of spread categories with odds of 4-6 vs 1-3 for 1991 vs. 2018. Where odds ratios were greater than one the level one effects were more likely to have category 4-6 values.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.17	<.0001*	0.10	0.28
SIB	CC	0.81	0.2645	0.57	1.17
SIB	RED	4.83	<.0001*	3.38	6.91
CC	RED	5.94	<.0001*	3.62	9.74
CC	SIB	1.23	0.2645	0.86	1.76
RED	SIB	0.21	<.0001*	0.14	0.30
Odds Ratios for Year					
2018	1991	0.12	<.0001*	0.27	0.3
1991	2018	8.16	<.0001*	2.98	3.71
Odds Ratios for Weather					
AVG	EX	71.37	<.0001*	51.10	99.71
EX	AVG	0.01	<.0001*	0.01	0.02

*Significant at $p \leq .05$ level

4.2.2.2 Nominal Logistic Regression for Percentage

The main effects for percentage of rate of spread instances in category 4-6 were significant ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$) (Table 3-11). As with the previous regression, all two-way interactions were significant ($p = .00019$, $p \leq .0001$, $p \leq .0001$). The three-way interaction, year*park*weather was also significant ($p \leq .0001$) meaning that the effect of year percentage of category 4-6 was dependent on the park they occurred in and under which weather scenario (Table 4-10).

Table 4-10: Nominal logistic regression effects test for the estimated percentage of rate of spreads in category 4-6 for 1991 vs. 2018.

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	77.29	<.0001*
Year	1	151.49	<.0001*
Weather	1	626.49	<.0001*
Year * Park	2	35.66	<.0001*
Park * Weather	2	12.51	0.0019*
Year * Weather	2	110.24	<.0001*
Year * Park * Weather	2	30.91	<.0001*

*Significant at $p \leq .05$ level

The pairwise analysis graph of the three-way interaction showed all six combinations trended downwards, representing a decrease in category 4-6 rate of spreads when going from 1991 to 2018 (Figure 4-8). This was most evident in CC AVG, where the decrease in percentage was sharper than SIB AVG and RED AVG (Figure 4-8). The decline in the percentage of category 4-6 from 1991 to 2018 was very similar for CC EX and SIB EX. CC AVG changed from 14.74% in 1991 to 0. 21% ($p \leq .0001$) and under extreme weather it reduced from 66.02% in 1991 to 59.15% in 2018 ($p = 0.0104$) (Table 4-11). SIB AVG and SIB EX had similar reductions, changing by 5.01% and 5.21% respectively ($p \leq .0001$, $p \leq .0001$). Finally, for RED, the percentage of category 4-6 fell from 3.52% in 1991 to 0.027% in 2018 ($p \leq .0001$) in the average weather scenario; but in the extreme weather scenario it fell from 30.80% in 1991 to 23.09% in 2018 ($p \leq$ .0001).

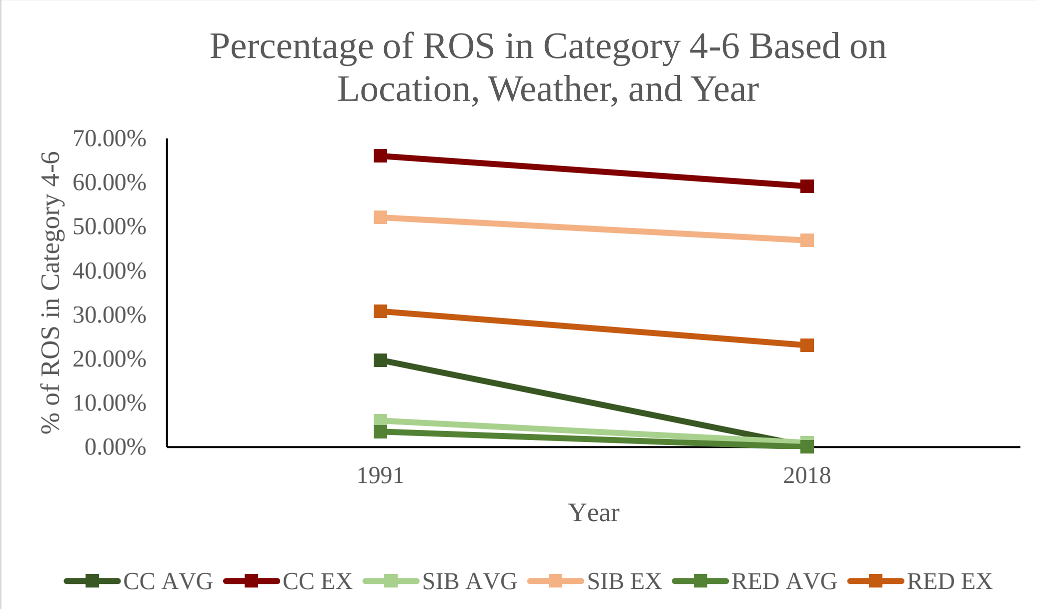

Fig. 4-8: The percent of the modeled rate of spreads in category 4-6, ≥ 10 m/min, for 1991 vs. 2018 based on the park location and weather scenario.

Table 4-11: The estimated percentage of modeled rate of spreads in category 4-6 for 1991 vs. 2018 based on the park location and weather scenario with Bonferroni adjusted p-values.

EFFECT	*Estimated % 1991*	*Estimated % 2018*	*Adj p*
CC * AVG	19.74%	0.21%	<.0001*
CC * EX	66.02%	59.15%	0.0104*
SIB * AVG	6.00%	0.99%	<.0001*
SIB * EX	52.08%	46.87%	<.0001*
RED * AVG	3.52%	0.02%	<.0001*
RED * EX	30.80%	23.09%	<.0001*

*Significant at $p \leq 0.05$ level

4.2.3 Fireline Intensity Results (kW/m) 1991 vs. 2018

As with the previous results fireline intensity decreased when going from average to extreme weather for both years (Figure 4-9, 4-10). 2018 had much lower fireline intensities under the average weather conditions than 1991 (Figure 4-9). CC consistently showed that under extreme weather for both years there was a high concentration of fireline intensities in class 6 (Figure 4-10). However, in 2018 there were more areas of lower fireline intensities than in 1991 (Figure 4-10).

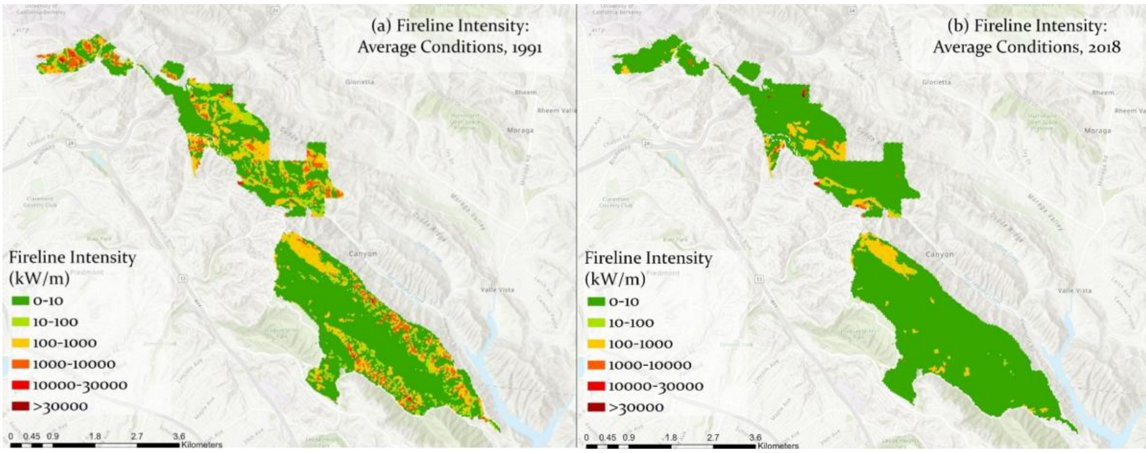

Fig. 4-9: Modeled fireline intensity instances under average weather scenario for 1991 (a) and 2018 (b). Fireline intensity instances were classified based on the six standard fire intensity classes for fireline intensity.

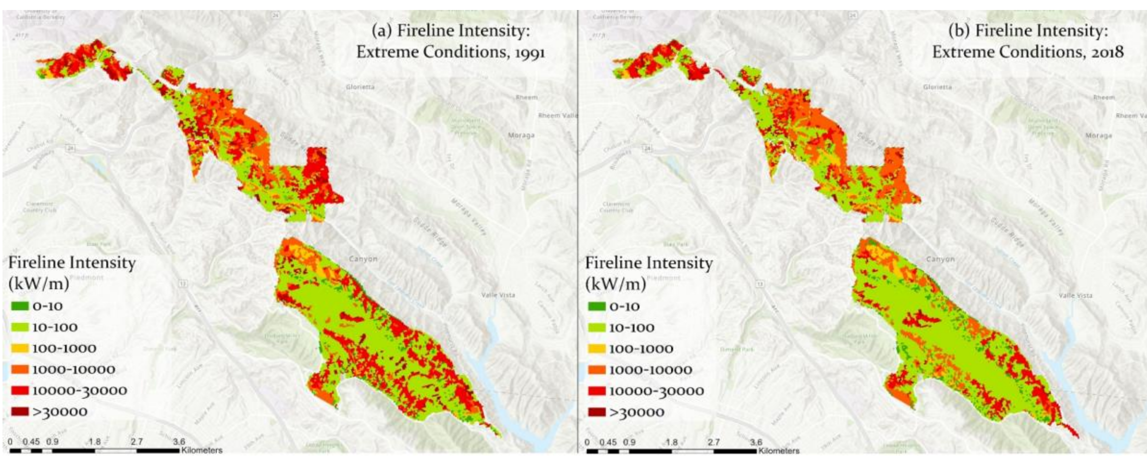

Fig. 4-10: Modeled fireline intensity instances under extreme weather conditions for 1991 (a) and 2018 (b). Fireline intensity was classified based on the six fire intensity classes for fireline intensity

<u>4.2.3.1 Nominal Logistic Regression for Likelihood</u>

As with the previous logistic regressions all three main effects were significant ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$) (Table 4-12). The two-way interactions were significant as well ($p \leq .0001$, $p = 0.0389$, $p \leq .0001$). The year*park*weather three-way interaction was also significant ($p \leq .0001$) resulting in the likelihood being effected by year which varied based on park location and weather scenario (Table 4-12).

Table 4-12: Effects of nominal logistic regression for the likelihood of fireline intensity categories for 1991 vs. 2018.

SOURCE	*df*	*L-R* χ^2	*p*
Park	2	435.30	<.0001*
Year	1	928.30	<.0001*
Year * Park	2	98.98	<.0001*
Weather	1	9265.04	<.0001*
Park * Weather	2	6.49	0.0389*
Weather * Year	1	523.49	<.0001*
Year * Park * Weather	2	82.80	<.0001*

*Significant at $p \leq .05$

For fireline intensity, CC was significantly more likely to have fireline intensities be in category 4-6 than all other parks ($p \leq .0001$, $p \leq .0001$) (Table 4-13). RED was the least likely park to have category 4-6 fireline intensities ($p \leq .0001$). As with previous odds ratios, 1991 had a significantly higher likelihood than 2018 ($p \leq .0001$). The extreme weather scenario was 36 times more likely to have category 4-6 fireline intensities than the average weather scenario and this was highly significant ($p \leq .0001$) (Table 4-13).

Table 4-13: Odds ratio details for fireline intensity with odds of 4-6 vs 1-3 for 1991 vs. 2018. Ratios that were greater than one were more likely to have category 4-6 fireline intensity.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.19	<.0001*	0.15	0.24
SIB	CC	0.60	<.0001*	0.51	0.72
SIB	RED	3.19	<.0001*	2.73	3.73
CC	RED	5.27	<.0001*	4.25	6.55
CC	SIB	1.65	<.0001*	1.39	1.96
RED	SIB	0.31	<.0001*	0.27	0.37
Odds Ratios for Year					
2018	1991	0.21	<.0001*	0.19	0.25
1991	2018	4.65	<.0001*	4.00	5.40
Odds Ratios for Weather					
AVG	EX	0.03	<.0001*	0.02	0.03
EX	AVG	36.87	<.0001*	31.76	42.81

*Significant at $p \leq .05$ level

4.2.3.2 Nominal Logistic Regression for Percentage

The main effects in this nominal logistic regression where significant as well ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$) (Table 4-14). The interaction between park and weather was not significant ($p = 0.064$). Year*park and year*weather were significant ($p \leq .0001$), so the effect of year varied based on park location and varied based on weather. However, the three-way interaction was significant resulting in the percentage varying based on year but this variance was dependent on park and weather (Table 4-14).

Table 4-14: Nominal logistic regression effects test for the estimated percentage of fireline intensity in category 4-6 for 1991 vs. 2018.

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	271.95	<.0001*
Year	1	406.92	<.0001*
Weather	1	2241.61	<.0001*
Year * Park	2	76.43	<.0001*
Park * Weather	2	5.49	0.064
Year * Weather	2	258.17	<.0001*
Year * Park * Weather	2	65.12	<.0001*

*Significant at $p \leq .05$ level

All park and weather combinations saw a downward trend in the percentage of fireline intensity in category 4-6 when going from 1991 to 2018 (Figure 4-11). For the average weather scenarios this was most notable in CC (Figure 4-15). CC EX, SIB EX, and RED EX had similar rates in decline in category 4-6 when going from 1991 to 2018 (Figure 4-11). CC in the average scenario had a large decrease in category 4-6 going form 23.05% in 1991 to 1.47% in 2018 ($p \leq .0001$) (Table 5-15). RED decreased by 5.24% under average conditions and by 7.76% under extreme conditions (Table 4-15). However, in the extreme weather scenario, while there was a higher amount of category 4-6, CC only decreased by 7.02% from 1991 to 2018 ($p = .0067$) (Table 3-16). SIB AVG and SIB EX changed by 6.44% ($p \leq .0001$, $p \leq .0001$) (Table 4-15).

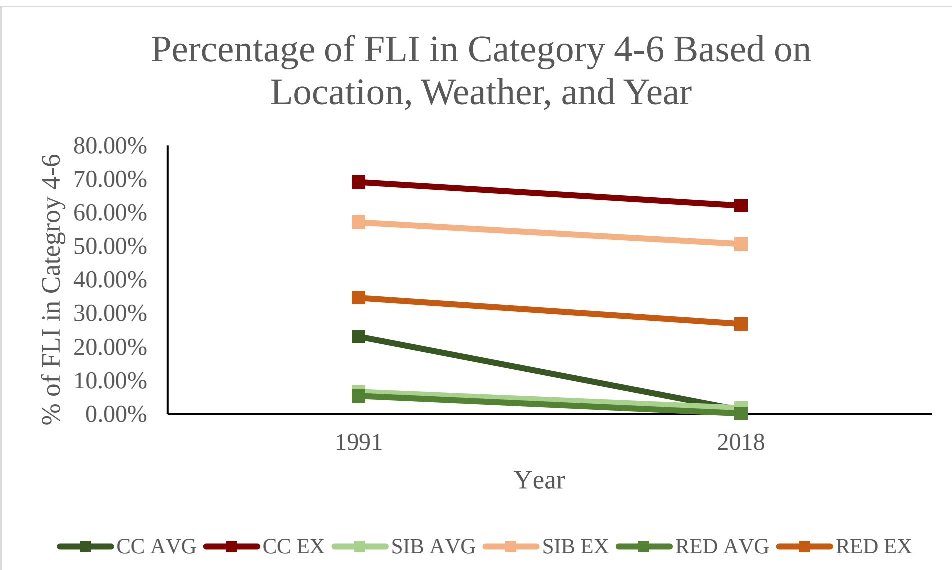

Fig. 4-11: The percent of modeled fireline intensity in category 4-6, ≥ 1000 kW/m, for 1991 vs. 2018 based on the park location and weather scenario.

Table 4-15: The estimated percentage of modeled fireline intensity in category 4-6 for 1991 vs. 2018 based on the park location and weather scenario

EFFECT	*Estimated % 1991*	*Estimated % 2018*	*Adj p*
CC * AVG	23.05%	1.14%	<.0001*
CC * EX	69.07%	62.05%	0.0067*
SIB * AVG	6.58%	1.76%	<.0001*
SIB * EX	57.07%	50.63%	<.0001*
RED * AVG	5.39%	0.15%	<.0001*
RED * EX	34.59%	26.83%	<.0001*

*Significant at $p \leq 0.05$ level

4.3 MITIGATION ASSESSMENT FIRE BEHAVIOR RESULT

The same statistical analysis was used to compare the differences in fire behavior in the untreated landscape and the treated landscape. FlamMap 6 produced three fire behavior models for each scenario. Each fire behavior output was analyzed with two nominal logistic regression, one for the likelihood of category 4-6 and the other for the percentage of category 4-6 based on the interaction between scenario and park. The effects were park (CC, SIB, and RED), scenario (untreated and treated), and the two-way interaction scenario*park. The outcome of the regressions were binary. The parameter estimates for the first nominal logistic regression were interpreted as odds ratios modeling for the likelihood over fire behavior being in category 4-6 over category 1-3. The estimates from the second nominal logistic regression were interpreted using pairwise analysis and Bonferroni adjusted *p*-values.

4.3.1 Flame Length (m) Results Untreated vs. Treated

Overall flame length conditions in the untreated landscape were fairly similar to the treated landscapes (Figure 4-12). There were areas where flame lengths were reduced, and this was most noticeable for CC in the untreated landscape to the treated landscape (Figure 4-12).

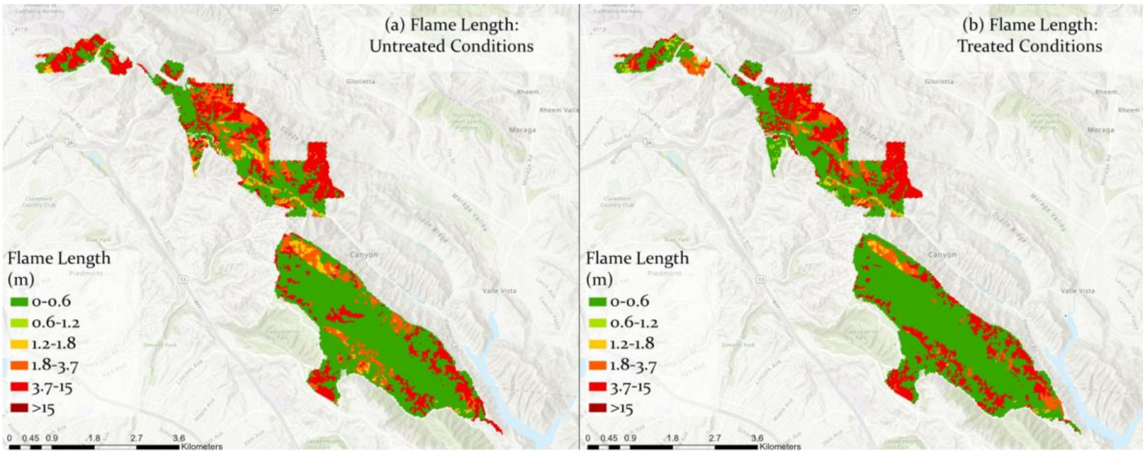

Fig. 4-12: Modeled flame lengths from FlamMap 6 comparing the untreated landscape (a) to the treated landscape (b). Flame lengths were classified into the six standard fire intensity classes from flame length.

4.3.1.1 Nominal Logistic Regression for Likelihood

The effects test showed that both the main effects and the two-way interaction were significant with p-values of $\leq .0001$ (Table 4-16). However, because the two-way interaction was significant the effect of the scenario had on the likelihood of flame lengths being in category 4-6 varied by the park location (Table 4-16).

Table 4-16 Nominal logistic regression effects test for the estimated percentage of flame length in categories 4-6 for the untreated vs. treat scenario.

SOURCE	*df*	*L-R* χ^2	*p*
Park	2	2307.09	<.0001*
Scenario	1	150.73	<.0001*
Scenario * Park	2	55.89	<.0001*

*Significant at p≤0.05 level

The odds ratios found that CC and SIB were significantly ($p \leq .0001$, $p \leq .0001$) more likely to produce flame lengths in category 4-6 than RED (Table 4-17). However, there was no significant difference in the odds of flame lengths being in category 4-6 when comparing CC to SIB. The odds between the mitigation treatment scenarios showed that the untreated scenario was significantly more likely to have flame lengths in category 4-6 than the treated scenario was (Table 4-17).

Table 4-17: Odds ratios details for untreated vs. treated flame length with odds of 4-6 vs. 1-3. Odds ratios that are greater than one meant that the level 1 effect was more likely to have category 4-6 flame lengths.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.32	<.0001*	0.29	0.36
SIB	CC	1.09	0.090	0.99	1.20
SIB	RED	3.32	<.0001*	3.15	3.49
CC	RED	3.04	<.0001*	2.76	3.36
CC	SIB	0.92	0.090	0.83	1.01
RED	SIB	0.30	<.0001*	0.29	0.32
Odds Ratios for Scenario					
Treated	Untreated	0.65	<.0001*	0.60	0.69
Untreated	Treated	1.54	<.0001*	1.44	1.65

*Significant at $p \leq .05$ level

4.3.1.2 Nominal Logistic Regression for Percentage

The main effects were significant ($p \leq .0001$, $p \leq .0001$) (Table 4-18). The two-way interaction was also significant; meaning that the effect scenario had on the percentage of flame lengths in category 4-6 varied by which park it was in (Table 4-18). The main effects were significant ($p \leq .0001$, $p \leq .0001$) (Table 4-18). The two-way interaction was also significant; meaning that the effect scenario had on the percentage of flame lengths in category 4-6 varied by which park it was in (Table 4-18).

Table 4-18 Nominal logistic regression effects test for the estimated percentage of flame length in categories 4-6 for the untreated vs. treat scenario.

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	2224.99	<.0001*
Scenario	1	147.81	<.0001*
Scenario * Park	2	55.11	<.0001*

*Significant at $p \leq 0.05$ level

Pairwise comparison showed that under each scenario, the parks produced different percentages of category 4-6 flame lengths (Figure 4-13). Overall, the three parks displayed a reduction in the percentage of category 4-6 flame lengths when moving from the untreated scenario to the treated scenario (Figure 4-13). CC had the biggest reduction with flame lengths in category 4-6 reducing from 62.36% in the untreated scenario to 41.01% in the treated scenario (*p* ≤ .0001) (Table 4-19). SIB had a moderate when changing from the untreated scenario treated scenario (*p* ≤ .0001) (Table 3-20). RED had the smallest reduction in the percentage of category 4-6 flame lengths only changing by 2.69% (*p* = .0002) (Table 4-19).

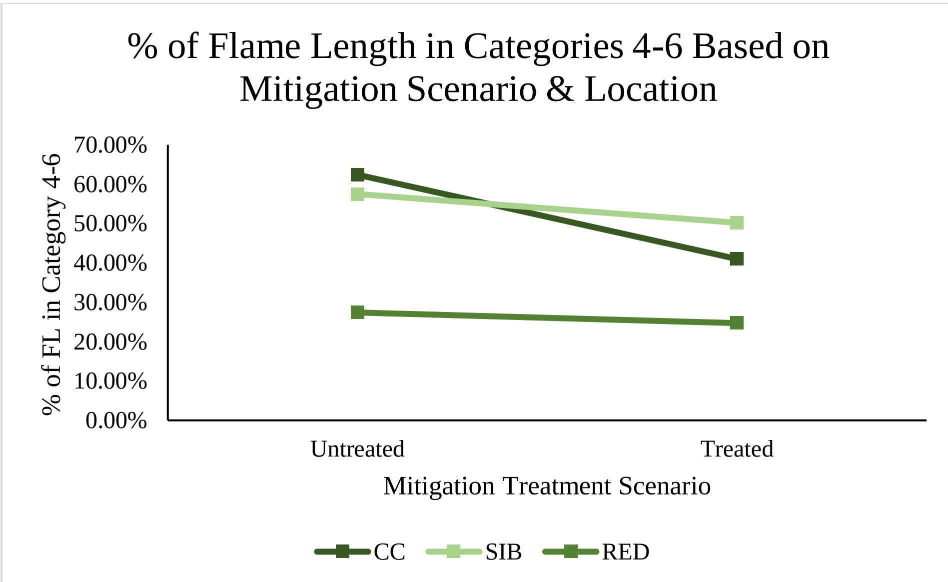

Fig. 4-13: The percent of modeled flame lengths in category 4-6 for each mitigation scenario untreated vs. treated with the three park locations.

Table 4-19: The estimated percentage of modeled flame lengths in categories 4-6 based on mitigation scenario and park location the untreated vs. treated landscape.

EFFECT	*Untreated %*	*Treated %*	*Adj p*
CC	62.36%	41.01%	<.0001*
SIB	57.51%	50.25%	<.0001*
RED	27.43%	24.74%	0.0002*

*Significant at *p* ≤ .05 level

4.3.2 Rate of Spread (m/min) Results Untreated vs. Treated

In both scenarios, there was noticeably faster rate of spreads along the edges of the parks (Figure 4-15). CC had the most visible change with large abundance of class 6 reducing in the treated model. The upper half of SIB had little change when going from the untreated to the treated conditions, especially when compared to the lower half of SIB which displayed a reduction in the rate of spread speed. Overall RED remained relatively similar under both scenarios (Figure 4-15).

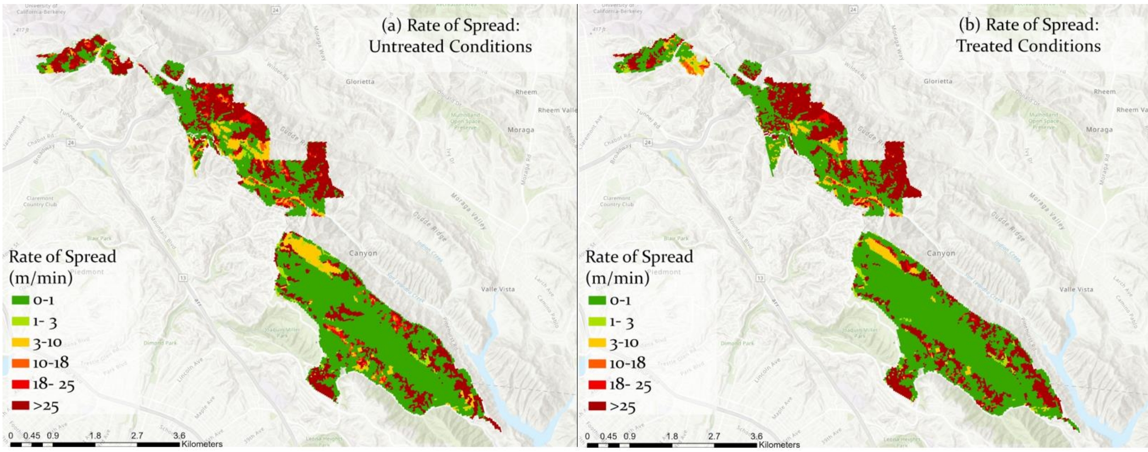

Fig. 4-15: Modeled rate of spread output from FlamMap 6 for the untreated conditions (a) and the treated conditions (b). The rate of spread outputs was classified based on the six standard fire intensity classes for the rate of spread.

4.3.2.1 Nominal Logistic Regression for Likelihood

The effects test showed that both main effects and the two-way interaction were significant ($p \leq .0001$, $p \leq .0001$, $p \leq .0001$) (Table 3-21). Because the two-way interaction was significant for the rate of spreads, the likelihood of instances being in category 4-6 was affected by mitigation scenario but this effect varied by park location (Table 4-20).

Table 4-20: Effects test of nominal logistic regression for the likelihood rate of spread categories for the untreated vs. treated scenario

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	1843.34	<.0001*
Scenario	1	101.16	<.0001*
Scenario * Park	2	133.09	<.0001*

*Significant at $p \leq .05$ level

The odds ratio details found that CC was two times more likely and SIB was three times more likely to have a rate of spread instances in category 4-6 that RED was ($p \leq .0001$, $p \leq .0001$) (Table 4-21). However, the comparison between CC and Sib was insignificant ($p = 0.079$) neither park had a higher likelihood than the other. For the mitigation scenarios, there was a statistical difference between the untreated scenario and the treated scenario. The untreated scenario was 1.3 times more likely to have a rate of spreads in category 4-6 than the treated scenario ($p \leq .0001$) (Table 4-21).

Table 4-21: Odds ratio detailed for the rate of spread with odds of 4-6 vs. 1-3 for the untreated vs. treated scenario. Odds ratios that were greater than one indicated that the level one effect was more likely to have a rate of spreads in category 4-6.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.36	<.0001*	0.32	0.39
SIB	CC	1.09	0.079	0.99	1.21
SIB	RED	3.06	<.0001*	2.90	3.23
CC	RED	2.79	<.0001*	2.53	3.09
CC	SIB	0.91	0.079	0.83	1.01
RED	SIB	0.33	<.0001*	0.31	0.34
Odds Ratios for Scenario					
Treated	Untreated	0.69	<.0001*	0.65	0.74
Untreated	Treated	1.44	<.0001*	1.34	1.55

*Significant at $p \leq 0.05$ level

4.3.2.2 Nominal Logistic Regression for Percentage

As with the previous regression the main effects were significant ($p \leq .0001$, $p \leq .0001$) as was the two-way interaction ($p \leq .0001$) (Table 4-22). So once again the effect that scenario has on the percentage of rate of spread in category 4-6 was dependent on park (Table 4-22).

Table 4-22: Nominal logistic regression effects test for the estimated percentage of rate of spread in category 4-6 in the untreated vs. treated scenario.

EFFECT	*Estimated Percentage*	*Adj p*
Untreated * CC	59.15%	<.0001*
Treated * CC	32.09%	<.0001*
Untreated * SIB	46.87%	0.551
Treated * SIB	48.17%	0.551
Untreated * RED	23.09%	1.000
Treated * RED	22.57%	1.000

*Significant at $p \leq 0.05$ level

The reduction category 4-6 rate of spreads for CC was quite extreme (Figure 4-16), going from 59.15% in the untreated scenario to 32.09% in the treated scenario ($p \leq$

.0001) (Table 4-23). Though SIB showed a slight uptick in the percentage of category 4-6 in the treated scenario (Figure 4-16) this change was not significant (p = 0.551) (Table 4-23). The change in the percentage of category 4-6 rate spreads for RED was only slight and insignificant (p = 1.00) (Table 4-23).

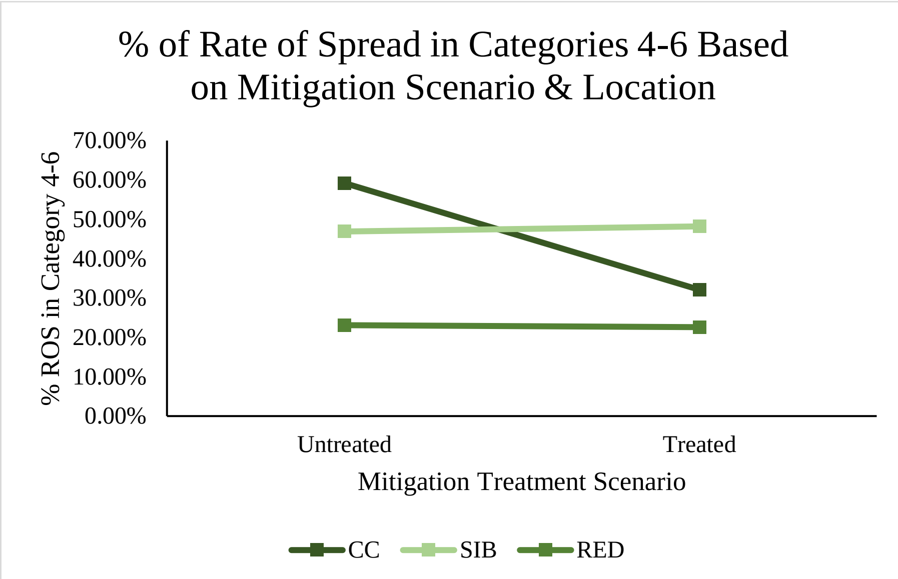

Fig. 4-16: The percent of the rate of spread instances that fell in category 4-6, comparing the untreated scenario to the treated scenario amongst the three park locations.

Table 4-23: The estimated percentage of modeled rate of spread instances in category 4-6 based on mitigation scenario and park location.

EFFECT	*Untreated %*	*Treated %*	*Adj p*
CC	59.15%	32.09%	<.0001*
SIB	46.87%	48.17%	0.551
RED	23.09%	22.57%	1.000

*Significant at $p \leq .05$ level

4.3.3 Fireline Intensity (kW/m) Results in Untreated Vs. Treated

When comparing the two FlamMap 6 models there was a noticeable reduction in the upper fireline intensity classes in CC and RED (Figure 4-17). The change in RED was much less obvious and mostly concentrated in the center of the park and along the northwest edge.

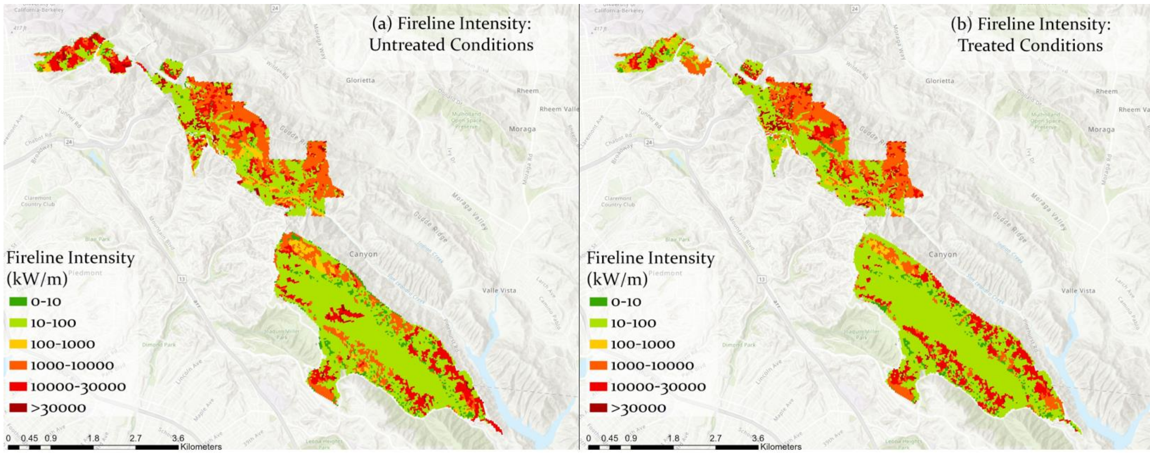

Figure 4-17: Fireline intensity outputs from FlamMap 6 comparing the untreated scenario (a) to the treated scenario (b). Fireline intensity outputs were classified based on the six fire intensity classes for fireline intensity.

4.3.3.1 Nominal Logistic Regression for Likelihood

As with the other fire behavior outputs the main effects and the two-way interaction were significant ($p \leq .0001$, $p \leq .0001$) (Table 4-24). Therefore, while the scenario does affect the likelihood of fireline intensity being in category 4-6 this effect was affected by park location (Table 4-24).

Table 4-24: Effects test of nominal logistic regression for the likelihood fire intensity categories.

SOURCE	*df*	*L-R* χ^2	*p*
Park	2	1921.05	<.0001*
Scenario	1	91.97	<.0001*
Scenario * Park	2	71.63	<.0001*

*Significant at $p \leq 0.05$ level

Consistent with the previous odds ratios, the odds between CC and RED as well as between SIB and RED were significant ($p \leq .0001$, $p \leq .0001$) (Table 4-25). Both CC and SIB had a higher likelihood for category 4-6 fireline intensities than RED. However, between CC and SIB, neither park was more likely as their odds ratio was insignificant ($p = 0.388$). For the mitigation scenarios, the untreated landscape had a higher likelihood for category 4-6 fireline intensities ($p \leq .0001$) (Table 4-25).

Table 4-25: Odds ratios details for fire intensity categories with odds of 4-6 vs. 1-3 for the untreated vs. treated mitigation scenarios. Odds ratios that were greater than one meant that the level one effect was that many times more likely to have category 4-6 fireline intensities.

Odds Ratios					
Odds Ratios for Park					
Level 1	*Level 2*	*Odds Ratio*	*p*	*Lower 95%*	*Upper 95%*
RED	CC	0.32	<.0001*	0.29	0.36
SIB	CC	0.96	0.388	0.87	1.06
SIB	RED	2.95	<.0001*	2.80	3.10
CC	RED	3.08	<.0001*	2.79	3.39
CC	SIB	1.04	0.388	0.95	1.15
RED	SIB	0.34	<.0001*	0.32	0.36
Odds Ratios for Scenario					
Treated	Untreated	0.71	<.0001*	0.66	0.76
Untreated	Treated	1.40	<.0001*	1.31	1.50

*Significant at $p \leq .05$ level

4.3.3.2 Nominal Logistic Regression for Percentage

The two main effects and the interaction between scenario and park were significant ($p \leq .0001$, $p \leq .0001$) (Table 4-26). As with the previous effects test, though the scenario affected the percentage of category 4-6 fireline intensity this was dependent the park (Table 4-26).

Table 4-26: Nominal logistic regression effects test for the estimated percentage of fireline intensity categories for the untreated vs. treated scenario.

SOURCE	*df*	*Wald* χ^2	*p*
Park	2	1865.52	<.0001*
Scenario	1	90.48	<.0001*
Scenario * Park	2	70.35	<.0001*

*Significant at $p \leq .05$ level

When comparing the percentage for category 4-6 fireline intensities in the untreated landscape versus the treated landscape CC and RED displayed a reduction in percentage whereas SIB showed an increase in percentage (Figure 4-18). The percentage of category 4-6 in CC reduced by 21.35% ($p \leq .0001$) and in RED it reduced by 2.43% ($p = 0.0009$) (Table 4-27). Despite SIB showing an increase in category 4-6 fireline intensities, this change was not significant (Table 3-28).

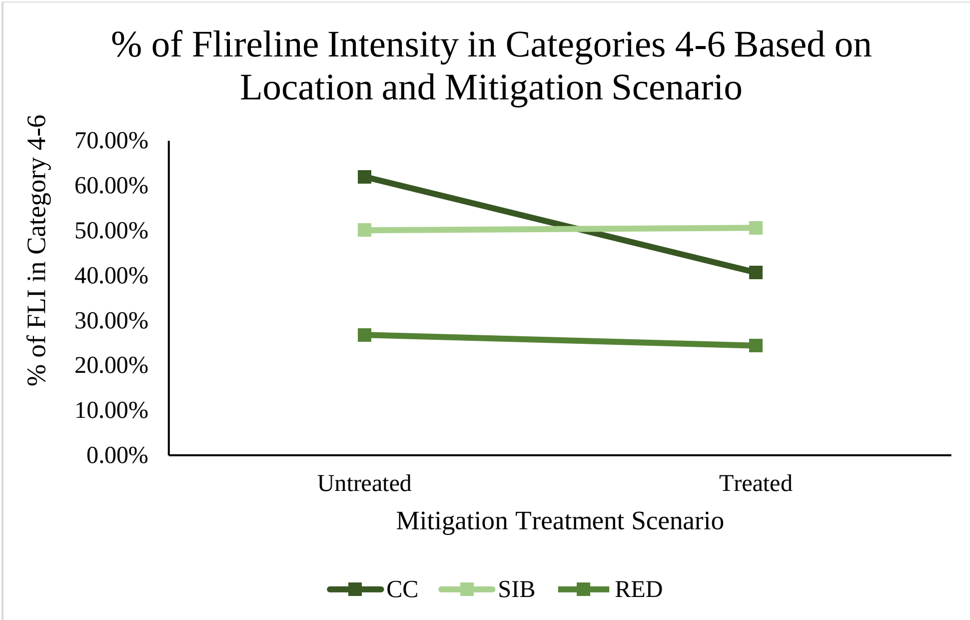

Fig. 4-18: The percent of modeled fire intensity instances within category 4-6, ≥ 1000 kW/m, for each mitigation treatment scenario, untreated vs. treated, in the three park locations.

Table 4-27: The estimated percentage of modeled fireline intensity in category 4-6 based on mitigation scenario and park location.

EFFECT	*Untreated %*	*Treated %*	*Adj p*
CC	62.05%	40.70%	<.0001*
SIB	50.08%	50.63%	1.000
RED	26.83%	24.40%	0.0009*

*Significant at $p \leq .05$ level

CHAPTER 5: DISCUSSION AND CONCLUSIONS

5.1 DISCUSSION

The purpose of this study was to understand how the fire hazard in the Oakland Hills has changed since the 1991 Tunnel Fire. The goal was to evaluate the change in fuel and fire behavior and the potential effect that mitigation actions may have on extreme fire behavior.

5.1.1 1991 vs. 2018 Fuel Assesment

Fuel models were used to understand the changes in fuel between 1991 and 2018. Fuel models can describe the fuel status of an area and correlate with fire behavior modeling (Polinova et al., 2019; Radke, 1995; Scott & Burgan, 2005; Xiao-rui et al., 2008). However, because there was no extensive fuel data for 1991, the conditions needed to be recreated with ariel imagery. Remote sensing and direct mapping allowed for the recreation of the historical fuel conditions and model present-day conditions (Fensham, Fairfax, Holman, & Whitehead, 2002; Keane et al., 2002; Polinova et al., 2019; Rollins, Keane, & Parsons, 2004). This technique can capture fuel changes on a local level which in turn better captures the local fire hazard (Keane et al., 2002; Xiao-rui et al., 2008).

In total, there were twenty-one of the forty-one standard fuels present across the three parks. Fuel is standardized and organized into seven fuel type categories that share burning characteristics (Scott & Burgan, 2005). Fuel is further classified into forty-one individual fuel models which are based on species characteristics and their potential fire behavior (Scott & Burgan, 2005; Xiao-rui et al., 2008). The majority of fuels within the project area fell into three fuel type categories grassland fuels, shrub fuels, and timber fuels. These fuels were predominately dry climate fuel models that varied from moderate to high fuel loading.

When comparing the 1991 fuel conditions to the 2018 fuel conditions only one fuel model showed a significant change in hectares. Meaning that the status of the remaining twenty fuels in 2018 was not significantly different from the fuel conditions in 1991. This is the fuel composition that allowed the Tunnel Fire to move quickly through parklands and then into homes (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; U.S Fire Adiministration, 1991). One fuel of concern was fuel model 189, Blue Gum Eucalyptus, *Eucalyptus globulus*, (LSA Associates Inc. & East Bay Regional Park District, 2010c, 2010b; Scott & Burgan, 2005) as it caused major firebrands in the Tunnel Fire Event (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; U.S Fire Adiministration, 1991). However, the amount of Eucalyptus hasn't significantly changed between the two years. And because they are originally part of a plantation, the stands are dense making it very easy for leaf and bark litter to build up in them, which are the primary carriers for fire in this fuel model (Agee, Wakimoto, Darley, & Biswell, 1973; Scott & Burgan, 2005). As the project is within a managed park system it is not surprising that there are not large-scale fuel changes. There also has not been a major disturbance event since the 1991 fire that would drive large-scale conversion (Calkin et al., 2015). However, the current fuel conditions are very similar to 1991, which present a potentially very high fire hazard for Oakland.

Though the majority of fuels were the same, one fuel did change, fuel model 147. This is a shrub fuel model that is classified as a very high load dry climate shrub (Scott & Burgan, 2005) and is very common in chaparral and coastal communities in WUI areas

(Syphard et al., 2007). Loading can be at a depth between 4-6ft and the rate of spread and flame length is high (Barro & Conard, 1991; Scott & Burgan, 2005). The primary carrier of fire for this fuel is the shrubs themselves and their litter (Barro & Conard, 1991; Davis, Keller, Parikh, & Florsheim, 1989; Keeley & Zedler, 1978; Scott & Burgan, 2005). In Oakland, fuel 147 is mostly comprised of Coyote Brush, *Baccharis pilularis* (LSA Associates Inc. & East Bay Regional Park District, 2010c, 2010b). It is a fuel that can produce very extreme fire behavior (Barro & Conard, 1991; Sun *et al.*, 2006). From 1991 to 2018, fuel model 147 was reduced by an average of 86 hectares, enough to be significant. Having a hazardous fuel reduction is a positive sign for Oakland. However, this reduction was detected based on the total project area. Differences based on individual park location were not able to be detected as there was only one fuel observation per location. It is also unknown what fuel replaced fuel 147. Therefore, further investigation is needed to determine where and why this fuel changed. Although, 147 changed the other twenty fuels remained the same, the fuel load that resulted in the 1991 Tunnel Fire is largely still present.

5.1.2 1991 vs. 2018 Fire Behavior

The Tunnel Fire exhibited extreme fire behavior and there is concern that if a fire occurred again, it would behave similarly as it did in 1991. In the original event, it took less than a half-hour for the rate of spread to become extreme and smoke inundation severe (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; Radke, 1995; U.S Fire Adiministration, 1991). The fire was considered to be a total loss of control within the first hour (U.S Fire Adiministration, 1991) Extreme fire behavior was observed with 30m flame lengths, winds pushing the rate of spread to extreme speeds, fire whirls, and embers tossed across the eight-lane freeway (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; Radke, 1995; U.S Fire Adiministration, 1991). The extreme nature of Tunnel Fire is why it was crucial to understand the current potential fire behavior and how it measured up to the past. Comparing the fire behavior from the Tunnel Fire to present conditions goes beyond standard fire history analysis common in fire hazard assessments. The values this type of analysis is it does more than simply establishing an area's fire hazard but rather contextualizes into a more digestible and interpretable manor. It can not only help determine the severity of the current fire hazard but also demonstrates the consistency of extreme fire behavior in the area. Thus, making the fire hazard easier to understand for managers and the public alike.

When the fire behavior between 1991 and 2018 was compared on a total landscape level, the fire behavior in 1991 was overall more extreme than the modeled fire behavior in 2018. Meaning that should fire occur with today's conditions it would not be as extreme as it was in 1991. However, this does not mean that there is no fire hazard in 2018 nor that a potential fire under today's conditions wouldn't exhibit extreme fire behavior. Currently, the project area is classified as a very high fire hazard severity zone by CAL FIRE (CAL FIRE, 2008). This was further supported by the results. The area is in a Mediterranean climate and under average weather conditions is not very fire-prone (Mitsopoulos et al., 2014), as all three fire behavior outputs had less than 40% occurrences in category 4-6. This trend was true for 1991 and 2018; though in 2018 the average weather scenario produced fewer instances of fire behavior in category 4-6. However, when fire behavior was modeled under extreme weather conditions both

1991 and 2018 spiked in the percentage of extreme fire behavior. Meaning that currently, the area still has the potential to host an extreme wildfire. It is important to note that while the extreme weather conditions are considered 97th percentile, weather conditions like this do occur in the area each year, in fact, the Tunnel Fire happened under this type of weather (California Office of Emergency Services, 1992; Ewell, 1995; Pagni, 1993; Radke, 1995; U.S Fire Adiministration, 1991). Therefore, while 2018 did not exhibit as extreme fire behavior as 1991, if ignition occurs during 97th percentile weather, extreme fire behavior is likely to happen and put the Oakland Hills community at risk.

When fire behavior was examined on the individual park scale it was more complex as fire in each park behaved differently. Of the three parks, the smallest park CC had the most notable fire behavior. In 1991 the Tunnel Fire originated from CC, where it gained speed and energy burning through eucalyptus and dense chaparral before moving into homes (California Office of Emergency Services, 1992; Ewell, 1995; U.S Fire Adiministration, 1991). As it stands CC had the highest fire hazard and exhibits the most extreme fire behavior. CC had the highest percent occurrence of category 4-6 fire behavior for flame length, rate of spread, and fireline intensity. This was true for 1991 and 2018. But the percentage of category 4-6 instances did decrease when going from 1991 to 2018. It's important to note, that despite this decrease in percentage, in 2018 59%-60% of fire behavior was still in category 4-6. The decrease in extreme fire behavior was not enough to lower the majority of fire occurrences below the extreme category. This is concerning as this park was the origin point of the Tunnel Fire and it is still capable of producing extreme fire behavior. If a fire happens in CC under the current conditions, it would likely produce very extreme flame lengths, rate of spread, and fireline intensity and may be very difficult to stop.

The second-largest park SIB had the second-highest extreme fire behavior. The Tunnel Fire only burned into the edge of SIB (California Office of Emergency Services, 1992; U.S Fire Adiministration, 1991). However, this does not mean an ignition could not occur here nor that a fire couldn’t spread to the park. The fire behavior in SIB was more varied than the other parks; fire behavior in CC was overwhelmingly extreme and in RED it was consistently low. The rate of spread and fireline intensity followed similar trends in SIB. Both outputs decreased in extreme fire behavior from 1991 to 2018. Though there was a decrease, in 2018 extreme fire behavior was still over 50%. However, flame length in SIB behaved very differently from the other parks. It is not unusual that SIB had different trends in fire behavior when comparing the years. Fuel models can produce fire behavior that is more extreme in one behavioral output than others (Albini, Anderson, & Anderson, 1982; Scott & Burgan, 2005). It is also possible for fire models to only exhibit extreme fire behavior when the specific weather conditions are met (Albini et al., 1982; Scott & Burgan, 2005). Under the average weather scenario, SIB followed the trend of minimal extreme fire behavior that further decreased in 2018. However, when the extreme weather scenario was applied extreme fire behavior jumped from 23% in 1991 to 57% in 2018. This was a significant jump in extreme fire behavior and shows that SIB has gotten more hazardous than it was in 1991. Further investigation into SIB and how it changed after 1991 may shed light on why there was a spike in extreme fire behavior.

Though RED is the largest of the three parks with the lowest fire hazard. In 1991 the fire did not reach RED (California Office of Emergency Services, 1992; LSA Associates Inc. & East Bay Regional Park District, 2010a; U.S Fire Adiministration, 1991). In the model, RED ranked last for likelihood of extreme fire behavior and had the lowest occurrences of category 4-6 fire. As with the previous parks, this was true for the 1991 fire behavior models and 2018 fire behavior models. In 1991 all three fire behavior outputs only had about 30% occurrence in category 4-6, which further dropped to around 20% in 2018. If a fire ignited today under "red flag" fire weather the majority of fire behavior in RED would fall in the low to moderate range. A potential reason why fire behavior is so much lower in RED was that the fuel in RED consists predominately of Redwood (*Sequoia sempervirens*) and Coast Live Oak (*Quercus agrifolia*) which are encompassed by fuel model 182. Fuel model 182 is a timber fuel model that typically has low to moderate fire behavior (Holmes et al., 2008; Scott & Burgan, 2005). Nevertheless, this does not mean it cannot be hazardous. The Basin Complex, the Soberanes Fire, and the CZU Lighting Complex had similar fuel composition to RED yet exhibited extreme fire behavior (CAL FIRE, 2021; Morris, 2020; Varner & Jules, 2016). It is also important to consider that while RED was the largest park and fire behavior tended to be very low, some locations did produce very extreme fire behavior, such as the lower park arm (Figure 4-4. 4-7, 4-10). It is possible that the effect of extreme fire behavior was masked by the large park area and if the park had been smaller it may have impacted the model more.

However, it is important to note that fire behavior was modeled based on conditions specific to the project area, so caution must be taken when interpreting fire behavior outside the project parameters.

5.1.3 Mitigation Assessment

Mitigation can be used to lower fire hazards in an area by reducing extreme fire behavior via fuel modification (Ager et al., 2010; Charnley et al., 2015; B. M. Collins et al., 2010; Finney et al., 2007; Safford et al., 2009; Toman et al., 2011; Vaillant et al., 2013). This is done by altering the fuel arrangement and reducing fuel loads to change how fire burns on a landscape (M A Cochrane et al., 2012; Mark A Cochrane et al., 2011; Safford et al., 2009; Vaillant et al., 2013). To have significant lasting effect mitigation needs to have occurred on 20-30% of the landscape (M A Cochrane et al., 2012; B. M. Collins et al., 2010; Finney et al., 2007). After the Tunnel Fire, the EBRPD started creating their Wildfire Hazard Reduction and Resource Management Plan (LSA Associates Inc. & East Bay Regional Park District, 2010a). The plan sets clear vegetation management goals and mitigation actions to reduce the hazardous conditions that caused the 1991 Tunnel Fire. Prescribed fuel treatments are predominantly mechanical and hand treatments with prescribed fires in only a few locations (LSA Associates Inc. & East Bay Regional Park District, 2010e). In total the proposed treatments would affect 15.53% of the project area. Under the best-case scenario, where all mitigation was completed and operating at peak effectiveness, the EBRPD mitigation plan would affect extreme fire behavior. After mitigation was modeled all three fire behavior outputs produced less extreme fire behavior on a landscape level. Meaning that if the EBRPD can successfully implement their plan it can significantly affect the current wildfire hazard in the Oakland

Hills. However, this effect was seen when all mitigation was completed and it was hard to say when that would be achieved and how long the impacts would last. Independently the actions may not be enough to lower the fire hazard.

When mitigation was examined on the landscape level the impact to fire behavior was clear; however, when the three parks were considered independently each park was impacted differently. The effect mitigation treatment can have will vary based on the landscape, fuel load, and treatment goals (Mark A Cochrane et al., 2011). The same treatment could be carried out in three different locations and produce three very different effects. (Mark A Cochrane et al., 2011). CC only makes up a small amount of the project area; however, of the three parks, it has the highest percentage of mitigation. 75.37% of the land in CC is allocated to wildfire mitigation. Treatment at this level has the potential to last for many years (M A Cochrane et al., 2012; B. M. Collins et al., 2010; Finney et al., 2007) and may also reduce severity and intensity outside the treatment zones (M A Cochrane et al., 2012). This amount of mitigation is consistent with CC having the highest fire hazard and where the Tunnel Fire started (California Office of Emergency Services, 1992; Ewell, 1995; U.S Fire Adiministration, 1991). The mitigation prescribed to CC focuses on addressing the Eucalyptus grove and the chaparral density (LSA Associates Inc. & East Bay Regional Park District, 2010e). When this was modeled mitigation had a large effect on fire behavior. All fire behavior outputs saw a significant reduction in extreme fire behavior post-treatment. In the untreated conditions over 55% of fire behavior were classified as extreme. However, in the treatment scenario, extreme fire behavior dropped to below 45% for the three outputs. The proposed treatment actions were able to lower extreme fire behavior for flame length, rate of spread, and fireline intensity by 20%. If all the treatment are able to be carried out in CC it would be successful in lowering the fire hazard, but maybe not as low as the desired management goals.

RED is the largest park in the project area, has the lowest fire hazard, and the least amount of prescribed mitigation. Only about 8.59% of the park area has planned mitigation. This mitigation was able to lower the extreme fire behavior in the park to below 25% for flame length and fireline intensity. Although there was a significant reduction, in the untreated scenario extreme fire behavior was already below 30% for those outputs. The rate of spread was not significantly altered in the treated scenario. There was the same level of extreme rate of spread in the untreated conditions and the treated conditions. The effect mitigation can have on fire behavior is not unilateral, treatments can be focused only affect certain aspects of fire behavior (M A Cochrane et al., 2012). The recommended treatment for RED is mostly concentrated on the northwest border where a Eucalyptus grove exists (Figure 3-3). The lower arm of RED has a concentration of extreme fire behavior (Figure 3-3) but there is only one small recommended treatment. This is a potential issue as there are homes near this section of the park. Because the original plan was created in 2010 it is possible that now the recommended treatment is misaligned with the current fire hazard.

The recommended mitigation was least effective in SIB. Under the mitigation plan, only 15.78% of SIB is prescribed fuel treatment, despite SIB having the second-highest fire hazard. Under the recommended treatment plan only flame length was reduced. Though there was a significant reduction in extreme flame length it remained above 50%. Meaning that more than half of the modeled flame lengths were still in the extreme category despite treatment. Furthermore, the proposed treatments did not have enough of a significant impact on the amount of extreme rate of spread and fireline intensity. Overall, there was still a large percentage of fire behavior that was classified as extreme despite fuel modification. The EBRPD fuel treatment recommendations are based on original fuel mapping and subsequent fire modeling that occurred in 2010 (LSA Associates Inc. & East Bay Regional Park District, 2010b, 2010c). Because it has been over ten years since the original recommendation, at that time these actions may have been appropriate however, currently the treatments no longer match the present conditions. Since the fire behavior in SIB has increased in extremity fuel modification for the park should be evaluated. Not addressing the change in conditions for SIB have the potential to be detrimental.

5.1.4 Project Limitations

Though the project sheds light on valuable information it is not without limitations. One limitation is the it was not able to determine causation between fuel and fire behavior. However, a relationship between the two can be inferred as fuel was only input to change whereas all other model inputs remained constant. Additionally, fuel models are standardized and directly correlate to specific fire behavior responses. Secondly, it was not possible to establish differences based on fuel and location. There was only one fuel model observation per location, which was not enough to capture localized fuel changes. And while this was not the level of observation that the project focused on, it is a future area for further analysis. Thirdly, the effect mitigation can have on fire behavior is something that is still trying to be understood. While the short-term impacts are well established, long-term studies are limited (Vaillant et al., 2013). Though modeled mitigation was able to affect fire behavior on the project site it is not clear how long this effect would last. This effect is dependent on all the recommended treatments having been achieved and it is unknown when this goal would be reached. Finally, the study did not address social dynamics of fire hazards. Fire hazards are not just a biophysical issue but a social one as well. This is an area for further research.

5.2 AREAS FOR FURTHER RESEARCH

This thesis focused on the biophysical dynamics of fire hazards, fuel and fire behavior. While the study was able to examine how a fire hazard changed in a given locality it did not examine the perspective of residents in the Oakland Hills. Future research is needed to understand how resident of WUI areas with significant fire history measure fire hazards in comparison to land managers and fire professional. Understanding this dynamic may not only shed light on gaps between resident and professional fire hazards assessment but also provide insight on steps to be taken to close said gaps.

5.3 CONCLUSIONS

The 1991 Tunnel Fire opened eyes to the dangers and hazards in urban WUI areas. In Oakland, this is a hazard that continues to persist. However, it is a hazard that has changed. Although today's landscape still largely reflects the condition that existed before the Tunnel Fire there was a reduction in hazardous fuels. There was also a change in extreme fire behavior that overall resulted in less extreme occurrences; however, not to the point in which the fire hazard disappeared. Currently, there is a very real fire hazard across the landscape especially in CC and SIB. If the EBRPD mitigation plan is fully carried out the fire hazard can be lowered to a more manageable level with reservations.

The plan addresses the overall fire hazard and the hazard in CC it is not equally as effective on the other parks. While action needs to be taken it also needs to be ensured the prescription fits the landscape, and reevaluation may be necessary for certain areas. In conclusion, if ignition occurs in the Oakland Hills today it will likely burn; but management actions can be taken to avoid or minimize another disaster in this wildland urban interface.

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PUBLICATION PLANS

After final approval I will submit the entirety my thesis to the Cal Poly Digital Commons in the Kennedy Library. Within sixth months of completing my master's program I will initiate the publication process. I plan on submitting a manuscript of my thesis to a special issue of the scientific journal *Fire*. The special issue is "Wildfire Hazard and Risk Assessment" and I believe my research will be a good fit for this issue.

APPENDIX

Table A-1: RTA details describing the location, proposed action, current vegetation, goal vegetation, and new fuel. For the park, CC is Claremont Canyon Preserve; SIB is Sibley Volcanic Preserve, and RED is Redwood Preserve.

RTA	PARK	PROPOSED ACTION	CURRENT VEGITATION	GOAL VEGETATION	NEW FUEL
CC001	CC	Thin eucalyptus, remove pines, mechanical treatment, 50%-70% brush reduction, remove dead trees, herbicide	Eucalyptus Forest/Plantation Oak-Bay Woodland Coastal Scrub California Annual Grassland Coyote Brush Scrub	Open Eucalyptus Oak-Bay Woodland Patches of Scrub Grass Buffers	161 182 122 104
CC002	CC	Grazing & mowing	Annual Grassland Oak-Bay Woodland Coyote Brush	Annual Grassland North Coastal Scrub Oak-Bay Woodland	104 142 182
CC003	CC	Grazing, mowing, pile/burn, limbing, & tree removal (pines under 24" DBH, eucalyptus, cypress & invasive species	Coastal Scrub California Annual Grassland Broom Scrub Coyote Brush Eucalyptus Plantation	Perennial Grassland Annual Grassland Oak-Bay Woodland	104 182
CC004	CC	Thin eucalyptus & eventually remove, plant native understory, thin understory, & remove 1/3 of bay trees	Eucalyptus Forest/Plantation	Easter Half Grassland and Oak-Bay Western Half Oak-Bay (Closed Canopy)	122 182
CC005	CC	Reduce shrubs, remove debris, limb up trees	Eucalyptus Forest/Plantation	Northern Coastal Scrub Oak Woodland	142 182
CC006	CC	Grazing & limb up trees	Oak-Bay Woodland Coastal Scrub	Oak-Bay Woodland with Little Understory	182 122

				Grass with Scattered/Low-Volume Shrub	
CC007	CC	Grazing, herbicide, mowing, hand labor, & pile/burn	Coastal Scrub, California Annual Grassland	Perennial Grassland Annual Grassland	104
CC008	CC	Reduce fuels by Gelston structure, mowing, herbicide, grazing, & pile/burn	Oak-Bay Woodland Developed Coyote Brush Scrub Coastal Scrub Eucalyptus Forest/Plantation	Landscaping Scrub & Oak Woodland Reduced Understory	93 141 182
CC09	CC	Mowing (only plants that can cure), possible prescribe burn, & mechanical treatment	Coastal Scrub Oak-Bay Woodland Coyote Brush California Annual Grassland Non-Native Coniferous Forest	Young North Coastal Scrub Oak Woodland, Annual Grassland Non-Native Coniferous Forest, North Coastal Scrub	141 182 104 184 142
CC010	CC	Invasive plant concern, grazing, mechanical treatment, hand treatment, understory & scrub reduction, limbing, & remove 2/3 small bays & 1/3 medium trees	Oak-Bay Woodland Coyote Brush Eucalyptus Forest/Plantation Coastal Scrub	North Coastal Scrub Oak Woodland Eucalyptus Forest	142 182 182
CC011	CC	Lower priority, concern for spreading broom, & potential prescribed burn	Coastal Scrub Coyote Brush Oak-Bay Woodland	Grass, Component If Non-Native Weed Oak Woodland	104 141 182

CC012	CC	Invasive concern, understory shrub removal, young pine removal, weak pine removal, limited mechanical treatment, maintain adjacent fuel break, grazing &/or hand labor	Oak-Bay Woodland Non-Native Coniferous Forest Coyote Brush	Oak-Bay Woodland Monterey Pine with Sparse Understory	142 183
SR001	SIB	Removal of understory shrubs, young pine removal, limbing mature pines, remove hazardous pines, limit mechanical treatment, maintain fuel break adjacent to private land, grazing &/or hand labor	Oak-Bay Woodland Non-Native Coniferous Forest Coyote Brush	Oak-Bay Woodland, Monterey Pine with Sparse Understory	182 181
SR002a	SIB	All treatment methods possible, remove all eucalyptus & reduce shrubby fuels	Eucalyptus Forest/Plantation Oak-Bay Woodland Coastal Scrub Broom Scrub Coyote Brush Scrub	Oak-Bay Woodland Scattered North Coastal Scrub	182 141
SR002b	SIB	All treatment methods possible, remove all eucalyptus & reduce shrubby fuels	Eucalyptus Forest Broom Scrub California Annual Grassland Oak-Bay Woodland Coastal Scrub	Oak-Bay Woodland Scattered North Coastal Scrub	182 141
SR003	SIB	Reduction of surface fuels by shortening grass and keeping scrubs less than 3% cover, all treatment methods suitable	California Annual Grassland	Annual Grassland Scattered North Coastal Scrub	104 141
SR004	SIB	Reduce surface fuels along the ridgeline, reduce ladder fuels, heavily thin pines & eucalyptus, remove young eucalyptus & pines, reduce brush by 50%-70%, treat eucalyptus	Oak-Bay Woodland Coyote Brush Eucalyptus Forest/Plantation Non-Native Pine	Oak-Bay Woodland Scattered North Coastal Scrub Annual Grassland	182 141 104

		& acacia with herbicide, pile/burn, limbing, remove dead/dying trees, & treat brush areas with herbicide			
SR005	SIB	Remove eucalyptus & pine within 100ft of the ridgeline, remove hazardous trees along roads/trails, pine trees/plants around pallid manzanita, & defensible space around private land	Oak-Bay Woodland Non-Native Coniferous Forest Coyote Brush Coastal Scrub California Annual Grassland Riparian Woodland Developed Coastal Scrub	Oak-Bay Woodland Scattered North Coastal Scrub Annual Grassland Riparian Woodland	182 141 104 182
SR006	SIB	Create defensible space around communication tower, thin eucalyptus to 25ft spacing, remove trees above well-developed oak-bay woodland, remove smaller trees, surface fuel reduction under retained trees, prune trees, mechanical treatment for tree removal & all other treatments for surface fuels	Eucalyptus Forest/Plantation	Thinned Eucalyptus Monterey Pine Oak-Bay Woodland Scattered North Coastal Scrub	182 184 182 141
SR007	SIB	Reduce shrubs beneath eucalyptus by grazing & tree spacing precludes mechanical	Eucalyptus Forest/Plantation	Red-Gum Eucalyptus with Sparse Understory	182
HP001	SIB	Erosion control measures for mechanical treatment, remove all eucalyptus within 100ft of the ridgeline, thin trees below the ridgeline to 25ft spacing, prune all remaining trees, & empathize surface fuel reduction	Eucalyptus Forest/Plantation	Oak-Bay Woodland Near the Road Thinned Eucalyptus	182

HP002	SIB	The presence of Pallid Manzanita requires hand labor, remove non-native shrubs, & pile/burn	Oak-Bay Wood Northern Maritime Chaparral Pallid Manzanita	Oak-Bay Woodland Pallid Manzanita Scattered North Coastal Scrub	182 147 141
HP003	SIB	The presence of Pallid Manzanita requires hand labor, remove non-native shrubs, & pile/burn	Northern Maritime Chaparral Pallid Manzanita	Oak-Bay Woodland Pallid Manzanita Scattered North Coastal Scrub	182 147 141
HP004	SIB	The presence of Pallid Manzanita requires hand labor, remove non-native shrubs, & pile/burn	Oak-Bay Woodland, Coastal Scrub, Pallid Manzanita	Oak-Bay Woodland Pallid Manzanita Scattered North Coastal Scrub	182 147 141
RD001	RED	Historical fuels management, firefighter safety zone is a high priority, remove small/unhealthy pines, maintain low fuel load under Monterey Pines above Phillip's Loop, reduce coastal scrub, & remove all brooms, all treatment methods suitable	Non-Native Coniferous Forest Eucalyptus Forest California Annual Grassland Oak-Bay Woodland Coastal Scrub Broom Scrub Developed	Open Monterey Pine Grassland Scattered Shrubs Annual Grass	182 122 104
RD002	RED	Additional mitigation measures needed due to slope, remove all eucalyptus within 100ft of the ridgeline, thin trees below the ridgeline, selectively remove trees around developed oak-bay woodland, prune remaining trees, & reduce surface fuel loads	Eucalyptus Forest Plantation	Oak-Bay Woodland Near the Road Thinned Red Gum Below	182 182
RD003	RED	Lower priority, reduce shrubs beneath eucalyptus via grazing, not	Eucalyptus Forest Riparian Woodland Coyote Brush	Red-Gum Eucalyptus with A Sparse Understory	182 182

		conducive to mechanical treatment or hand labor	Oak-Bay Woodland Redwood Forest Developed	Oak-Bay Woodland	
RD004	RED	A long history of treatment, reduce surface fuel load, all treatments suitable, remove eucalyptus sprouts, remove broom, enhance conditions for Oakland Star Tulip and Western Leatherwood	Non-Native Coniferous Forest Oak-Bay Woodland California Annual Grassland Coyote Brush Developed Eucalyptus Forest	Annual Grassland Scattered Monterey Pine Oak-Bay Woodland	104 183 182
RD005a	RED	Installation of a firefighter safety zone, remove all eucalyptus trees, & brush removal	Eucalyptus Forest	Annual Grassland	102
RD005b	RED	High priority is to create defensible space around Chabot Space & Science Center, remove all structurally unsound pine trees, prune all remaining trees, remove shrubs under tres, consider removing young pines & keeping shrub cover to <30%	Non-Native Coniferous Forest Developed Redwood Forest Coyote Brush California Annual Grassland Oak-Bay Woodland	Scattered Monterey Pine Oak-Bay Woodland Annual Grassland Redwood Landscaping	183 182 104 181
RD006	RED	Recommend creating/maintain defensible space around the recreational facility	Oak-Bay Woodland Redwood Forest Developed	Redwood Forest Oak-Bay Woodland Landscaping	182 182 93
RD007	RED	Installation of a firefighter safety zone, remove all eucalyptus trees, & brush removal	Eucalyptus Forest	Annual Grassland	102
RD008	RED	Creating/maintain defensible space around Trudeau Center, coordinate treatments with Serpentine Pirerae Restoration Project, hand labor, low-fuel landscaping, remove trees incompatible with serpentine prairie,	Coyote Brush Scrub Developed Non-Native Coniferous Forest Serpentine Bunchgrass	Perennial Grassland Landscaping Scattered Northern Coastal Scrub Pines	104 93 141 104

		prescribed burns as feasible, & enhance conditions for Presidio Clarkia		Resorted Serpentine Bunchgrass	
RD009	RED	Creating/maintain defensible space around the fire station & Piedmont Stables is a high priority, remove coyote brush to restore annual grassland within 200ft of structures, remove all shrubs/small trees under eucalyptus/oak-bay trees, pine trees to 8ft, & thin eucalyptus grove of smaller trees	Eucalyptus Forest/Plantation Developed Coastal Scrub Oak-Bay Woodland	Oak-Bay Woodland Near The Road Perennial Grassland Annual Grassland	182, 104 161
RD010	RED	Installation of the firefighter safety zone with mechanical treatment	Oak-Bay Woodland Non-Native Coniferous Forest Developed Eucalyptus Redwood Forest	Annual Grassland	104
RD011	RED	Installation of the firefighter safety zone	Coastal Scrub	Annual Grassland	104